New Energy Exploitation and Application
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Article

Application of Mixed Strategist Dynamics and Grid-Oriented Optimization for Evaluation of Plug-in Electric Vehicle Load Scheduling

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Received: 19 October 2025; **Revised:** 19 December 2025; **Accepted:** 26 December 2025; **Published:** 6 February 2026

Abstract: This paper presents an enhanced and comprehensive framework for optimal scheduling of Plug-in Electric Vehicle (PEV) charging by integrating Mixed Strategist Dynamics (MSD) with Forward Dynamic Programming (FDP) to achieve both user-level fairness and grid-oriented optimization. The MSD mechanism generates probabilistic charging strategies that distribute demand across time slots while incorporating equity-based payoff functions to prevent synchronized charging peaks. Building on these probabilistic schedules, an FDP-based deterministic refinement layer is introduced to ensure accurate State-of-Charge (SoC) fulfilment, minimize operating cost, and satisfy grid operational constraints. To ensure technical feasibility, the proposed hybrid MSD–FDP approach is validated on the IEEE 34-bus radial distribution system using Backward/Forward-Sweep (BFS) power-flow analysis. A voltage-penalty cost component is incorporated to restrict bus-voltage deviations within 0.955–1.05 p.u. and to prevent transformer overloading under high EV penetration. The model also integrates Vehicle-to-Grid (V2G) capability, enabling controlled discharging during peak-load conditions to support voltage recovery and improve feeder stability. Simulation results demonstrate that the proposed hybrid framework achieves substantial improvements over MSD-only scheduling and uncoordinated charging. Peak-load demand is reduced by approximately 27%, and the minimum bus voltage is improved from 0.91 p.u. to 0.958 p.u. Additionally, fairness among EVs is significantly enhanced with entropy values averaging 1.77–1.79, indicating balanced access to charging resources. The findings confirm that coordinated charging with V2G support can effectively transform EV fleets into flexible distributed energy assets while ensuring cost efficiency, technical reliability, and scalability for real-world smart-grid applications.

Keywords: Plug-in Electric Vehicles (PEV); Mixed Strategist Dynamics (MSD); Forward Dynamic Programming (FDP); Grid-Oriented Optimization; Vehicle-to-Grid (V2G); IEEE 34-Bus

1. Introduction

The rapid electrification of transportation has become a key component in global sustainability and decarbonization initiatives. Plug-in Electric Vehicles (PEVs) play a significant role in reducing emissions and enabling flexible demand-side management. However, the increasing penetration of PEVs introduces substantial operational challenges to existing power distribution networks. When many vehicles charge simultaneously—particularly during evening peak hours—distribution feeders experience severe load spikes, transformer overloading, and voltage instability. These issues degrade system reliability and efficiency, especially in networks originally designed for predictable residential consumption.

To address these challenges, several charging-scheduling strategies have been proposed. Centralized optimiza-

https://doi.org/10.54963/neea.v5i1.1714

tion methods such as mixed-integer programming provide high-quality optimal solutions but require extensive communication, high computational power, and raise data-privacy concerns. In contrast, decentralized and game-theoretic scheduling frameworks offer better scalability and autonomy but often struggle to guarantee fairness among participating users, deterministic fulfillment of State-of-Charge (SoC) requirements, and strict compliance with grid operational limits. Additionally, most prior studies focus either on user-centric economic objectives or system-level voltage stability, without achieving a balanced integration of both perspectives.

To bridge this gap, this work presents a hybrid multi-layer scheduling architecture that integrates Mixed Strategist Dynamics (MSD) with Forward Dynamic Programming (FDP), incorporating realistic grid constraints and Vehicle-to-Grid (V2G) capability. MSD generates probabilistic charging distributions enhanced with fairness-oriented payoff functions, while FDP produces deterministic charging trajectories that satisfy SoC and operational grid constraints. A power-flow validation module based on Backward/Forward Sweep (BFS) enforces voltage limits and transformer loading constraints on the IEEE 34-bus system. V2G support further enables peak-load relief and voltage improvement through controlled discharging.

The novelty of this work lies in its unified scheduling framework that simultaneously ensures fairness, deterministic optimization, and grid reliability—achieving significant improvements in peak-load reduction, voltage quality, and operational cost efficiency under high PEV penetration.

Major Contributions of This Work

The major contributions of this work are summarized as follows:

1. Development of a hybrid MSD–FDP scheduling framework that combines probabilistic fairness-driven coordination with deterministic optimization for SoC fulfilment.
2. Introduction of a voltage-penalty cost formulation to enhance grid stability and enforce technical feasibility under realistic distribution-system constraints.
3. Integration of V2G capability to provide peak-load mitigation and support voltage regulation during high-demand periods.
4. Validation on the IEEE 34-bus feeder demonstrating real-world applicability using BFS power-flow analysis.
5. Significant performance improvements, achieving approximately 27% peak-load reduction and improving minimum bus voltage from 0.91 p.u. to 0.958 p.u. under coordinated scheduling.
6. Enhanced fairness among users, demonstrated through entropy-based equity metrics with values between 1.77–1.79, ensuring balanced access to charging resources.

The remainder of this paper is organized as follows. Section 2 describes the system model and the proposed MSD–FDP scheduling framework. Section 3 presents the simulation results and grid-level performance analysis. Section 4 discusses the implications and limitations of the proposed approach. Finally, Section 5 concludes the paper and outlines future research directions.

2. Materials and Methods

The proposed methodology is based on an integrated cyber-physical framework that models the interaction between Plug-in Electric Vehicles (PEVs), charging infrastructure, tariff signals, and distribution-grid operational constraints. The system enables fair, cost-efficient, and grid-safe charging coordination by combining probabilistic decision-making and deterministic optimization. Each vehicle is modelled as an energy-storage unit with a capacity of 20–24 kWh, and the State of Charge (SoC) is restricted between 20% and 90% to protect battery lifecycle. Level-2 charging (3.3 kW) and Vehicle-to-Grid (V2G) discharging (−3.2 kW) capabilities are considered along with realistic arrival and departure time variations.

The overall architecture consists of three functional layers—user layer, scheduling layer, and grid layer—as shown in **Figure 1**. The user layer models individual EV behavior and energy demand patterns. The scheduling layer coordinates charging using Mixed Strategist Dynamics (MSD) and Forward Dynamic Programming (FDP) to ensure fairness and deterministic fulfilment of SoC requirements. The grid layer evaluates technical feasibility through power-flow validation, enforcing voltage and transformer-loading constraints.

