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Evaluation of Enhanced Escort Energy Distribution Algorithm for Optimal Integration of Electric Vehicles

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***Abstract*—The growing adoption of Electric Vehicles (EVs) has created a strong need for smart and reliable charging strategies that can support large-scale integration without overloading the power grid. This work presents an Enhanced Escort Energy Distribution Algorithm designed to improve the efficiency and stability of EV charging systems. The algorithm is built upon the core concept of Escort Dynamics for EV Load Management, a decentralized evolutionary approach in which EVs gradually adjust their charging behavior based on system conditions. To make this framework more robust and practical, three key extensions are introduced. First, a Logarithmic Barrier Algorithm is added to ensure that every EV strictly follows battery limits, charger ratings, and other operational constraints. Second, a Centralized Optimization Model is used as a benchmark to compare optimality and performance, allowing a clear evaluation of how the decentralized method performs against traditional scheduling. Third, principles from Escort Evolutionary Game Theory are incorporated to strengthen theoretical guarantees related to convergence and stability. Simulation results show that the enhanced algorithm reduces peak demand, distributes charging more evenly, and maintains better overall stability compared to unmanaged charging and standard centralized approaches. Overall, this research offers a practical and scalable solution for future smart-grid EV integration.**

***Index Terms*—Escort Dynamics, Electric Vehicle Charging, Evolutionary Game Theory, Logarithmic Barrier Algorithm, Centralized Optimization, Decentralized Energy Management, Smart Grid Integration, Load Scheduling, State-of-Charge Constraints, Enhanced Energy Distribution.**

I. INTRODUCTION

The rapid growth of Electric Vehicles (EVs) is changing the way modern power systems operate, making smart and reliable charging strategies more important than ever. As more EVs connect to the grid, uncontrolled charging can lead to high peak demand, voltage issues, and additional stress on distribution networks. These challenges show the need for intelligent energy management systems that can distribute charging load efficiently and respond to changing grid conditions. With the increasing push toward smart grid development, the ability to manage EV charging in a flexible and grid-friendly way has become a key area of research.

Traditional centralized charging methods offer optimal scheduling but come with practical limitations. They require complete system information, heavy computation, and continuous communication with all EVs, making them less suitable for real-time use in large-scale environments. Because of this, decentralized strategies—where each EV makes its own decisions based on system feedback—are becoming more attractive. Evolutionary-based models, in particular, provide a natural way to describe how EVs can gradually adapt their charging behavior while maintaining stability across the grid.

Escort Dynamics is one such approach, using evolutionary game theory to guide EVs toward balanced and stable charging patterns. It allows charging decisions to evolve smoothly, making the system more adaptive and better aligned with grid conditions. However, real-world EV charging also involves strict limits on battery State-of-Charge (SoC), charger capacities, and operational boundaries. This requires additional mechanisms to ensure that EV behavior remains safe, feasible, and consistent with physical constraints.

To address these needs, this research develops an Enhanced Escort Energy Distribution Algorithm that brings together evolutionary learning, improved constraint handling, and performance comparison with traditional optimization techniques. By combining these elements into a unified framework, the proposed method offers a practical and scalable solution for EV charging coordination. Simulation results show improvements in load balancing, peak demand reduction, and overall grid stability, demonstrating its potential for future large-scale smart-grid applications.

II. SYSTEM DESCRIPTION

The proposed system represents an integrated framework that combines EV behavioural dynamics, evolutionary decision-making, constraint-aware optimization, and distribution grid validation. This unified model captures both user-side charging adaptation and network-side operational limits, enabling realistic assessment of the Enhanced Escort Energy Distribution Algorithm.

- EV and Evolutionary Modelling**:** Each EV is treated as an adaptive charging agent whose strategy evolves over time based on escort dynamics. EVs respond to payoff values that reflect grid loading, voltage sensitivity, and energy availability. The model accounts for stochastic arrival patterns, variable energy demand, charger constraints, and SoC boundaries, ensuring realistic representation of user behaviour within a probabilistic environment.
- Constraint Enforcement Mechanism**:** To ensure safe and feasible operation, logarithmic barrier functions are embedded into the escort update rule. These barrier terms restrict EVs from violating SoC limits, charger power ratings, and feasible energy intervals. This smooth constraint handling guarantees that strategy evolution remains strictly within physical and operational boundaries without interrupting the learning process.
- Decision and Benchmark Layer**:** A centralized optimization module is included to generate globally optimal charging schedules for comparison. This benchmark provides a reference for evaluating the efficiency, fairness, and convergence quality of the decentralized escort-based strategy. The enhanced algorithm thus combines autonomous adaptation with verifiable performance relative to traditional optimal control methods.
- Distribution Network Validation: The evolved charging strategies are evaluated against grid constraints such as feeder loading, transformer capacity, voltage boundaries (0.95–1.05 p.u.), and phase balancing requirements. Load-flow analysis ensures that the escort-based schedules remain compatible with real distribution network conditions under high EV penetration.

The entire system can be conceptualized as a three-layer coordinated framework consisting of:
(i) the EV Layer, representing individual user behaviour and charging requirements;
(ii) the Evolutionary Decision Layer, where escort dynamics and barrier-augmented optimization generate feasible charging strategies; and
(iii) the Grid Layer, which validates these strategies against distribution network constraints to ensure reliability and operational safety. This layered structure forms the analytical foundation of the Enhanced Escort Energy Distribution Algorithm.

