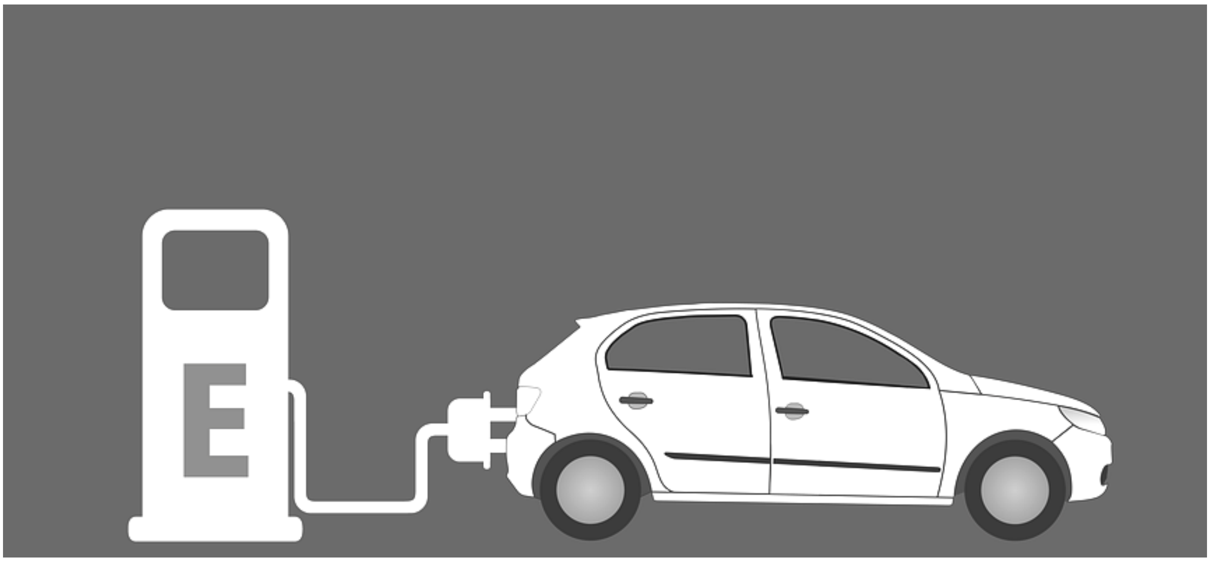

Exploring electric vehicle charging dynamics: Literature review and future framework

Selin Ataç

Matthieu de Lapparent

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Selin Ataç
Institut Interdisciplinaire du Développement de l'Entreprise (IIDE)
Haute Ecole d'Ingénierie et de Gestion du Canton de Vaud (HEIG-VD)
selin.atac@heig-vd.ch

Matthieu de Lapparent
Institut Interdisciplinaire du Développement de l'Entreprise (IIDE)
Haute Ecole d'Ingénierie et de Gestion du Canton de Vaud (HEIG-VD)
matthieu.delapparent@heig-vd.ch

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Abstract

While fossil fuels currently dominate the energy landscape, the anticipated widespread transition to electric vehicles (EVs) in the near future introduces challenges related to infrastructure development and changing mobility patterns. This study explores the obstacles and possibilities associated with the increasing use of EVs and the essential charging station infrastructure. In contrast to studies relying on aggregated data, this work emphasizes the significance of analyzing individual user behaviors, trip characteristics, and socio-economic contexts based on microeconomic foundations. In this work, we provide a literature review and reveal four key dimensions within the EV landscape: (i) competition between users and energy providers, (ii) user travel behavior by integrating discrete choice modeling, (iii) trip chain modeling to understand trip purposes and their relationship to charging station infrastructure, and (iv) optimization of charging station location and allocation to meet user needs. After positioning the existing works in the proposed framework, we finally identify research gaps based on the framework, suggest potential research directions, and provide a comprehensive view of the evolving EV landscape.

Keywords

charging station; competition; disaggregate modeling; electric vehicles; optimization; travel behavior

Suggested Citation

1 Introduction

The adoption of electric vehicles (EVs) has gained substantial momentum due to their eco-friendly nature, marked by the absence of harmful emissions, unlike internal combustion engine vehicles (ICEVs). There exist two types of EVs: battery electric vehicles, which we refer to as EV, and plug-in hybrid electric vehicles (PHEVs). The former relies solely on the battery, which makes it all electric, while the latter involves both a fuel tank and a battery. In this work, we center ourselves around EVs.

