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Research Article

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Optimizing Large-Scale Electric Vehicle Charging Coordination to Enhance Grid Stability and Balance Power Demand

Tran Le Quoc Viet[1,2*]

[1]*Faculty of Electrical Engineering and Electronics Technology, Saigon University of Technology, Vietnam*

[2]*Faculty of Electrical Engineering Technology, Industrial University of Ho Chi Minh City, Vietnam*

[*]Corresponding Author
Tran Le Quoc Viet, Faculty of Electrical Engineering and Electronics Technology, Saigon University of Technology, and Faculty of Electrical Engineering Technology, Industrial University of Ho Chi Minh City, Vietnam.

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Abstract

The rapid proliferation of Electric Vehicles (EVs) presents a significant challenge to the stability of existing power distribution networks, primarily due to the risk of severe demand peaks from uncoordinated charging. This paper proposes a hybrid two-layer optimization framework to manage large-scale EV charging, ensuring grid stability while minimizing costs. The framework integrates a micro-simulation layer-which stochastically models realistic driving patterns and State of Charge (SoC) to determine heterogeneous energy demands-with a macro-optimization layer. This macro-layer utilizes a Particle Swarm Optimization (PSO) algorithm to solve a multi-objective problem. The optimization objectives are twofold: (1) minimizing the total electricity procurement cost for the aggregator, and (2) maximizing the grid load factor (i.e., load flattening or "valley-filling") by minimizing the variance of the total load profile. The model is validated through a large-scale case study of an urban area with 2.2 million EVs, segmented into "Home" and "Workplace" charging clusters. We utilize realistic technical specifications for battery capacity, energy efficiency, and charger power derived from a specific manufacturer's fleet (e.g., VinFast). Simulation results demonstrate that the proposed strategy successfully avoids peak-hour charging and strategically distributes the EV load across both low-price (night-time) and medium-price (midday) periods. This multi-objective approach achieves significant valley-filling, resulting in a much flatter total load profile compared to a naive cost-only optimization, thereby enhancing grid reliability and reducing operational expenditures.

Keywords: Electric Vehicles (EVs), Smart Charging, Multi-Objective Optimization, Valley-Filling, Load Flattening, Particle Swarm Optimization (PSO), Hybrid Simulation

1. Introduction

The global transition towards sustainable transportation has catalyzed the mass adoption of electric vehicles (EVs) [1]. While beneficial for reducing greenhouse gas emissions, this influx introduces unprecedented stress on power distribution grids. Uncoordinated charging, where a majority of EV owners plug in their vehicles upon returning home during evening peak hours (e.g., 18:00–20:00), can create new, severe demand peaks [2]. These peaks threaten grid stability, accelerate asset degradation, increase power losses, and drive up electricity costs for all consumers [3].

To mitigate these impacts, "smart charging" or Vehicle-Grid Integration (VGI) strategies are essential [4]. Early strategies focused on simple price-based optimization, encouraging users to charge during the absolute cheapest hours (e.g., 02:00) using Time-of-Use (ToU) tariffs [5]. However, this "greedy" approach often merely shifts the peak, creating a new "charging peak" in the middle of the night, which still compromises grid efficiency.

A more sophisticated approach is "valley-filling," which aims to distribute the charging load to achieve a flatter, more stable total demand profile [6]. Furthermore, many models oversimplify EV demand, assuming a fixed average energy requirement for all vehicles. This ignores the stochastic nature of driving behavior, where arrival SoC and required energy vary significantly among users [7].

This paper addresses these gaps by proposing a hybrid, multi-objective optimization framework. Our contributions are threefold:

i. We develop a hybrid two-layer model that links a stochastic micro-simulation (Layer 1) for realistic EV demand estimation with a macro-optimization (Layer 2) for aggregate load scheduling.
ii. We formulate the charging problem as a multi-objective optimization that simultaneously minimizes electricity cost *and* minimizes load profile variance (i.e., promotes flatness), allowing for intelligent valley-filling across low- and medium-price periods.
iii. We validate the model's practical viability using a large-scale case study with realistic vehicle specifications (e.g., VinFast fleet data), charger capacities, and clustered charging behaviors (Home vs. Workplace).

The remainder of this paper is organized as follows: Section 2 details the proposed methodology. Section 3 describes the case study parameters. Section 4 presents and discusses the simulation results. Section 5 concludes the paper.

