1. Introduction

The transformation of the global automobile industry toward electric mobility is underway. Many factors may influence the EV market penetration:

Anxiety of Range: The phenomenon termed “range anxiety” is common among potential EV owners. Range anxiety refers to the worry that an EV has insufficient reach to get to its destination and would leave the driver stranded. It is one of the key barriers to EV adoption [5]. This fear can be mitigated by the availability of a comprehensive, convenient, and reliable charging network, thus directly linking EV market penetration to charging infrastructure [6].

Which trend?

Infrastructure: A critical factor influencing this trend is the availability and accessibility of Electric Vehicle (EV) charging infrastructure. It has been widely studied and proven that the prevalence of charging stations strongly influences the acceptance and adoption of EVs [1] [2] [3] [4]. In the U.S., a positive correlation between public infrastructure and EV uptake haseen proven [4]. When charging infrastructure was more available and accessible, the likelihood of consumers purchasing an EV increased. Moreover, a study examined the influence of various factors on international electric vehicle policies and EV sales in 30 countries [7]. They found that charging infrastructure was among the most substantial determinants of national electric vehicle market share [8].

Policies and Regulations: Government policies also play a crucial role in the proliferation of charging stations and, consequently, the promotion of EV adoption. Incentives like grants, subsidies, and tax reductions have been applied in various countries to accelerate the deployment of EV charging stations [9]. Such policy measures have substantially impacted both the expansion of charging infrastructure and the adoption of electric vehicles.

EV Prices, Battery Capacity: While the charging infrastructure is a significant factor, other elements like EV prices, government subsidies, and battery capabilities are also key contributors to EV market penetration [9]. Reductions in battery prices and improvements in battery technology have increased the affordability and driving range of EVs, thereby supporting the growth of the EV market. Nevertheless, widespread EV adoption remains a challenge without an extensive and reliable charging network.

1.1 Factors Affecting Charging Station Location

The decision regarding the ideal placement of Electric Vehicle Charging Stations (EVCS) is a sophisticated process encompassing a plethora of considerations. Several interrelated quantitative and qualitative factors influencehis decision, including but not limited to operator economics, driver satisfaction, vehicle power loss, traffic congestion, and power grid safety [10].

add year

Falvo et al.'s work illustrates the role of reducing energy consumption by exploiting the capabilities of existing power plants. They draw attention to the interconnectivity of different transportation systems - EVs and subways - highlighting the potential for symbiotic relationships to optimize power usage. Their research sheds light on the strategic importance of aligning EVCS locations with the current power grid for energy efficiency, operational economics, and grid safety. It serves as a reminder that the placement of charging stations should be an integral part of broader urban energy planning [11].

Guo et al. present an alternative approach to the problem, employing a fuzzy TOPSIS method to assess potential locations. Their approach considers practical or economic factors and a broad array of environmental, economic, and social benchmarks. This underscores the importance of a holistic, multi-faceted evaluation process for locating EVCS. Beyond the fundamental requirements of power supply and accessibility, Guo et al. emphasize the need to assess potential locations' broader societal impact, environmental implications, and economic viability. These findings underscore that the decision-making process should not be limited to infrastructure and logistics alone but should strive to align with wider sustainable development goals [12].

Similarly, Asamer et al. propose a comprehensive, integrative approach to the placement of EVCS. They contend that several variables must be factored into the decision-making process, ranging from environmental conditions to the availability of power and legislative considerations. Significantly, they also highlight the importance of empirical data, employing taxi data as a proxy to assess charging demand. The utilization of real-world data, they suggest, can provide invaluable insights into patterns of use and potential demand hotspots, thus allowing for more targeted and effective placement of charging stations [13].

Building upon this foundation, Zhu et al. introduce an economic perspective into the analysis, evaluating how costs - both to the user and those associated with establishing and operating the charging stations - impact the final number and location of EVCS. This underscores the need for a detailed cost-benefit analysis as part of the decision-making process. It also raises an important question of user satisfaction and accessibility, emphasizing that the locations need to be convenient for the end users to encourage uptake and continued use of EVs [14].

Complementing these perspectives, Sun et al. propose an innovative, user-centric approach. They consider residents' travel patterns, categorizing them as either short-distance or long-distance travelers. This differentiation aids in determining not only the optimal location for charging stations but also the appropriate number of stations needed. It serves as a reminder that the deployment of EVCS should not be a one-size-fits-all solution. Instead, it should be tailored to meet local residents' needs and ensuring maximum usability and efficacy [15].

In summary, the complex interplay of factors affecting the location of EVCS necessitates a multi-faceted and integrative approach. The studies mentioned above underline the need for strategies that balance technical requirements, economic feasibility, societal impact, and end-user needs. Through this careful balancing act, the optimal location for EVCS can be determined, thereby promoting widespread EV adoption and the resultant environmental benefits. The findings from these studies collectively demonstrate that the placement of EVCS is an intricate process, interweaving numerous factors and requiring comprehensive, multidimensional planning and assessment [10] - [15].

1.2 Optimization Models for EV Charging Station Distribution

This section discusses various optimization models proposed by researchers for the distribution of EVCS. These models consider a broad spectrum of factors to help enhance the adoption of EVs and user satisfaction.

Frade et al. used a maximal covering model to identify potential demand areas and possible EVCS locations in Lisbon, aiming to maximize covered demands [16]. He et al. proposed a double-layer mathematical model considering vehicle driving distances and charging needs, underlining the importance of daily mobility patterns of EV users [17].

