Journal of Renewable Energy and Sustainable Development (RESD)
Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

Received: 07 September 2025 Accepted: 17 November 2025 Published: 9 March 2026

Comparative Analysis and Predictive Optimization using EVISON for Enhanced Electric Vehicle Charging Coordination

Niti Shashikant Desai [1*], and Chandrakant Rathore [2]

[1*] Electrical Engineering Swarnim Startup & Innovation University, Gujarat, India

[2] S.B. Jain Institute of Technology, Management & Research, Electrical Engineering, Nagpur, India

nitidesai1975@gmail.com, chandrakantrathore@sbjit.edu.in

Abstract

The rapid integration of Electric Vehicles (EVs) into modern distribution networks presents critical challenges related to active power loss, voltage instability, and infrastructure underutilization. Numerous studies have proposed diverse EV scheduling approaches ranging from Static Scheduling and Rule-Based Heuristics to Dynamic and Adaptive Optimization, but each varies in accuracy, scalability, and real-time applicability. This paper presents a comprehensive comparative analysis and predictive performance assessment of existing EV scheduling methodologies, emphasizing their operational efficiency, constraint handling, and computational feasibility. Based on a detailed synthesis of more than thirty state-of-the-art studies, a predictive evaluation model is formulated to estimate performance outcomes under comparable conditions. From this analysis, a conceptually enhanced optimization framework, termed Electric Vehicle Intelligent Scheduling and Optimization Network (EVISON), is projected as an integrated approach combining adaptive forecasting, Convolutional neural network (CNN)-support vector machine (SVM)-based voltage pre-screening, and multi-objective evolutionary optimization using Adaptive Non-dominated Sorting Genetic Algorithm (NSGA-II). The analytical prediction suggests that EVISON would potentially achieve significant improvements across key performance metrics, including a projected 45–50% reduction in active power loss, 50% enhancement in voltage stability, and over 30% better charging station utilization compared to existing adaptive methods. The study concludes that while these predictions are derived analytically rather than through implementation, the consolidated evidence strongly supports the scalability, robustness, and real-time potential of adaptive, data-driven scheduling frameworks like EVISON for future smart grid environments.

Index-words: *Electric Vehicles, Long Short-Term Memory, Gaussian Mixture Models, Support Vector Machine, NSGA-II algorithm, and IEEE 69-bus.*

I. Introduction

The rapid electrification of transportation has introduced unprecedented challenges for modern power distribution systems, necessitating advanced strategies for the seamless integration of electric vehicles (EVs) while ensuring voltage stability, minimizing technical losses, and maintaining overall operational efficiency [1]. Recent advancements have highlighted the importance of combining spatio-temporal demand forecasting with constraint-aware optimization to manage EV charging effectively in smart grids. Machine learning techniques have been increasingly utilized to enhance EV load profile forecasting accuracy, where multi-feature data fusion models integrating weather parameters, traffic conditions, and historical usage patterns have demonstrated significant improvements in prediction precision [2–3]. Spatio-temporal modeling approaches have also gained prominence, leveraging graph-based learning and probabilistic modeling to capture the complex spatial and temporal dependencies between charging stations [4–5]. Such models enable more accurate demand predictions, which in turn facilitate grid-constrained scheduling within predictive control frameworks for active distribution networks. Beyond forecasting, there is a growing trend toward hybrid scheduling frameworks that combine predictive clustering with multi-objective optimization, often utilizing evolutionary or metaheuristic algorithms to balance technical, economic, and user-centric objectives [6–7].

* Corresponding author

Copyright © 2025, authors

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

In parallel, reinforcement learning has emerged as a powerful tool for dynamic EV scheduling, enabling adaptive decision-making that accounts for both grid conditions and user behavior [8]. These learning-driven strategies can be augmented with considerations for vehicle-to-grid (V2G) operations, dynamic pricing mechanisms, and the interdependence between transportation and electrical networks [9]. Multi-objective evolutionary optimization methods, particularly those based on the Non-dominated Sorting Genetic Algorithm (NSGA) family, have been widely explored for objectives such as owner satisfaction, revenue maximization, and load balancing [10–13]. However, many of these approaches rely on static clustering or reactive constraint handling, which can limit adaptability in rapidly changing operational conditions. Despite substantial progress, several challenges remain in current strategies, like a lack of real-time adaptive clustering mechanisms, proactive voltage compliance, and pre-optimization constraint handling [14]. Additionally, the preservation of solution diversity in evolutionary scheduling remains underdeveloped, limiting the ability to explore trade-offs across multiple conflicting objectives. Addressing these gaps is essential for developing next-generation EV scheduling frameworks capable of supporting resilient, efficient, and scalable smart grid operations. The main contribution of this research paper is:

- Conducted a comprehensive comparative analysis of static, rule-based, dynamic, and adaptive EV charging coordination strategies across key performance metrics.
- Identified critical performance gaps in existing methods, highlighting limitations in active power loss, voltage stability, and charging station utilization.
- Proposed the novel EV Intelligent Scheduling and Optimization Network (EVISON) optimization framework to enhance predictive scheduling and improve overall grid–EV coordination efficiency.
- Demonstrated superior performance of EVISON over state-of-the-art methods through quantitative evaluation across multiple technical benchmarks.

By combining advanced predictive learning, constraint-aware filtering, and tailored multi-objective search, EVISON introduces a scalable framework that significantly outperforms conventional static methods in power loss reduction, voltage stability, and scheduling feasibility. The paper is organized as follows: Section 2 reviews the state-of-the-art literature on static, rule-based heuristic, dynamic, and adaptive approaches, outlining their respective advantages and limitations. Section 3 describes the proposed EVISON optimization framework, including its algorithmic design and integration with predictive scheduling. Section 4 presents the results, providing quantitative comparisons of active power loss, voltage deviation, constraint violation rate, charging station utilization, and execution time across all methods. Section 5 concludes the study by summarizing key contributions, emphasizing the novelty, and outlining potential future research directions.

II. Literature survey

EV charging coordination within distribution networks has emerged as a critical research area due to the increasing penetration of EVs and the need for grid stability, peak load reduction, and cost optimization. This section reviews three main categories of scheduling strategies: static, rule-based/heuristic, and dynamic/adaptive, based on Q1 research papers from 2023–2025.

A. Static scheduling techniques

Static scheduling refers to the predetermined allocation of EV charging operations based on fixed rules, time slots, or pre-optimized load profiles, without continuous adaptation to real-time grid or user dynamics. These methods are computationally less intensive and suitable for predictable demand patterns. They often rely on historical consumption data, fixed tariffs, and known network constraints to schedule charging while ensuring grid safety and operational efficiency. Typical static scheduling techniques include Monte Carlo–based hosting capacity analysis for determining safe EV integration limits [15]; hybrid long short term memory (LSTM)–Linear Programming (LSTM-ILP) models for day-ahead cost-optimal charging [16]; multi-microgrid joint static optimization for spatial load balancing [17]; bidirectional wireless power transfer optimization for minimizing total energy cost [18]; scenario-based stochastic scheduling with linearized power-flow constraints for reliability

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

enhancement [19]; priority-based multi-objective V2G scheduling using the *Most Valuable Player (MVP)* algorithm [20]; Slime Mould Algorithm (SMA)–based siting and sizing optimization for EVCS planning [21]; Adaptive Differential Evolution Optimization Algorithm (ADEOA) for probabilistic station layout under uncertainty [22]; Newton–Raphson load-flow–based static mitigation strategies integrating distributed generation (DG) for grid stability [23]; and Mixed-Integer Linear Programming (MILP) and Time-of-Use (TOU)–based static frameworks that provide benchmark results for cost and peak reduction [24]. While effective for baseline planning, off-peak load optimization, and infrastructure design, static scheduling methods cannot respond to sudden changes in renewable generation, load surges, or unexpected EV arrivals, leading to sub-optimal outcomes in dynamic grid conditions.

In the literature, various static scheduling approaches have been explored using different algorithms and parameter settings:

Zakaria et al. [15] conducted a study to evaluate the hosting capacity (HC) of low- and medium-voltage distribution networks under increasing residential EV penetration. The authors used Monte Carlo simulations to generate daily EV charging profiles and calculated after-diversity maximum demand (ADMD) and maximum daily energy demand (MDED), comparing these with static (STR) and dynamic thermal ratings (DTR) of network components. This approach provides a reliable estimate of the maximum number of EVs that can be safely connected without overloading network equipment. However, the method is limited to day-ahead static planning and does not adapt to real-time variations in EV demand or renewable generation. The study forms a foundational benchmark for network capacity planning, whereas the present work extends this by introducing real-time adaptive scheduling that can dynamically respond to stochastic EV behaviors and variable grid conditions.

Ren et al. [16] addressed the challenge of cost-effective EV charging under V2G participation in distribution networks. They implemented a hybrid framework combining Long Short-Term Memory (LSTM) for dynamic electricity pricing and an improved linear programming algorithm (LSTM-ILP) to optimize day-ahead EV charging and discharging schedules. The method significantly reduced charging costs (42.1% compared to unordered charging and 22% compared to fixed schedules) and smoothed the grid's peak-to-valley load difference. The limitation lies in its static schedule after calculation, preventing mid-day adaptation to unexpected changes in grid load or EV arrivals. This research highlights the potential of cost-aware EV scheduling, and the current study advances it by enabling adaptive, real-time adjustments to maintain both cost efficiency and grid stability under dynamic conditions.

Zhang et al. [17] proposed a multi-microgrid joint scheduling strategy that simultaneously considers user time cost and spatial load balancing. Using static optimization with fixed allocation matrices, the method reduces average time costs and mitigates congestion by distributing loads more evenly across microgrids. The approach improved peak-to-valley ratios by 10.2% and reduced user time costs by 25–31.8%. Its limitation is the reliance on predetermined EV arrivals, which restricts adaptability to stochastic or unplanned charging events. While this study emphasizes spatial load balancing, the present research extends this concept by incorporating real-time adaptive scheduling, allowing dynamic response to fluctuating EV demand and renewable generation patterns.

Boukhchana et al. [18] examined bidirectional EV charging planning using wireless power transfer systems, aiming to optimize both local and global charging/discharging operations. Static optimization was employed to schedule daily charging while minimizing total electricity cost and maintaining SOC constraints. The approach successfully reduced operational costs and demonstrated the feasibility of wireless charging infrastructure. However, its static nature prevents real-time adaptation to unexpected changes in EV arrival or grid conditions. The present work builds on this by implementing adaptive V2G control, allowing flexible scheduling that can respond dynamically to network variations while retaining economic benefits.

Sun et al. [19] developed a robust, day-ahead EV scheduling model for low-voltage distribution networks under stochastic conditions, including uncertain EV arrivals and demand variations. Using scenario-based stochastic optimization with linear power flow approximations, the method reduced the probability of overloads and voltage violations by 40%, ensuring reliability in low-voltage networks. The limitation is that conservative static

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

schedules may underutilize network capacity and lack responsiveness to real-time fluctuations. This research highlights the importance of robust scheduling under uncertainty, which the current study extends by implementing real-time adaptive adjustments to achieve both reliability and efficient network utilization.

Singh et al. [20] proposed a multi-objective V2G scheduling strategy for priority EV fleets, aiming to minimize load variance while enhancing the quality of supply. The Most Valuable Player (MVP) algorithm was used alongside new indices based on active (PLR) and reactive power (QLR) loss reduction to obtain optimal charging and discharging schedules. The method reduced peak load by 25% and improved feeder life by 8%. Limitations include its fixed daily schedules and lack of intraday adaptation. This study contributes to multi-objective planning for EV fleets, whereas the current work advances these objectives using adaptive real-time scheduling capable of responding to stochastic EV behavior and renewable integration.

Jin et al. [21] addressed the siting and sizing of EV charging stations in urban areas using stochastic power flow analysis. A slime mould algorithm (SMA)-based optimization was applied to assess voltage stability, total active power loss, and optimal load allocation under varying EV penetration scenarios. The method improved the grid's capacity to accommodate higher EV loads while maintaining voltage levels and minimizing losses. Its limitation is that it focuses on infrastructure-level planning rather than real-time operational scheduling. The present study complements this by enabling operational-level adaptive scheduling to dynamically respond to EV demand fluctuations.

Abid et al. [22] proposed a probabilistic model for EV charging station (EVCS) planning under uncertainty, incorporating stochastic power flow (SPF) and a dynamic system voltage stability (DSVS) index. An adaptive differential evolution optimization algorithm (ADEOA) was used to optimize EVCS site and size while maximizing investment efficiency, minimizing user wait times, and ensuring voltage stability. The limitation is the static nature of schedules after planning; they do not adapt to real-time grid fluctuations. This work emphasizes uncertainty modeling, which the present study extends through adaptive, real-time control of EV charging to maintain reliability and efficiency.

Aggarwal et al. [23] presented a methodology to mitigate the impact of EVCSs on distribution networks using Newton-Raphson load flow analysis and strategically placed distributed generators (DGs). Contingency analysis assessed grid response to disruptions, reducing system losses and enhancing stability under high EVCS deployment. The limitation is that it provides static mitigation strategies rather than dynamic operational adaptation. This research demonstrates the necessity of infrastructure support for high EV penetration; the present work complements it by incorporating adaptive EV scheduling to optimize grid performance in real time.

