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Review

Research Progress and Prospects of Public Transportation Charging Station Layout Methods

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Abstract: Electric buses have been vigorously promoted and implemented in major countries worldwide and have generated a huge demand for charging stations. Optimizing the daily charging experience of electric buses, adapting the daily operation scheduling, improving the utilization rate of charging stations, reducing the load on the power grid, and improving the operation efficiency of electric bus line networks require the reasonable layout of the charging stations. In this study, public transportation charging station layout and siting is the research object. We summarize the progress of analysis methods from the charging station and vehicle sides; introduce related research on the planning and layout of charging stations based on optimization models, including cost analysis and siting and layout for electric bus systems; summarize the data-driven station planning and siting research; and provide an overview of the current charging demand estimation, accuracy, and charging efficiency. Finally, we address the problems of the charging demand estimation accuracy, the mismatch between the charging station layouts for electric buses, and the charging demand on a long time scale. We suggest that research be conducted on data fusion for the temporal and spatial refinement of charging demand prediction in the context of the electrification of public transportation systems and the big data of telematics.

Keywords: electric bus; charging station site planning; charging demand analysis; cost analysis; summarize

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1. Introduction

Global climate change, caused by massive greenhouse gas (GHG) emissions, is significantly impacting ecosystems and human societies. In the last decade, governments worldwide have committed to developing and utilizing clean energy, and it has become crucial to replace fossil fuels with clean energy in order to reduce GHG emissions. The day-to-day functioning of modern cities generates significant amounts of GHGs, and the transport sector is among the key emitters, accounting for 22% of the total carbon dioxide (CO_2) emissions, with road transport accounting for three quarters of this [1]. As an important part of urban road transportation, public transportation is essential in promoting green travel modes to reduce carbon emissions, and scholars are committed to promoting green travel for this reason [2]. The electrification of urban public transport systems can reduce the use of fossil fuels and environmental pollution and is the key to building clean and efficient urban transport, as well as the basis for future urban development.

The number of electric buses in major cities worldwide has increased in recent years. As of 2017, Shenzhen, China has replaced all 16,000 buses in operation with electric buses, becoming the world's first city to fully electrify its franchised bus fleet. The neighboring city of Guangzhou also had more than 14,800 electric buses in operation by the end of 2021. In 2014, the city of Seneca, South Carolina, USA, which replaced all of the vehicles in its bus lines with electric buses, became the world's first city to operate all electrified buses.

Relevant studies suggest that the electric bus market in Europe is expected to grow by 18.6% from 2022 to 2027 [3].

However, owing to the operating characteristics of electric buses, the battery power must be kept above a certain threshold during operation, and the power needs to be replenished in a timely manner during daily driving. Therefore, the reasonableness of the layout of charging stations will affect the daily operation of the entire public transportation system. In recent years, more studies have examined the siting and layout of EV charging stations, with optimization models aimed at minimizing various costs and subsequent optimal siting models considering driver behavior, bus energy consumption, and bus route placement. Other studies have investigated the siting and layout of EV charging stations based on multi-source data in a data-driven manner. The review in this paper includes these two siting methods, and since an analysis of the charging demand is a necessary step in the charging station siting process, this paper also reviews the related research. The main structure of this paper is shown in Figure 1.

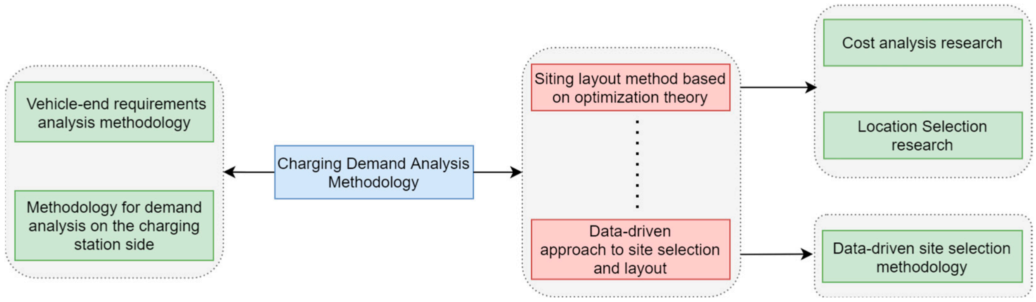

Figure 1. Main content structure.

Currently, electrifying public transportation systems is a major trend, and intelligentization and network connectivity are having a profound impact on the development of the automotive industry. The rapid development of telematics and big data has provided a new direction for the interaction of information between vehicles and charging stations, whereas massive vehicle operation data and machine learning algorithms have provided a new solution to the industry's development dilemma. In this environment, a review of relevant studies on the siting of electric bus charging stations over the past decade, a comprehensive overview of the research progress of the relevant issues, and a summary of the research methods and content are important to support the rational layout of charging stations in the future, the optimization of urban bus operation networks, and the development of the electrification of public transportation.

2. Charging Demand Analysis Methodology

Charging demand analysis is the basis for the planning and layout of charging stations, and the simplified logic of the planning and layout is shown in Figure 2. It is important to have accurate demand data for the planning of the locations of charging stations, the determination of the capacity of power stations, the layout of electric power grids, and the management of electric loads. The charging demand accuracy mainly depends on the accurate analysis and modeling of the EV travel chain, charging and discharging laws, and charging behavior. Current research can be broadly divided into two perspectives: the charging station perspective and the electric vehicle perspective.