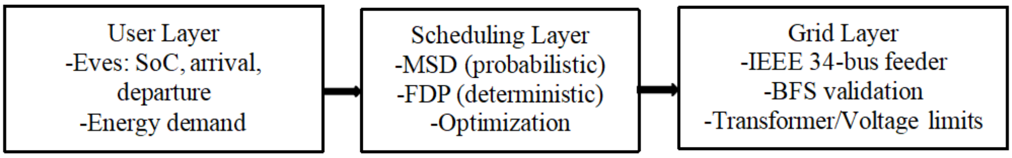


Figure 1. Three-layer scheduling framework for EV load management.

2.1. EV and System Modelling

The SoC transition of each vehicle is represented as:

$$SoC_i(t+1) = SoC_i(t) + \eta \cdot \frac{P_i(t) \cdot \Delta t}{C_{\text{bat},i}} \tag{1}$$

$$SoC_{min} \le SoC_i(t) \le SoC_{max}, \quad P_{min} \le P_i(t) \le P_{max} \tag{2}$$

where η represents the charging efficiency, $P_i(t)$ denotes the charging (positive) discharging (negative) power of vehicle i at time t, Δt is the scheduling interval, and $C_{bat,t}$ is the battery capacity of the i-th vehicle.

To ensure safe operation and limit battery degradation, the state of charge and charging power are constrained as shown in Equation (2).

Typical values used in this study are SoC_{min} = 20%, η = 95%, P_{max} = 3.3 kW, and P_{min} = −3.2 kW under V2G operation.

Charging and discharging losses during V2G operation are modeled through the efficiency parameter η, which accounts for inverter and battery conversion losses.

2.2. Mixed Strategist Dynamics (MSD)

MSD represents EVs as agents competing for limited charging opportunities using probabilistic rather than deterministic strategies to avoid synchronized peaks. The charging-strategy update rule is expressed as:

$$p_i(t+1) = p_i(t) + \alpha[U_i(t) - \bar{U}_i(t)]p_i(t) \tag{3}$$

$$U_i = -\lambda C_i - \beta T_i - \gamma W_i + \delta F_i \tag{4}$$

$$F_i = -(p_1 log(p_1) + p_2 log(p_2) + \dots + p_m log(p_m)) \tag{5}$$

where α is the learning rate, $P_i(t)$ represents the mixed strategy probability of vehicle i at time t, $U_i(t)$ denotes the individual payoff, and \bar{U}_i(t) is the average payoff across all strategies.

The payoff function integrates multiple objectives, including charging cost C_i, tariff penalty T_i, battery wear cost W_i, and a fairness rewar term F_i.

Fairness among users is quantified using an entropy-based measure, which encourages a balanced distribution of charging probabilities across users.

Higher entropy values indicate more equitable participation. MSD enables decentralized learning using only local information, improving scalability and privacy.

The overall MSD process is illustrated in **Figure 2**.

2.3. Forward Dynamic Programming (FDP)

FDP refines MSD outputs into deterministic power trajectories and ensures SoC satisfaction while minimizing economic cost and grid impact. The SoC update rule is:

The state-of-charge transition during the FDP stage follows the EV system model defined in Equation (1).

$$J = \sum_{t=1}^{T} \left[(L_{\text{base}}(t) + P_i(t))^2 \cdot Tariff(t) + \lambda_v \cdot \emptyset(V_t) \right] \tag{6}$$

where $L_{base}(t)$ represents the non-EV demand, $Tariff(t)$ is the time-varying electricity price, λ_v is the voltage-penalty coefficient, and $\emptyset(V_t)$ is a voltage constraint function that penalizes deviations outside 0.95–1.05 p.u.

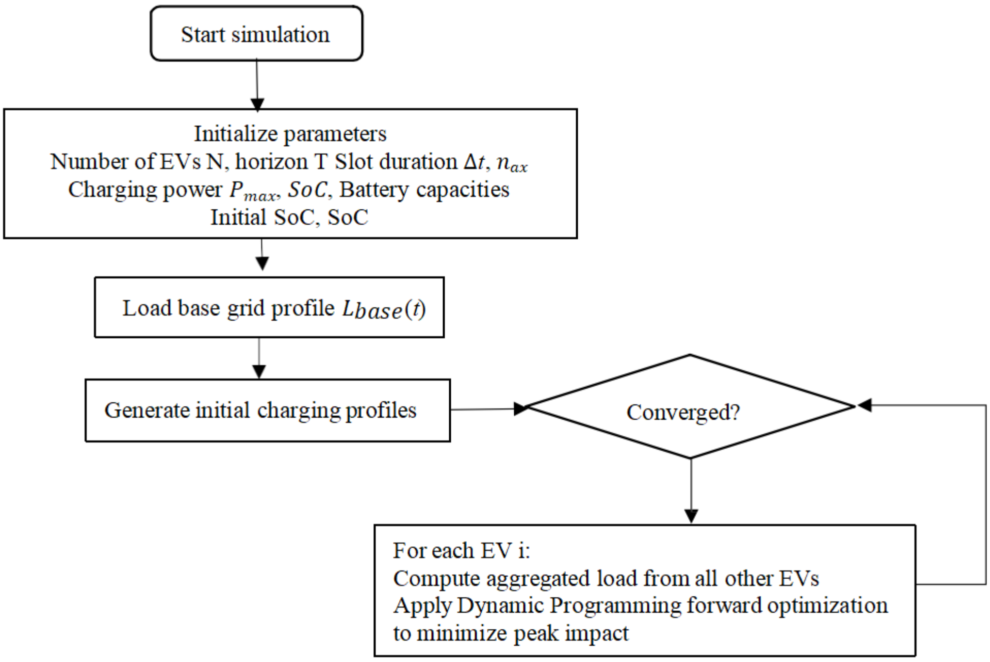


Figure 2. Flowchart of the Mixed Strategist Dynamics (MSD) scheduling process, showing probabilistic strategy updates based on fairness-aware payoffs.

