International Journal Of Innovative Trends In Multi Disciplinary Scientific Research
ISSN (Online): 3139 – 2687
(www.ijtmsr.co.in) Volume 9, Issue 6, 2026

AI-Based Power Flow Optimization in Electrical Networks with Solar PV and EV Integration

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Abstract

The increasing adoption of Solar Photovoltaic (PV) systems and Electric Vehicles (EVs) is transforming modern power systems by promoting sustainable and environmentally friendly energy utilization. However, the integration of renewable energy sources and EV charging infrastructure introduces significant challenges in power flow management due to the intermittent nature of solar generation and the dynamic behaviour of EV charging demand. These uncertainties can lead to voltage fluctuations, increased transmission losses, and reduced overall system efficiency. This study proposes an Artificial Intelligence (AI)-based power flow optimization framework for electrical networks integrating solar PV systems and EV loads. The proposed approach uses machine learning and reinforcement learning-based optimization to analyze real-time data related to solar power generation, grid demand, weather conditions, and EV charging patterns, and dynamically allocates available energy resources to minimize power losses, improve voltage stability, maximize solar energy utilization, and reduce dependence on conventional grid supply. Solar power and EV charging demand were forecast using Linear Regression, Random Forest, XGBoost, and LSTM models, with the solar prediction model achieving an R^2 of 0.96 and the EV load forecasting model achieving an R^2 of 0.95. Simulation results demonstrate that the AI-based optimization framework significantly enhances network performance compared to conventional power flow management: power losses were reduced from 145 kW to 92 kW, voltage deviation improved from 8.2% to 2.7%, solar energy utilization increased from 72% to 93%, grid dependency fell from 48% to 21%, and the EV charging completion rate rose from 85% to 97%. These results confirm that AI-based optimization can meaningfully improve power system efficiency, reliability, and renewable energy integration, contributing to the development of smart, sustainable, and energy-efficient power systems for future smart grid applications.

Keywords: *Artificial Intelligence, Power Flow Optimization, Solar Photovoltaic, Electric Vehicles, Smart Grid.*

1. INTRODUCTION

The electrical power sector has undergone significant transformation due to the increasing integration of renewable energy resources and the growing adoption of Electric Vehicles (EVs) [1]. Traditional power systems, designed for centralized generation and predictable load patterns, are evolving into more complex and dynamic networks as Solar Photovoltaic (PV) systems become one of the most widely adopted renewable technologies, converting sunlight directly into clean electricity without harmful emissions [2]. At the same time, EVs offer a sustainable alternative to internal combustion engine vehicles, and government incentives worldwide are accelerating the number of EVs connected to power systems through charging infrastructure [3].

Despite these advantages, integrating solar PV systems and EV charging infrastructure introduces operational challenges. Solar power generation is inherently intermittent, depending on weather conditions, irradiance, cloud cover, and time of day [4], while EV charging demand is highly variable, depending on user behaviour, vehicle arrival times, battery state of charge, and travel patterns; large numbers of EVs charging simultaneously can create peak demand conditions and stress the electrical network [5]. The simultaneous variability of renewable generation and EV demand creates uncertainty that can lead to voltage fluctuations, increased transmission losses, and inefficient renewable energy utilization — challenges that conventional power flow methods, relying on fixed operating rules, often cannot address effectively [6].

Artificial Intelligence (AI), Machine Learning (ML), and Reinforcement Learning (RL) offer advanced capabilities for forecasting generation and demand, optimizing power flow, and supporting real-time decision-making. By intelligently coordinating solar energy resources, EV charging activities, and grid power supply, AI-based optimization frameworks can improve system efficiency, enhance voltage stability, reduce grid dependency, and

promote sustainable smart grid operation. This study proposes such a framework, combining solar power and EV load forecasting with reinforcement learning-based power flow optimization.

