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Optimal management of electric vehicle charging loads for enhanced sustainability in shared residential buildings

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Demand management of electric vehicles (EVs) in shared residential parking lots presents challenges for sustainable transportation systems. Especially, in shared parking lots where multiple EVs share the same parking space, such as residential apartments. This is challenging due to involvement of various factors such as limited number of chargers, limited capacity of transformer, and diverse driving behavior of EV owners. To address this issue, this study proposes an optimal demand management framework that addresses limited chargers, transformer capacity, and diverse driving behavior to promote sustainable EV integration. By estimating driving behavior, energy consumption, and utilizing a linear programming-based optimization model, power allocation to EVs is optimized based on multiple factors. A satisfaction index is introduced to measure the satisfaction level of the EV community, further emphasizing user-centric sustainability. Performance analysis includes factors such as power usage, charger utilization, and community satisfaction. The performance of the proposed method is compared with a conventional method and the proposed method increase the satisfaction index of the community by up to 10%. In addition, sensitivity analysis is used to explore the impact of factors like charger availability, EV penetration, and transformer capacity limits. Results show that with 3% EV penetration, satisfaction levels exceed 75%, reaching over 80% with five chargers and 6% EV penetration.

KEYWORDS

electric vehicle charging, demand management, sustainable transportation, shared residential buildings, user satisfaction, resource optimization, integrated sustainability, sustainable communities

1 Introduction

1.1 Motivation

Emissions in transportation represent a critical contributor to global environmental challenges, accounting for a significant portion of greenhouse gas emissions worldwide. It accounts for about a quarter of the total emissions (Vision, 2050), necessitating urgent decarbonization efforts to align with international climate agreements. Electric vehicles

(EVs) are considered a viable option to reduce emissions from the transport sector, especially if they are charged with renewable power (Hussain and Musilek, 2022a). Therefore, the penetration of EVs is increasing day by day. For example, a total of 14% of all new cars sold were electric in 2022, up from around 9% in 2021 and less than 5% in 2020. Over 2.3 million EVs were sold in the first quarter of 2023, about 25% more than in the same period last year. It is expected that about 14 million EVs will be sold by the end of 2023, representing a 35% year-on-year increase (IEA Global EV, 2023). The International Energy Agency (IEA) has also increased the expected share of EVs by 2030 to 35% from 25% in the previous year's outlook report (IEA Global EV, 2023). In addition different issues related to power electronics and their monitoring and control are discussed in (Liu, 2021; Wang et al., 2022). Similarly, the impacts on weak grids is discussed in (Shao et al., 2023) and on low carbon energy economy in (Luo et al., 2024).

However, the transition to EVs as a viable solution for reducing greenhouse gas emissions in the transportation sector presents several challenges for the power sector (Khan et al., 2022; Zhang et al., 2022). For example, at the power system level, accommodating the increased demand necessitates additional power plants to cater to EVs' energy needs and serve as reserves (Heuberger et al., 2020). This heightened demand strains local infrastructure, causing technical issues like voltage fluctuations, network congestion, and phase imbalances, particularly at the distribution level (Hou et al., 2017). Moreover, in residential circuits, the peak EV load coincides with the peak residential load (weekday evenings) and can easily overload the local equipment (Fachrizaral et al., 2021; Zhang H. et al., 2023). This is especially challenging for apartment complexes where several EVs are parked and charged together (Hussain and Musilek, 2022b). In addition, the impact of EVs on the air quality in China is assessed in (Lyu et al., 2024) for different cities throughout the lifecycle of EVs. Different types of dispatch strategies are also discussed in the literature such as distributed dispatch (Li et al., 2022) and dynamic dispatch (Duan et al., 2023). Finally, decentralized energy control is discussed in (Shirkhani et al., 2023) and an adaptive lightweight defect detection model is proposed in (Lei et al., 2023).

1.2 Literature review

To address these issues, related to equipment overloading in distribution systems, several studies are conducted in literature. These studies can be broadly divided into two categories. In the first group of studies, system-level measures are suggested to manage the load of EVs. For example (Almutairi and Alyami, 2021), proposes per-unit load estimation of EVs to model and analyze various penetration levels of EVs in different locations (Tran et al., 2019). suggests using home solar panels to charge EVs, aiming to reduce power surges and enhance grid stability (Kong et al., 2022). introduces an optimization model for managing EV charging loads in distribution networks, employing a bi-level programming approach to select charging stations and manage loads. Additionally (Mazhar et al., 2023), evaluates machine learning-based methods for managing EV load in smart cities. Several studies also proposed dynamic pricing as a method to manage EV loads. For instance (Limmer and Rodemann, 2019), proposes

dynamic pricing at EV charging stations to reduce peak demand charges and increase operator profits. Similarly (Moghaddam et al., 2019), suggests dynamic pricing to shift loads during evening peaks, aiming to minimize overlaps with residential peak hours and reduce network instability risks. Furthermore (Sayarshad et al., 2021), introduces a dynamic pricing model for urban freight transport involving electric and conventional vehicles, aiming to reduce costs and delays. Different aspects of EVs models such variations in electrical parameters and underlying voltage tracking control are discussed in (Zhang et al., 2021; Zhang X. et al., 2023).

However, several studies report that system-level management and pricing policies alone may not be suitable for effectively managing the load of EVs (Hussain and Musilek, 2021; Geotab, 2023; Hussain and Musilek, 2021; Zhang et al., 2021; Zhang X. et al., 2023; Sayarshad et al., 2021; Moghaddam et al., 2019; Limmer and Rodemann, 2019; Mazhar et al., 2023; Kong et al., 2022; Tran et al., 2019; Almutairi and Alyami, 2021; Lei et al., 2023; Shirkhani et al., 2023; Shirkhani et al., 2023; Duan et al., 2023). This is primarily due to local equipment, especially in distribution systems, often experiencing overload from direct connections of EVs, resulting in technical issues such as voltage fluctuations and network congestion (Geotab, 2023). Moreover, implementing EV charging infrastructure might not universally suit all communities, especially in residential or commercial settings (Almutairi and Alrumayh, 2022). Consequently, a second group of studies has emerged recently, focusing on local demand management of EVs to mitigate local equipment overload, discussed below.

The growing adoption of EVs is discussed in (Tulabing et al., 2018), where localized demand control is proposed to prevent grid congestion. Simulations suggest that a 40% EV participation rate ensures grid resilience despite 100% EV adoption. Additionally (Chen and Chang, 2016), introduces a demand response-based method for EVs, employing cloud-based management to minimize costs. Meanwhile (Hussain et al., 2023), presents a welfare-focused model for realizing Vehicle-to-Vehicle (V2V) communication to manage EV charging stations with multiple EVs (Ahmadi et al., 2023). discusses various approaches for mitigating EV charging costs, including strategies such as solar power connections and V2X approaches. Furthermore, a comprehensive review conducted in (Zhang et al., 2020) focuses on energy management strategies for EVs, highlighting clustered EV demand management as a significant challenge.