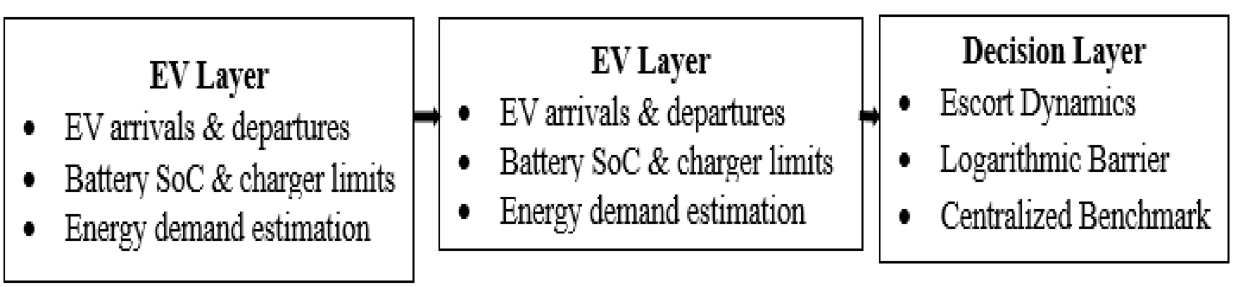

Figure 1: Three-layer system architecture of the Enhanced Escort Energy Distribution Algorithm

III. METHODOLOGY AND PROBLEM SOLUTION

The proposed framework integrates Enhanced Escort Energy Distribution (EEED) for decentralized charging coordination, logarithmic barrier–based constraint enforcement, and voltage-aware grid modelling to ensure fairness, stability, and technical feasibility in large-scale EV integration. The Enhanced Escort Framework extends traditional escort dynamics by embedding barrier functions, multi-phase capabilities, and grid-interactive evaluations. Together, these components enable robust EV charging that respects battery limits, grid constraints, and fairness requirements.

3.1 Battery Model: Each Electric Vehicle (EV) is modelled as an energy storage device with charging/discharging capabilities and operational boundaries. The state of charge (SoC) evolves according to:

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

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

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

Typical values are $SoC_{min} = 20\%$, $SoC_{max} = 90\%$, and a charging efficiency of about 95%. For Level-2 chargers, a maximum charging rate of 3.3 kW and discharging rate of –3.2 kW (under V2G) is considered.

This battery model is foundational for the Escort Energy Distribution Algorithm because charging behavior directly influences strategy updates and constraint enforcement.

3.2 Enhanced Escort Energy Distribution (EEED): Escort dynamics treat each EV's power allocation across time slots as a population distribution, allowing smooth and continuous energy scheduling. Unlike classical replicator dynamics, the Enhanced Escort method incorporates intersection escort functions and logarithmic barrier terms to enforce strict operational limits.

Escort-Based Strategy Update:

The evolution of the charging proportion x_k assigned to time slot k is:

$$\dot{x_k} = \phi(x_k)\big(f_k(x) - f(x)\big) \quad (3)$$

Where $f_k(x)$ payoff associated with time slot k, $\bar{f}$(x) population-weighted average payoff, $\phi(x_k)$ escort function enforcing constraints.

Intersection Escort Function:

To maintain upper and lower bounds:

$$\phi_{l_0}(x_k) = \frac{x_k - x_k^{lo}}{\sigma_{lo}}, \quad \emptyset_{up}(x_k) = \frac{x_k - x_k^{up}}{\sigma_{up}} \quad (4)$$

Combined escort:

$$\emptyset(x_k) = \phi_{l_0}(x_k)\emptyset_{up}(x_k) \quad (5)$$

This ensures that population values never violate physical constraints.

Barrier-Enhanced Payoff Function:

To further enforce feasibility, logarithmic barrier functions are used:

$$\mathrm{B}(x) = -\mu \sum_k ln\left(x_k^{up} - x_k\right) - \mu \sum_k ln\left(x_k - x_k^{lo}\right) \quad (6)$$

Final payoff:

$$f_k^{enh} = f_k - B(x) \quad (7)$$

Thus, infeasible charging schedules are penalized immediately and strongly.

Fairness and Multi-objective Payoff:

The payoff incorporates:

- Charging cost
- Tariff penalties
- Battery degradation
- Fairness reward via entropy

$$F = -\sum_{k=1}^{m} x_k \log(x_k) \quad (8)$$

The escort dynamics converge to a stable equilibrium distribution that is fair, feasible, and cost-efficient.

3.3 Logarithmic Barrier–Based Constraint Enforcement (Extension 1)

This extension strengthens the core Escort Algorithm by embedding logarithmic barrier functions directly into the optimization process. This provides:

- Guaranteed constraint satisfaction
- Smooth convergence
- Feasibility preservation in every iteration

The algorithm automatically maintains:

- Power limits
- Voltage bounds
- SoC constraints
- Transformer loading limits

Through dynamic barrier tuning, the method avoids oscillations and aggressively prevents boundary violations.

3.4 Voltage-Aware Grid Modelling (Extension 2)

To ensure grid compatibility, charging schedules are validated using a linearized distribution network model:

$$v_k = \frac{1}{V_{nom}} A x_k + v_k^0 \quad (9)$$

Where: A= voltage sensitivity matrix, x_k = load at time k, v_k^0= base voltage.

