Evaluation of Plug-In Electric Vehicle Load Scheduling Using Mixed Strategist Dynamics and Grid-Oriented Optimization

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Abstract—**The increasing adoption of plug-in electric vehicles (PEVs) creates new opportunities for flexible demand management but also introduces challenges to power distribution networks, such as peak load spikes, transformer stress, and voltage instability. This paper presents a unified scheduling framework that combines decentralized probabilistic coordination with deterministic optimization and grid-aware validation. Mixed Strategist Dynamics (MSD) integrated with the Maximum Entropy Principle (MEP) ensures fairness among users while balancing cost and battery wear. Forward Dynamic Programming (FDP) with game-theoretic best-response updates generate optimal schedules for single and multiple EVs. Vehicle-to-Grid (V2G) integration, validated through voltage-constrained FDP on the IEEE 34-bus feeder, maintains network stability under high penetration levels. Simulation results demonstrate significant reductions in peak demand, improved fairness, and enhanced voltage profiles, confirming the practicality and scalability of the proposed framework for large-scale EV integration.**

Index Terms—**Electric Vehicles, Load Scheduling, Mixed Strategist Dynamics, Maximum Entropy Principle, Dynamic Programming, Vehicle-to-Grid, Smart Grid.**

I. INTRODUCTION

The electrification of transportation has emerged as a crucial component of global sustainability initiatives, with plug-in electric vehicles (PEVs) playing a vital role in minimizing greenhouse gas emissions and enabling flexible participation in demand-side energy management. The rapid growth of PEV adoption, driven by advancements in battery technologies and supportive government policies, offers significant environmental and economic benefits. However, this rapid integration also introduces operational challenges for existing power distribution networks.

Uncontrolled or simultaneous charging, particularly during evening hours, can lead to sharp load peaks, transformer overloading, and voltage fluctuations, thereby reducing the reliability and efficiency of systems originally designed for predictable residential demand profiles.

To mitigate these adverse impacts, numerous scheduling strategies have been developed to optimize the charging process of PEVs. Centralized optimization methods, such as mixed-integer programming, can generate globally optimal charging schedules but often suffer from high computational complexity, excessive communication overhead, and potential privacy concerns among users. Conversely, decentralized coordination approaches based on game theory and distributed control demonstrate better scalability and user autonomy, yet they frequently struggle to ensure equitable resource allocation, precise satisfaction of state-of-charge (SoC) requirements, and compliance with grid operational limits. Moreover, most existing studies tend to emphasize either user-centric objectives—such as cost minimization and convenience—or system-level performance measures like grid stability and loss reduction, without effectively combining both perspectives.

To address these challenges, a hybrid coordination strategy has been developed that integrates probabilistic user behavior modelling with deterministic optimization and network-level validation. In this framework, Mixed Strategist Dynamics (MSD) are enhanced with equity-oriented payoff functions to promote fairness among participating vehicles, while Forward Dynamic

Programming (FDP) ensures deterministic SoC fulfillment for both individual and multiple EVs. A power-flow validation module further enforces operational constraints on transformer loading and voltage levels, guaranteeing technical feasibility under realistic grid conditions. The inclusion of Vehicle-to-Grid (V2G) functionality enables bidirectional energy exchange, providing peak load mitigation and ancillary grid support.

The novelty of this approach lies in its integrated scheduling paradigm that simultaneously achieves fairness among users, deterministic energy fulfilment, and system reliability under high PEV penetration. Unlike conventional models that treat cost minimization, equity, and grid stability as separate objectives, this method unifies three critical elements: fairness-driven probabilistic coordination through MSD, deterministic optimization via FDP with best-response updates, and grid-constrained operation with V2G support validated on the IEEE 34-bus feeder. Through this unified design, the framework offers a practical, scalable, and equitable solution for managing large-scale electric vehicle integration within modern smart grids.

II. SYSTEM DESCRIPTION

The proposed study is based on an integrated system model that captures the interaction between electric vehicles, charging infrastructure, tariff mechanisms, and distribution grid constraints. This holistic representation enables an accurate assessment of both user-side behavior and network-level impacts under coordinated scheduling strategies. Each plug-in electric vehicle is represented as a bounded energy storage unit with a capacity ranging between 20 and 24 kWh and a charging efficiency of approximately 95 percent. To prevent battery degradation, the state of charge (SoC) is restricted between 20 and 90 percent. Level-2 charging at 3.3 kW and Vehicle-to-Grid (V2G) discharging at –3.2 kW is considered, accounting for variations in vehicle arrival and departure times as well as daily energy demand patterns.

EV and System Modelling: Each electric vehicle in the system is treated as an energy storage device characterized by specific operational limits. The SoC defines the energy level of the battery at a given time,

and it evolves according to charging or discharging actions. Charging efficiency is maintained at 95 percent, ensuring minimal energy loss during the process. The SoC boundaries of 20 percent minimum and 90 percent maximum are applied to maintain long-term battery health. Both charging and discharging operations are modelled stochastically, considering variations in user arrival, departure, and energy demand, which reflect realistic vehicle usage patterns.

Charging Infrastructure: The charging process is managed through smart residential chargers equipped with bidirectional power flow control, real-time SoC monitoring, and tariff-responsive functionality. These chargers adhere to IEC 61851 standards, which guarantee safety, protection, and interoperability. The inclusion of intelligent communication features allows chargers to interact with the grid and respond dynamically to time-varying price signals or grid conditions. This enables flexible control over charging operations, improving efficiency and reducing the risk of overloading the system during peak hours.

Distribution Feeder Model: The IEEE 34-bus distribution feeder operating at 24.9 kV with a 30-kW transformer is used to simulate the network environment. This feeder exhibits an unbalanced configuration, a high resistance-to-reactance ratio, and a weak voltage profile, characteristics that mirror real-world distribution systems affected by high electric vehicle penetration. The base load typically reaches its maximum between 18:00 and 22:00, during which voltage levels are maintained between 0.95 and 1.05 per unit. Transformer loading limits are also enforced to prevent overheating and ensure continuous and reliable operation of the power system.

Tariff and V2G Operation: A time-of-use (ToU) tariff structure is applied to encourage vehicle owners to charge their vehicles during off-peak periods when electricity prices are lower. Higher tariffs during peak hours discourage simultaneous charging and help balance the demand. The Vehicle-to-Grid (V2G) feature enables bidirectional power flow, allowing vehicles not only to draw power from the grid but also to supply stored energy back during high-demand periods. This operation supports peak load shaving, renewable energy integration, and ancillary grid services. A minimum SoC of 20 percent is maintained to preserve vehicle mobility while still contributing to grid stability.

