REPUBLIC OF TURKEY

ADANA ALPARSLAN TÜRKEŞ SCIENCE AND TECHNOLOGY UNIVERSITY

GRADUATE SCHOOL OF ENGINEERING

DEPARTMENT OF INDUSTRY ENGINEERING

CHARGING STATION PLACEMENT FOR ELECTRIC VEHICLES BY USING FAHP AND K-MEANS CLUSTERING

KÜBRA OKTA

MASTER OF SCIENCE

ADANA 2024

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SUPERVISOR

PROF. DR. MUSTAFA GÖÇKEN

ADANA 2024

CERTIFICATION OF APPROVAL

(CHARGING STATION PLACEMENT FOR ELECTRIC VEHICLES BY USING FAHP AND K-MEANS CLUSTERING)

This **M.Sc.** thesis, **completed under the conditions determined by the relevant regulations**, by **[Kübra OKTA] with student number** [20800701001] in **Adana Alparslan Türkeş Science and Technology University Institute of Graduate School** Indistrual Engineering **Department**, has been evaluated by the following academic committee, and approved in accordance with the relevant articles of the "Adana Alparslan Türkeş Science and Technology University Graduate Education Regulations".

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22/04/2024

DECLARATION OF CONFORMITY

In this thesis study, which was prepared following the thesis writing rules of Adana Alparslan Türkeş Science and Technology University Institute of Graduate School, I declare that I provide all the information, documents, evaluations and results in accordance with scientific ethics and moral codes without resorting to any means or assistance that would be contrary to scientific ethics and traditions. I also declare that I refer to all of the articles I used in this study with appropriate references and accept all moral and legal consequences if a situation is found contrary to my statement regarding my work.

22/04/2024

Kübra OKTA

ABSTRACT

CHARGING STATION PLACEMENT FOR ELECTRIC VEHICLES BY USING FAHP AND K-MEANS CLUSTERING

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In recent years, a rapid increase has been observed in the number of vehicles in traffic, as well as the spread of harmful gases released from vehicles. As problems such as air pollution and global warming increase, especially in metropolises, it has become almost imperative to increase and develop the use of renewable energy resources instead of using fossil fuels. In order to reduce this air pollution and the damage it causes to nature, studies are carried out to reduce gas emissions, and studies are directed towards the development of electric vehicles. Most of these studies emphasize that electric vehicles demonstrate an environmentally friendly approach and enhance quality of life.

With the increasing use of electric vehicles both in Türkiye and worldwide, the problem of finding easily accessible charging stations on the road has become apparent. Several criteria are considered in determining the optimal locations for the installation of charging stations. In this study, seven different districts of Istanbul were considered, and the importance levels of criteria and alternatives were determined using the Fuzzy Analytic Hierarchy Process (FAHP) method to identify the most suitable locations for charging stations. Finally, optimal locations were selected by clustering among the candidate locations in the selected districts. This study represents a comprehensive approach using Multi-Criteria Decision-Making (MCDM) and K-means techniques to determine the locations of electric vehicle charging stations.

Keywords: electric vehicle, charging stations, fuzzy analytic hierarchy process (FAHP), K-means clustering, multi-criteria decision-making methods (MCDM)

ÖZET

BAHP VE K-MEANS KÜMELEME KULLANILARAK ELEKTRİKLİ ARAÇLAR İÇİN ŞARJ İSTASYONU YERLEŞİMİ

Kübra OKTA
Endüstri Mühendisliği Anabilim Dalı
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İkinci Danışman: Doç. Dr. Aslı BORU İPEK
Nisan 2024, 84 sayfa

Son yıllarda, trafikteki araç sayısında hızlı bir artış gözlemlenmiş ve araçlardan salınan zararlı gazların yayılması da artmıştır. Hava kirliliği ve küresel ısınma gibi sorunlar özellikle metropollerde arttıkça, fosil yakıtların kullanımı yerine yenilenebilir enerji kaynaklarının kullanımını artırmak ve geliştirmek neredeyse kaçınılmaz hale gelmiştir. Oluşan hava kirliliğini ve doğaya verdiği zararı azaltmak için gaz emisyonlarının azaltılmasına yönelik çalışmalar yapılmakta ve elektrikli araçların geliştirilmesine yönelik çalışmalar yapılmaktadır. Bu çalışmaların çoğu elektrikli araçların çevre dostu bir yaklaşım sergilediğini ve yaşam kalitesini arttırdığını vurgulamaktadır.

Türkiye ve dünya genelinde elektrikli araçların giderek artan kullanımıyla birlikte, yolda kolayca erişilebilir şarj istasyonlarının bulunmaması sorunu ortaya çıkmıştır. Şarj istasyonlarının kurulması için en uygun konumların belirlenmesinde çeşitli kriterler dikkate alınmaktadır. Bu çalışmada, İstanbul'un 7 farklı ilçesi ele alınmış ve şarj istasyonlarının en uygun konumlarını belirlemek için Bulanık Analitik Hiyerarşi Süreci Yöntemi (BAHY) kullanılarak kriterlerin ve alternatiflerin önem düzeyleri belirlenmiştir. Son olarak, seçilen ilçedeki aday lokasyonlar arasında kümeleme ile küme merkezlerine en yakın optimal lokasyonlar belirlenmiştir. Bu çalışma, elektrikli araç şarj istasyonlarının yerlerini belirlemede Çok Kriterli Karar Verme (ÇKKV) ve K-means tekniklerinin kullanıldığı kapsamlı bir yaklaşımı temsil etmektedir.

Anahtar Kelimeler: elektrikli araç, şarj istasyonları, bulanık analitik hiyerarşi süreci yöntemi (BAHP), K-means kümeleme, çok kriterli karar verme yöntemleri (ÇKKV)

to my precious family

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NOMENCLATURE

EV	: Electric Vehicle
EVCS	: Electric Vehicle Charging Station
EPA	: Environmental Protection Agency
AC	: Alternating Current
DC	: Direct Current
IEC	: International Electrotechnical Commission
SAE	: Society of Automotive Engineers
AHP	: Analytic Hierarchy Process
FAHP	: Fuzzy Analytic Hierarchy Process
FCS	: Fixed Charging Stations
MCS	: Mobile Charging Stations
MC-IMS	: Mobile Charging Information Management System
CS	: Charging Stations
MCDM	: Multi-Criteria Decision Making
TLBO	: Teaching Learning Based Optimization
GIS	: Geographical Information Systems
EDS	: Electrical Distribution Systems
HOA	: Hybrid Optimization Algorithm
MINLP	: Mixed Integer Non-Linear Programming
ALNS	: Adaptive Large Neighborhood Search
CI	: Consistency Indicator
RI	: Random Indicator
EAM	: Extent Analysis Method

1. INTRODUCTION

Fluctuations in global gasoline prices, coupled with the environmental impact and high costs associated with gasoline vehicles, have led to a decline in interest in these vehicles over time. The concern over the greenhouse gas emissions produced by gasoline-powered vehicles has prompted both companies and individuals to increasingly consider electric vehicles (EVs) as an alternative. In recent years, the rise in greenhouse gas and carbon dioxide (CO_2) emissions worldwide has become a pressing environmental issue, causing significant damage each day. The continuous increase in CO_2 emissions poses a substantial and irreversible threat to the environment, necessitating urgent control measures. Failure to address this issue promptly will likely result in a gradual escalation of environmental pollution globally, leading to noticeable climate changes. Various natural and artificial factors contribute to the surge in CO_2 emissions, including transportation, electricity production, industrial activities, homes and workplaces, and agricultural and animal production, as outlined by National Geographic in (Environmental Protection Agency: Carbon Footprint Calculator, 2019). Notably, the transportation sector, encompassing vehicles, ships, trains, and planes, plays a pivotal role in contributing to high CO_2 emissions, especially for those utilizing fossil fuels, making it the highest-emitting category, according to the Environmental Protection Agency (EPA) in (2014). Electricity production stands as a major contributor to the increase in CO_2 emissions, ranking second only to transportation in elevating global carbon levels. The surge in global population and heightened production demands have intensified the requirement for electricity, leading to a growing reliance on fossil fuels over natural and renewable resources in the electricity generation process. The utilization of fossil fuels to meet the escalating electricity demands has resulted in a substantial increase in CO_2 emissions, posing significant environmental harm, as outlined by the Environmental Protection Agency (EPA) in (United States Environmental Protection Agency, 2014).

The production of electrical energy, which fuels EVs, results in carbon emissions. To reduce indirect carbon emissions from EVs, charging stations (CSs) should use renewable energy sources such as wind and solar power. However, current electric vehicle charging systems mostly rely on energy generated from fossil fuels. Figure 1.1 compares electric and conventional vehicles in terms of fuel. When generating electricity for an electric vehicle using standard methods, which involve a combination of fossil fuels and renewable resources, 23 tonnes of carbon dioxide are produced.

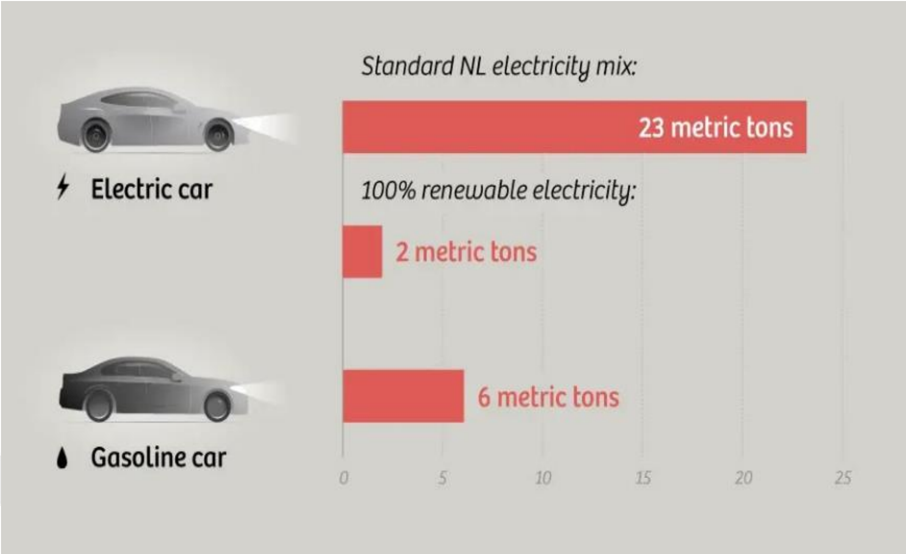

Figure 1.1. Carbon emissions during vehicle use (Doğan, 2020a).

However, if renewable resources are employed instead, the quantity decreases significantly to just 2 tonnes. Conversely, the production of fuels utilised by conventional vehicles, including gasoline, diesel, and LPG, results in an average of 6 tonnes of carbon dioxide being produced. Therefore, while EVs may offer a solution to reducing carbon emissions, they may not be the sole solution to humanity's carbon emission problem. This issue is not related to the structure of the vehicle, but rather to the production and power systems. While EVs do not emit carbon directly, their impact on reducing air pollution in crowded cities can be significant. For EVs to be considered truly zero-emission, the energy used to power them must come entirely from renewable sources, and no carbon emissions should be produced during vehicle production. As demonstrated in Figure 1.2, EVs produce fewer carbon emissions than conventional vehicles, even when indirect emissions are taken into account. However, several countries are increasing their use of renewable energy sources. In the future, renewable energy can be used in electric vehicle charging stations (EVCSs) to reduce the indirect carbon emissions caused by EVs. EVs emit around 30% less carbon than conventional vehicles, even under the worst conditions.

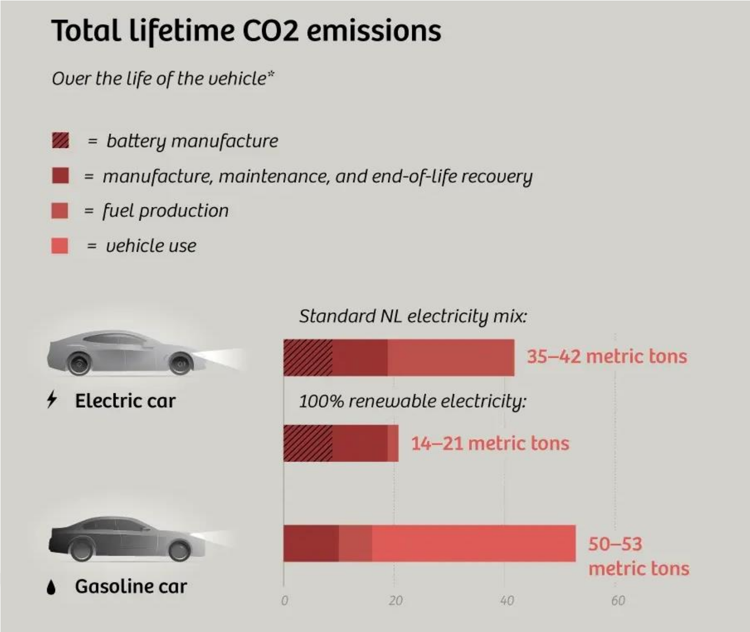

Figure 1.2. Total lifetime CO_2 emissions (Doğan, 2020b).

The use of EVs has been steadily growing as societies worldwide prioritize sustainability and seek cleaner alternatives to traditional internal combustion engine vehicles. EVs offer a significant reduction in greenhouse gas emissions, contributing to efforts to combat climate change. Beyond their environmental benefits, EVs also contribute to energy efficiency and resource conservation. Advancements in battery technology have improved the driving range of EVs, making them increasingly practical for daily use. Many individuals and businesses are recognizing the economic advantages of EVs, such as lower operating costs, reduced maintenance requirements, and potential incentives from governments promoting the adoption of green technologies. As charging infrastructure continues to expand, EVs become more accessible, alleviating concerns about range anxiety. From compact cars to sport utility vehicle (SUV)s and even commercial vehicles, the electric vehicle market encompasses a diverse range of options, appealing to a broad spectrum of consumers. Governments and industries worldwide are investing in research and development to further enhance the performance and affordability of EVs, anticipating a future where sustainable transportation becomes the norm, fostering a cleaner, greener, and more resilient mobility landscape.

1.1. History of Electric Vehicle

The history of EVs dates back to the 19th century. While they have become more popular in recent years, EVs have a long and fascinating history.

Early Experiments (19th Century):
The first experiments with EVs can be traced back to the early 19th century. In 1828, Hungarian engineer Ányos Jedlik created a small-scale model of a vehicle powered by a simple electric motor, as shown in Figure 1.3. It was a rudimentary design, and the technology was in its infancy.

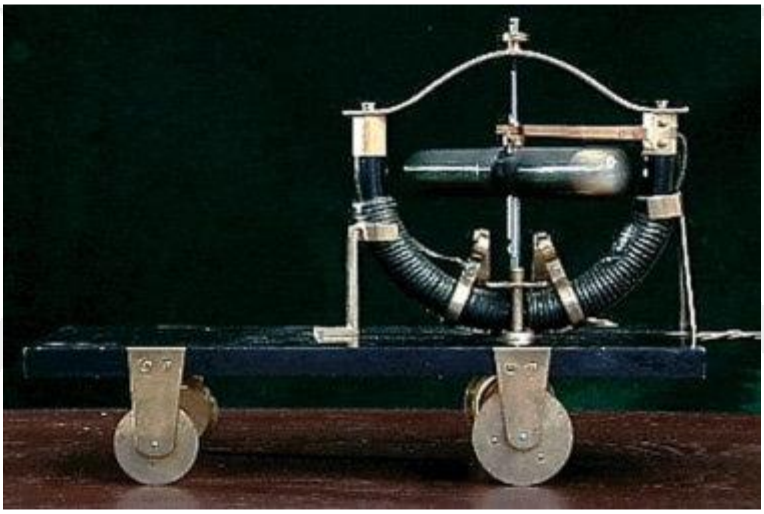

Figure 1.3. Early electric motor experimenter (Design and Fabrication of Motorised Vehicle, 1828).

First Practical Electric Car (Late 19th Century):
In the Netherlands, in 1835, Professor Straitingh created the first electric vehicle model ever. Following that, Robert Davidson created an electric locomotive in 1838 that had a top speed of 6.4 km/h (Chan, 2013). After 1859, lead-acid batteries were created and utilized in the first electric cars (Ünlü et al., 2003).

Growth of Electric Taxis (Late 19th Century):
Electric taxis became popular in major cities like New York and London in the late 19th century. These early EVs had a limited range but were well-suited for urban use. They were quiet and emitted no tailpipe emissions, making them an attractive option.

Electric Vehicle Advancements (Early 20th Century):
EVs continued to evolve in the early 20th century. In 1900, the Lohner-Porsche, one of the first hybrid electric cars, was developed by Ferdinand Porsche. It used a gasoline engine to generate electricity for the electric motors.

Challenges and Decline (Mid-20th Century):
The mid-20th century brought challenges for EVs. Gasoline-powered cars became dominant due to their greater range and the widespread availability of gasoline. EVs were largely used for niche applications like industrial trucks and forklifts.

Resurgence of Interest (Late 20th Century):
Concerns about pollution and oil dependence led to renewed interest in EVs in the late 20th century. Experimental EVs, including prototypes like GM's EV1, gained attention. However, many of these early efforts were not commercially successful.

Modern Electric Vehicle Era (21st Century):
The 21st century has seen a significant resurgence of EVs, driven by advancements in battery technology, environmental concerns, and government incentives. The introduction of the Tesla Roadster in 2008 marked a turning point, as it was one of the first EVs to offer a practical range.

Mainstream Adoption (2010s and beyond):
In the 2010s, EVs became increasingly mainstream. Numerous automakers introduced electric models, and advancements in battery technology improved range and affordability. Governments around the world introduced incentives to promote EV adoption.

Diverse EV Models and Infrastructure (Present):
Today, the electric vehicle market is diverse, with various models available, including electric cars, plug-in hybrids, electric buses, and commercial EVs. Charging infrastructure has expanded significantly, and there is a growing focus on sustainability and renewable energy sources for EVs.
Recent years have witnessed a rapid expansion in the EV market, driven by the desire for cleaner transportation and the development of advanced battery technology. This trend is

expected to continue as EVs play an increasingly important role in addressing environmental and energy challenges.

1.2. Electric Vehicle Charging Station (EVCS)

EVs are attracting increasing attention as an environmentally friendly and sustainable transportation alternative. However, their range limitations and long charging times are some of the main problems that users face in daily life and long-distance travel. The maximum distance that many EVs can travel on a single charge is still less than that of internal combustion engines. (Karapınar & Dalbakan, 2022). This necessitates advance planning and strategic placement of CSs for long distance travel. Therefore, the appropriate positioning and expansion of CSs is expected to significantly impact the safety and travel experience of EV users.

EV users may face long waiting times where charging infrastructure is inadequate or incomplete, which may negatively impact the user experience. This may limit the widespread acceptance and use of EVs. In this context, the importance of CSs is a decisive factor to promote the use of EVs and ensure the widespread adoption of sustainable transportation. The expansion and improvement of CSs should be considered as a strategic step towards reducing the environmental impact of EVs while promoting their easier acceptance by society. As a result, the availability and accessibility of EVCSs facilitates the daily use of these vehicles, while contributing to society's adoption of sustainable transportation. Therefore, it is crucial to develop and distribute a large number of CSs, such as the one shown in Figure 1.4, in order to ensure a more widespread and effective adoption of EV technology.

Figure 1.4. Electric vehicle charging (Babalık & Ayyıldız, 2022)

Types of Charging Stations:

Various options for charging EVs are available through different types of CSs. These options are classified as Level 1 (Alternating Current - AC), Level 2 (AC), and Level 3 (Fast Charging - DC) stations, based on the technological infrastructure used for charging EVs.

Table 1.1 provides essential parameters associated with each type of charging station, including voltage, amperage, charging capacity, and charging time. These parameters are important in determining the amount of energy and time required for users to charge their EVs. AC CSs are a suitable option for meeting daily charging needs, as they can be used similarly to standard electrical outlets found in homes or workplaces. In contrast, DC fast CSs are designed to support longer-distance travel and provide fast charging capability while on the move. These CSs provide users with greater flexibility by enabling faster battery charging, which facilitates longer trips. The choice between AC and DC CSs depends on various factors, such as user requirements, the technical specifications of the electric vehicle, and the availability of charging infrastructure. It is important to carefully consider this selection to meet users' daily charging needs and optimize travel plans. In this context, the variety of CSs offers electric vehicle users multiple charging options, thereby increasing convenience and flexibility.

