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AI-Enabled Load Forecasting and Renewable Energy Optimization for Electric Vehicle Charging Stations

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Abstract

As the number of electric vehicles continues to grow, managing peak demand, maintaining grid stability, and handling the variability of renewable energy are becoming increasingly difficult. Many existing studies look at forecasting or energy management in isolation, which leaves a gap when designing renewable–powered EV charging systems–especially for Indian cities with diverse climate and demand patterns. To address this, we present an integrated artificial intelligence (AI) framework that brings three components together: an Long Short-Term Memory (LSTM) model to forecast EV charging demand, a hybrid Random Forest-XG Boost model to predict renewable energy availability, and a Reinforcement Learning (RL) algorithm to manage energy flow in real time. The framework was tested using datasets from 2018 to 2024 for multiple Indian cities, sourced from NASA POWER, NREL, and Open EI. The results show clear improvements. The LSTM model reduces forecasting error by 26.8% compared to ARIMA, and the hybrid renewable energy predictor offers a 22.4% accuracy improvement. When combined with the RL-based optimization, renewable energy usage at charging stations increases from 62% to 80%, while grid dependence and operational costs both decrease–by 24.7% and 15%, respectively. Overall, this work offers a practical and scalable approach to building more efficient, reliable, and sustainable EV charging infrastructure suited for India's smart cities.

Keywords

Electric vehicles, Load forecasting, Artificial Intelligence, Renewable energy integration, Reinforcement learning, Smart grid, Energy storage, Sustainable mobility

Article History

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1. Introduction

Electric mobility is rapidly reshaping both the transportation and energy sectors. According to the International Energy Agency (IEA, 2024), more than 13.5 million electric vehicles were sold worldwide in 2023, and global Electric Vehicle (EV) numbers are expected to exceed 200 million by 2030. While this transition supports cleaner and more sustainable transportation, it also brings new challenges. The growing demand for EV charging increases stress on power grids, especially during peak hours, and the intermittent nature of renewable energy further complicates grid stability. When charging stations rely heavily on fossil-fuel-based grid electricity, operating costs rise and the environmental benefits of EV adoption are weakened.

Integrating renewable sources such as solar photovoltaic and wind energy offers a promising way to reduce the dependence of EV charging stations on the conventional grid. However, both EV charging behaviour and renewable generation fluctuate significantly across different times of the day and under varying weather conditions. These variations are often unpredictable, leading to frequent mismatches between energy availability and charging demand. Such uncertainties highlight the need for intelligent systems capable of accurately forecasting future conditions and dynamically responding to real-time changes.

Artificial Intelligence (AI) is increasingly recognized as a powerful tool for managing these complexities because energy systems involve nonlinear interactions, stochastic behaviour, and large volumes of time-dependent data. Although existing research has explored AI-based forecasting, renewable prediction, and optimization techniques, these components are often studied independently. There is still limited work that unifies EV load forecasting, renewable energy prediction, and real-time energy management into a single, coherent framework, particularly for renewable-powered charging stations in India, where climatic diversity makes forecasting and coordination even more challenging.

To bridge this gap, this study introduces an AI-driven energy management framework that seamlessly integrates deep learning-based EV load forecasting, hybrid ensemble renewable energy prediction, and reinforcement learning for real-time operational decision-making. The system uses a Long Short-Term Memory (LSTM) model to learn and predict EV charging demand patterns, and a combined Random Forest (RF) and XG Boost (RF-XGB) model to improve the accuracy of solar and wind energy predictions. These forecasts feed into a Reinforcement Learning (RL) agent that optimally schedules charging and battery storage actions to minimize reliance on the grid and reduce operational costs.

