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From rooftops to roads: Bilbao's geospatial solar and EV fusion

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ABSTRACT

The electrification of mobility is a promising solution to effectively reduce CO_2 emissions in urban areas. The integration of electric vehicles (EVs) and solar energy is a practical approach for mitigating the strain on power grids and storing surplus energy. However, the selection of sites for EV charging stations (EVCS) integrated with renewable sources is challenging. This study aims to develop a scalable and highly spatially explicit methodology for identifying optimal locations for EVCS powered by photovoltaic (PV). A novel decision framework for EVCS site selection is put forward, entailing the design of a parametric solar tool, and integrating PV and EV systems to power EVCS. This GIS-based methodology can be used to evaluate the parameters and constraints for EVCS placement, estimate solar rooftop potential, and integrate them into the power grid. The local solar energy potential complements the installation of additional on-street charging points in power substations. Results show that the city centre and a small region in the east are the most suitable locations for installing EVCS in Bilbao. Moreover, the results demonstrate the potential for charging 16% more EVs through a grid-connected PV system without increasing the capacity of the distribution substations of a district in Bilbao.

1. Introduction

It is widely accepted that climate change can be effectively mitigated by transitioning from fossil fuels to renewable energy sources (RES). Energy transition reduces greenhouse gas (GHG) emissions, which are a primary driver of climate change. The energy consumption of transportation systems accounts for ~68% of GHG emissions in urban areas (Zhang et al., 2021). Electric vehicles (EVs) are a promising solution to global challenges such as the energy crisis and GHG emissions (Ding, Prasad, & Lie, 2017; Feng, Xu, & Li, 2021; Polisetty, Jayanthi, & Veerraju, 2023; Yu, Wu, Li, & Bai, 2022). However, inadequate access to charging infrastructure remains a critical barrier to the spread of electromobility in urban areas (Chen, Xu, Song, & Jermsittiparsert, 2021; Hsu & Fingerman, 2021).

Numerous studies have explored the possible advantages of EVs, highlighting their high efficiency and environmentally friendly nature. Compared to traditional vehicles, EVs primarily reduce emissions by using green sources of electricity (Bibra et al., 2021). Reports show that EVs can reduce GHG emissions by ~17-30% compared with conventional vehicles (European Environment Agency, 2018). Additionally, deploying EVs is crucial for decarbonising urban energy systems and reducing the dependency on traditional power sources, primarily through integration with RES (Yap, Chin, & Klemeš, 2022). EVs can be considered net-zero technologies if powered by RES (Rane et al., 2023). Moreover, EVs have a lower autonomy and require longer charging times, necessitating the installation of charging points that require additional space and infrastructure (Huang & Sun, 2023). This has led to significant challenges in the widespread adoption of EVs.

Among the primary obstacles to the widespread electrification of vehicles are high costs (Kaya, Tortum, Alemdar, & Çodur, 2020; Loni & Asadi, 2023), range anxiety (Li & Jenn, 2022; Roy & Law, 2022), inadequate equipment supply for EVs (Feng et al., 2021; Li & Jenn, 2022), insufficient distribution of charging points (Ma, Pei, Zhang, Xu, & Li, 2023; Roy & Law, 2022), and long charging times (Li, Luo, & Song, 2022; Loni & Asadi, 2023). Among these obstacles, inadequate electric vehicle charging station (EVCS) infrastructure is the primary constraint hindering the widespread penetration of the EV market (Li et al., 2022). Currently, the number of EVCS is limited in most cities worldwide, making it impossible to provide sufficient charging services and convenient options to EV owners (Huang & Sun, 2023). Range anxiety refers to EV owners' concerns about depleting their vehicles' power and the challenges of quickly recharging batteries. Additionally, the

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Table 1
Summary of the related works.

Category	Case study	Research focus	Applied method	Reference
MCDM and spatial analysis	Xian, China	EVCS site selection at the directional road segments	TOPSIS- spatial analysis in GIS	(Yu et al., 2022)
	Istanbul, Turkey	Site selection of electric taxi charging stations	Fuzzy AHP- TOPSIS- spatial analysis in GIS	(Kaya, Alemdar, & Çodur, 2020)
	Mumbai, India	Proposing site selection approach to widespread adaptation of EVCS	TOPSIS- Multi Influencing Factor (MIF), spatial analysis in GIS	(Rane et al., 2023)
	Dublin, Ireland	Suitable site selection of community EVCS	AHP- spatial analysis in GIS	(Charly, Thomas, Foley, & Caulfield, 2023)
	Beijing, China	Comprehensive MCDM framework for the site selection of charging points	FAHP- spatial analysis in GIS	(Ju, Ju, Gonzalez, Giannakis, & Wang, 2019)
Mathematical and spatial analysis	Orange County, USA	Identify and address the spatial disparities in EVCS using social, economic, demographical, and EVCS and solar data.	Machin learning	(Roy & Law, 2022)
	Chengdu, China	Route planning and public charging station placement	Genetic algorithm and simulated annealing	(Li, Liu, & Wang, 2022)
	Jeju Island, South Korea	Optimal EVCS placement to obtain charging demand	Genetic algorithm	(Woo et al., 2023)
	San Fransisco, USA	Equitable distribution of EVCS	TOPSIS- Genetic algorithm and spatial analysis	(Loni & Asadi, 2023)
	London, UK	Maximal coverage of EVCS by optimization of charging point placement	Bayesian spatial log-Gaussian Cox	(Dong et al., 2019)
Optimization	-	Optimal allocation and sizing of fast charging stations considering the uncertainty of renewable sources.	Mixed integer linear programming	(Sa'adati, Jafari-Nokandi, & Saebi, 2021)
	-	Optimal distribution and sizing of distributed generation and EVCS	Grasshopper optimization algorithm and fuzzy approach	(Gampa et al., 2020)
	Allahabad, India	Planning of optimal sizing and placing EVCS	Genetic algorithm and Particle Swarm Optimization	(Awasthi et al., 2017)
	-	Optimal allocation of EVCS within the distribution system	Genetic algorithm and Particle Swarm Optimization	(Rene, Fokui, & Kouonchie, 2023)

mismatch between charge supply and demand can fail during pick hours, resulting in extended wait times and dissatisfaction among EV owners. Moreover, deploying accessible and affordable EVCS to extend their coverage is crucial for addressing these issues (Loni & Asadi, 2023).

It is generally acknowledged that appropriate site selection for EV charging points plays a crucial role in the life cycle of EV infrastructure (Guo & Zhao, 2015), improving system efficiency (Yu et al., 2022) and encouraging customer interest in EVs (Feng et al., 2021). The widespread adoption of EVs requires spatially feasible solutions for deploying charging infrastructures. Because the adoption of EVs is progressive and occurs at different speeds in every country and city, implementing effective planning strategies to deploy infrastructure with available resources is crucial. Efficient planning should involve a technical analysis of the site selection of EVCS to reduce the total cost (Kaya et al., 2020). Moreover, integrating charging points with RES such as solar and wind energy has the potential to promote energy transitions and achieve climate-neutral targets. Hence, developing a comprehensive methodology to evaluate the optimal geographical distribution of EVCS and the feasibility of integrating EVs and PV systems across various urban regions plays a crucial role in the widespread deployment of EVs.

Integrating EVs with solar power is an innovative approach that offers various advantages to the electricity grid, primarily through Vehicle-to-Grid (V2G) systems (Van der Kam, Meelen, Van Sark, & Alkemade, 2018). The integration of PV system with EVs (PV+EV) is a cost-effective approach for decarbonising urban areas. Although this fusion can meet a substantial portion of power requiremnts, a comprehensive assessment of its energy potential is imperative, as each district features diverse built environments, load patterns, and parking capacity (Kobashi, Choi, Hirano, Yamagata, & Say, 2022). Multiple approaches have been proposed to integrate EVs and solar energy within a power grid. Developing microgrids that incorporate RES and EVs can effectively combine PV with EV technology (Himabindu, Hampannavar, Deepa, & Swapna, 2021). Furthermore, the implementation of V2G technology has assisted in integrating solar energy, EVs, and power grids (Shi, Li, Zhang, & Lee, 2020).

Given the various conflicting criteria in the site selection process for an EVCS, this can be considered a Multiple-Criteria Decision-Making (MCDM) problem (Feng et al., 2021). Social, economic, environmental, and operational parameters must be considered to spatially define the locations of on-street charging points. Integrating Geographic Information System (GIS) and MCDM assists researchers in exploring solutions related to spatial challenges and evaluating diverse criteria, particularly in the context of EVCS placement (Rane et al., 2023). This study aimed to develop a geospatial model for the broad deployment of an ECVS within a power distribution grid. It also proposes a practical methodology for applying this geospatial model at the district level while evaluating the potential for solar rooftop deployment. Furthermore, this methodology offers a spatially feasible approach for developing an EVCS while integrating it with solar energy at the district level. This paper describes a methodology and geospatial model developed to assist decision making for the broad deployment of ECVS at the district or city level. The method and model allow the selection of suitable sites for EVCS by spatially considering diverse urban criteria, solar electricity production potential, and power distribution grid capacity.

The remainder of this paper is organised into five sections. The second section focuses on a literature review on site selection for EVCS. Section 3 introduces the methodology in three steps: developing a parametric solar tool, selecting the EVCS site in Bilbao, and evaluating EV penetration within a designated district in Bilbao City. Section 4 introduces Bilbao City as the primary case study. Section 5 presents the results obtained from the solar tool and site selection process for Bilbao. It also discusses the feasibility of integrating EVs with PV systems based on the power capacity. Section 6 concludes the paper by providing a concise summary of the findings.

2. Literature review

Integrating the EV infrastructure with RES is essential for creating sustainable cities and societies by mitigating GHG emissions and promoting sustainable transportation. In the literature, three main approaches have been identified for the site selection of EVCS: the first uses optimisation algorithms (Deb, Tammi, Gao, Kalita, & Mahanta, 2020; Gampa, Jasthi, Goli, Das, & Bansal, 2020), the second applies optimisation or mathematical algorithms integrated with geospatial analysis (Roy & Law, 2022; Woo, Son, Cho, Kim, & Choi, 2023), and the third employs MCDM with geospatial analysis (Rane et al., 2023; Yu et al.,

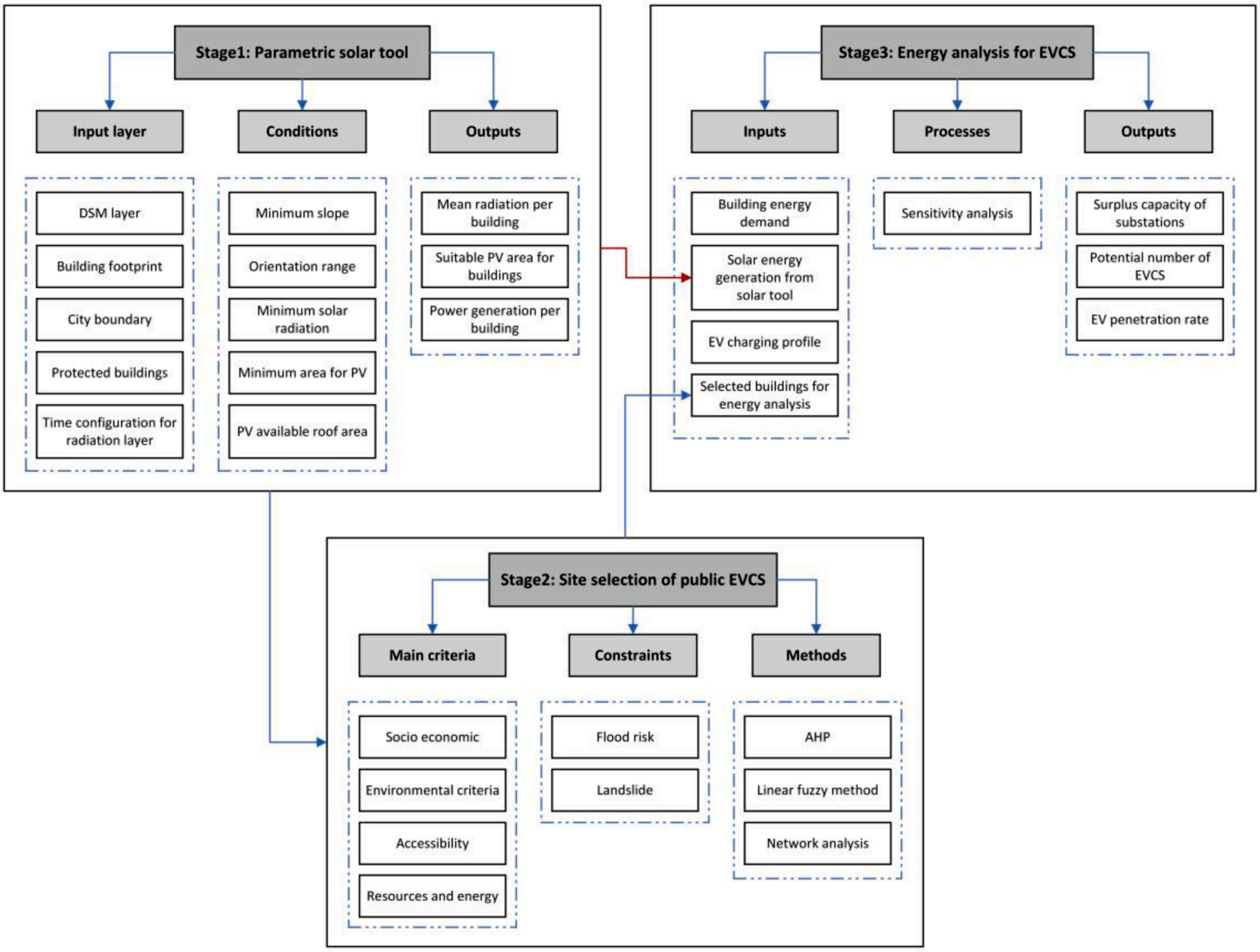


Fig. 1. Research methodology of integrating EVCS and power distribution system in the geospatial context.