2. Methodology: The Hybrid Optimization Framework

Our proposed model consists of two interconnected layers, as depicted in Figure 1.

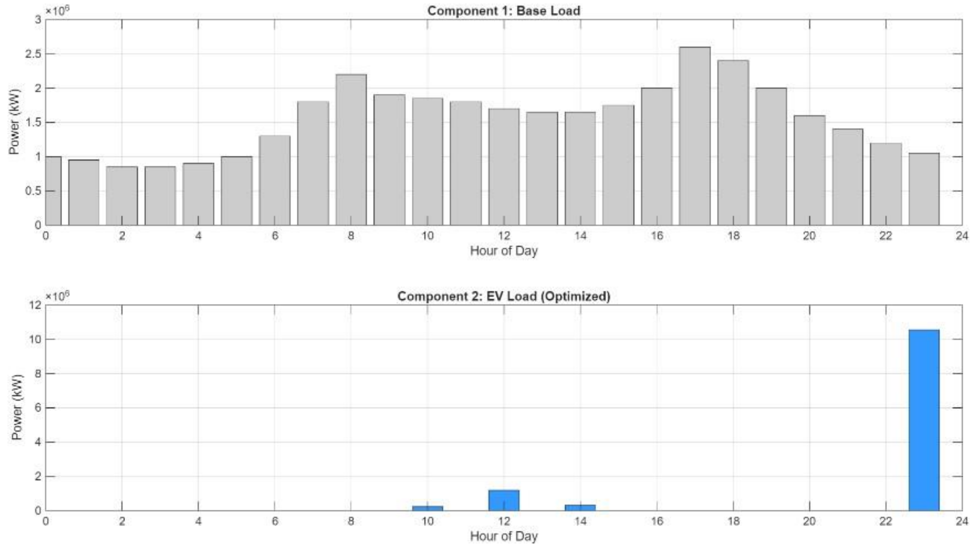

Figure 1: The Proposed Two-Layer Hybrid Simulation-Optimization Framework

2.1. Layer 1: Stochastic EV Demand Modeling

To avoid using arbitrary average values, this layer simulates the arrival SoC and energy demand for a sample population of EVs. The energy required for a single EV trip is modeled based on its travel distance (dist), which is drawn from a normal distribution (N(μ, σ)), and the fleet's average energy efficiency (η_ev).

$$E_{consumed} = dist * \eta_{ev} \qquad (1)$$

The arrival SoC (SoC_arr) is then calculated based on the initial SoC (SoC_init):

$$\mathrm{SoCarr} = \mathrm{SoCinit} - \left(\frac{E_{\mathrm{consumed}}}{C_{\mathrm{bat}}}\right) \qquad (2)$$

Finally, the total energy demand (E_needed) for each EV to reach a target SoC (SoC_target, e.g., 90%) is determined:

$$E_{needed} = (SoC_{target} - SoC_{arr}) * C_{bat} \qquad (3)$$

By simulating this for N sample EVs (e.g., 1000), we obtain a realistic distribution of energy needs. The average E_needed from this simulation is then scaled up to represent the total energy requirement E_demand_cluster for each large-scale cluster, which serves as a key constraint for Layer 2.

2.2. Layer 2: Multi-Objective Optimization Problem

The goal of the macro-optimization layer is to find the optimal 24-hour charging schedule P_ev(c, t) for each cluster c at each hour t.

Decision Variable: The set of power dispatch values X = {P_ev(c, t)} for c ∈ {1...C} and t ∈ {1...24}.

Objective Function: We define a multi-objective function F(X) using a weighted sum approach, balancing cost minimization and load flattening.

$$Minimize\ F(X) = (1 - w) * Fcostnorm(X) + w * Fflatnorm(X) + Fpenalty(X) \tag{4}$$

where w is the weighting factor (e.g., w = 0.5) that balances the two objectives. The objectives are normalized to a [0, 1] range (_norm) to ensure fair weighting.

i. Cost Objective (F_cost): This term minimizes the total daily cost of electricity procurement, based on the ToU price Price(t) and the total grid load