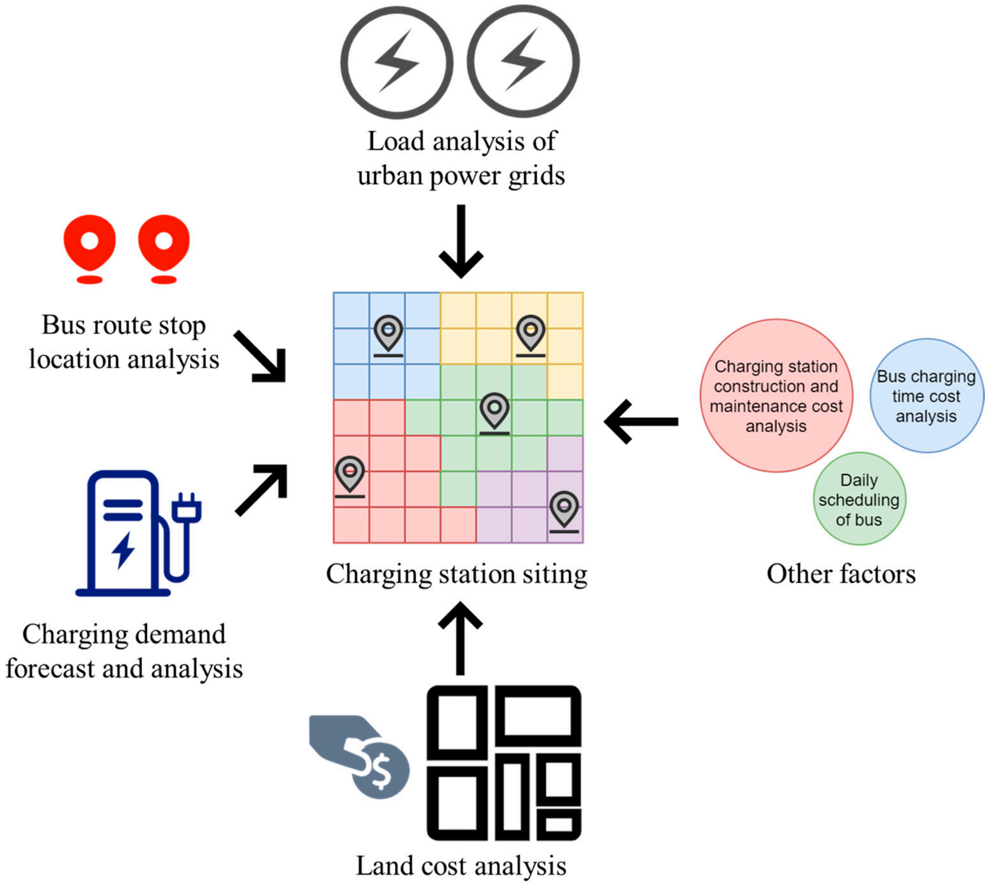

Figure 2. Logical diagram of the planning and layout.

2.1. Methodology for Analysis of Demand from the Charging Station Perspective

Research on the charging demand from the charging station perspective usually involves analyzing historical charging and charging load data from charging stations and using the results to forecast the charging demand. Another approach is to build a relevant model to analyze the charging demand based on the traffic flow of the roadway in the vicinity of the charging station.

With the rise in research on the siting and layout of electric vehicle charging stations, studies have increasingly predicted the charging demand from the charging station perspective. Majidpour [4] forecasted the charging demand for electric vehicles using two datasets, customer profile data (charging data) and socket data (power station data), utilizing time-series forecasting models, support vector machines, and random forest algorithms. The results based on customer data were more accurate, but personal privacy was a concern; because this method does not involve the specific analysis of traffic behavior and traffic flows, it may be less effective in predicting other types of data. Zhang [5] investigated the traffic flows of road sections and the open index of parking lots. They constructed a spatial distribution dataset of the charging demand, used the clustering method of peak density to obtain alternative clusters, and ultimately collected and quantified the charging demand within the coverage of the clusters to obtain the final charging demand. The study analyzed various traffic data and constructed datasets at a macro level, providing a more accurate estimation of the regional charging demand. However, because it starts from a macro level, the methodology ignores the stochastic nature of users' choices and driving behaviors.

Contrary to the explicit prediction of the charging demand mentioned above, Arias [6] did not start directly from the traffic flows of road sections but used spatiotemporal modeling to predict the electric power demand for EV charging in urban areas. The study adopted the Markov chain to model and analyze the arrival rated of vehicles at road sections near charging stations and revealed the charging demand curve of charging stations in urban areas. In addition to addressing the stochastic nature of the charging demand, An [7] proposed a stochastic integer planning model to jointly optimize the locations of charging stations and the size of the bus fleet based on the stochastic charging demand, taking into account the price of electricity during the time of use. This study addresses the gap in the research regarding the stochastic charging demand at the charging station end from a relatively novel perspective.

2.2. Methodology for Analysis of Demand from the Vehicle Perspective

Analyzing the charging demand from the vehicle perspective, analyzing users' travel patterns and travel chains in depth, and producing accurate simulations are key to obtaining the charging demand.