2022). Table 1 summarises related works aligned with their applied methods and research focus. This study focuses on the latter category, which incorporates the MCDM and geospatial approaches to EVCS placement. As a comprehensive approach, this framework includes diverse sustainability criteria integrated with a geospatial analysis to provide a robust decision-making process.

Several studies have been conducted on placing EVCS or integrating PV and EV systems into power grids at a municipal scale. Kobashi et al. (2020) investigated the cost/benefits of incorporating PV and EV systems within Kyoto's power grid and assumed that 70% of building rooftops are suitable for PV installation. Dong, Ma, Wei, and Haycox (2019) proposed a methodology for the placement of EVCS using a mathematical model to maximise the coverage of EVCS in London; however, this study overlooked environmental aspects, renewable energy potential, and required infrastructure. Huang and Sun (2023) developed a methodology for optimising solar-powered EVCS for high-density urban areas. However, they did not consider the height and shape of the buildings, and used a sampling method to estimate suitable parts of the rooftops. Li et al. (2022) developed a spatial statistical method to assess the equitability of the EVCS distribution, which can be used as a tool for policymakers in EVCS planning.

Moreover, Kaya et al. (2020) studied the site suitability of an EVCS with geospatial analysis and MCDM in Istanbul, but still needed to evaluate the availability of energy infrastructure. Kobashi et al. (2022) investigated the potential of combining EV and PV in residential and commercial buildings, and compared them with PV and battery storage systems. Gue and Zhao (Guo & Zhao, 2015) studied the site selection of charging points based on environmental, economic, and social components; however, they encompassed only a narrow range of essential variables. Schmidt, Zmuda-Trzebiatowski, Kiciński, Sawicki, and Lasak (2021) developed a framework to design a network of EVCS through a multi-criteria geospatial-based methodology but excluded environmental, social, and energy-related factors. Erbaş, Kabak, Özceylan, and Çetinkaya (2018) investigated the site suitability of an EVCS in Istanbul using a geospatial Fuzzy-based Analytic Hierarchy Process (AHP) methodology, but overlooked the availability of RES.

Despite several studies on the site selection of EVCS, there is a significant knowledge gap in EV and PV system integration according to their geospatial context. Hence, this study attempts to address the need for more knowledge to develop a high-resolution spatial approach. Its primary objective is to precisely estimate the solar energy potential and integrate it into the EVCS site selection process at the municipal scale. Furthermore, this study attempted to bridge the existing knowledge gap by determining a feasible number of EVCS based on the available solar potential and power grid capacity at the district scale.

This study contributes to the existing literature on EVCS site selection in various ways. First, a highly spatially explicit tool was developed to estimate the solar-generation potential of building rooftops at the municipal scale. Using high-resolution Airborne Light Detection and Ranging (LiDAR) data, we obtained an annual mean solar radiation map, which was imported into a solar tool to precisely estimate solar generation. To the best of the authors' knowledge, this is the only study focusing on EVCS site selection that has developed a highly spatially explicit tool to measure solar generation as a potential source for

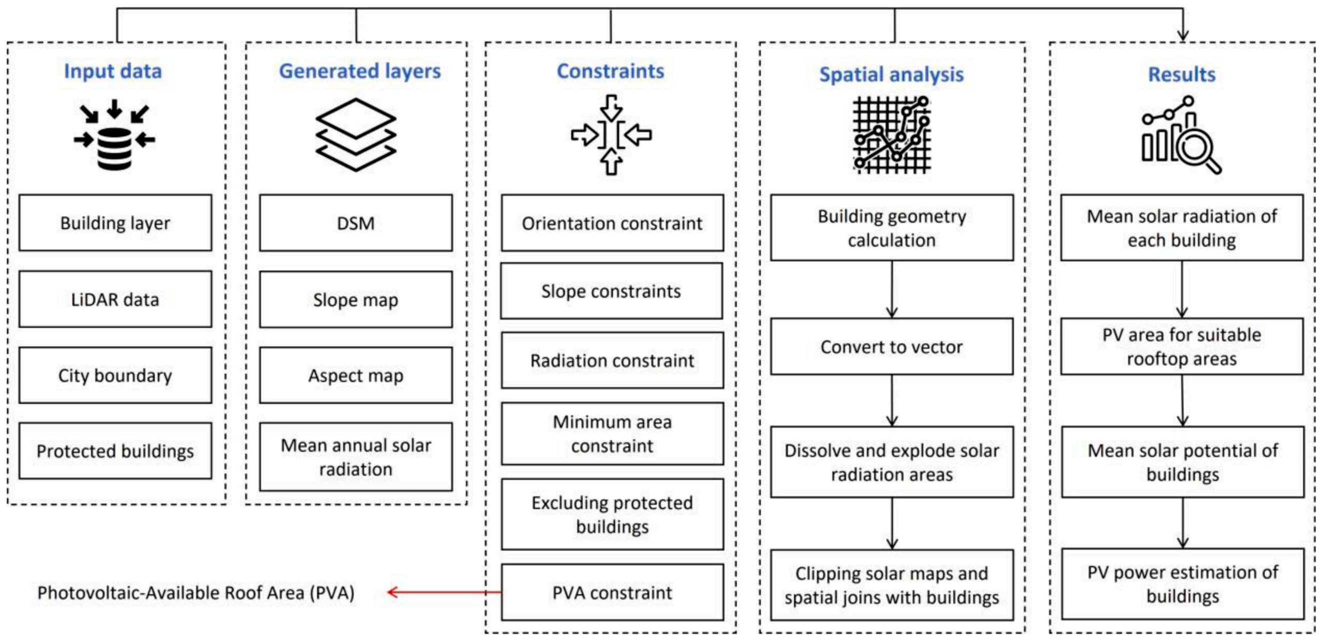


Fig. 2. The diagram of the parametric solar tool in ArcGIS Pro using Model Builder.

charging EVCS.

Second, the site selection of the EVCS was performed based on various urban-related aspects, which is essential for suggesting a spatially feasible plan for the vast development of EVs. Most previous studies focused on evaluating the socioeconomic and environmental factors of site selection for EVCS. However, only a few studies, including ours, have considered the accessibility criteria and resource availability required to meet the energy demands of these charging points. Furthermore, most studies have utilised Euclidean distance analysis, which is not an accurate approach for estimating the proximity of urban amenities, infrastructure, and land use. In contrast, our study employed network analysis as a precise method to measure the proximity of various sub-criteria such as accessibility to public transportation.

Finally, the proposed methodology aids in the incorporation of PV and EV systems to reduce the burden on the power grid to charge more electric vehicles. Therefore, we analysed EV penetration by focusing on a case study selected from the site suitability map of EVCS in Bilbao City. To the best of our knowledge, this is the first study to simultaneously combine a high-resolution geospatial solar tool within the framework of EVCS site selection to estimate the prospective number of charging points and EVs. This methodology is reproducible and can be effectively adapted to any case study, albeit with some modifications according to data availability and the relative importance of the distinct site selection criteria.

3. Materials and methods

The methodology was developed in three main stages: Stage1 involved developing a tool for estimating solar power on building rooftops; Stage2 focused on the site selection of the EVCS using the parametric solar tool as a leading indicator; and Stage3, a group of buildings was selected from the site selection stage to analyse the energy profile of the EVCS and EVs. Additionally, a solar energy tool was employed in Stage 3 to estimate the solar potential of the buildings. Fig. 1 presents an overview of the proposed methodology.

3.1. Stage1: developing a parametric solar tool

This section outlines the rationale behind the developed solar tool, which aims to estimate solar energy generation. It identifies suitable areas on building rooftops for installing photovoltaic (PV) panels and assesses the resulting electricity generation. ESRI's potential solar radiation solution for building rooftops was refined and developed into a parametric tool using ArcGIS Pro (Khanna, 2023). One of the main inputs for solar tools is Digital Surface Model (DSM) data, which represents the Earth's surface in 3D, including built-up and natural features (Nemmaoui, Aguilar, Aguilar, & Qin, 2019). LiDAR is a cutting-edge technology that has recently been used to extract and capture DSMs (Cheng et al., 2020; Gehrke, Morin, Downey, Boehrer, & Fuchs, 2010).

The most suitable parts of building rooftops for PV installation were determined using various geospatial criteria, including orientation, slope, available roof area, minimum annual mean radiation, and available space. Rooftop slopes greater than 60° are unsuitable for PV installation (Song et al., 2018). Buffat, Grassi, and Raubal (2018) suggested a threshold of 50° for rooftop slope suitability. Notably, building orientation and other geometric aspects significantly affect solar irradiance absorption (Buffat et al., 2018; Song et al., 2018). Because the entire rooftop area might not be suitable for PV, it is essential to consider the ratio of the effective PV available roof area (PVA). PVA was used because many sections of rooftops are unsuitable for PV installation owing to their irregular form, shadow effects, and the presence of utilities such as heat, ventilation, and air conditioning (HVAC) on the rooftops (Izquierdo, Rodrigues, & Fueyo, 2008; Singh & Banerjee, 2015).

Moreover, a payback analysis was used to define the lowest mean yearly solar radiation and determine suitable rooftop areas. A minimum space of 6 square meters is required to install a 1Kw PV system (Jackman, 2022). In this study, protected and listed buildings were intentionally excluded from the results, as they require meticulous assessment to determine the feasibility of PV adaptation. PV adaptation in these buildings is subject to specific local regulations and restrictions, necessitating a distinct methodology for evaluation compared to other buildings. Fig. 2 shows the main components of the parametric solar tool designed using ArcGIS Pro and the model builder. Each component includes several geospatial analyses to extract the power capacity across various scales, from individual buildings to municipality levels.

A systematic methodology was employed to calculate the solar PV capacity of the building rooftops. Initially, LiDAR data were converted into the LAS format and merged to generate the DSM layer using LasTools within the QGIS. Subsequently, a mean solar radiation map was

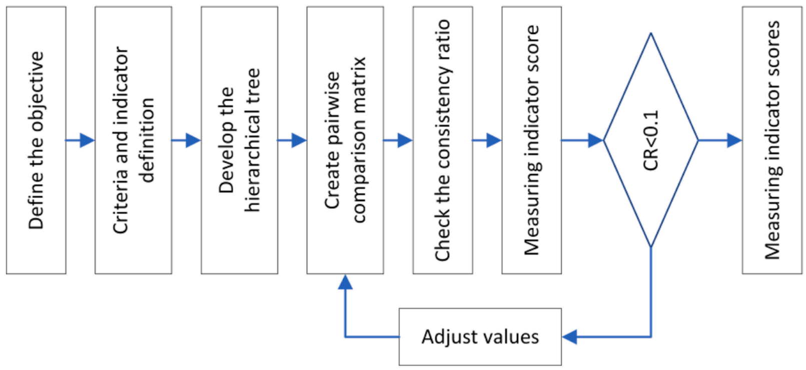


Fig. 3. The flowchart of the AHP process.

constructed by importing the DSM map into the area solar radiation tool available in ArcGIS Pro. The slope and aspect maps were created from the DSM layer at the municipal scale. Areas with slopes of 10-45 degrees and north-facing parts were excluded from the results. The solar radiation of the buildings was extracted from the city map using an extract-by-mask tool and converted into vector format. Next, the vector layer was processed using the dissolved tool, and a multipartial-to-single-part conversion was used to calculate the areas suitable for PV installation.

