UNIVERSIDADE ESTADUAL PAULISTA
“JÚLIO DE MESQUITA FILHO”
Faculdade de Engenharia
Câmpus de Ilha Solteira

WILSON ENRIQUE CHUMBI QUITO

A MCDA-BASED APPROACH FOR FACILITY LOCATION: AN ASSESSMENT OF EV CHARGING STATION PLACEMENT

Ilha Solteira
2024

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Thesis submitted to the school of Engineering of Ilha Solteira – UNESP in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Electrical Engineering.

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Potential impact of this research

This research impacts urban mobility, energy management, and environmental sustainability. Firstly, it strategically placing charging stations to alleviate range anxiety among EV users, enhancing EV adoption and contributing to decarbonizing the transportation sector. Secondly, it provides a systematic approach to site selection, integrating demographic and energy density criteria, aiding urban planners and policymakers in making informed decisions. Thirdly, it assesses the impact of charging stations deployment on distribution substation capacities, ensuring that the electrical grid can handle the increased load from EV charging. Overall, this research promotes urban mobility through sustainable transportation and serves as a foundational input for further research on hosting capacity analysis and the long-term impacts of EV infrastructure on power distribution systems.

Potencial impacto desta pesquisa

Esta pesquisa impacta a mobilidade urbana, a gestão de energia e a sustentabilidade ambiental. Em primeiro lugar, ao posicionar estrategicamente as estações de carregamento para aliviar a ansiedade de autonomia entre os usuários de veículos elétricos (VE), ela promove a adoção de VEs e contribui para a descarbonização do setor de transporte. Em segundo lugar, oferece uma abordagem sistemática para a seleção de locais, integrando critérios demográficos e de densidade energética, auxiliando planejadores urbanos e formuladores de políticas na tomada de decisões. Em terceiro lugar, avalia-se o impacto das estações de carregamento nas capacidades das subestações de distribuição, garantindo que a rede elétrica possa suportar a carga adicional proveniente do carregamento de VEs. No geral, esta pesquisa promove a mobilidade urbana através de um transporte sustentável e serve como base para pesquisas futuras sobre a análise da capacidade de hospedagem e os impactos a longo prazo da infraestrutura de VEs nos sistemas de distribuição de energia.

UNIVERSIDADE ESTADUAL PAULISTA

Câmpus de Ilha Solteira

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This work is for all the incredible people who have crossed my path, sharing laughter, wisdom, and love. Special thanks to my family.

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"Let your joy be in your journey—not in some distant goal. When you focus on the work itself, success will find you."

(Tim Cook)

ABSTRACT

The number of electric vehicles (EVs) is rising in the automobile market, driven by public policies aimed at the global decarbonization of the transportation sector. The primary challenge with the growing EV presence is related to recharging issues. Careful location of public EV charging stations is crucial to maximize EV usage and address range anxiety among users. As the electricity demand for EV charging represents new load behavior, it is essential to assess the impact of charging station locations on long-term electrical grid planning. The selection of the most suitable site involves conflicting criteria, requiring the application of multi-criteria analysis. This study applies a geographic information system-based Multicriteria Decision Analysis (MCDA) approach to address charging station site selection, incorporating demographic criteria and energy density to model EV growth. Several methods, including Fuzzy TOPSIS, are applied to validate the selection of suitable sites. In this evaluation, a high EV penetration scenario is used to assess the impact of increased EV charging stations on substation capacity planning. The proposed method is applied in Cuenca, Ecuador. Results show the effectiveness of MCDA in assessing the impact of charging stations on power distribution systems, ensuring proper system operation within substation capacity limits.

Keywords: electric vehicle charging station; geographic information systems; geographically weighted regression; multi-criteria decision making; suitability analysis.

RESUMO

O número de veículos elétricos (VEs) está aumentando no mercado automobilístico, impulsionado por políticas públicas voltadas para a descarbonização global do setor de transporte. O principal desafio com o crescimento da presença de VEs está relacionado às questões de recarga. A localização cuidadosa das estações de recarga pública de VEs é crucial para maximizar o uso dos VEs e enfrentar a ansiedade de abastecimento entre os usuários. Como a demanda de eletricidade para a recarga de VEs representa um novo comportamento de carga, é essencial avaliar o impacto das localizações das estações de recarga no planejamento de longo prazo da rede de distribuição elétrica. A seleção do local mais adequado envolve critérios conflitantes, exigindo a aplicação de uma análise multicritério. Este estudo aplica uma abordagem de Análise de Decisão Multicritério (MCDA) baseada em sistemas de informação geográfica para resolver a seleção do local das estações de recarga, incorporando critérios demográficos e densidade energética para modelar o crescimento dos VEs. Vários métodos, incluindo o Fuzzy TOPSIS, são aplicados para validar a seleção dos locais adequados. Nesta avaliação, um cenário de alta penetração de VEs é usado para avaliar o impacto do aumento das estações de recarga de VEs no planejamento da capacidade das subestações. O método proposto é aplicado em Cuenca, Equador. Os resultados mostram a eficácia do MCDA em avaliar o impacto das estações de recarga nos sistemas de distribuição de energia, garantindo a operação adequada do sistema dentro dos limites de capacidade das subestações.

Palavras-chave: análise de conformidade; estações de carga de veículos eléctricos; regressão ponderada geográfica; sistemas de informação geográfica; tomada de decisão multicritério.

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LIST OF ABBREVIATIONS AND ACRONYMS

Abbreviations:

AC	Alternative Current
AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
BEV	Battery Electric Vehicle
BWM	Best Worst Method
CDF	Customer Damage Function
CCS	Combined Charging System
CENTROSUR	“Empresa Eléctrica Regional Centro Sur C.A.”
DC	Direct Current
DEMATEL	Decision-Making Trial and Evaluation Laboratory
ENEME	Estrategia Nacional de Electromovilidad para el Ecuador
EPRI	Electric Power Research Institute
EV	Electric Vehicle
EVCS	Electric Vehicle Charging Station
FAD	Fuzzy Axiomatic Design
FAHP	Fuzzy Analytical Hierarchy Process
FDM	Fuzzy Delphi Method
FC	Fast Charging
FNIS	Fuzzy Negative Ideal Solution
FPIS	Fuzzy Positive Ideal Solution
FMDA	Fuzzy Multi-Criteria Decision Analysis
GAT	Group Aggregation Technique
GHG	Green Houses Gases
GIS	Geographic Information System
GRA	Grey Relation Analysis
GRP	Grey Relational Projection
GWR	Geographically Weighted Regression
HFLTS	Hesitant Fuzzy Linguistic Term Set
IDB	Inter-American Development Bank
IEA	International Energy Agency
IEEE	The Institute of Electrical and Electronics Engineers, Inc.
IFS	Intuitionistic Fuzzy Sets (IFS)
LEW	Linguistic Entropy Weight
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi-Criteria Decision-Making
MOORA	Multi-Objective Optimization on the Basis of Ratio Analysis
MTOP	Ministerio de Transporte y Obras Públicas
ONAN	Oil Natural Air Natural
PROMETHEE	Preference Ranking Organization Method for Enrichment of Evaluations
PVCS	Photovoltaic Charging Stations
SAE	Society of Automotive Engineers
SOC	State of Charge

S/E	Substation
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijuska Optimizacija I Komoromisno Resenje
WLC	Weighted Linear Combination.

Units:

GWh	Gigawatt hour
km	kilometer
kV	kilovolts
kWh	kilowatt hour
min	minutes
km^2	Square kilometer
USD	United States Dollar

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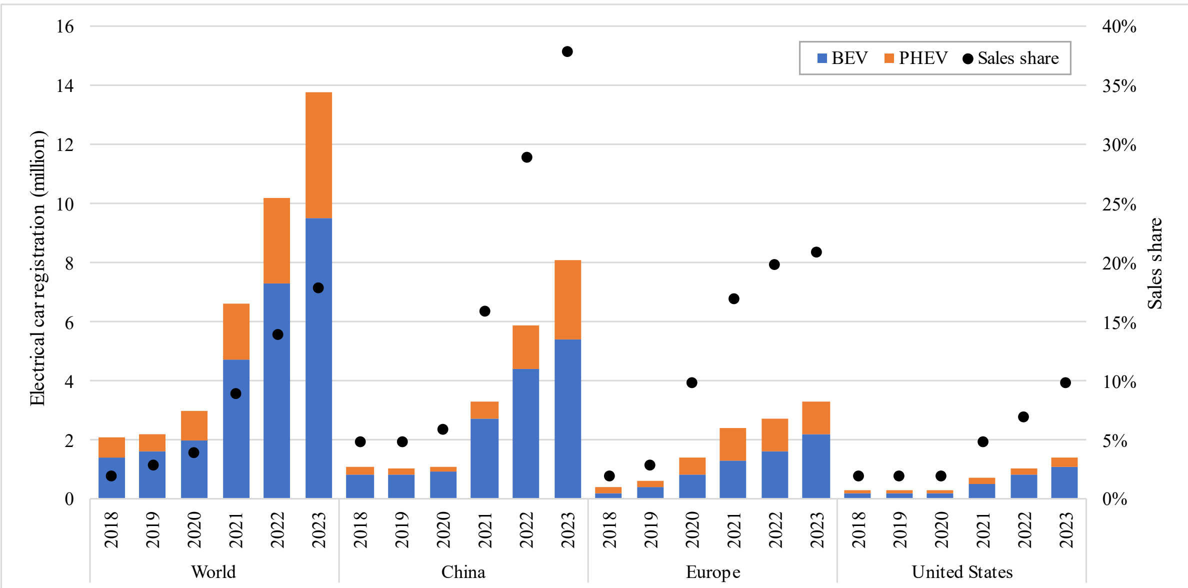
1 INTRODUCTION

At the Paris climate change conference in December 2015, a total of 195 countries for the first time adopted a legal and universal agreement to face climate change, known as the Paris Agreement. This agreement establishes a global action plan to keep the temperature of global warming well below 2°C, above pre-industrial levels (UNFCCC, 2015). This ambitious plan requires a significant reduction in the emission of greenhouse gases (GHG). According to the International Energy Agency (IEA), the concentration of GHG in the atmosphere, in the long term, should be limited to about 450 ppm carbon dioxide (CO_2) (IEA, 2011). Nowadays, a quarter of GHG emissions come from, specifically, the internal combustion engines (ICE) used by conventional vehicles. In addition, when burning fossil fuels, ICEs release pollutants that are harmful to health that significantly degrade air quality (OICA, 2008).

In this sense, electric vehicles (EV) emerge as an innovative and promising mobility alternative to drastically reduce GHG emissions and harmful pollutants generated by ICEs. In 2020, the promising EV market had around 10 million EVs on the road worldwide (Koch *et al.*, 2022). According to IEA's Sustainable Development Scenario, no less than 230 million EVs are needed across the globe by 2030 to meet the climate goals of the Paris Agreement (IEA, 2021). Figure 1 shows the global EV market share, with blue bars representing all-electric vehicles and orange bars representing plug-in hybrid electric vehicles (PHEVs). Nearly one in five cars sold in 2023 was electric, with sales reaching close to 14 million. Approximately 95% of these sales were concentrated in China, Europe, and the United States. China accounted for nearly 60% of new electric car registrations, Europe for just under 25%, and the United States for 10%. These three markets, representing about two-thirds of global car sales and stocks, have a significant impact on global greenhouse gas reduction. Electric car sales in 2023 were 3.5 million higher than in 2022, marking a 35% year-on-year increase and a more than sixfold increase from 2018. Electric cars made up approximately 18% of all car sales in 2023, compared to 14% in 2022 and just 2% in 2018. These trends indicate that growth remains robust as electric car markets mature.

Significant economic incentives and new policies have been introduced across the world to reach this goal. Governments around the world spent USD 14 billion on direct acquisitions incentives and tax refunds for EVs in 2020 (IEA, 2021, 2023). A significant increase in EVs is expected, so it will be necessary to enhance and expand the charging infrastructure for EVs. In Latin America, electric car sales had surpassed 90,000 in 2023, with Brazil, Colombia, Costa Rica and Mexico leading the region. Brazil, saw electric car registrations nearly tripled year-on-year to more than 50,000, a market share of 3%. This growth was driven by Chinese carmakers entering the market. Road transport electrification could bring significant climate benefits due to its low-emissions power, and reduce local air pollution. However, EV adoption has been slow, given the national prioritization of ethanol-based fuels since the late 1970s for energy security. At the end of 2023, Brazil launched the Green Mobility and Innovation Programme, offering over BRA 19 billion (USD 3.8 billion) in tax incentives from 2024 to 2028 for developing and manufacturing low-emissions road transport technology. As a result, major carmakers in Brazil are now developing hybrid ethanol-electric models and going fully electric.

Figure 1 — Global EV registrations and sales over the last five years



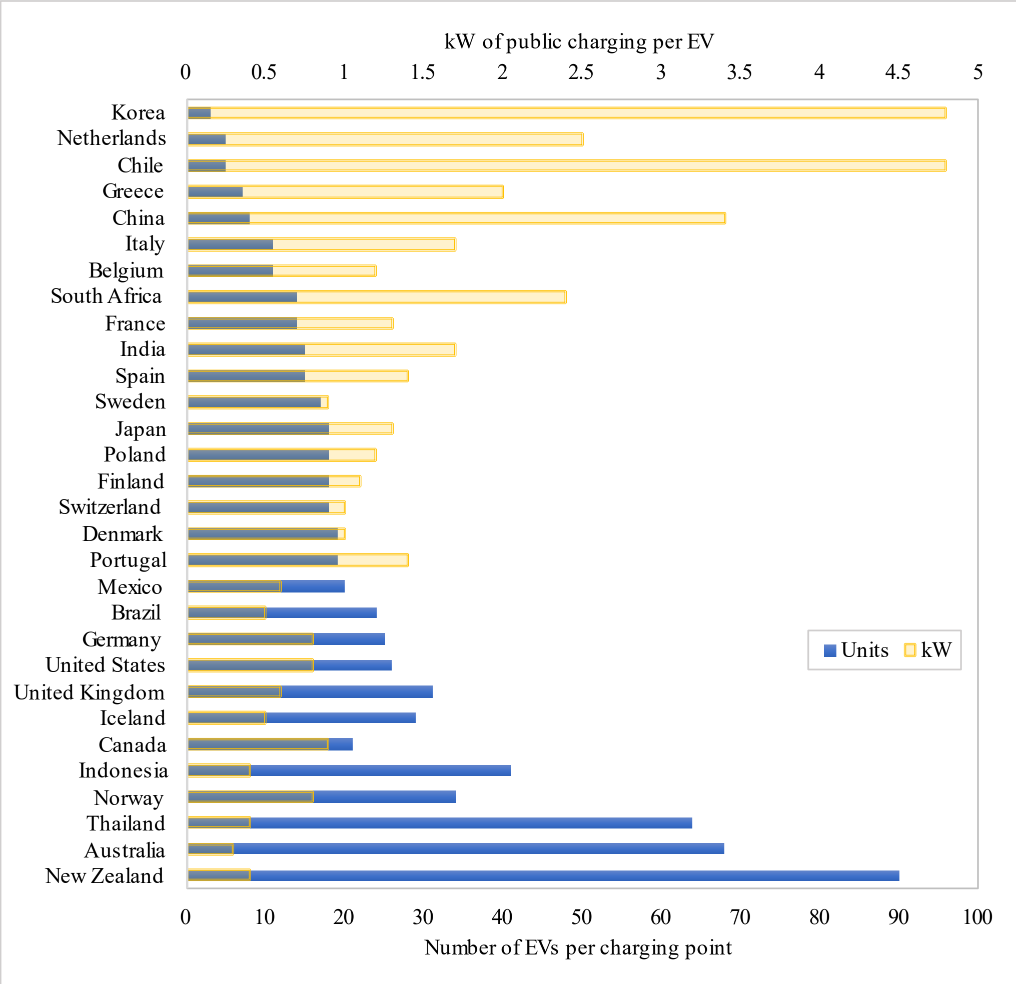
Source: Adapted from (IEA, 2024a).

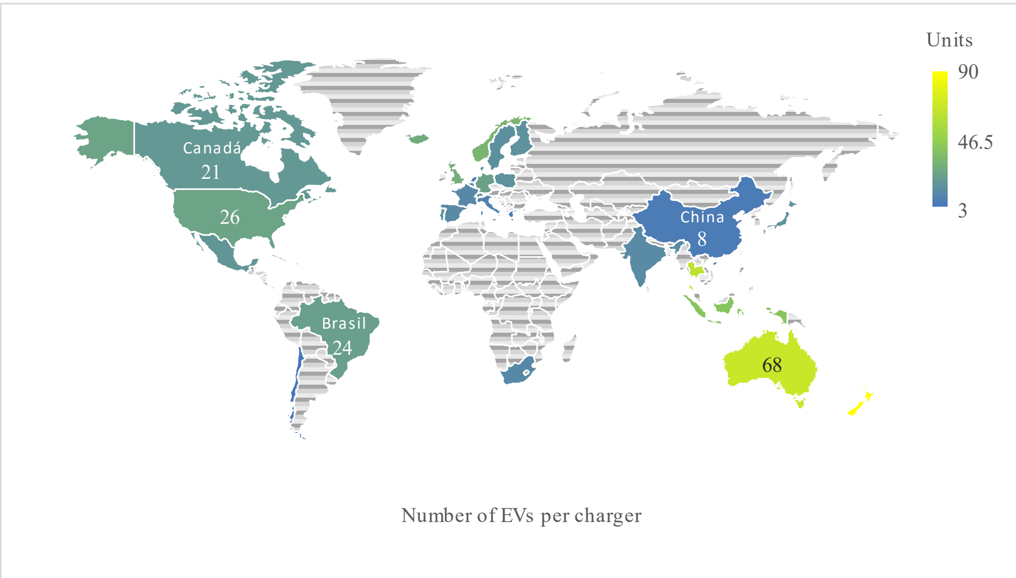
The rise of public charging stations must keep up with the growth of EV sales. Insufficient charging infrastructure can cause discomfort, while overbuilt infrastructure leads to underutilization and reduced profitability. Charging ratios vary depending on the government's priorities for slow versus fast charging. In this way, Figure 2 shows per country both the number of EVs per station (blue bars and choropleth map) and the charging capacity per EV (orange bars). The choropleth map mirrors the blue bars. Despite having the most vehicles per charger, New Zealand outperforms Australia and Thailand when considering charging capacity per EV. This is due to New Zealand prioritizing fast public chargers over slow ones, leading to the highest proportion of fast chargers to slow chargers. The largest proportions globally are found in New Zealand, South Africa, China, and Norway at 75%, 53%, 44%, and 41%, respectively. In contrast, countries like the Netherlands and Korea, which have prioritized slow public chargers, with fast public chargers comprising only 4% and 10%, respectively.

