38th International Electric Vehicle Symposium and Exhibition (EVS38) Göteborg, Sweden, June 15-18, 2025

Hardware-in-the-loop Simulation of Multistorey Charging Carpark for Wireless (Dis)Charging Electric Vehicles

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Executive Summary

This paper presents hardware-in-the-loop (HIL) simulations of wireless-(dis)charging-enabled electric vehicles in the multistorey charging carpark (MCC) surrounded by buildings in urban settings, which employs a combination of optimal control based on convex optimization and bidirectional wireless chargers with full-bridge converters built inside HIL equipment. From a high-level energy management standpoint, the central control center gathers real-time data from various entities. After running the optimal control algorithm with this collected information, it allocates optimal (dis)charging instructions to each bidirectional wireless charger. Besides, from the low-level power electronics perspective, bidirectional wireless power transfer (WPT) is also achieved with high efficiency. The proposed method achieves the goal of reducing the peak wireless charging load by an average of 21.98% while preserving the health of batteries at the same time provided that charging requirements are met. Both theoretical analysis and HIL simulations are provided to verify the feasibility and effectiveness of the proposed approach.

Keywords: Electric vehicles, smart charging, V2G, smart grid integration and grid management, wireless power transfer

1 Introduction

As power electronics rapidly advance, wireless power transfer (WPT) is increasingly valued for its convenience, safety, and flexibility [1] [2] [3]. WPT research spans diverse applications, with electric vehicle (EV) wireless charging emerging as a transformative direction, enabling both static and dynamic charging to enhance convenience and reduce reliance on cables [4] [5] [6]. In industrial and robotic applications, WPT advances wireless motor systems and servo drives, supporting contactless energy delivery for automated machinery and bidirectional robotic motion [7] [8] [9] [10]. Wireless lighting systems, such as ballastless fluorescent setups, eliminate hazardous wiring and improve safety in environments like warehouses or public spaces [11] [12]. Wireless heating innovations focus on homogeneous induction heating for industrial processes or consumer appliances, ensuring efficient and uniform thermal energy transfer [13]. Underpinning these advancements is WPT system optimization, where techniques like mutual inductance analysis [14], soft-switching modulation [15], and multi-frequency designs aim to maximize efficiency, reduce losses, and enable scalable, adaptable power delivery across all applications. Together, these directions highlight WPT's role in reshaping energy infrastructure, industrial automation, and everyday technology.

To be more specific, static wireless charging/discharging, a prominent application of wireless power transfer, significantly enhances convenience by removing the manual connection process—enabling EVs to start charging automatically when aligned with a wireless pad. The absence of exposed cables improves safety, minimizing hazards such as electrical shocks or weather-induced damage from loose wiring. Encased components further boost reliability by resisting moisture, dust, and environmental wear. Moreover, stationary wireless systems can seamlessly integrate with autonomous driving, smart parking infrastructure, and automated payment platforms, simplifying user interactions and enabling fully automated workflows. Thus, both industry and academia view WPT as a (dis)charging method with great potential, especially for static wireless charging of EVs [16] [17] [18]. Besides, wireless discharging, in other words, wireless vehicle-to-grid (V2G), has also drawn attention, which can provide power quality services [19] [20]. Since most personal vehicles are parked most of the time [21], and given the restricted and crowded urban spaces in Hong Kong, the multistorey charging carpark (MCC) can be an ideal place for EVs to exchange energy with the power infrastructure. Therefore, the research scenario of interactions between EVs with WPT capabilities and MCC should be investigated. Currently, there exists some research considering the integration of MCC with wireless-(dis)charging-enabled EVs, a sensorless wireless charging system for EVs in multistorey charging carparks using a symmetric high-order network is presented in [22], with its controller-free design reducing components and enhancing sustainability by autonomously managing wireless charging through frequency switching. Moreover, a multistage constant-current wireless charging method with pulse frequency modulation that shows high efficiency, fast charging, low complexity, and fewer harmonics without extra converters for multistorey EV carparks is proposed in [23]. However, the aforementioned research focuses entirely on unidirectional wireless charging and pure power electronics-related hardware perspectives, the bidirectional wireless power transfer of EVs with both system-level energy management and low-level hardware combined research is merely studied under such research scenario. In this paper, the main purpose is to present the feasibility and effectiveness of wireless charging and discharging (V2G) for EVs in the MCC, by using a novel combination of convex optimization-defined optimal control and full-bridge converters-equipped bidirectional WPT systems constructed within hardware-in-the-loop (HIL) equipment.