Moreover, an area constraint was applied to exclude regions smaller than 6 square meters. The feature-to-point and spatial join tools link suitable solar areas to buildings by converting them into points and connecting them to their respective buildings. To further improve the results, the PVA indicator removed regions of buildings designated for other functions, and protected buildings were excluded from the process. Protected buildings were excluded from this process. Subsequently, Zonal statistics were used as a table and join tool to allocate the mean solar radiation on each building's rooftop and join the data to the building database. The solar radiation was calculated in kilowatt-hours (kWh) by multiplying the building's PV area by the mean solar radiation derived from the zonal statistics. This result was then converted into power by multiplying the energy efficiency by the performance ratio of the PV panels.

The energy generation of each building was calculated using Eq. (1) (Pedrero, Hernández, & Martínez, 2021): Here I_{mean} is the total solar radiation on PV panels, L_m is the miscellaneous losses, η is the inverter efficiency of PV, α is the roof area ratio, and S_{ij} is the total PV area for each building (Huang & Sun, 2023). This equation is used to estimate the annual energy production. In this study, the sigma component was ignored because energy generation was considered for the mean annual solar energy generation per hour.

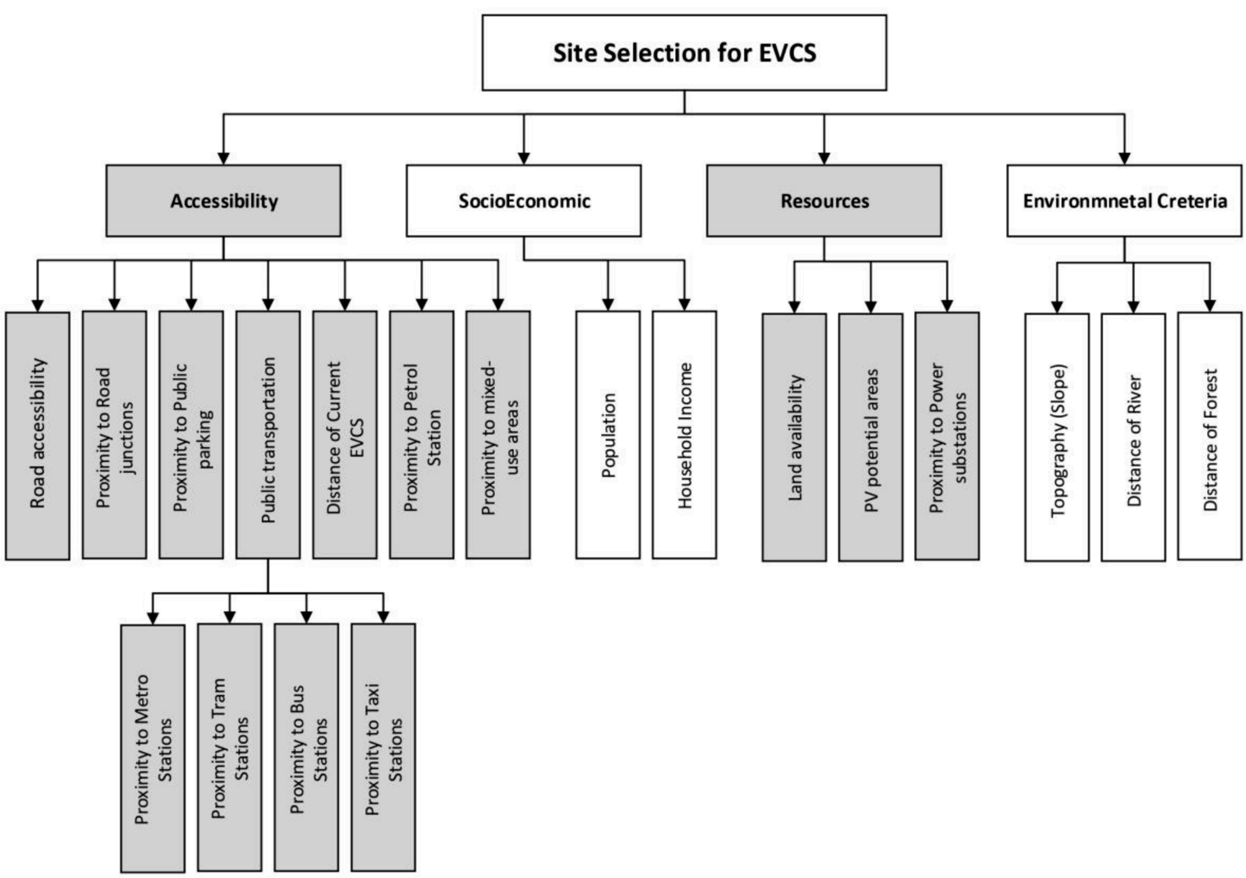


Fig. 4. Site selection criteria and indicators.

$$E_{pv,ij} = \sum_{t=1}^{8760} \left(I_{mean} \times L_m \times \eta \times \left(\alpha \times S_{ij} \right) \right) \quad (1)$$

3.2. Stage2: site suitability of public EVCS

The site suitability of the EVCS has three main objectives: first, to identify optimal areas to establish charging points, prioritise locations for charging station installation, and extend coverage to improve the service area of the charging points. Multi-criteria decision-making (MCDM) is an effective tool for selecting the best choice among multiple criteria (Colak, Memisoglu, & Gercek, 2020). As an MCDM method, the Analytic Hierarchy Process (AHP) is used to obtain the relative priority of factors and alternatives by decision-makers' judgments (Al-Harbi, 2001). The AHP is a comprehensive MCDM method that offers a flexible and pragmatic approach for selecting desired options according to decision-making criteria (Ahadi, Fakhrabadi, Pourshaghaghy, & Kowsary, 2023) and structuring the problem by creating a hierarchical framework, as depicted in Fig. 3. It employs a pairwise comparison matrix to compare objects at each hierarchical level with respect to the upper-level superior element (Krejčí & Stoklasa, 2018). Moreover, AHP are frequently applied in different fields, including environmental studies (Chen, Li, Wang, & Cheng, 2020; Saffarian, Mahmoudi, Shafiee, Jasemi, & Hashemi, 2020), energy planning (Ahadi et al., 2023; Colak et al., 2020; Coruhlu, Solgun, Baser, & Terzi, 2022), and urban and regional planning (Eren & Katanalp, 2022; Feltynowski & Szajt, 2021; Mortazavi Chamchali, Mohebbi Tafreshi, & Mohebbi Tafreshi, 2021).

Matrix A (n × n) is a pairwise comparison matrix used to evaluate n alternatives, as shown in Eq. (2): This matrix includes objects 'a_{ij}', where 'i' expresses the primary comparison criteria of row i, and 'j' represents the criterion being compared against criterion i (Awad & Jung, 2022). In Eqs. (3) and (4), W is the matrix weight criteria, and 'λmax' refers to the maximum Eigenvalue estimated through the pairwise comparison matrix (Thakur, 2022). As an expert's judgment should be consistent and logical, Saaty proposed a consistency index (CI) to measure the consistency ratio (CR); see Eq. (5) (Saaty, 1987). The CR is calculated by dividing the CI by the random index (RI) value obtained from the CR table, which should remain below 0.1; see Eq. (6) (Saaty, 2004). We used the geometric mean to compute the weights assigned to both the criteria and the sub-criteria. The prioritisation of objects is obtained by calculating the geometric means of the pairwise comparison within each row, as shown in Eq. (7):

$$A = \begin{bmatrix} 1 & a_{12}\ldots & a_{1n} \\ \vdots & \ddots & \vdots \\ 1/a_{12} & 1/a_{1n}\ldots & 1 \end{bmatrix} \quad (2)$$

$$AW = \lambda_{max} W \quad (3)$$

$$downright \begin{bmatrix} 1 & a_{12}\ldots & a_{1n} \\ \vdots & \ddots & \vdots \\ 1/a_{12} & 1/a_{1n}\ldots & 1 \end{bmatrix} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = \lambda_{max} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} \quad (4)$$

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (5)$$

$$CR = \frac{CI}{RI} < 0.1 \quad (6)$$

$$GM = \left(\prod_{i=1}^{n} \mathrm{aij} \right)^{\frac{1}{n}} \quad (7)$$

The first step in identifying suitable sites involves gathering and analysing data to create input layers for overlaying. A wide range of socioeconomic, environmental, mobility, and energy factors were studied to determine the site suitability of EVCS, as shown in Fig. 4. These layers were obtained by reclassifying and normalising the subcriteria. Moreover, fuzzy logic has been effectively employed to normalise the layers in a GIS. Two fuzzy membership functions, linear ascending and linear descending, were applied to normalise the values of all GIS layers, see Table 2. The input receives a value in the range of 0, indicating no membership, to 1, indicating definite membership (Noorollahi, Senani, Fadaei, Simaee, & Moltames, 2022). A linear ascending method can be used when higher membership values indicate higher suitability. By contrast, we used the linear descending method when higher values indicated lower suitability.

Table 2
Fuzzy membership functions.

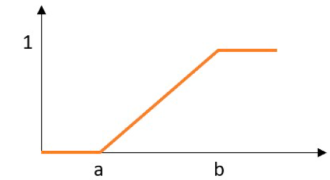
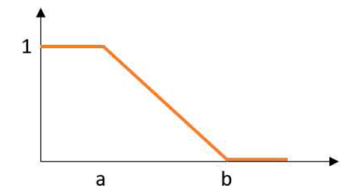
Function	Equation	Schematic figure
Linear ascending	$\mu_x = \begin{cases} 0 & x \le a \\ \frac{x-a}{b-a} & a < x < b \\ 1 & x \ge b \end{cases}$	
Linear descending	$\mu_x = \begin{cases} 1 & x \le a \\ \frac{x-b}{a-b} & a < x < b \\ 0 & x \ge b \end{cases}$	

Table 3 lists the main criteria and indicators of EVCS site suitability and their measurement methods extracted from an extensive literature review. Geospatial methods have been suggested to measure these indicators. The weighted sum tool in ArcGIS combines the sub-criteria into the main criteria layers, and the resulting scores are normalised using a fuzzy linear method. A specific score was assigned to each indicator using the AHP method, indicating its importance compared to others.

The geospatial procedure involves several steps to import data, reclassify, normalise, and overlay layers, and export the site selection output. Different approaches such as network analysis and Euclidean distance have been employed for these distances. Fig. 5 illustrates the general site suitability model for the EVCS.

The methodology for geospatial analysis utilised various tools and spatial processes to identify suitable locations for EVCS. The spatial analysis method for the five selected sub-criteria is shown in Fig. 6. A network dataset was built in ArcCatalog to assess public transportation and was imported into the service analysis layer tool. Subsequently, the results were reclassified and converted into a raster format. Null and Con tools were then used to manage the No Data cells. Furthermore, normalisation via the fuzzy membership tool was conducted to estimate the proximity to the metro, bus, tram, and taxi stations. The weighted sum tool combines all these layers as public transportation criteria. Similar techniques have been applied in public parking areas, EV charging stations, and petrol stations.

The road accessibility layer was analysed using data imported from an Open Street Map source (OSM). The Euclidean distance was applied to the road layer, and the results were reclassified, followed by the use of Is Null, Con, and Fuzzy membership tools. The road map was dissolved using the unsplit line and intersection tool to identify road junctions via the point output type. Subsequently, inverse distance weighting (IDW) was used for raster surface interpolation, and a fuzzy membership tool was employed to normalise the outcomes. Proximity to the public and mixed-use area layers was assessed using the point density tool to extract the mixed-use area density and the fuzzy membership tool to normalise the values. The proximity to water bodies and forests was evaluated using Euclidean distance, reclassification, and fuzzy membership tools. A reclassification tool was applied, and the results were normalised to

Table 3
EVCS`` site selection criteria and indicators.