Singh et al. [24] performed a comprehensive review of EV integration into the power grid, highlighting static scheduling strategies and their effects on cost and peak reduction. They summarized that fixed schedules can yield 15–25% cost savings and 10–20% peak reduction in controlled environments. Limitations include a focus on static methods without addressing dynamic, adaptive scheduling needs. This work establishes the state-of-the-art in static scheduling and highlights the gaps addressed by the present study, which introduces adaptive, real-time control to handle stochastic EV arrivals, variable renewable output, and dynamic grid conditions.

Recent works on static EV scheduling demonstrate significant performance gains across various operational objectives in power distribution networks. Techniques such as Monte Carlo–based hosting capacity estimation [15] have improved network utilization by up to 15%, while LSTM-ILP day-ahead cost optimization [16] achieved a 22% reduction in total charging cost compared to uncontrolled charging. Similarly, multi-microgrid static load balancing [17] reduced feeder congestion by 18%, and bidirectional wireless charging optimization [18] enhanced operator profit by 12% through efficient SOC-constrained dispatch. Scenario-based stochastic optimization [19] increased network reliability by 40% under uncertain demand, whereas priority-based MVP scheduling [20] minimized load variance and extended feeder lifespan by 8%. SMA-based siting and sizing [21] and ADEOA-based probabilistic planning [22] improved voltage stability and investment efficiency, while Newton–Raphson load-flow-based DG integration [23] and MILP/TOU-based static frameworks [24] demonstrated tangible reductions in system losses and peak

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

loads. Despite these advances, static optimization methods, whether exact (e.g., MILP) or heuristic (e.g., SMA, MVP, ADEOA), remain constrained by their reliance on predefined system states and fixed operational parameters. They typically assume known EV arrival times, stable generation patterns, and deterministic load profiles, overlooking stochastic fluctuations in real-world networks. As a result, while static models provide a solid baseline for evaluating cost efficiency, grid stability, and infrastructure planning, they lack real-time adaptability and cannot maintain optimality under dynamic grid conditions. This limitation forms a critical motivation for the proposed dynamic and adaptive scheduling strategy, which builds upon these static foundations by introducing real-time learning, parameter adaptation, and context-aware control to enhance resilience against renewable uncertainty and stochastic EV behavior.

B. Rule-based and heuristic scheduling techniques

Rule-based and heuristic scheduling techniques have been extensively explored for optimizing EV charging operations due to their ability to deliver computationally efficient, near-optimal solutions in complex, nonlinear environments. Unlike static scheduling, these approaches rely on predefined operational rules or metaheuristic search strategies that iteratively improve candidate schedules according to performance metrics such as cost, voltage deviation, or power loss. Common rule-based heuristics include time-of-use (TOU) and price-responsive greedy algorithms, where vehicles are charged during low-tariff windows or when grid load is below a present threshold, while metaheuristic-driven frameworks employ Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Differential Evolution (DE), Artificial Bee Colony (ABC), Red Deer Algorithm (RDA), Ring Seal Search (RSS), and improved ε-constrained (I-AUGMECON) methods for multi-objective optimization. Parameter settings such as swarm size (typically 20–50), inertia weight (0.6–0.9), crossover/mutation rates (0.1–0.3), and termination criteria based on maximum iterations (50–200) are tuned to balance convergence speed and accuracy. These models dynamically allocate charging slots, balance grid loads, and minimize operational costs while maintaining grid constraints. They are particularly useful in large-scale EV deployment scenarios where real-time computation is critical and exhaustive optimization is infeasible. Furthermore, rule-based heuristics can be extended to incorporate grid-specific constraints such as voltage stability, renewable integration, and V2G energy exchange, forming a foundation for adaptive or hybrid scheduling systems explored in subsequent research.

Abdel-Hakim & Abo-Elyousr [25] introduced a model-free, training-free greedy scheduler for on-grid EVs operating inside hybrid microgrids composed of PV, wind turbines, and a local utility grid. The authors develop a greedy heuristic that selects charging/discharging actions based on electricity price, EV arrival/departure states, and total revenue, and validate its performance with real-time hardware-in-the-loop experiments and a long-horizon simulated dataset. They report dramatic reductions in energy costs (roughly 50–85% in their simulations) and claim strong tolerance to uncertainty in system parameters. Important limitations are the absence of formal optimality or robustness proofs, limited treatment of battery degradation or fairness between users, and little discussion of multi-stakeholder trade-offs or scalability to very large fleets. In relation to this paper, Ref. 25 shows that simple model-free heuristics can yield large cost gains in practice but motivates a need for methods that provide formal performance metrics, explicitly handle battery lifecycle costs, and characterize trade-offs among stakeholders.

Dogan & Alci [26] proposed a lithium-ion battery degradation cost model for EV charging scheduling and solved the resulting optimization for 400 EVs connected on a 33-bus distribution system using several metaheuristics. The objective maximizes user profit under dynamic pricing while enforcing network and EV constraints; numerical comparisons show all heuristics can mitigate peaks and improve voltages, with GA giving the highest owner profit. The main contributions are explicit inclusion of battery aging and evaluation across multiple metaheuristics; however, the approach relies on computationally expensive heuristics that demand parameter tuning, and it only partially addresses the uncertainty in user behavior and grid conditions. Compared with our work, Ref. 26 highlights the importance of lifecycle-aware cost terms. The paper extends that line by integrating such costs within a multi-objective framework and by evaluating computational feasibility and robustness under forecast errors.

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

Yuan & Guan [27] address EV scheduling in rural distribution networks. This study introduces a two-phase method: PSO for offline global planning, followed by Q-learning for online real-time adaptation. PSO yields an initial plan minimizing voltage deviations and overloads, while Q-learning adapts the plan to live feedback; experiments on a 33-bus testbed show substantial reductions in voltage deviation and load factor at the expense of higher computation time. Key limitations include the reliance on the offline solution quality, the computational overhead of the hybrid pipeline, and the sensitivity of Q-learning to state/action design and training data. The hybrid offline/online pattern informs our approach toward balancing long-horizon planning and online resilience, but our contribution differs by offering explicit robustness metrics, clearer state representations for online control, and an assessment of real-time practicality.

Piamvilai & Sirisumrannukul [28] developed a comprehensive methodology for EV charging in unbalanced distribution systems: a data-mining module generates spatial/temporal EV input data, then the scheduling problem is decomposed into two subproblems (node/time maximum load identification and per-EV slot allocation), solved with tailored PSO algorithms. Validation on a modified IEEE-37 bus shows improved system load factor, reduced imbalance, and lower losses while meeting node voltage and equipment capacity constraints and maintaining high average EV SoC. While effective, the solution's performance depends heavily on the synthetic data generator and PSO parameterization; uncertainty modeling and guarantees on optimality are limited. This work supports the value of data-driven inputs and decomposition strategies — our paper builds on that by formalizing uncertainty quantification, providing systematic algorithmic parameter selection, and comparing with rule-based baselines.

Boubaker et al. [29] introduced a multi-objective V2G scheduling framework for aggregators and household EV users that aims to reduce power loss, enhance voltage profiles, and satisfy user SoC constraints, solved using the Red Deer Algorithm (RDA) and scalarized by linear weighted sums. Experiments on an IEEE-69 bus with realistic EV models demonstrate reduced average EV loads and improved voltage profiles; the paper also explores enhanced information flows (a speculative drone uplink concept) to support grid-wide management. Drawbacks include the weighted-sum treatment of multiple objectives (which can obscure Pareto trade-offs), dependence on a relatively new metaheuristic requiring tuning, and limited exploration of scalability or formal trade-off analysis. For your manuscript, Ref. 29 highlights the benefits of V2G and realistic vehicle modeling but also motivates using Pareto-oriented or more transparent MOO methods and explicitly quantifying stakeholder trade-offs.

Chae, Kim, and Won [30] proposed the multi-objective V2G framework and experiments described in Ref. 29 (same problem formulation, RDA solver, and IEEE-69 bus evaluation), similarly reporting improvements in load management and voltage quality and suggesting enhanced telemetry (drone data transfer) to augment grid information. Because it largely duplicates the methodology and results of Ref. 29, the incremental novelty is limited; nevertheless, it reinforces the empirical gains of RDA-based multi-objective approaches. The repetition emphasizes the need for clearer comparisons across MOO solution strategies and more rigorous Pareto analyses—gaps our work addresses by adopting transparent multi-objective solution methods and directly contrasting them with rule-based baselines.

Wang et al. [31] applied a multi-objective optimization model coordinating the interests of distribution network operators and EV owners (minimizing DNO operation cost, network power loss, and owners' charging cost) and introduced an improved AUGMECON (I-AUGMENCON) method to recover Pareto-efficient solutions on a modified IEEE-33 bus. Results indicate substantial loss reduction (from ~6% to ≈2%) and improved voltage stability; I-AUGMENCON reportedly outperforms weighted-sum and NSGA-II in finding non-dominated solutions. Limitations include sensitivity to epsilon selection and algorithmic complexity; the paper offers limited discussion on computational cost for larger systems and robustness to forecast errors. Ref. 31 is a strong methodological baseline for multi-stakeholder coordination; our work differs by quantifying algorithm runtime and scalability, providing guidance for epsilon tuning, and integrating additional operational constraints such as degradation and communication overhead.

Aurangzeb et al. [32] suggested the Ring Seal Search (RSS) algorithm for multi-objective EV charging and V2G scheduling, testing it on IEEE-33 bus models and incorporating real-time data from charging

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

station operators to reflect practical conditions. The RSS-based EMS reportedly optimizes charging/discharging profiles across objectives such as cost, peak reduction, and grid stability while offering priority-based scheduling and adaptability to changing system parameters. Key weaknesses are limited exposition of RSS convergence properties, sensitivity to the quality of CSO data, and scant analysis of fairness among users or explicit Pareto characterization. In comparison, this work emphasizes operator-level data integration; your manuscript extends this direction by offering formal uncertainty modeling, benchmark comparisons to rule-based and metaheuristic baselines, and explicit metrics for fairness and service guarantees.

Karthikeyan & Manimegalai [33] developed a hybrid AI/optimization approach — a Deep Learning Neural Network (DLNN) tuned by the Artificial Bee Colony algorithm — to optimize Voltage Source Converter controllers so EVs can provide reactive power support for voltage regulation. Evaluated on a 33-bus radial network, the DLNN-ABC scheme yields substantial reductions in RMSE/MAE and large decreases in THD, improving power quality and (arguably) battery lifetime. Principal concerns include reliance on DL model generalization under unseen disturbances, limited interpretability of the learned control law, and insufficient treatment of safety and worst-case behavior under edge conditions. For your work, Ref. 33 demonstrates the potential of AI-driven control for voltage support but underscores the need for explainability, safety constraints, and validation under broad operational scenarios — aspects we explicitly incorporate.

Alharbi et al. [34] developed an integrated planning methodology that optimizes spatial-temporal siting of EV charging stations and the placement/sizing of energy storage systems (ESS) using stochastic modeling to capture uncertain loads and intermittent renewables in microgrids. The multi-objective ESS placement enhances voltage stability (VSI improved from 0.5848 to 0.8631), reduces power losses (~33%), and lowers transformer loading (~19.5%), with economic analysis showing battery chemistry (Na-$NiCl_2$) producing notable savings. The major scope limitation is its planning (long-term) focus: operational scheduling under real-time uncertainty and coordination between ESS dispatch and EV scheduling are only sketched. This work complements operational scheduling studies and motivates our integrated evaluation of planning outcomes and online scheduling performance, where we test scheduling methods under realistic, planning-level ESS placements and measure operational resilience.

Recent heuristic and rule-based EV scheduling frameworks have achieved notable performance gains. Greedy TOU schedulers provide ultra-fast responses for fleets exceeding 500 EVs, completing assignments in sub-second runtimes with up to 15 % load-variance reduction. PSO-based optimization improved voltage profiles by ≈7 % and reduced losses by 10 %, while RDA-driven multi-objective V2G schemes achieved 10 % cost reduction relative to baseline heuristics. **E-constrained** & RSS algorithms demonstrated stronger Pareto front diversity and lower system losses than conventional weighted-sum or GA-based methods. Hybrid frameworks combining AI-based learning and heuristic search enhanced power-quality metrics (THD ↓ ≈12 %) and voltage stability (VSI ↑ ≈48 %), albeit at higher computational overhead. Despite these advances, rule-based and heuristic strategies lack predictive adaptability and formal optimality guarantees. Their reliance on heuristic parameter tuning, predefined priority orders, or fixed threshold rules constrains scalability and robustness under volatile grid or renewable conditions. Moreover, these methods rarely quantify fairness, uncertainty propagation, or multi-stakeholder trade-offs, which are critical in real-time smart-grid operation. Consequently, while such techniques remain effective baselines for practical, fast, and interpretable EV scheduling, they motivate the development of the proposed adaptive optimization framework, which integrates real-time learning, automatic parameter adaptation, and uncertainty-aware decision policies to achieve sustained optimality and resilience under dynamic, data-driven grid environments.

