Strategic Locations of Electric Vehicle Charging Facilities Utilizing Mixed-Integer Linear Programming and Genetic Algorithm Models

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ABSTRACT: *Electric vehicles have experienced significant advancement through technological innovations and robust policy support, leading to increased demand for charging stations. The challenge is notably critical for addressing the charging requirements of the increasingly numerous fleets of vehicles powered by alternative fuels. This paper introduces a new practical method for the optimal placement of charging stations within urban transit networks for electric vehicles and propose a method that employs Mixed Integer Linear Programming and Genetic Algorithms to determine the optimal locations for charging infrastructure in urban environments. Our method employs data on traffic patterns and types of land use, alongside multiple constraints, to optimize the siting of new electric vehicles charging stations. The effectiveness of this approach is shown through a practical example in Madrid, Spain.*

KEYWORDS -*Electric Vehicles, public EVs charging stations, charging demand, optimal location, MILP, GA.*

I. INTRODUCTION

The strategic positioning of electric vehicles (EVs) charging stations (EVCEs) within expansive transportation networks, along with battery electric vehicles, is broadly recognized as an effective and sustainable strategy to lower traffic-related emissions, encompassing greenhouse gases.

The anticipation is that EVs will eventually become a practical substitute for fossil fuel-driven vehicles. Acknowledging their beneficial effects, it's essential to overcome two primary obstacles to ensure electric vehicles (EVs) receive widespread market approval: their limited driving range and scarce charging facilities. Addressing the restricted range requires a calculated placement of charging infrastructure along the most frequented routes. Moreover, it should be feasible to access at least one charging station from any starting point within the transport network before the vehicle's battery is depleted [1], [2].

The issue of EVs not being able to reach their intended destination before their energy source is completely exhausted is known as range anxiety. This can lead to psychological stress for drivers. Therefore, a crucial question for decision-makers and stakeholders in promoting market acceptance of EVs is where to place charging stations [3], [4].

A strategic layout of charging facilities can help mitigate range concerns for electric vehicle owners and also decrease the upfront expenses involved in setting up new charging points, while at the same time lessening the load on the electrical grid.

Despite their higher initial cost, electric vehicles can lead to considerable savings in maintenance and running costs for owners.

Nevertheless, for EVs to become prevalent in urban transportation, and to hasten the shift from traditional to electric vehicles, it is crucial to remove barriers and implement policies that foster the adoption of these innovative vehicles. Cities, anticipating this shift, must gear up to integrate EVs seamlessly into their transportation matrices.

EVs operate on electrical power, store energy in onboard batteries, and require regular charging. The limited range of these batteries, often no more than 100–200 km, along with the significant time needed for recharging, which can span from 20 minutes to 8 hours, pose considerable challenges.

The charging duration for an EV is contingent upon both the vehicle's specifications and the charging infrastructure's capability and technology. Charging points can be installed at residences, offices, private properties, and public locales. The availability of charging facilities in public areas is deemed critical to the success of electromobility by reducing 'range anxiety'—drivers' concerns about running out of battery far from home or the workplace.

There is also a burgeoning field of research dedicated to optimizing the placement of EVCEs. Various optimization techniques have been introduced to solve the puzzle of where to locate EV infrastructure, typically focusing on maximizing user convenience or minimizing travel and charging time costs.

II. LITERATURE REVIEW

The strategic and optimal siting of new EVCEs is a critical element for the successful development, and this challenge has garnered significant interest within the research community. Numerous approaches for the optimal distribution of EVCEs within a transportation network have been suggested in scholarly articles. These proposed strategies can be broadly categorized into several types as proposed in [5]:

- Flow-capturing models (e.g. [6, 7, 8, 9]).
- Set-covering models (e.g. [10, 11]).
- Vehicle movement simulation models (e.g. [12, 13]).
- Agent-based models (e.g. [14]).
- Equilibrium models (e.g. [15, 16, 17]).

In Table I, some of the most significant existing works are reviewed.

