A Novel Stochastic Approach for Modifying Non-Residential Buildings Demand Curve Using an Electric Vehicle Parking Lot

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This paper addresses the critical challenge of managing peak load growth, which places significant financial burdens on governments due to the need for new power plants or upgrades to existing infrastructure. Flattening the demand curve through effective peak shaving and valley filling presents an opportunity to reduce these costs, yet traditional nonlinear optimization models struggle with the complexities introduced by the increasing prevalence of electric vehicles. To overcome these challenges, we propose a linearized approach based on a piecewise linear approximation technique, enhancing computational efficiency while maintaining accuracy. Additionally, we address the inherent uncertainty associated with electric vehicle arrival and departure times using Hong's two-point estimation method. A microgrid case study utilizing real-world data collected at ten-minute intervals demonstrates the effectiveness of our approach, achieving a notable reduction in peak demand of 25.3% and decreasing computation time by 80% compared to conventional nonlinear models. Furthermore, sensitivity analysis conducted on parking availability, initial energy levels of the vehicles, and energy requirements for subsequent trips indicates the robustness and efficiency of the proposed framework. The findings suggest that this method not only optimizes electric vehicle charging management but also supports the integration of electric vehicles into the power grid, paving the way for sustainable energy management practices.

Keywords: *electric vehicle, peak shaving, point estimate, valley filling, vehicle-to-building.*

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1. Introduction

In recent years, the rapid expansion of electrical demand, particularly during peak hours, has become a critical issue for energy systems worldwide. The increasing frequency and magnitude of peak loads impose significant financial and operational burdens on governments and utility providers, necessitating the construction of new power plants or the costly upgrade of existing infrastructure to meet these transient demands. This challenge is further amplified by the growing adoption of electric vehicles (EVs), which introduces additional volatility into the demand curve. Traditional approaches to mitigating these peaks, often through nonlinear optimization models, have proven to be computationally expensive and time-consuming. As a result, there is an urgent need for more efficient and scalable strategies to manage peak load while addressing the uncertainties associated with EV charging behaviors.

Peak demand in power networks presents various challenges. During times of peak consumption, the electrical load increases suddenly, placing significant stress on the infrastructure, which can lead to instability or power outages [1]. Additionally, meeting high demand may require reliance on non-renewable energy sources, resulting in negative environmental impacts [2]. The challenges associated with controlling this high demand are discussed in [3]. In [4], a pattern recognition technique is proposed to predict peak electricity consumption before it occurs, with results indicating a 96.2% accuracy in predicting peaks 24 hours in advance.

In recent decades, traditional methods of demand curve flattening have been widely used as effective strategies for managing electrical load. These methods primarily focus on shifting the timing of large industrial and residential loads, utilizing time-based tariffs, and deploying energy storage systems. For example, improving the load factor of the power grid through the use of distributed energy resources and peak load management is explored in [5]. The study employs a mixed-integer linear programming (MILP) model to improve the load factor by shifting the operation of large household, commercial, and industrial appliances throughout the day. The results demonstrate that this model can effectively enhance the load factor and reduce energy wastage. In [6], a convex multi-objective optimization for filling the demand curve valleys using a time-variable pricing scheme is presented. One challenge of this study is the need for precise data and the time-consuming nature of implementing optimization models. A resilient and intelligent energy management system using a first-price sealed-bid auction algorithm for microgrids is introduced in [7]. The proposed framework aids in the optimal allocation of resources, improving the system's flexibility and stability. In [8], the development of a final control algorithm for peak load reduction to optimize the use of energy storage systems is discussed. The proposed control algorithm effectively reduces peak loads and optimizes the charging and discharging cycles of energy storage systems, with results showing a 28.12% reduction in peak demand. Strategies for peak shaving and valley filling using solar energy systems and battery storage are examined in [9]. They demonstrate that using rule-based algorithms and day-ahead forecasts for both load and solar energy generation can effectively optimize battery charging and discharging schedules, thereby reducing demand peaks. In [10], an integrated energy management system for electrical and heating systems is proposed. The study shows that by utilizing flexible energy resources such as EV parking lots, energy storage systems, and demand response programs for both electrical and thermal demands, the demand curve can be significantly improved, enhancing the operational flexibility of the grid.

Demand response methods often require changes in consumer behavior or restrictions on energy consumption, which can be inconvenient for users. Additionally, energy storage systems require significant investment and are typically installed in specific locations. In contrast, EVs, with their flexible charging schedules, can automatically utilize cheaper energy during off-peak hours without altering consumer behavior. These vehicles contribute to flattening the demand curve and improving grid stability by reducing pollution and fossil fuel consumption, acting as mobile storage units. For instance, [11] investigates the role of Vehicle-to-Grid (V2G) systems in peak shaving and filling demand valleys. The study shows that the integration of EVs and V2G systems can effectively reduce peak demand and fill demand valleys. Their results indicate that unmanaged charging can increase peak demand by up to 5%, whereas off-peak charging can reduce peak demand by 2% and fill demand valleys by 3%. In [12], coordinated optimization of EV charging and charging stations in an integrated transportation system is examined. The authors employ a hybrid technique to reduce peak demand, control voltage, and minimize operational costs. This hybrid technique leverages advanced algorithms and real-time data to enhance the performance of EV charging systems. An economic-environmental planning strategy for a microgrid with integrated EVs is discussed in [13]. Using a two-stage optimization strategy, the study demonstrates that V2G services can effectively reduce load pressure and improve other grid parameters. The impact of valley filling through coordinated EV charging in distribution networks is analyzed in [14]. The study shows that coordinated charging methods can significantly increase energy consumption during valley periods, helping to regulate grid stress. In [15], peak demand reduction in commercial buildings through Vehicle-to-Building (V2B) systems and machine learning methods is explored. This research proposes a new system for predicting daily demand profiles and optimizing EV charging and discharging to reduce peak electricity demand. The proposed model includes a machine learning algorithm to predict electricity demand and a demand management optimization model to determine the optimal EV charging and discharging schedule. Case study results show that using two EVs, one energy storage system (ESS), and a 40kW photovoltaic (PV) system can reduce peak demand by up to 36%. A multi-objective scheduling model for EV charging aimed at reducing the peak-valley difference in the grid's demand curve is presented in [16]. The study results indicate that this model benefits both the power grid and EV users by mitigating the negative impacts of EVs on grid stability and security, while also reducing charging costs for users. In [17], a charging and discharging strategy for EVs is examined, considering the correction factor for grid peak and valley load. The study shows that the proposed strategy can effectively reduce the peak-valley difference and improve charging costs. Simulation results suggest that this strategy can lower charging costs by up to 40% and increase charging station profits by 30%. A limitation of this study is the need for precise data and the time-consuming nature of model implementation.

