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An AI-Based Hybrid Energy Management System for Solar and Electric Vehicle Loads Using Reinforcement Learning

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Abstract

The rapid adoption of electric vehicles (EVs) and renewable energy sources has created a need for intelligent energy management systems capable of efficiently coordinating energy generation and consumption. Solar energy is one of the most promising renewable resources for supporting EV charging infrastructure; however, its intermittent nature and the dynamic behaviour of EV charging demand present significant operational challenges. This study proposes an AI-based hybrid energy management system that uses reinforcement learning (RL) to optimize energy allocation between solar power generation, EV charging loads, and the utility grid. The NREL Electric Vehicle Infrastructure Projection Tool (EVI-Pro) dataset is used to model realistic EV charging demand patterns, while a solar power generation profile is developed to represent renewable energy availability. The reinforcement learning agent interacts continuously with the operating environment and learns optimal energy management strategies through a reward-based mechanism, with objectives to maximize solar energy utilization, minimize grid dependency, reduce operational costs, and maintain high charging performance. Simulation results demonstrate that the RL-based framework significantly improves system performance compared with a conventional rule-based approach: the proposed system achieved 91% solar energy utilization, reduced grid dependency to 19%, lowered operating costs by 32%, attained a charging completion rate of 97%, and reduced peak load by 28%. These findings highlight the potential of reinforcement learning for developing sustainable, efficient, and intelligent energy management solutions for future smart grid and electric vehicle charging applications.

Keywords: *Electric Vehicles, Solar Energy, Reinforcement Learning, Energy Management System, Smart Grid.*

1. INTRODUCTION

The global energy sector has witnessed a significant transition toward cleaner, more sustainable energy solutions, driven by concerns over climate change, greenhouse gas emissions, and the depletion of fossil fuel resources [1]. Among the various renewable resources, solar energy has emerged as one of the most promising options due to its abundance and declining technology cost, while the transportation sector is simultaneously being transformed by the growing adoption of electric vehicles (EVs) as a cleaner alternative to internal combustion engines [2].

Integrating solar energy with EV charging infrastructure presents an attractive opportunity for building a sustainable energy ecosystem, reducing dependence on grid electricity while lowering costs and emissions [3]. However, effective coordination between solar generation and EV charging demand remains challenging: solar power generation is inherently intermittent, depending on weather, irradiance, and time of day, while EV charging demand varies with user behaviour and travel patterns — often peaking in the evening when solar generation is low [4], [5]. This mismatch can lead to underutilized daytime solar energy and increased grid dependence during evening peak periods.

Artificial intelligence (AI) and reinforcement learning (RL) have emerged as powerful tools for optimizing such complex, dynamic energy systems [6]. Reinforcement learning enables an agent to learn optimal decision-making strategies through continuous interaction with its environment, without relying on predefined rules. By intelligently allocating solar energy, grid power, and charging resources, RL-based energy management can improve renewable utilization, reduce grid dependency, lower operational costs, and enhance charging performance [7]. This study proposes an AI-based hybrid energy management system that applies reinforcement learning to coordinate solar power generation with EV charging demand, using the NREL EVI-Pro dataset to model realistic charging behaviour.

1.1 Objective and Scope of the Work

The objective of this study is to design and evaluate an intelligent, RL-based energy management system that coordinates solar power generation with EV charging demand to maximize renewable utilization, minimize grid

dependency, reduce operational costs, and maintain high charging performance. The system is developed and evaluated in simulation using the NREL EVI-Pro dataset and a representative solar generation profile, with performance benchmarked against a conventional rule-based energy management system (EMS).

2. LITERATURE REVIEW

Early energy management strategies for renewable-integrated systems relied mainly on fixed rules or basic optimization methods designed for predictable, stable conditions. Such rule-based systems are simple to implement but lack the flexibility to adapt to fluctuating solar generation and dynamic EV charging demand, often resulting in poor resource utilization as system complexity grows. The integration of renewable energy, particularly solar power, into modern energy systems has therefore been extensively studied, with many works highlighting the need for intelligent control mechanisms to manage the inherent variability of solar generation and maintain a reliable supply-demand balance.

