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Coordinated Electric Vehicle Charging in Distribution Networks Under Uncertain Residential Demand

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Abstract: Uncoordinated residential electric vehicle (EV) charging increases evening peaks and may cause voltage drops and feeder overloads. This study develops a scenario-based coordination framework accounting for uncertain arrivals, next-day departures, and initial states of charge. A synthetic fleet of 300 EVs is modeled with truncated normal distributions; 1,000 Monte Carlo charging scenarios are reduced to 12 weighted representatives using peak-period-stratified k-medoids. A multiobjective model minimizes normalized procurement cost, network losses, and daily peak-to-valley range while enforcing charging windows, energy demand, facility limits, and network constraints. The IEEE 33-bus case is solved by linear programming with updated loss sensitivities and verified by nonlinear power flow. Compared with uncoordinated charging, coordination reduces weighted peak power by 28.94%, peak-to-valley range by 71.33%, procurement cost by 8.27%, and network losses by 7.76%. In the worst representative scenario, minimum voltage rises from 0.863307 to 0.903665 p.u., and maximum line loading falls from 133.510% to 98.758%. All EV charging requirements are met. Results indicate that scenario-based coordination can improve the simulated feeder's economy and operating security under the specified synthetic assumptions.

Keywords: electric vehicles; charging uncertainty; Monte Carlo simulation; scenario reduction; coordinated charging; distribution network optimization

1. INTRODUCTION

Increasing residential EV adoption changes both the magnitude and timing of distribution feeder demand. Charging immediately after a commuter returns home tends to coincide with the evening residential peak and may increase line loading, energy losses, and voltage violations [1]. Yet the available overnight parking window often provides considerable scheduling flexibility. Effective coordination must represent heterogeneous EV behavior while respecting the electrical network and the energy required by each vehicle.

Recent research has examined multiobjective EV charging [2], distributionally robust scheduling [3], correlated demand and price uncertainty [4], grid-aware station control [5], and distribution-network charging capacity [6]. Although these methods address important uncertainties and operating limits, a reproducible benchmark that connects individual residential charging behavior, stochastic scenario selection, and feeder-level verification remains useful. Measured charging datasets also illustrate the diversity of residential sessions [7]; the probability distributions in this study are nevertheless illustrative assumptions, not parameters fitted to that dataset.

This paper combines (i) continuous-time overlap accounting for arrivals and departures within hourly intervals, (ii) Monte Carlo scenario generation and peak-period-stratified k-medoids reduction, and (iii) network-constrained charging with post-optimization nonlinear power-flow checks. The study uses a synthetic fleet and the IEEE 33-bus system to compare no-EV, uncoordinated, and coordinated charging. The scenario-wise optimization provides an offline, scenario-informed performance benchmark rather than a demonstrated real-time control policy.

2. UNCERTAIN RESIDENTIAL EV DEMAND

2.1 Vehicle Model and Assumptions

The modeled residential fleet contains 300 private EVs, each with one overnight charging event per 24-h cycle. Charging is unidirectional (no vehicle-to-grid operation); charger availability, communication failures, and queuing are not modeled. Battery capacities are 48, 60, and 72 kWh in proportions of 30%, 50%, and 20%, respectively. Rated charger powers are 7 kW (80% of vehicles) or 11 kW (20%). Charging efficiency is 0.92, and all vehicles have a target state of charge (SOC) of 0.90. Battery capacity and power types are shuffled independently across vehicles.

Arrival time follows a truncated normal distribution with underlying mean 19:00 and standard deviation 1.5 h on [16:00, 24:00]. Next-day departure follows a truncated normal distribution with underlying mean 07:30 and standard deviation 1.0 h on [05:00, 10:00]; it is mapped to the continuous time range 29:00–34:00. Initial SOC follows a truncated normal distribution with underlying mean 0.40 and standard deviation 0.15 on [0.10, 0.80]. All distributions and fleet proportions are synthetic scenario settings rather than location-specific survey estimates.

For vehicle i in scenario s, the electricity required from the network is

$$E_{i,s} = \frac{C_i\left(SOC_i^{\mathrm{tar}} - SOC_{i,s}^{\mathrm{ini}}\right)}{\eta_i}.$$

A sampled event is retained only if its charging demand can be supplied within its parking interval at rated charging power. For uncoordinated charging, the vehicle begins charging upon arrival and continues until $E_{i,s}$ is delivered. Actual temporal overlap with each 1-h dispatch interval is used instead of rounding arrival and finishing times to whole hours; cross-midnight intervals are mapped to the same daily 24-h profile.

