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Research paper

Identifying locations for electric vehicle charging stations in urban areas through the application of multicriteria techniques

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A R T I C L E I N F O

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A B S T R A C T

The incorporation of electric vehicles (EVs) into urban mobility is increasing daily, driving the need to incorporate urban charging stations (EVCSs) additionally. This study proposes a methodology for identifying adequate EVCS locations within an urban area. This methodology is based on the joint application of multicriteria decision-making methods (MCDMs) to solve urban planning problems related to the placement of EVCSs. As a starting point, the locations of the existing fossil fuel supply stations in each city are used as alternatives. The city of Cuenca, Ecuador, is used as a case study. Criteria and subcriteria have also been determined based on the available information and are used to propose three scenarios based on their value variation, which is established as preponderance weights. Among the results obtained, three alternatives scored better than the rest in most of the evaluations. As there was no conclusive result, a statistical analysis was conducted to strengthen the decision-making process and determine the most favourable potential locations.

1. Introduction

The effects of climate change have complicated economic and security aspects and promote rapid decarbonization in sectors such as transportation (Campaña and Inga, 2019). Several organizations have presented studies showing that one of the main causes of climate change is combustion vehicles' emission of exhaust gases. However, the transition from combustion vehicles to electrically powered vehicles could reduce air pollution by 84 % (Ahmadi, 2019). In several regions of the world, a transition from nearly all fuel vehicles to nearly all-electric vehicles (EVs) is already expected (Rietmann et al., 2020). However, this would require an infrastructure that allows EV users to recharge their vehicles. To achieve this outcome, the optimal location of charging points must be carefully analysed to identify strategic sites for electric

Abbreviations: EVs, Electric Vehicles; EVCSs, Electric Vehicles Charging Stations; MCDM, Multi-Criteria Decision-Making Methods; FDM, Fuzzy Delphi Method; AHP, Analytical Hierarchy Process; TOPSIS, Technique for Order Preference by Similarity to Ideal Solution; GIS, Geographic Information System; VIKOR, VIseKriterijumska Optimizacija I Kompromisno Resenje; PROMETHEE, Preference Ranking Organization Method for Enrichment Evaluation; ANP, Analytic Network Process; MULTIMOORA, Multi-Objetive Optimization by Ration Analysis; DEMATEL, Decision Making Trial and Evaluation Laboratory; HFLTS, Hesitant Fuzzy Linguistic Terms; EWM, Entropy Weighting Method; GRA, Grey Relational Analysis; FAHP, Fuzzy Analytical Hierarchy Process; TFN, Triangular Fuzzy Numbers; EMOV, Public Mobility Company Empresa pública de movilidad, in spanish; ARCERNNR, Agencia de Regulación y Control de Energía y Recursos Naturales no Renovables; GADs, Decentralized Autonomous Governments Gobierno Autónomo descentralizado, in spanish.

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vehicle charging stations (EVCSs) (Chen et al., 2015).

In the Ecuadorian context, the “Organic Law of Energy Efficiency” provides the legal framework for the promotion of the efficient use of energy in all of its forms. Chapter III, article 14 establishes that all urban and interparish transport vehicles incorporated from the year 2025 and onwards must use electric propulsion. Additionally, its section on transitory provisions indicates that decentralized autonomous governments (GADs, following its Spanish acronym) must establish incentives to encourage the use of EVs (NACIONAL and ECUADOR, 2019). The municipal GAD of the city of Cuenca, through its mobility plan, promotes sustainable mobility. To this end, it has proposed connecting strategic points with bicycle lanes, implementing charging stations in the main parks, and operating the tram system. Higher education institutions also conduct technical research projects to promote electric mobility (Ilustre Municipalidad de Cuenca, 2015; Iñiguez-Morán et al., 2023)Various decision-making techniques are used to solve different types of problems involving several unrelated factors that could influence the desired result. Multicriteria decision-making methods (MCDMs) are methods that help to identify better alternatives for solving a problem from varied criteria (Ecer, 2021). These criteria can come from different categories and are generally evaluated in different ways. When using the MCDM, these criteria can be related through weighting processes as evaluated using the method to obtain the best alternatives. The results obtained through MCDMs are influenced by the importance given to each criterion by the decision maker, who must be an expert in the related field (Karaşan et al., 2020).

H. Zhao and N. Li (Zhao and Li, 2016) used the MCDM to determine the optimal location of EVCSs in five districts that make up the city of Tianjin in China. In the investigations in (Bian et al., 2019; Pacheco and Contreras, 2008), the districts in each study area were used as alternatives for evaluation. In (Kaya et al., 2020), the entire Istanbul area was considered the study area, and a geographic information system (GIS) was used for the analysis. In such a study, the most suitable points can be detected through MCDM. R. Jahanandish (Jahanandish et al., 2020) asserted that the proposed alternatives should be specific places in each district, such as shopping centres.

More recently, advances have proposed new methodologies to improve the efficiency of locating EV charging stations within urban areas. In Cai et al. (Cai et al., 2024) defined the optimal charging station site selection for EV logistics vehicles, concluding that strategically locating the stations could be reduce the path length by 11 % and the number of charging stations by 25 %. Alshareef and Fathy (Alshareef and Fathy, 2024) developed a methodology to establish the optimal allocation of fast charging stations using the Raid-Tailed Hawk algorithm. Though this process, they found the potential to reduce voltage oscillations affecting the grid configuration by 30 %. Hu et al. (Hu et al., 2024) integrated environmental and economic considerations for charging station planning through an improved Quantum Genetic Algorithm, which also allowed them to define the appropriate sizing of these stations accordingly. Kim (Kim, 2024) proposed a method for efficient vehicle routing in concordance with the state of the charging stations, developing route plans to reach the more efficient and cost-effective solutions, defining that is necessary to consider the situation of each charge station and it also depends on its allocation.

Decision-making models use different methods from those used to evaluate zones, places, or sites, allowing for the establishment of one or more locations. B. Csonka and C. Csiszár (Csonka and Csiszár, 2017) applied a multicriteria method that consists of weighting candidate areas for the placement of roads in counties, districts and the urban area of Budapest. Several factors, including economic, demographic, and environmental and public transport usage factors, were considered to apply the model. For the interstate highways, an evaluation was carried out by using rest areas and border stations as candidate points. For the urban environment, the territorial units were divided into hexagons covering the Újbuda area of Budapest and then evaluated. The study concluded that the main variables for highways are the distance to the nearest fast charging station and the services available. For urban environments, the placement of recharging points is recommended, principle in more concentrated areas and accounting for the fact that users may stay in the charging area for a long timestamp).

This research’s main novelty lies in applying a methodological approach that integrates several MCDM. These methodological processes are powerful tools that allow alternatives to be evaluated and compared based on multiple criteria, making them especially useful in complex situations where different aspects must be considered before deciding. By integrating multiple MCDMs, the strengths of each are leveraged: some methods may be better suited for handling certain types of data or problem structures, while others may excel at optimizing different objectives or managing uncertainty more effectively.

This diversity of MCDM methods allows for mitigating potential disadvantages associated with using a single method, such as sensitivity to researcher assumptions or dependence on chosen parameters. By evaluating the same problem from different approaches, a more complete and robust perspective is obtained, which reduces the risk of bias or limitations inherent to a single method. Furthermore, by combining the results of several MCDM methods, a more robust and reliable consensus can be obtained, which increases the credibility and validity of the conclusions obtained.

In summary, the integration of different MCDM methods in this research makes it possible to take advantage of their strengths but also contributes to overcoming the possible limitations and disadvantages associated with their individual use, allowing for more decisive conclusions and obtaining the best result.

2. Literature review

Selecting a proper location for charging stations is not a trivial issue. In this context, (Charly et al., 2023) propose a method to identify the optimal locations for vehicle charging stations using an open-source GIS approach. The study identifies the site selection criteria for charging stations, such as lamp posts, population density, houses and apartments, motorways, roads, trip attractors and existing charging stations. This work carried out in Dublin identified 770 suitable locations for the initial installation of charging stations. However, this study does not consider the real electric distribution network in the city. Other works integrate multiple approaches to solve this concern, for example (Liladhar et al., 2023), use Multi Influencing Factor (MIF) weights integrated to a GIS, then a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) ranks the charging stations based on suitability index values decreasing the uncertainty in the solution of electrical vehicle charging station problems. The results can be further validated using other MCDM techniques. In this sense, (Iravani, 2022) uses a multicriteria GIS-based decision-making approach to finding the optimal electrical vehicle charging stations. This study considers equity and efficiency to maximize accessibility to charging stations into two levels. The first level solves the Set Covering Location Problem (SCLP) according to a threshold where the distance between the user and the EV charging station is less than or equal to a given value. The second level solves the Maximum Coverage Location Problem (MCLP) by considering several criteria to satisfy the demand of the initial adopters. This work provides a tool that can be used as a guideline, enabling planning more prudently and efficiently. However, the limitations of this type of study lie in the real number and power capacity of the charging stations in the real world.

When seeking to maximize or minimize a result, decision methods that propose the resolution of a single objective problem present a series of limitations when analysing a problem in which multiple unrelated objectives are raised for different scenarios (Stojčić et al., 2019). Moreover, MCDMs allow the evaluation and resolution of complex problems when various scenarios are posed with multiple objectives and criteria. MCDMs are thus used in different sectors, such as resource management, planning, transportation, and health care (Tzeng and

Huang, 2011). The structure of a problem can be summarized using three main components: i) the elements that compose the problem, ii) the processes involved, and iii) the results. Based on these components, MCDM allows a decision to be made through selecting, ordering, and classifying each of the alternatives (Pacheco and Contreras, 2008). Table 1 presents a summary of the background research.

3. Methodology

3.1. Methodology structure

Table 1 presents the main evaluation methods used to determine the location of EVCSs found in the literature. Based on this information, the use of combined techniques in different investigations is noted. Each MCDM has advantages and disadvantages for specific applications, so combining two or more methods could increase the degree of reliability of the results (Liu et al., 2019; Tzeng and Huang, 2011). Since the choice

Table 1
Investigations regarding the location selection of load centres.