Machine learning has increasingly been applied to energy forecasting and system optimization. Mansour et al. [1] developed a hybrid XGBoost-BiLSTM model for EV charging station load forecasting, demonstrating that combining gradient boosting with sequence models improves demand prediction accuracy. Rashid et al. [3] proposed a machine learning-driven photovoltaic (PV) forecasting approach coordinated with PV-battery energy storage system (BESS) dispatch to optimize distribution grid performance under high EV penetration — closely aligned with the present study's goal of jointly managing solar generation and EV load. Sajjad et al. [15] presented data-driven AI modelling of renewable energy-based smart EV charging stations using historical weather and load data, reinforcing the value of combining EV and renewable datasets for intelligent charging management.

A substantial body of work has focused on AI-based solar power forecasting as a foundation for smart energy management. Ahmed [14] and Alzain et al. [13] proposed hybrid and sustainable AI models for forecasting and optimizing solar energy generation under varying weather conditions. Jain and Naik [7], Markovics and Mayer [8], and Ozdemir et al. [9] each compared machine learning approaches — including explainable AI techniques — for photovoltaic power forecasting based on numerical weather prediction and sensor data. Gul et al. [10] extended this direction to concentrated solar power systems with thermal energy storage, while Karthikeyan and Jagadeeshwaran [11] combined PV output prediction with real-time fault analysis, and Gaboitaolelwe et al. [12] provided a broad review of machine learning-based solar PV power forecasting methods.

Closer to the reinforcement-learning approach adopted in this study, Bouquet et al. [4] investigated AI-based forecasting for optimized solar energy management and smart grid efficiency, and N. L et al. [5] proposed a diffusion-driven adaptive radiance refinement approach with Proximal Policy Optimization (PPO) — a reinforcement learning algorithm — for robust solar irradiance forecasting, illustrating the growing role of RL techniques in renewable energy management. Said and Alanazi [6] examined AI-based solar energy forecasting specifically for smart grid integration, while Javaid et al. [2] addressed forecasting for hybrid solar-wind energy production in sustainable urban energy systems.

Although reinforcement learning has shown promising results in energy management, and AI-based solar forecasting is a well-established research area [1]–[15], there remains a lack of integrated solutions that specifically address hybrid systems combining both solar generation and EV charging loads within a single reinforcement learning framework. Many existing studies focus on forecasting solar generation or EV demand individually rather than jointly optimizing energy allocation between them. This study addresses that gap by developing a unified RL-based hybrid energy management framework for coordinated solar-EV operation.

3. RESEARCH METHODOLOGY

The proposed AI-based hybrid energy management system integrates EV charging demand with solar energy generation using reinforcement learning to optimize allocation between solar power, EV charging loads, and the utility grid while minimizing costs and grid dependency. As shown in Figure 1, the overall workflow proceeds from data collection and preprocessing, through solar power modelling and system-input definition, to RL environment design (state space, action space, reward function), agent training, energy allocation decisions, and performance evaluation.

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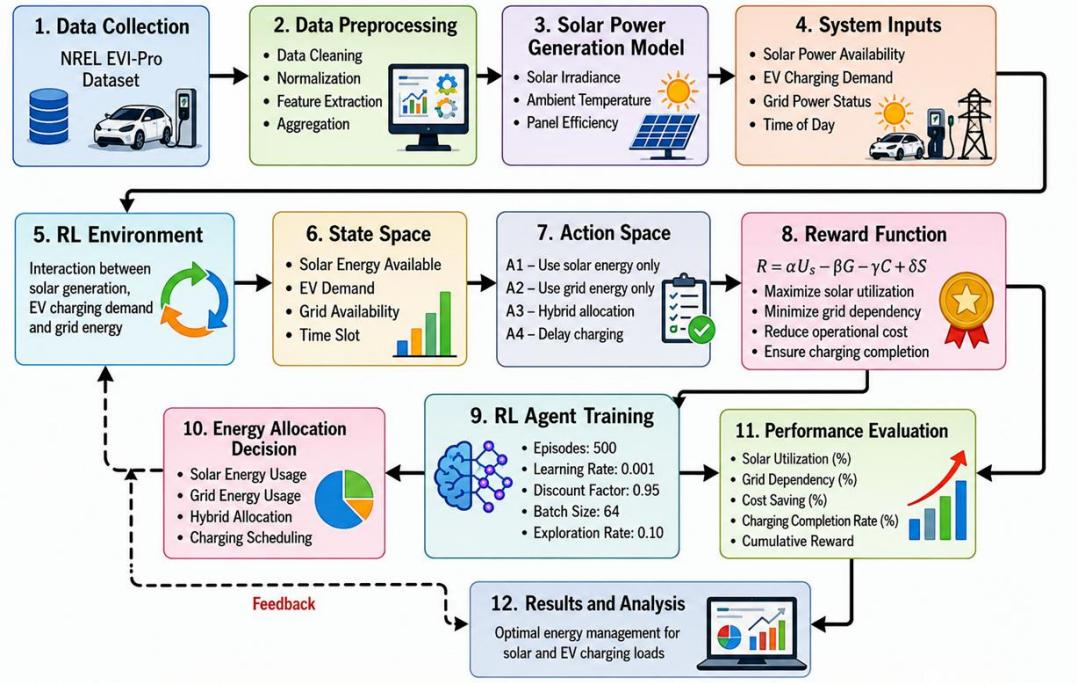