2.4. Grid-Oriented Optimization

Grid validation is performed using the Backward/Forward-Sweep (BFS) power-flow algorithm on the IEEE 34-bus system to verify voltage limits and transformer loading. V2G operation provides controlled discharging during peak periods to enhance system stability and reduce peak loading (**Figure 3**).

$$P_{min} \leq P_i(t) \leq P_{max}, \quad SoC_i(t) \geq SoC_{min} \tag{7}$$

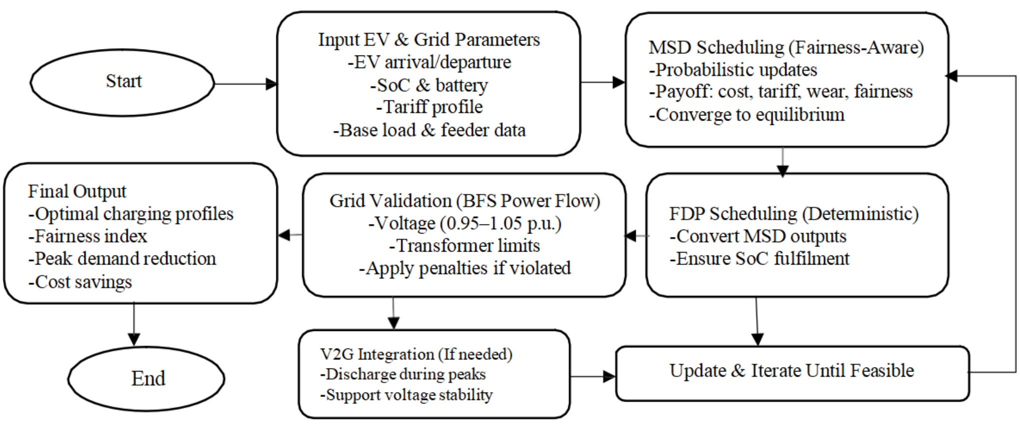


Figure 3. Overall scheduling framework integrating MSD, Forward Dynamic Programming (FDP), grid validation using Backward/Forward Sweep (BFS), and Vehicle-to-Grid (V2G) support.

Forward Dynamic Programming Flowchart Explanation: The proposed FDP algorithm operates in sequential stages to determine the optimal charging and discharging profile for each Plug-in Electric Vehicle (PEV). The process begins by initializing the vehicle parameters, including battery capacity, initial and desired SoC, and maximum charging power. In each time step, the algorithm evaluates all feasible actions (charging, discharging, or idle) while satisfying SoC and power limits. The instantaneous cost is computed using the time-dependent tariff and the voltage-penalty term derived from bus-voltage deviations. The algorithm then updates the SoC for the next state and accumulates the total cost across the scheduling horizon. This forward recursion continues until all time slots are processed. The optimal path, corresponding to the minimum cumulative cost, yields the final power trajectory that satisfies both cost minimization and grid-stability constraints.

2.5. Simulation Setup and Parameters

Simulations are conducted on the IEEE 34-bus distribution feeder with 10–50 vehicles and realistic residential demand profiles. **Table 1** summarizes the parameters used in performance evaluation, while **Tables 2** and **3** describe the case-study scenarios and feeder constraints.

Table 1. Simulation parameters used for performance evaluation.

Parameters	Values	Remarks
Number of EVs	10–50	Fleet size varied across scenarios
Battery capacity (C_{bat})	20–24 kWh	Compact to mid-size EVs
Charging efficiency (η)	95%	Typical Level-2 chargers
Discharging power (V2G)	0–3.2 kW	Enabled in V2G cases
SoC limits	20–90%	Preserves battery health
Arrival time (T_{a})	17:00–20:00	Residential evening plug-in
Departure time (T_{d})	06:00–08:00	Morning departure
Energy demand (E_{require})	8–15 kWh	Based on daily travel patterns
Scheduling interval (Δt)	15 min (96 slots/day)	Resolution for charging control
Charging power (P_{ch})	0–3.3 kW	Level-2 charging limit

Additional case studies and feeder parameters are detailed in **Tables 2** and **3**.

Table 2. Case-study configuration used to evaluate different coordination scenarios.

Case	Description	Key Features
Case 1	Uncoordinated charging	Immediate charging at arrival
Case 2	MSD scheduling without fairness	Probabilistic strategy updates only
Case 3	MSD scheduling with fairness	Entropy-based fairness payoff included
Case 4	FDP scheduling	Deterministic SoC fulfilment
Case 5	FDP with grid constraints and V2G integration	Voltage/transformer validation, V2G support

Table 3. IEEE 34-Bus Feeder Parameters and Operational Constraints.

Parameter	Value	Remarks
Nominal voltage	24.9 kV	Standard distribution level
Network configuration	Radial, long feeder	High R/X ratio, weak end buses
Transformer rating	30 kW	Local distribution transformer
Base load profile	Evening peak 18:00–22:00	Residential + light commercial demand
Voltage limits (p.u.)	0.95–1.05	IEEE Std.
Regulation devices	Regulators, capacitors	Limited support under high EV load
Constraint checks	Transformer loading, bus voltage	Applied during FDP iterations

3. Results

This section presents the performance evaluation of the proposed coordinated scheduling framework under various operational scenarios. The results analyse Mixed Strategist Dynamics (MSD), Forward Dynamic Programming (FDP), and grid-constrained optimization, focusing on convergence behavior, fairness improvement, peak-load reduction, voltage stability, and computational efficiency.

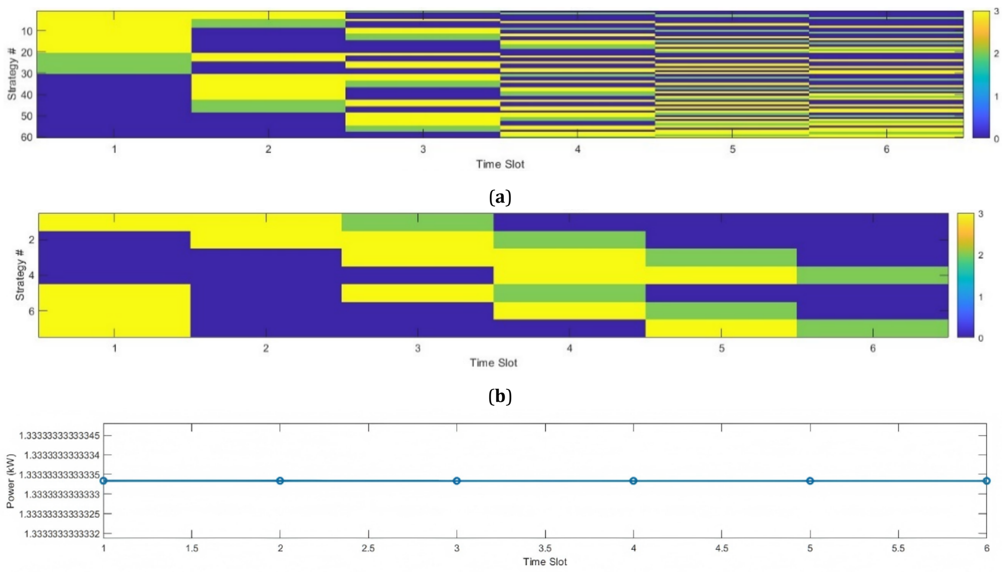
3.1. MSD-Based Scheduling Results

The application of Mixed Strategist Dynamics enables decentralized coordination among EVs by progressively reducing the number of feasible charging strategies from an initial set of sixty options to seven stable equilibria. This reduction significantly improves convergence speed and computational tractability. At equilibrium, the charging power is uniformly distributed at approximately 1.33 kW per time slot, with charging probabilities converging near 0.133.

