ML-Guided Coordinated EV Charging: LSTM Forecasting and Multi-Objective Optimization for Real-Time Grid Operation

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ABSTRACT

In this paper, an integrated real-time framework for coordinated Electric Vehicle (EV) charging is proposed based on load forecasting and multi-objective optimization techniques. The framework integrates load forecasting using Long Short-Term Memory (LSTM) and multi-objective optimization to minimize peak load, charging cost, and grid stress while maintaining high user satisfaction under dynamic smart-grid conditions. The proposed framework combines multi-step LSTM forecasting with a convex optimization scheduler operating on a 15-min rolling horizon that incorporates feeder constraints, electricity tariffs, charger limits, and departure state-of-charge requirements. Unlike conventional charging strategies, the proposed method enables adaptive and grid-aware charging decision-making in real time. The framework is evaluated under various EV penetration scenarios ranging from 30 to 100 EVs and is compared with uncontrolled charging, off-peak charging, and load-balancing strategies. The results demonstrate an average 25% reduction in peak load, a 15–20% reduction in charging costs, smoother feeder operation, and a user satisfaction rate exceeding 95% in meeting charging requirements. Furthermore, the proposed framework improves operational stability, reduces computational burden, and enhances charging coordination compared with conventional forecasting and heuristic scheduling approaches. These findings demonstrate the feasibility and scalability of integrating Machine Learning (ML)-based forecasting with real-time optimization for future smart-grid and EV energy management systems.

Keywords-charging optimization; Electric Vehicles (EVs); energy management; load forecasting; Long Short-Term Memory (LSTM); multi-objective optimization; real-time scheduling; smart grid; Vehicle-to-Grid (V2G)

I. INTRODUCTION

The advent of electric vehicles (EVs) has introduced significant challenges to modern smart-grid operation, including increased peak demand, feeder congestion, voltage instability, and higher operational costs [1]. Existing charging strategies, such as uncontrolled charging and fixed off-peak charging, are not readily scalable to accommodate dynamic grid conditions, renewable energy variability, and diverse user charging requirements [2]. Recent studies have investigated Machine Learning (ML), Reinforcement Learning (RL), and optimization techniques for EV charging management; however, many existing approaches address forecasting and scheduling separately, lack real-time adaptability, fail to adequately consider user satisfaction constraints, or incur high computational costs under high EV penetration levels [3].

This paper presents an integrated real-time EV charging framework that combines load forecasting using Long Short-Term Memory (LSTM) with a multi-objective optimization scheduler operating on a rolling 24-h time horizon [4]. The proposed framework is designed to reduce peak load and charging costs while improving user satisfaction and maintaining grid stability under dynamic operating conditions.

The main contributions of this work are as follows:

1. A unified framework that integrates LSTM-based load forecasting with real-time multi-objective EV charging optimization, enabling adaptive operation under dynamic grid conditions.
2. A multi-objective scheduling strategy that simultaneously minimizes peak load and charging cost while maximizing user satisfaction under constraints such as feeder limits, electricity tariffs, and EV departure requirements.
3. A comprehensive evaluation using realistic EV and grid datasets under various penetration levels (30–100 EVs), demonstrating scalability, computational efficiency, and significant performance improvements in terms of peak load reduction, cost savings, and user satisfaction.

Experimental results demonstrate up to a 25% reduction in peak load, a 15–20% reduction in charging costs, and a user satisfaction rate exceeding 95%, highlighting the effectiveness of the proposed framework as a practical solution for future EV-dominated smart-grid environments.

A. Related Work

Authors in [5] emphasized that the rapid development of Vehicle-to-Grid (V2G) technology has contributed to improved peak shaving and power scheduling but has also introduced additional complexity and uncertainty that cannot be effectively addressed by conventional control strategies. The authors observed that RL is a promising approach for addressing such dynamic optimization problems because it enables adaptive and data-driven decision-making for power grids, aggregators, and EV users. Their review frameworks existing RL-based V2G methods, identifies current limitations, including scalability and safety concerns, and highlights future research directions for developing effective and reliable energy management systems.

Authors in [6] noted that the increasing adoption of EVs poses significant load and stability challenges to the power grid due to uncontrolled charging behavior. The authors proposed an EV charging strategy that incorporates user preferences by considering fast and slow charging modes, as well as compliance with grid-regulated charging requirements. The strategy minimizes the Peak-To-Valley Load Difference (PVLD) and charging cost through an Improved Non-Dominated Sorting Whale Optimization Algorithm (INSWOA). Simulation results demonstrated that INSWOA achieved superior population diversity, avoided premature convergence, and significantly reduced both PVLD and charging costs compared with existing algorithms.