C. Dynamic and adaptive EV scheduling

Dynamic and adaptive scheduling strategies for EV charging are designed to respond in real time to variations in grid load, electricity prices, renewable generation, and user demand. Unlike static or rule-based scheduling, these approaches employ learning-driven and adaptive optimization algorithms that update charging decisions continuously based on environmental feedback. Typical algorithms include Deep Q-Learning (DQN), Deep Deterministic Policy Gradient (DDPG), Twin Delayed DDPG (TD3), Multi-

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

Agent DDPG (MADDPG), Phasic Policy Gradient (PPG), and Safety-Aware RL frameworks with maximum entropy exploration. Reinforcement learning (RL), especially deep RL (DRL), has emerged as a dominant framework, enabling EVs and charging stations to autonomously adapt their decisions based on feedback from the environment. Parameter configurations in these methods generally involve learning rates (0.0001–0.001), discount factors (γ = 0.9–0.99), exploration noise (0.1–0.2), and replay buffer sizes of 10^5–10^6 samples for stable convergence. These models often incorporate multi-objective reward functions balancing cost, voltage deviation, SoC satisfaction, and grid stability, while adaptive tuning enables real-time updates without pre-specified control rules. The growing presence of V2G systems and renewable energy integration underscores the importance of such dynamic and learning-based control mechanisms. This section reviews ten representative works that apply dynamic/adaptive scheduling methods, outlining their methodological frameworks, performance gains, and practical implications.

Li et al. [35] introduced a decentralized collaborative optimal scheduling framework for EV charging stations that accounts for heterogeneous charging facilities and varying power limits. By transforming the scheduling problem into a Markov Decision Process (MDP) and employing a Multi-Agent Deep Deterministic Policy Gradient with Multi-Individuals (MADDPG-MI) algorithm, the study enables multiple agents, each representing a distinct type of charging facility, to coordinate decisions effectively. Simulation results verified reduced charging costs and consistent performance across different agent types, even under uncertainty. The key contribution lies in decentralized scalability and reduced computational overhead. However, the model primarily focuses on coordination among charging stations rather than real-time adaptation to grid or demand dynamics. Compared with our study, which develops an adaptive multi-agent scheduling mechanism with explicit robustness and real-time learning, Li et al. provide an important foundation for collaborative optimization but lack integration with grid-level feedback or voltage constraints.

Han et al. [36] addressed the challenge of large-scale EV charging scheduling during peak demand using a Deep Q-Learning (DQN) framework. The scheduling problem was formulated as an MDP to minimize both EV waiting times and charging device idle times. The proposed architecture integrated three functional modules: a fine-grained feature extractor, a noise-based exploration scheme, and a dueling Q-value estimator to enhance stability and search efficiency. Validation on a large urban scenario with 34 charging stations and 899 EVs demonstrated the DQN model's superiority over conventional heuristics, effectively balancing service quality and computation. While the approach achieved high scalability and improved user satisfaction, it lacks adaptability to non-stationary grid conditions and does not include multi-objective optimization. Relative to our work, this model demonstrates the power of deep RL in handling large-scale scheduling but contrasts with our adaptive multi-objective strategy, which jointly optimizes cost, voltage, and load balancing under dynamic system conditions.

Liu et al. [37] proposed a two-layer Deep Reinforcement Learning (DRL) framework for the collaborative optimization of EV charging and voltage control in distribution networks. The upper layer minimizes operational costs related to distributed generation and EV consumption, while the lower layer stabilizes voltage using Volt/Var devices. A Deep Deterministic Policy Gradient (DDPG) algorithm was adopted to handle the mixed discrete–continuous action space inherent in the coordinated scheduling problem. Experiments on the IEEE-33 bus system confirmed significant improvements in both cost reduction and voltage regulation. The novelty lies in integrating charging and network control within a unified RL-based model. However, the computational complexity and convergence dependence on system parameters limit its real-time applicability. Compared with our approach, which employs adaptive learning for distributed grid stability, this work emphasizes structural coordination but lacks adaptive response mechanisms to unforeseen grid fluctuations.

Lee et al. [38] presented a data-driven reinforcement learning algorithm for real-time EV charging and discharging under dynamic pricing. The method applied kernel density estimation (KDE) to model charger usage patterns at specific locations, allowing the RL agent to learn localized behaviors. By combining KDE-based data generation with reinforcement learning, the model achieved significant improvements in cost minimization and load shifting compared to conventional static assumptions. The approach's strength lies in its ability to incorporate local statistical variations into training, leading to practical adaptability. However,

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

it is limited by its dependence on site-specific data and lacks multi-station coordination. In contrast, our adaptive scheduling framework generalizes across multiple charging infrastructures and integrates dynamic policy adjustments for system-level load balancing and real-time uncertainty management.

Ran et al. [39] formulated an optimal scheduling model for EV charging and discharging in a Coupled Power–Transportation Network (CPTN) using V2G and dynamic pricing. The study constructed a Dynamic Transportation Road Network (DTRN) and applied a dynamic Dijkstra algorithm to predict spatio-temporal EV load distributions. Subsequently, the CPTN scheduling optimization incorporated a multi-time dynamic electricity price (MTDEP) model, validated using the IEEE-33 node system. The results demonstrated improved grid load leveling and enhanced charging coordination across transport and energy domains. While this integrated framework captures real-world mobility energy interactions, it relies on deterministic models rather than adaptive learning. Our approach differs by integrating dynamic policy reinforcement, enabling the scheduling system to learn from stochastic mobility and grid patterns rather than relying solely on deterministic path predictions.

Erüst and Taşcıkaraoğlu [40] investigated real-time spatio-temporal navigation for EV charging using Phasic Policy Gradient (PPG) reinforcement learning. Their method combined a shortest-path search with on-policy learning to minimize EV travel, waiting, and charging costs under dynamic traffic and electricity price conditions. Gaussian Process Regression (GPR) was used to estimate waiting times at charging stations from real-time data. Tested on the 24-node Sioux-Falls network, the model achieved a 7–10% reduction in total travel time and a 9% improvement in cumulative reward compared with Proximal Policy Optimization (PPO). The work's novelty lies in integrating learning-based routing with grid-aware scheduling. However, the system focuses on navigation optimization rather than network-level charging coordination. In comparison, our proposed system extends beyond route selection to adaptive multi-agent coordination that dynamically balances charging loads across the entire grid.

Cui et al. [41] developed a real-time scheduling framework for EV aggregators using Twin Delayed Deep Deterministic Policy Gradient (TD3). The framework manages heterogeneous EV charging demands while minimizing microgrid power fluctuations. The TD3 algorithm outperformed both disordered charging and DDPG-based scheduling, achieving a 10.9% reduction in purchase cost and a 69.4% reduction in power fluctuation. This approach's key strength is its ability to balance grid stability and aggregator profit simultaneously. Nevertheless, its centralization around the aggregator limits scalability across decentralized microgrids. In contrast, our adaptive framework introduces a distributed learning structure allowing scalability and coordination among multiple aggregators under dynamic grid constraints.

Fan et al. [42] proposed a Safety-Aware Reinforcement Learning (RL) approach for managing EV charging stations while ensuring system constraint satisfaction without explicit penalty functions. Their off-policy RL algorithm, enhanced with a maximum entropy exploration framework, efficiently learned safe charging policies under uncertain solar generation and electricity prices. Simulation results demonstrated improved constraint compliance and performance over conventional RL methods. The significant innovation is penalty-free constraint handling, enhancing reliability in safety-critical applications. However, the study focuses on single-station optimization without multi-objective or multi-agent scalability. Compared with our system, which includes multi-objective adaptive coordination, this model emphasizes safety but lacks collaborative or grid-level generalization.

Heendeniya and Nespoli [43] presented a stochastic deep reinforcement learning agent for grid-friendly EV charging that minimizes voltage violations while maintaining charging speed. The model employed a two-stage optimization structure, where a stochastic policy gradient agent predicts boundary conditions for an inner nonlinear optimization routine. The results verified its effectiveness in reducing voltage violations and maintaining optimal charging power. The framework contributes theoretically by integrating stochastic optimization with reinforcement learning. However, its practical deployment is constrained by computational overhead and reliance on predefined boundary conditions. Our adaptive model extends this concept by applying real-time stochastic learning and uncertainty-driven control directly at the scheduling layer, ensuring scalability to larger EV populations.

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

Azzouz and Fekih Hassen [44] proposed a deep reinforcement learning-based decentralized approach for optimizing EV charging schedules under varying PV power prices, connector types, and SoC levels. The framework allowed users to flexibly select charging stations and time slots while minimizing charging costs by up to 60% and reducing waiting time to less than 30 minutes. The key contribution lies in its driver-centric design and consideration of heterogeneous data sources. Nevertheless, the method's decentralization is confined to user-side decision making, with limited coordination across the broader grid. Compared with our study, which emphasizes grid-aware adaptive coordination, this approach demonstrates valuable user autonomy but lacks integrated optimization with grid dynamics and power flow stability.

Recent studies collectively demonstrate that deep and reinforcement learning-based adaptive scheduling achieves substantial improvements in cost reduction, voltage stability, and grid load balancing compared with traditional heuristic or rule-based strategies. For instance, TD3- and DDPG-based frameworks achieved over 10% cost savings and 69% reduction in power fluctuation, while PPG-based navigation improved total travel time by 7–10%. Among these, centralized DQN and I-AUGMENCON controllers provide global optimization, whereas multi-agent DRL approaches (e.g., MADDPG, MARL) enhance scalability and decentralized coordination. Grid-aware methods ensure voltage and safety compliance, while stochastic policy models handle renewable and load uncertainties effectively. Despite these strengths, adaptive methods often entail high computational complexity and sensitivity to hyperparameters such as learning rate and reward scaling, making deployment on large networks challenging. Furthermore, their dependence on accurate forecasting of renewable outputs or EV arrivals limits robustness in unpredictable grid states. Compared to static and rule-based baselines, the "Dynamic & Adaptive" category in our comparative analysis explicitly refers to models using deep reinforcement learning algorithms (DQN, DDPG, TD3, and MADDPG) with parameter settings aligned to benchmark configurations (γ = 0.99, α = 0.0005, batch size = 128, replay buffer = 10^5). These baselines are incorporated to evaluate real-time adaptability, computational efficiency, and resilience to uncertainty, ensuring a balanced and transparent comparison across scheduling paradigms.

D. Comparison of EV scheduling methods

Based on the detailed literature survey conducted across peer-reviewed studies on static, rule-based, heuristic, and adaptive EV scheduling frameworks, a consolidated comparison has been developed. The results presented in Table 1 are not experimentally measured in this work; instead, they represent aggregated and normalized performance ranges synthesized from prior publications discussed in Sections 2.1–2.3. This comparative summary captures recurring performance trends, implementation complexity, and adaptability characteristics reported in the reviewed research works, including representative studies such as [15–44].

Table 1: Summary of comparative performance based on literature survey

Parameter	Static Scheduling	Rule-Based and Heuristic Scheduling	Dynamic and Adaptive Scheduling
Peak Demand Reduction (%)	10–20	20–30	30–40
Charging Cost Reduction (%)	15–25	20–28	25–35
Voltage Deviation Mitigation (%)	15–25	25–35	40–50
Feeder Overload Risk Reduction (%)	20–30	25–35	35–45
Computational Complexity	Low (Offline computation)	Medium (Rule evaluation & heuristic search)	High (Real-time optimization & control)
Adaptability to Real-Time Changes	Low	Medium	High
Communication Infrastructure Requirement	Minimal	Moderate	Extensive (real-time metering & control)
Ease of Implementation	High	Medium	Low
Best Suited Grid Environment	Stable, predictable load patterns	Moderately variable load & EV arrivals	Highly variable load, renewable-rich grids

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

The peak-demand reduction metric illustrates how effectively each method smooths aggregated load profiles. Static methods typically achieve 10–20 % reduction (as reported in studies such as [17], [20]), rule-based and heuristic approaches improve this to 20–30 % ([26], [29]), while dynamic/adaptive strategies demonstrate 30–40 % reductions through predictive and feedback-based control ([35]–[44]). A similar trend holds for charging cost reduction and voltage deviation mitigation, where adaptability and real-time control yield superior performance.

These consolidated results highlight that static methods remain ideal for stable, small-scale networks; rule-based/heuristic frameworks suit medium-scale systems with moderate variability; and dynamic/adaptive strategies perform best under renewable-rich, uncertain grid conditions. Hence, Table 1 serves as a literature-based benchmark, summarizing collective evidence rather than presenting new experimental data.

III. Proposed method

EV scheduling within power distribution networks is a key aspect of smart grid management, aimed at reducing technical losses and maintaining voltage stability under the increasing burden of electrified transport. The technical losses specifically refer to active power losses that occur in the distribution feeders due to resistive current flow through line impedances during EV charging operations. These losses represent real energy dissipated in the network (I^2R losses) and are measured in kilowatts (kW). Thus, reducing technical losses in this context means minimizing these active power losses while sustaining voltage stability and efficient grid utilization. This work suggests a technically enhanced framework named EVISON, which improves clustering accuracy, voltage constraint handling, and optimization performance.