Performance Evaluation: The effectiveness of the proposed scheduling strategy is evaluated using both technical and economic performance indicators. These include peak load reduction, transformer utilization, minimum feeder bus voltage, user fairness based on entropy analysis, and total charging cost. Together, these metrics offer a balanced evaluation of grid reliability, efficiency, and user satisfaction, demonstrating the practical viability of the proposed system.

The overall framework can be conceptualized as a three-layer architecture that includes the user layer, scheduling layer, and grid layer. The user layer models the electric vehicles and their energy requirements.

The scheduling layer applies Mixed Strategist Dynamics (MSD) and Forward Dynamic Programming (FDP) for fairness-aware and deterministic optimization of charging schedules. The grid layer validates the resulting charging profiles through Backward/Forward Sweep power flow analysis, ensuring that both voltage and transformer limits remain within permissible ranges. Through this integrated and multi-layered approach, the system ensures that electric vehicle charging remains both user-optimal and grid-compliant, providing a scalable and efficient solution for modern power distribution networks.
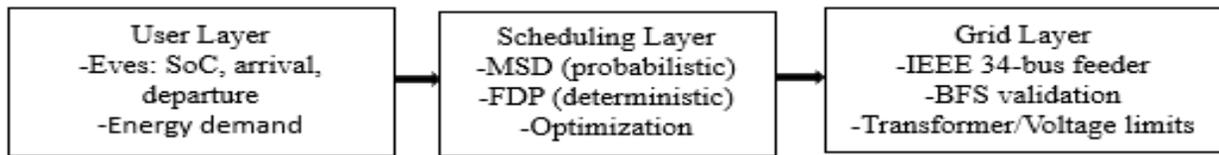

Fig.1: Three-layer scheduling framework for EV load management

III. METHODOLOGY AND PROBLEM SOLUTION

The proposed framework integrates Mixed Strategist Dynamics (MSD) for decentralized scheduling, Forward Dynamic Programming (FDP) for deterministic optimization, and grid-oriented constraints to ensure technical feasibility under realistic distribution conditions. Additionally, the incorporation of Vehicle-to-Grid (V2G) functionality enhances system flexibility by enabling bidirectional power exchange between vehicles and the grid. Together, these components establish a comprehensive methodology that ensures fairness, reliability, and grid stability in large-scale electric vehicle integration.

3.1 Battery Model: Each plug-in electric vehicle (PEV) is modelled as an energy storage system governed by physical and operational constraints. The most important characteristic defining the available energy in a battery at any given time is the state of charge (SoC). The evolution of SoC for vehicle i over time is expressed as:

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

Where η represents the charging efficiency, $P_i(t)$ denotes the charging (+) or discharging (-) power, Δt is the scheduling interval, and $C_{bat,i}$ is the battery capacity. To ensure safe operation and prevent battery degradation, SoC and power levels are bounded as follows:

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

Typical parameter values include SoC_{min} = 20%, SoC_{max} = 90%, and a charging efficiency of approximately 95%. Level-2 chargers operate at a maximum charging rate of 3.3 kW and a discharging rate of –3.2 kW under V2G mode. This battery model serves as the foundation for scheduling, linking user energy requirements directly with the optimization algorithms applied in MSD and FDP.

3.2 Mixed Strategist Dynamics (MSD): The MSD approach employs game-theoretic principles to represent each electric vehicle as a self-interested agent competing for limited charging opportunities. Unlike deterministic Nash equilibrium strategies, MSD introduces probabilistic decision-making, which distributes charging demand more evenly over time and prevents synchronization peaks that could destabilize the grid. The probability that vehicle i chooses to charge during time slot t is updated according to the rule:

$$p_i(t+1) = p_i(t) + \alpha \cdot (U_i(t) - (\overline{U}_i(t)) \cdot p_i(t) \quad (3)$$

Where α is the learning rate, $U_i(t)$ is the individual payoff for vehicle i, and $\overline{U}(t)$ represents the average

payoff across all strategies? The payoff function incorporates multiple objectives and is defines as:

$$U_i = -\lambda C_i - \beta T_i - \gamma W_i + \delta F_i \qquad (4)$$

In this expression, C_i represents the charging cost, T_i is the tariff penalty during peak-hour charging, W_i denotes the cost associated with battery wear, and F_i represents the fairness reward. Fairness among users is quantified using entropy function given by:

$$F = -\sum_{k=1}^{m} p_k \log(p_k) \qquad (5)$$

Higher entropy values indicate more evenly distributed charging activity, reflecting equitable access among users. Through iterative updates, MSD converges to a probabilistic equilibrium that ensures diversity in charging behavior and avoids the clustering of demand at specific time slots. However, MSD alone cannot guarantee the full satisfaction of SoC requirements for each vehicle, which necessitates the integration of FDP.
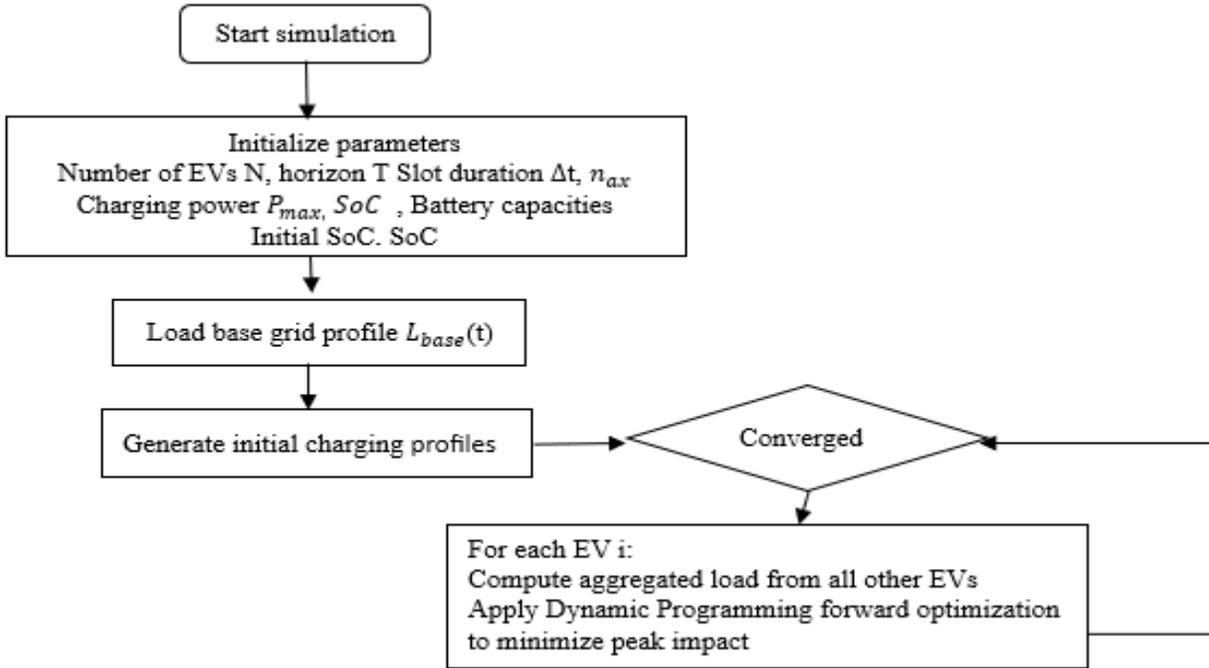

