International Journal of Creative and Open Research in Engineering and Management
ISSN: **3108-1754 (Online)**
Volume 02 Issue 05 May-2026 | Impact Factor: 3.5

Impact of Electric Vehicle Charging Stations on Urban Power Distribution Networks: A MATLAB-Based Simulation Study on the IEEE 33-Bus System

Akriti Kumari
Dept. of EEE
MSIT, New Delhi.
Kumariakriti842@gmail.com

Dr. Mamta Rani
Assistant Professor, Dept. of EEE.
MSIT, New Delhi.
mamtaholia@msit.in

Dr. Rakhi Kamra
Assistant Professor, Dept. of EEE.
MSIT, New Delhi.
rakhikamra@msit.in

Impact of Electric*Abstract*— The accelerating integration of electric vehicles (EVs) into urban environments places progressively concentrated stress on power distribution infrastructure originally designed for conventional load patterns. This paper presents a rigorous simulation-based investigation into the technical consequences of EV charging stations on the IEEE 33-bus radial distribution system, implemented in MATLAB using a Backward/Forward Sweep (BFS) load flow algorithm. Six structured experiments are conducted: (i) quantification of voltage profile degradation and active power losses under EV penetration levels of 10%, 30%, and 50%; (ii) comparative evaluation of uncoordinated versus coordinated charging strategies; (iii) time-domain analysis contrasting base load, peak EV charging, and controlled charging scenarios; (iv) assessment of random versus optimised strategic EV charging station placement; (v) voltage deviation analysis under uncontrolled and controlled charging; and (vi) optimised charging strategy evaluation. Results demonstrate that uncoordinated 50% EV penetration raises active power losses to approximately 430 kW and suppresses remote bus voltages below 0.87 p.u., while coordinated charging reduces losses by 54.4% to 197.1 kW. Peak simultaneous charging produces losses of 595.4 kW — a 257% escalation above base load — confirming that temporal load management is as consequential as penetration control. Optimised charging yields the lowest voltage deviation profile across all 33 buses, closely approximating base-load conditions. The findings establish a quantitative foundation for evidence-based smart EV charging infrastructure planning in urban distribution networks.

Keywords— Electric Vehicles, EV Charging Stations, IEEE 33-Bus System, Urban Distribution Networks, Backward/Forward Sweep, Voltage Profile, Power Losses, Smart Charging, Optimised Strategic Placement, Vehicle-to-Grid.

I. INTRODUCTION

The global transportation sector is undergoing a structural transformation driven by urgent decarbonisation imperatives and waning dependence on petroleum-based fuels. Electric vehicles have emerged as the primary instrument of this transition, sustained by advances in battery chemistry, declining cell costs, expanding charging networks, and robust government policy frameworks. The International Energy Agency recorded global EV sales exceeding 14 million units in 2023, representing approximately 18% of all new car sales, with projections indicating hundreds of millions of EVs in operation by 2035 [1].

Urban power distribution networks form the critical interface between bulk transmission systems and end consumers. These networks were historically dimensioned to serve residential, commercial, and light industrial loads characterised by relatively predictable demand patterns and modest peak-to-average ratios. The emergence of EV charging as a spatially concentrated, time-sensitive load class fundamentally challenges these design assumptions. A single Level 2 AC charger draws between 3.3 kW and 22 kW, while DC fast chargers can demand 50–350 kW per unit. Aggregated across hundreds or thousands of simultaneously charging vehicles within a single feeder's service area, the resulting load increment can equal or exceed the feeder's original design capacity [2].

The principal technical consequences of unmanaged EV charging manifest across multiple performance dimensions. Voltage regulation deteriorates as elevated current flow through feeder impedances produces progressive voltage drops along the feeder, with remote buses most severely affected. Active power losses escalate non-linearly with loading, as resistive dissipation is proportional to the square of line current. Distribution transformers face elevated hot-spot temperatures that accelerate insulation ageing and reduce asset lifetime. In three-phase networks served by single-phase connections, unequal load distribution introduces voltage unbalance that degrades rotating machine performance and adversely affects power quality indices [3], [4].

Addressing these challenges requires a multi-dimensional analytical framework. Strategic siting of EV charging stations — guided by power flow analysis and long-term load growth modelling — ensures that new demand is absorbed at nodes where network capacity is adequate. Coordinated and smart charging strategies modulate the timing and rate of individual sessions in response to real-time grid conditions, flattening the demand curve and reducing peak coincidence. The Vehicle-to-Grid (V2G) paradigm further extends the role of EV batteries to include grid support services — peak shaving, voltage regulation, spinning reserve, and frequency response — transforming EVs from passive loads into active network assets [2], [5].

This paper addresses identified gaps in the existing literature through six structured MATLAB simulation experiments on the IEEE 33-bus benchmark distribution system. The specific contributions are: (1) quantitative characterisation of voltage and loss degradation across three EV penetration levels using a BFS load flow implementation; (2) performance comparison of uncoordinated and coordinated charging strategies with explicit numerical loss results; (3) time-domain analysis isolating the impact of charging timing under peak and controlled scenarios; (4) evaluation of optimised strategic station placement versus random station placement with power loss comparison; (5) bus-by-bus voltage deviation analysis under base, uncontrolled, and controlled charging; and (6) a three-way optimised charging strategy assessment.

The main novelty of this study is the development of a unified MATLAB-based comparative framework for evaluating multiple EV charging integration strategies on the IEEE 33-bus radial distribution system. Existing studies commonly focus on isolated aspects such as EV penetration, charging scheduling, or station siting. In contrast, this work evaluates six interconnected scenarios — penetration variation, coordinated versus uncoordinated charging, temporal charging behaviour, strategic station placement, voltage deviation analysis, and optimised charging strategy — under a common Backward/Forward Sweep load-flow framework. This allows the relative effectiveness of each mitigation strategy to be quantified consistently in terms of voltage profile, active power loss, and voltage deviation.