Table 1.1. Types of charging stations (Brodd & Kristi, 2017)

CHARGING STATIONS	AC LEVEL ONE	AC LEVEL TWO	DC FAST CHARGE
VOLTAGE	120V 1-Phase AC	208V or 240V 1-Phase AC	208V or 480V 3-Phase AC
AMPS	12-16 Amps	12-80 Amps	>100 Amps
CHARGING LOAD	1.4-1.9 kW	2.5-19.2 kW	50-350 kW
CHARGING TIME	3-5 Miles per Hour	12-60 Miles per Hour	60-80 Miles in 20 min.

1.3. Future of Electric Vehicles

The global market for EVs has experienced a consistent and notable increase. Global EV sales have grown from 125 thousand in 2012 to 6.75 million in 2021. The environmental and economic advantages of EVs are evident, including the fact that they do not require fossil fuels for electricity generation and can run on renewable energy sources. In this context, countries are also taking significant steps in this regard. For instance, the United Kingdom has established a goal of eliminating the sale of conventional vehicles by 2040. Similarly, other countries, including Denmark and China, have made comparable commitments to achieve net zero emission targets (Pasha et al., 2024).

The advantages of EVs are becoming more pronounced as technology advances. In particular, the field of artificial intelligence (AI) plays a pivotal role in the advancement of EV technology, and it is a key enabler of sustainable development in line with the 21st century focus on energy conservation and environmental protection. The integration of AI-based systems into EVs not only enhances current traffic safety and road utilization, but also transforms them into aesthetically appealing consumer options. The applications of AI in EVs are numerous and far-reaching. Firstly, AI integrates driver assistance systems and autonomous driving features in a way that provides both comfort and safety for users. Furthermore, AI optimizes the charging processes, planning charging schedules and effectively managing energy consumption (Rauf et al., 2024).

In conclusion, the proliferation of EVs represents a promising future scenario in terms of its environmental impact, driving comfort, and the convenience it offers with the support of technology.

1.4. Research Objective and Contribution

The objective of this study is to determine the optimal locations for the siting of EVCSs. As with many siting problems in the literature, MCDM methods were used to identify these locations. Istanbul, the largest metropolitan city in Türkiye with the highest number of EVs, was chosen as the study area. Specific districts within Istanbul were considered as alternatives, and criteria were determined through a literature review and also expert opinions. The study area was narrowed down based on the prioritization of alternatives and criteria. In this study, the FAHP method, which is widely used in the literature for site selection problems, is applied. The reason for choosing FAHP is that it gives a more precise measurement result compared to AHP. The aim is to allow decision makers to prioritize using fuzzy numbers in order to obtain a more accurate result. It is observed that the number of criteria for the placement of EVCSs is relatively low in the literature. This study identified 4 main criteria, 16 sub-criteria and 7 alternatives. The most distinctive feature of this study, which sets it apart from others, is its broader evaluation framework. In order to determine the optimal candidate locations, existing points were clustered and cluster centres were identified. The points closest to these cluster centres were identified as the optimal candidate locations. The clustering of a particular area in the study shows areas of high station density and the suitability of charging infrastructure in these areas. The aim is to build new stations at these cluster centres to meet future demand in these regions. These candidate locations are typically found in areas such as shopping centres, residential areas, commercial plazas or institutional facilities that are frequented by people and where they spend a significant amount of time during the day.

The number of EVs is increasing both globally and in Türkiye, leading to a growing demand for CSs. This increase in demand may result in longer wait times and queues at CSs. The aim of this study is to mitigate potential issues such as long queues or wait times at future CSs. An increase in the number of CSs allows EV users to charge their vehicles without encountering any problems in crowded areas. Therefore, the accurate placement of Cs is of utmost importance. In this study, FAHP and K-means clustering methods were used to select candidate locations and determine optimal placements. The integration of the FAHP and K-means methods for EVCS placement aims to contribute to existing literature by providing insights into the determination of optimal candidate locations.

2. LITERATURE REVIEW

2.1. Electric Vehicle Charging Stations

Yang et al. (2013a) suggested that fixed charging stations (FCSs) and mobile charging stations (MCSs) have smart grid networks for charging EVs. In this study, a Mobile Charging Information Management System (MC-IMS) is presented, which combines the FCS network and information in the MCS network to reduce waiting times in FCS, and simulation experiments are performed to calculate the performance of this proposed IMS.

Yang (2013b) examined the EV charging problem and the waiting problem at stations. In the study, "local" and "global" CS-selection algorithms are defined for the Taiwan National Highway 1 route. There are 3 local CS selection algorithms: the closest CS, the randomly selected CS, and the longest CS. On-board unit (OBU) (GPS-based navigator) information is local; that is, it does not provide information about the waiting times of EV at stations. Therefore, global information should be integrated into OBUs. In the study, the performance of global and local selection algorithms was measured by a simulation experiment, and the global CS selection algorithm gave better results.

Qin (2011) addresses the problem of vehicle routing to fast CSs located at entry-exit points on a highway system. Each vehicle is charged at one of the stations located on the shortest route between the start and end points of the journey. EVs interact with CSs as well as with nearby EV. The vehicle gives information about its location, speed, charge status, destination, and route to a station it passes by. The stations transfer this information to each other and determine the station where the vehicle will wait the least. The EV receives the standby time information from the stations and provides the opportunity to select the desired charging station.

Shahraki (2015) conducted a case study to determine the optimal locations of public CSs for EVs in Beijing. A mathematical model was formulated over 40 existing stations. In order to test the model with real data, the movements of 11,880 taxis in the city were monitored for three weeks. The study indicates that the most favorable CSs are typically situated in proximity to the city centre. As the number of CSs increases, the optimal stations tend to expand towards the areas further away from the city centre. However, the benefit of each new CS decreases as the total number increases.

Additionally, the research suggests that an increase in CSs can lead to an increase in the total distance travelled by EVs and a reduction in traffic congestion. This study has contributed significantly to the effective planning of EV charging infrastructure.

Frade et al. (2011) calculated the day and night fuel demands of EVs in the neighborhood of Lisbon and performed regression analysis and created an optimization model for the positioning of CSs.

He (2019) used a new flow refueling location model (FRLM) to determine the optimum locations of US fast CSs for long-distance travel with EVs. Optimum positioning has been made for different station numbers, taking into account the average total cost of each station. In this study, very large-scale input data were used and data incorporates 90% of long-distance car travel nationwide.

Keskin (2016) proposed a model for partial charging of EVs in their study. A mathematical model was established to minimize the total energy cost by considering three types of chargers, normal, fast and super-fast with parameter values (Keskin & Çatay, 2018).

Ghamami (2013) aimed to choose battery size and charging capacity to minimize cost. This cost represents a measure of the sum of factors such as battery size, charging capacity, battery replacement, and charging station construction costs. The study also examined the impact of battery replacement and charging station construction costs on the overall cost.

Ghamami (2016) proposed a comprehensive corridor model to optimize the charging infrastructure for long-distance intercity travel. The model aimed to minimize the total system cost, including infrastructure investment, battery expenses, and user costs. Analyses underscored the significance of charging delay costs in the design of charging infrastructure and highlighted the cost-effectiveness of dense charging networks with smaller batteries.

Uimonen (2020) ensured that the maximum charging power of the chargers was adjusted with the help of simulation modeling, considering the charging times and the distribution of charging start times on weekends and weekdays. Data are collected from a university campus area in Finland. They also showed the mean values of successful charging events and stated that this mean value was in the 95% confidence interval.

EVLibSim is a Java library used to manage EV activities such as charging and discharging batteries while using energy from renewable sources, changing batteries, parking, determining the number and types of chargers. Rigas (2018) increased the efficiency of EVLibSim, tested it and evaluated the experience of the users.

Badea (2018) examined the possibility of using Romanian solar energy sources to provide energy support to an EV charging station. In this study, the solar system of the EV charging station can operate in an isolated mode using 100% renewable energy. They performed a simulation model assuming that the photovoltaic station is continuously charging at full capacity for one day.

Yazdekhasti (2021) studied EV charging station positioning in a real-life California highway network. First, they determined the traffic load of each region with the Monte Carlo simulation and determined the appropriate strategies for drivers and charging station users, taking into account the optimal location of the CSs, the optimal number of charging sockets at each station, and the minimization of costs. Moreover, along with the route selection policy, they conducted a study to support the use of spare batteries and drivers with different risk preferences to travel on intercity routes.

Gönül (2021) conducted a SWOT analysis (short for strengths, weaknesses, opportunities, threats) of EV in Türkiye, considering the current situation of EVs in the world and in the EU (European Union). Currently, the EVCS network is mainly located in the country's most populated cities such as Istanbul, Ankara, and Izmir. In the article they argue that the use of EVs in Türkiye should be encouraged.

Brenna (2017) measured the power in railway infrastructures and the power needed by CSs and a study was conducted to connect them. In the study, they showed that the amounts of power in the system match and it is possible to connect them with the help of simulation modeling. They showed how the power quality of railway systems is affected by EVCS.

Daşcıoğlu (2019) applied a mathematical model based on the flow-refueling location model to determine the placement of CSs for EVs in cities on the Anatolian side of Istanbul. An application was carried out on the Anatolian side of Istanbul to maximize the total flow rate calculated with the flow-refueling location model used as the solution methodology. The mathematical model was run for nine different p values and the most appropriate solutions were obtained. Electric charging stations and the roads captured by these stations were determined for different p values.

Güler (2019) conducted a study on the selection of CSs for EVs in the neighboring districts of Üsküdar, Kadıköy and Ataşehir. In the study, they weighted the criteria determined by using the FAHP. They presented a solution proposal with MCDM methods according to 4 different suitability indexes: population density, distance to transportation stations, distance to parking lots and slope.

Aydın (2018) mentioned the inadequacy of EVCS in Türkiye. The necessary design stages listed in 7 steps to solve this problem. The charging station drew attention to the importance of determining the most suitable parking lots.

Khaksari (2021) made decisions about the number and types of installed CSs to minimize the investment cost of CS operators. Considering smart charging capabilities for CS operators, they presented a methodology to increase service quality. Thus, they developed the CS sizing optimization model in the literature. At the end of the model, simulation was used and in line with the results, the infrastructure costs of smart charging were reduced by more than 50%.

Deb (2021) used the Chicken Swarm Optimization (CSO) and Teaching Learning Based Optimization algorithm (TLBO) hybrid algorithm for EVCS positioning and compared it with other hybrid algorithms. In the model, the objective function is set up to minimize the cost. In recent studies on charging station layout problems, the reliability of the power distribution network has been neglected. In the study, they considered its safe operation. The data obtained as a result of the study showed that the placed CSs can be applied to the real-world environment.

Goel et al. (2021) conducted to address the problem of insufficient charging facilities in EVs. The aim of this study is to examine why the interest in EVs is low in India and to increase and encourage interest in EVs. The public in India wanted to raise awareness about the advantages of EVs over fossil powered vehicles. The application area of the study is based on the developing country of India. The solution was to develop the new Vehicle-to-Grid concept, creating an extra power source when renewable energy sources are not available.

In Anwarzaia (2017), MCDM method and GIS were used for the installation of wind turbine and solar energy technology. The criteria are divided into 2 groups, the first is unsuitable areas (physical restrictions) and the second is areas suitable for some conditions. Eligible areas are also divided into 2 groups; including the selection by location tool and the selection by attribute tool.

Arias (2017) investigated electrical distribution systems (EDS). In the study, 3 metaheuristic optimization technique was used. These are taboo search, grasp and Hybrid Optimization Algorithm (HOA). The aim function has been determined to minimize the total operating cost of EDS. A 449-node distribution system has been established. The results of these 3 methods were then compared and the best result is achieved using HOA method.

The problem in García-Álvarez (2018) is that the arrival times and charging times of the vehicles in the real environment are not known in advance. They are discussed under two headings: static and dynamic problems. As a method, GRASP (Given, Required, Analysis, Solution, and Paraphrase) and Memetic algorithms were used to plan charging times. Three scenarios were determined related to a real-life application, and in the first scenario, it was assumed that the vehicles came to the stations every day (a normal weekly day), and in the 2nd and 3rd scenarios, it was assumed that the vehicles came to the stations. The vehicles arrived at the stations at the same time. 3 lines were determined and 180 vehicles were shared. (The power consumed by the 3 lines should always be balanced.) It has been seen that the static problem gives better results with the applied metaheuristic methods.

Jordán (2022) focuses on the strategic placement of EVCSs in Valencia, Spain. Through experiments conducted using a simulation model with real data, the necessity of having an adequate number of CSs distributed throughout the city is highlighted. The best solution, determined through a genetic algorithm, involves placing CSs at specific points in the city to minimize idle time at the stations. The study emphasizes the effectiveness of genetic algorithms and simulation in charging station placement. Additionally, it's noted that the solution derived from real data could be beneficial for planning new CSs in the future.

In Liu (2021), the study started based on the problem of unequal distribution of increasing charge piles. Particle swarm optimization (PSO) was applied as a method in the study using MATLAB software. As a solution, unequal distribution of original charging station resources was adjusted to minimize the cost.

In Jia (2012), on the other hand, there are also problems with the construction, placement and sizing of EVCS. A study was also carried out on this topic. The data used in the study were obtained from Stockholm, Sweden, for the year 2007. The formulation in the case study is a mixed-integer quadratic programming problem with different constraints and is solved using the commercial optimisation software Cplex.

In Gampa (2020), there are many studies in the literature regarding the optimum sizing and placement of EVCS. For example, the aim of the study is the optimum sizing and placement of Distributed Generations (DGs), Shunt Capacitors (SCs) and EVCS for distribution systems. In the study, a fuzzy multi-objective approach based on Grasshopper Optimization Algorithm (GOA) is proposed.

Shen (2018) provides an in-depth analysis of various methodologies used for selecting optimal charging station locations. It covers a wide range of factors, including demand patterns, infrastructure development, and sustainable urban planning.

Ghorbani (2018) reviews mathematical models and algorithms used for electric vehicle charging infrastructure planning. It discusses key aspects such as location, capacity, and network design.

Zou's (2019) study examines spatial analysis techniques and site selection methods for EVCSs, with a focus on the role of Geographic Information Systems (GIS) in optimizing charging infrastructure. The study explores how GIS techniques can be used to determine optimal charging station locations and investigates their impact on charging infrastructure effectiveness.

Feng (2017) provides a broader perspective, covering key themes in the research on charging infrastructure, including technology, policy, and market factors. Emerging trends such as fast-charging networks are also discussed.

Leite (2018) focuses on the environmental and economic aspects of CSs. It discusses life cycle assessments and cost-benefit analyses, considering the sustainability of charging infrastructure.

Talari (2018) explores the integration of renewable energy sources into CSs with a focus on sustainability. The study also discusses the potential for solar and wind power to support electric vehicle charging.

There are many criteria for the positioning of EVCSs. When the studies in the literature are examined, it has been determined that the locations of the CSs differ according to many different criteria. Fuzzy MCDM methods are also used in studies for charging station location selection. MCDM methods are used to determine the criterion weights in the solution of complex problems. In addition, it is seen that MCDM methodology based on GIS is used in many site selection studies (Anwarzaia, 2017).

TOPSIS is used to determine the best alternative by calculating the shortest distance between each alternative and the ideal solution and the farthest distance to the non-ideal solution. It has found applications in areas like environmental assessment and quality control (Hwang, 1981).
ELECTRE methods are a family of outranking methods developed in the 1960s. They focus on ranking and sorting alternatives based on preference relations. ELECTRE methods are commonly applied in environmental management and urban planning (Roy, 1991).
PROMETHEE is another family of outranking methods. It evaluates and ranks alternatives by comparing their performance with respect to multiple criteria. PROMETHEE has been applied in various fields, including transportation planning and healthcare (Brans, 1986).

2.2. Fuzzy Logic and Fuzzy Set Theory

Lotfi A. Zadeh proposed the mathematical concept of fuzzy logic in his 1965 article "Fuzzy Sets," which was printed in the journal "Information and Control." The sets created by objects with gradual and continuous membership are known as fuzzy sets, according to Zadeh. In contrast to classical sets, fuzzy set elements are those that are allocated by a membership function and have membership degrees that range from 0 to 1 (Zadeh, 1965).
When there is uncertainty, judgements are made, but they are not exact and are merely approximations. Fuzzy sources are defined as incomplete information sources like complexity and uncertainty, which typically take on several forms (Sen, 2009). Information that is complete but vague is referred to as fuzziness. Most of the time, blurring applies to verbal, or linguistically conveyed, information. In order to convey their opinions and solve difficulties in their daily and professional lives, people employ verbal and linguistic terms.
The idea of "fuzzy logic" is connected to comprehending and verbally conveying ambiguity in these situations, as well as employing it to solve issues. In situations where there is a lack of sufficient knowledge or data regarding a topic or event, fuzzy logic is utilized, incorporating human assessments, viewpoints, and deliberations. Thus, one can take part in the process of using human intuition and problem-solving skills. A broader description and manner of thinking that encompasses classical logic is fuzzy logic. Classical logic does not address ambiguous or unclear situations; in other words, it does not permit a conclusion other than true or false.

Fuzzy logic creates a more realistic perspective by presenting truth values aside from this clear division, whereas classical logic or binary logic divides occurrences into two truth values. As a result, fuzzy logic is sometimes considered to be more similar to the human thinking system. It allows us to use graded truth values from our fuzzy logic language, like "very good," "good," and "poor," that are relevant to real-world situations. It is ensured that fuzzy logic is utilized in solving problems with uncertainty and fuzziness by identifying the degree of belonging of linguistic expressions to fuzzy sets with fuzzy set theory and fuzzy numbers. Fuzzy set theory uses numerical expressions to model uncertainties, making it possible to solve decision-making issues including uncertainty.

While FAHP is a powerful method, it has challenges such as the complexity of pairwise comparisons and the subjectivity of linguistic judgments. Research in this area continues to develop techniques to mitigate these challenges and improve the applicability of FAHP. For instance, Herrera (2000) proposed some solutions.

Zok (2006) used FAHP to evaluate the performance of academic staff. Özbek (2014) used the FAHP to evaluate seven executive candidates based on twelve criteria and selected the best one for a non-governmental organization. In Fathi's (2017) application of FAHP and fuzzy COPRAS (COmplex PRoportional Assessment) algorithms to the personnel selection decision problem, triangular fuzzy numbers were employed.

2.3. K-Means Clustering Method

Ontoseno's (2017) study aims to address the optimal placement and sizing process of distributed generation using the K-Means Clustering Method. Distributed generation refers to the decentralized production of electricity, often done locally. To enhance the efficiency of such systems, accurately determining the locations and sizes of distributed generation is crucial. The K-Means clustering method is employed for this purpose, as it is effective in grouping data based on similar characteristics and identifying similarities within specific clusters. The study aims to determine optimal placement and sizing strategies for distributed generation in electric distribution systems. In a similar study, the aim was also to utilize the K-means clustering method for determining the optimal placement of distributed generation sources within electrical distribution systems. Similarly, the objective of the above-mentioned article aligns with this goal (Scarlatache, Grigoraş, Chicco, & Cârţină, 2012).

Mam et al. (2017) introduced a distribution planning method in a geographical network using an enhanced K-means clustering algorithm and compared it with the conventional Euclidean distance-based K-means clustering algorithm.

The objective of this study was to determine the optimal locations for EVCSs within a designated district in Istanbul. To achieve this, the FAHP and K-means clustering methodology were combined. The research aims to provide valuable insights into the selection of CS locations and make a significant contribution to the existing literature in this field.

2.4. Literature Review Summary in EVCS

In recent years, there has been a significant increase in research on the strategic positioning of EVCSs. This surge has led to in-depth investigations into the optimal placement and effective distribution of EVCSs, resulting in the development of a comprehensive scientific literature in this field. As a result, several research articles addressing various aspects of EVCS deployment have been published. Table 2.1 is a synthesis of articles that highlight the methodological diversity and findings of studies related to EVCS placement.

The studies aim to determine the most suitable locations for EVCSs using various methods and analytical tools. Methodological approaches used in this field include computer simulations, Geographic Information Systems (GIS), SWOT analysis, metaheuristic algorithms, MCDM methods, regression analysis, genetic algorithms, and fuzzy Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), among others. These methods use both quantitative and qualitative data to assess the impact of different factors, such as demand forecasts, spatial constraints, and economic factors, on the optimal placement of EVCSs. Academic research on EVCS placement plays a crucial role in promoting the widespread adoption of EVs and fostering sustainable transportation. Optimal placement can mitigate environmental impacts by increasing electric vehicle usage and enhancing overall energy efficiency within communities. This research serves as a valuable guide for urban planners and professionals in the electric vehicle industry.