The most appropriate ratio of EV chargers is challenging due to varying supply and demand dynamics in each country. However, the deployment of EV chargers should align with power grid developments to ensure new load connections are consistent with the wider grid-planning horizon, optimizing the utilization and profitability. When not managed appropriately, charging can lead to a surge in peak demand, making it important to ensure that transmission and distribution grids are appropriately sized and equipped to avoid becoming a barrier to deploying charging infrastructure. Therefore, understanding breakdown the counts and levels of chargers needed is important. For instance, to meet the 2030 goal, California will need over 700,000 public and shared private chargers to support 5 million EVs (AB 2127) and nearly 1.2 million chargers to support 8 million EVs (Executive Order N-79-20) (Hochschild, 2021), as shown in

Figure *3*, where blue bars indicate the charger need for 5 million EVs and orange bars represent the additional charger need for 8 million EVs. Counts for workplace, public, and multiunit dwelling chargers generally indicate Level 2 needs, with some Level 1 chargers sufficient for select multiunit dwellings. Level 1 chargers are most commonly used in single-family homes.

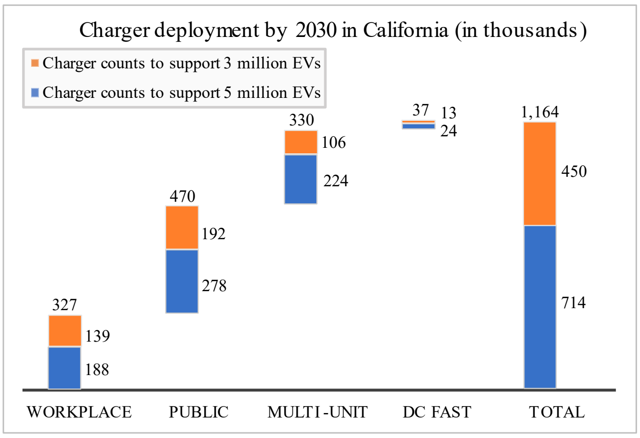
Figure 2 — Number of EVs per public charging station and charging capacity per EV in 2023





Source: Adapted from (IEA, 2024b).

Figure 3 — Counts of chargers' type in California



Source: Adapted from (Hochschild, 2021).

The Electric Power Research Institute (EPRI), the Society of Automotive Engineers (SAE), and the International Electro-Technical Commission (IEC) through standard IEC 61851 (IEC 61851-1, 2017) have characterized different charging modes/levels: AC - Level 1, AC - Level 2, DC fast charging Level 3, and Extreme Fast Charging (XFC) level 4. Table 1 summarizes the key characteristics of each charging level according to the SAE J1772 standard (EERE, 2018b; Savari *et al*., 2023; Spendiff-Smith, 2022).

Level 1 EV charging is the slowest charging method, but it is sufficient for drivers who charge their vehicle overnight. Charging cables typically come with the vehicle and are plugged into a standard outlet 120V AC with a current rating of 15 A or 20 A. This charging level can take between 8 to 16 hours to reach 100% battery State of Charge (SOC) and it can handle a power of 1.4 to 1.9 kW without requiring installation of additional equipment. Level 1 charging works well for charging at home, work, or anywhere with a standard outlet and when there is enough time to charge (Narasipuram; Mopidevi, 2021). In this charging level support for communication control is not available. Level 1 charger uses a standard J1772 or Tesla connector that can be connected to any electric vehicle, either directly or via an adapter (Savari *et al*., 2023).

Level 2 EV charging is considerably faster than level 1 charger but requires the installation of a dedicated single-phase electric circuit 240V/208V AC with a current rating up to 40A to plug in at private place. In the case of public places, it requires three-phase electric circuit 400V AC with a current capacity up to 80 A (Narasipuram; Mopidevi, 2021). Therefore, level 2 stations are found in many public places and workplaces, but also in homes. This charging level can take between 4 to 8 hours for complete charge and can handle a power of 7.7 to 25.6 kW (Narasipuram; Mopidevi, 2021). Level 2 charger uses connectors based on standards IEC 62196-2 Type 1, IEC 62196-2 Type 2, and GB / T 20234.2 (González; Siavichay; Espinoza, 2019).

Level 3 EV charging, referred to as DC fast charging, converts AC to DC inside the charger itself, resulting in faster power delivery. DC fast charging stations operate on a three-phase supply, 480 V in North America and 400 V in Europe, as usual in commercial and industrial locations. Then, highway rest areas and other public places, such as malls, airports, parks, hotels, and petrol pumps, are appropriate for installing DC fast charging. This charging level uses the CHAdeMO, Tesla Superchargers (NACS), and Combined Charging System (CCS) connectors. DC fast charging support above 350 kW and it can fully charge a standard EV in less than 20 minutes, depending on the EV's charge acceptance rate (Spendiff-Smith, 2022).

Extreme fast charging (XFC) levels supply DC power for ultra-rapid charging to accommodate quick charging needs during longer trips. XFC is envisioned for public places along heavy-traffic corridors at installed stations. They aims to deliver power above 350 kW, potentially reducing charging times to only a few minutes for a significant charge (80% battery SOC) (Savari *et al*., 2023).

The public charging infrastructure is primarily Level 2 and DC fast charging, as per pilot programs (EERE, 2018a; Lehrman, 2021; NYC DOT, 2023). They are most often sited in parking garages, stores and distributed across streets. In Boulder, Colorado, with a population of 108,250 as the 2020 US census, there are 19 station locations, with three designs, as illustrated in Table 2: Fifteen stations with two Level 2 EV chargers, three stations with four Level 2 EV chargers, and one station with four Level 2 and four DC Fast chargers. In New York City, until May 2023, there were 1,900 public location stations. The network of public and private chargers includes stations with two, four, and six Level 2 EV chargers. The public charging infrastructure in the US is 86% Level 2 and 14% DC fast. Across the major urban areas, new charging installations include more chargers per location, involving workplace charging infrastructure (Slowik; Lutsey, 2018).

Table 1 — Charging levels according to SAE J1772 standard

Charging Level	**Typical Use**	**Charging Power (kW)**	**Voltage**	**Current (A)**	**Charging time (hours)**	**Description**
Level 1	Home	1.4 1.9	120V AC	15 20	4-11 11-36	Basic charging from a standard electrical outlet
Level 2	Home, work-place	4 8 19.2	240V AC 400V AC	40 80	1-4 2-6 2-3	Advanced charging at home or public stations
Level 3 (DC Fast Charging)	Public outlets	30-150 250-350	480V+DC	–	0.2-1.5	Rapid charging at specialized public stations
Extreme Fast Charging (XFC)	Highway	Over 350kW	–	–	Up to 0.1	Ultra-rapid charging technology for future infrastructure

Source: Elaborated by the author.

Table 2 — Charging stations in Boulder, Colorado

Design	**Number of Stations**	**Number of Ports**		**kW Station**	**kW Total**
		L2 (19.2kW)	**DC Fast (150kW)**		
1	15	2	0	38.4	576
2	3	4	0	76.8	230.4
3	1	4	4	676.8	676.8
	19	46	4		1483.2

Source: Elaborated by the author.

EV charging station site selection requires the analysis of multiple conflicting criteria such as economic, environmental, energy, geographic and transportation (Zhang *et al.*, 2018). By considering those conflicting criteria, the multi-criteria decision-making problem (MCDM) is one of the most accurate methods in the site selection process (Mahdy *et al.*, 2022; Xu *et al.*, 2018). MCDM problems are addressed by a group of expert decision makers who evaluate the most suitable alternatives based on their individual criteria and combine them into an overall evaluation (Saint; Lawson, 1994). Solving MCDM problems requires multi-criteria decision analysis (MCDA) approaches, which facilitate identification-prioritization of alternative sites and are effective in dealing with the lack of valid data considering complex and conflicting criterion (Malczewski; Rinner, 2015). Therefore, MCDM methods become the main tool adopted in this work to deal with several criteria involved in the identification of alternative sites for EV charging infrastructure.

1.1 PROBLEM STATEMENT

The rapid adoption of EVs necessitates a robust and well-distributed network of charging stations as a supplement to residential charging to mitigate range anxiety and maximize the profitability. Optimal charging infrastructure development as placement and size, involves addressing the question: "Given all-electric vehicles and plug-in hybrid electric vehicles, where are the best placements and sizes of EV charging stations necessary to support daily travel in a given city, and how will EV charging impact electricity demand and power distribution network planning". This problem requires a systematic approach to balancing diverse location criteria, including population density, transportation networks, environmental impacts, and proximity to key features. Usually, the main goal is to minimize the distance EV users must travel to access charging facilities while maximizing coverage and service levels across both urban and suburban landscapes. It involves Mixed Integer Linear Programming (MILP) models integrating binary decision variables for station presence and continuous variables for demand and flow.

As the EV market grows, the main issue is identifying charging infrastructure locations that meet EV users' supply needs and align with power distribution system's constraints, facilitating the transition to electric mobility while maintaining the power grid's integrity. Optimization, spatial analysis, and simulation are commonly used approaches to solve them. (i) Optimization techniques focus on mathematical models, in which MILP and metaheuristics algorithms are commonly used to evaluate single or multi-objective models, including cost, demand, and service coverage. (ii) Spatial Analysis employs geographic information systems (GIS) to assess suitability charging station sites based on spatial data across urban and suburban areas. (iii) Simulation methods involve modeling real-world scenarios to evaluate the performance of proposed charging station locations. Techniques like waiting time analysis and cost-benefit assessments are used to understand user behavior and station utilization.

1.2 OBJECTIVES

The main question of this work is: “What are the best sites for public EV charging stations in order to maximizing their availability and accessibility, and ensure a smooth transition to electric mobility?” To answer that question, a geographical information system-based MCDA methodology is considered.

The methodology focuses on the following objectives:

i. *Criteria Development:* Develop an in-depth set of criteria for evaluating potential sites for charging stations, including energy density, proximity to commercial centers, and insurance costs, among others. This involves spatial restrictions such as airports, military zones, and protected lands;

ii. *Multi-Criteria Decision Analysis (MCDA):* Implement a Fuzzy TOPSIS MCDA framework to assess and rank suitability sites based on GIS data, addressing the uncertainties of human judgment in the process of weighing criteria through fuzzy theory;

iii. *Impact Assessment:* Evaluate the impact of new charging stations on the capacity of distribution substations under high EV penetration scenarios. This ensures that the electrical substations can support the additional load introduced by the deployment of charging infrastructure;

iv. *Expert Involvement:* Engage decision-makers from technical, economic, and social perspectives to provide knowledge on the weighting process and validate the criteria, ensuring an integrated approach to site selection.

1.3 LITERATURE REVIEW

Despite the fast rising in the use of plug-in EVs, there are still some technical-economic barriers that limit the integration of EVs such as high purchase cost, long recharging times, and lack of charging facilities infrastructure (Riemann; Wang; Busch, 2015; Tu *et al.*, 2016). Among the technical-economic barriers mentioned, the low development of public charging infrastructure is one of the barriers with the greatest impact to increase the introduction of EVs (Funke; Gnann; Plötz, 2015). In this way, the deployment of a convenient, efficient, and economical EV charging infrastructure would enhance demand coverage for EVs and boost the EV industry. The optimal location of the charging stations is a significant factor associated with improved EV usage. It has an important impact on the city's traffic network, the quality of service, and its efficient operation. Approach-wise, charging station placement is susceptible to both quantitative and qualitative criteria evaluation under different perspectives, namely economic, societal, environmental, technological factors (Zhao; Li, 2016).

Commonly employed methods for MCDM include Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Best Worst Method (BWM), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), Weighted Linear Combination (WLC), and Preference Ranking Organization Method for Enrichment of Evaluations (PROMETHEE) *(Kaya et al*., 2021) (Wu *et al*., 2016). Authors in (Kaya *et al*., 2021) applied a combination of AHP and TOPSIS techniques to select the most suitable location for EV charging station. Due to the ambiguity and intangibility of human qualitative judgments, some factors cannot be measured with precise values. Thus, the integration of MCDM methods with fuzzy logic techniques enabled the quantification of criteria that aligned more effectively with fuzzy values than numerical values (Guo; Zhao, 2015). Moreover, the efficiency of MCDM methods depends on the quality of the data used to generate the criteria maps. In that sense, GIS capabilities have become fundamental to the processing of data. Table 3 summarizes some works that have used MCDM methods for suitable charging station location.

Some scholars have addressed the charging infrastructure placement problem by integrating GIS-based MCDM methodologies with fuzzy theory. The main characteristic of this methods is that they capture the vagueness of human perception through fuzzy theory. Erbaş *et al*. (2018) (Erbaş *et al*., 2018) used the Fuzzy Analytical Hierarchy Process (FAHP) and TOPSIS to account for the uncertainty inherent in subjective evaluations. The GIS-based FMDA approach presented in the paper aimed to calculate available EV charging station locations by considering various evaluation criteria, such as traffic density and geographical distribution, among the main ones. Zhou *et al*. 2020 (Zhou *et al*., 2020) proposed a framework for location decision of photovoltaic (PV) charging stations. The subjective and objective criteria weights are processes using interval numbers with an interactive MCDM method, which is supported by GIS. The rankings were compared with two commonly used methods: TOPSIS and VIKOR. Kaya *et al*. (2020) (Kaya *et al*., 2020) applied a GIS-based MCDM method using AHP, PROMETHEE, and VIKOR to optimize alternative and current locations for electric taxis. PROMETHEE and VIKOR were used to rank the sites, while fuzzy AHP was used to weight the criterion. The findings were the evaluation criteria under different decision-making perspectives and the use of fuzzy theory to collect qualitative information in selecting optimal locations.

In recent years, the ranking comparison of alternative locations has gotten much more attention to demonstrate the stability of proposal MCDM methods. The sensitivity analysis outcomes are compared to evaluate the changes in alternative locations. Zhao *et al*. (2016) (Zhao; Li, 2016) applied a sustainability perspective that considered economy, society, environment and technology criteria to identify the best location for charging stations. They utilized Fuzzy Delphi Method (FDM), combination weighting, and fuzzy Grey Relation Analysis (GRA-VIKOR) approaches to assess the stability of their strategy. Ju *et al*. (2019) (Ju *et al*., 2019) proposed an framework employing the FAHP technique and the Grey Relational Projection (GRP) method to assess and select the optimal charging station site. The main characteristic of this method is that it uses a new aggregation operator to integrate fuzzy information into the representation of the experts' attitudes. The ranking and sensitivity analysis are performed on six suitable locations. Karaşan *et al*. (2020) (Karaşan; Kaya; Erdoğan, 2020) developed an combined Intuitionistic Fuzzy Sets (IFS) MCDM method using Decision Making Trial and Evaluation Laboratory (DEMATEL) to determine dependency relations among criteria: traffic convenience and power system security as the most important. In order to check the robustness, the changes in the ranks of alternative locations are analyzed based on the main criteria's weight test.

Guler *et al*. (2020) (Guler; Yomralioglu, 2020) calculated suitability indexes applying GIS techniques. Spatial analysis is previously carried out to generate spatial layers associated with each criterion. With this information, the AHP and fuzzy AHP methods are used to compute the weights of criteria. Then, the suitability index is calculated by means of WLC under three perspectives: environmental, accessibility, and fuzzy. Finally, the alternative locations are ranked by TOPSIS method. Feng *et al*. (2021) (Feng; Xu; Li, 2021) presented an MCDM approach that used to the Linguistic Entropy Weight (LEW) method to determine criteria weights and Fuzzy Axiomatic Design (FAD) to select the most suitable location for an EV charging station. The risk of possible failure in site selection reduced by considering the probability of success of each criterion. The proposed method was compared to the TOPSIS, VIKOR, and MOORA methods, obtaining similar ranking results. Yagmahan *et al*. (2022) (Yagmahan; Yılmaz, 2022) developed another approach to assess alternative locations, integrating Group Aggregation Techniques (GATs). Two different group of GATs are used to get aggregated weights with AHP. The sensitivity analysis outcomes come from TOPSIS and Multi-Objective Optimization Based on Ratio Analysis (MOORA), which were applied to compare five ranking alternative locations.

The above literature review shows that previous works do not consider any criteria that model the massive adoption of EVs and, therefore, the charging infrastructure location. Most criteria relate to current EV users to deal with range anxiety criteria, while potential EV adopters are not taken into account. Thus, academics are still looking into the evaluation criteria under different decision-making perspectives as well. Besides, fuzzy theory in MCDM problems is being widely used to deal with the vagueness of human perception to identify the optimal location for charging stations. The MCDM frameworks presented in the literature review integrate weighting criteria methods through fuzzy theory and ranking methods using mathematical foundations, mostly leaving out the GIS environment. The sensitive analysis results without GIS data do not include all alternative locations; this is a critical limitation that requires to be addressed for an effective decision-making process on EV charging infrastructure.