Cai [8] assumed that electric cabs had the same driving behavior as traditional fuel cabs and used parking hotspots in Beijing's cab trajectory data as an indicator for the estimation of the charging demand. However, the simulation of vehicle driving behavior and vehicle activity was relatively brief. Similarly, Pan [9] considered the user's driving behavior in an EV to be consistent with that in a conventional fuel vehicle. The authors proposed a charging decision process to simulate charging choice behavior, which involved the EV driver's current activities, the charging station availability, range anxiety, and energy consumption for the remainder of the trip. This method can accurately describe certain behavioral activities of drivers from actual data; however, it is difficult to describe the differences between drivers of traditional diesel and electric vehicles, because this method is based on traditional fuel vehicles and ignores the unique travel characteristics and driving patterns of electric vehicles. Ghamami [10] captured the electric vehicle charging demand by capturing residents' travel patterns. Chung [11] predicted the charging demand and post-charging dwell time based on historical charging behavior using support vector regression (SVR), random forest regression (RF), and Gaussian and diffusion-based kernel density estimators. The data collection for this prediction method is relatively simple and the data are easy to analyze; however, this study could only estimate the charging demand after charging and did not predict the user's charging decision, and the applicable scenarios were relatively limited.

In a study aimed at estimating the charging demand of electric buses, Nicolaides [12] accurately formulated the parameters of a vehicle simulation tool based on speed, positional coordinates, and electric motor performance and used the validated simulation tool to estimate the electric demand of electric buses for a defined drive cycle. On the other hand, to obtain the charging demand of electric buses, Wu [13] started from the actual operation scheduling of public transportation, obtained the spatial and temporal distribution characteristics of buses based on the operation scheduling data, and simulated the daily operation based on the spatial and temporal distribution characteristics. Similarly, Wang [14] calculated the charging demand of daytime buses based on their daily operating cycles and scheduling arrangements. Chen [15] conducted a more detailed study on the charging demand. Using actual operational data, they generated 100 samples containing all-day bus service schedules. Each sample consisted of all service trips of the studied bus routes in a day, and each trip in turn contained pairs of randomly selected travel times and energy consumption levels from an aggregated real dataset, which were clustered to simulate transit-dependent travel times and electrical energy consumption.

Su's study of the charging demand started from bus operation data; systematically examined the EV fleet composition, market share, and charging patterns in New Zealand; and utilized multiple vehicle travel survey datasets to quantitatively determine the charging behavior and driving patterns of EVs. They developed a Monte Carlo simulation (MCS)-based methodology that generated results close to the daily electricity demand under actual usage scenarios [16]. This study considers more factors and describes the charging behavior of electric buses more accurately; however, the above method estimates the charging demand more macroscopically, and it is difficult to obtain the charging demand at smaller scales.

2.3. Research Review

Analyzing the charging demand is the basis of charging station planning and is crucial in the site layout stage. A summary of relevant studies from both the vehicle and charging station perspectives is shown in Figure 3. And a summary table of relevant important studies is shown in Table 1.

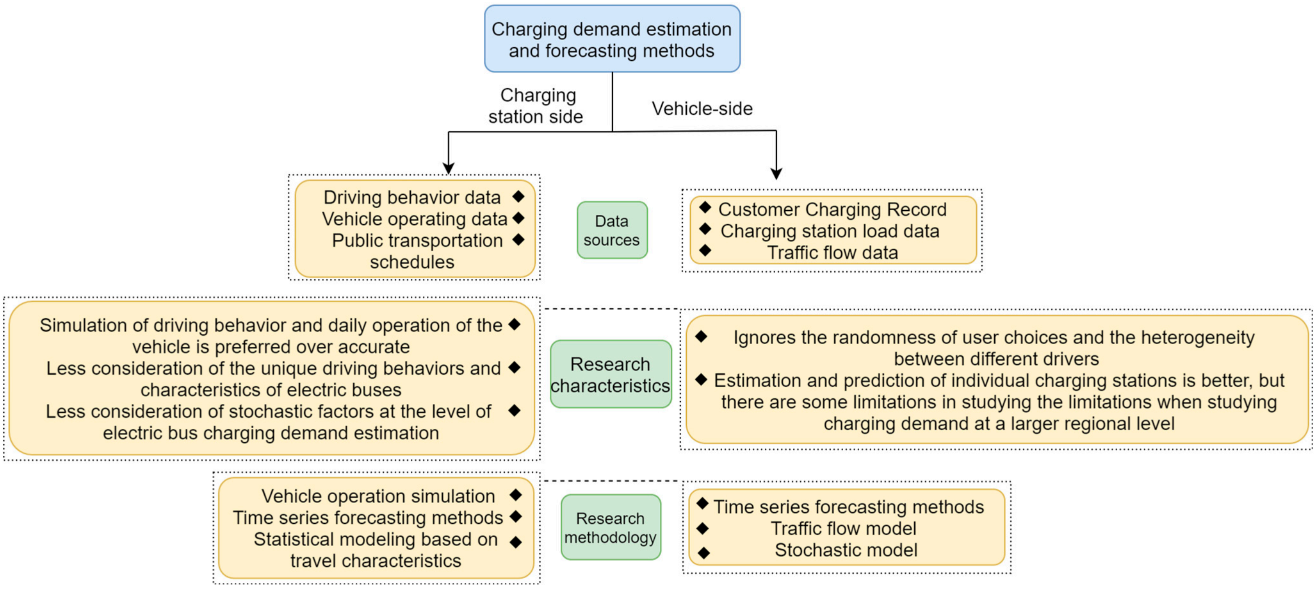

Figure 3. Charging demand research summary.

Table 1. Charging demand analysis methodologies.