Uncoordinated (immediate) charging results in steep evening load peaks that overload distribution transformers. In contrast, MSD scheduling effectively flattens the load curve by spreading charging demands across time, thereby preventing simultaneous charging and enhancing grid stability. The entropy-based fairness metric demonstrates balanced access to charging slots, achieving values between

1.77 and 1.79, indicating equitable participation.

Figures 4–9 illustrate the convergence of strategy sets, comparison of unmanaged versus MSD-managed charging, SoC trajectories, and improvements in fairness and aggregate load behavior. The results confirm that MSD avoids synchronized demand peaks and ensures reliable SoC fulfilment for all EVs.



(**a**)

(**b**)

(**c**)

Figure 4. Convergence of MSD charging strategies: (**a**) Full set of 60 feasible strategies; (**b**) Reduced set of 7 strategies; (**c**) Final equilibrium charging profile.

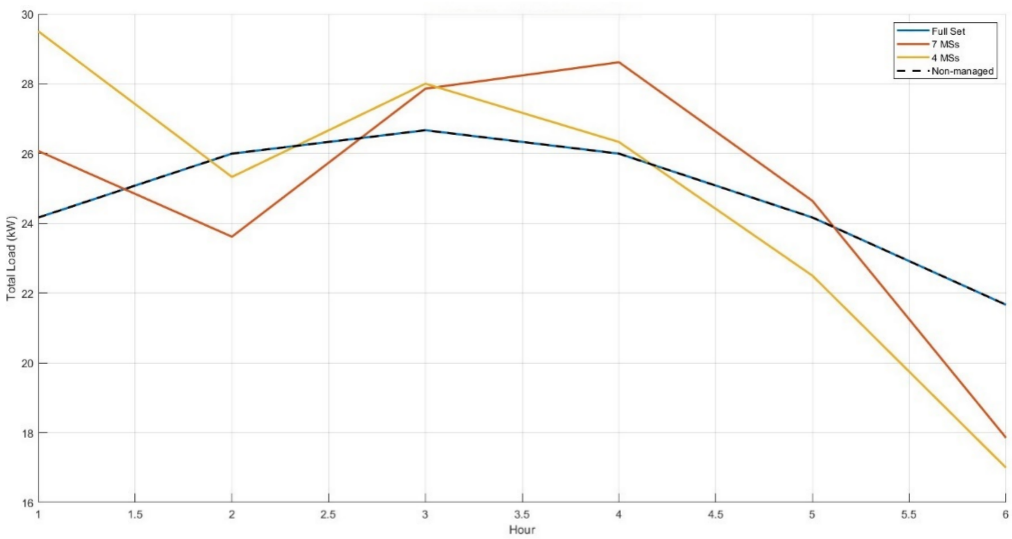


Figure 5. Total grid load under unmanaged charging and MSD-managed strategies.

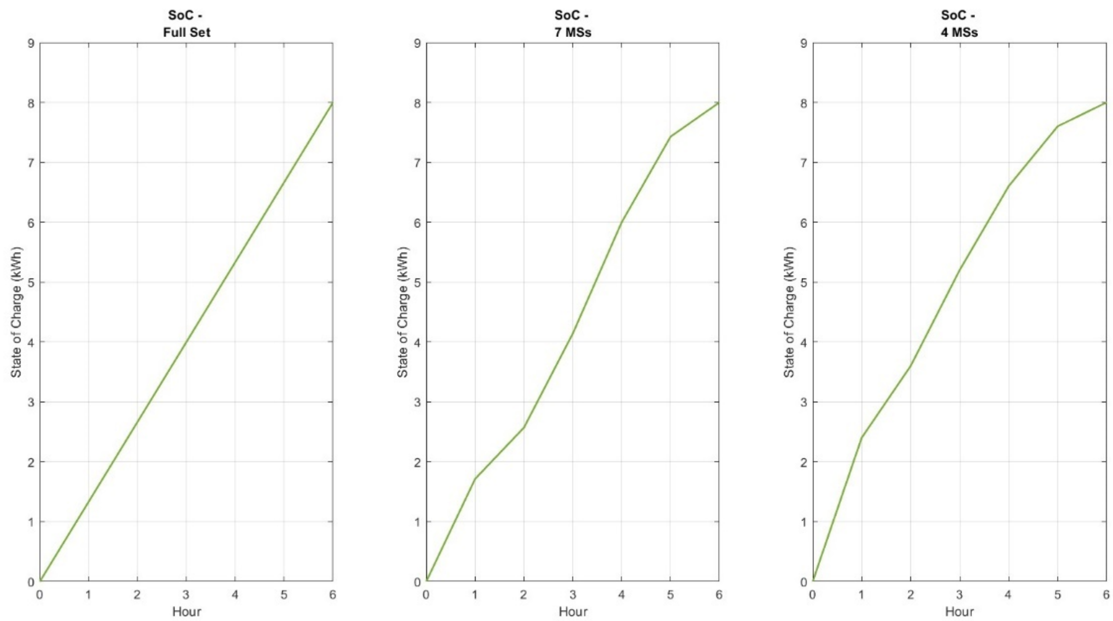


Figure 6. SoC trajectories under fairness-aware MSD-managed strategies (Full, 7-MS, and 4-MS sets).