1.3 Research gap and contributions

From the literature review, it is evident that numerous studies have explored managing EV load both at the system and local levels. However, most of these studies have concentrated on single homes, analyzing their collective impact on the system. In shared parking stations like residential apartments and commercial centers, EVs can readily overload local equipment, such as transformers. Additionally, allocating power to EVs during system peak load hours poses a complex challenge, involving factors such as customer satisfaction levels, available equipment capacity, and the number of chargers in each locality. The existing literature has not comprehensively considered all these factors together. It is

imperative to consider all these factors collectively to present various options for policymakers aimed at maximizing EV owners' satisfaction. These options may include installing more chargers or upgrading local equipment by the utility. Furthermore, this multi-factor analysis is essential for selecting the optimal number of chargers for a given number/percentage of EVs in any shared parking location.

To address the research gaps identified in the previous paragraphs, a multi-factor EV load management framework is proposed in this study. The aim of this framework is to offer insights into determining the optimal number of chargers and capacity constraints of local equipment (transformers). These insights will assist policymakers and utilities in planning system upgrades and installations suitable for accommodating a specific level of EVs. The framework's implementation involves several steps. The major contributions of this study are as follows:

- EV driver behavior is estimated using the National Household Travel Survey (NHTS) dataset. Subsequently, EV parameters are utilized to determine the daily energy demand of EVs.
- An optimization model is then developed to allocate the available power among EVs within the charging station of a residential apartment complex. This consideration encompasses a shared parking lot accommodating both conventional vehicles and EVs.
- A satisfaction index is proposed to quantitatively measure EV owners' satisfaction levels by comparing the allocated energy demand with the actual demand before their departure time.
- A sensitivity analysis is conducted to assess various parameters, including the number of chargers, EV penetration levels, and transformer capacity limits.

This analysis aims to further enhance the understanding of the framework's performance under different conditions.

The reminder of the paper is organized as follows. Introduction section is followed by modeling of EV demand (Section 2), where vehicle driving parameters and EV parameters are extracted. In section 3, an optimization problem is formulated to allocate power to EVs considering various factors such as number of chargers, number of EVs, and capacity of the distribution equipment such as transformers. The performance of the proposed method is evaluated for a residential apartment complex in Section 4. A sensitivity analysis of various factors, including the number of chargers, the penetration level of EVs, and the limits of the transformer's capacity in conducted in Section 5. Finally, conclusions and future research direction are discussed in Section 6.

2 Demand management of electric vehicles

Managing the demand of EVs in shared parking lots, particularly in residential apartment complexes poses significant challenges. These challenges arise from the limited availability of charging spots and the constraints imposed by local transformers. Consequently, this section begins with the estimation of EV load, followed by strategies for load management specifically focusing on EVs (Section 3).

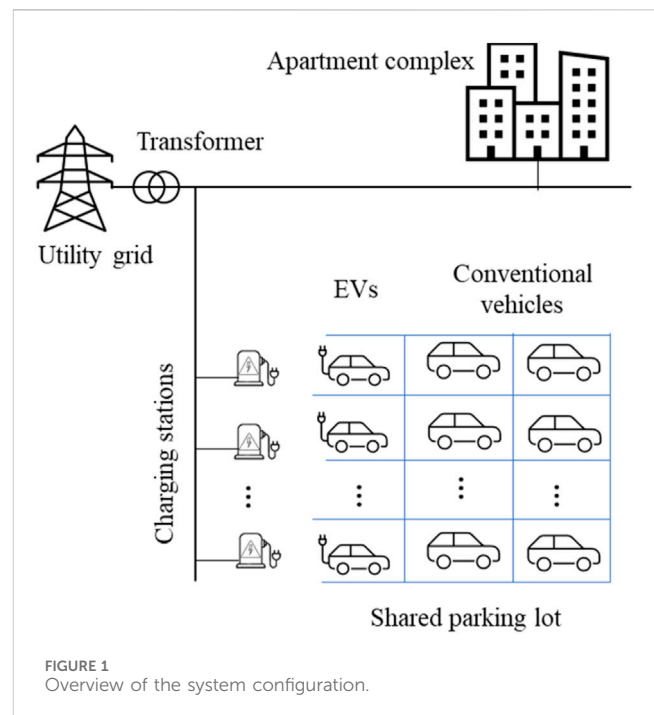


FIGURE 1
Overview of the system configuration.

2.1 System configuration

While the adoption of EVs is increasing worldwide, their penetration levels remain relatively low compared to conventional vehicles. Consequently, most shared parking lots are primarily designated for conventional vehicles, with only a limited number of slots equipped with chargers for EVs. This study considers this prevalent scenario where conventional vehicles dominate the parking spaces. Figure 1 illustrates the system configuration, comprising a residential apartment complex with a shared parking lot. The designated EV spots within the parking lot are equipped with chargers. Both the building and the charging stations are connected to the utility grid via the same transformer. Hence, effective management of the EV load in the charging station becomes crucial since the peak load of residential buildings often coincides with the peak load of EVs. This synchronization occurs because many EV owners tend to park their vehicles and commence charging upon arriving home in the evenings.

2.2 Demand modeling of electric vehicles

Estimating the load of EVs involves several sequential steps. Initially, data pertaining to drivers' travel behavior is required, followed by data related to EVs (Yang et al., 2024). Due to the limited availability of large datasets specifically for EV drivers, conventional vehicle data is commonly utilized, as seen in other studies (NHTS, 2023). The NHTS data is considered reliable and has been utilized by numerous researchers for similar analyses. Therefore, in this study, NHTS data is employed to estimate driver behavior. An overview of the various steps involved is presented in Figure 2. The data is first pre-processed to rectify any erroneous reporting, such as missing fields or unrealistic speeds. Subsequently, vehicle trips are recorded, and daily mileages are computed for each vehicle.