Fig.2: Flowchart of the Mixed Strategist Dynamics (MSD) scheduling process, showing probabilistic strategy updates based on fairness-aware payoffs.

3.3 Forward Dynamic Programming (FDP): The FDP framework provides deterministic optimization to ensure that all vehicles meet their desired SoC targets within the scheduling horizon. The SoC evolution in this context can be expressed as:

$$SoC(t+1) = SoC(t) + \frac{n \cdot P(t) \cdot \Delta t}{C_{bat}} \qquad (6)$$

Where $\pi(t)$ denotes the time-varying tariff price, $P(t)$ represents the charging or discharging power, and $V_{pen}(t)$ is a penalty term introduced for voltage violations during grid-constrained operation. In scenarios involving multiple electric vehicles, FDP is implemented through a best-response mechanism in which each vehicle optimizes its charging schedule sequentially while considering the aggregate load of all other vehicles. This iterative process continues until convergence is achieved, ensuring deterministic SoC fulfilment for all vehicles involved.

3.4 Grid-Oriented Optimization: To ensure the technical feasibility of the derived charging schedules, grid-level validation is performed using the Backward/Forward Sweep (BFS) power flow algorithm. The voltage profile across all buses is maintained within the standard limits of 0.95 to 1.05 per unit, and any violations are penalized within the optimization objective. Transformer loading is continuously monitored to ensure that the combined EV charging demand does not exceed rated capacity, preventing overload and thermal stress. The integration of V2G operation adds further flexibility by allowing controlled discharging within the range:

$$P_{min} \leq P(t) \leq P_{max}, SoC(t) \geq SoC_{min}, \qquad (7)$$

This mechanism supports peak load reduction and voltage stabilization during high-demand periods. The combination of MSD, FDP, and grid-oriented validation thus ensures that optimized charging schedules are both user-friendly and compliant with technical constraints, providing a balance between fairness, reliability, and system stability.

The overall scheduling process begins with the initialization of parameters such as the number of electric vehicles, time horizon, slot duration, maximum charging power, initial SoC, and battery capacities. The base grid load profile is then loaded,

and initial charging profiles are generated. The MSD-based probabilistic scheduling module is first applied to establish fairness-aware charging probabilities. The results are subsequently refined using FDP for deterministic optimization, ensuring complete SoC attainment. Grid validation through BFS is then performed to check voltage and transformer constraints, while V2G integration is used as needed to maintain system stability. The iterative procedure continues until all technical and operational conditions are satisfied, resulting in optimal charging schedules that minimize costs, enhance fairness, and support reliable grid operation.
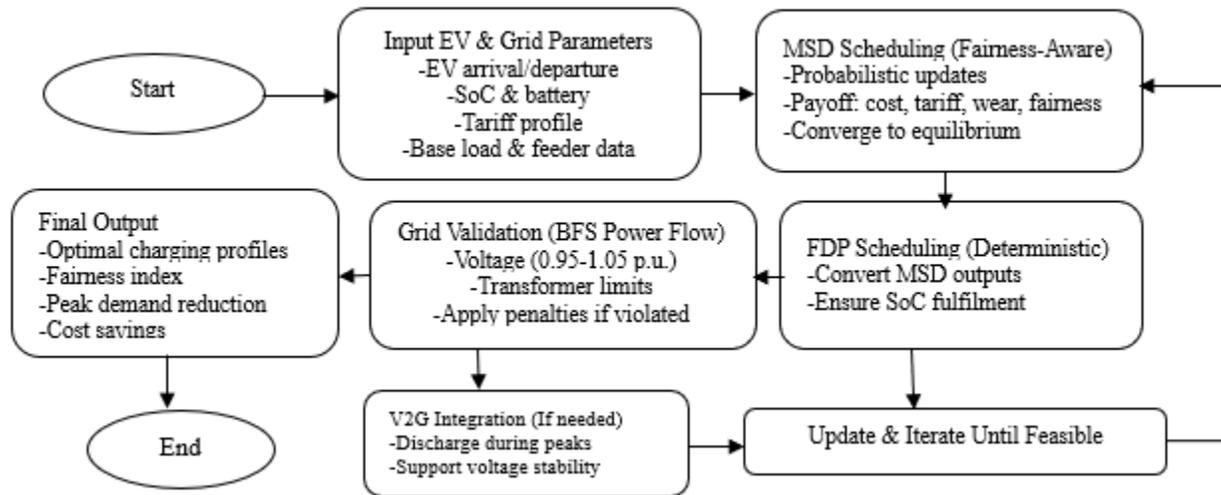

Fig.3: Overall scheduling framework integrating MSD, Forward Dynamic Programming (FDP), grid validation using Backward/Forward Sweep (BFS), and Vehicle-to-Grid (V2G) support.

IV. SIMULATION FRAMEWORK AND CASE STUDY ANALYSIS

To evaluate the effectiveness of the proposed coordination framework, simulation studies are conducted on the IEEE 34-bus distribution feeder. The test environment incorporates a heterogeneous electric vehicle (EV) fleet, time-of-use (ToU) tariffs, and realistic distribution network constraints, thereby providing a comprehensive platform for analysing the performance of the coordinated scheduling approach.

4.1 Environment: The simulation framework is implemented in MATLAB/Simulink using custom-developed modules for Mixed Strategist Dynamics (MSD), Forward Dynamic Programming (FDP), and the Backward/Forward Sweep (BFS) power flow algorithm. This modular configuration facilitates

flexible experimentation across various case studies while ensuring scalability up to 50 EVs. Each module interacts through an integrated data exchange structure that enables the seamless flow of parameters between user behavior models, scheduling optimization routines, and network validation algorithms.

