

Sustainable EVs Intelligent Management Framework with Multi-Objective Differential Parrot Optimization

Niti Shashikant Desai^{1*} and Chandrakant Rathore²

¹ Research Scholar, Department of Electrical Engineering, Swarnim Startup & Innovation University, Gujarat – 382422, India.

Email: nitiphd2021@gmail.com

² Department of Electrical Engineering, S.B. Jain Institute of Technology, Management & Research, Maharashtra – 441501, India.

Email: chandrakantrathore@sbjit.edu.in

*Corresponding Author

ARTICLE INFO	ABSTRACT
Received: 02 Oct 2024 Revised: 20 Nov 2024 Accepted: 29 Nov 2024	The increasing penetration of Electric Vehicles (EVs) and rooftop photovoltaic (PV) systems introduces substantial operational complexities into radial distribution networks, including voltage instability, harmonic distortion, and uneven power flows. Existing methodologies often treat planning and control separately, lacking real-time adaptability under stochastic demand-generation patterns. To bridge this critical gap, this study proposes a novel Multi-Objective Differential Parrot Optimization (MODPO) algorithm integrated with a Hierarchical Reinforced Predictive Load Control (HRPLC) framework. The MODPO algorithm ensures optimal siting and sizing of EV charging stations and PV units by minimizing power loss, voltage deviation, and operational cost. Simultaneously, HRPLC coordinates dynamic G2V/V2G operations using a deep deterministic policy gradient (DDPG) agent embedded within a predictive MPC layer. Extensive simulations on an IEEE 69-bus system show a 60.38% cost reduction, 9.84 kW loss minimization, and voltage deviation contained to 4.06%, while 100% PV utilization is achieved under harmonic and voltage unbalance constraints. This unified optimization-control framework provides a scalable pathway for reliable, cost-efficient, and quality-assured operation of future distribution networks with high DER proliferation. Keywords: Electric vehicles (EVs), Distributed Renewable Energy Sources (DRES), energy management, Reinforcement Learning (RL), and Optimization.

1. Introduction

The increasing urgency to address carbon dioxide emissions and mitigate global warming, coupled with the transition toward zero-emission transportation, has accelerated the adoption of Plug-in Electric Vehicles (PEVs). These vehicles are anticipated to significantly contribute to lowering air pollution levels in the transportation sector [1]. Moreover, implementing effective strategies for PEV operation and charging schedule optimization can yield substantial economic advantages, including notable reductions in fuel expenditure. Unlike traditional internal combustion engine vehicles, PEVs rely on battery recharging through charging stations connected to the power grid [2]. Consequently, PEVs introduce additional load on distribution networks, which, if not properly managed, can lead to challenges such as transformer and transmission line overloading, increased power losses, peak demand surges, poor voltage profiles, and overall voltage stability concerns [3]. Uncoordinated PEV charging and improper placement of charging stations further exacerbate these issues, necessitating strategic planning for optimal Electric Vehicle Charging Stations (EVCS) integration [4]. The integration of EVCS powered by Renewable Energy Sources (RES), such as solar and wind, plays a

crucial role in promoting sustainable energy solutions and mitigating greenhouse gas emissions [5]. The increasing adoption of EVs is primarily driven by the rising costs of fossil fuels and the global push towards eco-friendly transportation [6]. However, this surge in EV demand places a significant burden on the existing grid infrastructure. In this context, EVCSs that utilize RES like PV and wind power offer a viable alternative to conventional grid-based charging stations, thereby enhancing sustainability and reducing dependency on fossil fuels [7].

RES, particularly solar PV systems, have become increasingly prominent in reducing environmental pollution and mitigating the greenhouse effect [8]. As a well-established and widely adopted power generation technology, PV energy aligns with the Sustainable Development Goals and enhances energy security. With advancements in distributed generation (DG), PV systems can now operate on a smaller scale as Distributed Energy Resources (DERs) [9]. This decentralized approach to power generation ensures that energy is supplied closer to the load demand, thereby minimizing transmission losses and enhancing system efficiency. Nevertheless, photovoltaic (PV) energy is inherently intermittent and variable, primarily influenced by fluctuations in solar irradiance, transient cloud cover, the orientation of panels, and the accumulation of dust, all of which can adversely impact the stability of power generation [10]. Furthermore, substantial PV penetration within distribution networks may lead to operational challenges, including voltage rise, reverse power flow, and elevated energy losses, thereby underscoring the necessity for well-optimized PV integration methodologies [11].

However, inadequate integration of large-scale EVCSs can pose significant risks to power systems, including distribution feeder imbalances, increased current levels, and bi-directional power flow complications [12]. Moreover, unregulated and haphazard EV charging can result in excessive power losses and voltage fluctuations that exceed permissible limits, potentially compromising grid stability and reliability. To address these challenges, optimal EVCS placement in distribution networks is essential to minimize adverse effects and ensure efficient operation [13]. Several studies have focused on employing heuristic techniques for optimizing EVCS allocation within distribution networks. Heuristic algorithms are widely favoured due to their ability to provide rapid and practical solutions for scheduling and planning problems [14]. These algorithms offer immediate and easily interpretable results, making them particularly suitable for real-world applications. Through the application of heuristic optimization techniques, researchers seek to determine optimal locations for EVCSs that minimize adverse effects on the power grid, improve overall energy utilization, and facilitate the smooth integration of RES [15]. With the rapid shift toward sustainable transportation, the formulation of advanced optimization frameworks for EVCS deployment becomes essential to maintaining the long-term reliability, stability, and resilience of contemporary power distribution systems. In this context, the present study proposes an innovative co-optimization and control framework designed for the strategic planning and adaptive management of distribution networks characterized by substantial PV and EV penetration based upon the following contribution:

- A MODPO algorithm is developed to ensure optimal siting and sizing of PV systems and EV charging stations, minimizing power loss, voltage deviation, and operational cost under multi-constraint conditions.
- A Hierarchical Reinforced Predictive Load Control (HRPLC) strategy is proposed, combining DDPG-based real-time learning with MPC-based grid forecasting to coordinate G2V/V2G dynamics adaptively.
- The proposed system integrates harmonic filtering and smart inverter control, enabling power quality preservation through localized voltage and THD mitigation.
- Extensive simulations on the IEEE 69-bus network validate the framework's superiority over existing methods, showing significant reductions in operational cost (60.38%), power losses (9.84 kW), and enhanced PV utilization (100%).

Section 2 describes the literature works done much related to this proposed work. Section 3 details the proposed MODPO and HRPLC frameworks. Section 4 presents simulation setups and data

generation processes and discusses results, comparative analysis, and sensitivity studies. Finally, Section 5 concludes with key findings and future research directions.

2. Literature Survey

In recent years, the rapid adoption of EVs has significantly increased the focus on deploying EVCS as a key element in promoting environmental sustainability. A substantial body of literature has explored the environmental benefits associated with EVCS, yet integrating these stations into existing distribution grids poses considerable challenges. Researchers have reported that the incorporation of DRES and Battery Energy Storage Systems can further complicate grid operations, leading to issues such as elevated power losses and voltage instability. To address these technical challenges, recent studies have increasingly investigated smart charging schemes, where the distribution system operator (DSO) strategically oversees EV charging operations to achieve specific technical and financial objectives. This literature survey provides an overview of current research on EVCS integration, highlighting the complex interplay between renewable integration, grid stability, and the emerging role of smart charging strategies.

Ali et al. [16] developed a multi-objective planning framework aimed at determining the optimal placement of EVCSs alongside the sizing and siting of RES. The framework addresses three key objectives: minimizing voltage deviations, reducing line energy losses, and improving EV user satisfaction. The optimization strategy incorporates advanced control mechanisms for coordinating RES inverter operations with EVCS charging and discharging processes. To address the inherent trade-offs among the objectives and variables, a two-level multi-objective metaheuristic was formulated using the Multi-Objective Dragonfly Algorithm. Evaluations across three case studies demonstrated substantial performance gains, with RES-enabled inverters delivering improved reactive power support, reducing voltage deviations by 96%, and decreasing energy losses by 71%.

Ahmadi et al. [17] proposed a robust and adaptable optimization methodology for managing the bidirectional charging of PEVs, employing a stochastic, multi-objective heuristic approach based on the Firefly Algorithm. The framework seeks to minimize operational costs and CO₂ emissions while accounting for uncertainties related to RES generation, load demand, and charging/discharging schedules. Implemented on a modified IEEE 69-bus system within a MATLAB simulation environment, the method achieved a 48% reduction in operating expenses and a 55% decrease in CO₂ emissions. The results further suggested operating PEVs in grid-to-vehicle (G2V) mode when electricity prices and emission levels are low, and adopting vehicle-to-grid (V2G) operation during periods of high prices and emissions. This approach yielded notable economic benefits for PEV owners, with daily cost savings estimated at \$787.7, while improving the network's voltage profile by up to 6%.

Muthusamy et al. [18] introduced the Honey Badger Optimization Algorithm (HBOA), a novel metaheuristic designed to enhance convergence speed and optimize multi-objective performance metrics. The algorithm determines EVCS placement by considering V2G operation capabilities and user driving patterns over a full 24-hour period. When tested on the modified IEEE 69-bus and the Indian 28-bus radial distribution networks, the method delivered significant outcomes, including a 62% reduction in power losses for the IEEE 69-bus system and a 66% reduction in CO₂ emissions for the Indian 28-bus system.

KK.N. et al. [19] investigated the influence of EVs and RES on the Voltage Unbalance Factor (VUF) and operational characteristics of distribution networks, including voltage stability, reliability, and the voltage–reliability–power loss (VRP) index, using a modified IEEE 33-bus system under three distinct operating scenarios. To maintain VUF within acceptable thresholds, a coordinated charging–discharging strategy was proposed. The inherent uncertainties in solar and wind generation, as well as their availability during varying load demands, were modeled using a Monte Carlo Simulation (MCS). A fuel cell system was incorporated as a backup source to address variability in renewable generation.

The optimization problem was solved using two metaheuristic approaches: a modified JAYA algorithm and the Whale Optimization Algorithm (WOA).

Abdelaziz et al. [20] addressed the optimal placement and sizing of EVCSs, PV units, and Distribution Static Compensators (DSTATCOMs) to enhance grid performance. The study employed the Renewable Distributed Generation Hosting Factor (RDG-HF) and EV Hosting Factor (EV-HF) as primary metrics, in combination with the Hippopotamus Optimization Algorithm (HO) for strategic planning within the IEEE 69-bus network. Simulation results indicated power loss reductions of up to 31.5% and reactive power loss reductions of up to 29.2%. An economic analysis demonstrated payback periods ranging from 2.7 to 10.4 years, with potential profits reaching \$1,052,365 over a 25-year operational horizon.

Niknami et al. [21] proposed a comprehensive operational planning framework for microgrids aimed at enhancing both economic performance and system resilience. The model incorporated uncertainties related to weather variability, EV charging patterns, RES integration, market price fluctuations, and load demand, while also accounting for EV user satisfaction and demand-side management. The approach coordinated network topology reconfiguration, EV movement patterns, and weather impacts, with MCS applied to represent uncertainties. A multi-objective optimization algorithm was employed to maximize profits for both network operators and private sector stakeholders. Results demonstrated notable improvements, including a 37.1% reduction in unsupplied energy costs, a 5% increase in operator profits, and a 23.1% increase in EVCS profits.

Das et al. [22] developed a probabilistic load modeling framework for Plug-in Electric Vehicle (PEV) charging demand at public stations, utilizing probability distribution functions (PDFs) to represent charging start time, initial state of charge, and daily travel distance. A centralized scheduling scheme based on time-of-use (TOU) pricing was incorporated into a multi-objective smart charging model, which was reduced to a single-objective problem using the weighted sum method. The objectives considered included minimizing power losses, reducing load variance, and lowering charging costs. Testing on IEEE 33-bus and IEEE 69-bus distribution systems revealed that the proposed strategy enhanced grid performance while delivering economic benefits to consumers.

Eisa et al. [23] focused on the optimal integration of distributed generators (DGs) into radial distribution networks (RDNs) operating under uncoordinated PEV charging conditions. The study sought to minimize daily energy losses, improve voltage profiles, and enhance voltage stability. The Walrus Optimization Algorithm (WO) was applied to determine the optimal DG locations and capacities while minimizing the multi-objective function (MOF) without violating network constraints. The proposed model was validated on IEEE 33-bus, IEEE 69-bus, and a real distribution system in El-Shourok City (District 8), Egypt. Results confirmed that the WO-based approach significantly improved RDN performance when integrated with PEV loads, offering high-quality and computationally efficient solutions.