The charging behavior of EVs is subject to uncertainty due to various factors such as usage patterns, battery charge levels, and the timing of connection to the grid. Given these inherent uncertainties in energy consumption patterns and EV driver behavior, stochastic approaches have increasingly gained attention in studies focused on flattening the demand curve. These approaches enable researchers to model uncertainties and potential variations in consumption patterns, leading to more optimized and efficient solutions. For example, in [18], a charging and discharging management framework for EV parking lots is proposed to optimize the demand curve of an office building. The demand curve uncertainties are modeled using machine learning techniques. The impact of widespread EV integration into the grid and the use of V2G technology on energy resources is investigated in [19]. This study utilizes linearized equations to explore uncertainties related to EV charging demand and optimal planning of integrated energy systems. The potential for peak shaving and economic analysis of V2B systems is examined in [20]. A virtual microgrid system and Monte Carlo methods are used to simulate EV charging and discharging processes, accounting for uncertainties associated with EV battery loading and discharging. The results indicate that increasing the proportion of charging stations significantly reduces load fluctuations. In [21], a two-level planning and scheduling framework for EV charging stations aimed at peak shaving and congestion management in low-voltage distribution networks is studied. The research uses real-world data and probabilistic models to analyze optimal locations for installing charging stations and scheduling EV charging. The findings show that optimal charging station placement can reduce network losses and voltage deviations by 39.38% and 15.32%, respectively. A reinforcement learning approach using Markov decision processes for battery energy storage control within smart contract frameworks is introduced in [22]. This study demonstrates that such an approach can effectively enhance the stability and flexibility of microgrid systems, helping prevent blackouts. In [23], energy management of EVs using reinforcement learning methods is proposed. The study shows that an energy management system utilizing Q-learning can significantly improve the efficiency and stability of distribution networks by considering uncertainties. These studies emphasize the important role of stochastic approaches in load management and energy consumption optimization, owing to their flexibility in handling unpredictable changes and their capability to model diverse scenarios.

The existing literature shows strong interest in optimizing EV charging and discharging. However, several key challenges remain unresolved. One major issue is computational speed, which is crucial for real-time applications. Nonlinear models used in previous studies provide accurate results but suffer from slow processing and no guaranteed convergence. AI-based methods have also been explored, but they rely on large datasets and require significant training time, limiting their use in fast-paced environments. Additionally, EVs face many uncertainties, which Ignoring these uncertainties can make energy management systems ineffective. Addressing this is essential for reliable solutions. Most studies have used hourly scheduling, which is inadequate for future smart grids. Lastly, using real-world data is crucial for accurate results. Unfortunately, many studies rely on simulations, limiting their practical relevance.

In this paper, a framework for managing the charging and discharging of EVs in a university parking lot is presented, aimed at peak shaving and valley filling of the university building's demand curve using real-world data. Initially, a nonlinear model was established as the foundation of the work. This model was then linearized using a piecewise linear approximation method, which not only guarantees convergence but also significantly enhances computational speed. To address the uncertainties associated with EVs, a probabilistic model was introduced. This model takes into account the uncertainties related to the presence of EVs in the parking lot by employing Hong's point estimation method. This approach allows for a more accurate representation of the variability in EV behavior, leading to improved energy management strategies. Overall, this research contributes to the development of robust solutions for EV charging management that can effectively adapt to real-world conditions. Therefore, the main contributions of this work are as follows:

Table 1. Comparison of this study with the previous studies.

Ref	Year	Type of vehicle	Peak Shaving	Valley Filling	Uncertainty	Battery Degradation	Dispatch Time	Software	Model Type
[11]	2022	V2G	✓	✓	Monte Carlo	×	*hour*	Monte Carlo with MATLAB	linear
[12]	2022	EV	✓	×	Stochastic Modeling, Scenario-based Analysis	✓	*hour*	HOMER	nonlinear
[17]	2023	EV	✓	×	Fuzzy Logic, Monte Carlo Simulation	×	*hour*	Python	nonlinear
[10]	2023	EV	✓	×	Probabilistic Approach, Stochastic Optimization	✓	*hour*	GAMS	linear
[5]	2023	EV	✓	×	Scenario-based Analysis	×	*hour*	DIgSILENT PowerFactory	nonlinear
[14]	2023	EV	✓	×	Monte Carlo Simulation	✓	*hour*	MATLAB/Simulink	nonlinear
[6]	2023	EV	✓	×	Stochastic Programming	×	*hour*	Python with Pandas and Numpy	nonlinear
[15]	2023	EV	✓	×	Fuzzy Logic	✓	*hour*	OpenDSS	linear
[8]	2023	EV	✓	×	Scenario-based Analysis, Monte Carlo Simulation	✓	*hour*	MATLAB/Simulink	linear
[7]	2024	EV	✓	×	Stochastic Modeling	×	*15 min*	HOMER	nonlinear
[19]	2024	EV	✓	×	Monte Carlo Simulation, Scenario-based Analysis	×	*hour*	DIgSILENT PowerFactory	nonlinear
[9]	2024	EV	✓	×	Fuzzy Logic, Stochastic Optimization	✓	*hour*	MATLAB/Simulink	nonlinear
[20]	2024	EV	✓	×	Probabilistic Approach	×	*hour*	Python	nonlinear
[22]	2024	EV	✓	×	Monte Carlo Simulation	×	*15 min*	MATLAB/Simulink	nonlinear
[23]	2024	EV	✓	×	Stochastic Modeling, Fuzzy Logic	×	*hour*	HOMER	linear
[9]	2024	EV	✓	✓	Genetic Algorithm, Scenario-based Analysis	✓	*hour*	Genetic Algorithm in MATLAB	nonlinear
[7]	2024	V2G	✓	✓	Monte Carlo Simulation, Scenario-based Analysis	✓	*hour*	MATLAB/Simulink	nonlinear
[24]	2024	V2G	✓	×	×	×	*15 min*	MATLAB/Simulink	nonlinear
This work		V2G	✓	✓	point estimate	✓	*10 min*	GAMS-MATLAB	linear

1-Improved Computational Speed: The study introduces a piecewise linear approximation method that transforms a nonlinear model, ensuring convergence while significantly enhancing computational efficiency for real-time energy management.

2-Probabilistic EV Behavior Modeling: This research employs a probabilistic model that captures uncertainties in EV presence and behavior using Hong's point estimation method, leading to more accurate energy management strategies.

3- Utilization of Real-World Data: By leveraging real-world data from a university parking lot, the framework enhances practical relevance and applicability, contrasting with previous studies that often rely on simulations.