[18]	Propose a decision support system grounded in agent-based modeling to guide the placement of EVCEs.
[19]	In a different approach, is constructed a two-phased model that integrates traffic allocation with stochastic user equilibrium and the principle of entropy maximization.
[20]	Introduces a planning model that considers multiple objectives, drawing on the demand patterns observed at traditional gas stations.
[21]	A multi-criteria optimization framework incorporating spatial factors is employed.
[22]	The authors put forward a strategy for distributing charging facilities along major highways.
[23]	An integer-programming model is formulated, that concurrently resolves routing for vehicles and the location of EVCEs, with the aim of minimizing overall costs, which include travel, recharging, and implementation expenses.
[24]	Propose a mixed-integer programming method using parking necessity as a stand-in for the demand for electric vehicle (EV) charging, aiming to reduce travel expenditure.
[25]	Apply an active set strategy for the strategic placement of charging points for hybrid plug-in vehicles, targeting the amplification of community benefits. Emphasize the importance of including public charge points and electricity tariffs in the initial planning stages.
[26]	The authors concluded that the optimal location of EVCEs facilities is contingent on the chosen optimization parameters, but the level of service offered does not vary.
[27]	Examine strategies for positioning stations along highways, devising an algorithm that minimizes the detour from planned routes.
[28]	It takes advantage of the particle swarm optimization (PSO) technique to develop a scheme for the ideal layout of charging stations, with the aim of reducing the duration of aggregate transportation.
[29]	Uses OD data combined with a dynamic consumption model for Lyon, aiming to lower the fixed costs of charging stations and vehicular movement expenses. Their findings advocate for the installation of semi-rapid chargers in public parking areas and swift chargers at gas stations, based on an analysis that calculates a minimal time distance among the demand clusters and integrates consumption details.
[30]	The authors fashioned a model to ascertain the optimal quantity and placement of chargers within existing parking facilities.

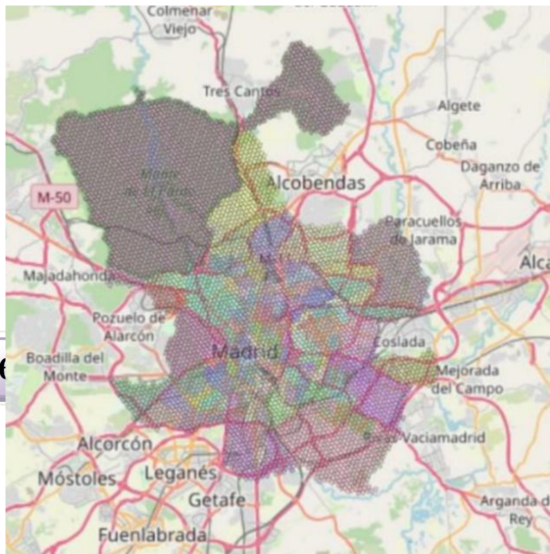
[31]	It delves into how the residual battery life and consequent driver conduct affect EV charging habits, using stochastic frontier analysis.
[32]	Explores the effect of charging station siting on network efficiency. Integrating charging necessities into a distance-limited equilibrium framework, they scrutinized alternative sites for charging.
[33]	This article proposes a two-tier optimization approach aimed at reducing the risk of fuel depletion as well as the overall travel duration within the network, using a probabilistic model for the remaining fuel range.
[34]	In this work is utilized a two-tiered stochastic queuing model for locating charge points specifically for electric taxis.
[35]	The authors introduced a graph-theoretical approach reliant on demand and supply, with the objective of minimizing the sum of investment and operational costs.
[36]	This paper conducted a comprehensive study on the use of genetic algorithms (GAs) for addressing various facility location challenges, including capacitated and un-capacitated fixed charge, maximum coverage, p-median, and centroid issues. Their research indicated that while GAs may take longer to produce solutions compared to other optimization methods, this does not detract from their utility in strategic decision-making scenarios such as facility location, often yielding superior outcomes with the exception of fixed charge location problems.
[37]	Introduces a GA-based method that integrated grid partitioning for identifying EV charging spots.
[38]	AGA is applied to minimize the aggregate costs in facility placement.
[39]	This paper design a GA framework aimed at reducing 'range anxiety', which they defined as the total number of unfulfilled trips within a network. This was done using GPS data from standard vehicles and a survey on household travel preferences.
[40]	The issue of placing electric vehicle charging facilities in Thessaloniki is examined using Origin-Destination data from traditional vehicles. A maximum coverage algorithm is applied, and a sensitivity analysis is conducted to ascertain the ideal number of charging stations required in the city.

III. STUDY AREA

Madrid city, encompassing roughly 605 km², is the focus area for this study. The applied models take into account several key aspects linked to the geographic characteristics of the area, such as traffic patterns and charger accessibility, influencing the optimal placement of EVCEs based on the distribution and demand for charging. Charging needs in this research are determined using daily traffic counts at various locations. Traffic flow measurement points are unevenly spread and may not exist in some regions, leading to the creation of a grid network to efficiently utilize traffic flow data.

In this study, geospatial analysis plays a crucial role in integrating economic, social, and technical elements. The study area is divided into grid sections to chart the distribution of EV charging requirements, based on land use types. As depicted in Figure 1, the area is segmented into uniform small grids, with the center of each grid serving as a demand node for ease of study. Both the grid side and the charging station's service radius are set at 500 meters, considering this as the maximum distance drivers are willing to walk to charge their vehicle.