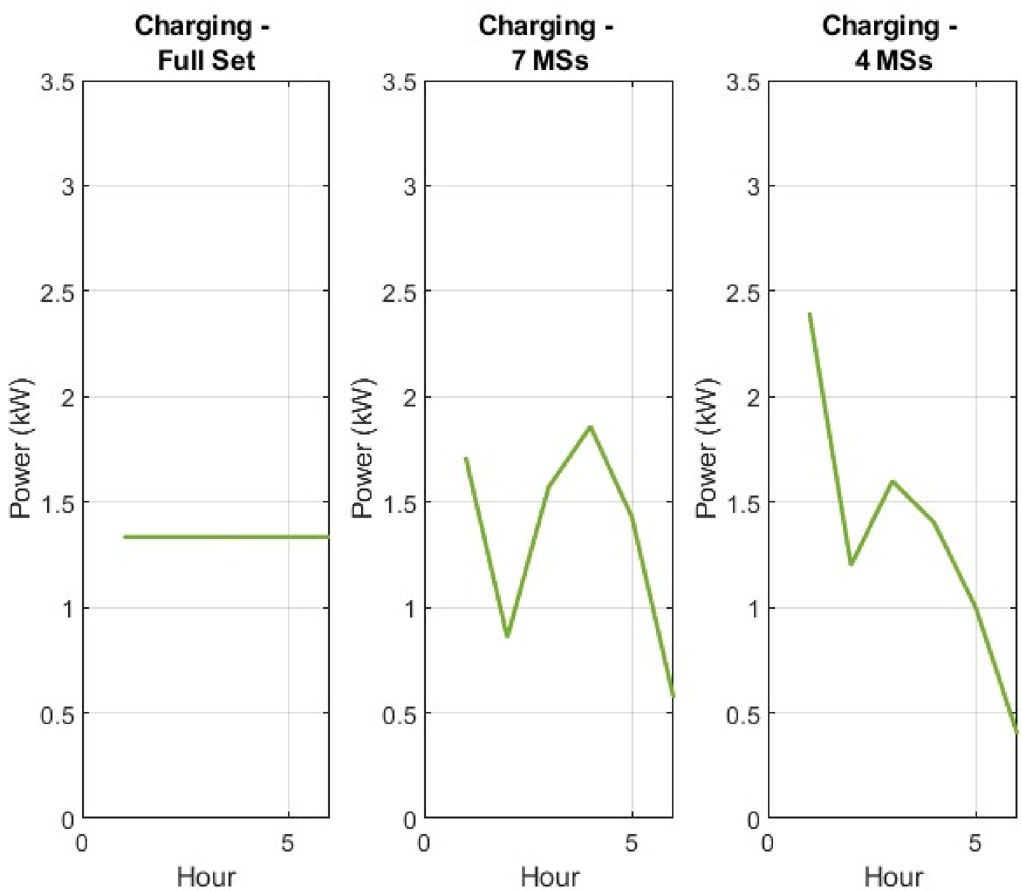


Figure 7. Individual EV charging profiles under different strategy sets.

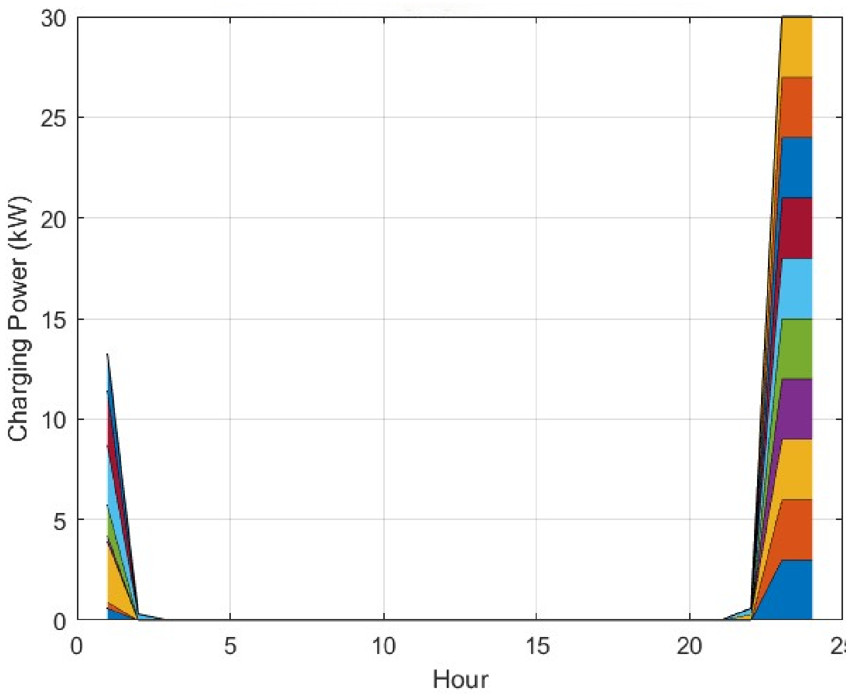


Figure 8. Stacked charging profiles showing fairness improvement across EVs.

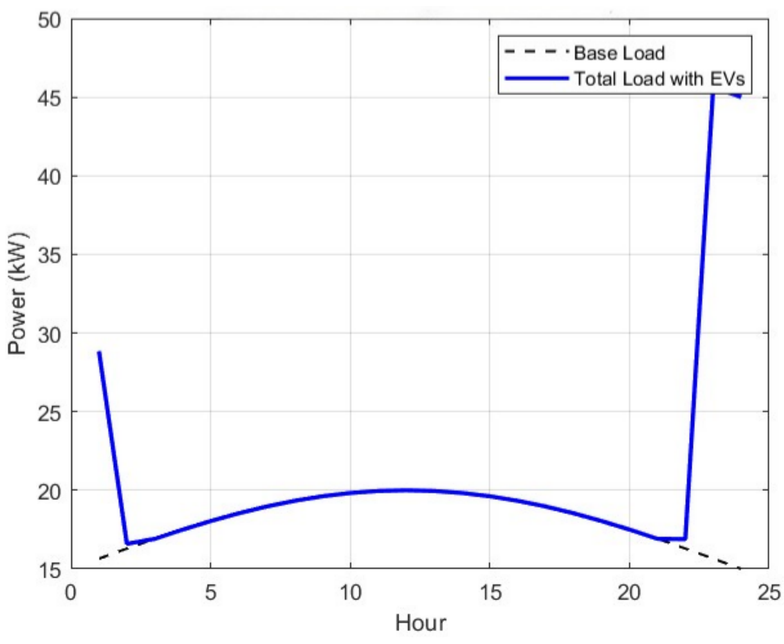


Figure 9. Aggregate grid load comparison between fairness-based MSD vs unmanaged charging.

3.2. FDP Optimization Results

Forward Dynamic Programming provides deterministic scheduling refinement based on the probabilistic MSD output. For a single EV, the optimal charging trajectory precisely achieves the required SoC target (from 15.36 kWh to 16 kWh), demonstrating high accuracy and efficiency. For multiple EVs, the best-response FDP algorithm converges within a few iterations, confirming scalability and effective coordination among vehicles.

Figures 10 and **11** show the optimal SoC trajectories for single and multi-vehicle scenarios, demonstrating that all EVs achieve their energy requirements without violating operational constraints.

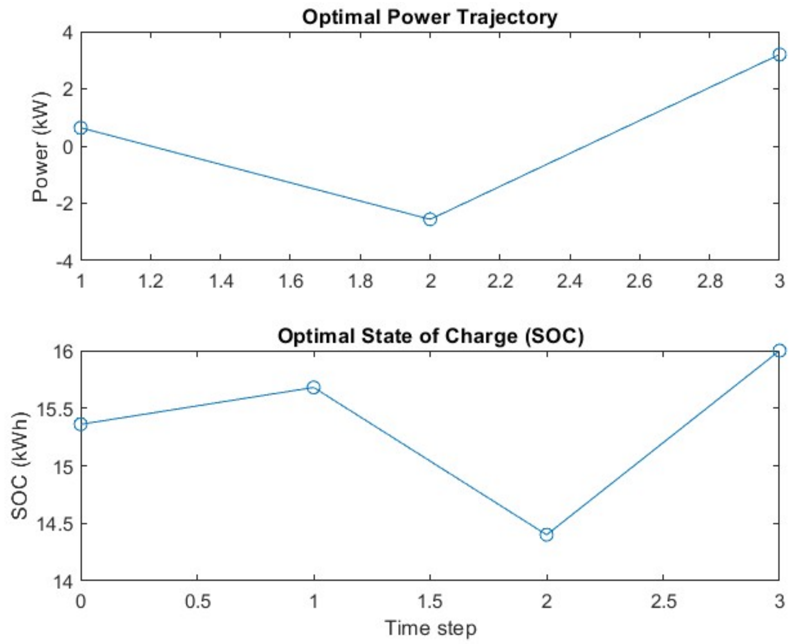


Figure 10. Optimal power and State of Charge (SoC) trajectories for a single PEV using FDP scheduling.