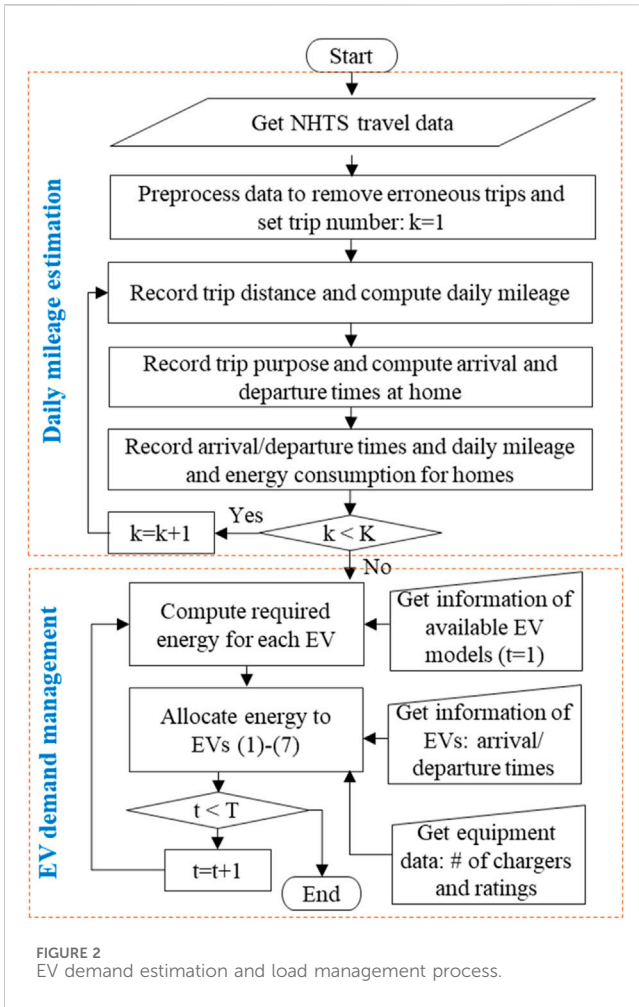


FIGURE 2 EV demand estimation and load management process.

In this study, stochastic simulation models for PEV deployment are implemented using a data-driven approach that integrates key components such as driver behavior, PEV characteristics, charging infrastructure, grid integration, and policy and market factors. The models utilize historical data and statistical methods to simulate driver behaviors, including trip lengths, frequencies, and charging preferences, based on datasets like the NHTS. The models also consider the need for charging infrastructure and assess the grid impact of PEV charging, taking into account factors like charger placement and capacity. Policy and regulatory analysis are incorporated to evaluate the impact of government policies on EV adoption.

2.2.1 Daily mileage estimation

To estimate the daily mileage of vehicles, each vehicle is assigned an ID and is tracked for each day. Then, the daily mileage is computed based on the total number of trips and distance covered during each trip. The extracted data is shown in Figure 3. It can be observed that most of the vehicles travel under 100 km daily. Details about the estimation process can be found in (Fathy et al., 2023). In this study, home is considered as the test case for EVs. However, it should be noted that the same process can be used to track EVs to different locations such as workplace or any specific location such as commercial centers. The problem formulation remains the same, irrespective of the location.

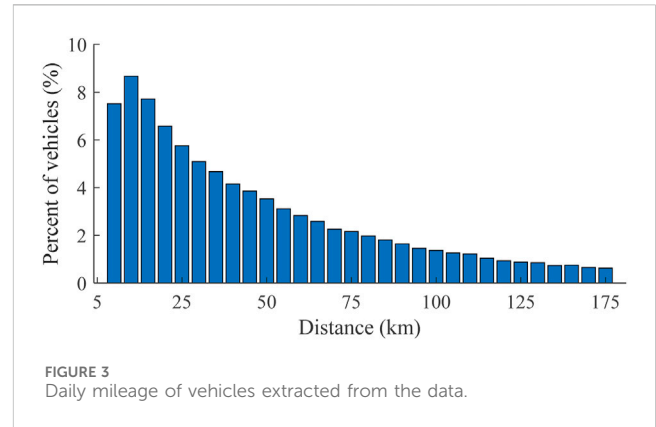


FIGURE 3 Daily mileage of vehicles extracted from the data.

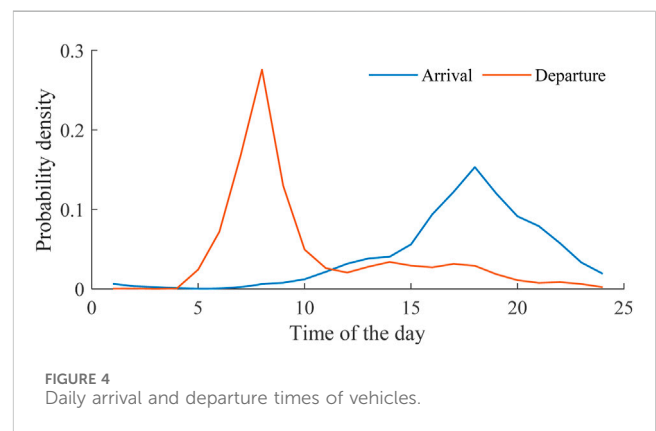


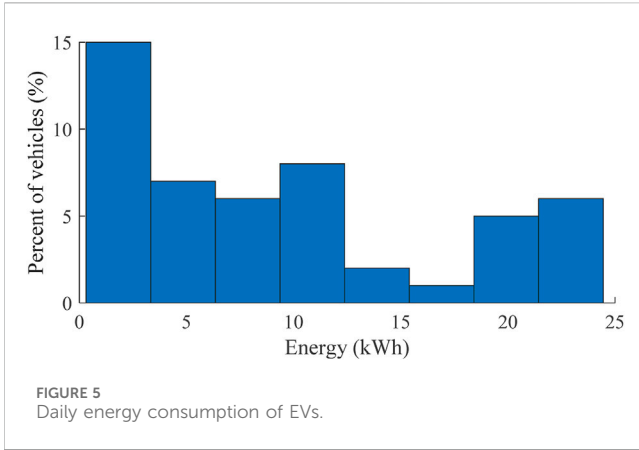
FIGURE 4 Daily arrival and departure times of vehicles.

2.2.2 Arrival and departure time estimation

The study records the origin and destination of each vehicle to ascertain their respective arrival and departure times at home. Notably, a vehicle might have multiple visits to the home, but for this study, the last arrival time and the first departure time are considered. The extracted arrival and departure times of vehicles are depicted in Figure 4, revealing that a majority of vehicles arrive home during the evening hours between 15:00 and 19:00.

2.2.3 Energy demand modeling

Following the estimation of daily mileage for vehicles, the study incorporates technical parameters specific to EVs. The data pertaining to commercially available EVs can be found in (EV Database, 2023). This dataset includes information on the mileage efficiency and useable battery size of various EV models. As per the database, the average energy efficiency across all EVs stands at 195 Wh/km, while the average useable battery size is recorded at 68.9 kWh (as of November 2023). This data serves as the basis for computing the daily energy consumption of EVs. Figure 5 illustrates the daily energy consumption of EVs, revealing that the majority of EVs consume under 25 kWh of energy on a daily basis. This observation aligns reasonably well with the average vehicle mileage of under 100 km per day and an average energy efficiency of 195 Wh/km.