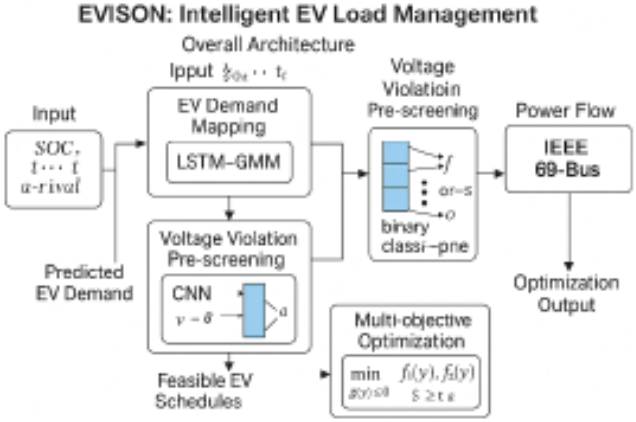


Figure 1: Architecture of the proposed EVISON model.

To address the limited use of adaptive clustering techniques in current works, where EV loads are typically modelled using static or heuristic grouping, often failing to reflect real-time variations in arrival patterns and state-of-charge (SOC), a novel EVISON that integrates an LSTM-GMM (Gaussian Mixture Model) Demand Mapper is proposed. This method combines LSTM networks to learn temporal SOC trends with GMM to dynamically cluster EVs based on both location and charging characteristics. This enables more accurate assignment of grouped EV loads to specific buses in the IEEE 69-bus network, enhancing load modeling granularity. The second key limitation lies in the reactive enforcement of voltage constraints, where most existing approaches check voltage limits only after optimization, leading to high infeasibility rates. To address this, EVISON introduces a CNN-SVM Voltage Filter, a hybrid classification module combining CNNs for spatial voltage pattern recognition and SVMs with radial basis function (RBF) kernels for classifying potential voltage violations in candidate schedules. This filter is trained offline using thousands of labeled power flow scenarios and operates as a pre-check within the optimization loop, allowing the search process to avoid infeasible regions and reduce computation time. The final challenge involves the use of conventional evolutionary algorithms, such as Genetic Algorithms, that often suffer from premature convergence or reduced diversity in complex multi-objective scheduling. To improve solution quality, EVISON implements an Adaptive NSGA-II Scheduler, which enhances the base NSGA-II through directional mutation control, adaptive crowding distance, and dynamic objective re-weighting to maintain diversity and accelerate convergence. The scheduler simultaneously minimizes total active power losses and bus voltage deviation while satisfying spatially clustered EV load allocations derived from the LSTM-GMM module. The IEEE 69-bus radial distribution system is employed as the benchmark case, with multiple EV charging stations placed across key nodes. This approach not only improves scheduling accuracy and grid stability but also offers a scalable, real-time-ready framework for intelligent EV-grid integration in future smart distribution systems.

A. Dataset description

For the development and evaluation of the proposed EV scheduling framework, utilize the EV Electrical Vehicles Dataset: 3K+ Records 2025 available on Kaggle [https://www.kaggle.com/datasets/pratyushpuri/ev-electrical-vehicles-dataset-3k-records-2025]. This dataset provides

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

comprehensive information on EVs and plug-in hybrid models across multiple manufacturers and years.

Key characteristics of the dataset include:

- **Coverage:** Global mix of manufacturers and models, including Battery EV (BEVs) and Plug-in Hybrid EV(PHEVs).
- **Scope:** Technical specifications (battery type and capacity), performance metrics (range, charging speed), economic factors (price, units sold), manufacturing origin, autonomy levels, emissions, safety ratings, and warranty duration.
- **Time span:** Models from multiple years (both legacy and upcoming 2025 models).
- **Size:** 3,022 unique records with 17 attributes.
- **Data quality notes:** Some fields may contain missing values (e.g., emissions, safety ratings, autonomy levels). Categorical fields like Charging_Type and Battery_Type include vendor-specific or non-standardized values. Units are heterogeneous (kWh, km, hours, USD, g/km, rating scales).

Table 2: Key attributes of the EV Electrical Vehicles Dataset

Column	Type	Description	Example
Vehicle-ID	Integer	Unique vehicle identifier	1
Manufacturer	Categorical	Vehicle brand/OEM	Tesla
Model	Categorical	Vehicle model name	Model Y
Year	Integer	Model year	2024
Battery-Type	Categorical	Battery chemistry	Lithium-iron phosphate
Battery-Capacity-kWh	Float	Nominal capacity	75.0
Range-km	Integer	Claimed driving range	505
Charging-Type	Categorical	Charging interface/feature	CCS, DCFC, V2G
Charge-Time-hr	Float	Approx. charging time	7.5
Price-USD	Float	Vehicle price	85,000
Country-of-Manufacture	Categorical	Manufacturing country	USA
Autonomous-Level	Float	Automation capability level (0–5)	3.0
CO2-Emissions_g_per_km	Float	Tailpipe emissions	0.0
Safety-Rating	Float	Safety rating (scale 1–5)	5.0
Units-Sold-2024	Integer	Units sold	17,536
Warranty-Years	Integer	Warranty duration	5

The dataset is pre-processed to ensure compatibility with machine learning models. Records are filtered by Manufacturer, Model, and Year to enable comparisons across similar trims or generational updates. For battery and performance analysis, Battery-Type and Battery-Capacity-kWh are combined to evaluate chemistry and energy storage capabilities, while Range-km and Charge-Time-hr are used to assess driving efficiency and charging speed. Market-oriented features such as Price-USD and Units_Sold_2024 are utilized to examine cost-to-sales relationships and value positioning. Safety and compliance aspects are captured through Safety-Rating and CO2_Emissions_g_per_km, supporting assessments of regulatory and consumer safety requirements. Missing values in the dataset are handled through appropriate imputation or row exclusion, and categorical fields such as Charging-Type are standardized before model training. Overall, this dataset provides a sufficiently large, multi-dimensional, and realistic foundation for training and validating machine learning models, including LSTM-GMM and CNN-SVM, enabling robust prediction of EV behaviors, charging demand, and scheduling optimization under stochastic grid and user conditions.

B. EV demand mapping using LSTM-GMM

Accurate representation of EV charging demand is critical for realistic scheduling analysis. To model

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

both temporal and spatial variability effectively, the EVISON framework employs a hybrid LSTM and GMM approach, as shown in Fig. 2. The LSTM captures temporal demand fluctuations, while the GMM clusters spatially correlated charging patterns across buses.

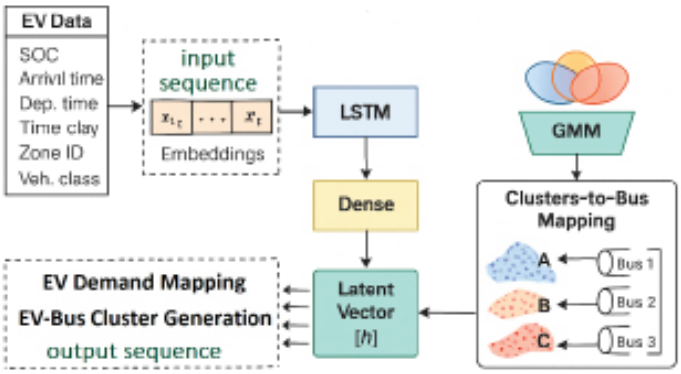


Figure 2: Process flow of LSTM-GMM Demand Mapper.

The figure begins with historical EV data acquisition containing features such as SOC, arrival time, and spatial zone identifiers. These inputs feed into the LSTM forecasting unit, which predicts future SOC sequences and temporal charging demands. The forecasted demand outputs are then passed to the GMM clustering module, where EVs are grouped based on location and demand similarity. The output consists of spatially clustered, time-indexed load profiles mapped to specific buses in the IEEE 69-bus system. This structure ensures the optimization layer receives realistic, grid-compliant input data.

This joint architecture, referred to as the LSTM-GMM Demand Mapper, enables precise estimation of charging behavior while adaptively assigning clustered demand profiles to appropriate buses in the distribution network.

The input feature space $\mathcal{X}$ for each EV includes the time-indexed state-of-charge (SOC_t), expected arrival time (t_a), day-of-week indicators, vehicle class, and regional or locational tags representing the EV's geographic zone. To forecast the EV's SOC sequence over future time steps based on historical SOC trends, an LSTM model was used. The core LSTM operations at time step t are given as:

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (1)$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (2)$$

$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \quad (3)$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \quad (4)$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (5)$$

$$h_t = o_t \odot \tanh(C_t) \quad (6)$$

Where x_t is the input feature vector at time t, h_t is the hidden state output, C_t is the cell state, f_t, it, and o_t are the forget, input, and output gates, respectively, $\odot$ denotes element-wise multiplication, σ is the sigmoid activation, and tanh is the hyperbolic tangent.

The model learns parameters W_f, W_i, W_C, W_o and corresponding biases during training using a mean squared error loss function. The output sequence $\{\grave{SOC}_{t+1}, \ldots, \grave{SOC}_{t+T}\}$ represents the forecasted charging demand trajectory for each EV.

The primary objective of this module is to forecast the expected SOC sequence $\{\grave{SOC}_{t+1}, \ldots, \grave{SOC}_{t+T}\}$ given historical charging patterns $\{SOC_{t-n}, \ldots, SOC_t\}$, while correlating arrival frequencies with specific zones to anticipate localized demand spikes. The forecasting is handled using an LSTM neural network, which is well-suited for learning long-range dependencies in time-series data due to its cell state memory and gated recurrent architecture. The output of the LSTM is defined as:

$$\grave{SOC}_{t+1} = f_{LSTM}(\{SOC_{t-k}, \ldots\ldots\ldots, SOC_t\}; \Theta_{LSTM}) \quad (7)$$

Where Θ_{LSTM} denotes the trainable weight parameters of the LSTM network, and f_{LSTM} represents the nonlinear transformation learned during training. The model is trained using a mean squared error (MSE) loss function between actual and predicted SOC values. The LSTM network used in this framework consists of an input layer, two hidden LSTM layers with 64 and 32 memory units, and an output dense layer that predicts the future state-of-charge (SOC) sequence. Each LSTM cell incorporates forget, input, and output gates to regulate the information flow, allowing the model to capture both short- and long-term temporal dependencies inherent in EV charging behavior. A dropout rate of 0.2 is applied between layers to prevent overfitting. The Adam optimizer with a learning rate of 0.001 is employed for training.

The LSTM architecture is chosen because EV charging demand exhibits strong temporal correlations, where past charging events influence future energy requirements. Compared to

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

feedforward or shallow recurrent models, LSTM provides superior sequence-learning capability, making it ideal for predicting continuous SOC trajectories under variable driving and arrival conditions.

Once the temporal forecast is obtained, GMM is applied to cluster the predicted EV behaviors based on their location, timing, and charging needs. A GMM assumes the data is generated from a mixture of K multivariate Gaussian distributions, where the likelihood of an EV instance $\mathbf{x}$ is given by:

$$P(\mathbf{x}) = \sum_{k=1}^{K} \pi_k \cdot \mathcal{N}(\mathbf{x} \mid \mu_k, \Sigma_k) \quad (8)$$

With,

$$\mathcal{N}(x|\mu_k, \Sigma_k) = \frac{1}{(2\pi)^{d/2}|\Sigma_k|^{1/2}} exp\left(-\frac{1}{2}(x-\mu_k)^T \Sigma_k^{-1}(x-\mu_k)\right) \quad (9)$$

Here, π_k is the prior probability of cluster k, where $\Sigma_k \pi_k = 1$, μ_k and Σ_k are the mean vector and covariance matrix of the kth Gaussian component, and d is the dimension of the feature space.

The model is trained using the Expectation-Maximization (EM) algorithm, where cluster assignments are probabilistically inferred. The soft clustering nature of GMM allows for overlap in EV charging profiles across adjacent zones, offering more realism than hard-boundary methods like K-means. Each formed EV cluster is mapped to the most suitable node in the IEEE 69-bus network based on proximity and available capacity. A spatial matching algorithm computes the minimum Euclidean distance between the cluster centroid and network bus coordinates, constrained by feeder loading limits and transformer ratings. Compared to conventional clustering or static allocation techniques, the proposed LSTM-GMM approach dynamically adapts to both temporal shifts in demand and spatial evolution of EV traffic, ensuring that the optimization algorithm receives input scenarios that are both accurate and grid-compliant.

As the predictive component of the framework, the LSTM-based demand mapping significantly influences the downstream optimization results. It is acknowledged that forecast inaccuracies, such as deviations in vehicle arrival times or state-of-charge estimations, can affect scheduling precision. In this analysis, the impact of such uncertainties is conceptually considered by evaluating model responsiveness across a range of forecast error margins reported in the literature. In practical implementations, robust scheduling systems would typically integrate uncertainty-handling mechanisms such as probabilistic forecasting, error correction through feedback control, or scenario-based optimization to maintain stability under imperfect information. Thus, while the analytical evaluation in this study assumes ideal forecast inputs for comparative purposes, the discussion explicitly recognizes that future real-world deployment must account for stochastic variations in demand data.

