Energy Proceedings
Vol 59, 2025
ISSN 2004-2965

Refined Strategies and Benefit Evaluation of "Vehicle-Building-Grid" Collaborative Optimization in Shenzhen Business Districts

Cheng Fan [1,2,3*], Jiena Cai[3], Yonghang Xie[3], Yutian Lei[3]

1 State Key Laboratory of Subtropical Building and Urban Science (Shenzhen University), Shenzhen, China

2 Key Laboratory for Resilient Infrastructures of Coastal Cities, Ministry of Education, Shenzhen University, Shenzhen, China

3 Sino-Australia Joint Research Center in BIM and Smart Construction, Shenzhen University, Shenzhen, China
(Corresponding Author: fancheng@szu.edu.cn)

ABSTRACT

The rapid growth of electric vehicles (EVs) presents challenges to power system stability. This study investigates six core business districts in Shenzhen, using a 500-meter spatial grid and proposing a fine-grained "vehicle-building-grid" coordinated optimization framework to enhance urban energy resilience. Commercial building energy profiles are modeled using prototype buildings, while EV load data are generated via Monte Carlo simulations. Incorporating time-of-use electricity pricing and regional energy patterns, the study regulates unordered EV charging behavior to quantify EV flexibility and emergency power potential. Results show that optimized charging reduces energy costs by an average of 2.68% at the district level and by 0.81%–3.59% at the spatial grid level. When minimizing the peak-valley load gap, average reductions reach 37.7%, with spatial grid-level reductions ranging from 17.18% to 42.63%. The study provides both theoretical and empirical support for planning distributed urban energy storage systems.

Keywords: business districts, electric vehicles, Monte Carlo simulation, optimization control, benefit evaluation

1. INTRODUCTION

Amid the global push for carbon neutrality [1], the transportation sector, a major contributor to energy use and emissions [2], is undergoing electrification [3]. While EVs support low-carbon mobility, large-scale deployment poses grid challenges. Uncoordinated charging can create load peaks, risking outages [4]. Feng et al. used Monte Carlo simulations in a 50.4 km² region of Hebei and observed a 649 kW peak-valley difference from overlapping EV and residential charging [5].

To manage this, coordinated charging strategies have been introduced to shift EV charging to off-peak hours, improving load balance and reducing costs. Du et al. applied a particle swarm optimization model for 300 EVs and achieved reductions in cost and peak-valley difference [6]. EVs can also act as mobile storage through Vehicle-to-Grid (V2G) technology [7, 8]. Mojumder et al. emphasized V2G's role in enhancing grid flexibility, while noting current gaps in policy and business frameworks[9].

Current research ranges from single-building models[10] to city-wide assessments [11]. However, many overlook the spatiotemporal behavior of EV users, which is essential for accurate demand forecasting. Business districts are key urban centers with high energy use and concentrated office buildings [12]. Private vehicles often remain idle at workplaces for 4.3 to 10.2 hours daily, offering significant storage potential if electrified [13]. Proper coordination of charging and discharging could enhance energy stability and provide emergency power via Vehicle-to-Building (V2B) systems.

This study conducts an integrated data-driven analysis of commercial office buildings and private EVs across six major business districts in Shenzhen to evaluate the potential of EVs for regional load regulation. A fine-grained optimization framework is developed, establishing 500-meter spatial grids and utilizing real-world trajectory data to model the movement patterns of EV clusters at the regional level. Statistical analysis is used to quantitatively assess control performance across districts and grids under different optimization objectives. The findings support the development of practical and generalizable control strategies for assessing the comprehensive benefits of EV clusters within urban regions.

This is a paper for the 11th Applied Energy Symposium: Low Carbon Cities & Urban Energy Systems (CUE2025), July 18-22, 2025, Kitakyushu, Japan.

