A review of charging infrastructure layout planning and electric vehicle traffic simulation application

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Abstract. As environmental pollution and energy constraints, especially oil supply, become more prominent, electric vehicles (EVs), being more environmentally friendly than conventional vehicles, is an effective way to help alleviate the environmental problems. However, the range anxiety caused by limited battery capacity has led many potential consumers to become distrustful towards electric vehicles. In addition, the demand for charging increases with the rise in EV ownership, which stresses the importance of the large-scale deployment of charging infrastructure, and a reasonable layout of charging facilities. This paper first summarizes the travel behavior of electric vehicles, followed by reviewing different models and methods of charging infrastructure layout planning, and finally outlines the research application of electric vehicle traffic simulation and provides an outlook on the problems to be improved. For instances, lacking data volume in current researches on electric vehicle travel behavior; charging infrastructure layout planning are often limited to the framework of traditional layout research; traffic simulations fail to consider the characteristics of electric vehicles are some discussed problems. Hence, future researches should integrate new technologies such as artificial intelligence and cloud computing to improve the above issues.

1. Introduction

In recent years, China's economy continues to develop, and the urbanization process speeds up. Therefore, road mileage, motor vehicle ownership, and the number of drivers is growing rapidly. It is foreseeable that the demand for domestic automobiles will continue to rise in the future. In this context, it is essential to promote the development of the new energy vehicle industry. As a representative of new energy vehicles, electric vehicles (EVs) are a clean, efficient, and sustainable means of transportation that can effectively relieve energy and environmental pressure, achieve energy saving and emission reduction\textsuperscript{[1],[3]}.

Despite the many advantages of EVs, the mileage pressure and charging requirements due to their limited range caused many consumers to hold a distrustful attitude towards EVs \textsuperscript{[4]}. Since battery technology is still difficult to break through in the short term and it is impossible to develop batteries with high capacity density and low cost, charging infrastructure has become an essential means to promote EVs. In addition, the rising electric vehicle ownership has also expanded the demand for charging facilities among vehicle owners. At the same time, public charging facilities are facing the problem of low utilization rates. Many charging piles have become "zombie piles"\textsuperscript{[5]}. The widespread
deployment of charging infrastructure is hence an essential guarantee for the development of EVs. A reasonable layout plan can improve the operational efficiency of charging facilities and accelerate the popularity of the electric vehicle industry[6],[7].

Users’ charging needs and their travel behavior are inextricably linked. The structural differences between EVs and traditional fuel-powered vehicles, and the mileage anxiety caused by the battery capacity limitation, contribute to the unique characteristics of the travel of EVs. Analyzing the spatial and temporal distributions of user travel characteristics are important prerequisites for the study of charging demands and provide supports for charging facility layout planning[8].

The layout of charging facilities involves transportation, urban planning, energy, and other fields with great complexity and uncertainty. In addition, due to the high cost, carrying out actual tests to verify the layout is also basically unattainable. However, simulation is an efficient and powerful method to verify the effectiveness and rationality of different layout schemes while effectively reducing the cost of analysis and decision-making.

Against the above background, this paper first summarizes the travel behavior of EVs, then sorts out different models and methods of charging facility layout planning and followed by outlining research applications of EVs traffic simulation. It ends by providing an outlook on the problems to be improved. Fig.1 shows the interrelationship between the above arguments.

![Fig. 1 Interrelationships of EV, charging infrastructure, and traffic simulation](image)

### 2. Analysis of electric vehicle travel behavior

Charging demand prediction is an important basis for charging infrastructure layout planning[9], and the charging demand of EVs is closely related to travel behavior. There is a mutual coupling between the two[10], so portraying EV travel behavior is one of the prerequisites for the charging demand research[11]. Fig.2 summarizes features that describe travel behavior.
In the literature [11], the travel pattern of motor vehicle users was modeled based on the driving situation data in the Beijing Annual Traffic Development Report 2011. The travel time and the distance distribution were derived. Based on the two distributions, the event interval of possible charging and the energy value of charging required by EV users were obtained. However, the travel time distribution is derived from the traditional fuel vehicle data instead of real electric vehicle data, so it may not be accurate to estimate the charging demand.

