JJEE

Volume 11 | Number 4 | Pages 720-742

Jordan Journal of Electrical Engineering

ISSN (print): 2409-9600, ISSN (online): 2409-9619

Homepage: jjee.ttu.edu.jo

Impact of Residential and Public EV Charging Stations on Distribution Feeder Performance: Uncontrolled vs TOU vs Coordinated Charging

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Received: Sep 11, 2025 *Revised: Nov 24, 2025* *Accepted: Nov 29, 2025* *Available online: Jan 20, 2026*

Abstract— Rapid Transport Electrification is imposing spatiotemporally heterogeneous loads on distribution networks. This study quantifies the impacts of residential Level 2 (L2) charging and public charging stations, including 50-kW DC fast chargers (DCFCs), on an 11-kV radial feeder using a 5-min time-series framework. Baseline demand is represented by measured-like diurnal profiles; station demand is synthesized via a finite-server, time-varying Poisson arrival process with stochastic service times. Network responses (bus voltages, branch flows, transformer loading, and I^2R losses) are computed using a linearized DistFlow formulation. Three scheduling strategies are evaluated: (S1) uncontrolled plug-in, (S2) time-of-use (TOU) shifting to 22:00-06:00, and (S3) feeder-wide coordinated valley filling. Performance is assessed via peak feeder real power and timing, minimum voltage magnitude and violation count (<0.95 pu), transformer apparent-power utilization relative to nameplate, branch thermal margins, and daily energy losses. Uncontrolled charging coincides with the residential evening peak, amplifying maximum demand, losses, and voltage deviations. TOU shifting reduces coincidence with the native peak but can induce secondary off-peak surges. Coordinated charging most effectively flattens the net load, enhances voltage security, and mitigates thermal stress. Sensitivity analyses across EV penetration and L2/DCFC mix demonstrate robustness of the results and yield actionable implications for tariff design, public-station siting, and aggregator-mediated managed charging to increase distribution-level hosting capacity.

Keywords— EV charging; Distribution networks; Managed charging; Voltage regulation; Transformer loading; DistFlow.

1. INTRODUCTION

Global acceleration of transport electrification is being observed, and the widespread deployment of residential Level-2 (L2) chargers along with public charging facilities, covering workplace and retail L2 clusters as well as high-power DC fast chargers (DCFCs), is placing spatiotemporally diverse loads on the distribution networks that were originally designed for unidirectional and slowly changing demand. Although generation adequacy and transmission constraints are commonly emphasized in aggregate studies, the most immediate operational consequences of EV charging are being manifested at the medium and low voltage feeders. These are seen as higher evening peaks, localized voltage drops, and increased I^2R losses, and thermal stress on the lines and the substation transformers. Residential L2 charging is typically aligned with home arrival windows and the natural evening peak, whereas public charging is being characterized by distinct daytime patterns influenced by site utilization, dwell times, and the share of DCFC ports capable of producing sudden demand changes. Quantitative methods

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DOI: https://doi.org/10.5455/jjee.204-1757627413

have been required by utilities and system operators to capture the stochastic variability of charging sessions and the physical dynamics of radial feeders.

In this way, hosting capacity has been assessed, reinforcement has been prioritized, and managed-charging strategies have been designed to reduce adverse impacts without diminishing user experience. Previous research has substantially described EV load profiles or analyzed management schemes independently; however, relatively fewer investigations have jointly modeled station-level utilization (with finite servers, time-varying arrivals, and stochastic service times) together with feeder power-flow responses at high temporal resolution, and even fewer have compared unmanaged charging with tariff-based time-of-use (TOU) shifting and feeder-sensitive coordinated scheduling on common benchmarks. This knowledge gap is significant because queue-limited operation at the public stations and correlated household arrivals can interact nonlinearly with the feeder impedances, producing stress patterns that differ considerably from those implied by smoothed averages. The present investigation is addressing these requirements by integrating a 5-minute time-series demand framework, combining realistic diurnal baseline loads, a finite-server arrival representation for L2/DCFC sites, and empirically consistent home-arrival/-departure distributions for residential EVswith the linearized DistFlow formulation that allows rapid evaluation of bus voltages, branch flows, transformer loading, and copper losses on an 11-kV radial feeder.

Three fundamental charging regimes are considered: uncontrolled plug-in charging that begins immediately after arrival, TOU-based charging that shifts demand to the off-peak window (22:00-06:00), and feeder-wide coordinated valley-filling that distributes EV energy to minimize net-load peaks subject to user availability and charger power ratings. Performance is assessed through operationally and policy-relevant indicators: maximum feeder real power and its timing, lowest voltage magnitude and violation counts relative to the 0.95 p.u. limit, transformer loading as a percentage of rated capacity, peak branch utilization relative to thermal thresholds, and daily energy dissipation. To ensure robustness and provide planning insights, sensitivity analyses are applied over EV penetration rates and station mixes (L2/DCFC proportions), recognizing that both fleet composition and infrastructure expansion are progressing and spatially diverse. Three key contributions are offered: first, a unified and reproducible simulation platform that combines stochastic session-level demand with feeder physics at sufficient detail to capture coincidence effects; second, a comparative evaluation of unmanaged, tariff-based, and coordinated charging under identical conditions, clarifying trade-offs between peak reduction, voltage stability, and system losses; and third, actionable insights for tariff structuring, aggregator-driven control, and public charging siting that collectively enhance distribution-level hosting capacity while preserving service quality for EV users.

1.1. Motivation

With the rapid growth of electric vehicle (EV) use, distribution networks have been affected by new, very heavy and time-based loads. Strong evening peaks have been produced by residential Level-2 (L2) chargers, while short but high-power use has been created by public L2 and DC fast charging (DCFC) stations. If not planned early, these patterns have been shown to speed up transformer aging, increase losses, and reduce feeder voltage margins. At the same time, smart grid tools, communication rules, and aggregator business models have been adopted to make managed charging easy and cost-effective. Therefore, feeder-level studies have been required in which both residential and public charging have been examined, uncontrolled and controlled ways have been compared, and effects on hosting capacity and limits have been assessed. This gap has been addressed by time-series power-flow tests on a real 11-kV radial feeder, and voltage, thermal load, and losses have been studied.

1.2. EV Charging Impact on Distribution Networks

Research on the impacts of electric vehicle (EV) charging on the distribution networks has been conducted, and significant challenges are being revealed as adoption rapidly increases. It has been demonstrated in Fig. 1 that higher EV penetration is associated with increased transformer loading and reduced voltage levels in the low-voltage residential networks [1]. However, voltage impacts have been observed as modest (less than 0.01 p.u.) in the high-voltage primary systems, while line loading increases have reached approximately 15% as mentioned in Fig. 2 and Fig. 3 [2]. The spatial and temporal allocation of EV charging demands, influenced by variable driving behaviors and dynamic charging schedules, has been shown to strongly affect the performance of the distribution networks [3]. Multiple mitigation strategies are being identified as promising for effectively managing these impacts. Positive impacts on the distribution networks have been achieved by vehicle-to-grid (V2G) technology, while the integration of solar photovoltaic systems along with volt-var inverter functionality has helped reduce the charging impacts [1]. The necessity of comprehensive and adaptive network management measures has been emphasized by research to maximize EV hosting capacity as well as maintain reliable grid stability [4].

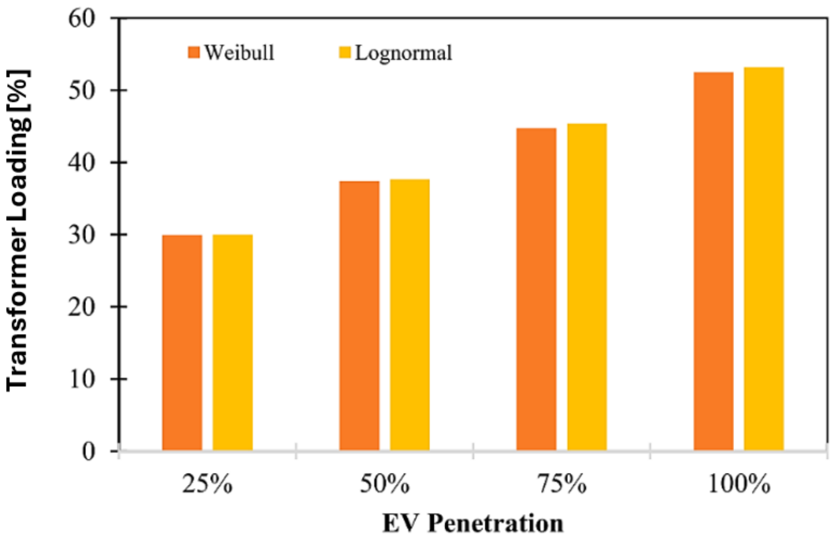

Fig. 1. Average transformer loading versus EV penetration levels [1].