Table 3 — Summary of the main characteristics of previous MCDM works

				Sustainable Criteria					
Method	**City**	**Year**	**GIS-based method**	**Technical**	**Economic**	**Social**	**Demographic**	**Environment**	**Reference**
Fuzzy TOPSIS	Beijing, China	2015			✓	✓		✓	(Guo; Zhao, 2015)
Fuzzy Delphi method (FDM), combination weighting, and fuzzy grey relation analysis GRA-VIKOR	Tianjin, china	2016		✓	✓	✓		✓	(Zhao; Li, 2016)
Fuzzy analytical Hierarchy Process (FAHP) and TOPSIS	Ankara, Turkey	2018	✓	✓	✓			✓	(Erbaş *et al.*, 2018)
FAHP technique and the traditional grey relational projection GRP method under picture fuzzy environment	Beijing, China	2019		✓	✓	✓		✓	(Ju *et al.*, 2019)
FAHP, PROMETHEE, and VIKOR	Anatolian, Turkey	2020	✓	✓	✓	✓		✓	(Kaya *et al.*, 2020)

Continue.

Table 3 — Summary of the main characteristics of previous MCDM works (*Continuation*)

				Sustainable Criteria					
Method	**City**	**Year**	**GIS-based method**	**Technical**	**Economic**	**Social**	**Demographic**	**Environment**	**Reference**
Decision-making trial and evaluation laboratory (DEMATEL), AHP and TOPSIS	Istanbul, Turkey	2020		✓	✓	✓		✓	(Karaşan; Kaya; Erdoğan, 2020)
AHP, fuzzy AHP, Weighted Linear Combination (WLC), and TOPSIS	Istanbul, Turkey	2020	✓	✓	✓	✓		✓	(Guler; Yomralioglu, 2020)
Linguistic entropy weight (LEW) method and fuzzy axiomatic design (FAD)	Chengdu, China	2021		✓	✓	✓		✓	(Feng; Xu; Li, 2021)
AHP, TOPSIS	Istanbul, Turkey	2021	✓	✓			✓	✓	(Kaya *et al.*, 2021)
Integrated group aggregation techniques (GATs) with AHP, TOPSIS and MOORA methods and sensitivity analysis results	Bursa, Turkey	2022		✓	✓	✓		✓	(Yagmahan; Yılmaz, 2022)
Machine learning framework (random forests, multinomial logistic regression and support vector machines)	Orange, Southern California	2022	✓	✓			✓	✓	(Roy; Law, 2022)
AHP, WLC	Winchester, UK	2022	✓	✓					(Mahdy *et al.*, 2022)
Combination weighting	Dublin, Ireland	2023	✓	✓					(Charly *et al.*, 2023)
This work	Cuenca, Ecuador	2024	✓	✓	✓	✓	✓	✓	

Check (✓): considered

End.

Source: Elaborated by the author.

1.4 CONTRIBUTIONS

In the context of EV charging station placement, this work presents a Fuzzy TOPSIS framework that consolidates key criteria and contrast it with several GIS-based MCDA methods. The main contributions are as following:

i. This paper takes into account several criteria simultaneously as socio-demographics and environmental, which can play a decisive role in the massive adoption of EVs to determine EV charging station;
ii. The density element for this analysis is important as it captures those customer strata in residential customers where EV adoption is more likely and a greater reliance on public infrastructure is required. It uses a high-resolution density electric load criteria in the analysis to determine the suitable sites for EV charging station;
iii. This work employs a TOPSIS MCDA approach with Fuzzy theory to address uncertainties and imprecision in human judgment during decision-making. It employs linguistic membership functions and fuzzy sets in the criteria-weighting process to incorporate technical, economic, and social perspectives;
iv. The proposed GIS-based MCDA framework supports capacity transformer assessment in substations based on EV trends. It uses a charging station growth scenario to determine the expected electrical capabilities required to service future EVs in the area.

2 BACKGROUND

EV adoption rates can boost from geographically dense charging infrastructure, particularly through public charger placement at popular locations to mitigate range anxiety. However, the location decision of public charging infrastructure is affected by direct or indirect criteria including proximity to features, terrain, traffic patterns, mobility preferences, vehicle-to-grid interests, and spatial constraints like land usage, environmental regulations, and property rights. The literature review highlights the significance of sociodemographic criteria when analyzing potential EV adopters. Spatial restrictions also impact site selection due to differences in private land requirements and permission processes. For example, certain areas may have different requirements related to privately-owned lands and obtaining permissions to use the land may be more challenging in some cases.

Therefore, this section delves three domains. Firstly, geographical criteria are defined, which are useful for understanding and analyzing data based on its geographic location. Secondly, the concept of geographically weighted regression (GWR) is discussed aiming modeling the spatial relationship between sociodemographic variables and identify potential EV adopters. Lastly, geostatistical interpolation, a method that utilizes spatial information to estimate unknown values in unsampled locations, is examined to identify critical areas with high air pollutant concentrations.

2.1 CRITERIA DEFINITION

The criteria were chosen based on a comprehensive review of existing literature and consultations with relevant experts. A hybrid approach encompassing socio-demographic variables and spatial factors was employed. The location decision criteria are categorized under five main titles, as summarized in Table 4. The features considered for selecting sites for EV charging stations are therefore: energy, economic & social, transportation, socio-demographics, and environmental criteria.

Table 4 — Background and criteria categorization

Main criteria	Sub criteria	Description	Reference
C1: Energy criteria	Electric substations	Distance between closest electrical substation and the candidate charging station location.	(Erbaş *et al*., 2018; Kaya *et al*., 2020, 2021)
	Petrol stations	Distance between closest petrol station and the candidate charging station location.	(Erbaş *et al*., 2018; Guler; Yomralioglu, 2020; Kaya *et al*., 2020; Mahdy *et al*., 2022)
	Current EV charging stations	Distance between closest charging station and the candidate charging station location.	(Charly *et al*., 2023; Erbaş *et al*., 2018; Kaya *et al*., 2020; Mahdy *et al*., 2022; Roy; Law, 2022)
	Energy density	Spatial distribution of energy consumption, calculated by total energy/land area.	(Zambrano-Asanza; Quiros-Tortos; Franco, 2021)
C2: Economic and Social criteria	Commercial centers	Distance between closest commercial center and the candidate charging station location.	(Guler; Yomralioglu, 2020; Kaya *et al*., 2020, 2021; Zhou *et al*., 2020)
	Health facilities	Distance between closest health facility and the candidate charging station location.	(Zambrano-Asanza *et al*., 2021)
C3: Transportation criteria	Main roads	Distance between closest principal road and the candidate charging station location.	*(Charly et al., 2023; Erbaş et al., 2018; Guler; Yomralioglu, 2020; Kaya et al., 2020, 2021; Mahdy et al., 2022; Zhou et al.*, 2020)
C4: Socio-demographics criteria	Insurance costs	Household insurance cost.	(Mejia *et al*., 2020)
	New housing	Residential buildings' age.	(Mejia *et al*., 2020)
	Building materials	Households employing high-end building materials in their residences.	(Mejia *et al*., 2020)
C5: Environmental criteria	Air quality	Annual mean concentration particulate matter level. Measures (NO_2) recorded by monitoring stations.	(Kaya *et al*., 2020, 2021)
	Noise	Day-averaged noise level on a weekday. Traffic noise (dB) derived from the monitoring stations.	(Zambrano-Asanza *et al*., 2021)

Source: Elaborated by the author.

Electrical substations. Degree of power loss, supply reliability and project cost depends on the distance of the station from the point of connection to the electrical substation. Therefore, well-suited areas for EV charging station are those near electrical substations.

Petrol stations. The presence of petrol stations reflects a well-organized facility distribution across the entire area, aligning with the traffic flow patterns. Therefore, the ideal location of the charging station should be near these supply points.

Current EV charging stations. The presence of existing EV charging station reduces the number of new ones to build in the sense of giving rise to the waste of resources. The charging station should be located as far as possible to existing EV charging station.

Energy density. The most likely EV adoption is on the residential upper load strata. In this perspective, the necessity for charging stations is greater in areas where load density is high. So, the higher the density, the better.

Commercial centers. Commercial centers attract short, medium, and long duration parking. Well-suited areas for EV charging station are those near shopping centers, chain stores, retail stores.

Health facilities. Medical campuses, hospitals, and health clinics have adequate 24 hours parking space for employee and visitors. EV owners can benefit from charging stations located close to health facilities.

Main roads. The EV charging stations should be strategically positioned with convenient connectivity to a significant network of roads, ensuring short travel times and swift access. A site for EV charging station should be located near the main roads. The nearer the better.

Insurance costs. If the insurance cost of people in a household increase, the higher the odds that a member from this household will be a new technology adopter. The map layer is created by using insurance costs of districts. If the location has a high contribution rate, it will be more suitable.

New housing. The ownerships of new house buildings are in favor to purchase new technology. In other words, people living in new buildings are more likely to be EV adopters. The map layer is prepared by using the count of construction loans that are in every district.

Building materials. The building materials taken into consideration as an economic factor seem to have a positive impact as a predictor of new technology adoption. The district score map layer is prepared by counting the flooring installation for high quality housing.

Air quality. In the use stage, EVs emit much fewer environmental pollutants than internal combustion engine vehicles. After the construction of a public EV charging station (EVCS) is completed, the new infrastructure brings certain less pollution. Well-suited areas for EVCS are those where pollution is high.

Noise. Electric motors are eco-friendly. They offer better acceleration, silent operation and less emissions and noise pollution. The operation of EV charging stations has positive impacts on the daily lives of locals. If the location has high pollution, it will be more suitable.

2.2 GEOGRAPHICALLY WEIGHTED REGRESSION

Ordinary least squares (OLS) regression is a technique used to identify factors causing a phenomenon. It employs a statistical method for evaluating the relations between variables based on data and trends. OLS regression offers a global model across geographic space, with a single regression equation representing the entire study area, thus assuming that relationships are fixed. The regression model is shown in (1).

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \varepsilon \quad (1)$$

In the regression model (1), y is the dependent variable, while X represents the variables used to explain y. The regression coefficients β measure the strength of the relationship between the dependent and the independent variables. β_0 is the expected value for y when all-independent variables are zero. Residuals ε indicate the difference between observed and modeled values. Coefficients can be positive, negative, or zero, with a larger coefficient indicating a stronger relationship.

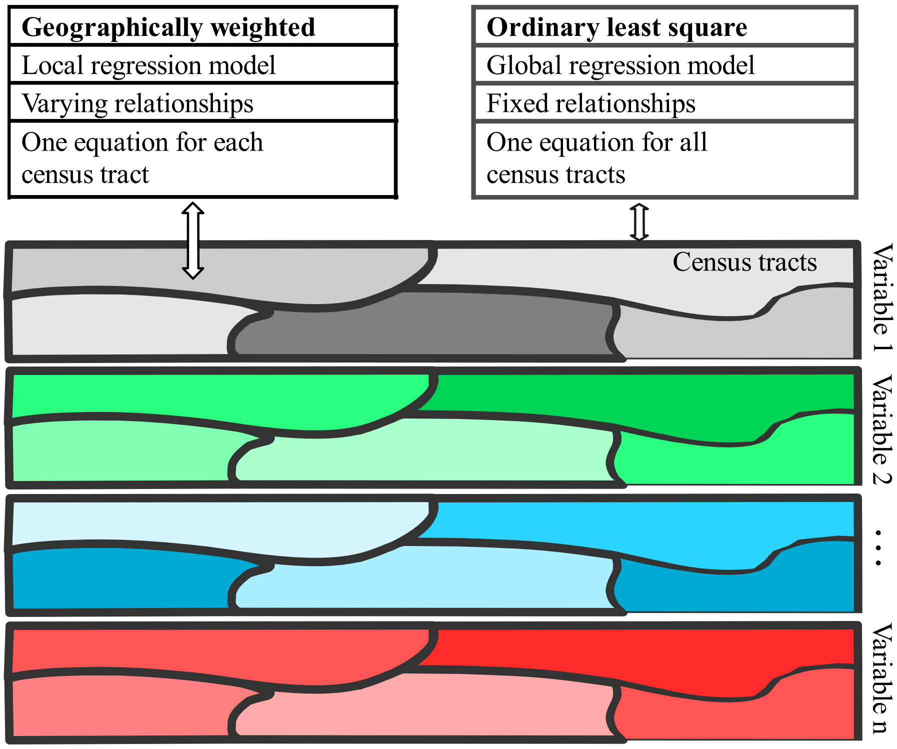
In a geographic space representation, OLS regression offers a global model across geographic area, with a single regression equation representing the entire study area and assuming fixed relationships. Figure 4 shows the variables referred to as geographic data layers[1], which are divided by census tracts[2] or meshblocks, with data attributes represented using a particular

[1] Data layers are collections of geographic data represented as points, lines, polygons, or surfaces on maps, based on spatial data properties.

[2] Census tracts are the smallest homogeneous territorial units for which demographic and economic data are available.

color scale. It shows the primary characteristics as global and local form of linear regression as well.

Figure 4 — The OLS regression model employs geographic data layers to define variables



Source: Elaborated by the author.

OLS serves as a foundational global model, offering a starting point for understanding other spatial analysis techniques that take non-stationary variables into consideration. The influence of local factors and the heterogeneity in spatial data in a geographic area make that the variables turn non-stationary and the relationships vary by locality (Fotheringham; Brunsdon; Charlton, 2002). In demographic analysis context, Geographically Weighted Regression (GWR) is a spatial analysis method that examines how relationships between socioeconomic variables change across different districts within a study area. By fitting unique regression models to each census tracts, GWR explores spatial phenomena evaluating regression coefficients of the local models (Mejia *et al.*, 2020). These analyses utilize data from local population censuses and the influence of the neighboring census tracts. This helps in understanding why certain residents of certain areas are prospective buyers of end-use electrical technology ($Y_{s,t,d}$). Separate equations are constructed for every district using (2).

$$Y_{s,t,d} = \beta_{s,t,d}^{1} X_{d}^{1} + \beta_{s,t,d}^{2} X_{d}^{2} + \cdots + \beta_{s,t,d}^{k} X_{d}^{k} + \varepsilon_{s,t,d} \tag{2}$$

where X_d^k is a k variable of socioeconomic characteristics of the population in district d, $\varepsilon_{s,t,d}$ is the residual between the values $Y_{s,t,d}$ and $Y_{s,t,d}^{Obs}$; $\beta_{s,t,d}^{k}$ is calculated as shown in (3).

$$\beta_{s,t,d}^{k} = \left(x_d^{k^T} W_d x_d^k \right)^{-1} x_d^{k^T} W_d Y_{s,t,d}^{Obs} \tag{3}$$

where W_d is a square matrix as given in (4).

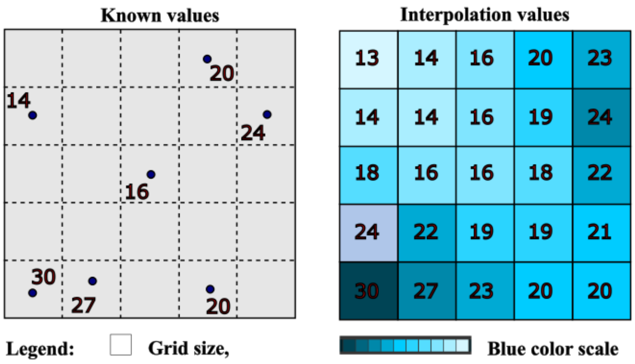
$$W_d = \begin{bmatrix} W_{d,1} & 0 & \cdots & 0 \\ 0 & W_{d,2} & 0 & 0 \\ \vdots & 0 & \ddots & \vdots \\ 0 & 0 & \cdots & W_{d,j} \end{bmatrix} \tag{4}$$

The diagonal elements $W_{d,j}$ are the weights that relate the spatial proximity among districts on the study area. These values depend on the shape and extent of all neighborhoods used for each local regression equation being analyzed. They are calculated using a Gaussian and Bisquare method to controls how smoothness of the kernel model. GIS tools, such us ARCGIS® and GEODA®, could be employed to calculate the parameters $W_{d,j}$, $\beta_{s,t,d}^{k}$, and $Y_{s,t,d}$.

2.3 GEOSTATISTICAL INTERPOLATION

To construct an air pollution surface or map over a broad region using limited air quality monitoring stations, interpolation techniques are essential for estimating pollution levels at unsampled locations. Since surface data originate from discrete points, modeling continuous representations of pollutants like particulate matter, nitrogen dioxide, and ozone requires spatial interpolation methods. Figure 5 depicts known air pollution levels for specific areas on the left side and predicted values via interpolation on the right side to cover unmeasured areas.

Figure 5 — Surface coverage (right) derived from point values (left) through interpolation



Source: Elaborated by the author.

Spatial interpolation methods in GIS can be deterministic or geostatistical, relying on spatial autocorrelation -the similarity of neighboring sample points- to generate the surface. Deterministic methods use an initial data condition and a distance weighting parameter specified by the decision-maker. Geostatistical methods are founded on the principles of statistical spatial autocorrelation, assuming that model parameters are subject to random variation and measurement error. Kriging is a geostatistical method that acknowledges that modeling the spatial variation of a continuous attribute value is not possible with a simple, smooth mathematical function (Yang, 2018). Then, Kriging is used when sample attribute data exhibit substantial variation beyond the capability of simpler modeling methods.

