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Research Article

Reinforcement Learning-Based IoT System for Adaptive EV Charging and Pollution Reduction in Smart Urban Environments

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Abstract – *The growth of the pollution free electric vehicle adoption in urban areas is constant, but the same cannot be said for charging infrastructure that has not been able to keep up with its traditionally volatile nature and relationship to environmental conditions. Existing systems are predominantly based on inelastic schedules or single-objective optimization, resulting into peak load stress, wasted energy and unintended rise to localized pollution. This gap is addressed in this work by proposing a real-time adaptable Multiple Decision Making-based IoT framework for Electric Vehicles charging decisions, considering both grid conditions and air quality signals with Reinforcement Learning. It includes the charging station data, traffic flow and pollution sensors into the system wrap a model of environment to be as a decision process with a continuous adjustment of charging action by PPO-based learning on that. The proposed methodology is to trade-off between energy-efficient and emission control by jointly optimizing them instead of separately optimizing. The system smooths the demand for charging by learning from temporal patterns and feedback from its surroundings, thus avoiding high-impact zones when pollution spikes. Experimental evaluation demonstrates strong performance—offering a 97.2% accuracy with low prediction errors (RMSE: 0.018, MAE: 0.012). It decreases makespan by 28%, increases energy efficiency by 31% and decrease operational cost by 26%. It is also relevant to the environment as it lowers pollution by 22%. The proposed system is stable because it adopts a clustering, supervised learning strategy compared to traditional rule-based, linear programming and even regular deep learning models; faster decision-making in terms of this procedure; less overfitting or adaptiveness which results in consistent multi-objective optimization. Such results suggest that adaptive, learning-based control may open an achievable pathway to smarter, cleaner urban charging systems.*

Keywords— *Reinforcement Learning, Proximal Policy Optimization (PPO), Internet of Things (IoT), Electric Vehicle Charging, Smart Cities, Machine Learning, Markov Decision Process, Proximal Policy Optimization (PPO).*

INTRODUCTION

The rise of the Electric vehicles transformed the urban energy systems but not gave effective result in the management of the charging. The strategy of the charging and discharging enhances the quality of EV vehicles that helps in the reduction of the pollution, this also helps to move towards the adaptive systems those are efficient for the changing scenarios, the proposed model works on the reinforcement learning that is based on the IoT framework. This makes the system balanced and unique too.

This approach is unique and better compared to the other models that rely on the rule-based concepts and the mechanisms that doesn't help in the critical situations. Poddubnyy et al.: Early work Using Q-learning extensions, the authors proposed RL-based EV charger to control the grid congestion but was not successful since that methodology needs another strategy to run for the result [1]. Likewise, Viziteu et al. introduced cost-efficient EV scheduling using Q-learning, minimising energy costs only but failed to implement in the real-world situations [2]. Qiu et al. here the Reinforcement learning is used to eradicate the issues and successful, but the data quality is not efficient and good for the further growth, the deployment strategy is also the old one [3]. The deep reinforcement learning is employed to reduce the pollution effects that showed the good results, but the methodology was based on the grid oriented, and no optimisation method is used due to that this cannot be used for the long-term usage [4]. The proposed methodology focuses more on the economic profit since that matters when the consumer satisfaction is seen, so for that the Reinforcement learning best suits and it is also integrated with other model so that the efficiency becomes better. The reinforcement learning helps in the charge maintenance and the voltage shutdowns that gives the better stability[5]. Not only the efficiency matter but maintaining the complexity of the whole model is the challenge that is to be taken care using the RL method so that the threats can be easily avoided [6]