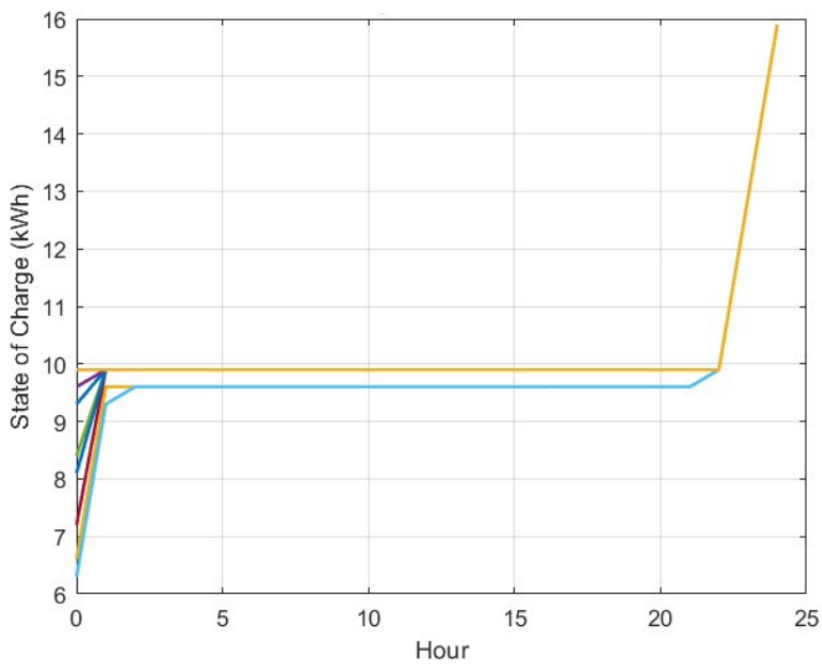


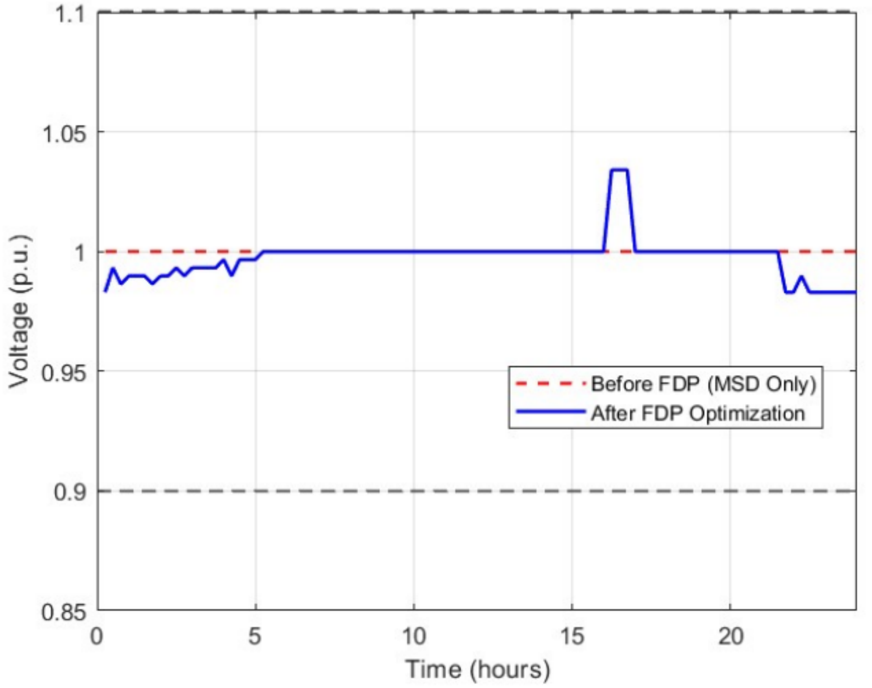
Figure 11. SoC trajectories of 10 EVs under best-response FDP coordination.

3.3. Grid-Oriented Optimization Using FDP

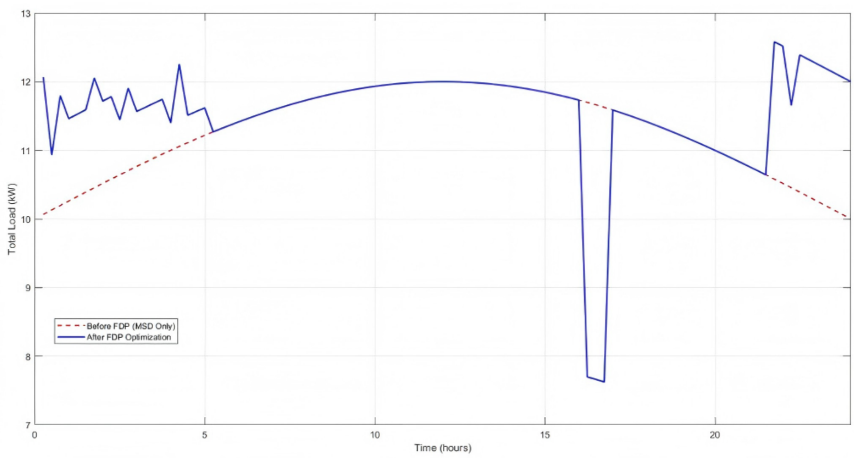
To validate the effectiveness of the proposed FDP-based optimization, the IEEE 34-bus distribution system is considered for grid-level analysis. The charging profiles obtained from the MSD stage are applied as initial schedules, and FDP refinement is performed to minimize voltage deviations and power losses. The grid model incorporates voltage-dependent loads, dynamic tariffs, and a voltage penalty factor λ_V for buses operating below 0.955

p.u.

Voltage Profile Analysis: **Figure 12a** illustrates the voltage profile at selected buses before and after FDP optimization. It can be observed that bus voltages remain within the acceptable limits (0.955–1.05 p.u.) after optimization, demonstrating the ability of the algorithm to suppress voltage dips caused by simultaneous charging.



