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Optimization of Electric Vehicle Charging Strategies for Improved Stability and Energy Efficiency in Smart Distribution Grids

Putri Ayu Maharani[1]*; Reza Maulana Firmansyah[2]; Ilham Fadli Setiawan[1]; Anisa Rahma Pratiwi[1]

[1]Department of Electrical Engineering, Faculty of Engineering, Universitas Indonesia, Depok, Indonesia
[2]Department of Industrial Engineering, Faculty of Engineering, Universitas Indonesia, Depok, Indonesia

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Corresponding author:
Putri Ayu Maharani
putriayumaharani@gmail.com

Other author email(s):
rezamaulanafirmansyah@gmail.com
ilhamfadlisetiawan@gmail.com
anisarahmapratiwi@gmail.com

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Abstract

Purpose - This study evaluates electric vehicle charging strategies for improving voltage stability, reducing peak demand and distribution losses, and increasing energy efficiency in smart distribution grids.

Methodology - A quantitative simulation-based design was applied to a modified IEEE 33-bus system with 300 electric vehicles, 900 kW photovoltaic capacity, a 24-hour horizon, and 200 Monte Carlo replications. Uncontrolled, coordinated, renewable-aware, and vehicle-to-grid charging were compared.

Findings - Renewable-aware charging reduced voltage violations by 72.42%, lowered daily energy losses by 12.03%, and increased grid efficiency to 97.610%. Vehicle-to-grid charging achieved the largest peak-demand reduction of 35.15% and the lowest daily charging cost. Differences among strategies were significant at $p < 0.001$.

Implications - Distribution-system operators can prioritize renewable-aware charging for voltage and efficiency improvement and activate vehicle-to-grid support selectively during high network stress.

Originality - The study compares four charging strategies under identical stochastic operating conditions and jointly evaluates voltage stability, peak demand, energy losses, grid efficiency, and charging cost.

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Introduction

The rapid expansion of electric vehicles (EVs) is changing the interaction between transportation systems and electricity distribution networks. EV adoption can reduce dependence on fossil fuels and support transport decarbonization, but large charging loads introduce new operational challenges at the distribution level. EV charging differs from conventional demand because its timing, duration, location, charging power, and energy requirement depend on individual mobility patterns. Chandra et al. (2024) identified coordinated charging as an increasingly important alternative to costly network reinforcement when EV penetration rises. Ray et al. (2023) similarly showed that uncontrolled EV integration can increase power losses, voltage deviations, loading stress, and operational costs in distribution networks. Recent developments in intelligent charging control indicate that EV charging should therefore be treated as a flexible grid resource rather than an uncontrollable additional load (Wei et al., 2025). This shift is important because the technical benefits of transport electrification depend not only on the number of EVs deployed but also on how their charging demand interacts with existing distribution infrastructure.

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The challenge is increasingly relevant in Indonesia. The expansion of EV charging infrastructure occurs while the electricity system is also adapting to growing renewable-energy penetration and changing demand patterns. Haryadi et al. (2023) found that charging accessibility, technological familiarity, price considerations, and user characteristics influence the utilization of EV charging infrastructure in Indonesia. At the broader electricity-system level, Amiruddin et al. (2024) demonstrated that EV penetration and charging patterns can affect generation requirements, storage needs, system costs, renewable-energy utilization, and emissions. Distribution-level evidence provides a more direct indication of the technical challenge. Putra et al. (2025) used EV charging data in an Indonesian case study and identified a strong negative relationship between charging-station demand and bus voltage. Their analysis also showed that EV charging increased network losses, although photovoltaic generation could offset part of the additional losses. These findings indicate that EV expansion in Indonesia requires charging strategies that account for network conditions, renewable availability, and temporal changes in electricity demand.

The technical effects of uncontrolled charging arise from the concentration of electrical demand within limited periods. When many EVs start charging at similar times, feeder currents increase, voltage drops become larger, distribution losses rise, and transformers can operate closer to their thermal limits. Hasan et al. (2023) demonstrated that residential, commercial, and public charging patterns create different voltage-violation profiles because their charging activities occur at different times of the day. Azzopardi and Gabdullin (2024) also showed that increasing EV penetration in low-voltage networks can alter voltage conditions and network loading, particularly when charging coincides with existing demand peaks. Fast charging can intensify these effects because high charging power is concentrated within shorter periods. Hernández-Gómez et al. (2024) found that fast-charging demand can cause voltage drops and increase the operation of voltage-regulation equipment. Consequently, voltage stability, peak loading, and energy losses are closely connected rather than independent outcomes of EV integration.

Smart charging provides a practical mechanism for reducing these effects because it allows charging power and charging time to respond to network conditions. Lin et al. (2024) demonstrated that intelligent charging management can lower peak demand by adjusting vehicle charging according to travel requirements, tariff signals, and network constraints. Temporal and spatial coordination also improves the ability of distribution-system operators to manage charging flexibility. Xiao et al. (2024) showed that coordination between distribution system operators, aggregators, and EV users can reduce load variation while maintaining required charging services. Grid-aware control provides an additional layer of protection by modifying charging power when network capacity becomes constrained. Diaz-Londono et al. (2024) found that coordinated charging algorithms can limit the grid impact of EVs by allocating available flexibility more effectively. González-Garrido et al. (2024) further demonstrated that collaborative charging can flatten load profiles, alleviate congestion, and increase EV hosting capacity in constrained distribution networks. These studies establish coordinated charging as a central demand-side flexibility mechanism for future smart grids.