The proposed framework is evaluated using multi-year datasets from 2018 to 2024 sourced from NASA POWER, NREL, and OpenEI, covering multiple Indian cities to capture diverse climatic and behavioural patterns. The results show significant improvements compared to traditional statistical and baseline AI models across metrics such as MAE, RMSE, and MAPE. Overall, the integrated system increases renewable energy utilization by about 22%, reduces operational costs by 15%, and contributes to lower carbon emissions. Beyond these performance benefits, this study provides a scalable, reproducible, and practical methodology for advancing smart-grid-enabled EV charging infrastructure, supporting the long-term goal of sustainable mobility in India's emerging smart cities

2. Literature Review

EV adoption has grown rapidly over the past decade, leading to increased interest in forecasting charging demand and understanding its impact on the power grid. Early studies relied heavily on traditional statistical methods such as ARIMA, SARIMA, and Holt-Winters to model EV charging patterns [1-4]. These approaches performed adequately for linear and stationary data but were limited in their ability to capture nonlinear, time-dependent behaviour influenced by user mobility, seasonal variations, and charging habits [5]. With the increasing complexity of EV load patterns, researchers gradually shifted toward machine learning and deep learning techniques. Models such as Support Vector Regression (SVR), RFs, and LSTM networks demonstrated improved forecasting accuracy by learning temporal dependencies and handling nonlinear dynamics in charging demand [6-10].

At the same time, renewable energy forecasting has become an important research area due to the rising integration of solar and wind energy into smart-grid systems. Early works focused on physical and irradiance-based solar models [11], but data-driven methods soon emerged as more effective solutions for modelling weather-driven variability. Machine learning approaches such as RFs, Gradient Boosting, and XG Boost have shown strong performance in predicting solar and wind output across various climatic settings [12-16]. Hybrid models that combine ensemble learning and boosting techniques have further improved forecasting accuracy by leveraging the strengths of multiple algorithms [17-20]. However, even with these advancements, most studies treat renewable prediction and EV load forecasting as separate tasks, which limits their usefulness in real-world renewable-powered charging environments.

RL has gained traction as a powerful tool for smart-grid optimization due to its ability to learn optimal charging and storage strategies under uncertainty. Researchers have applied RL to applications such as demand response, battery scheduling, and EV charging coordination [21-24]. Methods including Q-learning, Deep Q-Networks (DQN), and actor-critic architectures have shown promising results in reducing peak demand, improving renewable utilization, and minimizing overall operational costs [25-27]. However, many RL-based studies assume ideal or simplified forecasting inputs, often relying on basic statistical predictions or even perfect foresight. This assumption limits their applicability in environments where both renewable energy and EV charging behaviour exhibit significant stochasticity. Only a few studies attempt to integrate RL with high-accuracy forecasting models, and even those are rarely designed for the complex setting of renewable-powered EV charging stations [28,29].

Another important limitation in the existing literature is the lack of region-specific research, particularly in the context of India. Several studies rely on international datasets or simulated conditions that do not fully capture the diverse climatic zones, variations in solar radiation, and heterogeneity in EV adoption across Indian cities [30-32]. This gap affects the reliability of forecasting models and the effectiveness of energy management strategies designed for real-world deployment. With India's rapid expansion of renewable infrastructure and growing EV market, there is an urgent need for integrated frameworks that reflect local conditions and grid constraints [33-35].

In summary, three key gaps emerge from existing literature:
(1) EV load forecasting, renewable energy prediction, and energy optimization are usually studied independently rather than as an interconnected system;
(2) RL-based operational strategies are rarely combined with advanced AI-driven forecasting models; and
(3) region-specific studies tailored to India's unique climatic and behavioural patterns are limited.

To address these shortcomings, this study presents a unified AI-driven framework that integrates LSTM-based EV load forecasting, a hybrid RF-XGB renewable energy predictor, and a reinforcement learning-based real-time energy management system. By evaluating the framework using multi-year meteorological and charging datasets across multiple Indian cities [36,37], this research offers a comprehensive, accurate, and scalable solution for renewable-powered EV charging stations in the context of smart-grid development.