1.1 Objective of the Work

The primary objective of this study is to develop an intelligent system that optimizes power flow in electrical networks integrating solar PV systems and EV loads — reducing power losses, maintaining voltage stability, maximizing solar energy utilization, and effectively managing EV charging demand through real-time, AI-based decision-making, supporting the development of smarter and more sustainable power systems.

2. LITERATURE REVIEW

Traditional power flow analysis techniques such as the Newton-Raphson and Gauss-Seidel methods have long been used for conventional power systems with stable, predictable operating conditions, but are not well suited to the rapid changes in generation and demand introduced by renewable energy sources and distributed loads. The integration of solar PV in particular introduces weather-dependent variability that requires advanced control strategies to manage fluctuations and ensure reliable operation, motivating growing interest in machine learning approaches capable of handling large datasets, identifying complex patterns, and offering greater flexibility than conventional techniques.

Several studies have applied AI specifically to EV charging infrastructure integrated with renewable energy. Gül and Garcia [1] designed AI-tuned controllers for three-phase EV charging stations operating within renewable energy grids, improving controller adaptability under variable generation. Sumanasena et al. [5] applied AI across the full EV infrastructure pipeline — demand profiling, data augmentation, demand forecasting, explainability, and charge optimization — providing a comprehensive framework closely aligned with the present study's forecasting-plus-optimization approach. Khan et al. [6] proposed AI-driven dynamic allocation and management optimization for EV charging stations, while Shern et al. [7] developed an AI-based EV smart charging system evaluated in a real-world deployment context.

Several works have addressed the joint optimization of solar and EV charging resources directly. Bhupathi and Chinta [8] integrated AI with renewable energy to develop systems that optimize the use of solar or wind energy specifically for EV charging, while D'Ulizia et al. [9] proposed an AI-powered integrated management model for sustainable EV charging infrastructure. Kotla et al. [12] presented a techno-economic, AI-enabled multi-objective planning framework for solar-integrated EV charging infrastructure, and Promasa et al. [10] applied AI-based load forecasting to optimize battery energy storage system (BESS) sizing for residential EV charging installations — highlighting the economic and infrastructure-planning dimensions of solar-EV integration alongside the operational focus of the present study.

Forecasting accuracy for EV charging stations has also been studied directly: Akshay et al. [13] modelled power consumption prediction for EV charging stations together with income forecasting, and Subashini and Sumathi [14] developed smart algorithms for power prediction in smart EV charging stations, both relevant to the solar and EV load forecasting stage adopted here. Alharbi [15] integrated neural forecasting with multi-objective optimization for sustainable EV infrastructure in smart cities, and Lata and Jindal [17] provided a broad review of AI-driven solutions for efficient EV charging management systems. Closer to the reinforcement-learning approach used in this study, Hassan [18] applied machine learning optimization to hybrid EV charging within renewable microgrids, Safder et al. [20] reviewed techniques and challenges for enhancing microgrid stability and energy management, and Adil et al. [21] proposed a reward-based charging and discharging framework for EVs using deep Q-learning and a Stackelberg game formulation, directly paralleling the RL-based reward function adopted in the present work.

Although these studies collectively demonstrate strong progress in AI-based solar forecasting, EV charging management, and renewable-EV integration [1], [5]–[10], [12]–[15], [17], [18], [20], [21], most treat solar generation and EV charging demand as largely separate problems, or address only forecasting without extending to network-level power flow optimization. There remains a need for an integrated framework that jointly forecasts solar generation and EV demand and applies that forecast within a reinforcement learning-based power flow optimization controller — the gap this study addresses.

3. RESEARCH METHODOLOGY

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The proposed AI-based power flow optimization framework manages energy distribution in an electrical network integrating solar PV generation and EV charging infrastructure. As shown in Figure 1, the system comprises five layers: input sources (solar PV, EV charging stations, grid power, load demand, weather data), data acquisition and preprocessing, AI prediction models for solar power and EV load, an AI-based power flow optimization stage built around a reinforcement learning agent, and an optimized power flow output stage — supported by a continuous monitoring and feedback loop that returns performance data to the optimization agent.

