Energy Proceedings
Vol 58, 2025
ISSN 2004-2965

An Electric Vehicle Dispatch Framework for Enhancing Urban Energy Resilience to Mitigate Building Power Outages#

Yujia Li1, Zhaohui Dan1, Yuyu Zheng1, Shuncheng Lee1,3*, Yuekuan Zhou1,2,4,5*
1 Sustainable Energy and Environment Thrust, Function Hub, The Hong Kong University of Science and Technology (Guangzhou), Nansha, Guangzhou, 511400, Guangdong, China
2 Division of Emerging Interdisciplinary Areas, The Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong SAR, China
3 Earth, Ocean and Atmospheric Sciences Thrust, Function Hub, The Hong Kong University of Science and Technology (Guangzhou), Nansha, Guangzhou, 511400, Guangdong, China
4 Department of Mechanical and Aerospace Engineering, The Hong Kong University of Science and Technology, Clear Water Bay, Hong Kong SAR, China
5 HKUST Shenzhen-Hong Kong Collaborative Innovation Research Institute, Futian, Shenzhen 518048, China
(* Corresponding Author: shunchenglee@hkust-gz.edu.cn)

ABSTRACT

With the expansion of urban electric vehicle (EV) fleets, utilizing EVs as distributed energy storage has become a key approach to enhancing energy system resilience, particularly in power shortage scenarios. This study proposes a proactive heuristic dispatch method for EVs, which integrates dynamic resource partitioning and user willingness modeling. The method enables intra-zone discharging of available EVs prior to outages, based on priority rules, to alleviate power shortages. In addition, it incorporates outage detection and EV behavior simulation modules base on real-world data, that provides reliable spatiotemporal data to support dispatch decisions. Simulation results indicate that the proposed method has the potential to alleviate power outages through EV dispatch, but its current effectiveness remains limited due to practical constraints—particularly the restricted availability of discharging locations at electric vehicle charging station (EVCS). Nevertheless, it provides preliminary validation and practical insights into the potential of EV dispatch for enhancing urban energy resilience.

Keywords: urban energy resilience, electric vehicle dispatch, power outage mitigation, proactive dispatch, user willingness

1. INTRODUCTION

With the continuous expansion of urban EV adoption, EV-based distributed energy storage is increasingly recognized as a vital approach to enhancing the resilience of urban energy systems. Under extreme weather conditions and during peak load periods, urban power grids frequently encounter localized power shortages and outage risks, necessitating efficient and intelligent energy coordination and dispatch strategies. Empirical studies have identified high localized load levels as a direct trigger for equipment failures in distribution systems [1].

Current research on vehicle-to-grid (V2G) dispatch primarily focuses on load shifting, price-based demand response, or event-driven outage recovery. However, two major limitations persist: (1) most studies emphasize post-event emergency responses, lacking proactive, anticipatory scheduling mechanisms oriented toward forecasted gaps and risks [2,3,4]; and (2) many models remain confined to small-scale or idealized scenarios, lacking micro-level dispatch modeling for large-scale urban EV populations [4,5,6].

Traditional centralized scheduling struggles to scale with a large number of EVs, hindering the balance between efficiency and accuracy [7,8]. Especially when user behavioral randomness, and spatial constraints are considered, the computational complexity increases exponentially [5,9]. Therefore, developing a dispatch framework that is scalable to urban-level scenarios is a critical challenge for improving practical applicability and implementation potential [3,4].

To address these issues, this study proposes an EV dispatch framework in response to power outages to mitigate building outages in urban, with three major innovations:

To address potential risks of load overflow and power shortages in the grid, this study proposes a proactive EV scheduling model based on energy gap detection. The method dynamically partitions the city

This is a paper for the 11th Applied Energy Symposium: Low Carbon Cities & Urban Energy Systems (CUE2025), July 18-22, 2024, Kitakyushu, Japan.