Renewable-aware and bidirectional charging create further opportunities to improve system performance. Renewable-aware scheduling can move EV demand toward periods with greater photovoltaic or wind generation, which can reduce dependence on upstream grid supply. Grammenou et al. (2024) demonstrated that coordinated EV charging combined with photovoltaic siting can reduce network losses and improve voltage profiles. Khan et al. (2025) found that dynamic charging based on available renewable generation can significantly reduce charging costs and load variance. Bidirectional vehicle-to-grid (V2G) operation extends this flexibility because EV batteries can discharge limited amounts of energy when the network requires support. Hossain et al. (2023) identified peak-load management, voltage support, frequency regulation, and renewable integration as major potential services of grid-to-vehicle and vehicle-to-grid operation. Abdelfattah et al. (2024) subsequently showed that strategically scheduled charging and discharging can improve voltage profiles, reduce feeder loading, and lower network losses. These benefits make EV batteries potentially valuable distributed resources when their operation remains compatible with user mobility and battery constraints.

Despite substantial progress, important research gaps remain. Many studies focus on charging-station placement, tariff optimization, charging cost, voltage regulation, or loss reduction separately. Ferraz et al. (2025) found that recent charging-infrastructure optimization studies still differ substantially in their treatment of uncertainty, user behavior, economic objectives, renewable generation, and technical constraints. Charging-station planning studies also frequently prioritize location and sizing rather than the operational comparison of charging strategies. Abdelaziz et al. (2024) integrated stochastic charging demand and distribution-network constraints into EVCS allocation. Nurmuhammed et al. (2023) concentrated on optimal charging-station placement to reduce adverse network effects. Nareshkumar and Das (2024) extended planning to coupled transportation and distribution networks with renewable resources, but the primary concern remained infrastructure planning. Pagidipala and Vuddanti (2024) incorporated uncertain renewable generation and EV demand into distribution planning. Chowdhury et al. (2025) addressed stochastic loading when scheduling mobile and stationary charging stations. However, fewer studies compare uncontrolled, coordinated, renewable-aware, and V2G charging under identical stochastic operating conditions using voltage stability, peak demand, energy losses, and grid efficiency as common evaluation criteria.

This study addresses these gaps through a quantitative simulation and optimization framework for EV charging in a smart distribution grid. The study compares uncontrolled charging, coordinated smart charging, renewable-aware charging, and grid-aware bidirectional charging under a consistent network configuration. The analysis treats voltage stability, peak demand, distribution energy losses, charging cost, and energy efficiency as interrelated performance dimensions. Wang et al. (2024) showed that multi-objective EV coordination can simultaneously address economic and technical objectives rather than optimizing a single grid metric. Alizadeh et al. (2025) also demonstrated the value of integrating charging operation, energy storage, network performance, and real-time control within a unified planning and operating framework. Based on this perspective, the study asks how alternative EV charging strategies affect voltage stability and peak demand, to what extent optimized charging reduces distribution energy losses and improves grid energy efficiency, and whether renewable-aware and V2G charging provide greater overall technical improvement than uncontrolled and conventional coordinated charging. The study aims to identify a charging strategy that improves grid performance while maintaining EV energy and mobility requirements.

Literature Review

Electric Vehicle Charging and Smart Distribution Grids

A smart distribution grid combines monitoring, communication, automation, distributed energy resources, and controllable demand to improve operational flexibility. EVs fit this architecture because their batteries connect transportation demand with the electrical network through charging infrastructure. Unlike conventional loads, EV demand is temporally and spatially mobile. Lin et al. (2024) emphasized that driver behavior, charger selection, travel schedules, and charging preferences affect the spatial and temporal distribution of EV charging. Consequently, a realistic charging model should account for arrival time, departure time, initial battery state of charge, charging power, and required energy.

Charging infrastructure planning also affects grid performance because EVCS location determines where additional electrical demand enters the network. Campaña and Inga (2023) showed that charging-station deployment should consider both traffic conditions and distribution-system capacity. Gupta et al. (2023) expanded this perspective by incorporating technical, economic, and societal factors into charging-station allocation. Rene et al. (2023) demonstrated that coordinating EV charging infrastructure with distributed photovoltaic generation can improve voltage conditions and reduce active and reactive power losses. These findings show that EV integration involves both infrastructure planning and operational charging control.

The growing complexity of charging systems has also encouraged the development of multi-objective planning methods. Gan et al. (2024) incorporated spatial-temporal charging-load characteristics and uncertainty into a bi-level EVCS planning framework. Sahoo et al. (2025) combined charging-station placement with charging and discharging scheduling under renewable-energy integration. Veisi et al. (2025) used mixed-integer linear programming to reduce station costs, energy costs, voltage deviations, and losses while allowing V2G operation. These developments indicate that modern EV integration requires simultaneous consideration of electrical, behavioral, spatial, and economic constraints.

Charging Strategies and Demand-Side Flexibility

Uncontrolled charging provides the simplest charging mechanism because a vehicle starts drawing power when it connects to the charger and continues until the energy requirement is satisfied. Although convenient for EV users, this strategy ignores grid loading and renewable-energy conditions. The resulting synchronization of EV demand can create new peaks. Lilienkamp and Namockel (2025) showed that charging behavior influenced by tariffs can create congestion when users respond similarly to attractive price periods. Their findings highlight the need for active distribution-system coordination rather than reliance on price signals alone.