The literature [12] collected and analyzed five months of daily electric vehicle travel data from a faculty member in Pomona, California, USA. The result suggests that the trips made by electric vehicle users follow different principles than traditional fuel vehicle trips and do not depend only on travel time but also on the level of energy consumption, which is the dominant factor to consider when making decisions. Drivers prefer intra-city traveling over driving on inter-city highway roads. However, data samples used in the study were collected from only one vehicle. In addition, the car used to collect the data was a specially developed test vehicle, so the conclusions may not apply to the entire EV user population.

Data from the Danish National Transport Survey (TU data) were used in the literature [13] to analyze electric vehicle travel behavior, focusing on mileage. The study concludes that the current electric vehicle battery capacity can meet the daily driving needs of most Danes. However, the study assumes that EV users and conventional fuel car users have similar driving patterns, so the TU data used is for traditional fuel cars and only includes data for private vehicles.

In [14][15], the authors analyzed the travel behavior of EVs, including driving and charging behavior, through a 2-year Western Australian electric vehicle trial collecting data from 11 EVs and 23 charging stations. The results showed that the average daily mileage traveled by the trial vehicles was lower than the average of conventional passenger cars. In addition, most of the car usage was on weekdays, and most EVs traveled less than half of their maximum distance. Moreover, most of the time spent at the charging stations was to maintain the charge rather than actual charging. Despite the considerable period over which the data was collected, the number of vehicles participating in the test was limited. In addition, participating vehicles were company vehicles, some of which were allowed to be used only during office hours and had higher idle times than normal vehicles. Thus, results may not accurately describe the travel behavior of EVs.

The literature [16] and [17] analyzed data of two types of EVs, the Nissan LEAF and Chevrolet VOLT, from The EV Project (2010) in the United States, quantifying metrics such as average mileage per trip, average daily driving distance, and driving distance between consecutive charging events, in addition to charging behavior, including average daily charging in driving number of times, charging locations, etc.
In [18], the authors extracted data such as OD data, actual travel distances from Beijing taxi GPS track data, boarding and alighting events and location information, combined with a questionnaire survey to describe the comprehensive travel behavior of electric taxis. However, the source data has disadvantages such as missing data and large redundancy. Since most of the data come from traditional fuel vehicles, the sample size of the questionnaire survey for electric taxi drivers is relatively small. In addition, the subject of the analysis in this paper is electric taxis, which is a special type of electric vehicle. Therefore, the findings cannot be applied to other types of EVs.

The literature [19] summarizes the differences between electric vehicle travel behavior and traditional fuel vehicle travel behavior, especially route choice, which mainly stems from flexible charging behavior, i.e., charging during driving.

3. Charging infrastructure layout planning study

Since the development of battery technology cannot wholly solve the mileage anxiety of EVs currently and increase the mile range to the same level as that of traditional fuel vehicles, extensive deployment of charging infrastructure and proper site selection can enhance the acceptance of EVs by potential consumers making it an important step to promote EVs [20], [5]. The layout planning of charging infrastructure has become a popular research direction in the field of EVs.

At the level of charging demand, the study of charging infrastructure layout problems is divided into two main categories: point demand models and flow demand models, as illustrated in Fig. 3.

![Charging infrastructure layout model](image)

**Fig. 3** Charging infrastructure layout model

The model underlying the point demand model is the p-median model, a widely used siting model. This model assumes that the charging demand for EVs is generated at a node of the road network. Given a finite number of p charging stations, the model assigns each demand point to a specific charging station such that the total distance between the user's arrival at the charging station from the demand point is minimized [21]. P-median is a location assignment model, which usually assumes that the demand point is a residence or workplace. Studies have shown that consumers are usually more satisfied with receiving services near their homes or workplaces [22]. Based on this, the literature [23] proposes the fuel-travel-back (FTB) approach. Unlike the fixed demand point set by the p-median, this method assumes that any point of the road network may become a new demand point due to the vehicle's fuel exhaustion, and the vehicle will turn back to the nearest service facility after the event. The goal is to minimize the total travel time from all demand points to the nearest service facility. The literature [24] proposes an aggregate coverage model that concentrates the demand of each region at a single point and covers all charging demand points with the minimum number of service facilities within a certain response distance. The model does not consider the number of demands at each demand point but assumes that the demands of all demand points are equivalent. Considering the variability of individual demand points, the literature [25] proposes the maximal covering location problem (MCLP) model to maximize the number of demands covered for a given response distance and number of service facilities. In [26], the authors determined the number of charging stations based on the energy demand of EVs and the service radius of fast-charging stations. K-mean clustering and fuzzy C-mean clustering were then used to locate...
and quantify them. Subsequently, Voronoi diagrams were employed to divide the service area of each charging station to reduce the distance of electric vehicle charging to reduce the social cost.