Table 2.1. Literature review summary in EVCS

Number	Publishing Name	Author(s)	Methods	Objective(s)
1	Charging scheduling with minimal waiting in a network of electric vehicles and charging stations	Qin, and Zhang, (2011)	Delay minimization and Simulation	Minimize waiting in EV charging networks
2	Optimal location of charging stations for electric vehicles in a neighborhood in Lisbon, Portugal	Frade, Ribeiro, Gonçalves, and Antunes, (2011)	Regression analysis	Determine optimal charging station locations in Lisbon
3	Optimal siting and sizing of electric vehicle charging stations	Jia, Hu, Song, Luo (2012)	Graph theory	EVCS optimization for cost reduction and user convenience using variables, graph theory, and Cplex.
4	Charge scheduling of electric vehicles in highways	Yang et al. (2013a)	CS-selection algorithms, The simulation model	Optimize EV charging in highways
5	Mobile charging information management for smart grid networks	Yang (2013b)	Simulation experiments	Manage charging in smart grids
6	Optimal locations of electric public charging stations using real world vehicle travel patterns	Shahraki, Cai, Turkay, Xu (2015)	Optimization model, Mixed Integer Non-Linear Programming (MINLP) model	Find optimal locations for public charging stations
7	Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective	Guo and Zhao (2015)	Fuzzy TOPSIS Method	Sustainable selection of EVCS sites by considering environmental, economic, and social criteria
8	Optimal siting and sizing of rapid charging station for electric vehicles considering Bangi city road network in Malaysia.	Islam, Shareef, and Mohamed (2016)	Gravitational Search Algorithm, Genetic Algorithm, Particle Swarm Optimization	Optimize the siting and sizing of rapid electric vehicle charging stations in a metropolitan area in Malaysia

Table 2.2. Literature review summary in EVCS (continued)

9	An adaptive large neighborhood search approach for solving the electric vehicle routing problem with time windows	Keskin and Çatay (2016)	Metaheuristics, Adaptive Large Neighborhood Search (ALNS) approach	Develop a routing algorithm for EVs with time windows
10	A general corridor model for designing plug-in electric vehicle charging infrastructure to support intercity travel	Ghamami, Zockaie, Nie (2016)	Metaheuristic, Simulated Annealing	Minimising system cost by considering actual demand and density at charging stations
11	Modelling and simulation of electric vehicle fast charging stations driven by high speed railway systems	Brenna, Longo, Yaïci (2017)	Modelling and Simulation	Examining the potential for high-speed rail lines to be used to feed fast charging stations in motorway service areas
12	A metaheuristic method for the electric vehicle routing problem with time windows and fast chargers	Keskin and Çatay (2018)	Metaheuristic approach which combines ALNS with an exact method	Optimizing decisions to charge EVs on a fixed route.
13	Design and simulation of romanian solar energy charging station for electric vehicles	Badea, Felseghi, Varlam, Filote, Culcer, Iliescu, and Răboacă (2018)	Improved Hybrid Optimization by Genetic Algorithms (IHOGA)	The aim is to support the EVCS with solar energy resources for energy supply
14	EVLibSim: A tool for the simulation of electric vehicles' charging stations using the EVLib library	Rigas, Karapostolakisa, Bassiliadesa, Ramchurn (2018)	Simulation	Develop a tool called EVLibSim, which simulates the activities of electric vehicles at charging stations
15	Determination of the design stages required for the installation of electric vehicle (EV) charging stations in urban car parks	Aydın, Çakmak, Yıldırım (2019)	Literature review	Explaining the importance of identifying the most suitable car parks for CSs

Table 2.3. Literature review summary in EVCS (continued)

16	Optimal locations of U.S. fast charging stations for long-distance trip completion by battery electric vehicles	He, Kockelman, and Perrine (2019)	FRLM model system, MATLAB's Optimization	Identify optimal locations for fast charging stations in the U.S.
17	A model for determining the locations of electric vehicles' charging stations in Istanbul	Daşcıoğlu, Tuzkaya, Kılıç (2019)	Flow-refuelling location model	Determining the best locations for EVCS
18	Selecting EVCS Locations with Open Source GIS Software	Güler and Yomralıoğlu (2019)	Geographic Information Systems (GIS), FAHP	Finding Solutions for EVCSs with GIS-Supported MCDM Methods
19	Simulation of electric vehicle charging stations load profiles in office buildings based on occupancy data	Uimonen and Lehtonen (2020)	Simulation Algorithm	Presentation of a modelling approach to understand the charging capacity and demand response potential of EVs
20	Optimal sizing and sitting of EVCS in the distribution system using metaheuristics: A case study	Chen, Xu, Song, and Jermsittiparsert, (2021)	Balanced Mayfly Algorithm	Optimize the sizing and placement of EVCS
21	A novel chicken swarm and teaching learning based algorithm for electric vehicle charging station placement problem	Deb, Gao, Tammi, Kalita, and Mahanta (2021)	Chicken Swarm Optimization (CSO) and Teaching Learning Based Optimization algorithm (TLBO)	Proposing an effective placement solution for Electric Vehicle charging stations, optimizing the associated costs
22	Electric vehicles and charging infrastructure in Turkey: An overview	Gönül, Duman, Güler (2021)	SWOT Analysis	Analysing Turkey's position in EV technology

3. MATERIALS AND METHODS

3.1. Materials

This section describes the scope of the study, how the criteria were defined, and what the main and sub-criteria are. Four main criteria and sixteen sub-criteria were identified for the selection of EV charging station locations. Detailed explanations of these criteria are provided in the Criteria Selection section. After the criteria are determined, seven alternatives are defined. In this study, MCDM and K-Means techniques are applied to find suitable EVCS locations.

3.1.1. Application Area

The location with the highest number of EVs and charging stations in Türkiye is Istanbul. This is supported by the increasing number of companies operating in the installation of EVCSs, especially considering the city's dense population and the rapid advancement of technology. In a metropolis like Istanbul, numerous factors should be considered. In this study, various factors such as economic conditions, population density, traffic conditions, charging infrastructure, and environmental factors were considered, and a detailed examination was conducted in a specific region.

3.1.2. Determination of Criteria

Firstly, determining an optimal region for installing charging stations in Istanbul is crucial. To achieve this, defining criteria and alternatives is of utmost importance. For the identification of criteria, an extensive literature review was conducted, along with surveying experts in the field. Additionally, insights from the founders of Next Geography and specialists in the area were considered, alongside the Pre-Feasibility Report by the Ministry of Industry and Technology of the Republic of Turkey, focusing on Electric Vehicle Charging Station Installation in Istanbul. Based on these inputs, main criteria, sub-criteria, and alternatives were determined for the FAHP method.

The main criteria and sub-criteria are illustrated in Figure 3.1. Four main criteria have been identified: location, demographic structure, traffic, and environment. The sub-criteria under the location main criterion include distance to hospitals, distance to malls, distance to parking areas, distance to oils, and distance to green areas. The demographic structure main criterion consists of the following sub-criteria: population density, level of education, job employment, and welfare level. The traffic main criterion includes the following sub-criteria: the number of EVCSs and charging power. Lastly, the sub-criteria under the environment main criterion are food and beverage areas, government agencies, health institutions, hotels/accommodation, and business centers/plazas.

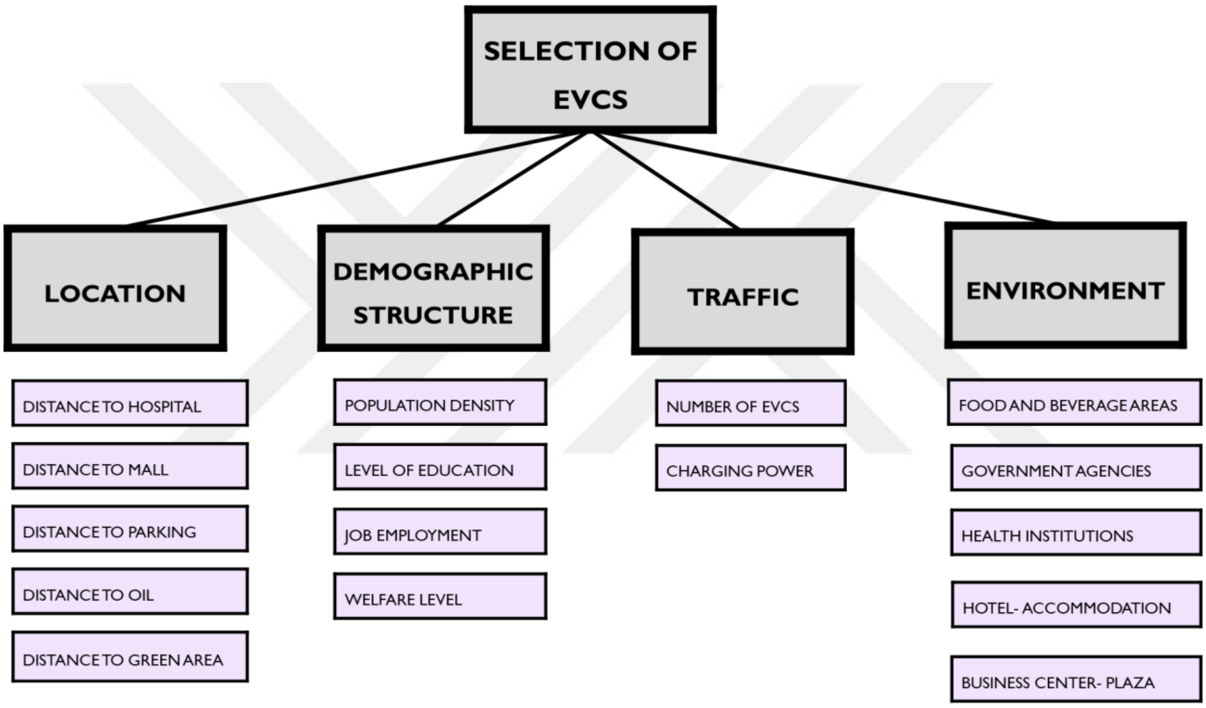

Figure 3.1. Diagram of criteria and sub-criteria for EVCS

LOCATION

Distance to Hospital (C1)

The distance of EVCSs from hospitals is important because medical emergencies may require rapid intervention, so easy access to a hospital is essential. In addition, the proximity of a hospital can be a significant advantage for vehicle users in the event of an emergency during the charging process. Finally, as hospitals are often located in busy areas, the presence of charging points in these areas is essential to meet the needs of EV users.

Distance to Mall (C2)

The distance between EVCSs and mall is important because vehicle users can spend their time shopping or doing other activities while their vehicles are being charged. In addition, this proximity can increase the attractiveness of shopping centers and encourage the use of EVs. Charging points located in high-traffic areas, such as shopping centers, have the potential to reach a wider audience and encourage the uptake of EVs.

Distance to Parking (C3)

EVCSs being close to parking lots is important because it provides vehicle users with convenient access to charging facilities while they park their vehicles. This proximity enhances user convenience and encourages the adoption of EVs by ensuring that charging is readily available during routine activities. Additionally, having charging stations in parking lots contributes to the overall infrastructure for electric vehicle usage, promoting sustainability and reducing reliance on traditional fuel sources.

Distance to Oil (C4)

The distance between EVCSs and petrol stations is important because users want to assess and charge their vehicles before travelling. This proximity ensures a safe and comfortable driving experience. It also meets users' needs by providing quick charging options in emergencies or unexpected situations, thereby promoting the use of EVs.

Distance to Green Area (C5)

The distance between electric vehicle charging points and green spaces is important for several reasons. Firstly, it contributes to the preservation of the natural environment. Secondly, users may prefer to spend time in green spaces while their vehicles are charging, enhancing their charging experience. Finally, as EV users are often environmentally conscious individuals, proximity to green areas can attract this user demographic and promote the adoption of EVs. Therefore, locating charging stations near green spaces supports environmental sustainability and increases user satisfaction.

DEMOGRAPHIC STRUCTURE

Population Density (C6)

In the installation of EVCSs, population density criterion is important for several reasons. Firstly, densely populated areas are likely to have a higher number of potential users, indicating greater demand for charging stations. Secondly, stations located in densely populated regions can better cater to the daily needs and travel patterns of users, potentially influencing their decision to adopt EVs. Additionally, the usage of EVs in densely populated areas can have a larger impact on reducing environmental effects and improving sustainability. Therefore, considering population density is crucial in strategically locating CSs.

Level of Education (C7)

The education level criterion is important for the installation of EVCSs for several reasons. Firstly, it helps determine the level of technology and environmental awareness among users. Individuals with higher education levels tend to be more interested in innovations and environmental issues, potentially increasing the demand for EV usage and CSs. Additionally, users in areas with higher education levels may have more knowledge about EV technology and charging infrastructure, which can encourage the effective utilization of CSs. Therefore, the education level criterion is an important factor to consider in the strategic placement of CSs.

Job Employment (C8)

Employment is a fundamental factor for the economic development and vitality of a region. The installation of large-scale projects such as EVCSs can increase local employment, thereby enhancing the economic potential of the area. The increase in employment contributes to the development of skills and abilities within the local workforce. The acquisition of the technical knowledge and skills required for the installation of EVCSs by the local workforce enhances the region's long-term competitiveness. Therefore, employment represents an important factor that contributes to the healthy and sustainable development of the local economy and society.

Welfare Level (C9)

The criterion of income level indicates a higher potential for intensive usage in areas with higher income. Therefore, it plays a crucial role in the strategic placement of CSs as it assists in selecting optimal locations to meet the high demand in these areas and promote sustainable transportation.

TRAFFIC

EVCS (C10)

The number of CSs in an area determines the accessibility of charging facilities for EV users in their daily lives and travels. Therefore, having an adequate number of CSs enables users to confidently use their EVs and charge them, allowing them to travel without concerns. Additionally, a higher number of CSs in an area can promote the widespread adoption of EV usage and support sustainable transportation.

Charging Power (C11)

Charging power is a critical factor in the installation of EVCSs because it provides fast charging capabilities, allowing users to charge their vehicles in shorter time frames. High-powered CSs enable the simultaneous charging of more vehicles during peak usage periods, reducing wait times and increasing usage efficiency. This enhances the daily convenience of EV users and provides a more comfortable experience during long-distance travels.

ENVIRONMENT

Food and Beverage Areas (C12)

Areas with food and beverage establishments are typically where people spend extended periods and take breaks. Having CSs in these areas allows users to spend time and meet their needs while charging their vehicles. EV users often want to engage in nearby activities or satisfy their dining needs while charging their vehicles. Therefore, the presence of dining establishments near CSs ensures users have a more comfortable and enjoyable charging experience. Furthermore, CSs situated near dining areas encourage EV usage and facilitate users in planning their travels more comfortably.

Government Agencies (C13)

Government institutions are typically located in areas with high accessibility to public services. CSs situated in these areas provide EV users with the opportunity to charge their vehicles while accessing public services. Additionally, areas where government institutions are located often experience heavy traffic and frequent visits. Therefore, having CSs in these areas enhances accessibility and convenience for EV users.

Health Institutions (C14)

Healthcare institutions play a crucial role in the installation of EVCSs. These stations need to be conveniently located for access by patients, healthcare staff, and visitors. Additionally, having charging stations near healthcare facilities can enhance the availability of EVs during emergencies. Furthermore, the support of healthcare institutions promotes environmentally friendly initiatives, contributing to improved air quality. Therefore, the active involvement of healthcare institutions in the installation of EVCSs is vital.

Hotel- Accommodation (C15)

The hotel and accommodation sector plays a significant role in the installation of EVCSs as it enhances guest satisfaction and service quality. Hotels with charging stations attract electric vehicle owners, gaining a competitive edge and projecting an eco-friendly image. Additionally, this demonstrates their environmental responsibility while increasing innovation and customer segmentation.

Business Center- Plaza (C16)

Business center plazas play a crucial role in the installation of EVCSs due to their central location and high foot traffic from professionals. Providing charging infrastructure in these areas enhances accessibility for a diverse range of users and contributes to the convenience of electric vehicle owners. Moreover, offering such amenities aligns with corporate social responsibility efforts, promotes environmental sustainability, and fosters a positive image for businesses within the plaza. Therefore, integrating EVCSs into business center plazas serves both practical and strategic purposes, catering to the needs of the modern workforce and demonstrating commitment to sustainability.

3.1.3. Determination of Alternatives

Firstly, due to Istanbul's status as a major city, it is necessary to privatize the workspace. Istanbul comprises a total of 39 districts. In order to determine the districts most suitable for the installation of charging stations, literature reviews, expert opinions, and the Pre-Feasibility Report for the Installation of Charging Stations for Electric Vehicles in Istanbul, prepared by the Ministry of Technology and Industry of the Republic of Turkey, are considered. As shown in Figure 3.2, alternative districts were identified for this study, namely Kadıköy, Şişli, Bakırköy, Fatih, Beşiktaş, Beyoğlu and Üsküdar. The selection of these districts was influenced by the factors described in the following subsections.

Table 3.1 was created based on the data obtained from Next Geography firm. The table shows the number of candidate locations for EVs in Istanbul. Since gas stations, shopping malls, educational institutions, government agencies, car dealerships, parking lots, healthcare facilities, tourist attractions, dining areas, and residential areas are considered the places where people spend the most time, these areas have been considered potential locations for charging stations. According to this data, Fatih is seen as one of the potential districts for location with 1571 candidate locations. It is followed by Şişli with 805 candidates, Beyoğlu with 697 candidates, Kadıköy with 632 candidates, and Üsküdar with 631 candidates.

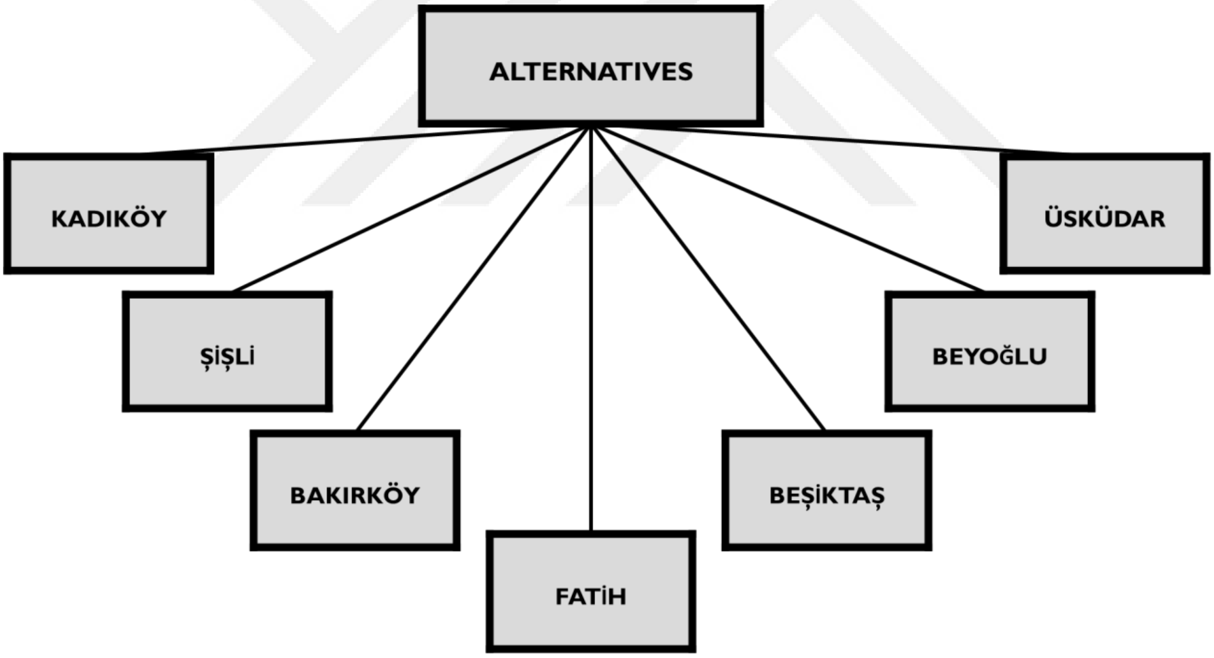

Figure 3.2. Alternatives to the FAHP Method

Table 3.1. Candidate location numbers of districts in Istanbul

Districts	Fuel Stations	The Mall	Educational Institutions	Government Agencies	Auto Dealers	Parking Lots	Health Institutions	Touristic Locations	Eating, Drinking Areas	Settlements	Total
Fatih	11	1	6	676	0	452	25	364	36	0	1571
Şişli	12	13	2	136	5	375	24	92	142	4	805
Beyoğlu	16	5	5	267	3	211	9	152	28	1	697
Kadıköy	25	2	2	176	17	186	28	31	121	44	632
Üsküdar	30	4	3	317	9	153	29	7	75	4	631
Ümraniye	35	13	2	260	15	93	16	14	86	25	559
Beşiktaş	9	9	3	160	7	208	10	31	95	1	533
Sarıyer	16	9	6	211	31	142	12	11	79	2	519
Pendik	59	9	0	208	4	48	19	18	66	38	469
Bakırköy	27	13	1	116	3	142	21	20	95	7	445
Bağcılar	54	11	1	166	9	80	28	16	38	17	420
Eyüpsultan	26	10	1	209	7	76	7	7	30	16	389
Ataşehir	23	13	3	123	24	46	19	23	97	9	380
Küçükçekmece	37	7	2	131	6	75	25	21	40	17	361
Maltepe	30	6	2	130	18	49	22	11	66	9	343
Beykoz	11	1	3	240	3	34	6	9	26	2	335
Esenyurt	47	19	1	110	16	21	16	14	65	25	334
Bahçelievler	19	11	0	86	21	88	22	23	53	4	327

Table 3.2. Candidate location numbers of districts in Istanbul (continued)

Kartal	25	5	1	126	18	64	14	8	48	15	324
Kağıthane	16	2	1	143	10	75	9	12	33	11	312
Başakşehir	21	17	1	105	6	56	5	2	47	17	277
Gaziosmanpaşa	26	2	0	160	0	33	21	2	25	1	270
Büyükçekmece	42	11	1	113	12	23	9	15	20	9	255
Avcılar	20	3	1	62	17	61	14	12	25	4	219
Arnavutköy	36	1	0	142	5	7	7	7	10	1	216
Zeytinburnu	18	3	5	92	10	45	10	11	17	4	215
Tuzla	41	3	3	89	10	17	5	10	24	9	211
Sancaktepe	32	7	0	92	20	14	6	2	26	4	203
Sultanbeyli	23	2	0	126	2	25	7	0	13	5	203
Beylikdüzü	21	18	0	63	12	24	11	3	35	13	200
Bayrampaşa	20	4	0	80	12	38	8	10	22	0	194
Silivri	55	2	1	98	1	15	4	12	5	1	194
Sultangazi	18	3	0	128	0	22	11	0	6	1	189
Çekmeköy	21	2	1	81	9	8	5	2	23	14	166
Güngören	12	4	0	63	3	44	7	10	14	2	159
Esenler	12	2	0	87	8	32	6	3	7	0	157
Şile	13	0	1	97	0	1	1	21	4	0	138
Çatalca	30	0	0	90	0	5	1	1	1	0	128
Adalar	0	0	0	56	0	1	0	10	2	0	69

In the Pre-Feasibility Report for the Installation of Charging Stations for Electric Vehicles in Istanbul prepared by the Ministry of Technology and Industry of the Republic of Turkey, the socio-economic development level of the districts plays an important role in the positioning of EVCSs. In this study conducted by the Ministry of Industry and Technology, 7 dimensions and 32 variables such as demographic structure, education level, employment rate, health data, competition status, financial data, and quality of life considered. Additionally, factors such as the distribution of sub-stations in Istanbul, the distribution of existing charging stations, station types, etc., have also been considered (Technology, 2021).

