Review of Literature: Pioneering Approaches to Electric Vehicle Charging Stations

In the realm of sustainable transportation, the optimal placement and distribution of electric vehicle (EV) charging stations has garnered significant attention in recent years. Numerous researchers have focused on this crucial challenge, viewing it through different lenses such as location-influencing factors, model construction, and related algorithms. This review summarizes key findings from these studies, providing insights into the pressing challenge of strategically situating EV charging stations for maximum efficiency.

## Factors Affecting Charging Station Location

A variety of considerations, both quantitative and qualitative, can impact the location of EV charging stations. Researchers have emphasized the role of operator economics, driver satisfaction, vehicle power loss, traffic congestion, and power grid safety [20]. These factors are multifaceted and interrelated, complicating the process of locating charging stations.

For instance, Falvo et al. prioritized the reduction of energy consumption by encouraging the use of existing power plants for both EVs and subways [21]. Guo et al. employed a fuzzy TOPSIS approach to evaluate potential locations using environmental, economic, and social benchmarks [22]. A comprehensive method factoring in several variables, including environmental factors, power supply, and legislation was proposed by Asamer et al., using taxi data to gauge charging demand [23].

Additional work has shed light on the relationship between user costs and charging station expenses. Zhu et al. studied how these costs impact the number and placement of charging stations [24]. Sun et al. considered residents' travel habits, categorizing them as short-distance or long-distance travelers to better inform the determination of charging station quantity and location [25]. These various factors, interacting in complex ways, pose a significant challenge to decision-makers striving to identify optimal locations for EV charging stations.

The decision regarding the ideal placement of Electric Vehicle Charging Stations (EVCS) is a sophisticated process encompassing a plethora of considerations. There are several interrelated quantitative and qualitative factors influencing this decision, including but not limited to operator economics, driver satisfaction, vehicle power loss, traffic congestion, and power grid safety[20].

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, not just for energy efficiency, but also for 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[21].

Guo et al. present an alternative approach to the problem, employing a fuzzy TOPSIS method for the assessment of potential locations. Their approach takes into account not just practical or economic factors, but a broad array of environmental, economic, and social benchmarks. This underscores the importance of a holistic, multifaceted evaluation process for locating EVCS. Beyond the fundamental requirements of power supply and accessibility, Guo et al. emphasize the need to assess the broader societal impact, environmental implications, and economic viability of potential locations. These findings underscore the fact that the decision-making process should not be limited to infrastructure and logistics alone but should strive to align with wider sustainable development goals[22].

Similarly, Asamer et al. propose a comprehensive, integrative approach to the placement of EVCS. They contend that several variables - ranging from environmental conditions to the availability of power and legislative considerations - must be factored into the decision-making process. 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[23].

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 the establishment and operation of 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[24].

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 the specific needs and habits of local residents, thereby ensuring maximum usability and efficacy[25].

In summary, the complex interplay of factors affecting the location of EVCS necessitates a multifaceted and integrative approach. The aforementioned studies underline the need for strategies that balance technical requirements, economic feasibility, societal impact, and end-user needs. It is through this careful balancing act that 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[20-25].

## Models for Optimal Location Determination

Researchers have introduced a range of models to evaluate the optimal number and distribution of EV charging stations. For instance, Frade et al. utilized a maximal covering model to identify the number and capacity of charging stations in Portugal’s capital [26]. He et al. leveraged a double-layer mathematical model to optimize charging station positions, taking into account vehicle driving distances and charging demands [27].

In a distinct approach, Shahraki et al. presented an optimization model that maximized vehicle mileage based on driving patterns and used real data to define charging station location and scale [28]. Similarly, Wu et al. developed a stochastic flow capturing location model to optimize charging station distribution [29]. Tu et al. and Luo et al. respectively incorporated time and space constraints and a second-order planning model into their frameworks [30][31].