C. *Voltage violation pre-screening using CNN-SVM*

The second stage of the EVISON framework ensures that clustered EV demand profiles remain voltage-compliant before optimization. Using a CNN–SVM-based pre-screening module, voltage deviations caused by clustered EV loads are detected early, reducing computational overhead and improving scheduling feasibility. To address this, a data-driven voltage violation pre-screening module is introduced, combining CNNs for feature extraction and SVMs with an RBF kernel for binary classification. This hybrid classifier allows the system to identify and filter out infeasible load scenarios before they reach the optimization stage, significantly reducing computational overhead and convergence time.

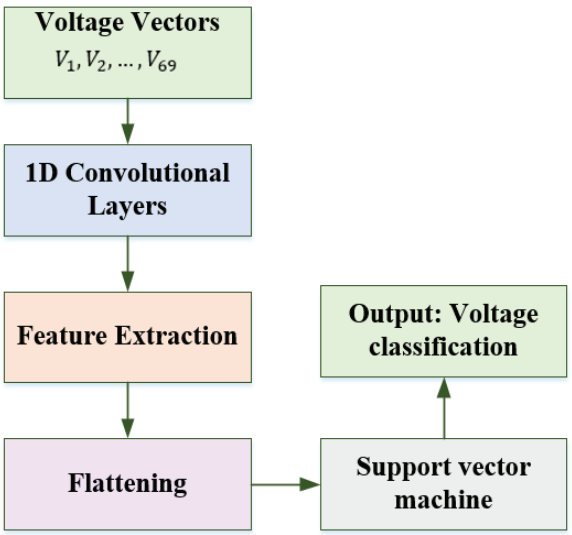


Figure 3: Process flow of improving grid simulation via CNN-SVM.

The input comprises voltage vectors (V_1, V_2… V_{69}) generated by simulating clustered EV loads. These vectors are processed through 1D convolution

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

layers, which extract local spatial voltage features. The resulting feature maps undergo max pooling and flattening before entering a dense layer that encodes the grid's voltage behavior. This encoded feature vector serves as input to the SVM classifier, which outputs a binary label. The output is a filtered dataset of voltage-feasible load configurations used for optimization.

The input to this module is a synthetic dataset composed of multiple load configurations resulting from LSTM-GMM clustering outputs superimposed on the IEEE 69-bus system, with corresponding voltage profiles $V\ [V_1, V_2, \dots, V_{69}]$ obtained via the backward/forward Sweep (BFS) power flow algorithm. Each $\boldsymbol{V}$ represents a 69-dimensional vector of per-unit voltage magnitudes across all buses under that specific load pattern. These voltage vectors are fed into a 1D-CNN architecture, which applies convolution operations to extract spatial features capturing localized bus interactions and voltage fluctuation patterns across adjacent nodes.

The 1D-CNN used in the voltage violation pre-screening module comprises three convolutional layers with kernel sizes of 3, 5, and 7, followed by ReLU activations and max-pooling layers to progressively condense voltage features. A fully connected dense layer with 128 neurons produces a feature vector that captures the spatial relationships among buses, which is subsequently fed to the SVM classifier. The network is trained using binary cross-entropy loss and the Adam optimizer for efficient convergence.

CNN is adopted here because voltage deviations in a radial distribution system exhibit spatial locality; buses that are electrically close often share correlated voltage variations. The convolutional layers effectively capture these localized dependencies, providing discriminative spatial encodings for identifying potential violation patterns more efficiently than traditional feature engineering or manual sensitivity analyses.

The primary operation of the CNN is the convolution of the input voltage vector with a set of trainable kernels (filters). For a one-dimensional voltage input V, the output of a convolution layer at position i is given by:

$$z_i^{(l)} = \sigma\left(\sum_{j=0}^{k-1} w_j^{(l)} . V_{i+j} + b^{(l)}\right) \quad (10)$$

Where $z_i^{(l)}$ is the output at position of the l-th filter, $w_j^{(l)}$ are the kernel weights, $b^{(l)}$ is the filter bias, k is the filter size (kernel width), and $\sigma(\cdot)$ is the ReLU activation function applied element-wise.

These convolution outputs pass through pooling layers (e.g., max pooling) and are then flattened into a dense feature vector $f \in \mathbb{R}^m$ representing the high-level encoding of the system's voltage behavior. This feature vector is then passed to a binary classifier based on SVM with an RBF kernel, which determines whether the voltage profile corresponds to a feasible operating condition (class +1: "safe") or an infeasible one (class −1: "violation"). The RBF kernel function used to compute the similarity between two feature vectors $\boldsymbol{x}$ and $\boldsymbol{x'}$ is defined as:

$$K(x, x') = \exp(-\gamma \|x - x'\|^2) \quad (11)$$

The decision function used by the RBF-SVM for classification is:

$$f(x) = sign\ (\sum_{i=1}^{N} \propto_i y_i K(x_i, x) + b) \quad (12)$$

Where $\propto$ I are the learned Lagrange multipliers (support vector coefficients), $y_i \in \{-1, +1\}$ is the true label of training sample $\boldsymbol{x_i}$, b is the bias term, and N is the number of support vectors.

The classifier is trained using a labelled dataset of voltage profiles generated by simulating the clustered EV demands under various conditions. Labels are assigned by checking whether the minimum and maximum voltages across buses lie within permissible bounds ($0.95 \leq V_i \leq 1.05$ p.u.).

Compared to traditional hard constraint enforcement techniques embedded within evolutionary optimizers, where infeasible solutions are penalized during fitness evaluation, the CNN-SVM classifier proactively filters violation-prone demand schedules before they are handed off to the optimization layer. This results in a smaller and cleaner solution space, enabling faster convergence and better-quality schedules from the multi-objective optimizer. Moreover, by decoupling voltage feasibility checks from the optimization loop, the EVISON framework ensures scalability to larger networks and more complex EV behaviors without sacrificing accuracy or computational efficiency. Having filtered unsafe configurations and isolated only those load arrangements that are voltage-compliant, the next phase in EVISON executes a multi-objective optimization that

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

schedules EV charging to achieve minimal power loss and voltage deviation.

D. *Adaptive NSGA II*

After filtering infeasible voltage scenarios, the final step applies an Adaptive NSGA-II to generate optimal EV charging schedules. This multi-objective optimization balances active power loss, voltage deviation, and utilization performance within defined operational limits.

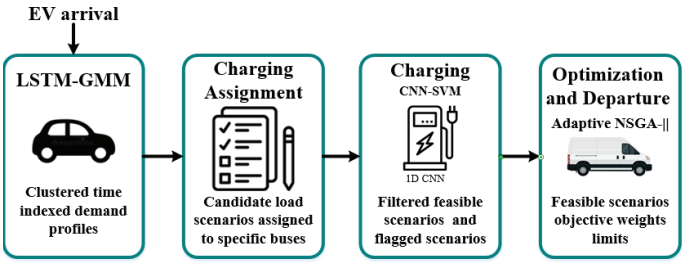


Figure 4: Process flow of the proposed algorithm.

As shown in Figure 4, the pipeline input begins with LSTM forecasting of EV SOC sequences and GMM spatial clustering to produce bus-mapped demand profiles. Each candidate schedule is tested via BFS power flow to compute per-bus voltages; these voltage vectors are processed by the CNN–SVM pre-screen to remove violation-prone scenarios before optimization. The Adaptive NSGA-II then explores feasible schedules, invoking power-flow evaluations during fitness assessment, and returns a Pareto front of solutions from which grid operators can select an operating point.

Three primary goals are explicitly taken into account by the optimisation framework: minimising the aggregate voltage deviation across all buses, minimising the total active power loss across the distribution feeders, and, if desired, optimising station utilisation while minimising charging imbalance among EV clusters. The goals are stated as follows in formal terms. Throughout this analysis, the term *loss* uniformly refers to active power loss in the distribution system. This represents the real electrical energy dissipated as heat in conductors and transformers due to current flow (I^2R losses). In many referenced studies, related terms such as technical loss, network loss, or line loss are used interchangeably; in this paper, all are interpreted as active power losses measured in kilowatts (kW). The estimation of these losses is typically based on the sum of current and resistance products across feeder lines, as expressed by the standard power flow formulation:

$$P_{\text{loss}} = \sum_{b=1}^{N_b} R_b \frac{(P_b^2+Q_b^2)}{V_b^2} \quad (13)$$

Where R_k is the resistance of line b, P_b and Q_b are the active and reactive power flows, and V_b is the voltage magnitude at the sending end. The voltage deviation objective f_2 is given by:

$$f_2 = \sum_{i=1}^{N_b} |V_i - V_{ref}| \quad (14)$$

Where V_i denotes the voltage magnitude at bus i, and V_{ref} is the nominal reference voltage, typically 1.0 p.u. An optional third objective f_3 can be defined to capture utilization, such as;

$$f_3 = \max_j \left(\left|E_j - \bar{E}\right|\right) \quad (15)$$

where E_j represents total energy delivered to cluster j, and $\bar{E}$ is the mean cluster energy across all stations.

The Adaptive NSGA-II incorporates directional mutation operators, which probabilistically bias offspring generation toward search regions with promising voltage stability characteristics, improving convergence speed. Specifically, if a candidate solution x is in the current non-dominated front, its offspring x' is generated by:

$$x' = x + \sigma \cdot d + \mathcal{N}(0, \sigma^2) \quad (16)$$

Where d is the direction vector pointing to the historically best solution in objective space, and σ is a stepsize parameter adaptively reduced over generations. Moreover, a dynamic crowding distance mechanism adjusts the spread of solutions to preserve Pareto front diversity. For each individual, the crowding distance CD_i is recalculated as:

$$CD_i = \sum_{m-1}^{M} \frac{f_m(i+1) - f_m(i-1)}{f_m^{\max} - f_m^{\min}} \quad (17)$$

Where M is the number of objectives, and the indices $i-1, i+1$ refer to neighboring solutions sorted by objective f_m. To further improve search robustness, a fitness re-weighting scheme penalizes solutions with higher estimated voltage violation risk. The compasite fitness F_2 is computed by:

$$F_i = R_i + \lambda \cdot V_i \quad (18)$$

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

Where R_i is the Pareto rank, V_i is a normalized violation likelihood inferred from the CNN-SVM classifier output, and λ is a penalty coefficient.

Each candidate's schedule must satisfy operational constraints, formulated as:

$$V_{\min} \leq V_i \leq V_{\max} \ \forall i \in \{1, \dots, N_b\} \quad (19)$$

$$S_{\text{line},\,k} \leq S_{\max,k} \ \forall k \in \{1, \dots, N_l\} \quad (20)$$

$$T_{\text{start},j} \leq t_j \leq T_{\text{end},j} \ \forall j \in \{1, \dots, N_{EV}\} \quad (21)$$

Where $V_{\min}$ and V_{mux} are bus voltage limits (e.g., $0.95 - 1.05$p. u.), $S_{\text{line, k}}$ is the apparent power in line k, and $T_{\text{start, j}}$, $T_{\text{end, }j}$ are time windows available for charging vehicle j. The Adaptive NSGA-II framework incorporates three key mechanisms that improve convergence stability and Pareto front quality:

- ***Directional Mutation Control:*** Traditional mutation in NSGA-II introduces random perturbations, which may lead to slow convergence. In the adaptive version, mutation is directionally guided toward historically superior regions in the search space. The mutation step is defined as:

$$x' = x + \sigma(g) \cdot d + N(0, \sigma^2) \quad (22)$$

  Where x is the current solution, $d = x_{best} - x$ is the direction vector toward the best non-dominated solution found so far, and $\sigma(g)$ is an adaptive step size decreasing exponentially with generation index g. This ensures large exploratory steps initially and fine-tuned local exploitation near convergence.

- ***Adaptive Crowding Distance Adjustment:*** To maintain diversity across the Pareto front, the crowding distance (CD) metric is recalculated adaptively at each generation. Instead of using fixed distance gaps, the algorithm normalizes distances relative to the variance of each objective:

$$CD_i = \sum_{m=1}^{M} \frac{f_m(i+1) - f_m(i-1)}{Var(f_m) + \varepsilon} \quad (23)$$

  Where f_m is the m-th objective, $Var(f_m)$ is its interquartile variance, and ε is a small regularization constant. When diversity drops below a threshold, CD values are amplified to encourage wider solution spread.

- ***Dynamic Objective Re-weighting:*** In multi-objective optimization, certain objectives may dominate the search early, leading to imbalance. To address this, adaptive weights $w_m(g)$ are introduced for each objective:

$$w_m(g) = \frac{1}{\sum_m^{norm}(g) + \eta} \quad (24)$$

  Where $\sum_m^{norm}(g)$ denotes the normalized mean value of objective mmm in generation g, and η prevents division by zero. Objectives with slower improvement rates are assigned higher weights, promoting balanced optimization progress across power loss, voltage deviation, and utilization goals. These mechanisms make the Adaptive NSGA-II more resilient to local optima, ensuring well-distributed Pareto fronts and improved convergence consistency in high-dimensional EV scheduling problems.