Author	Year	Classification and Data Support
Majidpour et al. [4]	2016	Station side; customer profile and socket data
Zhang et al. [5]	2021	Station side; traffic flows of road sections and open index of parking lots
Arias et al. [6]	2017	Station side; arrival rates of vehicles at road sections near charging stations
Nicolaides et al. [12]	2019	Bus side; bus speed, positional coordinates, and electric motor performance
Wang et al. [14]	2022	Bus side; daily bus operating cycles and scheduling arrangements
Su et al. [16]	2019	Bus side; EV fleet composition, market share, and charging patterns

1. Demand analysis model for charging stations

This type of method is mostly used to analyze the charging demand of electric vehicles, which leads to the better prediction of a single charging station because the data come from the charging station; however, there are some limitations when studying the charging demand at a larger regional level, and the generalizability and portability are poor. Because of the data support problem, this method is unable to analyze the driving behavior of vehicles; thus, it ignores the randomness of user choices and the heterogeneity among drivers, which may result in the final charging demand prediction differing significantly from the actual demand.

2. Charging demand estimation model for vehicles

When analyzing the charging demand of electric cars and buses, the data support is obviously different owing to the large differences in their operating characteristics. For private electric cars, the driving and charging behaviors of drivers are mainly simulated based on parking, charging behavior, and travel chain data. For electric buses, the daily operation simulation is mainly based on the schedules of each line and existing operation data, which are used to estimate the charging demand in the corresponding cycle.

Starting from the various types of data generated in the actual operation of public transportation, the charging demand is estimated by building various models or mining the actual data. Data can be obtained relatively easily via this method, and the simulation of the daily operation of public transportation is more accurate; however, it fails to consider more detailed factors, such as the fleet composition and specific charging modes. At the same time, because the simulation follows a more uniform operation mode, the stochastic factors in daily operation are less considered, which may lead to a shift in the final charging demand estimation results.

Meanwhile, due to the limitations in the current electrification process of public transportation systems, the data sources are often traditional fuel buses. Furthermore, descriptions of the operation characteristics and charging behaviors of electric buses may be biased owing to the lack of complete data on the actual operation of electric buses and scheduling schemes.

3. Siting Layout Method Based on Optimization Theory

The electrification of public transport systems and private cars in major cities worldwide has been progressing since 2010, and research on the siting of charging stations has been increasing since 2014. Most studies on charging station siting and layout utilize optimization models that determine the locations of charging stations by obtaining or assuming the relevant parameters, aiming to optimize the cost and other variables, and considering factors such as the power grid, passenger waiting time, and transit scheduling.

Earlier studies focused more on charging station siting and layout for electric vehicles. To address the planning process for the deployment of battery replacement infrastructure, Mak [17] proposed optimization models and used them to investigate the potential impact of battery standardization and technological advances on an optimal infrastructure deployment strategy. The authors proposed a "battery-swap" strategy that can provide layout planning for the switching of infrastructure, with the limitation that there is scarce information on the rate of adoption for the deployment of such facilities. He [18] proposed an equilibrium modeling framework to maximize the social benefits of plug-in hybrid electric vehicle (PHEV) charging paths, which takes into account charging opportunities and real-time electricity prices. The study provides insights into the allocation of the corresponding resources, but the model only gives the distribution of the number of charging stations between regions and does not give specific deployment locations. Building on this foundation, He [19] considered driver specificity, taking into account both spontaneous regulation and travel decisions, and proposed a two-layer mathematical planning model to determine the locations of electric vehicle charging stations. The approach considered drivers' travel characteristics and analyzed the travel process to reconstruct a travel chain. It derived the optimal locations and types of public charging stations, and it was able to predict the utilization rates of charging stations and the composition of users. However, it did not consider the queuing phenomenon that can arise at charging stations, and the modeling of the interior of the charging stations was relatively poor.

Research on the layout of charging stations for electric cars has become a hotspot, and research on the siting and layout of charging stations for electric buses has emerged more recently. Most of the studies have analyzed the cost of electric bus systems or determined the siting of charging stations with the goal of optimizing various types of costs [20–22].

3.1. Cost Analysis Research

Focusing on the overall cost of an electric bus system, Xylia [22] demonstrated that the total cost of operating the system is negligible compared to the cost of operating a 100% fuel system, and that the cost of the charging infrastructure can be offset by the reduced fuel costs of electric buses. They analyzed the cost of the electrified bus system as a whole and established the feasibility of electrifying the system on an economic level. Regarding the cost optimization of charging stations, Leou [23] considered the fare characteristics of bus routes and the operational guidelines of bus companies and proposed an optimization model to determine the optimal capacity and minimum energy cost of charging stations. In the actual operation of a bus system, many uncertainties that can have an impact on daily operations exist, and relevant scholars have considered the impact of uncertainties such as the travel demand, traffic conditions, and weather conditions on the daily operation and cost of buses. Based on a robust optimization model with the objective of optimizing the total cost of ownership, Liu [21] considered the uncertainty of the energy consumption of buses, along with the instability of traffic conditions and the travel demand. Their results revealed that the model could ensure the optimal deployment of facilities for electric bus systems. Based on factors such as the traffic conditions, passenger demand, and weather, which can significantly affect the charging efficiency of electric buses, Wang [24] designed a real-time bus charging scheduling system based on the Markov decision process to analyze charging and operating costs, and it could significantly reduce the charging costs and electricity consumption of buses. In addition to addressing stochastic issues such as ridership and weather, Esmaeilnejad [25] optimized the passenger waiting times and operational costs of bus routes. They also addressed weather-induced stochasticity in ridership and battery performance and evaluated the impact of charging station failures related to maximum charging times on the operational schedules and costs of BEBs.

The impact of the vehicle composition of bus fleets and even the act of charging itself on the cost of a transit system has also been considered. Rogge [26] considered the fleet composition in an optimized cost model and focused on the impact of different types of buses in the fleet on the costs. Clairand [20] discussed the cost implications of charging electric buses at bus stops and proposed a new approach to the clustering of electric buses that reduced the energy costs while meeting the grid constraints.