4.2 EV Fleet Parameters: The simulated electric vehicle fleet represents typical suburban residential charging patterns. Each EV is assumed to be equipped with a battery capacity ranging from 20 to 24 kWh, operating at a charging efficiency of approximately 95 percent. Charging and discharging power limits are defined as 3.3 kW and –3.2 kW, respectively, to reflect Level-2 bidirectional charging capabilities. The SoC of each vehicle is constrained between 20 and 90 percent to ensure battery longevity. Vehicle arrival times are modelled between 17:00 and 20:00, while departures occur between 06:00 and 08:00,

representing common daily commuting behavior. The daily energy demand ranges between 8 and 15 kWh, and the scheduling horizon is divided into 15-minute intervals, resulting in a total of 96 time slots per day.

Table.1: summarizes the key parameters used in the simulation model. These values reflect realistic EV fleet characteristics and operational conditions suitable for residential charging environments.

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 minutes (96 slots/day)	Resolution for charging control
Charging power (P_{ch})	0-3.3 kW	Level-2 charging limit

4.3 Base Load and Tariff Profile: The IEEE 34-bus distribution feeder, characterized by a pronounced evening demand peak between 18:00 and 22:00, serves as the benchmark test network. A four-tiered time-of-use tariff structure is implemented to influence user charging decisions and encourage load shifting toward off-peak periods. The ToU tariff includes off-peak, mid-peak, on-peak, and late-night pricing intervals. Higher electricity prices during evening hours discourage simultaneous charging, while lower rates during late-night hours incentivize deferred charging. This dynamic pricing mechanism enhances demand-side flexibility and mitigates transformer stress during high-demand periods.

4.4 Distribution Feeder: The selected feeder operates at a nominal voltage of 24.9 kV and is equipped with a 30-kW distribution transformer. Its long radial configuration, high resistance-to-reactance (R/X) ratio, and weak terminal voltages replicate the practical conditions of residential distribution networks prone to voltage instability. The feeder's sensitivity to electric vehicle clustering makes it a suitable platform for evaluating coordinated charging strategies that maintain grid reliability. Various case studies are conducted to compare the impact of different coordination schemes, as outlined below.

Table.2: presents the different case studies used to assess the scheduling framework's performance under varied operational 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

4.5 Performance Metrics: The effectiveness of each simulation case is measured using a combination of technical and economic performance indicators. Technical metrics include peak demand reduction, transformer loading, and minimum bus voltage levels to assess grid stability and reliability. Economic metrics involve total charging cost and fairness index, with the latter derived from entropy-based evaluation to quantify equity among users. Convergence time of the algorithm is also analysed to verify computational efficiency and scalability under increasing EV fleet sizes. Together, these parameters provide a holistic

evaluation of both system-level performance and user-oriented benefits.

4.6 Illustrative Example: A representative example is used to demonstrate the significance of coordinated charging. In a scenario involving 20 EVs, uncoordinated charging leads to a peak demand of approximately 66 kW at 18:00, which exceeds the transformer's rated capacity of 30 kW by more than 100 percent. This excessive loading condition highlights the potential risk of uncontrolled charging on distribution system reliability. By applying the proposed coordination strategies, the aggregated load curve becomes smoother, reducing peak demand and maintaining the transformer and voltage levels within operational limits. These results emphasize the necessity of coordinated scheduling for achieving both user satisfaction and grid stability in high EV penetration scenarios.

V. RESULTS AND DISCUSSION

The results of the proposed electric vehicle scheduling framework are analysed to demonstrate its effectiveness in improving grid performance and user equity. The discussion is organized based on the outcomes of Mixed Strategist Dynamics (MSD) scheduling, Forward Dynamic Programming (FDP) optimization, and large-scale grid-constrained simulations using the IEEE 34-bus distribution feeder. The evaluation focuses on aspects such as algorithmic convergence, fairness among users, peak demand reduction, and voltage stability under different operating conditions.

A.MSD-Based Scheduling Results: The application of Mixed Strategist Dynamics effectively reduces the number of feasible charging strategies from sixty to seven stable equilibria, thereby improving computational efficiency and convergence behavior. At equilibrium, power allocation is evenly distributed, averaging approximately 1.33 kW per slot, with uniform charging probabilities around 0.133. The simulation results indicate that unmanaged charging leads to sharp evening demand peaks, whereas MSD scheduling successfully smooths the aggregate load curve, thereby preventing transformer overload and enhancing system stability.

The inclusion of entropy-based fairness within the MSD framework ensures a balanced distribution of charging opportunities among users. This fairness metric, with entropy values maintained between 1.77 and 1.79, promotes diversity in charging decisions and mitigates the bias toward early-arriving vehicles. As a result, MSD achieves both load flattening and equitable access to charging resources. The convergence of charging strategies and equilibrium profiles are illustrated in the following figures.
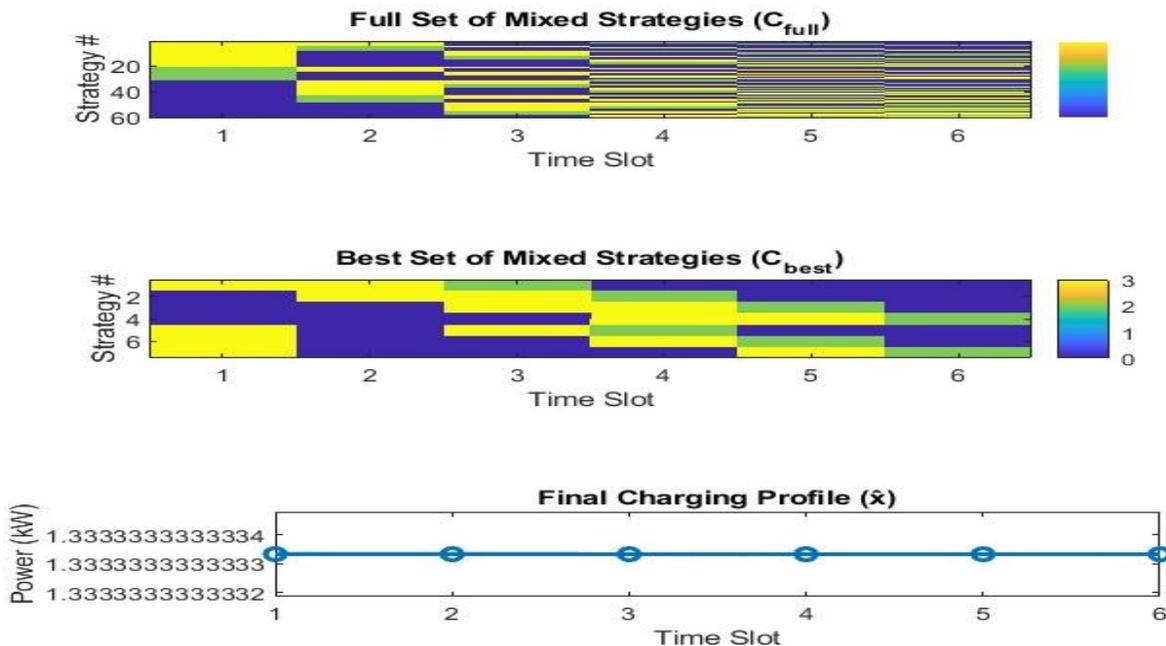