4- Focused Demand Management: The framework targets peak shaving and valley filling for the university building's demand curve, effectively stabilizing the grid and reducing dependency on non-renewable energy sources during peak periods.

The rest of the paper is organized as follows: Section 2 provides a statistical analysis of the capacity of EVs to make a role in the grid. Section 3 describes the proposed model and the simulation inputs. The simulation results are presented and discussed in Section 4. Finally, the paper concludes with the findings in the last section.

2. The Performance Framework of EVBs

To understand the significance of electric vehicle batteries (EVBs), it is essential to recognize that an EV cannot function without them. EVBs are crucial components in all EVs that are capable of connecting to power grids. When an EV is plugged into the grid, its battery can serve both as a controllable load and as a rapid-response generator, making it a valuable tool for frequency regulation. Therefore, studying the various types and functions of EVBs is of critical importance.

When EVs are in use, they rely on the energy stored in their batteries. However, research indicates that EVs typically utilize only up to 40% of their stored energy [24]. Additionally, statistics show that EVs spend approximately 22 hours per day parked. As a result, grid-connected EVs offer a range of potential uses. Since these vehicles are distributed across various locations throughout a city rather than concentrated in one area, they present diverse opportunities for utilization. This study focuses on employing EVs for short-distance urban travel. An analysis of traffic patterns in the United States, as shown in Figure 1, reveals that around 80% of drivers travel fewer than 60 miles (95 km) per day [25]. This highlights the potential of EVs to meet short-distance travel demands, further supporting the need to explore efficient methods for integrating EVs into the power grid.

Currently, the distances traveled by EVs often fall below the maximum energy capacity of their EVBs, leading to daily underutilization of stored energy. In terms of responsiveness, EVBs exhibit exceptional performance as quick-response devices. They can deliver maximum power in under a millisecond, outperforming the startup speeds of conventional power plants. This capability makes EVBs highly suitable for frequency regulation within the power grid. Additionally, EVBs can be fully recharged in a relatively short period, typically in five hours or less [26]. Their power output ranges from 0.2 to 6.4 kW [27], providing flexibility for various applications.

Figure 2 [27] offers a comprehensive illustration of the daily energy exchange of EVBs, depicting the typical flow of energy throughout the day. This includes a scenario in which a vehicle owner commutes to work, parks the vehicle, and later returns home to reconnect the vehicle to the grid for recharging. The figure outlines a complete daily energy exchange cycle.

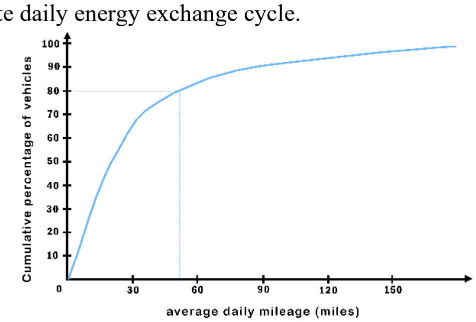


Fig. 1. Cumulative percentage of vehicles in terms of daily mileage.

As shown in Figure 2, the minimum state of charge (SOC) required for energy storage or use is approximately 60%. Consequently, throughout the day, EVs connected to the grid maintain a minimum SOC of 60%. This leads to the conclusion that EVBs are valuable assets for grid integration, as they remain partially charged during the connection process and do not fully discharge.

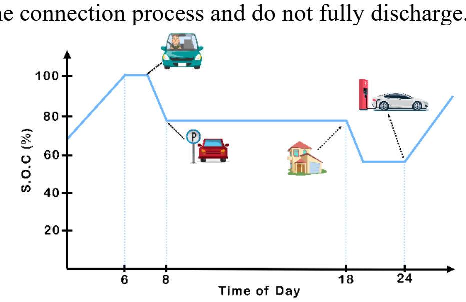


Fig. 2. Garlic SOC change of an EVB during the day.

2.1. Tasks of EVB Aggregators

This While the energy stored in each individual EVB may seem negligible, the cumulative impact of multiple EVBs can significantly influence the power grid. When grouped together, aggregated EVBs have the potential to provide a range of services that can substantially affect grid dynamics. The concept of EVB aggregation involves transforming individual EVBs into a coordinated system with a combined power capacity at the megawatt (MW) scale, enabling them to function as large-scale power generators or consumers [24].

The energy from these aggregated EVBs can be traded in both retail and wholesale electricity markets. In this process, aggregators play a crucial role. These emerging entities are responsible for organizing and managing groups of EVBs to achieve MW-scale power generation. Aggregators act as decision-making entities, capable of trading energy and interacting directly with Independent System Operators (ISOs) for energy transactions or the provision of specific grid services. They are tasked with optimizing the configuration of EVBs within the group, carefully selecting which batteries to include in order to maximize the overall performance and capabilities of the aggregated system.

3. Methodology

This study employed EVs in a parking lot during the day, as suggested by [28]. There are m charging points available. The day was divided into 10-minute intervals, which formed a set of n intervals. The time periods during which EVs were present in each parking spot are presented in Fig. 3. Each line represents an EV.

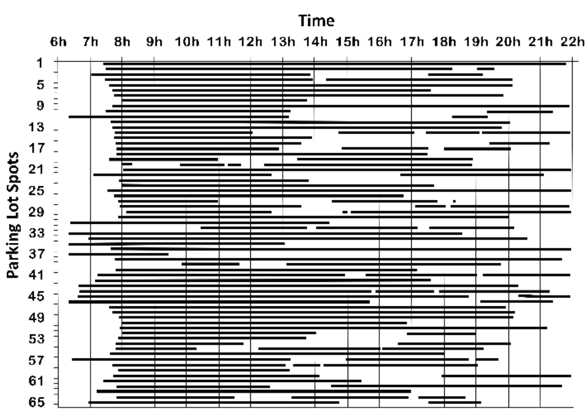


Fig. 3. Parking lot occupancy [18].