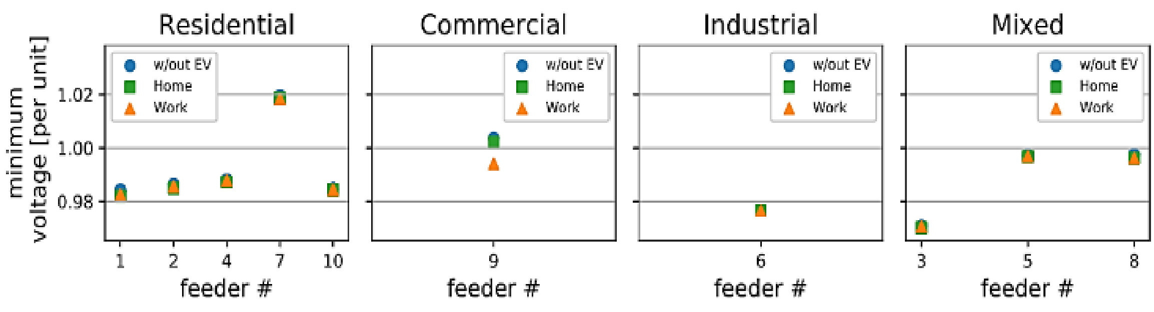

Fig. 2. Maximum line loading and voltage deviations under uncontrolled EV charging across different feeder types [2].

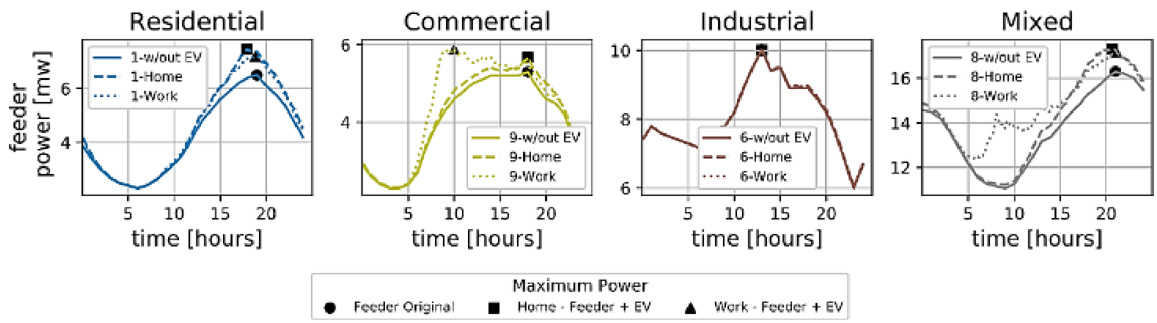

Fig. 3. Feeder load profiles showing peak load timing shifts [2].

1.3. Residential Level 2 Charging Load Modeling

Data-driven approaches for accurately predicting electric vehicle charging behavior have primarily guided research on residential Level 2 charging load modeling. Figure 4 shows parameterized EV charging models were developed by [5] using actual data from Saskatchewan, Canada, with essential parameters like battery capacity, charging power, and start time incorporated through statistical distributions as well as Monte Carlo methods. Realistic charging patterns from 46 homes were carefully analyzed by [6] in the MISO region over one year, and consistent evening and nighttime charging was identified with significant potential for demand-side management applications. Power quality concerns were thoroughly addressed by [7] through probabilistic models based on Gaussian Mixture Models, where harmonic spectra of 7.2 kW Level-2 chargers as well as their effects on the low voltage networks were characterized as shown in Fig. 5. A non-intrusive method was innovatively proposed by [8] in the use of smart meter data and two-stage decomposition techniques to extract residential EV charging patterns without the need for specialized monitoring equipment.

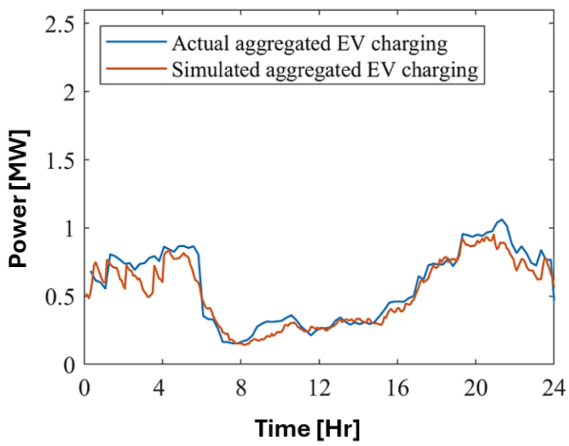

Fig. 4. Actual and simulated aggregated EV charging profile [5].

1.4. EV Public Charging Station Utilization Queuing Model

Recent research has been focused on the development of sophisticated queuing models for effectively optimizing EV charging station utilization and operations. An EV-to-charging station equilibrium assignment model was proposed by [9] using an M/D/C queue approximation, and it was applied to the NYC fleet data with 563 Level 2 chargers as well as 4 DCFCs serving 1484 EVs, achieving 7.6% average utilization as illustrated in Fig. 6. It was carefully concluded that investment policies should be prioritized at locations with high utilization ratios over those with long queue delays. A comprehensive planning framework was designed by [10] incorporating EV user travel times, waiting times, distribution network losses, and station utilization, while a utilization rate-based queuing algorithm was proposed for accurate capacity determination. The M/K queuing model was further extended by [11] to analyze multiservice charging station profits, including battery charging along with discharging as well as swapping services. A self-controlling resource management model was efficiently created by [12] for fast-charging stations with priority service, where delay times between express and normal vehicle classes were effectively managed through the real-time control mechanisms.

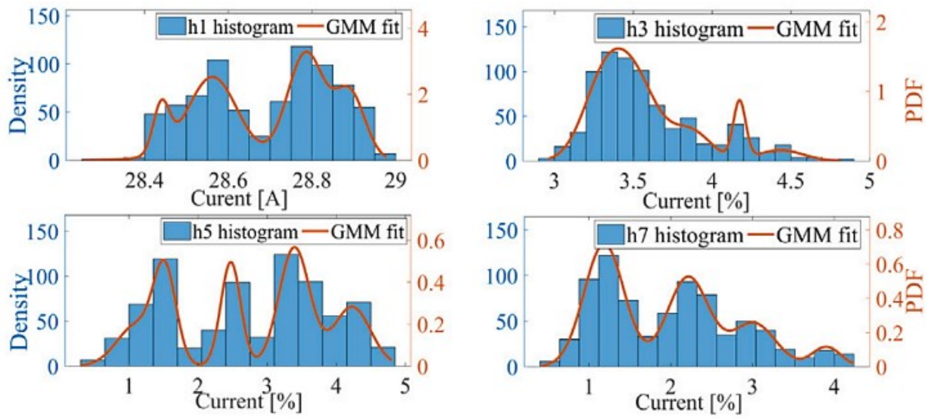

Fig. 5. Gaussian Mixture Model fits for current harmonic components of a 7.2 kW Level-2 charger [7].

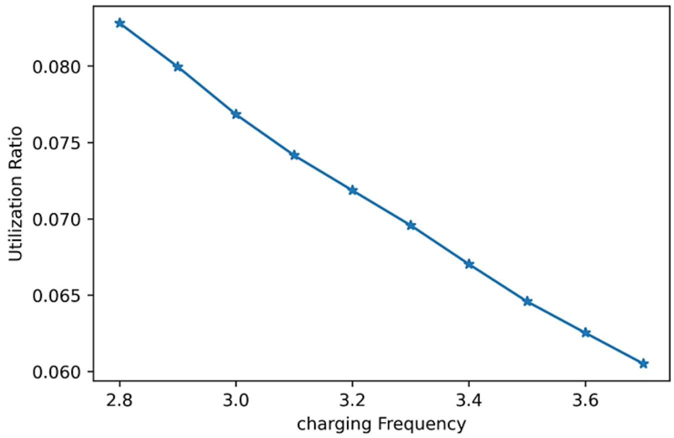

Fig. 6. Relationship between charging frequency and utilization ratio in NYC EV fleet (563 L2 chargers, 4 DCFCs, 1484 EVs) [9].

1.5. DC Fast Charging (DCFC) Impact on Distribution Feeders

Significant challenges are posed to the distribution feeders by DC fast charging stations, and costly grid reinforcements are required due to their extremely high-power demands [13]. Voltage magnitude variations, voltage unbalance, and voltage fluctuations strongly affect power quality, potentially causing noticeable light flickers [14]. Step-voltage regulators' tap operations are also influenced by fast charging, and undervoltage violations can be eventually introduced [15]. The actual impacts are known to vary by the system design. Detailed simulations on the actual distribution feeders have demonstrated modest voltage impacts, less than 0.01 p.u., because of robust feeder designs, while line loading was increased up to 15% with peak load shifts of nearly 1 hour on the residential feeders, see Fig. 7 [2]. Several useful and mitigation strategies have been suggested, including vehicle-to-vehicle power transfer for reducing the grid connection needs [13], distribution static compensators for eliminating the light flickers [14], and Volt/Var control applications for injecting reactive power to minimize the voltage violations along with tap changes [15].