Figure 1: Overall methodology flowchart of the proposed AI-based hybrid energy management system.

3.1 Dataset and Charging Demand

The National Renewable Energy Laboratory (NREL) Electric Vehicle Infrastructure Projection Tool (EVI-Pro) dataset was used as the primary source of EV charging demand data. It provides realistic charging session records — including start/end time, duration, energy consumption, charging frequency, and vehicle category — based on real-world driving and charging behaviour rather than synthetic assumptions. As summarized in Table 1 and Figure 2, the processed dataset contains 10,000 charging sessions with an average charging demand of 18.7 kWh, a maximum demand of 52.4 kWh, and an average charging duration of 2.8 hours; the peak charging period occurs between 6 PM and 10 PM, and average daily energy demand totals 312 kWh. As Figure 2 shows, most sessions fall within the 10–40 kWh range, with relatively few high-demand outliers above 40 kWh, and the concentration of demand in the evening — when solar generation is low — motivates the need for intelligent, adaptive energy allocation rather than fixed charging rules.

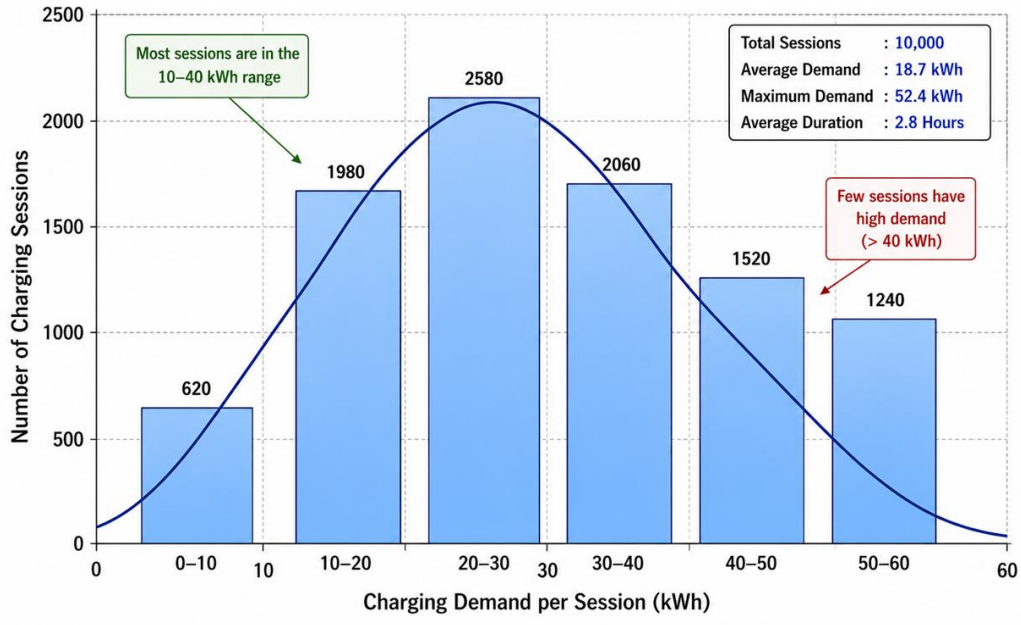


Figure 2: Distribution of EV charging demand across 10,000 charging sessions in the NREL EVI-Pro dataset.