3 Problem formulation

In this section, an optimization problem is formulated to allocate power to EVs considering various factors such as number of chargers, number of EVs, and capacity of the distribution equipment such as transformers. A linear programming-based model is developed which is guaranteed to be convex and can easily be solved by commercial optimization tools. Due to the convexity of the problem, it can be easily solved in a very short time using commercial software such as CPLEX, making it suitable for real-time applications.

3.1 Objective function

The objective function is designed to minimize the energy difference between the required energy demand (E_i^{dem}) and the allocated energy (E_i^{all}) for EV i . In this study, to emulate the real-life behavior of EV consumers, a first-come-first-served approach is implemented. Therefore, the energy gap is penalized based on the difference between the maximum number of intervals (T) and the arrival time of EV i (Ta_i). This penalization ensures that the EVs arriving first will occupy the available chargers. It should be noted that E_i^{all} is the decision variable in the objective function while all other factors are parameters.

$$\min \sum_{i \in I} ((E_i^{dem} - E_i^{all}) \cdot (T - Ta_i)) \quad (1)$$

3.2 Constraints

Several constraints are necessary to ensure the equitable allocation of available energy among EVs while adhering to physical constraints such as the availability of chargers and the capacity of the transformer. For instance, Eq. 2 ensures that the total allocated power to any EV (E_i^{all}) should not exceed the required power (E_i^{dem}) for that EV. It is important to note that an EV may not be fully charged within a single time interval t . Thus, the total allocated power to any EV becomes the accumulation of power allocated to it across all intervals before its departure, mathematically represented as Eq. 3 where $E_{i,t}^a$ is the energy allocated to EV i at time t . Moreover, within each interval t , the

maximum chargeable power for any EV is constrained by the charger's rating, as depicted in Eq. 4. Here, R^{ch} denotes the charger's rating in kW, and $B_{i,t}^{ch}$ is a binary variable introduced to monitor the active chargers. For instance, if a charger is in use during any time interval t for any EV i , the value of $B_{i,t}^{ch}$ will be 1; otherwise, it will be zero. It should be noted that E_i^{all} , $E_{i,t}^a$, and $B_{i,t}^{ch}$ are variables in these constraints while all other factors are parameters.

Additional constraints are necessary to ensure that the capacity limits of the transformer are not breached. Eq. 5 stipulates that the total power drawn by all EVs during any time interval t should be less than or equal to the capacity of the transformer (C_t^{tx}). It is important to note that C_t^{tx} represents the remaining capacity of the transformer after catering to the building's load. Eq. 6 signifies that the sum of chargers utilized by all EVs during any time interval t should be less than or equal to the number of available chargers (N^{ch}). Furthermore, EVs are only allowed to charge when they are available at the parking station. To enforce this constraint, (7) is introduced. This equation implies that outside of parking intervals, such as before the arrival time (Ta_i) and after the departure time (Td_i), the amount of power allocated to EV i should be forced to zero.

$$E_i^{all} \leq E_i^{dem} \quad (2)$$

$$E_i^{all} = \sum_{t \in T} E_{i,t}^a \quad (3)$$

$$E_{i,t}^a \leq R^{ch} \cdot B_{i,t}^{ch} \quad (4)$$

$$\sum_{i \in I} E_{i,t}^a \leq C_t^{tx} \quad (5)$$

$$\sum_{i \in I} B_{i,t}^{ch} \leq N^{ch} \quad (6)$$

$$E_{i,t}^a = 0 \text{ if } t \geq Td_i \text{ or } t < Ta_i \quad (7)$$

3.3 Satisfaction index

To evaluate the effectiveness of the proposed allocation scheme and to offer insights to policymakers, this study introduces an index. This index gauges the satisfaction level of EV owners by assessing the allocated power to each EV and comparing it with the required energy. It can be mathematically modeled as

$$SI_i = 100 \cdot \left(1 - \frac{(E_i^{dem} - E_i^{all})}{E_i^{dem}} \right) \quad (8)$$

Where E_i^{dem} represents the energy demand, and E_i^{all} signifies the allocated energy to EV i . This index is designed to reach a value of 100 when the entire energy demand is met before the departure time. Conversely, it will assume a value of zero when no energy demand is fulfilled, and the departure time has arrived. Operating as a continuous index, it spans values from zero to 100 inclusively, contingent upon the amount of energy received by each EV.

4 Performance evaluation

This section evaluates the performance of the proposed method using a residential apartment complex comprising 320 vehicles. For

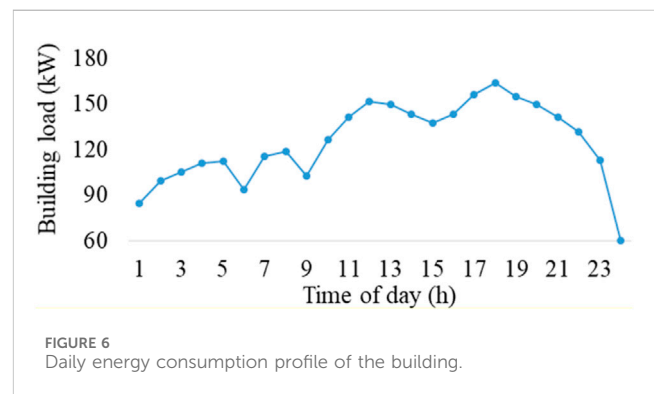
TABLE 1 Input data of EV fleet used in this section.

EV ID	Load demand (kWh)		Fulfilled (continuous)	Time (h)		
	Original	Fulfilled (proposed)		Arrival	Departure	Parking duration
1	12	12	12	14	19	5
2	12	12	12	15	21	6
3	33	30.4	33	16	0	8
4	35	30.4	35	17	22	5
5	15	15	0	17	1	8
6	30	15.2	0	18	20	2
7	35	30.4	35	18	2	8
8	28	22.8	28	19	2	7
9	13	0	0	20	1	5
10	32	15.2	15.2	21	4	7

this case, the ratio of EVs is approximately 3% (10EVs). Subsequent sections conduct an analysis across different percentage levels. The developed linear programming model is implemented in Python, integrating the optimization tool CPLEX (IBM CPLEX, 2023). This study considers a scheduling horizon of 1 day ($T = 24$) with a sample period of an hour ($t = 1$). It should be noted that the performance of the proposed framework is tested for a scheduling horizon of 1 day. However, the formulations are generalized and can be used for any time horizon, such as a week, month, or year. Given the residential nature of the building, most vehicles arrive home in the evening and depart in the morning the following day. Hence, the scheduling horizon spans from 10 a.m. and extends until 10 a.m. the subsequent day. Additionally, most residential buildings utilize level 2 chargers for community charging. Consequently, this study employs level 2 chargers rated at 7.6 kW power.