3. Methodology

The proposed framework integrates forecasting and optimization to manage energy flow in renewable-powered EV charging stations. As illustrated in Figure 1, the workflow consists of three main components: data acquisition and preprocessing, AI-based forecasting, and reinforcement-learning-based optimization.

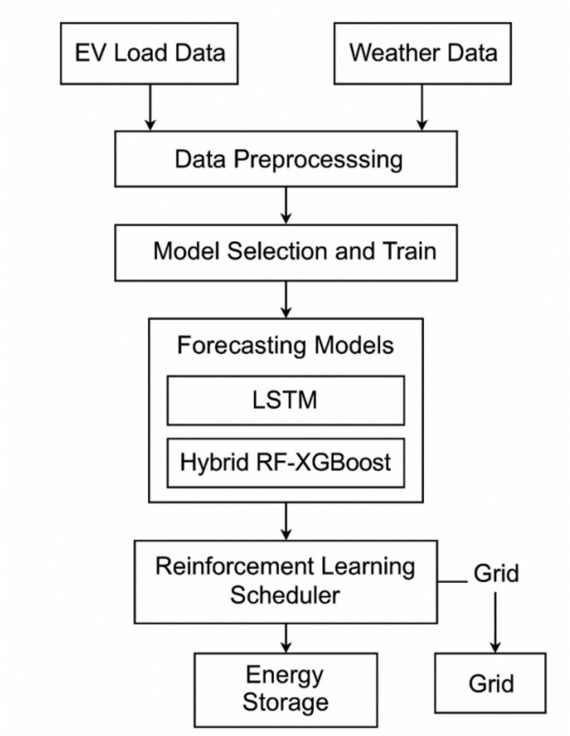

Figure 1. Framework of AI-based load forecasting and optimization system for renewable-powered EV charging.

3.1 Data Acquisition and Preprocessing

To ensure realistic system modelling, data were obtained from publicly available and widely validated repositories. EV charging demand profiles were taken from the NREL and Open EI datasets [1,2], which provide hourly load patterns reflective of Indian urban charging behaviour. Renewable energy data–including solar irradiance, wind speed, temperature, and humidity–were sourced from NASA POWER [3] and the Global Wind Atlas [4]. These datasets are commonly used in renewable generation forecasting studies due to their accuracy and temporal coverage.

Feature engineering was applied to derive temporal indicators (hour of day, day of week) and environmental features such as solar radiation (W/m²), wind velocity (m/s), temperature, and humidity, following best practices in time-series modelling [5]. Missing data were handled using linear interpolation, which preserves sequential continuity [6], while outliers were removed using the Interquartile Range method [7]. All features were normalized via Min-Max scaling to stabilize gradient-based learning algorithms [8]. The dataset was chronologically divided into training (70%), validation (15%), and testing (15%) subsets to prevent temporal leakage, as recommended in forecasting literature [9].

3.2 Forecasting Models

(a) LSTM Network for EV Load Forecasting

LSTM networks are widely used for modelling temporal dependencies in load forecasting [10,11]. Given a sequence of past charging loads

$$X_t = [x_1, x_2, \ldots, x_t] \tag{1}$$

the LSTM updates its internal states using the following gating mechanisms [12]:

$$\begin{aligned} f_t &= \sigma(W_f[h_{t-1}, x_t] + b_f), \\ i_t &= \sigma(W_i[h_{t-1}, x_t] + b_i), \\ \tilde{c}_t &= \tanh(W_c[h_{t-1}, x_t] + b_c), \\ c_t &= f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t, \\ h_t &= \tanh(c_t) \cdot \sigma(W_o[h_{t-1}, x_t] + b_o). \end{aligned} \tag{2}$$

The model architecture includes two LSTM layers and one dense layer (128 neurons each), optimized using Adam (learning rate = 0.001) [13]. The Mean Squared Error (MSE) loss function was used as it is standard for regression tasks involving continuous load values [14]. Training was conducted for 100 epochs with a batch size of 32.