Voltage constraints:

$$v_{min} \le v_k \le v_{max} \quad (10)$$

Any violations trigger penalty increments in the payoff.

3.5 Integration of Reference Escort Replicator Theory (Extension 3)

The third extension incorporates the theoretical foundations from the reference paper:

- Escort dynamics guarantee Evolutionary Stable Strategy (ESS)
- A Lyapunov function ensures monotonic improvement
- Population-based updates allow smooth and stable energy allocation

The Lyapunov function derivative:

$$\dot{V}(x) = Z_\phi(x)\,\mathrm{Var}_\phi(f(x)) \quad (11)$$

Any violations trigger penalty increments in the payoff.

Which increases when charging is more evenly distributed.

Through iterative updates, MSD converges to a probabilistic equilibrium. This ensures diversity in charging decisions and avoids clustering of demand. However, MSD alone cannot guarantee that each EV will achieve its required SoC before departure, motivating the integration of FDP.

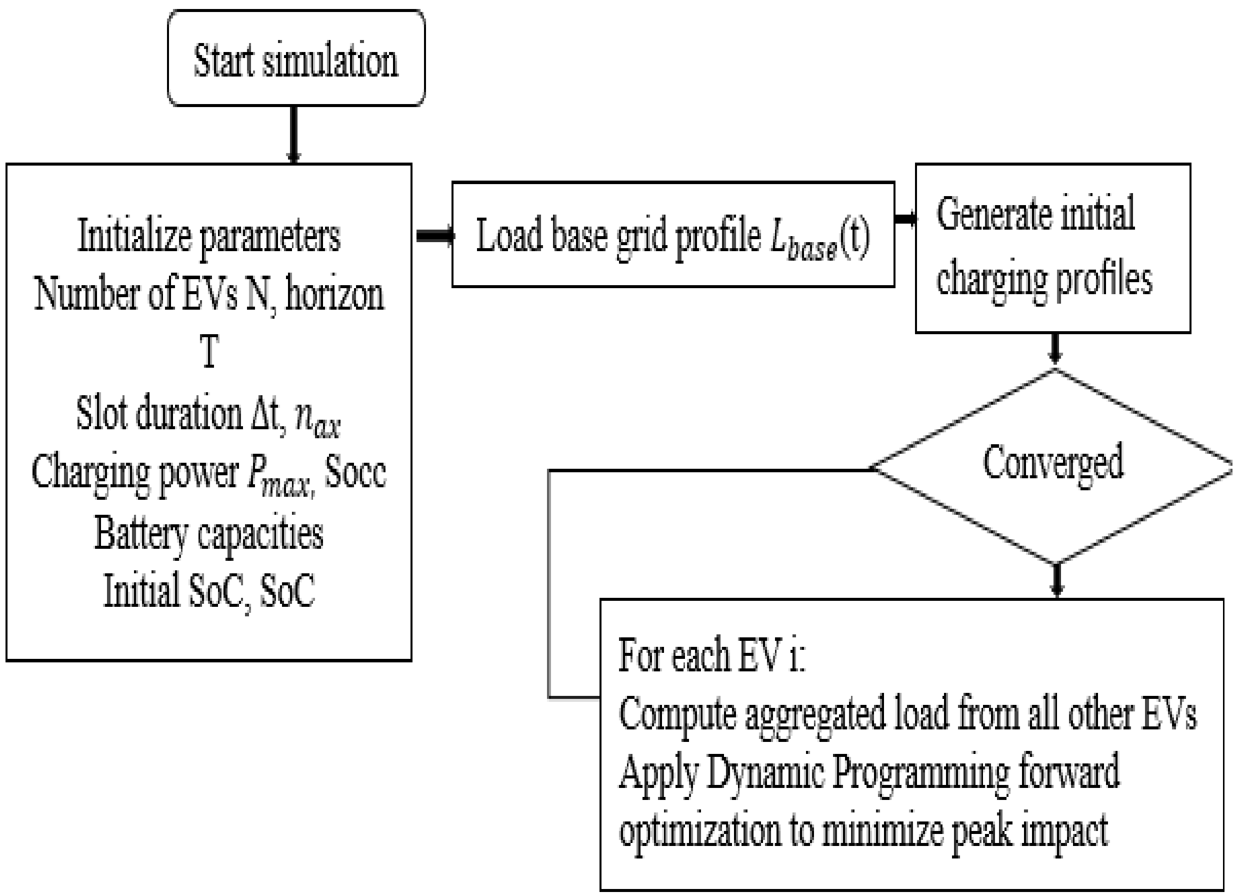

Figure 2. Flowchart of the Mixed Strategist Dynamics (MSD) scheduling process, showing probabilistic strategy updates based on fairness-aware payoffs.