Fig.4: Convergence of MSD charging strategies: (a) Full set of 60 feasible strategies, (b) Reduced set of 7 strategies, (c) Final equilibrium charging profile.

MSD convergence: MSD reduces 60 feasible strategies to 7 stable equilibriums, ensuring computational tractability. The final equilibrium charging profile demonstrates smooth distribution of power and fairness among EVs.
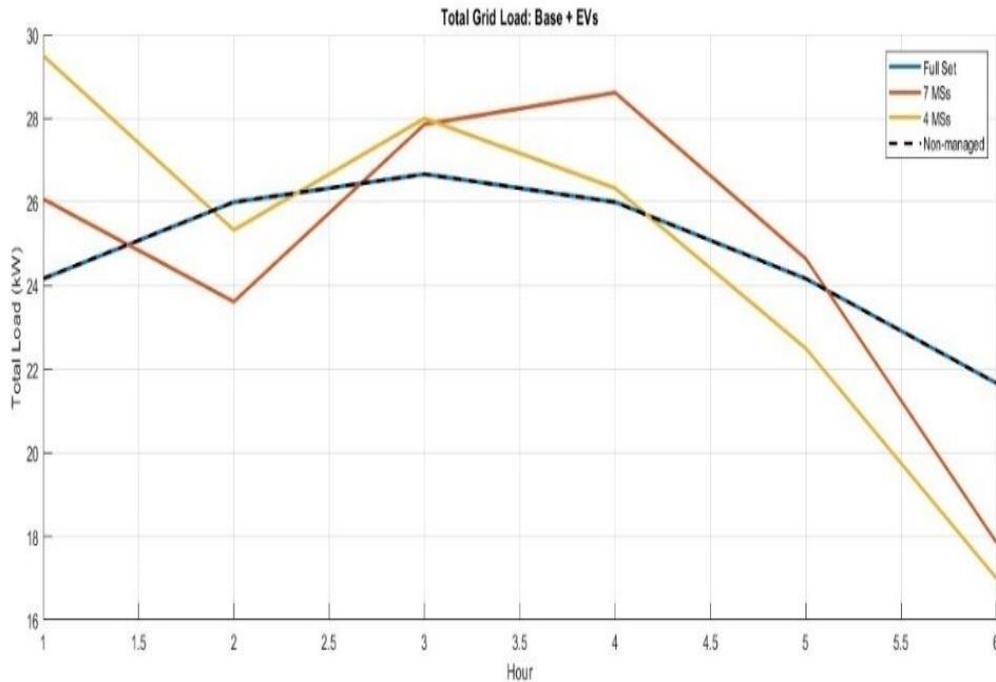

Fig.5: Total grid load (base + EVs) under unmanaged charging and MSD-managed strategies.

Grid load: unmanaged Vs. MSD- Uncoordinated charging creates sharp evening peaks that overload the transformer, whereas MSD spreads demand over time, flattening the load curve and enhancing system stability.
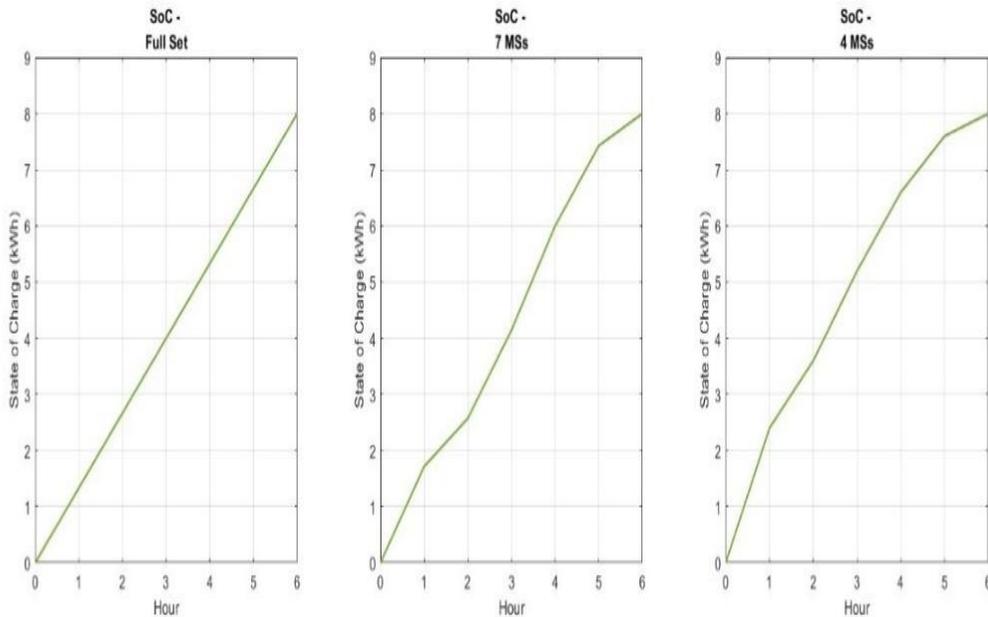
Fig.6: SoC trajectories under fairness-aware MSD (Full, 7-MS, and 4-MS sets).