M×N matrices can be used to display information about the presence time of each EV at each parking spot. Each row and column represent parking spots and a 10-minute interval, respectively. The matrix is called f_{mi}, as shown in (1). f_{mi} is a binary matrix; each element can be either 0 or 1. For example, if $f_{9,60}$ is equal to 1, it means that during the 60th interval (hour 10), there was an EV in parking spot 9.

$$f_{mi} = \begin{cases} 1 & \textit{if the parking spot } m^{th} \textit{ is occupied in the interval } i^{th} \\ 0 & \textit{otherwise} \end{cases} \tag{1}$$

The power delivered to or received from the grid by each vehicle in the m^{th} parking spot and during the i^{th} interval is denoted by x_{mi}. When the vehicle receives power from the grid, x_{mi} is positive, and when it delivers power to the grid, x_{mi} is negative. The total energy exchanged between the grid and parking lot during the i^{th} interval is denoted by y_i, defined by (2) [28]. If the power received by parking lot during the i^{th} interval was higher than the power delivered to the grid in that time, y_i becomes positive, and otherwise, it becomes negative.

$$y_i = \sum_{m \in M} x_{mi} f_{mi} \tag{2}$$

Due to technical limitations of charging and discharging devices for EVs, the energy exchanged with the grid during each interval is restricted. As shown in (3), the charge and discharge limitations are denoted by P_{max}^c and P_{max}^d respectively [28]. In (4), the minimum or maximum charged and discharged energy until the i^{th} interval is represented [26]. The maximum amount of energy stored in an EVB is equal to 80 percent of its capacity, while the minimum amount is 20 percent. E_m^{ini} is the stored energy in the vehicle parked in the m^{th} spot upon entering the parking lot, and E_m^{cap} is the maximum capacity of the vehicle parked in the m^{th} spot. $Q(i)$ is the set of time intervals preceding the i^{th} interval. Since all EVs were assumed to be identical, the maximum battery capacity was 24 kWh [24]. A normal distribution function was used to calculate the E_m^{ini} values, with an average value of 12.2 and a standard deviation of 1.9 [24].

$$-P_{max}^d \le x_{mi} \le P_{max}^c \tag{3}$$

$$0.2E_m^{cap} \le E_m^{ini} + \sum_{k \in Q(i)} \tau x_{mk} f_{mk} \le 0.8E_m^{cap} \tag{4}$$

As shown in (5), E_m^{fin} must be sufficient to complete the next trip at the end of the charge/discharge process for each vehicle in the m^{th} spot [28]. (5) is imperative since it ensures the energy necessary to complete the next trip. E_m^{T+1} is the energy required by the vehicle parked in the m^{th} spot to complete the next trip. A normal distribution function with an average value of 7.2 and a standard deviation of 1.5 was used to determine E_m^{T+1}. It is not expected for EV owners to have a lower battery charge level after leaving the parking lot than when they parked their vehicles. Therefore, the energy exchange by the vehicle parked in the m^{th} spot needs to be a positive value, as shown in (6) [28].

$$E_m^{fin} = E_m^{ini} + \sum_{i \in N} \tau x_{mi} f_{mi} \ge E_m^{T+1} \tag{5}$$

$$\sum_{i \in N} \tau x_{mi} f_{mi} \ge 0 \tag{6}$$

By defining Pu_i as the power consumption of the building during the i^{th} interval and constant C in (7), the objective function, Problem 1, is defined by (8). Aims to minimize the difference between the curve obtained by adding up the load and energy exchanged by parking lots during each interval, and the average of load. Constant C is considered the ideal average load, and Pu is illustrated in Fig. 4.

$$C = \frac{max(Pu_i) + min(Pu_i)}{2} \tag{7}$$

$$Z = \sum_{i \in N} \left(Pu_i + y_i - C \right)^2 \tag{8}$$

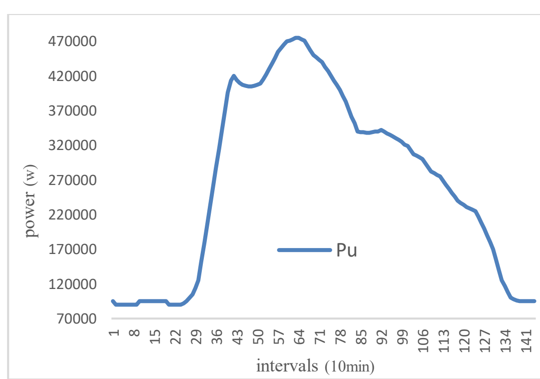


Fig. 4. Power consumption profile of the microgrid.

The proposed model is nonlinear. Although nonlinear methods provide high accuracy, they do not guarantee convergence. Therefore, linearizing the proposed model can reduce computation time and ensure convergence. Since optimization constraints are linear, it is only necessary to linearize the objective function. Due to the constant value of Pu_i and C for each i, (9) is defined as T_i and (8) is expanded leading to (10)-(13).

$$T_i = Pu_i - Ci \tag{9}$$

$$Z=\left(y_i + T_i\right)^2 \tag{10}$$

$$Z=y_i^2+2y_iT_i+T_i^2 \tag{11}$$

$$Z=y_i^2+2y_i\left(Pu_i - C\right)+\left(Pu_i - C\right)^2 \tag{12}$$

$$Z=\sum_{m\in M} x_{mi}^2 f_{mi}^2 + \sum_{m\in M} 2x_{mi}f_{mi}\left(Pu_i - C\right)+\left(Pu_i - C\right)^2 \tag{13}$$

The only nonlinear term in (13) is x_{mi}^2, since Pu_i, C, and f_{mi} are constants. This means that the term only needs to be linearized. For this purpose, the Piecewise Linear Approximation was applied. If we consider x_{mi}^2 equal to ψ, then ψ is a second-order parabolic function. If we divide $(-P_{max}^d, P_{max}^c)$ into j divisions, ψ_j can be calculated by multiplying slope ζ_j of the line between both endpoints of j^{th} interval by Δx_{mij}, as shown in (14). If j is large enough, the approximation is more accurate, and Δx_{mij} can be replaced by xx_{mij}. By substituting (14) into (13), the linearized objective function (Problem 2) is described by (15).

$$x_{mi}^2 = \sum_j \psi_j = \sum_j \zeta_j \Delta x_{mij} \tag{14}$$

$$Z = \sum_{m\in M}\left(\sum_j \zeta_j xx_{mij}\right) f_{mi}^2 + \sum_{m\in M} 2x_{mi}f_{mi}\left(Pu_i - C\right)+\left(Pu_i - C\right)^2 \tag{15}$$

After the linearization of the objective function and due to the linearity of the constraints, no further change is needed, but a few new constraints must be added to the problem. First, the constraint indicates that the sum of xx_{mij} must be equal to x_{mi}, Which is shown in (16).

$$\sum_j xx_{mij} = x_{mi} \tag{16}$$

Since the maximum energy exchange of an EV during the i^{th} interval is in the range of $(-P_{max}^d, P_{max}^c)$, and x_{mi} is divided into j divisions, the xx_{mij} value would be in the range of $(-\frac{P_{max}^d}{j}, \frac{P_{max}^c}{j})$, as shown in (17). For positive values of xx_{mij}, ζ_j is negative and vice versa. So, (18) holds for all values.