The Kriging uses the semivariogram to represent the autocorrelation. The semivariogram measures the strength of the statistical correlation as a function of distance among the samples (Oliver; Webster, 1990). Equations (5) and (6) are used to determine the Kriging estimate $z^*(x_0)$ and the error estimation variance ${\sigma_k}^2(x_0)$ at every point x_0, respectively.

$$z^*(x_0) = \sum_{i=1}^{n} \lambda_i z(x_i) \tag{5}$$

$$\sigma_k^2(x_0) = \mu + \sum_{i=1}^{n} \lambda_i \gamma(x_0 - x_i) \tag{6}$$

where λ_i are the weights; μ is the Lagrange constant; $\gamma(x_0 - x_i)$ is the semivariogram value corresponding to the distance between x_0 and x_i; and the coordinate component is denoted by $x_0(x, y)$.

Semivariograms are the fundamental tool that summarizes the spatial continuity for all possible pairings of data. Using the intrinsic hypotheses and regionalized variable theory, semivariogram can be written by (7) and (8):

$$2\gamma(h) = E[Z(x_i) - Z(x_i + h)]^2 \tag{7}$$

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2 \tag{8}$$

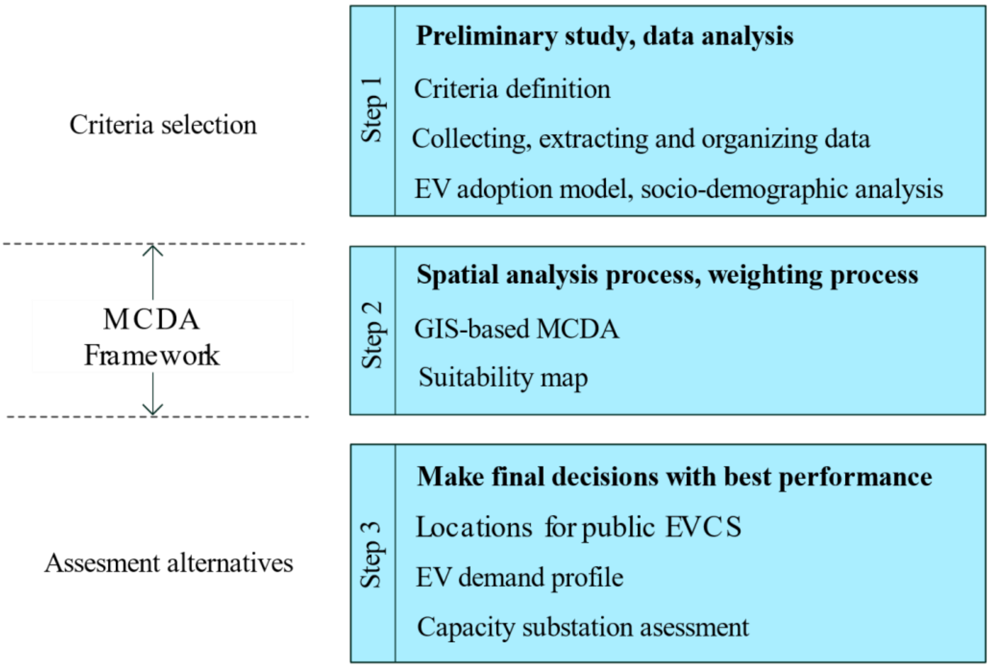
where $\gamma(h)$ is the semivariance, h is the distance (or lag), Z is a random function with a steady mean, $N(h)$ is the number of pairs of samples separated by a distance h, $Z(x_i)$, and $Z(x_i + h)$ are values of Z at points x_i and $x_i + h$.

3 METHODOLOGY

This section presents the proposed framework that combines spatial analysis and spatial decision-making processes. The integration of these two fields, known as GIS-based MCDA methods, is used in suitability analysis for EV charging station placement. The framework consists of three primary steps, as illustrated in Figure 6. Initially, during the pre-processing step, diverse geospatial datasets are collected, encompassing all defined criteria. The primary feature at this step entails performing an EV adoption model. GWR model identifies key criteria influencing new technology acquisition by exploring spatial relationships and patterns. Thus, GWR is used to identify socio-demographic criteria that establish the relation between spatially referenced data and potential EV adopters' profiles, as it identifies where EV adoption is more likely and thus where upcoming EV charging station placements are required.

The findings work as input for the second step, wherein several spatial analysis techniques such as WLC, TOPSIS, and VIKOR are employed. To conduct a comparative analysis, different variations, including combining AHP and Fuzzy Logic to establish weights, along with spatial analysis techniques, are implemented. Thus, four suitability maps can be obtained by applying AHP+WLC, AHP+TOPSIS, AHP+VIKOR, and Fuzzy+TOPSIS. The resulting suitability map and projected EV demand profiles enable the assessment of the impacts of charging station load profiles on the substation load profiles.

Figure 6 — Framework for EV charging station suitability analysis



Source: Elaborated by the author.

3.1 ANALYTIC HIERARCHY PROCESS

AHP is a rating method to estimate weights of each criterion within a judgment decision-making approach. It requires a comparison pairwise on a basis of a predetermined scale, called "*Saaty's Fundamental Scale*" (Saaty, 1980). The decision maker employs a pair wise comparison matrix with values from 1 to 9 to rate the preferences with respect to a pair of criteria.

The comparison matrix $C = [c_{kp}]_{n\times n}$ is reciprocal, i.e., $c_{pk} = \frac{1}{c_{kp}}$ with ones all diagonal elements. Saaty scale is used to define relative weights c_{kp} for the k-th and p-th criteria through comparison pairwise. After that pairwise comparison matrix is established, the vector of criterion weights w can be computed by (9).

$$Cw = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ \frac{1}{c_{12}} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{1}{c_{1n}} & c_{2n} & \cdots & 1 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{bmatrix} = \lambda_{max} w \tag{9}$$

subject to:

$$\sum_{k=1}^{n} w_k = 1 \quad \forall k = 1,2,\dots,n$$

$$0 \le w_k \le 1$$

where λ_{max} is the largest eigenvalue of C. One of the most used methods to solve (9) is averaging over normalized columns, proposed by (Saaty, 1980). So, the entries in the matrix C are normalized with (10) and finally the weights are computes using (11).

$$c^*_{kp} = \frac{c_{kp}}{\sum_{k=1}^{n} c_{kp}} \quad \forall k = 1,2,\dots,n \tag{10}$$

$$w_k = \frac{\sum_{p=1}^{n} c^*_{kp}}{n} \quad \forall p = 1,2,\dots,n \tag{11}$$

The pairwise comparison requires measuring the inconsistency according to the transitivity principle. In general, the principle of transitivity can be defined as follows: a consistent set of pairwise comparisons in which human judgment is to some degree inconsistent (Malczewski; Rinner, 2015). The consistency ratio (*CR*) is defined by (12).

$$CR = \frac{\lambda_{max} - n}{RI(n-1)} \tag{12}$$

where, RI is the random index, which depends on the number of criteria being compared, i.e., for $n = 2,3,4,5,6,7,8$, $RI = 0.00, 0.52, 0.89, \dots, 1.40$, respectively. The consistency ratio, $CR < 0.1$, indicates a reasonable level of consistency, and $CR \ge 0.1$ indicates inconsistent judgment in the pairwise comparisons. If the consistency ratio CR indicates inconsistent judgment, the pairwise comparison matrix C should be reconsider and the original values c_{kp} revised.

3.2 FUZZY LOGIC

Proposed by Zadeh in 1965, Fuzzy Theory is used to map linguistic terms into numerical counterparts within human judgments. Fuzzy sets are commonly employed to handle uncertainty and imprecision when weighing criteria and rating alternatives in MCDM problems (Yager; Zadeh, 1992). So, a fuzzy set A in a referential universe of discourse X is characterized by a membership function A, which associates with each element $x \in X$ a real number $A(x) \in [0,1]$, having the interpretation $A(x)$ as the membership grade of x in the fuzzy set A. In this way, $A(x) = 1$ means full membership of x in A, while $A(x) = 0$ means non-membership. A fuzzy set is identified with its membership function. Notations that are generally used are the following $\mu_A(x) = A(x)$ (Bede, 2013). The membership function of a classical set $A \subseteq X$ can be defined with its characteristic function as given in (13).

$$\mu_A(x) = \begin{cases} 1 & if\ x \in A \\ 0 & otherwise \end{cases} \tag{13}$$

The triangular fuzzy number is one of the most popular shapes of fuzzy numbers. It can be defined as a triplet $A = (\alpha_1, \alpha_2, \alpha_3)$, as defined by (14).

$$\mu_A(x) = \begin{cases} 0, & x \prec \alpha_1 \\ \dfrac{x - \alpha_1}{\alpha_2 - \alpha_1}, & \alpha_1 \leq x \leq \alpha_2 \\ \dfrac{\alpha_3 - x}{\alpha_3 - \alpha_2}, & \alpha_1 \leq x \leq \alpha_2 \\ 0, & x \succ \alpha_3 \end{cases} \tag{14}$$

Assuming two triangular fuzzy numbers $A = (\alpha_1, \alpha_2, \alpha_3)$ and $B = (b_1, b_2, b_3)$, the next properties are satisfied as given in (15) and (16).

$$A(+)B = (\alpha_1 + \alpha_2 + \alpha_3)(+)(b_1 + b_2 + b_3) = (\alpha_1 + b_1, \alpha_2 + b_2, \alpha_3 + b_3) \tag{15}$$

$$A(-)B = (\alpha_1 + \alpha_2 + \alpha_3)(-)(b_1 + b_2 + b_3) = (\alpha_1 - b_3, \alpha_2 - b_2, \alpha_3 - b_1) \tag{16}$$

A fuzzy matrix is a gathering of vectors in which a fuzzy vector is a certain vector that includes an element with value between 0 and 1. So, the operations on given fuzzy matrices A and B are addition, product, and scalar multiplication:

$$A + B = max\left[\alpha_{i,j}, b_{i,j}\right] \tag{17}$$

$$A \cdot B = max\left[min\left(\alpha_{i,k}, b_{k,j}\right)\right] \tag{18}$$

$$\lambda A \tag{19}$$

where $0 \leq \lambda \leq 1$.

The calculation of the distance between two triangular fuzzy numbers can be performed through the vertex method using (20).

$$d(A, B) = \sqrt{\frac{1}{3}[(\alpha_1 - b_1)^2 + (\alpha_2 - b_2)^2 + (\alpha_3 - b_3)^2]} \tag{20}$$

A linguistic variable is one whose values represent crisp information in a form of words or sentences in its context. For example, ‘Age’ can take the values young, not young, old, very old, etc., rather than 18, 25, 40, 65 (Zadeh, 1975). This kind of variables can well be represented by triangular fuzzy numbers.

3.3 MCDM FRAMEWORK

Decision-makers can comprehensively evaluate potential sites for EV charging stations, considering multiple criteria, such as accessibility, demand, environmental impact, and infrastructure suitability, by employing MCDM techniques. AHP WLC, AHP TOPSIS, AHP VIKOR, and Fuzzy TOPSIS are among the commonly utilized methods in literature review. WLC enables the linear combination of different criteria by assigning weights to each criterion based on its importance from pairwise comparison, thereby facilitating a comprehensive assessment. TOPSIS ranks alternatives based on their proximity to the ideal solution and furthest from the negative ideal solution. VIKOR, on the other hand, identifies the best compromise solution among alternatives by considering both the maximum group utility and the minimum individual regret. Lastly, Fuzzy TOPSIS accommodates the imprecision and uncertainty inherent in decision-making processes by employing fuzzy sets to represent linguistic terms to express preferences.

WLC is one of the simplest and most widely used technique for sites scoring within spatial analysis approach (Malczewski, 2000). It consists of a map combination procedure, i.e., for each geographic location (x_i, y_i) a weighted summation of a set of criteria weights, $w_1, w_2, \ldots, w_n$, and criterion values, $a_{i1}, a_{i2}, \ldots, a_{in}$, is computed. The performance of the alternative is measured (e.g., distance to main roads, land use, energy density) and transformed into a normalized or standardized score. Then, the map combination consists of two components: criterion weight w_k and a performance score $v(a_{ik})$, as given in (21).

$$V(A_i) = \sum_{k=1}^{n} w_k v(a_{ik}) \cdot \prod r_i \tag{21}$$

where $v(a_{ik})$ refers to a normalized performance score over a scoring function according to human judgment (to reflect a positive or reversed rank). There are many normalizing techniques, including linear sum-based, linear min-max, logarithmic, and more. $V(A_i)$ denotes the final score for the suitability value. The subscript "i" represents the i-th alternative at coordinates (x_i, y_i). Within a raster GIS-based decision analysis, each cell of a map layer is considered to be an alternative. The spatial restrictions are included by using the restricted alternatives component r_i.

Through straightforward, the WLC method requires careful consideration of normalization and weighing criteria to ensure that the final scores accurately reflect decision-making priorities. Each criterion's weight can be defined using techniques such as AHP, which represents its relative importance in the decision-making process. The normalization process, typically using linear min-max scaling (usually between 0 and 1) as defined in (22), ensures that no single criterion dominates the analysis due to differences in units or scales. The normalization process can be combined with categorization techniques, which can be helpful for setting thresholds or meaningful classifying of numerical data (performance values) when it is not uniformly distributed. Categorization techniques include natural breaks (Jenks method), quantile, stratification by minimal variance (Dalenius-Hodges Method), and more.

$$x_{ij}^{'} = \frac{x_{ij} - x_j^{-}}{x_j^{*} - x_j^{-}} \tag{22}$$

where x_{ij}' is the normalized value for alternative i on criterion j, x_{ij} is the performance for alternative i on criterion j. x_j^{*}, x_j^{-} are the maximum and minimum values for criterion j across all alternatives.

The AHP WLC method provides a structured approach to decision-making by the following seven steps:

1. Identify and define criteria for site suitability;
2. Establish a hierarchy of criteria, conduct pairwise comparisons using AHP, and derive normalized weights;
3. Assess alternatives against criteria, classifying ang assigning normalized performance scores;
4. Multiply scores by normalized weights and sum for each alternative, and for each alternative, multiply the restricted condition;
5. Rank alternatives based on composite scores;
6. Assess the impact of changes in criteria weights;
7. Make the final decision.

The TOPSIS method compares the distance of each one of the alternatives to an ideal and anti-ideal solution (Papathanasiou; Ploskas, 2018). It involves selecting the greatest alternative closest to the positive ideal solution and farthest from the negative-ideal solution. It uses a decision matrix with m alternatives $A_1, \dots, A_m$ and n criteria, $C_1, \dots, C_n$. At first, each alternative is evaluated with respect to each of the n criteria to form a decision matrix $X = \left(x_{ij}\right)_{m \times n}$. The vector of the criteria weights obtained from AHP method is $W = \{w_1, \dots w_n\}$, where $\sum_{j=1}^{n} w_j = 1$.

In the decision matrix, each element indicates the performance of an alternative based on the criteria. It is written as follows in (23).

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \tag{23}$$

Each element of the decision matrix is normalized to ensure that all criteria are comparable using (24). Then, the values are weighted to reflect the relative importance of each criterion. The weighted normalized decision matrix V is calculated by multiplying each normalized value r_{ij} by the weight w_j of criterion j, as in (25).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \qquad i = 1, \dots, m; \; j = 1, \dots, n \tag{24}$$

$$V = \begin{bmatrix} w_1 r_{11} & w_2 r_{12} & \cdots & w_n r_{1n} \\ w_1 r_{21} & w_2 r_{22} & \cdots & w_n r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ w_1 r_{m1} & w_2 r_{m2} & \cdots & w_n r_{mn} \end{bmatrix} \tag{25}$$

where $v_{ij} = w_j \times r_{ij}, i = 1, \dots, m, j = 1, \dots, n$.

The ideal solution A^* and negative-ideal solution A^- are determined by selecting the best and worst values for each criterion. For maximization criteria, A^* and A^- are determined by (26). For minimization criteria, A^* and A^- are determined by (27).

$$A^* = \{\max v_{ij} \mid j \in N\}, \qquad A^- = \{\min v_{ij} \mid j \in N\} \tag{26}$$

$$A^* = \{\min v_{ij} \mid j \in N'\}, \qquad A^- = \{\max v_{ij} \mid j \in N'\} \tag{27}$$

where N and N' are the sets of criteria for maximization (benefit) and minimization (cost) criteria, respectively.

The separation measures are calculated using the Euclidean distance formula given in (28) and (29).

$$S_i^* = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^*\right)^2} \tag{28}$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - A_j^-\right)^2} \tag{29}$$

where S_i^* is the separation of alternative i from the ideal solution and S_i^- is the separation of alternative i from the negative-ideal solution.

The relative closeness to the ideal solution is given in (30).

$$C_i^* = \frac{S_i^-}{S_i^* + S_i^-} \tag{30}$$

where C_i^* is the relative closeness of alternative i to the ideal solution, $(0 \leq C_i^* \leq 1)$. The alternative with the highest C_i^* value is considered the most preferable option.

The AHP TOPSIS algorithm consists of six steps:

1. Normalize the decision matrix;
2. Calculate the weighted normalized decision matrix;
3. Determinate the ideal and anti-ideal solutions;
4. Calculate the separation measures;
5. Calculate the relative closeness to the ideal solution;
6. Rank the preference order.

VIKOR is considered to be effective in cases where the decision maker cannot be certain how to express his/her preferences coherently and consistently at the initial stages of the system design (Papathanasiou; Ploskas, 2018). Like TOPSIS, VIKOR theoretical background is based on “closeness to the ideal”, but it’s helpfully when non-commensurable and conflicting criteria are included.

VIKOR method, denoted by mco, has been developed to solve the MCDA problems by selecting the best alternative as given in (31).

$$mco_i = \{(f_{ij}(A_i), i = 1,2,\ldots,m), j = 1,2,\ldots,n\} \tag{31}$$

where m is the number of feasible alternatives; n is the number of criteria; $A_i = x_1, x_2, \ldots, x_m$ is the i-th alternative generated with certain values of system variables x; f_{ij} is the performance value of the j-th criterion function for the alternative A_i. Below are the key equations used in the method.