3.2. Location Selection Research

Wang [27] presented an integer linear programming problem with the objective of minimizing the installation costs of charging facilities by considering that charging stations should be located directly in bus stations, and they investigated two cases of finite and infinite vehicle battery capacity. Their work was an early investigation into the specific determination of bus charging station locations and proved the layout problem to be NP-hard. Subsequent scholars have taken more factors into account when selecting specific locations, and the objectives are not only related to the selection of locations but also to the capacity of charging stations, the fleet size, and the development of charging plans. An [7] proposed a stochastic integer planning model based on the stochastic charging demand to jointly optimize the charging station locations and bus fleet sizes, considering real-time electricity prices at the time of charging. Ferro [28] also considered the fleet size and proposed a hybrid nonlinear planning model for charging station siting and capacity setting. Uslu [29] determined the locations and fixed capacities of charging stations with an approach that focused on passenger waiting times, taking into account differences in bus networks and the charging needs of the routes, modeled with the constraint of finite waiting times. Similarly, Hu [30] considered the time delay caused by charging and examined the joint optimization problem of installing charging facilities. They developed a charging plan at a specific bus stop, taking into account penalty costs if additional waiting times and travel times are caused by charging activities.

In non-specific location-determined siting layout studies, the objectives usually do not involve the selection of specific locations for charging stations but rather focus on the overall deployment of an electric transit system, which usually involves a larger number of study objectives. Based on a cost optimization model to determine the deployment of charging stations, the design of bus battery sizing, and the installation of energy storage systems, He [31] demonstrated that installing fast charging stations at bus terminals, where buses can stay for relatively long periods of time, or at street-level bus stops, where many bus routes are shared, may be the most effective way to reduce the size and total cost of the on-board batteries of a transit system. Considering the unique spatiotemporal characteristics of bus systems, Wei [32] introduced a spatiotemporal optimization model to determine the deployment of an electric bus system. Gairola [33] considered the impact of the queue length while charging on bus scheduling from a microscopic viewpoint. The authors proposed a base optimization model and its stochastic version considering different energy demand scenarios under different operating conditions. Their results ultimately showed the impact of waiting time constraints on the sizes of bus batteries and the locations and capacities of the charging stations.

Considering the close connection between the design of charging stations and the operational strategies of bus routes, studies that closely link bus scheduling and charging station deployment have been more frequent in recent years. Such studies usually involve the construction of frameworks to optimize each objective. He [34] proposed a two-stage optimization framework for electric bus charging infrastructure planning and charging scheduling, which integrates a model for the simultaneous optimization of charging station deployment, the on-board battery capacity, and charging schedules using a rolling time-domain approach. Gairola [35] considered both charging station planning and charging scheduling and proposed an integrated modeling framework for the deployment of an electric transit system. The model required the investment cost of charging stations and the cost of electricity to be kept as low as possible. Their results revealed that the configuration of charging stations and the scheduling of charging were interconnected. To compare the optimization potential with sequential planning, Olsen [36] considered the problems of the simultaneous optimization of bus vehicle scheduling and charging station planning and solved them using a variable neighborhood search algorithm, which demonstrated that simultaneous optimization is necessary and sequential planning significantly increases the costs. Zeng [37] adopted a novel bus scheduling optimization approach. They assumed that a bus with a low battery capacity can be driven to a charging station, where the passengers will be transferred to a fully charged "standby" bus, which completes the remaining bus trips. Based on this scheduling approach, they proposed a nonlinear integer programming model to solve the bus scheduling and charging infrastructure planning problems.

3.3. Research Review

Cost analysis and siting studies based on optimization models are relatively similar in terms of the study limitations, as they are partly influenced by the current process of the electrification of electric bus systems. A summary of relevant studies from both cost analysis research and location selection research is shown in Figure 4. And a summary table of relevant important studies is shown in Table 2.

Table 2. Siting layout methods based on optimization theory.

Author	Year	Content and Considerations
Xylia et al. [22]	2017	Cost analysis; feasibility of electrifying system
Leou and Hung [23]	2017	Cost analysis; fare characteristics and operational guidelines
Liu et al. [21]	2018	Cost analysis; uncertainty of energy consumption and travel demand, etc.
Rogge et al. [26]	2018	Cost analysis; fleet composition
Wang et al. [27]	2017	Location selection; minimizing installation cost of charging facility
An et al. [7]	2020	Location selection; stochastic charging demand
Ferro et al. [28]	2023	Location selection; fleet size
Uslu and Kaya [29]	2021	Location selection; passenger waiting times and charging needs of routes, etc.
Gairola et al. [33]	2023	Location selection; waiting time constraints and different energy demands
Gairola et al. [35]	2023	Location selection; charging station planning and charging scheduling
Olsen and Kliewer [36]	2022	Location selection; simultaneous optimization and sequential planning