Aljafari et al. [24] explored the often-overlooked aspect of reliability and resilience enhancement in DRES. The study introduced optimization techniques based on the Spotted Hyena Optimization Algorithm to determine the optimal size and location of DG units and EVCSs operating in V2G mode. The approach was designed to strengthen RDS performance by evaluating the effects of EVCS loads and DG integration on consumer and energy-oriented reliability indices, voltage stability, and power delivery capacity.

Rene et al. [25] presented a hybrid optimization framework combining Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) for the optimal siting of PEVCS within distribution networks with high Distributed Generation (DG) penetration. Photovoltaic units with a power factor of 0.95 were modeled as DGs, and six penetration scenarios were examined. The objective was to minimize both active and reactive power losses and reduce voltage deviation indices. The methodology was tested on IEEE 33-bus and IEEE 69-bus networks using MATLAB simulations. Results demonstrated that the

inclusion of PEVCSs maintained minimum bus voltages within acceptable limits, with the IEEE 69-bus case yielding a minimum voltage of 0.973 p.u. The findings reinforced the role of EV integration in reducing emissions and supporting the transition toward a carbon-neutral energy landscape.

Table 1 Comparative table of existing literature works

Reference	Test system	Scope	Key performance gains	Limitations identified
[16]	Modified 69-bus	Multi-objective EVCS & RES placement using MODA considering voltage deviation, losses, and user dissatisfaction	Reduction in voltage deviation by 96%, decrease in energy loss by 71%	Does not consider dynamic vehicle behavior or operational cost
[17]	Modified 69-bus	Stochastic EV charge/discharge optimization with Firefly algorithm under RES/load uncertainties	Decrease in operating cost by 48%, decrease in CO ₂ emissions by 55%, increase in Voltage by 6%	Ignores grid-side constraints and long-term planning aspects
[18]	69-bus & Indian 28-bus	EVCS placement with V2G support using Honey Badger Optimizer	Decrease in power loss by 62%, reduction in CO ₂ emissions by 66%	Demand forecasting and economic aspects not addressed
[19]	Modified 33-bus	Impact of EV & RES on VUF, VRP index; uses Monte Carlo + hybrid optimization	Maintains VUF within limits, improves voltage and reliability	Relies on assumed fuel cell backup, lacks cost-performance analysis
[20]	69-bus	Optimal placement of PV, EVCS, and DSTATCOM using Hippopotamus Optimizer	Power loss by 31.5%, Reactive losses decreased by 29.2%, Payback <10 years	System-wide resilience and dynamic EV usage patterns not explored
[21]	Microgrid & Real-world networks	Operational planning with uncertainties in RES, EVs, and load; economic profit maximization	Eliminated unsupplied energy by 37%, improved EV profits by 23.1%, and operator profit by 5%	High computation cost, lacks control flexibility for real-time operation.
[22]	IEEE 33 & 69-bus	Smart PEV load modeling with multi-objective pricing and charging control	Improves load variance, cost, and power loss mitigation	Focuses on centralized pricing; ignores reactive power and grid congestion
[23]	33-bus, 69-bus, Egypt Real System	DG planning with EV integration using Walrus Optimizer	Improved voltage profile and minimized daily energy loss	No coordinated EV charge scheduling; reactive power handling limited
[24]	Radial network	Resilience improvement with V2G-enabled EVCS and DG placement using Spotted Hyena Optimization	Improved reliability indices and voltage stability	Lacks economic analysis; limited consideration of user-side behavior
[25]	33 & 69-bus	PEVCS placement with DG using GA-PSO; evaluates voltage and power loss	Maintains voltage $\geq$ 0.973 pu under high DG & PEVCS penetration	Cost impact and THD/VUF factors not evaluated

Table 1 concisely presents comparative insights, contextualizes each study's methodology and scope, and pinpoints where your proposed method fills the gap, especially regarding dynamic EV-PV coordination, cost reduction, and grid resilience under uncertainty. When studies overlook the unpredictable and variable charging demands of EV owners as well as the intermittency of renewable energy generation, they fail to account for several critical variables. On the EV side, these include the time when vehicles arrive and depart, the state-of-charge (SOC) upon arrival, the battery capacity, and the duration of charging sessions. On the renewable generation side, key variables include solar irradiance and temperature fluctuations, which are influenced by weather conditions such as cloud cover, temperature, and seasonal patterns, as well as the inherent ramp-up and ramp-down rates of solar panels and wind turbines. Together, these factors introduce significant uncertainty into system planning and operation, necessitating advanced modeling and management strategies to ensure grid stability and efficiency.

3. Proposed Methodology

To address the increasingly intricate interdependence between EVCS infrastructure and RES penetration in modern distribution systems, this study introduces a novel, holistic control strategy, Sustainable EVs Intelligent Management Framework (SEIMF), which unifies infrastructure planning with dynamic operational optimization. The existing works on EVCS-RES integration tend to compartmentalize optimization goals, often prioritizing cost or loss minimization, while overlooking critical grid reliability parameters, such as the Voltage Unbalance Factor (VUF), Total Harmonic Distortion (THD), and dynamic load imbalances induced by stochastic EV charging behaviours. Furthermore, RES, particularly PVs, are inherently intermittent and affected by environmental conditions, which compounds the complexity of real-time load and voltage management. Conventional methods often lack the adaptive capability to accommodate such volatility, leading to localized voltage deviations, thermal stress on grid components, and inefficient utilization of available renewable energy.

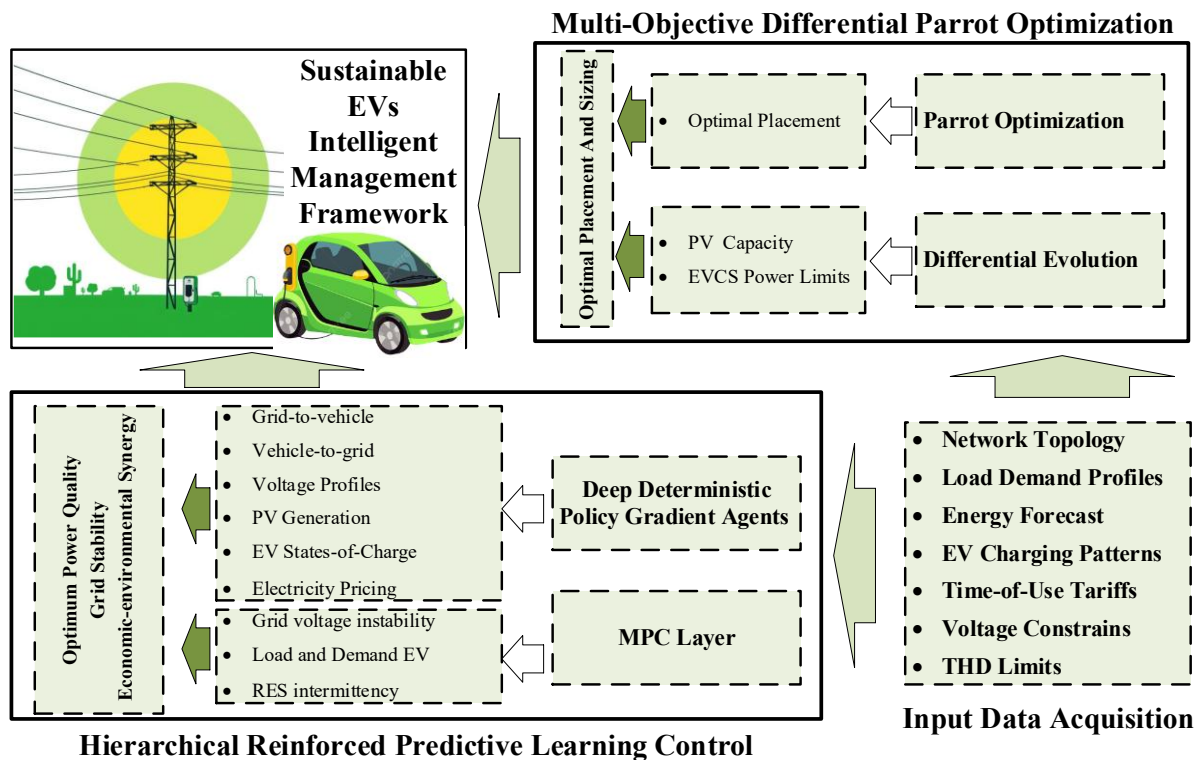


Figure 1: System architecture of the proposed SEIMF framework integrating MODPO-based planning and HRPLC-based control in EVCS-RES-grid coordination.

The SEIMF framework addresses these limitations by proposing an integrated architecture that combines infrastructure-level optimization with intelligent, decentralized control mechanisms. The overall architectural layout of SEIMF is illustrated in Figure 1, which displays the interplay between optimization, forecasting, learning control, and grid interfaces, facilitating comprehensive system coordination. At its core lies a novel Multi-Objective Differential Parrot Optimization (MODPO) algorithm, which simultaneously determines optimal siting and sizing of EVCS and PV systems using a two-phase search strategy that balances convergence efficiency and Pareto front diversity. A Hierarchical Reinforced Predictive Learning Control (HRPLC) module, wherein deep reinforcement learning (DRL) agents adaptively manage G2V/V2G operations based on real-time grid states and forecasted load-generation profiles, guided by a centralized Model Predictive Control (MPC) layer that forecasts grid dynamics over a 24-hour horizon, further augments this. The synergy between RL agents and MPC ensures pre-emptive voltage regulation and congestion avoidance. Additionally, the use of smart inverters embedded with harmonic filters facilitates localized power quality correction. By jointly addressing planning, operation, and quality aspects under a single integrated paradigm, SEIMF ensures grid resilience, economic feasibility, and environmental sustainability, demonstrating significant advancement over existing siloed approaches.

3.1 Distribution System Model and Objective Functions

The standard IEEE 69-bus radial distribution test system, which is frequently used in the literature to assess grid performance in distributed energy integration scenarios, is used to model and validate the suggested framework. With its high R/X ratios, unbalanced node configurations, and mix of residential and commercial load profiles, the network is an ideal testbed for evaluating the effects of RES and EVCS in real-world operating scenarios. Figure 2 illustrates the simplified architecture of the IEEE 69-bus radial distribution network incorporating PV generation and EVCS. The schematic highlights the integration of key system elements: the main grid connection at Bus 1, distributed feeder lines, and strategically located PV arrays and EVCS units across selected buses such as 11, 17, 52, and 64. The PV array injects renewable power into the feeder, while EVCS units support both G2V and vehicle-to-grid (V2G) operations, dynamically interacting with the distribution system.

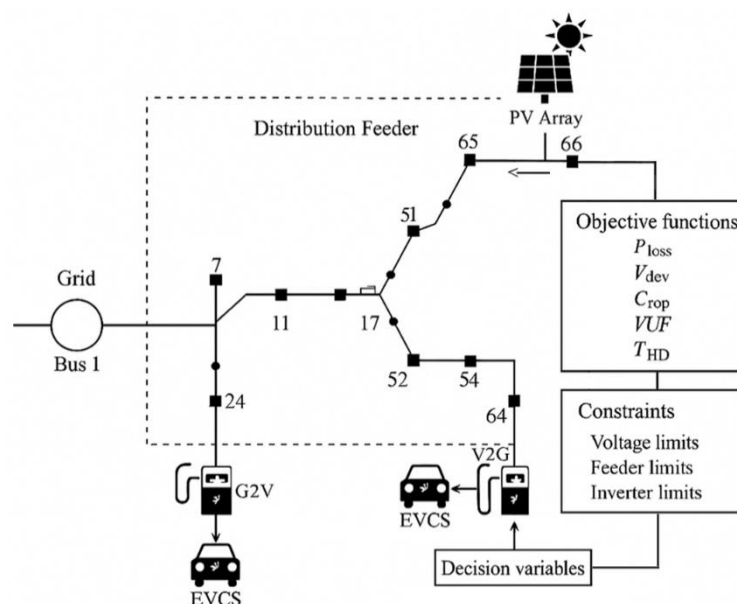


Figure 2: Part of the network in the proposed distribution system model

Selected nodes from the proposed methodology in this study are set up to support EVCS and PV arrays while maintaining system operational limitations like feeder capacity, phase load balancing, and voltage magnitude limits. To capture the variability introduced by PV generation, solar irradiance

and ambient temperature are modelled as time-dependent variables, with irradiance profiles derived from standardized test conditions and typical meteorological data. The EVCS is assumed to serve PEVS whose arrival, dwell time, and energy demand are modelled probabilistically, though detailed stochastic modelling is abstracted to maintain tractability. Power flows are computed using backward-forward sweep techniques, and the system is operated over a 24-hour time horizon divided into equal time slots to accommodate load and generation fluctuations.