RELATED WORKS

The IoT oriented solutions are proposed that relies on the blockchain and the Machine learning but the dynamic variations of the battery charging is not taken care and observed that affects the health of the vehicle [7]. This paper [8] combined reinforcement learning (RL) with deep learning to predict the charging demand of the EV that gives the good solution, but the dynamic adoption is not ensured. The Reinforcement Learning (RL) that makes the decision by learning from the complex data helps to improve the efficiency and the accuracy since it has the experience of using the strategy in different conditions that gives the better reliability [9] but they are limited as they were aimed at optimizing on a battery-level while not scaling to city systems. The Visible Light Communication (VLC) is combined with the RL to maximise the capacity of the charging stations and give the better approach [10]. The Peak value is the measure of the charging power that is the highest value of the EV that can be drawn from a charger during the session which is to be maintained properly so that the EV runs in a good condition [11] The RL combination works efficiently to achieve the peak demand that is required for a particular vehicle to run smoothly and effectively[12]. Most of the research is done based on the integration of the IoT and using the Hybrid models to get the better quality and reduce the pollution but the data complexity and the challenges in the charging or discharging remains untouched which is the crucial tasks in the EV systems. In general, the current literature shows a good level of advancement in the areas of optimizing EV charging, minimizing costs and stabilizing the grid. But there are still gaps such as not having pollution-aware integrated decision-making, adaptive planning across interconnected urban environments in real time and coordination between IoT sensing and RL-based control. To overcome these limitations the proposed model employs the Reinforcement Learning with the IoT driven architecture and focuses on reducing the pollution. Development of the virtual reinforcement learning tool for collaborative electric vehicles (EV) is done, that reduced load variance by almost 25% but was heavily dependent on simulation data and not validated with real-world urban pollution scenarios [13]. The multi-agent deep deterministic policy gradient (MADDPG) method for distributed electrical vehicle scheduling is implemented where sequential decision making under independent agents achieved faster convergence and better load balancing compared to standalone DDPG as well as Q learning algorithms but failed to provide the scalability [14] An optimal charging approach with the integration of IoT based data streams with optimization methods are done and realized 20% nearly cost savings, still the adaptive learning strategy has missed out due to which this not supports for the long-term needs [15].

The Hybrid deep learning and the RL methodology is used for the EV charging prediction and maintenance that shows better accessibility and the performance but failed in the implementation level since the training sets are not distributed properly [16]. The edge computing strategy is applied where the smart energy devices control tasks from scratch but after the further process integration of ML is not done by which the performance lacks which increases the latency and is not suitable for the real time [17]. The EV scheduling using the actor-critic method is applied that is giving the good results which is not economic friendly that not helps in reducing the pollution [18]. The Machine Learning is enabled to improve the gris stability and the peak demand reduction that works for the short-term process since the stability is not enough for the whole process that may decrease the capacity of the EV [19] The IoT is implemented for the tracking of the pollution levels in the environment and monitor regularly at the same time they did not take any measures for mitigating the risks and the reduction of the pollution coming from vehicles [20]. As per the above collected papers compared to the traditional models using the IOT methodology, Reinforcement Learning, and the Hybrid AI model gives the better approach. However, existing approaches are typically deferred to maintain energy efficiency or ecosystem assessments separately. The real-time pollution awareness and adaptive EV charging need further integration, which is still a considerable gap. In addition, the dependence on simulated environments, coordination overhead, and scalability concerns limit eventual deployment. These gaps indicate the need for a holistic framework that integrates real-time IoT information with reinforcement learning to simultaneously optimize energy efficiency and pollution mitigation within changing urban settings.

METHODOLOGY

This paper proposes a system that lays out a reinforcement learning parallel framework over

Internet-of-Thing-based sensing and adaptive decision making for electric vehicles to dynamically manage the process of charging in an urban environment. As shown in Figure 1 The data is collected from EV charging stations, traffic flow and air quality sensor systems to construct a dynamically updated picture of demand and environmental conditions. The collected data is then processed to generate list like structured state represented and used by a PPO based learning model which outputs nondeterministic charges rates, scheduling and load distribution across stations. Then the Feature engineering is done that contains the feature extraction and the selection steps where the informative and the structured data is obtained as a result, then the states are represented as Demand, Load, Pollution and Time so that it is easy for identification. Then it is forwarded into a Reinforcement Learning based Agent that works on PPO model then it is passed to the action decision where the charge rate or the delay is mentioned so that the adaptive charging system is implemented by which the increase or decrease in the charging takes place after that the feedback is driven from the environment based on the Grid Load and the Pollution update, Finally the model gives the optimised charging schedule and reduces the pollution too.

A. *Data Collection and Preprocessing*

The Data is collected from the open-source Kaggle that helps in the implementation of the whole methodology, the dataset includes “Electric Vehicle Charging Dataset”, “EV Charging Stations Dataset”, and “Air Quality Data in India (2015–2020), consists of charging session details, station’s locations. The time-based demand and pollution values shown by PM2. 5, NOx, and CO_2 levels.