EVs are known for their superior efficiency compared to ICEVs, but they still face challenges due to established infrastructure and longer driving ranges in ICEVs. Nevertheless, EVs provide numerous environmental (at least at the use level), economic, technological, and social advantages. Firstly, the reduced environmental impact of EVs, particularly when powered by renewable energy sources, stands as a compelling motivator (Costa *et al.*, 2021). Secondly, the economic appeal of lower fuel costs and operational expenses, coupled with government incentives, is accelerating EV adoption (Naumov *et al.*, 2023). Thirdly, the attraction of advanced technology and convenience, previously a resistance factor, is being supported by advancements in battery technology and an expanding charging infrastructure (Haustein *et al.*, 2021). Finally, the reduction of noise pollution, the potential to alleviate urban congestion, and the surge in environmental consciousness contribute to the appeal of EVs in metropolitan areas (Corradi *et al.*, 2023). All these factors collectively drive the shift from ICEVs to EVs. In fact, according to FSO (2023b), the share of EVs has increased exponentially since 2007 for the case of Switzerland. Consequently, it is essential to understand what role these factors play in charging station (CS) demand and, therefore, the design of its infrastructure.

In transportation, users define their trips by choosing their origins and destinations, the path to go from origin to destination, the mode to be taken, the time of the day to start the trip, etc. Each of these decisions is affected by several attributes. For example, path choice can be affected by the path length, the time it takes to traverse, the extra costs (such as tolls), and some other unobserved reasons. The user might also have constraints such as time and budget limitations, which restrict the possible number of paths. Regarding EVs, the vehicle range poses another restriction on the choices. These constraints result in different user travel behaviors in EVs compared to ICEVs (Yang *et al.*, 2016). Range anxiety for EVs due to inadequate infrastructure and prolonged charging times compared to ICEV refueling impedes widespread adoption of EVs. Notably, the scarcity of CSs is a central concern, reflecting both insufficient battery capacity for extended ranges and underdeveloped charging infrastructure. The literature finds evidence proving that even though ICEV users plan to purchase an EV, they tend to keep their ICEV as the main car and use it for occasional longer trips (Metais *et al.*, 2022). This finding shows that the behavior of the EV users should be further analyzed to both support the full transition to EV adoption and optimize CS infrastructure.

Nevertheless, the transition to EVs is entangled in a classic chicken-egg dilemma: does the infrastructure (i.e., supply) come first, or does EV adoption (i.e., demand) (Metais *et al.*, 2022)? This challenge raises questions about the starting point of this transformation. Although governments encourage users through incentives, overcoming this obstacle requires a holistic approach that recognizes the symbiotic relationship between infrastructure development and EV use. This paper focuses on EVs and how they are covered in the literature. As a baseline assumption, we will consider personally owned cars and will not take EVs used in public transportation or electric taxis into consideration. We present a literature review in Section 2. Later, we identify the research gaps in the literature in Section 3. Finally, we sum up with concluding remarks in Section 4.

2 Literature review

The literature consists of stated-preference (SP) experiment designs that explore EV user behavior through route choice (Ashkrof *et al.*, 2020), regular charging behavior (Ashkrof *et al.*, 2020), and occasional charging behavior (Visaria *et al.*, 2022). These surveys are then used to develop choice models such as mixed logit (ML) model to account for unobserved heterogeneity (Ashkrof *et al.*, 2020; Visaria *et al.*, 2022), nested logit (NL) model (Ren *et al.*, 2022), and conditional logit model (Liu *et al.*, 2022). Some factors affecting EV user's choice are found to be the route type, charger type, state-of-charge (SOC) at the origin and destination, slow-charging availability at the destination, fast charging duration, and waiting time. Regarding occasional charging, Visaria *et al.* (2022) observe that facility availability at the charging location, higher likelihood of available chargers, and lower costs encourage users to deviate from their original route. This finding supports the need for smart location and allocation of CSs as well as pricing schemes. There also exists works that jointly models several choices, such as activity choice, duration, and in-travel productivity with respect to typical office conditions using copula approach (Pawlak *et al.*, 2017).