The planning and control tasks are framed as a constrained multi-objective optimization problem. The goal is to simultaneously minimize total real power losses P_{loss} , voltage deviations V_{dev} , operational cost C_{op} , VUF, and THD, while maximizing the effective utilization of renewable energy U_{res} .

The decision variable vector x encapsulates the siting and sizing of PV and EVCS, as well as real-time operational set points. Power loss P_{loss} is defined as the sum of branch-wise losses over all lines $l \in \mathcal{L}$:

$$P_{loss} = \sum_{l \in \mathcal{L}} R_l \left(\frac{P_l^2 + Q_l^2}{V_l^2} \right) \quad (1)$$

Here, R_l is the resistance of line l , P_l and Q_l are the real and reactive power flows, and V_l is the sending-end voltage magnitude.

Voltage deviation is computed as the aggregated squared deviation of all bus voltages from the nominal voltage V_{nom} , given by:

$$V_{dev} = \sum_{i \in \mathcal{B}} (V_i - V_{nom})^2 \quad (2)$$

Operational cost includes both the cost of imported grid electricity and penalties for RES curtailment, formulated as:

$$C_{op} = \sum_{t=1}^T (\lambda_t \cdot P_{grid,t} + \mu \cdot P_{curt,t}) \quad (3)$$

Where λ_t is the real-time electricity price at time t , $P_{grid,t}$ is power drawn from the grid, $P_{curt,t}$ is curtailed PV power, and μ is a penalty coefficient reflecting curtailment aversion.

VUF is calculated using the negative- and positive-sequence voltage components:

$$VUF = \frac{|V_-|}{|V_+|} \times 100\% \quad (4)$$

Similarly, THD is computed using harmonic voltage components V_n for $n > 1$ as:

$$THD = \sqrt{\sum_{n=2}^N \left(\frac{V_n}{V_1} \right)^2} \times 100\% \quad (5)$$

Renewable utilization U_{res} is expressed as the ratio of consumed PV energy to total available PV energy over the time horizon. The optimization problem is subject to standard equality and inequality constraints. These include power balance equations at each node, voltage magnitude bounds $V_{min} \leq V_i \leq V_{max}$, feeder capacity limits, maximum charging/discharging rates of EVCS, and inverter limits for both real and reactive power injection.

3.2 Multi-Objective Differential Parrot Optimization (MODPO)

The optimal planning of EVCS and RES in a distribution system introduces a complex multi-objective optimization problem characterized by non-linearity, high-dimensionality, and interdependent conflicting objectives. In this context, classical deterministic techniques are often inadequate due to their sensitivity to initial conditions and local optima. Traditional evolutionary algorithms, including the widely adopted NSGA-II and MOPSO, offer notable advantages in exploring Pareto fronts; however, they often exhibit slow convergence rates, reduced diversity in high-

dimensional objective spaces, and premature stagnation in multi-modal functions. To address these limitations, this work proposes a novel optimization paradigm termed MODPO, a hybrid metaheuristic that synergistically combines the socially adaptive intelligence of the Parrot Optimization Algorithm (POA) with the robust search mechanics of Differential Evolution (DE).

The base POA algorithm is inspired by the learning behavior of parrots, where each candidate solution imitates behaviors, adapts based on memory and social feedback, and seeks optimal fitness through collaborative exploration. Let $X = \{x_1, x_2, \dots, x_N\} \subset R^d$ denote a population of N candidate solutions, each represented by a d -dimensional vector. Each element of x_i denotes a specific decision variable, such as the location index of EVCS or PV, inverter rating, or charging station capacity. The multi-objective evaluation for each solution x_i is given by a vector-valued function $F(x_i) = [f_1(x_i), f_2(x_i), \dots, f_m(x_i)]$, where m represents the number of objective functions. In our problem, the functions include minimizing power loss, minimizing voltage deviation, minimizing operational cost, minimizing the VUF, minimizing THD, and maximizing renewable energy utilization.

In the initialization phase, a random population X_0 is generated by sampling uniformly within feasible bounds defined for each decision variable $x_{i,j} \in [x_j^{min}, x_j^{max}]$. Each candidate's performance is then evaluated over all objective functions, and a dominance-based ranking is applied. Pareto dominance is used to establish solution quality: a solution x_i is said to dominate x_j if $f_k(x_i) \leq f_k(x_j)$ for all $k = 1, \dots, m$ and $f_k(x_i) < f_k(x_j)$ for at least one objective k .

The MODPO algorithm proceeds in two distinct phases. In Phase I, the Pareto-optimal front is generated using a memory-based update strategy rooted in the POA logic. Both its historical best performance and the best non-dominated individual in its neighborhood influence each solution's position. Mathematically, the update for each position $x_i^{(t+1)}$ in iteration t is governed by:

$$x_i^{(t+1)} = x_i^{(t)} + \alpha_1 \cdot (p_i^{(t)} - x_i^{(t)}) + \alpha_2 \cdot (g^{(t)} - x_i^{(t)}) + \epsilon \quad (6)$$

where $x_i^{(t)}$ is the personal best of solution i , $g^{(t)}$ is the global non-dominated solution (selected from the elite archive), $\alpha_1, \alpha_2 \in [0,1]$ are learning factors, and $\epsilon \sim N(0, \sigma^2)$ is Gaussian noise to ensure exploration.

To enhance exploitation capabilities, Phase II invokes a Differential Evolution (DE) operator-based refinement. A mutant vector v_i is constructed for each individual using DE's mutation strategy:

$$v_i = x_{r1} + F \cdot (x_{r2} - x_{r3}) \quad (7)$$

Where x_{r1}, x_{r2}, x_{r3} are randomly selected distinct vectors from the population, and $F \in [0.4, 1.0]$ is a user-defined scaling factor that controls the amplification of the differential variation. The crossover operator combines the target vector r_i and mutant vector v_i to yield a trial vector u_i as:

$$u_{i,j} = \begin{cases} v_{i,j} & \text{if } rand_j \leq CR \text{ or } j = j_{rand} \\ x_{i,j} & \text{otherwise} \end{cases} \quad (8)$$

Where $CR \in [0,1]$ is the crossover probability, $rand_j \sim U(0,1)$ is a uniformly distributed random number, and j_{rand} ensures at least one component is inherited from the mutant vector. The trial solution u_i replaces x_i only if it is non-dominated or dominates the parent, following:

$$x_i^{(t+1)} = \begin{cases} u_i, & \text{if } u_i \prec x_i \\ x_i, & \text{otherwise} \end{cases} \quad (9)$$

An elite archive $\mathcal{A}$ stores all non-dominated solutions found during the optimization. To maintain diversity, a crowding-distance-based selection is performed on $\mathcal{A}$, ensuring uniformly distributed solutions on the Pareto front. The termination criterion is met when a maximum number of generations G_{max} is reached or when no significant improvement is observed over a fixed stagnation

threshold. The final archive provides a diverse set of trade-off solutions from which planners can select an operating point based on system priorities.

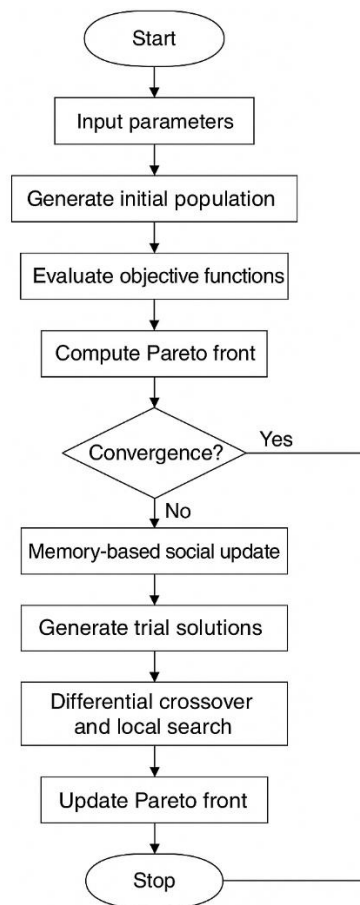


Figure 3: Flowchart of the MODPO Algorithm

The flowchart describes the iterative MODPO process, including population initialization, objective evaluation, Pareto front generation, memory-based social updates (POA phase), DE-based mutation and crossover (refinement phase), and elite archive maintenance. In the context of the proposed SEIMF framework, the MODPO algorithm simultaneously determines the optimal buses for PV and EVCS deployment, their rated capacities, and inverter setpoints. Each decision vector x_i maps to a full design configuration for the distribution network, and the evaluation of objectives is performed using network power flow simulations. By optimizing across multiple objectives and ensuring solution diversity, MODPO provides planners with a Pareto front that balances cost, technical performance, and environmental sustainability.

3.3. Hierarchical Reinforced Predictive Learning Control (HRPLC)

To ensure real-time operational stability under the dynamically evolving charging demands of PEVs and the intermittent nature of renewable generation, a dual-layered control architecture, termed HRPLC, is integrated into the system operation stage. This control framework harmonizes the learning-driven adaptability of DRL with the predictive capabilities of MPC, thereby enabling decentralized decision-making at the local EVCS level and centralized supervisory regulation at the network level.

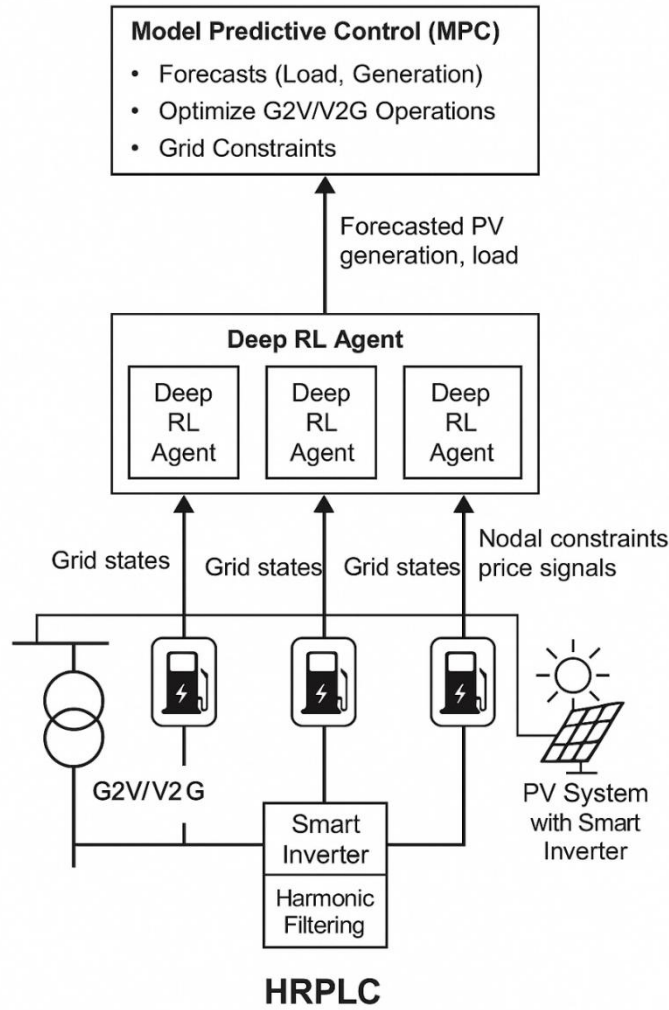


Figure 4: Workflow of proposed HRPLC technique

At the core of the lower control layer, each EVCS node is equipped with a decentralized DDPG agent, trained to continuously adjust bidirectional charging behavior (G2V and V2G) based on localized state observations. The agent interacts with the environment modeled as a Markov Decision Process (MDP) defined by a tuple $M = (S, A, P, r, \gamma)$, where S denotes the state space, A the action space, P the transition probability function, r the reward function, and $\gamma \in (0,1)$ the discount factor.