At first, to evaluate the relative importance of each criterion, a decision matrix is established as in (32). The matrix consists of numerical values representing the performance of each alternative based on the criteria. From the decision matrix, the best and worst values for each criterion are obtained with (33) and (34) respectively.

$$D = \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{1n} \\ f_{21} & f_{22} & \cdots & f_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ f_{m1} & f_{m2} & \cdots & f_{mn} \end{bmatrix} \tag{32}$$

$$f^* = \left(\max_i f_{ij}, \forall j \in N\right) \tag{33}$$

$$f^- = \left(\min_i f_{ij}, \forall j \in N\right) \tag{34}$$

where f_{ij} represents the performance of alternative i with respect to criterion j, and N is the set of criteria.

To compute the Utility Measure (S), which reflects how close an alternative is to the ideal solution, and Regret Measure (R), which indicates how much an alternative falls short of the ideal solution, the formulas are given in (35) and (36) respectively. The utility measure is obtained by summing the normalized distances from the ideal solution across all criteria, while the regret measure concentrates on the criterion where the alternative performs the worst relative to the ideal solution.

$$S_i = \sum_{j=1}^{n} w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \tag{35}$$

$$R_i = \max_j \left(w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right) \tag{36}$$

where f_j^* is the ideal (best) solution, f_j^- is the negative ideal (worst) solution, and w_j is the weight of the j-th criterion. f_{ij} is the performance value of alternative i under the j-th criterion.

In the VIKOR method, the compromise solution is calculated using three main equations: the utility measure (S), the regret measure (R), and de VIKOR index (Q). The VIKOR index is calculated in (37). It combines the utility and regret measures into a single value by using a compromise parameter v to balance the utility and regret components.

$$Q_i = v * \frac{S_i - S^*}{S^- - S^*} + (1 - v) * \frac{R_i - R^*}{R^- - R^*} \tag{37}$$

where v is a weight that reflects the decision maker's preference for the utility over the regret $(0 \leq v \leq 1)$, typically set to $v = 0.5$. The alternative with the lowest Q_i value is considered the best compromise solution.

The steps of the AHP VIKOR procedure consist of nine steps:

1. Determine the best and worst values of all criteria functions;
2. Compute the values S_i and R_i, representing Separation Measure and Individual Regret, respectively;
3. Compute the values Q_i named Maximum Group Utility;
4. Rank the alternatives;
5. Propose a compromise solution;
6. Determine the weight stability interval for each criterion;
7. Determine the trade-offs;
8. Adjust the trade-offs;
9. Verify conditions for algorithm' termination.

Fuzzy TOPSIS methodology adopted from Chen's work uses the TOPSIS approach extended into group decision making involving linguistic variables (Saaty, 1980). Fuzzy TOPSIS incorporate fuzzy sets by linguistic terms, such as "low", "medium", or "high", which are then converted into fuzzy numbers. This approach overcomes uncertainties and imprecision in human judgment when determining crisp values for criteria weights and alternative evaluations.

The linguistic variables are commonly expressed in positive triangular fuzzy numbers on alternative i under criterion j, $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$, $i = 1, 2, \dots, m$, $j = 1, 2, \dots, n$. The fuzzy decision matrix is constructed as (38) and the vector of the criteria weights as (39).

$$\widetilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{38}$$

$$\widetilde{W} = [\widetilde{w}_1, \widetilde{w}_2, \dots, \widetilde{w}_n] \tag{39}$$

where $\tilde{x}_{ij}$ are linguistic variables for the linguistic ratings of the alternatives i. $\widetilde{w}_j$ are the linguistic variables for the importance weight of the criteria j, $\widetilde{w}_j = \left(w_{j1}, w_{j2}, w_{j3}\right)$.

The normalized fuzzy decision matrix denoted by $\tilde{R} = \left[\tilde{r}_{ij}\right]_{m\times n}$, $\tilde{r}_{ij} = \frac{\tilde{x}_{ij}}{\text{best/worst value}}$ is built with (40) for maximizing criteria and (41) for minimizing criteria.

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \quad j \in N, \quad i = 1, 2, \dots, m \tag{40}$$

$$\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right), \quad j \in N', \quad i = 1, 2, \dots, m \tag{41}$$

where c_j^* is the upper bound of the fuzzy number representing the best performance for criterion j, and a_j^- is the lower bound representing the worst performance. N and N' are the sets of criteria for maximization (benefit) and minimization (non-beneficial) criteria, respectively. Additionally, $c_j^* = \max_i c_{ij}$ if $j \in N$ and $a_j^- = \min_i a_{ij}$ if $j \in N'$.

The fuzzy weighted normalized decision matrix $\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n}$ is obtained in (42).

$$\tilde{v}_{ij} = \tilde{r}_{ij}(\cdot)\widetilde{w}_j, \quad i = 1, 2, \dots, m, \quad j = 1, 2, \dots, n \tag{42}$$

where $\tilde{v}_{ij}$ are normalized positive triangular fuzzy numbers ranging from 0 to 1.

The Fuzzy Positive Ideal Solution (FPIS, A^*) and the Fuzzy Negative Ideal Solution (FNIS, A^-) are defined in (43) and (44).

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*) \tag{43}$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-) \tag{44}$$

where $\tilde{v}_j^* = \left(\max_i c_{ij}, \max_i b_{ij}, \max_i a_{ij}\right)$ and $\tilde{v}_j^- = \left(\min_i a_{ij}, \min_i b_{ij}, \min_i c_{ij}\right)$.

The distance of each of the alternatives from FPIS and FNIS can be calculated by using the Euclidean distance adapted for fuzzy numbers, (45) and (46) respectively.

$$D_i^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right) \tag{45}$$

$$D_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right) \tag{46}$$

where $d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right) = \sqrt{\frac{1}{3}\left[\left(a_{ij} - a_j^*\right)^2 + \left(b_{ij} - b_j^*\right)^2 + \left(c_{ij} - c_j^*\right)^2\right]}$ is the distance between fuzzy numbers $\tilde{v}_{ij}$ and , $\tilde{v}_j^*$.

The closeness coefficient of each alternative is defined in (47).

$$CC_i = \frac{D_i^-}{D_i^* + D_i^-} \tag{47}$$

where the alternatives with the highest CC_i (closer to 1) are the best.

Fuzzy TOPSIS algorithm consists of six steps:

1. Form a committee of decision makers, then identify the evaluation criteria;
2. Choose the linguistic variables;
3. Perform aggregations;

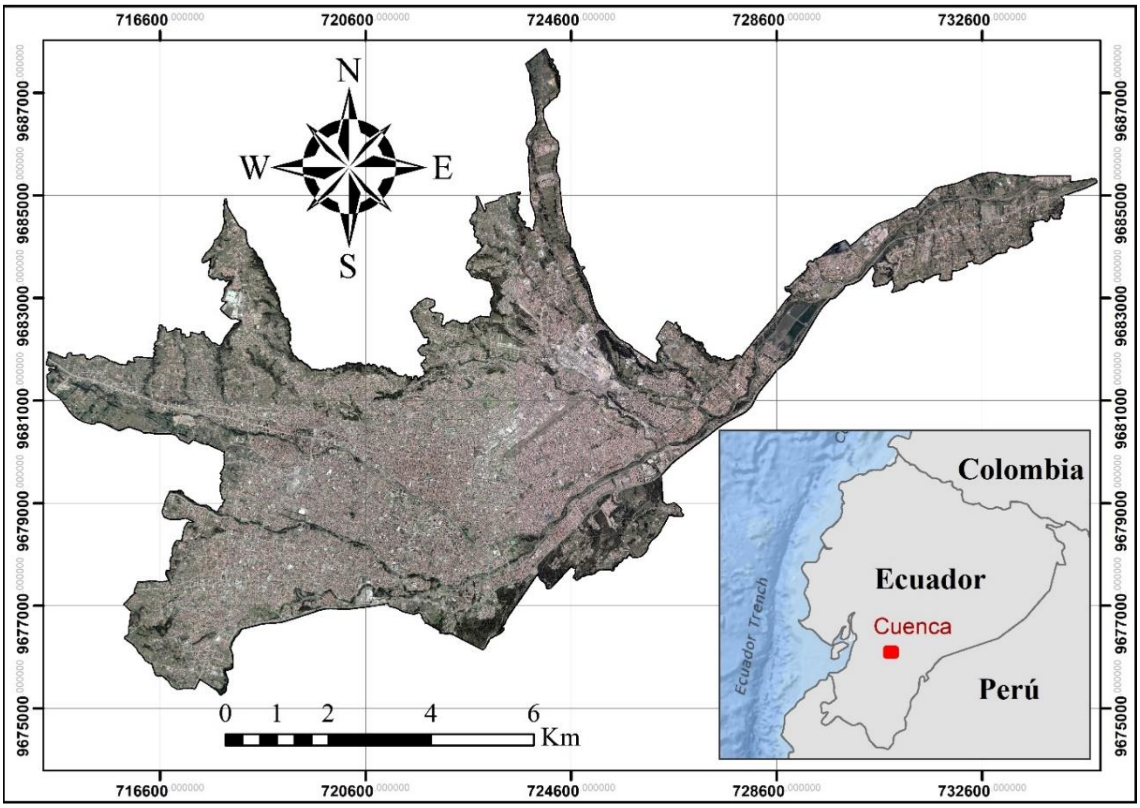
4. Construct the fuzzy decision matrix and the normalized fuzzy decision matrix;
5. Construct the fuzzy weighted normalized decision matrix;
6. Determine the fuzzy positive ideal solution (FPIS) and the fuzzy negative ideal solution (FNIS);
7. Calculate the distance of each alternative from FPIS and FNIS;
8. Calculate the closeness coefficient of each alternative;
9. Rank the alternatives.

4 CASE STUDY AND DISCUSSION

The proposed approach was implemented using an electrical system of "Empresa Eléctrica Regional Centro Sur C.A." (Centrosur) in Cuenca, Ecuador, covering an extensive service area of 30,234 km^2, constituting 11.8% of Ecuador's territory. In 2018, the 393,953 customers, predominantly residential (88%), commercial (11%), and industrial (1%), consumed 1,074.10 GWh of energy, with a peak demand reaching 194.93 MW. The study area, shaded dark in Figure 7, represents approximately 75% of the utility's energy demand and accommodates 214,082 consumers as of the base year 2022.

According to the National Institute of Statistics and Censuses (INEC) historical data (2022), Ecuador had approximately 2.5 million motorized vehicles in 2021, which represents an increase of 7.4% compared to the previous year and an average annual growth of 5.6%. Particularly, in the province of Azuay, there were 163,598 registered vehicles, accounting for 6.45% of the nationwide total. Base on (INEC, 2019), 33 EVs have been registered until 2021 in the province of Azuay. Although the population grows at an average rate of 2% per year in Cuenca, the number of vehicles increases by 5% (Mendieta, 2022).

Figure 7 — Geographical location of the study area: Cuenca, Ecuador



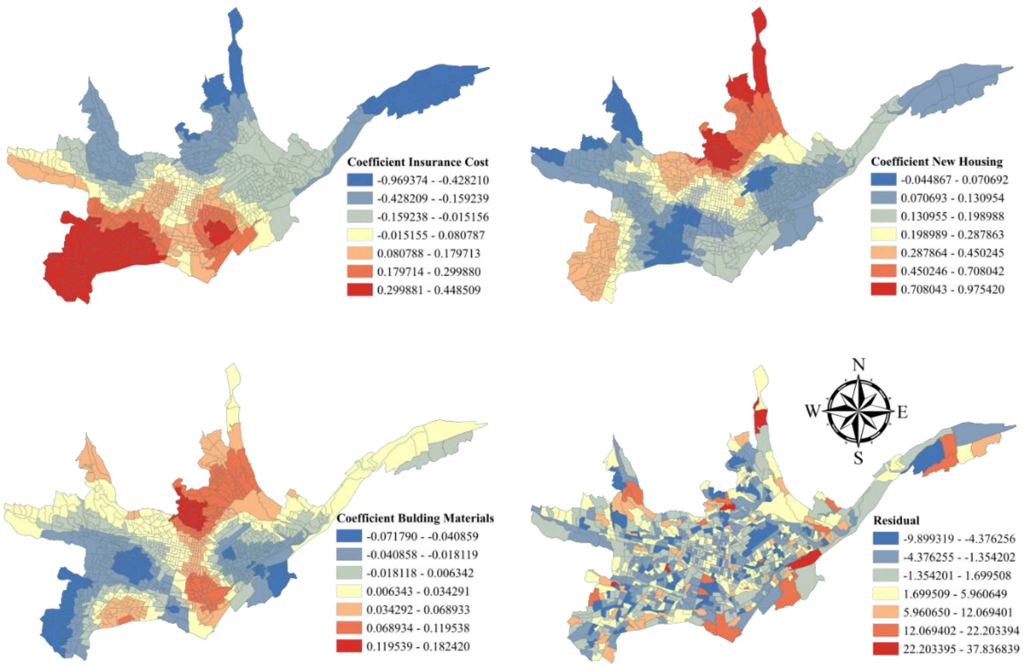
Source: Elaborated by the author.

4.1 EV ADOPTION MODEL

GWR model identifies socio-demographic criteria influencing new technology acquisition. The criteria, known as predictor variables, are gathered from a literature review as well as from the available population census data in the city of Cuenca. Socio-demographic variables such as education level, income, and household size are recognized as key determinants of EV purchasing behavior (Priessner; Sposato; Hampl, 2018). However, depending on where the study was developed, the degree of influence between these variables varies by adopters' location (Namdeo; Tiwary; Dziurla, 2014).

The INEC conducts the census in Ecuador, providing population statistics, with the most recent in 2022. The census gathers information about the age, gender, education level, housing units, number of rooms, building materials of households, access to basic services, etc. The city of Cuenca has a total of 775 census tracts. Over these census tracts, the GWR tool from ArcGIS® was applied to find the best combination of predictor variables. The tool generated a diagnostic values report, with the adjusted R-squared statistic serving as a measure of model performance. GWR was executed with the population census data as independent variables and the electric stove adopters as the dependent variable. Through an exploratory regression process, the model achieved an adjusted R-squared of 0.436. This suggests that the model explains about 44% of the variation in stove adoption. The model identifies three predictor variables that have a significant impact on EV adoption: insurance costs, aging households, and building materials. These predictor variables, with regression coefficients depicted as heatmaps in Figure 8, will be considered later as spatial criteria for EV purchasing.

Figure 8 — Regression coefficients from the GWR model



Source: Elaborated by the author.

4.2 CRITERIA AND RESTRICTIONS ANALYSIS

The processing of spatial criteria consists of four types of spatial analysis as detailed in Table 5: proximity, density, spatial regression, and interpolation. After processing, each of the spatial criteria described in Section 2.1 is illustrated in Figure 9. The study imposed spatial restrictions on airports, military zones, watercourses, rivers, parks, recreational areas, protected land, and petrol stations.

Table 5 — The study's criteria and the associated GIS analysis

Main Criteria	**Sub Criteria**	**GIS analysis**
C1: Energy criteria	Electric substations	Euclidean distance
	Petrol stations	Euclidean distance
	Currents EVCS	Euclidean distance
	Energy density	Point density
C2: Economic and Social criteria	Commercial centers	Euclidean distance
	Health facilities	Euclidean distance
C3: Transportation criteria	Main roads	Euclidean distance
C4: Socio-demographics criteria	Insurance costs	GWR
	New housing	GWR
	Building materials	GWR
C5: Environmental criteria	Air quality	Kriging interpolation
	Noise	Kriging interpolation

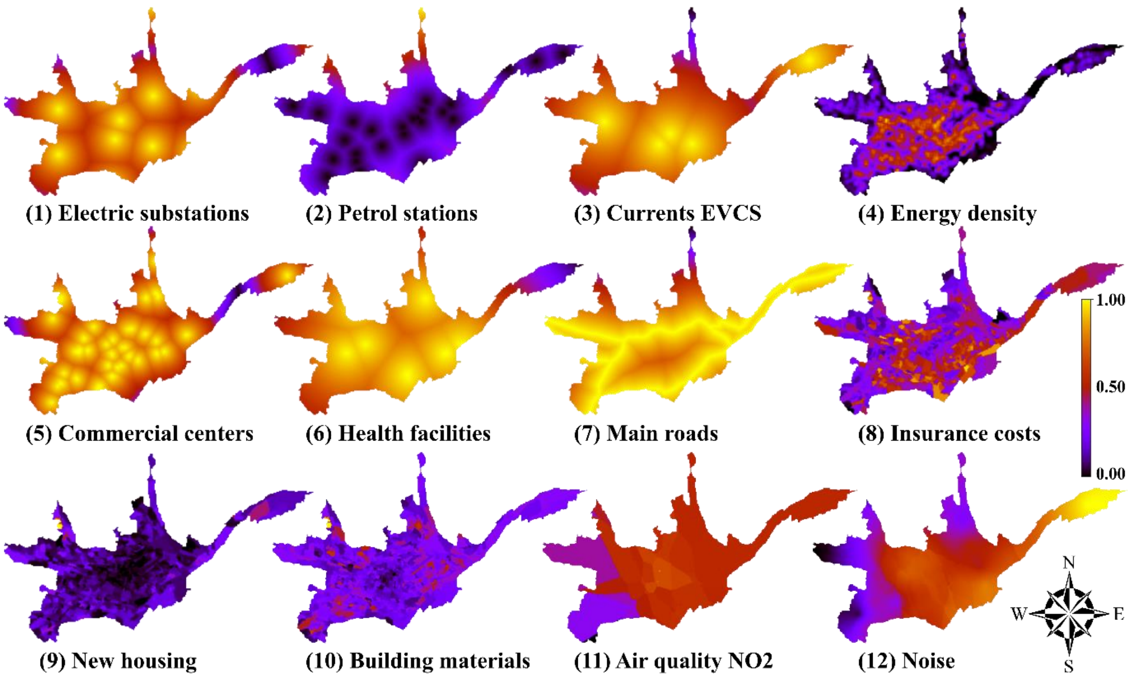
Source: Elaborated by the author.