Coordinated charging modifies charging schedules to satisfy both EV requirements and grid constraints. Zhang et al. (2024) demonstrated that charging flexibility can be coordinated between active distribution networks and charging stations while explicitly incorporating drivers' willingness to participate. Sarkhosh and Fattahi (2025) proposed distributed coordination between EV aggregators and distributed generators, allowing independent agents to optimize operation while maintaining acceptable network voltages. Such approaches support demand-side management because they shift EV electricity consumption without eliminating the energy required for mobility.

Dynamic tariffs can further influence charging behavior. Wang et al. (2025) developed a tariff adjustment framework that aligns charging demand with renewable availability and network conditions. Ran et al. (2024) combined dynamic electricity pricing with V2G scheduling in a coupled transportation and power network, showing that charging and discharging decisions can reduce load fluctuations and charging costs. These studies indicate that pricing can support grid objectives when price formation incorporates network conditions rather than using fixed or uniform charging tariffs.

Voltage Stability, Peak Demand, and Energy Efficiency

Voltage stability is a major concern in radial distribution networks because increased current produces larger voltage drops along feeders. High EV penetration can therefore create greater deviations at electrically distant buses. Muthusamy et al. (2024) demonstrated that optimized EVCS integration can improve the voltage stability index while substantially reducing power losses. Thangaraj et al. (2023) similarly found that strategic integration of EV charging with distributed generation and reactive-power support can reduce real power losses and strengthen voltage performance under uncertain load conditions.

Charging-station location also influences voltage and reliability. Kumar and Aneesa Farhan (2024) showed that joint allocation of charging stations and capacitors can reduce energy-loss costs while improving distribution-system reliability. Soliman et al. (2024) demonstrated that combining EVCS allocation, distributed generation, V2G capability, and reactive compensation can improve voltage stability and minimize total energy losses. Yuvaraj et al. (2024) also reported that coordinated placement of charging stations, distributed generation, and DSTATCOM resources can mitigate the effect of charging demand on radial distribution systems.

Energy loss represents another critical performance measure. Distribution losses increase approximately with the square of branch current, so high simultaneous charging can have a disproportionate effect on energy efficiency. Kashki et al. (2024) demonstrated that optimized charging and distributed energy management can reduce network losses and voltage deviations. Panda and Ganguly (2025) further showed that coordinated G2V and V2G scheduling, combined with network reconfiguration, can reduce energy losses, lower peak demand, and improve voltage profiles. These results support a multi-indicator evaluation in which voltage quality, peak demand, and efficiency are assessed together.

Renewable-Aware Charging and Vehicle-to-Grid Operation

Renewable-aware charging links EV energy consumption to the availability of renewable generation. This approach is particularly useful in distribution systems with photovoltaic generation because daytime charging can absorb locally generated electricity that might otherwise create reverse power flows or curtailment. Alhasnawi et al. (2025) proposed smart EV charging that increases the utilization of renewable and distributed resources while reducing dependence on the main grid. The integration of renewable generation and EV charging therefore provides an opportunity to coordinate transport electrification with distribution-system decarbonization.

However, renewable generation introduces uncertainty. Solar and wind output vary with environmental conditions and do not necessarily coincide with EV charging demand. The scenario-based analysis of Putra et al. (2025) confirms that both PV generation and EV charging uncertainty influence voltage and distribution losses. This uncertainty makes deterministic schedules less robust when actual operating conditions differ from forecasts. Renewable-aware charging therefore requires flexible schedules that can adapt to changing supply and demand conditions.

V2G creates an additional flexibility mechanism by allowing EV batteries to discharge electricity to the grid. Liang et al. (2024) showed that incorporating V2G into coordinated transportation and distribution-network planning can increase network flexibility while accounting for user routing and charging decisions. Abdelfattah et al. (2024) demonstrated that bidirectional charging can reduce feeder stress and improve voltage conditions when charging and discharging are scheduled strategically. However, V2G must preserve minimum battery energy for mobility and limit unnecessary cycling.

Battery health is particularly important when EVs participate repeatedly in grid services. Panda and Ganguly (2025) incorporated battery-health considerations directly into V2G scheduling. González-Garrido et al. (2024) also included battery-aging effects in collaborative charging control. These studies suggest that technically beneficial V2G schedules should not rely on unrestricted battery cycling. A realistic optimization model should therefore enforce state-of-charge limits, departure requirements, charger ratings, and mutually exclusive charging and discharging states.

Multi-Objective Optimization and Uncertainty

EV charging creates conflicting objectives. Distribution operators seek lower peak demand, losses, congestion, and voltage deviations, while EV users prioritize charging completion, low cost, convenience, and battery preservation. Wang et al. (2024) formalized this conflict through a multi-objective framework that jointly considered network operation costs, distribution losses, and user charging costs. The study showed that Pareto-based optimization provides a more informative solution than focusing on a single objective.

Advanced optimization techniques have consequently become common in EV integration studies. Liu et al. (2023) used deep reinforcement learning for EV charging scheduling while considering distribution-network voltage stability. Lin et al. (2024) applied intelligent optimization to coordinate charging decisions with network and demand-response conditions. Muthusamy et al. (2024) used the honey badger optimization algorithm to address charging-station integration and multi-objective grid performance. These approaches differ computationally, but they share the goal of finding charging decisions that satisfy technical constraints while improving multiple performance measures.

Uncertainty is equally important because EV availability and energy requirements depend on human mobility. Abdelaziz et al. (2024) modeled stochastic EV demand using travel behavior before optimizing charging-station allocation. Pagidipala and Vuddanti (2024) incorporated uncertainties in EVCS demand and renewable generation through probabilistic modeling. Khan et al. (2025) used Monte Carlo modeling to represent charging-time and travel uncertainty within renewable-aware charging. This evidence supports stochastic evaluation rather than relying on a single deterministic EV profile.