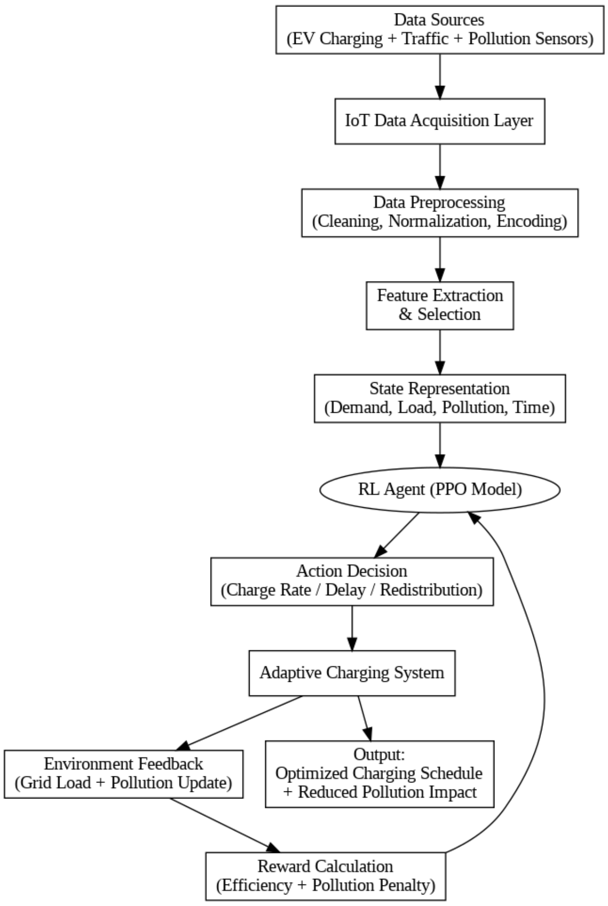

Fig. 1. Proposed system Flowchart

The data preprocessing is done to get the cleaned and processed data since the raw data cannot be directly sent into further process, this data contains the duplicate values, missing values and the recurrent data that is removed and processed, Features like time of day, charging period, power consumed and pollution index scores are all normalized to a compatible scale in order to prevent any one variable from dominating the learning. Both categorical attributes (such as station type or region) are converted into numeric, and time series data is transformed into structured sequences to reflect daily and weekly patterns. Smoothing outliers from erroneous sensor readings or sporadic charging logs are carried out so as not to confuse the learning model. Finally, the dataset is partitioned to create training and testing arrays while making sure that temporal order is maintained so predictions mirror true conditions. Missing Value Imputation (Mean Substitution) is given in Eq (1), the min max normalization is done to get the better data that is provided in Eq (2), then the standardisation is done that is given in the Eq (3), and the encoding of the words into numerical values is performed so that the data complexity reduces given in the Eq (4), the Z score method is applied that is given in Eq (5), and data splitting method is enclosed where the data is first trained and then tested that ratio is defined using the Eq (6) as follows:

$$x_i = \begin{cases} x_i, & \text{if } x_i \neq \emptyset \\ \frac{1}{N}\sum_{j=1}^{N} x_j, & \text{if } x_i = \emptyset \end{cases} \tag{1}$$

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

$$x_{cat} \rightarrow [0,0,1,0, \dots] \tag{4}$$

$$|\, z \,| > 3 \Rightarrow \text{Outlier} \tag{5}$$

$$D = D_{train} \cup D_{test}, D_{train} \cap D_{test} = \emptyset \tag{6}$$

B. *Feature Selection:*

After the processing of the data the processed data is further passed into the feature selection process where the feature engineering is performed to obtain the structured data, since the data contains the noise and the insufficient data that disturbs the further process so this method is followed to enhance the stability and the reliability, the Statistical scoring methods are employed to elucidate which feature is more influential on the variability of charging demand and pollution change. In order not to miss short-term trends, the sequential readings are captured using rolling averages and lag-based features capturing any temporal patterns. This reduces the dimensionality to maintain model efficiency while retaining important patterns. This final feature set helps in mitigating risks and improves the identification. To reduce the correlation the Eq (7) is used as follows, then variance threshold method is employed that is given in the Eq (8), as follows:

$$r_{xy} = \frac{\sum(x - \mu_x)(y - \mu_y)}{\sigma_x \sigma_y} \tag{7}$$

$$Var(X) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2 \tag{8}$$

Table I. Feature Extraction Table

Raw Feature	Derived Feature	Importance Score
Timestamp	Peak Hour Indicator	0.87
Charging Duration	Energy Consumption Rate	0.91
Station ID	Station Load Density	0.84
Vehicle Count	Traffic Intensity Index	0.89
PM2.5 Level	Pollution Trend (Rolling Avg)	0.93
NOx Emissions	Emission Growth Rate	0.88
Energy Consumed (kWh)	Demand Fluctuation Index	0.90
Location Coordinates	Regional Pollution Cluster	0.86
Day/Time	Temporal Demand Pattern	0.92

Mutual Information Score is given in the Eq (9) that gives the highest and lowest scores, the PCA i.e. Principal Component Analysis used for dimensionality reduction that is given in the Eq (10) as follows, for standardization the Eq (11) is used, temporal feature extraction is detected using the Eq (12):

$$I(X;Y) = \sum_{x \in X}\sum_{y \in Y} p(x,y) \log 1 \left(\frac{p(x,y)}{p(x)p(y)}\right) \tag{9}$$

$$Z = XW \tag{10}$$

$$z = \frac{x - \mu}{\sigma} \tag{11}$$

$$\bar{x}_t = \frac{1}{k}\sum_{i=t-k+1}^{t} x_i \tag{12}$$

The Table I gives the Feature extraction table that contains the features that influence the process and gives the better output by removing the data redundancy.