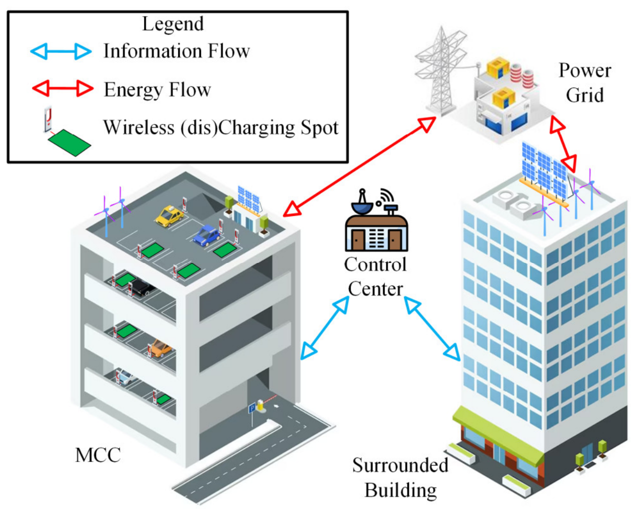


Figure 1: Renewable energy-integrated MCC with wireless-(dis)charging-enabled EVs and bidirectional wireless chargers.

HIL simulations can offer powerful frameworks on testing and validating complex systems by integrating hardware components with virtual models in real-time. This approach enables rigorous evaluation of system performance under controlled, repeatable conditions without exposing hardware to real-world risks or costly operational failures. HIL testing also enhances safety by allowing simulations of extreme or hazardous scenarios safely, such as electrical faults or environmental stressors, while validating optimal control algorithms. It also reduces development costs and time by identifying design flaws early, minimizing the need for physical prototypes. Additionally, HIL simulations support iterative refinement of hardware-software interactions, ensuring robustness and reliability before deployment in critical applications like EV systems or energy infrastructure. By bridging the gap between theoretical models and real-world operation, HIL accelerates innovation while maintaining precision and scalability in system development [24]. Therefore, HIL simulations are also adopted in this study. Particularly, the peak charging load from wireless-

(dis)charging-enabled EVs can be reduced with the EV battery health being simultaneously protected, and its feasibility and effectiveness are demonstrated through comparative case studies using HIL simulations.

The remaining parts of this work are structured in the following manner. Section 2 details the microgrid-integrated MCC's structure and the optimal control architecture for the wireless (dis)charging control. The modeling of the bidirectional WPT system used in the HIL simulations is described in Section 3. Besides, the optimal control formulations and constraints are also mentioned in Section 3. Section 4 lists the key parameter settings used in this study with comparative case evaluations to demonstrate the effectiveness and feasibility of the proposed approach. Section 5 summarizes and draws the conclusion of this paper.

2 Structure of Multistorey Charging Carpark and Charging Control Architecture

2.1 Multistorey Charging Carpark Structure

Since human society is striving for a more sustainable and low-carbon future [25], renewable energy sources (RES) like solar and wind generations can also be integrated into the MCC and surrounding office buildings to reduce dependence on traditional fossil-fuel power generation [26]. Also, EVs with bidirectional WPT capabilities can be viewed as small-scale energy storage systems and therefore the entire system forms a small-scale microgrid [27] [28] [29]. Additionally, rooftop and nearby renewable energy systems, for instance, solar and wind power, can act as efficient elements for fulfilling the energy demands of buildings in the microgrid [30]. The MCC with wireless-(dis)charging-enabled EVs accompanied by buildings in the urban setting is illustrated in Fig. 1, where employees can park their cars in the MCC during work hours or while on leave. The MCC is a multi-level parking facility containing numerous parking spaces on each floor. While some spaces are standard parking spots without any charging or discharging infrastructure, others are equipped with both wired and wireless charging equipment. This study excludes wired (dis)charging for EVs, as the focus lies on the development and optimization of wireless (dis)charging models, with wired charging analysis falling outside the scope of this research.