We provide a point layer with associated coordinate data for the substations under study. The electrical substation criterion is then represented as a raster[3] with the Euclidean distance to the nearest substation. Petrol stations, current EV charging stations, commercial centers (markets and malls), and health facilities (hospitals) are also provided as point layers. The main roads is provided as a line layer, from which the Euclidean distance raster is generated. For the energy density criterion, the point layer includes customer power data along with coordinate information. The criteria for air quality and noise generate interpolation rasters by taking into account the point layers that include measured values (annual mean concentration particulate matter level –NO2 and weekday day-averaged noise level –dB, respectively) and related coordinates.

[3] A raster is a pixel grid where each pixel contains color information, forming a surface. Pixel values can represent attributes like brightness, distance, elevation, and more.

Once the predictor variables have been determined using the GWR model, the rasters from the census tract data should be generated in accordance with each criterion. For the insurance cost criterion, the raster accounts for the kind of insurance and the number of households with it. New housing criteria take into account the number of construction loans to generate the raster, indicating that future residential buildings will have the necessary infrastructure to accommodate new loads. The count of dwellings using high-end building materials is used to generate the raster and create the building materials criterion.

Figure 9 — Spatial criteria maps



Source: Elaborated by the author.

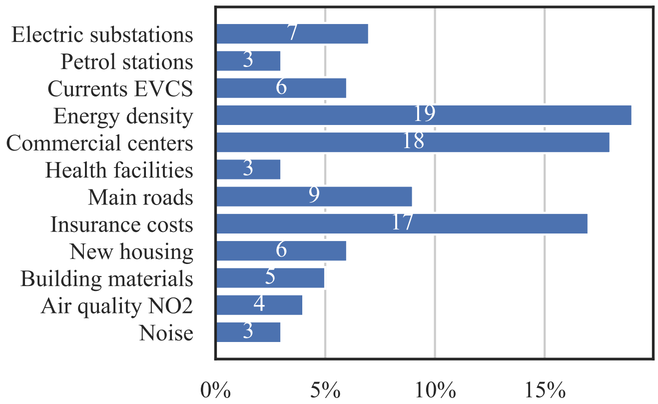
The weighting of the set of criteria needs to be carried out before the spatial analysis procedure for suitability analysis is started. The AHP approach is applied to assign weights on twelve sub-criteria categorized under five main criteria: energy, social and economic, transportation, demographic, and environmental. The expert's understanding of decision-making is expressed by the AHP approach using crisp numbers. Those values are given through a pair-wise comparison based on the Saaty scale. The matrix comparison is shown at Table 6. The percentage weights calculated for each of the twelve sub-criteria are shown in Figure 10. Three criteria are highlighted: energy density, commercial centers and insurance costs.

Table 6 — Relative weights in the reciprocal matrix

Criteria	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**
1: Electric substations	1	5	3	1/4	6	1/2	1/3	1/6	1/2	1/2	2	2
2: Petrol stations		1	1/3	1/7	2	1/3	2	1/3	2	1/5	1/3	1/3
3: Currents EVCS			1	1/4	3	1/5	2	1/6	3	1/7	2	3
4: Commercial centers				1	6	2	4	5	5	1/2	3	4
5: Health facilities					1	1/4	1/2	1/8	1/3	1/4	3	2
6: Main roads						1	2	1/5	2	1/3	2	3
7: New housing							1	1/7	2	1/3	3	3
8: Insurance costs								1	7	1/4	2	2
9: Building materials									1	1/5	3	2
10: Energy density										1	4	3
11: Air quality NO2											1	2
12: Noise												1

Source: Elaborated by the author.

Figure 10 — Weights of spatial criteria



Source: Elaborated by the author.

Three decision-makers from technical, economic, and social perspectives were selected considering their varied educational backgrounds and subject-matter expertise. Given the inherent uncertainty and imprecision in human judgment, the weighting of these criteria poses a significant challenge. Therefore, it is anticipated that the three experts will do so using the linguistic terms. The decision-makers assessment, employing linguistic terms, is presented in Table 7. The linguistic terms are characterized by a triangular fuzzy number as follows in the

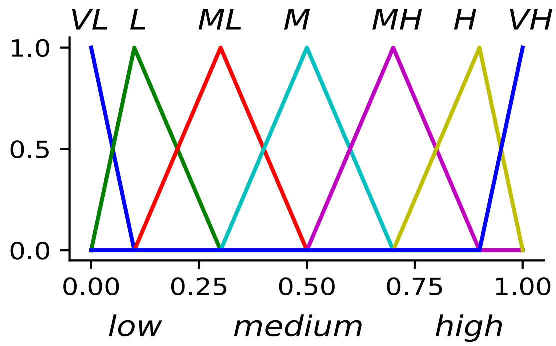
Figure 11. There are seven triangle membership functions that are employed: Very High (VH), High (H), Medium High (MH), Medium (M), Medium Low (ML), Low (L), and Very Low (VL).

Table 7 — Linguistic rating of the criteria weights

Decision Maker	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1: Technical	M	L	ML	VH	H	VL	M	H	L	L
2: Economic	VH	M	L	L	VH	H	M	ML	H	L
3: Social	M	H	L	ML	H	VH	VH	M	H	L

Source: Elaborated by the author.

Figure 11 — Membership functions for fuzzy triangles

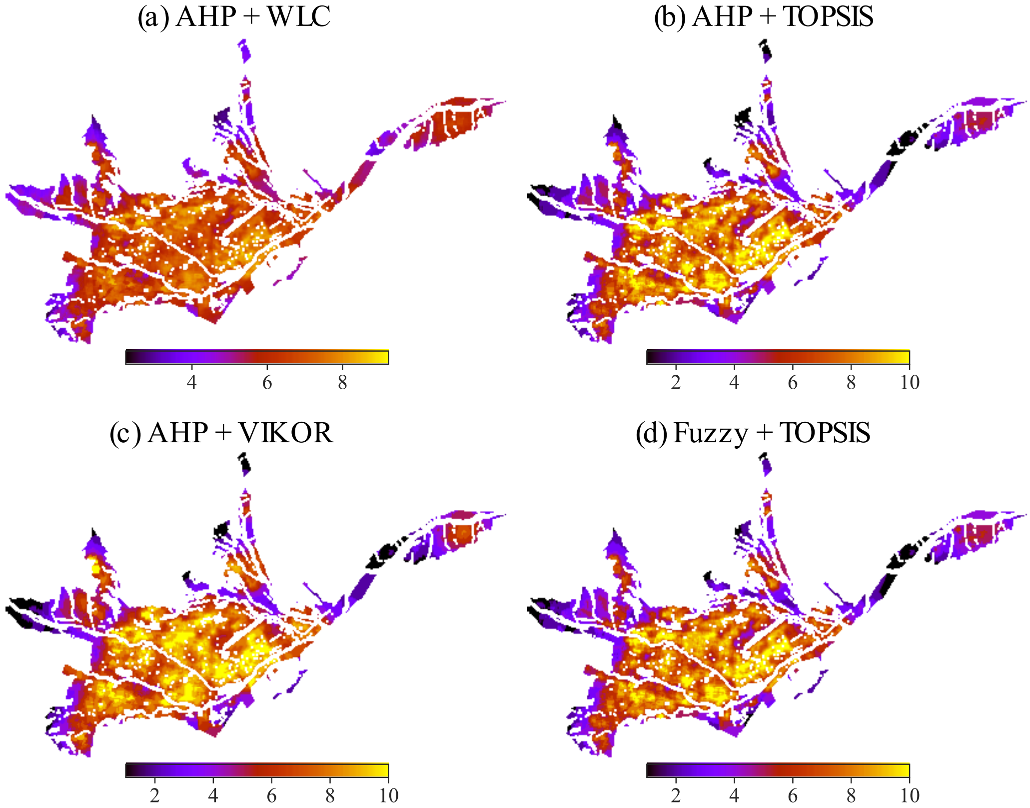


Source: Elaborated by the author.

4.3 SUITABILITY LOCATIONS

The layers are joined with spatial analysis techniques after a criterion weighting process, and the ranked alternative sites for EV charging station are discovered. For comparison analysis purposes, four techniques are applied between the combined methods of AHP+WLC, AHP+TOPSIS, AHP+VIKOR, and FUZZY+TOPSIS. The consistency of algorithms' outcomes is displayed in Figure 12. The outcomes, as heatmaps, are adjusted with a higher ranking for the most suitable sites. The suitable spatial pattern seems consistent across all model results. One noteworthy feature is that AHP+WLC shows a comparable spatial pattern, but at a reduced scale.

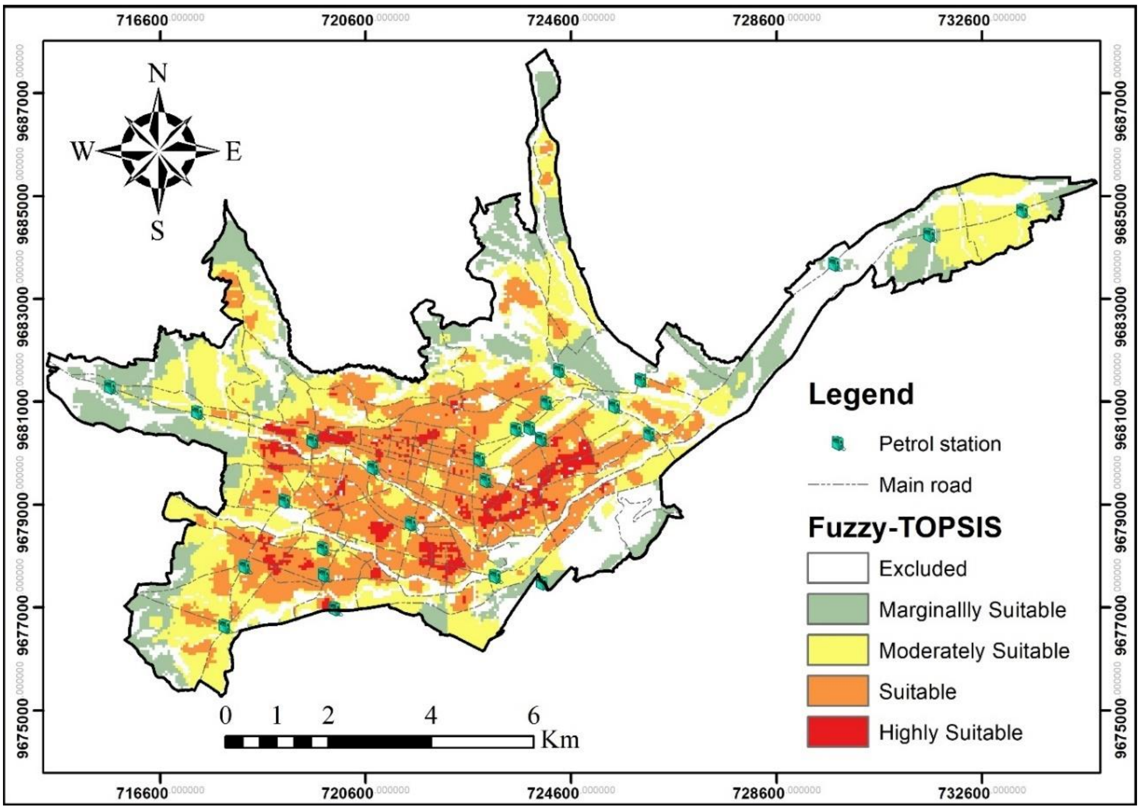
Figure 12 — Suitability maps from AHP WLC, AHP TOPSIS, AHP VIKOR, and Fuzzy TOPSIS



Source: Elaborated by the author.

As seen in Figure 12, all results depict the same spatial pattern. The southwest and south of the city are the primary areas of suitability. The commercial centers are the primary influence points, supported by high-consumption residential neighborhoods. Areas with high insurance costs add valuable preference, as do roads that promote easy access. The fuzzy-TOPSIS result, Figure 13, is chosen to locate new public charging stations. Fuzzy method takes advantage of the fuzzy membership of the weights, unlike the crisp values obtained from the AHP method.

Figure 13 — Suitability map for EVCS locations using Fuzzy-TOPSIS MCDA

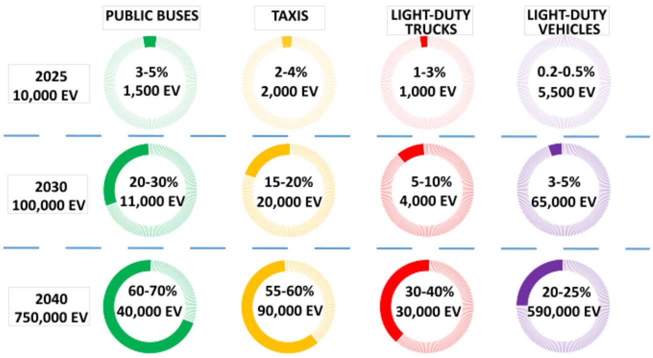


Source: Elaborated by the author.

4.4 EV CHARGING STATION ADOPTION

On September 30, 2021, the "Ministerio de Transporte y Obras Públicas" (MTOP) with the technical support of the Inter-American Development Bank (IDB) introduced the National Electromobility Strategy (MTOP, 2021), aiming to reach 10,000 Battery Electric Vehicles (BEVs) by 2025, 100,000 BEVs by 2030, and eventually 750,000 BEVs by 2040, equating to around 60-70% of public buses, 60% of taxis, 30-40% of light cargo trucks, and 20-25% of all light vehicles in the country. The goal strategy to reduce the carbon footprint of the transportation sector in Ecuador is shown in Figure 14. This would bring significant economic and environmental benefits, including \$6.4 billion in foreign currency savings, \$700 million in CO2 emission reductions, and \$143 million in reduced greenhouse gas emissions (Hinicio, 2021). In Cuenca city alone, there are 139,818 light-duty vehicles. The overall policy goal established by INEC is to achieve 25% of light-duty vehicles supported by electric vehicles by 2040. As a result, 34,955 electric vehicles are expected to be on the road by 2040.

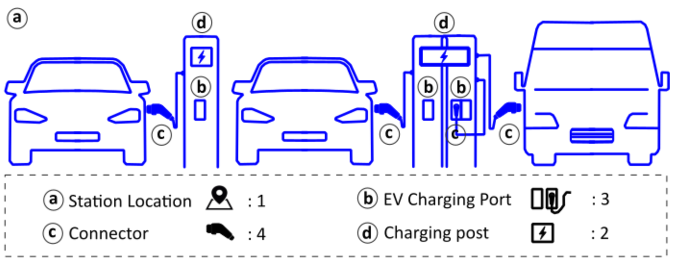
Figure 14 — Goal strategy for achieving Ecuador's commitment to reduce the carbon footprint of the transportation sector by 2040



Source: Adapted from (Hinicio, 2021).

Four levels of EV charging are determined by the type of connector and consumer requirements. They offer different charging experiences based on their power output capacities over time. There is no standard design 'one size fits all' solution to providing operational feasibility for EV users. The right public charging station will need to consider the most appropriate mix of connectors, while balancing the road user demand and infrastructure cost. Figure 15 depicts one station location according to the Open Charge Point Interface (OCPI) protocol, including 3 EV charging ports, 4 connectors, and 2 charging posts. (a) A station location is a site with one or more EV charging ports at the same address. (b) An EV charging port provides power to charge only one vehicle at a time even though it may have multiple connectors. (c) A connector is what is plugged into a vehicle to charge it. (d) A charging post is the unit that houses EV charging ports, which can have one or more EV charging ports.

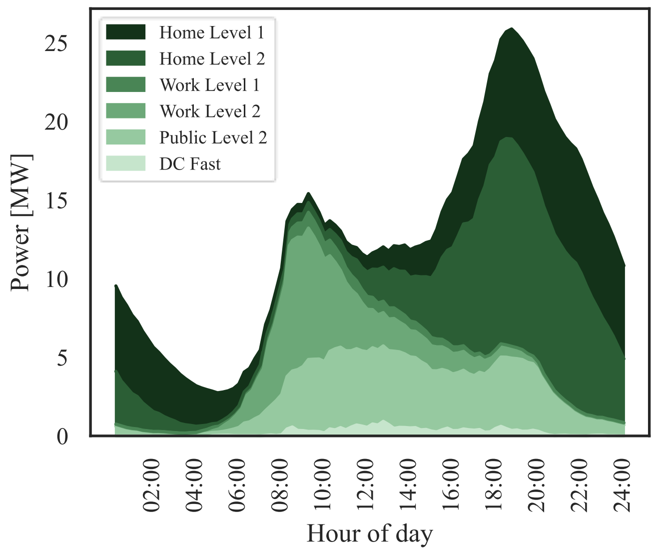
Figure 15 — Charging station infrastructure



Source: Elaborated by the author.

Deploying a convenient network of charging stations is crucial in accelerating the adoption of EVs and lowering EV owners' range anxiety. For widespread adoption of EVs, a robust network of charging stations needs significant electrical upgrades to support them. These charging stations consist of public charging, workplace charging, and home charging as shown in Table 1. The EVI-Pro Lite tool (EERE, 2018c) is available to estimate the quantity and type of charging infrastructure necessary to support regional EV adoption. The electric vehicle infrastructure required is drawn on detailed data about personal vehicle travel patterns, EV attributes, and charging station characteristics. Additionally, it helps determining the impact of EV charging on electricity demand through a load profile. Load profiles are built from a load research process that is supported by many measurements of consumption habits. By using this tool, a weekday electric profile for expected 35,000 EVs is produced (Figure 16). From this, work levels 1 and 2, public level 2, and DC fast electric profiles are used in this study.