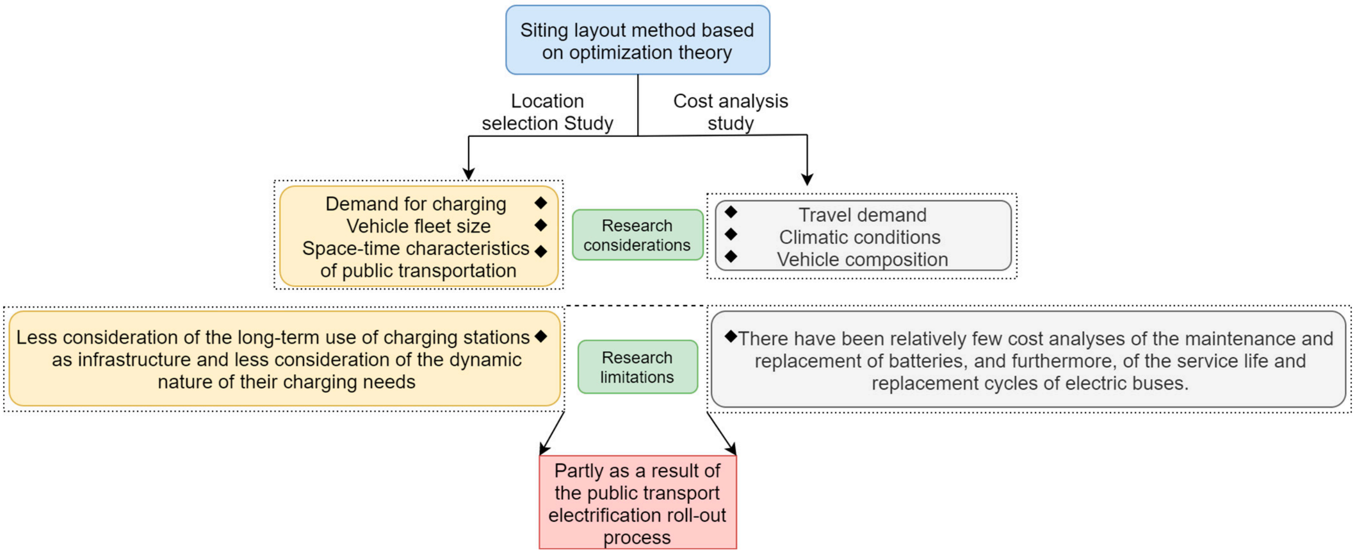

Figure 4. Summary of optimization model-based charging station planning research.

1. Cost analysis research

It is important to consider the costs of constructing and operating related infrastructure and procuring electric buses, and the total changes in the cost of the public transportation system caused by energy costs in the process of promoting electrification.

2. Location selection research

Earlier studies focused on electric vehicle charging stations. After studies emerged related to electric vehicle charging station deployment, studies on the siting of electric bus charging stations began to appear in 2017. Studies involving the selection of specific locations for charging stations also considered other factors, such as the charging demand, real-time electricity prices, passenger waiting time, differences in bus line networks, and so on. The objectives of the current studies not only include the selection of specific locations, but also the capacity of charging stations, the determination of fleet sizes, and the development of charging plans. Although the factors considered are increasingly comprehensive, and buses have more unique driving characteristics compared to cars, there is still a lack of research on the specific locations of charging stations to consider for bus scheduling and the actual operation of bus lines. Additionally, because this method of site selection is more specific, and actual land use is less considered, the final site selection results may be difficult to apply in reality.

In studies using non-specific locations to determine the siting layout, the goal is usually not related to the specific locations of charging stations but is mainly related to the overall deployment of an electric public transportation system. As this type of research is more comprehensive, the overall deployment of the system has greater practical significance. However, as the research is mostly based on static data, the selection of station sites is usually based on the current usability only, with less consideration given to the long-term usability characteristics of charging stations as infrastructure, as well as the dynamics of the charging demand. Furthermore, bus routes may be subject to route corrections, additions, and deletions due to various factors. Thus, the rapid development of battery charging and storage technologies may ultimately result in the planning of charging stations not being able to match the dynamic charging demand of electric buses in the future.

4. Data-Driven Approach to Site Selection and Layout

4.1. Data-Driven Site Selection Methodology

In contrast to constructing an optimization model for charging station layout and site selection, the data-driven approach usually integrates multi-source data to analyze factors such as hotspots of EV stays, driving behavior, land costs, and traffic conditions, and the research methods are more diverse.

This approach usually requires a large amount of actual data, and while, initially, there were fewer such studies, the number has gradually increased in recent years. Li [38] performed a time-series simulation using Beijing cab trajectory data and applied k-means clustering to charging station location selection to derive a series of strategies related to charging station deployment. The method is easily transferable and applicable to other vehicles. However, because of the single data source and few factors to consider, there may be a large deviation between the site selection results and actual needs. Subsequent studies have considered more factors. Based on the enhanced heuristic gradient descent algorithm (EHDG), Othman [39] generated a Voronoi diagram to represent the optimal layout of charging stations based on the distribution of a bus line network, energy consumption profile, and operating costs. To determine the best candidate locations for electric bus charging stations, Zhang [40] used a grid-nearest neighbor propagation (AP) clustering algorithm based on the rasterization of geographic information of the city, which takes into account a variety of factors, such as the land cost and traffic conditions. To determine an allocation strategy for relevant competitive resources, Li [41] applied game theory to formulate the planning and siting of charging stations based on market-based mechanisms. Introducing game theory into charging station planning provides a new approach to determining related resource allocation strategies. Türk [42] applied fuzzy decision making to the selection of electric bus charging station locations and proposed a simulated interval type-2 fuzzy decision-making method improved by annealing. The results revealed that the method can produce more efficient fuzzy systems and achieve more reliable results for the selection of electric bus charging station locations. Unlike clustering and other methods, the construction of a fuzzy system for site selection in this study is more consistent with reality.