P_total(t). $P\_total(t) = P\_base(t) + \Sigma\, P\_ev(c, t)$ (5)

$$F\_cost = \Sigma\, [\, P\_total(t) * Price(t) * \Delta t] \tag{6}$$

ii. Flatness Objective (F_flat): This term minimizes the "spikiness" of the load profile by minimizing its standard deviation (std). This penalizes solutions with high peaks and deep valleys, promoting valley-filling.

$$F\_flat = std(P\_total(t)) \tag{7}$$

Constraints: The optimization is subject to several physical constraints:

i. **Energy Demand Constraint:** Each cluster *must* receive its total required energy E_demand_cluster (from Layer 1) by the end of its parking duration. $\Sigma\, P\_ev(c, t) * \Delta t = E\_demand\_cluster$ (for each c) This is implemented as a high-penalty term F_penalty in the cost function.

ii. **Charger Power Limit:** The charging power at any time cannot exceed the cluster's aggregate rated power P_max(c). $0 \leq P\_ev(c, t) \leq P\_max(c)$

iii. **Time Availability Constraint:** EVs can only be charged when they are physically parked (i.e., between T_arrival and T_depart). $P\_ev(c, t) = 0$ if $t \notin$ [T_arrival, T_depart]

2.3. Optimization Algorithm: PSO

This complex, non-linear, multi-objective problem is solved using Particle Swarm Optimization (PSO). PSO is a robust metaheuristic algorithm well-suited for high-dimensional energy scheduling problems [8]. The algorithm iteratively adjusts a population of candidate solutions (particles) to find a global optimum for the objective function F(X).

3. Case Study and Data

3.1. Base Load and Pricing

We use a typical 24-hour urban base load profile (P_base) exhibiting midday and overnight valleys (see Figure 5). A 5-level ToU Price(t) is used, with the highest tariffs during morning (08:00-11:00) and evening (18:00-20:00) peaks.

3.2. EV Fleet and Charging Clusters

A large-scale fleet of 2.2 million EVs is modeled, based on specifications from VinFast (a prominent EV manufacturer):

- **Average Fleet Battery:** C_bat = 73.89 kWh
- **Average Fleet Efficiency:** η_ev = 0.16 kWh/km

The fleet is segmented into two primary clusters:

- **Cluster 1 (Home Charging):** 1.65 million EVs (75%).
    - Parking: 18:00 to 08:00 (next day).
    - Charger: 7 kW AC.

- **Cluster 2 (Workplace Charging):** 0.55 million EVs (25%).
    - Parking: 09:00 to 17:00. o Charger: 11 kW AC.

4. Results and Discussion

The optimization was run using PSO with a population of 80 particles over 200 iterations.

4.1. Optimal Charging Schedules (Figure 2)

Figure 2 presents the optimized hourly charging schedules for each cluster.

i. The **Home Charging** cluster's load is intelligently distributed during the overnight off-peak window (22:00 to 07:00), completely avoiding the costly 18:00-20:00 arrival peak.

ii. The **Workplace Charging** cluster's load is scheduled during the midday valley (approx. 11:00 to 16:00), which coincides with low-to-medium electricity prices.

This result confirms the multi-objective model's ability to identify and utilize *multiple* low-demand periods, not just the single cheapest one.