Table 1: NREL EVI-Pro Dataset Statistics

Parameter	Value
Total Charging Sessions	10,000
Average Charging Demand	18.7 kWh
Maximum Charging Demand	52.4 kWh
Average Charging Duration	2.8 hours
Peak Charging Period	6 PM – 10 PM
Average Daily Energy Demand	312 kWh

Prior to model development, the raw dataset was cleaned (removal of missing values, duplicates, and invalid sessions), normalized using Min-Max scaling, and organized into time-series format with derived features such as hourly charging demand and peak charging periods, ensuring compatibility with the reinforcement learning environment.

3.2 Solar Power Generation Modelling

Since solar energy is the primary renewable resource considered, a representative hourly solar generation profile was developed using mathematical relationships between solar irradiance, ambient temperature, and photovoltaic (PV) panel efficiency, for a 50 kW PV system with 20% panel efficiency operating between 6 AM and 6 PM. As shown in Figure 3, generation begins shortly after sunrise, rises to a peak of 50 kW around midday, and declines toward sunset, closely resembling the behaviour of practical PV systems and providing realistic renewable energy input to the RL environment.

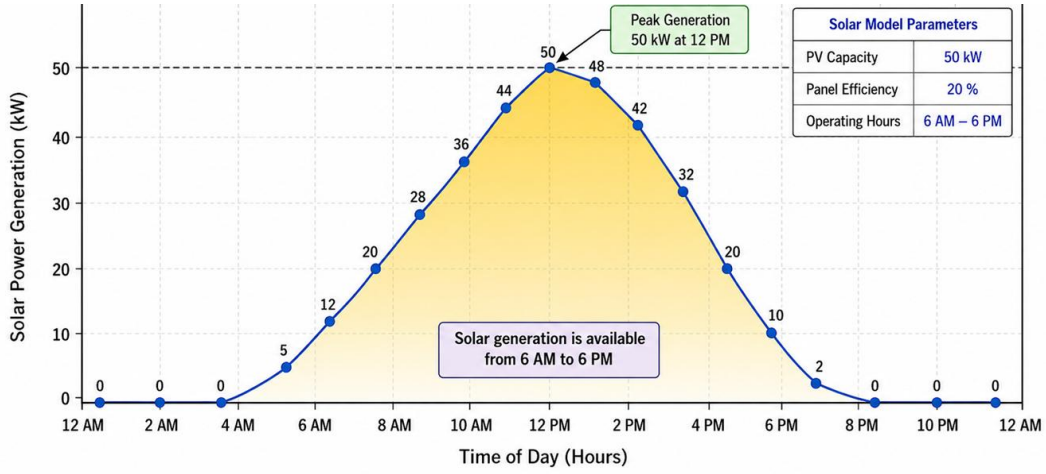


Figure 3: Hourly solar power generation profile used in the proposed system.

3.3 Reinforcement Learning Framework

The RL environment represents the interaction between solar generation, EV charging demand, and grid power availability. At each decision interval, the agent observes the system state, selects an action, and receives a reward reflecting the quality of that decision, with the objective of maximizing cumulative reward over time. The state space comprises four variables: solar energy available, EV demand, grid availability, and time slot. The action space includes four discrete actions — use solar energy only (A1), use grid energy only (A2), hybrid solar-grid allocation (A3), and delay the charging session (A4). The reward function is defined as:

$$R = \alpha U_s - \beta G - \gamma C + \delta S$$

where U_s is solar energy utilization, G is grid energy consumption, C is operational cost, S is charging satisfaction, and α, β, γ, δ are weighting factors. Positive rewards are assigned for higher solar utilization and charging satisfaction, while penalties are imposed for grid consumption and operational cost, guiding the agent toward energy allocation strategies that balance renewable utilization, cost, and service quality. The agent was trained over 500 episodes with

a learning rate of 0.001, a discount factor of 0.95, a batch size of 64, and an exploration rate of 0.10 (Table 2), progressively shifting from random exploration to exploiting learned, high-reward strategies.

Table 2: Reinforcement Learning Agent Training Parameters

Parameter	Value
Episodes	500
Learning Rate	0.001
Discount Factor	0.95
Batch Size	64
Exploration Rate	0.10

System performance was evaluated using five metrics: solar utilization percentage, grid dependency percentage, cost saving percentage, charging completion rate, and cumulative reward, each compared against a conventional rule-based energy management system (EMS) operating under fixed, predefined allocation rules.