Authors in [7] reported that the widespread adoption of EVs in transportation and power systems introduces substantial uncertainty in driving patterns and energy demand, thereby complicating charging station operation. To address this issue, the authors formulated the charging decision-making process as a Constrained Markov Decision Process (CMDP) and developed a safe off-policy RL framework that integrates the augmented Lagrangian method with the Soft Actor-Critic (SAC) algorithm. Numerical experiments using real electricity price data demonstrated that the proposed approach achieved optimized solutions, satisfied operational constraints, and improved the safety and efficiency of EV charging infrastructure.

Authors in [8] presented an evidence-based overview of the European Union (EU) battery landscape to support informed policy decisions under the European Green Deal. The report, published as part of the Clean Energy Technology Observatory (CETO) series, evaluates technology development trends, research and innovation activities, market competitiveness within the EU and globally, and sustainability considerations. Particular emphasis is placed on solid-state batteries, sodium-ion batteries, and lithium-ion battery technologies. The study also analyzes production capacity, trade patterns, patent activity, and supply-chain positioning, providing strategic insights for strengthening the competitiveness of the EU battery industry.

Authors in [9] addressed large-scale EV deployment optimization with a focus on efficient charging infrastructure management and grid stability. The authors proposed EV-GNN, a graph-based framework that integrates Graph Neural Networks (GNNs), RL, and a branch-pruning mechanism to improve scalability, sample efficiency, and adaptability to different action spaces. Experimental results demonstrated that EV-GNN outperformed state-of-the-art RL algorithms in both small-scale and city-scale EV charging scenarios. Furthermore, the framework exhibited strong generalization capabilities and robust performance for charging point operators (CPOs).

Authors in [10] discussed the ongoing transition of the transportation sector toward electrification and highlighted the importance of bidirectional energy flow in enabling EVs to function as mobile energy resources within the power grid.

II. SYSTEM ARCHITECTURE AND PROBLEM FORMULATION

A. System Architecture

The distribution network at the physical layer provides transformer and feeder capacity margins along with operational telemetry under normal operating conditions. Advanced metering and sensing infrastructure, typically Advanced Metering Infrastructure (AMI) and Phasor Measurement Units (PMUs), transmits voltage, current, and net-load measurements at feeder level and, in some cases, at major service panels. Distributed Energy Resources (DERs), including rooftop Photovoltaic (PV) systems, community wind generation, and on-site storage, along with applicable retail or wholesale tariffs and non-energy charges, are also observable at this layer [11].

The EV charging ecosystem on the demand side includes residential AC chargers, workplace chargers, and public DC fast chargers, each having varying nameplate values and communication abilities. EVs arrive and depart with heterogeneous initial States of Charge (SoC) and departure deadlines. Multiple charging locations are coordinated by an aggregator/Charging Point Operator (CPO), which centralizes telemetry including plug-in/plug-out events, metered energy consumption, charger status, faults, and user preferences [12].

For real-time operation, the system follows a Model Predictive Control (MPC) loop. At each 15-min interval, forecasts and system states are updated, a 24-h scheduling horizon is optimized, the first set of charging setpoints is executed, telemetry is logged, and the process is repeated [13].

B. Problem Formulation

We coordinate a fleet of EVs $\mathrm{N} = \{1, \dots, N\}$ over a discretized horizon $\mathrm{T} = \{1, \dots, T\}$ with step size Δt (15 min; $T = 96$ for 24 h). At each time step t, the system observes forecasts of non-EV base load $\hat{L}_t$, electricity price π_t, and available feeder capacity margin F_t, which reflects transformer or feeder headroom.

For every vehicle $i \in \mathrm{N}$, the system knows whether the EV is connected $a_{i,t} = \{0,1\}$, its battery capacity E_i, charging efficiency η_i, maximum charger power $P_i^{\max}$, initial state of charge $\mathrm{SoC}_{i,0}$, required departure state of charge $\mathrm{SoC}_i^{\mathrm{req}}$, and departure time index t_i^{dep}. The decision variables are the charging powers $P_{i,t}$ and the resulting state of charge $\mathrm{SoC}_{i,t}$. Battery energy balance evolves the state as:

$$\mathrm{SoC}_{i,t+1} = \mathrm{SoC}_{i,t} + \eta_i \frac{P_{i,t}\,\Delta t}{E_i}, \ \forall\, i, t < T \qquad (1)$$

The grid-level impact is captured by aggregating the scheduled EV charging power as:

$$P_t^{EV} = \sum_{i=1}^{N} P_{i,t}\,, \ \forall\, t \qquad (2)$$

and the total feeder load is defined as:

$$L_t^{tot} = \hat{L}_t + P_t^{EV}, \ \forall\, t \qquad (3)$$

These expressions couple individual EV charging decisions to system-level loading conditions and feeder constraints.