The studies point out the gap in understanding individual-level EV charging patterns (Ren *et al.*, 2022). Some simplistic approaches such as trip analysis based on floating car data (Brancaccio and Deflorio, 2023), empirical charging behavior of PHEVs (Mandev *et al.*, 2022), and GPS-based travel survey data (Kontou *et al.*, 2019) provide useful information such as charging frequencies. The analysis can be conducted based on various factors such as user groups and charging days (Mandev *et al.*, 2022). For example, Mandev *et al.* (2022) find that the users do not charge their PHEVs only on 3-7% of the nights. Following this finding, we could expect that this ratio is even smaller for EV users as they solely rely on the battery, implying that it is more crucial to have CS accessibility in the case of unavailability of home charging.

We also observe works that take it a step forward and use agent-based simulation (Pagani *et al.*, 2019), trip chain modeling (TCM; Tang and Wang, 2015; Aghajan-Eshkevari *et al.*, 2023), agent-based TCM (Lin *et al.*, 2019; Ren *et al.*, 2022; Liu *et al.*, 2022), and multiple logistic regression Javid and Nejat (2017) to study the potential factors that are relevant to purchasing an EV and consequences of user behavior on EV charging infrastructure. Pagani *et al.* (2019) observe in their Swiss case study that competition in the public charging marketplace can pose financial challenges and note that home and work charging are major sources of increased electricity demand, with distinct usage patterns, and accurate infrastructure modeling is essential for identifying necessary grid upgrades. Tang and Wang (2015) consider both spatial and temporal distribution of moving EVs. Their model, which is based on random trip chain and Markov decision process, assesses the nodal charging demand. Lin *et al.* (2019) develop an agent-based TCM that simulates the heterogeneous travel and charging patterns of EVs. This model allows them to study complex transportation systems and associated energy consumption, and identify strategies to optimize the use of grid load. Ren *et al.* (2022) use meter-level real-world data and find that most EVs in the study area do not charge during one-day trips, and users tend to maintain moderate SOC levels before departure, with factors like distance, speed, and weather influencing charging choices. As expected, they find that the longer the distance traveled, the more fast charging is adopted. By combining realistic travel and charging behavior in their model, Liu *et al.* (2022) are able to analyze high-resolution spatiotemporal demand and state that it is necessary to install CSs at work/public locations as they are found to cover more than half of the total charging demand. On the other hand, they highlight that their results should be supported by real-world data. Aghajan-Eshkevari *et al.* (2023) also employ TCM for modeling EVs' daily trips to optimize the routing and power management of EVs together with the power distribution and transportation network whereas Wu and Pang (2023) focus on optimal scheduling of charging and discharging of EVs through TCM. Javid and Nejat (2017) point out that household's income, maximum level of education in the household, the buyer's car-sharing status, CS density, and gas prices have a significant effect on EV adoption. However, such studies only focus on demand and do not formally address the CS provider economic problem.

Supported by findings in the literature, we see the importance of infrastructure planning and CS density. The optimization models in the literature concerning the location and allocation of CSs leverage aggregate demand data such as the number of trips between an origin and destination (OD; e.g., Arslan and Karaşan, 2016). However, since the travel behavior of EV users depends on the CS locations, user activity patterns, and socio-economic characteristics, the effect of these attributes should be examined at an individual level to reach a more representative infrastructure (Ashkrof *et al.*, 2020). The studies consider three primary methods for CS location optimization: (i) node-based approach formulates the problem as a facility location problem and usually uses aggregate data, (ii) path-based approach captures the flows of the EVs and places CSs on the links rather than nodes, and (iii) tour-based, also known as activity-based, approach does not only consider the EV flows but also the activity patterns of the EV user (Metais *et al.*, 2022). The tour-based approach is able to combine advantages of both node-based and tour-based with the help of disaggregate information, which implies that it requires very detailed data. Furthermore, adopting a supply side approach requires rich input data (Patil *et al.*, 2023). Data from surveys and simulations can be used to achieve the necessary level of detail in designing such formulations.

Solution methodologies proposed in the literature include the extension of Flow Refueling Location Problem to efficiently locate CSs for both EVs and PHEVs (Arslan and Karaşan, 2016), and a nonlinear integer programming problem to solve fast CS location and sizing while maximizing operator's profit (Gan *et al.*, 2020). Most of the works develop efficient solution methodologies based on their models such as Benders decomposition (Arslan and Karaşan, 2016) and genetic algorithm-based heuristic (Gan *et al.*, 2020). Gan *et al.* (2020) also incorporates demand elasticity with respect to distance to the CS and waiting time at the CS. The cut selection techniques proposed by Arslan and Karaşan (2016) demonstrate the efficiency of the Pareto-optimal cut generation scheme in reducing solution times.