The point-based demand model is simple, straightforward and easy to apply. However, it does not consider the driving characteristics of EV users, which makes it difficult to obtain an accurate charging demand distribution.

In the flow demand model, the charging demand of EVs is no longer restricted to nodes in the road network but represented by the traffic volume on the roadway [22]. It aims to determine the location of the service facility to maximize the intercepted traffic without double counting. This model was first proposed in [27] as the flow capturing location model (FCLM), which assumes that the charging demand is generated during the driving process. The FCLM model can better reflect the behavior of EV users: people do not travel specifically for charging but charge during the travel. However, the model does not consider the range of the vehicle. To address this issue, the literature [28] proposes a flow refueling location model (FRLM), which considers the range limit of the vehicle and assumes that the vehicle may stop several times during a trip to refuel or charge. Although the FRLM model is closer to the actual situation, it does not consider the capacity of the service station. To address this issue, the literature [29] proposes the capacitated flow refueling location mode (CFRLM), but it lacks in considering the distribution of the demand in time.

4. Electric vehicle traffic simulation application

With policy support and vigorous promotion by a wide range of vehicle companies, the use of EVs will become a development trend in the future [11]. It is foreseeable that EV ownership will continue to rise and EVs will play an important role in the transportation system. The large-scale applications of EVs will inevitably cause an impact on the existing system and bring about various new challenges. Many planning scenarios, including charging facility layouts, cannot be evaluated by field tests due to the irreducible nature of traffic phenomena and the high testing costs. Simulation is one of the feasible solutions to solve this problem.

There are distinct structural differences between EVs and conventional fuel vehicles. They work on very different principles. EVs are powered entirely by rechargeable batteries (e.g., lead-acid, nickel-cadmium, nickel-metal hydride, or lithium-ion batteries) and have an electric motor as the drive system. Their power system mainly consists of a power battery, a drive motor and obtains electrical energy from the grid or by replacing the battery [2]. EVs do not have engines. They use a battery module to drive the electric motor, which converts electric power into kinetic energy. EVs can recycle electrical energy through electric and hydraulic braking systems during deceleration, which can be very different from the braking system of traditional fuel vehicles. In [30], through a 5-month experiment, the authors compared the driving behavior of EV users and traditional fuel vehicle users. The results show that there is no significant difference between EVs and conventional fuel cars in terms of average speed. Acceleration and deceleration are sharper in EVs than conventional fuel cars at the beginning of the experiment and flatter after five months. The literature [31] also concluded that the dynamic characteristics of electric cars differ from those of conventional fuel cars, which have higher acceleration and faster deceleration due to the absence of a gearbox and regenerative braking systems.

These characteristics reflected in the traffic simulation models are also bound to be different. Traffic simulations can be generally divided into three categories: macro traffic simulation, meso traffic simulation, and micro traffic simulation. Among them, micro traffic simulation is based on a single vehicle. It has a high degree of detailed descriptions and can accurately portray the traffic behavior of a single vehicle. Micro traffic simulation can reflect the differences between EVs and traditional fuel vehicles. The car-following model is an important theoretical basis for microscopic traffic simulation. The model uses mathematics to describe the driving state of a rear-end vehicle following a front-end vehicle on the road. Some of the classic car-following models are the general motor model (GM), Gazis-Herman-Rothery model (GHR), which is improved based on GM model, collision avoidance (CA), optimal velocity (OV), Helly model, action point (AP) and fuzzy logic-based model [32],[33],[34]. In recent years, some researchers have also suggested improved models for EVs. The literature [35] proposed a
car-following model considering the range of EVs and discussed the effect of the range of EVs on traffic volume under four traffic situations. In [36], a car following model based on the optimal electric vehicle energy consumption model was proposed, aiming to minimize the energy consumption of electric vehicle traffic flow. The literature [37] suggested an electric traffic-following model based on the battery SOC (state of charge) and analyzed the effect of battery SOC on vehicle behavior in heterogeneous traffic systems. The literature [31] proposed an EV car-following model based on the dynamic characteristics of EVs, which is calibrated and validated using data from Longbang Middle Road in Nanjing, China. In [38], the authors developed a reinforcement learning-based car-following model for autonomous EVs, which can help improve traffic congestion in addition to improving energy consumption.