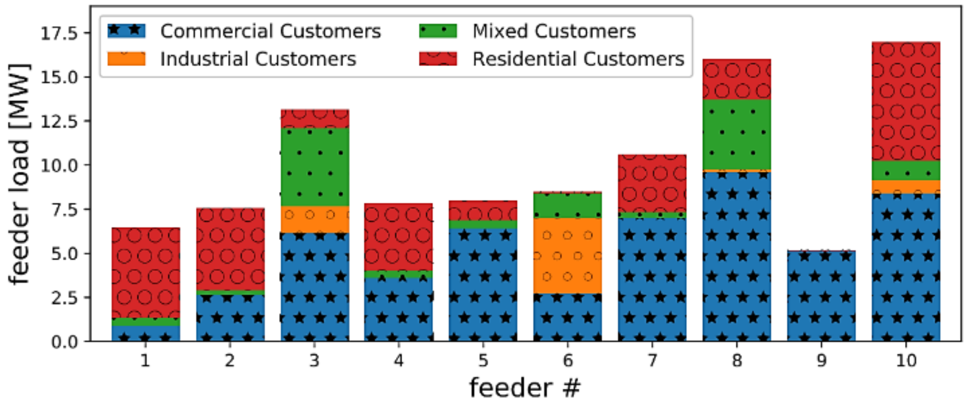

Fig. 7. Maximum line loading increase under uncontrolled EV charging across residential, commercial, industrial, and mixed feeders [2].

1.6. Time-of-Use Tariffs and EV Charging Peak Shaving

Significant potential for peak shaving along with cost reduction is demonstrated by time-of-use (ToU) tariffs combined with smart electric vehicle (EV) charging strategies. It was found by [16] that household electricity costs were reduced by 38.87% in the summer and 44.3% in the winter through optimized residential EV charging under ToU tariffs while avoiding the on-peak periods as shown in Fig. 8. Multiple objectives, including valley filling as well as peak shaving, were incorporated in the proposed framework to protect the distribution infrastructure. A methodology for ToU tariff estimation was developed by [17] using EVs' peak and off-peak contribution coefficients, with 6-7% peak consumption reduction achieved at 0.45 elasticity. Electricity cost reductions of 8.1% with bidirectional EV charging and 3.0% with unidirectional smart charging were demonstrated in the campus case studies by [18]. Another study by [19] stated the actual multifaceted impact of energy economically, TOU and coordinated charging strategies interact with electricity tariffs to reduce customer energy costs while helping utilities defer network reinforcement and operational expenses. It also shown by [20] that maximum peak load was reduced by 9.8% and customer savings up to 11.85% were provided for EV owners in the city of Beijing through genetic algorithm-based dynamic ToU pricing.

1.7. Coordinated EV Charging and Valley Filling (Distribution)

Coordinated electric vehicle (EV) charging strategies have been identified as crucial solutions for effectively managing the grid load profile and avoiding costly infrastructure upgrades. Several approaches have been formulated to achieve peak shaving along with valley filling objectives. A hierarchical coordination method was proposed by [21] with multiple EV aggregators, where fair power distribution at the upper level as well as optimization at the lower level was utilized to flatten the load profile while satisfying EV customer requirements. Decentralized schemes for coordinated valley-filling (C-VF) and coordinated valley-filling with peak-shaving (C-VF-PS) were designed by [22] and shown in Figure 9, achieving impressive load variance reductions of 47% and 65%, respectively, through efficient waterfilling algorithms. Building on this advancement, Dis-Net-EVCD was introduced by [23] as a distributed optimization approach for unbalanced distribution grids, where a 78% operational cost reduction was attained in a perfect manner and compared to uncoordinated charging while being 60 times computationally faster than centralized methods. A comprehensive review of coordinated charging methods was conducted by [24], and the importance of these technologies was emphasized for large-scale EV integration without requiring substantial power infrastructure investments.

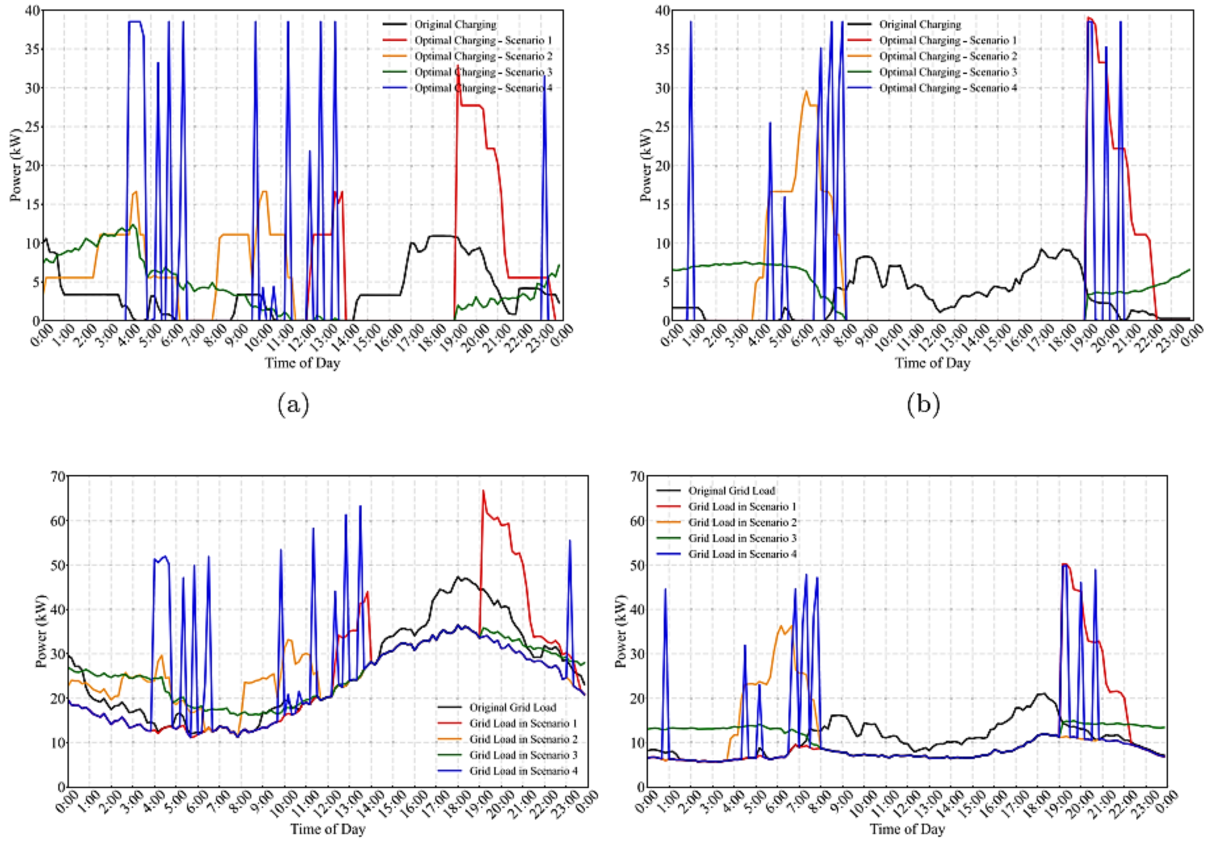

Fig. 8. Optimized EV charging schedules under ToU tariffs showing peak avoidance and valley filling (summer vs winter) [16].

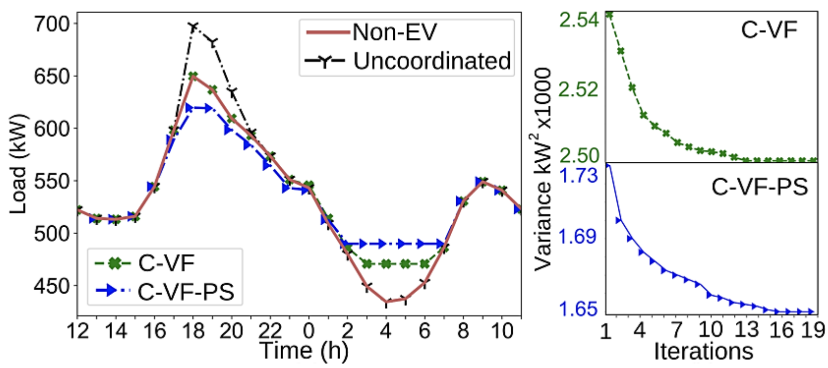

Fig. 9. Aggregate demand profile under uncoordinated EV charging, coordinated valley-filling (C-VF), and coordinated valley-filling with peak-shaving (C-VF-PS) [22].