2. MATERIAL AND METHODS

2.1 Research outline

This study proposes a fine-grained, region-level "vehicle-building-grid" coordinated optimization strategy to guide EV cluster charging and assess the value of different control methods. A prototype-building approach is used to simulate regional building energy demand, while EV travel and charging patterns are modeled using Monte Carlo simulation. Based on trajectory data from 20,000 electric taxis and 31.6 million m² of commercial office buildings across six major business districts in Shenzhen, the study integrates EV and building loads to design and evaluate coordinated charging strategies. Office buildings are treated as rigid loads, while EV clusters include flexible components that can shift demand through response control. The strategies are assessed by peak-valley load reduction and energy cost savings, demonstrating the potential of EVs to enhance energy flexibility in dense urban districts.

2.2 Prototype Building Energy Consumption Simulation

This study presents a prototype-based method for efficiently estimating energy consumption in business districts. Building attributes—such as function, floor area, height, and shape coefficient—are extracted by combining Point of Interest (POI) data with building footprints. Commercial office buildings are identified and clustered using area, height, and shape coefficient, with the optimal number of clusters determined via the elbow method [14] and grouped using the K-means clustering algorithm [15] to define representative prototype buildings. These are modeled in SketchUp, configured in OpenStudio with occupancy and HVAC details, and simulated in EnergyPlus for hourly energy demand. Real buildings are matched to prototypes and scaled by floor area to estimate regional energy use. This scalable approach enables energy modeling without detailed consumption data, though some adjustments may be needed for climate or structural differences.

2.3 EV Behavior Prediction Model

2.3.1 EV Physical Characteristics

The physical characteristics of EVs are critical factors influencing their charging/discharging behavior and energy management. In this study, key parameters such as charging/discharging power, battery capacity, and initial SOC are specified to ensure the realism of the EV model. The physical parameters of electric vehicles are defined based on references [10,16-18], as detailed in Table 1.

Tab.1 Vehicle physical parameters

Physical parameters	Content	Refer
Charge and discharge power (P_{ch}/P_{dis})	6.6kW	[10]
Charge/ discharge efficiency (η)	0.95	[16]
Average energy consumption (E_{cons})	20.7kWh/100km	[17]
Battery Capacity (C)	Normal distribution μ=0.8, σ=0.1	investigation
Initial state of charge(SOC_{ini})	Normal distribution μ=0.5137, σ =0.1772	[18]

2.3.2 EV Behavior Model

It is assumed that there is one EV for every 100 m² of office space in business districts, approximating one vehicle per 2–3 people[19]. All private cars in the study area are considered battery electric vehicles.

(1) EV Travel Behavior Simulation

Modeling EV travel behavior enables estimation of vehicle distribution across time in business districts, which is critical for assessing potential peak charging or discharging loads. A Monte Carlo method is employed to simulate departure and arrival times for each EV during working hours, capturing variability in behavior. It is assumed that 50% of vehicles leave the area during lunch breaks, while the other half remain parked throughout the day. Using a single cumulative distribution function across the entire day can produce illogical sequences (e.g., lunch return before departure, or work shifts shorter than an hour). To avoid this, time is divided into four intervals: morning arrival (6:00–10:59), lunch departure (11:00–12:59), lunch return (13:00–14:59), and evening departure (16:00–20:59). Time samples are drawn independently from each period to ensure logical behavior.

(2) EV Travel Behavior Simulation

In business districts, EVs are assumed to follow an unordered charging strategy—charging immediately upon arrival and continuing until either fully charged or departure, without user participation in load regulation. A Monte Carlo approach is used to simulate the stochastic characteristics of each EV, including trip timing, travel distance, battery capacity, and initial SOC. The SOC at arrival and the corresponding charging duration can be calculated based on Eqs. (1)–(3).