Shahraki et al. presented an optimization model maximizing vehicle mileage based on driving patterns, emphasizing the role of real-world data in location decisions [18]. Wu et al. designed a stochastic flow-capturing location model reflecting the randomness in EV users' traveling behavior [19].

Models by Tu et al. and Luo et al. included temporal and spatial constraints, making these models more realistic by considering variable parking availability, congestion levels, and EV owners' home and work locations [20] [21].

Battery characteristics have been factored into models by Liu et al. and Mehrjerdi et al., highlighting the need for different strategies for different charging applications, and the importance of power and capacity of charging facilities [22] [23].

He et al. and Davidov et al. incorporated economic aspects in their models, considering costs such as battery, charging station, and energy storage system expenses [24] [25].

Hosseini et al. integrated quantitative and qualitative aspects into their models, underlining the importance of subjective factors and user experience [26] [27].

Zeng et al. integrated human behavior into their station-level optimization framework, pointing out that station networks must accommodate user preferences [28].

Hodgson et al. further refined the models by considering EV charging during long trips and the limited range of EVs, which resulted in the Flow Refueling Location Problem (FRLP) [29] [30] [16].

The FRLP model has been extended to consider limited charging station capacity, alternative paths, different types of stations and vehicles, and congestion at stations [31] [32] [33] [34] [35] [36] [37]. Multi-period deterministic extensions of FRLP have been suggested, allowing for a dynamic opening of new stations and considering limited station capacity [38] [39].

Few studies have addressed uncertainties in EV charging infrastructure planning, such as unpredictable driving range or variability in recharging demand. Some recent works have introduced the concept of portable charging stations and advocated for robust optimization approaches [40] [41] [42] [43] [44].

These diverse models demonstrate the multi-faceted nature of EVCS placement and the need for comprehensive, flexible approaches incorporating demand characteristics, technical specifications, cost factors, and human behaviors to promote EV adoption and environmental benefits [16] - [28].

1.3 Algorithm for Optimal EV Charging Station Configuration

This section discusses various optimization techniques used to determine optimal configurations of EVCS. The methods include optimization methods, genetic algorithms, decomposition algorithms, clustering methods, and combinations of these techniques.

Sadeghi-Barzani et al. used a mixed-integer non-linear programming (MINLP) optimization method and a genetic algorithm to find the optimal EVCS location and scale [45]. Arslan et al. utilized the Benders decomposition algorithm to optimize EVCS location, aiming to maximize mileage and minimize transportation costs [46].

Zhang et al. introduced a decentralized valley-filling charging strategy that used a cost-minimization pricing scheme, emphasizing the importance of pricing mechanisms [47]. Dong et al. applied the SNN clustering algorithm for optimizing EVCS placement on expressways [YYY].

Zhu et al. and Akbari et al. used genetic algorithms for optimizing EVCS locations, acknowledging the interplay between technical specifications, user charging demand, and spatial factors [48] [49]. Awasthi et al. combined a genetic algorithm with particle swarm optimization to determine optimal EVCS location and size [50].

Particle swarm optimization algorithms have been used by Li et al. and Chen et al. to determine EVCS deployment strategy and charging facility distribution [XXXX] [51]. Clustering methods like k-means cluster analysis were employed by Zhang et al. and Straka et al. to understand dynamic charging demand trends and user behavior [52] [53].

Wu et al. used approximate dynamic programming and an evolutionary algorithm to determine optimal charging start times for EVs, demonstrating the interest in smart charging strategies [54].

Despite these advancements, the article identifies gaps, including the lack of comprehensive analyses considering total social cost, underutilization of genetic algorithms, and limited case studies of specific charging station scenarios, like those in Ireland.

To address these gaps, the article proposes an optimal distribution model of EVCS based on total social cost, utilizing a genetic algorithm for iterative simulation. This model deviates from traditional reliance on Euclidean distance and includes a road bending coefficient. The article also incorporates a case study of Ireland, reflecting actual EV charging demand in five major cities. This approach provides a promising direction for future EVCS optimization research [45] - [54].

Very well display of the state-of-the-art!
Maybe parts of it can be moved towards
a state of the art chapter.

1.4 Structure of this work and novelty

This section aims to summarize the fundamental points of this work and the innovations compared to similar works. The first peculiarity is to approach the problem using graph

In the intoduction you should motivate for your topic and the approach you are choosing:
1) Why is there a research gap (--> Why are all the papers and approach not perfect yet,
OR what is the difference to your work and why is that important?)
2) In general try to make a motivation for your approach in chapter 1.4

theory. Each charging station is considered a point (of which latitude and longitude are known) and is connected to every other point below a search distance. This distance is calculated as road distance (including one-way streets and dead ends) and therefore, represents a good approximation. Each edge of the graph is weighted with the distance between the two points that the branch connects. By doing so, a national graph is obtained from which it is possible to calculate parameters useful for optimization (e.g., diameter). Using these parameters ensures that positioning the charging stations not only follows the logic of demand-population (which creates large urban agglomerations as in the case of Berlin), but also improves the network by including peripheral areas and connecting points that, before, were divided. This way, clusters are not created in Munich and Berlin, but points are also inserted so that Munich and Berlin can be reached by car at a finite number of stations/stops.

A genetic algorithm was used to optimize the network as it is the most flexible to consider multiple parameters. Another novelty in the work is that predictive methods have been used within the algorithm to identify the optimal position for the initial population. This is done to obtain a more plausible provision and, indirectly, mimic the different economic and political positions of the various Lands on this issue. To accentuate the objective of extending the network to the suburbs, in addition to the parameters of the graph, the relationship between the area covered by the network and the territorial extension of Germany is also used.

The first sction should have something like: Research objectives. This is where