The Generalized Social Integration Analysis (GSIA) was used to calculate the socio-economic development level. As a result of this comprehensive pre-feasibility study, regions have been identified in three stages: 1st, 2nd, and 3rd stages. Accordingly, out of the 39 districts, 24 are in the 1st stage in terms of development level, 14 districts are in the 2nd stage, and 1 district is in the 3rd stage. The scoring list is shown in Table 3.2. The overall ranking in the table shows the socio-development ranking among 970 districts in Türkiye. The values in the Socio-Economic Development Ranking Score column represent the ranking of the 39 districts of Istanbul in terms of socio-economic development. As a result, the highest score of 7.730 has been calculated in the Şişli district. This is followed by Beşiktaş, Kadıköy, Bakırköy, and Fatih districts (Ministry of Industry and Technology, 2021). With the data and expert opinions, the alternative districts have become clearer.

Table 3.3. Socio-economic development ranking of districts in Istanbul (SEGE, 2017)

District Name	Sorting of General	Sorting of Provinces	Socio-Economic Development Ranking Score	Level
Şişli	1	1	7.730	1
Beşiktaş	2	2	6.365	1
Kadıköy	4	3	4.678	1
Bakırköy	5	4	4.457	1
Fatih	8	5	3.501	1
Tuzla	13	6	2.78	1
Başakşehir	16	7	2.67	1
Ümraniye	17	8	2.656	1
Beyoğlu	18	9	2.602	1
Üsküdar	19	10	2.57	1
Ataşehir	21	11	2.402	1
Büyükçekmece	25	12	2.278	1
Sarıyer	28	13	2.166	1
Beylikdüzü	29	14	2.163	1

Table 3.4. Socio-economic development ranking of districts in Istanbul (continued)

Esenyurt	33	15	2.074	1
Bahçelievler	34	16	2.042	1
Zeytinburnu	35	17	2.027	1
Bağcılar	37	18	2.012	1
Küçükçekmece	39	19	1.955	1
Maltepe	41	20	1.928	1
Pendik	42	21	1.906	1
Bayrampaşa	48	22	1.855	1
Beykoz	51	23	1.812	1
Kartal	52	24	1.804	1
Kağıthane	57	25	1.692	2
Adalar	58	26	1.688	2
Güngören	62	27	1.628	2
Eyüp	64	28	1.608	2
Silivri	71	29	1.518	2
Avcılar	78	30	1.451	2
Gaziosmanpaşa	82	31	1.378	2
Şile	100	32	1.259	2
Çekmeköy	108	33	1.208	2
Çatalca	128	34	1.015	2
Sancaktepe	132	35	1.003	2
Esenler	152	36	0.936	2
Sultanbeyli	204	37	0.645	2
Sultangazi	218	38	0.583	2
Arnavutköy	238	39	0.47	3

3.2. Methods

A summary of the steps that are used in the method is shown in Figure 3.3. Initially, the step of problem definition and identification of objectives was performed. This step formed the basis of the analysis process and clarified the purpose of the analysis. Then, the stage of determining the criteria and alternatives was started. At this stage, the criteria used to determine the scope of the analysis were defined with the help of experts and literature review.

Afterwards, a questionnaire study was carried out by consulting expert opinions. The opinions of the experts contributed to the analysis process to be more robust and comprehensive. Then, the FAHP method is used to select the most appropriate district from seven different districts. FAHP is used as an effective tool for solving complex decision-making problems.

For cluster analysis, the appropriate number of clusters of the data set was determined using the Elbow Method in Phyton and cluster centres are calculated using the K-means method in SPSS.

Finally, the optimal candidate locations were identified based on the identified criteria. These steps ensured that the analysis process proceeded in a systematic and guided manner and increased the accuracy of the results of the analysis.

Figure 3.3. Methodological Framework

3.2.1. Multi Criteria Decision Making (MCDM)

Real-world problems are often complex, requiring consideration of multiple criteria or objectives. Decision makers must balance these criteria to make the best decision. MCDM methods are designed to address this complexity and support the decision-making process. By providing decision makers with an analytical framework, these methods assist in breaking down complex problems into more manageable parts and evaluating the results in a more rational manner. Real-life decision-making processes are often fraught with uncertainty. Uncertainties refer to situations where decision makers face uncertain information or risk about the future. Such uncertainties can increase the probability that decisions are incorrect. MCDM methods provide various techniques for handling uncertainties. For instance, methods like AHP assist decision-makers in reducing uncertainties and establishing a more robust foundation for decision-making.

The study aims to determine the criteria and alternatives for the optimal layout of EVCSs. The MCDM method is chosen due to the various factors involved in the charging station location, such as demographic structure, employment, traffic, and environment. By considering these and other criteria, optimal locations can be identified. Therefore, this method is preferred to consider multiple criteria simultaneously. The literature shows that MCDM methods have achieved optimal results in solving settlement problems. This study considers multiple criteria, including main and sub-criteria, to determine the optimal location among alternatives.

3.2.2. Analytical Hierarchy Process (AHP)

Thomas Saaty developed AHP in the 1970s as a useful MCDM technique for solving problems involving decision making (Saaty, 1977). AHP can be described as a decision-making and estimation method used when the decision hierarchy can be defined, providing percentage distributions of decision points based on factors influencing the decision. AHP is based on one-to-one comparisons on a decision hierarchy using a predefined comparison scale, both in terms of the factors affecting the decision and the significance of the decision points in terms of these factors.

As a result, differences in importance turn into a percentage distribution over decision points. One of the major advantages of this method is that it allows analytical evaluation of criteria without numerical values by comparison methods.

It is used to select from, or rank, the choice options selected by the decision maker. By pairwise contrasting the choice options and the criteria chosen for each alternative, the approach essentially provides an evaluation. As a result of comparing alternative choices and criteria, a selection or ranking is determined through a series of procedural steps. The steps to be taken to solve a decision-making problem with AHP are given as follows:

Step 1: Identify the Decision-Making Problem

The first step of AHP is to define the problem. The goal to be achieved and the objectives to be set to achieve this goal need to be defined. Criteria to achieve the objectives are determined, which generally represent the important factors in the decision-making process. Alternatives to be considered in the decision-making process are identified. These alternatives are the options that will be evaluated according to the determined criteria. Current conditions, constraints, and other important factors related to the problem are considered.

Step 2: Creating a Comparison Matrix

In this stage, the second step of the AHP, a comparison matrix is created to determine the relative importance of the factors. The comparison matrix contains numerical values that indicate the importance of each factor compared to the other factors. A square matrix is created, with its rows and columns representing the factors to be compared. The numbers in this square matrix are written according to their meanings as specified in Table 3.3. By assigning a value of 1 to the elements on the diagonal of the matrix, it is indicated that each factor is equal to itself.

- If two factors are equally important, a value of 1 is assigned.
- If one factor is slightly more important than the other, a value of 3 is assigned.
- If one factor is significantly more important than another, a value of 5 is assigned.
- If one factor is considerably more important than another, a value of 7 is assigned.
- If one factor is absolutely more important than another, a value of 9 is assigned.
- If one factor is definitely superior to another, the element in the opposite position is assigned a value of 1/9.

To ensure consistency in the comparison matrix, the values for each factor pair are cross-checked.

During this stage, as part of the AHP, a comparison matrix is created to determine the relative importance of factors. The matrix contains numerical values that represent the importance of each factor in comparison to others.

An example of such a matrix is shown below:

$$A = \begin{bmatrix} 1 & 3 & 5 \\ 1/3 & 1 & 2 \\ 1/5 & 1/2 & 1 \end{bmatrix}$$

This matrix illustrates the relative importance levels of three different factors. The value of 3 in cell (1,2) indicates that Factor 1 is considered three times more important than Factor 2. Conversely, the value of 1/3 in cell (2,1) signifies that Factor 2 is one-third as important as Factor 1. The interpretation of other cells follows the same logic.

Step 3: Normalization of Generated Matrices

The normalized matrix is obtained by dividing each column value by the sum of the individual columns. Then, the average weight of the option or criterion is determined by calculating the line averages of the normalized matrix.

Table 3.5. Scores for the Importance of Variable

Importance Scale	Definition of Importance Scale
1	Equally Importance Preferred
2	Equally to Moderately Importance Preferred
3	Moderately Importance Preferred
4	Moderately to Strongly Important Preferred
5	Strongly Importance Preferred
6	Strongly to Very Strongly Importance Preferred
7	Very Strongly Importance Preferred
8	Very Strongly to Extremely Importance Preferred
9	Extremely Importance Preferred

Matrix A represents the relationships between the criteria or alternatives evaluated in the decision-making process. The values are denoted by a_{ij}. The main purpose of AHP is to analyze the relationships between different criteria or alternatives in the decision-making process. Matrix A represents these relationships, while the vector w_{ij} indicates the degree of importance of each criterion or alternative. The column vector D represents the weighted sums obtained by multiplying each column of matrix A by the vector w_{ij}.

Multiplying the matrix A by the w_{ij} vector Column vector (D) is calculated.

$$D = \left[\left[a_{11} \ \cdots \ a_{1n} \ \vdots \ddots \vdots \ a_{n1} \ \cdots \ a_{nn} \ \right]\right] \times \left[w_1 \ w_2 \ w_3 \cdots \ w_n \ \right], \qquad D = A \times w_{ij} \tag{3.1}$$

In the event that the performance values of an alternative are presented in a decision matrix and its weight in the weight vector is known, the weighted value of the alternative is calculated in accordance with the Equation (3.2). The arithmetic means of these values (Equation 3.3) gives the basic value (λ) of the comparison.

$$E = D / w_{ij} \tag{3.2}$$

$$\lambda = \frac{\sum_{i=1}^{n} E}{n} \tag{3.3}$$

Once λ is calculated, the Consistency Indicator (CI) can be calculated using Equation (3.4).

$$CI = (\lambda - n) / (n-1) \tag{3.4}$$

Step 4: Calculating Consistency Indicator

In the next step, the CI is divided by the standard correction value shown in Table 3.4, called the Random Indicator (RI) (Equation 3.5) to obtain Consistency Ratio (CR). The value corresponding to the number of factors is selected from Table 3.4. For example, the RI value to be used in a 3-factor comparison would be 0.58 from Table 3.4.

$$CR=CI/\ RI \tag{3.5}$$

If the calculated CR value is less than 0.10, the comparisons made by the decision maker are consistent. A CR value greater than 0.10 indicates either a calculation error in AHP or inconsistency in decision making comparisons.

Table 3.6. Random consistency index

Matrix size	1	2	3	4	5	6	7	8	9	10
Random Consistency Index	0.00	0.00	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Step 5: Determining Relative Importance of Factors and Decision Points in Percentage

The objective of this step is to determine the relative importance of each factor and decision point in the decision-making process in percentage terms. This is achieved by multiplying the priority vectors by the decision matrix (w), which is obtained by multiplying the priority vectors. The resulting column vector shows the percentage distribution of the degree of importance of the decision points. This indicates which decision points are more important than others in the decision-making process.

Step 6: Find the Distribution of Results at Decision Points

The result is that when the decision matrix (w) is multiplied by the column vector (priority vector), the column vector L with m elements is obtained. Column L gives the percentage distribution of decision points. In other words, the sum of the elements of the vector is 1. This distribution also shows the order of importance of the decision points.

AHP is advantageous in terms of usability based on clear and precise data in the decision-making process. It is preferred to manage the decision-making process quickly and accurately in situations where measurable and specific values are available. On the other hand, the FAHP method is used in situations where uncertainties are high or experts need to make subjective evaluations. This method allows experts to manage the decision-making process by taking into account their experience and specialized knowledge.

3.2.3. Fuzzy Analytical Hierarchy Process (FAHP)

There are many reasons why the FAHP is preferred. In daily life, there are many different fields, sectors, and businesses that have difficulties in making decisions. There may be situations that involve many probabilistic situations, both due to the presence of too many criteria and because of the sub-criteria of the main criteria, and also because these criteria can be not only quantitative but also qualitative. With these constraints, it becomes increasingly difficult to decide between options. These options, namely the alternatives, are scored for each main criterion and each sub-criteria, and the weight of that alternative, that is, the degree of importance in our problem, is calculated. While this scoring is being done, clear scores may not be given, but staying within a certain range actually enables us to make more accurate decisions. Therefore, fuzzy numbers have emerged. The FAHP method supports a more comprehensive approach to the problem with fuzzy numbers. Similarly, each criterion should have a degree of importance among the criteria and a certain weight of importance. Considering these degrees of importance, the result obtained allows us to see the most correct option among the alternatives and also shows the order of importance of the other alternatives. These steps are actually similar to the human thought system. In order to make the right decision, multiple situations are taken into account and all of them are compared with each other, revealing the most optimal option. Charging station placement of EVs is an example of such problems. There are multiple alternatives, multiple criteria, and multiple sub-criteria.

In addition to concrete conceptions, abstract concepts are also useful when individuals are making judgments in their daily lives and when there is uncertainty. The person who had to make a judgment in this uncertain situation looked for many solutions and used fuzzy logic. Because fuzzy logic is so similar to the logic of human thought, decisions made using methods that incorporate this logic are more accurate.

The FAHP has been developed by merging fuzzy logic with AHP since the analytical hierarchical process, one of the MCDM methods, is not entirely adequate for decision making in the case of uncertainty. In general, the decision-maker will find that intermittent evaluation is more trustworthy than evaluation using precise values. Numerous researchers have introduced FAHP approaches in the literature. (Kahraman, Cebeci, & Ulukan, 2003)

FAHP has been applied in various fields, including environmental management, engineering and construction, healthcare, and financial decision-making. In environmental management, it is used to assess the environmental impact of projects, select waste disposal sites, and control pollution. In engineering and construction, it is used to select the best design alternatives, evaluate suppliers, and assess risks in construction projects. In healthcare, data analysis is applied to areas such as hospital site selection, medical equipment selection, and patient satisfaction analysis. In financial decision-making processes, it is used for portfolio optimization, investment risk analysis, and credit risk assessment.

The FAHP is a decision-making methodology that integrates fuzzy logic into the traditional AHP to address uncertainty in complex decision problems. The process starts with defining the decision problem, identifying its criteria and alternatives. Experts or decision-makers provide subjective judgments in the form of fuzzy numbers in pairwise comparison matrices to represent the relative importance of criteria and alternatives. These fuzzy numbers are then normalized to ensure comparability across judgments. Aggregation methods, such as the weighted geometric mean, are used to combine pairwise comparisons into global priority vectors. Consistency checks are conducted to ensure coherence among judgments. Weighted priorities for criteria are determined by normalizing aggregated criteria matrices. Fuzzy evaluation of alternatives is then conducted based on the criteria, followed by ranking based on fuzzy performance scores. Sensitivity analysis can be optionally performed to assess the robustness of the decision under various scenarios. Finally, a decision is made based on the fuzzy ranking of alternatives and the results of sensitivity analysis. FAHP enables decision-makers to navigate complex decision-making scenarios by managing uncertainty and vagueness in their judgments.

Table 3.5 shows rules for making correct decisions and analyses when working with uncertain data and fuzzy numbers. These rules can be used in conjunction with fuzzy set theory and similar uncertainty models to provide a constructive approach to complex decision problems. FAHP is a commonly used as an effective method in many studies. Chang's extended analysis method was chosen for this study because of its capability of dealing with more complex decision problems. Chang's methodology provides a comprehensive sensitivity analysis of decision-makers' subjective judgments and decision-making steps.

Table 3.7. Fuzzy arithmetic

Operation	Result
Addition	$(l_1\ m_1\ u_1) \oplus (l_2\ m_2\ u_2) = (l_1{+}l_2\ \ m_1{+}m_2\ \ u_1+u_2)$
Multiplication	$(l_1\ m_1\ u_1)\ \Theta\ (l_2\ m_2\ u_2) = (l_1.l_2\ \ m_1.m_2\ \ u_1.u_2)$
Scalar Multiplication	$\lambda\ \Theta\ (l_1\ m_1\ u_1) = (\lambda.l_1\ \lambda.m_1\ \lambda.u_1)$
Inverse (Triangular Fuzzy Number)	$(l_1\ m_1\ u_1)^{-1} = (1/u_1\ 1/m_1\ 1/l_1)$
Inverse (Trapezoidal Fuzzy Number)	$(l_1\ m_1\ n_1\ u_1)^{-1} = (1/u_1\ 1/n_1\ 1/m_1\ 1/l_1)$

3.2.4. Chang's Extent Analysis Method (1996)

The Chang Extent Analysis Method, commonly referred to as Chang's Extent Analysis Method (EAM), stands as a significant contribution to the field of multi-attribute decision-making (MADM). Introduced by Jih-Jeng Chang in 1996, this methodology provides a systematic approach to tackling decision problems characterized by imprecise or uncertain information. In the realm of decision analysis, especially in complex scenarios where there are multiple attributes or criteria to consider, EAM proves to be a valuable tool. The method involves a comprehensive evaluation process that aims to determine the optimal alternative from a given set of options. By incorporating imprecision and uncertainty into the decision-making process, Chang's EAM addresses the real-world complexities often encountered in various domains, offering a nuanced and effective approach to decision support. Researchers and practitioners alike have recognized the versatility of Chang's EAM, making it a well-established method for decision-makers seeking robust solutions in the face of uncertain and imprecise information.

In several cases where FAHP was used, Chang (1996)'s extended FAHP approach was used. Cut-off levels are not necessary with this strategy (Güner, 2005). Along with yapay artificial, this technique is characterised by simple level ordering and mixed total ordering. The biggest significant feature of this method is that it uses the same steps as traditional AHP but requires less calculation and no additional processing. The drawback is that it only makes use of ambiguous triangular numbers (Durdudiller, 2006).