$$-\frac{P_{max}^d}{j} \le xx_{mij} \le \frac{P_{max}^c}{j} \tag{17}$$

$$x_{mi}^2 = \sum_j \zeta_j xx_{mij} \ge 0 \tag{18}$$

Upon linearization, the objective function becomes a sum of three linear terms, where the first and third terms are invariably positive due to their even exponents. So, to minimize the objective function, the second term must always be negative, but not to the extent that it leads to a negative objective function. According to (19), the sum of the first and third terms must be larger than the magnitude of the second term. The last constraints, (20) and (21), ensure that the output curve is always at a margin of 25% from C values.

$$\left|\sum_{m\in M}\left(\sum_j \zeta_j xx_{mij}\right) f_{mi}^2 + \left(Pu_i - C\right)^2\right| \ge \left|\sum_{m\in M} 2x_{mi}f_{mi}\left(Pu_i - C\right)\right| \tag{19}$$

$$-0.25C \le \left(\sum_{m\in M} x_{mi}f_{mi} + Pu_i\right) - C \le 0.25C \tag{20}$$

$$-0.75C \le \sum_{m\in M} x_{mi}f_{mi} + Pu_i \le 1.25C \tag{21}$$

All parameters in the proposed model were deterministic. However, most parameters have a level of uncertainty in reality. So, a purely deterministic approach may lead to inaccurate solutions. It should be noted that accounting for uncertainties results in increased computational complexity and effort, but the results would be more accurate. A key parameter in our study is whether an EV occupies a parking spot during different time intervals (f_{mi}), which was assigned a deterministic value for every interval. The f_{mi} uncertainty was considered by Hong's two-point estimation [29]. The Hong method is illustrated in Fig. 5.

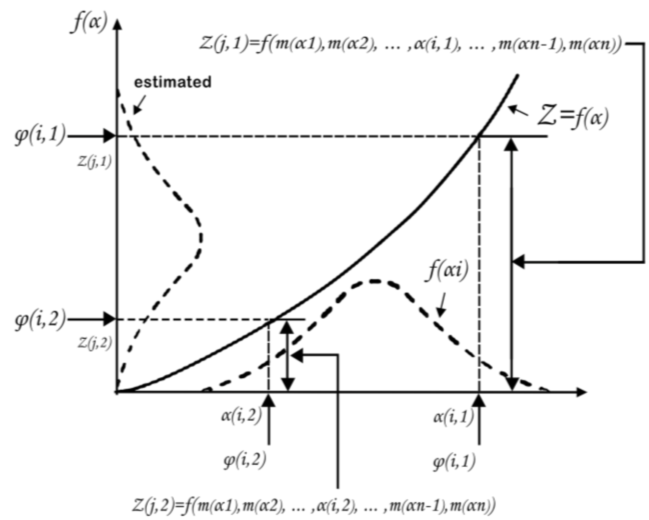


Fig. 5. Visual representation of Hong 2n point estimation method [30].

By disregarding intervals less than 20 minutes, Fig 4 indicates that there were 90-time intervals with entry and exit points. Using the two-point estimation, two new points were generated for each interval, creating four additional intervals. Thus, the 90 intervals were increased to 360 intervals, and calculations were repeated for each interval. Therefore, a new dimension called probabilistic state was added, and the f_{mi} matrix (M×N) would turn into a three-dimensional matrix (M×N×S).

Regarding the new dimension for entry/exit data and the exchanged energy, (2)-(6) become (22)-(26). Obviously, (17) and (18) do not change since for a given m and i, the xx_{mij} remains the same for all probabilistic states (s). (19)-(21) also turn into (27)-(29).

Finally, updating (15) leads to the new objective function (Problem 3), (30) where W represents the weighting coefficients for probabilistic states as determined by the Two-Point Estimation method in MATLAB. The estimated values were multiplied by the weighting coefficients to obtain the expected value for indeterministic parameters. First-order and second-order moments were used to calculate the derivation from the standard Z.

$$y_{is} = \sum_{m\in M} x_{mis} f_{mis} \tag{22}$$

$$-P^{d}_{max} \le x_{mis} \le P^{c}_{max} \tag{23}$$

$$0.2E^{cap}_{m} \le E^{ini}_{m} + \sum_{k\in Q(i)} \tau x_{mks} f_{mks} \le 0.8E^{cap}_{m} \tag{24}$$

$$E^{fin}_{m} = E^{ini}_{m} + \sum_{i\in N} \tau x_{mis} f_{mis} \ge E^{T+1}_{m} \tag{25}$$

$$\sum_{i\in N} \tau x_{mis} f_{mis} \ge 0 \tag{26}$$

$$\left|\sum_{m\in M}\left(\sum_{j} \zeta_{j} xx_{mij}\right) f^{2}_{mis} + \left(Pu_{i} - C\right)^{2}\right| \ge \left|\sum_{m\in M} 2x_{mis} f_{mis} \left(Pu_{i} - C\right)\right| \tag{27}$$

$$-0.25C \le \left(\sum_{m\in M} x_{mis} f_{mis} + Pu_{i}\right) - C \le 0.25C \tag{28}$$

$$-0.75C \le \sum_{m\in M} x_{mis} f_{mis} + Pu_{i} \le 1.25C \tag{29}$$

$$Z = \sum_{s\in S} W \times \left(\begin{array}{c} \sum_{m\in M}\left(\sum_{j} \zeta_{j} xx_{mij}\right) f_{mis} + \sum_{m\in M} 2x_{mis} f_{mis} \\ \times\left(Pu_{i} - C\right) + \left(Pu_{i} - C\right)^{2} \end{array} \right) \tag{30}$$

4. Results

This study introduces a novel method for managing the charging and discharging schedules of EVs within a microgrid, aiming to modify the demand curve based on actual data collected from EVs parked in a specific location. The proposed model was initially linearized using the linear piecewise approximation method. To account for uncertainties in entry and exit data, the point estimation method was employed. The model was implemented through simulations using GAMS software, with an algorithm developed in MATLAB. It is assumed that the energy exchange between each vehicle and the grid affects the building's demand curve: charging—where each vehicle draws energy from the grid—increases the demand curve, while discharging—where each vehicle injects energy back into the grid—decreases it.

Figure 3 illustrates the parking duration of EVs in the parking lot throughout the day. It can be observed that the majority of parking spots were occupied by EVs for extended periods. Additionally, specific parking spots experienced turnover with up to six different EVs, as depicted in Fig. 6. The proposed nonlinear model was then applied to the load curve, as shown in Fig. 4, to plan the charging and discharging of EVs. In the figure, NLP represents the new demand curve, while the constant line C represents the target demand curve.