Research Gap and Conceptual Positioning

The literature confirms that smart charging can improve distribution-grid operation, but existing studies remain fragmented across planning and operational objectives. Okika and Musonda (2025) concluded that smart charging, V2G, renewable-powered charging, battery technologies, and charging infrastructure all contribute to EV-grid integration, yet practical optimization must coordinate these technologies rather than assess them independently. Ferraz et al. (2025) similarly identified uncertainty, user behavior, environmental objectives, and multiple operational constraints as continuing gaps in EVCS optimization research.

Another limitation is the dominance of individual optimization scenarios. Some studies optimize EVCS location, while others optimize charging cost, renewable utilization, network losses, or voltage. Sahoo et al. (2025) jointly considered placement and scheduling. Alizadeh et al. (2025) integrated EVCS and battery-storage planning with real-time operational control. These studies advance the field but do not eliminate the need for a controlled comparison of fundamentally different charging strategies under identical EV, network, and renewable conditions.

The present study therefore adopts a demand-side flexibility perspective. It treats EV charging strategy as an operational decision that determines the temporal direction and magnitude of EV power exchange with the distribution grid. Four progressively flexible strategies are compared: uncontrolled charging, coordinated charging, renewable-aware charging, and V2G charging. This design separates the effect of charging strategy from changes in network configuration. It also provides a consistent basis for evaluating voltage stability, peak demand, energy losses, grid efficiency, and charging cost.

Hypothesis Development

Optimized EV Charging and Voltage Stability

EV charging increases active-power demand at distribution buses and raises current flow through upstream feeders. When charging occurs simultaneously, the additional current can increase voltage drops and cause buses to approach operating limits. Hasan et al. (2023) showed that EV charging profiles can create distinct periods of voltage violation and that coordination can substantially reduce these problems. Hernández-Gómez et al. (2024) confirmed that high-power charging can intensify voltage drops in distribution networks.

Optimized charging can reduce this effect by limiting or shifting charging demand when voltage conditions become unfavorable. Grammenou et al. (2024) demonstrated that optimized EV charging can improve voltage profiles while reducing distribution losses. Therefore, the first hypothesis is:

> ***H1: Optimized electric vehicle charging significantly improves voltage stability in smart distribution grids compared with uncontrolled charging.***

Optimized EV Charging and Peak Demand

Uncontrolled charging can create a secondary demand peak when EV arrival times overlap with existing residential or commercial peak periods. Coordinated charging can shift flexible demand toward periods with greater network capacity. Lin et al. (2024) demonstrated that intelligent charging and demand-response coordination can reduce peak loading. Xiao et al. (2024) also showed that temporal-spatial charging coordination reduces load variation while satisfying EV charging requirements.

Distribution-system intervention can further prevent excessive synchronization. Lilienkamp and Namockel (2025) found that targeted intervention strategies can alleviate congestion created by flexible charging behavior. This leads to the second hypothesis:

H2: Optimized electric vehicle charging significantly reduces peak grid demand compared with uncontrolled charging.

Optimized EV Charging and Energy Efficiency

Distribution losses depend strongly on branch current. Concentrated charging increases current and consequently increases resistive losses. Wang et al. (2024) demonstrated that coordinated multi-objective charging can reduce distribution-network losses while balancing operator and user objectives. Kashki et al. (2024) similarly reported lower energy losses when EV charging was incorporated into an optimized energy-management framework.

Improved scheduling can therefore raise grid efficiency by distributing charging demand more evenly across the operating horizon. Soliman et al. (2024) showed that coordinated EV integration with supporting distributed resources can reduce energy losses and improve voltage stability. Accordingly:

H3: Optimized electric vehicle charging significantly reduces distribution energy losses and improves grid energy efficiency compared with uncontrolled charging.

Advanced Grid-Aware Charging and Overall Grid Performance

Conventional coordinated charging primarily controls when EVs consume electricity. Renewable-aware charging additionally considers local generation, while V2G allows EVs to return energy to the grid. This increased flexibility should provide stronger technical benefits. Liang et al. (2024) showed that V2G can increase distribution-network flexibility when charging infrastructure and user decisions are properly coordinated. Ran et al. (2024) found that V2G combined with dynamic pricing can reduce load fluctuations while maintaining charging requirements.

Renewable-aware charging can also align EV demand with periods of high clean-energy availability. Khan et al. (2025) demonstrated that dynamic renewable-based charging can reduce load variance. Panda and Ganguly (2025) showed that bidirectional scheduling can simultaneously improve peak demand, losses, voltage profiles, and charging costs. Therefore:

H4: Grid-aware renewable and bidirectional charging strategies significantly improve overall distribution-grid performance compared with conventional coordinated and uncontrolled charging.

Research Methods

Research Design and Simulation Scenarios

This study used a quantitative simulation-based comparative design. A modified IEEE 33-bus radial distribution system served as the test network because it provides a standardized configuration for examining voltage behavior, loading, and distribution losses. The system was evaluated over a 24-hour operating horizon divided into fixed intervals Δt. The model incorporated conventional load, EV charging demand, and photovoltaic generation. The simulation included 300 EVs, 900 kW of installed photovoltaic capacity, and 200 Monte Carlo replications. Four scenarios were evaluated under identical network and EV conditions: S0, uncontrolled charging; S1, coordinated smart charging; S2, renewable-aware coordinated charging; and S3, bidirectional V2G charging. The same EV population, arrival and departure profiles, initial state of charge, battery capacities, conventional load, and renewable profiles were used across scenarios. This common-condition design allowed differences in grid performance to be attributed to the charging strategy.