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Table 1. Main settings of the synthetic EV and network case

Parameter	Value
Fleet size / horizon	300 EVs / 24 h, 1-h step
Battery capacities	48 / 60 / 72 kWh (30 / 50 / 20%)
Charger ratings	7 / 11 kW (80 / 20%)
Efficiency / target SOC	0.92 / 0.90
EV connection buses	7, 14, 18, 24, 30, 32
Voltage operating range	0.90–1.05 p.u.
Objective weights	Cost 0.40; losses 0.25; range 0.35
Fleet / mapping random seeds	20260713 / 20260716

2.2 Monte Carlo Generation and Scenario Reduction

A fixed random state (20260713) is used to draw behavior variables and build 1,000 independent charging-load scenarios, with the same fleet composition in every scenario. Each scenario contains 300 vehicle records and an hourly uncoordinated charging profile. The resulting mean scenario energy is 9,454.51 kWh, and the mean scenario peak is 1,726.65 kW. Across 1,000 scenarios, the respective standard deviations are 159.63 kWh and 48.71 kW. The dominant peak intervals are 20:00–21:00 (68.3% of scenarios) and 21:00–22:00 (31.7%).

Direct optimization of all 1,000 individual-vehicle scenarios would be computationally burdensome. Following the scenario-selection principle in [8], peak-period-stratified k-medoids clustering is used to retain realizable charging profiles, rather than synthetic cluster centroids, so that their vehicle records can be recovered. Euclidean distances are computed between 24-h uncoordinated load profiles; peak-timing strata are maintained, including extreme peak cases. The representative scenario weight is $\rho_s = N_s/1000$, where N_s is the number of original scenarios assigned to medoid s. Candidate sets of 5, 8, 10, and 12 scenarios are compared using deviations in hourly mean load and empirical 5th–95th percentile boundaries.

Table 2. Accuracy of reduced scenario sets

Medoids	Max. mean error (kW)	Max. quantile-bound error (kW)
5	16.43	88.59
8	21.55	99.75
10	19.71	73.06
12	16.97	60.32

The prespecified acceptance limits are 20 kW for the maximum hourly mean deviation and 65 kW for the maximum quantile-bound deviation. Only the 12-scenario set satisfies both. Its mean-load root-mean-square error is 4.45 kW; weighted peak and energy deviations are 0.3086% and 0.4466%, respectively. This reduces the number of scenarios by 98.8% without requiring that all risk be summarized by the mean alone.

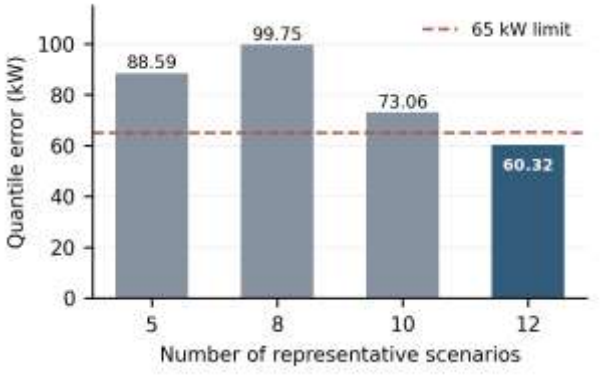


Figure 1. Quantile-bound error versus representative scenario count (dashed: 65-kW limit).

3. NETWORK-CONSTRAINED CHARGING MODEL

3.1 Decision Variables and Objectives

Let $p_{i,t,s}$ denote the grid-side average charging power assigned to EV i during hour t in scenario s. Define $\gamma_{i,t,s} \in [0,1]$ as the fraction of that hour overlapping the vehicle's available arrival-to-departure interval. Charging decisions must satisfy

$$0 \le p_{i,t,s} \le \gamma_{i,t,s} P_i^{\max},$$

$$\sum_{t=1}^{24} p_{i,t,s}\,\Delta t = E_{i,s}, \qquad \Delta t = 1 \text{ h}.$$

The aggregate EV demand at bus j equals $\sum_{i\in\mathcal{E}_j} p_{i,t,s}$ and is constrained by the installed charging-facility capacity at that bus. This representation retains partial-hour availability and prevents energy shortfalls or unrequested overcharging. No EV discharging is considered.