$$\mathrm{SOC}_{\min} \leq \mathrm{SOC} \leq \mathrm{SOC}_{\max} \quad (1)$$

$$SOC_{arr} = SOC_{ini} - \frac{l * E_{cons}}{C} \quad (2)$$

$$t_{ch} = \frac{(SOC_{max} - SOC_{arr}) * C}{P_{ch} * \eta} \quad (3)$$

Where: SOC_{min}=0.1, SOC_{max}=0.95, E_{cons} = 0.207kWh/km, Pch=6.6kW, η=0.95

The SOC of an electric vehicle at a given time *t* during the study period is defined as shown in Eq. (4).

$$SOC_t = SOC_{arr} + \frac{P_{ch} * t}{60 * C} \quad (4)$$

The charging load at each time *t* within the region is defined as shown in Eqs. (5)–(6).

$$\begin{cases} if \ \ t < t_{ch} \ , \ \ then \ P_{ch,EV_{i,t}} = 6.6 \\ if \ \ t \geq t_{ch} \ , \ \ then \ P_{ch,EV_{i,t}} = 0 \end{cases} \quad (5)$$

$$P_{EV,t} = \sum_{i=1}^{N_{grid}} P_{ch,EV_{i,t}} \quad (6)$$

Where: $P_{ch,EV_{i,t}}$ denotes the charging power of the *i*-th electric vehicle at time *t* in the region, while $P_{EVs,t}$ represents the total charging load of the electric vehicle fleet in the region at time *t*.

By calculating the total dwell time of each vehicle in the region and evaluating its state of charge according to Eq. (7), vehicles can be classified as either adjustable or non-adjustable.

$$\begin{cases} \text{if} \quad t_{total} \leq t_{ch} \ , \ \ then \ \ EV_i = Unadjustable \ vehicle \\ \text{if} \quad t_{total} > t_{ch} \ , \ \ then \ \ EV_i = Adjustable \ vehicle \end{cases} \quad (7)$$

Starting with the first vehicle, parameters are sampled from the probability distributions of relevant variables, and its minute-level charging load is computed using Eq. (5). This process is repeated for all vehicles within each spatial grid to generate the total charging load for one Monte Carlo run. Different spatial grids reflect varying vehicle counts and behaviors. To determine the appropriate number of simulation iterations, 50 spatial grids were randomly selected for 1,500 Monte Carlo runs each. The standard deviation at each iteration count was recorded. As shown in Fig. 1, the normalized standard deviation trend informed the final selection of 800 iterations per grid to ensure result reliability.

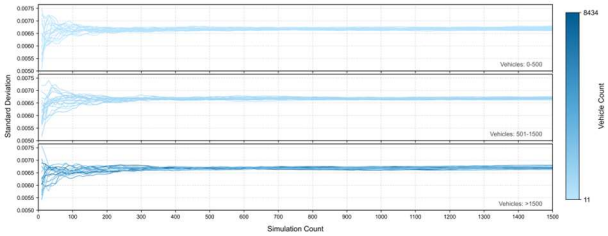

Fig. 1 Standard deviation of different cycle numbers

According to Eq. (7), if a vehicle is not fully charged upon departure, its charging load is defined as a rigid load, and the vehicle is classified as non-controllable. Otherwise, it is considered a flexible load and controllable. By analyzing the rigid load size alongside the total charging load of the electric vehicle fleet in the business districts, the distribution of flexible loads can be derived using Eq. (8). This serves as the basis for subsequent studies on ordered charging control.

$$P_{EV,t,Adj} = P_{EVs,t} - \sum P_{EV_{Unadj},t} \quad (8)$$

Where: $P_{EVs,t,Adj}$ represents the controllable load of the EVs in the area at time t, while $P_{EV_{Unadj},t}$ represents the uncontrollable load of EVs in the area at time *t*.

2.4 Coordinated Energy Optimization Strategy

2.4.1 Scenario Design

To evaluate the effectiveness of coordinated strategies integrating EV charging and building energy use, two scenarios are considered: one without EV load adjustment, and one with EV charging adjustment. The latter is optimized using the Sequential Least Squares Quadratic Programming (SLSQP) algorithm to determine the optimal charging schedules for the EV fleet.