4.1 Input data

To facilitate visualization, this section focuses on 10 selected EVs, constituting roughly 3% of the total vehicle fleet. Table 1 displays the parameters associated with these selected EVs. The original load demand for each EV is randomly generated within the range of (Liu, 2021; EV Database, 2023) kWh, aligning with the survey data discussed in the previous section. Furthermore, the arrival times of these EVs correspond to the survey data, reflecting the trend of vehicles arriving home mostly during the afternoon and evening hours. Similarly, the departure time of most vehicles is early morning the following day. Therefore, the arrival and departure times for each EV are randomly generated (separately) following a normal distribution. The mean and standard deviation of EV arrival and departure times are based on the NHTS survey data, discussed in the previous section. EVs with both short and long parking durations are selected for this analysis to consider different types of drivers. The parking duration is determined based on the arrival and departure times. In this section, two chargers are considered. Additionally, the transformer's capacity (remaining capacity after serving the building load) is set at 35 kW. The profile of the



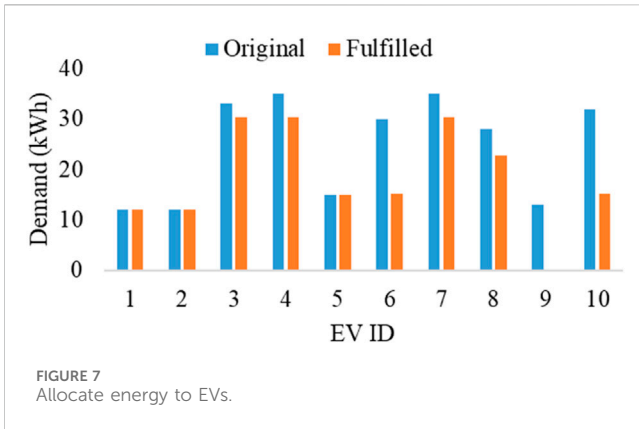
residential apartment complex on a selected day is shown in Figure 6.

4.2 Performance evaluation

This section conducts an analysis of the proposed method's performance using a fleet of 10 EVs based on the parameters outlined in the input data section. The evaluation assesses the performance concerning energy allocation, charger utilization, and driver satisfaction (utilizing the proposed satisfaction index). The performance of the proposed method is compared with conventional method (named as continuous), where once EVs occupies the charger it remains connected until it is fully charged.

4.2.1 Energy allocation

An overview of the original demand for each EV and the total allocated energy before their departure time is depicted in Figure 7. Notably, it is evident that the energy demand of EV1, EV2, and EV5 is entirely satisfied owing to their relatively lower energy demands and medium to high parking durations (refer to Table 1). Furthermore, for EV1 and EV2, the chargers were available since they were the first two EVs to arrive home (Table 1). Interestingly, despite being parked for 5 h, none of the



energy demands for EV9 are fulfilled. This occurred because both chargers were occupied by other EVs, remaining unavailable before EV9’s departure. This observation aligns with the data presented in Table 2, detailing the hourly charging for each EV. For all other EVs, their demand is only partially fulfilled due to various factors such as lower parking durations, higher energy demands, and/or charger unavailability. In the case of the conventional method, the energy demand of EV5, EV6, and EV9 is not fulfilled because both chargers were occupied by EVs that arrived earlier. Details about the charger utilization can be found in Table 3.

4.2.2 Charger utilization

The developed framework ensures that, at any given time interval, no more chargers are utilized than the available count. The binary variable data, employed in the problem formulation to monitor charger usage, has been extracted and visualized in Figure 8. The plot demonstrates that at no point are more than two chargers employed simultaneously. For improved clarity, distinct colors designate different

time intervals in the visualization. Moreover, verification from Table 2 reaffirms the usage of a maximum of two chargers throughout any time interval. During intervals 14, 2, and 3, only one charger is in use, attributed to the availability of only one uncharged EV during those periods. Conversely, both chargers are efficiently utilized during the remaining intervals. It is important to note that Table 2 exclusively displays intervals with non-zero values of charging power, rather than representing the entire scheduling horizon.

4.2.3 Driver satisfaction

The evaluation of the proposed satisfaction index for all 10 EVs is illustrated in Figure 9. Notably, the majority of EVs exhibit a satisfaction index exceeding 50%. However, EV9 and EV10 have satisfaction indices below 50%. The average index for the entire community stands at 75%. Contrarily, in case of the continuous method, the satisfaction index of EVs 5, 6, and 9 is zero. In addition, the overall satisfaction index of the community is 65% which is lower than the proposed method.

Improving the index can be achieved through multiple strategies. Firstly, augmenting the number of chargers could notably enhance satisfaction, considering the current limitation of only two chargers available in the building. Additionally, incentivizing EVs to alter their charging and arrival behavior could optimize the utilization of the available chargers, subsequently augmenting the satisfaction index.