EV Battery Model

For EV i, the state of charge at the next simulation interval was calculated using Equation (1). Charging and discharging efficiencies were modeled separately so that bidirectional operation did not assume loss-free battery conversion.

$$\mathrm{SOC}_{i,t+1} = \mathrm{SOC}_{i,t} + \frac{\eta_i^{ch} P_{i,t}^{ch} \Delta t}{E_i^{cap}} - \frac{P_{i,t}^{dis} \Delta t}{\eta_i^{dis} E_i^{cap}} \tag{1}$$

Battery state of charge was maintained within the technical limits shown in Equation (2), while Equation (3) required each vehicle to reach the minimum departure state of charge needed for the next trip.

$$\mathrm{SOC}_i^{min} \le \mathrm{SOC}_{i,t} \le \mathrm{SOC}_i^{max} \tag{2}$$

$$\mathrm{SOC}_{i,t_i^{dep}} \ge \mathrm{SOC}_i^{req} \tag{3}$$

Simultaneous charging and discharging were prevented using the binary variable z_i,t. The charging and discharging power constraints are given in Equations (4) and (5), where the maximum values reflect charger and battery limits.

$$0 \le P_{i,t}^{ch} \le z_{i,t} P_i^{ch,max} \tag{4}$$

$$0 \le P_{i,t}^{dis} \le \left(1 - z_{i,t}\right) P_i^{dis,max}, \qquad z_{i,t} \in \{0,1\} \tag{5}$$

Multi-Objective Optimization

The optimization minimized voltage deviation, total distribution energy loss, peak demand, and net EV charging cost. Because these indicators use different units, each objective was normalized before aggregation. The objective function is given in Equation (6), subject to the non-negative weighting structure in Equation (7).

$$\min J = w_V \widetilde{VD} + w_L \tilde{E}_{loss} + w_P \tilde{P}_{peak} + w_C \tilde{C}_{EV} \tag{6}$$

$$w_V + w_L + w_P + w_C = 1, \qquad w_k \ge 0 \tag{7}$$

Voltage deviation was measured across all buses and time intervals using Equation (8). The nominal reference voltage was 1.0 p.u., and acceptable operating voltage was constrained between 0.95 and 1.05 p.u. as expressed in Equation (9).

$$VD = \sum_{t \in \mathcal{T}} \sum_{b \in \mathcal{B}} \left| V_{b,t} - V^{ref} \right| \tag{8}$$

$$V^{min} \le V_{b,t} \le V^{max} \tag{9}$$

Energy Loss, Peak Demand, and Charging Cost

Total electrical energy loss was obtained by integrating branch resistive losses over the simulation horizon, as shown in Equation (10). Peak demand was defined as the maximum net power drawn from the upstream grid in Equation (11).

$$E_{loss} = \sum_{t \in \mathcal{T}} \sum_{\ell \in \mathcal{L}} R_\ell \left| I_{\ell,t} \right|^2 \Delta t \tag{10}$$

$$P_{peak} = \max_{t \in \mathcal{T}} P_{grid,t} \tag{11}$$

Net EV charging cost incorporated electricity purchases and V2G compensation using Equation (12). Grid energy efficiency was calculated from the relationship between distribution energy losses and total input energy using Equation (13).

$$C_{EV} = \sum_{t \in \mathcal{T}} \left[\lambda_t^{buy} \sum_i P_{i,t}^{ch} - \lambda_t^{sell} \sum_i P_{i,t}^{dis} \right] \Delta t \tag{12}$$

$$\eta_{grid} = \left(1 - \frac{E_{loss}}{E_{in}}\right) \times 100\% \tag{13}$$

Uncertainty and Statistical Analysis

Monte Carlo simulation represented uncertainty in EV arrival time, departure time, initial SOC, charging-energy requirement, conventional demand, and photovoltaic output. The same stochastic realization was applied to all four charging scenarios within each replication to provide paired and directly comparable outcomes. Primary outcomes were minimum bus voltage, mean voltage deviation, voltage-limit violations, peak demand, total energy loss, grid energy efficiency, and charging cost. Differences among the four strategies were tested at $p < 0.05$. The Friedman test was applied to the paired stochastic outcomes, followed by Wilcoxon signed-rank comparisons with Holm adjustment when appropriate. Kendall's W was reported as the effect-size measure. Sensitivity to EV penetration and renewable-generation conditions was evaluated to assess robustness.

Results and Discussion

The simulation evaluated four EV charging strategies under identical operating conditions in the modified IEEE 33-bus distribution system. The model included 300 EVs, 900 kW of installed photovoltaic capacity, a 24-hour operating horizon, and 200 Monte Carlo replications. The stochastic simulation varied EV arrival time, departure time, initial state of charge, required charging energy, conventional electricity demand, and photovoltaic generation. Voltage-limit violations were identified when bus voltage fell below 0.95 p.u. or exceeded 1.05 p.u. The results show substantial performance differences among the four charging strategies.

Overall Distribution Grid Performance

The simulation results indicate substantial differences among the four charging strategies. Uncontrolled charging created the highest technical stress on the distribution system. It produced the lowest minimum bus voltage, the greatest number of voltage violations, the highest peak demand, and the highest daily energy loss. Coordinated charging improved all major indicators, while renewable-aware and V2G strategies produced additional benefits. Table 1 summarizes the principal performance measures.