2.2 Proposed Charging Control Architecture

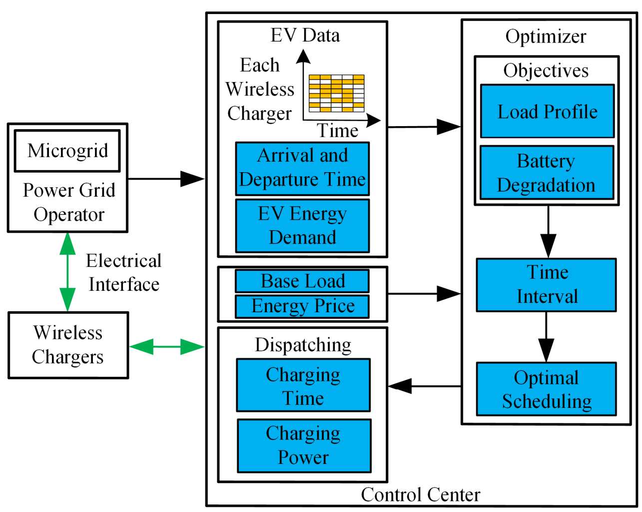


Figure 2: Charging control architecture.

The charging control architecture is illustrated in Fig. 2. The control center receives real-time information from the MCC, buildings, and the main grid simultaneously on the arrival (departure) time and energy demand of wireless-(dis)charging-enabled EVs, as well as the building load profile and RES generation conditions. Furthermore, the time-of-use (TOU) energy pricing is sourced from the power grid operator. Subsequently, these data are then forwarded to the optimizer, which pinpoints the optimal control timeframe, establishes objectives to minimize EV battery degradation costs and alleviate peak load, and executes the optimal control to calculate the optimal wireless charging/discharging power and schedule. Then it sends these optimal wireless (dis)charging decisions to each bidirectional wireless charger in the MCC. Specifically, the optimizer's architecture is thoroughly explained in its description in the below section. EV users are also informed of the associated charging expenses. In summary, the control center oversees the entire optimization process to optimize EV battery degradations and wireless-(dis)charging-enabled EVs' charging load.

3 Methodology

3.1 Modeling of Bidirectional WPT System

For the low-level power electronics aspect, bidirectional wireless chargers for wireless-(dis)charging-enabled EVs in the MCC are shown in Fig. 3. The transmitting frequency is chosen as 85 kHz. The transmitted power can be calculated using (1). When $\dot{U}_s$ leads $\dot{U}_p$, the power transmits from the primary side to the secondary side. When $\dot{U}_p$ leads $\dot{U}_s$, the power transmits from the secondary side to the primary side. The transmission power reaches its maximum value when $\theta = \pm\pi/2$.

$$P = \frac{U_p U_s \sin\theta}{M\omega}, \dot{U}_p = U_p \angle 0^\circ, \dot{U}_s = U_s \angle \theta \tag{1}$$

where $\dot{U}_p$ stands for the input voltage at the primary side, $\dot{U}_s$ is the output voltage at the secondary side, with U_p and U_s being magnitude and θ being the corresponding phase angle respectively. ω is the resonance frequency and M symbolizes the mutual inductance.

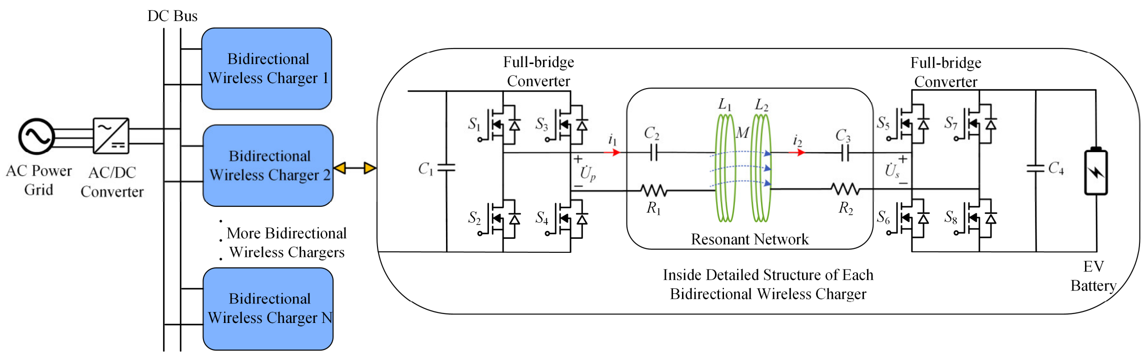


Figure 3: Proposed bidirectional WPT systems connecting to the DC Bus within MCC.