5 Discussion and analysis

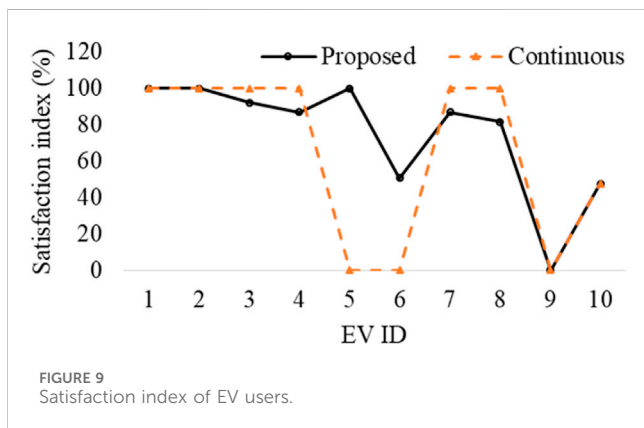
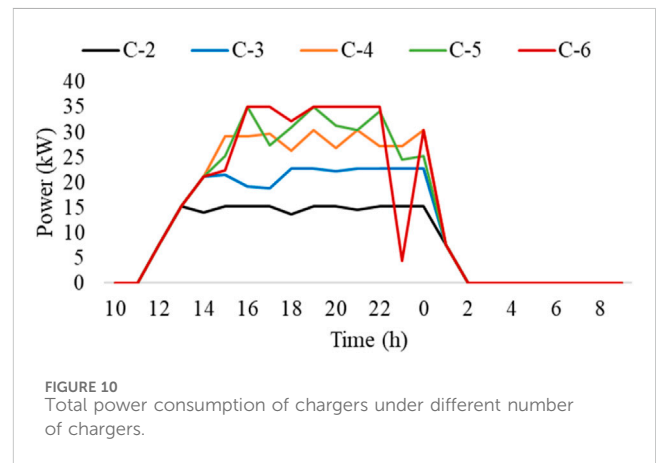
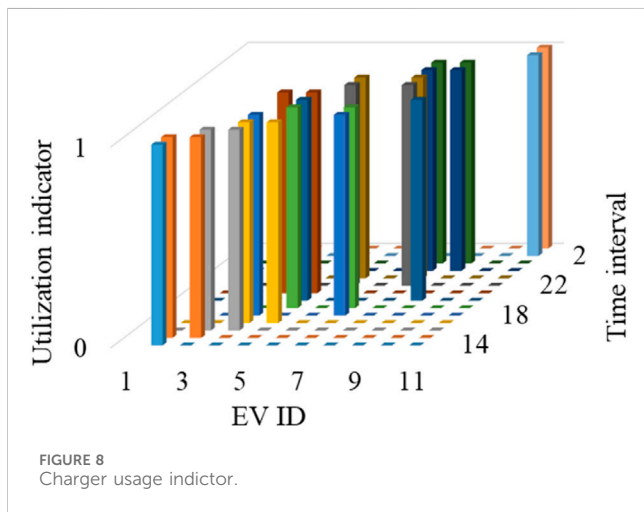
This section conducts a sensitivity analysis of various factors, including the number of chargers, the penetration level of EVs, and the limits of the transformer’s capacity. Detailed discussions regarding each parameter are presented in the subsequent section.

TABLE 2 Interval-wise power allocation to each EV under proposed method.

Interval	EV1	EV2	EV3	EV4	EV5	EV6	EV7	EV8	EV9	EV10
14	7.6	0	0	0	0	0	0	0	0	0
15	4.4	4.4	0	0	0	0	0	0	0	0
16	0	7.6	7.6	0	0	0	0	0	0	0
17	0	0	7.6	7.6	0	0	0	0	0	0
18	0	0	7.6	0	0	7.6	0	0	0	0
19	0	0	0	7.6	0	7.6	0	0	0	0
20	0	0	0	7.6	0	0	0	7.6	0	0
21	0	0	7.6	7.6	0	0	0	0	0	0
22	0	0	0	0	7.4	0	7.6	0	0	0
23	0	0	0	0	7.6	0	7.6	0	0	0
0	0	0	0	0	0	0	7.6	7.6	0	0
1	0	0	0	0	0	0	7.6	7.6	0	0
2	0	0	0	0	0	0	0	0	0	7.6
3	0	0	0	0	0	0	0	0	0	7.6

TABLE 3 Interval-wise power allocation to each EV under continuous method.

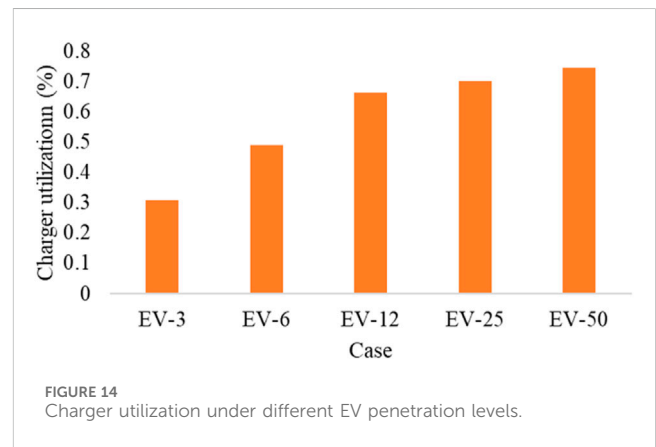
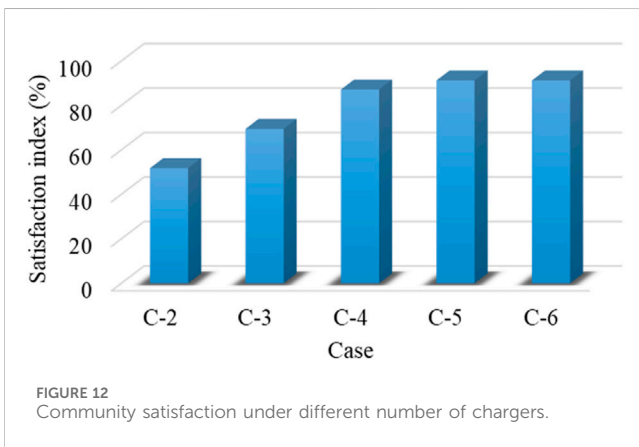
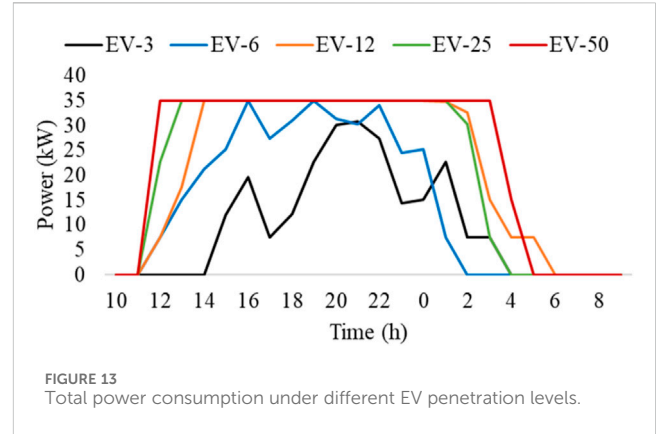
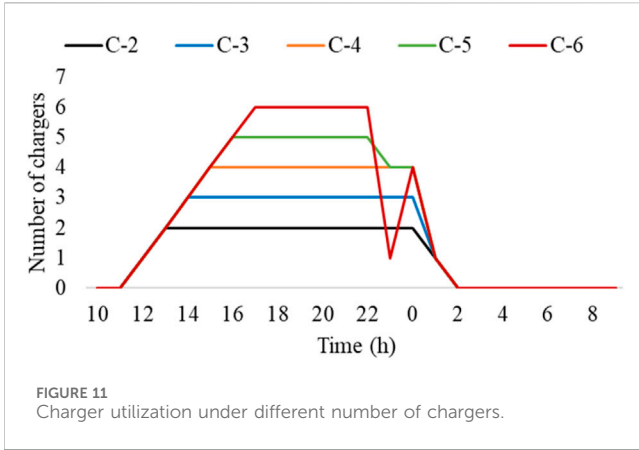
Interval	EV1	EV2	EV3	EV4	EV5	EV6	EV7	EV8	EV9	EV10
14	7.6	0	0	0	0	0	0	0	0	0
15	4.4	7.6	0	0	0	0	0	0	0	0
16	0	4.4	7.6	0	0	0	0	0	0	0
17	0	0	7.6	7.6	0	0	0	0	0	0
18	0	0	7.6	7.6	0	0	0	0	0	0
19	0	0	7.6	7.6	0	0	0	0	0	0
20	0	0	2.6	7.6	0	0	0	0	0	0
21	0	0	0	4.6	0	0	7.6	0	0	0
22	0	0	0	0	0	0	7.6	7.6	0	0
23	0	0	0	0	0	0	7.6	7.6	0	0
0	0	0	0	0	0	0	7.6	7.6	0	0
1	0	0	0	0	0	0	4.6	5.2	0	0
2	0	0	0	0	0	0	0	0	0	7.6
3	0	0	0	0	0	0	0	0	0	7.6