Three scenario-specific objectives are evaluated: electricity procurement cost $C_s = \sum_t c_t P_{0,t,s}\Delta t$, branch energy loss $L_s = \sum_t \sum_{(i,j)} r_{ij}\,\ell_{ij,t,s}\Delta t$, and the daily root-power range $R_s = P_{0,s}^{\max} - P_{0,s}^{\min}$. Here c_t is the time-of-use tariff, $P_{0,t,s}$ is feeder root power, r_{ij} is line resistance, and $\ell_{ij,t,s}$ is the squared branch current. To avoid mixing monetary, energy, and power units, each objective is divided by its value under uncoordinated charging in the same scenario. The overall performance index is

$$\min J = \sum_{s\in\mathcal{S}_r} \rho_s J_s,$$

$$J_s = 0.40\frac{C_s}{C_s^{\text{unc}}} + 0.25\frac{L_s}{L_s^{\text{unc}}} + 0.35\frac{R_s}{R_s^{\text{unc}}}.$$

The weights are illustrative design choices and have not been established as globally optimal. Each representative scenario is optimized independently before its results are aggregated using ρ_s; the model does not impose interscenario nonanticipativity.

3.2 Network Constraints and Numerical Solution

The distribution system is represented as a radial network with active/reactive power balances, voltage-drop relations, root power bounds, and line-flow limits. The operating limits used for final verification are 0.90–1.05 p.u. bus voltage and 100% of the study-specific line rating. As the case33bw dataset does not specify thermal ratings, line capacities are constructed for this experiment from the base-peak apparent power and downstream installed EV capacity, rather than claimed to be original IEEE feeder data.

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For computational tractability, the scheduling subproblem uses linearized voltage and capacity constraints and current-point network-loss sensitivities. MATLAB's *linprog* solves the resulting linear program, and loss sensitivities are updated four times. The resulting schedules are then evaluated by nonlinear backward/forward sweep power flow. Slightly conservative optimization boundaries (0.902 p.u. and 98% line loading) provide room for linearization error; final results are accepted only after nonlinear verification. This procedure is a sequential linearized approach, not a direct solution of the nonlinear DistFlow equations or a second-order-cone program.

4. CASE STUDY AND RESULTS

4.1 IEEE 33-Bus Case Configuration

The test feeder uses MATPOWER's case33bw [9], with 33 buses, 32 closed branches, 12.66-kV nominal voltage, a 10-MVA base, and nominal active/reactive loads of 3,715 kW/2,300 kvar. A synthetic 24-h multiplier with minimum 0.52, maximum 1.00, and mean 0.7546 is applied to the base loads. The time-of-use tariff ranges from 0.42 CNY/kWh during 00:00–06:00 to 1.16 CNY/kWh during 17:00–22:00. Three conditions are studied: no EV charging, immediate uncoordinated charging, and optimized charging. For each representative scenario, both charging strategies use identical vehicle records and connection buses.

The 300 EVs are allocated to buses 7, 14, 18, 24, 30, and 32 (42, 48, 36, 54, 66, and 54 vehicles). The six bus-level charging capacities are 250, 275, 215, 305, 390, and 320 kW, totaling 1,755 kW. Installed nominal charger power totals 2,340 kW. These capacity settings, the 24-h load shape, and the tariff are scenario assumptions for method assessment and have not been calibrated against a particular real feeder.

4.2 Peak Reduction and Operating Cost

Table 3 summarizes the probability-weighted results across the 12 representative scenarios. Without EVs, the feeder peak is 3,917.68 kW. Immediate charging increases it to 5,541.54 kW, and increases the daily peak-to-valley range to 3,544.56 kW. Coordination lowers weighted peak demand to 3,937.76 kW and the range to 1,016.29 kW, corresponding to reductions of 28.94% and 71.33%. Procurement cost and line energy losses decrease by 8.27% and 7.76%, respectively, relative to the same uncoordinated EV demand. The resulting energy and cost remain above the no-EV baseline because the added vehicles still require charging.