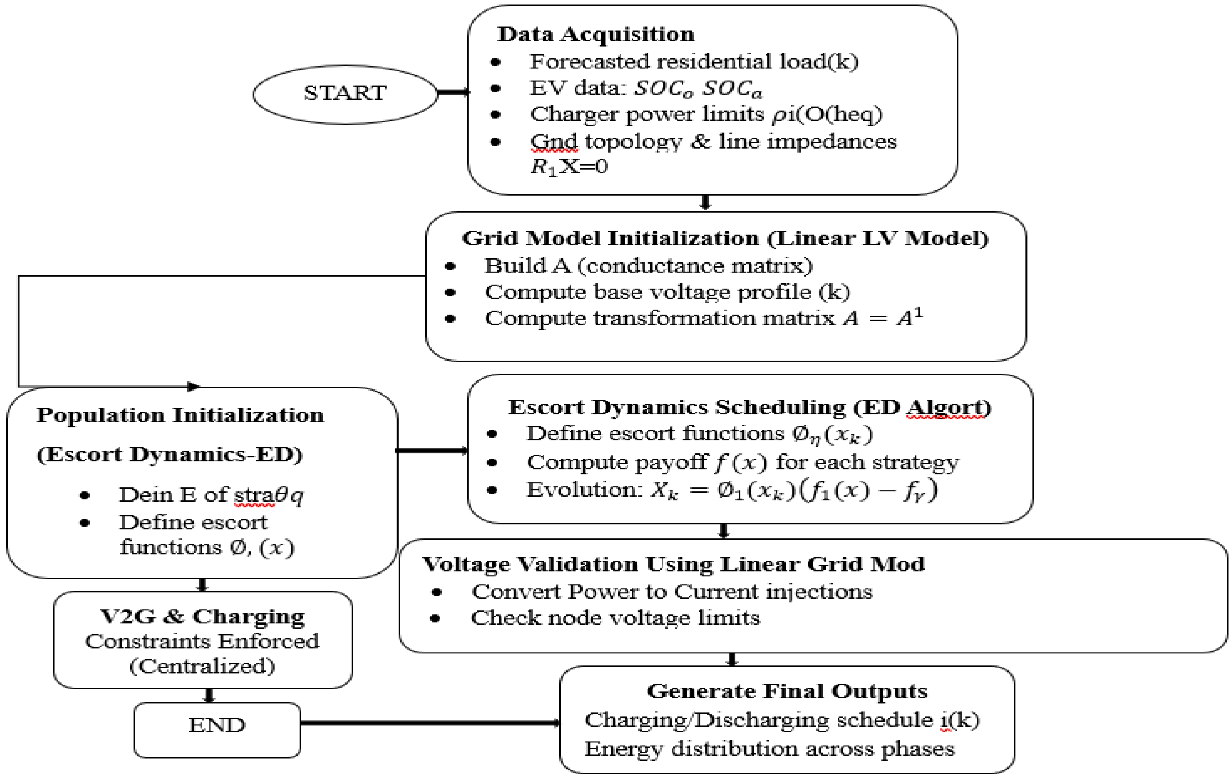

Figure 3: Evaluation of Enhanced Escort Energy Distribution Algorithm for Optimal Integration of Electric Vehicles

IV. SIMULATION SETUP

This section describes the simulation framework developed to evaluate the proposed Enhanced Escort Energy Distribution (E-EED) algorithm. The test environment combines Escort Dynamics, grid-aware constraints, and a linear voltage model to analyse coordinated EV scheduling performance under varying loading conditions. The simulations are executed using time-coupled energy populations, reactive-support populations, and distribution-grid voltage validation.

4.1 Environment: The proposed Enhanced Escort Energy Distribution (E-EED) framework was implemented in MATLAB. The setup combines the Escort Dynamics algorithm, the linear voltage model from Chapter 2, and a constraint-checking block that ensures feasibility during each iteration.

4.2Energy and Reactive-Power Populations: EV charging is represented using two populations: an energy distribution population and a reactive-power support population. These populations evolve over the scheduling intervals using escort functions until a stable solution is reached. Upper/lower bounds and energy requirements are applied at every update.

Table 1: summarizes the key simulation parameters.

Parameter	Value / Range
Time Resolution	15-minute intervals (96 slots/day)
Energy Requirement	Fixed daily charging energy distributed by Escort Dynamics
Voltage Model	Linear LV model using reduced conductance matrix (A-matrix)
Voltage Limits	$v_{min} \le v(k)v_{max}$checked at each iteration
Escort Dynamics	Energy + reactive-power populations evolving to ESS
Simulation Cases	ED-only, ED with voltage limits, and ED with V2G

4.3 Distribution Network Model: The distribution feeder is modelled using the linear voltage equations derived in Chapter 2. EV power injections are converted into node voltages using the reduced conductance matrix. Voltage limits are checked at every step, and any violations are corrected through updated population evolution.

4.4 Case Studies: Multiple simulation cases were created, ranging from simple energy allocation to full Escort Dynamics with voltage limits and V2G support. These cases help observe how the algorithm behaves under different grid and charging conditions.

Table 2: outlines the case study scenarios defined for analysis.

Case	*Description*
Case 1	Uncoordinated charging where EVs charge immediately after arrival.
Case 2	Escort Dynamics (ED) without reactive-power support.
Case 3	Full ED scheduling with energy and reactive-power populations.
Case 4	ED with voltage-constraint validation using the linear grid model.
Case 5	ED with voltage constraints and V2G support enabled.

4.5 Performance Metrics: The method is evaluated based on voltage deviation, energy distribution smoothness, reactive-power contribution, and the convergence behavior of the Escort Dynamics process.