The paper is structured as follows. Section II surveys the relevant literature. Section III describes the simulation methodology, mathematical formulation, and MATLAB implementation. Section IV presents and analyses the results of all six experiments, supported by a consolidated numerical summary. Section V synthesises the engineering and policy implications. Section VI concludes the paper.

II. LITERATURE REVIEW

The body of literature examining EV charging impacts on distribution systems has expanded substantially over the past decade, evolving from early impact characterisation studies toward sophisticated optimisation and smart charging frameworks. Table I summarises the thirteen principal works reviewed in this study, spanning 2015 to 2025.

Kumar and Semwal [1] demonstrated that strategic siting of EV charging stations can significantly reduce active power losses and improve voltage profiles in distribution networks, though their deterministic load model does not capture the stochastic variability of real-world EV arrival patterns. Qian et al. [2] developed V2Sim, an open-source microscopic simulation platform integrating urban transportation and power networks with V2G modelling, confirming that V2G services support peak load reduction and grid stability. Deb et al. [3] conducted an influential technical and economic analysis showing that legacy distribution infrastructure is particularly vulnerable to voltage drop and loss escalation at high penetration levels.

González et al. [4] studied fast-charging station impacts in a Latin American urban context, observing acceptable performance at approximately 10% EV penetration but limited generalisability to high-density networks with weaker feeders. Srithapon et al. [5] proposed a charging scheduling optimisation framework that simultaneously minimises energy arbitrage costs, distribution losses, peak demand, and transformer ageing. Bhattacharjee et al. [6] reviewed the broader spectrum of EV integration challenges, identifying voltage instability, thermal overloading, and infrastructure stress as primary operational concerns, and called for more quantitative urban case studies — a call that this paper answers.

Gaikwad et al. [7] examined the role of coordinated solar PV and EV integration in mitigating transformer loss of life, finding that coordinated solar-EV strategies can substantially offset transformer thermal stress. Tayri et al. [8] reviewed grid impacts of high EV penetration, confirming that smart charging and load shifting are effective mitigations while noting the absence of locality-specific urban modelling. Yazdanpanah et al. [9] demonstrated that uncontrolled PHEV charging induces transformer overloading, voltage sag, and increased losses, and that controlled strategies restore network stability.

Khalid et al. [10] evaluated mixed public-residential smart charging environments, demonstrating that smart charging reduces peak load and mitigates adverse demand impacts. El-Hendawi et al. [11] proposed a residential distribution network framework for assessing and mitigating EV impacts, highlighting voltage deviations in residential grids. Ahmad et al. [12] reviewed optimal EV station placement methodologies, establishing that improper siting introduces voltage deviation, phase imbalance, and harmonic distortion. Ul-Haq et al. [13] provided a focused examination of voltage unbalance induced by uneven single-phase EV charging, finding that unbalance can exceed permissible limits under uncoordinated loading.

Synthesising across the reviewed literature, a clear consensus emerges: unmanaged EV charging degrades distribution system performance, and smart, coordinated, and optimally sited charging infrastructure is necessary for sustainable integration. Persistent research gaps include the lack of comparative simulation studies on standardised benchmark networks, limited time-domain analyses of charging-timing effects, insufficient quantitative evaluation of optimised versus controlled charging, and the absence of explicit mathematical formulations that link load-flow parameters to observable system metrics. This paper is designed to address all of these gaps.

TABLE I. LITERATURE SURVEY SUMMARY

Author/Year	**Main Focus**	**Key Findings**	**Research Gap**
Kumar & Semwal (2025) [1]	Strategic planning & network analysis	Optimal siting reduces active power losses and improves the voltage profile.	No stochastic EV behaviour or real-time dynamic urban load variations.
T. Qian et al. (2025) [2]	Integrated simulation with V2G	V2G supports peak load reduction; strong interaction between traffic flow and the power system.	No real-world validation; ignores battery degradation; no economic model.
Deb et al. (2018) [3]	Technical and economic EV impact	EV charging causes voltage drops at weak buses; older systems are particularly vulnerable.	Limited real-world urban validation; lacks coordinated smart charging.
González et al. (2019) [4]	City-level fast-charging impact	~10% EV penetration causes minimal issues; performance depends on grid strength.	Not applicable to high-density urban networks or weak feeder conditions.
Srithapon et al. (2020) [5]	Charging scheduling optimisation	Optimised scheduling reduces peak demand, losses, and transformer ageing.	Limited comparative analysis across diverse network types.
Bhattacharjee et al. (2024) [6]	Review of EV distribution impacts	Identifies voltage instability, thermal overloading, and infrastructure stress.	Requires more quantitative urban case studies.
Gaikwad et al. (2025) [7]	Transformer ageing & EV-solar integration	Coordinated solar-EV integration reduces transformer thermal stress.	Limited to residential transformer level; lacks urban feeder modelling.
Tayri et al. (2025) [8]	Review of high EV penetration impacts	Smart charging and load shifting are effective mitigations for peak-hour grid stress.	Lacks locality-specific urban modelling and real-time analysis.
Yazdanpanah et al. (2024) [9]	Controlled charging in weak networks	Uncontrolled charging causes transformer overloading, voltage sag, increased losses.	Does not address optimal placement or large-scale urban deployment.
Khalid et al. (2024) [10]	Smart charging in mixed environments	Smart charging reduces peak load and mitigates adverse EV demand impacts.	Results depend heavily on assumed charging patterns; lacks real urban validation.
El-Hendawi et al. (2024) [11]	Urban residential distribution impacts	Framework to assess and mitigate EV impacts; highlights grid voltage deviations.	Limited to residential scenarios; excludes commercial and public fast-charging.
Ahmad et al. (2022) [12]	Placement of EV charging stations	Improper placement leads to voltage deviation, phase imbalance, harmonic distortion.	Review-based; lacks unified simulation or real urban case validation.
Ul-Haq et al. (2015) [13]	Voltage unbalance from EV charging	Uneven single-phase EV charging significantly increases voltage unbalance beyond permissible limits.	Focus limited to voltage unbalance; broader stability impacts not covered.