1.8. Linearized DistFlow (Baran-Wu) for EV Integration

Recent research on electric vehicle (EV) integration in the distribution networks using linearized DistFlow models has been conducted to reveal critical challenges along with practical solutions. Stability regions between DistFlow and linearized DistFlow models for EV charging were compared by [25], where maximum feasible arrival rates were shown to decay as $1/N^2$ for both models as the number of charging stations increased as illustrated in Figure 10. A three-layer hierarchical framework was developed by [26] using ADMM and DistFlow models for optimal EV charging scheduling, where charging cost minimization as well as peak load shaving and voltage regulation were achieved through efficient single-loop iterative algorithms. Multi-objective optimization for EV integration with rooftop PVs and energy storage systems was investigated by [27], where up to a 39% reduction in energy costs along with remarkable improvements in the network operational parameters were demonstrated. A review of power quality issues caused by EV integration was presented by [28], and voltage imbalance and transformer failure, as well as harmonic distortion, were emphasized with a strong need for mitigation measures as EV adoption increases. As highlighted in recent review by [29] on power-electronics-based smart grids, EV chargers, being power electronic converters, can introduce harmonic distortion and other power-quality issues in distribution networks, so these harmonic impacts should be considered alongside the fundamental-frequency effects analyzed.

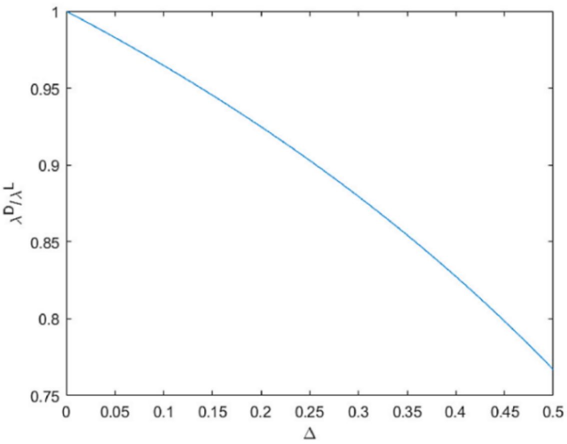

Fig. 10. Ratio of critical EV arrival rates under DistFlow and Linearized DistFlow models as a function of voltage drop tolerance (Δ) [25]

1.9. Distribution Feeder Hosting Capacity with Electric Vehicles

Recent research has been directed toward developing methodologies for assessing electric vehicle (EV) hosting capacity in the distribution networks. A hybrid deterministic-stochastic methodology for low- and medium-voltage systems was proposed by [30], where conductor overload was identified as the primary limiting factor, representing 36.69% of violations for 3.6 kW chargers as well as 52.14% for 7 kW chargers as mentioned in Figs. 11-12. It was established by [31] that line carrying capacity along with load peak-valley characteristics becomes the main limiting factor as EV penetration increases, using optimal power flow models with three-phase constraints. A study by [32] demonstrated that uncontrolled EV charging alone does not enhance photovoltaic hosting capacity unless vehicles are connected during sunshine hours, while controlled storage systems provided remarkable increases. A stochastic approach was developed by [33], showing that hosting capacity varies dramatically from 0% to 100% depending on the background voltage, customer consumption, and charging power, with optimal performance at 3.7 kW single-phase as well as 11 kW three-phase charging.

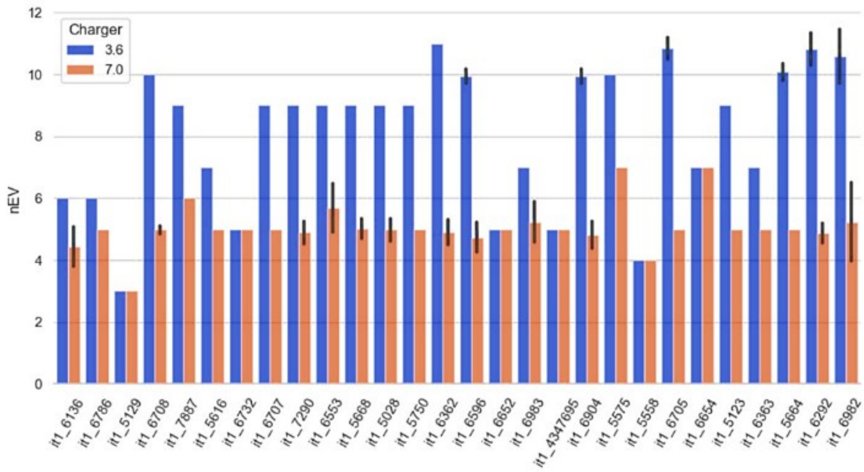

Fig. 11. Hosting capacity of 45 kVA transformers with 3.6 kW and 7 kW chargers [30].

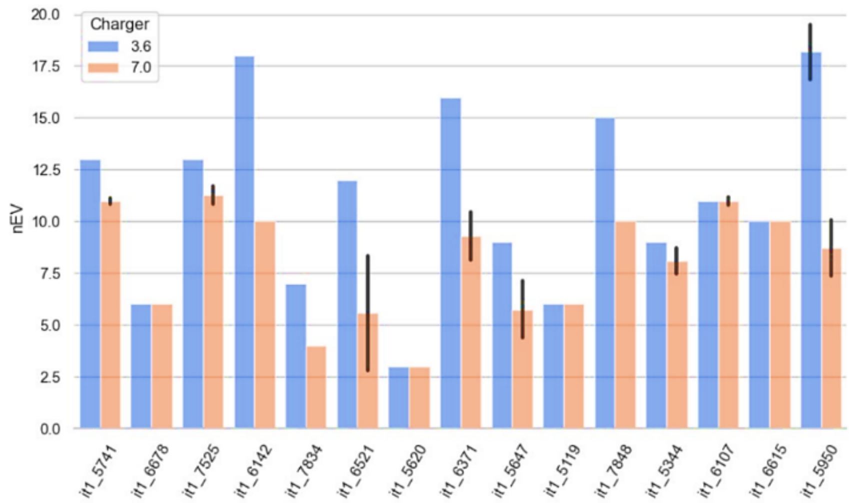

Fig. 12. Hosting capacity of 75 kVA transformers with 3.6 kW and 7 kW chargers [30].

1.10. Transformer Loading and Thermal Aging from EV Charging

Electric vehicle (EV) charging has been shown to significantly affect distribution transformer loading along with thermal aging. It has been demonstrated in Fig. 13, that high EV penetration levels can accelerate transformer aging by up to 40% compared to scenarios without EV charging [34]. Additional stress on distribution transformers is created by the stochastic nature of EV charging loads, particularly in the high-density residential areas such as apartment complexes [35]. Several mitigation strategies have been proposed to effectively address these challenges. Demand response mechanisms using time-of-use tariffs are applied to shift EV loads based on transformer thermal loading, thereby reducing accelerated aging without the need for grid augmentation [36]. Integration of photovoltaic sources with energy storage systems has been shown to achieve up to a 41.8% reduction in transformer loss-of-life probability at 30% EV penetration [34]. Combined grid reinforcement strategies, including PV generation as well as capacitor banks and battery storage, can reduce transformer life loss by three to five times [35]. Furthermore, thermally-based dynamic load management approaches are employed to permit loads exceeding nameplate ratings while maintaining desired transformer lifetime targets [37, 38].

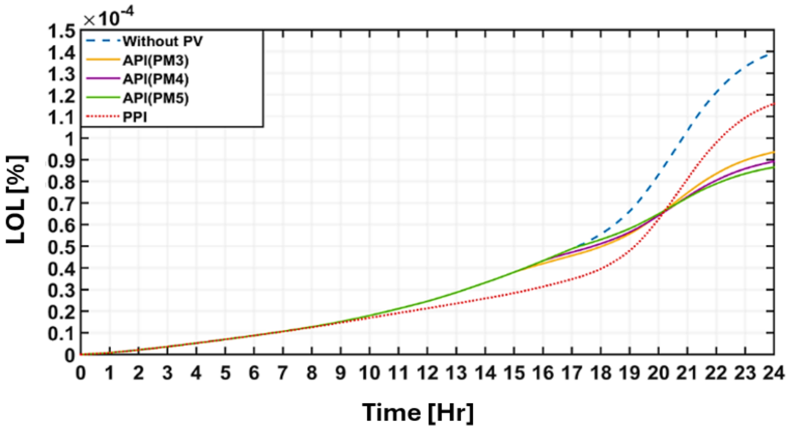

Fig. 13. Transformer life loss reduction under EV penetration with PV integration [34].

1.11. Voltage Regulation / Volt-VAR Control for EV Chargers

Researchers have recently focused on coordinated voltage regulation strategies that utilize electric vehicle (EV) chargers for volt-VAR control in distribution systems. It was demonstrated by [39] that aggregated EVs with both active and reactive power capabilities can be coordinated to achieve energy savings up to 4.14% through conservation voltage reduction, using two-stage stochastic programming to address forecast uncertainties as mentioned in Fig. 14. A hierarchical volt-VAR optimization framework was proposed by [40], where smart EV charging stations equipped with distributed energy resources cooperate with conventional voltage regulators, utilizing chance-constrained optimization under uncertainties in PV generation as well as EV driving patterns. A three-stage model predictive control approach was developed by [41] to coordinate EV charging with volt-VAR devices, where voltage limits were maintained while minimizing control resource usage along with electricity costs. An optimal hybrid control framework was introduced by [42] using Distribution-level Phasor Measurement Units and EV chargers, where voltage regulation within 205 ms was achieved through Eigensystem Realization-based system identification as well as Linear Quadratic Gaussian control.