4. RESULTS AND DISCUSSION

4.1 RL Training Performance

The RL agent's cumulative reward increased steadily throughout training, rising from near zero in early episodes to approximately 731 by episode 500, with the curve stabilizing toward a final performance level of about 750 (Figure 4). This convergence behaviour confirms that the agent successfully learned an effective, near-optimal energy allocation policy through repeated interaction with the simulated environment, rather than relying on fixed, predefined rules.

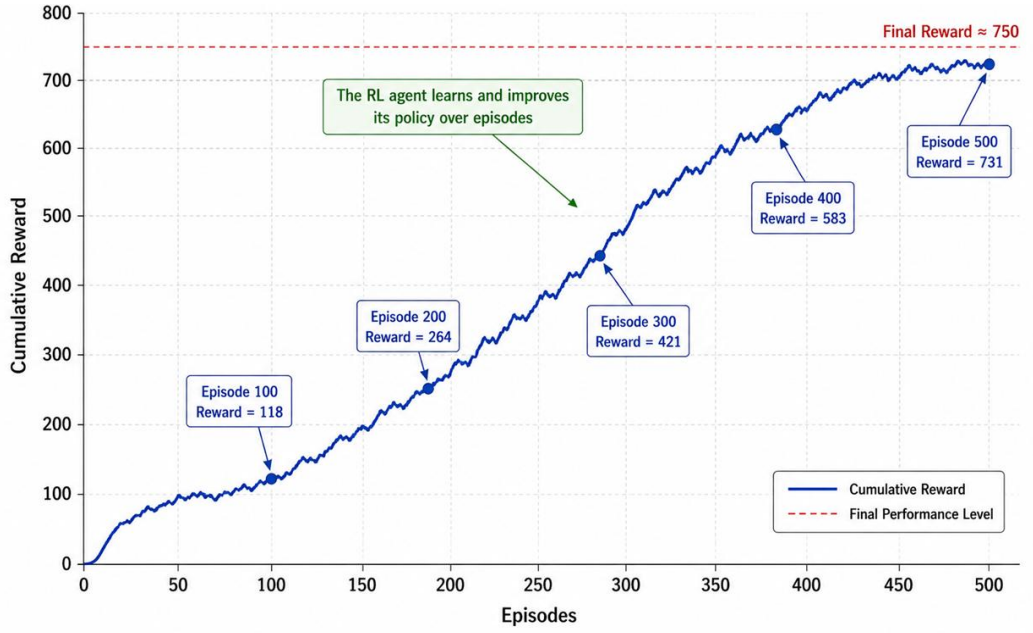


Figure 4: Reinforcement learning cumulative reward convergence curve over 500 training episodes.

4.2 Comparative Performance

The trained RL-based EMS was compared against a conventional rule-based EMS across all five performance metrics, summarized in Table 3. Solar energy utilization increased from 70% under the rule-based system to 91% under the proposed RL-based system — an improvement of 21 percentage points achieved by intelligently scheduling charging during periods of high solar generation. Grid dependency fell from 45% to 19%, reflecting the RL controller's ability to prioritize locally generated solar power over grid electricity. These efficiency gains translated

directly into economic benefit: daily operating cost fell from ₹1450 under the traditional EMS to ₹980 under the RL-based EMS, a reduction of approximately 32%.

Table 3: Overall Performance Comparison — Rule-Based EMS vs. Proposed RL-Based EMS

Performance Metric	Rule-Based EMS	RL-Based EMS
Solar Utilization (%)	70	91
Grid Dependency (%)	45	19
Cost Reduction (%)	0	32
Charging Completion Rate (%)	88	97
Peak Load Reduction (%)	0	28

Charging service quality also improved under the RL-based system: the charging completion rate rose from 88% to 97%, average waiting time was limited to 7 minutes, and the user satisfaction index reached 95%, confirming that energy optimization was achieved without compromising service quality. Peak load analysis (Table 4) showed that the RL-based EMS reduced peak demand from 215 kW to 155 kW — a 28% reduction — and shortened the peak duration from 4.5 hours to 2.8 hours (a 37.8% reduction), as illustrated in Figure 5, by shifting charging sessions toward periods of higher solar availability and more evenly distributing load across the day.