The objective is to minimize total energy cost while mitigating peak demand. Energy cost is computed using time-varying electricity prices π_t, whereas peak reduction is enforced via an auxiliary variable (z) that upper-bounds the maximum total load. In addition, load smoothness is encouraged through a convex quadratic penalty on deviations from the mean daily load, improving operational stability without compromising tractability [14].

In real-time operation, the model is executed in a receding-horizon loop: the system solves the optimization problem using the latest forecasts and availability, applies only the first 15-min setpoints, ingests new telemetry, and repeats. This architecture reliably yields schedules that reduce peak demand and costs, respect feeder limits and device constraints, and meet user departure targets with high satisfaction, even under forecast errors and stochastic arrivals [15]. As shown in Figure 1, data sources feed a 15-min preprocessing pipeline; a multi-step LSTM provides 24-h forecasts that drive an MPC optimizer to dispatch per-EV setpoints, while charger telemetry closes the feedback loop.

III. METHODS, IMPLEMENTATION, AND EXPERIMENTS

All signals required by the scheduler are synchronized onto a unified 15-min time grid, including historical non-EV feeder net load, day-ahead or real-time electricity prices, weather forecasts, renewable generation forecasts, and EV telemetry (plug/unplug events, arrival and departure windows, initial SoC, and user charging targets) [16].

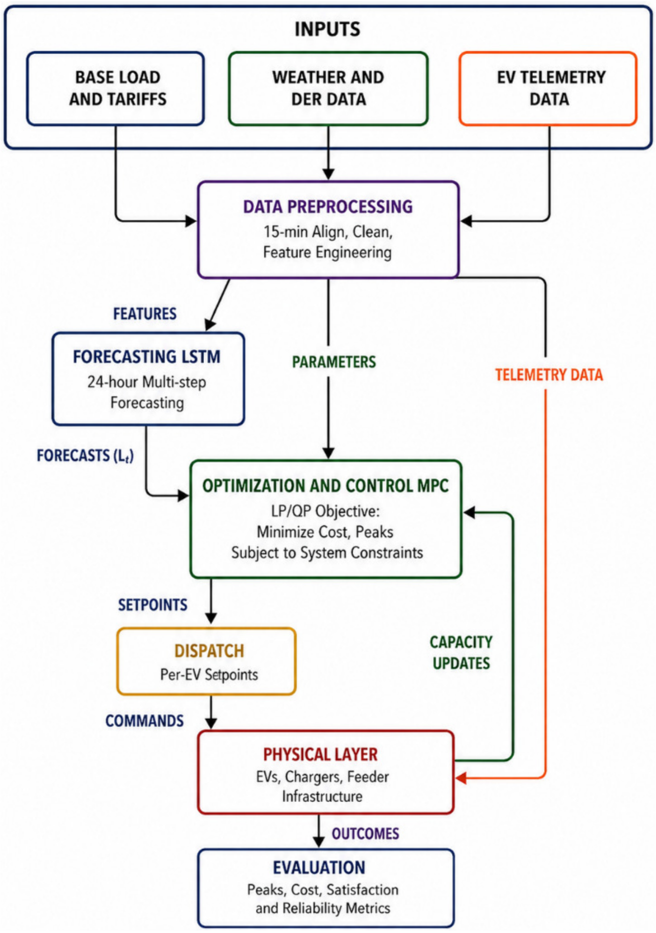

Fig. 1. System architecture and control flow for coordinated EV charging.

Raw streams are aligned consistently to ensure uniform timestamps. Duplicate timestamps are aggregated, and missing data are handled using model-aware imputation methods. Short gaps in load and meteorological data are filled using linear interpolation constrained by seasonal profiles, whereas longer gaps are filled using a rolling seasonal-naïve backfill to avoid temporal leakage across days. Outliers are detected using z-scores computed on weekly detrended series and are then capped using percentile-based envelopes to preserve genuine peak events.