Various land-use categories such as villa-dominated residential areas, apartment complexes, business sectors, commercial areas, and mixed-use spaces have been identified to diversify charger types and enhance electric vehicle charging options in different locales. The assumption is that rapid charging stations would be located in commercial or mixed-use areas, whereas slower charging alternatives would be installed in business zones or regions primarily made up of apartment structures. Moreover, in zones where people are likely to pause and remain for a while, like commercial, business, and residential districts (excluding residential areas with villas, as the inhabitants there typically possess home chargers), the likelihood of charging an EV is high. Conversely, in regions where individuals do not linger, such as forests or



agricultural lands, the possibility of charging is extremely low or even non-existent. A single grid may encompass multiple types of land-use.

Fig. 1. The grid covering the study area is color-coded according to different neighborhoods. (Madrid City).

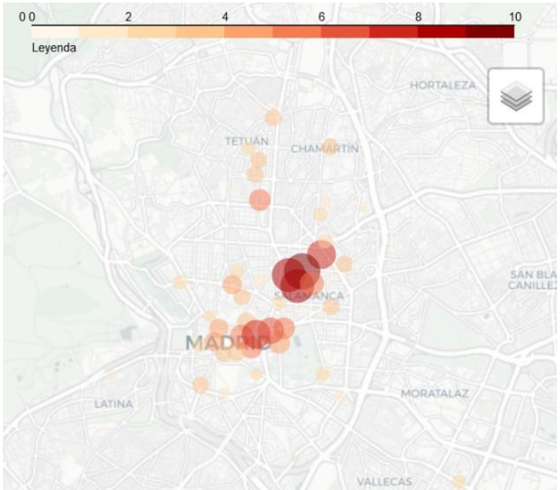
IV. DATA

To project the upcoming need for electric vehicle charging in Madrid, an analysis utilizing the city's traffic data was carried out. This analysis leveraged a dataset accessible via datos.gob.es, which compiles data on traffic incidents within Madrid as compiled by the municipal government. Spanning from 2013 to 2023, this dataset is categorized into several segments that ease the breakdown and understanding of the city's traffic patterns. Detailed information on the composition of each file within the dataset is outlined in accompanying documentation, which spans the selected timeframe. It's imperative to note data discrepancies observed between the pre- and post-2019 records, a result of alterations in the dataset's structure. Such inconsistencies are a familiar obstacle faced by data analysts during the data preprocessing phase, arising from an absence of a standardized structure throughout the dataset's timeline. These inconsistencies may manifest as changes in the count and types of variables or the units of measure employed. Highlighting the necessity for exhaustive documentation for each open data set is essential, ensuring clarity on its structure for accurate and meaningful analysis.

V. METHODOLOGY

For an effective EVs charging station deployment strategy, comprehending the charging demand is crucial. Recognizing the patterns of EVs charging demand, as illustrated in Figure 2, is pivotal for the strategic positioning of charging infrastructure. Given the typically dispersed layout of charging facilities, the paucity of comprehensive data often hinders the accurate modeling of demand. Therefore, it is critical to establish a model that correlates EVs charging requirements with supplemental data like Points of Interest (PoI) and traffic flow. These correlations not only facilitate a deeper insight into the charging demand but also elucidate the drivers influencing this need. Furthermore, such a model permits the forecasting of prospective demand at proposed sites, even in the absence of historical usage data, by considering these ancillary factors. Furthermore, the anticipated demand at a potential location where no past demand data exists can be forecasted using external factors.

Charging needs were derived from the daily vehicular traffic volume at various monitoring points. Due to the irregular distribution of these traffic flow points, and their absence in certain zones, a grid matrix was developed to



estimate the mean traffic volume within each grid section. For grids lacking direct measurement data, the traffic volume was inferred from the average of adjacent grids.

The categorization of land usage also played a role in identifying prime spots for different types of charging stations. It is presumed that rapid charging stations would be situated in areas zoned for commerce or mixed uses, whereas residential regions, particularly those with apartment buildings, would be equipped with slower charging options.

Fig. 2. EV charging demand.

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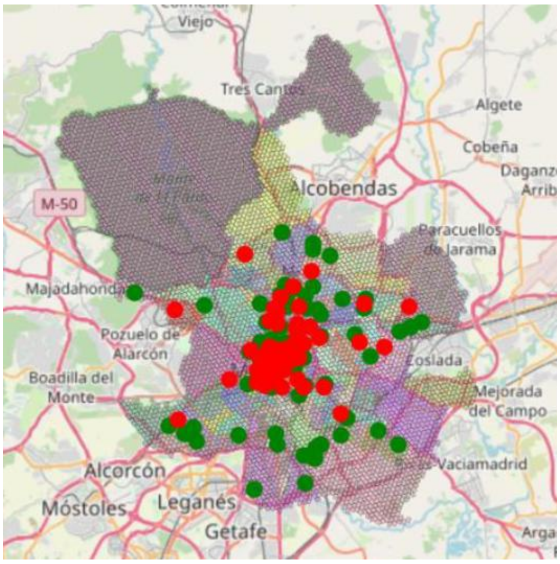
Figure 3 illustrates potential locations for EV charging (marked with red dots), selected primarily from council-managed parking facilities due to the easy accessibility of this data. The figure also highlights current EV charging stations (marked with green dots), indicating regions where the demand for charging is already satisfied. Our strategy requires the integration of this information to pinpoint the car parks that present the highest



need for charging infrastructure.