2.4.2 Objective Functions

Large fluctuations in energy load can affect grid stability. Considering Shenzhen's time-of-use electricity pricing, optimization focuses on two objectives: minimizing energy cost and reducing the peak-valley difference, as shown in Eqs. (9)–(10). Cost-oriented optimization encourages shifting load from peak to off-peak periods, while peak-valley optimization helps smooth demand fluctuations and improve grid resilience.

$$minCost = \sum_{t=1}^{n} P_{tota} * t * Price_{E,i} \quad (9)$$

$$min\Delta P = P_{peak} - P_{valley} \quad (10)$$

2.4.3 Constraints

During charging and discharging optimization, EVs must meet the following SOC requirements: arrival SOC no less than 0.1, departure SOC no less than 0.3, and SOC throughout the process not exceeding 0.95. Only adjustable loads are eligible for modification, and total charging energy before and after optimization must remain unchanged.

2.4.4 Emergency Power Potential

Regardless of the scenario defined in Section 2.4.1, the SOC at departure is consistently maximized across the EV fleet. Based on this feature, Eqs. (11)–(12) establish a dynamic assessment model to quantify SOC variations and evaluate the energy supply potential of EV clusters as emergency power sources. This approach highlights the societal value of EV fleets and offers a reference for grid emergency backup capacity planning.

$$t_{dis} = \frac{(SOC_{arr} - 0.3) * C}{P_{dis} / \eta} \quad (11)$$

$$P_{EVs,t} = \sum_{i=1}^{N_{grid}} P_{dis,EV_{i,t}} \quad (12)$$

2.5 Data Experiment

2.5.1 Data Description

(1) Study Area

This study examines the social value of vehicle–building integration across six major business districts in Shenzhen. Fig. 2 shows the selected districts include Science and Technology Park Business District, Houhai Business District, Chegongmiao Business District, Futian CBD Business District, Huaqiangbei Business District, and Caiwuwei Business District—recognized as the city's most mature and economically active business districts. To enable fine-grained analysis, each district is divided into 500 m × 500 m spatial grids, allowing for detailed comparisons both between and within districts.

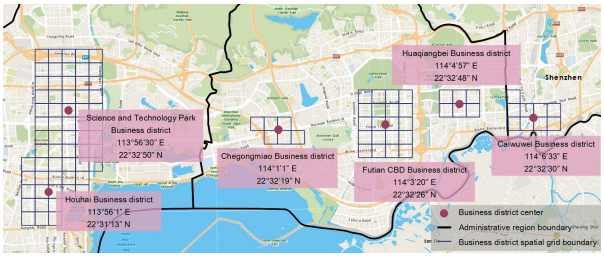

Fig. 2 Distribution of business district locations

(2) Dataset

Using Shenzhen's 2020 enterprise POI data and 2022 building footprints, commercial office buildings were spatially matched and clustered into three categories based on physical attributes using the elbow method and K-means. Median values from each cluster defined three prototype buildings, whose hourly energy use was simulated and scaled by floor area to estimate annual demand. Travel behavior was derived from 21.9 million trip records of 20,000 electric taxis in September 2019. Origin-destination data was mapped to spatial grids within six business districts to estimate EV cluster charging loads at the grid level.

2.5.2 Experimental Setup

The experiment is structured around three key aspects. First, a baseline scenario without control is established to evaluate the proposed optimization strategy, where energy costs for buildings and EV clusters are calculated under unordered charging. In the optimization scenario, EV charging is adjusted based on forecasted building demand, generating time-based control signals. Each 500 m × 500 m grid undergoes 800 Monte Carlo simulations to enhance result reliability and improve computational efficiency. All scenarios aim to maximize EV battery SOC upon departure, allowing assessment of emergency power potential. The study analyzes 104 spatial grids across six major business districts under varying energy and mobility conditions. Time-of-use electricity prices are listed in Table 2.