4.6 Illustrative Example: In a sample run, the initial energy allocation was uneven and caused voltage issues. After applying Escort Dynamics with voltage validation, the energy distribution shifted to safer time periods, voltage stayed within limits, and the solution converged smoothly. This confirms the effectiveness of the proposed framework.

V. RESULTS AND DISCUSSION

This section presents the performance evaluation of the proposed Enhanced Escort Energy Distribution Framework, including the base Escort Dynamics (ED) model and three incremental extensions. The results assess fairness, grid impact, voltage compliance, price responsiveness, and feasibility for multi-PEV coordination. A. Escort Dynamics (ED) Results – Base work Model.

A. Escort Dynamics Base Work Results The Base Escort Dynamics model generates feasible active and reactive power schedules while ensuring all EVs reach their required final SoC. The aggregated phase profiles and per-vehicle power behavior demonstrate how the ED algorithm distributes charging demand without violating transformer loading limits.

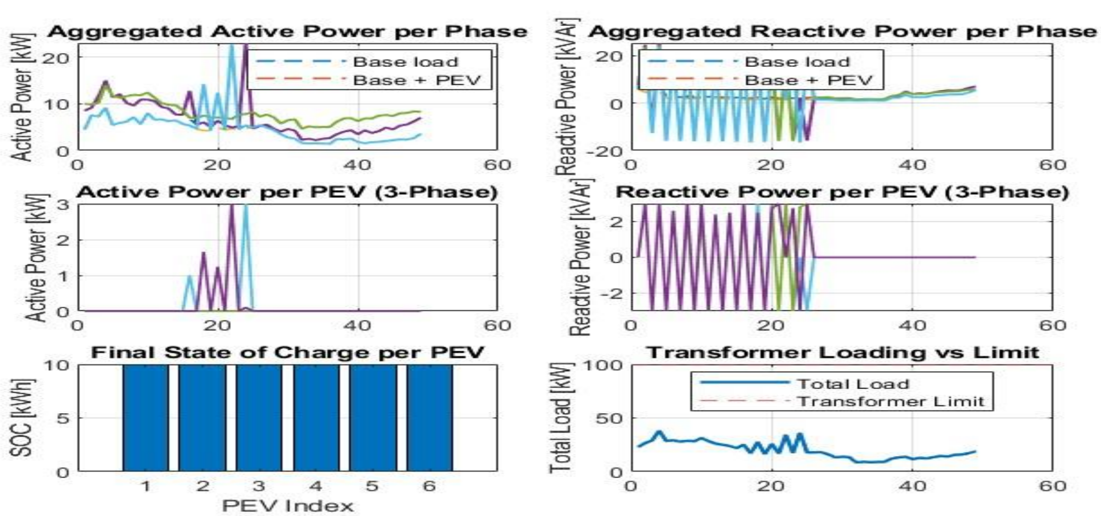

Figure. 4 –Aggregated Active and Reactive Power Profiles with PEV Charging, Final SOC, and Transformer Loading.

Interpretation: This figure shows that the aggregated 3-phase power remains well balanced, and all six EVs successfully reach their final SoC. Transformer loading stays below its limit, confirming that the base ED mechanism prevents overload under normal operating conditions.

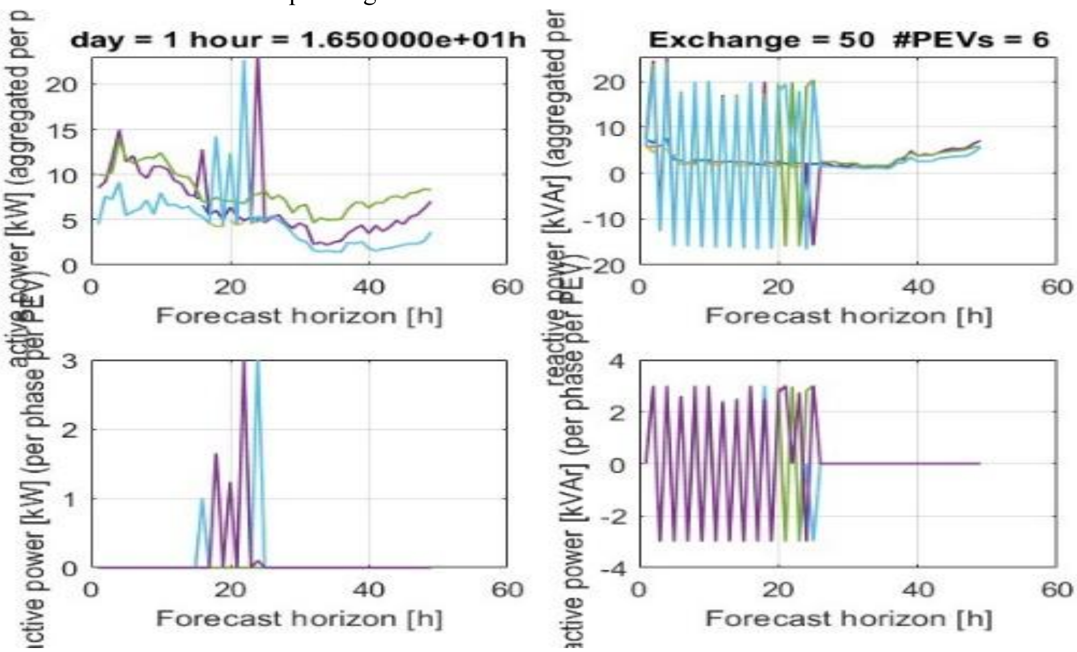

Figure. 5- EV Fleet Active and Reactive Power Profiles (Aggregated and Per Phase)

Interpretation: The forecast-horizon results reveal initial oscillations that gradually stabilize as the ED algorithm converges. Each EV charges in a distinct time window, reducing simultaneous peaks and maintaining phase-level balance across the horizon.