Researchers have also focused on models that factor in the characteristics of batteries. Liu et al. used a multi-objective biogeography-based optimization model to devise strategies for different charging applications, with battery characteristics as a key input [33]. In another instance, Mehrjerdi et al. focused on the power and capacity of charging facilities and energy storage battery systems to optimize the charging network [34].

He et al. considered battery costs alongside charging station expenses and energy storage system costs, establishing a mixed integer linear programming model to guide the charging station deployment and battery and energy storage system designs [38]. Furthermore, Davidov et al. aimed to minimize charging station layout costs while exploring the impact of mileage and service quality on charging station layout and total costs [39].

In contrast, some researchers have proposed models that encompass both quantitative and qualitative aspects. For instance, Hosseini and Sarder introduced a Bayesian Network model that took subjective factors into account [40]. Chen et al. developed a two-layer mathematical model that minimized the travel path and charging waiting time [42].

Other models have also incorporated human behavior. Zeng et al. proposed a unique station-level optimization framework that integrated human behavior into the charging decision-making process [44]. Such diverse model constructions showcase the vast potential for optimizing the placement of EV charging stations.

### Optimization Models for EV Charging Station Distribution

The progression of Electric Vehicle (EV) adoption is tightly interwoven with the development and availability of EV Charging Stations (EVCS). The placement of these stations is a crucial decision in promoting EV adoption and ensuring user satisfaction. Researchers have proposed various models to determine the optimal number and distribution of EVCS, often embodying different mathematical, geographical, technical, and human-centric perspectives.

Frade et al. adopted a maximal covering model, a popular approach in location science, to study the potential for EV adoption in Lisbon, Portugal's capital. Their model used potential demand areas and possible charging station locations to maximize the number of covered demands. This approach illustrates the usefulness of a demand-based method in quantifying the required number and capacity of charging stations[26].

In a similar vein, He et al. employed a double-layer mathematical model to optimize EVCS distribution, considering both vehicle driving distances and charging demands. By modelling EV driving behavior and coupling it with charging demand, their work highlights the importance of user travel patterns in designing EVCS networks. The findings underscore the need to consider the daily mobility patterns of EV users in the station location problem[27].

Shahraki et al. presented an optimization model that maximized vehicle mileage based on driving patterns. They used real data to define charging station location and scale, an approach that underscores the importance of empirical data in informing station location decisions. Similarly, Wu et al. developed a stochastic flow capturing location model that reflects the randomness in EV users’ traveling behavior. This approach recognizes the complexity and variability of human behavior, a critical consideration in EVCS location planning[28][29].

Other researchers have incorporated different constraints into their models. Tu et al. and Luo et al. have respectively taken into account the temporal and spatial constraints and a second-order planning model. These constraints can reflect real-world scenarios such as the variable availability of parking spaces, congestion levels at different times, and EV owners' home and work locations, making these models more realistic[30][31].

Battery characteristics have also been a focal point in some models. Liu et al. developed a multi-objective biogeography-based optimization model that considered battery characteristics as a key input. They highlighted the different strategies needed for different charging applications, depending on the batteries’ specifications[33]. Similarly, Mehrjerdi et al. examined the power and capacity of charging facilities and energy storage battery systems in their optimization model, thereby underlining the significance of technical aspects in determining the charging network[34].

Cost considerations have been extensively studied. He et al. incorporated battery costs, charging station expenses, and energy storage system costs in their model, providing a holistic economic perspective[38]. Davidov et al. also aimed to minimize charging station layout costs, demonstrating how mileage and service quality impact station layout and overall costs[39].

Some researchers have proposed models that factor in both quantitative and qualitative aspects. Hosseini and Sarder introduced a Bayesian Network model that encompassed subjective factors, emphasizing that the decision-making process is not purely mathematical but involves human judgment as well[40]. Chen et al. developed a model minimizing the travel path and charging waiting time, striking a balance between the quantitative objective of minimizing travel distance and the qualitative goal of enhancing user experience[42].

Further expanding on human-centric perspectives, Zeng et al. integrated human behavior into their station-level optimization framework, illustrating the profound impact human decisions can have on charging station utilization. This approach recognizes that even the best-planned charging station network can fail if it does not accommodate the preferences and behaviors of its users[44].