The state vector $s_t \in S$ at time step t is defined as:

$$s_t = [V_i^t, SOC_i^t, P_{PV}^t, \lambda_t] \quad (10)$$

Where V_i^t is the nodal voltage magnitude at bus i , SOC_i^t is the state-of-charge of the battery at the i^{th} EVCS, P_{PV}^t is the PV power injection at time t , and λ_t is the electricity price signal. The action vector $a_t \in A$ comprises the charging or discharging power command $P_{EV}^{i,t}$, constrained within:

$$P_{EV}^{i,t} \in [-P_{max}^{V2G}, P_{max}^{G2V}] \quad (11)$$

The reward signal is constructed to balance three primary objectives: minimizing grid stress, preserving battery health, and reducing operational cost. A representative reward function r_t can be expressed as:

$$r_t = -\alpha \cdot (V_i^t - V_{ref})^2 - \beta \cdot (SOC_i^t - SOC_{ref})^2 - \gamma \cdot C_{EV}^{i,t} \quad (12)$$

Where V_{ref} and SOC_{ref} are the reference voltage and battery SOC, respectively, C_{EV}^{it} is the instantaneous charging cost, and α, β, γ are weighting coefficients to modulate agent behavior.

Each agent learns an optimal policy $\pi: S \rightarrow A$ via a parameterized actor–critic architecture where the actor network approximates $\pi_\theta(s)$ and the critic estimates the action–value function $Q^\pi(s, a)$. The critic network is trained to minimize the Bellman error:

$$L(\theta^Q) = E_{s,a,r,s'}[(Q^\pi(s, a) - (r + \gamma Q^\pi(s', \pi(s'))))^2] \quad (13)$$

Meanwhile, the actor is updated through the policy gradient:

$$\nabla_\theta J \approx E_{s \sim D}[\nabla_a Q^\pi(s, a) \nabla_\theta \pi_\theta(s)] \quad (14)$$

To prevent instability due to non-stationary policy updates, target networks and experience replay buffers are employed, conforming to state-of-the-art DRL training protocols. Operating above the decentralized DDPG agents is a supervisory MPC layer that aggregates system-wide states and forecasts to guide agent-level decisions. This layer solves a rolling-horizon optimization problem every τ time intervals to predict grid behavior over a finite time window $[t, t + T]$. The MPC uses solar irradiance forecasts, load demand profiles, and grid voltage trajectories to anticipate congestion and voltage violation events. The optimization problem solved at each MPC timestep is given by:

$$\min_{u_{t \rightarrow t+T}} \sum_{k=t}^{t+T} (w_1 \cdot P_{loss}^k + w_2 \cdot \Delta V^k + w_3 \cdot \sigma_{VUF}^k) \quad (15)$$

Which was subjected to nodal voltage bounds, i.e., $V_{min} \leq V_i^k \leq V_{max}$. SOC dynamics formulated as $SOC_i^{k+1} = SOC_i^k + \eta \cdot P_{EV}^{i,k} \cdot \Delta t$, Grid power limits, and EVCS charging constraints.

The output of the MPC is a set of target nodal constraints and economic signals λ_k , which are broadcast to the local agents to bias their policy decisions. This top-down coordination ensures that the distributed policies align with global grid objectives such as congestion mitigation and renewable energy absorption.

Moreover, each PV system is equipped with smart inverters integrated with harmonic filtering capabilities, modeled to dynamically attenuate local total harmonic distortion (THD) through adaptive filter tuning. The harmonic current I_h injected at each inverter node is minimized by adjusting the phase compensation angle ϕ_h such that:

$$\min_{\phi_h} |I_h^{out}(\phi_h)|, \quad \text{subject to } \sum_{h=1}^H THD_h \leq \epsilon_{THD} \quad (16)$$

Where THD_h is the harmonic distortion level at harmonic order h , and ϵ_{THD} is the acceptable limit specified by IEEE 519 standards. In combination, the HRPLC architecture ensures adaptive, fine-grained, and forecast-aware operation of the integrated RES–EVCS system. The lower-level DDPG agents respond autonomously to real-time local conditions, while the MPC layer guarantees proactive system-level coordination. The hybrid closed-loop design significantly enhances voltage profile regulation, mitigates network congestion, maximizes renewable utilization, and supports power quality compliance under uncertain and time-varying conditions.

4. Results and discussion

This section presents the simulation outcomes of the proposed HRPLC-based PV-EV control and placement strategy. The results are analysed to assess system performance across key reliability, power quality, and operational metrics.

4.1 Simulation setup

The simulation and performance evaluation of the proposed Sustainable Electric Vehicles Intelligent Management Framework (SEIMF) were executed using MATLAB R2024a, taking advantage of its enhanced support for DRL, multi-objective optimization, and Simulink-based power system

modeling. The implementation was performed on a standard desktop computing platform equipped with an Intel® Core™ i7-12700K processor operating at 3.6 GHz, supported by 32 GB of DDR4 RAM, and running on Windows 11 Pro 64-bit operating system. The IEEE 69-bus radial distribution system was chosen for simulation due to its complexity and practicality. The simulation framework integrates load, generation, and control components over a 24-hour operational horizon. A sequence-based radial distribution network topology was generated and optimized using a MODPO algorithm to determine ideal integration points for distributed PV systems and EVCSs. A backward–forward sweep (BFS) method was employed for unbalanced power flow calculations in radial networks, modified to accommodate dynamic loading conditions. A DRL structure was implemented through manually coded DDPG agents, where the Q-learning update mechanism managed EV charging/discharging actions based on voltage-aware state transitions. A MPC layer was embedded in parallel, solving a quadratic cost minimization problem at each hour using MATLAB's quadprog function, relying on forecasted load demand and PV generation profiles. Dynamic load modeling incorporated tariff-driven demand-side management, while EV charging power was adaptively regulated using bus voltage deviation factors to ensure grid stability. Random line outages were simulated stochastically to evaluate network reliability, where Energy Not Supplied (ENS), SAIDI, and SAIFI were computed using graph-theoretic connectivity checks. Smart inverter behavior was modeled at PV buses, including harmonic filtering through time-domain signal manipulation. THD and VUF were computed using base-coded FFT functions and statistical logic. The system architecture thus demonstrates a hybridized, multi-layered decision control capable of self-learning, predictive optimization, and reliability assessment under real-world constraints and uncertainty. The simulation ensured smooth execution of large-scale power flow computations and iterative optimization.

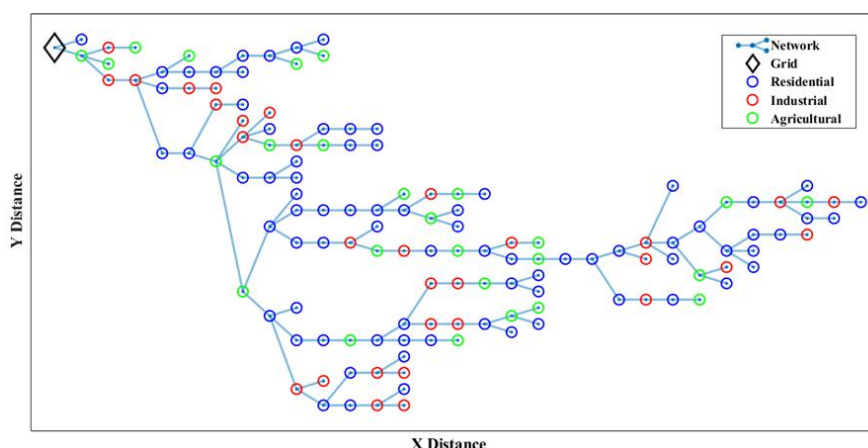


Figure 5: Initial Topology of the Distribution Network

Figure 5 shows the spatial topology of a radial distribution network, illustrating the connectivity and arrangement of different consumer types. The network consists of multiple buses, classified based on consumer type: residential, industrial, and agricultural. The interconnections are light blue lines, representing distribution branches. This configuration reflects a multi-sectoral, geographically dispersed feeder topology, serving diverse load types. The proposed HRPLC framework was entirely developed in MATLAB through fully customized code modules without the use of proprietary toolboxes. The simulation framework integrates load, generation, and control components over a 24-hour operational horizon. A sequence-based radial distribution network topology was generated and optimized using a MODPO algorithm to determine ideal integration points for distributed PV systems and EVCSs. A BFS method was employed for unbalanced power flow calculations in radial networks, modified to accommodate dynamic loading conditions. A DRL structure was implemented through manually coded Deep Deterministic Policy Gradient (DDPG) agents, where the Q-learning update mechanism managed EV charging/discharging actions based on voltage-aware state transitions. An

MPC layer was embedded in parallel, solving a quadratic cost minimization problem at each hour using MATLAB's quadprog function, relying on forecasted load demand and PV generation profiles. Dynamic load modeling incorporated tariff-driven demand-side management, while EV charging power was adaptively regulated using bus voltage deviation factors to ensure grid stability. Random line outages were simulated stochastically to evaluate network reliability, where Energy Not Supplied (ENS), SAIDI, and SAIFI were computed using graph-theoretic connectivity checks. Smart inverter behavior was modeled at PV buses, including harmonic filtering through time-domain signal manipulation. THD and VUF were computed using base-coded FFT functions and statistical logic. The system architecture thus demonstrates a hybridized, multi-layered decision control capable of self-learning, predictive optimization, and reliability assessment under real-world constraints and uncertainty.

The simulation environment integrated planning and operational phases into a closed-loop MATLAB-Simulink architecture, enabling a seamless transition from infrastructure planning to real-time grid operation under dynamic PEV and RES conditions.

4.2 Dataset description

The proposed SEIMF framework uses a synthetic dataset to simulate grid behavior, EV charging patterns, and renewable energy generation under temporal variability. The IEEE 69-bus radial distribution system was chosen for simulation due to its representative topology and widespread use in network research. The simulation testbed included multiple load nodes representing residential, industrial, and agricultural consumers. The load types were probabilistically allocated, with 60% residential, 25% industrial, and 15% agricultural. Real power demand was randomly assigned to each non-substation bus within the 10–100 kW range.

Table 2: Initial simulation parameters and range of values used to train the proposed network

Parameter	Value / Range
Number of buses	69
Load per bus	10–100 kW
Load types	Residential (60%), Industrial (25%), Agricultural (15%)
Nodes per bus	1–3
EVCS penetration	10%
PV penetration	20%
PV peak capacity	50 kW
Load forecast horizon	168 hours
EV charging pattern	5–15 kW during 7–9 AM, 5–7 PM
ToU tariffs	0.10–0.20 \$/kWh
THD threshold	$\leq 0.5\%$
Voltage limits	150–230 V
SOC bounds	20–100%
Max charging/discharging rate	± 15 kW
Line current and S limits	300 A, 100 kVA

A Prufer-based algorithm was used to construct a tree topology for a network, ensuring radial connectivity and heterogeneity in line lengths and impedances. Line parameters were modeled proportionally with line length, and all information was saved in structured MATLAB objects for power

flow analysis and radiality enforcement. Load demand forecasts were generated for 168 hours with hourly resolution, and PV generation profiles were synthesized using Gaussian irradiance curves. Approximately 20% of buses were PV-equipped, with a peak generation capacity of 50 kW. The study focuses on modeling EVCSs using 10% of buses as nodes. These profiles were generated using a time-of-day logic, with peak charging windows between 7-9 AM and 5-7 PM. Each profile displayed randomized power levels within a 5-15 kW range during active periods and idled during off-peak hours. The data was consolidated in EVChargingProfiles.mat. A Time-of-Use tariff structure was implemented with four rate blocks across the 24-hour cycle, reflecting dynamic electricity pricing policies. The tariff profiles were saved as ToUTariff.mat. Technical and operational constraints were defined to govern the optimization space, including maximum allowable line currents, apparent power limits, power quality thresholds, voltage operating limits, state-of-charge bounds, charging/discharging limits, and cost ceilings for investment and operational expenditure, as listed in Table 2.