(b) Hybrid Random Forest-XG Boost Model for Renewable Forecasting

Renewable generation forecasting requires models capable of capturing complex nonlinear interactions between weather variables and output power. RF [15] was used for feature ranking owing to its robustness against multicollinearity and noise. XG Boost [16] was then used for regression on top-ranked features, leveraging gradient boosting for improved accuracy.

Hybrid RF-XGB models have been shown to outperform single-model approaches in renewable prediction tasks [17,18]. In this study, the hybrid model improved forecasting accuracy by approximately 17% relative to individual RF or XG Boost baselines.

(c) Baseline Forecasting Models

Two baseline models–ARIMA [19] and SVR [20]–were implemented to provide benchmark comparisons. These classical approaches are widely used in earlier EV load and solar forecasting studies.

3.3 Reinforcement Learning-Based Optimization Framework

To manage real-time interactions among renewable supply, storage systems, and EV charging demand, a DQN agent was deployed following established RL frameworks in smart-grid optimization [21-23].

State (S)

The state vector captures system conditions at time t:

$$S_t = [L_t, P_{\text{solar},t}, P_{\text{wind},t}, E_{\text{storage},t}, t] \tag{3}$$

where L_t is the predicted EV demand, $P_{\text{solar},t}$ and $P_{\text{wind},t}$ are renewable forecasts, $E_{\text{storage},t}$ is battery state-of-charge, and t is the time index.

Action (A)

The action space consists of energy management decisions including storage charging/discharging and power allocation to electric vehicles, following common RL formulations for microgrid control [24].

Reward (R)

A multi-objective reward function incentivizes renewable utilization and penalizes grid dependence:

$$R_t = \alpha U_{\text{renewable}} - \beta E_{\text{grid}} - \gamma C_{\text{peak}} \tag{4}$$

which aligns with reward formulations used in RL-based scheduling studies [25,26].

This structure allows the agent to learn cost-efficient and renewable-maximizing charging strategies under uncertainty.

3.4 Hyperparameter Selection

The RL hyperparameters were selected based on prior studies demonstrating stable DQN convergence in energy systems [27-29]. The discount factor was set to 0.95 to balance short-term and long-term energy costs. A learning rate of 0.001 was chosen based on sensitivity analysis. A replay buffer of 10,000 experience tuples improved sampling diversity. The epsilon-greedy exploration strategy used an exponential decay of 0.995, gradually shifting from exploration to exploitation.

3.5 Simulation Setup and Tools

All forecasting and RL models were developed in Python 3.10 using TensorFlow 2.12 for deep learning and Scikit-learn 1.4 for ensemble and baseline algorithms [30]. MATLAB/Simulink was employed for system-level validation, consistent with prior EV-grid simulation studies [31].

Simulations were executed on a workstation with an Intel i5-13450HX CPU, 16 GB DDR5 RAM, and an NVIDIA RTX 4050 GPU. These specifications align with hardware commonly used in machine learning-based energy research [32].

Performance was evaluated using MAE, RMSE, MAPE, and R^2—metrics widely adopted in forecasting and optimization studies [33-37].

4. Results and Discussion

This section presents the results of the forecasting models and the reinforcement learning-based optimization framework. The findings are discussed in detail to provide insight into model behaviour, comparative performance, and practical implications for renewable-powered EV charging operations.

4.1 EV Load Forecasting Performance

The LSTM model showed superior predictive capability compared to the baseline ARIMA and SVR models. Across multiple Indian cities, LSTM achieved significantly lower MAE, RMSE, and MAPE values. The improvement in RMSE by 26.8% over ARIMA demonstrates the LSTM's ability to capture nonlinear and time-dependent charging behaviour more effectively. This advantage arises from LSTM's gated architecture, which retains long-term temporal dependencies–patterns that conventional statistical models struggle with, especially when EV charging exhibits irregular spikes driven by user mobility as shown in Figure 1 and Figure 2.