5.1 Number of chargers

In this section, the variation of the number of chargers from 2 to 6 is simulated across five different cases. A fleet of 20 EVs is considered, with a transformer limit set at 35 kW. For each case, computations include the total power consumed by the chargers, the utilization count of chargers in each interval, and the overall satisfaction of the community. The respective results are displayed in Figures 10–12, specifically showcasing intervals with non-zero values of charging power.

Figure 10 demonstrates an anticipated increase in power consumption with the rising number of chargers. Notably, the total power consumption is constrained to 35 kW for specific intervals in the C-5 and C-6 cases, aligning with the



transformer’s available capacity. Figure 11 illustrates that the maximum count of chargers is employed during the evening hours due to the arrival of a higher number of EVs at home. However, it is essential to note that, across each case, the maximum available chargers are utilized.

Examining the satisfaction index in Figure 12 reveals a significant increase in satisfaction levels for the initial three cases, reaching a saturation point in the last two cases. Notably, the satisfaction level for the last two cases remains consistent. This outcome suggests that, considering the fixed transformer capacity and driving behaviors of EV owners, increasing the number of chargers beyond 5 does not notably affect satisfaction. Such results hold vital importance for policymakers to determine the minimum necessary number of chargers for a given EV count.

5.2 Penetration level of EVs

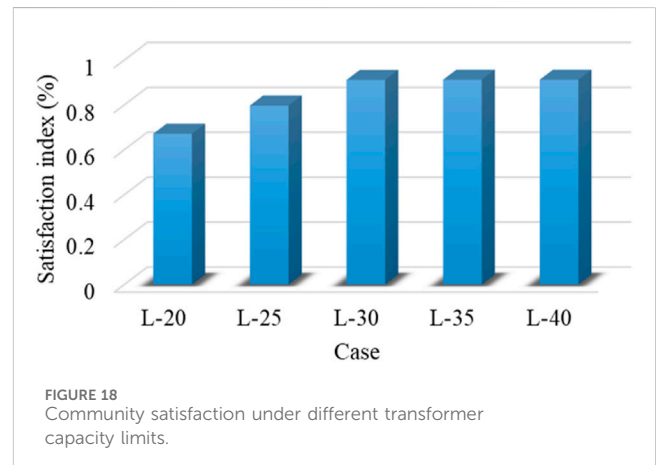
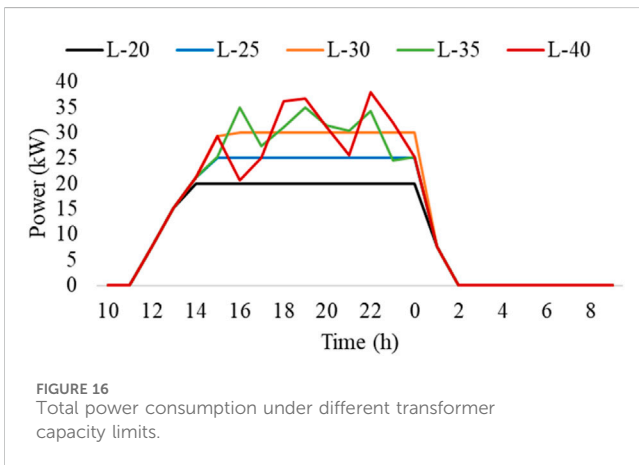
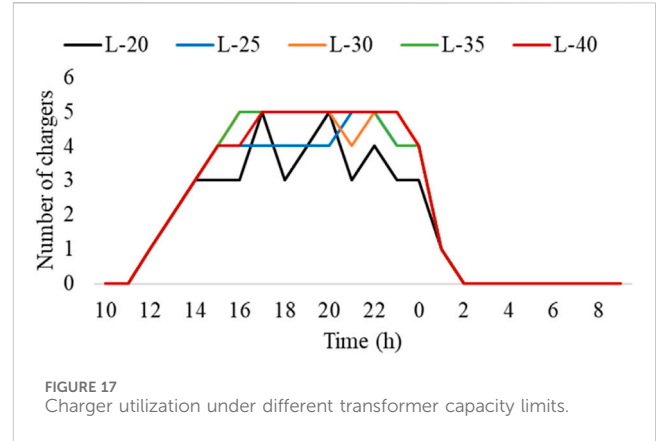
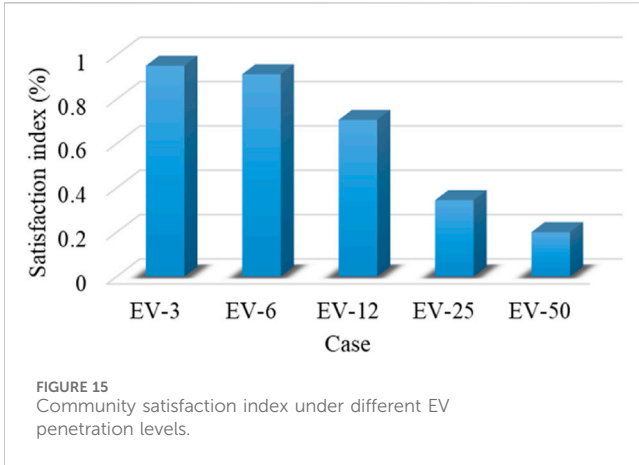
In this section, the share of the EV fleet incrementally increased up to 50% across five simulation cases. Starting from around 3% of the total fleet (320 vehicles), the penetration rate is doubled in each case until it reaches 50% (160 EVs). For consistency, the number of chargers remains fixed at five, and the transformer capacity is set at 35 kW throughout these simulations.