3.2 Optimal Control Problem Formulation

3.2.1 Control Objectives

This section outlines the development of an optimal control framework via convex optimization, introducing two objective functions aimed at alleviating power load profile and minimizing EV battery degradation costs, while accounting for the priorities of both grid operators and EV owners.

A major concern for power grid operators is regulating the daily variations in power load profiles. Unmanaged EV charging elevates peak demand and burdens power infrastructure, amplifying strain on the grid. Thus, minimizing total load variability is critical for coordinating EV charging efficiently within scheduled intervals [31] [32] [33]. In this work, the aggregate total load includes both the base load and EV wireless charging demand, where the base load comprises the office building consumption load profile [34] and RES generations [35] [36]. The EV wireless charging load is formulated through the Monte-Carlo simulation method using the information of the hourly number of wireless-(dis)charging-enabled EVs available in the MCC that is calculated from the arrival and departure time of each individual vehicle, and wireless-(dis)charging-enabled EVs' energy demand derived from their initial and target state of charge (SOC) information [37]. And the hourly number of wireless-(dis)charging-enabled EVs is also scaled down accordingly due to the current still increasing adoption of wireless-(dis)charging-enabled EVs. The system-level energy management scheme incorporates the methodology of convex optimization-defined optimal control as defined in (2), with the first term in the objective function being the load variation minimization term aims at alleviating the peak wireless charging load from wireless-(dis)charging-enabled EVs to reduce the load burden on the main grid.

From the EV owner's perspective, when managing the cost-effective operation of EVs, it is essential to account for battery degradation costs, as the daily use of EVs—characterized by repeated charging and discharging cycles—can substantially impact the battery's durability over time. Such continuous usage patterns may accelerate the wear and tear on the battery, highlighting the need to integrate precise estimates of long-term battery degradation costs into immediate energy allocation strategies for wirelessly charged EVs in the MCC. To accurately represent the expense dynamics of wirelessly charged EVs, the degradation costs are analyzed and quantified through precise mathematical formulations. Battery lifespan deterioration is influenced by two core elements. The first is capacity fade, which reflects the loss of stored energy available for use. The second relates to cycling dynamics, such as the regularity of charge/discharge cycles, aging from repeated cycling, and energy transfer rates—factors that highlight how improper usage can hasten degradation and lead to early battery failure. Beyond these, environmental temperature and SOC also play roles in reducing battery durability. High temperatures amplify degradation, while extreme SOC levels (very high or low) harm charging/discharging efficiency. SOC represents the remaining stored energy as a proportion of the battery's total capacity. In practice, however, thermal management systems are often employed, mitigating temperature-related degradation effects. As a result, the dominant contributors to battery wear are depth of discharge (DOD), defined in equation (6), and cycle life, as calculated in equation (5) [38]. Therefore, another essential objective is to maintain proper battery health while the charging demand is satisfied, which can be transferred to the minimization of battery degradations during wireless (dis)charging, as shown by the second term in the objective function.

$$\min_{X}\{\sum_{t=1}^{T}(\alpha_1(L_{total}^t - L_b^t) + \frac{\alpha_2}{2}({L_{total}^t}^2 - {L_b^t}^2)) + \frac{K_{Batt}\Delta t\,|\,X_{t,i}\,|}{2\eta DODE_{cap,i}N_{CL}}\} \tag{2}$$

$$L_{total}^t = L_{WCEVs}^t + L_b^t \tag{3}$$

$$L_b^t = L_{bldg}^t - L_{RES}^t \tag{4}$$

$$N_{CL}(\Delta t, t) = \gamma_1 e^{\gamma_3(1-DOD(\Delta t,t))} DOD(\Delta t, t)^{-\gamma_2} \tag{5}$$