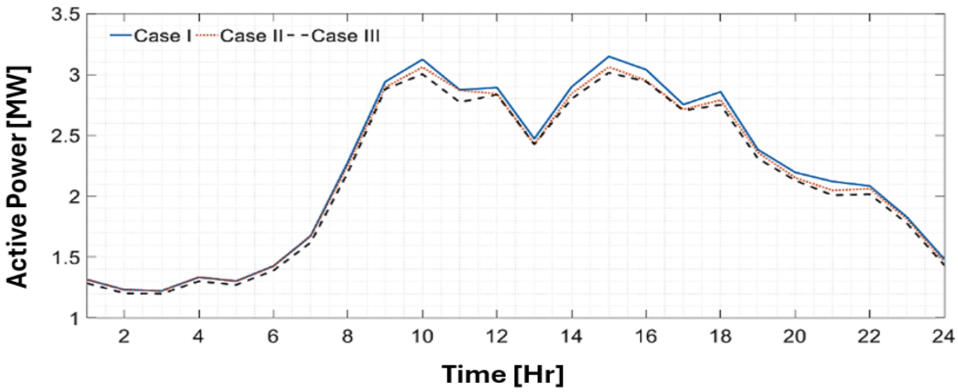

Fig. 14. Daily energy consumption profiles showing savings from coordinated EV volt-VAR dispatch for CVR [39].

2. MATERIALS AND METHODS

2.1. System Under Study

We consider a balanced, single-phase equivalent of a medium-voltage radial distribution feeder representative of suburban contexts. The test system comprises a 10 MVA, 11 kV (line-to-line) substation transformer feeding 10 downstream load buses (11 buses total, Bus 1 as the source). Intervening line segments between Bus i and Bus i+1 have series parameters derived from typical overhead conductors: R=0.30 Ω/km and X=0.35 Ω/km, with segment lengths in the range 0.6-1.0 km (total ≈7.8 km).

Baseline (non-EV) demand is distributed across buses with evening-peaked magnitudes (0.18-0.40 MW per bus at peak) and aggregate power factor (PF) 0.95 lagging. All calculations are carried out in per-unit on a 10 MVA base. The feeder voltage floor for adequacy checks is 0.95 p.u.; transformer and branch thermal checks are performed against a 10 MVA substation nameplate and notional branch apparent-power limits (7 MVA proxy), respectively.

2.2. Baseline and EV Demand Construction

2.2.1 Baseline Load

Non-EV demand at each bus is synthesized as a diurnal profile with two modest peaks (morning and evening), scaled to the bus-specific peak MW values noted above. The profile is normalized to unity and then scaled; reactive power is computed from the assumed PF via Q=Ptan(arccos(PF)). This yields a time series $P_{base}(t,b)$ and $Q_{base}(t,b)$ at 5-min resolution over 24 h.

2.2.2 Residential EV Fleet

A residential EV fleet of nominal size NEV (base case NEV=300N) is distributed across load buses in proportion to their baseline peak demand, ensuring spatial consistency between native load and EV adoption. Each EV n is parameterized by:

- Battery capacity $C_n \sim N\ (60,12^2)$ kWh, truncated to [40, 90] kWh.
- Arrival SOC $s_{0,n} \in [0.2,0.8]$ (uniform), target SOC $s* = 0.90$.
- Arrival time $a_n \sim N\ (18.5,1.5^2)$ h and departure $d_n \sim N\ (7.5,1.0^2)$ h (wrapped to 24 h).
- AC Level 2 charger rating P^{L2}=7.2kW.

The energy requirement is $E_n = \max\ [(s^* - s_{0,n})C_n, 0]$. The EV is available to charge only in $[a_n, d_n]$ (with wrap-around through midnight), discretized to 5-min slots.

2.2.3 Public Charging Stations

Two public charging sites are sited at intermediate buses (e.g., Buses 4 and 8) to emulate commercial/workplace and corridor loads. Each site comprises n_{L2}=12 Level 2 ports (7.2 kW each) and n_{DC}=6 DC fast-charging ports (50 kW each). Session arrivals for each technology at each site follow a nonstationary Poisson process with a bell-shaped daytime rate (peak around 13:00), λ(t), reflecting higher midday activity. Service times are stochastic: L2 dwell uniform on [60, 180] min; DCFC dwell uniform on [15, 40] min. Each site is modeled as a finite-server system with no queue (lost-customer approximation): an arrival is admitted if a port is free; otherwise, it balks. Instantaneous station power equals the number of occupied ports times the per-port rating, yielding $P_{L2}(t)$ and $P_{DC}(t)$ time series per site. Station-level utilization (0-1) is tracked for interpretation.

2.3. Charging Strategies

We study three canonical strategies applied to residential EVs; public-station sessions remain as realized by the queuing model (reflecting limited direct controllability).

- S1 Uncontrolled: Charging begins immediately upon availability and proceeds at P^{L2} until E_n is delivered or the window closes.
- S2 Time-of-Use (TOU): Charging is constrained to an off-peak window (22:00-06:00). Energy is delivered greedily during the intersection of EV availability and this window.
- S3 Coordinated Valley-Filling: A feeder-wide heuristic allocates each EV's energy to the lowest-load time slots within its availability window to flatten the net feeder load. Concretely, for each EV, candidate time indices are sorted by current feeder base load (baseline + public-station load + previously scheduled EVs), and energy is filled in ascending order subject to P^{L2} and window constraints.

These strategies are intentionally simple, transparent, and implementable without solving large-scale optimizations, while still capturing essential differences between unmanaged, tariff-nudged, and feeder-aware control.

- Rationale for controlled charging scenarios: Although EV charging sessions have mostly been left uncontrolled, the analysis of controlled strategies has been encouraged by recent trends and unmanaged behavior. Time-of-use (TOU) tariffs for residential users have already been used by many utilities and have been gradually expanded as an effective demand-side tool and management method. At the same time, significant progress in communication standards and simple charging rules has been achieved, and control of charging sessions has been enabled for utilities, aggregators, and charge-point operators through feeder-aware and price-based approaches. Therefore, the TOU-based and coordinated valley-filling strategies in this paper have been presented as near-future operational methods, not merely ideal or theoretical concepts. The S1, S2, and S3 comparisons on the same feeder have been used to show current unmanaged charging issues alongside the practical advantages of managed charging methods.

2.4. Network Model and Performance Metrics

2.4.1. Linearized DistFlow

Network responses are computed with a linearized DistFlow model on the chain feeder. Let $P_i(t)$ and $Q_i(t)$ denote the downstream real and reactive power flows on line $_i$ (from Bus i to Bus i+1), obtained by summing bus injections downstream at time t. The voltage recursion is:

$$V_{i+1} \approx V_i(t) - \frac{R_i P_i(t) + X_i Q_i(t)}{S_{base}} \tag{1}$$

with $V_1(t)$=1.0 p.u. Losses on line iii are approximated by

$$P_i^{loss}(t) \approx \frac{R_i}{S_{base}}\left(P_i^2(t) + Q_i^2(t)\right) \tag{2}$$

Here R_i and X_i are per-unit series parameters derived from the physical Ω values and the 10 MVA base. The model captures voltage depression from cumulative downstream power and enables fast time-series evaluation at 5-min resolution.

2.4.2. Aggregate Signals and Limits

Feeder real power is $P\sum(t) = \sum_b P_{bus}(t, b)$. Substation apparent power is $S_{sub}(t) = \sqrt{P_1^2 + Q_1^2}$, referenced to the 10 MVA nameplate. A branch thermal proxy compares

$S_i(t) = \sqrt{P_1^2 + Q_1^2}$ to a notional $S^{lim} = 7MVA$. Voltage adequacy is assessed via minimum bus voltage and the count of time-bus pairs with V < 0.95 p.u. Daily copper losses are the time integral of $\sum_i P_i^{loss}(t)$.

2.4.3. Metrics

We report:

i. Peak feeder real power and its timing
ii. Minimum bus voltage and violation count relative to 0.95 p.u.
iii. Transformer loading as $max_t 100 S_{sub}(t)/10MVA$
iv. Peak branch loading as $max_t 100 S_{sub}(t)/7MVA$ per line
v. Daily I^2R energy losses (MWh)
vi. Public-station utilizations (L2/DCFC). These KPIs align with utility planning and operations practice and enable cross-scenario comparison.