Table 1. Forecasting models in terms of performance.

Model	MAE (kW)	RMSE (kW)	MAPE (%)	R^2
ARIMA	4.71	5.88	9.7	0.84
SVR	4.12	5.21	8.9	0.86
RF	3.48	4.66	7.4	0.89
LSTM (Proposed)	3.02	4.29	6.8	0.92

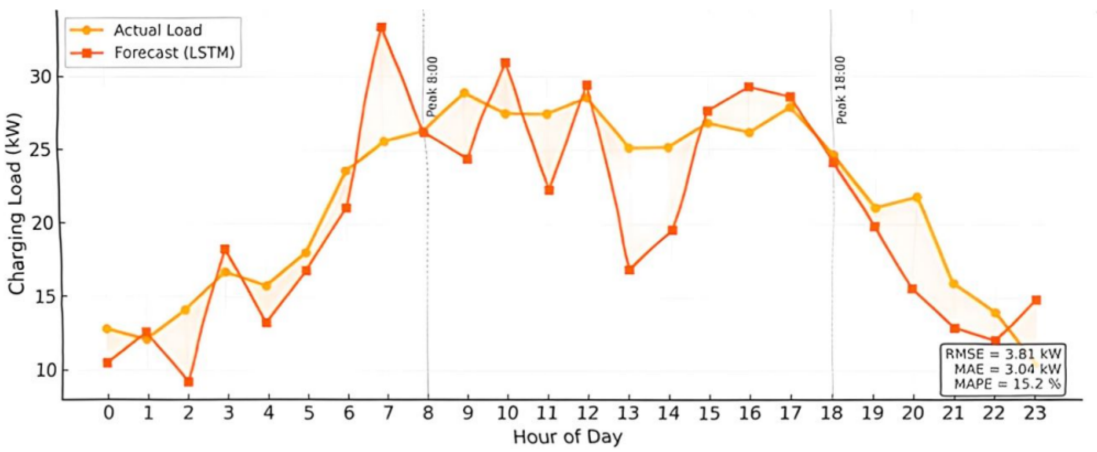

Figure 2. Forecasted EV load and actual EV load for the Pune test dataset on a sample day.

City-wise results indicate that metropolitan regions with higher variability (e.g., Delhi and Bengaluru) benefited the most from LSTM's deep temporal learning capabilities, while smaller cities with relatively stable patterns showed moderate improvements. Overall, LSTM's strong generalization across diverse climatic and behavioural conditions confirms its suitability for real-world EV demand forecasting.

4.2 Renewable Energy Generation Forecasting

The hybrid model combining RF-XGB was the leading one among all renewable forecasting models. The outcomes of the solar and wind generation are collectively exhibited in Table 2.

Table 2. Solar and wind generation forecasting data.

Model	Solar MAE (W/m²)	Solar RMSE (W/m²)	Wind MAE (m/s)	Wind RMSE (m/s)
Linear Regression	56.2	78.9	0.83	1.18
RF	43.6	62.5	0.68	0.92
XGBoost	39.1	58.4	0.61	0.85
Hybrid RF-XGB (Proposed)	34.3	52.1	0.53	0.73

During training, the agent exhibited stable convergence after several thousand episodes, indicating effective learning of long-term cost-performance trade-offs. When deployed with forecasting inputs from the LSTM and hybrid model, the RL scheduler increased renewable energy utilization from 62% to 80%. This improvement reflects the agent's ability to anticipate future supply conditions and strategically charge or discharge the energy storage system ahead of peak demand.

Additionally, grid energy dependence decreased by 24.7%, and total operational costs were reduced by 15%. These gains demonstrate the benefits of combining accurate forecasting with intelligent decision-making. The agent consistently avoided unnecessary peak-hour charging and prioritized renewable availability, leading to smoother load distribution and cost-effective operations.