Tab.2 Electricity prices in each period

Time period	Unit price(RMB/kWh)	Meter Information
00:00-07:59	0.284	Valley period
08:00-09:59; 12:00-13:59; 19:00-23:59	0.783	Flat period
10:00-11:59; 14:00-18:59	1.179	Peak period

3. RESULTS AND DISCUSSION

3.1 Building and EV Load Analysis

3.1.1 Building Energy Consumption Analysis

Based on the forecasting method in Section 2.2, the annual energy use of the three prototype office buildings was estimated at 329.46, 342.66, and 396.39 MJ/m². Weighted by building type distribution, the estimates deviate by 11.3% from Shenzhen's 2022 benchmark[20]. Hourly energy demand for summer weekdays was then calculated for each business district and spatial grid. As shown in Fig. 3, the prototype displays a clear "double peak" pattern, with consistent peaks between 8:00–10:59 and 12:00–15:59 — key periods for demand response.

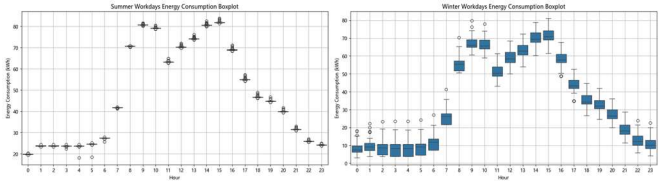

Fig.3 Hourly energy consumption of the prototype building

3.1.2 EV Charging Load Prediction Results

Fig. 4 shows the distribution of unordered charging load and the number of parked EVs across business districts during the study period. The line indicates the unordered charging power, while the shaded area represents the number of vehicles parked in the area. Results reveal that from 11:00 onward, some vehicles have already reached full charge and stopped charging. This indicates potential for adjusting charging schedules to better align overall energy use with demand targets.

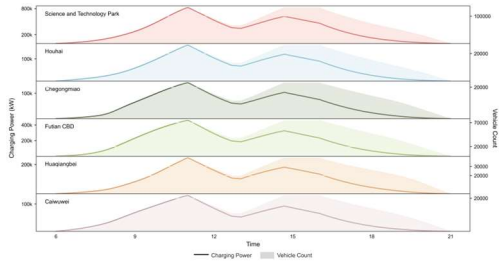

Fig.4 Minute-level disorderly charging power and the number of vehicles in the business districts

3.2 Scenario Analysis and Optimization Control

Based on the energy consumption profiles of both EV clusters and buildings, the EV demand load is aggregated into an hourly profile. As shown in Fig. 5, under Scenario 1, when all vehicles in the area are fully electrified, unordered charging significantly amplifies the regional peak load. This is mainly because energy demand is low during off-peak hours due to fewer office occupants, while peak demand coincides with commuting hours. The simultaneous charging of a large number of EVs upon arrival leads to a "peak-on-peak" effect in overall energy consumption.

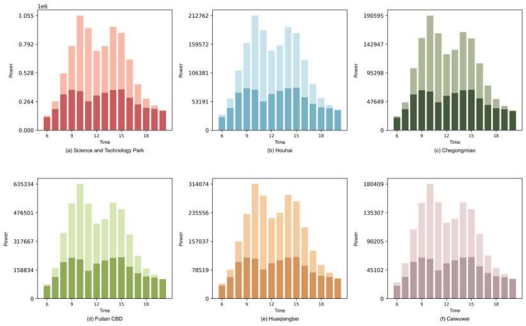

Fig.5 Energy consumption distribution of Scenario 1

3.3 Optimization strategy effect verification

3.3.1 Optimization Results of Unordered Charging

Scenario 2 focuses on adjusting EV charging schedules to optimize energy use. As shown in Section 4.1.2, some vehicles are fully charged by the afternoon and remain idle, making it possible to shift charging from peak-price hours (14:00–18:59) to off-peak periods (after 19:00) or from building peak loads to lower demand periods. Fig. 6 presents the outcomes for minimizing both energy cost and peak-valley difference.