The FAHP involves several key steps (Chang, 1996). The decision problem is structured hierarchically, with objectives, criteria, and alternatives defined. Decision-makers provide pairwise comparisons of criteria and alternatives using linguistic terms such as 'much more important' or 'slightly preferable'. Fuzzy numbers represent imprecise judgments in pairwise comparisons. The reliability of the provided data is ensured by assessing the consistency of the pairwise comparisons. The weights of criteria and the overall ranking of alternatives are determined by calculating the aggregated judgments using FAHP.

The EAM employs a dominance measure to assess the relative importance of each attribute in relation to the decision problem. The dominance measure reflects the degree to which one alternative is superior to another with respect to a specific attribute. The core of the method involves performing extent analysis. This analysis involves two steps. First, extent values are computed for each alternative and attribute. These values indicate the extent to which each alternative dominates the others in terms of that attribute. The extent value is calculated by comparing each alternative to all other alternatives for that particular attribute. The overall dominance measure is then determined by combining the extent values for each attribute. This provides a comprehensive assessment of the alternatives.

Chang's method has found application in various areas such as environmental decision making, financial decision analysis and project selection. It provides a structured approach for evaluating and ranking alternatives in complex decision scenarios. Firstly, the problem is defined and then alternatives and criteria are defined. For each attribute, pairwise comparisons are made to determine dominance relationships between alternatives. The formulations to be followed are as follows:

When X= $\{x_1, x_2, x_3 \ldots\ldots x_n\}$ is a criterion set and u= $\{u_1, u_2, u_3 \ldots\ldots u_n\}$ is a goal set, each criterion is taken according to Chang's method and rank analysis is applied for each goal. In other words, synthetic values are obtained for each purpose according to each criterion. In this way, m synthetic values are obtained for each criterion, equal to the number of criteria. These values are shown as follows:

$$M_{gi}^1, M_{gi}^2 \ldots\ldots M_{gi}^m \qquad \text{i=1,2……. N} \tag{3.6}$$

where M_{gi}^j j= (1,2……m) is the triangular fuzzy number.

3.2.4.1. Pairwise Comparison of Main Criteria

Fuzzy numbers of pairwise comparison between the main criteria are shown in Table 3.6. Tables 3.7, Table 3.8, Table 3.9 and Table 3.10 show the pairwise comparison of the sub-criteria of the main criteria.

Table 3.8. Pairwise comparison of main criteria

Main Criteria	Location	Demographic Structure	Traffic	Environment
Location	(1,1,1)	(7,8,9)	(6,7,8)	(7,8,9)
Demographic Structure	(1/9,1/8,1/7)	(1,1,1)	(1/8,1/7,1/6)	(1/9,1/8,1/7)
Traffic	(1/8,1/7,1/6)	(6,7,8)	(1,1,1)	(1,1,1)
Environment	(1/9,1/8,1/7)	(7,8,9)	(1,1,1)	(1,1,1)

CI: 0,029

Table 3.9. Pairwise comparison of sub-criteria for location main criterion

Location	Distance to Hospital	Distance to Mall	Distance to Parking	Distance to Oil	Distance to Green Area
Distance to Hospital	(1,1,1)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(7,8,9)
Distance to Mall	(7,8,9)	(1,1,1)	(7,8,9)	(2,3,4)	(6,7,8)
Distance to Parking	(6,7,8)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,1,1)
Distance to Oil	(7,8,9)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)	(7,8,9)
Distance to Green Area	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1,1,1)	(1/9,1/8,1/7)	(1,1,1)

CI:0,048

Table 3.10. Pairwise comparison of sub-criteria for demographic structure main criterion

Demographic Structure	Population Density	Level of Education	Job Employment	Welfare Level
Population Density	(1,1,1)	(1/6,1/5,1/4)	(1/6,1/5,1/4)	(1/9,1/8,1/7)
Level of Education	(4,5,6)	(1,1,1)	(1,2,3)	(1,1,1)
Job Employment	(4,5,6)	(1/3,1/2,1)	(1,1,1)	(1,1,1)
Welfare Level	(7,8,9)	(1,1,1)	(1,1,1)	(1,1,1)

CI:0,039

Table 3.11. Pairwise comparison of sub-criteria for traffic main criterion

Traffic	EVCS	Charging Power
EVCS	(1,1,1)	(1/4,1/3,1/2)
Charging Power	(2,3,4)	(1,1,1)

CI:0

Table 3.12. Pairwise comparison of sub-criteria for environment main criterion

Environment	Food and Beverage Areas	Government Agencies	Health Institutions	Hotel-Accommodation	Business Center-Plaza
Food and Beverage Areas	(1,1,1)	(7,8,9)	(7,8,9)	(1/4,1/3,1/2)	(1/3,1/2,1)
Government Agencies	(1/9,1/8,1/7)	(1,1,1)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1/9,1/8,1/7)
Health Institutions	(1/9,1/8,1/7)	(5,6,7)	(1,1,1)	(1/9,1/8,1/7)	(1/8,1/7,1/6)
Hotel-Accommodation	(2,3,4)	(6,7,8)	(7,8,9)	(1,1,1)	(2,3,4)
Business Center-Plaza	(1,2,3)	(7,8,9)	(6,7,8)	(1/4,1/3,1/2)	(1,1,1)

CI:0,0211

Tables 3.11, 3.12, 3.13, 3.14 and 3.15 show the pairwise comparison between the alternatives for each sub-criteria of the Location main criterion. Based on the table values, it is evident that the Şişli district has a more advantageous position than other districts in terms of distance to shopping centres. For instance, it has a superiority of 9 compared to Beşiktaş and 8 compared to other districts.

Table 3.13. Pair comparison of alternatives according to distance to hospitals sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/3,1/2,1)	(3,4,5)	(6,7,8)	(2,3,4)	(3,4,5)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1)	(3,4,5)	(6,7,8)	(4,5,6)	(4,5,6)
KADIKÖY	(1,2,3)	(1,2,3)	(1,1,1)	(4,5,6)	(6,7,8)	(5,6,7)	(5,6,7)
BAKIRKÖY	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1,1,1)	(7,8,9)	(6,7,8)	(6,7,8)
FATİH	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(2,3,4)
BEYOĞLU	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1,1,1)	(1,1,1)	(5,6,7)
ÜSKÜDAR	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1/4,1/3,1/2)	(1/7,1/6,1/5)	(1,1,1)

CI:0,0271

Table 3.14. Pair comparison of alternatives according to distance to malls sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(8,9,9)	(7,8,9)	(7,8,9)	(7,8,9)	(7,8,9)	(7,8,9)
BEŞİKTAŞ	(1/9,1/9,1/8)	(1,1,1)	(1,1,1)	(7,8,9)	(7,8,9)	(7,8,9)	(7,8,9)
KADIKÖY	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,1,1)	(7,8,9)	(7,8,9)	(7,8,9)
BAKIRKÖY	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
FATİH	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1/7,1/6,1/5)	(1/6,1/5,1/4)
BEYOĞLU	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1,1,1)	(5,6,7)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1,1,1)	(4,5,6)	(1,1,1)	(1,1,1)

CI:0,0229

Table 3.15. Pair comparison of alternatives according to distance to parking lots sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/3,1/2,1)	(3,4,5)	(3,4,5)	(3,4,5)	(3,4,5)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1)	(3,4,5)	(4,5,6)	(4,5,6)	(4,5,6)
KADIKÖY	(1,2,3)	(1,2,3)	(1,1,1)	(3,4,5)	(3,4,5)	(3,4,5)	(3,4,5)
BAKIRKÖY	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1,1,1)	(4,5,6)	(4,5,6)	(4,5,6)
FATİH	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1,1,1)	(1/6,1/5,1/4)	(1/3,1/2,1)
BEYOĞLU	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(4,5,6)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1,2,3)	(1,1,1)	(1,1,1)

CI:0,0157

Table 3.16. Pair comparison of alternatives according to distance to oils sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/3,1/2,1)	(3,4,5)	(1,1,1)	(1,1,1)	(3,4,5)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/5,1/4,1/3)	(2,3,4)	(1,1,1)	(1,1,1)	(3,4,5)
KADIKÖY	(1,2,3)	(3,4,5)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(6,7,8)
BAKIRKÖY	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1,1,1)	(6,7,8)	(6,7,8)	(6,7,8)
FATİH	(1,1,1)	(1,1,1)	(1,1,1)	(1/8,1/7,1/6)	(1,1,1)	(1/4,1/3,1/2)	(1,1,1)
BEYOĞLU	(1,1,1)	(1,1,1)	(1,1,1)	(1/8,1/7,1/6)	(2,3,4)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1,1,1)	(1,1,1)	(1,1,1)

CI:0,0161

Table 3.17. Pair comparison of alternatives according to distance to green areas sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/3,1/2,1)	(3,4,5)	(1,1,1)	(1,1,1)	(3,4,5)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/5,1/4,1/3)	(2,3,4)	(1,1,1)	(1,1,1)	(3,4,5)
KADIKÖY	(1,2,3)	(3,4,5)	(1,1,1)	(1,2,3)	(1,1,1)	(1,1,1)	(6,7,8)
BAKIRKÖY	(1/5,1/4,1/3)	(1/4,1/3,1/2)	(1/3,1/2,1)	(1,1,1)	(6,7,8)	(6,7,8)	(6,7,8)
FATİH	(1,1,1)	(1,1,1)	(1,1,1)	(1/8,1/7,1/6)	(1,1,1)	(1/4,1/3,1/2)	(1,1,1)
BEYOĞLU	(1,1,1)	(1,1,1)	(1,1,1)	(1/8,1/7,1/6)	(2,3,4)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1,1,1)	(1,1,1)	(1,1,1)

CI:0,0342

Tables 3.16, 3.17, 3.18 and 3.19 show the pairwise comparison between the alternatives for each sub-criteria of the second main criterion, demographic structure. For instance, based on the sub-criterion of population density, Bakırköy has a significance level of 7 in comparison to Beşiktaş.

Table 3.18. Pair comparison of alternatives according to population density sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(2,3,4)	(1/4,1/3,1/2)	(1,1,1)	(2,3,4)	(1,2,3)	(2,3,4)
BEŞİKTAŞ	(1/4,1/3,1/2)	(1,1,1)	(1/4,1/3,1/2)	(1/8,1/7,1/6)	(1,2,3)	(1,2,3)	(2,3,4)
KADIKÖY	(2,3,4)	(2,3,4)	(1,1,1)	(1,1,1)	(2,3,4)	(2,3,4)	(2,3,4)
BAKIRKÖY	(1,1,1)	(6,7,8)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
FATİH	(1/4,1/3,1/2)	(1/3,1/2,1)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)	(1/3,1/2,1)	(1,1,1)
BEYOĞLU	(1/3,1/2,1)	(1/3,1/2,1)	(1/4,1/3,1/2)	(1,1,1)	(1,2,3)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)	(1/3,1/2,1)	(1,1,1)

CI:0,013

Table 3.19. Pair comparison of alternatives according to level of education sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(6,7,8)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(6,7,8)
BEŞİKTAŞ	(1/8,1/7,1/6)	(1,1,1)	(1,1,1)	(1,1,1)	(6,7,8)	(6,7,8)	(6,7,8)
KADIKÖY	(1,1,1)	(1,1,1)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(7,8,9)
BAKIRKÖY	(1/9,1/8,1/7)	(1,1,1)	(1/9,1/8,1/7)	(1,1,1)	(5,6,7)	(6,7,8)	(5,6,7)
FATİH	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)	(1/3,1/2,1)	(1,1,1)
BEYOĞLU	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1,2,3)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)	(1/3,1/2,1)	(1,1,1)

CI:0,0130

Table 3.20. Pair comparison of alternatives according to job employment sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(6,7,8)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(6,7,8)
BEŞİKTAŞ	(1/8,1/7,1/6)	(1,1,1)	(1,1,1)	(1,1,1)	(6,7,8)	(6,7,8)	(6,7,8)
KADIKÖY	(1,1,1)	(1,1,1)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(7,8,9)
BAKIRKÖY	(1/9,1/8,1/7)	(1,1,1)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
FATİH	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,2,3)	(1,1,1)
BEYOĞLU	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1,1,1)	(1/3,1/2,1)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1/3,1/2,1)	(1,1,1)

CI:0,0109

Table 3.21. Pair comparison of alternatives according to welfare level sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(6,7,8)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(6,7,8)
BEŞİKTAŞ	(1/8,1/7,1/6)	(1,1,1)	(1,1,1)	(1,1,1)	(6,7,8)	(6,7,8)	(6,7,8)
KADIKÖY	(1,1,1)	(1,1,1)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(7,8,9)
BAKIRKÖY	(1/9,1/8,1/7)	(1,1,1)	(1/9,1/8,1/7)	(1,1,1)	(5,6,7)	(6,7,8)	(5,6,7)
FATİH	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)	(1,2,3)	(1,1,1)
BEYOĞLU	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/3,1/2,1)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1,1,1)	(1/3,1/2,1)	(1,1,1)

CI:0,0131

Tables 3.20 and 3.21 show the pairwise comparison between the alternatives for each sub-criteria of the traffic main criterion. Based on the data, it can be concluded that Fatih has the lowest number of EVCS and the lowest charging capacity, indicating a lower level of importance in this respect.

Table 3.22. Pair comparison of alternatives according to EVCS sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(5,6,7)	(1/4,1/3,1/2)	(2,3,4)	(7,8,9)	(5,6,7)	(5,6,7)
BEŞİKTAŞ	(1/7,1/6,1/5)	(1,1,1)	(1/7,1/6,1/5)	(1/3,1/2,1)	(6,7,8)	(6,7,8)	(7,8,9)
KADIKÖY	(2,3,4)	(5,6,7)	(1,1,1)	(7,8,9)	(8,9,9)	(5,6,7)	(6,7,8)
BAKIRKÖY	(1/4,1/3,1/2)	(1,2,3)	(1/9,1/8,1/7)	(1,1,1)	(6,7,8)	(5,6,7)	(4,5,6)
FATİH	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/9,1/8)	(1/8,1/7,1/6)	(1,1,1)	(1/7,1/6,1/5)	(1/4,1/3,1/2)
BEYOĞLU	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1/7,1/6,1/5)	(5,6,7)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/7,1/6,1/5)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/6,1/5,1/4)	(2,3,4)	(1/3,1/2,1)	(1,1,1)

CI:0,0181

Table 3.23. Pair comparison of alternatives according to charging power sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(5,6,7)	(1/4,1/3,1/2)	(2,3,4)	(7,8,9)	(5,6,7)	(5,6,7)
BEŞİKTAŞ	(1/7,1/6,1/5)	(1,1,1)	(1/7,1/6,1/5)	(1/3,1/2,1)	(6,7,8)	(6,7,8)	(7,8,9)
KADIKÖY	(2,3,4)	(5,6,7)	(1,1,1)	(7,8,9)	(8,9,9)	(1/7,1/6,1/5)	(6,7,8)
BAKIRKÖY	(1/4,1/3,1/2)	(1,2,3)	(1/9,1/8,1/7)	(1,1,1)	(6,7,8)	(5,6,7)	(4,5,6)
FATİH	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/9,1/8)	(1/8,1/7,1/6)	(1,1,1)	(1/7,1/6,1/5)	(1/4,1/3,1/2)
BEYOĞLU	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1/7,1/6,1/5)	(5,6,7)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/7,1/6,1/5)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/6,1/5,1/4)	(2,3,4)	(1/3,1/2,1)	(1,1,1)

CI:0,0181

Pairwise comparisons between alternatives for each sub-criteria of the environment main criterion are shown in Tables 3.22, 3.23, 3.24, 3.25 and 3.26.

Table 3.24. Pair comparison of alternatives according to food and beverage areas sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(1,1,1)	(1/4,1/3,1/2)	(6,7,8)	(7,8,9)	(6,7,8)	(5,6,7)
BEŞİKTAŞ	(1,1,1)	(1,1,1)	(1/8,1/7,1/6)	(1,2,3)	(5,6,7)	(5,6,7)	(2,3,4)
KADIKÖY	(2,3,4)	(6,7,8)	(1,1,1)	(6,7,8)	(7,8,9)	(7,8,9)	(7,8,9)
BAKIRKÖY	(1/8,1/7,1/6)	(1/3,1/2,1)	(1/8,1/7,1/6)	(1,1,1)	(6,7,8)	(6,7,8)	(3,4,5)
FATİH	(1/9,1/8,1/7)	(1/7,1/6,1/5)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1,1,1)	(1/3,1/2,1)	(1,2,3)
BEYOĞLU	(1/8,1/7,1/6)	(1/7,1/6,1/5)	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1,2,3)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/7,1/6,1/5)	(1/4,1/3,1/2)	(1/9,1/8,1/7)	(1/5,1/4,1/3)	(1/3,1/2,1)	(1,1,1)	(1,1,1)

CI:0,0148

Table 3.25. Pair comparison of alternatives according to government agencies sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/5,1/4,1/3)	(6,7,8)	(1,1,1)	(1,2,3)	(1,1,1)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/4,1/3,1/2)	(6,7,8)	(1,1,1)	(1,1,1)	(1,1,1)
KADIKÖY	(3,4,5)	(2,3,4)	(1,1,1)	(7,8,9)	(1,1,1)	(1,2,3)	(1,1,1)
BAKIRKÖY	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
FATİH	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(2,3,4)
BEYOĞLU	(1/3,1/2,1)	(1,1,1)	(1/3,1/2,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/4,1/3,1/2)	(1,1,1)	(1,1,1)

CI:0,0159

Table 3.26. Pair comparison of alternatives according to health institutions sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/3,1/2,1)	(3,4,5)	(6,7,8)	(2,3,4)	(3,4,5)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1)	(3,4,5)	(6,7,8)	(4,5,6)	(4,5,6)
KADIKÖY	(1,2,3)	(1,2,3)	(1,1,1)	(4,5,6)	(7,8,9)	(5,6,7)	(5,6,7)
BAKIRKÖY	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1,1,1)	(7,8,9)	(6,7,8)	(6,7,8)
FATİH	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1,1,1)	(1/7,1/6,1/5)	(1/4,1/3,1/2)
BEYOĞLU	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(5,6,7)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/7,1/6,1/5)	(1/8,1/7,1/6)	(2,3,4)	(1,1,1)	(1,1,1)

CI:0,0167

Table 3.27. Pair comparison of alternatives according to hotel-accommodation sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(3,4,5)	(1/5,1/4,1/3)	(3,4,5)	(1,1,1)	(2,3,4)	(3,4,5)
BEŞİKTAŞ	(1/5,1/4,1/3)	(1,1,1)	(1/3,1/2,1)	(3,4,5)	(1,1,1)	(4,5,6)	(4,5,6)
KADIKÖY	(3,4,5)	(1,2,3)	(1,1,1)	(3,4,5)	(1,1,1)	(3,4,5)	(3,4,5)
BAKIRKÖY	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1/5,1/4,1/3)	(1,1,1)	(1,1,1)	(4,5,6)	(4,5,6)
FATİH	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)	(1/6,1/5,1/4)	(1/3,1/2,1)
BEYOĞLU	(1/4,1/3,1/2)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(4,5,6)	(1,1,1)	(1,1,1)
ÜSKÜDAR	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1/5,1/4,1/3)	(1/6,1/5,1/4)	(1,2,3)	(1,1,1)	(1,1,1)

CI:0,0319

Table 3.28. Pair comparison of alternatives according to business center-plaza sub-criteria

Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
ŞİŞLİ	(1,1,1)	(7,8,9)	(1,1,1)	(7,8,9)	(7,8,9)	(6,7,8)	(6,7,8)
BEŞİKTAŞ	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(6,7,8)	(6,7,8)	(6,7,8)	(7,8,9)
KADIKÖY	(1,1,1)	(1,1,1)	(1,1,1)	(7,8,9)	(7,8,9)	(7,8,9)	(7,8,9)
BAKIRKÖY	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1,1,1)	(1,1,1)
FATİH	(1/9,1/8,1/7)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1/7,1/6,1/5)	(1,1,1)
BEYOĞLU	(1/8,1/7,1/6)	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1,1,1)	(5,6,7)	(1,1,1)	(1,2,3)
ÜSKÜDAR	(1/8,1/7,1/6)	(1/9,1/8,1/7)	(1/9,1/8,1/7)	(1,1,1)	(1,1,1)	(1/3,1/2,1)	(1,1,1)

CI:0,0114

3.2.4.2. Synthetic Order Values for Main Criteria and Sub-Criteria

The synthetic order values represent the relative weights of the main criteria and sub-criteria based on the results obtained using fuzzy logic. These values are employed to assist decision makers in complex decision-making processes. The synthetic ranking values of the main criteria and sub-criteria are utilized to ascertain which factors are of greater importance in the decision-making process and to facilitate the prioritization of these factors according to their relative importance.