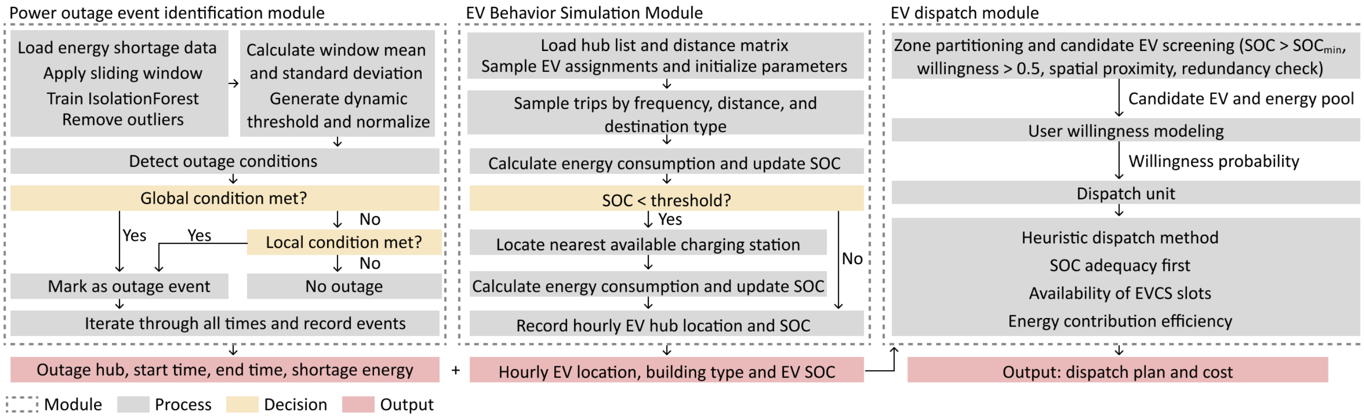

Fig. 1 Framework of the proposed EV dispatch method

into flexible energy management zones according to identified outage events, and spatially aggregates EV resources to fulfill dispatch tasks and compensate for shortages. It enables preemptive discharging before outages occur, thereby mitigating blackout risks. The proposed scheduling strategy adopts a heuristic approach that prioritizes local energy matching and zone-level autonomy, enabling rapid, low-complexity dispatch decisions under realistic operational constraints to enhance the resilience of urban energy systems.

The outage detection mechanism employs a dynamic threshold algorithm based on Isolation Forest and sliding window statistics. Potential high-risk load points are treated as anomalies and excluded to construct adaptive threshold ranges, while accounting for the city's overall energy supply limits. The system automatically identifies outage risks and triggers collaborative dispatch accordingly.

To provide fine-grained, realistic inputs for scheduling, this paper constructs a microsimulation model of EV behavior using real-world urban data and spatial partitioning (Hubs). The model generate high-resolution spatiotemporal EV distributions and SOC time series supplies the model with rich behavioral and physical parameters, enhancing the realism, applicability, and engineering feasibility of the results.

2. MATERIAL AND METHODS

The EV dispatch method, integrating three modules: outage detection, EV behavior simulation, and EV Dispatch, as illustrated in Fig. 1. The modules work collaboratively to enhance the interaction between the power grid and large-scale EV fleets.

This study adopts the spatial partitioning results from a submitted paper, which aggregates urban buildings into energy units, hubs, as illustrated in Fig. 2. These hubs are the fundamental units for energy dispatch and modeling.