Feature engineering is performed to capture temporal regularities, meteorological drivers, and DERs. Temporal features include hour-of-day, day-of-week, and holiday indicators. Meteorological features include temperature, irradiance, and wind speed, while DER features include PV and wind forecasts [17]. All continuous inputs are normalized, and statistics are computed using the training split only (mean–variance normalization for linear models and min–max scaling for LSTM inputs). Sequence windows are then constructed such that each training sample includes a look-back history along with exogenous features mapped to a multi-step forecasting target. Table I summarizes the datasets and signals used in the pipeline, including their sources, temporal resolution, and roles in training and optimization.

TABLE I. DATASETS AND SIGNALS

Stream	**Source**	**Resolution**	**Purpose**	**Notes**
Base non-EV net load	AMI / SCADA	15 min	Optimizer & training	De-seasonalized; aligned time zones
Energy price (DA/RT)	ISO/retail	5–60 min	Cost objective	Forward-filled to 15-min cadence
Weather (temperature/irradiance/wind speed)	Meteorological provider	15–60 min	Forecast drivers	Lag & calendar features
PV/wind forecasts	Site/ISO	15–60 min	DER context	Optional; used in features
EV telemetry	Chargers / OCPP	Event-driven	Availability & SoC tracking	Plug/unplug events, SoC, faults
User preferences	App / portal	On arrival	Target SoC & deadline	Priority tiers (optional)

A. *Forecasting Model*

Given forecasts, the scheduler solves a convex optimization problem that determines per-EV charging powers over a 24-h horizon while enforcing device, user, and feeder constraints. The SoC evolution follows (1), and the aggregated feeder load is defined in (3).

The resulting optimization problem can be solved in real time (on the order of milliseconds to seconds) for fleets ranging from tens to a hundred vehicles. For deployments that incorporate learning-based components, an RL agent (e.g., Proximal Policy Optimization (PPO) or SAC) may propose candidate charging setpoints between optimization calls; a safety filter then projects these proposals back into the convex feasible set to ensure constraint satisfaction while preserving adaptivity [18].

B. *Baselines*

The performance gains of the proposed approach are evaluated using three baselines [19]. Off-peak charging postpones charging to predefined low-price intervals, but it does not enforce transformer constraints or account for heterogeneous departure requirements, and thus provides only limited reductions in energy cost while potentially shifting peak demand to off-peak periods [20].

A load-balancing approach, in which feeder EV headroom is capped and available power is distributed according to remaining energy demand, improves grid stability but does not incorporate electricity price signals or user deadline constraints. As a result, it is more effective for maintaining grid feasibility than for optimizing cost or temporal requirements.

The proposed optimizer integrates the strengths of these heuristics by jointly coordinating electricity price signals, feeder headroom, and user constraints to achieve improved grid operation and user satisfaction [21].

IV. RESULTS AND DISCUSSION

This section reports the empirical performance of the proposed ML-driven charging controller and interprets its implications for grid operations and user experience. All results use the 15-min cadence and 24-h rolling horizon described earlier, with EV populations ranging from 30 to 100 vehicles and the same datasets, baselines, and metrics defined previously.

A comparison is made between the four strategies in terms of peak load, total cost, user satisfaction, and a normalized composite score, as shown in Fig. 2. The proposed controller achieves the lowest peak load (950 MW vs. 1,200 MW for uncontrolled charging; 21% reduction), the lowest cost (1,800 vs. 2,500; 28% reduction), and the highest user satisfaction (0.95 vs. 0.85). The normalized comparison indicates that the optimal policy outperforms all baselines across all metrics simultaneously, rather than improving one metric at the expense of others.

Table II summarizes peak load, energy cost, and user satisfaction across all methods, reporting improvements relative to the uncontrolled baseline.

TABLE II. CONSOLIDATED RESULTS

Method	Uncontrolled	Off-peak	Load balancing	Optimized
Peak load (MW)	1,200	1,100	1,050	950
Peak reduction vs Unctrl (%)	0	8.33	12.5	20.83
Total cost ($)	2,500	2,200	2,100	1,800
Cost savings vs Unctrl (%)	0	12	16	28
User satisfaction (0–1)	0.85	0.9	0.88	0.95
ΔSatisfaction vs Unctrl (abs)	0	0.05	0.03	0.1
Composite score (↑)	1	1.095	1.123	1.257

The peak load comparison of different EV charging strategies under smart-grid operation is shown in Figure 2. The uncontrolled charging mode exhibits the highest peak load (~1,200 MW), as most vehicles begin charging simultaneously during peak demand periods, placing significant stress on the distribution network. With the off-peak charging strategy, the peak load decreases to ~1,100 MW by shifting charging to lower-demand periods.