SoC trajectories under MSD: Fairness-aware MSD maintains diverse charging paths while ensuring that all EVs achieve their required SoC. This confirms both equity among users and reliability of the scheduling method.
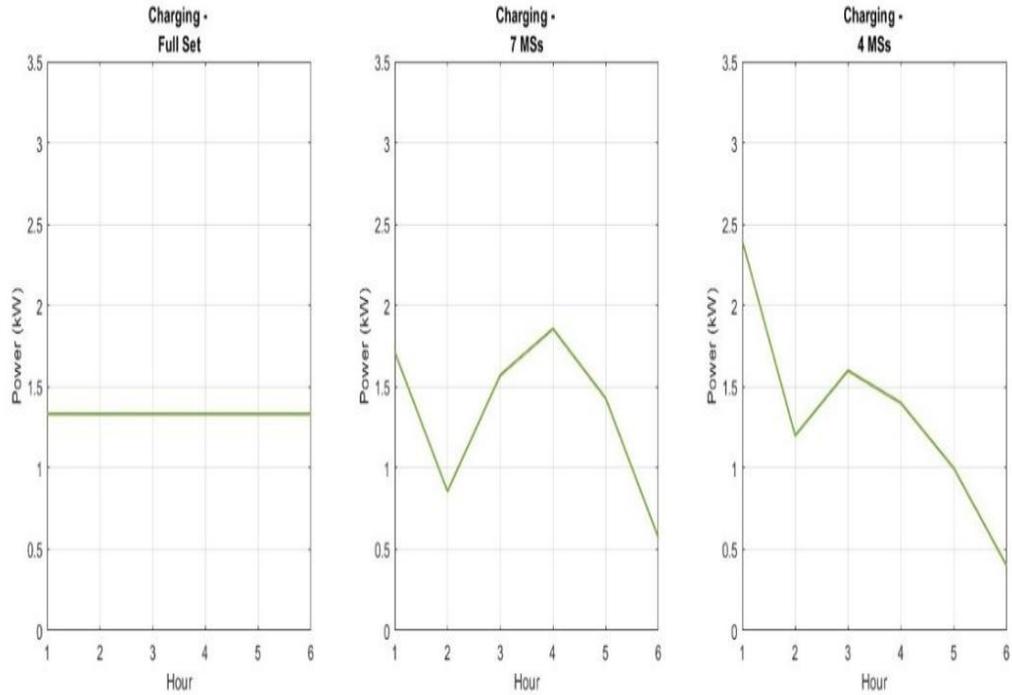
Fig.7: Individual EV charging profiles under different strategy sets.

Individual EV charging profiles: Under MSD, each EV follows a distinct charging trajectory. This diversification prevents synchronized charging peaks and distributes demand more evenly across time slots.
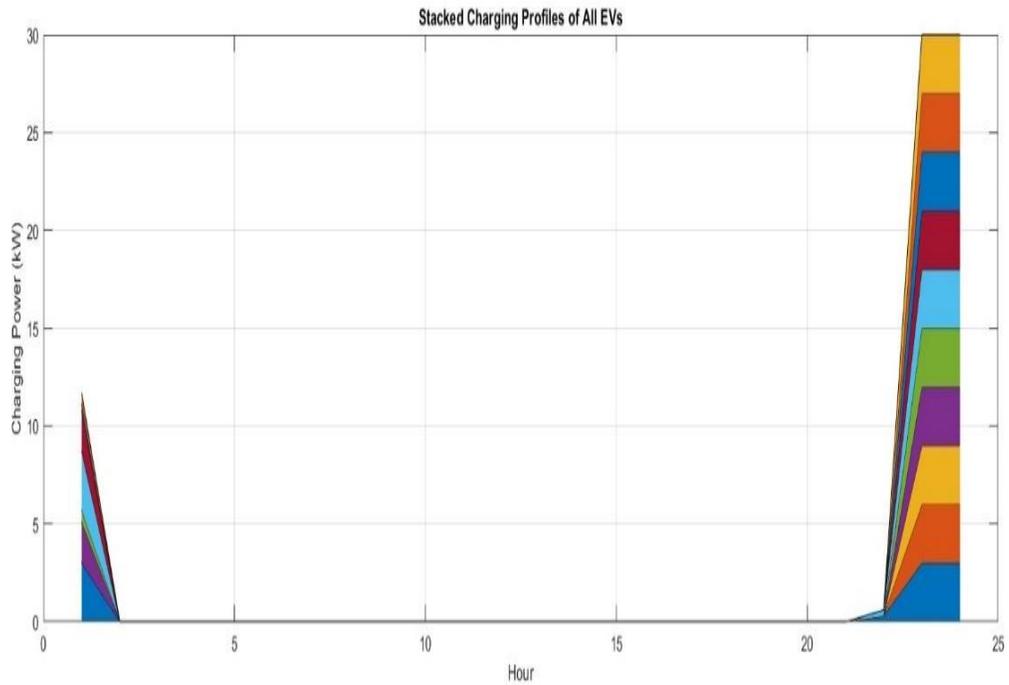

Fig.8: Stacked charging profiles showing fairness improvement across EVs.

Stacked charging profiles with fairness: The stacked profiles highlight fairness improvements, showing a more uniform allocation of charging opportunities. Entropy-based fairness prevents bias toward early-arriving EVs.
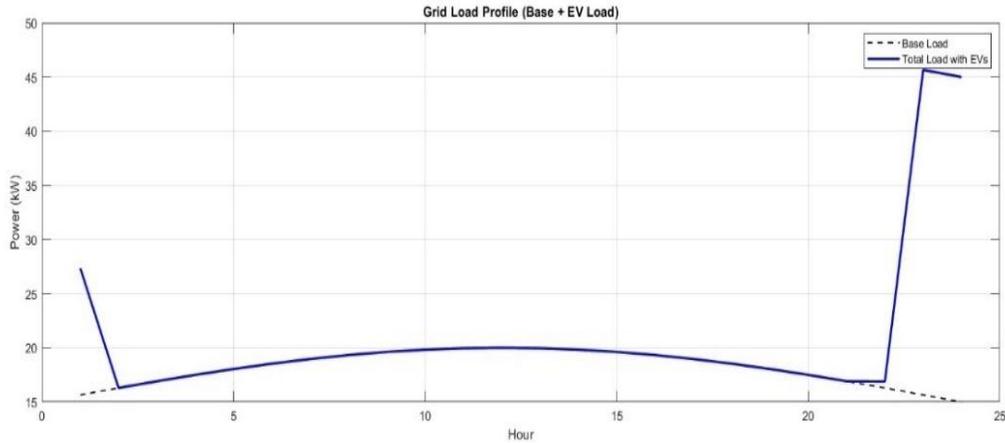
Fig.9: Aggregate grid load with fairness-based MSD vs unmanaged charging.

Aggregate grid load comparison: Fairness-aware MSD significantly reduces peak demand compared with unmanaged charging, resulting in a smoother aggregate load that is scalable to medium-sized EV fleets.