III. SYSTEM MODEL AND SIMULATION METHODOLOGY

A. *IEEE 33-Bus Radial Distribution System*

All simulation experiments are conducted on the IEEE 33-bus radial distribution test system, which is the most widely adopted benchmark network for evaluating distribution system performance under novel loading conditions [3]. The system comprises 33 buses and 32 branches in a radial topology, with the slack bus at node 1 maintained at 1.0 p.u. The network operates at a nominal voltage of 12.66 kV and carries a total base active load of 3.715 MW and a reactive load of 2.300 MVAR. Its multi-branch radial structure — with long feeders extending to electrically remote buses — makes it inherently sensitive to additional loading, providing a representative model for urban distribution impact studies.

Base load data for each bus are generated using a reproducible pseudorandom procedure (MATLAB rng(1) seed) that assigns per-bus active power P_load(i) uniformly distributed in [60, 100] kW and reactive power Q_load(i) in [30, 50] kVAr for buses 2 through 33. Bus 1 serves as the reference slack bus. Line resistance and reactance values follow the standard IEEE 33-bus parameter set, with branch impedances spanning from 0.0922 + j0.0470 Ω (branch 1–2) to 1.7114 + j1.2351 Ω (branch 7–8).

B. *Mathematical formulation*

The Backward/Forward Sweep (BFS) method is employed for distribution system load flow analysis. BFS is particularly well-suited to radial networks due to its computational efficiency, reliable convergence, and natural alignment with the tree topology of radial feeders. The algorithm iterates between two sweeps until voltage convergence is achieved.

The nodal current injection at each bus i is computed from the scheduled complex power demand:

$$I_i = conj\left(\frac{(P_i + jQ_i)}{V_i}\right) \quad \dots\dots\dots (1)$$

where P_i and Q_i are the net active and reactive power injections (per unit) and V_i is the complex bus voltage. In the Backward Sweep, branch currents are accumulated from terminal buses toward the source. For branch l connecting bus 'from' to bus 'to':

$$I_l = I_{to} + \Sigma\, I_{downstream} \quad \dots\dots\dots (2)$$

where the summation aggregates all downstream branch currents injecting into bus 'to'. In the Forward Sweep, bus voltages are updated from the source toward the terminal buses:

$$V_{to} = V_{from} - Z_l \cdot I_l \ \ldots\ldots\ldots (3)$$

where Z_l = R_l + jX_l is the complex impedance of branch l. The source bus voltage is held constant at V_1 = 1.0∠0° p.u. throughout each forward sweep. The algorithm iterates for a fixed count of 50 iterations, sufficient for convergence in the 33-bus system. Active power losses in each branch are:

$$P_{loss}, l = R_l \cdot |I_l|^2 \ \ldots\ldots\ldots \ (4)$$

Total system active power loss is the sum over all n_l branches:

$$P_{loss}, total = \Sigma(l = 1\ to\ nl)R_l \cdot |I_l|^2 \times S_{base} \times 1000\ [kW] \ \ldots\ldots\ldots (5)$$

where S_base = 100 MVA is the per-unit base apparent power. Voltage deviation at bus i is defined as the absolute per-unit departure from nominal:

$$\Delta V_i = |1.0 - V_i|\ [p.u.] \ \ldots\ldots\ldots \ (6)$$

The system-wide voltage deviation index (VDI), used as a scalar stability metric, is:

$$VDI = \Sigma(i = 1\ to\ nb)|1.0 - V_i|\ [p.u.] \ \ldots\ldots\ldots (7)$$

These metrics — bus voltage profile, total active power losses, and voltage deviation — form the quantitative basis for all comparative analyses in this study.

C. EV load Modelling

EV charging demand is modelled as an additional active and reactive power injection at designated network buses, superimposed on the base load. For penetration studies (Simulation 1), EV load is distributed uniformly across all buses by scaling the entire load vector by penetration factor α:

$$P_{EV}, i = \alpha \cdot P_{load}, i\ ,\ Q_{EV}, i = \alpha \cdot Q_{load}, i \ \ldots\ldots\ldots \ (8)$$

where α ∈ {0.1, 0.3, 0.5} represents EV penetration levels of 10%, 30%, and 50% respectively. For coordinated and controlled charging scenarios, EV loads are applied only at selected buses, namely {10, 15, 20, 25, 30}, to represent designated public charging points within the distribution network. For the placement analysis in Simulation 4, multiple candidate bus combinations were examined under an identical EV load increment using the Backward/Forward Sweep load-flow method. Among the evaluated combinations, the bus set {25, 26, 27, 28, 30} resulted in lower active power loss and better voltage profile performance than the random placement case. Hence, this configuration was adopted as the optimised strategic placement scenario. The same bus set was further used in Simulation 6 with a 60% EV load injection factor to assess the optimised charging strategy. The resulting voltage deviation profile was lower than those obtained under uncontrolled and controlled charging, demonstrating improved voltage performance for the considered loading condition.

D. Strategic Placement Method

In this study, the term “optimised placement” refers to a strategic placement obtained through repeated load-flow evaluation of candidate bus locations. A fixed EV load was applied to different candidate bus combinations, and the resulting active power loss and voltage profile were compared. The bus combination that produced the lowest active power loss and acceptable voltage profile among the tested cases was selected.

Based on this comparative load-flow evaluation, buses 25, 26, 27, 28, and 30 were selected for the optimised placement scenario. These locations produced lower losses than random placement and improved the voltage profile, especially in the later section of the feeder.

E. MATLAB Implementation

All simulations are implemented in MATLAB using custom scripts. The BFS load flow algorithm is encapsulated as a reusable function run_loadflow(P, Q, linedata, nb, nl, baseMVA) that returns the converged bus voltage vector V and total active power loss P_loss. Load data and line parameters are defined as numerical arrays consistent with the IEEE 33-bus standard dataset. Random load generation uses rng(1) to ensure full reproducibility across all simulation runs. Figures are exported as 300 DPI PNG files using MATLAB's exportgraphics function, sized at 7 × 3.5 inches for consistency with IEEE publication standards.