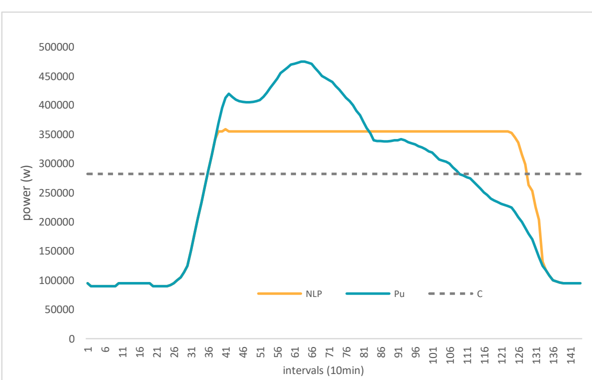


Fig. 6. Nonlinear modeling power consumption profile.

The results demonstrate that the demand curve was modified only during intervals when EVs were present in the parking spots, engaging in energy exchange. The consumption load curve initially began to rise around 5:00 but gradually moved towards the target curve starting from approximately 6:30, coinciding with the entry of EVs into the parking spaces. This trend persisted until 22:00, indicating that the proposed method successfully adjusted the demand curve based on the charging and discharging activities of the EVs.

The load curve of the EVs in parking spots or the total exchanged energy of vehicles in parking spots in each interval is shown in Fig. 7. When the values were negative during peak demand, the total exchanged energy was negative, and the parking lot was delivering energy to the grid. During valley hours, the values were positive, indicating that the total amount of energy exchanged was positive, and the parking lot was receiving energy from the grid.

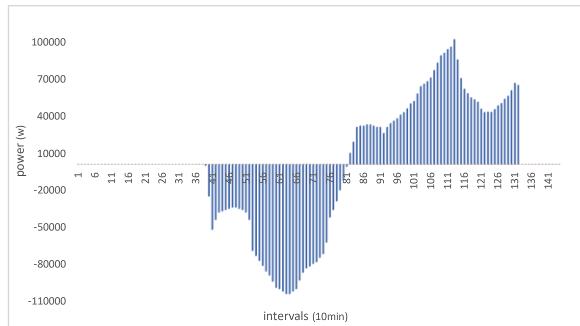


Fig. 7. Non-linear modeling parking lots power consumption curve.

During the hours when vehicles are in the parking spots (6:30 to 13:30), the overall exchanged energy was negative. This means that the EVBs were plugging energy into the grid to respond to peak demand and flatten the load curve. Between 13:30 and 22:00, the total exchanged energy was positive. From 13:30 to 22:00, the total exchanged energy was positive. It shows the grid provided energy to vehicles to increase energy consumption and flatten the load curve. However, the behavior of the vehicles differed from one another and from the trend in total energy consumption. Fig. 8 shows the exchanged energy in random parking spots 21, 45, and 50. The charging and discharging trend varies between intervals, but it is the total exchanged energy that is crucial for flattening the load curve.

Despite their accurate results, nonlinear models add complexity to the problem and require more time to reach the optimal solution. However, they do not guarantee convergence. A linearized model is less computationally complicated and requires less time to reach the optimal solution. It also ensures an optimal solution. The linearized model used to schedule EV charging/discharging was applied to the load curve in Fig. 4, and the results are shown in Fig. 9, where C represents the target line, and MILP represents the new demand curve.

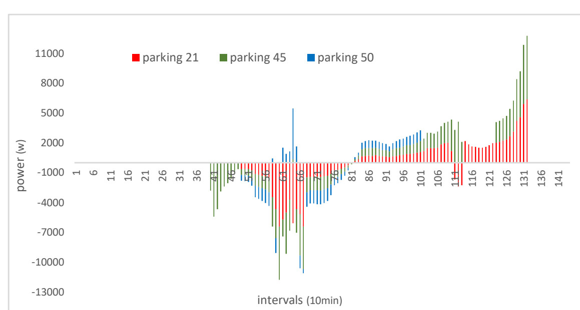


Fig. 8. Non-linear modeling power consumption curve of 21, 45, and 50 parking lots.

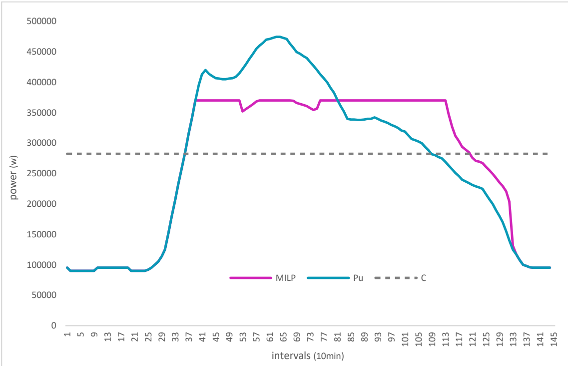


Fig. 9. Linear modeling power consumption profile.

Fig. 10 shows the load curve of EVs in parking spots using the linearized model. There was a negative value during peak demand, indicating that the parking lot was delivering energy to the grid. As a result of the positive values during valley hours, the total exchanged energy was positive, and the parking lot was receiving energy from the grid.

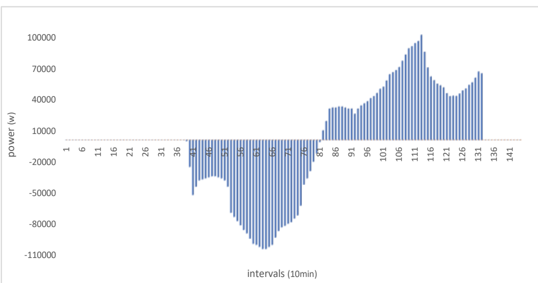


Fig. 10. Linear modeling parking lots power consumption curve.

During the hours when vehicles are parked (6:30 to 13:30), the overall exchanged energy was negative. Therefore, the EVBs were supplying energy to the grid in order to meet the peak energy demand and flatten the load curve. Between 13:30 and 22:00, the total exchanged energy was positive. This indicates that vehicles received energy from the grid to increase their energy consumption and flatten the load curve. However, the vehicles' behavior varied from one another and from the overall energy trend. Fig. 11 illustrates the exchanged energy in random parking spots 21, 45, and 50. The charging and discharging trend varies between intervals, but it is the total exchanged energy that is crucial for flattening the load curve.

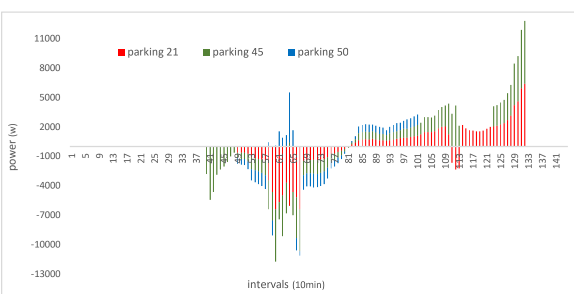


Fig. 11. Linear modeling power consumption curve of 21, 45, and 50 parking lots.