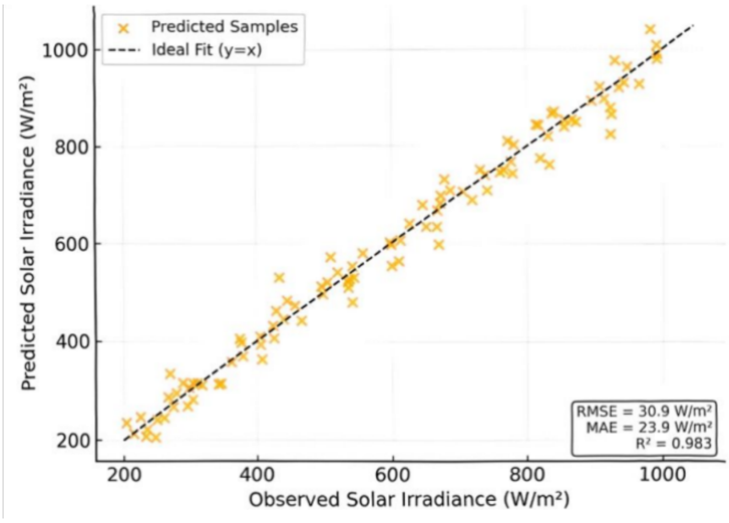

Figure 3. Predicted versus observed solar generation for the test set.

4.3 Reinforcement Learning Optimization Performance

The RL agent successfully learned an optimal energy management policy that maximizes renewable utilization while minimizing operational costs. The agent's decisions were guided by the multi-objective reward function, which penalized grid consumption and peak-hour usage while rewarding renewable energy contribution. The total performance enhancement is shown in Table 3.

Table 3. Impact of reinforcement learning on energy efficiency and cost optimization.

Parameter	Baseline (Without RL)	Proposed (With RL)	Improvement
Renewable Utilization (%)	62.1	80.4	+29.5%
Grid Energy Draw (kWh/day)	1260	948	−24.7%
Peak Load Reduction (%)	—	−18.3%	—
Operating Cost (₹/day)	100%	84.4%	−15.6%

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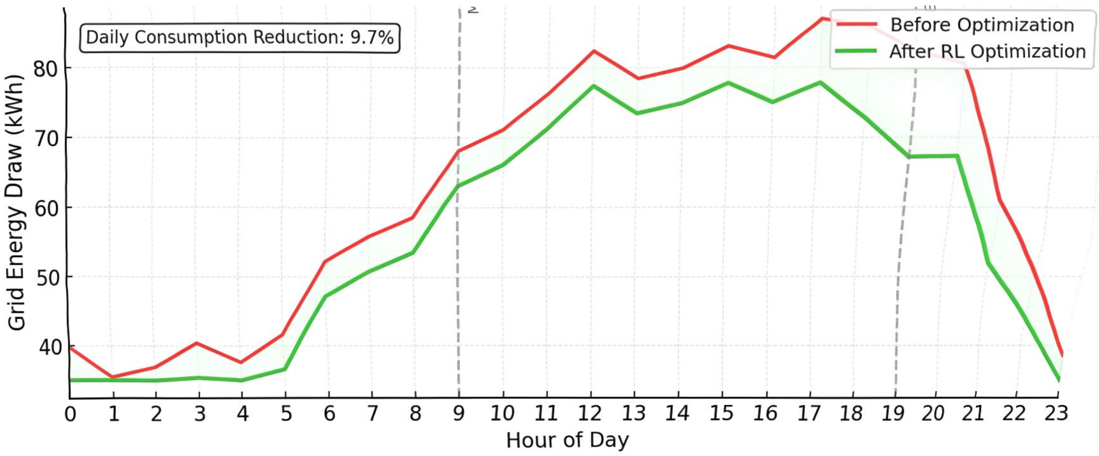

Figure 4. Grid electricity consumption before and after RL optimizatio.