The steps of Chang's (1996) rank analysis can be shown as follows:

The value of fuzzy synthetic degree in terms of element is expressed as follows:

$$S_i = \sum_{j=1}^{m} M_{gi}^{j} \text{ x } \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} \quad (3.7)$$

To obtain the expression $\sum_{j=1}^{m} M_{gi}^{j}$, fuzzy addition process is applied to m order analysis value as shown below.

$$\sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{j=1}^{m} l_j \sum_{j=1}^{m} m_j \sum_{j=1}^{m} u_j\right) \tag{3.8}$$

$$\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j} = \left(\sum_{i=1}^{n} l_i \sum_{i=1}^{n} m_i \sum_{i=1}^{n} u_i\right) \tag{3.9}$$

Then the inverse of the vector is obtained by the formula:

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_{gi}^{j}\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i}\right) \tag{3.10}$$

Tables 3.27 to 3.31 contain values calculated using Equation (3.7), which was obtained using Equations (3.8, 3.9 and 3.10).

As shown in the Table 3.27, according to the district selection for EVCS, Location has the highest priority. The lowest value is 0.422, the medium value is 0.537 and the highest value is 0.682. Next priorities are assigned to Environment, Traffic and Demographic Structure according to the obtained weights.

Table 3.29. Synthetic order values for main criteria

MAIN CRITERIA	L	M	U
LOCATION	0,422	0,537	0,682
DEMOGRAPHIC STRUCTURE	0,027	0,031	0,037
TRAFFIC	0,163	0,205	0,257
ENVIRONMENT	0,183	0,227	0,282

As shown in the Table 3.28, according to the location main criterion, Distance to Mall is the highest priority. The lowest value is 0.304, the medium value is 0.402 and the highest value is 0.525. Next priorities are assigned to Distance to Oil, Distance to Parking, Distance to Hospital and Distance to Green Areas according to the obtained weights.

Table 3.30. Synthetic order values of sub-criteria for location

LOCATION	L	M	U
DISTANCE TO HOSPITAL	0,110	0,140	0,177
DISTANCE TO MALL	0,304	0,402	0,525
DISTANCE TO PARKING	0,121	0,151	0,189
DISTANCE TO OIL	0,215	0,273	0,347
DISTANCE TO GREEN AREA	0,031	0,036	0,042

As shown in the Table 3.29, according to the Demographic Structure, Welfare Level is the first priority. The lowest value is 0.2972, the medium value is 0.3790 and the highest value is 0.4843. Next priorities are assigned to Level of Education, Job Employment and Population Density according to the obtained weights.

Table 3.31. Synthetic order values of sub-criteria for demographic structure

DEMOGRAPHIC STRUCTURE	L	M	U
POPULATION DENSITY	0,0429	0,0525	0,0663
LEVEL OF EDUCATION	0,2081	0,3101	0,4439
JOB EMPLOYMENT	0,1883	0,2584	0,3632
WELFARE LEVEL	0,2972	0,3790	0,4843

As shown in the Table 3.30, according to the Traffic, Charging Power has the highest priority. The lowest value is 0.462, the medium value is 0.750 and the highest value is 1,176. Next priorities are assigned to EVCS according to the obtained weights.

Table 3.32. Synthetic order values of sub-criteria for traffic

TRAFFIC	L	M	U
EVCS	0,192	0,250	0,353
CHARGING POWER	0,462	0,750	1,176

As shown in the Table 3.31, according to the Environment, Hotel-Accommodation has the highest priority. The lowest value is 0.230, the medium value is 0.328 and the highest value is

0.459. Next priorities are assigned to Business Center-Plaza, Food and Beverage Areas, Health Institutions and Government Agencies according to the obtained weights.

Table 3.33. Synthetic order values of sub-criteria for environment

ENVIRONMENT	L	M	U
FOOD AND BEVERAGE AREAS	0,200	0,266	0,362
GOVERNMENT AGENCIES	0,019	0,023	0,029
HEALTH INSTITUTIONS	0,081	0,110	0,149
HOTEL- ACCOMMODATION	0,230	0,328	0,459
BUSINESS CENTER- PLAZA	0,195	0,273	0,379

The synthetic order value helps to determine the best or most suitable alternatives by evaluating the performance of alternatives. Tables 3.32, 3.33, 3.34, and 3.35 display the synthetic rank values of the alternatives for each sub-criterion.

Table 3.34. Synthetic order values for location main criterion

Location	Alternatives	L	M	U
Distance to Hospitals	ŞİŞLİ	0,133	0,223	0,306
	BEŞİKTAŞ	0,135	0,192	0,289
	KADIKÖY	0,167	0,245	0,370
	BAKIRKÖY	0,149	0,200	0,284
	FATİH	0,033	0,047	0,070
	BEYOĞLU	0,056	0,075	0,107
	ÜSKÜDAR	0,015	0,019	0,028
Distance to Malls	ŞİŞLİ	0,291	0,365	0,452
	BEŞİKTAŞ	0,199	0,249	0,313
	KADIKÖY	0,159	0,198	0,248
	BAKIRKÖY	0,035	0,038	0,043
	FATİH	0,017	0,020	0,024
	BEYOĞLU	0,055	0,068	0,086
	ÜSKÜDAR	0,048	0,061	0,077
Distance to Parking Lots	ŞİŞLİ	0,223	0,272	0,391
	BEŞİKTAŞ	0,130	0,160	0,202
	KADIKÖY	0,194	0,234	0,334
	BAKIRKÖY	0,110	0,207	0,204
	FATİH	0,042	0,053	0,079
	BEYOĞLU	0,027	0,037	0,057
	ÜSKÜDAR	0,027	0,038	0,060

Table 3.35. Synthetic order values for location main criterion (continued)

Distance to Oils	ŞİŞLİ	0,125	0,183	0,269
	BEŞİKTAŞ	0,085	0,124	0,179
	KADIKÖY	0,142	0,213	0,311
	BAKIRKÖY	0,200	0,273	0,373
	FATİH	0,054	0,065	0,080
	BEYOĞLU	0,072	0,096	0,130
	ÜSKÜDAR	0,037	0,045	0,057
Distance to Green Areas	ŞİŞLİ	0,125	0,183	0,269
	BEŞİKTAŞ	0,085	0,124	0,179
	KADIKÖY	0,142	0,213	0,311
	BAKIRKÖY	0,200	0,273	0,373
	FATİH	0,054	0,065	0,080
	BEYOĞLU	0,072	0,096	0,130
	ÜSKÜDAR	0,037	0,045	0,057

Table 3.36. Synthetic order values for demographic structure main criterion

Demographic Structure	**Alternatives**	**L**	**M**	**U**
Population Density	ŞİŞLİ	0,106	0,194	0,336
	BEŞİKTAŞ	0,064	0,128	0,234
	KADIKÖY	0,137	0,248	0,423
	BAKIRKÖY	0,137	0,189	0,269
	FATİH	0,048	0,068	0,115
	BEYOĞLU	0,056	0,107	0,202
	ÜSKÜDAR	0,047	0,066	0,106
Level of Education	ŞİŞLİ	0,229	0,300	0,391
	BEŞİKTAŞ	0,142	0,186	0,241
	KADIKÖY	0,202	0,261	0,338
	BAKIRKÖY	0,123	0,163	0,216
	FATİH	0,019	0,024	0,032
	BEYOĞLU	0,024	0,043	0,068
	ÜSKÜDAR	0,019	0,024	0,033
Job Employment	ŞİŞLİ	0,258	0,334	0,431
	BEŞİKTAŞ	0,160	0,207	0,266
	KADIKÖY	0,227	0,292	0,372
	BAKIRKÖY	0,040	0,045	0,052
	FATİH	0,033	0,046	0,063
	BEYOĞLU	0,028	0,042	0,064
	ÜSKÜDAR	0,028	0,034	0,044
Welfare Level	ŞİŞLİ	0,229	0,300	0,391
	BEŞİKTAŞ	0,142	0,186	0,241
	KADIKÖY	0,202	0,261	0,338
	BAKIRKÖY	0,123	0,163	0,216
	FATİH	0,024	0,035	0,050
	BEYOĞLU	0,019	0,031	0,050
	ÜSKÜDAR	0,019	0,024	0,033

Table 3.37. Synthetic order values for traffic main criterion

Traffic	Alternatives	L	M	U
EVCS	ŞİŞLİ	0,164	0,229	0,321
	BEŞİKTAŞ	0,134	0,180	0,248
	KADIKÖY	0,220	0,302	0,407
	BAKIRKÖY	0,112	0,162	0,232
	FATİH	0,012	0,015	0,021
	BEYOĞLU	0,049	0,073	0,106
	ÜSKÜDAR	0,025	0,039	0,061
Charging Power	ŞİŞLİ	0,171	0,240	0,336
	BEŞİKTAŞ	0,140	0,188	0,259
	KADIKÖY	0,197	0,270	0,362
	BAKIRKÖY	0,118	0,170	0,243
	FATİH	0,013	0,016	0,022
	BEYOĞLU	0,051	0,076	0,111
	ÜSKÜDAR	0,026	0,041	0,064

Table 3.38. Synthetic order values for environment main criterion

Environment	Alternatives	L	M	U
Food And Beverage Areas	ŞİŞLİ	0,182	0,246	0,334
	BEŞİKTAŞ	0,105	0,155	0,224
	KADIKÖY	0,249	0,341	0,465
	BAKIRKÖY	0,115	0,161	0,226
	FATİH	0,020	0,033	0,055
	BEYOĞLU	0,024	0,037	0,055
	ÜSKÜDAR	0,021	0,027	0,040
Government Agencies	ŞİŞLİ	0,157	0,221	0,302
	BEŞİKTAŞ	0,124	0,157	0,201
	KADIKÖY	0,190	0,272	0,375
	BAKIRKÖY	0,052	0,060	0,070
	FATİH	0,095	0,122	0,156
	BEYOĞLU	0,067	0,082	0,109
	ÜSKÜDAR	0,074	0,086	0,102
Health Institutions	ŞİŞLİ	0,132	0,202	0,303
	BEŞİKTAŞ	0,134	0,195	0,286
	KADIKÖY	0,173	0,257	0,377
	BAKIRKÖY	0,148	0,203	0,282
	FATİH	0,013	0,017	0,024
	BEYOĞLU	0,055	0,076	0,106
	ÜSKÜDAR	0,033	0,049	0,073

Table 3.39. Synthetic order values for environment main criterion (continued)

Hotel- Accommodation	ŞİŞLİ	0,128	0,202	0,312
	BEŞİKTAŞ	0,131	0,196	0,297
	KADIKÖY	0,145	0,234	0,366
	BAKIRKÖY	0,102	0,149	0,219
	FATİH	0,053	0,067	0,091
	BEYOĞLU	0,066	0,094	0,137
	ÜSKÜDAR	0,036	0,057	0,090
Business Center- Plaza	ŞİŞLİ	0,243	0,312	0,398
	BEŞİKTAŞ	0,188	0,242	0,311
	KADIKÖY	0,215	0,273	0,345
	BAKIRKÖY	0,030	0,034	0,039
	FATİH	0,024	0,028	0,032
	BEYOĞLU	0,058	0,081	0,110
	ÜSKÜDAR	0,026	0,030	0,039

3.2.4.3. The Degree of Possibility for Main Criteria and Sub-Criteria

In this approach, decision-makers are permitted to express both uncertainty and certainty. The degree of probability represents the level of uncertainty associated with the primary criteria and sub-criteria, based on the results obtained through the use of fuzzy logic. These values assist decision-makers in comprehending the uncertainties inherent to the decision-making process and in devising strategies for addressing such uncertainties. The degrees of probability of the main criteria and sub-criteria are employed to ascertain which factors are more certain or more uncertain in the decision-making process, thereby enabling decision makers to act in accordance with these factors.

The likelihood degree of $M_2 = (l_2, m_2, u_2) \geq M_1 = (l_1, m_1, u_1)$ is defined as:

$$V(M_2 \geq M_1) = sup_{y \geq x}\lfloor min\mu_{M_1}(x), \mu_{M_2}(y)\rfloor \quad (3.11)$$

This expression can be equivalently expressed as follows:

$$V(M_2 \geq M_1) = \text{hgt}(M_1 \cap M_1) = \mu M_2(d) \quad (3.12)$$

$$\begin{cases} 1 & if \quad m_2 \geq m_1 \\ 0 & if \quad l_1 \geq u_2 \\ \frac{(l_1-u_2)}{(m_2-u_2)-(m_1-l_1)} & \text{other} \end{cases} \quad (3.13)$$

We can express $V(M_2 \geq M_1)$ as d and the highest intersection point between μ_{M_1} and μ_{M_2} being the ordinate of D, as seen in the figure 3.4 below:

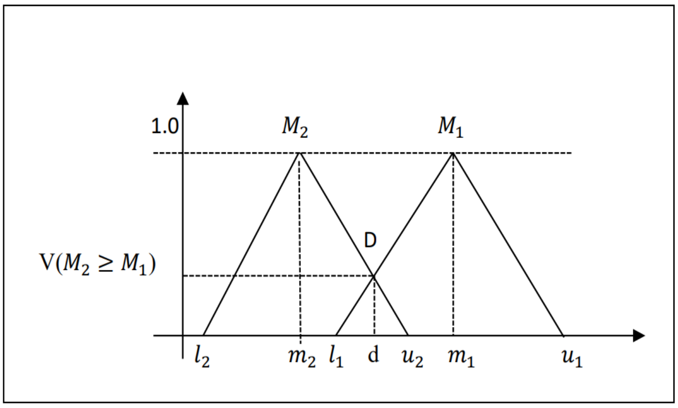

Figure 3.4. Triangular Fuzzy Number

In order to compare M_1 and M_2, both V($M_2 \geq M_1$) and V($M_1 \geq M_2$) values should be known. The values in Tables 3.36, 3.37, 3.38, 3.39 and 3.40 were calculated using Equation (3.13). This likelihood degree indicates that the performance of the criteria is uncertain or ambiguous. If m_2 is greater than m_1, a value of 1 is assigned. If l1 is greater than u_2, a value of 0 is assigned. Otherwise, the calculation was made using Equation (3.13) and the resulting value was assigned.

Table 3.40. The degree of possibility for main criteria

Main Criteria	Location	Demographic Structure	Traffic	Environment
Location	1	1	1	1
Demographic Structure	0	1	0	0
Traffic	0	1	1	0,770
Environment	0	1	1	1

Table 3.41. The degree of possibility of sub-criteria for location

LOCATION	Distance to Hospital	Distance to Mall	Distance to Parking	Distance to Oil	Distance to Green Area
Distance to Hospital	1	0	0,838	0	1
Distance to Mall	1	1	1	1	1
Distance to Parking	1	0	1	0	1

Table 3.42. The degree of possibility of sub-criteria for location (continued)

Distance to Oil	1	0,249	1	1	1
Distance to Green Area	0	0	0	0	1

Table 3.43. The degree of possibility of sub-criteria for demographic structure

DEMOGRAPHIC STRUCTURE	Population Density	Level of Education	Job Employment	Welfare Level
Population Density	1	0	0	0
Level of Education	1	1	1	0,680
Job Employment	1	0,750	1	0,354
Welfare Level	1	1	1	1

Table 3.44. The degree of possibility of sub-criteria for traffic

TRAFFIC	EVCS	Charging Power
EVCS	1	0
Charging Power	1	1

Table 3.45. The degree of possibility of sub-criteria for environment

ENVIRONMENT	Food and Beverage Areas	Government Agencies	Health Institutions	Hotel-Accommodation	Business Center-Plaza
Food and Beverage Areas	1	1	1	0,679	0,957
Government Agencies	0	1	0	0	0
Health Institutions	0	1	1	0	0
Hotel-Accommodation	1	1	1	1	1
Business Center-Plaza	1	1	1	0,732	1

Values in Tables 3.41, 3.42, 3.43 and 3.44 are calculated using Equation (3.13). These values indicate the degree of likelihood, which expresses the level of preference of alternatives under uncertainty. This degree allows for a more realistic modeling of the decision-making process, considering situations where the performance of a criterion is imprecise or uncertain. In this way, it helps decision makers better evaluate alternatives and make decisions under uncertainty.

Table 3.46. The degree of possibility for location main criterion

Location	Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
Distance to Hospitals	ŞİŞLİ	1	1	0,869	1	1	1	1
	BEŞİKTAŞ	0,831	1	0,698	0,946	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0,865	1	0,724	1	1	1	1
	FATİH	0	0	0	0	1	0,341	1
	BEYOĞLU	0	0	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	0	0	1
Distance to Malls	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0,161	1	1	1	1	1	1
	KADIKÖY	0	0,488	1	1	1	1	1
	BAKIRKÖY	0	0	0	1	1	0	0
	FATİH	0	0	0	0	1	0	0
	BEYOĞLU	0	0	0	1	1	1	1
	ÜSKÜDAR	0	0	0	1	1	0,754	1
Distance to Parking Lots	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0,963	1	0,988	1	1	1	1
	KADIKÖY	0,977	1	1	1	1	1	1
	BAKIRKÖY	0,725	0,756	0,762	1	1	1	1
	FATİH	0	0	0	0	1	0	0,375
	BEYOĞLU	0	0	0	0,083	1	1	1
	ÜSKÜDAR	0	0	0	0	1	0,454	1
Distance to Oils	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0	1	0,097	0,664	1	1	1
	KADIKÖY	0,746	1	1	1	1	1	1
	BAKIRKÖY	0	1	0,262	1	1	1	1
	FATİH	0	0	0	0	1	1	1
	BEYOĞLU	0	0	0	0	0,495	1	0,965
	ÜSKÜDAR	0	0	0	0	0,550	1	1
Distance to Green Areas	ŞİŞLİ	1	1	0,811	0,434	1	1	1
	BEŞİKTAŞ	0,479	1	0,297	0	1	1	1
	KADIKÖY	1	1	1	0,649	1	1	1
	BAKIRKÖY	1	1	1	1	1	1	1
	FATİH	0	0	0	0	1	0,204	1
	BEYOĞLU	0,054	0,616	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	0,0998	0	1

Table 3.47. The degree of possibility for demographic structure main criterion

Demographic Structure	Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
Population Density	ŞİŞLİ	1	1	0,789	1	1	1	1
	BEŞİKTAŞ	0,661	1	0,448	0,614	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0,971	1	0,694	1	1	1	1
	FATİH	0,072	0,459	0	0	1	0,604	1
	BEYOĞLU	0,524	0,865	0,315	0,440	1	1	1
	ÜSKÜDAR	0,001	0,398	0	0	0,960	0,546	1
Level Of Education	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0,098	1	0,342	1	1	1	1
	KADIKÖY	0,739	1	1	1	1	1	1
	BAKIRKÖY	0	0,768	0,123	1	1	1	1
	FATİH	0	0	0	0	1	0,315	0,990
	BEYOĞLU	0	0	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	1	0,322	1
Job Employment	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0,061	1	0,314	1	1	1	1
	KADIKÖY	0,727	1	1	1	1	1	1
	BAKIRKÖY	0	0	0	1	0,939	1	1
	FATİH	0	0	0	1	1	1	1
	BEYOĞLU	0	0	0	0,897	0,885	1	1
	ÜSKÜDAR	0	0	0	0,270	0,461	0,643	1
Welfare Level	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0,098	1	0,342	1	1	1	1
	KADIKÖY	0,739	1	1	1	1	1	1
	BAKIRKÖY	0	0,768	0,123	1	1	1	1
	FATİH	0	0	0	0	1	1	1
	BEYOĞLU	0	0	0	0	0,877	1	1
	ÜSKÜDAR	0	0	0	0	0,446	0,640	1

Table 3.48. The degree of possibility for traffic main criterion

Traffic	Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
EVCS	ŞİŞLİ	1	1	0,580	1	1	1	1
	BEŞİKTAŞ	0,632	1	0,185	1	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0,505	0,846	0,077	1	1	1	1
	FATİH	0	0	0	0	1	0	0
	BEYOĞLU	0	0	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	1	0,264	1
CHARGING POWER	ŞİŞLİ	1	1	0,821	1	1	1	1
	BEŞİKTAŞ	0,632	1	0,431	1	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0,505	0,846	0,310	1	1	1	1
	FATİH	0	0	0	0	1	0	0
	BEYOĞLU	0	0	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	1	0,264	1

Table 3.49. The degree of possibility for environment main criterion

Environment	Alternatives	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
FOOD AND BEVERAGE AREAS	ŞİŞLİ	1	1	0,473	1	1	1	1
	BEŞİKTAŞ	0,319	1	0	0,955	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0,340	1	0	1	1	1	1
	FATİH	0	0	0	0	1	0,879	1
	BEYOĞLU	0	0	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	0,790	0,624	1
GOVERNMENT AGENCIES	ŞİŞLİ	1	1	0,688	1	1	1	1
	BEŞİKTAŞ	0,409	1	0,085	1	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0	0	0	1	0	0,110147	0
	FATİH	0	0,479	0	1	1	1	1
	BEYOĞLU	0	0	0	1	0,261	1	0,886
	ÜSKÜDAR	0	0	0	1	0,154	1	1
HEALTH INSTITUTIONS	ŞİŞLİ	1	1	0,700	0,989	1	1	1
	BEŞİKTAŞ	0,960	1	0,645	0,944	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	1	1	0,667	1	1	1	1
	FATİH	0	0	0	0	1	0	0
	BEYOĞLU	0	0	0	0	1	1	1
	ÜSKÜDAR	0	0	0	0	1	0,395	1
HOTEL-ACCOMMODATION	ŞİŞLİ	1	1	0,838	1	1	1	1
	BEŞİKTAŞ	0,967	1	0,800	1	1	1	1
	KADIKÖY	1	1	1	1	1	1	1
	BAKIRKÖY	0,635	0,654	0,467	1	1	1	1
	FATİH	0	0	0	0	1	0,491	1
	BEYOĞLU	0,076	0,052	0	0,379	1	1	1
	ÜSKÜDAR	0	0	0	0	0,798	0,405	1
BUSINESS CENTER-PLAZA	ŞİŞLİ	1	1	1	1	1	1	1
	BEŞİKTAŞ	0,497	1	0,761	1	1	1	1
	KADIKÖY	0,724	1	1	1	1	1	1
	BAKIRKÖY	0	0	0	1	1	0	1
	FATİH	0	0	0	0,251	1	0	0,724
	BEYOĞLU	0	0	0	1	1	1	1
	ÜSKÜDAR	0	0	0	0,704	1	0	1

3.2.4.4. Normalized Weight Vectors for Main Criteria and Sub-Criteria

Normalised weight vectors assist decision-makers in comparing the effects of different criteria or sub-criteria and determining which factors have greater influence in the decision-making process. The normalisation process ensures that the sum of each vector is equal to 1, thereby facilitating a more comprehensive understanding of the relative contribution of each criterion or sub-criteria. The resulting normalised weight vectors provide decision-makers with a more precise understanding of the contribution of each criterion or sub-criteria in percentage terms. The results permit decision-makers to compare the effects of different criteria or sub-criteria and determine which factors have greater influence in the decision-making process.