Title	Objective	Methodology	Key Findings	Conclusion	Ref.
Joint Planning of Smart EV Charging Stations and DGs in Eco-Friendly Remote Hybrid Microgrids	Jointly allocate and size EV charging stations and DGs to minimize costs and emissions	Multi-objective mixed integer non-linear program, genetic algorithm	Provides a Pareto frontier balancing economic and environmental objectives	Effectively allocates DGs and EV stations with a compromise solution	(Shaaban et al., 2019)
A Hybrid Multi-Objective Chicken Swarm Optimization and Teaching Learning-Based Algorithm for Charging Station Placement Problem	Optimize EV charging station placement to reduce costs and ensure grid stability	Hybrid multi-objective evolutionary algorithm (CSO TLBO), fuzzy decision-making	Superior performance in solving charging station placement and benchmark problems	Promising results for charging station placement and future applications	(Deb et al., 2020)
Optimal Allocation of Electric Vehicle Charging Stations With Adopted Smart Charging/ Discharging Schedule	Optimal allocation and smart charging/discharging of EVCS within the distribution network	Multi-Objective Particle Swarm Optimization (MOPSO), Monte Carlo simulation	Efficient scheduling improves network load characteristics and profitability	Demonstrates effectiveness in optimizing EVCS allocation	(Hadian et al., 2020)
Mitigation of Complexity in Charging Station Allocation for EVs Using Chaotic Harris Hawks Optimization Charge Scheduling Algorithm	Reduce waiting times and improve utilization in EV charging stations	Chaotic Harris Hawks Optimization (CHHO), VANET simulation	Reduces waiting times and enhances EV utilization	CHHO algorithm offers an efficient solution for EV charging management	(Kumar et al., 2023)
Charging station site selection optimization for Electric Logistics vehicles taking into account Time window and Load constrains	Locating charging stations in concordance the optimal transportation path, considering time efficiency	Proposal of an improved genetic algorithm application for optimizing locations, and in consequence time	The path could be reduced in an 11 %, and it is possible to reduce the charging stations number in a 25 %	It is possible to reduce time, energy, charging stations units and the costs of the logistics company when applying automated algorithms	(Cai et al., 2024)
Optimal Allocation of Fast Charging Stations on Real Power Transmissions Network with Penetration of Renewable Energy Plant	To optimize the location of EV fast charging stations in a grid to enhance its realibility	The Raid-Tailed Hawk Algorithm to determine the best option to locate EV charging stations.	It is possible to reduce in a 30 % the grid voltage oscillations	It was possible to determine and reduce the voltage fluctuation by applying logical algorithms	(Alshareef and Fathy, 2024)
Integrating Environmental and Economic and Economic Considerations in Charging Stations Planning: An Improved Quantum Generic Algorithm	To optimize charging station locations and sizing considering social costs and environmental impact	The application of a quantum genetic algorithm with dynamic rotation angles and simulated annealing to optimize charging station location and sizing	Highlights the effectiveness of the Improved Quantum Gentecit Algorithm for finding the optimum location and size accordingly	Improved Quantum Gentecit Algorithm shows in the analysed case the location and size of the charge station balancing economic and environmental aspects	(Hu et al., 2024)
Electric vehicle routing with States of Charging Stations	Optimizing routes strategy according to the variability of the situation of each charging station	It proposes an optimized model to for routing EV conducting numerical experiments to validate the solution approach	Development of route plans optimization showcasing the impact of different algorithms on the travel costs	For leading the most cost-effective solution to vehicle routing is essential to consider the states of charging station	(Kim, 2024)
Identifying optimal locations for community electric vehicle charging Anna	Demonstrate how cities worldwide will have to examine the methods by which charging infra-structure is introduced to the urban realm	Open source GIS approach and selection criteria.	Identified 770 suitable locations for the initial installation of changing stations.	This study segregates the proposed charging points into high-priority sites, which may be installed by 2025 and medium-priority sites, which may be established by 2030.	(Charly et al., 2023)
An integrated GIS, MIF, and TOPSIS approach for appraising electric vehicle charging station suitability zones in Mumbai, India	Delineate the optimal places for new electric vehicle charging stations (EVCS) in study area.	Multi Influencing Factor (MIF) weights integrated to a GIS, and a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)	The zone falling between 297.587 and 488.520 suitability index has suitability for EV charging stations.	This study provides a scientific framework for evaluating, analyzing, and identifying suitable locations for EVCS.	(Liladhar et al., 2023)
A multicriteria GIS-based decision-making approach for locating electric vehicle charging stations	Systematically determine the locations of EV charging stations	Solves the Set Covering Location Problem (SCLP) according a threshold where the distance between the user and the EV charging station, and solves the Maximum Covering Location Problem (MCLP)	A combined SCLP & MCLP methodology consider both equity and efficiency in determining the locations of EV charging stations.	Provide a tool that can be used as a guideline, enabling planning in a more prudent and efficient manner.	(Iravani, 2022)

of an MCDM cannot guarantee that the obtained result is 100 % reliable, for this investigation, three methods that are considered to be the most suitable to the context and the available resources were used. These methods are VIKOR, TOPSIS, and PROMETHEE (Feng et al., 2021; Tzeng and Huang, 2011).

The VIKOR, TOPSIS and PROMETHEE methods are valuable tools in multicriteria decision-making (MCDM), each specializing in different but complementary approaches. VIKOR stands out for its ability to handle uncertain data and provide a balanced solution between alternatives. TOPSIS, on the other hand, is based on the distance to the ideal and worst solution, allowing a robust evaluation, although it may be sensitive to extreme values when giving a result. While PROMETHEE focuses on the weighting of criteria and the compensation between them, this method offers flexibility in decision-making. Therefore, when evaluating the same problem with these methods, the result can be improved by taking advantage of the specific strengths of each method and addressing different aspects of the problem comprehensively, leading to accurate decision-making. By applying these methods, it is possible to observe the differences in the results and then analyse the best alternatives that result in each case. To apply the three chosen methods, three scenarios were used based on the weighting of the criteria. This process allows us to determine the extent to which criteria importance influences the obtained results (Anastasiadou et al., 2021; Liu et al., 2019).

In Fig. 1, the investigative methodological structure is presented. First, alternative EVCS locations are defined. Then, criteria and

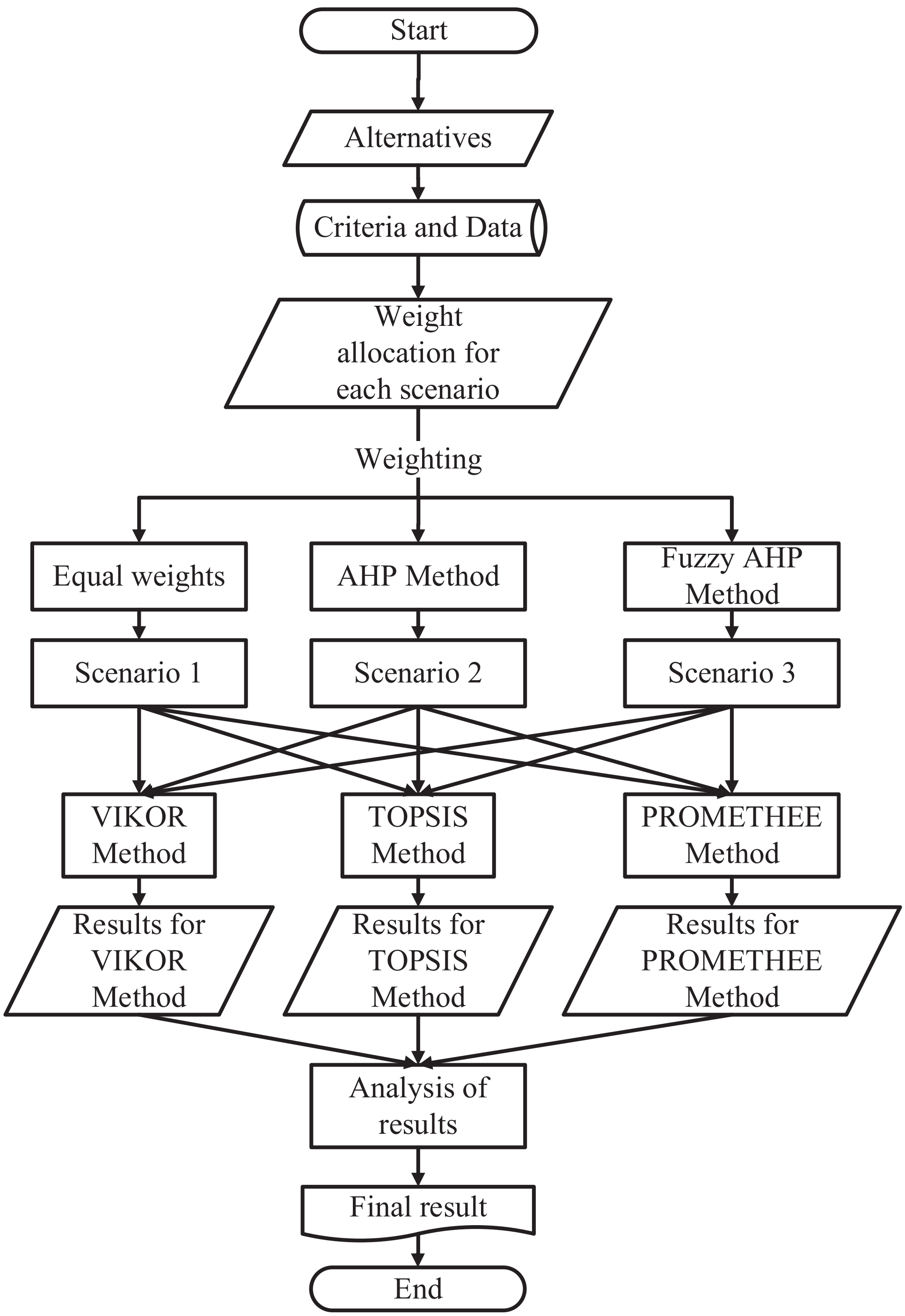


Fig. 1. Diagram of the proposed methodology.

subcriteria are selected based on the usual practices in this matter, which are found in the literature. Later, we evaluate each subcriterion using the alternatives. Then, weights are assigned to the subcriteria. This process is fundamental when applying the MCDM, and this weighting process depends on the decision-makers and, therefore, on the objectives and the available data. We propose to evaluate three scenarios using each method. For the first scenario, all subcriteria are weighted the same (Tzeng and Huang, 2011). Then, to define the weights for the second scenario, 12 professionals in research and related fields, including electrical, civil, and architectural engineering, were surveyed. Based on these experts' criteria, the importance of each criterion is weighed. After obtaining the survey information, the AHP method is applied to calculate the weights of each criterion (Anastasiadou et al., 2021; Hadikurniawati et al., 2019); however, this method has disadvantages since the assignment of weights is not always precisely conducted, as it depends on subjective judgements. For the third scenario, the fuzzy analytical hierarchy process method (FAHP), which is a variant of the AHP method, is implemented, and concepts from the theory of fuzzy logic are applied (Anastasiadou et al., 2021).