Figure 16 — Weekday electric load profile of 35,000 plug-in electric vehicles



Source: Elaborated by the author.

4.5 FINAL DISCUSSIONS

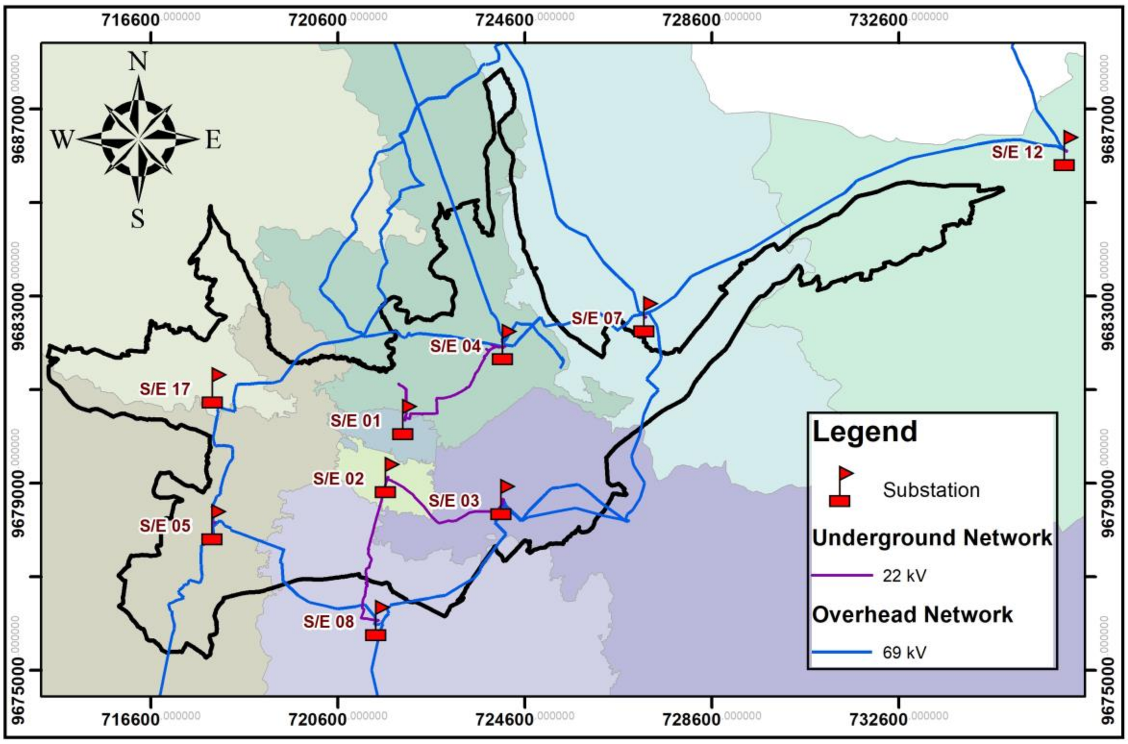
The substations are the connection place of the transmission and distribution systems, taking power at high voltage level and routing it to primary voltage feeders. The transformers are the most distinguishing characteristic of a distribution substation and the sum of all transformer ratings defines a substation's capacity. In substation-level planning, a substation's size is typically determined by adding up all of the feeder loads (cumulative loads) and incorporating load forecasting. There are nine distribution substations in the study area. The SE01 and SE02, located in the core urban area, are part of the 22 kV network. The remaining ones make up the 69 kV network. Accordingly, under Oil Natural – Air Natural (ONAN) cooling, the core urban area's capacity is 30 MW, while the remaining area has a capacity of 246 MW. Table 8 summarizes the substations' characteristics, showing the current peak load reached at each one. Reserve capacity refers to the remaining capability of transformers, based on their rated power, to accommodate load growth. Figure 17 shows the substation connection through the subtransmission network.

Table 8 — Substations within the study area

Substation	**Voltage (kV)**	**Peak Load (MW)**	**Rated capacity ONAN (MW)**	**Reserve (MW)**
S/E 01	22/6.3	5.57	15	9.43
S/E 02	22/6.3	7.08	15	7.92
S/E 03	69/22	18.23	48	29.77
S/E 04	69/22	27.65	48	20.35
S/E 05	69/22	24.71	48	23.29
S/E 07	69/22	14.45	34	19.55
S/E 08	69/22	13.47	24	10.53
S/E 12	69/22	7.59	20	12.41
S/E 17	69/22	8.35	24	15.65
		125.70	276	

Source: Elaborated by the author.

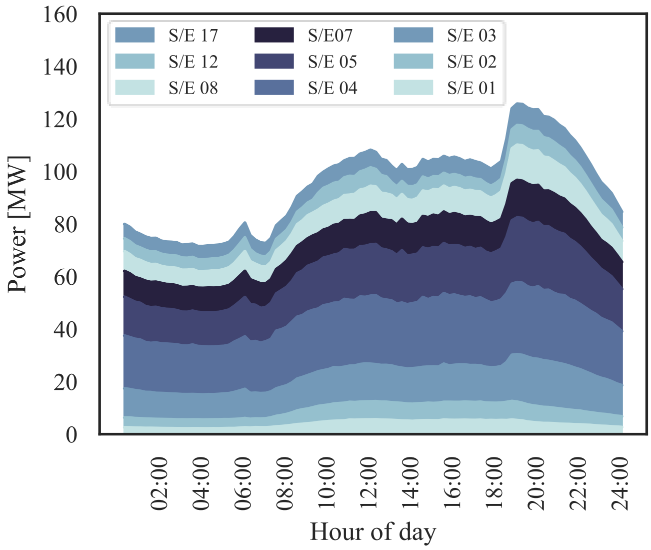
Figure 17 — Subtransmission network and service area of each substation.



Source: Elaborated by the author.

The total peak load attained is 125.70 MW, as shown in Table 8. The weekday electric load profile measured in 2023 is shown in Figure 18, with the total peak load occurring over about 19:00 h. Typically, the electric load profiles of every substation have high consumption rates around 6, 12, and 19:00 h. These current load profiles of the substation are obtained with the Utility's metering equipment, and these records are stored in its SCADA system.

Figure 18 — Weekday electric load profile of substations measured in 2023



Source: Elaborated by the author.

This work considers 40 charging stations. However, a different number of charging stations could also be considered. Table 9 shows the three-charging station designs that were established based on Table 2. The peaks of the electric load profiles depicted in Figure 16 are used to calculate the number of ports for each level of EV charging. In order to meet the Work Level 1 electric load profile, at least 256 of 4 kW ports are required. Likewise, 1056 of 8 kW ports for Work Level 2, 276 of 19.2 kW ports for Public Level 2, and 12 of 150 kW ports for DC Fast Level are needed. The total capacity of the charging stations is 16.6 MW, with the same 400 kW capacity for all designs.

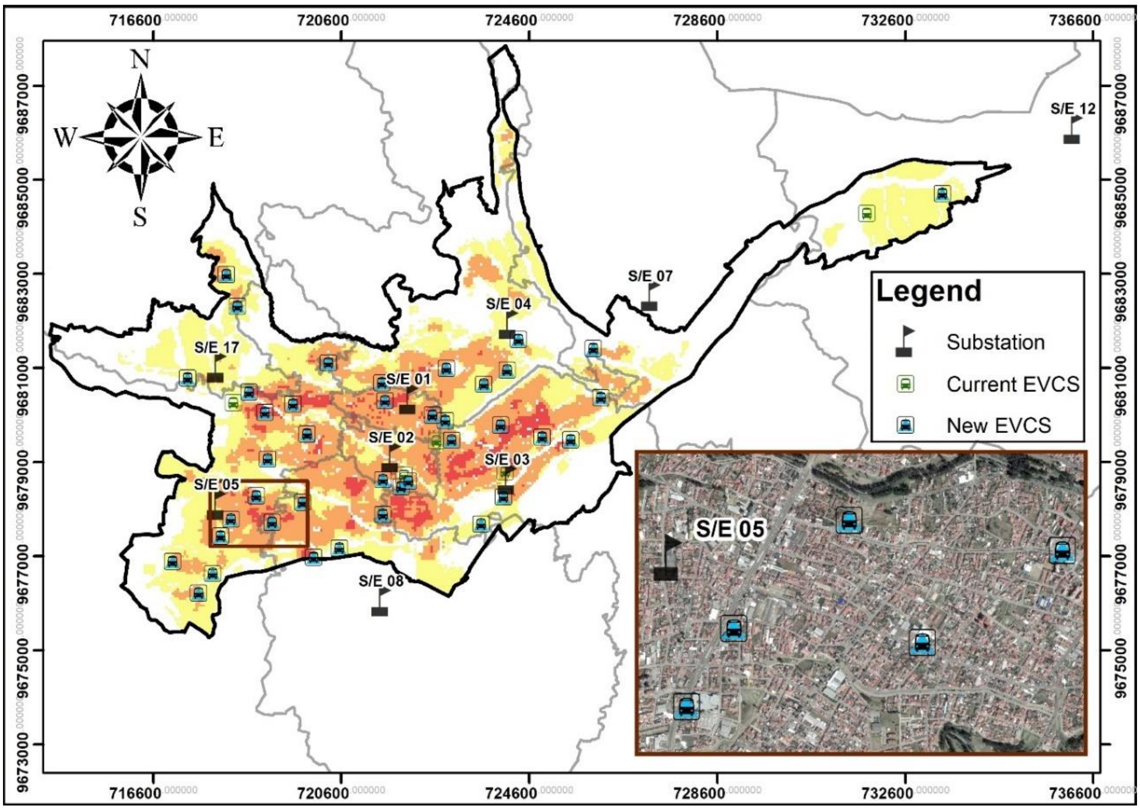
Table 9 — EV charging stations characteristics

Design	**No. of Sta-tions**	**%**	**Number of ports per station**				**kW per Station**	**Total (kW)**
			Work L1 (4 kW)	**Work L2 (8 kW)**	**Public L2 (19.2 kW)**	**DC Fast (150 kW)**		
1	8	20%	11	34	5	0	412	3296
2	28	70%	6	28	8	0	401.6	11244.8
3	4	10%	0	0	3	3	507.6	2030.4
	40		256	1056	276	12		16571.2

Source: Elaborated by the author.

The forty charging stations are located throughout the suitability map, taking into account suitable and highly suitable levels. Type 1 stations are located near apartment buildings. Stores and parking garages are the locations of type 2 stations. Type 3 stations are dispersed throughout the city's primary access routes. Figure 19 illustrates the current and new charging stations' locations, as well as the substation's locations with their service area across the suitability map.

Figure 19 — Location of potential public and work EVCS, for the year 2040 in Cuenca- Ecuador



Source: Elaborated by the author.

The charging station's placement contributes to awareness of the substation's capacity. Table 10 highlights the load growth by substation and the port count by EV charging level. The 'total MW' column represents the load growth due to EVs, which is separate from customer-related load forecasting and will be added to the current peak load. S/E 05 is the one that supports the highest charging station load; however, it has a 23 MW reserve capacity. No substation's capacity is compromised. The total number of ports complies with Table 9 to satisfy the peak electric load profile shown in Figure 16.

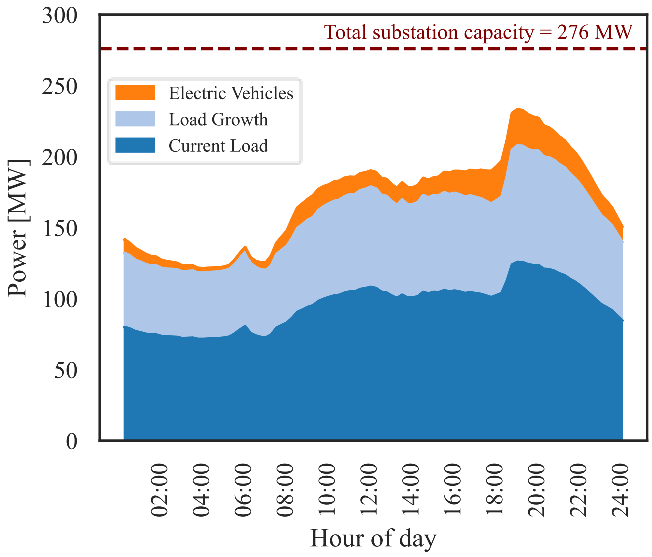
Table 10 — Power by substation

Substation	Number of ports				Total (MW)
	Work Level 1	Work Level 2	Public Level 2	DC Fast	
S/E 01	12	56	16	0	0.80
S/E 02	18	84	24	0	1.20
S/E 03	57	214	50	3	3.35
S/E 04	41	174	48	3	2.93
S/E 05	86	332	79	3	4.97
S/E07	6	28	8	0	0.40
S/E 08	18	84	27	3	1.71
S/E 12	6	28	8	0	0.40
S/E 17	12	56	16	0	0.80
Total	256	1056	276	12	16.57
Max Power (kW)	4	8	19.2	150	
Total (MW)	1.024	8.448	5.30	1.80	

Source: Elaborated by the author.

Although EV demand doesn't exceed any substation capacity, it significantly raises the load profile, especially around 19:00 h. The EV load profile, along with the electric load profile forecast for 2040, is depicted in Figure 20. The 'Current Load' in blue represents customer demand at the substation level for the base year. The 'Load Growth' in light blue corresponds to the vegetative growth of customers and changes in consumption habits projected for the long-term load forecast (the year 2040). The orange area labeled 'Electric Vehicles' represents the EV load from Figure 16 forecasted for the horizon year. As a result, substations are capable of handling 35,000 EVs demand via a public network of charging stations that meet the aforementioned characteristics.

Figure 20 — Load profile forecast for the year 2040



Source: Elaborated by the author.

5 CONCLUDING REMARKS

To support the transition to Electric Vehicles (EVs) in accordance with emission-free mobility policies, this work provides a Multi-Criteria Decision Analysis (MCDA) approach based on geographic information system (GIS). Demographic criteria, along with energy, economic, social, transportation, and environmental criteria, were combined. These five main criteria contain four, two, one, three and two sub-criteria respectively. Energy, economic, demographic, and transportation criteria were the most influential factors that played a significant role in EV charging station suitability site selection.

As part of the selection process, an evaluation system was constructed consisting of five key criteria: energy, economic and social, transportation, socio-demographics, and environmental. This facilitated the weighting process made through expert judgment in terms of technical, economic and social perspectives.

The density element contained in the energy criteria for this analysis catches those customers strata in housing where the likelihood of EV adoption is higher. Density along with demographic criteria contribute to reduce the spatial mismatch between where chargers are located and where the bulk of prospective EV owners live.

Through exploratory GIS analysis, geographically weighted regression (GWR) discovers those variables that correlate to a phenomenon's occurrence. In the performed analysis, GWR was used to discover demographic criteria for the MCDA that catch where new technology adoption is most likely. Early adopters of new technology were identified through both the rate of adoption at which households acquire electric stoves and the census population database. Early adopters typically had high insurance rates, newly constructed dwellings, and upscale building materials. The demographic criteria that influence the adoption of EVs and consequently the location of EV charging station were insurance cost, new housing, and building materials.

Four comparative techniques were applied between the combined methods of AHP+WLC, AHP+TOPSIS, AHP+VIKOR, and FUZZY+TOPSIS to validate the model results. From the combined methodologies, the suitable spatial pattern was consistent across all model results. FUZZY+TOPSIS differs from the others in that it uses linguistic membership rather than crisp numbers for criterion weighting. Thus, two human judgment procedures were involved, i.e. pair wise comparison and fuzzy. The weights of sub-criteria were assigned by three experts based on their membership in a fuzzy set, in terms of technical, economic, and social perspectives. The FUZZY+TOPSIS result was used to identify suitable sites for EV charging station placement.

The proposed framework allows substation capacity assessment with the integration of EV charging stations into the distribution system. Load capacity assessments involve incorporating EV charging station load profiles into the daily substation load profile. This approach was applied in the urban area of an Ecuadorian city. It is important to note that the substation's capacity does not reach its nominal power, and with the exception of SE 03 and SE 05, in all substations the added power is less than 3 MW. Then, the results showed that there would be no compromise on any substation capacity reserves. Every substation houses a different number of charging stations, revealing the importance of using spatial analysis tools to determine the increase in demand resulted from charging station deployment. These understandings are necessary for network planners to monitor the impact of charging station growth scenarios on the power distribution system in major cities.

This study lacks an analysis of hosting capacity in the primary and secondary distribution networks, which is crucial given the exponential growth in electric vehicle adoption and the resulting increase in load magnitudes. Without addressing this issue, distribution network may not be prepared for that increase, making this a key area for future research. The current research scope serves as a primary input for a hosting capacity analysis. In the next stage, we plan to conduct simulations of power flows (using quasi-static time series) and short circuits to evaluate potential impacts on the network and quantify the hosting capacity of the distribution network. This work provides a general overview of load growth to give application and discussion to the results of this first scope of the research.

On the other hand, a fuzzy TOPSIS MCDA framework releases various limitations:

- *Subjectivity in weighting criteria:* Expert judgment is a strength but this resource may not be readily available in all contexts. While AHP and fuzzy theory help assign weights to criteria, the method maintains dependence on expert judgment, introducing subjectivity that can lead to bias due to the uncertainty and imprecision in human assessment;

- *Limited scope of criteria:* Although the research considers multiple criteria, it may not encompass all key factors influencing site selection. Identifying significant criteria in a data-driven way could improve model's applicability. Hybrid AI approaches could address this issue by partially or fully automating the selection process, improving accuracy and integrity;
- *Dynamic Nature of EV Adoption:* The study doesn't account for the fast-evolving EV landscape. As EV technology evolves and becomes more widespread, the criteria for site selection may also change, potentially reducing the relevance of the findings over time.