$$DOD(\Delta t, t) = \frac{X_{t,i}\Delta t}{E_{cap,i}} \tag{6}$$

where α_1 and α_2 are load-leveling coefficients. L_{total}^t represents the total load profile within the optimal control time frame, which is the summation between the EV wireless charging load L_{WCEVs}^t and the base load L_b^t, and the base load is composed of the RES generations L_{RES}^t and office building load L_{bldg}^t. K_{Batt} is the price of EV batteries. $X_{t,i}$ denotes the decision variables for optimal control, which are the (dis)charging power and timing of wireless-(dis)charging-enabled EVs. η and $E_{cap,i}$ are the wireless (dis)charging efficiency and the capacity of EV batteries. N_{CL} is the cycle life for the EV battery, where $\gamma_1, \gamma_2, \gamma_3$ are modeling parameters derived through curve-fitting, which depend on the battery's specifications and empirical data supplied by the manufacturer. DOD is defined as the depth of discharge, the optimal control time interval is Δt, and t and T represent the current control timestep and the entire optimal control horizon, respectively. i is the individual indices of wirelessly charged EVs.

3.2.2 Constraints

This optimal control problem is additionally bounded by the physical limitations of wireless charging systems and EVs. Specifically, the target functions must align with the energy demands of EVs, the SOC boundaries of their batteries, and the permissible charging/discharging power ranges of bidirectional wireless charging units.

$$P_{dischar} < X_{t,i} < P_{char},\ \forall t \in T,\ \forall i \in N_{EV} \tag{7}$$

$$0 < E_{ini,i} + \sum_{t=t_{con,i}}^{t_{discon,i}} x_{t,i}\Delta t \le E_{cap,i},\ \forall t \in [t_{con,i}, t_{discon,i}],\ \forall i \in N_{EV} \tag{8}$$

$$E_{ini,i} + \sum_{t=t_{con,i}}^{t_{discon,i}} x_{t,i}\Delta t \ge E_{discon,i}, \forall i \in N_{EV} \tag{9}$$

$$SOC_{EV,Min} \le \frac{x_{t,i}\Delta t}{E_{cap,i}} \bullet 100\% \le SOC_{EV,Max} \tag{10}$$

where $P_{dischar}$ and P_{char} are the lower and upper limits of the wireless (dis)charging power. N_{EV} is the total number of wirelessly charged EVs. $E_{ini,i}$ and $E_{discon,i}$ are the initial energy levels and desired energy levels when wireless-(dis)charging-enabled EVs arrive and leave the wireless chargers. $t_{con,i}$ and $t_{discon,i}$ are the arrival and departure times of wirelessly charged EVs. $SOC_{EV,Min}$ and $SOC_{EV,Max}$ are the lower and upper bound SOC of wireless-(dis)charging-enabled EVs, where they are used to ensure the EV battery is not over (dis)charged.

Constraint (7) defines the operational boundaries for wireless charging/discharging power in EVs. Constraint (8) ensures the battery's energy level remains within a practical range, maintaining the feasibility of the optimal control strategy. Constraint (9) mandates that the battery's final energy meets the travel demands specified by EV users. Finally, constraint (10) safeguards against excessive charging or discharging to avoid accelerated battery degradation and prolong lifespan.