After obtaining the weights and evaluating the subcriteria, the three scenarios are implemented using the VIKOR, TOPSIS and PROMETHEE methods. The results obtained by each method are exhaustively evaluated and analysed. If a conclusive result is not reached or a significant discrepancy occurs between the results given by each method, an additional statistical analysis will be carried out. This analysis will allow us to determine the robustness and reliability of the conclusions obtained. Through this rigorous process, we will seek to guarantee the validity and reliability of the best alternatives for implementing electric vehicle charging stations (EVCS) within the city.

3.2. AHP method

The analytic hierarchy method (AHP) consists of three operations: i) the construction of hierarchies, ii) priority analysis, and iii) consistency verification. The method is used to perform a paired comparison in which an underlying scale is applied, as shown in Table 2. In this way, equal importance is determined between the two criteria (Sivakumar et al., 2015; Wang et al., 2019)

Once the pairwise importance of each criterion has been established, matrix A is created for pairwise comparison. Matrix A is a square matrix $n\times n$, where x is the importance value of the paired comparison between criteria, as shown in (1). When $aij = x$, then $aji = 1/x$ with $1/9 \leq x \leq 9$. If the criterion in i is the same as that in j, $x = 1$, that is, $aij = aji = 1$. Additionally, $aii = 1\ \forall\ i$ (Sivakumar et al., 2015).

$$A = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & & \ddots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix}, \quad i,j = 1, 2, 3, \ldots n \tag{1}$$

Table 2
Pairwise comparison scale.

Value	Definition	Explanation
1	Equal importance	Criterion A and B are equally important.
3	Weak importance	Criterion A is slightly important with respect to criterion B.
5	Strong importance	Criterion A has a large importance with respect to criterion B.
7	Very great importance	Criterion A has a strong importance with respect to criterion B.
9	Extreme importance	Criterion A is extremely important with respect to criterion B.
2,4,6,8	Intermediate values	Intermediate values that can be used if it is necessary to qualify.

3.3. FAHP method

The FAHP method combines the AHP method with fuzzy comparison. This method allows for decision-making while reducing the uncertainty presented by the AHP method (Aldrin Wiguna et al., 2017). Within Boolean logic, there are only two values ("true", "false") or (0,1), which limits the accuracy of its representation of real-life phenomena. The application of a fuzzy number, on the other hand, allows for interpolation between 0 and 1. There are different types of fuzzy numbers, among which triangular and trapezoidal numbers are the most commonly used (Brajkovic et al., 2015).

Triangular fuzzy numbers (TFNs) are based on a linguistic set. This linguistic set is defined by three numbers that represent different parameters. The elements "l" and "u" indicate the maximum and minimum limits that "m" can take, as presented in Fig. 2 and (Nag and Helal, 2019).

As in the AHP method, a linguistic scale made up of a TFN scale is used to assign the corresponding evaluations to each criterion or subcriterion. The description and assessment of this scale are presented in Table 3, while its graphic representation is shown in Fig. 3 (Nag and Helal, 2019).

As in the AHP method, the comparison matrix **M** is constructed, but only in each criterion is a TFN assigned, where each element M_{ij} is made up of parameters (l, m, u). The parameters' values when comparing a criterion with itself are (1,1,1).

3.4. VIKOR method

This method is an updated version of the TOPSIS method used to calculate the proportion of positive and negative ideal solutions that can eliminate the impact of a phenomenon. Information normalization is performed linearly, while the selection and classification of alternatives are based on contradictory criteria (Aghabali et al., 2021; Wolbertus and Van den Hoed, 2019).

The most important steps in the method are as follows:

1) Determine the best and worst values.
2) Calculate the values of S_j and R_j, where S_j is the weighted and normalized Manhattan distance, while R_j is the weighted and normalized Chebyshev distance.
3) Calculate the distance Q_j based on the distance calculation performed in Step 2.
4) Classify the alternatives according to the values of S, R, and Q, leading to the formation of three lists.
5) Set the trade-off among the last three ranking lists.

As an update of the TOPSIS method, the advantages and versatility of the VIKOR method are expanded, and it can be applied in more analysis fields, such as manufacturing engineering, the health and medical fields, business administration, and mechanical engineering (Tzeng and Huang, 2011).

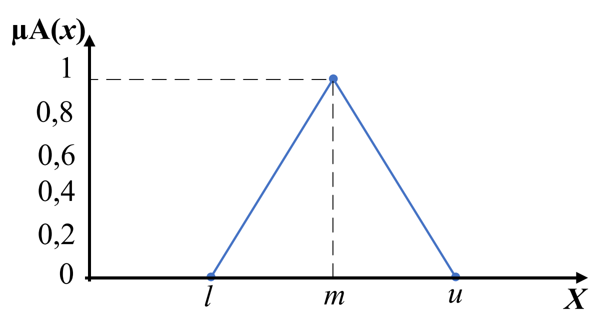


Fig. 2. Membership or triangular fuzzy number function.

Table 3
Triangular fuzzy scale.

Linguistic scale for importance	Fuzzy number	Fuzzy scale (l, m, n)
Exactly equal		(1,1,1)
Equal importance	1	(1,1,3)
Moderate importance	3	(1,3,5)
Strongly equal	5	(3,5,7)
Very strong importance	7	(5,7,9)
Extremely important	9	(7,9,9)

3.5. TOPSIS method

TOPSIS, which was developed in 1981 by Hwang and Yoon, works in multidimensional space, where positive and negative solutions are used to locate the ideal alternative, which is further from the negative ideal (Aghabali et al., 2021; Wolbertus and Van den Hoed, 2019). The best alternative is positioned at the closest distance to the ideal and the furthest from the negative ideal. The advantage of this method is its ease of use in working with quantitative and/or qualitative (Aghabali et al., 2021; Wolbertus and Van den Hoed, 2019).

The steps of the method are as follows:

1) Calculate the decision matrix.
2) Normalize the item data.
3) Calculate the positive and negative solutions.
4) Calculate the relative distances and proximities between the solutions.

The data used to inform this method can be interdependent or independent. For this reason, this method is popular in logistics, energy management, chemical engineering, water resources management, and planning (Tzeng and Huang, 2011).

3.6. PROMETHEE method

This method is used to classify alternatives according to preference by evaluating their weaknesses and strengths. The problem's alternatives are compared in pairs by identifying the dominant action among criteria. Actions are evaluated based on different criteria, which must be minimised or maximised (Aghabali et al., 2021; Wolbertus and Van den Hoed, 2019)

PROMETHEE is used in two forms of action classification: i) PROMETHEE I, which is used to conduct a partial evaluation, and ii) PROMETHEE II, which is used to conduct a complete evaluation. These modalities were presented in 1982 by Jean-Pierre Brans (Aghabali et al., 2021; Wolbertus and Van den Hoed, 2019).

The main steps for implementing the PROMETHEE method are obtained as follows:

1) Determine the evaluation matrix for the pairwise comparison.
2) Assign the preferred function according to the needs of the problem.
3) Calculate the global matrix and determine ranks by adding the column that presents a dominant alternative.

This method can be used with uncertain or confusing quantitative or qualitative information, and it is therefore used in risk analysis, structural analysis, engineering, energy, and the environment (Tzeng and Huang, 2011).

4. Case study

The actions taken by the municipal GAD of Cuenca promote electromobility within the city's urban area by managing the tramway system, constructing bicycle lanes, and providing charging stations in strategic public parking lots. Other institutions, such as universities, the CENTRO SUR electricity company, and the Public Mobility Company (EMOV) of the city of Cuenca, have carried out various research and social projects to promote electromobility as a way of addressing the transportation problems that arise in the city (Iñiguez-Morán et al., 2023). Due to population growth, mobility has become the main issue to be solved. Regarding modes of transportation, 43.1 % of travellers use public transport by bus, which is the most common mode, followed by 35.9 % using private cars and 1.9 % using taxis (Ilustre Municipalidad de Cuenca, 2015). According to the Public Mobility, Transit and Transport Company, EMOV EP, 98,527 private vehicles were registered in 2021, representing an average of 1.5 units for every 10 inhabitants (Empresa Pública de Movilidad, 2021).

As a signatory of international agreements against climate change, Ecuador develops policies, rules, and regulations meant to gradually modify its modes of transport. The ARCONEL 007_19 regulation established a model to supply electricity for EV charging in public places (NACIONAL and ECUADOR, 2019). The Agency for the Regulation and Control of Energy and Non-Renewable Natural Resources (Agencia de Regulación y Control de Energía y Recursos Naturales no Renovables, ARCERNNR) has established a tariff schedule for electric power stations. Limit costs have been established for EV recharging: the cost for semi-fast charging, where AC $\leq$ 20 kW, is 17.15 [ctvs./kWh]; for fast charging, where AC$>$ 20 kW, it is 19.94 [ctvs./kWh]; and for ultrafast charging, where DC $\geq$ 50 kW, it is 28.51 [ctvs./kWh]. These costs are currently in effect in Ecuador as of 2023 (Renovables, 2022).

Vehicles, and therefore their associated pollution, are concentrated in densely populated urban areas, and the conversion of combustion vehicles to EVs at all scales is strategic (Ahmadi, 2019). One of the barriers to accelerating this process is the limited availability of EVCSs for the user (Hardman et al., 2018). It is expected that 292,472 EVs will have been incorporated in Ecuador by 2032. By then, the required infrastructure will need to be in place, including charging stations, rest areas, health services, telecommunications systems, transformation centres, and various types of protection, among others (Arias et al., 2020).