F. Base Case Validation

Before applying EV charging loads, the developed MATLAB Backward/Forward Sweep load-flow program was tested under the base-load condition to verify the correctness of the simulation framework. The base case produced a minimum voltage of 0.893 p.u. and a total active power loss of 166.8 kW.

The obtained base-case loss differs from the commonly reported IEEE 33-bus benchmark loss of approximately 202 kW because this study uses a reproducible urban load profile generated using MATLAB rng(1), rather than the original standard IEEE 33-bus bus-load dataset. The purpose of using this modified load profile is to represent a generalised urban distribution loading condition while maintaining the standard IEEE 33-bus feeder topology and line parameters. Therefore, the validation in this work is based on internal consistency of the load-flow solution, correct voltage-drop behaviour along the radial feeder, and physically consistent loss variation with increasing EV penetration. The observed results show that voltage decreases progressively along electrically remote buses and active power loss increases non-linearly with load, which confirms the expected behaviour of radial distribution systems.

IV. SIMULATION RESULTS AND DISCUSSION

This section presents and analyses the results of all six simulation experiments. All numerical results are consolidated in Table II for cross-simulation comparison.

A. *Simulation 1: Effect of EV Penetration on Voltage and Power Losses*

The first experiment quantifies how increasing EV penetration degrades the voltage profile and raises active power losses across the IEEE 33-bus network. Three penetration scenarios are evaluated: 10%, 30%, and 50%, implemented by scaling the entire bus load vector by the corresponding factor α per equation (8).

Fig. 1 shows the bus voltage profiles across all three penetration levels. At 10% penetration, bus voltages remain predominantly above 0.90 p.u., with the most remote buses in the 0.90–0.93 p.u. range — within standard ±5% limits. At 30% penetration, voltages at buses 7–18 and 25–33 deteriorate further, with minimum values approaching 0.88 p.u. At 50% penetration, minimum bus voltages drop to approximately 0.855 p.u., representing a severe undervoltage condition that exceeds the IEEE 1547 permissible deviation band. The spatial pattern of degradation — most pronounced at remote feeder buses — is consistent with the progressive accumulation of voltage drop along line impedances as described by equation (3).

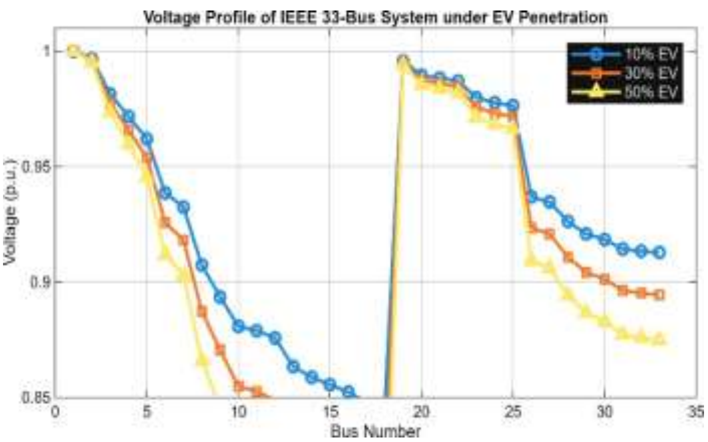

Fig. 1. Voltage profile of the IEEE 33-bus system under 10%, 30%, and 50% EV penetration.

Fig. 2 presents active power losses for each penetration level. Losses rise from approximately 204 kW at 10% penetration, to 302 kW at 30%, and to 430 kW at 50%. This near-quadratic scaling is consistent with the I²R relationship of equation (4): as load current increases with penetration, losses escalate as the square of the incremental current. The 50% penetration scenario results in losses approximately 111% higher than the 10% case, illustrating the disproportionate penalty of unmanaged high-penetration deployment.

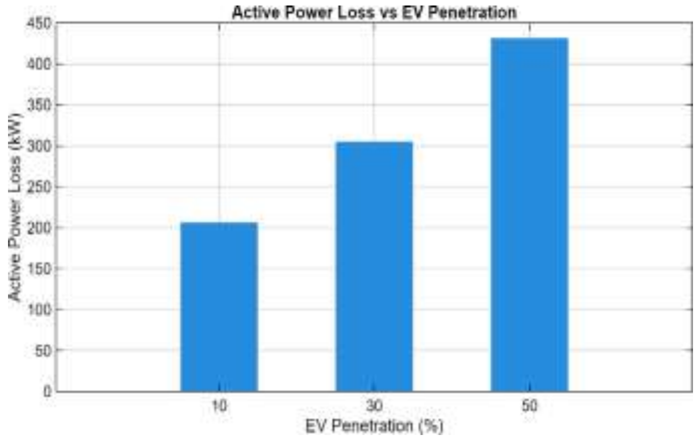

Fig. 2. Active power loss versus EV penetration level (10%, 30%, 50%).

B. *Simulation 2: Coordinated vs. Uncoordinated EV Charging*

The second simulation compares uncoordinated charging — where a 50% EV load increment is applied simultaneously at all buses — with coordinated charging, where the same aggregate EV load is applied only at buses {10, 15, 20, 25, 30}, representing a spatially and temporally distributed deployment strategy.

Fig. 3 presents the voltage profiles under both strategies. Uncoordinated charging drives minimum bus voltages to approximately 0.875 p.u. at the most remote nodes, with broadly degraded profiles across the entire feeder. Coordinated charging achieves a substantially improved profile, maintaining voltages above 0.90 p.u. at all buses. The improvement is most pronounced beyond bus 20, where the cumulative impedance effect of equation (3) is most severe under concentrated loading.