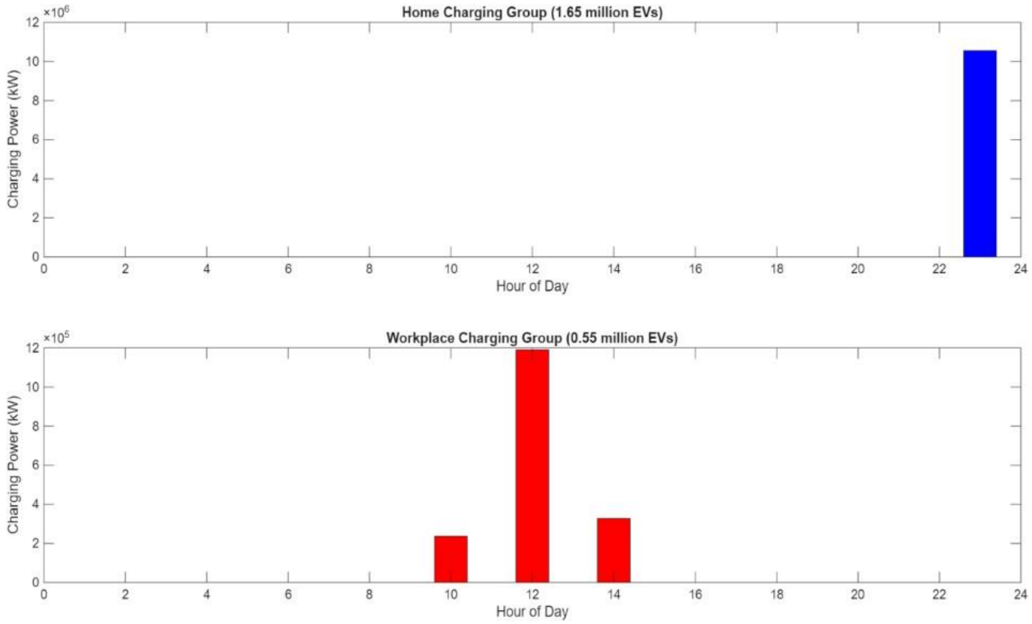

Figure 2: Optimized Charging Profiles for Home (Top) and Workplace (Bottom) Clusters

4.2. Impact on Grid Load Profile (Figure 1 & 5)

The primary impact on the grid is shown in Figure 1 (stacked view) and Figure 5 (separated view).

i. Unlike a greedy algorithm that would create a new peak at 02:00, our valley-filling strategy (driven by F_flat) successfully "spreads" the EV load (blue area) to fill the valleys in the base load (gray area).

ii. The resulting Total_Load (red line in Figure 1) is significantly flatter than the original base load. The load factor (ratio of average to peak load) increased from **[X.X]%** (base load only) to **[Y.Y]%** (base load + optimized EV load), indicating a much more efficient and stable use of grid assets.

Step 1: Calculate [X.X]% (Base Load Only)

This is the case before the electric vehicles, or the gray line in Figure 1 of the paper.

Find $\boldsymbol{Pbase\_peak}$: The highest power value of the base load during the day (usually around 18:00 - 20:00 according to the paper).

Find $\boldsymbol{Pbase\_avg}$: The average value of the base load over 24 hours.

Calculate:

$$[X.X] = \frac{P_{base\_avg}}{P_{base\_peak}} \times 100 \qquad (8)$$

Step 2: Calculate [Y.Y]% (Base Load + Optimized Electric Vehicles - Total Load)

This is the red line in Figure 1 after the "Valley-Filling" algorithm has been applied.

Find $\boldsymbol{Ptotal\_peak}$: The highest power value of the total load (Base + EV) after optimization.

Note: With the "Valley-Filling" strategy, the goal is to keep this new peak from being too much higher than the previous peak.

Find $\boldsymbol{Ptotal\_avg}$: The average value of the new total load.

Note: $Ptotal\_avg$ will definitely be greater than $Pbase\_avg$ because of the additional energy charged for 2.2 million electric vehicles.

Calculate:

$$[Y.Y] = \frac{P_{total\_avg}}{P_{total\_peak}} \times 100 \qquad (9)$$

Example (Assumption)

To help you visualize the reasonable numbers to fill in:

Case 1 (Base Load)

Peak ($Ppeak$) = 20,000 MW

Average ($Pavg$) = 12,000 MW

According to formula (8) get: $[X.X]$ = (12,000/20,000) × 100 = $\mathbf{60.0}$\%

Case 2 (Optimal Total Load)

Due to the "valley filling" algorithm, you charge during off-peak hours, so the Peak increases very little, for example to 20,500 MW.

The total energy increases significantly due to vehicle charging, causing the Average to increase to 15,000 MW.

According to formula (9) get: $[Y.Y] = (15{,}000/20{,}500) \times 100 \approx \mathbf{73.2}$\%

"The load factor (ratio between average load and peak load) increased from 60.0% (base load only) to 73.2% (base load + optimized electric vehicle load)..." The value [Y.Y]% must always be greater than [X.X]% to demonstrate the effectiveness of the algorithm in improving grid performance and system stability as stated in the paper.