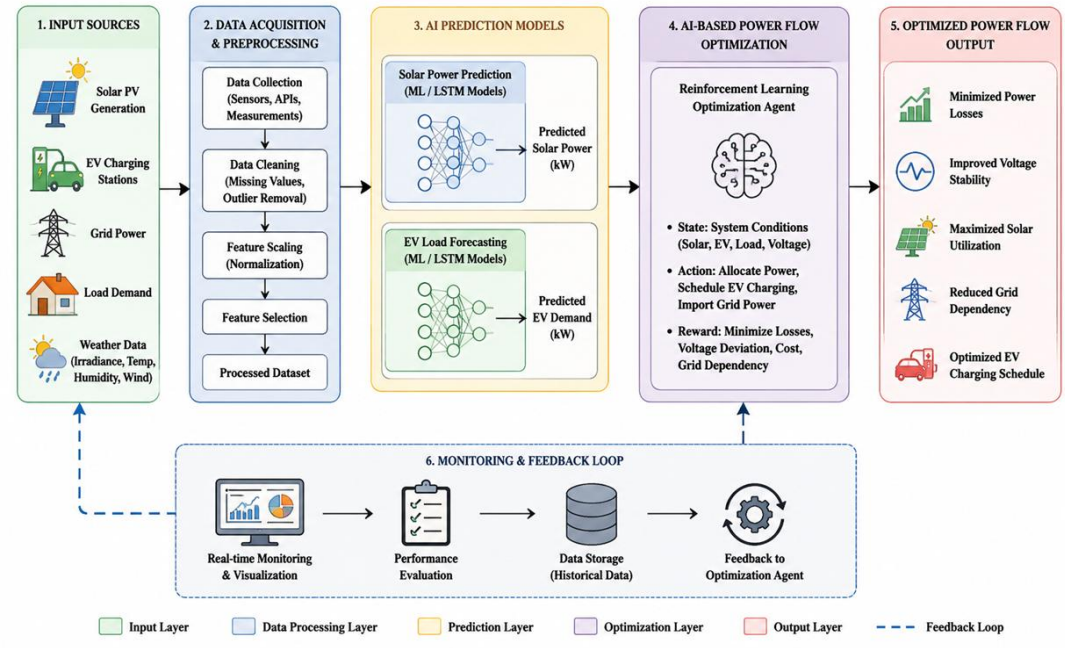


Figure 1: Overall system architecture of the proposed AI-based power flow optimization framework.

3.1 Dataset and Preprocessing

Solar and weather data were obtained from the NASA POWER (Prediction of Worldwide Energy Resources) database, providing solar irradiance, ambient temperature, relative humidity, and wind speed. EV charging data were generated to represent realistic charging station behaviour, including charging start time, duration, charging power, state of charge, and daily charging demand, while grid load data represented hourly residential and commercial consumption patterns. As illustrated in Figure 2, solar irradiance and EV charging demand were found to follow markedly different daily distributions, with solar irradiance concentrated around a mean of 612.3 W/m² (peaking near midday) while EV charging demand, with a mean of 164.8 kW, was more heavily concentrated during evening hours — the central temporal mismatch that motivates intelligent, coordinated energy allocation rather than fixed charging rules.