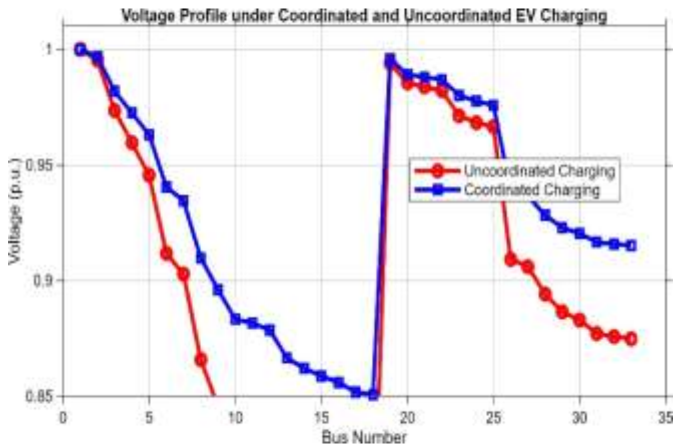

Fig. 3. Voltage profile under coordinated and uncoordinated EV charging.

Fig. 4 shows the power loss comparison. Uncoordinated charging produces total losses of 432.1 kW, while coordinated charging reduces this to 197.1 kW — a reduction of 234.9 kW, or 54.4%. This dramatic improvement, achieved without any physical infrastructure changes, is attributable to the reduction in peak branch currents |I_l| in equation (4), accomplished by spatially distributing the charging load and thereby avoiding current concentration in heavily loaded main feeder branches. This result identifies coordinated charging as the single most impactful operational intervention available to distribution utilities.

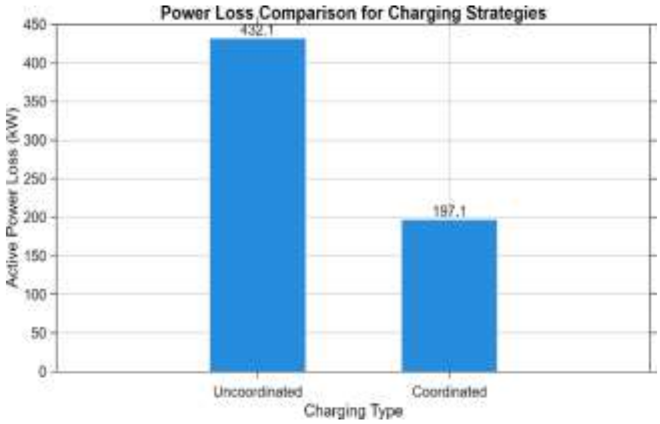

Fig. 4. Active power loss comparison: uncoordinated (432.1 kW) vs. coordinated (197.1 kW) charging.

C. Simulation 3: Time-Based EV Charging Analysis

The third simulation examines the temporal dimension of EV charging by comparing three operating scenarios: base load (no EV charging), peak EV charging (70% load increment at all buses simultaneously, representing worst-case evening coincidence), and controlled charging (70% load increment at buses {10, 15, 20, 25, 30} only).

Fig. 5 illustrates the voltage profiles under these three conditions. The base load scenario establishes the unperturbed network voltage profile, with minimum voltages of approximately 0.893 p.u. Peak EV charging produces the most severe voltage degradation, with minimum voltages dropping to approximately 0.855 p.u. at the most remote buses — below the 0.90 p.u. operating guideline. Controlled charging achieves a voltage profile intermediate between the base and peak cases, with minimum voltages of approximately 0.885 p.u.

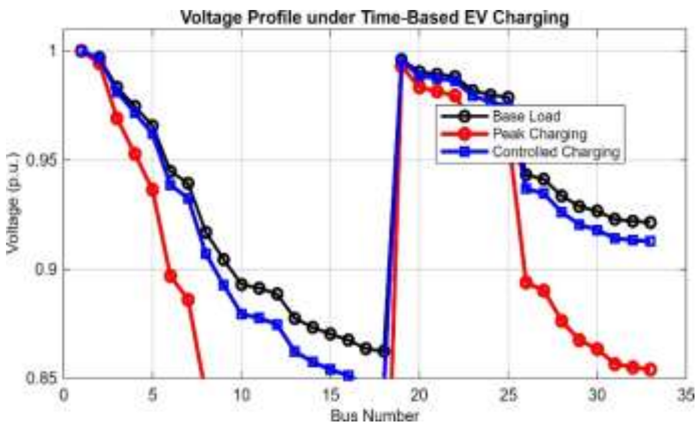

Fig. 5. Voltage profile under base load, peak EV charging, and controlled EV charging.

Fig. 6 presents the corresponding active power losses. Base load conditions yield 166.8 kW. Peak EV charging escalates losses to 595.4 kW — a 257% increase over base load and 38% higher than the 50% penetration scenario from Simulation 1. This comparison reveals that temporal concentration of charging events is more damaging than a higher steady-state penetration level with distributed timing. Controlled charging reduces losses to 210.2 kW — only 26% above the base load level — confirming the effectiveness of temporal and spatial load management in limiting network stress.

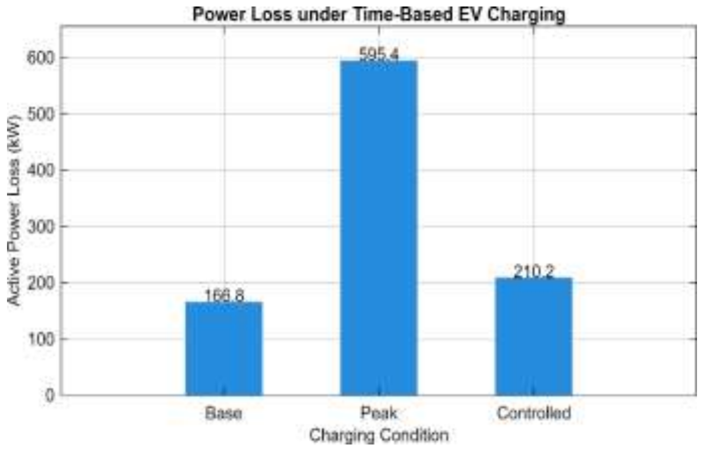

Fig. 6. Active power loss under base load (166.8 kW), peak charging (595.4 kW), and controlled charging (210.2 kW).