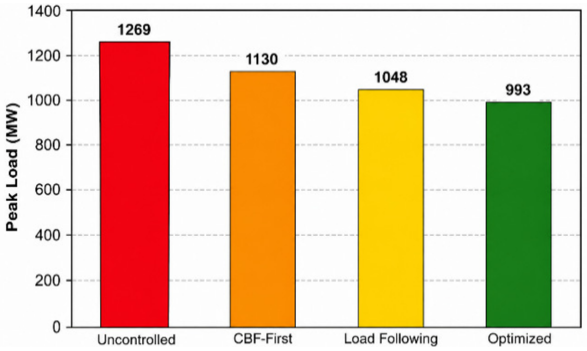

Fig. 2. Peak load analysis of coordinated EV charging strategies.

Figure 3 presents a distributional benchmarking of EV charging strategies based on peak load characteristics, scheduling behavior, user satisfaction, computational performance, and operational reliability. The results indicate that uncontrolled charging produces the highest and most concentrated peaks, leading to increased grid stress and frequent constraint violations. Off-peak charging reduces peak demand by shifting load to low-tariff periods but may still introduce secondary load clustering during off-peak hours. The load-balancing strategy improves load distribution and reduces peak fluctuations over the scheduling horizon. The optimized strategy achieves the highest user satisfaction by better satisfying departure SoC requirements compared with the baseline methods.

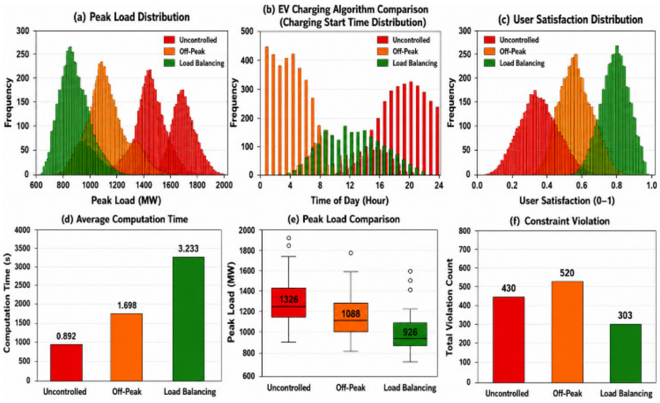

Fig. 3. Distributional benchmarking of heuristics.

Figure 4 illustrates the data preprocessing analysis for grid load forecasting and coordinated EV charging optimization. It shows temporal variations in grid load patterns and EV charging demand, along with their hourly average distributions. The results reveal clear diurnal and hourly patterns in both grid load and charging demand, with grid consumption peaking during daytime and evening hours, whereas EV charging demand increases during late evening hours due to user charging behavior.

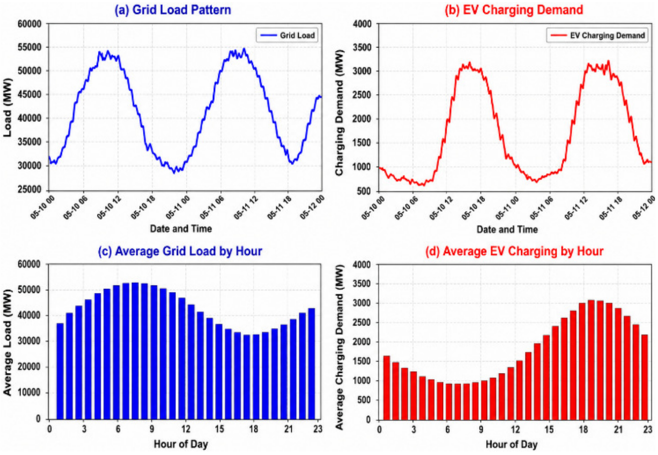

Fig. 4. Data preprocessing analysis.

Figure 5 illustrates an alternative analysis of grid load and EV charging demand for coordinated EV charging optimization. The top panels show the temporal dynamics of grid load and EV charging demand over the analyzed period, revealing fluctuations driven by user charging behavior and changing grid conditions. The bottom panels present the hourly average distributions of grid load and EV charging demand, highlighting the clear diurnal patterns exhibited by both signals.