Table 3. Weighted operating results under different EV charging modes

Indicator	Uncoordinated	Coordinated
Root peak power (kW)	5541.54	3937.76
Peak-to-valley range (kW)	3544.56	1016.29
Purchase cost (CNY)	64852.29	59488.31
Network losses (kWh)	3898.20	3595.76
Root minimum power (kW)	1996.97	2921.47

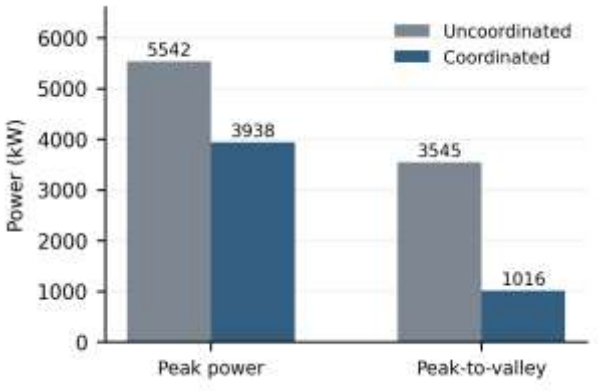


Figure 2. Weighted root peak and peak-to-valley range for two charging strategies.

The reduction in evening loading comes from shifting part of the overnight charging requirement toward off-peak hours while still enforcing per-vehicle departure requirements and feeder constraints. The coordinated schedule creates a controlled overnight demand plateau instead of a larger secondary peak.

4.3 Electrical Security and Charging Feasibility

Under uncoordinated charging, weighted minimum voltage is 0.870843 p.u. and weighted maximum line utilization is 121.146%, indicating operating-limit violations. After coordinated charging, these values improve to 0.904503 p.u. and 98.756%. In the most adverse representative conditions, minimum voltage increases from 0.863307 to 0.903665 p.u., whereas maximum line loading decreases from 133.510% to 98.758% (Table 4). These security indices are checked using nonlinear power flow after optimization, not inferred solely from linear constraints.

Table 4. Nonlinear power-flow and EV-feasibility checks

Verification metric	Uncoordinated	Coordinated
Weighted minimum voltage (p.u.)	0.870843	0.904503
Worst-case minimum voltage (p.u.)	0.863307	0.903665
Weighted max. line loading (%)	121.146	98.756
Worst-case max. line loading (%)	133.510	98.758

Across 12 representative scenarios and 300 EVs each (3,600 vehicle-scenario instances), all optimized charging demands are fulfilled. The maximum absolute energy balance error is 7.11×10^{-15} kWh, and the reported charging-power limit violation is zero. These results demonstrate feasibility within the modeled assumptions and adopted feeder limits.

4.4 Interpretation and Limitations

Scenario reduction retains the two observed evening peak-timing classes and the principal mean, quantile, energy, and peak statistics; it does not guarantee faithful representation of every extreme or rare operating event. Similarly, the independent scenario optimizations assume the scenario-specific vehicle records are known at the time of optimization. Consequently, their results describe achievable offline schedules under scenario information; an implementable day-ahead or rolling-horizon controller would need information constraints, updated forecasts, and recourse decisions. Robustness to unseen behavior distributions is not established.

Additional limits arise from the fixed EV-to-bus assignments, synthetic charging distributions, engineered line ratings, unmodeled charger competition, and omission of bidirectional charging, battery degradation, distributed generation, and transport-network interactions. Subsequent work should calibrate the vehicle distributions and feeder boundaries using field measurements, evaluate penetration and objective-weight sensitivity, and compare nonanticipative stochastic or receding-horizon control policies [10,11].

5. CONCLUSIONS

A scenario-based residential EV charging framework has been developed using stochastic user behavior, peak-period-stratified k-medoids reduction, and network-constrained coordinated charging. In a synthetic 300-EV IEEE 33-bus experiment, 1,000 Monte Carlo realizations were reduced to 12 representative scenarios while retaining major load characteristics. Compared with uncoordinated charging, the optimized benchmark reduced weighted feeder peak, peak-to-valley difference, procurement cost, and network losses by 28.94%, 71.33%, 8.27%, and 7.76%, respectively. The worst representative scenario achieved 0.903665 p.u. minimum voltage and 98.758% maximum line utilization, with every modeled EV charging requirement satisfied. The findings support the value of flexible residential charging but should be interpreted as scenario-informed simulation results rather than validated real-time dispatch performance.

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