Table 1. Distribution Grid Performance under Alternative EV Charging Strategies

Performance Indicator	S0 Uncontrolled	S1 Coordinated	S2 Renewable-Aware	S3 V2G
Minimum bus voltage (p.u.)	0.9058 ± 0.0040	0.9427 ± 0.0019	0.9446 ± 0.0016	0.9433 ± 0.0022
Mean voltage deviation (p.u.)	0.02568 ± 0.00037	0.02555 ± 0.00037	0.02554 ± 0.00037	0.02564 ± 0.00037
Voltage violations (bus-hour)	80.49 ± 3.16	35.27 ± 7.86	22.20 ± 5.95	24.17 ± 7.34
Peak grid demand (kW)	3446.06 ± 81.20	2383.98 ± 50.08	2383.98 ± 50.08	2234.71 ± 49.84
Daily energy loss (kWh)	1397.12 ± 31.35	1244.05 ± 24.65	1229.09 ± 25.50	1243.24 ± 25.83
Grid energy efficiency (%)	97.292 ± 0.053	97.582 ± 0.040	97.610 ± 0.042	97.588 ± 0.043
Daily EV charging cost (USD-equivalent)	1482.57 ± 30.48	994.56 ± 23.85	992.18 ± 22.82	986.18 ± 22.92

Source: Numerical simulation and statistical analysis processed by the authors (2026).

Table 1 shows that the optimized strategies did not provide identical benefits. Renewable-aware charging produced the strongest voltage and energy-efficiency performance. V2G produced the lowest peak demand and charging cost. This distinction is important because charging optimization involves trade-offs among technical and economic objectives rather than a single universally dominant solution. Wang et al. (2024) reached a similar conclusion through multi-objective EV charging optimization, where charging cost, network loss, and grid operating requirements needed to be balanced simultaneously.

Voltage Stability Improvement

Uncontrolled charging reduced the minimum network voltage to 0.9058 p.u., which fell below the specified lower operating limit of 0.95 p.u. The result indicates that concentrated EV charging can create considerable voltage stress, especially at buses located farther from the source. Hasan et al. (2023) also found that concentrated EV charging increases the probability of voltage violations in distribution networks.

Coordinated charging increased the minimum voltage to 0.9427 p.u. Renewable-aware charging produced the highest minimum voltage at 0.9446 p.u., while V2G achieved 0.9433 p.u. Although the mean minimum-voltage values remained slightly below 0.95 p.u. during the most severe stochastic conditions, the optimized strategies significantly reduced both the magnitude and duration of voltage violations.

The number of voltage violations provides stronger evidence of this improvement. S0 recorded an average of 80.49 bus-hour violations. S1 reduced this value to 35.27 bus-hour, while S2 produced only 22.20 bus-hour. S3 resulted in 24.17 bus-hour violations. Renewable-aware charging therefore reduced voltage violations by 72.42% relative to uncontrolled charging. Table 2 presents the improvement percentages relative to S0.

Table 2. Improvement of Optimized Charging Strategies Relative to Uncontrolled Charging

Performance Improvement	S1 Coordinated	S2 Renewable-Aware	S3 V2G
Increase in minimum voltage (%)	4.07	4.28	4.14
Reduction in mean voltage deviation (%)	0.53	0.58	0.16
Reduction in voltage violations (%)	56.18	72.42	69.98
Reduction in peak demand (%)	30.82	30.82	35.15
Reduction in daily energy losses (%)	10.96	12.03	11.01
Increase in grid efficiency (percentage points)	0.289	0.318	0.295
Reduction in charging cost (%)	32.92	33.08	33.48

Source: Numerical simulation and statistical analysis processed by the authors (2026).

The superior voltage performance of S2 can be explained by the synchronization of charging demand with photovoltaic generation. Local PV output reduces the amount of power supplied through upstream distribution branches during charging periods. This reduces feeder current and limits voltage drops. Grammenou et al. (2024) reported comparable improvements when EV charging and PV resources were coordinated within distribution networks.

V2G also provided strong voltage support because EV batteries could discharge limited energy during high-demand periods. Abdelfattah et al. (2024) showed that scheduled bidirectional charging can reduce feeder loading and improve network voltage profiles. However, S3 did not outperform S2 for minimum voltage because bidirectional energy exchange creates additional battery charging requirements at other periods. These findings support H1, which proposed that optimized EV charging improves voltage stability compared with uncontrolled charging.

Peak Demand Reduction

Peak demand reached 3446.06 kW under uncontrolled charging. Coordinated charging reduced this value to 2383.98 kW. Renewable-aware charging produced the same maximum grid-demand level, while V2G reduced the peak further to 2234.71 kW. The 30.82% reduction produced by S1 demonstrates the effectiveness of temporal charging coordination. Instead of allowing vehicles to begin charging immediately after connection, the optimization shifted flexible EV loads toward periods with greater available distribution capacity. Xiao et al. (2024) similarly found that coordinated EV scheduling can flatten the daily load profile while maintaining user charging requirements.

V2G achieved the strongest peak-load reduction at 35.15%. The strategy reduced peak demand by 1211.35 kW compared with uncontrolled charging. EVs therefore acted as distributed storage resources during critical demand periods. Liang et al. (2024) demonstrated that bidirectional EV operation can increase distribution-network flexibility when mobility constraints are incorporated into scheduling decisions. The distinction between S2 and S3 clarifies their different functions. Renewable-aware charging mainly moves electricity consumption toward periods with greater local renewable generation, whereas V2G can actively reduce net grid demand through battery discharge. The results support H2.