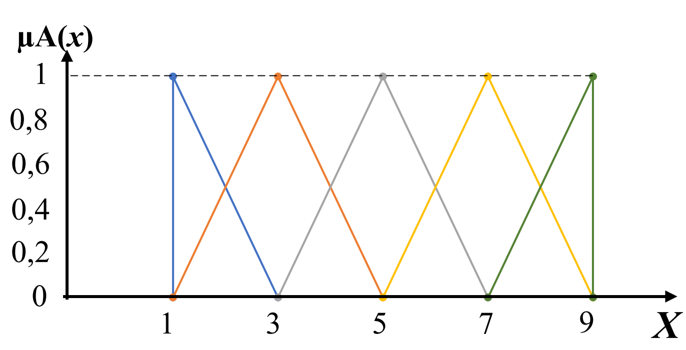


Fig. 3. Linguistic variables corresponding to fuzzy numbers.

Proper positioning of load centres allows for a more efficient supply of EV energy requirements. Different models have been applied to determine the optimal location of EVCSs in different parts of the world. In this paper, we propose applying MCDM techniques to identify suitable locations for EVCSs in Cuenca (Chen et al., 2020; Wolbertus and Van den Hoed, 2019).

4.1. Location of the study area

The city of Cuenca is located at the coordinates 2° 39 ‘“to 3° ”00’ south latitude and 78° 54‘” to 79° ”26’ west longitude (Fig. 4), and its average altitude is 2500 m above sea level. The Andean equatorial situation is that approximately 60 % of the urban energy consumption is used for transport, as buildings have no heating and cooling demands. Additionally, high irradiation levels present an ideal condition for supplying electricity through solar photovoltaic generation, with a potential output that exceeds the current electricity requirement at the national level by three times. This also indicates the transport sector’s strategic importance in reducing fossil fuel consumption in this city (Barragán-Escandón et al., 2020). The Cuenca canton is made up of 15 urban parishes and 21 rural parishes (Equipo Técnico Municipio de Cuenca, 2016).

5. Analysis

5.1. Alternatives

The current locations of the fossil fuel service stations in the urban area of Cuenca were initially identified and analysed (Fig. 5). Conventional gas stations already have spatial infrastructure that can be relatively easily adapted to EV charging (Ralf, Teresa Schmidt, 2018). In addition, the existing gas stations are attuned to the location of the population, essential and complementary services, mechanical support services, parking or refuelling areas, washing areas, commercial-leisure equipment, and administrative and aid infrastructure. Conventional gas stations can gradually incorporate electric stations. Apart from the technical, economic, and constructive challenges that this transition would entail, other aspects must be reconciled, such as setting the fee for this service (Ralf, Teresa Schmidt, 2018).

5.2. Criteria

Once the theoretical framework for MCDM application has been defined, the most frequently applied criteria should be searched and applied. The main criteria detected fall within the following four categories: technical, environmental, social, and economic. In addition, subcriteria have been defined. The four types of main criteria have not always been used, as they are based on the needs of the specific problem to be solved (Rottoli et al., 2021; Stojčić et al., 2019; Tzeng and Huang, 2011).

Technical criteria

These criteria are based on a location’s technological aspects. They can be defined quantitatively or qualitatively (Aghabali et al., 2021; Løken, 2007).

Environmental criteria

These criteria are used to assess a location’s environmental impact or evaluate its sustainable development. These criteria can be defined quantitatively or qualitatively (Aghabali et al., 2021; Løken, 2007).

Social criteria

Social and human aspects represent the public’s perception of a project. Most of these criteria are qualitatively weighted and then eventually quantitatively weighted (Aghabali et al., 2021; Løken, 2007).

Economic criteria

These criteria focus on costs, profits, losses, and economic impact on third parties, among others. The weighting is usually quantitative for economic criteria, although eventually, they can be further evaluated qualitatively (Aghabali et al., 2021; Løken, 2007).

5.2.1. Subcriteria

Based on each criterion, the most relevant subcriteria are selected. The choice of subcriteria depends on the context of the study area; in this case, that context entails the information available from the study points in Cuenca. The information comes from public or private institutions, reports, and local research.

The chosen technical subcriteria are the load implication of the substation corresponding to the supply capacity of the network, the distance from the substation to the candidate points, and, consequently, the losses due to the Joule effect and voltage drop in the connection point. The subcriterion of proximity was selected to avoid two or more EVCSs being positioned too close to one another, and the subcriterion of proximity to the city centre implies the importance of accounting for the greater economic and social concentration in the city. The available area

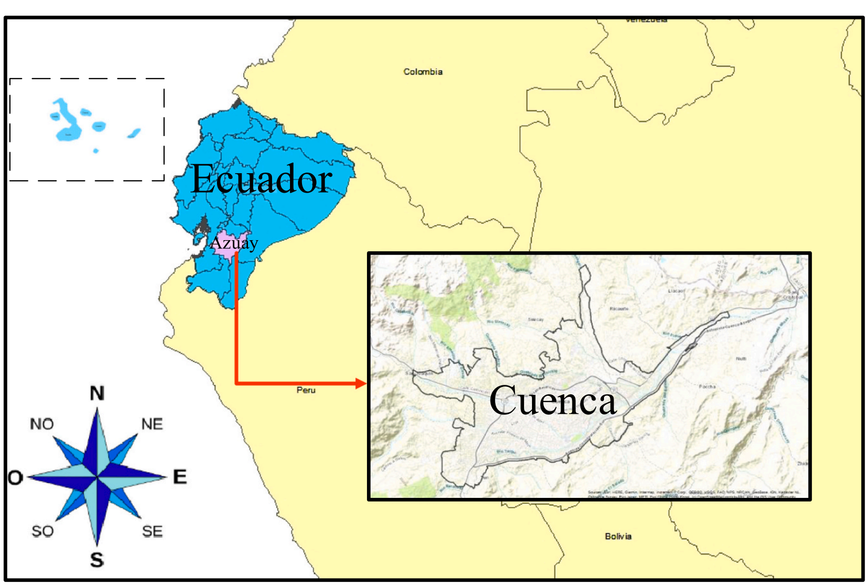


Fig. 4. Geographic location of the city of Cuenca.

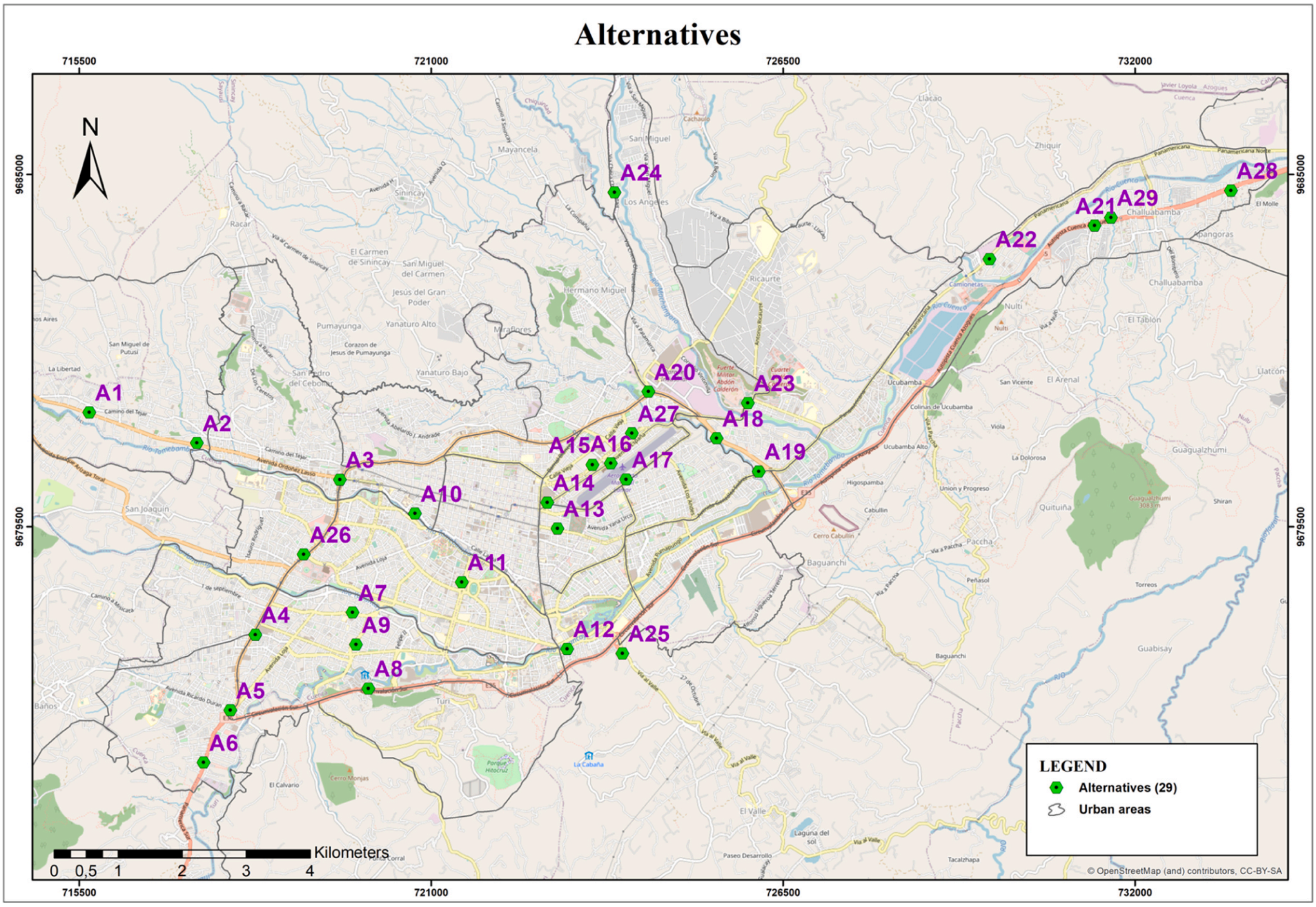


Fig. 5. Geographical position of each alternative.

is another subcriterion since the greater the surface area, the greater the number of possible load modules. When considering subcriteria regarding proximity to crossings, main roads, and access to basic services, the complementary infrastructures represented by existing gas stations are discarded. Aspects such as harmonic distortion, voltage fluctuation, installation permits, and the influence of power quality are also discarded during this initial stage due to the complexity of obtaining data. In a previous study, it was determined that in some sectors of Cuenca, there would be no impact on the networks of Cuenca's central area (González et al., 2019). However, a detailed case-by-case analysis is necessary to verify this.