4 Simulation Case Studies

4.1 Simulation Settings

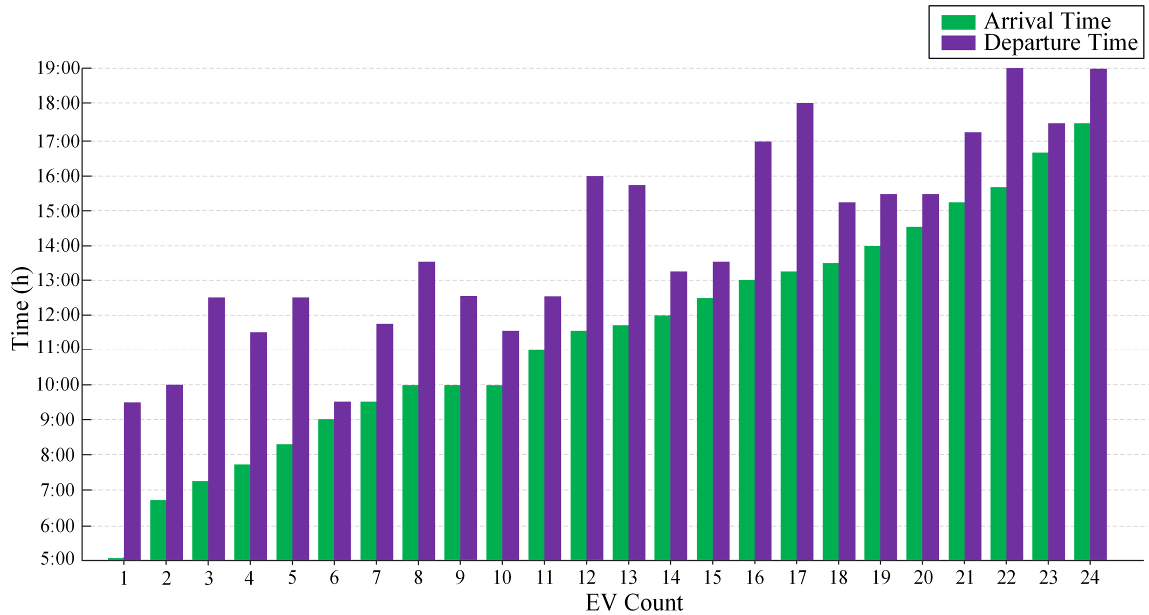
Figure 4: OPAL-RT power-hardware-in-the-loop (PHIL) simulation system.

For verifying the effectiveness and feasibility of the proposed approach, HIL simulations were conducted in RT-LAB using the OPAL-RT OP1420 PHIL (power-hardware-in-the-loop) test bench shown in Fig. 4. To better identify the system's performance, the wireless-(dis)charging-enabled EVs are (dis)charging at 7kW, and there are 15 wireless (dis)charging spots in the 3-floor MCC, where only a small portion of parking spots on each floor of the MCC has bidirectional wireless charging capabilities. Also, the load profile from the adjacent office building is modeled accurately from [34], and the RES generations are calculated using the real-world weather data from the NASA Geoworld database. The optimal control runs every 15 minutes for 24 hours. The implemented time-of-use electricity rates for charging are set at 0.753$ from 9 AM to 9 PM and 0.676$ from 10 PM to 8 AM from CLP Power Hong Kong. When EVs feed energy back into the grid, the selling price for electricity is fixed at 90% of the prevailing time-of-use rate for that period. In this study, the EV battery capacity is configured at 40 kWh, and the vehicle must achieve its target SOC before departure to ensure sufficient driving range. Furthermore, deep discharge cycles significantly degrade battery health and can accelerate aging. To mitigate this, if the SOC drops beneath a predefined minimum level, the battery management system's protective measures are triggered. Consequently, the EV's SOC is restricted to no lower than 10% to avoid over-discharging.