Based on using actual data, the calculations resemble reality. However, the actual data has a level of uncertainty. Consequently, Hong's point estimation [29] was used to account for the uncertainty of the entry/exit data on which the calculations were based.

The number of probabilistic states will be determined by the number of intervals when an EV was parked in a spot. By ignoring intervals of less than 20 minutes in the parking lot, there are 90 intervals or 90 EVs entering and exiting the parking lot. By applying the two-point estimation method, each starting or ending point will increase to two new points. In this way, there would be 360 probabilistic states for the parking lot. Hence, the binary matrix of entry/exit information for EVs becomes three-dimensional (M×N×S), where S is the number of probabilistic states. By determining the weighting coefficient of each probabilistic state, the problem can be analyzed in an indeterministic manner. The proposed linearized indeterministic model used to schedule EV charging/discharging was applied to the load curve in Fig. 4, and the results are shown in Fig. 12, where PEM MLP represents the new demand curve of the building.

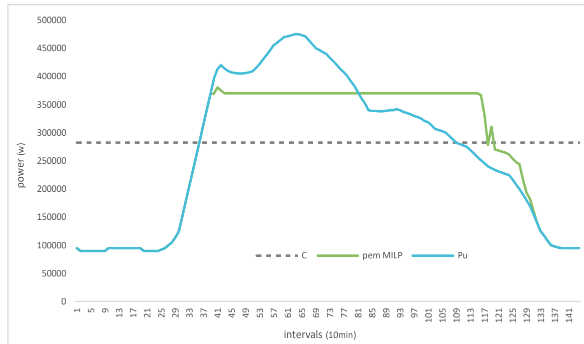


Fig. 12. Supplementary model power consumption profile.

The load curve of the EVs in parking spots or the total exchanged energy of vehicles in parking spots in each interval is shown in Fig. 13. When the values were negative during peak demand, the total exchanged energy was negative, and the parking lot was delivering energy to the grid. During valley hours, the values were positive, meaning the total exchanged energy was positive, and the parking lot was receiving energy from the grid. Although the uncertainty affected the charge/discharge behavior, the demand curve modification was consistent with previous models, demonstrating the efficiency of the linearized indeterministic model.

In the hours between 6:30 and 13:30, the total amount of energy exchanged was used to meet peak energy demand. Between 13:30 and 22:00, the total exchanged energy was used for valley filling. The energy exchange curve for each parking spot was calculated using the expected value. Fig. 14 illustrates the exchanged energy at random parking spots 21, 45, and 50. The different sizes and trends of these curves are attributed to the point estimation method. Charge/discharge behavior can be affected by changes in the intervals between the presence of EVs in parking spots, as well as weighting coefficients.

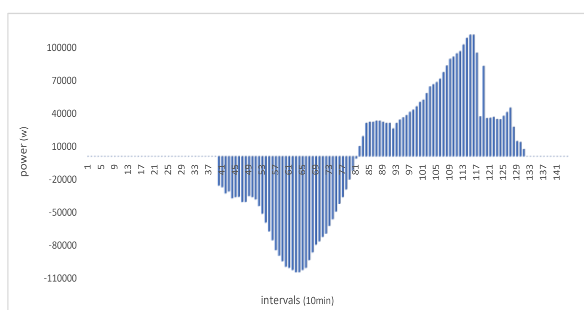


Fig. 13. Supplementary model parking lots power consumption curve.

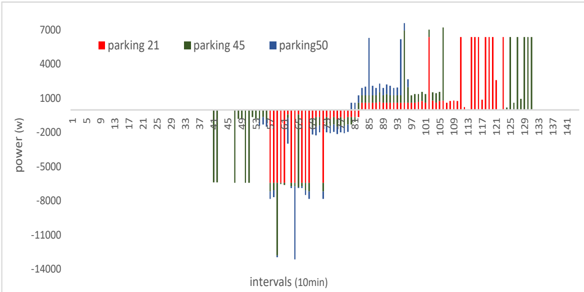


Fig. 14. Supplementary model power consumption curve of 21, 45, and 50 parking lots.

The demand curves for all proposed models are shown in Fig. 15. The difference between NLP and C was less than the difference between MILP and PEM MILP, but the NLP curve was smoother. Consequently, the variations in the NLP curve can be ignored for most intervals because nonlinear optimization models provide a more accurate and effective solution. There was a more constant trend in the PEM MILP curve than in the MILP curve. Since we accounted for the uncertainty of the actual data, our results were more accurate. It should be noted that demand curve modification is only possible in the presence of EVs in parking spots. The acceptable modification achieved in this study showed the efficiency of the proposed models.

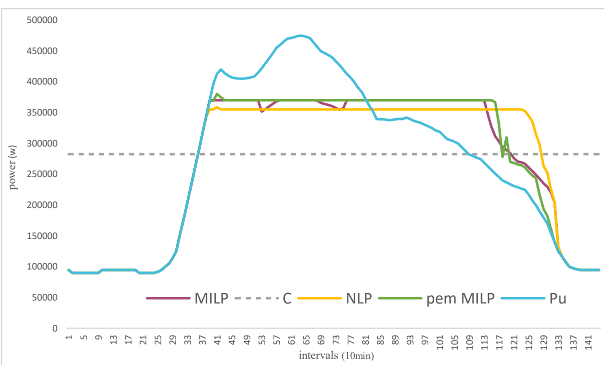


Fig. 15. Compare power consumption profiles.

By disregarding the availability of vehicles for shorter intervals than 20 minutes, a total of 90 EVs enter the parking lot and exchange energy. Fig. 16 illustrates the SOC of these 90 EVs. As expected, at the time of leaving the parking lot, none of the EVs had a lower SOC than when they arrived at the lot. Furthermore, the SOC was at its maximum in the best case. Vehicles that remained in the parking lot for a longer period of time or entered at off-peak times generally had a higher SOC when they left the lot.

In order to determine the sensitivity of the consumption load curve to the number of parking spaces, two sets of parking spots were randomly selected. The proposed charging and discharging plan have been implemented for a variety of parking spots. Fig. 17.a illustrates the effect of changing the parking spot from 6 to 27 and 65. Fig. 17.b presents the effects of changing the parking point for all values.

According to Fig. 17.b, the proposed model has been implemented with the remaining parking spots while one parking spot is randomly reduced each time. As expected, increasing the number of parking spaces or parking capacity results in a smoother load curve. Nevertheless, this improvement decreases when the number of vehicles exceeds a certain threshold, and an increase in parking capacity will not significantly improve the load curve.