Regarding environmental criteria, the subcriteria chosen are exhaust emissions from combustion vehicles. In addition, the subcriterion of noise pollution is considered, and electrical transport is treated as fundamental to reducing noise levels. The destruction and deterioration of soil and vegetation are ruled out because the area is urban and thus has already been impacted. Aspects such as distance to green areas, garbage management, risk of earthquakes, and distance from landslides are also discarded since the existing stations already require environmental studies to operate.

In terms of social subcriteria, population density, transit and mobility for leisure, work, or other activities are chosen. These aspects are decisive for defining high-traffic routes. On the other hand, subcriteria such as government support, private cargo competition, and road safety are areas where the alternatives have either overly similar or irrelevant information. Therefore, the subcriteria regarding car parks and vehicle owners have been ruled out due to a lack of specific local information.

Finally, the economic subcriteria are mobility as measured by economic activity and investment cost. The investment criterion focuses on the purchase of EVCSs in each of the alternatives. Regarding the cost of construction, cost of recovery, cost of maintenance, cost of operation, and payback period, a detailed economic study should be carried out for each alternative by professionals in the field; therefore, these subcriteria have not been applied in this research.

The selected criteria and subcriteria are presented in Table 4. For each criterion, the respective subcriteria are established according to the

Table 4
Selected criteria and subcriteria.

Criterion	ID	Subcriterion	Preference	Unit Analysis
Technical	CT−1	Substation capacity	MIN	[%]
	CT−2	Length of the electrical network from the substation	MIN	[km]
	CT−3	Proximity to other EVCSs (Alternatives)	MIN	[%]
	CT−4	Proximity to the city centre	MIN	[km]
	CT−5	Available area	MAX	[m^2]
Environmental	CA−1	Pollution level	MAX	[ug/m^3]
	CA−2	Noise pollution	MAX	[dB]
Social	CS−1	Service area population	MAX	[Hab/m^2]
	CS−2	Transit (vehicle destination)	MAX	[%]
	CS−3	Mobility for entertainment	MAX	[%]
Economical	CE−1	Mobility by economic activity	MAX	[%]
	CE−2	Investment cost	MIN	[USD]

availability of information.

Table 5 presents the complete list of evaluations of each of the criteria for the different alternatives. To obtain these data, information was provided by different institutions, including the Municipality of Cuenca and Empresa Eléctrica Regional Centro Sur, among other governmental and higher education institutions.

5.3. Scenarios

The different scenarios are based on modified weights assigned to the evaluated subcriteria in accordance with their importance as assigned by the decision maker. the AHP method is applied to weight the second scenario, while the FAHP method is used to weight the third scenario. All three scenarios y are presented in this section.

Scenario 1

In the first scenario, the equal weights method is applied, where each subcriterion has the same importance to the others. For this process, we use Eq. (2) and (Patnaik et al., 2020), which are defined as follows:

$$w_j = \frac{1}{n} \tag{2}$$

where w_j is the weight of each subcriterion, and n is the number of subcriteria.

Scenario 2

In the second scenario, the weights of the subcriteria are obtained by surveying knowledgeable professionals. A Likert scale (1−5) is used, with 1 representing very low importance and 5 representing great importance [46,47]. AHP is then applied to calculate the weight of each subcriterion.

To guarantee the reliability of the information, Cronbach's coefficient (α) was calculated with Eq. (3). As long as the value of α is close to 1, the answers are more coherent, and an α between 0.8 and 0.9 is good. An α between 0.7 and 0.8 is acceptable, while an α between 0.6 and 0.7 is questionable (Espinoza and Novoa-Muñoz, 2018).

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum V_i}{V_t}\right) \tag{3}$$

where α is the Cronbach coefficient,

k is the number of subcriteria,

V_i is the variance of each subcriterion, and

V_t represents the total variance.

The calculation of the Cronbach coefficient results in $\alpha = 0.74$, which is acceptable (Espinoza and Novoa-Muñoz, 2018).

In (Bagi et al., 2020; Supraja and Kousalya, 2016; Zhang et al., 2018), and (Hadikurniawati et al., 2019), to classify alternatives, the authors propose combining the AHP method (to weight the criteria) with other MCDMs. By using these methods, errors are reduced in establishing the importance of each criterion.

Therefore, combining two or more methods is considered to generate reliable results, reducing future uncertainties (Supraja and Kousalya, 2016; Zhang et al., 2018).

Scenario 3

This scenario is taken from the results of expert surveys. However, unlike the previous scenario, this scenario applies FAHP to increase the

Table 6
Weighting in each scenario.

Criterion	ID	Scenario 1	Scenario 2	Scenario 3
Technical	CT−1	0.0833	0.1477	0.1346
	CT−2	0.0833	0.1477	0.1346
	CT−3	0.0833	0.0319	0.0509
	CT−4	0.0833	0.0319	0.0444
	CT−5	0.0833	0.0668	0.0984
Environmental	CA−1	0.0833	0.0319	0.0369
	CA−2	0.0833	0.0163	0.0000
Social	CS−1	0.0833	0.1477	0.1346
	CS−2	0.0833	0.1477	0.1346
	CS−3	0.0833	0.0163	0.0000
Economical	CE−1	0.0833	0.0668	0.0964
	CE−2	0.0833	0.1477	0.1346

Table 5
Evaluation of each subcriterion for the different alternatives.

Alternative	CT-1 [%]	CT-2 [km]	CT-3 [%]	CT-4 [km]	CT-5 [m2]	CA-1 [ug/m^3]	CA-2 [dB]	CS-1 [Hab/m^2]	CS-2 [%]	CS-3 [%]	CE-1 [%]	CE-2 [USD]
A1	87 %	6.58	0.00 %	6.39	1856.88	25.85	68.29	1876.10	2 %	1.29 %	3.05 %	$ 955,956.96
A2	87 %	3.74	0.00 %	4.65	1460.98	24.02	70.00	1664.46	2 %	1.29 %	3.05 %	$ 1194,946.20
A3	87 %	3.27	6.90 %	2.34	909.26	26.86	72.58	2543.35	2 %	3.23 %	4.24 %	$ 819,391.68
A4	87 %	0.62	6.90 %	3.96	1106.25	25.74	72.61	1398.95	7 %	12.24 %	11.78 %	$ 751,109.04
A5	87 %	1.92	6.90 %	4.91	368.53	25.18	73.77	1177.83	3 %	2.99 %	4.78 %	$ 409,695.84
A6	87 %	2.81	3.45 %	5.74	1183.15	24.43	70.71	850.67	3 %	2.99 %	4.78 %	$ 785,250.36
A7	59 %	5.30	10.34 %	2.47	1734.93	27.39	62.58	3183.05	7 %	12.24 %	11.78 %	$ 990,098.28
A8	59 %	5.85	6.90 %	3.14	707.32	27.33	69.56	820.72	7 %	12.24 %	11.78 %	$ 512,119.80
A9	59 %	4.66	6.90 %	2.74	943.08	27.02	64.95	1820.08	7 %	12.24 %	11.78 %	$ 751,109.04
A10	51 %	1.34	6.90 %	1.08	426.14	33.28	77.45	14045.18	5 %	6.13 %	7.40 %	$ 341,413.20
A11	51 %	0.62	3.45 %	0.98	358.53	35.75	70.17	14007.81	14 %	9.85 %	8.63 %	$ 307,271.88
A12	60 %	1.76	3.45 %	2.36	966.46	26.29	73.72	5175.47	3 %	4.60 %	2.79 %	$ 614,543.76
A13	60 %	1.87	10.34 %	1.16	731.49	33.54	71.87	20610.13	4 %	5.04 %	3.84 %	$ 546,261.12
A14	75 %	3.35	10.34 %	1.05	580.72	34.14	72.02	16714.12	4 %	3.41 %	5.04 %	$ 546,261.12
A15	75 %	2.36	17.24 %	1.92	1309.44	30.84	69.43	9454.41	4 %	3.41 %	5.04 %	$ 1024,239.60
A16	75 %	2.20	13.79 %	2.22	401.38	29.01	69.05	9061.13	4 %	3.41 %	5.04 %	$ 512,119.80
A17	60 %	1.81	17.24 %	2.34	1517.23	26.50	70.21	9305.85	4 %	3.41 %	5.04 %	$ 648,685.08
A18	75 %	1.83	13.79 %	3.88	835.89	26.90	69.59	3531.56	2 %	2.27 %	4.31 %	$ 751,109.04
A19	75 %	3.09	6.90 %	4.38	933.95	24.50	71.15	1563.89	2 %	2.27 %	4.31 %	$ 1160,804.88
A20	75 %	0.52	17.24 %	3.30	1592.10	28.25	71.85	4329.06	5 %	8.02 %	9.84 %	$ 1092,522.24
A21	26 %	5.50	0.00 %	10.63	1553.26	27.17	76.58	246.04	1 %	2.13 %	3.27 %	$ 785,250.36
A22	74 %	4.20	0.00 %	8.93	1882.02	26.44	73.03	212.73	1 %	2.13 %	3.27 %	$ 921,815.64
A23	74 %	2.77	6.90 %	4.55	904.45	26.54	71.28	954.77	2 %	2.27 %	4.31 %	$ 887,674.32
A24	75 %	2.89	0.00 %	5.56	820.25	24.43	69.16	561.44	2 %	1.56 %	2.43 %	$ 375,554.52
A25	59 %	5.98	3.45 %	2.98	455.52	28.05	72.10	2076.38	3 %	4.60 %	2.79 %	$ 614,543.76
A26	87 %	1.91	10.34 %	2.84	1065.56	26.24	71.01	3260.21	6 %	14.64 %	3.76 %	$ 546,261.12
A27	75 %	1.98	17.24 %	2.72	612.36	28.70	70.62	7656.79	4 %	3.41 %	5.04 %	$ 477,978.48
A28	26 %	3.33	0.00 %	12.79	1204.25	27.77	75.50	180.56	1 %	2.13 %	3.27 %	$ 580,402.44
A29	26 %	5.19	0.00 %	10.91	742.32	27.26	76.89	253.49	1 %	2.13 %	3.27 %	$ 1058,380.92

reliability of the weights obtained for each subcriterion. Table 6 presents a summary of the resulting weighting in each of the scenarios after applying the three methods.

5.4. Results

The results obtained from the VIKOR, TOPSIS, and PROMETHEE methods are plotted under the same scenario.