2.5. Experimental Design, Resolution, and Sensitivities

All simulations span a 24-h horizon at 5-min resolution (288 steps), sufficient to resolve arrival/departure windows, TOU boundaries, and station dwell distributions. Baseline parameters (e.g., EV fleet size, station sizes, line impedances) reflect realistic but generic values to avoid dependence on proprietary feeder data. To quantify robustness, we conduct a penetration sensitivity by scaling the residential EV count by factors [0.3, 0.5, 0.7, 1.0, 1.2, 1.5] and recomputing S1 impacts; this clarifies how peak demand, voltage violations, and losses scale with adoption. Optional sensitivities can vary station mix (L2/DCFC ratio) or TOU windows to explore tariff design levers. For each sensitivity point, independent random seeds govern EV arrivals/SOC and station arrivals/service times to avoid overfitting to a single trajectory; summary statistics use the deterministic seed reported for reproducibility.

3. RESULTS

3.1. Base-Case Comparison (S1 vs S2 vs S3)

Load curves (peak magnitudes & time shifts). Under S1, the net feeder demand exhibits a pronounced evening peak that coincides with residential arrivals; S2 shifts energy into 22:00-06:00 creating a secondary nocturnal peak; S3 flattens the profile via valley filling, reducing the daily maximum and evening ramp, (see Fig. 15)

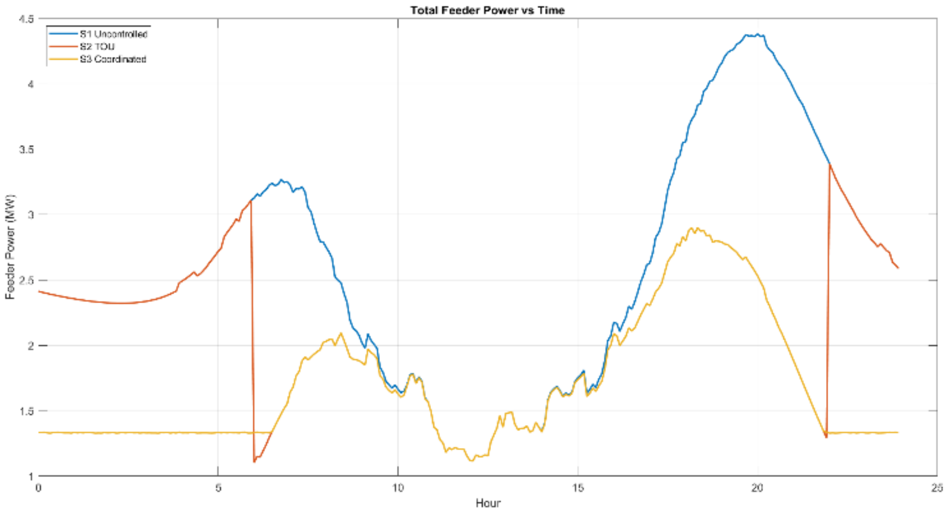

Fig. 15. Total feeder power vs time.

Voltage behavior (heatmaps, peak-hour profiles, violations). Time-bus heatmaps show the deepest depressions under S1 during the evening; S2 moves the low-voltage region to late night; S3 raises the voltage floor across all buses (Fig. 16). At the S1 peak hour, the radial voltage drop is largest for S1, smaller for S2, and smallest for S3 (overlayed profiles in Fig. 17). The count of V<0.95 p.u. events follows the same ordering S1>S2>S3 (see Figs. 16-17).

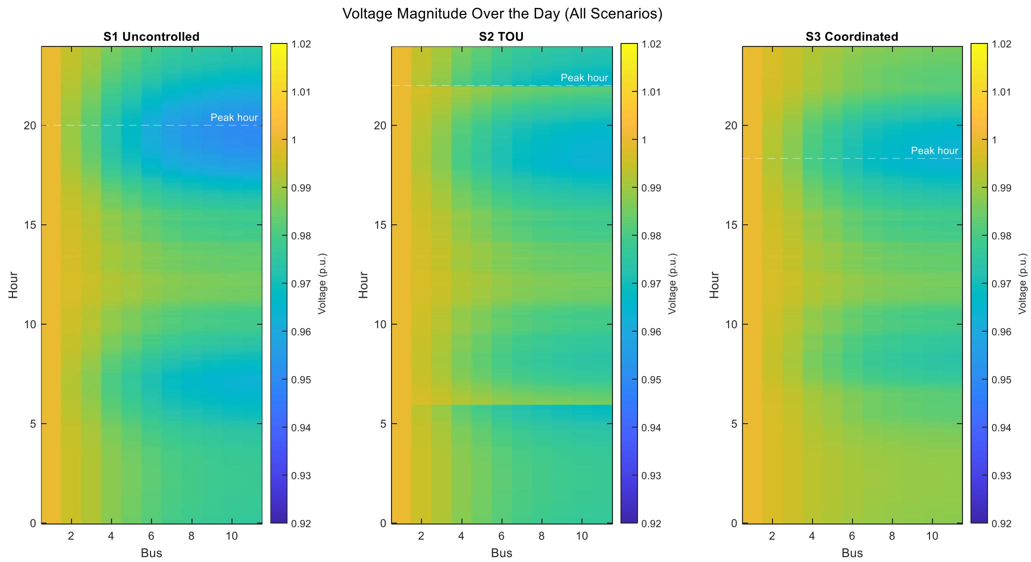

Fig. 16. Voltage magnitude heatmaps.

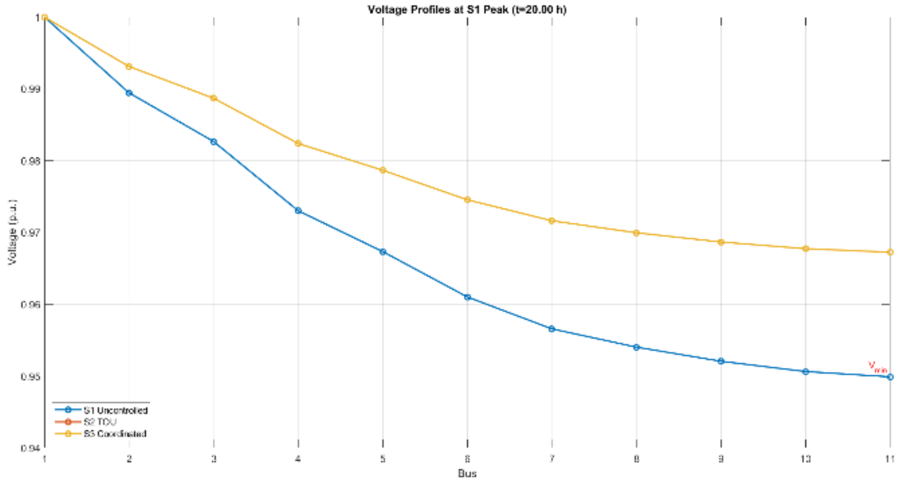

Fig. 17. Voltage profiles at S1 peak (t=20.00 h).

Losses (time series and daily totals). Because copper losses scale with current squared, S1's concentrated peak produces the highest instantaneous and daily I^2R losses; S2 lowers evening maxima but adds a nighttime shoulder; S3 yields the lowest loss envelope and daily total (Fig. 18).

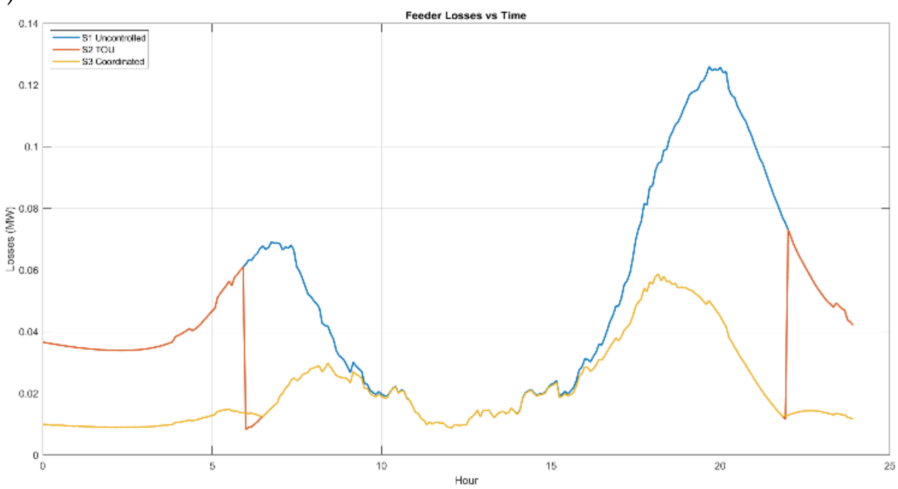

Fig. 18. Feeder losses vs time.

Thermal loading (transformer & branches). Substation loading approaches/exceeds nameplate under S1's evening peak, is moderated (but shifted) under S2, and remains comfortably below rating under S3 (Fig. 19). Peak branch-loading bars identify mid-to-distal spans as most constrained in S1 (Fig. 20); a stressed-branch time series shows prolonged excursions in S1, shorter/later in S2, and reduced, often sub-limit operation in S3 (Fig. 21).