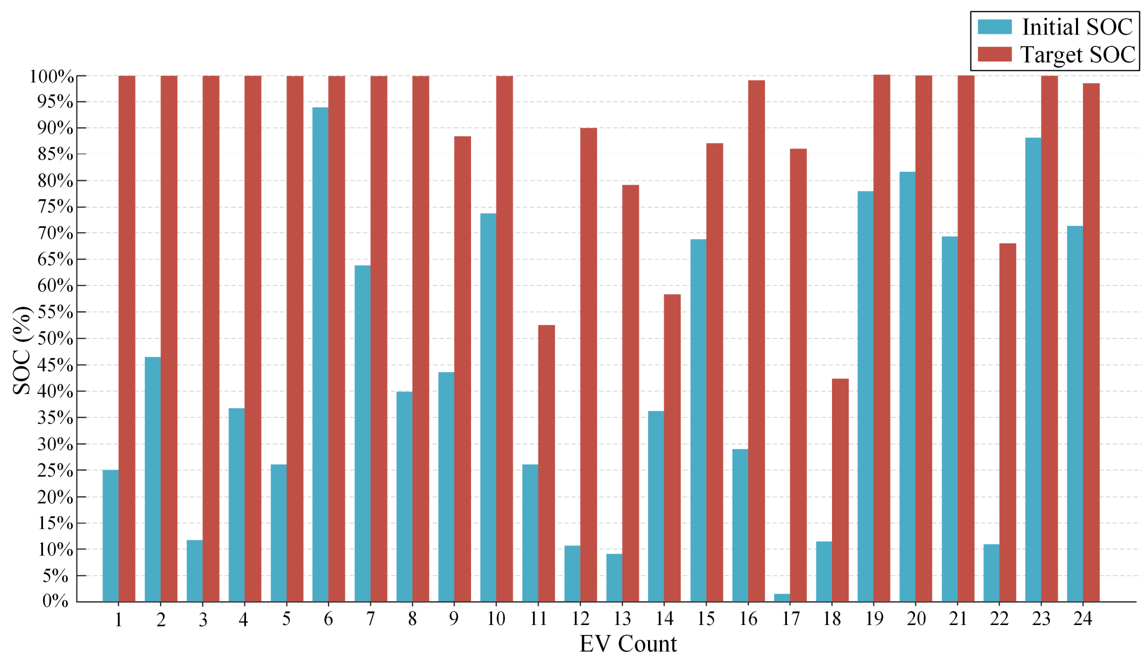
Table 1: Key parameters of EV battery

Variable	Value
Battery price (K_{Batt})	150$/kWh
Modeling parameter (γ_1)	3832
Modeling parameter (γ_2)	0.68
Modeling parameter (γ_3)	1.64

The optimal control-related computational tasks in this study were implemented using MATLAB R2024 on a Windows 11-based system equipped with an Intel i9 3.00 GHz processor and 96 GB of RAM. The EV battery-related parameters are listed in Table 1 [39]. Comprehensive data on wireless charging/discharging-capable EVs arriving at or exiting the MCC, generated via Monte Carlo simulations—including their arrival and departure timestamps, initial SOC, and target SOC at departure—are visually summarized for sampled wireless-(dis)charging-enabled EVs in Figure 5.



(a)



(b)

Figure 5: Sampled wireless-(dis)charging-enabled EV information including (a) arrival time and departure time (b) initial SOC and target SOC.

4.2 Comparative Case Evaluations

From the system-level energy management perspective, the effectiveness of the proposed method is proved by comparing it with results from the EV wireless direct charging without control, and the comparison result is in Fig. 6. For the uncontrolled direct wireless charging, it means the wireless-(dis)charging-enabled EVs get charged at the maximum charging power as soon as they arrive at the wireless charging pad and stop the charging once they reach their desired SOC defined by EV owners. It can be observed that the EV wireless charging load peak coincides with the base load peak from the office building. The peak wireless charging load between 10 AM and 1:30 PM is effectively reduced by an average of 21.98%, which indicates the power capacity of the microgrid consisting of MCC with integrated buildings allows for a reduction by at least 20%

of the total required charging power after using the proposed approach. From the low-level power electronics perspective, the power oscillogram of individual EVs from HIL simulations under controlled and uncontrolled wireless (dis)charging is presented in Fig. 7, which shows the wireless (dis)charging power for 13 EVs from 12:30 PM to 12:35 PM. It is obvious that all the EV wireless (dis)charging power under optimal control is significantly lower than that of the uncontrolled direct wireless (dis)charging, and there are 3 EVs implementing the wireless V2G, hence proving the feasibility and effectiveness of the proposed methodology.