Results for Scenario 1

In Fig. 6, the results of Scenario 1 are diagrammed for each of the three methods applied. In this scenario, the evaluation of equal weights is applied to all the subcriteria. The alternatives in the first position do not maintain their place across all three methods: in VIKOR, the best alternative is A13; in TOPSIS, A11 is the best; and in PROMETHEE, the best alternative is A10.

For Scenario 1, the top alternatives are A10, A11, and A13, the only difference in VIKOR is that A11 is in fourth place in VIKOR, having been surpassed by A10, and A14 is in second place. Only in VIKOR is A14 the second-best alternative. In TOPSIS, it is in sixth place, and in PROMETHEE, it is in sixteenth place. The alternatives in the last positions are A1 and A2 in VIKOR, A29 and A21 in TOPSIS and, finally, A2 and A1 in PROMETHEE.

Results for Scenario 2

In Fig. 7, the change in positions for every alternative can be seen after applying the three methods. Unlike the previous scenario, alternative A11 remains the best qualified in the VIKOR and TOPSIS methods, and only in PROMETHEE does it drop to second place. Additionally, locations A10, A11, and A13 remain in the first three positions without exception, as in Scenario 1.

A10 is in the second position in VIKOR, while in TOPSIS, it moves to third place; however, in PROMETHEE, it happens to be the best-qualified alternative and occupies first place. On the other hand, A13 remains in the third position in VIKOR and PROMETHEE, but in TOPSIS, A13 is in second place.

Subsequent alternatives present abrupt changes in their positions across methods. Among them are A14, who went from fifth place in VIKOR to fourth place in TOPSIS and later appeared to fourteenth place in PROMETHEE. Other alternatives with similar behaviour are A4, A7, A16, A20, and A25, among others. Finally, the alternatives with the worst rating in VIKOR are A1 and A2; in TOPSIS, they are A1 and A29; and in PROMETHEE, they are A2 and A1.

Results for Scenario 3

Fig. 8 shows the results obtained when applying the FUZZY-AHP method to calculate the weights of the subcriteria. In this scenario, the subcriteria CA-2 and CS-3 have zero weight, so they do not influence the presented results.

Once again, alternative A11 comes in first place in the VIKOR and TOPSIS methods, while PROMETHEE ranks second.

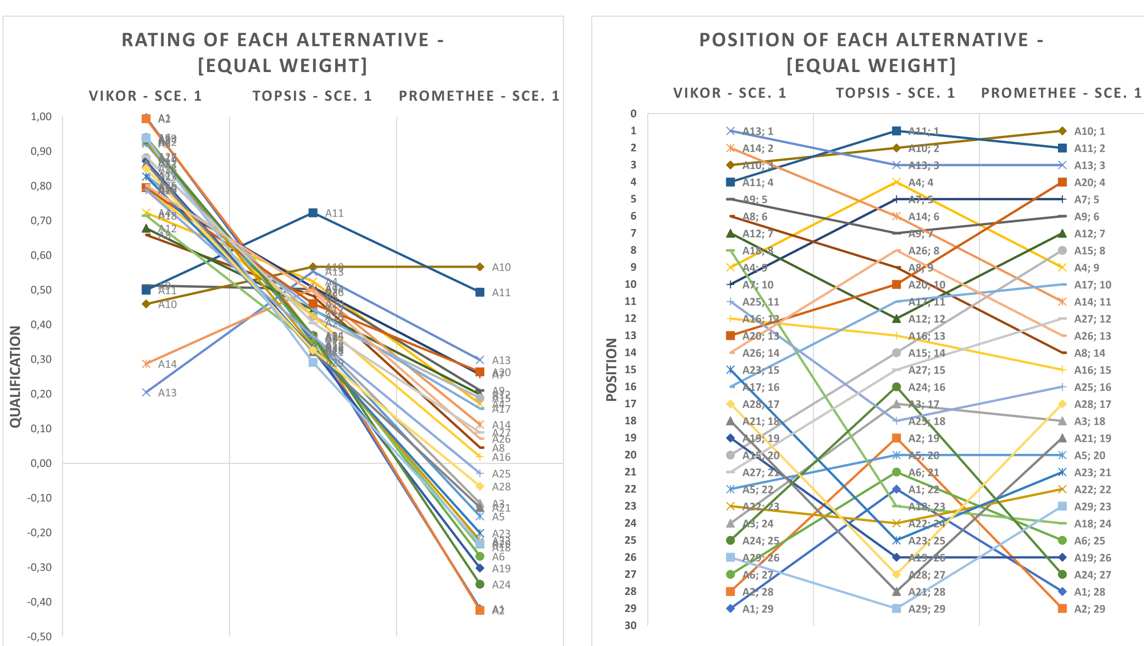
Unlike Scenario 2, alternatives A10, A11, and A13 are only among the top three in VIKOR and TOPSIS. In VIKOR, A10 is positioned in second place; in TOPSIS, it comes in third place; and in PROMETHEE, it moves to second place. On the other hand, A13 is the third-best qualified in VIKOR and the second-best in TOPSIS, but it drops to sixth place in PROMETHEE.

In PROMETHEE, the alternative that occupies the third position is A7; however, in TOPSIS, A7 is in the eleventh position, and in VIKOR, it is in ninth place. In the same way as in Scenario 2, A14 occupies different positions since it moves from fifth place in VIKOR to fourth in TOPSIS, and finally to fifteenth in PROMETHEE. In Scenario 3, the alternatives that occupy the last positions with the worst scores are A1 and A2 in VIKOR, A29 and A1 in TOPSIS, and finally, A2 and A1 in PROMETHEE.

5.5. Final result

To determine the final result, the alternatives from the first 15 positions in each scenario were selected, and the method was applied as shown in Fig. 9. Each alternative varies in position when applying the VIKOR, TOPSIS, and PROMETHEE methods in each scenario. 19 alternatives are among the first 15 positions in all the results. However, 8 alternatives are not present in all the results. Alternatives A15, A17, and A27 are not found in the VIKOR method for Scenario 1. A26 falls outside the top 15 positions in VIKOR for both Scenario 2 and Scenario 3, while A18 only appears in these results. Finally, A23, A25, and A28 are only present in a single result: A23 and A25 in VIKOR for Scenario 1 and A28 in VIKOR for Scenario 2.

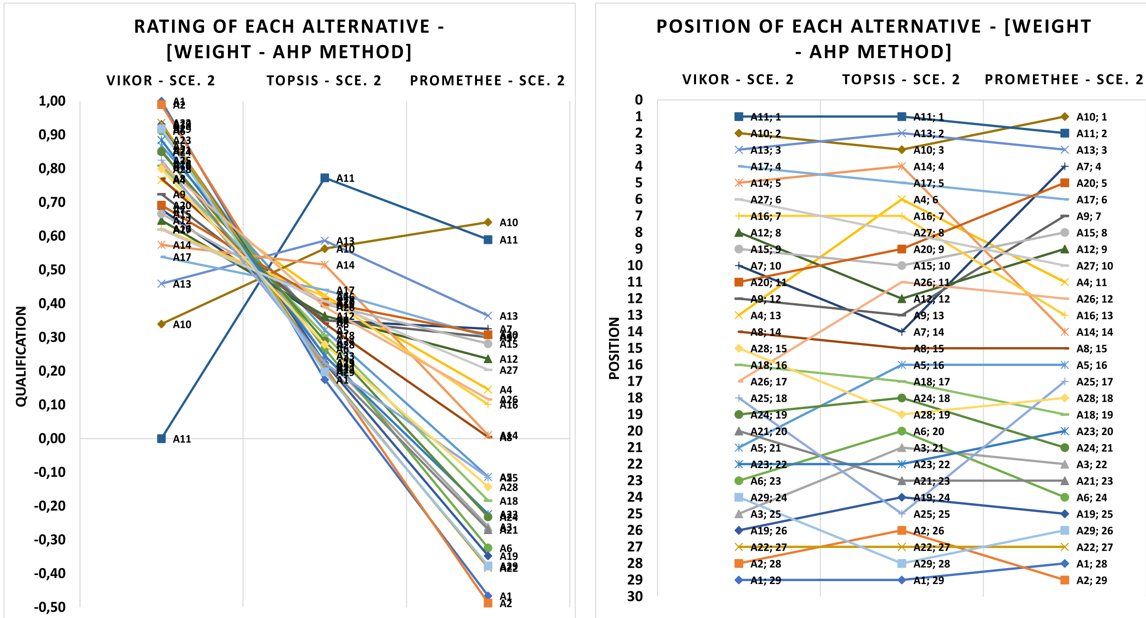
The alternatives present in all results were selected, as shown in



a) Rating of each alternative

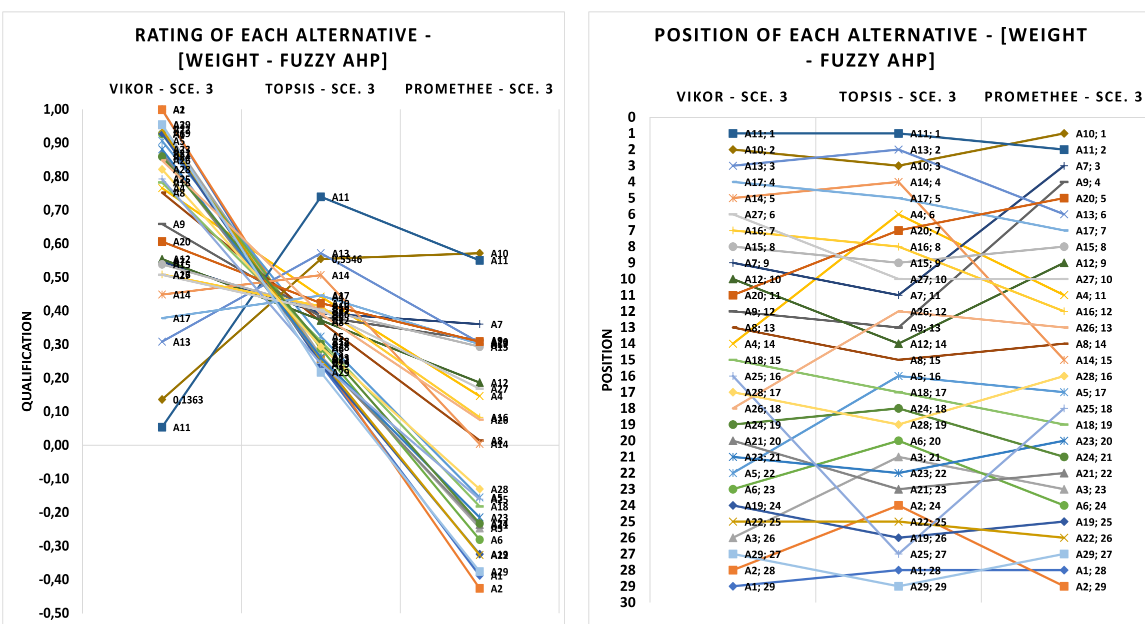
b) Position of each alternative

Fig. 6. Qualification and positions of the alternatives in the first scenario.



a) Rating of each alternative b) Position of each alternative

Fig. 7. Qualification and positions of the alternatives in the second scenario.



a) Rating of each alternative b) Position of each alternative

Fig. 8. Qualification and positions of the alternatives in the third scenario.