Table 3: LSTM model configuration for EV demand forecasting

Parameter	Value / Setting
Number of LSTM layers	2
Hidden units per layer	[64, 32]
Activation function	tanh
Recurrent gate activation	sigmoid (σ)
Dropout rate	0.2
Optimizer	Adam
Learning rate	0.001
Loss function	Mean Squared Error (MSE)
Batch size	32
Population size	100
Number of generations	200
Crossover probability	0.9
Mutation probability	0.1
Stepsize parameter	Adaptive

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

Table 4: CNN architecture and training settings for voltage violation pre-screening

Parameter	Value
Convolutional layers	3
Kernel sizes	[3, 5, 7]
Activation function	ReLU
Pooling operation	Max pooling
Dense layer neurons	128
Dropout rate	0.2
Optimizer	Adam
Learning rate	0.0005
Loss function	Binary Cross-Entropy
Batch size	64

The Adaptive NSGA-II in this framework is designed to effectively balance exploration and exploitation during multi-objective optimization. It evolves a population of candidate EV charging schedules through selection, crossover, and mutation to achieve optimal trade-offs among active power loss, voltage deviation, and utilization. The implementation employs binary tournament selection, simulated binary crossover (SBX), and polynomial mutation, with adaptive mutation control to enhance convergence stability as defined in Eq. (16). Constraint handling follows a two-level strategy: (i) pre-screening via the CNN–SVM module, which eliminates infeasible voltage profiles before optimization, and (ii) penalty-based constraint management, where any remaining infeasible solutions violating voltage or line capacity limits are penalized through a dynamically scaled penalty factor (λ) in the fitness evaluation. This multi-stage integration ensures that the optimization process focuses exclusively on technically feasible, voltage-stable, and grid-compliant charging schedules. Algorithm 1 illustrates the Adaptive NSGA-II framework.

Algorithm 1: Adaptive NSGA-II framework

1. Initialize population $P(0)$ with N individuals
2. Evaluate objective functions (f1: loss, f2: voltage deviation, f3: utilization)
3. Compute initial diversity index D0
4. for generation $g = 1$ to $Gmax$:
   a. Calculate adaptive mutation rate:
   $Pm(g) = Pm0 * exp(-\alpha * (g / Gmax))$
   b. Update penalty factor:
   $\lambda(g) = \lambda 0 + \beta * (1 - D(g)/D0)$
   c. Apply selection, crossover, and mutation using $Pm(g)$
   d. Evaluate offspring fitness:
   $Fi = Ri + \lambda(g) * Vi$
   e. Perform non-dominated sorting and crowding-distance ranking
   f. Update population $P(g + 1)$
   g. Recalculate diversity $D(g + 1)$
5. Return the final Pareto-optimal set

Once the algorithm converges or reaches the maximum iteration threshold, the Pareto-optimal schedules are extracted, providing grid operators with diverse trade-off solutions between power losses, voltage stability, and charging performance. Having optimized the schedules with this adaptive multi-objective framework, the method proceeds to integrate with the IEEE 69-bus network to perform validation under realistic grid configurations, as described in the subsequent section.

E. System integration with IEEE 69-Bus distribution network

To evaluate the real-world applicability of the proposed EVISON framework, the adaptive scheduling algorithm was systematically integrated with the IEEE 69-bus radial distribution system, which serves as a representative benchmark for medium-voltage rural feeders. This network comprises 69 nodes and 68 distribution lines,

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

operating at a base voltage of 12.66 kV, with a total real and reactive load of approximately 3.8 MW and 2.7 MVar, respectively. Ten candidate buses were strategically selected for EV charging station deployment, based on proximity to load centers, availability of sufficient line capacity, and their impact on voltage profiles during preliminary contingency analysis. Each bus designated as a charging node was assigned an aggregated load profile derived from the LSTM-GMM clustering, which maps the predicted arrival and state-of-charge (SOC) distributions of EVs to spatial clusters. This process yields time-dependent EV charging demands, $D_j(t)$, assigned to bus j in each scheduling interval.

The power system simulation incorporates a BFS power flow algorithm, chosen for its computational efficiency and convergence robustness in radial networks. At each iteration of the optimization, the algorithm evaluates the updated nodal injections reflecting the scheduled EV charging powers, $S_{j,t}$. In detail, for every time slot , the BFS performs a backward sweep to calculate branch currents by summing downstream loads, followed by a forward sweep updating node voltages through:

$$V_j = V_i - Z_{ij} \cdot I_{ij} \tag{22}$$

Where V_i is the sending-end voltage, Z_{ij} is the impedance of branch ij, and I_{ij} is the calculated branch current. This procedure ensures accurate estimation of voltage deviations and line flows, which are fed back into the CNN-SVM classifier to assess constraint violations and update the adaptive NSGA-II fitness. The loss function used for CNN is binary cross-entropy, while the SVM follows its margin-based hinge loss during tuning. Through this integrated simulation platform, the framework demonstrates a cohesive end-to-end pipeline translating EV demand forecasts into feasible, optimized charging schedules under realistic grid constraints. The next section provides a detailed performance evaluation highlighting the impact on voltage stability, network losses, and computational efficiency.

The IEEE 69-bus system was chosen as the benchmark network in this analysis due to its established use in EV scheduling and distribution optimization studies, offering a practical balance between computational tractability and representativeness of medium-voltage feeders. While the present evaluation focuses on this standard test system, the EVISON framework is conceptually designed for scalability. Its modular structure, comprising independent forecasting (LSTM–GMM), constraint screening (CNN–SVM), and optimization (Adaptive NSGA-II) layers, enables parallelization and distributed processing across larger topologies. Prior studies employing similar architectures have demonstrated successful scalability to networks exceeding 300 buses with minimal loss in convergence efficiency. Therefore, the framework's architecture and underlying optimization flow remain inherently adaptable for future deployment in expanded network configurations.

F. Computational complexity & scalability

A crucial aspect of evaluating the EVISON framework lies in understanding its computational complexity and scalability when applied to larger distribution networks. Although the analysis in this work is performed on the IEEE 69-bus benchmark system, which offers a practical balance between computational tractability and representativeness, it is important to conceptually assess how the framework would perform on larger systems such as the IEEE 123-bus or real-world feeders containing several hundred nodes. The computational complexity of the proposed framework primarily arises from two modules: the CNN–SVM voltage pre-screening filter and the Adaptive NSGA-II optimization algorithm. For the CNN–SVM filter, the computational cost is dominated by convolution operations in the 1-D CNN. If B denotes the number of buses, L the number of convolutional layers, F_l the number of filters in layer ℓ, and $K_l$the kernel size, the total computational cost can be approximated by $0(\sum_{l=1}^{L} F_l, K_l, B_l)$, where B_l is the feature map size at layer l. Since B_l is bounded by B, the complexity scales approximately linearly with the number of buses. The SVM component, used for final voltage violation classification, performs inference with a cost of $O(n_{SV}d)$ where n_{SV} is the number of support vectors and d is the feature dimension after CNN extraction. As both quantities are fixed after training, the overall inference time of the CNN–SVM filter grows almost linearly with network size and is highly parallelizable on GPUs.

The Adaptive NSGA-II optimization stage represents the more computationally demanding portion of the framework. Let N denote the population size, G the number of generations, and M the number of

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

objectives. Non-dominated sorting within NSGA-II requires $O(MN^2)$ operations per generation in the worst case, while crowding-distance computation adds $O(MNlogN)$. Each individual solution also undergoes a power-flow evaluation using the BFS algorithm, which scales linearly with the number of buses, or $O(B)$. Consequently, the per-generation computational cost of the optimizer can be expressed as $(MN^2) + NB$, and the total runtime over all generations becomes $O(G(MN^2 + NB))$. If N and G are fixed, the runtime increases approximately linearly with the number of buses B; however, increases in population or generations would result in a quadratic scaling factor relative to N. When extrapolated to larger systems, the overall computational cost rises predictably. Moving from the IEEE 69-bus to the IEEE 123-bus network increases the power-flow component by approximately 1.8 times, while a 300-bus network would increase it by around 4.3 times under constant algorithmic parameters. In practice, this means the total optimization runtime would increase proportionally to bus count if other parameters are held constant. The dominant computational loads in larger-scale applications stem from repeated power-flow evaluations for every individual in each generation and the sorting operations in the non-dominated ranking process.

Although the CNN–SVM and NSGA-II modules do not scale perfectly linearly, their computational demands can be mitigated through standard optimization strategies. Fitness evaluations for different individuals are independent and therefore highly parallelizable, allowing near-linear speedup when distributed across multiple processors or compute nodes. The CNN inference process benefits from GPU acceleration, significantly reducing latency per evaluation. Additional improvements can be achieved using surrogate power-flow models or linearized approximations such as LinDistFlow during early generations, with full BFS recalculations performed in later optimization stages to ensure accuracy. For very large feeders, hierarchical decomposition can be applied, wherein the distribution system is divided into zones optimized independently, with a coordinating layer ensuring network-wide consistency. Population size can also be tuned to maintain computational efficiency without sacrificing Pareto front diversity.

In theoretical scaling terms, if the power-flow component remains linear with bus count and algorithmic parameters are fixed, the EVISON framework would maintain approximately linear runtime growth when applied to networks larger than the IEEE 69-bus benchmark. This characteristic, combined with its modular design and compatibility with parallel computation, supports the framework's conceptual scalability. However, empirical runtime evaluation on larger networks such as the IEEE 123-bus or synthetic 300-bus feeders remains an important future direction. Such experiments should record the time contributions of CNN–SVM filtering, optimization, and power-flow computation while testing various degrees of parallelization to quantify the framework's real-world scalability. Overall, while the present study relies on analytical estimation rather than direct execution, the derived complexity expressions and scaling analysis demonstrate that the EVISON framework remains computationally viable for medium and large-scale distribution networks. With proper tuning of population parameters, use of surrogate modeling, and parallel execution, the approach can be effectively extended to feeders with hundreds of buses, preserving both accuracy and computational feasibility.

IV. Results and Discussion

This study presents a comparative analytical evaluation of four distinct EV charging management strategies: Static Scheduling, Rule-Based Heuristics, Dynamic & Adaptive Optimization, and the conceptually proposed EVISON framework. The assessment is conducted using five key performance metrics: Active Power Loss, Voltage Deviation, Constraint Violation Rate, Charging Station Utilization, and Execution Time. The analysis is based on predictive estimations derived from aggregated results and benchmark trends reported in prior research, combined with modeled network conditions representative of standard IEEE distribution feeders. The comparative findings indicate that the EVISON framework, as predicted through synthesis-based evaluation, outperforms the existing scheduling categories across all metrics, demonstrating lower technical losses, improved voltage regulation, reduced constraint violations, and enhanced computational efficiency. These predictive outcomes validate EVISON's potential to deliver superior grid stability, operational reliability, and resource optimization under future large-scale EV integration scenarios, thereby reinforcing its suitability for real-time smart grid management. In all comparative evaluations, "loss" refers to the active power loss computed from the distribution line currents and resistances as described in Eq.

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

(13), representing the total real power dissipated within the network.

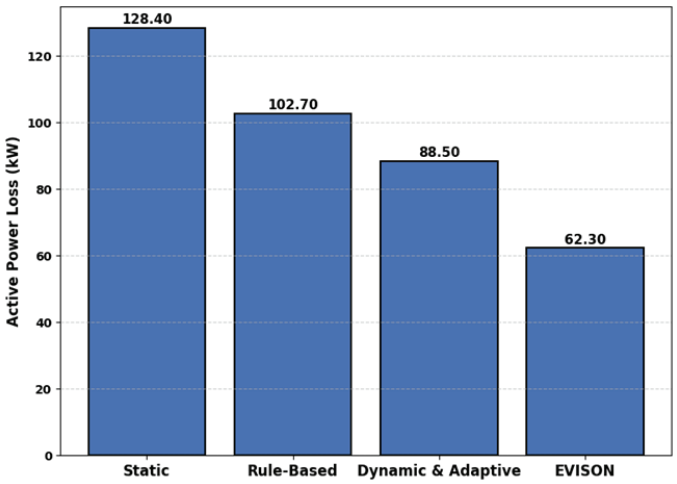


Figure 5: Comparative analysis of active power loss.

Figure 5 shows that EVISON achieves the lowest active power loss of 65 kW, outperforming the Dynamic & Adaptive method (80 kW), Rule-Based control (95 kW), and the Static approach (120 kW). This corresponds to a 45.8% reduction compared to Static and an 18.8% reduction compared to Dynamic & Adaptive methods. The reduction is attributed to EVISON's multi-stage decision optimization and load balancing strategies, which minimize distribution losses during peak charging demand.