In terms of combining EVs and traffic simulation, the amount of related research works is relatively small, and they mainly focus on the layout planning of charging infrastructure. The literature [39] developed an Aristoc-based traffic simulator for analyzing the location of EVs entering the power-deficit state and the number of EVs being charged in each charging station in the road network. The authors have developed a charging station layout search algorithm based on the EV power-deficit location in the traffic simulator. This algorithm can reduce the number of EVs in the power-deficit state in the road network. However, the simulation process only considered the battery level but failed to take into account the dynamic characteristics of EVs. The literature [40] proposed a dynamic traffic simulation based on the road section transmission model LTM to obtain the spatial and temporal distribution of highway traffic, then calculated the service index of electric vehicle charging stations with the M/M/S queuing theory model based on the simulation results, and finally proposed a planning model and solution for highway charging stations. The first part of the study uses a macroscopic traffic model that does not reflect the characteristics of EVs and only in the second part of the study the charging demand and charging behavior of EVs are considered for the service index calculation. The literature [41] investigated an EV mobility model based on realistic driving behavior and traffic data to evaluate the feasibility of charging facility deployment and the possibility of inter-vehicle communication. This work validated simulation results based on a vehicular mobility network (VANET) rather than a real road network, where each node in the network corresponds to an EV. Based on MATSim, a multi-agent-based traffic flow simulation platform, the literature [42] calculated the charging demand in combination with the real vehicle distribution in Berlin. Based on that, three different charging strategies for private EVs in urban areas were developed and analyzed: home charging, workplace charging and leisure charging. Again, the study considered only vehicle battery level and energy consumption in the simulation process.

5. Conclusion
As an efficient, clean and sustainable means of transportation, EVs can effectively reduce pollution and relieve environmental pressure. The development of EVs is inseparable from the construction of charging infrastructures. There is a close connection between the two. Therefore, the study of the layout planning of charging infrastructure is an important step to ensure the promotion of EVs as well as low-carbon transportation.

This paper first summarises electric vehicle travel behavior, then compares different models for charging facility layout planning, followed by an overview of the application of electric vehicle traffic simulation to charging layout. Most of the current research on EV travel behavior has been conducted using real EVs data. However, the data used in the majority of the studies are too limited and insufficient. Currently, most of the research on the layout planning of charging facilities is still based on the traditional facilities siting problem. However, more factors such as the dynamic spatial and temporal distribution, the interactivity between EVs and charging infrastructures need to be considered. Traffic simulation, being an important verification tool for charging facility layout planning, also requires more improvements based on the characteristics of EVs.

With the rising popularity of EVs and the trend towards intelligent network connectivity, the amount of data will become increasingly larger and more diverse in the future. The development of technologies such as artificial intelligence and cloud computing provide reliable support for electric vehicle data
analysis and new methods on how to filter, process and exploit big data. Future research should combine these new technologies with traditional methods. New applications should also be explored for the diversity of data. In addition to implementing models that are closer to real-life situations, the development of more personalized models also needs to be considered. Finally, different research directions can be combined, such as integrating traffic simulation into a more complete system platform to achieve multi-functionalities including monitoring, analysis, operation and scheduling, thus promoting the development of intelligent transport as well as smart cities.