Fig. 10. These are A4, A7, A8, A9, A10, A11, A12, A13, A14, A16, and A20. According to the results obtained by applying each of the different methods in the three scenarios, the alternatives most often in the first three positions are A10, A11, and A13. Therefore, they can be considered to be the most suitable for implementing EVCS stations. It should be noted that the positions of A10, A11, and A13 do not change in the different scenarios.

The remaining alternatives presented in Fig. 10 do not exhibit a definite tendency in their positions, which makes it difficult to make decisions. Therefore, the data were statistically analysed using the "Data Analysis" tool from Microsoft's Excel software. Thus, the positions of each alternative according to the three methods were jointly determined, and the final results are presented in Table 7. Alternative A11 occupies the first position with a mean of 1.67, a median and mode of 1, a first-place frequency of five, and a 56 % probability of occupying first place, which indicates that this is the best choice for EVCS implementation.

In second place is A10 with a mean and median of 2, a mode of 3, a third-place frequency of three, and a 33 % probability of appearing in this position. A13 remains in third position with a mean of 2.89, a median of 3, a mode of 3, a frequency of being in third place of five, and a probability of appearing in this position of 56 %. A10 and A13 ranked third more often than the other positions, but when analysing the results, A10 tended to be above A13.

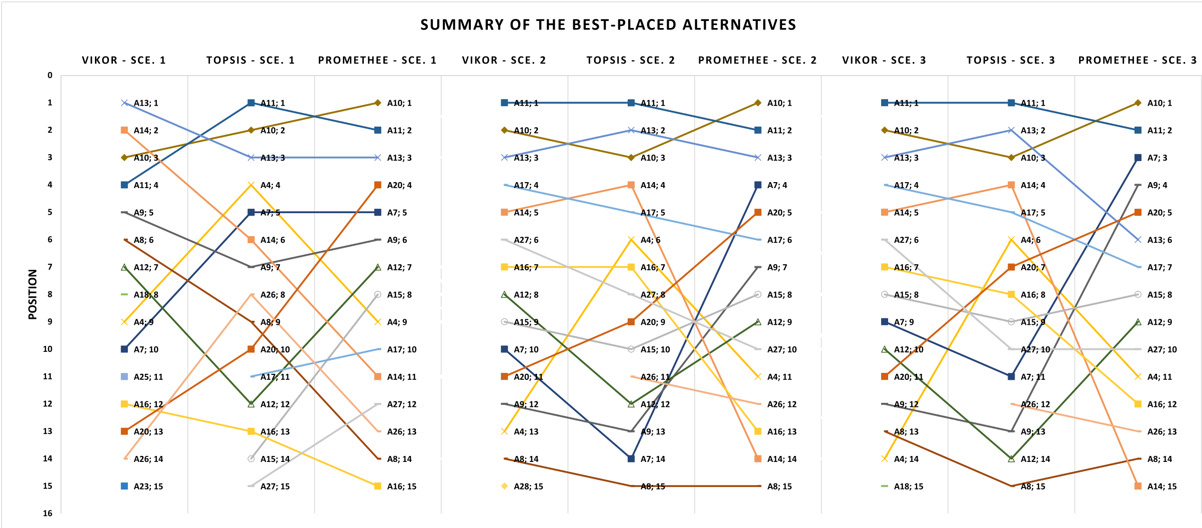


Fig. 9. Summary of the best positions of each alternative.

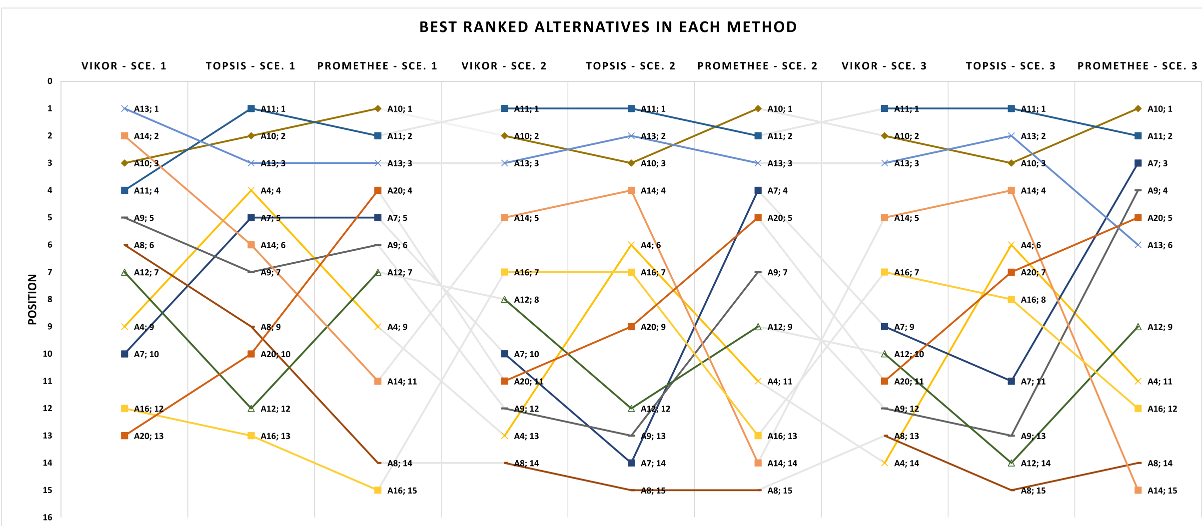


Fig. 10. Alternatives are present in all results.

Table 7
Statistical analysis of the results and final position of the best alternatives.

Alternative	Mean	Median	Mode	Frequency	Standard error	Probability
A11	1.67	1	1	5	0.33	56 %
A10	2.00	2	3	3	0.29	33 %
A13	2.89	3	3	5	0.45	56 %
A14	7.33	5	5	2	1.58	22 %
A7	7.89	9	5	2	1.25	22 %
A20	8.33	9	5	2	1.07	22 %
A9	8.78	7	7	2	1.22	22 %
A4	9.22	9	9	2	1.13	22 %
A12	9.78	9	7	2	0.81	22 %
A16	10.44	12	7	3	1.06	33 %
A8	12.78	14	14	3	1.05	33 %

Unlike alternatives A10, A11, and A13, the others exhibit very evident changes in position both across different scenarios and across the results of the three applied methods. The abrupt change in position that occurs in each scenario is determined by the level of importance assigned to each subcriterion. The differences in position between each method are determined by the structure of the algorithm and the sensitivity of the alternatives to subcriteria weights (Feng et al., 2021).

Alternative A14 ranks fourth with a mean of 7.33, a median and mode of 5, a frequency of 2, and a probability of 22 %. Alternatives A7 and A20 occupy the fifth and sixth place, respectively, and have a median of 9 and a mode of 5 with a frequency and probability of 22 %; the difference is that A7 has a mean of 7.89 while A20 has a mean of 8.33.

A9 comes in seventh place, with a median and mode of 7 and a seventh-place probability of 22 %; however, its average is 8.78. In eighth place is A4, with a mean of 9.22, a median and mode of 9, and a ninth-place probability of 22 %. Alternatives A12 and A16 have a mode of 7, with a probability of being in seventh place; however, A12 has a mean of 9.78, and A16 has a mean of 10.44. Alternative A12 has a median of 9, but A16 reaches 12. Finally, A8 occupies the eleventh and last place with a mean of 12.78, a median and mode of 14, and a fourteenth-place probability of 33 %.

The median and mode values do not coincide with the positions in which they are presented in Table 7 because the alternatives occupy different positions in the ranking in each result from the applied methods.

Geographically, alternative A11 corresponds to the coordinates (-2.905621626, −79.00759117) with a distance to the city centre of approximately 1 km. A10 is located at the coordinates (-2.895291839, −79.01280249) at approximately 1.08 km from the city centre. Finally, A13 is found at the coordinates (-2.898125021, −78.99403255) at 1.16 km from Cuenca's city centre. These points are shown in Fig. 11.

Fig. 11 shows the geographical position of the best alternatives shown in Table 7. The alternatives that shamelessly obtained low scores in the evaluations carried out are also included. It is observed that the best alternatives are concentrated around the city downtown, while the discarded alternatives are in rural areas. However, some alternatives that are in the urban area have also been ruled out, such as A15, A17 and A27.

6. Discussion

By applying the AHP and AHP FUZZY methods to determine the weights of each subcriterion using the VIKOR, TOPSIS, and PROMETHEE methods to rank the alternatives, we were able to determine the most suitable points for implementing EVCSs in Cuenca's urban area.

In (Liu et al., 2019), the combination of MCDMs is proposed for identifying the most suitable site in which to incorporate EVCSs. Due to the uncertainty of the variables, this approach is chosen to avoid ambiguity in linguistic evaluations. A. Karaşan et al. (Karaşan et al., 2020) also applied a combination of MCDMs; however, they proposed adding fuzzy logic to the selected methods to improve the reliability of the results in the face of information uncertainty.

In this paper, a methodology is proposed based on 29 existing fuel service stations within the city while considering specific points. This is unlike the work of H. Zhao and N. Li (Zhao and Li, 2016), detected pre-feasibility using expert criteria to predefine locations. Zhao and Li applied their methodology in the city of Tianjin in China, selecting 5 districts as candidate areas to locate EVCSs. For the selection, they determined locations to promote sustainable development and the EV industry. The 29 points selected in this work indicate that the best alternatives are based on the location and infrastructure of the already existing gas stations, which have services that are compatible with the new charging option, especially considering the period required for a vehicle's energy to be charged. This information serves as a starting point for a transition between conventional service stations and EVCSs.