The probability degree of a convex fuzzy number being larger than k convex fuzzy numbers M is calculated as follows.

$$V(M \geq M_1, M_2 \ldots\ldots\ldots.. M_k) = V[(M \geq M_1)\ldots(M \geq M_k)] = \min V(M \geq M_i) \quad (3.14)$$

i=1,2,…….,k

k= 1, 2…., n; for k$\neq j$ $d'(A_i)$=minV $(S_i \geq S_k)$ If equality is achieved, the weight vector becomes as follows;

$$W' = (d'(A_1), \ldots\ldots\ldots\ldots. d'(A_n))^T \quad (3.15)$$

The normalized version of the weight vector found is as follows, and note that this weight vector is not a fuzzy number.

$$W= (d(d(A_1), \ldots\ldots\ldots\ldots d(A_1))^T \quad (3.16)$$

The results shown in Tables 3.45 to 3.48 were obtained using Equations (3.14, 3.15 and 3.16). The normalization process ensures that the sum of the weights equals 1, which allows the weights to be expressed as percentages and provides a clear understanding of their contribution to the decision process. In complex decision-making problems where multiple criteria are evaluated, it is crucial that the sum of the weights equals 1. This ensures accurate and consistent results in the decision-making process.

Table 3.50. Normalized weight vectors for sub-criteria of location main criteria

NORMALIZED WEIGHT VECTORS(W')	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
Distance to Hospitals	0,26	0,21	0,30	0,22	0	0	0
Distance to Malls	0,86	0,14	0,00	0,00	0	0	0
Distance to Parking Lots	0,27	0,26	0,27	0,20	0	0	0
Distance to Oils	0,57	0	0,43	0	0	0	0
Distance to Green Areas	0,21	0	0,31	0,48	0	0	0

Table 3.51. Normalized weight vectors for sub-criteria of demographic structure main criteria

NORMALIZED WEIGHT VECTORS(W')	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
Population Density	0,24	0,14	0,31	0,21	0	0,10	0
Level of Education	0,54	0,05	0,40	0,00	0	0	0
Job Employment	0,56	0,03	0,41	0,00	0	0	0
Welfare Level	0,54	0,05	0,40	0	0	0	0

Table 3.52. Normalized weight vectors for sub-criteria of traffic main criteria

NORMALIZED WEIGHT VECTORS(W')	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
EVCS	0,31	0,10	0,54	0,04	0	0	0
Charging Power	0,32	0,17	0,39	0,12	0	0	0

Table 3.53. Normalized weight vectors for sub-criteria of environment main criteria

NORMALIZED WEIGHT VECTORS(W')	ŞİŞLİ	BEŞİKTAŞ	KADIKÖY	BAKIRKÖY	FATİH	BEYOĞLU	ÜSKÜDAR
Food and Beverage Areas	0,32	0	0,68	0	0	0	0
Government Agencies	0,39	0,05	0,56	0	0	0	0
Health Institutions	0,23	0,21	0,33	0,22	0	0	0
Hotel-Accommodation	0,27	0,26	0,32	0,15	0	0	0
Business Center-Plaza	0,45	0,22	0,33	0	0	0	0

Figure 3.49 shows that Şişli district is 80% suitable for EV deployment according to the FAHP results. This high suitability percentage indicates that the district holds a potential leadership position in achieving sustainable transportation goals and promoting EV usage. The successful performance of Şişli in providing optimal access for EV users and reducing environmental impacts can play a guiding role in regional planning and infrastructure development strategies.

Table 3.54. Final Table

Weights	1	0	0	0	
Alternatives / Criteria	Location	Demographic Structure	Traffic	Environment	Alternative Relative Weight
ŞİŞLİ	0,804396026	0,54694623	0,32029524	0,33900138	0,804396026
BEŞİKTAŞ	0,110450755	0,050069685	0,168207871	0,174773625	0,110450755
KADIKÖY	0,085153219	0,402984086	0,390341517	0,423850095	0,085153219
BAKIRKÖY	0	0	0,121155373	0,062374901	0
FATİH	0	0	0	0	0
BEYOĞLU	0	0	0	0	0
ÜSKÜDAR	0	0	0	0	0
TOTAL	1	1	1	1	1

3.2.5. K-Means Clustering Method

The K-means algorithm begins by randomly distributing k centroids throughout the dataset, with each centroid serving as an initial cluster center. Next, each data point in the dataset is assigned to the nearest centroid based on its Euclidean distance. This initial assignment establishes the initial formation of clusters. After completing the initial assignment, the algorithm proceeds to recalibrate the centroids by computing their new positions as the mean of all data points belonging to each cluster. This adjustment aims to enhance the centroids' representation of cluster centers, thereby refining the clustering arrangement.

Subsequent iterations involve recalculating distances between data points and centroids based on the updated centroid positions. Data points are then reassigned to the nearest centroid, potentially altering the cluster composition. This iterative cycle of recalibrating centroids, reassigning data points, and recalculating distances continues until a convergence criterion is met. The criterion is usually defined by the stabilization of centroid positions. This convergence shows that the algorithm has effectively divided the dataset into separate and stable clusters, each with a centroid representing its centre.

In summary, the K-means algorithm refines cluster centroids and data point assignments iteratively until it achieves an optimal clustering configuration, making it possible to identify cohesive and well-defined clusters within the dataset. The steps of the formula iterations are shown below.

3.2.5.1. Steps of K-Means Clustering

Step 1. Initialization of Centers:

Select k initial centers randomly. The centers represent the positions in the space of data points.

$C_1, C_2, \ldots\ldots C_k$ denote the k initial center points representing the starting positions in the space of data points.

Step 2. Assignment of Points to Clusters:

Each data point is assigned to the nearest center.

When the x_i point is assigned to the C_j center, the following Equation (3.17) is used:

$$j = \arg min_j || x_i - C_j ||^2 \qquad (3.17)$$

Step 3. Update of Centers:

The new center of each cluster is updated as the average of data points in that cluster.

The formula for updating the center is:

$$C_j = \frac{1}{|S_j|} \sum \quad x_i \in S_j \; x_i \qquad (3.18)$$

where S_j is the set containing data points in cluster j.

Step 4. Iteration:

Steps 2 and 3 are repeated until the centers do not change or until a certain number of iterations is reached.

Step 5. Result:

The algorithm terminates when a certain condition is met, such as no change in centers or a change below a specified threshold.

In Table 3.50, the latitude and longitude information of the 31 candidate locations in the Şişli region, considered for potential charging station placements, is comprehensively presented.

These details form the basis for analyses conducted to strategically position the charging infrastructure and ensure effective accessibility for electric vehicle users. The geographical coordinates of candidate locations have undergone a detailed examination to provide decision-makers with valuable guidance in determining planning and placement strategies. The boundaries of the Sisli district are illustrated in Figure 3.5. It is necessary to determine the candidate points within these boundaries.

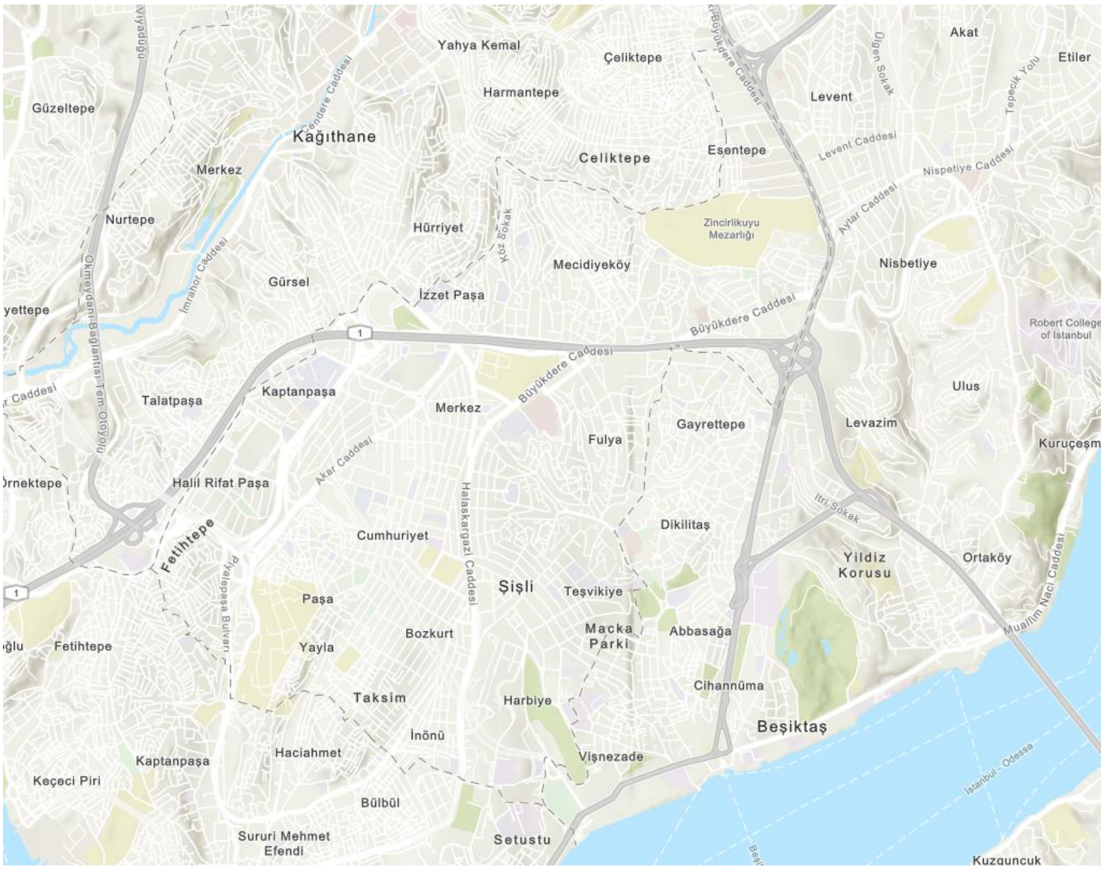

Figure 3.5. Map representation of Şişli district

Table 3.55. Latitude and longitude coordinates of existing CSs in Şişli

Places	**Type of Charge**	**Lat**	**Lon**
Adam Bosch Araç Servisi	ZES	41,0592630	28,9908320
Anthıll	GCHARGE	41,0568407	28,9759614
Ramada Plaza İstanbul Cıty Center	DMA	41,0510619	28,9874413
Tekfen Tower, 4. Levent	EŞARJ	41,0818385	29,0095146
Kanyon Avm, Levent	EŞARJ	41,0781840	29,0113100
Aytemiz, Şişli	EŞARJ	41,0587040	28,9657275
Hilton İstanbul Bomonti Hotel and Conference Center	EŞARJ	41,0582960	28,9794710
Fairmont Quasar İstanbul	ZES	41,0661690	29,0005990
Ibis Styles Hotel Bomonti	ZES	41,0612670	28,9789840
İspark Maçka Katlı Otopark 1	ZES	41,0460800	28,9895990
İspark Şişli Kapalı Otopark	ZES	41,0639690	28,9990910
Metrocity AVM	ZES	41,0758160	29,0122268
Grand Hyatt	Porsche	41,0410156	28,9864235
Radisson Blu Hotel Şişli	ZES	41,0616620	28,9887030
Özdilekpark İstanbul Avm	SHARZ	41,0773621	29,0116348
Gayrettepe Metro Otoparkı Zincirlikuyu	SHARZ	41,0688243	29,0098417
Keşan Petrol (Fulya)	SHARZ	41,0610420	29,0013270
İspark Maçka Katlı Otopark 2	SHARZ	41,0461159	28,9894524
The Rıtz - Carlton Istanbul	SHARZ	41,0404434	28,9920731
Cıty'S Nişantaşı	SHARZ	41,0510063	28,9924755
I Tower Bomonti	SHARZ	41,0604971	28,9802901
Cevahir Avm	VOLTRUN	41,0625997	28,9941240
Elıt Resıdence	VOLTRUN	41,0615180	28,9921860
Metrocıty Resıdence	VOLTRUN	41,0761850	29,0111460
Nidakule Levent	VOLTRUN	41,0796127	29,0089395
Nurol Tower	VOLTRUN	41,0680640	28,9862200
Şişli Belediye Otoparkı	VOLTRUN	41,0645650	28,9834676
İSPARK - MAÇKA	VOLTRUN	41,0484920	28,9902740
İSPARK - ŞİŞLİ	VOLTRUN	41,0641160	28,9992489
Divan Residence	VOLTRUN	41,0563540	28,9793480
Vital Otel	ZES	41,0570510	28,9970600

In the literature, there are numerous studies utilizing K-means clustering for location selection problems. The K-means clustering method, like the studies conducted by Ontoseno Penangsang (Ont173) in the literature, was employed to determine the optimal locations for installing EVCSs among 31 candidate locations. Initially, determining the number of clusters is crucial for K-means clustering.

3.2.5.2. Determination of Optimal Number of Cluster

The Elbow method is commonly employed in clustering algorithms, particularly when utilizing the K-means method, to determine the optimal number of clusters. This method involves identifying a point on the graph where the rate of error reduction significantly slows down, indicating the optimal number of clusters. In this study, the Elbow method was employed to determine the number of clusters, resulting in the determination of 4 clusters. The locations were then partitioned into clusters labelled 1, 2, 3, and 4, and the line graph depicting the distribution of candidate locations within the clusters is shown in Figure 3.6. The locations in the Şişli region, divided into clusters using ArcGIS software, are visualised in Figure 3.7. Cluster 1 is represented by purple points, cluster 2 by red points, cluster 3 by blue points and cluster 4 by green points.

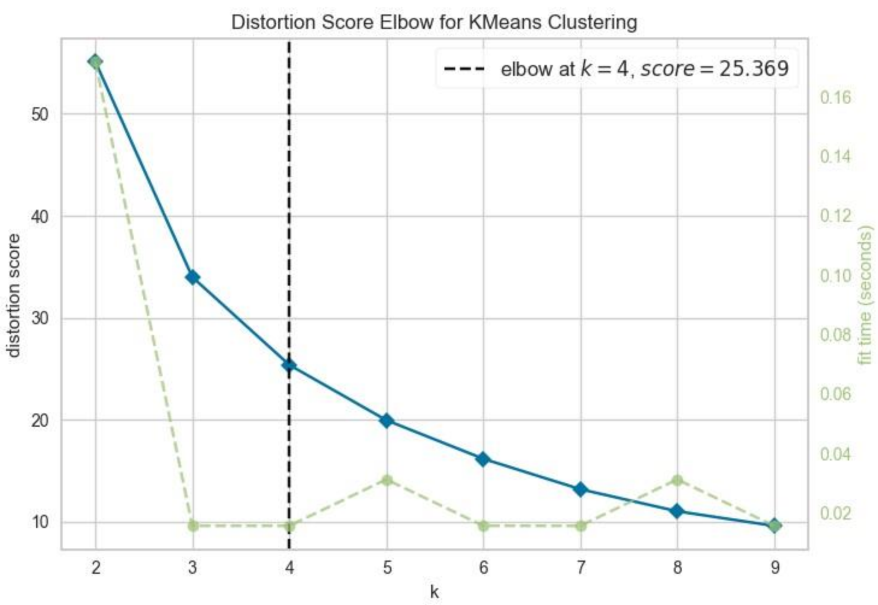

Figure 3.6. Elbow method for K-means clustering

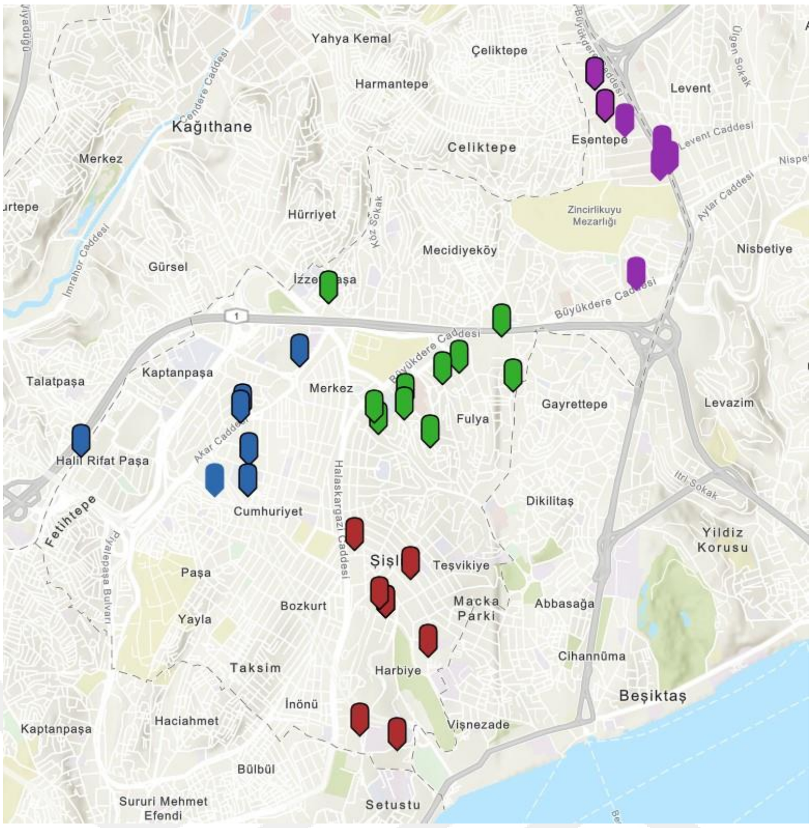

Figure 3.7. The distribution of candidate locations resulting from K-means clustering

3.2.5.3. Calculation of Cluster Centers

The strategic positioning and optimisation of electric vehicle (EV) charging stations necessitates the utilisation of clustering techniques. The objective of clustering is to calculate the centre points of candidate locations where charging stations are situated. These centre points will be expressed as the areas where EV usage is prevalent within each cluster. Consequently, the calculation of the centre point of each cluster is essential. Cluster centroids are representative of each group and are typically the points where the sum of the distances to other data points in that group is minimised. Cluster centres can be employed to distribute demand around charging stations in a balanced manner. This allows for a more efficient utilisation of resources and helps to avoid unnecessary costs. Cluster centres also facilitate the planning for future increases in demand or changing user behaviour.

The latitude and longitude coordinates of Cluster Centers resulting from K-means clustering are given in Table 3.51.