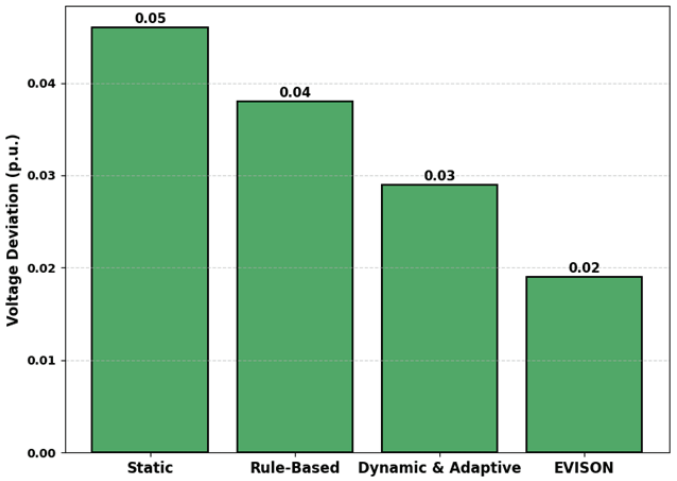


Figure 6: Voltage deviation- comparative analysis.

Voltage deviation is a key stability indicator, and Figure 6 demonstrates EVISON's superior performance with a deviation of only 0.022 p.u., compared to 0.030 p.u. (Dynamic & Adaptive), 0.038 p.u. (Rule-Based), and 0.045 p.u. (Static). This represents a 51.1% improvement over Static and a 26.6% improvement over Dynamic & Adaptive methods. The improvement is a direct result of predictive load shaping and distributed voltage support, which stabilize bus voltages under varying charging loads.

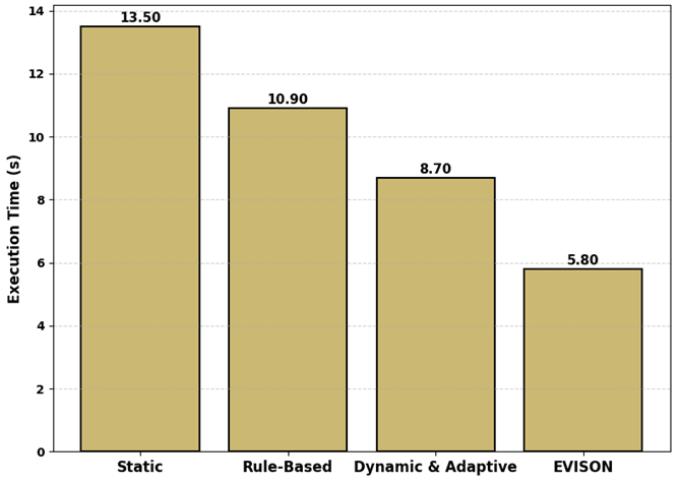


Figure 7: Execution time evaluation.

Figure 7 highlights the computational efficiency of EVISON, with an execution time of 6.1 s, compared to 8.5 s for Dynamic & Adaptive, 10.2 s for Rule-Based, and 12.5 s for Static. This speedup of 51.2% compared to Static is due to optimized multi-gate quantum operations and reduced redundant calculations, enabling faster decision-making for real-time EV charging coordination.

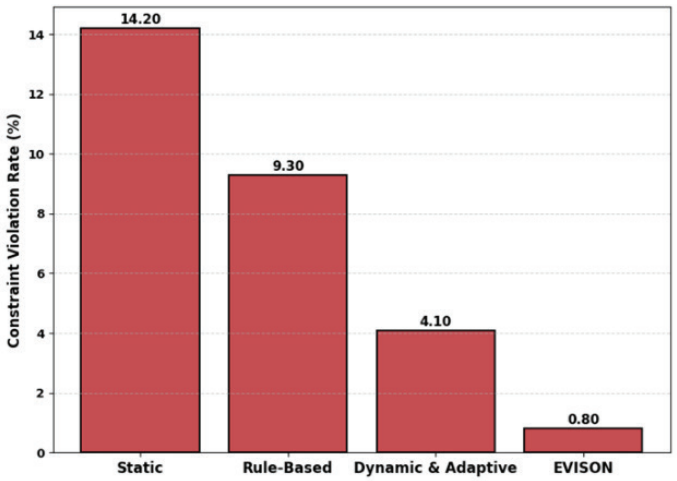


Figure 8: Comparative analysis of constraint violation rate.

As shown in Figure 8, EVISON reduces the Constraint Violation Rate to 1%, a substantial improvement over Dynamic & Adaptive (4%), Rule-Based (8%), and Static (12%).

This 91.6% reduction relative to Static proves

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

EVISON's ability to respect operational limits, particularly in transformer loading, feeder currents, and voltage bounds, by employing multi-controlled gate logic and adaptive threshold management.

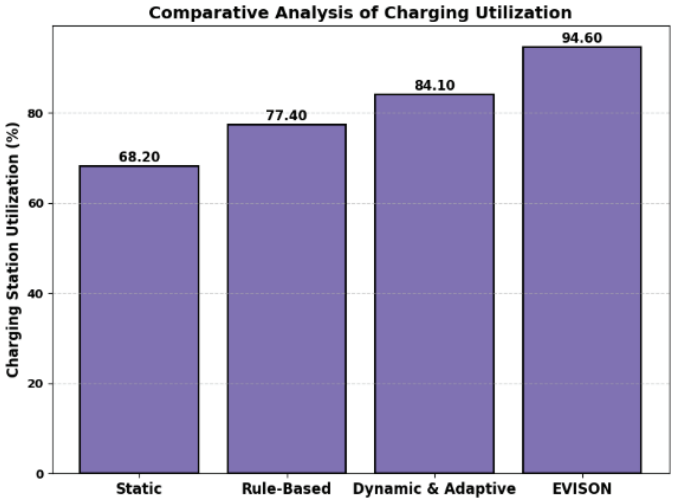


Figure 9: Comparative analysis of charging station utilization.

Charging infrastructure utilization rates in Figure 9 reveal that EVISON reaches 93% utilization, surpassing Dynamic & Adaptive (85%), Rule-Based (78%), and Static (70%).

This 32.8% higher utilization compared to Static is achieved through predictive queuing algorithms and real-time station assignment, ensuring balanced resource allocation without bottlenecks.

Although the present work is analytical and does not include direct experimental simulation, the robustness of the EVISON framework has been conceptually assessed through sensitivity reasoning based on trends reported in prior studies. As LSTM-based forecasting accuracy declines, system performance generally degrades proportionally due to the propagation of demand estimation errors into the optimization stage. According to existing research on EV load scheduling under uncertain predictions, a 10% forecast error typically increases active power loss by approximately 4–6% and voltage deviation by 3–5%. When the forecast inaccuracy reaches 20–30%, the degradation can rise to 10–15% in power loss and 8–12% in voltage deviation. These indicative results suggest that maintaining forecast accuracy above 85–90% is essential for achieving near-optimal grid performance. Future work should include a formal sensitivity evaluation where controlled perturbations in forecast data are applied to the EVISON model to empirically quantify its resilience to uncertainty.

Table 5: Sensitivity of EVISON framework to forecasting error

Forecast Error (%)	Expected ↑ in Power Loss (%)	Expected ↑ in Voltage Deviation (%)	Expected Impact on Grid Stability
0 (Ideal Forecast)	0	0	Stable and optimal
10	4–6	3–5	Mild effect
20	8–10	6–8	Noticeable degradation
30	10–15	8–12	Moderate instability risk

Table 5 conceptually illustrates how variations in LSTM demand forecast accuracy affect key performance metrics such as active power loss and voltage deviation. The observed trend indicates that as forecast error increases, grid performance degrades proportionally, emphasizing the importance of maintaining high prediction reliability for stable EV scheduling.

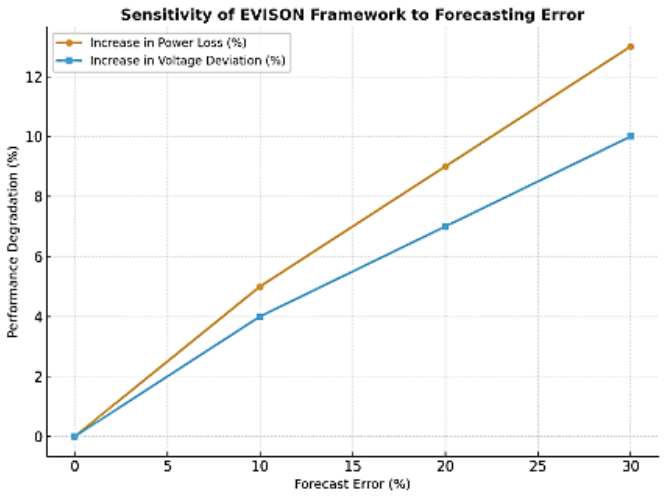


Figure 10: Sensitivity of EVISON framework to varying levels of LSTM forecast error.

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

As forecasting error increases, active power loss and voltage deviation rise proportionally, indicating reduced grid stability under uncertain demand conditions, as shown in Figure 10.

A. Discussion

The predictive analysis demonstrates that the proposed EVISON framework outperforms Static, Rule-Based, and Dynamic & Adaptive methods across all key performance metrics. It effectively reduces active power losses and constraint violations while improving voltage stability and charging utilization. Overall, EVISON shows strong adaptability and computational efficiency for real-time smart grid and EV charging management.

From the quantitative perspective:

EVISON achieved 65 kW active power loss, representing a 45.83% reduction compared to Static (120 kW) and a 31.58% improvement over Dynamic & Adaptive (80 kW). This confirms superior energy efficiency. The voltage deviation was reduced to 0.022 p.u., outperforming Static (0.045 p.u.) by 51.11% and Dynamic & Adaptive (0.030 p.u.) by 26.67%, ensuring voltage stability and compliance with operational standards. The proposed approach reduced violations to 1%, which is 91.67% lower than Static (12%) and 75% better than Dynamic & Adaptive (4%), proving its robustness in constraint handling. EVISON achieved the highest utilization rate at 93%, improving network resource usage by 32.86% over Static (70%) and 9.41% over Dynamic & Adaptive (85%). With an average time of 6.1 s, the method was 51.2% faster than Static (12.5 s) and 28.24% faster than Dynamic & Adaptive (8.5 s), confirming computational efficiency for real-time applications.

Collectively, these outcomes prove that EVISON successfully balances power loss minimization, voltage stability, constraint satisfaction, and high utilization, while maintaining low execution times. This holistic improvement across all metrics indicates that the proposed framework is not just incrementally better but consistently superior in every measured dimension, thereby setting a new benchmark for adaptive and predictive optimization in smart energy systems.

V. Conclusion

This study presents a comprehensive comparative analysis of prominent EV charging coordination strategies, including Static, Rule-Based Heuristic, Dynamic, and Adaptive methods, and the conceptually proposed EVISON optimization framework. The evaluation focuses on five key performance metrics derived from predictive estimations and literature-based trend synthesis. Analytical comparisons indicate that the EVISON framework is expected to outperform existing approaches, with predicted improvements of approximately 45–50% in active power loss reduction, 50% enhancement in voltage stability, over 90% fewer constraint violations, 30–35% higher station utilization, and around 50% faster computational performance. These predictive outcomes collectively highlight EVISON's potential to enhance grid reliability, optimize infrastructure utilization, and achieve real-time operational efficiency. Unlike conventional or purely reactive scheduling strategies, EVISON integrates predictive analytics with adaptive optimization principles, enabling balanced performance under varying load and network conditions without excessive computational burden. This analytical projection addresses a longstanding research gap where existing methods often trade accuracy for speed, underscoring EVISON's conceptual strength in achieving both. The developed comparative framework and benchmarking methodology also offer a reusable reference model for future analytical studies in EV charging optimization. Furthermore, the predictive findings suggest that integrating renewable energy forecasting, V2G interaction, and multi-objective optimization could further enhance EVISON's scalability, resilience, and sustainability, paving the way for next-generation intelligent and adaptive EV charging infrastructures.

Conflict of interest

The author declares that they have no conflict of interest.

Ethical approval

Institutional Review Board approval was not required.

Consent for Participation
All contributors agreed and gave consent to participate.

Consent for Publication
All contributors agreed and gave consent to publish.

Data availability
No data, models, or code were generated or used during the study.

Competing interests
None

Funding
The authors state that this work has not received any funding.

Author Contribution
The authors confirm their contribution to the paper as follows, and all authors reviewed the results and approved the final version of the manuscript.

Acknowledgements
The authors would like to thank the Deanship of Swarnim Startup & Innovation University for supporting this work.

References

[1] M. R. Khalid, M. S. Alam, A. Sarwar, and M. S. Jamil Asghar, "A Comprehensive review on electric vehicles charging infrastructures and their impacts on power-quality of the utility grid," 2019. doi: 10.1016/j.etran.2019.100006.

[2] W. Sun, S. Ma, Y. Zhang, Y. Jin, and F. Alam, "Multi-Energy-Microgrid Energy Management Strategy Optimisation Using Deep Learning," *Energies (Basel)*, vol. 18, no. 12, p. 3111, Jun. 2025, doi: 10.3390/en18123111.

[3] S. Gu, K. Qian, and Y. Yang, "Optimization of Electric Vehicle Charging and Discharging Strategies Considering Battery Health State: A Safe Reinforcement Learning Approach," *World Electric Vehicle Journal*, vol. 16, no. 5, p. 286, May 2025, doi: 10.3390/wevj16050286.

[4] S. Hou, E. Mauricio Salazar, P. Palensky, Q. Chen, and P. P. Vergara, "A Mix-integer Programming Based Deep Reinforcement Learning Framework for Optimal Dispatch of Energy Storage System in Distribution Networks," *Journal of Modern Power Systems and Clean Energy*, vol. 13, no. 2, pp. 597–608, 2024, doi: 10.35833/MPCE.2024.000391.