The limitations raised serve as a foundation for further refinement of the methodology to enhance its robustness and applicability in future investigations.

BIBLIOGRAPHY

BEDE, B. **Mathematics of fuzzy sets and fuzzy logic**. Germany: Springer Berlin/Heidelberg, 2013. v. 295, ISBN: 978-3-642-35220-1.

CHARLY, A.; THOMAS, N. J.; FOLEY, A.; CAULFIELD, B. Identifying optimal locations for community electric vehicle charging. **Sustainable Cities and Society**, Amsterdam, v. 94, p. 104573, jul. 2023. ISSN: 22106707.

EERE. **Alternative fuels data center: Developing infrastructure to charge electric vehicles**. 2018a.Disponível em: https://afdc.energy.gov/fuels/electricity_infrastructure.html. Acesso em: 2 fev. 2024.

EERE. **Alternative fuels data center: Electric vehicle charging stations**. 2018b.Disponível em: https://afdc.energy.gov/fuels/electricity_stations.html#terms. Acesso em: 12 fev. 2024.

EERE. **Alternative Fuels Data Center: Electric Vehicle Infrastructure Projection Tool (EVI-Pro) Lite**. 2018c.Disponível em: https://afdc.energy.gov/evi-x-toolbox. Acesso em: 20 mar. 2024.

ERBAŞ, M.; KABAK, M.; ÖZCEYLAN, E.; ÇETINKAYA, C. Optimal siting of electric vehicle charging stations: A GIS-based fuzzy Multi-Criteria Decision Analysis. **Energy**, London, v. 163, p. 1017–1031, nov. 2018. ISSN: 03605442.

FENG, J.; XU, S. X.; LI, M. A novel multi-criteria decision-making method for selecting the site of an electric-vehicle charging station from a sustainable perspective. **Sustainable Cities and Society**, Amsterdam, v. 65, fev. 2021. ISSN: 22106707.

FOTHERINGHAM, A. S.; BRUNSDON, C.; CHARLTON, M. **Geographically weighted regression: The analysis of spatially varying relationships**. Chichester, England ; Hoboken, NJ, USA: Wiley, 2002. ISBN: 978-0-471-49616-8.

FUNKE, S. Á.; GNANN, T.; PLÖTZ, P. Addressing the different needs for charging infrastructure: An analysis of some criteria for charging infrastructure set-up. **Green Energy and Technology**, Heidelberg, v. 203, p. 73–90, 2015. ISSN: 18653537.

GONZÁLEZ, L. G.; SIAVICHAY, E.; ESPINOZA, J. L. Impact of EV fast charging stations on the power distribution network of a Latin American intermediate city. **Renewable and Sustainable Energy Reviews**, Oxford, v. 107, p. 309–318, 2019. ISSN: 18790690.

GULER, D.; YOMRALIOGLU, T. Suitable location selection for the electric vehicle fast charging station with AHP and fuzzy AHP methods using GIS. **Annals of GIS**, Philadelphia, v. 26, n. 2, p. 169–189, 2020. ISSN: 19475691.

GUO, S.; ZHAO, H. Optimal site selection of electric vehicle charging station by using fuzzy TOPSIS based on sustainability perspective. **Applied Energy**, Oxford, v. 158, p. 390–402, nov. 2015. ISSN: 03062619.

HINICIO. **Estrategia Nacional de Electromovilidad para Ecuador (ENEM)**. Quito, Ecuador: BID, MTOP, Hinicio, mar. 2021.

HOCHSCHILD, D. **Assembly Bill 2127 Electric Vehicle Charging Infrastructure Assessment: Analyzing Charging Needs to Support Zero-Emission Vehicles in 2030**. California: California Energy Commission, jul. 2021.

IEA. **Accelerating ambitions despite the pandemic**. Paris, France: Global EV Outlook, 2021. Disponível em: https://www.oecd-ilibrary.org/energy/global-ev-outlook-2021_3a394362-en.

IEA. **Global EV data explorer**. 2023.Disponível em: https://www.iea.org/data-and-statistics/data-tools/global-ev-data-explorer. Acesso em: 1 fev. 2024.

IEA. **Trends in electric cars**. Paris, France: Global EV Outlook 2024, 2024. a. Disponível em: https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-cars. Acesso em: 17 ago. 2024.

IEA. **Trends in electric vehicle charging**. Paris, France: Global EV Outlook 2024, 2024. b. Disponível em: https://www.iea.org/reports/global-ev-outlook-2024/trends-in-electric-vehicle-charging. Acesso em: 17 ago. 2024.

IEA. **World energy outlook**. Paris, France: OECD/IEA, 2011. ISBN: 2989264124134.Disponível em: https://iea.blob.core.windows.net/assets/cc401107-a401-40cb-b6ce-c9832bb88d85/WorldEnergyOutlook2011.pdf.

IEC 61851-1. **Electric vehicle conductive charging system— Part 1: General requirements**. Edition 3.0 ed. Geneva, Switzerland: International Electrotechnical Commission, 2017. ISBN: 978-2-8322-3766-3.

INEC. **Anuario de Estadísticas de Transporte**. 2022.Disponível em: https://www.ecuadorencifras.gob.ec/transporte/. Acesso em: 2 fev. 2024.

INEC. **Instituto Nacional de Estadística y Censos**. 2019.Disponível em: https://www.ecuadorencifras.gob.ec/institucional/home/. Acesso em: 2 fev. 2024.

JU, Y.; JU, D.; GONZALEZ, E. D. R. S.; GIANNAKIS, M.; WANG, A. Study of site selection of electric vehicle charging station based on extended GRP method under picture fuzzy environment. **Computers and Industrial Engineering**, Oxford, v. 135, p. 1271–1285, set. 2019. ISSN: 03608352.

KARAŞAN, A.; KAYA, İ.; ERDOĞAN, M. Location selection of electric vehicles charging stations by using a fuzzy MCDM method: a case study in Turkey. **Neural Computing and Applications**, London, v. 32, n. 9, ISBN 32:45534574., p. 4553–4574, 2020. ISSN: 14333058.

KAYA, Ö.; ALEMDAR, K. D.; CAMPISI, T.; TORTUM, A.; ÇODUR, M. K. The development of decarbonisation strategies: A three-step methodology for the suitable analysis of current evcs locations applied to istanbul, turkey. **Energies**, Basel, v. 14, n. 10, 2021. ISSN: 19961073. Disponível em: https://doi.org/10.3390/en14102756.

KAYA, Ö.; TORTUM, A.; ALEMDAR, K. D.; ÇODUR, M. Y. Site selection for EVCS in Istanbul by GIS and multi-criteria decision-making. **Transportation Research Part D: Transport and Environment**, Oxford, v. 80, p. 102271, mar. 2020. ISSN: 1361-9209.

KOCH, N.; RITTER, N.; ROHLF, A.; SCARAZZATO, F. When is the electric vehicle market self-sustaining? Evidence from Norway. **Energy Economics**, Amsterdam, p. 105991, 2022. ISSN: 01409883.

LEHRMAN, M. **Electric vehicle charging stations**. 2021.Disponível em: https://bouldercolorado.gov/services/electric-vehicle-charging-stations. Acesso em: 2 fev. 2024.

MAHDY, M.; BAHAJ, A. S.; TURNER, P.; WISE, N.; ALGHAMDI, A. S.; HAMWI, H. Multi criteria decision analysis to optimise siting of electric vehicle charging points—Case study Winchester District, UK. **Energies**, Basel, v. 15, n. 7, p. 2497, 2022. ISSN: 19961073.

MALCZEWSKI, J. On the use of weighted linear combination method in GIS: Common and best practice approaches. **Transactions in GIS**, Chichester, v. 4, n. 1, p. 5–22, jan. 2000. ISSN: 1361-1682.

MALCZEWSKI, J.; RINNER, C. **Multicriteria decision analysis in geographic information science**. 2015th. ed. New York, U.S.: Springer, 2015. ISBN: 978-3-540-74756-7.

MEJIA, M. A.; MELO, J. D.; ZAMBRANO-ASANZA, S.; PADILHA-FELTRIN, A. Spatial-temporal growth model to estimate the adoption of new end-use electric technologies encouraged by energy-efficiency programs. **Energy**, London, v. 191, p. 116531, jan. 2020. ISSN: 03605442.

MENDIETA, C. S. **Hay 64.199 vehículos matriculados en Cuenca**. 2022.Disponível em: https://elmercurio.com.ec/2022/09/10/vehiculos-matriculados-en-cuenca/. Acesso em: 2 fev. 2024.

MTOP. **MTOP socializa la Estrategia Nacional de Electromovilidad para Ecuador con sectores estratégicos**. 2021.Disponível em: https://www.obraspublicas.gob.ec/mtop-socializa-la-estrategia-nacional-de-electromovilidad-para-ecuador-con-sectores-estrategicos/. Acesso em: 2 fev. 2024.

NAMDEO, A.; TIWARY, A.; DZIURLA, R. Spatial planning of public charging points using multi-dimensional analysis of early adopters of electric vehicles for a city region. **Technological Forecasting and Social Change**, New York, v. 89, p. 188–200, 2014. ISSN: 0040-1625.

NARASIPURAM, R. P.; MOPIDEVI, S. A technological overview & design considerations for developing electric vehicle charging stations. **Journal of Energy Storage**, Amsterdam, v. 43, p. 103225, 2021. ISSN: 2352-152X.

NYC DOT. **Curbside Level 2 EV charging pilot: Evaluation Report**. New York, U.S. Disponível em: https://www.nyc.gov/html/dot/html/motorist/electric-vehicles.shtml#/reports.

OICA. **Climate change and CO2**. Paris, France: International Organization of Motor Vehicle Manufacturers, 2008. Disponível em: https://www.oica.net/wp-content/uploads/climate-change-and-co2-brochure.pdf.

OLIVER, M. A.; WEBSTER, R. Kriging: a method of interpolation for geographical information systems. **International journal of geographical information systems**, Abingdon, v. 4, n. 3, p. 313–332, jul. 1990. ISSN: 0269-3798.

PAPATHANASIOU, J.; PLOSKAS, N. **Multiple criteria decision aid: methods examples and python implementations**. Gewerbestrasse, Switzerland: Springer, 2018. ISBN: 978-3-319-91646-0.Disponível em: https://doi.org/10.1007/978-3-319-91648-4.

PRIESSNER, A.; SPOSATO, R.; HAMPL, N. Predictors of electric vehicle adoption: An analysis of potential electric vehicle drivers in Austria. **Energy Policy**, London, v. 122, p. 701–714, 2018. ISSN: 0301-4215.

RIEMANN, R.; WANG, D. Z. W.; BUSCH, F. Optimal location of wireless charging facilities for electric vehicles: Flow-capturing location model with stochastic user equilibrium. **Transportation Research Part C: Emerging Technologies**, Oxford, v. 58, p. 1–12, 2015. ISSN: 0968-090X.

ROY, A.; LAW, M. Examining spatial disparities in electric vehicle charging station placements using machine learning. **Sustainable Cities and Society**, Amsterdam, v. 83, p. 103978, ago. 2022. ISSN: 22106707.

SAATY, T. L. **The analytic hierarchy process: planning, priority setting. Resource allocation**. xiii. ed. New York, NY, USA: McGraw-Hill, 1980.

SAINT, S.; LAWSON, J. R. **Rules for Reaching Consensus: A Modern Approach to Decision Making**. Hoboken, NJ, USA: Wiley, 1994. ISBN: 978-0-89384-256-7.

SAVARI, G. F.; SATHIK, M. J.; RAMAN, L. A.; EL-SHAHAT, A.; HASANIEN, H. M.; ALMAKHLES, D.; ALEEM, S. H. E. A.; OMAR, A. I. Assessment of charging technologies, infrastructure and charging station recommendation schemes of electric vehicles: A review. **Ain Shams Engineering Journal**, Cairo, v. 14, n. 4, p. 101938, 2023. ISSN: 2090-4479.

SLOWIK, P.; LUTSEY, N. **The continued transition to electric vehicles in U.S. cities**. Washington: ICCT, jul. 2018. Disponível em: https://theicct.org/wp-content/uploads/2021/06/Transition_EV_US_Cities_20180724.pdf.

SPENDIFF-SMITH, M. **Levels of EV charging ─EVESCO**. 2022.Disponível em: https://www.power-sonic.com/blog/levels-of-ev-charging/. Acesso em: 13 fev. 2024.

TU, W.; LI, Q.; FANG, Z.; SHAW, S. Lung; ZHOU, B.; CHANG, X. Optimizing the locations of electric taxi charging stations: A spatial–temporal demand coverage approach. **Transportation Research Part C: Emerging Technologies**, Oxford, v. 65, p. 172–189, 2016. ISSN: 0968090X.

UNFCCC. **Adoption of the Paris agreement**: **Conference of the parties Twenty-first session**. Paris, France: United Nations Framework Convention on Climate Change, 2015. Disponível em: http://unfccc.int/resource/docs/2015/cop21/eng/l09r01.pdf.

WU, Y.; YANG, M.; ZHANG, H.; CHEN, K.; WANG, Y. Optimal site selection of electric vehicle charging stations based on a cloud model and the PROMETHEE method. **Energies**, Basel, v. 9, n. 3, p. 157, mar. 2016. ISSN: 19961073.

XU, J.; ZHONG, L.; YAO, L.; WU, Z. An interval type-2 fuzzy analysis towards electric vehicle charging station allocation from a sustainable perspective. **Sustainable Cities and Society**, Amsterdam, v. 40, p. 335–351, jul. 2018. ISSN: 22106707.

YAGER, R.; ZADEH, L. **An Introduction to Fuzzy Logic Applications in Intelligent Systems**. 1. ed. New York, U.S.: Springer, 1992. ISBN: 978-0-7923-9191-3.Disponível em: https://doi.org/10.1007/978-1-4615-3640-6.

YAGMAHAN, B.; YILMAZ, H. An integrated ranking approach based on group multi-criteria decision making and sensitivity analysis to evaluate charging stations under sustainability. **Environment, Development and Sustainability**, Dordrecht, ISBN 0123456789., 2022. ISSN: 15732975. Disponível em: https://doi.org/10.1007/s10668-021-02044-1.

YANG, D. Kriging for NSRDB PSM version 3 satellite-derived solar irradiance. **Solar Energy**, Oxford, v. 171, p. 876–883, set. 2018. ISSN: 0038092X.

ZADEH, L. A. The concept of a linguistic variable and its application to approximate reasoning-I. **Information Sciences**, Philadelphia, v. 8, n. 3, p. 199–249, 1975. ISSN: 00200255.

ZAMBRANO-ASANZA, S.; CHUMBI, W. E.; FRANCO, J. F.; PADILHA-FELTRIN, A. Multicriteria Decision Analysis in Geographic Information Systems for Identifying Ideal Locations for New Substations. **Journal of Control, Automation and Electrical Systems**, Heidelberg, p. 1–12, maio 2021. ISSN: 2195-3899.

ZAMBRANO-ASANZA, S.; QUIROS-TORTOS, J.; FRANCO, J. F. Optimal site selection for photovoltaic power plants using a GIS-based multi-criteria decision making and spatial overlay with electric load. **Renewable and Sustainable Energy Reviews**, Oxford, v. 143, p. 110853, jun. 2021. ISSN: 13640321.

ZHANG, Q.; LI, H.; ZHU, L.; CAMPANA, P. E.; LU, H.; WALLIN, F.; SUN, Q. Factors influencing the economics of public charging infrastructures for EV – A review. **Renewable and Sustainable Energy Reviews**, Oxford, v. 94, p. 500–509, 2018. ISSN: 1364-0321.

ZHAO, H.; LI, N. Optimal siting of charging stations for electric vehicles based on fuzzy Delphi and hybrid multi-criteria decision making approaches from an extended sustainability perspective. **Energies**, Basel, v. 9, n. 4, p. 1–22, 2016. ISSN: 19961073.

ZHOU, J.; WU, Y.; WU, C.; HE, F.; ZHANG, B.; LIU, F. A geographical information system based multi-criteria decision-making approach for location analysis and evaluation of urban photovoltaic charging station: A case study in Beijing. **Energy Conversion and Management**, London, v. 205, p. 112340, 2020. ISSN: 0196-8904.

APPENDIX A – Scientific Production

The articles produced throughout the Ph.D. program, whether directly or indirectly related to this thesis, are listed below. These articles have been published in international journals rated with CAPES A1, B2 qualifications and presented at national conferences.

1. Chumbi, W.E., Martínez-Minga, R., Zambrano-Asanza, S., Leite, J.B., Franco, J.F. (2024). Suitable Site Selection of Public Charging Stations: A Fuzzy TOPSIS MCDA Framework on Capacity Substation Assessment. Energies, 17, 3452. https://doi.org/10.3390/en17143452

2. Chumbi, W.E., Chillogalli, J.E., Jaramillo-Leon B., Leite, J.B. (2022). Análise de métodos para agrupamento de cargas elétricas em redes de distribuição de grande porte usando sistema de informação geográfica, Congresso Brasileiro de Automática (CBA), vol. 3, Fortaleza, Brasil. doi: https://doi.org/10.20906/CBA2022/3269.

3. Zambrano-Asanza, S., Chumbi, W.E., Franco, J.F., Padilha-Feltrin, A. (2021). Multicriteria Decision Analysis in Geographic Information Systems for Identifying Ideal Locations for New Substations. J Control Autom Electr Syst 32, 1305–1316. https://doi.org/10.1007/s40313-021-00738-5