Table 3.56. Cluster Centers

Cluster Centers / Number of Clusters	1.Cluster Centers	2.Cluster Centers	3.Cluster Centers	4.Cluster Centers
Latitude	41,0768318	41,04631644	41,06005329	41,06238719
Longitude	29,01065906	28,98967697	28,97729228	28,99447777

The Haversine formula is frequently employed for precise computation of the distance between two geographical coordinates based on latitude and longitude data. This formula produces more accurate results by taking into account the spherical shape and curvature of the Earth. The steps used to calculate the distance between two points with the Haversine formula are as follows:

1. Take the latitude and longitude coordinates between the two points in degrees.
2. Calculate the central angles between the two points and the distance according to the average Earth radius based on the central angles.
3. Using the central angles obtained, the distance between the two points is found.

The distances between the two points were calculated using equations 3.19 and 3.20, with the Haversina formula in equation 3.21 employed to determine the distances in kilometres (Azdy & Darnis, 2020).

$$\Delta lat = latitude2 - latitude1 \tag{3.19}$$

$$\Delta long = \text{longitud}e2 - \text{longitude}1 \tag{3.20}$$

$$\text{distance} = 2.\text{R. arcsin}\left(\sqrt{sin^2\left(\frac{\Delta lat}{2}\right)} + cos(lat2).cos(lat1).sin^2\left(\frac{\Delta long}{2}\right)\right) \tag{3.21}$$

The radius of the sphere, designated by the symbol R, is typically assumed to be the radius of the Earth, which has a value of approximately 6371 km.

Table 3.52 shows the distances of the candidate points to the cluster centres in kilometers. The candidate location closest to cluster 1 is Metrocity Residence at 0.08269 km. Similarly, the closest candidate location to cluster 2 is İspark Maçka Katlı Otopark 1 at 0.02709 km. The closest location to cluster 3 is Hilton Istanbul Bomonti Hotel & Conference Center at 0.20603 km, and the closest location to cluster 4 is Cevahir Shopping Mall at 0.03794 km.

Tablo 3.52. Distances of Candidate Locations

Distance to Cluster Centres	
1. CLUSTER	Haversine Distance (km)
Tekfen Tower, 4. Levent	0,56492
Kanyon Avm, Levent	0,15995
Metrocity AVM	0,17328
Özdilekpark İstanbul Avm	0,10082
Gayrettepe Metro Otoparkı Zincirlikuyu	0,89302
Metrocity Residence	0,08269
Nidakule Levent	0,34116
2. CLUSTER	
Ramada Plaza İstanbul City Center	0,55998
İspark Maçka Katlı Otopark 1	0,02709
Grand Hyatt	0,64951
İspark Maçka Katlı Otopark 2	0,02918
The Ritz - Carlton Istanbul	0,68327
City's Nişantaşı	0,57186
İSPARK - MAÇKA	0,24703
3. CLUSTER	
Anthill Residence	0,32665
Aytemiz Şişli	0,99999
Hilton İstanbul Bomonti Hotel & Conference Center	0,20603
Ibis Styles Hotel Bomonti	0,22756
I Tower Bomonti	0,25062
Şişli Belediye Otoparkı	0,74712
Divan Residence	0,37940
4. CLUSTER	
Adam Bosch Araç Servisi	0,46272
Fairmont Quasar İstanbul	0,66347
İspark Şişli Kapalı Otopark	0,42488
Radisson Blu Hotel Şişli	0,49083
Keşan Petrol (Fulya)	0,59340
Cevahir Avm	0,03794
Elit Residence	0,21508
Nurol Tower	0,93687
İSPARK - ŞİŞLİ	0,44381
Vital Otel	0,63162

4. RESULTS AND DISCUSSIONS

4.1. Process of Determining Optimal Candidate Locations

As stated in the materials and methods section of the study, the study area was Istanbul, which has the highest concentration of EVs in the metropolitan area. The selection of criteria and alternatives was based on expert opinions. Four main criteria and sixteen sub-criteria were identified, along with seven alternatives. The Şişli region was ultimately chosen as the most suitable option using FAHP, based on expert survey scores. The study investigated suitable locations for EVCSs in the Şişli district. The focus was on the suitability of the existing charging infrastructure. A total of 32 candidate locations with existing charging stations were identified. Due to the increasing number of EVs and the assumption that the existing charging stations will not be sufficient and that there will be a high demand for these stations, the focus was on regions where the candidate locations are densely populated. In this study, candidate points were separated regionally using a clustering method. Cluster centres were identified and the candidate points closest to the cluster centres are determined.

4.2. Presentation of Results Using ArcGIS

After identifying the optimal points using the K-means method, the industry-standard geographic information systems (GIS) software, ArcGIS, was used to display them on the map. This allowed for a clearer view of the actual distance between the locations and better visualization capabilities. Metrocity Residence is selected as the optimal location for EVCS positioning because it is the closest candidate location to the first cluster centre, as shown in Figure 4.1.

The EVCS was optimally located at Ispark Maçka Katlı Otopark 1, as shown in Figure 4.2. This location is the closest to the centre of cluster 1. The Hilton Istanbul Bomonti Hotel and Conference Centre, which is the closest candidate location to the 3rd cluster centre, is selected as the optimum location for EVCS positioning, as visualised in Figure 4.3. According to Figure 4.4, the Cevahir Shopping Centre, which is the closest candidate location to the 4th cluster centre, is selected as the best location for EVCS positioning.

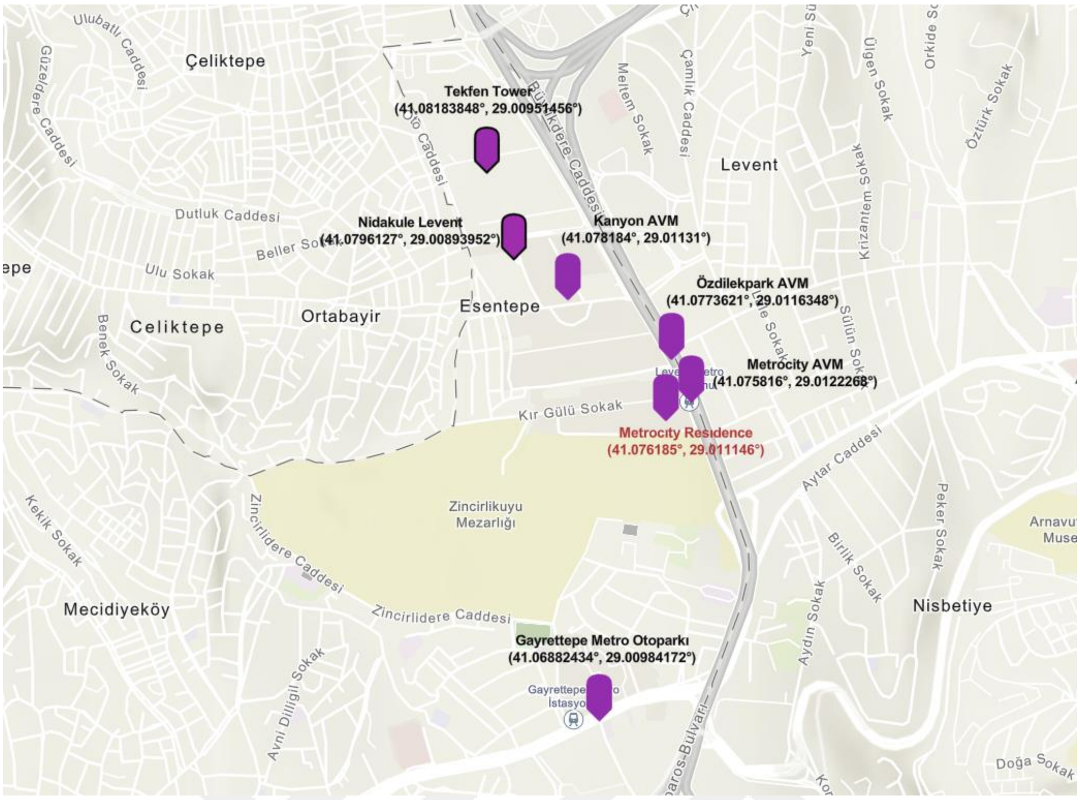

Figure 4.1. Candidate location in cluster 1 selected for EVCS placement.

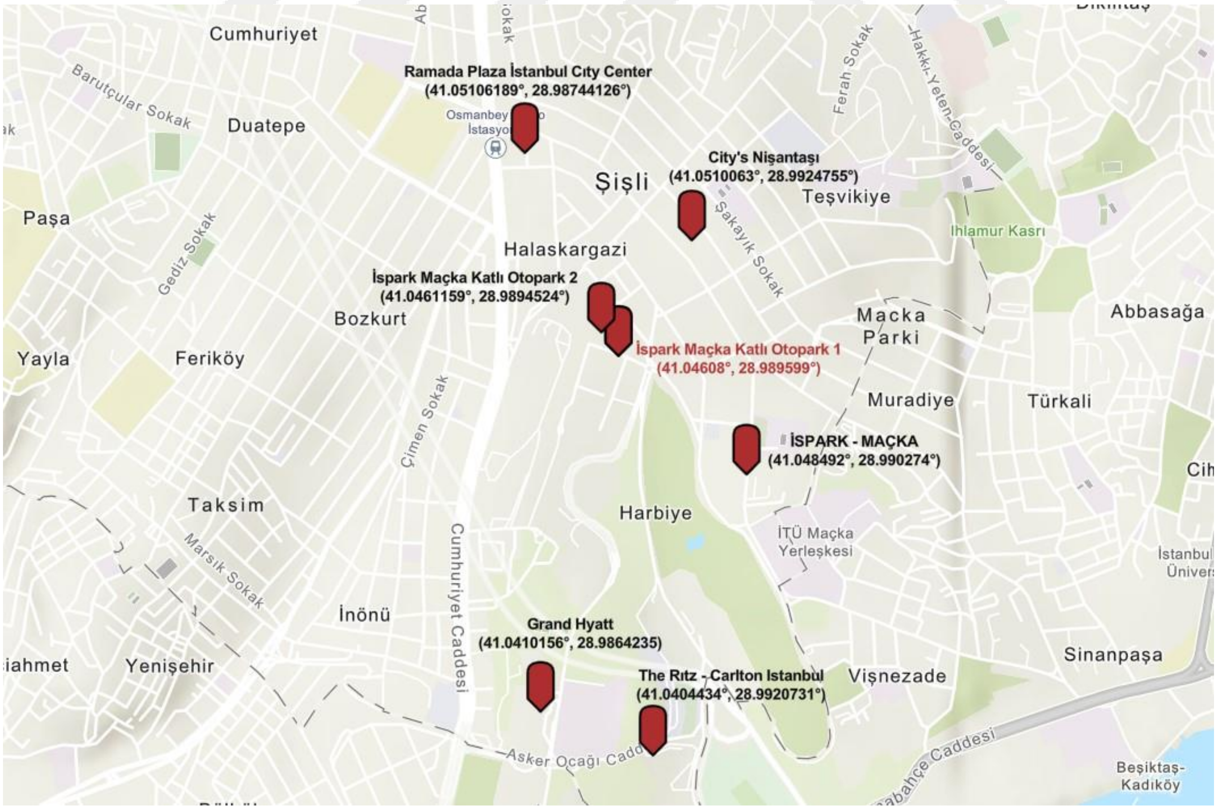

Figure 4.2. Candidate location in cluster 2 selected for EVCS placement.

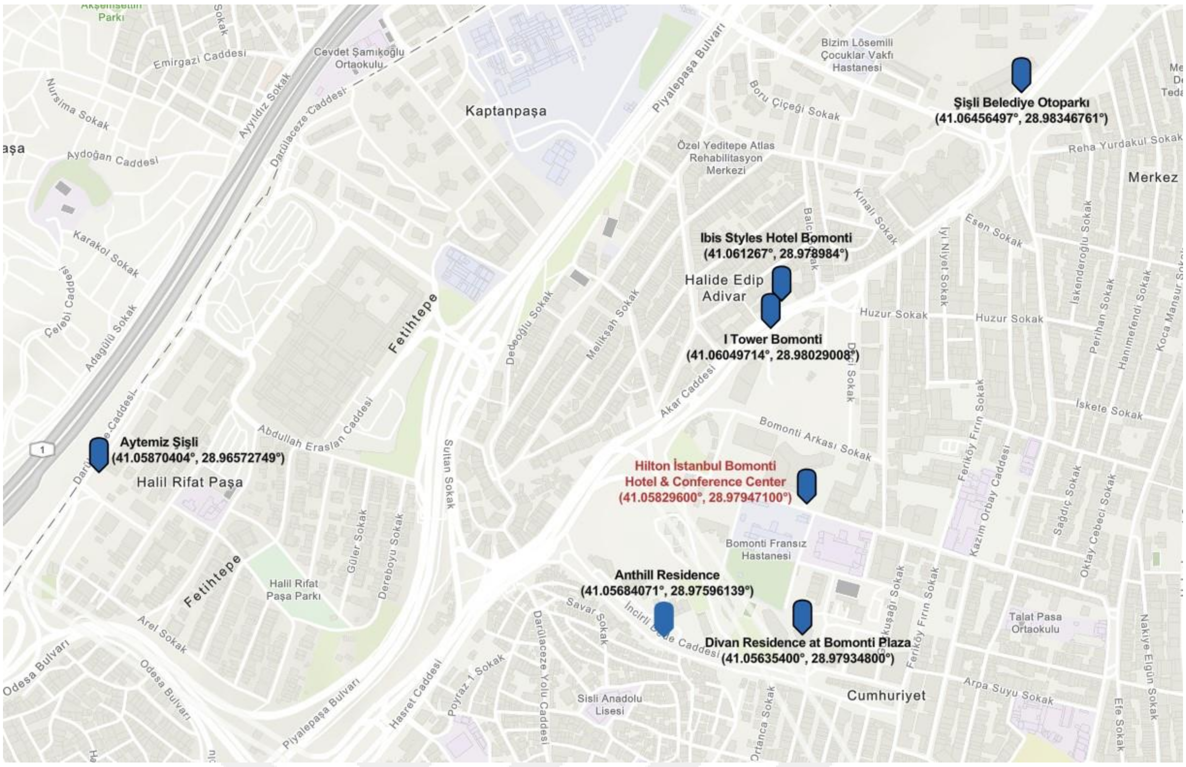

Figure 4.3. Candidate location in cluster 3 selected for EVCS placement

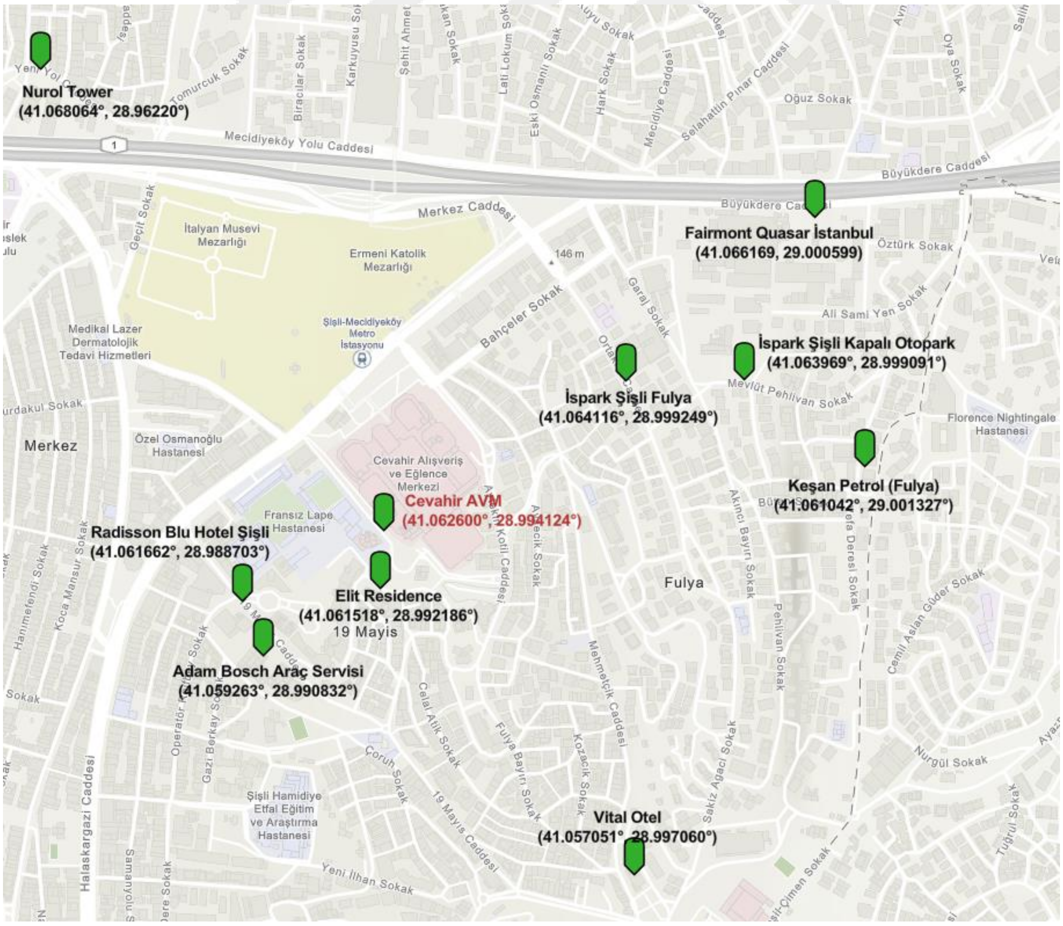

Figure 4.4. Candidate location in cluster 4 selected for EVCS placement

4.3. Evaluation of the Results of the K-Means Clustering Method

Each cluster shows candidate locations that are closely related in spatial proximity, providing valuable insights for decision-making processes. In cluster 1, Metrocity Residence is the candidate location nearest to the centroid, located at a distance of 0.08269 kilometers. This suggests that Metrocity Residence shares similar spatial characteristics with other candidate locations in cluster 1, potentially indicating commonalities in surrounding amenities or demographics. In Cluster 2 İspark Maçka Katlı Otopark 1 is the candidate location as it is the nearest location to Cluster 2's centroid, with a proximity of 0.02709 kilometers. The spatial proximity of candidate locations within this cluster suggests a shared geographical context or functional similarity, which may be relevant for urban planning or business development strategies. In cluster 3, the analysis has identified Hilton Istanbul Bomonti Hotel & Conference Center as the nearest candidate location, located approximately 0.20603 kilometers from its centroid. This proximity suggests that Hilton Istanbul Bomonti Hotel & Conference Center shares spatial characteristics with other candidate locations in cluster 3, potentially indicating a concentration of similar amenities or visitor demographics. Cluster 4 highlights Cevahir Shopping Mall as the nearest candidate location to its centroid, with a proximity of 0.03794 kilometers. The spatial clustering of candidate locations within this cluster may signify commonalities in commercial activities, consumer preferences, or urban infrastructure. The K-Means Clustering Method results enable informed decisions to be made regarding the placement of CSs among the candidate locations.

5. CONCLUSIONS

This study aimed to develop an effective decision support system for the placement of EVCS by integrating FAHP and K-means clustering methodologies. FAHP was applied effectively to address uncertainties and priorities among decision-makers, determining the weights of various criteria and sub-criteria in the process. The obtained weights were combined using the K-means clustering method to identify optimal regions for the strategic positioning of charging stations.

The K-means clustering method used to create homogeneous clusters by grouping regions with similar characteristics, aiming to ensure the optimal distribution of charging stations. This approach considered crucial factors such as accessibility for EV users, energy efficiency, and cost-effectiveness in determining the strategic locations of CS.

The results indicate that the combination of FAHP and K-means clustering methodologies provides an effective solution for planning and situating electric vehicle charging infrastructure. This study offers essential insights that can be used as a strategic planning tool to promote sustainable transportation and widespread adoption of EV. However, future research could enhance the model's reliability and improve results by incorporating more detailed data analysis and considering real usage scenarios.

6. RECOMMENDATIONS

This study has made a significant contribution to the placement of EVCS through the application of FAHP and K-means clustering methods. However, there are several recommendations that can be considered for future research based on similar studies. Firstly, increased participation and feedback from stakeholders such as local governments, energy providers, and city planners could contribute to a more comprehensive understanding of the strategic placement of charging stations.

Furthermore, expanding and updating the dataset used in this study could allow the model to produce more accurate and reliable results. In-depth analysis of dynamic factors such as real-time traffic data, electric vehicle demand projections, and user behavior could help determine more effective strategies for the placement of charging stations.

Emphasizing factors such as environmental sustainability and energy efficiency could lead to the development of a more comprehensive strategy for minimizing the environmental impact of charging station installations. Finally, the results of this study could be aligned with a broader institutional framework to be integrated into future charging infrastructure planning processes. These recommendations may guide future research towards the effective development and optimization of electric vehicle charging infrastructure.

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