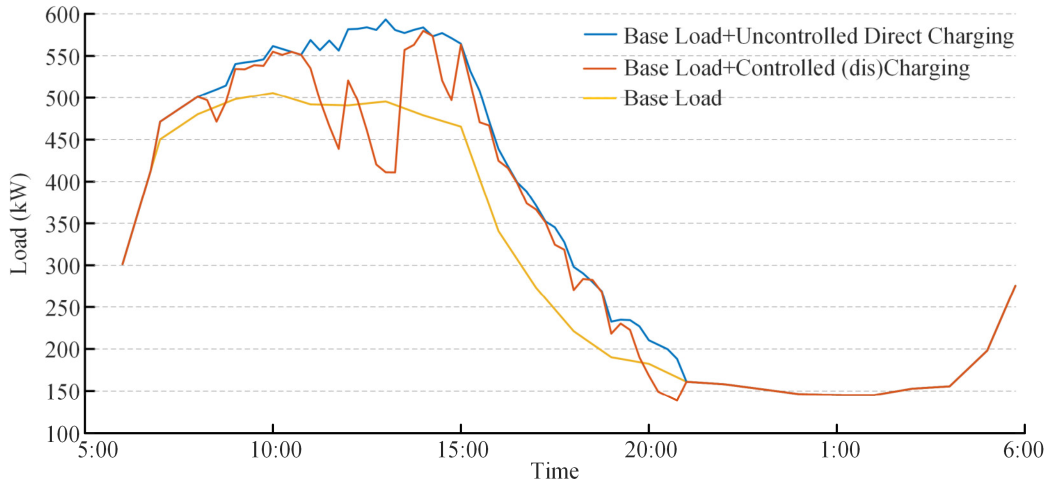


Figure 6: Load comparison results from HIL simulations.

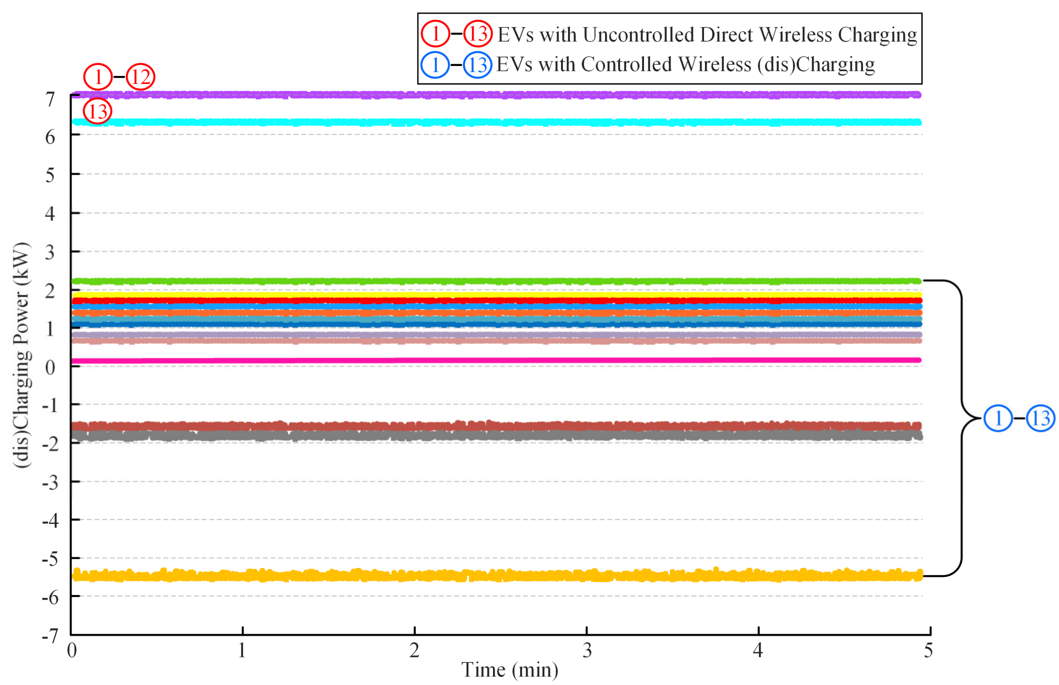


Figure 7: Power oscillogram of individual EVs under controlled and uncontrolled wireless (dis)charging.

5 Conclusion

This study demonstrates the integration of HIL simulations to evaluate full-bridge converters-based bidirectional wireless charging systems for wireless-(dis)charging-enabled EVs in the multistorey charging carpark, leveraging convex optimization-based optimal control for energy management. A centralized control framework collects real-time operational data, computes optimal (dis)charging strategies via an advanced optimal control algorithm, and distributes precise instructions to individual bidirectional wireless chargers. The approach not only ensures efficient bidirectional wireless power transfer at the component level but also reduces peak charging demand by an average of 21.98% at the system level while prioritizing battery longevity by integrating battery degradation costs into consideration. Comparative case validations and HIL simulation results confirm the system's viability, highlighting its dual effectiveness in balancing power load optimization and safeguarding EV battery health under urban energy infrastructure scenarios.

Acknowledgments
This work was fully supported by the grant from the Research Grants Council of the Hong Kong Special Administrative Region, China (Project No. T23-701/20-R).

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