B. ED–Barrier Scheduling Results: The ED-Barrier extension incorporates a logarithmic barrier to enforce SoC and power constraints smoothly. This results in significantly more stable, oscillation-free trajectories, especially over long horizons. The figures illustrate improved smoothness, enhanced phase balancing, and better alignment between grid load and EV charging behavior compared to the base ED model.

Figure. 6 – Total Three-Phase Aggregated Active Power Profile over Four Days

Interpretation: The 3-phase load distribution remains tightly clustered across phases, indicating strong phase balance. The barrier method avoids the oscillations seen in the base ED model, producing a smooth 96-hour load profile.

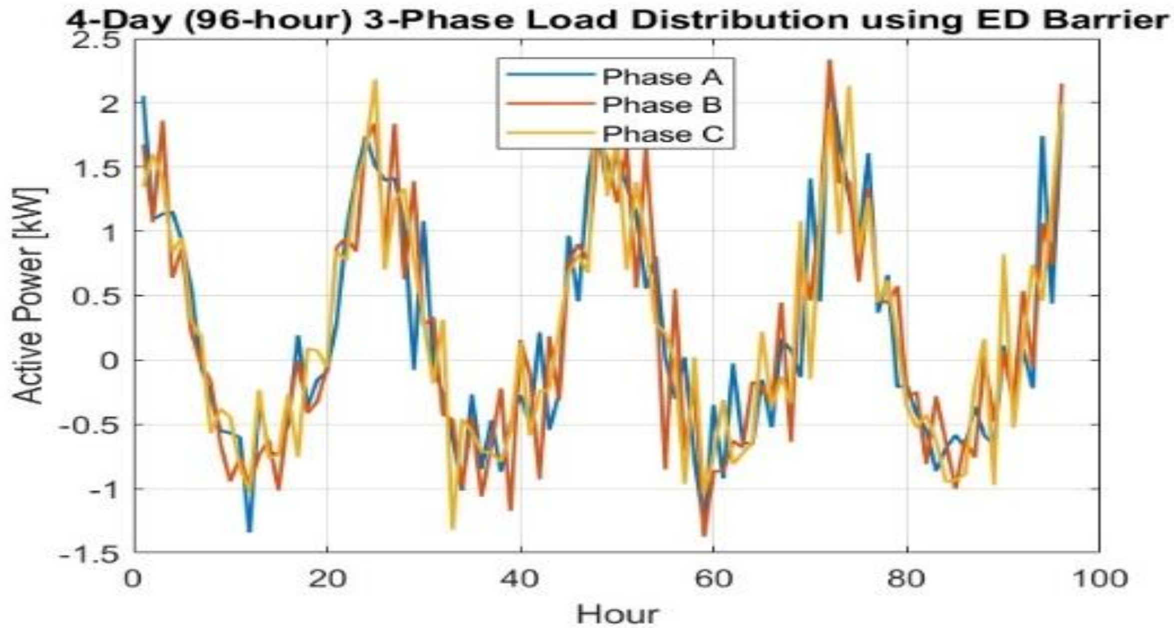

Figure. 7 – Four-Day (96-Hour) Three-Phase Load Distribution Using ED Barrier Method

Interpretation: The total 3-phase aggregate load closely follows the natural base-load pattern without introducing new peaks. This confirms that ED-Barrier shifts EV power intelligently while preserving overall grid stability.

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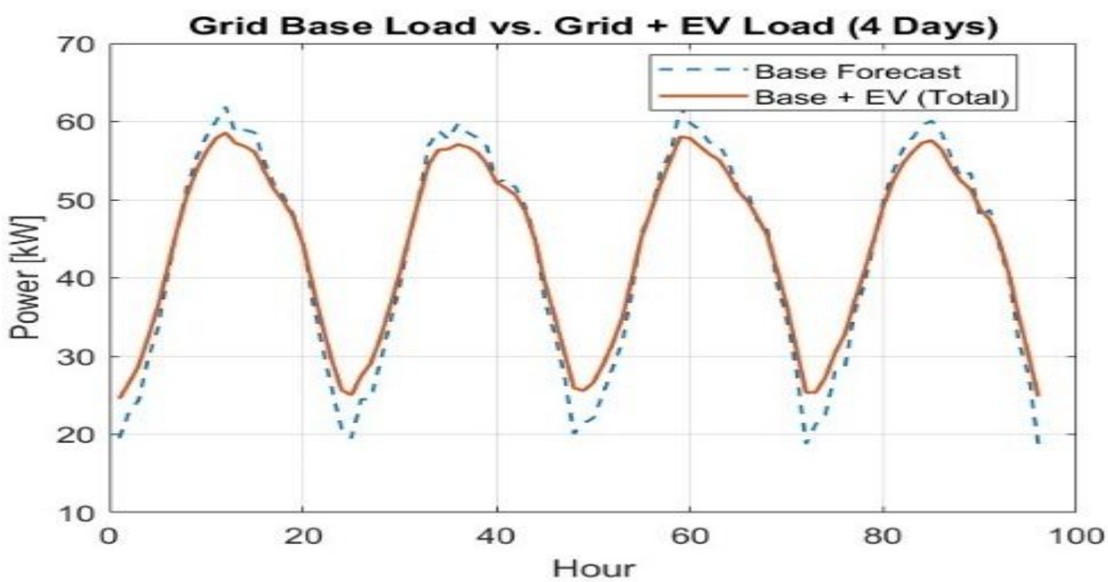