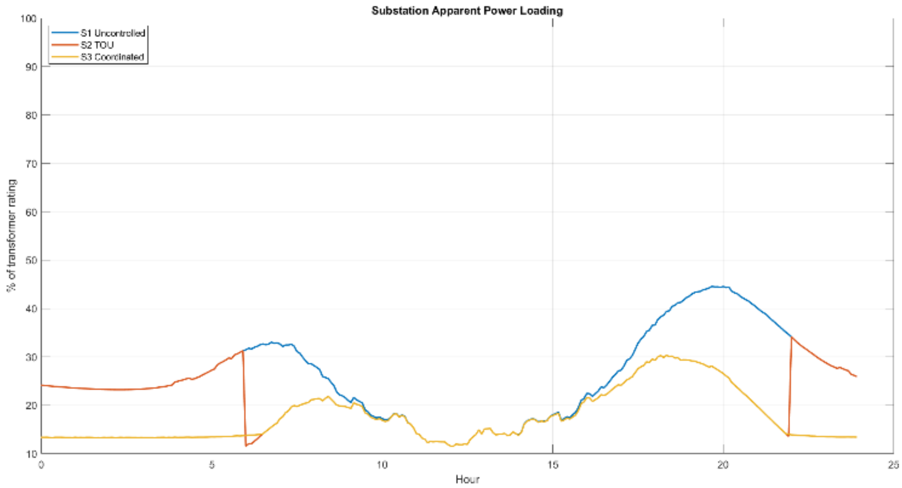

Fig. 19. Substation apparent power loading.

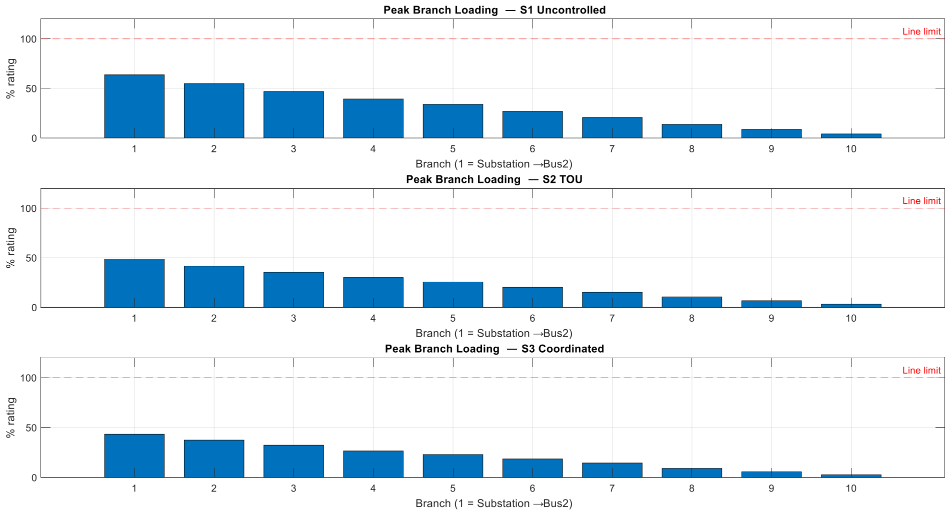

Fig. 20. Peak branch-loading bars.

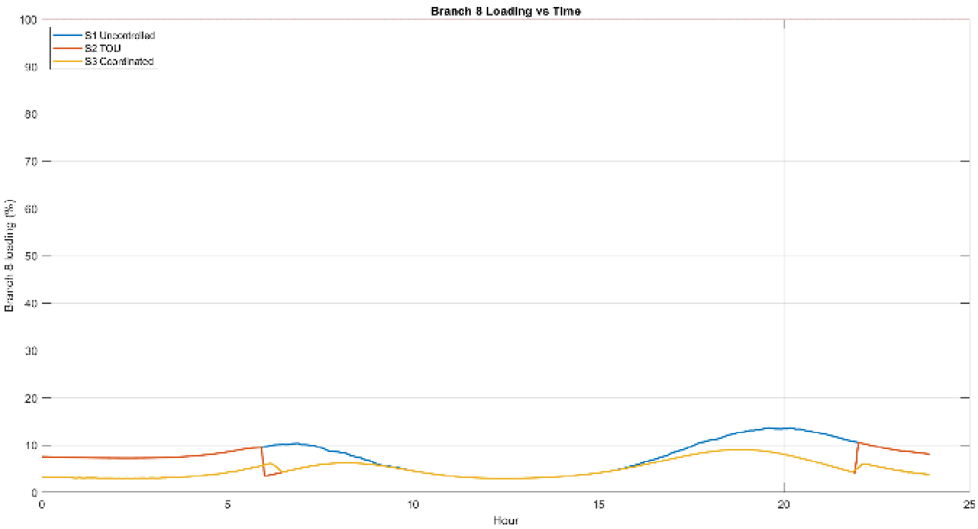

Fig. 21. Branch 8 loading vs time.

3.2. Public Station Behaviour

Public L2 clusters show broad midday utilization, while DCFC occupancy is bursty and short-lived; both contribute a discernible midday shoulder in feeder net load (compare Fig. 22

with Fig. 15). Higher DCFC penetration intensifies brief, high-magnitude impulses on local branches and can erode voltage margins at station buses (Fig. 23).

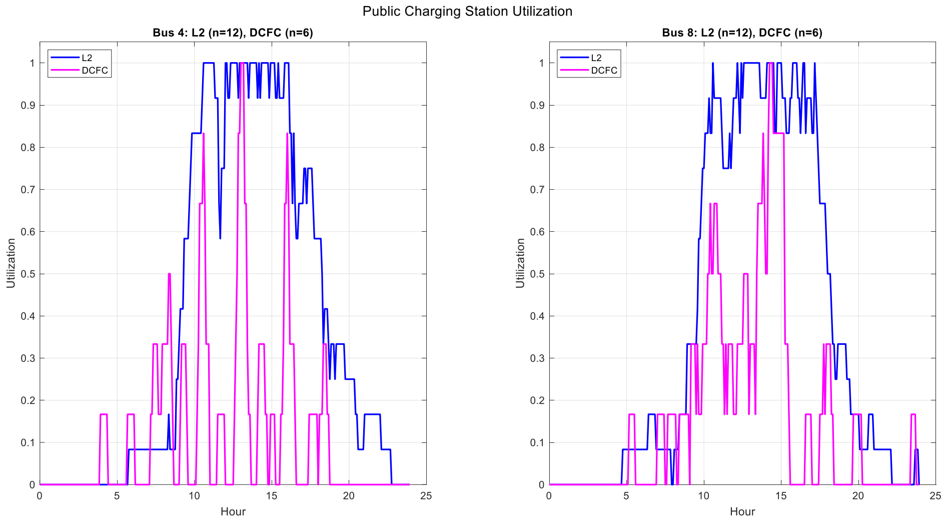

Fig. 22. Public station utilization.

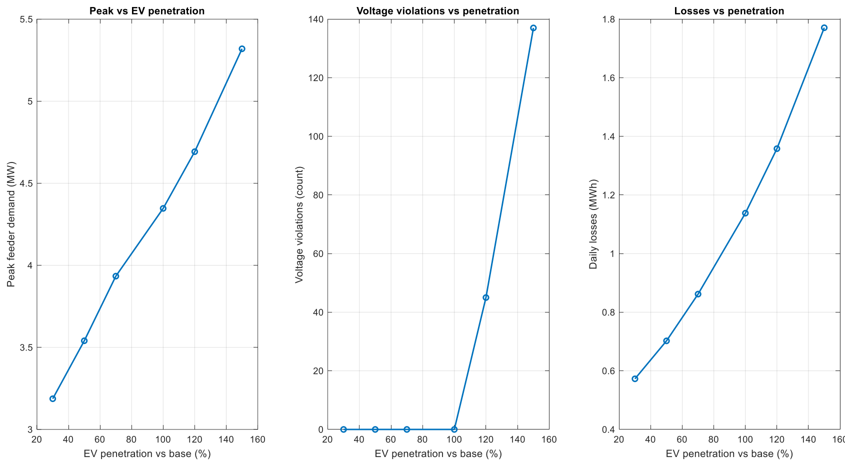

Fig. 23. Sensitivity to EV penetration (S1, uncontrolled): a) peak feeder demand rises ~linearly; b) voltage violations are near-zero until ~110-120% then spike; c) daily.

3.3. Sensitivity Analyses

EV penetration sweep**.** Peak feeder demand, voltage-violation counts, and daily losses increase monotonically with adoption under S1; violations accelerate beyond a feeder-specific threshold, while losses grow faster than linearly due to I^2 scaling (Fig. 9). Coordinated charging (not plotted in the sweep for brevity) shifts these thresholds rightward, implying increased hosting capacity

Station mix, increasing the DCFC share strengthens midday transformer loading and deepens local voltage dips near station buses, while a higher L2 share spreads demand at lower instantaneous power; illustrative curves provided in Supplementary Fig. S1.