Energy Loss and Grid Efficiency

Uncontrolled charging generated 1397.12 kWh of average daily distribution loss. S1 reduced energy loss to 1244.05 kWh. S2 achieved the lowest loss at 1229.09 kWh, while S3 produced 1243.24 kWh. Renewable-aware charging therefore reduced daily losses by 168.03 kWh, equivalent to 12.03% relative to uncontrolled charging. The improvement follows the electrical relationship between line current and resistive losses. As branch losses increase approximately with I^2R, reducing concentrated feeder current can produce a substantial reduction in energy losses. Kashki et al. (2024) also found that optimized EV charging can reduce network losses through improved energy management.

Grid efficiency increased from 97.292% under S0 to 97.582% under S1. S2 produced the highest value at 97.610%, while S3 reached 97.588%. S2 slightly outperformed S3 for both losses and efficiency. This result shows that V2G does not automatically minimize distribution losses because bidirectional charging requires energy to pass through the battery and charging equipment more than once. Panda and Ganguly (2025) similarly showed that V2G optimization involves trade-offs among loss minimization, peak shaving, battery operation, and charging costs. The results support H3.

Charging Cost

Uncontrolled charging produced an average daily EV charging cost of USD-equivalent 1482.57. Coordinated charging reduced this value to 994.56. Renewable-aware charging lowered it further to 992.18, while V2G achieved the lowest cost at 986.18. The cost reduction reached 33.48% under S3 because the optimization shifted charging toward lower-cost periods and permitted EV owners to receive limited compensation for electricity exported during V2G operation. Zhang et al. (2024) showed that coordinated interaction between charging stations, distribution networks, and EV users can reduce charging costs while maintaining system security.

The economic advantage of V2G should nevertheless be interpreted carefully. The reported charging cost represents energy purchasing and V2G compensation within the operational simulation. It does not represent the full lifetime cost of additional battery degradation. Frequent cycling can reduce battery life and change the economic attractiveness of V2G. Practical V2G operation should therefore prioritize high-value grid-support periods rather than continuous battery discharge.

Statistical Comparison

The study used the Friedman test because the four charging strategies were evaluated using the same 200 stochastic operating realizations. The test identified statistically significant differences across all major technical and economic indicators, as shown in Table 3.

Table 3. Statistical Differences among EV Charging Strategies

Performance Indicator	Friedman χ^2	p-value	Kendall's W	Effect Magnitude
Minimum bus voltage	488.54	<0.001	0.814	Large
Mean voltage deviation	600.00	<0.001	1.000	Very large
Voltage violations	549.47	<0.001	0.916	Very large
Peak grid demand	600.00	<0.001	1.000	Very large
Daily energy loss	541.94	<0.001	0.903	Very large
Grid energy efficiency	576.50	<0.001	0.961	Very large
EV charging cost	524.45	<0.001	0.874	Large

Source: Numerical simulation and statistical analysis processed by the authors (2026).

All tests produced $p < 0.001$, indicating systematic differences among the charging strategies. Kendall's W values ranged from 0.814 to 1.000, which indicates large to very large differences among the scenarios. Post-hoc Wilcoxon signed-rank comparisons with Holm adjustment confirmed significant differences between uncontrolled charging and each optimized strategy for the principal technical indicators at $p < 0.001$. The stochastic design strengthens these findings because EV arrival time, departure time, SOC, conventional load, and photovoltaic output changed across replications. Pagidipala and Vuddanti (2024) emphasized that uncertainty in renewable generation and EV charging demand can influence distribution-network optimization outcomes.

Putra et al. (2025) reached a similar conclusion in their probabilistic analysis of EV charging and photovoltaic integration. The present results extend that evidence by comparing four charging-control strategies using paired stochastic operating conditions rather than evaluating only a single charging configuration.

Comparative Performance of Renewable-Aware Charging and V2G

The results do not identify one charging strategy as superior for every objective. S2 achieved the highest minimum voltage, lowest voltage deviation, fewest voltage violations, lowest daily energy losses, and highest grid energy efficiency. In contrast, S3 achieved the lowest peak demand and lowest charging cost. Renewable-aware charging therefore appears more suitable when distribution-system operators prioritize voltage quality, technical efficiency, and utilization of local renewable generation. Its 72.42% reduction in voltage violations and 12.03% reduction in energy losses demonstrate this advantage.

V2G becomes more attractive when peak-load management has greater priority. Its 35.15% reduction in peak grid demand exceeded the reduction achieved by unidirectional optimized charging. Hossain et al. (2023) identified peak shaving as one of the primary technical services that EV batteries can provide to smart grids. A combined operating policy may therefore provide a stronger practical solution than the permanent use of one charging mode. Under normal operating conditions, distribution operators could prioritize renewable-aware charging. During periods of severe feeder loading or system peaks, the control system could activate V2G support from eligible vehicles.

Hypothesis Evaluation

The simulation and statistical analyses support the four hypotheses proposed in this study. Table 4 summarizes the empirical criteria and decisions.

Table 4. Hypothesis Testing Results

Hypothesis	Evaluation Criterion	Empirical Result	Decision
H1	Optimized charging improves voltage stability	Minimum voltage increased from 0.9058 to 0.9446 p.u.; voltage violations fell by up to 72.42%	Supported

H2	Optimized charging reduces peak demand	Peak demand decreased from 3446.06 to 2234.71 kW	Supported
H3	Optimized charging reduces losses and improves efficiency	Energy losses decreased by up to 12.03%; efficiency increased to 97.610%	Supported
H4	Advanced charging improves overall grid performance	S2 dominated voltage and efficiency; S3 dominated peak-load and cost measures	Supported

Source: Numerical simulation and statistical analysis processed by the authors (2026).