As shown in Fig. 6(a), optimizing for cost leads to consistent savings across business districts, averaging 2.68%. The Caiwuwei Business District achieves the highest reduction (2.99%), due to earlier EV arrivals and later departures, enabling more off-peak charging. This strategy also lowers the peak-valley difference by 9.44%–17.01%.

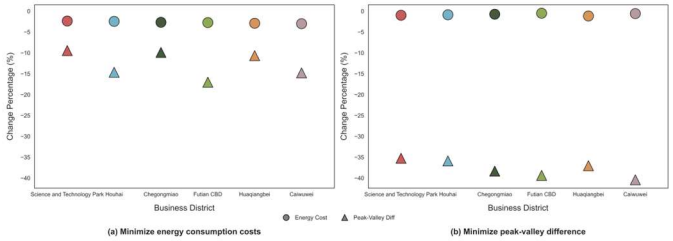

Fig.6 Adjustment benefits in Scenario 2

As shown in Fig. 7, from the perspective of spatial grids, energy costs can be reduced by 0.81%–3.59%. Among the six business districts, the reduction in energy cost across grids in the Futian CBD varies widely, indicating significant differences in cost-saving potential among its spatial grids. This is mainly due to the diversity of building types and differing spatial activity patterns. In contrast, the Huaqiangbei exhibits more uniform cost reductions, suggesting similar energy use behaviors across its spatial grids.

Fig.7 Spatial grid regulation benefits under the goal of minimum energy consumption cost in Scenario 2

As shown in Fig. 6(b), optimizing EV charging to minimize the peak-valley gap results in a 35.24%–40.39% reduction at the district level. From the spatial grid perspective (Fig. 8), the gap decreases by 17.18%–42.63%. Variations across grids are more pronounced in the Science and Technology Park due to diverse building types and activity patterns, while Huaqiangbei exhibits more balanced peak-valley gap reductions across spatial grids, indicating overall system stability.

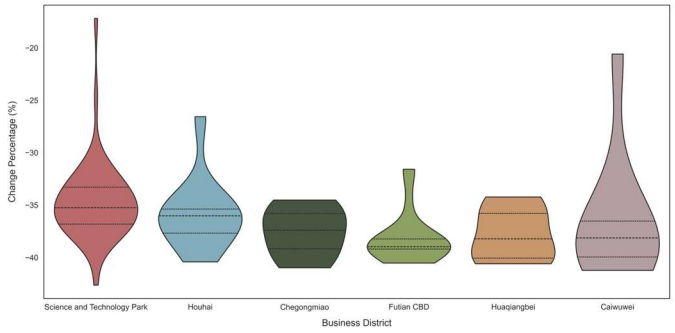

Fig.8 Spatial grid regulation benefits under the goal of minimizing the peak-valley difference in Scenario 2

3.3.2 Emergency Power Supply Potential Assessment

Scenario 3 evaluates the potential of EVs to act as energy storage systems with discharge capability. Using the remaining battery level at departure under unidirectional charging as the baseline, the scenario assesses the potential of EV clusters to supply emergency power the following day upon arrival at business districts, in the event of unexpected power outages. As shown in Fig. 9, EV clusters across the six business districts are capable of nearly fully covering the energy demand of commercial buildings between 10:00 and 16:00. During peak discharge hours, surplus energy is available, indicating the potential to support nearby buildings as well.