Criteria	Indicators		Definition	Estimating method	References
Accessibility	C1.1	Public transportation	Placing charging points close to public transportation reduces range anxiety and allows EV users to park, charge their EVs, and use public mobility services.	Network analysis	(Ghosh et al., 2021; Guler & Yomralioglu, 2020; Karolemeas, Tsigdinos, Tzouras, Nikitas, & Bakogiannis, 2021; Kaya et al., 2020; Kaya et al., 2020; Schmidt et al., 2021; Zhang, Teoh, & Zhang, 2022)
	C1.1.1	Proximity to metro			
	C1.1.2	Proximity to bus			
	C1.1.3	Proximity to tram			
	C1.1.4	Proximity to taxi			
	C1.2	Road accessibility	The proximity to the main roads directly correlates with the need for building EVCS.	Euclidean distance	(Erbaş et al., 2018; Ghosh et al., 2021; Guler & Yomralioglu, 2020; Guo & Zhao, 2015; Hisoglu, Tuominen, & Huovila, 2023; Kaya et al., 2020; Kaya et al., 2020; Schmidt et al., 2021; Sisman, Ergul, & Aydinoglu, 2021; Zhang et al., 2022)
	C1.3	Road junctions	Proximity to road junctions enhances service accessibility and provides drivers with a backup option during traffic congestion.	Point density	(Erbaş et al., 2018; Guo & Zhao, 2015; Kaya et al., 2020; Kaya et al., 2020; Sisman et al., 2021)
	C1.4	Public parking areas	Potential places for charging points that facilitate simultaneous parking and EV charging.	Network analysis	(Chen, Kockelman, & Khan, 2013; Efthymiou, Antoniou, Tyrinopoylos, & Mitsakis, 2012; Erbaş et al., 2018; Ghosh et al., 2021; Guler & Yomralioglu, 2020; Karolemeas et al., 2021; Kaya et al., 2020; Kaya et al., 2020; Zhang et al., 2022)
	C1.5	EV charging stations	Potential areas for new charging points that allow broader coverage across areas.	Network analysis	(Erbaş et al., 2018; Hisoglu et al., 2023; Kaya et al., 2020; Kaya et al., 2020; Li et al., 2022; Sisman et al., 2021)
	C1.6	Petrol stations	Combining petrol stations with charging points enhances accessibility and provides space.	Network analysis	(Erbaş et al., 2018; Ghosh et al., 2021; Guler & Yomralioglu, 2020; Kaya et al., 2020; Kaya et al., 2020; Phonrattanasak & Leeprechanon, 2012; Sisman et al., 2021)
	C1.7	Proximity to public and mixed-use areas	Locations like shopping centers and hospitals demand more EV charging due to the increased presence of people during daytime hours.	Point density	(Efthymiou et al., 2012; Ghosh et al., 2021; Guler & Yomralioglu, 2020; Karolemeas et al., 2021; Kaya et al., 2020; Kaya et al., 2020; Schmidt et al., 2021)
Socioeconomic Development	C2.1	Household income	A direct relationship exists between charging demand and car ownership, often influenced by household income.	Raster analysis	(Chen et al., 2013; Efthymiou et al., 2012; Guler & Yomralioglu, 2020; Kaya et al., 2020; Kaya et al., 2020; Namdeo, Tiwary, & Dziurla, 2014)
	C2.2	Population density	Areas with high population density require more charging points to meet the demand.	Kernel point density	(Dong et al., 2019; Efthymiou et al., 2012; Erbaş et al., 2018; Ghosh et al., 2021; Guler & Yomralioglu, 2020; Guo & Zhao, 2015; Hisoglu et al., 2023; Karolemeas et al., 2021; Kaya et al., 2020; Kaya et al., 2020; Schmidt et al., 2021; Sisman et al., 2021; Zhang et al., 2022)
Availability of resources	C3.1	Land availability	Space scarcity limits the construction of new EVCS.	Raster analysis	(Wu, Yang, Zhang, Chen, & Wang, 2016)
	C3.2	PV potential areas	Considering PV's potential to provide enough energy and reduce pressure on power grids	Solar tool	(Ghosh et al., 2021; Hisoglu et al., 2023; Kaya et al., 2020)
	C3.3	Distance from substations	Proximity to power substations enhances capacity efficiency and reduces infrastructure costs.	Euclidean distance	(Erbaş et al., 2018; Guo & Zhao, 2015; Hisoglu et al., 2023; Kaya et al., 2020; Kaya et al., 2020; Sisman et al., 2021; Wu et al., 2016; Xu, Zhong, Yao, & Wu, 2018)
Environmental criteria	C4.1	Proximity to water resources	The construction of EVCS should be away from natural resources such as water and forests to avoid potential environmental hazards.	Euclidean distance	(Erbaş et al., 2018; Guo & Zhao, 2015; Kaya et al., 2020; Kaya et al., 2020; Sisman et al., 2021; Wu et al., 2016; Xu et al., 2018)
	C4.2	Proximity to forest		Euclidean distance	(Erbaş et al., 2018; Guo & Zhao, 2015; Kaya et al., 2020; Kaya et al., 2020; Sisman et al., 2021; Wu et al., 2016; Xu et al., 2018)
	C4.4	Air and noise Quality	Locating EVs near high-pollution areas helps mitigate air and noise pollution.	Raster analysis	(Ghosh et al., 2021; Guo & Zhao, 2015; Kaya et al., 2020; Kaya et al., 2020)
	C4.3	Topography	Building charging points in flat terrain reduces construction and operation costs.	Slope analysis	(Erbaş et al., 2018; Guler & Yomralioglu, 2020; Guo & Zhao, 2015; Kaya et al., 2020; Kaya et al., 2020; Sisman et al., 2021)
		Landslide and flood	As a criterion for excluding from the result	Raster analysis	(Erbaş et al., 2018; Kaya et al., 2020; Kaya et al., 2020; Sisman et al., 2021)

analyse the air and noise quality criteria. The DSM layer was used to create a slope map, and the results were reclassified and normalised to evaluate the slope criteria.

The input layer was converted to a raster format for household criteria and normalised using the fuzzy membership tool. Population density criteria were assessed using kernel interpolation, followed by the Is Null, Con, and fuzzy membership tools. The input layer was converted into a raster format for land availability, and the results were reclassified. A substation distance analysis was performed using the Euclidean distance tool and processed by reclassification and normalisation. Analysing potential PV areas included converting the solar power layer to points, assigning values to an equally sized fishnet layer via spatial joins, converting the results to rasters, and managing No Data values. The AHP scores were assigned to each sub-criterion to obtain a criteria map. The AHP scores for each criterion were then applied using the weighted sum tool to generate a suitability map for the EVCS.

3.3. Stage3: energy profile analysis of EVCS

It is recommended to use energy simulation software when accurate building energy demand data are unavailable. In our case study, we employed the ENERKAD tool to estimate building energy demands

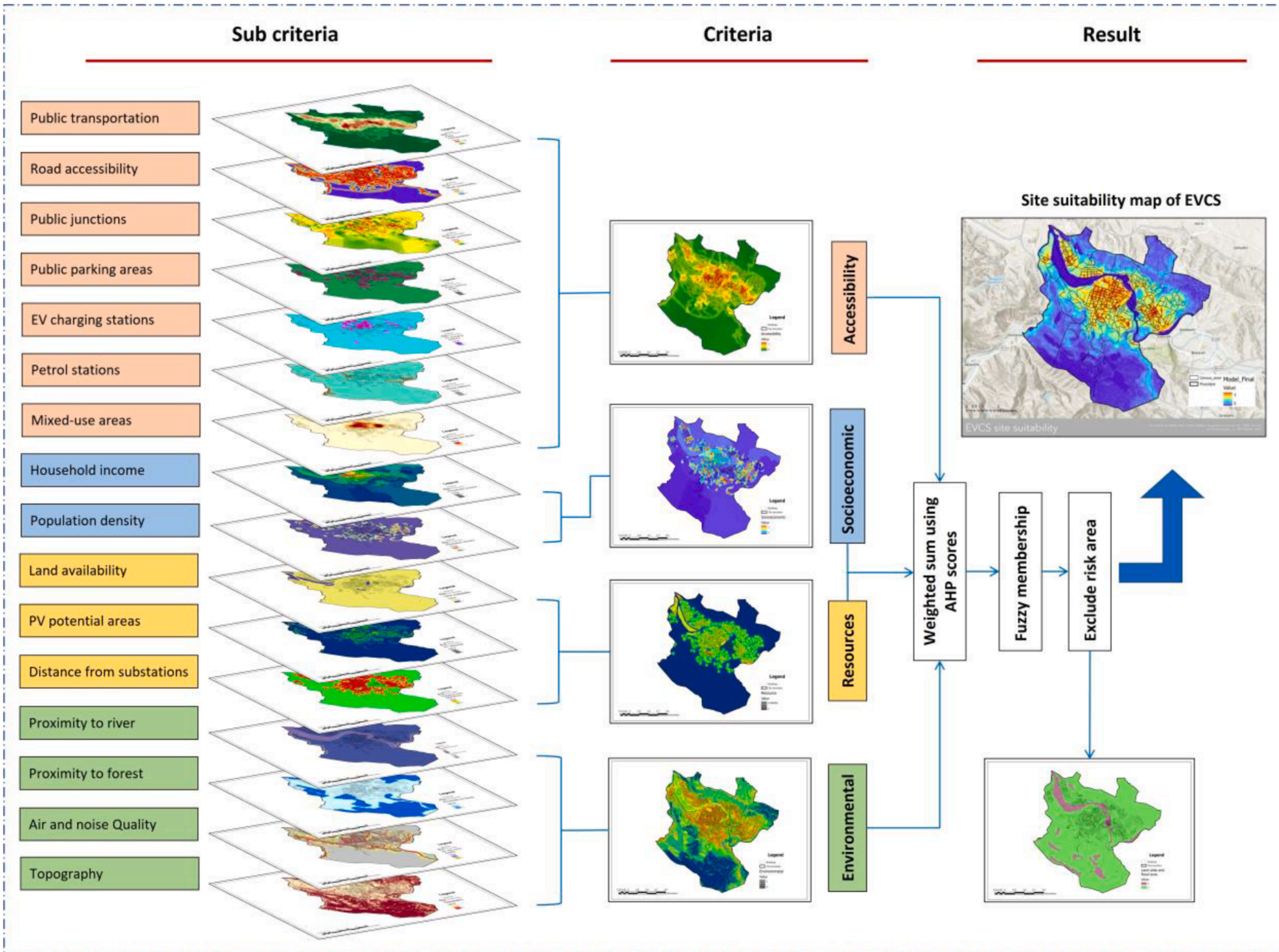


Fig. 5. Methodology of EVCS placement.

(Muñoz et al., 2020) and subsequently calibrated the results with data from an electricity distribution company. To assess the potential deployment of EVCS, it is essential to collect building demand and grid data to measure the surplus energy of each substation. Furthermore, the hourly solar energy generation was calculated using the developed solar tool for a selected district.

The EV charging load profile is a critical factor for estimating the potential number of EVCS and the adaptation of EVs. This factor varies across different types of EVCS, including public, private, and on-street charging points. Thus, selecting the charging load profile should align with the research objective and feasibility of the EVCS type within a specific area. The X-axis shows the hourly time division in this chart, and the Y-axis represents the normalised relative frequency of the charging demand, which adjusts the relative frequencies to sum to 100%. Fig. 7 illustrates the higher charging demand observed at on-street charging points during working hours 7 to 17 in Spain (Corchero García, 2015).

Moving beyond the basic role of distribution substations in managing the supply voltage, estimating the surplus capacity of substations is essential. The surplus capacity of the substations was calculated by excluding the building demand from the total power capacity of each substation. The average contracted power, which is 5.75 kW in Spain, was considered to estimate the substation power capacity (Ministerio de Industria y Turismo, 2023). The average contract power is multiplied by the number of contracted clients to calculate the maximum power of each substation. Subsequently, to evaluate the substation capacity, the total power was multiplied by 0.4, which is a simultaneous factor. To estimate the total surplus energy, solar power capacity was added to the power capacity of the substation.

A sensitivity analysis was conducted to estimate the distribution load of the EVCS and to determine the potential number of EVs that can be charged. The distribution load was calculated by multiplying the normalised value of the relative frequency of the EVCS by the power capacity required for charging the EVs. First, this calculation was executed on March 21st, the spring equinox, as a representative day with average solar radiation. Second, the same analysis was performed on two other dates: June 21st, with the highest solar radiation, and December 21st, with the lowest solar radiation. The number of potential EVCS was calculated by dividing the distribution load of each EVCS by its power capacity. Optimising the number of EVCS based on hourly demand profiles and high temporal resolution solar data is highly recommended.

4. The case study

In this research, the case study was Bilbao City, the capital of Basque Country, located on the Eastern Atlantic Seaboard, Fig. 8. Bilbao covers an area of ~41.3 Km^{2,} to have a population of 344,678 in 2022. Bilbao changed its role from an industrial city to a tourist destination and service city (Bilbao Information, 2022). The entire city of Bilbao was used as the case study for the site selection of EVCS.