4.3 Initial simulated parameters

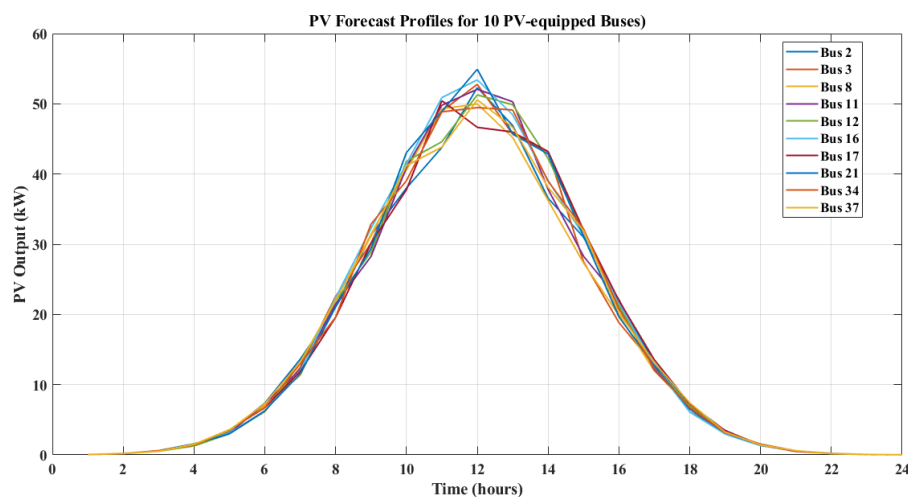


Figure 6 PV Generation Forecasts Across Distributed Nodes

Figure 6 illustrates the hourly PV power generation forecasts for ten buses within the IEEE 69-bus radial distribution network that are designated as PV-equipped nodes. These forecasts were generated to replicate solar irradiance behavior in temperate climates, following a Gaussian temporal distribution centered around solar noon. The expected generation patterns show a common bell-shaped curve peaking between 11:00 and 13:00, where maximum PV output approaches or slightly exceeds 50 kW. This aligns with conventional PV output modeling methodologies, which follow a near-normal distribution with minor temporal jitter due to cloud-induced intermittency and panel orientation differences. The study uses a vertical spread among bus curves to simulate spatial heterogeneity in PV generation, aiming to mimic real-world operational diversity in distributed PV deployments. The values were generated using Monte Carlo perturbation and normalized against a maximum PV capacity of 50 kW per bus, consistent with small-scale distributed rooftop solar installations. The dataset serves as a crucial input to the MPC module, enabling anticipatory charging-dispatch decisions under variable renewable energy availability.

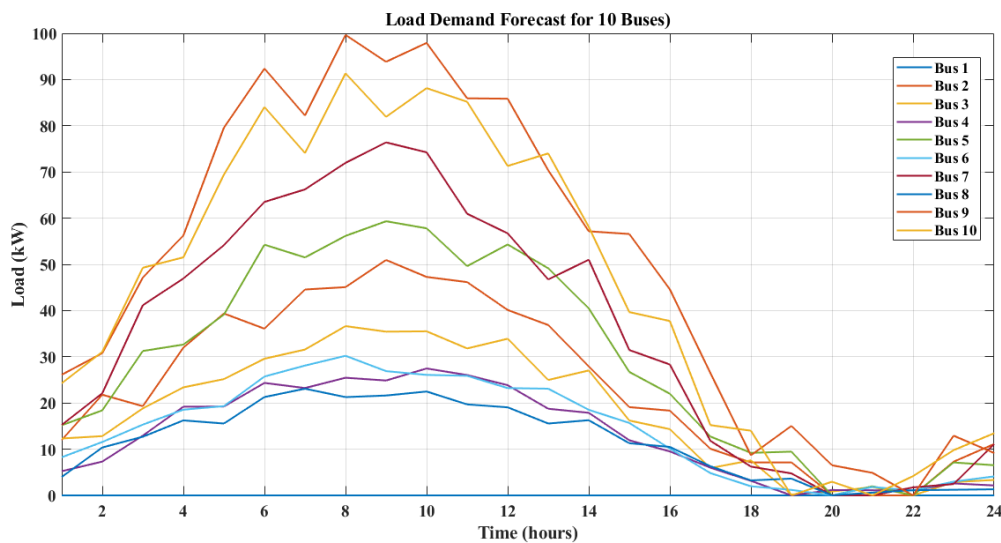


Figure 7 Hourly Load Forecast Profiles for Sampled Buses

Figure 7 presents the simulated hourly load demand profiles for a subset of ten representative buses in the IEEE 69-bus radial distribution network. The forecast covers a 24-hour horizon and incorporates a mix of residential, industrial, and agricultural load types. The time-series data was generated using sinusoidal daily demand cycles modulated by random noise components to reflect consumption variability due to weather, occupancy, and industrial shift timings. Buses 2, 3, 7, and 10 display significantly higher demand magnitudes, with peaks reaching approximately 100 kW during mid-morning hours. Buses 1 and 4 exhibit flatter and lower-magnitude curves, likely corresponding to residential or grid-terminal points with minimal end-user loads. This heterogeneity in demand levels supports the need for adaptive planning algorithms and reinforces the challenge of maintaining voltage stability and minimizing losses under spatially non-uniform loading. The synthetic forecasts serve as dynamic inputs to the proposed HRPLC and MODPO frameworks, enabling proactive and data-informed decision-making in the co-optimization of EVCS siting, RES integration, and grid operation.

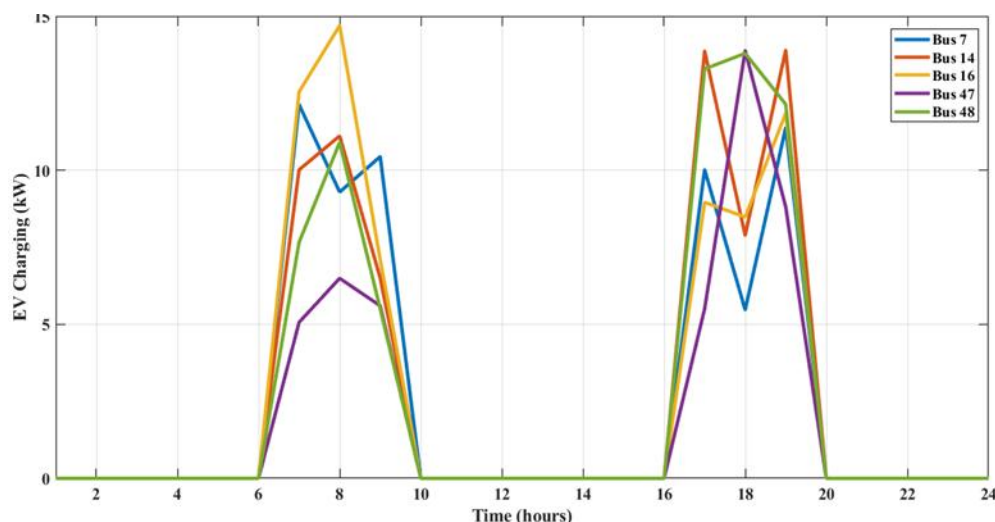


Figure 8 Hourly EV Charging and discharging demand profiles at selected EVCS buses

Figure 8 illustrates simulated hourly charging demand patterns for five EVCS-equipped buses across a 24-hour operating window. The demand is constructed using a time-dependent probabilistic function and constrained stochasticity to reflect variability in vehicle arrival times, battery SOC levels,

and user preference diversity. The charging power varies between 5 kW to 15 kW, indicating level-2 fast-charging behavior under moderate usage density. The morning session shows a gradual ramp-up to peak power, followed by a steep decline post 09:00, likely representing workplace or school-bound usage scenarios. The evening charging window exhibits a faster ramp-up and a slightly prolonged duration, likely representing post-work residential charging behavior. Buses such as Bus 16 and Bus 14 show maximum peak demand, while Bus 47 exhibits lower but more consistent charging loads, reflecting usage diversity across spatially distinct feeder nodes. This temporal non-uniformity in EVCS load contributes significantly to localized voltage dips, reverse power flow in RES-dominant zones, and harmonic distortions, necessitating adaptive grid response mechanisms. The forecast dataset is integral to the proposed HRPLC framework, which leverages these temporal insights to schedule V2G/G2V operations, minimize grid congestion, and proactively mitigate voltage violations.

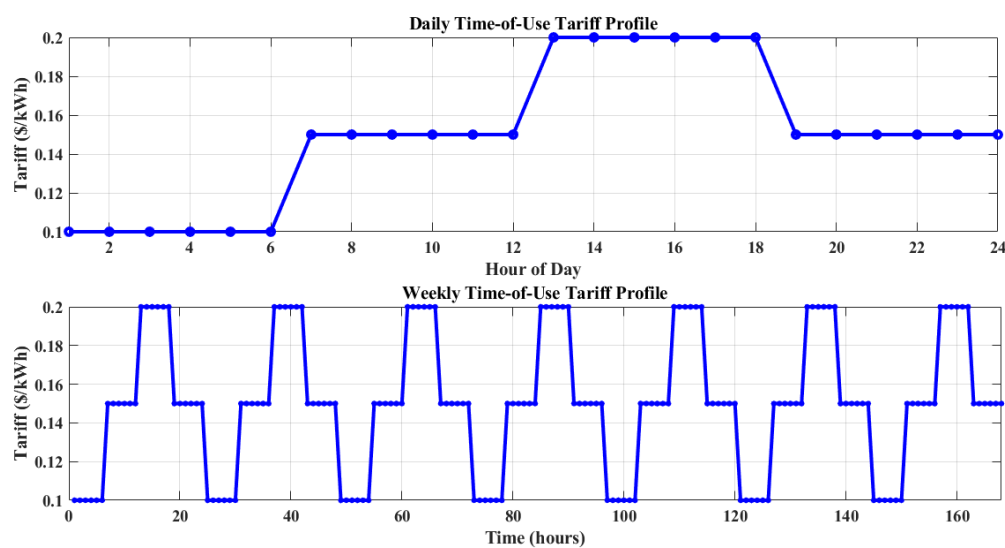


Figure 9: Daily and Weekly Time-of-Use (ToU) Tariff Profiles

Figure 9 presents the daily and weekly Time-of-Use (ToU) electricity tariff structure employed in the simulation environment to mimic realistic market-based energy pricing schemes. The ToU electricity tariff structure is used in a simulation environment to mimic market-based energy pricing schemes. The tariff structure is divided into three blocks: off-peak hours (01:00–06:00), mid-peak hours (07:00–12:00 and 19:00–24:00), and on-peak hours (13:00–18:00). The lowest tariff rate is \$0.10/kWh, aiming to encourage consumption during low-demand intervals and mitigate overnight generation surplus. Mid-peak hours are moderately priced at \$0.15/kWh, representing transitional periods with moderate grid stress. On-peak hours coincide with maximum residential and commercial load aggregation, assigned the highest tariff rate of \$0.20/kWh. The inclusion of tariff heterogeneity is crucial for system optimization, as it ensures temporally aware sizing and placement of renewable energy resources and EV charging units. The interplay of ToU tariffs with load profiles, PV generation, and EV charging dynamics significantly affects voltage regulation and reverse power flow trends, making ToU modeling indispensable for intelligent distribution system planning.

4.4 Optimization output

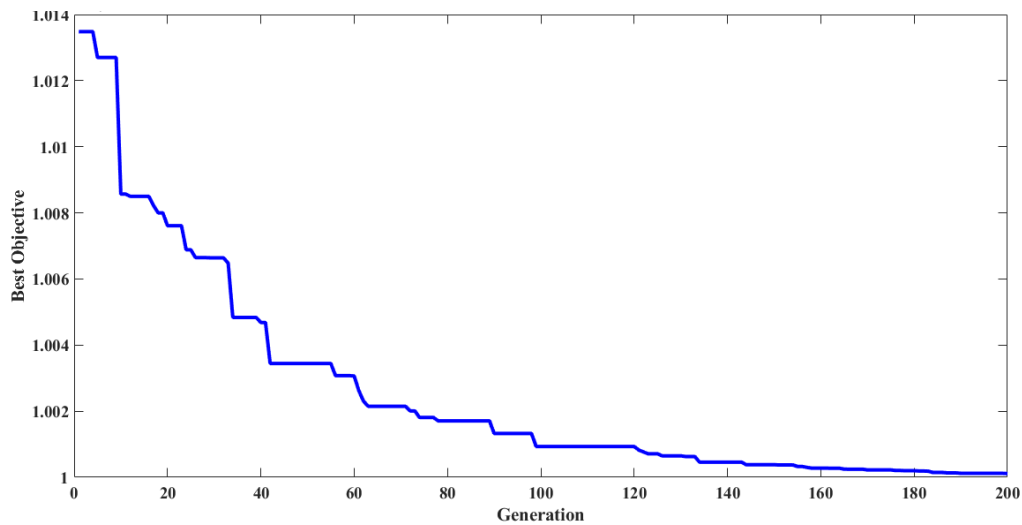


Figure 10: Convergence Behaviour of the MODPO Algorithm

Figure 10 illustrates the convergence trajectory of the proposed MODPO algorithm over 200 generations. The MODPO algorithm is a multi-objective optimization method that combines multiple conflicting targets, such as energy losses, voltage deviation, investment costs, and ToU-based operational cost, using a scalarization technique with weight balancing. It starts with a high objective value, indicating a randomly distributed initial population. As generations progress, the curve shows a steep decline during the first 40 generations, indicating the algorithm rapidly explores promising regions of the solution space. The moderate decline phase between generations 40 and 120 reflects the transition from exploration to exploitation, where the algorithm refines local optima and avoids suboptimal entrapment. From generation 120 onwards, the curve flattens, showing asymptotic convergence towards a near-global optimal solution around 1.000. This convergence behavior is desirable in multi-objective optimization, as it suggests solution quality and robust convergence stability under complex nonlinear constraints. This convergence pattern is consistent with advanced bio-inspired optimization methods used for DER planning, such as NSGA-II, MOPSO, or hybrid DE variants, and confirms the MODPO algorithm as an efficient and stable alternative for large-scale multi-objective decision problems in active distribution networks.