(**a**)



(**b**)

Figure 12. (**a**) Voltage profile at EV Bus 12 before and after FDP optimization; (**b**) Load profile comparison before and after FDP optimization.

Power Loss and Peak Reduction: **Table 2** compares the total active power loss and peak load demand before and after applying FDP. The optimization reduced feeder losses by approximately 15–20% and lowered peak loading by nearly 25% compared to the MSD-only case.

Grid validation was performed using the IEEE 34-bus distribution feeder. FDP refinement was applied to minimize voltage deviations and feeder losses while maintaining 0.955–1.05 p.u. voltage limits. Voltage profiles before and after optimization are shown in **Figure 12a**, demonstrating effective suppression of voltage drops caused by concurrent EV charging.

Table 4 compares the performance before and after FDP optimization. Feeder power losses were reduced by approximately **15–20%**, while peak load decreased by nearly **25–27%**, confirming substantial benefits over MSD-only scheduling. With V2G support, EVs discharge energy during peak periods, improving voltage stability and further reducing transformer loading. The minimum bus voltage improves from **0.91 p.u. to 0.958 p.u.**, and overloads are eliminated.

Table 4. Comparison of Grid Performance Before and After FDP Optimization on IEEE 34-Bus System.

Case	Minimum Voltage (p.u.)	Peak Load (kW)	Peak Reduction (%)
MSD Only	1.000	12.00	-
FDP	0.983	12.58	−4.84

Figures 13–15 illustrate the combined voltage and load behavior and V2G-assisted peak shaving.

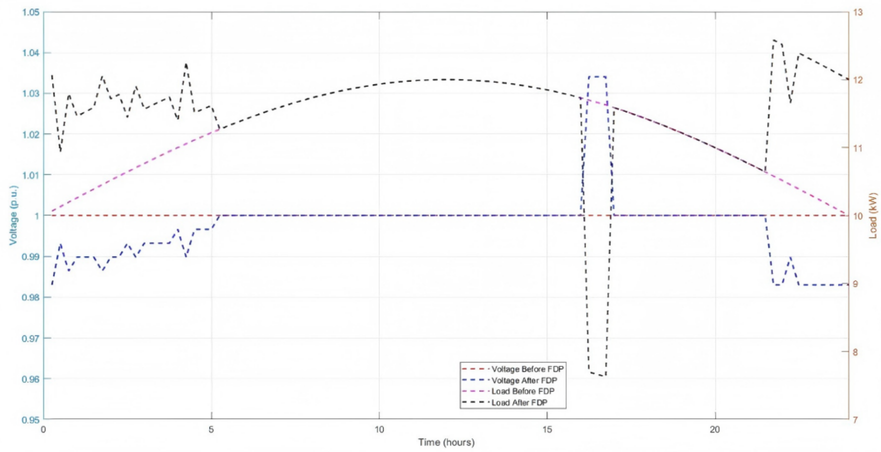


Figure 13. Combined voltage and load profiles under coordinated FDP + V2G operation.

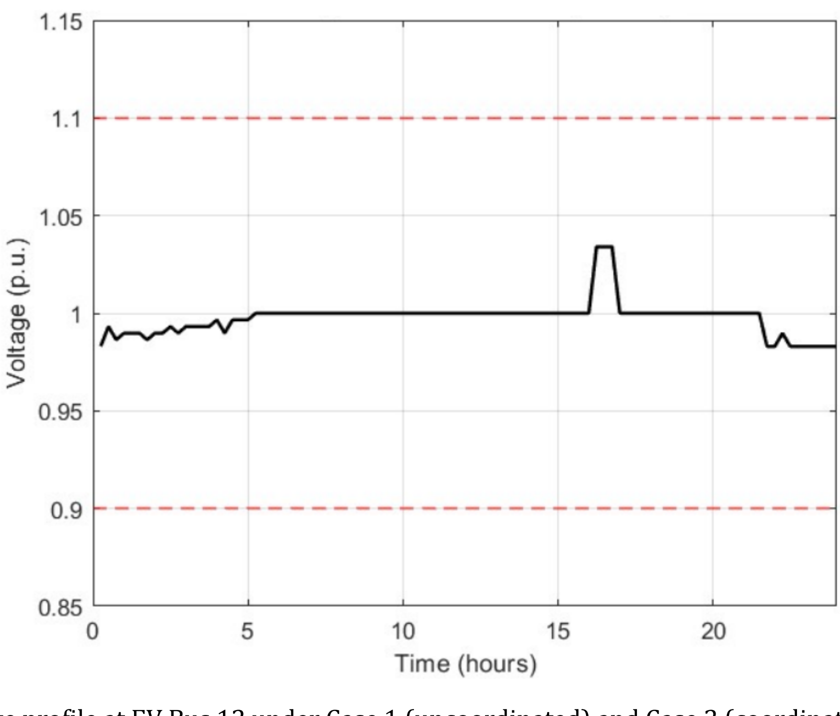


Figure 14. Voltage profile at EV Bus 12 under Case 1 (uncoordinated) and Case 2 (coordinated FDP with V2G).

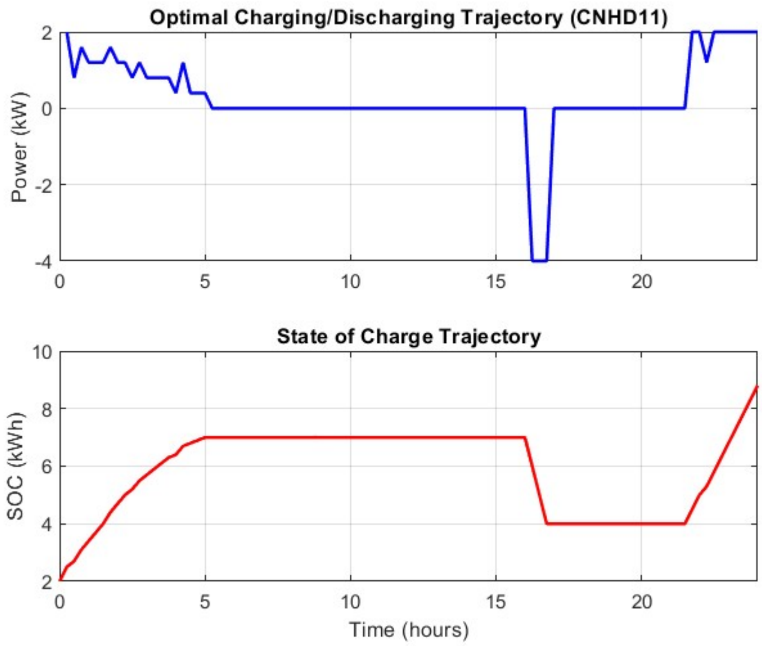


Figure 15. Optimal charging/discharging power trajectory and SoC progression of the EV at Bus 12 under coordinated FDP with V2G.