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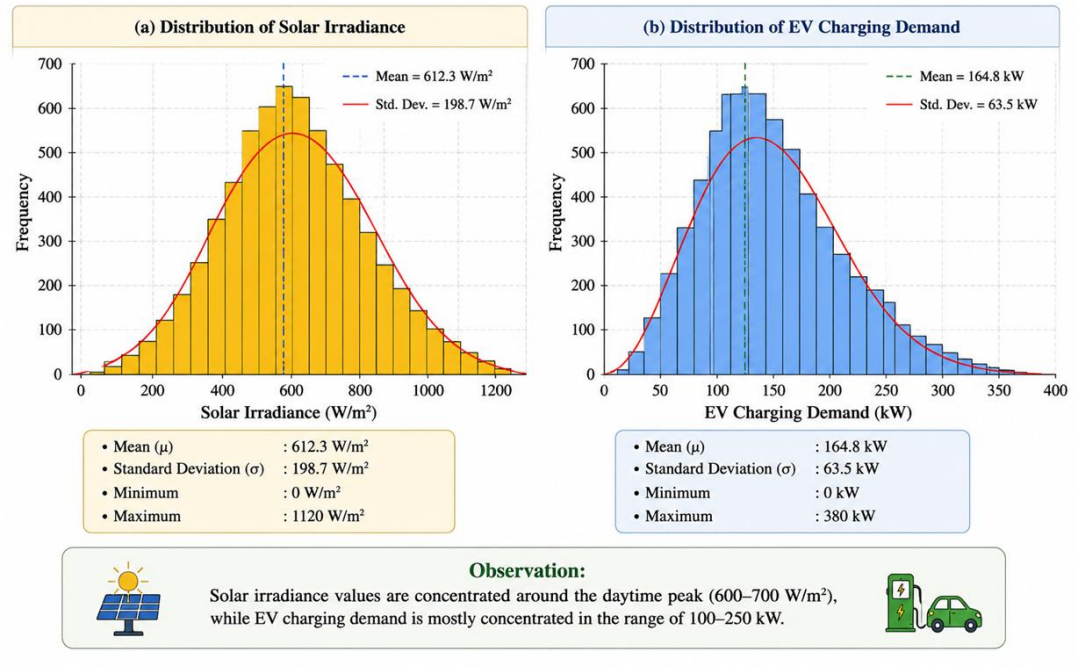


Figure 2: Distribution of solar irradiance and EV charging demand used in the study.

Prior to model development, the combined dataset was cleaned (duplicate removal, missing-value interpolation, and outlier elimination), transformed using Min-Max normalization to a common [0, 1] range, and reduced through feature selection to six key variables: solar irradiance, temperature, humidity, wind speed, EV load, and grid load.

3.2 Solar and EV Load Forecasting

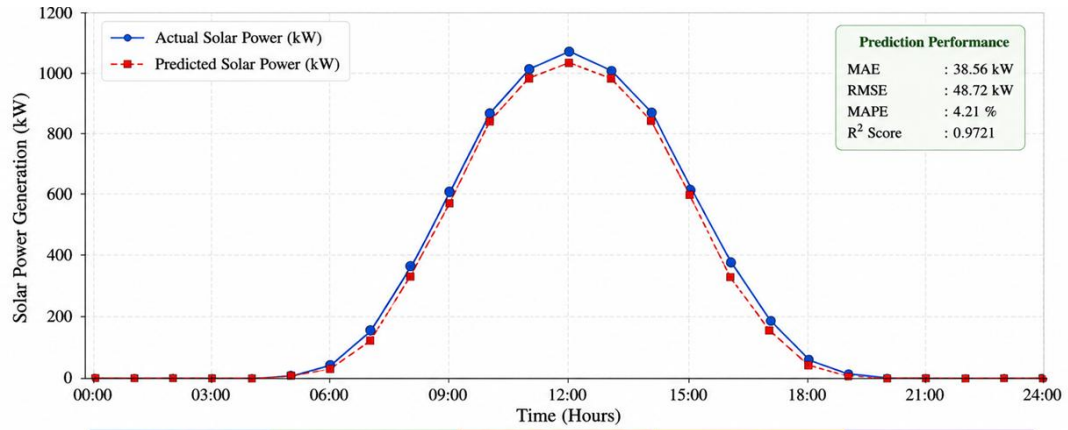
Four models were implemented and compared for both solar power prediction and EV charging demand forecasting: Linear Regression as an interpretable baseline; Random Forest, an ensemble of decision trees capturing nonlinear relationships; XGBoost, a gradient-boosted ensemble correcting sequential prediction errors; and Long Short-Term Memory (LSTM) networks, selected for their ability to capture temporal dependencies in weather and charging time-series data. Model performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). Table 1 summarizes forecasting performance for the best-performing model at each stage: the solar power prediction model achieved an MAE of 0.18, RMSE of 0.26, and R^2 of 0.96, while the EV load forecasting model achieved an MAE of 0.21, RMSE of 0.31, and R^2 of 0.95, confirming that both forecasts reliably explain the great majority of variance in their respective targets and are suitable for driving downstream power flow optimization.