H1 received support because the optimized charging strategies improved minimum bus voltage and significantly reduced voltage violations. H2 received support because all optimized scenarios lowered peak demand, with V2G producing the greatest reduction. H3 received support because optimized charging reduced daily distribution energy losses and increased overall grid efficiency. H4 also received support because renewable-aware and V2G strategies provided greater overall flexibility than uncontrolled and conventional coordinated charging, although their strongest technical benefits occurred on different performance dimensions.

Discussion and Implications

The findings demonstrate that EV integration does not affect distribution networks solely through the amount of additional electricity consumed. The timing, location, and direction of power exchange determine the magnitude of network stress. Uncontrolled charging provided the weakest performance because charging demand was concentrated without reference to feeder loading, voltage conditions, electricity prices, or renewable generation. Coordinated charging substantially improved system operation without requiring bidirectional chargers. Chandra et al. (2024) identified coordinated charging as an important mechanism for accommodating higher EV penetration without relying entirely on conventional network reinforcement.

Renewable-aware charging produced the strongest overall technical performance in terms of voltage and energy efficiency because it matched flexible EV demand with local PV availability. Khan et al. (2025) similarly demonstrated that renewable-linked dynamic charging can improve grid operation by aligning EV demand with available renewable energy. V2G produced the strongest peak-demand reduction and the lowest daily charging cost, but its slightly higher energy losses compared with S2 show that bidirectional charging should not be evaluated solely by its peak-shaving capability. Battery efficiency, degradation, user availability, and compensation mechanisms must remain part of the operational decision.

The findings also have direct relevance for distribution systems undergoing rapid EV growth. Putra et al. (2025) found that EV charging can increase network losses and worsen voltage conditions in an Indonesian distribution-system context. The present results show that these effects can be substantially reduced through charging optimization. Renewable-aware coordination may provide particular value in systems that simultaneously expand EV and distributed photovoltaic adoption. Distribution operators do not need to apply V2G continuously. Renewable-aware charging can serve as the normal operating strategy, while V2G can operate selectively when peak demand, feeder congestion, or voltage stress exceeds predetermined thresholds.

Overall, optimized EV charging can transform EV demand from an additional distribution-system burden into a flexible grid resource. Renewable-aware charging produced the strongest voltage and energy-efficiency performance, while V2G delivered the greatest peak-demand and charging-cost benefits. The optimal strategy therefore depends on the distribution system's operational priority. A smart charging framework that combines coordinated charging, renewable availability, and selective V2G support provides the most balanced pathway for maintaining grid stability and improving energy efficiency under increasing EV penetration.

Conclusion

This study demonstrates that electric vehicle charging strategy has a significant effect on the stability and energy efficiency of smart distribution grids. The simulation of a modified IEEE 33-bus system showed that uncontrolled charging created the highest network stress, while coordinated, renewable-aware, and V2G strategies improved system performance. Renewable-aware charging produced the best voltage and efficiency outcomes, with voltage violations reduced by 72.42%, daily energy losses reduced by 12.03%, and grid efficiency increased to 97.610%. V2G charging provided the strongest peak-shaving benefit by reducing peak demand by 35.15% and also produced the lowest daily charging cost. The statistical analysis confirmed significant differences among the charging strategies at $p < 0.001$, supporting all proposed hypotheses.

The findings indicate that no single charging strategy dominates every operational objective. Renewable-aware charging is more suitable when voltage quality, loss reduction, and renewable-energy utilization are the main priorities, while V2G is more effective for peak-demand management and cost reduction. A practical smart-grid framework should therefore combine coordinated charging with renewable-aware scheduling and activate V2G selectively during periods of high network stress. Future research should extend the model using real distribution-network data, dynamic electricity tariffs, battery degradation costs, larger EV populations, and higher renewable penetration to evaluate the long-term technical and economic performance of adaptive EV charging strategies.

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Author Contributions

Conceptualization: Putri Ayu Maharani; Reza Maulana Firmansyah
Data curation: Reza Maulana Firmansyah; Ilham Fadli Setiawan
Formal analysis: Putri Ayu Maharani; Ilham Fadli Setiawan
Investigation: Putri Ayu Maharani; Reza Maulana Firmansyah; Ilham Fadli Setiawan
Methodology: Putri Ayu Maharani; Reza Maulana Firmansyah
Project administration: Putri Ayu Maharani
Supervision: Reza Maulana Firmansyah
Validation: Reza Maulana Firmansyah; Ilham Fadli Setiawan
Visualization: Ilham Fadli Setiawan
Writing - original draft: Putri Ayu Maharani; Reza Maulana Firmansyah
Writing - review and editing: Putri Ayu Maharani; Reza Maulana Firmansyah; Ilham Fadli Setiawan

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Conflict of Interest

The authors declare that they have no conflict of interest related to this manuscript.

Statement on the Use of Artificial Intelligence

The authors used OpenAI ChatGPT and Anthropic Claude AI to assist with language refinement, grammatical editing, structural organization, and improving the clarity and readability of the manuscript. These tools were not used as authors and did not replace the authors' responsibility for the scientific content, methodological decisions, data analysis, interpretation of results, or verification of references. All AI-assisted output was reviewed and verified by the authors, who take full responsibility for the originality, accuracy, integrity, and final content of the manuscript.

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