In addition to single-dimension frameworks, some studies in the literature showcase holistic approaches. Combining CS network optimization and discrete choice modeling (DCM), Fazeli *et al.* (2020) aim to design CS networks within urban communities by considering both uncertainty and EV driver behavior. Their comprehensive framework incorporates CS and charger type choice, two-stage stochastic programming, and data-driven simulations. Results from a case study representing Detroit, Michigan, in the US indicate a preference for a mix of charger types, with level 2 chargers being favored when budgets are larger. Riemann *et al.* (2015) investigate the optimal location of wireless charging facilities for EVs and model the route choice. Their mixed-integer nonlinear program aims to locate a given number of facilities out of a set of candidate locations while trying to capture the maximum traffic flow on the network. They use linearization techniques to improve computation time.

Competition in oligopolistic markets is usually modeled using three models: (i) Bertrand, (ii) Cournot, and (iii) Stackelberg. They consider identical products. Decisions are made simultaneously among the competitors in Bertrand and Cournot whereas there is a leader and a follower in the Stackelberg model. In Bertrand model, the price is the output of the model whereas in Cournot and Stackelberg, the output is the quantity of the product. Nash equilibrium represents a stable state where each participant's strategy, such as pricing or quantity decisions, is optimal given the strategies chosen by others. Competition among EV users (Xiong *et al.*, 2017) and CS operators (Li *et al.*, 2021; Bernardo *et al.*, 2016; Lee *et al.*, 2018) are usually studied in combination with another aspect and stands as an important module as it affects pricing, hence EV users' choices. The works search for a Nash equilibrium within the given system environment. The competition among CS operators can be modeled as a Bertrand game (Bernardo *et al.*, 2016), as a Cournot game (Li *et al.*, 2021), and as a Stackelberg game (Lee *et al.*, 2018). In addition, collaboration or coordination among the CS operators is another interesting dimension to assess the value of interoperability of charging networks (Visaria *et al.*, 2022).