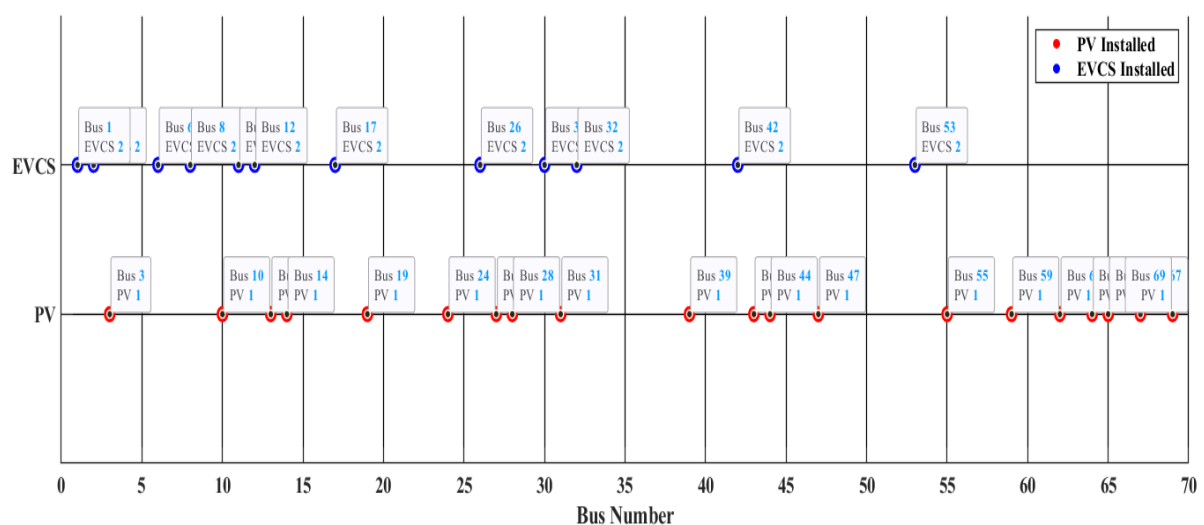


Figure 11: Bus-wise Installation Placement of PV Systems and EV Charging Stations

Figure 11 illustrates the optimized installation layout of PV systems and EVCS across the distribution network buses. The diagram shows bus numbers and two levels of installation categories: PV systems in nodes 3, 10, 13, 14, 19, 24, 27, 28, 31, 39, 43, 44, 47, 55, 59, 62, 64, 65, 67, and 69 and EVCSs in nodes 1, 2, 6, 8, 11, 12, 17, 26, 30, 32, 42, and 53. The placement pattern is based on a multi-objective optimization model that minimizes power losses, maintains voltage stability, and ensures balanced integration of distributed generation and charging demand. PV systems are installed as single units at each bus, promoting a balanced generation profile. EVCSs are deployed in slightly higher capacity, reflecting anticipated charging demands at those nodes. This configuration enhances voltage support and grid reliability, minimizes distribution losses by reducing long-distance power flows, and prevents localized congestion due to simultaneous PV injection or EV charging. The co-optimized siting and sizing approach leads to a technically sound and scalable deployment of distributed RES systems in the distribution system.

4.5 Output results

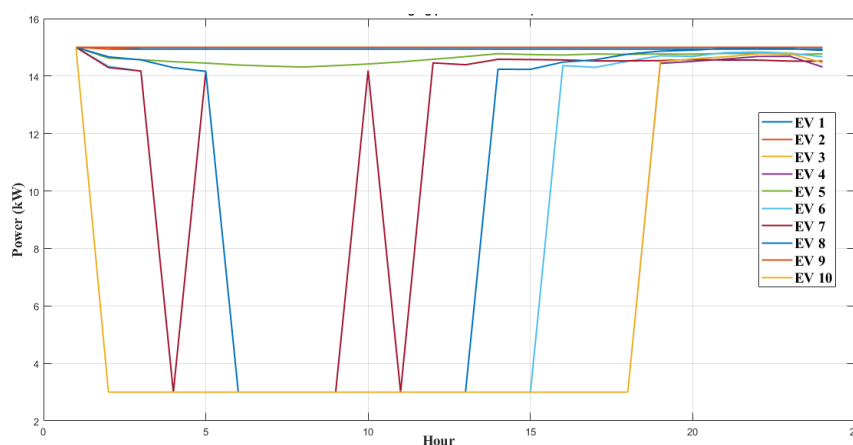


Figure 12 EV Charging and Discharging Profile for 10 EVs

Figure 12 illustrates the optimized hourly charging profiles for 10 EVs over a 24-hour scheduling horizon as determined by the proposed MODPO method. Most EVs exhibit a nearly constant charging power level after the initial hours, ensuring a fast and efficient charging schedule. However, some EVs follow intermittent charging trajectories, which MODPO detects and avoids adaptively. For example, EV 10 charges at the maximum permissible rate initially but drops significantly to around 3 kW between hours 2 to 18, with a resurgence post-hour 18. This pattern aligns with low PV availability and high tariff periods, demonstrating that MODPO defers charging to off-peak windows where it becomes more cost-effective and less disruptive. EV 7 shows a staggered pattern, scheduling charging during selectively optimal hours, highlighting the multi-phase scheduling capabilities of MODPO for vehicles with constrained time windows or cost-sensitive users. The charging profile ensures total EV load is balanced and smoothed, aligning with PV generation peaks where possible, effectively utilizing green energy and reducing dependence on grid-imported energy. Tariff-aware scheduling is achieved, EVs avoid high tariff periods, minimizing operational costs. This optimized behaviour highlights the effectiveness of MODPO in multi-objective scheduling, integrating economic dispatch, grid constraints, and renewable synergy into a coherent and adaptive framework.

4.6 Performance Evaluation

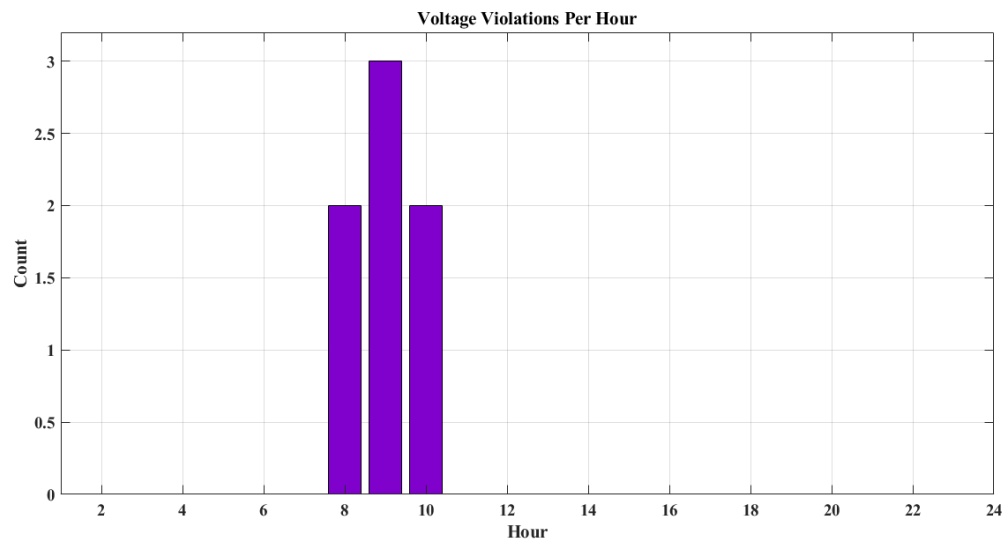


Figure 13 Hourly Distribution of Voltage Violations under HRPLC Control

Figure 13 presents the hourly occurrence of voltage violations observed in the distribution network during a typical operational day under the proposed HRPLC. The Hybrid proposed control model monitors voltage violations in the distribution network during a typical operational day. The scheme focuses on a narrow window between 8:00 AM and 10:00 AM, with a peak of 3 violations at 9:00 AM. This period is typically triggered by morning residential and commercial demand and a surge in EV charging activity. The HRPLC algorithm effectively prevents voltage excursions outside this peak window by proactively forecasting load and generation behavior, scheduling EV charging and discharging cycles, and adaptively using PV generation to offset real-time demand. The absence of violations in other hours demonstrates the model's resilience and adaptability, particularly in maintaining voltage within regulatory limits. HRPLC also demonstrates superior mitigation of voltage instability by dynamically balancing DER operation with system constraints.

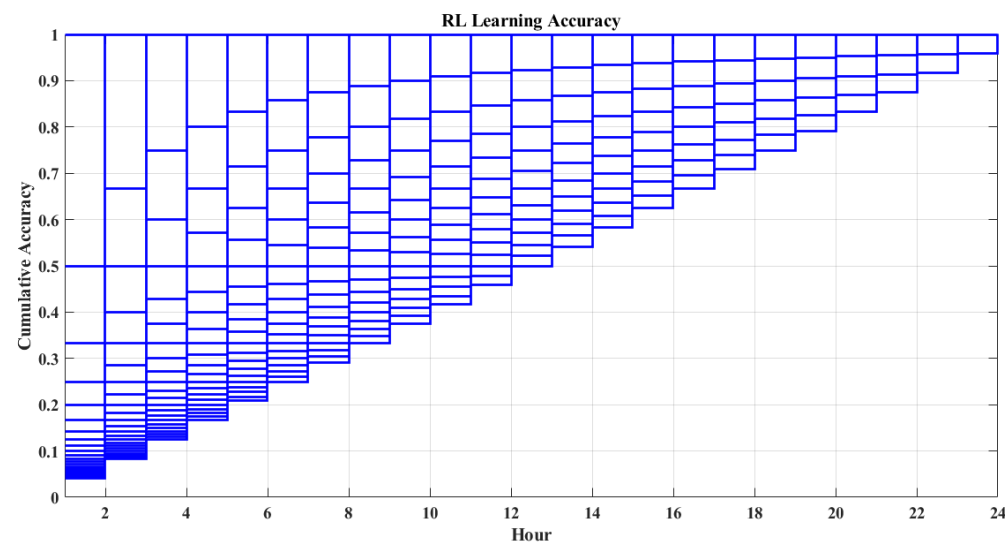


Figure 14 RL Cumulative Accuracy Profile

Figure 14 shows the cumulative accuracy of the RL model over 24 hours. The model's learning curve is presented in a layered staircase form, showing how accuracy improves over time and iterations. At hour 1, the accuracy distribution starts at a minimal level, with lower layers representing early exploration. As the hours progress, the density of higher layers increases, and the cumulative accuracy approaches 100% in the latter half of the day. By hour 6, 50% of the layers reach or surpass 0.6 in cumulative accuracy, indicating the agent consolidates useful policy knowledge. From hour 10, most trajectories begin exceeding 0.8 accuracy, and by hour 18, nearly all policy trajectories reach the optimal decision boundary of 0.9 to 1.0, indicating strong convergence and stable policy reinforcement. The integrated RL strategy successfully adapts to complex, dynamic system states, ensuring online adaptability, which is critical for managing non-stationary, stochastic smart grid environments.