Fig. 9 shows the index-based LiDAR data in the Laz format and the mean annual radiation map of Bilbao City. LasTools in QGIS were used to extract the DSM from these data. This information can be used to select the most suitable parts of the building rooftop for solar panels. Moreover, the mean radiation in Bilbao City was extracted using the area solar radiation tool in ArcGIS Pro. The DSM layer provided in the previous step was used as the input elevation surface raster to obtain a

Fig. 6. Model builder diagram for the process of spatial analysis for five selected sub criteria.

solar map. Detailed information shows that the mean annual radiation of the Bilbao municipality is 1032 kWh/m^2, and the maximum solar radiation is ~1379 kWh/m^2 annually.

In this case study, the methodology for site suitability of the EVCS was applied to the entire city (Stage 2 of the method). To showcase Stage 3 of the process, a small area, including 39 buildings and five substations, was selected to analyse the energy profile and the potential of the electricity infrastructure to support the EVCS. Each building was connected to a specific substation based on the proximity of the surrounding substations and basic information. Fig. 10 shows a detailed view of the substation locations with connected buildings. The remaining capacity of each substation can be measured by subtracting the substation capacity and energy demand of the connected buildings from those of each substation based on Table 4.

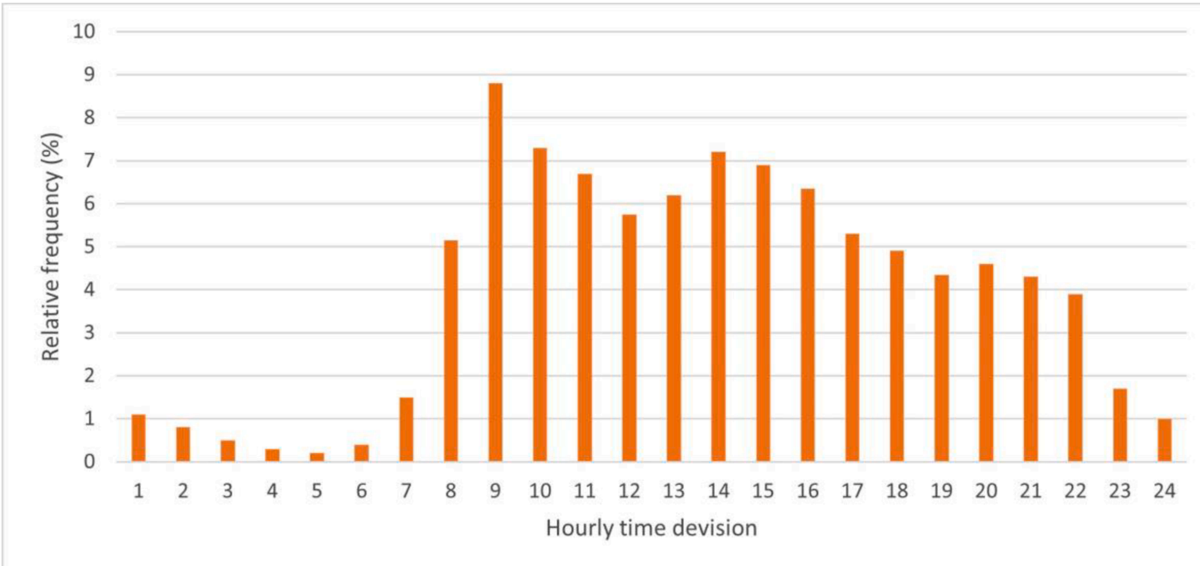


Fig. 7. Normalized EV load profile for on-street charging points.

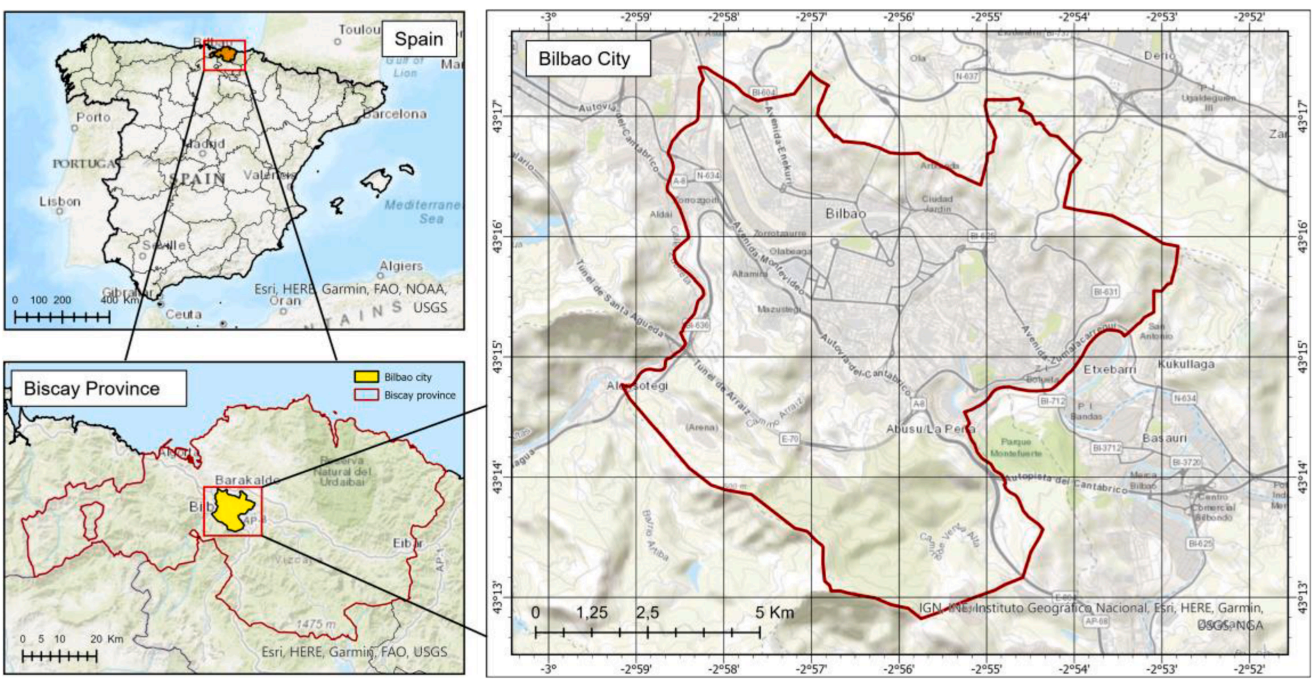


Fig. 8. Location of Bilbao city in Spain (OpenStreetMap, 2023).

5. Results and discussion

5.1. Applying the solar energy tool in Bilbao

This section describes the development of a tool to estimate the solar potential of rooftops based on geospatial conditions. The tool assumes that pitched rooftops with slopes less than 45° are suitable for installing PV panels. In contrast, north-oriented rooftops were excluded because they received insufficient solar energy. According to one study, the PVA ratio for buildings in Spain is ~0.346 (Singh & Banerjee, 2015). Rooftop areas smaller than 6 square meters were excluded from the analysis.

Approximately 500 protected structures that were unsuitable for PV installation were also excluded. A commercial monocrystalline panel was selected to calculate the actual electricity production with a PV module efficiency of 19.4%, inverter efficiency of 0.95%, and miscellaneous losses of 13% (Pedrero et al., 2021). The process and results of the solar potential tool were carefully checked at each step to ensure accuracy. Table 5 lists the solar tool results for each building, including the recommended PV area, mean annual radiation (kWh), and estimated energy generation (kWh).

According to the results, regions receiving solar radiation of over 925 kWh/m^2 per year have a potential solar energy generation of ~205 GWh annually on suitable rooftop areas. In Bilbao, the annual electricity consumption is ~419 and 484 GWh for residential and nonresidential buildings, respectively (Atelier, 2021). Consequently, solar PV energy generation can fulfil ~23% of the electricity demand in the built environment.

The existing electrical infrastructure is not always prepared to

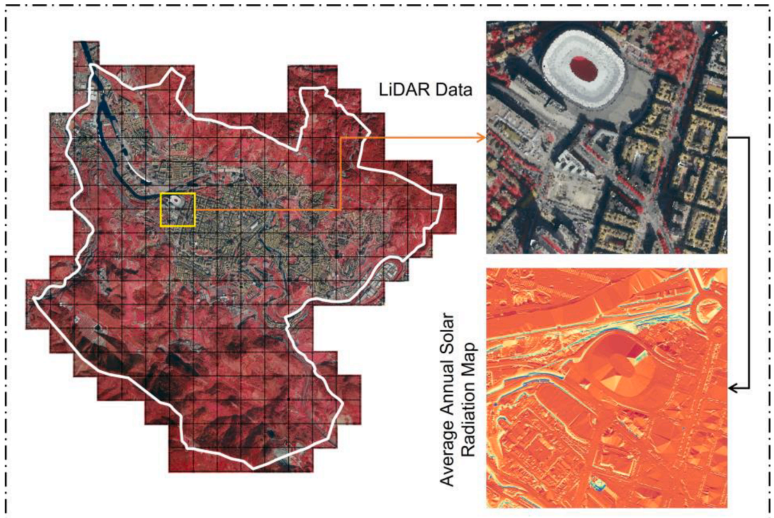


Fig. 9. LiDAR data and annual mean radiation map of Bilbao city.

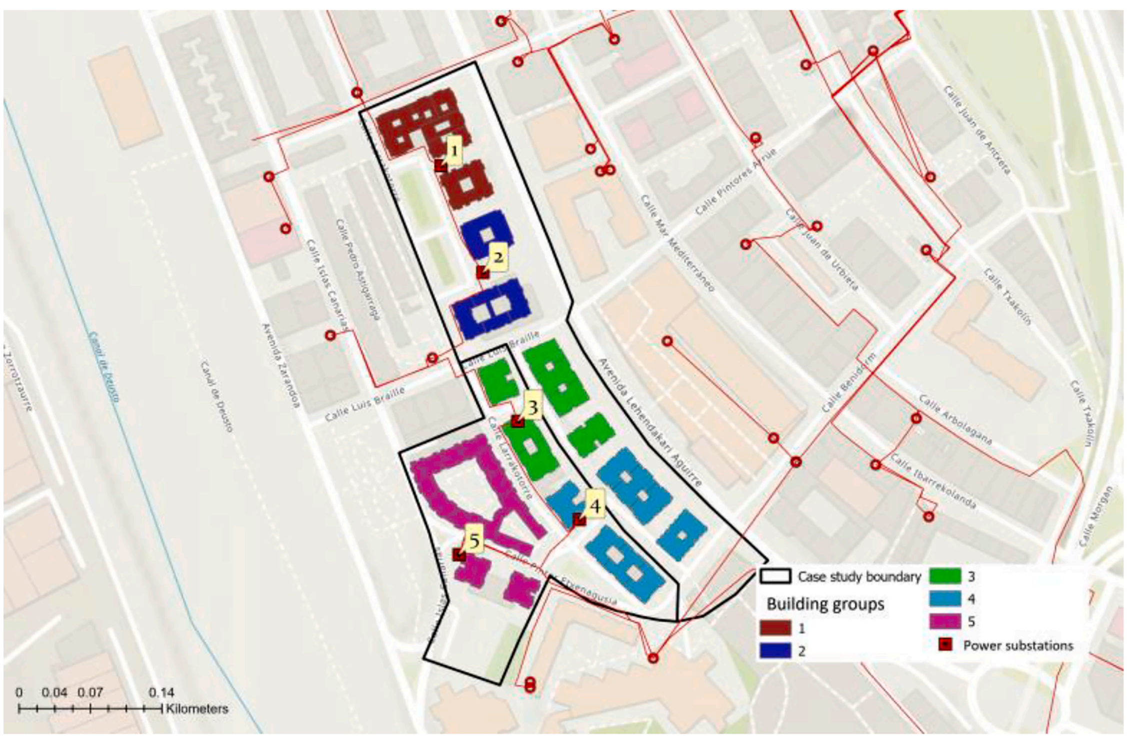


Fig. 10. Substations with connected buildings.

Table 4
The information of substations.

Substation number	Number of buildings	Residential gross area (m^2)	Non-residential gross area (m^2)	Power capacity (kW)
1	6	23787	-	428
2	4	27279	-	513
3	7	39350	-	633
4	8	44590	-	722
5	14	24305	1938	435

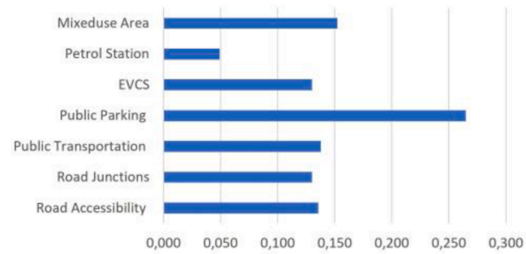
Table 5
Different scenarios of solar power generation.