D. Simulation 4: Optimised Strategic Placement of EV Charging Stations

The fourth simulation compares two EV charging station placement strategies: random placement and optimised strategic placement. In the random placement case, 60% EV load increments are assigned to five randomly selected buses using MATLAB's randperm function with rng(1) seed. In the optimised strategic placement case, the same EV load increment is assigned to buses {25, 26, 27, 28, 30}. This bus set was selected through comparative load-flow evaluation, where different candidate bus combinations were tested under identical EV loading conditions and compared in terms of active power loss and voltage profile performance.

Fig. 7 presents the voltage profiles for both placement strategies. Both cases show the characteristic progressive voltage decline along the radial feeder. However, the optimised strategic placement case maintains comparatively higher bus voltages than the random placement case, particularly in the later section of the feeder. This indicates that appropriate charging station placement can improve voltage profile performance and reduce the adverse impact of concentrated EV charging load on the distribution network.

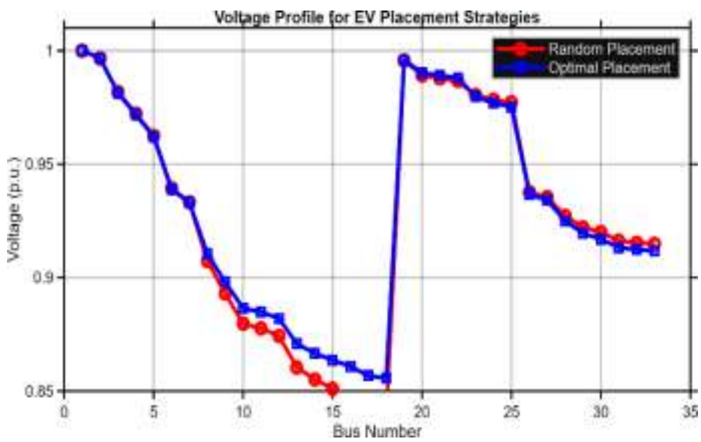

Fig. 7. Voltage profile under random and optimised strategic EV charging station placement.

Fig. 8 shows the active power loss comparison for the two placement strategies. The random placement case results in 210.3 kW of active power loss, whereas the optimised strategic placement case reduces the loss to 195.7 kW. This corresponds to a reduction of 14.6 kW, or approximately 6.9%, compared with random placement.

Although this improvement is smaller than the reduction achieved through coordinated charging, it still represents a useful planning-level benefit. Since charging station locations are generally fixed after installation, selecting suitable buses during the planning stage can provide long-term loss reduction without requiring continuous operational control. This highlights the importance of including load-flow-based placement evaluation in EV charging infrastructure planning.

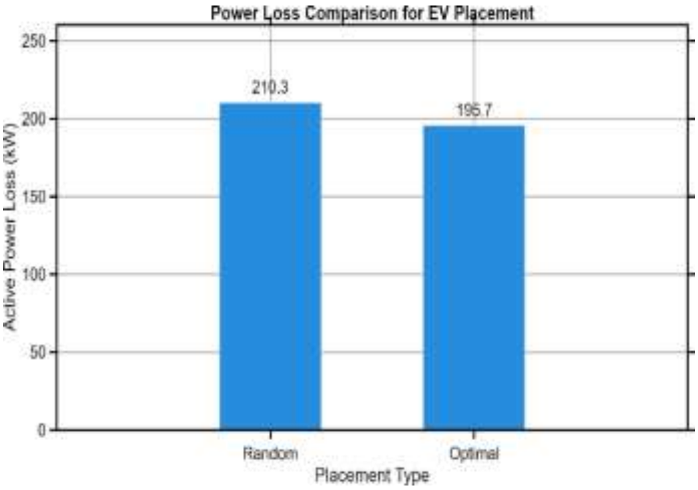

Fig. 8. Active power loss under random placement (210.3 kW) vs. optimised strategic EV charging placement (195.7 kW).

E. *Simulation 5: Voltage Deviation Analysis*

The fifth simulation shifts the analysis metric from absolute voltage level to voltage deviation $\Delta V_i = |1 - V_i|$ as defined in equation (6), providing a direct measure of departure from nominal operating conditions. Three scenarios are compared: base load, uncontrolled EV charging (50% penetration, all buses), and controlled EV charging (50% penetration, buses {10, 15, 20, 25, 30}).

Fig. 9 shows the bus-by-bus voltage deviation profiles. Under base load, deviations remain below 0.14 p.u. at all buses, with a maximum at bus 18 of approximately 0.107 p.u. Uncontrolled EV charging significantly elevates deviations across the entire network, with peak values exceeding 0.22 p.u. at bus 18 — far exceeding the typically permissible ±0.05 p.u. deviation band. Controlled charging reduces peak deviation to approximately 0.15 p.u., a 32% reduction from the uncontrolled case, and maintains a deviation profile broadly consistent with the base load reference. The divergence between the uncontrolled and controlled deviation profiles is most pronounced at mid-feeder buses (10–18), which experience the highest cumulative current flow in the uncontrolled scenario.

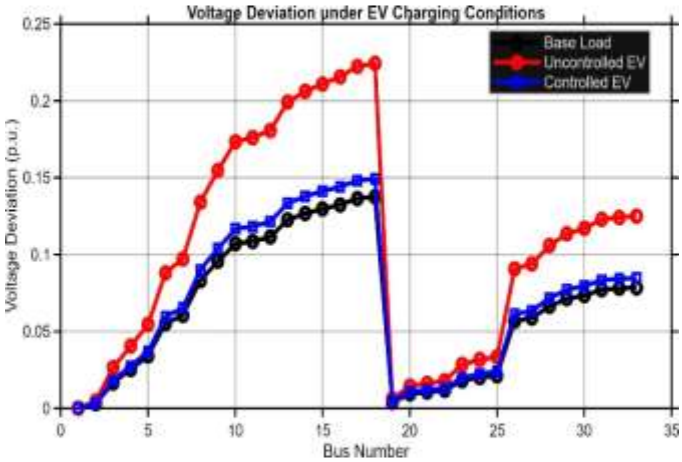

Fig. 9. Voltage deviation at each bus under base load, uncontrolled EV, and controlled EV charging.