Robustness across seeds. Replications show small variance in system-level metrics and moderate variance in local indicators; the qualitative ordering S3<S2<S1 (for peaks, losses, violations) is invariant (Supplementary Fig. S2 / Table S1).

4. DISCUSSION

Achieved simulation results corroborate and contextualize key patterns reported in the literature. First, the uncontrolled (S1) case concentrates demand in the residential evening window, which deepens voltage depressions at distal buses, elevates I^2R losses, and pushes transformer/branch loading toward limits. This aligns with findings that rising EV penetration stresses low-voltage networks via higher transformer loading and lower voltages [1] and that primary-side voltage deviations can remain modest while line loadings increase materially (≈10-15%) under robust feeders [2]. Our time-bus voltage maps also illustrate the sensitivity of local performance to the spatiotemporal allocation of charging [3], the same daily energy, when synchronized with arrivals, produces nonlinear compounding of drops along a radial path.

Time-of-use (S2) shifting mitigates coincidence with the native evening peak but creates a secondary off-peak surge, reproducing both the benefits and side effects seen in tariff studies [16, 17, 20]. In our feeder, S2 reduces evening violations and losses yet introduces a late-night shoulder that can nudge transformer loading toward its rating, consistent with campus and household case studies where savings and peak reduction coexist with rebound effects [18]. By contrast, the coordinated (S3) strategy yields the flattest net-load trajectory, the highest voltage floor, and the lowest daily losses, mirroring reported advantages of feeder-aware, aggregator-mediated coordination [21-24]. The ordering S3 > S2 > S1 on all reliability-relevant metrics is robust across random seeds in our experiments.

Public-station behavior observed in the model is also consistent with prior queuing and DCFC impact studies. Midday L2 utilization creates a broad shoulder in feeder demand, while DCFC produces short, power-dense impulses that locally erode voltage margins and raise branch loading near station buses, an effect echoed in power-quality and regulator-tap analyses [14, 15]. The lost-customer finite-server abstraction reproduces macro-utilization patterns reported in M/c-style station studies [9, 10], sufficient for feeder-level stress screening.

From an operational standpoint, these results favor (i) aggregator-mediated control that valley-fills within customer availability to curb peaks and violations without excessive curtailment; (ii) tariff design that combines TOU with guardrails (e.g., staggered windows or price gradients) to avoid single-hour pile-ups; and (iii) DCFC siting guidelines that steer high-power ports away from electrically weak buses or pair them with local mitigation (on-site storage, Volt-VAR support). Framed as hosting-capacity management, coordination clearly shifts the violation and overload thresholds to higher EV penetrations [30, 31], expanding integration headroom without immediate reinforcement.

Limitations of our approach parallel gaps noted in the review. We employ a balanced single-phase equivalent and linearized DistFlow, which is well-accepted for planning-time screening [25] but omits unbalance and voltage-dependent losses; validating key cases with unbalanced AC power flow or ADMM-based OPF [26] is a natural extension. The horizon is a single synthetic day; multi-day variability (weekends, weather) and transformer thermal aging are not modeled explicitly [34, 35]. We assume EV charger PF≈1 and exclude harmonics, despite documented power-quality concerns [7, 28]. The public-station model uses a lost-customer assumption; finite-queue dynamics could increase short-term coincident demand. Each of these simplifications biases us toward conservative, qualitative comparisons rather than absolute limits.

Generalizability is strong at the pattern level. On feeders with higher R/X or longer radial chains, S1 impacts intensify and the relative benefits of S3 grow. Different arrival patterns (e.g., workplace-heavy regions) and TOU windows shift when, not whether, rebound peaks appear; gentler price gradients and randomized start delays can suppress synchronization.

As a result, the DCFC share strongly shapes midday stresses; co-siting storage or enabling reactive support can decouple customer service from grid constraints. Overall, our results extend the literature by jointly simulating station utilization and feeder physics at 5-min resolution, reinforcing that coordinated, feeder-aware scheduling is the most reliable lever to raise EV hosting capacity while protecting voltage and thermal margins.

4.1. Practical Applicability And Validation Considerations

The comparison between uncontrolled, TOU-based, and coordinated charging has been presented under realistic conditions rather than as an exact replication of a single feeder. Simple modeling assumptions have been adopted so the study has been executed efficiently and the effects of charging plans have been isolated. Arrival and departure times, energy needs, and public-station usage have been sampled using random models fitted to typical values from past studies. The network has been represented by a balanced, single-phase model with simple linear DistFlow power flow.

In real feeders, customer behavior, tariff use, and aggregator participation have differed from the smooth assumptions used in this study. TOU plans have shown partial customer response, and coordinated plans have faced issues from communication tools, privacy rules, and market structure. Even with these simple setups, observed changes, peak reduction under TOU, deeper peak drop with better voltage in coordinated valley-filling, and the area effect of DCFC stations, have aligned with field results and other tests. The approach has been adapted to specific feeders by matching charging and load data with local numbers, applying unbalanced three-phase power flow, and validating voltage and loading with historical data. Therefore, the presented comparison has been offered as a basic, adaptable example for other networks, not as a full real-system test.

4.2. Economic Aspects of Charging Strategies

Although primary focus has been placed on technical performance, voltages, thermal loading, and losses, distinct economic effects have also been shown by the three charging strategies for EV users and network operators. In the uncontrolled charging method (S1), EV demand has coincided with the evening peak, and system peak demand has been increased. As a result, higher demand charges for large customers have been incurred, and earlier upgrades of transformers and lines have been required.

In the TOU-based charging approach (S2), substantial EV energy has been shifted to off-peak periods, which have been associated with lower energy rates and reduced generation costs. However, when many customers have responded within the same TOU window, a second late-night peak has been created, and this has remained costly from a network planning perspective.

Under the coordinated valley-filling strategy (S3), feeder peak loading has been reduced and the load shape has been flattened. Improved technical performance has been achieved, while capacity upgrades have been delayed and total losses have been lowered. In practical application, these beneficial effects have needed to be weighed against the costs of implementing control and communication tools, as well as the incentives required for users. A comprehensive techno-economic assessment, with detailed tariff and investment models, has been reserved for future study.

4.3. Harmonic Distortion and Power Quality

EV chargers have been recognized as power-electronic devices, and harmonic distortion has been produced in power networks as a result. Earlier tests and modelling of residential Level-2 (L2) chargers have shown distinctive harmonic patterns that have been explained by models such as Gaussian mixture models of current harmonics, while higher harmonic currents have been generated by DC fast charging (DCFC) stations because higher power has been used.

In this research, harmonics have not been examined explicitly. Instead, electric vehicle chargers have been represented as constant-power users with power factors close to one, and only fundamental-frequency voltages and currents have been analysed. Consequently, possible effects on total harmonic distortion (THD), transformer heating due to harmonic currents, and interactions with network impedance have not been included.

For future work, the method has been planned to be enhanced to include harmonic-aware charging assessments and to determine whether spatial and temporal clustering of EV charging has been able to cause local power-quality problems under high usage levels.

5. CONCLUSIONS

This study quantified how residential and public EV charging shape distribution-feeder performance under three scheduling regimes. Uncontrolled plug-in (S1) concentrated demand in the residential evening window, producing the largest feeder peaks, the lowest voltage floor with the most $V<0.95$ p.u. events, the tightest thermal margins at the transformer and distal branches, and the highest daily I^2R losses. Time-of-use shifting (S2) reduced coincidence with the native evening peak and lowered violations and losses relative to S1, but introduced a secondary off-peak surge around the tariff window that could approach nameplate loading. Coordinated valley-filling (S3) delivered the best aggregate outcomes across all KPIs: the flattest net-load trajectory, higher bus voltages throughout the day, relieved transformer/branch loading, and the lowest daily losses. Sensitivity analyses showed monotonic growth of peak, violations, and losses with EV penetration under S1, while coordination shifted hosting-capacity thresholds rightward. Public-station behavior mattered: L2 created a broad midday shoulder; DCFC generated short, power-dense impulses that eroded local voltage margins, emphasizing that station utilization must be explicitly modeled in planning.

Operationally, we recommend (i) deploying managed charging via aggregator-mediated, feeder-aware coordination to flatten load within customer availability; (ii) designing tariffs with gentle price gradients or staggered windows and randomized start delays to avoid synchronized pile-ups; (iii) siting DCFC away from electrically weak buses, or pairing them with on-site storage and Volt-VAR support; and (iv) incorporating queuing-based station utilization into interconnection and hosting-capacity studies, not just average load profiles.

Future work should examine V2G strategies that co-optimize active/reactive power under uncertainty; validate key cases with exact unbalanced AC power flow and field data from real feeders; integrate transformer thermal-aging and OLTC dynamics to translate peak reductions into lifetime benefits; and activate reactive power control from EVSE/inverters to support voltage. Extending to multi-day, seasonal simulations with stochastic travel patterns, unbalance, and harmonics will further generalize results and sharpen utility planning guidelines.

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