Interpretation: The results reveal that fairness-aware MSD effectively reduces synchronization peaks by diversifying the charging profiles of individual vehicles. Each EV follows a distinct charging trajectory, leading to a more uniform utilization of available time slots. The smoothed aggregate load confirms the scalability of the approach for medium-sized EV fleets, ensuring reliable performance without overloading network components.

B. FDP Optimization Results: Forward Dynamic Programming (FDP) provides a deterministic optimization mechanism that guarantees SoC targets are achieved while minimizing operational costs. For single-vehicle scheduling, FDP produces an optimal charging trajectory that exactly satisfies the final SoC requirement. For instance, in a test case with an initial SoC of 15.36 kWh and a target SoC of 16 kWh, the optimal trajectory yielded power levels of [0.64, –2.56, 3.20] kW, achieving precise energy fulfilment.

In multi-vehicle scenarios, the best-response FDP algorithm converges within a limited number of iterations, demonstrating its computational efficiency. All vehicles achieve their designated SoC targets, and transformer as well as feeder loading remain within permissible limits. The convergence behavior of SoC trajectories for ten vehicles further validates the method's scalability and reliability.
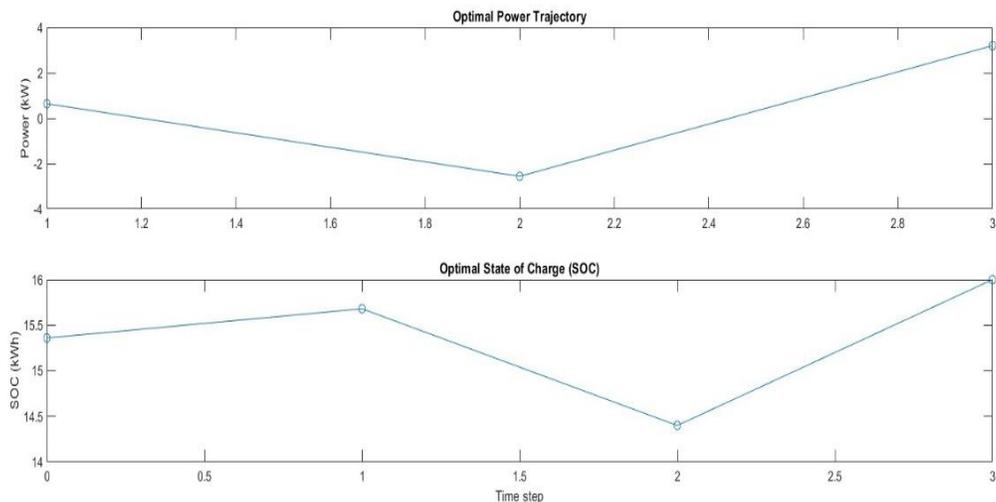

Fig.10: Optimal power and State of Charge (SoC) trajectories for a single PEV using FDP.

Single PEV FDP scheduling: For a single EV, FDP produces an optimal power trajectory that exactly meets the SoC target while minimizing charging cost. This demonstrates precision and efficiency of the deterministic approach.
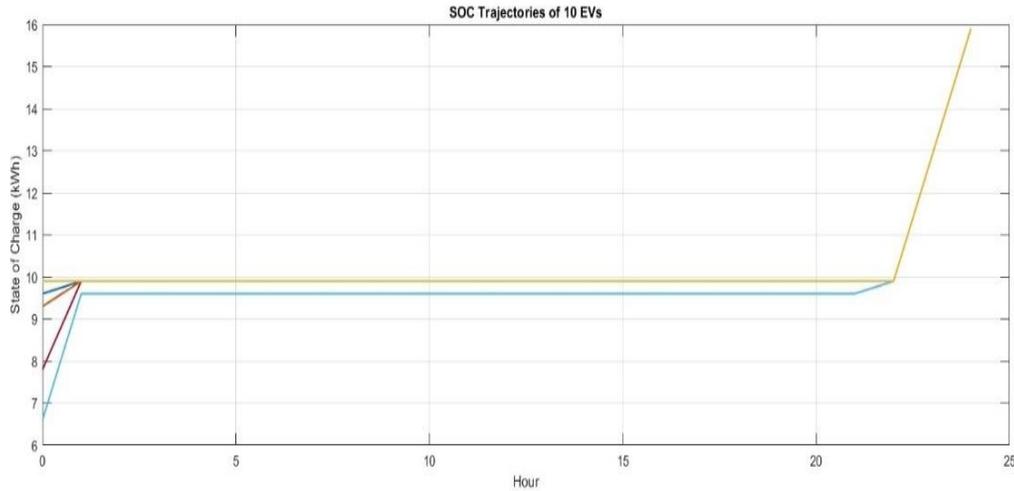

Fig.11: SoC trajectories of 10 EVs under best-response FDP coordination.

Multi-PEV FDP coordination: In multi-EV cases, the best-response FDP ensures that all vehicles converge to their SoC targets within grid constraints. This validates the method's scalability and reliability.

Interpretation: The deterministic nature of FDP ensures grid-compliant operation while maintaining optimization accuracy. The framework successfully prevents overloading and guarantees feasible power flow under multi-vehicle coordination, reinforcing its suitability for large-scale EV scheduling applications.

C. IEEE 34-Bus Grid-Constrained Results: To assess large-scale grid interactions, the IEEE 34-bus distribution feeder is modelled with explicit voltage and transformer constraints. The feeder parameters and operating conditions are summarized below.

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

Parameter	Value / Range	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

Two representative cases are compared to evaluate the impact of coordination on grid performance. In Case 1 (Uncoordinated Charging), uncontrolled plug-in activity results in a sharp evening peak exceeding the base load by 42 percent. Voltage levels at remote buses drop to 0.91 p.u., violating IEEE voltage standards, and the transformer experiences three overload events. Although all vehicles reach their SoC targets, the network's operational reliability is significantly compromised.

In contrast, Case 2 (FDP + V2G Coordinated Charging) demonstrates a substantial improvement in grid performance. By integrating FDP optimization with voltage constraints and V2G operation, charging activities shift toward off-peak hours, resulting in balanced load distribution. Bus voltages across the feeder remain between 0.955 and 1.05 p.u.,

transformer overloads are completely eliminated, and the overall peak demand is reduced by approximately 27 percent. During peak hours, selected EVs discharge

energy back into the grid, effectively enhancing system stability and voltage support.