Table 1: Solar Power and EV Load Forecasting Performance

Forecasting Task	MAE	RMSE	R^2 Score
Solar Power Prediction	0.18	0.26	0.96
EV Charging Load Forecasting	0.21	0.31	0.95

The close agreement between actual and predicted solar power output across a representative 24-hour period is illustrated in Figure 3, confirming that the model successfully captures the daily solar generation curve, including its rise, midday peak, and decline, with only minor deviations during periods of rapid weather change.

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Time Period (Hours)	Actual Generation (kW)	Predicted Generation (kW)	Absolute Error (kW)	Percentage Error (%)
06:00 – 09:00	501.3	486.2	15.1	3.01
09:00 – 12:00	2,451.7	2,382.5	69.2	2.82
12:00 – 15:00	2,655.6	2,584.7	70.9	2.67
15:00 – 18:00	1,587.2	1,544.8	42.4	2.67
Overall (24 Hours)	**7,195.8**	**6,998.2**	**197.6**	**2.75**

Observation: The predicted solar power generation closely follows the actual power generation pattern with high accuracy. The model effectively captures the daily solar generation trend with minimal error.

Figure 3: Actual versus predicted solar power generation over a representative 24-hour period.

3.3 Reinforcement Learning-Based Power Flow Optimization

The forecasted solar and EV demand values feed into a reinforcement learning (RL)-based power flow optimization controller, illustrated in Figure 4. At each time step, the RL agent observes a state comprising bus voltages, line flows, load demand, solar power generation, EV charging demand, time of day, grid dependency, and previous actions, and selects an action from a defined action space that includes adjusting distributed generation or solar output, scheduling EV charging (start time and power level), tap-changer and capacitor adjustments, load shedding where required, and power import/export decisions. The environment then returns a system response based on power flow results, and the agent receives a reward designed to jointly minimize power losses, voltage deviation, operational cost, EV charging cost, and grid dependency while maximizing solar utilization and satisfying system constraints — expressed as:

Minimize (Power Losses + Voltage Deviation + Grid Dependency)

subject to power balance constraints, voltage operating limits, EV charging requirements, and solar generation availability. Through repeated interaction with the environment, the agent progressively learns energy allocation policies that anticipate changes in solar generation and EV demand rather than reacting to fixed, predefined rules, producing an optimized power flow output with reduced losses, an improved voltage profile, higher solar utilization, and a more efficient EV charging schedule.