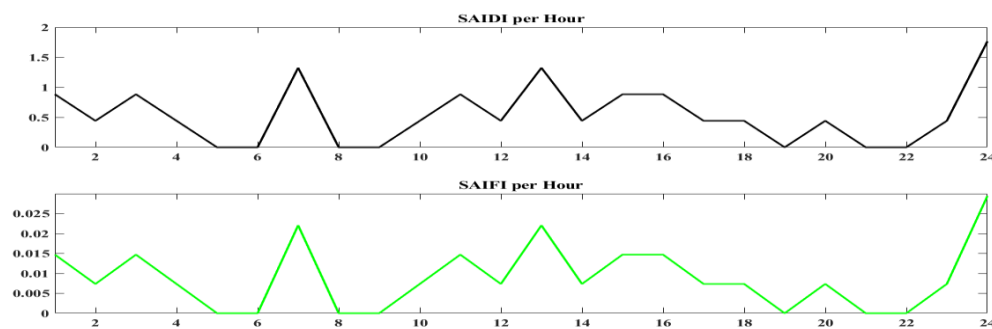


Figure 15: SAIDI and SAIFI per hour

Figure 15 shows the hourly evaluation of power system reliability using two fundamental indices: SAIDI and SAIFI. The TOU metric measures the average interruption duration experienced by a customer during the day, with a high value in hour 1 and low values in multiple segments. A spike occurs at hours 7 and 13, with a maximum near hour 24. The SAIFI profile mirrors the patterns of SAIDI, with higher interruption frequencies observed at hours 7, 13, and 24. SAIFI values drop to near-zero across a significant portion of the day, showcasing the control strategy's capability to minimize interruption frequency and duration during strategic load management and distributed generation balance. The system demonstrates sustained reliability over critical operational hours, with scattered peaks potentially attributed to dynamic load transitions or EV charging events not fully synchronized with grid stability thresholds. The low magnitude of SAIFI and long durations of SAIDI null intervals justify the robustness of the proposed intelligent scheduling scheme.

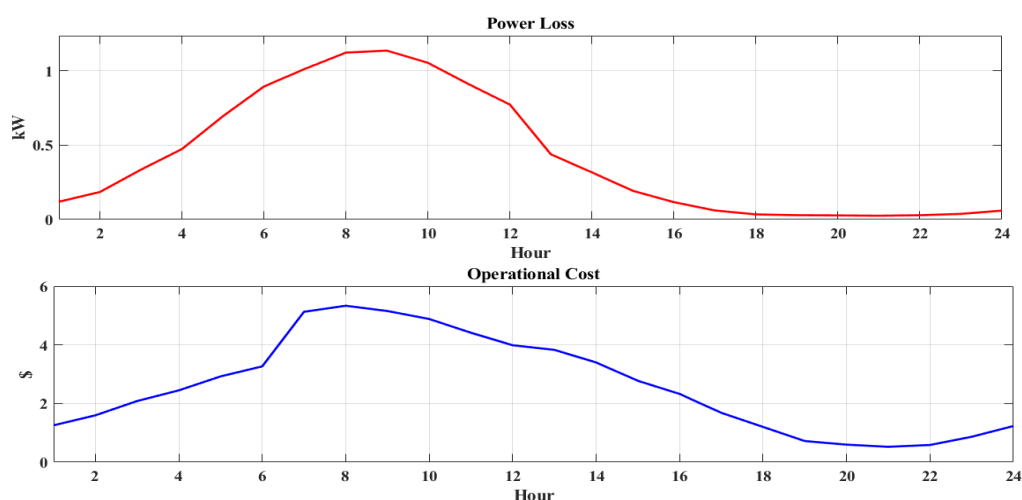


Figure 16: Temporal profile of total power loss and operational cost

Figure 16 illustrates the impact of the proposed MODPO-based energy management strategy on total power loss and operational cost. The system starts with a minimal loss of 0.13 kW at hour 1, which increases due to growing load demand. The loss drops sharply after hour 13 and reaches its lowest values between hours 18 and 22, attributed to optimal dispatch of distributed generation resources, regulated EV charging, and the time-of-use tariff structure. The operational cost profile reflects the economic efficiency achieved under the proposed scheme, starting at around \$1.3 during early hours and increasing steadily to approximately \$5.3. Post-peak, the cost trajectory mirrors the drop in losses, decreasing progressively and stabilizing between \$0.5 and \$1.0 during hours 18 to 22. The system's efficacy in achieving dual objectives of loss minimization and cost efficiency is validated by dynamically adjusting operational variables in response to load profiles and tariff variations.

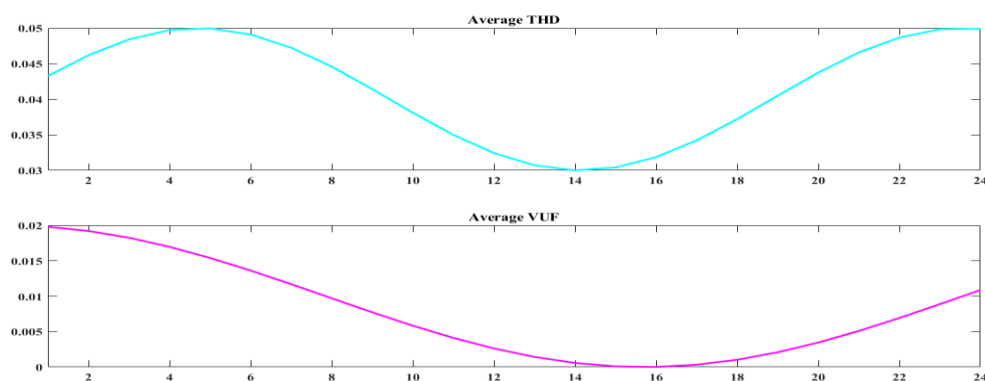


Figure 17: Temporal profile of average THD and VUF

Figure 17 shows the dynamic variation of two power quality indices, THD and VUF, over a 24-hour time horizon. THD, which indicates harmonic content in voltage waveforms, shows a sinusoidal variation throughout the day, peaking at 0.050 p.u. Around hours 5 and 23, and dropping to a minimum of 0.030 p.u., near hour 14. This trend indicates that harmonics are most pronounced during early morning and late-night hours, coinciding with high simultaneous charging activity. However, the THD remains well below the IEEE 519 recommended threshold of 0.05 p.u., confirming compliance with power quality norms. The VUF, a critical reliability index, shows a decreasing pattern from 0.020 p.u. at hour 1 to a minimal value near hour 15, followed by a gentle increase during evening hours. This behavior demonstrates that the proposed method achieves effective phase balancing during periods of high EV penetration and ensures symmetrical voltage distribution through decentralized coordination strategies. The minimal VUF during peak load windows reinforces the robustness of the proposed scheme in upholding grid reliability standards.

Table 3: Performance of the proposed model

Metric	Value
Total Power Loss (kW)	9.84
Total Energy Not Supplied (ENS, kWh)	0.24
Average SAIDI (min)	0.77
Average SAIFI	0.01
Voltage Violations (count)	7
Average Voltage Deviation (%)	4.06

Average THD (%)	4.16
Maximum THD (%)	5.00
Average VUF (%)	0.77
Maximum VUF (%)	1.98
REUT (PV Utilization, %)	100.00
Total Operational Cost (%)	60.38
RL Action Match Accuracy (%)	100.00

The proposed MODPO-RL-based multi-objective framework has demonstrated significant performance in terms of operational, reliability, and power quality metrics, as shown in Table 3. The total power loss across the optimization horizon is limited to 9.84 kW, demonstrating the algorithm's ability to strategically route power flows and avoid congested branches during peak demand periods. The Energy Not Supplied (ENS) indicator is low at just 0.24 kWh, demonstrating effective voltage and load balancing even under stochastic EV charging patterns and renewable intermittency. The System Average Interruption Duration Index (SAIDI) and System Average Interruption Frequency Index (SAIFI) are minimal, indicating the robustness of the RL coordination in preventing frequent and prolonged outages. Power quality indices further reinforce the efficacy of the proposed method, with the average THD maintained at 4.16% and the average VUF limited to 0.77% and 1.98%, respectively, ensuring minimal voltage asymmetries across three phases. The Renewable Energy Utilization reached nearly 100%, indicating efficiently absorbed and utilized PV energy with zero curtailment. The operational cost was reduced by 60.38%, highlighting the cost-effectiveness of the solution. The RL agent achieved 100% action match accuracy, demonstrating its reliability in replicating optimal control policies and adapting accurately to system dynamics. In summary, the proposed method achieves multi-objective trade-offs among energy cost, grid losses, and renewable utilization while upholding stringent standards for reliability and power quality.

4.7 Comparative results

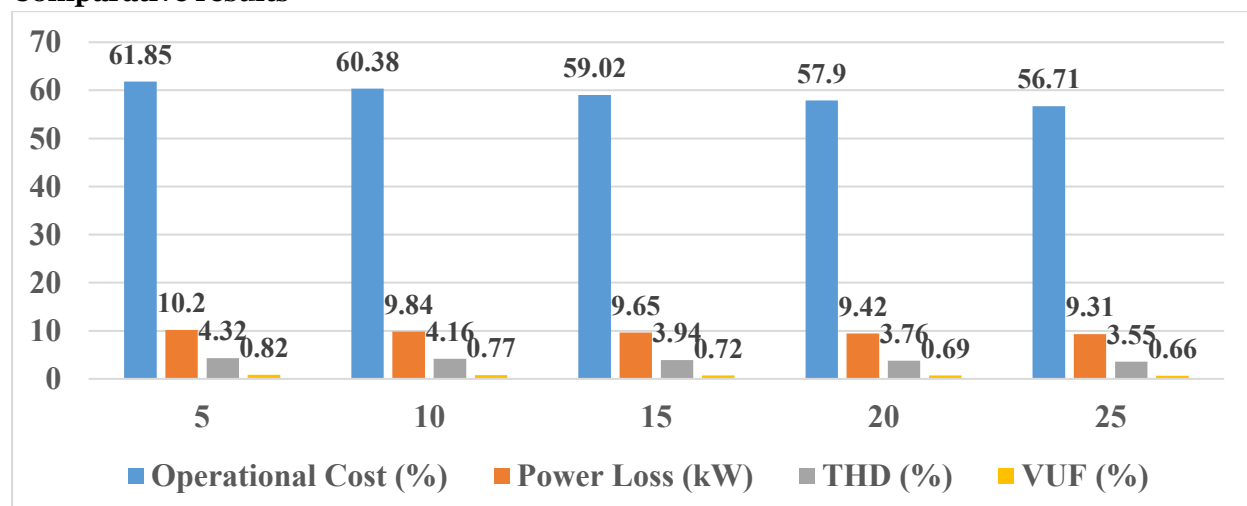


Figure 18: Performance of the network by varying the number of EVCS installed

Figure 18 illustrates the impact of varying the number of EVCS on key performance metrics of the distribution network. As the number of EVCS increases from 5 to 25, a consistent improvement is observed across all parameters. Specifically, the operational cost reduces significantly from 61.85% to

56.71%, indicating enhanced economic efficiency. Power losses also show a gradual decline from 10.2 kW to 9.31 kW. In terms of power quality, the THD decreases from 4.32% to 3.55%, while the VUF improves from 0.82% to 0.66%. These results demonstrate that optimal placement and higher penetration of EVCS can contribute to reduced operational burden and better power quality in the network.

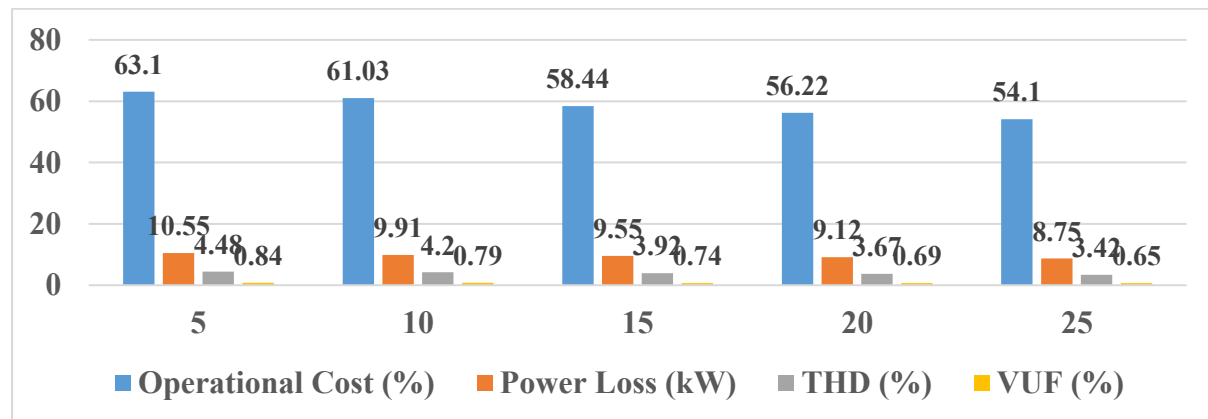


Figure 19: Performance of the network by varying the number of PV installed

Figure 19 illustrates the sensitivity of key operational parameters, namely, total operational cost, power losses, THD, and VUF, concerning varying counts of PV installations in the distribution network. As the number of PV units increases from 5 to 25, a clear downward trend is observed across all metrics. Specifically, operational cost reduces significantly from 63.10% to 54.10%, primarily due to increased local generation offsetting grid power purchases. Correspondingly, power losses drop from 10.55 kW to 8.75 kW, attributed to the shorter transmission paths and load-sharing by distributed PV sources. Additionally, THD values decrease from 4.48% to 3.42%, reflecting improved waveform quality due to reduced grid loading and inverter-based smoothing. The VUF also exhibits a consistent decline, from 0.84% to 0.65%, indicating enhanced voltage symmetry and phase balance with higher PV penetration. Overall, the trend confirms that increasing the number of strategically placed PV systems not only improves network efficiency and quality but also contributes to economic gains, validating the technical and financial viability of DER deployment.