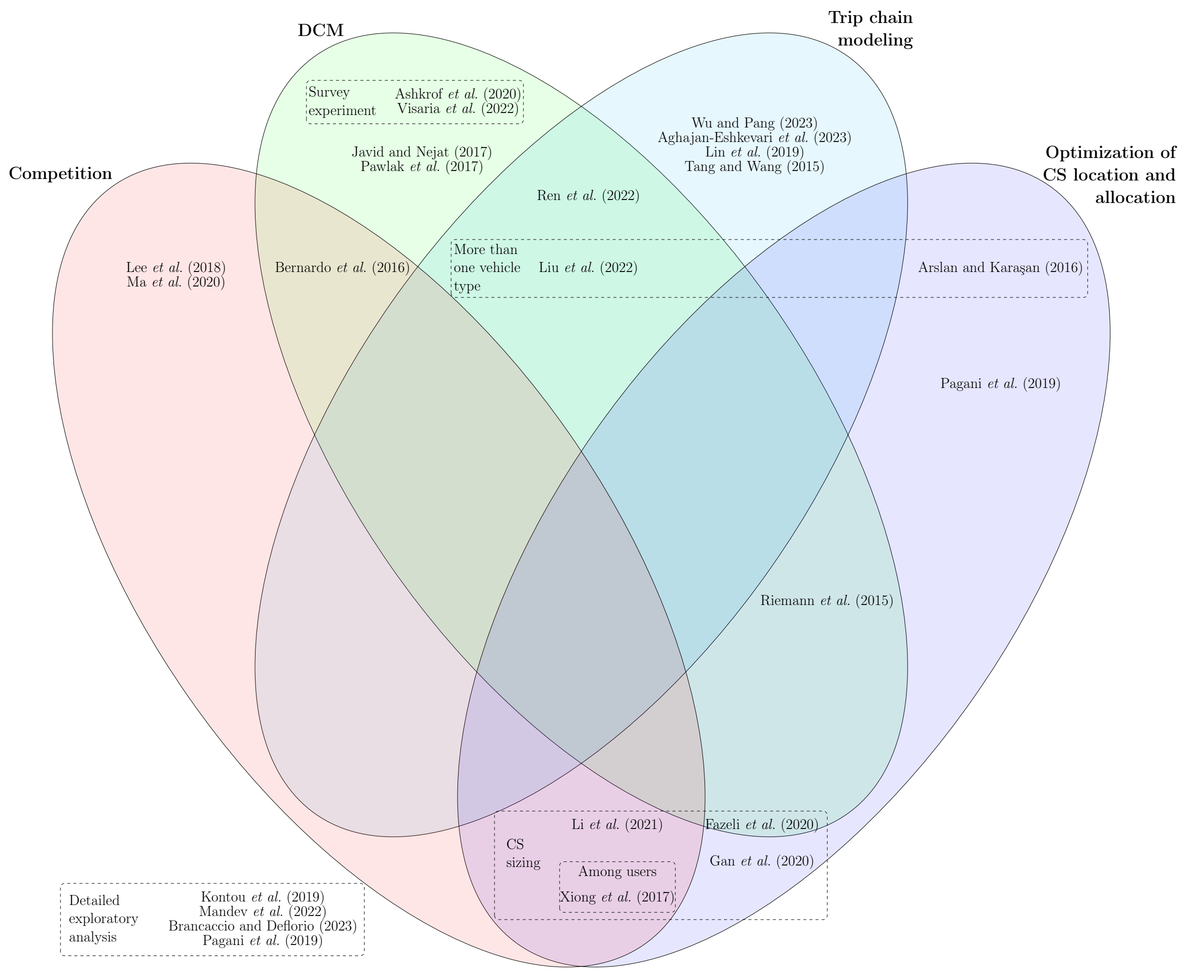
Xiong *et al.* (2017) study the competitive and strategic charging behaviors of EV users, as an EV user's charging cost depends on the choices of others, i.e., the availability of chargers. They formulate a bilevel optimization problem to determine the best CS location and allocation. They later transform it into a single-level nonlinear optimization problem by exploiting the equilibrium of the EV charging game. Li *et al.* (2021) aim at predicting EV charging demand and optimizing the competitive charger allocation through a Cournot competition. They also compute the number of necessary chargers at each zone of the city, i.e., optimal sizing of the CSs. They simplify the problem definition by assuming that the charging demand of a specific zone is linearly proportional to its traffic flow. In other words, the authors do not account for disaggregated demand when modeling the competition. On the other hand, Bernardo *et al.* (2016) put DCM and competition together in their framework and simulate entry and location of fast CSs in a full game of strategic interaction based on Bertrand model. They incorporate two choice models, a logit model for simulating the entry of firms and an MNL for an EV user selecting a CS to charge their vehicle. They state that lower EV penetration rates do not offer a solution for range anxiety, whereas starting from a 3% EV penetration rate, a "unique" stable equilibrium is reached. They observe spatial differentiation among firms when the firms compete on location and price. They conclude with the claim that the social welfare would improve with a policy intervention in the form of a uniform price lower than the one obtained in the free-pricing competitive scenario.

In conclusion, the reviewed literature provides a comprehensive understanding of EV user behavior, charging patterns, and the complex interaction between infrastructure planning and user choices. The studies delve into diverse methodologies, ranging from stated-preference experiments to agent-based simulations and trip chain modeling, shedding light on factors influencing EV adoption and charging decisions. The critical role of CS accessibility, location, and pricing schemes emerges as a common theme. Furthermore, the integration of competition models among users and CS operators underscores the need for strategic planning and policy interventions to enhance social welfare. The reviewed works collectively emphasize the necessity of individual-level analyses, detailed data, and sophisticated optimization models for informed decision-making in the rapidly evolving landscape of EV charging infrastructure. This comprehensive literature review sets the stage for Section 3, where we detail the research gaps and recommendations for future work.