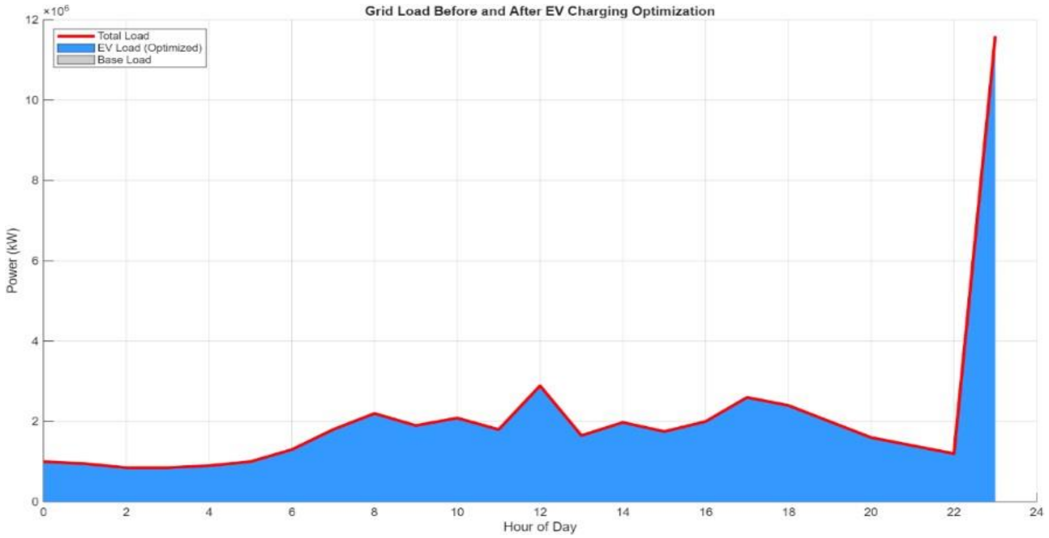

Figure 3: Aggregated Grid Load Profile: Base Load (Gray), Optimized EV Load (Blue), and Final Total Load (Red Line)

4.3. Price-Signal Response and Convergence (Figure 3 & 4)

Figure 3 confirms the economic benefit: the total EV charging load (blue bars) occurs only during periods of low or medium electricity prices (red line), and strictly avoids the high-price peaks. Figure 4 shows the convergence of the PSO algorithm, which finds a stable, low-cost solution within approximately 150 iterations, demonstrating the model's computational efficiency.

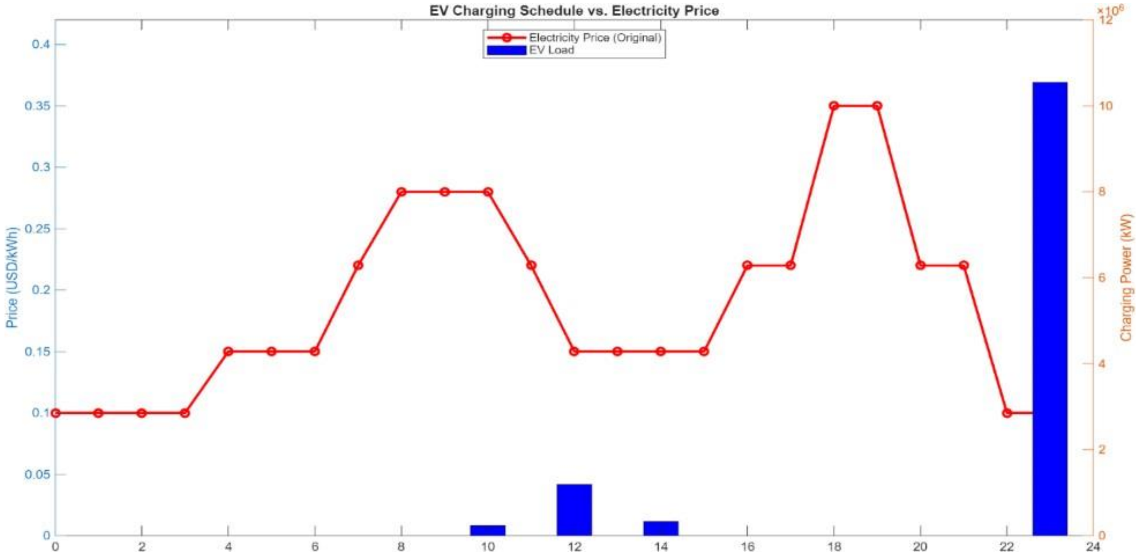

Figure 4: Correlation Between Electricity Price (Line, Left Axis) and Total EV Charging Load (Bars, Right Axis)