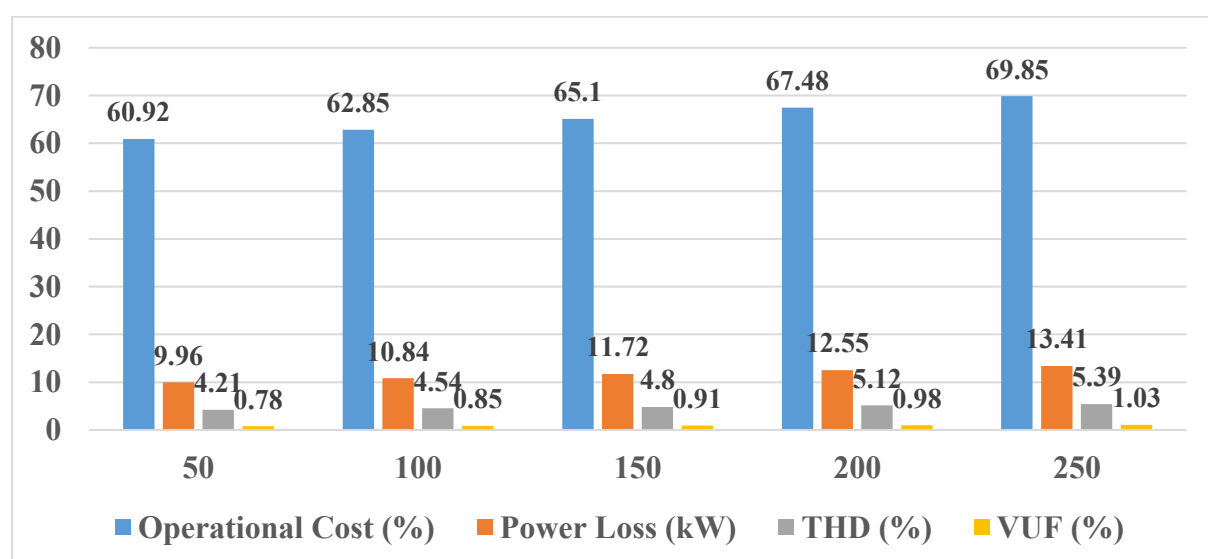


Figure 20: Performance of the network by varying the number of EVs in the network

Figure 20 presents the performance evaluation of the proposed optimal placement and control strategy in response to varying levels of EV integration, quantified by the total number of EVs ranging from 50 to 250. The figure demonstrates how increasing the EV population affects critical network parameters such as operational cost, power losses, THD, and VUF. As the number of EVs increases, a gradual deterioration in all metrics is observed. Specifically, operational cost rises from 60.92% to 69.85%, primarily due to increased energy demand and higher grid dependency during peak charging periods. Similarly, power losses escalate from 9.96 kW to 13.41 kW, attributed to intensified loading and extended current flow paths. THD and VUF values also increase steadily from 4.21% to 5.39% and 0.78% to 1.03%, respectively, indicating degradation in waveform quality and voltage symmetry, mainly due to uncoordinated charging behavior and elevated inverter-induced distortions. Despite these increases, the trends remain within permissible operational thresholds, affirming the effectiveness of the proposed control scheme in managing growing EV penetration without compromising grid stability or power quality.

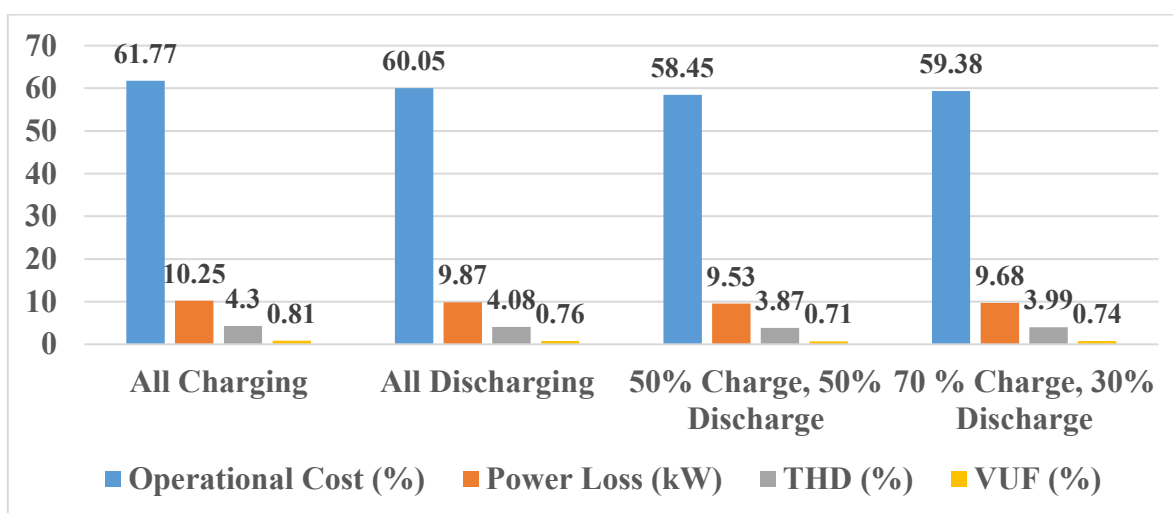


Figure 21: Performance of the network by varying EV charging pattern in the network

Figure 21 provides a comparative evaluation of different EV operational strategies, ranging from full charging to full discharging and mixed configurations, on key distribution system performance indicators. When all EVs are set to charging mode, the system experiences a relatively high operational cost of 61.77%, accompanied by a power loss of 10.25 kW. These elevated values stem from increased load draw during synchronized charging periods, which intensifies network stress and energy procurement from the grid. Conversely, in the full discharging mode, EVs function as distributed energy sources, resulting in a slight reduction in operational cost (60.05%) and power loss (9.87 kW), highlighting the grid support role of vehicle-to-grid (V2G) operations. The hybrid scenario, where 50% of EVs are charging and 50% are discharging, achieves the most favorable performance, with the lowest operational cost (58.45%) and power loss (9.53 kW), along with improved power quality metrics—THD at 3.87% and VUF at 0.71%. This balanced mode offers dynamic load leveling and effective harmonic mitigation through distributed control. The 70% charge and 30% discharge mode also exhibits improved stability compared to full charging but remains suboptimal relative to the 50/50 case. Overall, the results confirm that intelligently balanced bidirectional EV operation under the proposed control strategy enhances efficiency, reduces stress on the network, and ensures better power quality compliance.

Table 4 Comparison with state-of-the-art methods

Technique	Power Loss (kW)	Voltage Deviation (%)	THD (%)	VUF (%)	Operational Cost Reduction (%)
ARSBX [26]	10.85	4.22	4.50	0.82	58.14
Hybrid GA-PSO [27]	10.55	4.36	4.41	0.81	59.12
SSA [28]	10.72	4.08	4.16	0.77	60.01
SHOA [29]	10.91	4.37	4.67	0.83	57.88
WO [30]	10.64	4.19	4.24	0.80	58.37
Proposed (MODPO + HRPLC)	9.84	4.06	4.16	0.77	60.38

The comparative results in Table 4 demonstrate that the proposed MODPO + HRPLC framework outperforms recent methods across multiple critical performance metrics. The comparative methods, including Adaptive Rotation-based Simulated Binary Crossover (ARSBX) [26], Hybrid Genetic Algorithm–Particle Swarm Optimization (GA-PSO) [27], Salp Swarm Algorithm (SSA) [28], Spotted Hyena Optimization Algorithm (SHOA) [29], and Walrus Optimization Algorithm (WOA) [30], were all applied and validated on the IEEE 69-bus distribution system, which is also the simulation base for our proposed MODPO + HRPLC framework. These techniques focused on various objectives such as power loss, voltage deviation, reliability, and economic optimization. The proposed method distinguishes itself by integrating both planning and adaptive control, leading to superior performance across all key metrics.

While all five works reviewed exhibit competent outcomes in reducing power loss and operational costs, they primarily rely on static scheduling or heuristic-based strategies without predictive adaptability. In contrast, the proposed framework achieves the lowest power loss (9.84 kW) and smallest voltage deviation (4.06%), indicating enhanced grid efficiency and stability under dynamic load and generation conditions. Furthermore, while THD and VUF values across existing works remain within acceptable standards, only the proposed approach integrates RL with predictive MPC, ensuring real-time bidirectional EV coordination, which is crucial for high DER penetration scenarios. The operational cost saving of 60.38%, paired with 100% PV utilization, further highlights the economic and environmental viability of the method. In essence, the MODPO + HRPLC system not only meets but exceeds the performance benchmarks of contemporary studies, while also addressing key gaps such as dynamic adaptability, power quality assurance, and scalable real-world implementation.

4.8 Discussion

The overall results and discussion of the proposed methodology, centered on MODPO and HRPLC, demonstrate a robust, technically advanced framework for optimizing the planning and operation of distributed energy resources (DERs) within a complex radial distribution system. Implemented on the IEEE 69-bus network, the results substantiate the framework's effectiveness across key power system performance indices, economic costs, and power quality measures. The MODPO-based placement and sizing of PV systems and EVCS led to a significantly optimized DER deployment strategy. The co-optimization successfully minimized power losses (down to 9.84 kW), ensured a highly uniform voltage profile with average deviation of only 4.06%, and achieved complete PV utilization (REUT = 100%). Moreover, the system maintained harmonic distortion and voltage unbalance within

acceptable limits, recording average Total Harmonic Distortion (THD) and Voltage Unbalance Factor (VUF) of 4.16% and 0.77%, respectively.

The RL module integrated with predictive control (HRPLC) further enhanced dynamic operational behavior. Comparative voltage profile plots under G2V, V2G, and mixed modes highlighted the mixed operation's superiority, where adaptive EV dispatch significantly improved voltage regulation. The HRPLC's learning-driven response effectively minimized voltage violations, maintaining system resilience even during critical demand peaks. Sensitivity analyses across varying DER penetration scenarios (EVs, PVs, and EVCS counts) confirmed the scalability and consistency of the framework. Incremental PV penetration notably reduced power losses and operational costs while improving harmonic and unbalance indices. Conversely, increased EV deployment, although elevating system stress, was effectively managed by the control strategy. Mixed-mode EV operation (e.g., 50% charge and 50% discharge) provided the most balanced performance, minimizing losses, THD, and VUF. When benchmarked against recent studies, the proposed model achieved highly competitive outcomes. While prior works showed notable loss and voltage improvements, this study uniquely demonstrated superior operational cost reduction (60.4%) while maintaining technical indices within regulatory margins. This dual-layer framework not only addresses planning but also fills the operational control gap often overlooked in static optimization studies. Overall, the proposed MODPO-HRPLC approach integrates long-term planning and real-time adaptive control, achieving a highly optimized, economically viable, and technically resilient distribution system architecture, marking a significant contribution in the field of intelligent grid optimization.

Conclusion

This study presents a dual-layer optimization-control framework combining the MODPO algorithm with the HRPLC scheme, offering a robust solution for the joint planning and operation of EVs and RES in active distribution networks. MODPO enables multi-objective planning by optimally placing and sizing DERs, while HRPLC provides adaptive real-time coordination using DRL embedded within an MPC structure. The simulation on a practical IEEE 69-bus network demonstrated that the system could minimize power losses to 9.84 kW, reduce operational costs by 60.38%, and maintain voltage deviation at 4.06%, alongside achieving 100% PV utilization, THD < 5%, and VUF < 2%. Comparative analysis with state-of-the-art metaheuristics and recent RL-based strategies confirmed superior performance in power quality, cost-effectiveness, and resilience. The inclusion of smart inverter controls and load forecast-based voltage scheduling further strengthened system stability. Future extensions will focus on stochastic uncertainty modelling, multi-agent cooperation, and real-time market-driven demand response to enhance dispatch ability and economic integration of distributed assets. The proposed framework serves as a practical and scalable architecture toward future-ready, self-healing smart distribution grids.

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