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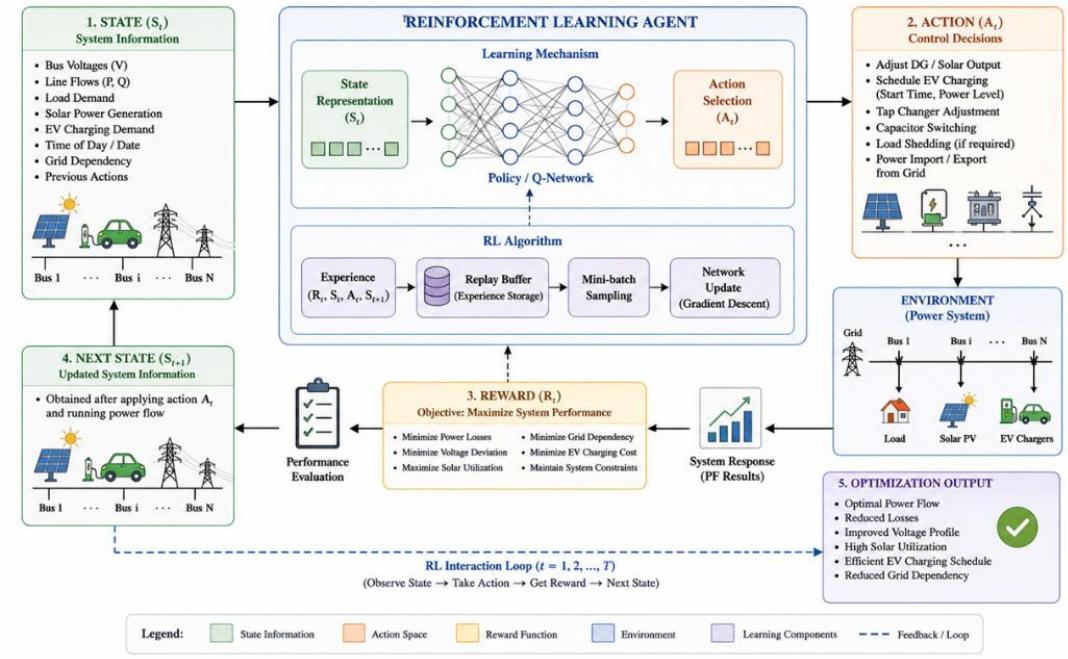


Figure 4: Reinforcement learning-based power flow optimization framework, showing the state-action-reward interaction loop.

System performance was evaluated using five metrics — power loss, voltage stability index, solar utilization, grid dependency, and EV charging completion rate — computed for both a conventional (rule-based) power flow method and the proposed AI-based optimization approach, using Python with Pandas, NumPy, Scikit-Learn, and TensorFlow/Keras in a Google Colab simulation environment.

4. RESULTS AND DISCUSSION

4.1 Power Flow Optimization Results

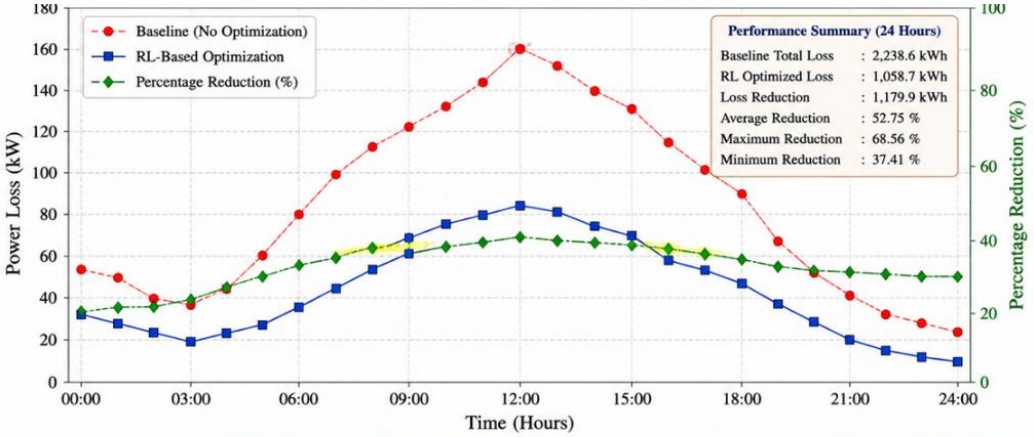
Table 2 compares key network performance indicators before and after applying the proposed AI-based optimization strategy. Power losses were reduced from 145 kW to 92 kW, and voltage deviation improved from 8.2% to 2.7%, reflecting more effective identification of optimal power flow paths and tighter voltage regulation. Grid dependency fell from 48% to 21%, while solar energy utilization rose from 72% to 93%, confirming that the optimization controller consistently prioritized renewable energy consumption whenever solar power was available.