Minimum solar radiation (kWh/m^2/yr)	Minimum area for PV (m^2)	Maximum slope (°)	Orientation condition	Power generation (GWh/yr)
850	6	45	S-E-W	208.0
925	6	45	S-E-W	205.0
925	100	45	S-E-W	193.3
1000	6	45	S-E-W	198.6
1000	100	45	S-E-W	191.7
1100	6	45	S-E-W	138.9
1100	100	45	S-E-W	137.0

ACCESSIBILITY CRITERIA MATRIX

	Road Accessibility	Road Junctions	Public Transportation	Public Parking	EVCS	Petrol Station	Mixeduse Area	Geometric Mean	Normalized values	W	AW
Road Accessibility	1,00	1,00	1,00	0,33	1,00	4,00	1,00	1,04	0,135	1,33	8,56
Road Junctions	1,00	1,00	1,00	0,33	1,00	3,00	1,00	1,00	0,130	1,19	8,13
Public Transportation	1,00	1,00	1,00	0,50	1,00	3,00	1,00	1,06	0,138	1,21	8,52
Public Parking	3,00	3,00	2,00	1,00	2,00	4,00	1,00	2,03	0,265	2,29	17,42
EVCS	1,00	1,00	1,00	0,50	1,00	2,00	1,00	1,00	0,130	1,07	8,09
Petrol Station	0,25	0,33	0,33	0,25	0,50	1,00	0,33	0,38	0,049	0,43	3,09
Mixeduse Area	1,00	1,00	1,00	1,00	1,00	3,00	1,00	1,17	0,152	1,29	9,66

Variables	λ	CI	RI	CR
Estimation	7,17	0,03	1,32	0,02



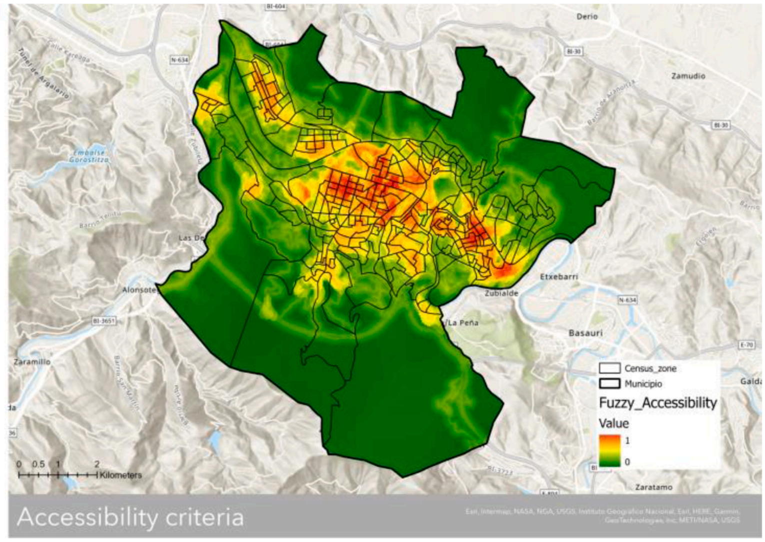
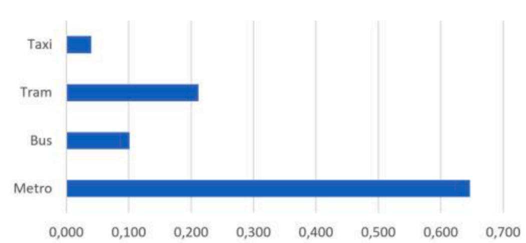


Fig. 11. AHP scoring for accessibility indicators and fuzzy-based accessibility map.

PUBLIC TRANSPORTATION INDICATOR MATRIX

	Metro	Bus	Tram	Taxi	Geometric Mean	Normalized values	W	AW
Metro	1,00	7,00	5,00	9,00	4,21	0,647	5,50	31,27
Bus	0,14	1,00	0,33	4,00	0,66	0,101	1,37	4,53
Tram	0,20	3,00	1,00	6,00	1,38	0,212	2,55	10,05
Taxi	0,11	0,25	0,17	1,00	0,26	0,040	0,38	1,76

Variables	λ	CI	RI	CR
Estimation	4,39	0,13	0,9	0,1



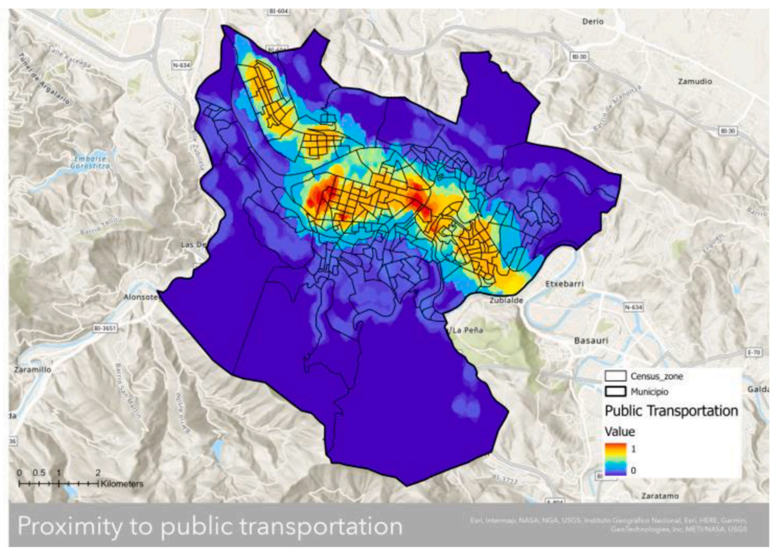


Fig. 12. AHP scoring and fuzzy-based mapping of the sub-criteria of public transportation indicators.

receive the energy generated by photovoltaic systems. Distributed and bidirectional generation characterizes the solar-pose grid control and management challenges. The implementation of intelligent automation and control technologies can facilitate the integration of PV into existing power grids. Advanced technology monitoring systems allow real-time generation and consumption tracking, enabling efficient grid management decision-making. In addition, microgrids enter the scene as an additional solution, allowing local generation and consumption in specific areas and reducing the burden on the main grids.

5.2. Site suitability of EVCS in Bilbao

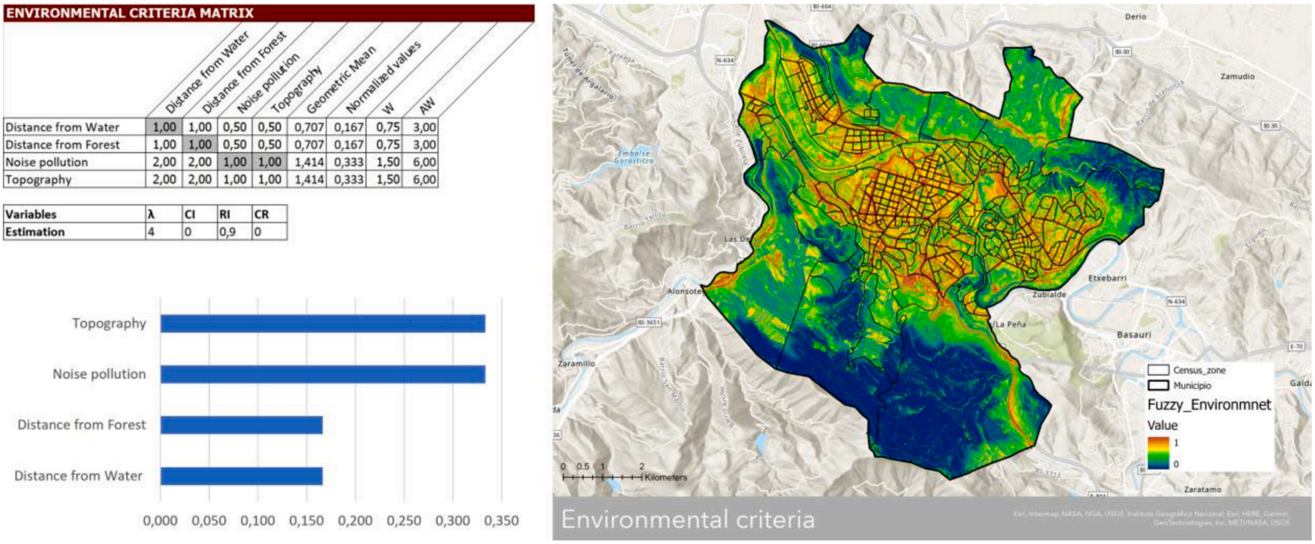
This section focuses on scoring the main criteria and their indicators based on expert judgment. Accordingly, a session was held with experts on the project and importance of site suitability indicators for EVCS. Subsequently, an AHP survey form was designed and shared with eight experts from the urban energy transition unit of TECNALIA.

5.2.1. Scoring of the accessibility criteria

Fig. 11 shows that public parking is the most crucial factor in the accessibility criteria, based on expert decisions. Other indicators received similar scores, including road intersections, public transportation, road accessibility, current EVCS, and mixed-use areas. Moreover, proximity to petrol stations received a deficient score compared to other factors. The judgments for this matrix are acceptable when the consistency ratio is 2%, which is less than the 10% threshold. Additionally, this result shows that the city centre has a high accessibility value. There are also small spots in the east with good accessibility compared with other parts of the city.

5.2.2. Scoring of the sub-criteria of public transportation

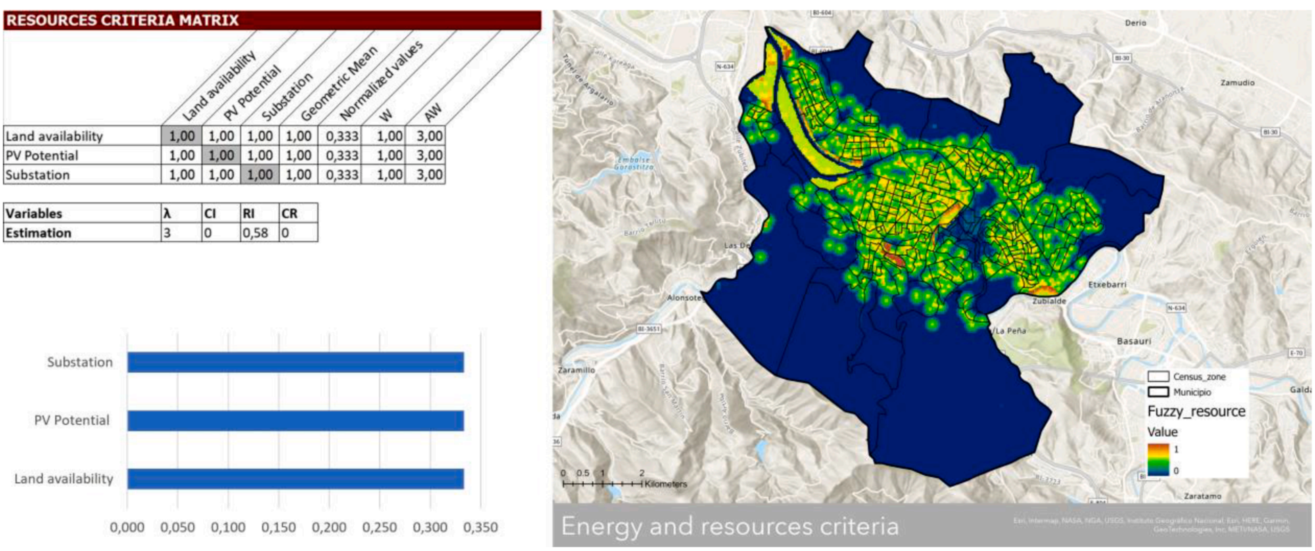
Because there are four types of public transportation stations in Bilbao City, a weighting matrix is required to compare the relative importance of each indicator. The score of proximity to each public transportation mode is shown through the weighting matrix and bar chart, see Fig. 12. Overall, metro stations received a higher score of 0.665, followed by proximity to tram stations. The same approach was applied to measure proximity to metro, bus, tram, and taxi stations. All four layers were overlaid to calculate their proximity to public transportation systems.



ENVIRONMENTAL CRITERIA MATRIX	Distance from Water	Distance from Forest	Noise pollution	Topography	Geometric Mean	Normalized values	W	λW
Distance from Water	1,00	1,00	0,50	0,50	0,707	0,167	0,75	3,00
Distance from Forest	1,00	1,00	0,50	0,50	0,707	0,167	0,75	3,00
Noise pollution	2,00	2,00	1,00	1,00	1,414	0,333	1,50	6,00
Topography	2,00	2,00	1,00	1,00	1,414	0,333	1,50	6,00

Variables	λ	CI	RI	CR
Estimation	4	0	0,9	0

Fig. 13. AHP scoring and fuzzy-based mapping of environmental criteria.