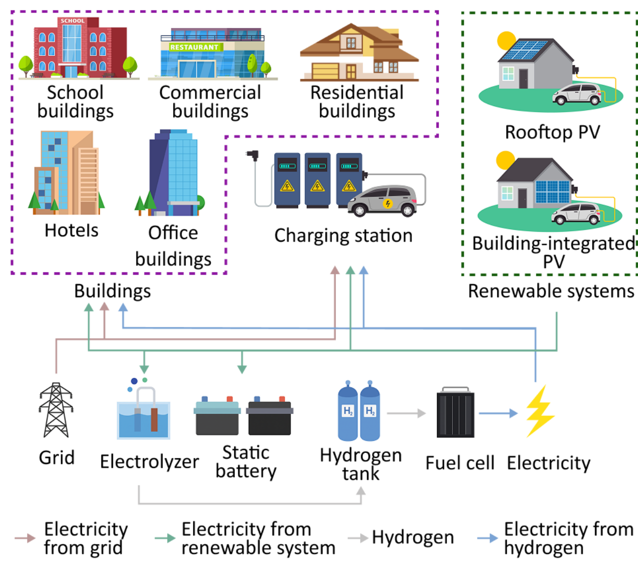

Fig. 2 Hub composition

To simplify the computation, both EV simulation and dispatch adopt a unified spatial mapping based on hub id. All location and distance calculations are conducted using inter-hub distances as an approximate substitute for actual geographic distances between EVs.

2.1 Outage detection module

This module detects power outage events in urban energy hubs based on hourly load data. For each hub, a sliding window combined with the Isolation Forest algorithm is used to identify and remove peak loads treated as anomalies. A dynamic threshold is then computed from the filtered load profile:

$$T_{i,t} = \mu_{i,t} + k \cdot \sigma_{i,t}$$

where $\mu_{i,t}$ and $\sigma_{i,t}$ denote the mean and standard deviation within the window, and k is an empirical coefficient (set to 2.5 in this study). This threshold represents the upper bound of normal load fluctuations at time t; exceeding it indicates a potential outage risk.

After computing the dynamic thresholds, outage events are identified based on two criteria. An outage is considered to occur at hub i and time t if either:

Global condition (for w consecutive time steps):

$$\sum_i G_{i,t} > Q_{\text{total}} \quad \text{and} \quad G_{i,t} > T_{i,t}$$

Local condition:

$$G_{i,t} > \alpha \cdot T_{i,t}$$

where $G_{i,t}$ is the actual load of hub i, and α is a local overload factor (set to 3.0). The algorithm scans all hubs hourly and records each detected event include outage start time, and the accumulated shortage. This event set serves as input for subsequent EV dispatch model.

2.2 EV behavior simulation module

To simulate the spatial distribution and SOC dynamics of EVs under power outage scenarios, this study develops a city-scale EV behavior simulation module.

The SOC is updated according to the following equation:

$$SOC_t + 1 = SOC_t - \frac{d_{ij} \cdot e_{\text{drive}}}{C_{\text{bat}}}$$

where d_{ij} , e_{drive} , and C_{bat} denote distance between the origin and destination hubs, consumption rate, and battery capacity, respectively.

If SOC falls below a threshold (e.g., 43.7%), the system inserts a detour to the nearest available EVCS, and SOC is updated after charging according to:

$$\text{SOC}_{after} = SOC_{before} + \frac{P_{\text{charge}} \cdot t_{\text{charge}} \cdot \eta_{\text{charge}}}{C_{\text{bat}}}$$

where P_{charge}, t_{charge}, and η_{charge} denote charging power, duration, and efficiency, respectively.

The module outputs each EV's hourly hub-level location and SOC trajectory, providing fine-grained input for subsequent EV dispatch model.

2.3 EV dispatch module

This module develops a heuristic scheduling model for urban power outages, integrating dynamic partitioning and user willingness to enable rapid dispatch decisions. Heuristic dispatch method refers to a rule-based, rather than globally optimized, approach that prioritizes vehicles with high discharging capacity, proximity to the target area, and willingness to participate. This method enables fast response and computational feasibility.

2.3.1 Dynamic partition model

The system selects the deficient hub as the center and dynamically expands to adjacent hubs until the cumulative dispatchable energy satisfies the following condition:

$$\sum_{e \in E_g} (SOC_e - SOC_{min}) \cdot C_e \geq \lambda \cdot \sum_{h \in H_g} D_{short,h}$$

Where E_g is the set of EVs with available energy, H_g the included hubs, $D_{\text{short},h}$ the energy shortfall at hub h, and λ = 1.3 is a redundancy factor ensuring sufficient supply margin.