3 Research gaps and recommendations

Following our literature review, we identify four main topics relevant to EVs: (i) competition, (ii) discrete choice modeling, (iii) trip chain modeling, and (iv) optimization of CS location and allocation. The first topic can happen both among users and among energy providers. Examining the strategic interactions and decision-making processes in accessing charging infrastructure provides crucial insights into the competitive landscape. The second examines the behavioral aspects of EV usage, shedding light on the factors influencing individual decisions such as charger selection, route preferences, and charging station choices. The third investigates the close relationship between travel behavior and EV usage. Understanding how mobility patterns, distances, and charging choices interconnect contributes to a better comprehension of the EV ecosystem. Finally, the fourth is concerned with the need for efficient charging infrastructure planning, i.e., optimal CS location and allocation. We present a diagram, illustrated in Figure 1, that positions the reviewed works with respect to their content and shows the research gaps in the

Figure 1: Summary of the literature review and positioning of our proposal



literature. We see that the four main topics are widely studied independent from each other. However, we see very few works investigating a combination of these main topics, which shows that multidimensional approaches suggest a promising research avenue.

Range anxiety is one of the main resistance factors that prevent high EV adoption. Therefore, the literature should focus more on innovative solutions, such as the development of choice models in the light of stated- and revealed-preference surveys, as well as the optimization of CS locations and allocations of different charger types, e.g., slow and fast charging, in those CSs. This research avenue is essential to satisfy the charging demand and facilitate the effective integration of EVs into our transportation ecosystem through reduction of range anxiety.

We see that the literature focuses on daily activities of users. However, according to FSO (2023a), the average distance per day per person traveled by car is found to be 20.8 kilometers in 2021 in Switzerland. We believe that taking this into account is essential as it is way less than the driving range of a standard EV. Therefore, daily simulations and activity-travel plan analysis are not sufficient. There exists two ways to tackle this issue: (i) multi-day structures can be incorporated (Zhang *et al.*, 2020) and (ii) the demand can have a probabilistic definition for a single day.

The literature usually considers homogeneous vehicles and homogeneous charging power levels. Nevertheless, accounting for variety allows for a better representation of the ecosystem. For example, one can define p types of batteries, allowing for representation of different vehicle types and brands, including hybrid vehicles, and k levels of charging power. Including these in the modeling framework is important as it changes the charging duration, therefore spatial and temporal demand for CS.

We fail to see works that combine competition and TCM. For example, Lin *et al.* (2019) uses a TCM to study the distribution of charging patterns. Including competition as another dimension in this framework would allow identifying high-demand areas and the times of the day, which would result in a better pricing strategy. When these two are also combined with DCM, the trip purposes are revealed, allowing the operator better analyze the trends.

Although we see works that combine (i) optimization and DCM and (ii) optimization and TCM, we do not find any study that combines the three of them. As discussed before, DCM and TCM aid in helping to explain the behavioral aspects of the users. Combining the two with optimization, one can solve the inefficiencies in the system such as pricing, CS location and allocation.

The combination of competition and optimization is already studied in the literature (Li *et al.*, 2021; Xiong *et al.*, 2017). These studies provide with an understanding the dynamics among users and among energy providers. Then, the prices are optimized accordingly. We could add TCM or DCM to this. The former would identify the disaggregate behavior and more precise modeling. Bortolomiol (2022) does the latter and make a connection to the trip purpose not on EV usage but in a parking choice study. They work on a framework where supply and demand interactions are considered through a Stackelberg game. They utilize advanced DCMs, multi-product offer by the suppliers, and price differentiation. Then, the competition between suppliers and the market are modeled using MILPs. Their model-based heuristic finds approximate equilibria of a deregulated competitive market. This approach enables them to determine market shares based on different pricing schemes.

In the ideal world, it is interesting to study all the aspects mentioned above in one framework. That is, combining (i) disaggregate demand information to model the demand through choice models, (ii) use the developed demand model to optimize the location, sizing, and pricing of CSs, and (iii) formally model competition among users and across operators, while incorporating (iv) modeling of heterogeneity of users' preferences, would represent the real-world from all aspects.

4 Conclusion

This paper presents a literature review and an analysis of research gaps in the literature related to EVs. Our review shows that there is no empirical industrial organization framework that jointly models disaggregate EV charging behavior through DCM and TCM, market structure (number and types of competitors, competing schemes) and optimal supply strategies (CS locations, charging power and prices). Therefore, any sensitivity analysis or scenario simulation do not lead to realistic results. We point out some future research directions. These include understanding the causes of range anxiety, multi-day modeling, and considering heterogeneous vehicles and charging power levels. Furthermore, we emphasize the importance of a holistic approach to the problem.

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