Three scenarios were evaluated, and weights were assigned to each subcriterion. In the first scenario, all of the subcriteria were given the same level of importance; in the second, the AHP method is applied; and finally, in the third, the FAHP method was applied. As in the work of K. Nag and M. Helal (Nag and Helal, 2019), in the third scenario, a rating of 0 was obtained; the lowest ratings influenced the results when applying the FAHP method, which are CA-2 (noise pollution) and CS-3 (mobility

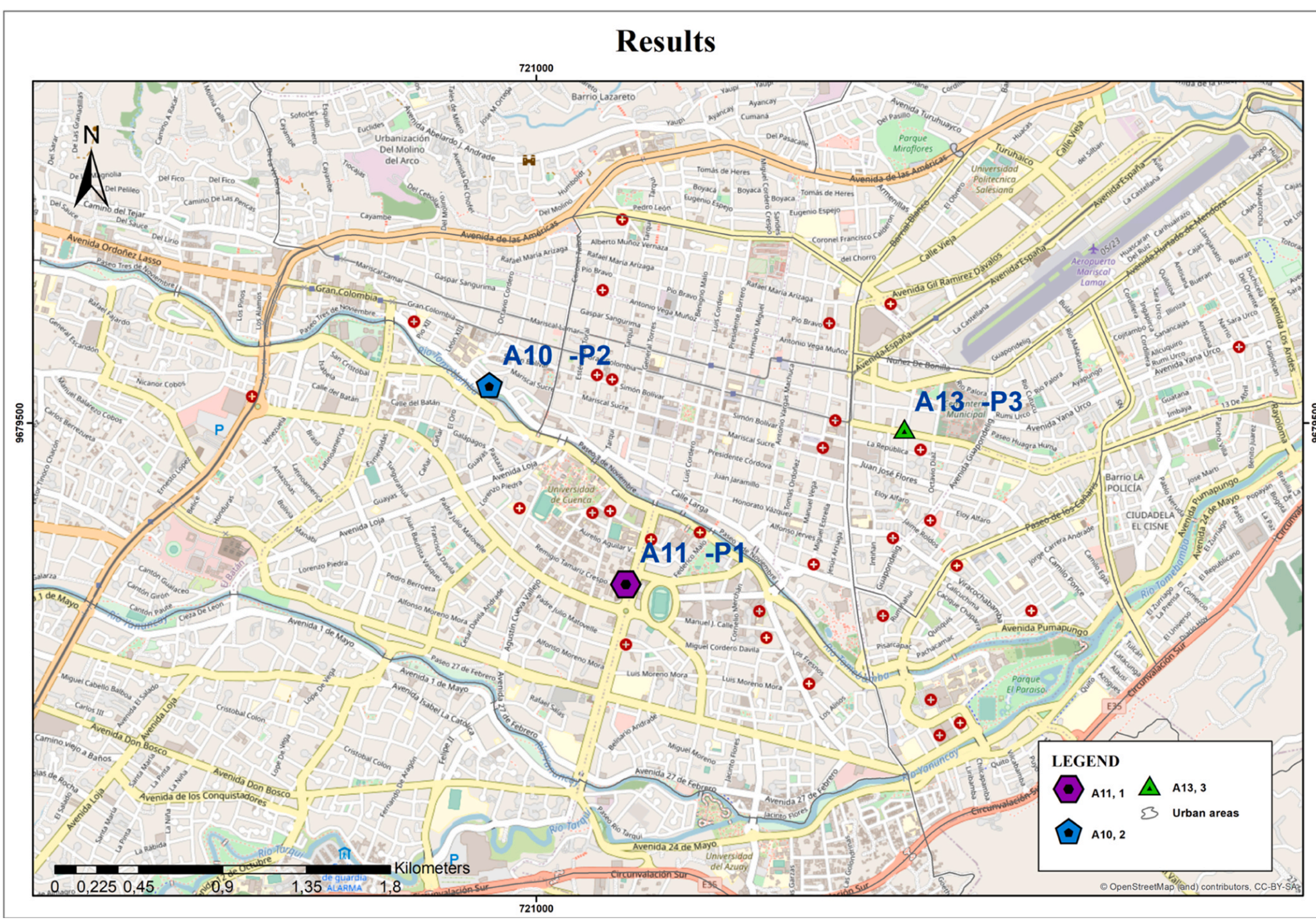


Fig. 11. Results with the best alternatives.

for entertainment). Additionally, in both the second and third scenarios, the subcriteria CT-1, CT-2, CS-1, CS-2, and CE-2 were the most important; these results are similar to those presented in (Nag and Helal, 2019).

This work proposes four main criteria: technical, environmental, social, and economic criteria. Thus, using the MCDM, the EVCS location problem can be solved through the use of unrelated information. In (Karaşan et al., 2020), three MCDMs are applied, but economic, geographic, infrastructural, social, reliability, and security criteria are used. The authors of (Karaşan et al., 2020) conclude that the application of the proposed methodology produced the expected results and that it can be used for future research. They also mention that the sets of criteria can be applied to other areas, which in turn would give greater reliability to the obtained results.

J. Feng et al. (Feng et al., 2021) concluded that the variation in the results obtained by the methods and scenarios occurs because the alternatives are susceptible to the criteria weights. Fig. 10 shows how different alternatives fluctuate between positions in each scenario, where the valuation of the weights of each subcriterion differs. This variation occurs more frequently with alternatives A4, A7, A9, A8, A9, A12, A14, A16, and A20, and it also includes those alternatives that were discarded because they were not among the first 15 positions in all scenarios. A10, A11, and A13 also undergo changes in their positions, but they remain among the first three positions excepting VIKOR for Scenario 1 and PROMETHEE for Scenario 3, as shown in Fig. 11.

L.G. González et al. (González et al., 2019) studied the impact of EVCSs on the electrical distribution network in Cuenca and proposed the most suitable location. The applied methodology is based on GIS data processing and applies technical, geographical, and social criteria. As a result, the most suitable area is located very close to alternative A11, which results from the methodology proposed in this work.

F. Vasquez (Vásquez, 2019) applied the AHP method to determine the location of EVCSs in the city of Cuenca. In his methodology, he proposed the division of the city into 9 areas, of which he selected shopping centres, educational establishments, places of entertainment, and workplaces as alternatives. The selection criteria are technical and mobility. The results show that the most suitable location is in a shopping centre relatively close to this study's alternative A11. However, power chargers could be placed in spots where fuels are not allowed, such as within the city's historical centre, but this alternative goes beyond the scope of this analysis.

7. Conclusions

With a growing population and economy, mobilization requirements need are continuously increasing. One solution to this issue involves incorporating EVs, and it is expected that in the short and medium term, this trend will become prominent in Ecuador. An infrastructure equipped with charging points is necessary to supply this potential demand. In Cuenca, there are already EVCSs located on university campuses and in other areas of the city that have not been sufficiently promoted. On the other hand, there are 29 conventional refuelling stations that are widely known by the public and that provide services compatible with recharging EVs. Exploiting this infrastructure, we set these as location alternatives in our analysis.

The MCDMs applied in this work have allowed us to evaluate criteria from different areas and magnitudes, so they are ideal for finding a solution to a problem whose complexity prevents it from being solved with mathematical optimization methods, heuristic methods, or other approaches. Thus, in the same problem, the data related to areas of electricity, geography, environmental pollution, population, mobility, and economy were evaluated.

The main novelty of this work corresponds to applying different MCDM methods for results improvements, and then observing that the results obtained have slight variations, indicating that a definitive conclusion cannot be reached by applying a single evaluation. Therefore, it is recommended that when carrying out an evaluation with MCDM methods, with two or more scenarios and methods when applied, validate different results of a problem under different circumstances. Since a final conclusion cannot yet be reached with this methodology, it is recommended to use a statistical method that allows the results to be evaluated in order to reach a satisfactory result.

The results show that the gas stations closest to the city centre are where priority should be given when initially incorporating EVCSs. Alternatives A10, A11, and A13 are located around the historic centre of the city and have high traffic flow. Therefore, by locating a charging station at these points, it will be possible to provide more alternatives to users who have EVs, which will also progressively promote technological change.

The results obtained will serve as a starting point for future research, such as the analysis of the behaviour of electrical systems incorporating EVCS in the service stations located on A10, A11 and A13. It will also be possible to evaluate the environment to find nearby spaces that allow greater accessibility for electric vehicle users. On the other hand, the same methodology can be applied in other cities, adapting to their reality, allowing studies to be carried out in a shorter time, and further promoting the penetration of electromobility in the world.

The change from conventional refuelling stations to EVCSs will not happen immediately but must be carried out according to the demands that arise. However, the city plan must begin working on the initial installations and necessary infrastructure that can promote the transition.

In this research, the combination of MCDM methods and the application of a statistical evaluation was carried out to reach a result in accordance with the problem posed. However, it cannot be completely guaranteed that the results will be the most optimal, unlike using a mathematical optimization method. On the other hand, the ease of applying MCDM methods and their versatility when evaluating a large number of criteria and alternatives allow us to reach an approximate optimal result in less time.

When evaluating different sites for the incorporation of EVCS, several criteria can be left aside to reduce the problem's complexity and resolution time. But by leaving aside some criteria, the results could undergo drastic changes, which would not allow us to reach the best result. For this reason, when applying the methodology presented in this research, it has been possible to cover criteria in four different areas, which has allowed the importance of each criterion to be varied and the behaviour of the results to be observed.

This research aims to demonstrate that the application of MCDM allows for obtaining an optimal result by identifying the best option for the incorporation of EVCS, each applied method has its limitations, but by carrying out a combination of them it is possible to evaluate the variations in the results and arrive at to a result that allows the problem posed to be satisfied.

CRediT authorship contribution statement

Julio Terrados Cepeda: Resources, Methodology, Investigation, Data curation. **Esteban Zalamea-León:** Writing – review & editing, Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Danny Ochoa-Correa:** Validation, Supervision, Methodology, Formal analysis, Conceptualization. **Xavier Serrano-Guerrero:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition, Formal analysis. **Edgar antonio Barragán-Escandón:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Formal analysis, Conceptualization. **William Morocho-Chicaiza:** Software, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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