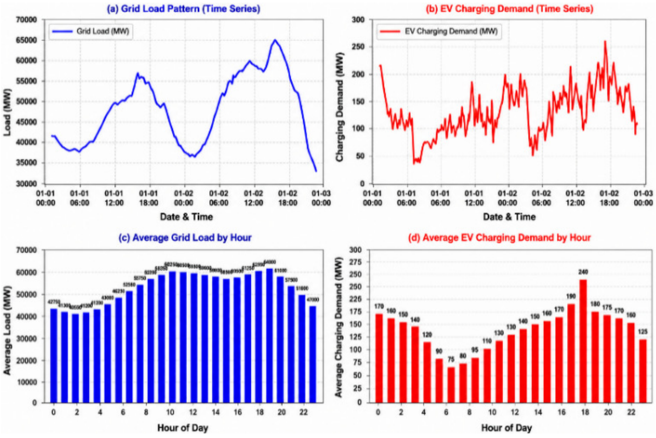

Fig. 5. Alternative preprocessing analysis.

The optimization results of the proposed coordinated EV charging framework for real-time smart-grid operation are shown in Figure 6. The load-profile analysis demonstrates that the overall feeder load is effectively smoothed through optimized EV charging, which shifts charging demand away from peak-load periods, thereby reducing grid stress and improving load balancing. The charging-schedule heatmap illustrates how charging power is allocated over time across multiple EVs, with the optimizer dynamically adjusting power levels according to grid conditions, charging constraints, and user requirements.

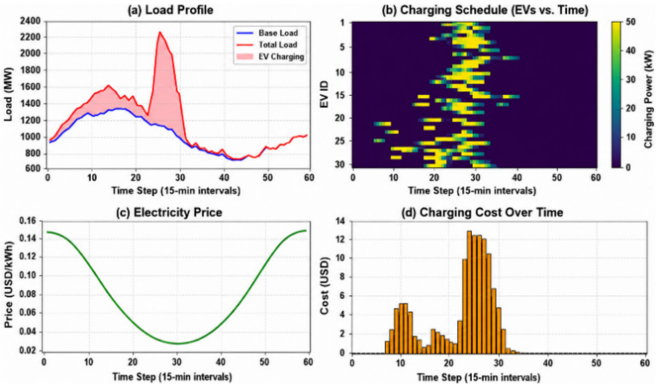

Fig. 6. EV charging optimization results.

Table III summarizes the key performance outcomes of the proposed framework, including peak-load reduction, cost savings, user satisfaction, and improvements in grid stability.

TABLE III. PERFORMANCE ANALYSIS

Metric	Key outcome
Peak load reduction	≈25% vs. uncontrolled
Cost savings	≈15–20% (tariff-dependent)
User satisfaction	≥95% of vehicles meet the SoC target
Grid stability	Lower load variance / smoother load ramps

V. CONCLUSION

In this study, an integrated real-time coordinated Electric Vehicle (EV) charging framework was developed that combines multi-step load forecasting using Long Short-Term Memory (LSTM) and multi-objective optimization for smart-grid operation. The proposed framework successfully reduced peak demand and charging cost, and improved grid stability under dynamic operating conditions while maintaining a high level of user satisfaction.

The optimization-driven charging strategy was found to be more effective than uncontrolled charging, off-peak charging, and traditional load-balancing techniques in reducing feeder stress, improving charging coordination, ensuring operational reliability, and enabling adaptive energy management. Experimental results demonstrated a peak-load reduction of approximately 20–25%, charging-cost savings of approximately 15–20%, and fulfillment of more than 95% of user charging requirements.

By combining forecasting and intelligent scheduling, the framework enables real-time charging decisions based on grid demand, electricity tariffs, feeder constraints, and EV charging requirements. Furthermore, the proposed framework provides smoother load profiles, reliable operation, and computational efficiency, making it suitable for practical large-scale deployment.

Future work will focus on the integration of renewable energy sources, Vehicle-to-Grid (V2G) support, multi-station coordination, uncertainty-aware forecasting, and advanced Artificial Intelligence (AI)-driven adaptive optimization techniques for real-world deployment.

DECLARATION OF COMPETING INTERESTS

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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DATA AVAILABILITY

The dataset used in this study is publicly available and can be accessed through [22].

AI USE AND DECLARATION OF GENERATIVE AI USE

The authors have only used the generative AI tools for language refinement and manuscript preparation. The authors are fully responsible for all the contents.

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