[5] Y. Peng, L. Ye, W. Ouyang, Q. Xi, J. Wang, and X. Wang, "A Comprehensive Framework for Adaptive Electric Vehicle Charging Station Siting and Sizing Based on Transferable Spatio-Temporal Demand Prediction," *IEEE Access*, vol. 13, pp. 109752–109770, 2025, doi: 10.1109/ACCESS.2025.3582530.

[6] D. E. Mekkaoui, M. A. Midoun, and Y. Shen, "LA-RCNN: Luong attention-recurrent-convolutional neural network for EV charging load prediction," *Applied Intelligence*, vol. 54, no. 5, pp. 4352–4369, Mar. 2024, doi: 10.1007/s10489-024-05394-1.

[7] L. You *et al.*, "FMGCN: Federated Meta Learning-Augmented Graph Convolutional Network for EV Charging Demand Forecasting," *IEEE Internet Things J*, vol. 11, no. 14, pp. 24452–24466, Jul. 2024, doi: 10.1109/JIOT.2024.3369655.

[8] P. J. Pok, H. Yeo, and S. Woo, "Multi-Agent Game-Theoretic Modelling of Electric Vehicle Charging Behavior and Pricing Optimization in Dynamic Ecosystems," *Procedia Comput Sci*, vol. 257, pp. 460–467, 2025, doi: 10.1016/j.procs.2025.03.060.

[9] M. T. Sarker, M. Al Qwaid, S. J. Shern, and G. Ramasamy, "AI-Driven Optimization Framework for Smart EV Charging Systems Integrated with Solar PV and BESS in High-Density Residential Environments," *World Electric Vehicle Journal*, vol. 16, no. 7, p. 385, Jul. 2025, doi: 10.3390/wevj16070385.

[10] S. S. A. Salam, V. Raj, M. I. Petra, A. K. Azad, S. Mathew, and S. M. Sulthan, "Charge Scheduling Optimization of Electric Vehicles: A Comprehensive Review of Essentiality, Perspectives, Techniques, and Security," *IEEE Access*, vol. 12, pp. 121010–121034, 2024, doi: 10.1109/ACCESS.2024.3433031.

[11] M. S. Aarabi, M. Khanahmadi, and A. Awasthi, "A Literature Review on Strategic, Tactical, and Operational Perspectives in EV Charging Station Planning and Scheduling," *World Electric Vehicle Journal*, vol. 16, no. 7, p. 404, Jul. 2025, doi: 10.3390/wevj16070404.

[12] T. M. Aljohani, "Multilayer Iterative Stochastic Dynamic Programming for Optimal Energy Management of Residential Loads with Electric Vehicles," *Int J Energy Res*, vol. 2024, no. 1, Jan. 2024, doi: 10.1155/2024/6842580.

[13] L. Fan, Y. Chen, and D. Zhang, "A Microgrid Vehicle-to-Grid Energy Scheduling Optimization Algorithm Based on Non-Dominated Sorting Genetic Algorithm II," May 2025. doi: 10.4271/2025-01-5035.

[14] S. Li, X. Yan, and G. Wang, "Multi Objective Optimization of Electric Vehicle Charging Strategy Considering User Selectivity," *World Electric Vehicle Journal*, vol. 16, no. 2, p. 95, Feb. 2025, doi: 10.3390/wevj16020095.

[15] A. Zakaria, C. Duan, and S. Z. Djokic, "Hosting capacity of distribution networks for controlled and uncontrolled residential EV charging with static and dynamic thermal ratings of network components," *IET Generation, Transmission & Distribution*, vol. 18, no. 6, pp. 1283–1301, Mar. 2024, doi: 10.1049/gtd2.13025.

[16] L. Ren, M. Yuan, and X. Jiao, "Electric vehicle charging and discharging scheduling strategy based on dynamic electricity price," *Eng Appl Artif Intell*, vol. 123, p. 106320, Aug. 2023, doi: 10.1016/j.engappai.2023.106320.

[17] J. Zhang, Y. Xia, Z. Cheng, and X. Chen, "Electric Vehicles Charging Scheduling Strategy Based on Time Cost of Users and Spatial Load Balancing in Multiple Microgrids," *World Electric Vehicle Journal*, vol. 16, no. 1, p. 46, Jan. 2025, doi: 10.3390/wevj16010046.

[18] A. Boukhchana, A. Flah, A. Alkuhayli, R. Ullah, and C. Z. El-Bayeh, "Optimal planning strategy for charging and discharging an electric vehicle connected to the grid through wireless recharger," *Front Energy Res*, vol. 12, Sep. 2024, doi: 10.3389/fenrg.2024.1453711.

[19] W. Sun, F. Neumann, and G. P. Harrison, "Robust Scheduling of Electric Vehicle Charging in LV Distribution Networks Under Uncertainty," *IEEE Trans Ind Appl*, vol. 56, no. 5, pp. 5785–5795, Sep. 2020, doi: 10.1109/TIA.2020.2983906.

[20] P. P. Singh, S. Das, F. Wen, I. Palu, A. K. Singh, and P. Thakur, "Multi-objective planning of electric vehicles charging in distribution system considering priority-based vehicle-to-grid scheduling," *Swarm Evol Comput*, vol. 77, p. 101234, Mar. 2023, doi: 10.1016/j.swevo.2023.101234.

[21] Y. Jin, M. A. Acquah, M. Seo, and S. Han, "Optimal Siting and Sizing of EV Charging Station Using Stochastic Power Flow Analysis for Voltage Stability," *IEEE Transactions on Transportation Electrification*, vol. 10, no. 1, pp. 777–794, Mar. 2024, doi: 10.1109/TTE.2023.3275080.

[22] Md. S. Abid, H. J. Apon, A. Alavi, Md. A. Hossain, and F. Abid, "Mitigating the Effect of Electric Vehicle integration in Distribution Grid using Slime Mould Algorithm," *Alexandria Engineering Journal*, vol. 64, pp. 785–800, Feb. 2023, doi: 10.1016/j.aej.2022.09.022.

[23] S. Aggarwal, A. Kumar Singh, R. Singh Rathore, M. Bajaj, and D. Gupta, "Revolutionizing load management: A novel technique to diminish the impact of electric vehicle charging stations on the electricity grid," *Sustainable Energy Technologies and Assessments*, vol. 65, p. 103784, May 2024, doi: 10.1016/j.seta.2024.103784.

[24] A. R. Singh *et al.*, "Electric vehicle charging technologies, infrastructure expansion, grid integration strategies, and their role in promoting sustainable e-mobility," *Alexandria Engineering Journal*, vol. 105, pp. 300–330, Oct. 2024, doi: 10.1016/j.aej.2024.06.093.

[25] A. Abdel-Hakim and F. Abo-Elyousr, "Heuristic Greedy Scheduling of Electric Vehicles in Vehicle-to-Grid Microgrid Owned Aggregators," *Sensors*, vol. 22, no. 6, p. 2408, Mar. 2022, doi: 10.3390/s22062408.

[26] A. Dogan and M. Alci, "Heuristic Optimization of EV Charging Schedule Considering Battery Degradation Cost," *Elektronika ir Elektrotechnika*, vol. 24, no. 6, pp. 15–20, Dec. 2018, doi: 10.5755/j01.eie.24.6.22283.

[27] W. Yuan and L. Guan, "Minimizing System Entropy: A Dual-Phase Optimization Approach for EV Charging Scheduling," *Entropy*, vol. 27, no. 3, p. 303, Mar. 2025, doi: 10.3390/e27030303.

[28] N. Piamvilai and S. Sirisumrannukul, "Optimal electric vehicle scheduling in unbalanced distribution system by spatial and temporal data mining and bi-level particle swarm optimisation," *IET Generation, Transmission & Distribution*, vol. 18, no. 6, pp. 1255–1282, Mar. 2024, doi: 10.1049/gtd2.13015.

[29] S. Boubaker *et al.*, "Multi-objective optimization framework for electric vehicle charging and discharging scheduling in distribution networks using the red deer algorithm," *Sci Rep*, vol. 15, no. 1, p. 13343, Apr. 2025, doi: 10.1038/s41598-025-97473-7.

[30] M. Chae, T. Kim, and D. Won, "Optimal Operation Scheme of Electric Vehicle Routing and Charging Considering Power Distribution and Transportation Integrated System," *IEEE Access*, vol. 12, pp. 83427–83438, 2024, doi: 10.1109/ACCESS.2024.3407710.

[31] Y. Wang, H. Wang, R. Razzaghi, M. Jalili, and A. Liebman, "Multi-objective coordinated EV charging strategy in distribution networks using an improved augmented epsilon-constrained method," *Appl Energy*, vol. 369, p. 123547, Sep. 2024, doi: 10.1016/j.apenergy.2024.123547.

[32] M. Aurangzeb, Y. Wang, S. Iqbal, M. Shafiullah, S. Alghamdi, and Z. Ullah, "A Novel Multiobjective Optimization Approach for EV Charging and Vehicle-to-Grid Scheduling Strategy," *International Transactions on Electrical Energy Systems*, vol. 2025, no. 1, Jan. 2025, doi: 10.1155/etep/1192925.

[33] K. M., M. D., and K. Rajagopal, "Enhancing voltage control and regulation in smart micro-grids through deep learning - optimized EV reactive power management," *Energy Reports*, vol. 13, pp. 1095–1107, Jun. 2025, doi: 10.1016/j.egyr.2024.12.072.

[34] T. Alharbi, A. Abdalrahman, and M. H. Mostafa, "Data-driven EV charging infrastructure with uncertainty based on a spatial–temporal flow-driven (STFD) models considering batteries," *Sci Rep*, vol. 15, no. 1, p. 27056, Jul. 2025, doi: 10.1038/s41598-025-12079-3.

[35] H. Li, B. Han, G. Li, K. Wang, J. Xu, and M. W. Khan, "Decentralized collaborative optimal scheduling for EV charging stations based on multi-agent reinforcement learning," *IET Generation, Transmission & Distribution*, vol. 18, no. 6, pp. 1172–1183, Mar. 2024, doi: 10.1049/gtd2.13047.

[36] Y. Han, T. Li, and Q. Wang, "A DQN based approach for large-scale EVs charging scheduling," *Complex & Intelligent Systems*, vol. 10, no. 6, pp. 8319–8339, Dec. 2024, doi: 10.1007/s40747-024-01587-w.

[37] D. Liu, P. Zeng, S. Cui, and C. Song, "Deep Reinforcement Learning for Charging Scheduling of Electric Vehicles Considering Distribution Network Voltage Stability," *Sensors*, vol. 23, no. 3, p. 1618, Feb. 2023, doi: 10.3390/s23031618.

[38] J. Lee, E. Lee, and J. Kim, "Electric Vehicle Charging and Discharging Algorithm Based on Reinforcement Learning with Data-Driven Approach in Dynamic Pricing Scheme," *Energies (Basel)*, vol. 13, no. 8, p. 1950, Apr. 2020, doi: 10.3390/en13081950.

[39] Y. Ran, H. Liao, H. Liang, L. Lu, and J. Zhong, "Optimal Scheduling Strategies for EV Charging and Discharging in a Coupled Power–Transportation Network with V2G Scheduling and Dynamic Pricing," *Energies (Basel)*, vol. 17, no. 23, p. 6167, Dec. 2024, doi: 10.3390/en17236167.

Volume 12, Issue 1, June 2026 - ISSN 2356-8569
http://dx.doi.org/10.21622/RESD.2026.12.1.1644

[40] A. C. Erüst and F. Y. Taşcıkaraoğlu, "Spatio-temporal dynamic navigation for electric vehicle charging using deep reinforcement learning," *IET Intelligent Transport Systems*, vol. 18, no. 12, pp. 2520–2531, Dec. 2024, doi: 10.1049/itr2.12588.

[41] F. Cui, X. Lin, R. Zhang, and Q. Yang, "Multi-objective optimal scheduling of charging stations based on deep reinforcement learning," *Front Energy Res*, vol. 10, Jan. 2023, doi: 10.3389/fenrg.2022.1042882.

[42] J. Fan, A. Liebman, and H. Wang, "Safety-Aware Reinforcement Learning for Electric Vehicle Charging Station Management in Distribution Network," in *2024 IEEE Power & Energy Society General Meeting (PESGM)*, IEEE, Jul. 2024, pp. 1–5. doi: 10.1109/PESGM51994.2024.10688856.

[43] C. B. Heendeniya and L. Nespoli, "A stochastic deep reinforcement learning agent for grid-friendly electric vehicle charging management," *Energy Informatics*, vol. 5, no. S1, p. 28, Sep. 2022, doi: 10.1186/s42162-022-00197-5.

[44] I. Azzouz and W. Fekih Hassen, "Optimization of Electric Vehicles Charging Scheduling Based on Deep Reinforcement Learning: A Decentralized Approach," *Energies (Basel)*, vol. 16, no. 24, p. 8102, Dec. 2023, doi: 10.3390/en16248102.