Figure. 8- Comparison of Grid Base Load and Grid-Plus-EV Total Load over Four Days

Interpretation: The comparison between base load and EV-integrated load shows that EV charging remains aligned with low-demand periods. The barrier term prevents aggressive charging during peak times, significantly improving demand flattening and system predictability.

C. Centralized Optimization Scheduling Results**:** The centralized optimization scheduler coordinates all EVs under strict grid constraints, generating optimal charging trajectories that satisfy SoC limits, transformer loading bounds, and voltage stability. The outputs show how centralized control ensures feasible system operation while minimizing violations.

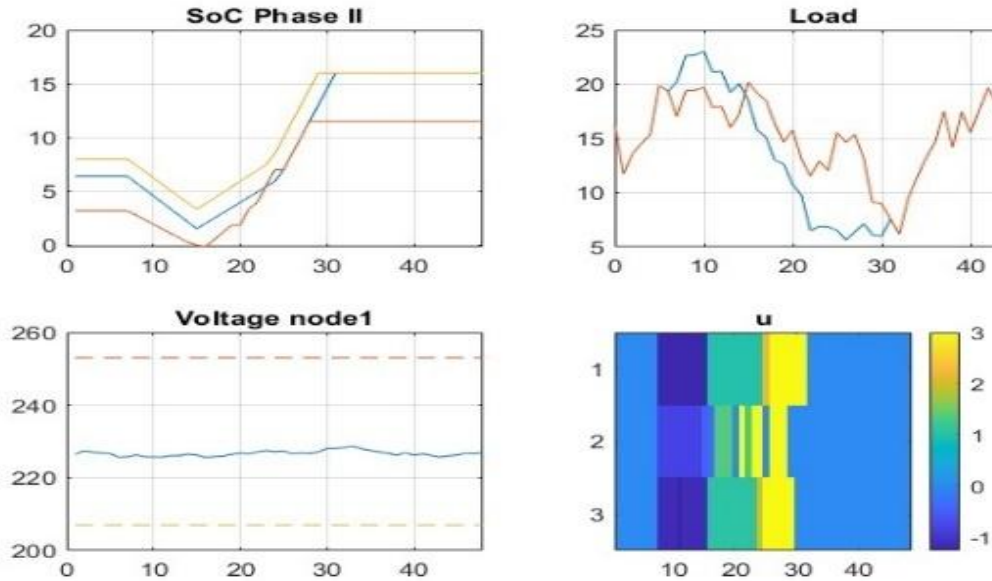

Figure. 10- Phase II Results: SoC Evolution, Load Profile, Node Voltage, and Control Action

Interpretation: SoC trajectories increase smoothly to their targets, and node-voltage levels remain within the allowable upper and lower bounds. The load pattern demonstrates coordinated EV charging that avoids peak periods and ensures non-violation of distribution constraints.

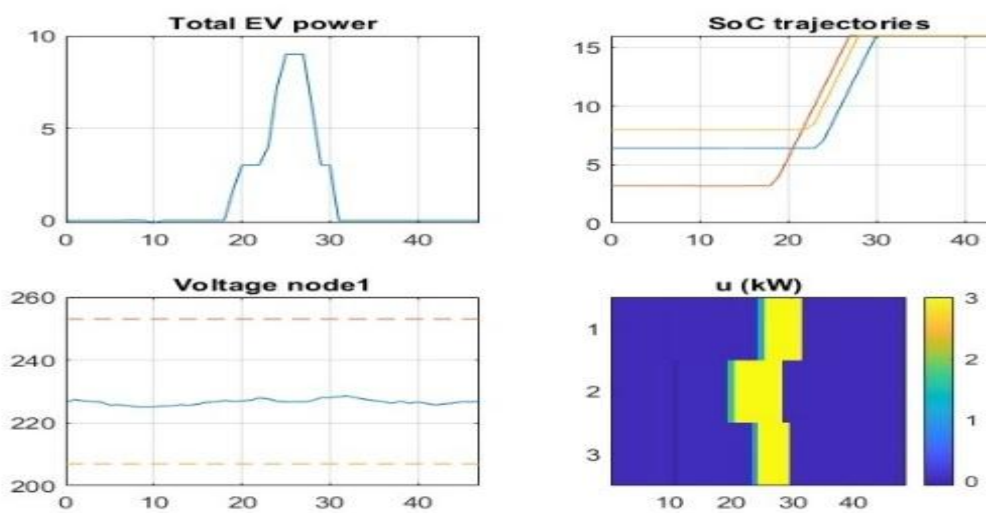

Figure. 11-EV Charging Results: Total EV Power, SoC Trajectories, Node Voltage, and Control Action

Interpretation: Total EV power is concentrated into a short, optimized charging window. The voltage profile remains well regulated, and the charging control matrix shows non-overlapping EV actions, proving effective coordination and grid-safe operation.