Studies have also evaluated the siting of electric bus charging stations from a framework analysis perspective. Gorosabel [43] proposed a standardized framework for the micro-scale analysis of potential charging locations for electric buses at a more microscopic scale, demonstrating the applicability of certain city center locations as charging points. To understand the logical relationship between charging station evaluation criteria, Sang [44] established a combined framework of fuzzy decision-making trial and evaluation laboratory (DEMATEL), preference ranking organizational methodology (PROMETHEE), and prospect theory (PT) to evaluate electric bus charging stations. These studies give criteria for evaluations between alternative sites and between charging stations, which provide the appropriate logic for an understanding of the differences between different sites and charging stations.

Considering the charging station selection behavior and driving route choices of drivers, Liu [45] built a three-structured black-box optimization model for complex charging station siting from the perspective of machine learning, assuming the use of dynamic charging facilities in a road network. This study fills the gap in the research on dynamic charging facility layout, but the model is a black-box model resulting from computer modeling, leading to relatively poor interpretability.

4.2. Research Review

A summary of relevant studies on the data-driven approach to site selection and layout is shown in Figure 5. And a summary table of relevant important studies is shown in Table 3. The data sources for data-driven site selection and layout studies are usually larger and are not limited to data related to the transportation system, such as land costs and site characteristics. Related studies use other methods, such as time-series prediction, clustering algorithms, game theory, and evaluation models, and the final site selection results are presented in a way that is quite different from those based on an optimization model.

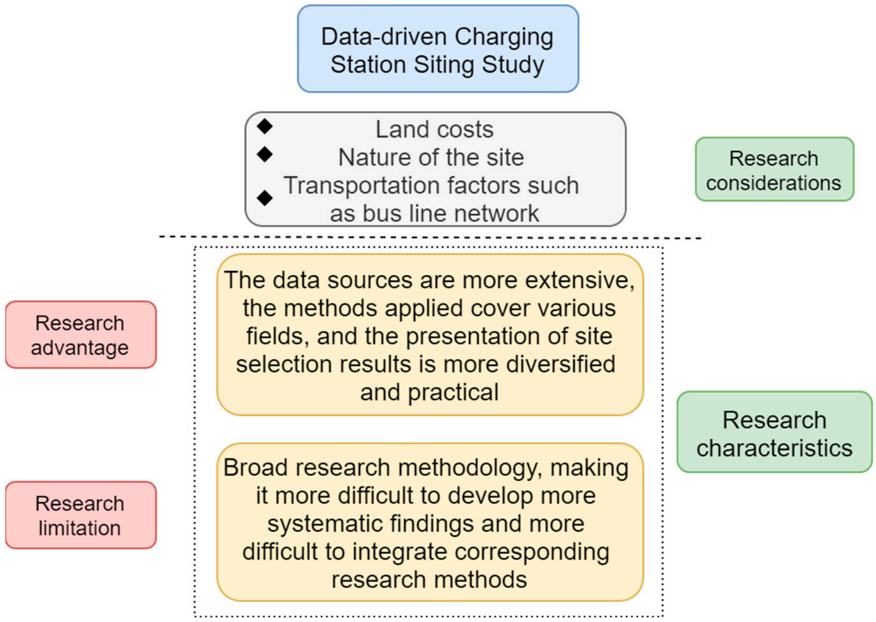

Figure 5. Summary of data-driven charging station planning research.

Table 3. Data-driven approaches to site selection and layout.

Author	Year	Methodology or Data Support
Li et al. [38]	2017	Time-series simulation; cab trajectory data
Othman et al. [39]	2020	Enhanced heuristic gradient descent algorithm; distribution of bus line network, energy consumption profile, and operating costs
Zhang et al. [40]	2021	Grid-nearest neighbor propagation clustering algorithm; land cost and traffic conditions
Li et al. [41]	2021	Game theory
Türk et al. [42]	2021	Simulated interval type-2 fuzzy decision-making method improved by annealing
Sang et al. [44]	2022	Fuzzy decision-making trial and evaluation laboratory (DEMATEL), preference ranking organizational methodology (PROMETHEE), and prospect theory (PT)

The data source of this type of site selection method is more extensive, and the application of the method involves various fields, resulting in a more diverse presentation of the results. This can provide a variety of practical applications and can take into account the factors that are more difficult to consider in the optimization method to compensate for the deficiencies. However, the limitation is that, owing to the wide range of methodological sources, it is more difficult to form more systematic conclusions and to integrate the research methods and conduct further research.

5. Outlook and Conclusions

In the context of the electrification of public transportation systems, many studies and experiments on the deployment of charging stations for electric buses have been conducted at home and abroad. Valuable results have been derived, which have greatly promoted the development of the electrification of public transportation systems. Research on the siting of charging stations began to emerge in 2013 and 2014, with earlier research targeting public charging stations used by electric cars. With the gradual advancement of public transport electrification, research on the siting and layout of charging stations for electric buses emerged around 2017. Initially, more studies focused on the cost of electric bus systems, considering the feasibility of electrification at the economic level and how to reduce the total cost of the system. This was followed by studies on the estimation of the charging demand and the siting of charging stations, which have gradually increased since 2019. Initially, such studies were conducted from a single perspective and used single factors, but as the research continues to deepen, specific scenarios and multiple perspectives and factors are being taken into account, and there is increasing consideration of the influencing factors and the specificity of the scenarios.