The diversity of these models reflects the multi-dimensional nature of the EVCS location problem. They collectively underscore the need for comprehensive and flexible modeling approaches that incorporate demand characteristics, technical specifications, cost factors, and human behaviors. This array of factors and the complex interactions among them require an integrative approach that can optimize the placement of EVCS, promoting widespread adoption of EVs and the associated environmental benefits[26-31][33-34][38-42][44].

## Algorithms for Model Solving

Accompanying model development, scholars have explored various algorithms to resolve the optimal configuration of EV charging stations. Sadeghi-Barzani et al. employed a mixed integer non-linear programming (MINLP) optimization method and genetic algorithm for optimal charging station location and scale [45]. Arslan et al. used the Benders decomposition algorithm to maximize mileage and minimize transportation costs [47].

Furthermore, Zhang et al. introduced a decentralized valley-filling charging strategy, which designed a pricing scheme through cost minimization and was compatible with device-level multi-objective charging optimization algorithms [46]. Similarly, Dong et al. applied the SNN clustering algorithm to optimize the placement of charging stations on circular expressways [YYY].

Genetic algorithms have been popular tools for optimizing charging station locations. Zhu et al. employed a genetic algorithm to determine the number of chargers and their locations [48]. Awasthi et al. combined genetic algorithm and particle swarm optimization to determine the optimal location and size of charging facilities in an Indian city [51]. Akbari et al. considered charging station power, charging time, and travel distance constraints and used a genetic algorithm to optimize the location of the charging station [54].

Particle swarm optimization algorithms also have been utilized in several studies. Li et al. proposed an EV charging station deployment strategy based on a particle swarm optimization algorithm [XXXX]. Furthermore, Chen et al. used a multi-objective particle swarm optimization method to determine the ratio and distribution of charging facilities [53].

Researchers have also employed clustering methods. Zhang et al. used the k-means cluster analysis method to evaluate the dynamic distribution of charging stations [55]. Straka et al. combined k-means clustering method and Dutch charging data to study user charging behavior [57]. Wu et al. paired approximate dynamic programming and an evolutionary algorithm to determine the optimal charging start time for each electric vehicle [58].

Overall, the aforementioned research has offered valuable insights into the optimization of charging station placement. However, comprehensive analyses considering total social cost are relatively rare. In addition, the utility of recognized genetic algorithms to solve these models has not been fully exploited. Additionally, detailed case studies of typical charging station scenarios, such as those in Ireland, are also scarce.

Consequently, this review proposes an optimal distribution model of charging stations based on total social cost, utilizing a genetic algorithm for iterative simulation. The proposed model deviates from traditional reliance on Euclidean distance, instead incorporating a road bending coefficient to calculate the distance between EVs and charging stations, aligning the model outcomes more closely with real-world requirements. Furthermore, this review includes a case study of Ireland, integrating coefficients to reflect actual EV charging demand in five major cities. This comprehensive approach, grounded in an extensive review of existing literature, offers a promising pathway for further research in the area of EV charging station optimization.

### Algorithms for Optimal EV Charging Station Configuration

The location and configuration of Electric Vehicle Charging Stations (EVCS) are crucial in promoting electric vehicle (EV) adoption and ensuring efficient energy use. As part of this complex issue, scholars have explored various algorithms and optimization methods to determine the optimal configuration of EVCS. The literature features an array of approaches that deploy optimization methods, genetic algorithms, decomposition algorithms, clustering methods, and even combinations of these techniques.

Sadeghi-Barzani et al. employed a mixed-integer non-linear programming (MINLP) optimization method along with a genetic algorithm to determine the optimal EVCS location and scale. Their work illuminates the use of advanced mathematical modeling combined with bio-inspired algorithms to tackle complex optimization problems like EVCS planning. The MINLP optimization model provides a powerful mathematical tool to represent complex constraints and objectives, while the genetic algorithm allows for an efficient search for global optima[45].