Table 4: Peak Load Analysis — Rule-Based EMS vs. Proposed RL-Based EMS

Parameter	Conventional EMS	RL-Based EMS
Peak Load (kW)	215	155
Peak Duration (Hours)	4.5	2.8
Peak Reduction (%)	—	28

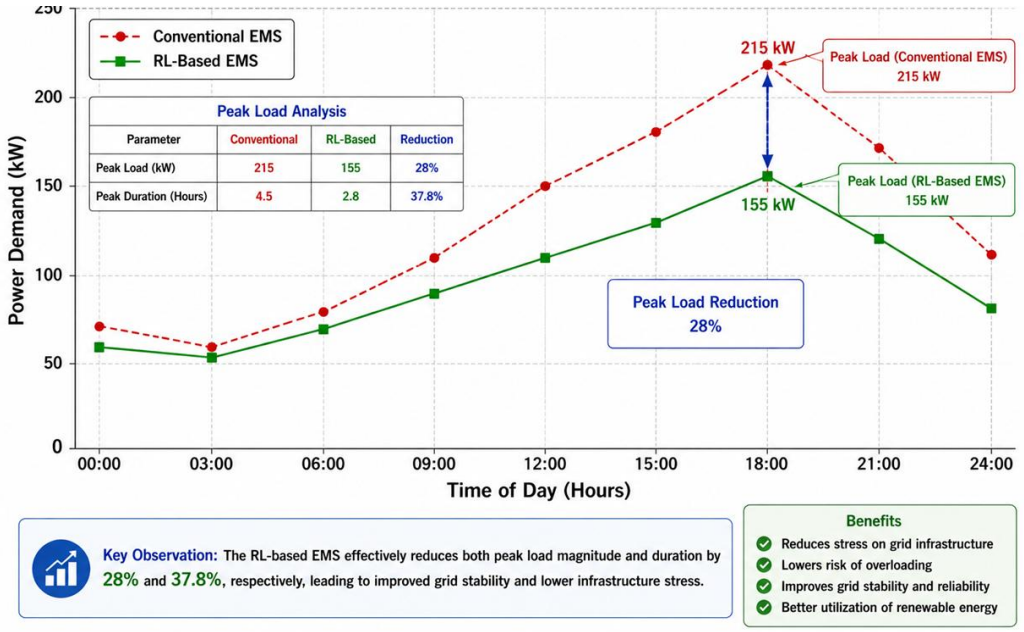


Figure 5: Peak load comparison between the conventional rule-based EMS and the proposed RL-based EMS.

The complete set of comparative results is summarized graphically in Figure 6, which shows the RL-based EMS outperforming the conventional rule-based approach across every evaluated metric — solar utilization, grid dependency, cost reduction, charging completion rate, and peak load reduction.