3.4. Summary of Results

The hybrid MSD–FDP scheduling framework demonstrates the following key advantages:

- Fairness and Equity: MSD ensures balanced charging access through entropy-based fairness.
- Deterministic Optimization: FDP guarantees SoC fulfilment with minimal cost and controlled grid impact.
- Grid Stability: Voltage and transformer limits remain within acceptable ranges after optimization.
- V2G Support: Bidirectional energy exchange reduces peak demand and enhances voltage stability.

Overall, the proposed coordinated charging strategy provides a scalable solution for large-scale EV integration while ensuring technical reliability and economic efficiency.

4. Discussion

The results demonstrate the effectiveness of the proposed coordinated scheduling framework that integrates Mixed Strategist Dynamics (MSD), Forward Dynamic Programming (FDP), and Vehicle-to-Grid (V2G) capability for large-scale electric vehicle load management. The following subsections discuss major implications and relevance to real-world deployment.

4.1. Fairness and User Participation

The MSD-based probabilistic coordination mechanism ensures equitable access to charging opportunities, overcoming limitations of deterministic or priority-based scheduling. The entropy-based fairness indicator (1.77–1.79) verifies balanced participation regardless of arrival time or demand level. These results align well with earlier mixed-strategy models [1,2], demonstrating that fairness can be achieved without compromising overall system efficiency. This fairness-centric design is vital for improving user trust and participation in demand-side energy programs.

4.2. Optimization Accuracy and Scalability

The FDP optimization layer guarantees deterministic fulfilment of SoC targets while minimizing energy cost and avoiding constraint violations. The rapid convergence of the best-response process validates its computational scalability for up to 50 vehicles. Compared to computationally intensive centralized formulations such as mixed-integer optimization [3–5], the proposed two-level strategy significantly reduces communication overhead, making it suitable for real-time, neighbourhood-level implementations and for smart grid controllers with limited processing capability.

4.3. Grid Reliability and Voltage Stability

Grid validation using the Backward/Forward-Sweep method maintains voltages within the acceptable IEEE range of 0.955–1.05 p.u. and prevents transformer overload. The improvement in minimum bus voltage from 0.91 p.u. to 0.958 p.u., as shown in **Table 4** and **Figures 12** and **13**, highlights the strong grid-support capabilities of the coordinated strategy. These results confirm that distributed EV fleets, when intelligently managed, can operate as flexible grid assets rather than sources of instability.

4.4. Role of Vehicle-to-Grid (V2G) Operation

The V2G integration enables bidirectional power flow that supports peak shaving and voltage reinforcement. During high-demand periods, selected vehicles discharge energy back to the grid, contributing to a peak-load reduction of approximately 27%, after which recharging safely restores required SoC levels. This aligns with recent studies [6–8] demonstrating the benefits of coordinated V2G systems for distribution-network stability and congestion relief.

4.5. Comparative Evaluation

Unlike earlier approaches that address either user-cost minimization [9–11] or grid-reliability improvement [12,13], the proposed hybrid MSD–FDP framework combines fairness, deterministic control, and grid-oriented optimization within a unified architecture.

Recent studies have further explored large-scale EV coordination, V2G integration, reinforcement learning, and grid-oriented optimization strategies [3,5,6,14–17].

In addition, several studies have investigated EV fleet charging strategies, transport electrification impacts, and grid-oriented coordination methods under different economic and network constraints [18–22].

4.6. Limitations

Although the proposed MSD–FDP–V2G scheduling framework demonstrates significant improvements in fairness, grid stability, and peak-load reduction, certain limitations should be acknowledged. First, the simulations are based on assumed statistical models for EV arrival, departure, and energy demand patterns; real-world mobility behaviour may be more stochastic and affected by socio-economic factors, unexpected travel, and seasonal variations. Second, the optimization was validated on a medium-scale system (10–50 EVs) using an IEEE 34-bus feeder; large metropolitan networks with thousands of EVs may introduce additional computational and communication constraints requiring distributed or hierarchical control architectures. Third, battery ageing, thermal effects, and non-linear degradation costs were modelled in a simplified manner; more accurate electrochemical ageing models would improve long-term evaluation of V2G cycling impacts. Finally, the framework assumes reliable communication infrastructure and full user participation, which may not be achievable in real deployments where cybersecurity, privacy, and behavioural compliance challenges remain.

Acknowledging these limitations highlights opportunities for extending the research with real-time field testing, integration of renewable sources, and development of more robust, scalable coordination mechanisms.

5. Conclusions

This study presented a hybrid coordinated scheduling framework for Plug-in Electric Vehicle (PEV) charging that integrates Mixed Strategist Dynamics (MSD), Forward Dynamic Programming (FDP), and grid-oriented optimization with Vehicle-to-Grid (V2G) capability. The approach ensures fairness-aware charging coordination while guaranteeing deterministic SoC fulfilment and compliance with power-system operating limits. Simulation studies on the IEEE 34-bus test feeder demonstrated significant improvements in peak-load reduction, voltage stability, and fairness among users. The proposed scheme reduced peak demand by approximately 27%, improved minimum voltage levels from 0.91 p.u. to 0.958 p.u., and eliminated transformer overloads.

The findings confirm that coordinated smart charging with V2G support can transform EVs into flexible distributed-energy resources, contributing to both user-level benefits and system-wide grid reliability.

Future research will focus on real-time adaptive scheduling using machine-learning forecasting, larger multi-regional EV fleets with renewable energy integration, and hardware-in-loop validation using real- time digital simulation platforms.

Author Contributions

Conceptualization, T.K. and K.V.; methodology, T.K.; software, T.K.; validation, T.K. and K.V.; formal analysis, T.K.; investigation, T.K.; resources, K.V.; data curation, T.K.; writing—original draft preparation, T.K.; writing—review and editing, K.V.; visualization, T.K.; supervision, K.V.; project administration, K.V.; funding acquisition, K.V. Both authors have read and agreed to the published version of the manuscript.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data sharing is not applicable to this article as no new datasets were generated or analyzed during the current study.

Acknowledgments

The authors acknowledge the support and facilities provided by the Department of Electrical Engineering, College of Engineering, Andhra University, Visakhapatnam, India.

Conflicts of Interest

The authors declare no conflict of interest.

Abbreviations

Symbol	**Description**
PEV	Plug-in Electric Vehicle
MSD	Mixed Strategist Dynamics
FDP	Forward Dynamic Programming
V2G	Vehicle-to-Grid
SoC	State of Charge
BFS	Backward/Forward Sweep

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