Arslan et al. adopted the Benders decomposition algorithm in their work to optimize EVCS location. They used the algorithm to maximize mileage and minimize transportation costs, demonstrating how sophisticated mathematical programming methods can offer practical insights into real-world transportation problems. This approach emphasizes the importance of minimizing operational costs while maximizing service coverage in the configuration of EVCS[47].

Taking a different route, Zhang et al. introduced a decentralized valley-filling charging strategy that was compatible with device-level multi-objective charging optimization algorithms. They designed a pricing scheme through cost minimization, showcasing how economic principles and market-based mechanisms can be deployed in EVCS planning. This method highlights the importance of efficient pricing mechanisms in shaping EV user charging behavior and thus the utilization rate of charging stations[46].

In line with this, Dong et al. applied the SNN clustering algorithm to optimize the placement of charging stations on circular expressways. Clustering algorithms allow for an organized, systematic grouping of data based on proximity, thereby offering valuable insights into patterns and trends that can inform EVCS location planning, particularly for transportation infrastructure like expressways[YYY].

Genetic algorithms have been popular tools for optimizing EVCS locations. For example, Zhu et al. used a genetic algorithm to determine the optimal number and placement of chargers[48]. The genetic algorithm, inspired by natural evolution, provides a robust search mechanism for exploring vast solution spaces, making it particularly effective in handling complex multi-objective problems like EVCS planning.

In an effort to leverage the strengths of multiple optimization techniques, Awasthi et al. combined a genetic algorithm with particle swarm optimization to determine the optimal location and size of charging facilities in an Indian city. This hybrid approach leverages the exploration capabilities of genetic algorithms and the exploitation abilities of particle swarm optimization, offering a comprehensive and robust framework for EVCS planning[51].

Akbari et al. used a genetic algorithm to optimize EVCS location, considering station power, charging time, and travel distance constraints. By considering these constraints, their work presents a comprehensive approach that acknowledges the interplay between technical specifications, user charging demand, and spatial factors in EVCS location decisions[54].

Further studies have employed particle swarm optimization algorithms. Li et al. proposed an EV charging station deployment strategy based on this algorithm[XXXX]. Similarly, Chen et al. used a multi-objective particle swarm optimization method to determine the ratio and distribution of charging facilities. These works illustrate how particle swarm optimization, inspired by the collective behavior of bird flocking, can help in exploring multidimensional and continuous search spaces[53].

Clustering methods have also been frequently used. Zhang et al. used the k-means cluster analysis method to evaluate the dynamic distribution of charging stations. This approach, grouping EVs into clusters based on their charging demand patterns, offers valuable insights into dynamic charging demand trends[55].

Straka et al. combined the k-means clustering method with Dutch charging data to study user charging behavior. Their research illustrates the powerful combination of clustering analysis and empirical data in providing nuanced understanding of EV user charging behavior, which can inform the timing and location decisions of EVCS[57].

Another interesting approach is the work of Wu et al., who paired approximate dynamic programming and an evolutionary algorithm to determine the optimal charging start time for each EV. Their research represents the growing interest in smart charging strategies that optimize the usage of electricity and grid stability[58].

Despite these extensive studies, comprehensive analyses considering total social cost are relatively rare. Moreover, the potential of genetic algorithms in solving these complex models has not been fully exploited. Additionally, detailed case studies of typical charging station scenarios, such as those in Ireland, are scarce.

Addressing these gaps, this review proposes an optimal distribution model of EVCS based on total social cost, utilizing a genetic algorithm for iterative simulation. The proposed model deviates from traditional reliance on Euclidean distance and incorporates a road bending coefficient to calculate the distance between EVs and EVCS. Furthermore, this review includes a case study of Ireland, integrating coefficients to reflect actual EV charging demand in five major cities. This comprehensive approach, grounded in an extensive review of existing literature, provides a promising direction for further research in the area of EVCS optimization[45][47][46][YYY][48][51][54][XXXX][53][55][57][58].