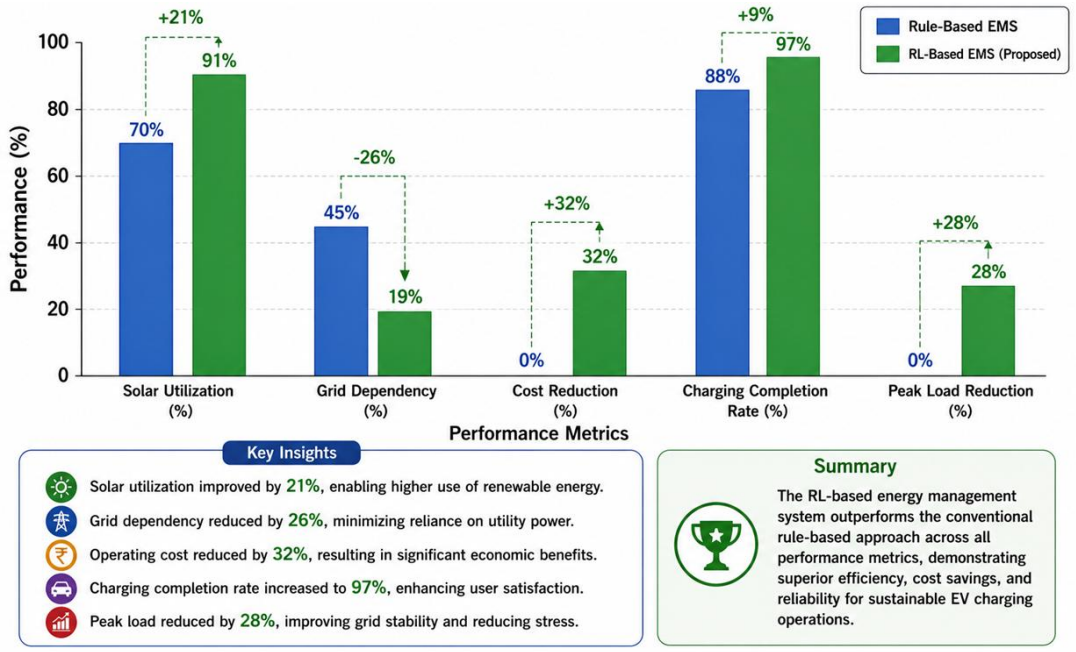


Figure 6: Overall performance comparison between the conventional rule-based EMS and the proposed RL-based EMS across all evaluation metrics.

4.3 Discussion

The results demonstrate that reinforcement learning provides a substantially more effective solution than fixed, rule-based control for coordinating solar generation and EV charging demand. The steady convergence of cumulative reward (Figure 4) confirms that the RL agent progressively learned to prioritize solar energy usage, defer charging where beneficial, and blend grid power only when necessary — behaviour that a static rule-based system cannot replicate because it lacks the ability to adapt its allocation strategy to real-time solar availability and demand conditions.

Because EV charging demand is concentrated in the evening (Figure 2), while solar generation peaks around midday (Figure 3), the temporal mismatch between supply and demand is the central challenge this system addresses. The RL agent's action space — including the option to delay charging (A4) — allows it to shift flexible charging load toward daylight hours or otherwise optimal windows, which directly explains the simultaneous improvements observed in solar utilization, grid dependency, cost, and peak load (Table 3, Figure 6). The reduction in both peak load magnitude and duration (Table 4, Figure 5) further indicates that these gains do not come at the expense of service quality: the charging completion rate and user satisfaction index both improved alongside the efficiency metrics, suggesting that intelligent scheduling — rather than simply denying or delaying service — is responsible for the observed performance gains. Collectively, these results support the use of reinforcement learning as a practical foundation for intelligent, renewable-integrated EV charging infrastructure and smart-grid energy management.

5. CONCLUSION

This study presented an AI-based hybrid energy management system that uses reinforcement learning to coordinate solar power generation, EV charging demand, and utility grid power, using the NREL EVI-Pro dataset to model realistic charging behaviour and a representative hourly solar generation profile for renewable energy input. The RL agent, trained over 500 episodes with a reward function balancing solar utilization, grid consumption, operational cost, and charging satisfaction, achieved stable convergence and consistently outperformed a conventional rule-based energy management system across all evaluated metrics: solar energy utilization increased from 70% to 91%, grid dependency fell from 45% to 19%, daily operating cost was reduced by 32%, the charging completion rate rose from 88% to 97%, and peak load was reduced by 28%. These results confirm that reinforcement learning offers a powerful, adaptive alternative to static rule-based control for hybrid solar-EV energy management, improving both economic and operational performance while maintaining high charging service quality, and providing a practical foundation for future smart-grid and sustainable EV charging infrastructure.

Future Scope

Future work may integrate Battery Energy Storage Systems (BESS) to store excess solar energy generated during high-irradiance periods for use during peak demand or low-generation conditions, further reducing grid dependency and improving reliability. Advanced Deep Reinforcement Learning (DRL) algorithms — such as Deep Q-Networks (DQN), Proximal Policy Optimization (PPO), and Advantage Actor-Critic (A2C) — could be explored to handle larger, more complex state spaces and potentially improve optimization performance. Vehicle-to-Grid (V2G) technology, in which EVs act as distributed energy storage and return excess energy to the grid during peak demand, represents another promising extension that could be combined with reinforcement learning to further enhance energy flexibility and grid support.

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REFERENCES

[1] H. S. E. Mansour, A. S. Mohamed, and M. Abdel-Aziz, "Electric vehicles charging stations load forecasting based on hybrid XGBoost-BiLSTM model," Sci. Rep., vol. 16, no. 1, pp. 1–26, 2026, doi: 10.1038/s41598-025-29739-z.