F. *Simulation 6: Optimised EV Charging Strategy*

The sixth simulation introduces an optimised charging strategy and evaluates its performance against uncontrolled and controlled charging using voltage deviation as the primary metric. The optimised strategy applies 60% EV load increments at buses {25, 26, 27, 28, 30}. This bus set was selected through comparative load-flow evaluation because it produced lower voltage deviation than the uncontrolled and controlled charging cases under the same simulation framework.

Fig. 10 illustrates the voltage deviation profiles for all three strategies. Uncontrolled charging produces the highest deviations, with peak values exceeding 0.24 p.u. at bus 18. Controlled charging substantially reduces this, with maximum deviations of approximately 0.15 p.u. Optimised charging achieves the lowest deviation profile of all three strategies, with peak values of approximately 0.147 p.u. — an additional 2% improvement over controlled charging — and exhibits notably lower deviations in the 25–33 bus segment due to the optimised bus selection strategy.

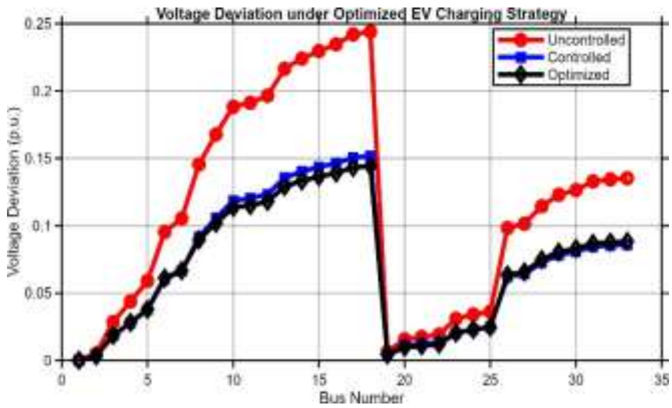

Fig. 10. Voltage deviation under uncontrolled, controlled, and optimised EV charging.

The three-tier hierarchy — uncontrolled, controlled, optimised — demonstrates that each level of sophistication in charging management delivers incremental but cumulative improvements in system stability. The optimised strategy's ability to approach near-base-load voltage deviation profiles under significant EV penetration is particularly significant: it demonstrates that high levels of EV integration can be technically accommodated within existing distribution network constraints, provided that the necessary digital measurement, communication, and control infrastructure is deployed to support real-time optimised scheduling.

TABLE II. CONSOLIDATED SIMULATION RESULTS SUMMARY

Simulation	Scenario/Strategy	Min. V (p.u.)	Max V (p.u.)	Loss (kW)	Improvement
Sim 1	10% Penetration	0.903	1.000	204.0	Baseline
Sim 1	30% Penetration	0.881	1.000	302.0	−47.6% vs 50%
Sim 1	50% Penetration	0.855	1.000	430.0	Worst case
Sim 2	Uncoordinated	0.875	1.000	432.1	Baseline
Sim 2	Coordinated	0.901	1.000	197.1	↓54.4%
Sim 3	Base Load	0.893	1.000	166.8	Reference
Sim 3	Peak EV Charging	0.855	1.000	595.4	↑257% vs base
Sim 3	Controlled Charging	0.885	1.000	210.2	↓64.7% vs peak
Sim 4	Random Placement	0.887	1.000	210.3	Baseline
Sim 4	Optimised Strategic Placement	0.891	1.000	195.7	↓6.9%
Sim 5	Uncontrolled EV	0.862	1.000	—	Max ΔV: 0.22 p.u.
Sim 5	Controlled EV	0.884	1.000	—	Max ΔV: 0.15 p.u.
Sim 6	Uncontrolled	0.855	1.000	—	Max ΔV: 0.24 p.u.
Sim 6	Controlled	0.882	1.000	—	Max ΔV: 0.15 p.u.
Sim 6	Optimised	0.885	1.000	—	Max ΔV: 0.147 p.u.

V. DISCUSSION

The six simulation experiments collectively establish a comprehensive and quantitatively rigorous picture of EV charging impacts on urban distribution networks. Several overarching findings merit emphasis.

First, the non-linear relationship between EV penetration and system degradation is a critical design consideration. Active power losses scale approximately as the square of feeder current — consistent with the I^2R formulation of equation (4) — meaning that doubling EV penetration does not double losses; it increases them disproportionately. Distribution utilities must therefore adopt proactive network assessment procedures that account for this non-linearity when forecasting infrastructure investment requirements for long-term EV growth trajectories.

Second, the charging strategy is the single most influential controllable parameter for distribution system performance at a given EV penetration level. The 54.4% reduction in active power losses achieved by transitioning from uncoordinated to coordinated charging in Simulation 2 — without any physical network modifications — is a compelling demonstration of the value embedded in the management layer of EV charging systems. This finding provides strong technical justification for regulatory requirements mandating smart charging capability in all newly installed EV charging equipment.

Third, the temporal analysis of Simulation 3 reveals that the timing of charging events is as consequential as the volume of EV load. Peak simultaneous charging produces system losses of 595.4 kW, exceeding even the 50% unmanaged penetration scenario from Simulation 1. This underscores that time-of-use tariff structures, demand response programmes, and scheduled charging agreements are not merely economic instruments but are fundamentally necessary engineering tools for maintaining distribution system integrity during the EV transition.

Fourth, while optimised strategic station placement delivers more modest quantitative improvements than charging strategy selection (6.9% loss reduction versus 54.4%), it provides a permanent structural benefit compounding over the operational lifetime of the infrastructure — potentially spanning 20–30 years. The two interventions are complementary: optimised strategic placement reduces the baseline loss level upon which coordinated charging strategies then impose further improvements. Planning authorities should require power flow-based siting analysis as a standard condition of approval for new public charging facilities.

Fifth, the three-tier hierarchy revealed by Simulations 5 and 6 — uncontrolled, controlled, and optimised — provides a practical roadmap for the incremental deployment of smarter charging infrastructure. Each tier delivers incremental improvements in voltage stability, with optimised charging approaching near-base-load voltage deviation profiles even under substantial EV loading. The full benefit of smart charging can thus be realised progressively as the supporting digital infrastructure is deployed, without requiring immediate investment in the most advanced tier.