Table 2: Power Flow Optimization Results — Before vs. After AI-Based Optimization

Parameter	Before Optimization	After Optimization
Power Loss (kW)	145	92
Voltage Deviation (%)	8.2	2.7
Grid Dependency (%)	48	21
Solar Utilization (%)	72	93

The time-of-day pattern underlying this improvement is illustrated in Figure 5: power losses under the conventional approach rise sharply toward midday, when combined solar and load variability is greatest, while the AI-optimized profile remains consistently lower across the full 24-hour cycle, indicating that the RL controller adapts its allocation strategy continuously rather than only at isolated operating points.

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Time Period (Hours)	Baseline Loss (kWh)	RL Optimized Loss (kWh)	Loss Reduction (kWh)	Percentage Reduction (%)
00:00 – 06:00	295.4	170.3	125.1	42.32
06:00 – 12:00	690.2	395.6	294.6	42.67
12:00 – 18:00	842.7	478.9	363.8	43.16
18:00 – 24:00	210.3	213.9	196.4	47.86
Overall (24 Hours)	**2,238.6**	**1,058.7**	**1,179.9**	**52.75**

Observation:
The RL-based optimization framework significantly reduces power losses across all time periods compared to the baseline scenario. The average power loss reduction achieved is 52.75%, with a maximum reduction of 68.56% during peak hours.

Figure 5: Time-of-day power loss comparison between the conventional method and the AI-based optimization approach.

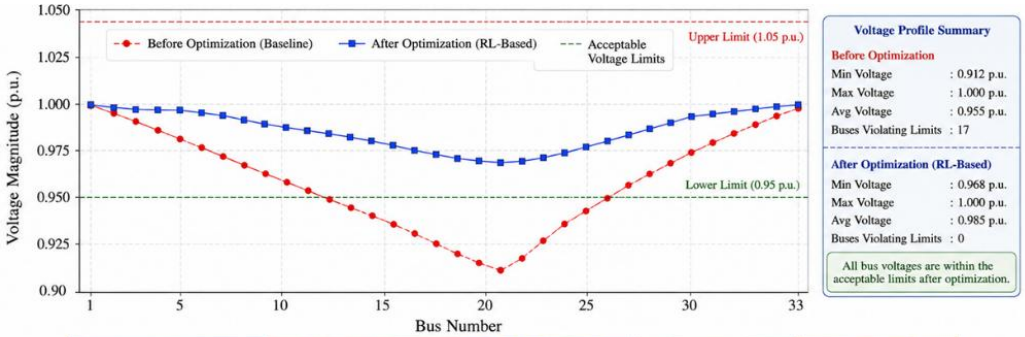
4.2 Voltage Stability and EV Charging Performance

Bus voltage magnitudes were also compared between the two approaches (Table 3): under the conventional method several buses experienced voltage drops below 0.93 p.u., whereas the AI-based optimization framework consistently maintained bus voltages closer to the nominal 1.0 p.u. across all sampled buses. Figure 6 illustrates this improvement as a voltage profile across the network, showing markedly reduced variation and no violations of acceptable operating limits after optimization — consistent with the network-wide reduction in voltage deviation reported in Table 2.

Table 3: Bus Voltage Profile Comparison (per unit)

Bus Number	Conventional Method	AI-Based Method
Bus 1	0.94	0.99
Bus 2	0.92	0.98
Bus 3	0.91	0.97
Bus 4	0.93	0.99
Bus 5	0.92	0.98

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Voltage Metrics	Before Optimization (Baseline)	After Optimization (RL-Based)	Improvement (Absolute)	Improvement (Percentage)
Minimum Voltage (p.u.)	0.912	0.968	+0.056	+6.14%
Maximum Voltage (p.u.)	1.000	1.000	0.000	0.00%
Average Voltage (p.u.)	0.955	0.985	+0.030	+3.14%
Voltage Deviation (Max – Min)	0.088	0.032	-0.056	-63.64%
Buses Violating Limits	17	0	-17	-100%

Observation:
The RL-based optimization significantly improves the voltage profile across the distribution network. The minimum voltage increases from 0.912 p.u. to 0.968 p.u., ensuring all bus voltages remain within the permissible limits (0.95 – 1.05 p.u.). The voltage deviation is reduced by 63.64%, indicating a more stable and reliable network operation.