Dispatch is performed autonomously within each dynamically defined zone, relying solely on local EV resources, with no cross-zone interference.

2.3.2 User Willingness Model

Each resulting zone is then treated as an independent dispatch unit for scheduling procedures.

To simulate user behavioral responses, a willingness probability is defined as:

$$p_e = \frac{1}{1 + \exp(\gamma \cdot C_{\text{dist}} - \delta \cdot R_{\text{gain}})}$$

$$C_{\text{dist}} = \left(d_{e,c} + d_{c,\text{dest}} - d_{e,\text{dest}}\right)^+$$

$$R_{\text{gain}} = y_{e,h,t} \cdot \max\left\{0, P_{\text{discharge}} - P_{\text{charge}}^{(t)}\right\}$$

Where C_{dist} represents additional travel cost, R_{gain} denotes the expected economic gain, γ and δ are the sensitivity coefficients for travel distance and price, respectively.

2.3.3 Dispatch module

The heuristic dispatch process prioritizes the mobilization of locally controllable EV resources to support discharging, with the objective of alleviating electricity shortages at the affected hub as effectively as possible.

At each dispatch time step, candidate electric vehicles within the predefined dispatch zone are filtered based on two criteria:

The SOC must exceed a minimum safety threshold:

$$\text{SOC}e(t) \geq s\text{min} = 0.2$$

The dispatch willingness probability must satisfy:

$$p_e \geq 0.5$$

These conditions ensure that selected EVs have sufficient energy and a positive behavioral response, thereby improving the feasibility and efficiency of the dispatch.

For all eligible EVs within the zone, a priority ranking is established based on their maximum discharging capacity:

$$y_e^{\max} = (\mathrm{SOC}e - s\mathrm{min}) \cdot C_e$$

Where C_e denotes the vehicle's battery capacity and $s_{\min}$ is the post-discharge SOC safety threshold. In the case of ties, vehicles closer to the target hub are prioritized.

Following this order, the system sequentially dispatches candidate vehicles to their nearest EVCS that has available charging slots. Each EV contributes energy based on its available capacity, and the system continuously accumulates the supplied energy until either the shortage at the current hub $D_h(t)$ is resolved, or the total available discharging capacity within the zone is exhausted:

$$\sum_{e \in \mathcal{E}'} y_{e,h,t} \geq D_h(t)$$

Where $\mathcal{E}'$ represents the set of EVs dispatched, and $y_{e,h,t}$ is the energy provided by EV e to hub h at time t.

To ensure operational validity and system stability, the dispatch process adheres to the following constraints:

SOC safety constraint:

$$\mathrm{SOC}e(t) - \frac{ye,h,t}{C_e} \geq s_{\min}, \quad \forall e \in \mathcal{E}'$$

Post-discharge SOC must not fall below the safety threshold.

Uniqueness Constraint:

$$y_{e,h,t} > 0 \Rightarrow e \notin \mathrm{Dispatched}_t$$

Each vehicle can be dispatched at most once per time step.

EVCS Capacity Constraint:

$$\sum_{e \in \mathcal{E}'_c} 1 \leq \mathrm{Cap}_c(t), \quad \forall \mathrm{EVCS}\ c$$

The number of EVs assigned to any EVCS must not exceed its available number of sockets.

This strategy offers a fast, low-complexity dispatch solution under realistic operational constraints, and provides a practical technical pathway and reference baseline for future research.

3. RESULTS

3.1 Outage detection results

The load data used for outage detection in this study are derived from the dataset of the mentioned submitted article, covering hourly electricity consumption for 13,717 hubs in Guangzhou over an entire year. The data account for renewable energy integration and represent the residual demand that must still be met by the grid after utilizing available renewable resources. Based on this, a load threshold was defined for each hub to facilitate outage detection. For validation, the detected annual outage duration in Guangzhou (1,182 hours) aligns closely with real-world statistics (1,131.62 hours [10]), confirming the method's accuracy and applicability.