D. Price-Based ED Scheduling Results: The price-based ED model incorporates dynamic electricity tariffs to steer charging toward low-cost periods. The resulting active/reactive power allocations and the SoC trajectory demonstrate that EV charging adapts economically while maintaining feasible operating limits.

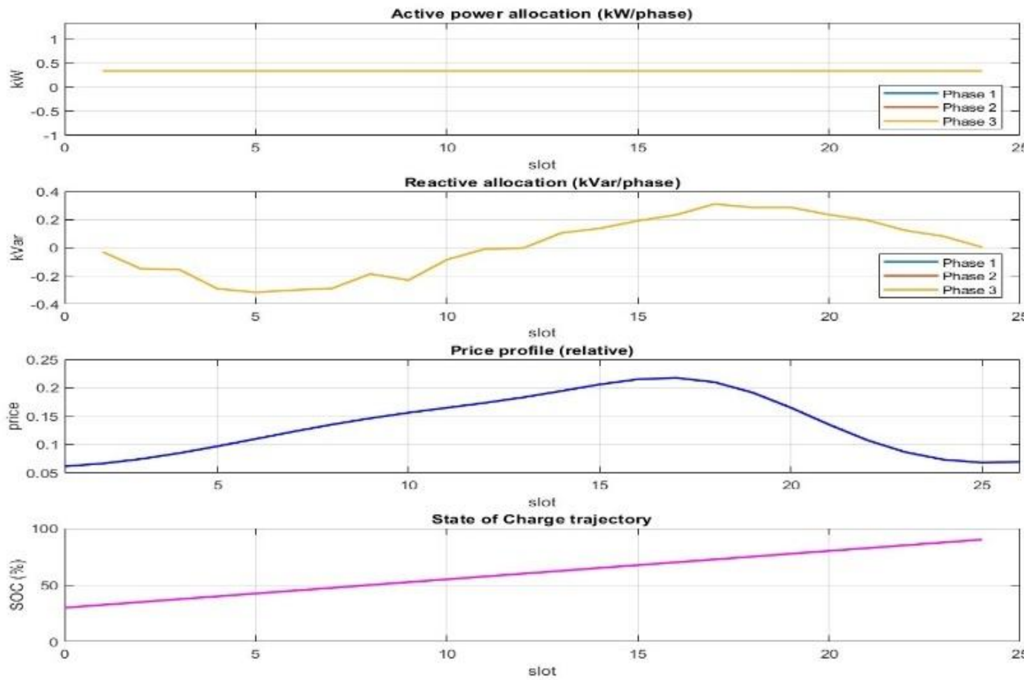

Figure. 12- Active and Reactive Power Allocation, Price Profile, and State-of-Charge Trajectory

Interpretation: Charging shifts away from high-price intervals and occurs mostly during low-tariff periods. Phase power remains balanced, reactive power supports voltage needs, and the SoC increases linearly, confirming cost-optimal and grid-compliant charging behavior.

Table 3: Comparison of EV Charging Scheduling Methods in Terms of Grid Performance and Operational Characteristics

Method	Fairness	Grid Impact	Voltage Safety	Cost Efficiency
Base ED	High	Low grid stress	Not enforced	No cost awareness
ED-Barrier	Very high	Very low stress	Improved	No cost awareness
Centralized Opt.	Guaranteed	Minimal stress	Strictly enforced	Moderate
Price-Based ED	High	Low stress	Indirectly supported	High (tariff-based)

Table 4: Summary of Key Performance Outcomes for Different EV Scheduling Methods

Metric	Base ED	ED-Barrier	Centralized	Price-Based ED
SoC Achievement	100%	100%	100%	100%
Peak Load Reduction	Medium	High	Very High	High
Voltage Compliance	Within limit	Better	Fully guaranteed	Stable
Charging Smoothness	Moderate	Very smooth	Optimal	Smooth
Transformer Overload	None	None	None	None

E. Summary of Results:
All four scheduling methods successfully achieve 100% SoC and prevent transformer overload. The ED-Barrier approach improves smoothness and reduces peaks compared to the base model. Centralized Optimization gives the best grid safety with strict voltage compliance, while Price-Based ED effectively shifts charging to low-tariff periods. Overall, the proposed methods enhance fairness, reduce peak load, and maintain stable grid operation during EV integration.

VI. CONCLUSION

This work evaluated an enhanced Escort Energy Distribution (ED) algorithm for achieving optimal and grid-safe integration of electric vehicles. The study demonstrated that the base ED model ensures feasible charging while maintaining balanced phase loading, and the ED-Barrier extension further improves stability by producing smooth, constraint-satisfying trajectories. The centralized optimization framework delivered the strongest grid compliance, guaranteeing voltage limits and minimizing transformer loading, while the price-based ED method effectively shifted charging to low-tariff periods, improving economic efficiency.
Across all methods, EVs consistently reached their required state of charge without causing overloads or voltage violations. The combined results confirm that the enhanced ED approach improves fairness, reduces peak demand, and maintains reliable grid operation. Overall, the proposed scheduling framework provides a robust and practical solution for future large-scale EV integration in distribution systems.

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