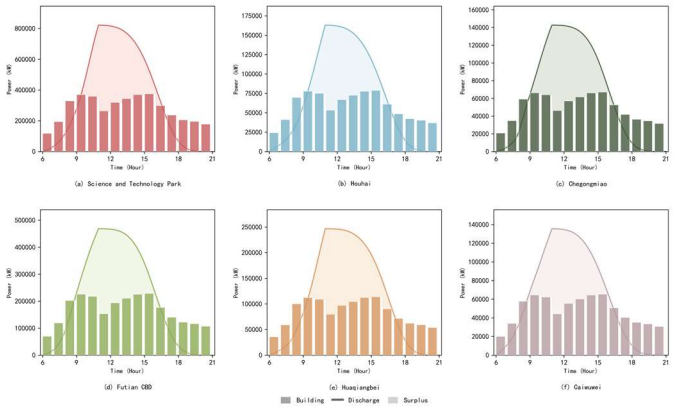

Fig.9 Energy supply potential of the EVs within the business districts

As shown in Fig. 10, the spatial contribution of EV clusters within business districts between 10:00 and 15:00 is mapped at the grid level. The Science and Technology Park and Huaqiangbei business districts exhibit relatively uniform distribution of contribution across grids. In contrast, higher contributions are observed near the Shenzhen Talent Park in the Houhai Business District and near the Shenzhen Golf Course in the Chegongmiao Business District. This reflects a common spatial pattern where commercial office buildings are more concentrated around scenic areas.

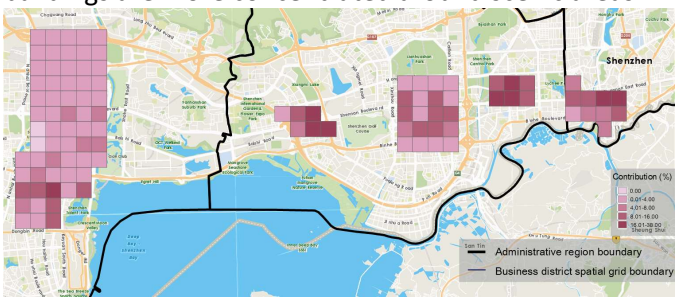

Fig.10 Contribution of spatial grid emergency energy

4. CONCLUSIONS

This study explores the flexible regulation potential of EV loads in urban areas by proposing an orderly charging strategy that incorporates the energy demand profiles of business district office buildings. Based on data from six major business districts in Shenzhen, the model is validated across varying building densities and vehicle levels. Key findings include:

(1) Under energy cost minimization, costs drop by an average of 2.68% at the district level and within a range of 0.81% to 3.59% at the grid level.

(2) When minimizing the peak-valley gap, the average reduction reaches 37.70%, with grid-level reductions between 17.18% and 42.63%.

(3) Huaqiangbei business districts is the most balanced among the six business districts in terms of building distribution and EV behavior.

(4) Assuming full vehicle electrification and use of the proposed control strategy, EVs could meet the next day's office building energy demand in business districts from 10:00 to 16:00, with peak supply potentials of 821.91 MW at the district level and 54.34 MW at the grid level.

The method can be adapted to different regional characteristics by adjusting parameters, enabling its application to other building types, such as residential or mixed-use developments. Future studies could evaluate its performance under more complex, long-term, and low-carbon scenarios, including building-side flexibility, EV discharging, and renewable energy integration. Further refinement of prototype building models—by incorporating factors such as building age and thermal performance—could improve the accuracy of energy demand estimates and enhance the robustness of system-level benefit assessments.

ACKNOWLEDGEMENT

The authors gratefully acknowledge the support of this research by the National Natural Science Foundation of China (No. 52278117), Guangdong Basic and Applied Basic Research Foundation (No. 2024A1515011549), Shenzhen Science and Technology Program (No. 20220531101800001, 20240813143330039 and 20220810160221001), and the Philosophical and Social Science Program of Shenzhen (SZ2024C006).

REFERENCE

[1] Yang F, Yang X, Li X. China's diverse energy transition pathways toward carbon neutrality by 2060[J]. Sustainable Production and Consumption, 2024, 47: 236-250.