The analysis primarily focuses on the total power consumption of the chargers for each case. Additionally, a charger utilization index is devised to estimate the chargers’ utilization under varying penetration rates. The community’s satisfaction is also evaluated, and the outcomes are visualized in Figures 13–15. Figure 12 illustrates a proportional increase in charger power consumption with the growing number of EVs, which is an expected outcome. However, the power consumption becomes constrained by the remaining capacity of the transformer (35 kW), notably evident in the last three cases. Consequently, it can be inferred that the current configuration of five chargers and a 35-kW transformer capacity cannot sustain more than a 6% penetration of EVs.

Figure 14 shows the utilization level of chargers during the scheduling horizon (24 h). The utilization is computed using

$$CU = \sum_{t \in T} \sum_{i \in I} \frac{B_{i,t}^{ch}}{T \cdot N^{ch}} \tag{9}$$

Where $B_{i,t}^{ch}$ is the binary variable indicating the usage status of the charger, T is the total number of intervals in the scheduling horizon (24 in this case), and N^{ch} is the number of chargers (5 in this case). Figure 14 illustrates that as the EV penetration increases, there’s a corresponding rise in charger utilization throughout the scheduling horizon. However, it is evident that there’s still some potential to further increase charger utilization in all cases. Nonetheless, this



potential expansion is curtailed by the transformer’s capacity limitation, as depicted by the power consumption trends in Figure 13.

Examining Figure 15 reveals a decrease in the satisfaction level of the EV community with the escalating EV penetration rates. This decline is directly linked to the transformer’s capacity limitations. As the number of EVs increases, more capacity becomes necessary. Consequently, these results suggest that an increasing number of EVs are unable to fulfill their energy demands before their departure times.

This analysis underscores that relying solely on charger utilization as a measure is not sufficient to determine the optimal number of chargers or the EV penetration level. It is imperative to consider both charger utilization and customer satisfaction collectively to determine the most suitable number of chargers for any EV community.

5.3 Impact of transformer capacity

In this section, five simulations are conducted by varying the capacity of the transformer. The analysis includes power consumption, charger utilization, and EV user satisfaction,

displayed in Figures 16–18. For these simulations, the number of chargers remains fixed at 5, with 20 EVs considered.

Figure 16 illustrates that the charging power is restricted by the transformer’s capacity limits in the initial three cases. However, in the last two cases, the power remains below the capacity limit for most intervals. Additionally, Figure 17 demonstrates that due to these capacity constraints, all chargers are not fully utilized in the first three cases. Conversely, in the last two cases, all five chargers are utilized to maximize consumer satisfaction.

The community satisfaction index in Figure 18 shows an increase during the first three cases and remains stable in the last two cases. This implies that, for this community comprising 20 EVs and 5 chargers, a transformer capacity exceeding 30 kW proves sufficient. Moreover, increasing the transformer capacity beyond this threshold does not significantly impact consumer satisfaction levels. Such insights are crucial for utilities in planning transformer upgrades considering a certain level of EVs and chargers.

5.4 Potential policy implications

Based on the findings of this study, following policy implications can be inferred. Firstly, the study demonstrates the effectiveness of

the proposed framework in efficiently allocating energy and utilizing chargers. The results show that with proper scheduling, EV energy demands can be met while ensuring charger availability and avoiding overloading the transformer. This suggests that policymakers should consider implementing similar optimization strategies in residential areas to manage EV charging effectively.

Secondly, the study highlights the importance of infrastructure planning. The analysis shows that increasing the number of chargers beyond a certain point does not significantly improve user satisfaction. This suggests that policymakers should focus on installing an optimal number of chargers based on factors such as transformer capacity and EV penetration rate. Additionally, the study suggests that increasing transformer capacity can improve user satisfaction up to a certain point, indicating that utilities should consider upgrading transformers in areas with high EV penetration.

Lastly, the study emphasizes the need for incentives to encourage EV owners to adjust their charging behavior. The satisfaction index shows that some EVs are not able to fulfill their energy demands due to charger unavailability. Incentives such as time-of-use pricing or rewards for off-peak charging could help distribute charging load more evenly and improve overall system performance.

6 Conclusion

A framework has been proposed to effectively manage the load of electric vehicles in shared parking lots, considering various critical factors such as the number of chargers, EV penetration levels, and the remaining capacity of the transformer. This framework utilizes a linear programming-based model to simulate diverse scenarios and introduces an index to quantitatively measure the satisfaction level of vehicle owners based on the energy charged before their departure time. Simulation outcomes have revealed that, for a given apartment complex, a consumer satisfaction level exceeding 75% can be achieved when 3% of the total vehicle fleet comprises EVs. Moreover, sensitivity analysis has demonstrated that merely five chargers can elevate the satisfaction level beyond 80% with an EV penetration level of up to 6% (20 EVs). However, the transformer capacity emerges as a pivotal factor in maximizing EV user satisfaction, particularly with higher EV penetration. The findings suggest that the transformer's capacity can become a bottleneck as EV penetration increases. Consequently, it is imperative for policymakers and utilities to collaboratively determine the optimal number of chargers concerning both the transformer's capacity and the expected EV penetration levels. Furthermore, planning equipment upgrades becomes crucial, necessitating considerations of imminent EV and charger penetration levels. Solely increasing the number of chargers is not advantageous under the constraints imposed by the transformer's limited capacity. Thus, a comprehensive approach integrating multiple factors is vital for optimizing EV load management and ensuring consumer satisfaction in shared parking lots.

In this study, the feasibility analysis of managing electric vehicle loads is conducted at a higher level, focusing on overall load management strategies without considering the detailed power

flow within the distribution system. The inclusion of power flow analysis would significantly enhance the practicality of this method by providing more detailed insights into how the proposed load management strategies would impact the distribution system's operation and performance. Power flow analysis would allow for a more accurate assessment of potential voltage fluctuations, line losses, and overall system stability, enabling policymakers and utilities to make more informed decisions regarding electric vehicle integration and infrastructure planning.

Data availability statement

The original contributions presented in the study are included in the article/Supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

AA: Conceptualization, Writing–original draft. NA: Methodology, Writing–review and editing. SA: Software, Writing–review and editing. OA: Validation, Writing–review and editing. HM: Formal Analysis, Validation, Writing–original draft.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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