RESOURCES CRITERIA MATRIX	Land availability	PV Potential	Substation	Geometric Mean	Normalized values	W	λW
Land availability	1,00	1,00	1,00	1,00	0,333	1,00	3,00
PV Potential	1,00	1,00	1,00	1,00	0,333	1,00	3,00
Substation	1,00	1,00	1,00	1,00	0,333	1,00	3,00

Variables	λ	CI	RI	CR
Estimation	3	0	0,58	0

Fig. 14. AHP scoring and fuzzy-based mapping of resources criteria.

5.2.3. *Scoring of environmental criteria*

According to the experts' judgments, topography and noise pollution received higher scores than the other indicators. Fig. 13 shows that the weight assigned to the distance between the river and forest was 0.167. Regarding environmental criteria, the city centre is the most suitable location for deploying EVCS, as it receives a higher score for noise pollution and distance from natural resources.

5.2.4. *Scoring of resources and energy criteria*

The expert judgment indicated that all three indicators of resources and energy were equally important. A closer look at the resource map in Fig. 14 shows that the high-potential areas for EVCS are distributed close to the available lands.

5.2.5. *Scoring of socioeconomic criteria*

The following table indicates that population density is more important than income for EVCS placement. Fig. 15 presents a normalised socioeconomic criteria map with highly populated areas and high-income households in red spots.

5.2.5. *Scoring of main criteria*

The following table compares the ranks of all criteria for the placement of EVCS. This indicates that the resource criterion received a higher score, closely followed by the accessibility criterion. In contrast, the environmental and socioeconomic scores were lower. Fig. 16 also illustrates the combined site selection indicators using the AHP scores; the higher the value of an area, the more suitable it is to instal an EVCS.

Table 6 compares the ranks and score, Eq. (7), of the main criteria and sub-criteria for site selection in the EVCS. This table shows that the resource criterion has a higher score than the other criteria, followed by the accessibility criterion with a score of 0.286.

Based on the census districts, Fig. 17 shows the areas with the highest potential for new electric vehicle charging points. The central part of the city is the most suitable area for developing public charging stations for electric vehicles owing to its higher accessibility to service areas and power sources. Moreover, this area is mainly located away from natural resources such as rivers, forests, and disaster-prone regions.

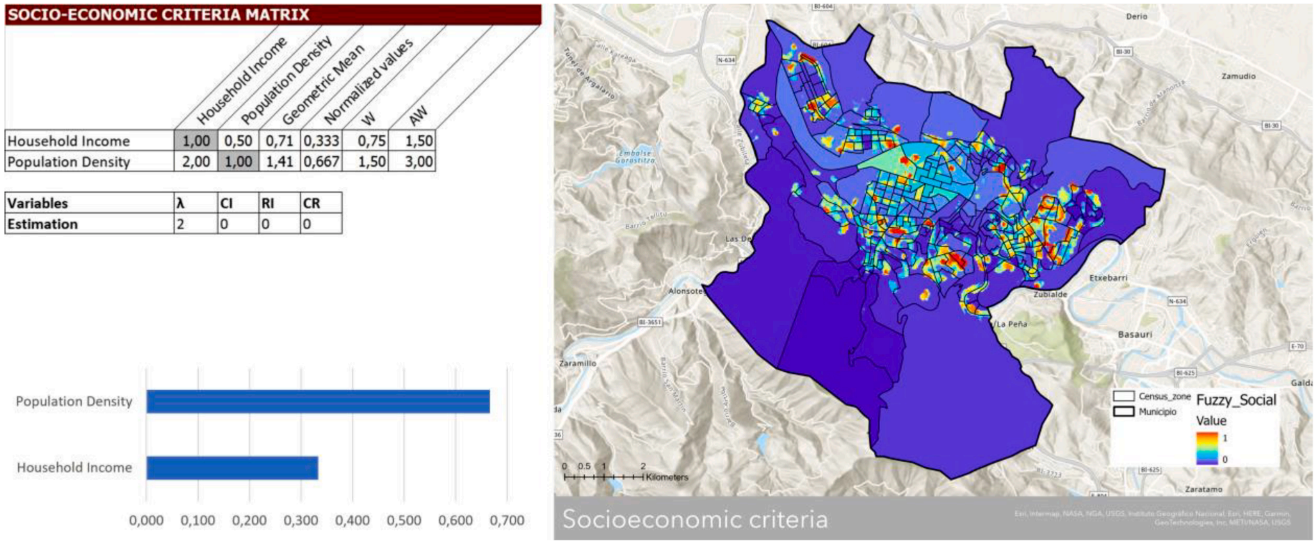


Fig. 15. AHP scoring and fuzzy-based mapping of socioeconomic criteria.

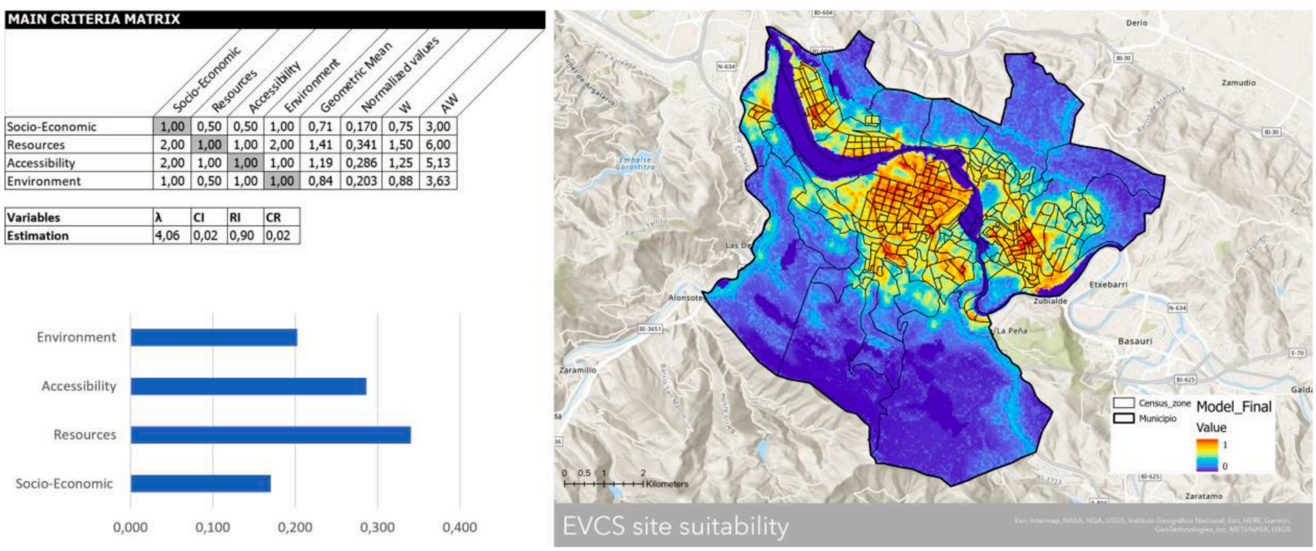


Fig. 16. Main criteria for AHP scoring and Fuzzy-based mapping of EVCS site selection.

Table 6
Weights of evaluation criteria via AHP.

C1 Accessibility		C1.1 Public transportation		C2 Socioeconomic		C3 Resources		C4 Environmental	
C1.1	0.138	C1.1.1	0.665	C2.1	0.333	C3.1	0.333	C4.1	0.167
C1.2	0.136	C1.1.2	0.086	C2.2	0.667	C3.2	0.333	C4.2	0.167
C1.3	0.130	C1.1.3	0.204			C3.3	0.333	C4.3	0.333
C1.4	0.265	C1.1.4	0.044					C4.4	0.333
C1.5	0.130								
C1.6	0.050								
C1.7	0.152								
Total	**0.286**				**0.170**		**0.341**		**0.203**

5.3. EVs and EVCS penetration in the case study

The typical power capacity of an EVCS for fast chargers ranges from to 7-22 Kw (Mostyn, 2021). In this case study, charger points with power capacities of 22 kW were considered to measure the potential number of EVCS. An average EV battery value of 40 kWh was selected to estimate the load distribution at the charging points. Fig. 18 shows the hourly solar energy generated hourly on March 21st, June, and December. These days represent the average, maximum, and minimum solar capacities during the year. Solar energy generation started to rise at 6, peaks at 12, and decreases from 13 to 17. Chart illustrates the energy consumption of different numbers of EVs and solar power potential in Substation 1.

According to our findings, substation1 could fully supply two on-

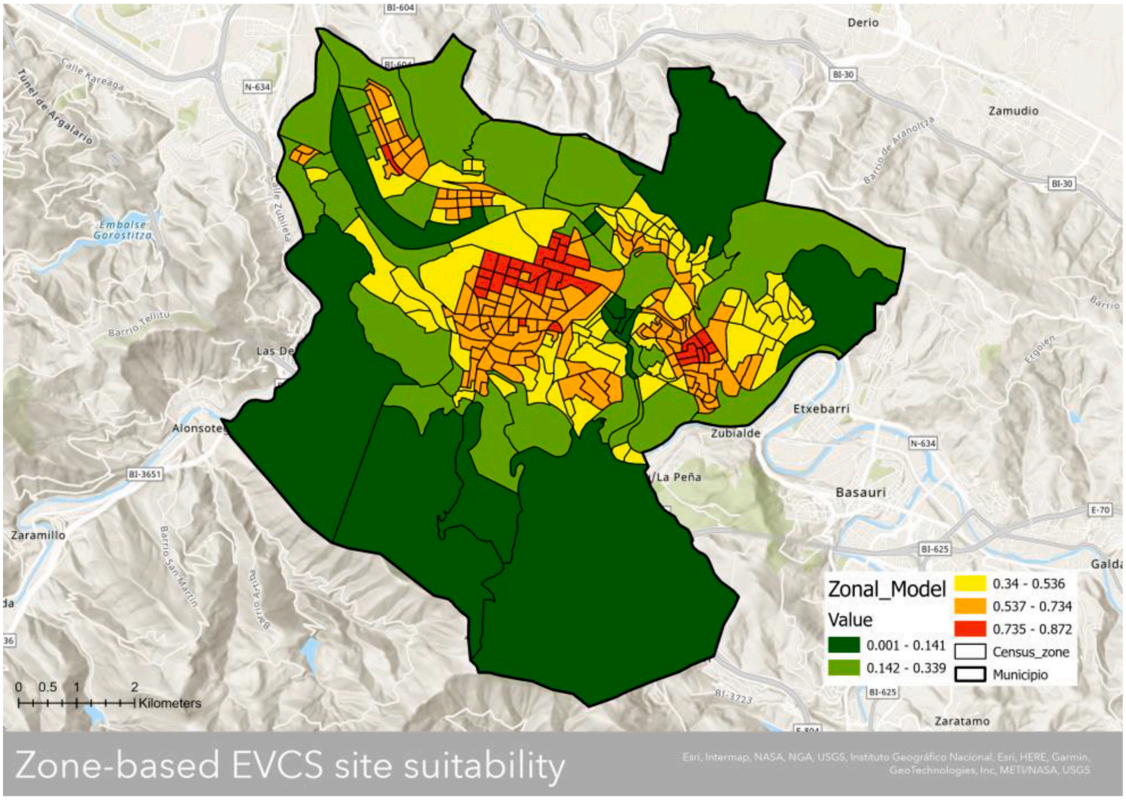


Fig. 17. Zone-based site suitability of EVCS.

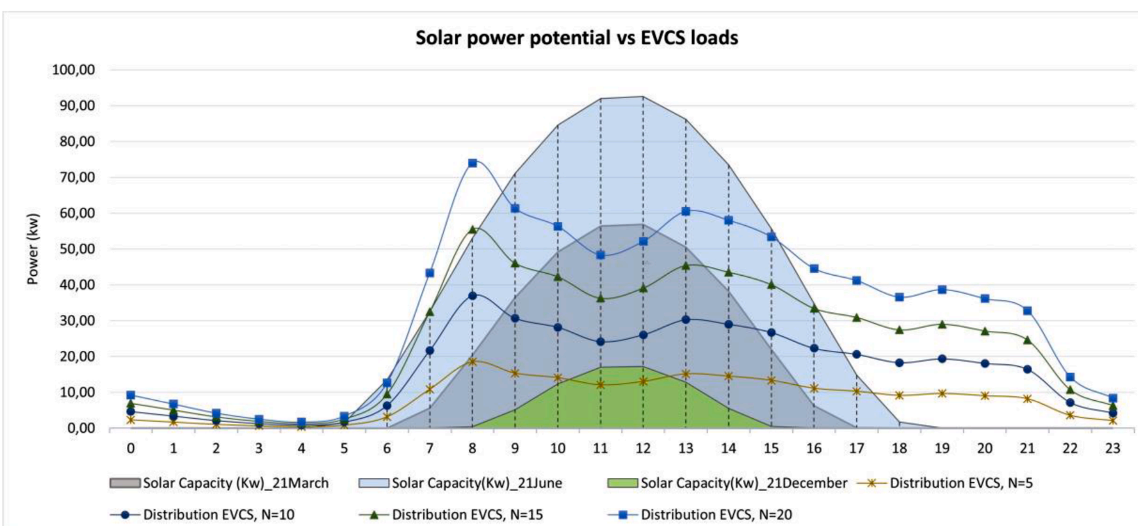


Fig. 18. Solar power generation potential vs. EVCS loads in substation 1.