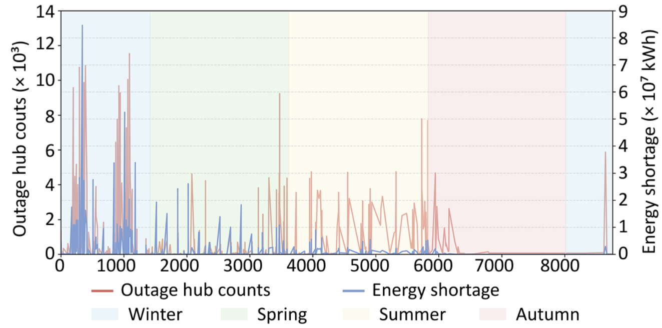

Fig. 3 Outage hub counts and energy shortage

Fig.3 illustrates the hourly outage situation, revealing a clear seasonal pattern. Outages are most frequent and severe during winter, when both the number of affected hubs and total energy shortages reach annual peaks. This reflects the combined pressure of increased heating demand and reduced renewable generation. In contrast, outage intensity is lower in spring and autumn, though noticeable fluctuations remain, indicating persistent imbalance risks even in milder seasons. Occasional peaks in summer are likely linked to localized cooling demand.

Notably, a strong positive correlation is generally observed between the number of outage hubs and the energy shortage, suggesting that broader outage often entail more severe supply gaps. However, large shortages occasionally arise from just a few hubs, highlighting the outsized impact of critical nodes such as high-demand or infrastructure-intensive areas.

These findings further substantiate the necessity of proactive EV dispatch strategies under foreseeable outage risks, providing a robust empirical basis for the design of dynamic zone-based dispatching and resource allocation optimization.

3.2 EV behavior simulation results

This study simulates the operational behavior of 300,000 EVs within Guangzhou, each assigned a unique id. The simulation spans a continuous one-week period and is mapped to represent a full year in the dispatch model. To enhance realism and applicability, EV and charging infrastructure parameters are derived from local sources, including sales data of mainstream EV models, the official charging infrastructure platform, and urban development plans, as documented in [11]. These inputs provide static EV parameters such as battery capacity and energy consumption. Mobility patterns, including travel frequency and departure time, are based on survey data of new energy vehicle users in Guangzhou. EV destinations are categorized into five building types: residential, office, school, hotel, and commercial, that the data from the submitted article referenced earlier. Building-specific arrival and dwell time patterns are differentiated by weekdays and weekends.

At initialization, EVs are probabilistically assigned to hubs and initialized with a default SOC of 90%. The system records hourly SOC, hub ID, and building type for each EV, while simultaneously tracking the number and identities of EVs present at each hub over time. To reflect real world charging constraints, the model imposes slot limitations at EVCS, simulates EV charging behavior accordingly, and records the usage status of each EVCS. This provides essential input for downstream scheduling that considers EVCS availability.

Figure 4 illustrates the SOC trajectories of five sampled EVs, demonstrating realistic behavioral patterns: stable SOC corresponds to dwelling within a building, decreasing SOC indicates vehicle movement, and rising SOC reflects charging actions triggered when SOC drops below a predefined threshold.