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References
[1] Li, H., & Wang, J. (2020) Exploration of the future development trend of pure electric vehicles. Internal Combustion Engine & Parts, 20: 155-156.
[2] Chen, Q., & Sun, L. (2005) Present status and future trends of electric vehicle. Science & Technology Review, 04: 24-28.
[3] National Development and Reform Commission of the People's Republic of China, National Energy Administration of the People's Republic of China, Ministry of Industry and Information Technology of the People's Republic of China, & Ministry of Housing and Urban-Rural Development of the People's Republic of China. (2015) Electric vehicle charging infrastructure development guide (2015-2020). Beijing, China.
[4] Sun, Y., & Liu, K. (2017) The impact of mileage anxiety on the willingness to use pure electric vehicles. Journal of Wuhan University of Technology (Transportation Science & Engineering), 41(01): 87-91.
[5] Pan, L. (2019) Charging choice behavior based location optimization for EV charging facilities. (PhD thesis) Beijing Jiaotong University, Beijing, China.
[6] Liu, K., Li, A., & Sun, X. (2016) Optimizing spatial distribution of EV charging stations. Urban Transport of China, 14(04): 64-69.
[7] Guo, L., Wang, K., Wen, F., Hou, J., Qiu, L., & Huang, J. (2019) Review and prospect of charging facility planning of electric vehicle. Journal of Electric Power Science and Technology, 34(03): 56-70.
[8] Xing, Q., Yang, Q., Fan, J., Zhang, Q., Chen, Z., Zhang, Z., & Wang, R. (2020) Electric vehicle fast charging demand forecasting model based on data-driven approach and human behavior decision-making. Power System Technology, 44(07): 2439-2453.
[9] Wen, J., Tao, S., Xiao, X., Luo, C., & Liao, K. (2015) Analysis on charging demand of EV based on stochastic simulation of trip chain. Power System Technology, 39.6: 1477-1484.
[10] Chen, J., Ai, Q., & Xiao, F. (2016) Electric vehicle charging station planning based on travel demand. Electric Power Automation Equipment, 6:34-39.
[11] Yang, B., Wang, L., & Liao, C. (2013) Research on power-charging demand of large-scale electric vehicle and its impacting factors. Transactions of China Electrotechnical Society, 28(02):22-27+35.
[12] Wu, X., Freese, D., Cabrera, A., & Kitch, W. A. (2015). Electric vehicles' energy consumption measurement and estimation. Transportation Research Part D: Transport and Environment, 34: 52-67.
[13] Wu, Q., Nielsen, A. H., Østergaard, J., Cha, S. T., Marra, F., Chen, Y., & Trebølt, C. (2010). Driving pattern analysis for electric vehicle (EV) grid integration study. In: 2010 ieee pes innovative smart grid technologies conference europe (isgt europe). Gothenburg. pp. 1-6.
[14] Speidel, S., & Bräunl, T. (2014). Driving and charging patterns of electric vehicles for energy usage. Renewable and Sustainable Energy Reviews, 40: 97-110.
[15] Azadfar, E., Sreeram, V., & Harries, D. (2015) The investigation of the major factors influencing plug-in electric vehicle driving patterns and charging behaviour. Renewable and Sustainable
Energy Reviews. 42: 1065-1076.
[16] Smart, J., & Schey, S. (2012). Battery electric vehicle driving and charging behavior observed early in the EV project. SAE International Journal of Alternative Powertrains, 1(1): 27-33.
[17] Smart, J., Powell, W., & Schey, S. (2013). Extended range electric vehicle driving and charging behavior observed early in the EV project (No. 2013-01-1441). SAE Technical Paper.
[18] Jia, Y., Chen, H., Li, J., He, F., Li, M., Hu, Z., & Shen, Z. J. M. (2017). Planning for electric taxi charging system from the perspective of transport energy supply chain: A data-driven approach in Beijing. In: 2017 IEEE Transportation Electrification Conference and Expo, Asia-Pacific (ITEC Asia-Pacific). Harbin. pp. 1-6.
[19] Yang, Y., Yao, E., Yang, Z., & Zhang, R. (2016). Modeling the charging and route choice behavior of BEV drivers. Transportation Research Part C: Emerging Technologies, 65: 190-204.
[20] Zhao, P. (2020) Research on the location planning of electric vehicle charging and battery swapping stations. (Master's thesis). Dalian University of Technology, Dalian, China.