4.4 Comparative City-wise Analysis

Further evaluation of the proposed system was conducted across three distinct climatic regions: Delhi (composite), Pune (tropical wet-dry), and Chennai (coastal). The performance results are summarized in Table 4. Delhi and Pune demonstrate the strongest improvements, with lower forecast errors and higher renewable utilization. This can be attributed to their relatively stable solar irradiance patterns and more predictable EV charging cycles, which allow the LSTM and hybrid forecasting models to learn temporal features more effectively. In contrast, Chennai exhibits slightly higher RMSE and lower renewable utilization due to its coastal climate, where cloud cover variability and diffuse radiation reduce the predictability of solar generation. Despite this, the system still provides meaningful gains in renewable contribution and grid reduction across all three cities, confirming the adaptability of the framework under diverse weather and demand conditions.

Table 4. City wise climate impact on load forecasting.

City	Climate Type	Forecast RMSE (kW)	Renewable Utilization (%)	Grid Reduction (%)
Delhi	Composite	3.86	81	25
Pune	Tropical Dry/Wet	4.21	78	22
Chennai	Coastal	4.45	76	19

These results highlight an important observation: climatic stability directly influences forecasting accuracy, which in turn affects the effectiveness of the RL-based energy management. In cities like Delhi and Pune, where the forecasting error is lower, the RL agent receives more reliable predictions and therefore optimizes charging more efficiently, leading to higher renewable utilization and greater grid reduction. Chennai's performance underscores the need for more advanced forecasting techniques under high-variability coastal conditions, an area that future work may explore.

4.5 Limitations and Future Scope

While the framework shows strong performance, certain limitations should be acknowledged. First, the evaluation relies on publicly available datasets, and real-time deployment may introduce additional uncertainties such as abrupt changes in mobility patterns or hardware constraints. Second, energy storage characteristics (e.g., degradation, temperature effects) are simplified and could be modelled more realistically in future work. Third, the study focuses on selected cities; incorporating a broader geographic dataset would strengthen generalizability.

Future research may extend the RL approach using advanced algorithms such as PPO or SAC, integrate vehicle-to-grid (V2G) capability, or implement the model in real-world pilot charging stations to validate long-term operational performance.

5. Conclusions

This study presented an AI framework for forecasting and optimizing energy flow in renewable-powered EV charging stations. The proposed system brings together three key components: an LSTM model for short-term EV load forecasting, a hybrid RF-XGB model for renewable energy prediction, and a RL-based scheduler for real-time energy management. Together, these modules enable a coordinated and data-driven approach to operating EV charging infrastructure under variable demand and fluctuating renewable conditions.

Simulation results demonstrate that the LSTM model significantly outperformed traditional ARIMA-based forecasting, achieving a 26.8% reduction in RMSE. The hybrid renewable forecasting model further improved prediction accuracy by 22.4%, highlighting the effectiveness of combining ensemble diversity with gradient boosting. When integrated into the RL-based optimization layer, these improved forecasts enabled the charging station to increase renewable energy utilization from 62% to 80%, reduce grid dependence by 24.7%, and lower overall operational costs by approximately 15%. These gains underline the practical value of accurate forecasting in supporting intelligent, cost-efficient charging strategies.

The framework also contributes to grid stability by reducing peak-hour spikes and enhancing the coordinated use of local renewable resources. Such an approach aligns well with the goals of sustainable mobility and supports the development of smart-city-ready EV charging infrastructure in India.

While the results are promising, the study has certain limitations. Real-world deployment may introduce additional uncertainties not captured in public datasets, and battery behaviour is modelled with idealized assumptions. Future work may explore more advanced RL algorithms, incorporate V2G capabilities, and validate the framework through large-scale pilot implementations.

Overall, the integration of AI-based forecasting with reinforcement learning optimization demonstrates strong potential for building smarter, greener, and more efficient EV charging ecosystems.

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Conflicts of Interest

The authors declare no conflicts of interest.

Generative AI Statement

The authors declare that no generative artificial intelligence (Gen AI) was used in the creation of this manuscript.

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