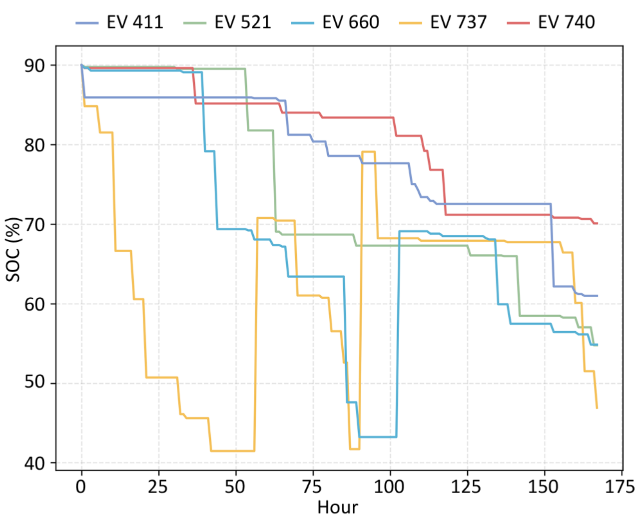

Fig. 4

3.3 EV dispatch method results

As shown in Fig.5, outage events are aggregated based on simultaneous outages across hubs occurring at the same timestamp. Due to the substantial variation in energy shortages among different events, along with the relatively limited energy supply from EVs, it is challenging to visualize the full range of data effectively. To enhance readability, the y-axis is truncated at the 80th percentile of the shortage distribution. Although extreme values beyond this threshold are not displayed in the figure, the full data can be referenced in Fig.3, and all outliers are retained in the statistical analysis and calculations.

Fig.5 demonstrates that EV dispatch tends to be more effective in responding to small-scale outages, where the total energy shortage is relatively low and the available EV resources within the affected area are generally sufficient to meet the demand. However, in scenarios where a large number of hubs experience outages simultaneously, the aggregated shortage significantly increases—often surpassing the discharge capacity of the local EV fleet—thereby reducing the effectiveness of the dispatch strategy.

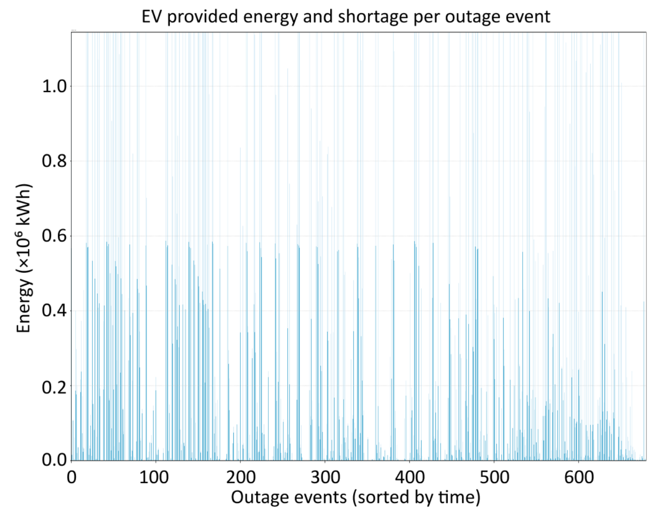

Fig. 5 Outage hub count and energy shortage

When each hub-level outage is considered individually (i.e., each sub-outage event), the simulation identifies a total of 531,440 sub-outage events. Among them, 29,107 events were successfully resolved through EV-based dispatch, resulting in a satisfaction rate of 5.48%. The total energy shortage exceeds 1.12 TWh, while EVs collectively contributed approximately 82.06 GWh, achieving an overall energy coverage rate of 7.29%. The dispatch strategy engaged approximately 215,000 EVs, the average response time (the time difference between the start of EV discharging and the onset of the corresponding outage event) is –0.15 hours, indicating that most discharging actions were initiated before the actual onset of outages, which is consistent with the proactive design of the scheduling mechanism.

Furthermore, the model incorporates constraints on available charging slots at EVCSs. As a result, many candidate EVs, although technically eligible for discharging, were unable to participate due to a lack of vacant charging points in the local area. This operational limitation significantly constrains the dispatch potential and is one of the key reasons why substantial energy shortages remain unresolved in certain outage events.