Although governments worldwide are now promoting the electrification of public transport systems, very few cities have achieved complete electrification. It is relatively difficult to obtain data on the operation of urban electric bus systems, and the electrification of bus systems as a whole is still at a relatively early stage, which has led to limitations in siting studies due to the constraints of this process. It is difficult for the charging demand analysis to achieve accurate forecasts due to the relatively coarse granularity of spatial and temporal data and the difficulty of obtaining electric bus operation data. Less consideration has been given in cost analysis to the differences between electric and conventional bus systems in terms of routine maintenance, repairs, and equipment life cycles. The specific level of the site selection of charging stations is mostly associated with static data, with the insufficient consideration of dynamic factors and less consideration of large time scales under the site selection problem. Currently, the electrification of public transportation systems is progressing gradually, and planning for charging stations remains a major research topic and is of practical significance. Meanwhile, with the development of telematics and big data technology, it has become possible to acquire massive traveling and charging data, and a fusion method combining data mining and big data technologies will provide new opportunities for research on charging station planning and siting. Combined with the content of the previous section, the future development directions of research elements in the field is summarized as follows (Figure 6).

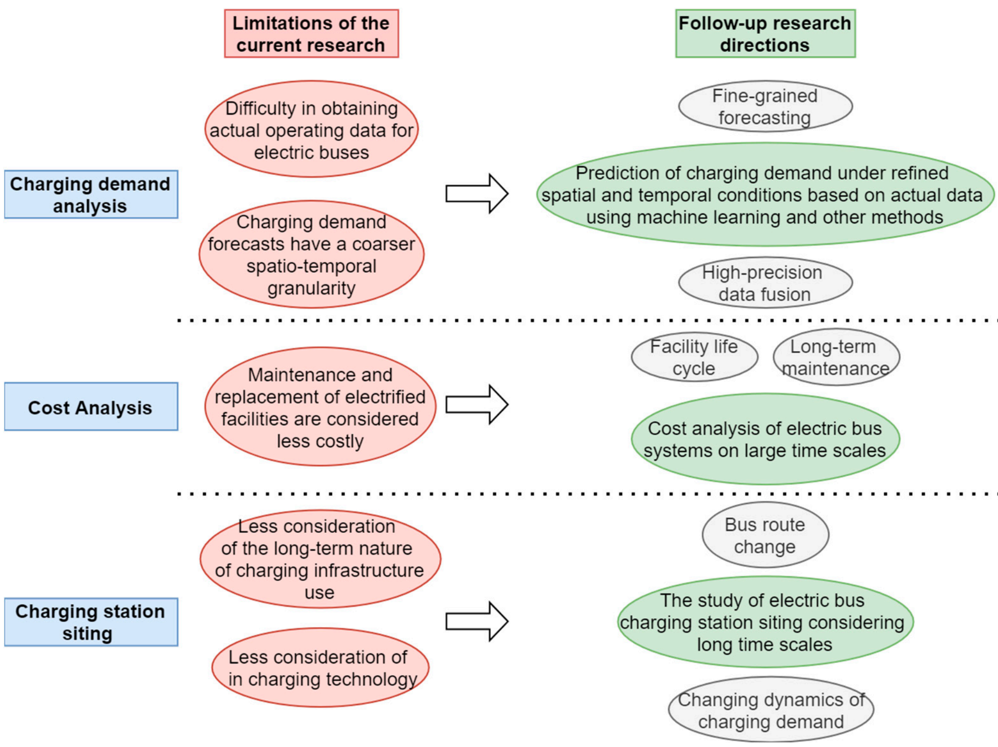

Figure 6. Research shortcomings and future prospects.

5.1. Outlook

1. Charging demand analysis

In the context of the Internet of Vehicles environment, and after the electrification of public transport to a large degree, the actual operating data of electric buses can now be collected in batches. Considering the important role of the charging demand in supporting charging station planning and bus scheduling, current charging demand forecasts that do not have fine-grained spatial and temporal granularity may not meet the needs of future transit system planning. Combining methods such as machine learning and data mining, machine learning algorithms that fuse data for charging demand prediction under refined spatiotemporal conditions represent an important future research direction.

2. Cost Analysis

In the context of the large-scale promotion and application of electric buses, obtaining data related to the routine maintenance and service life of electric buses and their ancillary facilities will be relatively easy. A cost analysis study of the maintenance, repair, and replacement of electric buses and charging facilities on a larger time scale will have greater practical significance and can provide theoretical support for the long-term operation and maintenance of electric bus systems.

3. Charging station siting

Most of the current research on charging station siting favors static studies in the short term, with less consideration of siting on long time scales. As bus routes may be subject to route corrections, additions, and deletions because of various factors, and owing to the rapid development of battery charging and storage technologies, this could ultimately result in the planning of charging stations not being able to match the dynamic charging demand of electric buses in the future. Therefore, the study of electric bus charging station siting considering a long time scale and the dynamic development of charging technology have strong practical significance and are important future research directions.

5.2. Conclusions

With a global emphasis on climate issues, the promotion and application of electric buses has become an important aspect of sustainable urban development. However, the current research focuses on the technology of electric buses, promotion policies, and so on, and there is little consideration of holistic solutions for charging stations and other supporting facilities. The current study takes the problem of laying out and siting public transportation charging stations as the basic object, and it discusses the research progress on the sub-problems of analyzing the public transportation charging demand, analyzing the cost, and siting charging stations. The problems related to support for public transportation charging station site selection and layout have not yet received sufficient attention from the academic community. To achieve a fit between the demand for public transport vehicles and the supply of charging stations, and to promote the process of electrifying public transport, research on issues related to charging stations for public transport should be strengthened in terms of analyzing charging demand forecasts under specific time and space conditions, analyzing costs considering the service life of electric buses and their ancillary facilities, and laying out and siting charging stations considering the future charging demand.

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