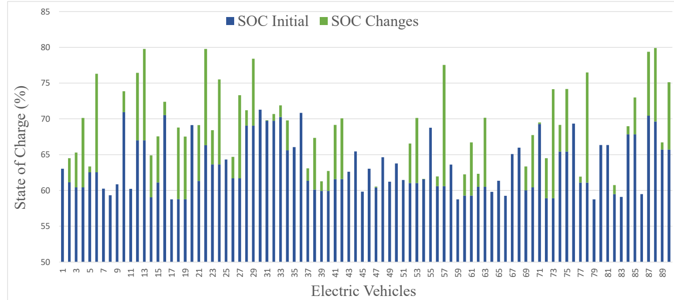


Fig. 16. EVB's SOC changes.

4.1. Sensitivity Analysis

One of the key parameters in this study is the initial charge level of EVs. Based on the findings from the EPRI institute, presented in Section 2, 80% of EVs do not experience a charge level below 60% during the day. Therefore, in this study, an initial charge level above 60% has been considered for EVs. However, to further investigate the impact of the initial charge level on demand curve shaping, a sensitivity analysis was conducted. The results of this analysis are shown in Fig. 18. As can be observed, the value of this parameter has a direct effect on the results, which is similar to the impact of changes in battery capacity or the number of EVs. The results are closely related to the number and capacity of the EV batteries.

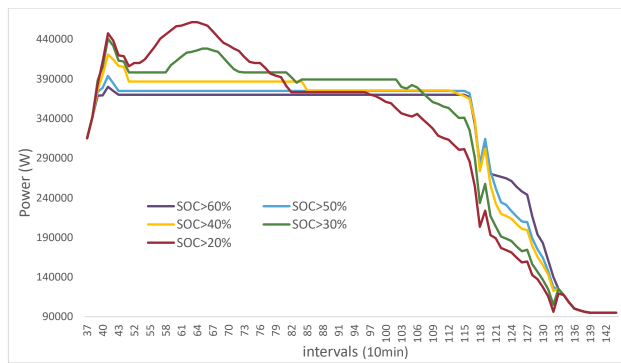


Fig. 18. Sensitivity analysis of initial SOC on demand curve.

The change in the charge/discharge status of an EVB significantly affects its lifespan. The total number of state transitions, i.e., switching between charging and discharging, in this study is kept within the permissible limits to ensure the longevity of EVBs. However, to investigate the impact of the allowed number of charge and discharge cycles on the performance of the proposed model, a sensitivity analysis has been conducted on this parameter. The results of this analysis are presented in Fig. 19.

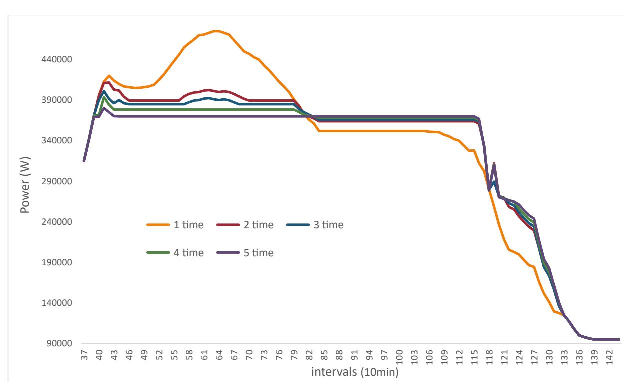


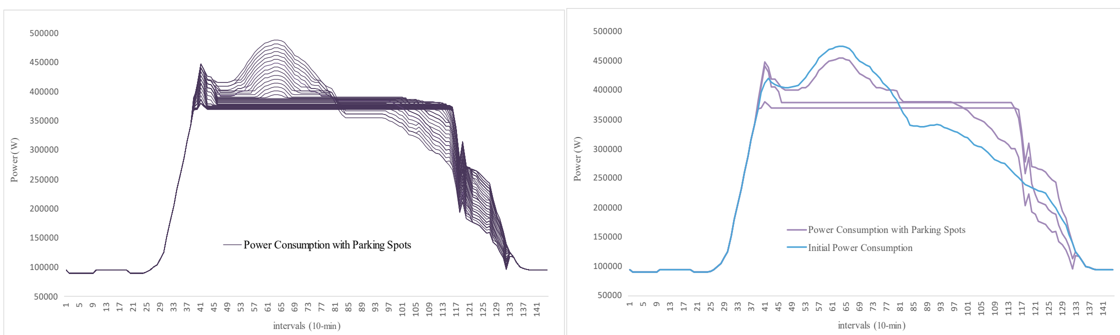
Fig. 19. Sensitivity analysis of charge and discharge cycle limitations on demand curve.

When the limitation is applied to allow only one charge cycle, based on (6), which ensures that the battery charge level when leaving the parking lot does not fall below the level upon entry, the EVs are only charged and participate in valley filling. Furthermore, since the EVs are not discharged during peak hours, they do not have sufficient empty capacity to contribute effectively to valley filling. However, as the number of allowable charge/discharge cycles increases, the influence of this parameter diminishes.

5. Conclusions

This This paper presents a charge/discharge model for EVs aimed at modifying the demand curve in a non-residential environment. The simulation results demonstrate the effectiveness of the proposed model, achieving a 25.3% reduction in peak power consumption—equivalent to over 120 kW—across 65 parking spots. The linearization of the nonlinear model through piecewise linear approximation significantly reduced computational time and complexity by 80%, while maintaining a high level of accuracy compared to the original nonlinear model. To address data uncertainty, Hong's two-point estimation method was employed, yielding results with a confidence level of 93%, which indicated acceptable accuracy and close alignment with the deterministic model. Despite the challenges associated with uncertainty affecting convergence time, its incorporation enhanced the accuracy of the optimal solutions. Additionally, the integration of V2G functionality in the model underscores its potential to support bilateral electricity contracts and offers significant benefits, such as demand curve flattening and reduced energy consumption, thereby helping to avoid financial penalties related to breaches of contracted energy agreements. Further investigation is warranted to explore this potential in greater depth.

Future studies should extend the model to include a larger number of EVs with diverse technical characteristics. An analysis of sensitivity concerning parking space availability, initial energy levels in EV batteries, energy requirements for subsequent trips, charge and discharge rates, maximum charging capacity, and microgrid load curves would provide valuable insights. While this study utilized a typical day's load curve, future investigations could benefit from incorporating anticipated load curves for day-ahead planning, thus enhancing the model's accuracy and applicability.



(a) (b)

Fig. 17. a: Contribution of each parking spot to modification of the power consumption curve. b: Power consumption profile with 6, 27, and 65 EV parking spots in use.

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