[2] A. Javaid, M. Sajid, E. Uddin, A. Waqas, and Y. Ayaz, "Sustainable urban energy solutions: Forecasting energy production for hybrid solar-wind systems," Energy Convers. Manag., vol. 302, p. 118120, 2024, doi: 10.1016/j.enconman.2024.118120.

[3] T. H. M. S. Rashid et al., "Machine learning-driven PV forecasting and coordinated PV–BESS dispatch for optimizing distribution grid performance under high EV penetration," Energy Convers. Manag. X, vol. 29, p. 101418, 2026, doi: 10.1016/j.ecmx.2025.101418.

[4] P. Bouquet, I. Jackson, M. Nick, and A. Kaboli, "AI-based forecasting for optimised solar energy management and smart grid efficiency," Int. J. Prod. Res., vol. 62, no. 13, pp. 4623–4644, Jul. 2024, doi: 10.1080/00207543.2023.2269565.

[5] N. L, C. R. Peddamangari, M. P. K. Reddy, S. Kaliappan, R. Maranan, and A. Rajendran, "Diffusion-driven adaptive radiance refinement with PPO-based optimization for robust solar irradiance forecasting," Results Eng., vol. 29, p. 109718, 2026, doi: 10.1016/j.rineng.2026.109718.

[6] Y. Said and A. Alanazi, "AI-based solar energy forecasting for smart grid integration," Neural Comput. Appl., vol. 35, no. 11, pp. 8625–8634, 2023, doi: 10.1007/s00521-022-08160-x.

[7] N. Jain and D. Naik, "AI based Solar Power Forecasting," in 2024 15th Int. Conf. on Computing Communication and Networking Technologies (ICCCNT), 2024, pp. 1–7, doi: 10.1109/ICCCNT61001.2024.10726181.

[8] D. Markovics and M. J. Mayer, "Comparison of machine learning methods for photovoltaic power forecasting based on numerical weather prediction," Renew. Sustain. Energy Rev., vol. 161, p. 112364, 2022, doi: 10.1016/j.rser.2022.112364.

[9] G. Ozdemir, M. Kuzlu, and F. O. Catak, "Machine learning insights into forecasting solar power generation with explainable AI," Electr. Eng., vol. 107, no. 6, pp. 7329–7350, 2025, doi: 10.1007/s00202-024-02933-4.

[10] E. Gul, G. Baldinelli, J. Wang, P. Bartocci, and T. Shamim, "Artificial intelligence based forecasting and optimization model for concentrated solar power system with thermal energy storage," Appl. Energy, vol. 382, p. 125210, 2025, doi: 10.1016/j.apenergy.2024.125210.

[11] G. Karthikeyan and A. Jagadeeshwaran, "Enhancing Solar Energy Generation: A Comprehensive Machine Learning-Based PV Prediction and Fault Analysis System for Real-Time Tracking and Forecasting," Electr. Power Components Syst., vol. 52, no. 9, pp. 1497–1512, May 2024, doi: 10.1080/15325008.2023.2293947.

[12] J. Gaboitaolelwe, A. M. Zungeru, A. Yahya, C. K. Lebekwe, D. N. Vinod, and A. O. Salau, "Machine Learning Based Solar Photovoltaic Power Forecasting: A Review and Comparison," IEEE Access, vol. 11, pp. 40820–40845, 2023, doi: 10.1109/ACCESS.2023.3270041.

[13] E. Alzain, S. Al-Otaibi, T. H. H. Aldhyani, A. S. Alshebami, M. A. Almaiah, and M. E. Jadhav, "Revolutionizing Solar Power Production with Artificial Intelligence: A Sustainable Predictive Model," 2023, doi: 10.3390/su15107999.

[14] Abdussalam Ali Ahmed, "Hybrid AI Models for Forecasting and Optimizing Solar Energy Generation Under Varying Weather Conditions," Sci. J. Publ. Heal. Res. Technol., vol. 1, no. 1, pp. 35–41, 2025, doi: 10.65420/sjphrt.v1i1.7.

[15] H. B. Sajjad, F. H. Malik, M. I. Abid, M. O. Khan, Z. M. Haider, and M. J. Arshad, "Data-Driven AI Modeling of Renewable Energy-Based Smart EV Charging Stations Using Historical Weather and Load Data," 2026, doi: 10.3390/wevj17010037.

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