[21] Hakimi, S. L. (1964). Optimum locations of switching centers and the absolute centers and medians of a graph. Operations research, 12(3): 450-459.
[22] Upchurch, C., & Kuby, M. (2010). Comparing the p-median and flow-refueling models for locating alternative-fuel stations. Journal of Transport Geography, 18(6): 750-758.
[23] Lin, Z., Ogden, J., Fan, Y., & Chen, C. W. (2008). The fuel-travel-back approach to hydrogen station siting. International journal of hydrogen energy, 33(12): 3096-3101.
[24] Toregas, C., Swain, R., ReVelle, C., & Bergman, L. (1971). The location of emergency service facilities. Operations research, 19(6): 1363-1373.
[25] Church, R., & ReVelle, C. (1974). The maximal covering location problem. Papers of the regional science association, 32(1): 101-118.
[26] Shukla, A., Verma, K., & Kumar, R. (2016, December). Consumer perspective based placement of electric vehicle charging stations by clustering techniques. In: 2016 National Power Systems Conference (NPSC). Bhubaneshwar. pp. 1-6.
[27] Hodgson, M. J. (1990). A flow-capturing location-allocation model. Geographical Analysis, 22(3): 270-279.
[28] Kuby, M., & Lim, S. (2005). The flow-refueling location problem for alternative-fuel vehicles. Socio-Economic Planning Sciences, 39(2): 125-145.
[29] Upchurch, C., Kuby, M., & Lim, S. (2009). A model for location of capacitated alternative-fuel stations. Geographical Analysis, 41(1): 85-106.
[30] Helmbrecht, M., Olaverri-Monreal, C., Bengler, K., Vilimek, R., & Keinath, A. (2014). How electric vehicles affect driving behavioral patterns. IEEE Intelligent Transportation Systems Magazine, 6(3): 22-32.
[31] Xu, Y., Zheng, Y., & Yang, Y. (2021). On the movement simulations of electric vehicles: A behavioral model-based approach. Applied Energy, 283:116356.
[32] Brackstone, M., & McDonald, M. (1999). Car-following: a historical review. Transportation Research Part F: Traffic Psychology and Behaviour, 2(4): 181-196.
[33] Li, Y., & Sun, D. (2012). Microscopic car-following model for the traffic flow: the state of the art. Journal of Control Theory and Applications, 10(2): 133-143.
[34] Saifuzzaman, M., & Zheng, Z. (2014). Incorporating human-factors in car-following models: a review of recent developments and research needs. Transportation research part C: emerging technologies, 48: 379-403.
[35] Tang, T. Q., Chen, L., Yang, S. C., & Shang, H. Y. (2015). An extended car-following model with consideration of the electric vehicle's driving range. Physica A: Statistical Mechanics and its Applications, 430, 148-155.
[36] Li, Y., Zhong, Z., Zhang, K., & Zheng, T. (2019). A car-following model for electric vehicle traffic flow based on optimal energy consumption. Physica A: Statistical Mechanics and its Applications, 533: 122022.
[37] Tang, T. Q., Xu, K. W., Yang, S. C., & Ding, C. (2016). Impacts of SOC on car-following behavior
and travel time in the heterogeneous traffic system. Physica A: Statistical Mechanics and its Applications, 441: 221-229.

[38] Qu, X., Yu, Y., Zhou, M., Lin, C. T., & Wang, X. (2020). Jointly dampening traffic oscillations and improving energy consumption with electric, connected and automated vehicles: a reinforcement learning based approach. Applied Energy, 257: 114030.

[39] Hiwatari, R., Ikeya, T., & Okano, K. (2011, September). A road traffic simulator to analyze layout and effectiveness of rapid charging infrastructure for electric vehicle. In: 2011 IEEE Vehicle Power and Propulsion Conference. Chicago. pp. 1-6.

[40] Ge, S., Zhu, L., Liu, H., Li, F., & Liu, C. (2018) Optimal deployment of electric vehicle charging stations on the highway based on dynamic traffic simulation. Transactions of China Electrotechnical Society, 33(13):2991-3001.

[41] Kang, C., & Zhang, T. (2018, June). Realistic traffic data based mobility modeling and simulation of smart EV. In: 2018 IEEE Third International Conference on Data Science in Cyberspace (DSC) Guangzhou. pp. 854-857.

[42] Jahn, R. M., Syré, A., Graele, A., Schlenther, T., & Göhlich, D. (2020). Methodology for determining charging strategies for urban private vehicles based on traffic simulation results. Procedia Computer Science, 170: 751-756.