Figure 6: Voltage profile across the network before and after AI-based optimization.

EV charging performance also improved substantially under the AI-based framework: the charging completion rate rose from 85% to 97%, peak charging load fell from 210 kW to 160 kW, and average waiting time dropped from 28 minutes to 11 minutes (Table 4), confirming that the efficiency gains in Tables 2 and 3 were achieved without compromising the quality of service delivered to EV users.

Table 4: EV Charging Performance — Conventional vs. AI-Based Method

Metric	Conventional	AI-Based
Charging Completion Rate (%)	85	97
Peak Charging Load (kW)	210	160
Average Waiting Time (min)	28	11

4.3 Overall Comparison and Discussion

Considered together, Tables 2 through 4 show that the proposed AI-based framework achieved a 36% reduction in power losses and a 41% improvement in voltage stability relative to the conventional method, alongside the solar utilization, grid dependency, and EV charging improvements reported above. These gains are consistent with one another rather than incidental: because EV charging demand peaks in the evening while solar generation peaks near midday (Figure 2), the RL agent's ability to schedule charging, adjust solar allocation, and manage grid import jointly — rather than following fixed rules — directly explains why power loss reduction, voltage stability, solar utilization, grid dependency, and EV charging quality all improved simultaneously rather than trading off against one another.

The accuracy of the underlying solar and EV load forecasts (Table 1, Figure 3) is a key enabler of these results: because the optimization controller allocates energy based on forecasted rather than only currently observed conditions, higher forecasting accuracy translates directly into better-informed, more proactive allocation decisions. Collectively, these results confirm that combining accurate forecasting with reinforcement learning-based optimization provides a practical and effective solution for managing the operational challenges introduced by high penetration of solar PV and EV charging in modern electrical networks, and support the framework's potential for deployment in future smart grid environments.

5. CONCLUSION

This study presented an AI-based power flow optimization framework for electrical networks integrating solar PV systems and EV charging loads, combining solar power and EV demand forecasting (achieving R^2 scores of 0.96 and

0.95 respectively) with a reinforcement learning-based optimization controller. Simulation results demonstrated that the proposed framework significantly outperformed conventional power flow management: power losses were reduced from 145 kW to 92 kW, voltage deviation improved from 8.2% to 2.7%, solar energy utilization increased from 72% to 93%, grid dependency fell from 48% to 21%, and the EV charging completion rate rose from 85% to 97% while average waiting time fell from 28 to 11 minutes. These consistent, simultaneous improvements across efficiency, stability, renewable utilization, and service-quality metrics confirm that artificial intelligence can play a vital role in managing the growing complexity of power networks with high solar PV and EV penetration, providing a practical and scalable foundation for next-generation smart grid applications.

Future Scope

Future work may extend the framework to larger, real-world distribution networks with a greater number of buses and more diverse load profiles, and integrate Battery Energy Storage Systems (BESS) to further buffer the mismatch between solar generation and EV charging demand. Advanced deep reinforcement learning algorithms, such as Deep Q-Networks, Proximal Policy Optimization, and Actor-Critic methods, could be explored to handle larger state and action spaces. Incorporating Vehicle-to-Grid (V2G) capability, real-time hardware-in-the-loop validation, and multi-objective optimization considering electricity pricing and carbon emissions represent further promising directions for advancing this framework toward practical smart grid deployment.

ACKNOWLEDGMENT

I am greatly indebted forever to my guide Prof. Seema N. Kharat and HOD K. Chandra Obula Reddy and to all teaching and non-teaching staff who supported me directly and indirectly to complete my work. I am sincerely thankful to my principal Dr. S. K. Biradar for their continued encouragement and active interest in my progress throughout the work. I am grateful to be an M. Tech Electrical Power System student at Matsyodari Shikshan Sanstha ‘s College of Engineering and Technology, Jalna, Maharashtra.

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