4. DISCUSSION

4.1 Conclusions

In the Guangzhou case study, although the overall energy shortage coverage rate remains low due to current limitations in EVCS slot availability, the dispatch strategy still proves effective in alleviating small to medium scale outages, demonstrating its potential to enhance the resilience of urban energy systems. The proposed framework exhibits strong scalability and practical adaptability. On one hand, the partitioning mechanism effectively reduces the complexity of responding to multiple simultaneous events, thereby improving the efficiency of local dispatch operations. On the other hand, the integration of spatiotemporal EV behavior simulation and infrastructure resource constraints ensures that the strategy remains well-aligned with real world conditions. Furthermore, the forward-looking discharging mechanism facilitates proactive intervention before outages occur, offering enhanced energy security under future extreme weather events or emergency scenarios.

4.2 Limitation

This study adopts a simplified modeling strategy for EV dispatch, the discharging tasks are inserted into predefined vehicle trajectories and SOC change paths without retroactively altering historical behaviors. Although a single outage event may involve thousands of hubs and EVs, the proportion of dispatch-related activity for each vehicle remains relatively small over the course of a year. This simplification helps reduce computational complexity with minimal impact on overall results, particularly for large-scale urban simulations. Nonetheless, this approach has inherent limitations.

The 1-hour dispatch look-ahead window, which constrains the amount and timing of EV discharging before outages occur. As a result, available EVCS slots may be quickly exhausted within a short time frame, preventing some EVs from accessing EVCS to discharge. Future work will address these challenges in several ways: examining the impact of longer dispatch horizons (e.g., 2 or 4 hours) on system performance and EVCS utilization; exploring infrastructure expansion strategies such as increasing the number of stations or charger density per site; and incorporating residential chargers into the modeling framework. The current model considers only public charging infrastructure, and future studies will develop a more comprehensive network that includes diverse charging facility types.

REFERENCE

[1] Bashkari MS, Sami A, Rastegar M. Outage cause detection in power distribution systems based on data mining. IEEE Trans Ind Inform 2021;17(1):640–9.

[2] Goh HH, Zhang Y, Yu S, Soh YC, Xue F. Orderly charging strategy based on optimal time-of-use price demand response of electric vehicles in distribution network. Energies 2022;15(5):1869.

[3] Xiong H, Li Z, Zhang C, Wu T, Chen C. A real-time robust method for post-disaster load restoration of coordinated power-transportation system with vehicle-to-grid response. IEEE Trans Smart Grid 2025. Advance online publication.

[4] Boubaker S, Kraiem H, Ghazouani N, Kamel S, Mellit A, Alsubaei FS, et al. Multi-objective optimization framework for electric vehicle charging and discharging scheduling in distribution networks using the Red Deer Algorithm. Sci Rep 2025;15:13343.

[5] He Y, Venkatesh B. Optimal scheduling for charging and discharging of electric vehicles. IEEE Trans Smart Grid 2012;3(3):1095–105.

[6] Li C, Zhang H, Wang J, Xu Y. A comprehensive review of vehicle-to-grid technology: Barriers and opportunities. Renew Energy 2023;213:118059.

[7] Chen Y, Lei X, Niu S, Jian L. Trustworthy V2G scheduling and energy trading: A blockchain-based framework. arXiv 2024. arXiv:2407.13988.

[8] Diaz-Londono C, Orfanoudakis S, Vergara PP, et al. A simulation tool for V2G enabled demand response based on model predictive control. arXiv 2024. arXiv:2405.11963.

[9] Sun Y, Chen Z, Li Z, Tian W, Shahidehpour M. EV charging schedule in coupled constrained networks of transportation and power system. IEEE Trans Smart Grid 2019;10(5):4706–17.

[10] Qiu Y, Deng N, Wang B, Shen X, Wang Z, Hultman N, et al. Power supply disruptions deter electric vehicle adoption in cities in China. Nat Commun 2024;15:6041.

[11] Dan Z, Song A, Zheng Y, Zhang X, Zhou Y. City information models for optimal EV charging and energy-resilient renaissance. Nexus 2025;2:100056.