Table 7
Solar capacity and building energy demands of substations.

Substation number	Solar power (kWh/day)	Building energy demand (kWh/day)
1	342	2833
2	204	3249
3	560	4687
4	626	5311
5	607	3338

street charging piles with solar energy between 10:00 and 14:00. Additionally, for substation2, one charging pile was fully powered between 10:00 and 14:00. However, the remaining substations could entirely support the charging demand of the three charging piles using solar energy from 10:00 to 15:00. The solar power of the building's rooftops on March 21st is represented in Table 7. The ENERKAD tool calculates the total energy demand of buildings connected to substations on the same day.

The solar energy potential for meeting the energy demand of buildings is relatively low, as this corresponds to a dense and high-rise district. It is important to note that the designed capacity of the substations is sufficient to cover the total energy demand, leaving some surplus

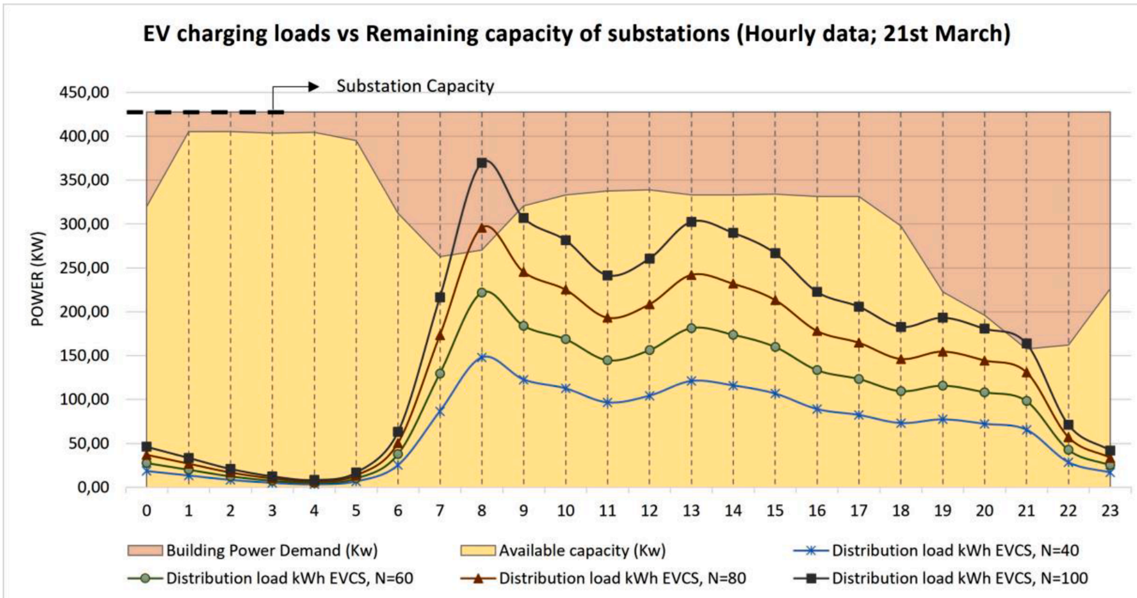


Fig. 19. EV charging loads vs. available capacity of substation number 1.

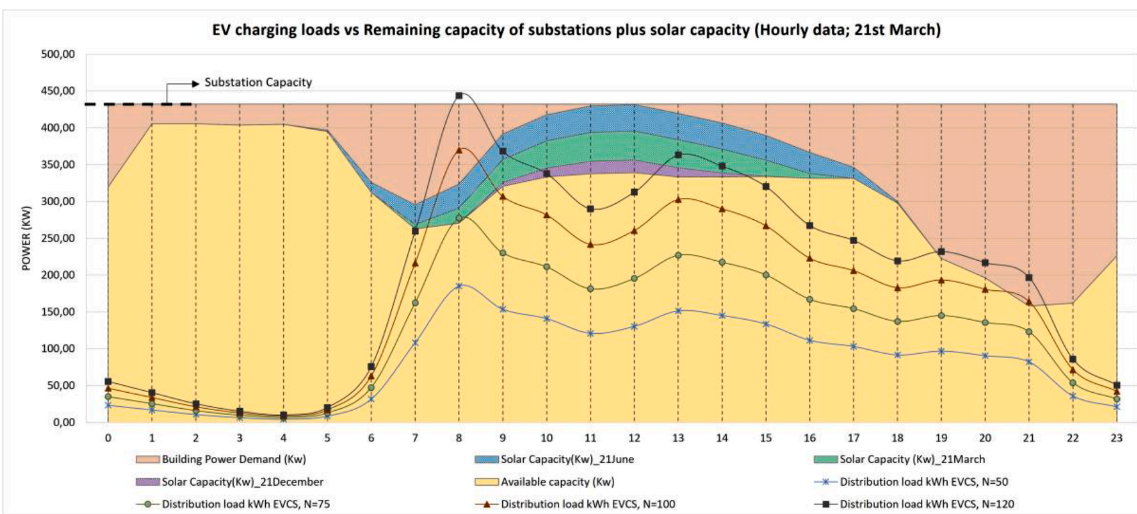


Fig. 20. EV charging loads vs. available capacity in substation number 1, including solar capacity.

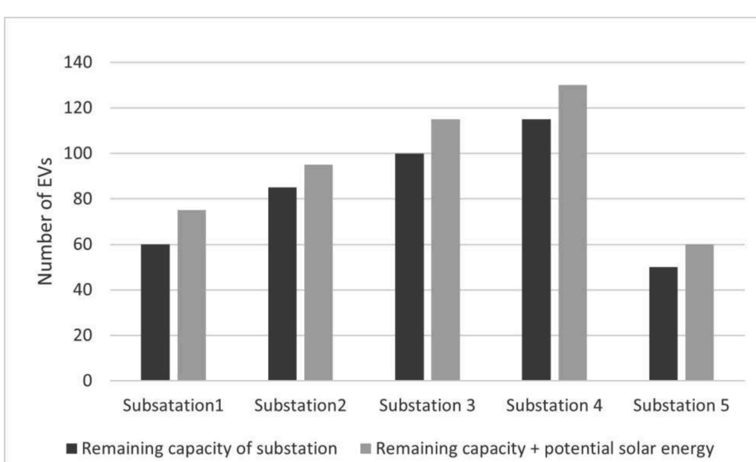


Fig. 21. Number of EVs based on available energy in substations.

power or remaining capacity throughout the day, depending on the actual distribution of the electricity use. In substation 1, this remaining capacity sharply declines from 17 to 22 o'clock, when residential electricity use was at its peak. Considering the EV charging profiles, Fig. 19 shows that up to 60 EVs can be charged during the day without exceeding the remaining substation capacity.

Substations 2 and 3 have sufficient capacity to charge 85 and 115 electric cars, respectively. With the defined distribution histogram, substation 4 had sufficient power to charge 115 EVs during the day. For substation 5, only 50 electric vehicles were charged daily. Fig. 20 illustrates the potential number of EVs that can be charged through the available capacity of substations and imported solar generation on March 21st, June, and December. This demonstrates the relative importance of using the available capacity of substations, both with and without solar energy. Notably, we assumed that the daytime energy demands of the building would remain consistent across these three time slots. According to the following chart, 75 EVs can be charged:

Fig. 21 shows the potential number of EVs based on the available energy for each substation. On average, 16% more EVs can be supplied using solar power on building rooftops. The solar potential was estimated on March 21st, a representative day for the average performance.

6. Conclusion

This project contributes to the literature by developing a novel methodology for integrating EVCS with solar energy and power distribution systems with high spatial resolution. In this study, a novel decision framework was developed that integrates MCDM and GIS for EVCS placement. In addition, a highly spatially explicit tool was designed in ArcGIS Pro to estimate the solar potential of rooftops at the local and municipal levels. Minor modifications can make the scalable methodology applicable to any case study. Moreover, an advanced approach was proposed to integrate the PV and EV systems to charge the EVCS.

Given the high cost of implementing an EVCS, determining suitable locations is essential for developing an e-mobility infrastructure. Although various factors are involved in the placement of EVCS, a methodology for evaluating the feasibility of developing charging points that are integrated with solar PV systems must be developed. Therefore, this study proposes a spatially feasible approach for developing an EVCS that incorporates solar energy at the district level. This study determined the best location for developing an EVCS and integrating solar energy with the power distribution grid. This methodology proposes a "PV + EV" system to mitigate the burden on the power grid and the penetration of more electric vehicles.

There is widespread agreement on the use of RES for charging electric vehicles, aiming to mitigate CO_2 emissions. Hence, this geospatial tool was developed to estimate the solar energy generation potential in Bilbao City, and can be applied to any city or region, regardless of size or location. The results of the solar tool are required for public EVCS placement and energy profile analysis to distribute the EVs and charging stations. In addition, the results show that PV installations in suitable parts of Bilbao's buildings can generate ~205 GWh of solar energy annually, accounting for 23% of the power demand of the built environment.

According to the site suitability map for the EVCS, both the city centre and a smaller region in the eastern part of Bilbao are found to be the most suitable for developing new charging points. The reasons for this include their proximity to amenities, high availability of resources, and high demand for EVCS in these areas. It is worth mentioning that these results are based only on the judgments of smart grids' and energy experts'. The results could vary if experts from different fields such as urban planning, transportation, engineering, and local stakeholders participated in the survey. The indicators used in this study were selected based on the findings of a literature review. Owing to the complexity and diversity of the urban system, it is more realistic to select these indicators based on the judgment of local experts and stakeholders. Furthermore, because Bilbao is still at the initial stage of developing EVs, it is advisable to establish these facilities in areas with upper-income households. However, including sites with lower-income families could be part of mid- or long-term planning.

To analyse the energy profile of the EVCS precisely, a case study was selected based on a site suitability map. This analysis aimed to estimate the potential number of EVCS and penetrating EVs based on the relative frequency of EV charging during the day. The results indicated that it is possible to charge 16% more EVs by transmitting solar energy to the substations without increasing their distribution capacity. Solar energy provides sufficient power and reduces the pressure on the power grid, thereby enabling the charging of more electric vehicles.

There are several limitations to the framework of this study that should be addressed in future research. Regarding the solar tool, a potential improvement involves estimating solar energy generation from building façades, and further enhancements could focus on increasing the temporal resolution to hourly analysis or including multiple timeslots to capture the solar potential and energy demand for an entire year. Furthermore, instead of considering limited specific days, as in this study for solar potential, a scenario-based analysis can cover the probabilities and uncertainties of EV distribution and solar energy production. Furthermore, the parametric solar tool does not consider the effects of daylight saving time, owing to the complexity and scope of this research. Therefore, future studies should explore the role of daylight-saving time in solar energy generation.

To improve the EVCS placement approach, the integration of optimisation methods into this MCDM-based framework can effectively incorporate sustainability criteria. This approach optimises the sizing and placement of the EVCS while considering the grid dynamics. Furthermore, it may be beneficial to propose short-, mid-, and long-term scenarios for the penetration of EVs, and develop a methodology for car sharing. Regarding PV integration into the EV system methodology, this study did not consider multiple uncertainties such as EV arrival/departure time, state of charge (SoC), and PV power. In future work, advanced scheduling algorithms, real-time data integration, information sharing, and advanced optimisation methods can be considered to improve grid stability and manage these uncertainties. Moreover, this study overlooked the dynamic nature of EV charging behaviour by using a simplified approach to estimate the EV load based on the number of cars served. It does not consider factors such as the simultaneous arrival of EVs, availability of charging piles at the EVCS, or queue times that can affect the EV load curve. Moreover, this framework must consider charging patterns, station capacities, and demand variations to reduce the complexity of the model.

CRediT authorship contribution statement

Komar Javanmardi: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Patxi Hernández:** Writing – review & editing, Writing – original draft, Validation, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Xabat Oregi:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology.

Declaration of competing interest

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

Data availability

No data was used for the research described in the article.

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