Fig. 3. Potential and existing EV charging.

Furthermore, various decision support system models are commonly employed in this domain. The most widespread among these is the MILP model (LP/NLP) [41, 42, 43, 44], favored for its established track record and versatility in tackling optimization problems. Additionally, the Genetic Algorithm (GA) has gained traction for efficiently determining the best configuration using origin-destination data [45, 46]. Moreover, multi-objective and multi-criteria decision models are utilized to address and balance multiple competing objectives [47, 48] when determining the ideal site for charging facilities.

In our study, we use mixed integer linear programming (MILP) and GAs to determine the most beneficial locations and capacities to install charging stations.

Initially, a GA is formulated that requires a list of possible EVCEs points (potential locations), with their coordinates, the anticipated charging demand and the distances between these locations as input. The analyst must also define additional parameters such as the size of the initial population, the probability of crossover between pairs of chromosomes, and the probability of mutation on an original chromosome. The output of the GA includes the locations of the stations and coverage nodes, which are displayed on Google Maps.

Conversely, MILP is employed to ascertain the ideal features of charging stations, aiming to maximize overall profits while adhering to five primary constraints. The MILP model employs a function to maximize the aggregate profits of all new EVCEs. In this model, the key variables include the positions of the EVCEs, the number of fast or regular chargers needed at each station, and the charging demands met by each station.

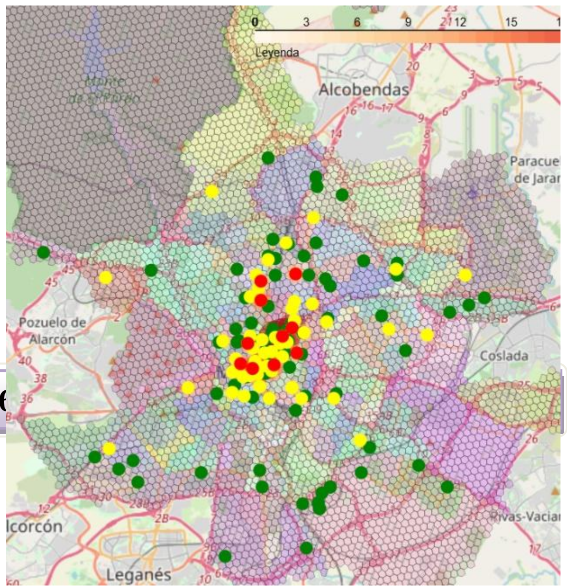
Meanwhile, a few indicators are used to evaluate the performance of the models:

• The objective function gain.
• Benefit of the gain.
• Time cost.

All algorithms and experiments were developed in Python and conducted on an Intel Core i7-12700 CPU with 32GB memory and a GeForce-RTX-3070-Ti-GPU (NVIDIA).

VI. RESULTS

When the optimization is constrained to the deployment of only 10 new EVs charging stations, the results depicted in figure 4 are obtained. The stations are strategically placed along the busiest entry points to the city, which correspond to areas with heightened charging requirements. Furthermore, the pinpointed locations for chargers are concentrated around zones of commercial or mixed utility, including



supermarkets, shopping centers, and dining establishments. It is also evident that a larger fraction of the EVCEs is positioned on the periphery of the city's core (top-center of the image). This distribution is deliberate, given that roughly one-quarter of all current EVs charging facilities are centrally located, adequately serving the demand in that sector.

Fig. 4. Potential (yellow), existing (green) and new calculated (red) EV charging.

VII. CONCLUSION

European nations are anticipated to support the transition to electric mobility within their city transportation systems. To alleviate the apprehension commonly known as "driver anxiety"—the fear of an electric vehicle's battery depleting—there is a need to establish extensive public charging networks. The goal of this research is to provide an optimal strategy for the rollout of EV charging facilities, utilizing a MILP framework alongside GA methodologies.

The strategic positioning of EVCEs is largely influenced by the spatial patterns of vehicular traffic and the varied charging opportunities that arise from land-use categorization, underscoring the significance of geographic data in the optimization equation.

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