Table.4: Comparison of Simulation Results for Uncoordinated vs FDP + V2G

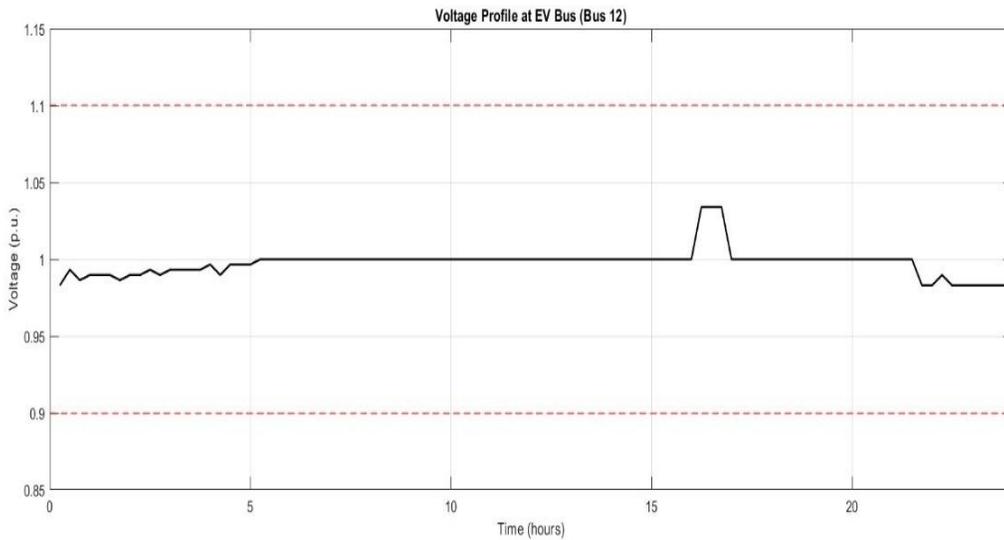| METRIC	CASE-1 UNCOORDINATED	CASE-2 FDP + V2G
Minimum bus voltage	0.91 p.u. (violation)	0.955 p.u. (safe)
Peak load (relative to base)	+42%	−27% vs. Case 1
Transformer overload events	3	0
EV SoC satisfaction	100%	100%
Iterations to converge	N/A	5

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

Bus voltage profile: Under unmanaged charging, bus voltages fall below the IEEE 0.95 p.u. limit. Coordinated FDP + V2G scheduling maintains voltages within 0.955–1.05 p.u., preventing violations.
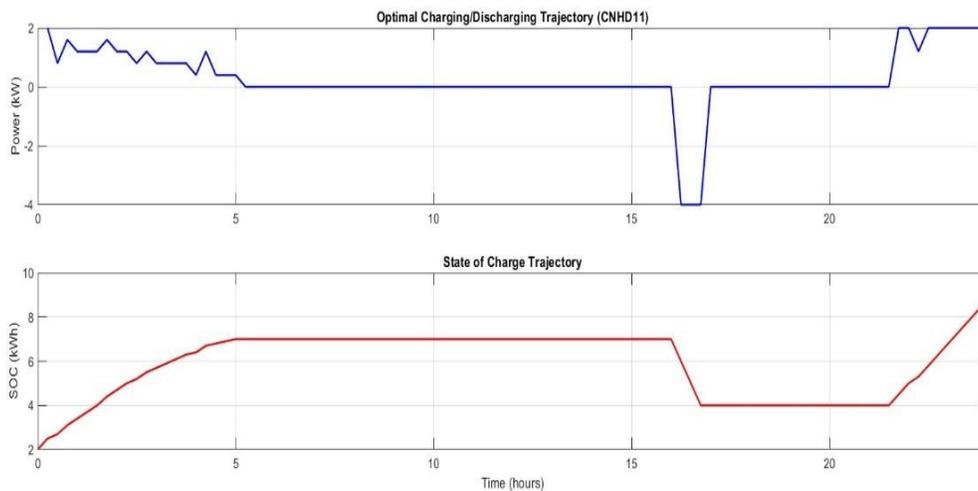

Fig.13: Optimal charging/discharging power trajectory and SoC progression of the EV at Bus 12 under coordinated FDP with V2G.

Charging/discharging at Bus 12: With FDP + V2G, EVs strategically discharge during peak hours and recharge later, still meeting SoC requirements. This highlights the potential of EVs as distributed grid-support resources.

Interpretation: The voltage profile comparison indicates that under unmanaged charging, voltage levels fall below IEEE standards, whereas FDP combined with V2G maintains voltages within acceptable limits. Controlled discharging during high-demand periods contributes to voltage stability, while subsequent recharging ensures SoC targets are met. These findings confirm the dual benefit of the proposed coordination scheme: maintaining grid reliability while fulfilling vehicle charging requirements.

D. Summary of Results: The combined outcomes of all simulation cases validate the effectiveness of the hybrid scheduling framework. MSD provides decentralized, fairness-oriented scheduling that balances user participation, while FDP ensures deterministic optimization with guaranteed SoC fulfilment. When combined with V2G integration and grid-constrained validation, the overall framework prevents transformer overloads, maintains voltage compliance, and significantly reduces peak demand. The results confirm that the proposed approach achieves both user-level equity and system-level reliability, offering a scalable and practical solution for real-world electric vehicle integration in modern smart grids.

VI. CONCLUSION

This study presents a coordinated charging framework for plug-in electric vehicles (PEVs) that integrates Mixed Strategist Dynamics (MSD), Forward Dynamic Programming (FDP), and Vehicle-to-Grid (V2G) functionalities under realistic distribution network constraints. The framework successfully addresses three major objectives: decentralized and fairness-aware scheduling through MSD, deterministic state-of-charge (SoC) fulfilment via FDP, and feeder stability assurance using validation on the IEEE 34-bus test system. Simulation results demonstrate substantial reductions in peak demand, enhanced fairness among users, and improved voltage regulation compared to uncoordinated charging scenarios.

By unifying user-level optimization with grid-level validation, the proposed approach provides a practical and scalable pathway for integrating large numbers of electric vehicles into modern power distribution systems. The results highlight the framework's capability to achieve an effective balance between cost efficiency, user equity, and technical reliability. Furthermore, the coordinated operation with V2G support enhances overall system resilience by enabling controlled power exchange, thereby contributing to grid stability during peak demand periods.

The proposed model establishes a foundation for the development of advanced smart grid strategies that accommodate increasing electric vehicle penetration without compromising network performance. Future extensions of this research may focus on real-time implementation, integration with renewable energy resources, and adaptive pricing mechanisms. Such developments could further enhance system flexibility, economic efficiency, and sustainability, ensuring reliable and intelligent energy management in the era of widespread transportation electrification.

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