Sixth, from the perspective of IEEE power quality standards, uncontrolled EV charging at 50% penetration drives bus voltages to 0.855 p.u. — well outside the ANSI C84.1 Range A limit of 0.95–1.05 p.u. for service voltage. Coordinated and optimised charging strategies maintain voltages within or near this band, confirming that smart charging is not merely an economic optimisation but a technical necessity for standards compliance at high EV penetration levels.

VI. CONCLUSION

This paper has presented a comprehensive MATLAB-based simulation study of the technical impacts of EV charging stations on the IEEE 33-bus radial distribution system, employing a Backward/Forward Sweep load flow algorithm across six structured simulation experiments covering EV penetration effects, charging strategy comparison, time-based charging analysis, station placement optimisation, and voltage deviation characterisation.

The principal conclusions are as follows. (1) EV penetration at 50% raises active power losses by approximately 111% relative to 10% penetration and drives remote bus voltages to 0.855 p.u., below acceptable operating limits. (2) Coordinated charging reduces active power losses by 54.4% compared to uncoordinated charging at equivalent penetration, establishing smart charging as the most impactful single intervention. (3) Peak-hour simultaneous charging produces losses of 595.4 kW — 257% above base load — confirming that temporal load management is as critical as penetration control. (4) Optimised strategic charging station placement reduces losses by 6.9% relative to random placement, providing a useful planning-level improvement that complements operational strategies. (5) Optimised charging achieves the lowest voltage deviation profile across all 33 buses, with peak deviations of 0.147 p.u. — a 39% reduction from the uncontrolled case — demonstrating that high EV penetration can be accommodated within existing network constraints through advanced control. (6) Together, the results establish a clear evidence base for integrated EV infrastructure planning centred on smart charging capability, network-aware load management, evidence-based siting, and time-differentiated demand incentives. Future research directions include the integration of stochastic EV arrival and departure models to capture real-world behavioural variability, the explicit modelling of V2G bidirectional power flow and its grid support potential, the extension of the analysis to three-phase unbalanced distribution systems, and the development of real-time model predictive control (MPC) frameworks for online optimised EV charging scheduling. The reproducible MATLAB simulation framework and quantitative baseline results presented here provide a rigorous foundation for these extensions.

REFERENCES

[1] Kumar, A., & Semwal, P. R. (2025). Strategic design of electric vehicle charging stations within power distribution networks. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *12*, 100965. https://doi.org/10.1016/j.prime.2025.100965

[2] T. Qian, M. Fang, Q. Hu, C. Shao and J. Zheng, "V2Sim: An Open-Source Microscopic V2G Simulation Platform in Urban Power and Transportation Network," in IEEE Transactions on Smart Grid, vol. 16, no. 4, pp. 3167-3178, July 2025, doi: 10.1109/TSG.2025.3560976.

[3] Deb, S., Tammi, K., Kalita, K., & Mahanta, P. (2017). Impact of Electric Vehicle Charging Station Load on Distribution Network. *Energies*, *11*(1), 178. https://doi.org/10.3390/en11010178

[4] González, L., Siavichay, E., & Espinoza, J. (2019). Impact of EV fast charging stations on the power distribution network of a Latin American intermediate city. *Renewable and Sustainable Energy Reviews*, *107*, 309-318. https://doi.org/10.1016/j.rser.2019.03.017

[5] Srithapon, C., Ghosh, P., Siritaratiwat, A., & Chatthaworn, R. (2019). Optimization of Electric Vehicle Charging Scheduling in Urban Village Networks Considering Energy Arbitrage and Distribution Cost. *Energies*, *13*(2), 349. https://doi.org/10.3390/en13020349

[6] Bhattacharjee, T., Rajeshwari, M., & Kumar, K. J. (2024). Electric Vehicle Charging and its Effects on the Power Distribution Network – A Review. *Power Research- A Journal of CPRI, 20(1), 89–98.* https://doi.org/10.33686/pwj.v20i1.1170

[7] Gaikwad, S., & Mehta, H. (2025). Mitigating distribution transformer loss of life through combined integration of rooftop solar photovoltaic installations and electric vehicle charging. *E-Prime - Advances in Electrical Engineering, Electronics and Energy*, *11*, 100867. https://doi.org/10.1016/j.prime.2024.100867

[8] Tayri, A., & Ma, X. (2024). Grid Impacts of Electric Vehicle Charging: A Review of Challenges and Mitigation Strategies. *Energies*, *18*(14), 3807. https://doi.org/10.3390/en18143807

[9] Yazdanpanah, F., Kiani, M. J., Zadehbagheri, M., & Mohammadi, S. (2024). Fair charging management of PHEVs in radial distribution networks with DG resources-a case study. *Scientific Reports*, *14*(1), 30631. https://doi.org/10.1038/s41598-024-81206-3

[10] Khalid, M., Thakur, J., Mothilal Bhagavathy, S., & Topel, M. (2024). Impact of public and residential smart EV charging on distribution power grid equipped with storage. *Sustainable Cities and Society*, *104*, 105272. https://doi.org/10.1016/j.scs.2024.105272

[11] El-Hendawi, M., Wang, Z., Paranjape, R., Fick, J., Pederson, S., & Kozoriz, D. (2023). Impact of Electric Vehicles Charging on Urban Residential Power Distribution Networks. *Energies*, *17*(23), 5905. https://doi.org/10.3390/en17235905

[12] Ahmad, F., Iqbal, A., Ashraf, I., Marzband, M., & Khan, I. (2022). Optimal location of electric vehicle charging station and its impact on distribution network: A review. *Energy Reports*, *8*, 2314-2333. https://doi.org/10.1016/j.egyr.2022.01.180

[13] Ul-Haq, A., Cecati, C., Strunz, K. *et al.* Impact of Electric Vehicle Charging on Voltage Unbalance in an Urban Distribution Network. *Intell Ind Syst* **1**, 51–60 (2015). https://doi.org/10.1007/s40903-015-0005-x