[2] Qiao Q, Eskandari H, Saadatmand H, et al. An interpretable multi-stage forecasting framework for energy consumption and CO2 emissions for the transportation sector[J]. Energy, 2024, 286: 129499.
[3] Chen L, Ma R. Clean energy synergy with electric vehicles: Insights into carbon footprint[J]. Energy Strategy Reviews, 2024, 53: 101394.
[4] Luo Y, Xu X, Yang Y, et al. Impact of electric vehicle disordered charging on urban electricity consumption[J]. Renewable and Sustainable Energy Reviews, 2025, 212: 115449.
[5] Feng J, Chang X, Fan Y, et al. Electric Vehicle Charging Load Prediction Model Considering Traffic Conditions and Temperature[J]. Processes, 2023, 11(8): 2256.
[6] Du W, Ma J, Yin W. Orderly charging strategy of electric vehicle based on improved PSO algorithm[J]. Energy, 2023, 271: 127088.
[7] İnci M, Çelik Ö, Lashab A, et al. Power System Integration of Electric Vehicles: A Review on Impacts and Contributions to the Smart Grid[J]. Applied Sciences, 2024, 14(6): 2246.
[8] Biswas P, Rashid A, Habib A K M A, et al. Vehicle to Grid: Technology, Charging Station, Power Transmission, Communication Standards, Techno-Economic Analysis, Challenges, and Recommendations[J]. World Electric Vehicle Journal, 2025, 16(3): 142.
[9] Mojumder M R H, Ahmed Antara F, Hasanuzzaman M, et al. Electric vehicle-to-grid (V2G) technologies: Impact on the power grid and battery[J]. Sustainability, 2022, 14(21): 13856.
[10] He Z, Khazaei J, Freihaut J D. Optimal integration of Vehicle to Building (V2B) and Building to Vehicle (B2V) technologies for commercial buildings[J]. Sustainable Energy, Grids and Networks, 2022, 32: 100921.
[11] Li Y, Huang Y, Liang Y, et al. Economic and carbon reduction potential assessment of vehicle-to-grid development in guangdong province[J]. Energy, 2024, 302: 131742.
[12] Liu L, Dong Y, Lang W, et al. The Impact of Commercial-Industry Development of Urban Vitality: A Study on the Central Urban Area of Guangzhou Using Multisource Data[J]. Land, 2024, 13(2): 250.
[13] Moody J, Farr E, Papagelis M, et al. The value of car ownership and use in the United States[J]. Nature Sustainability, 2021, 4(9): 769-774.
[14] Schubert E. Stop using the elbow criterion for k-means and how to choose the number of clusters instead[J]. SIGKDD Explor Newsl, 2023, 25(1): 36–42.
[15] Ahmed M, Seraj R, Islam S M S. The k-means Algorithm: A Comprehensive Survey and Performance Evaluation[J]. Electronics, 2020, 9(8): 1295.
[16] Liu Q, Li Y, Xu T, et al. Peak shaving potential and its economic feasibility analysis of V2B mode[J]. Journal of Building Engineering, 2024, 90: 109271.
[17] Gaete-Morales C, Kramer H, Schill W-P, et al. An open tool for creating battery-electric vehicle time series from empirical data, emobpy[J]. Scientific Data, 2021, 8(1): 152.
[18] Huang Y, Masrur H, Lipu M S H, et al. Multi-objective optimization of campus microgrid system considering electric vehicle charging load integrated to power grid[J]. Sustainable Cities and Society, 2023, 98: 104778.
[19] Jiang Y. PSDF(photovoltaic,storage,DC,flexible) ——A new type of building power distribution system for zero carbon power system[J]. Heating Ventilating & Air Conditioning, 2021, 51(10): 1-12.
[20] Shenzhen Large Public Building Energy Consumption Monitoring Report (2022), https://www.sz.gov.cn/attachment/1/1338/1338912/10787693.pdf; 2022 [accessed 12 January 2025].