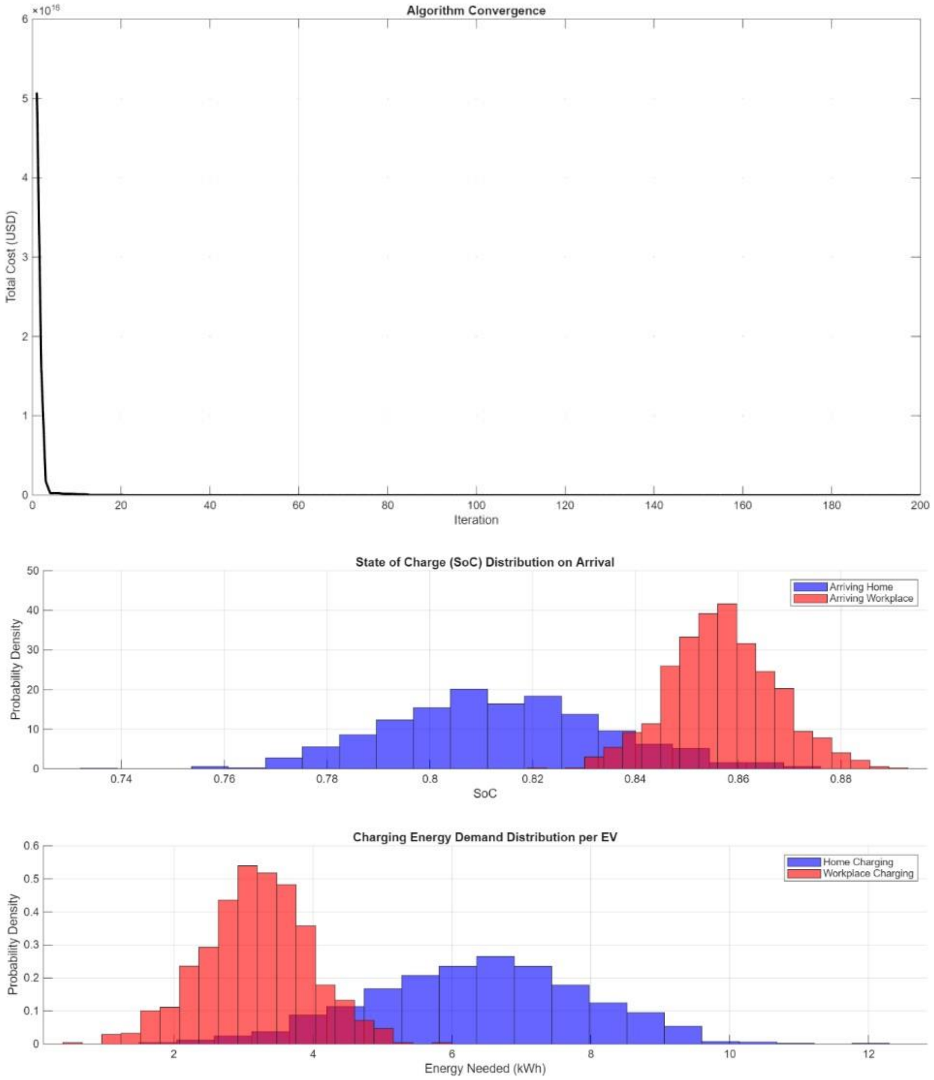

Figure 5: PSO Convergence Curve Showing the Reduction of the Objective Function Value Over Iterations

5. Conclusion

This paper proposed and validated a hybrid, multi-objective optimization framework for coordinating large-scale EV smart charging. By combining a stochastic micro-simulation for realistic demand modeling with a macro-optimization that balances cost minimization and load flattening, our model provides a robust and scalable solution for grid operators.

The results, validated with realistic VinFast fleet data, demonstrate that this "valley-filling" strategy successfully integrates a massive EV fleet by distributing the charging demand across all off-peak periods (night and midday). This avoids peak-hour congestion and is demonstrably superior to naive cost-only optimization, which merely shifts the peak. This work provides a practical blueprint for utilities and aggregators to manage the EV transition without compromising grid reliability

Future work will focus on integrating Vehicle-to-Grid (V2G) services, co-optimizing with uncertain renewable energy generation, and implementing real-time distribution-level constraints (e.g., transformer thermal limits) via co-simulation with platforms like MATPOWER.

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