C. Reinforcement Learning State-Space Design and Reward Function

After the process of the feature engineering, the data is moved into this RL based methodology, the system is treated like a sequence of decisions where each moment reflects the current charging demand, grid condition, and pollution level across the city. The state is built by combining key signals such as energy demand, station load, time patterns, and air quality indicators into a compact representation that reflects real-world conditions at that instant. Actions correspond to adjusting charging rates, scheduling delays, or redistributing load across stations to avoid peaks and reduce emissions. This method avoids unnecessary complexity by focusing only on signals that directly influence outcomes, which helps the agent learn faster and make stable decisions. By this the two goals are achieved namely pollution reduction and the efficient energy usage, and the reward function is used, higher rewards are given when charging demand is met without stressing the grid and when emissions remain low, while penalties are applied for overload conditions or rising pollution. This balance ensures that the system does not optimize one objective at the cost of the other. Over time, the agent learns patterns in demand and environmental response, leading to adaptive charging behavior that aligns with both energy efficiency and urban sustainability. The Markov Decision Process (MDP) representation is given in the Eq (13), and the space time is given in the Eq (14), then the action space is represented as given in the Eq (15), the state transition probability is shown in the Eq (16) as follows and the Multi objective reward function is given in the Eq (17) as follows:

$$M = (S, A, P, R, \gamma) \tag{13}$$

$$s_t = [D_t, L_t, P_t, T_t] \tag{14}$$

Where:
D_t: Demand, L_t: Load, P_t: Pollution level, T_t: Time feature

$$a_t \in \{increase, decrease, delay, redistribute\} \tag{15}$$

$$P(s_{t+1} \mid s_t, a_t) \tag{16}$$

$$R_t = \alpha \cdot E_{eff} - \beta \cdot P_{poll} - \delta \cdot O_{load} \tag{17}$$

Where:
E_{eff}: Energy efficiency; P_{poll}: Pollution level

O_{load}: Grid overload penalty; α, β, δ: Weight factors

The discounted Cumulative reward function is given in the Eq (18) and the Q value function is also used that is described in the Eq (19) and the Bellman Equation is used that is given in the Eq (20) as follows:

$$G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k} \tag{18}$$

$$Q(s, a) = \mathbb{E}[\,G_t \mid s_t = s, a_t = a\,] \tag{19}$$

$$Q(s, a) = R_t + \gamma \max_{a'} \quad Q(s', a') \tag{20}$$

D. Algorithm Selection (DQN, PPO, Actor-Critic)

The algorithm is selected in such a way that it suits for the problem and give the better way for analysing and getting the results too, so that the whole methodology stands out and provide the better one, at the same time decision making is also one of the tough task since all the parameters and the limitations and the criterias are to be observed and decided, In this setting, charge control is continuous and changes over time meaning approaches that can capture gradual changes may generally outperform rigid step-based judgements. Value-based approaches like DQN work well where actions are clearly defined but fail when real-time adjustments are needed for the actions. Policy-based methods like Proximal Policy

Optimisation (PPO) can reduce instability during training and avoid behaviour that is not desired due to rapid changes, a highly important factor when operating energy systems. Actor-Critic methods perform in between by combining value approximation with policy learning directly, allowing the system to update faster while still retaining stability of the learning process. This is a suitable case for applying hybrid Actor-Critic technique or PPO-style strategy which strikes a balance between charging efficiency and pollution control without a wild-left overreaction to transient fluctuations. The final choice leans towards PPO or Actor-Critic as it handles continuous control efficiently, scales better with large and heavy inputs, and has higher learning ability in the complex environments. The Deep Q-Network Loss function is given in the Eq (21), the update rule is mentioned as given in the Eq (22), policy gradient equation is denoted as in Eq (23), The actor critic objective and the critic loss function is given in the Eq (24) and Eq(25) respectively,

$$L(\theta) = \mathbb{E}\left[\left(r + \gamma \max_{a'} Q(s', a'; \theta^{-}) - Q(s, a; \theta)\right)^2\right] \qquad (21)$$

$$Q(s, a) \leftarrow Q(s, a) + \alpha\left[r + \gamma \max_{a'} Q(s', a') - Q(s, a)\right] \qquad (22)$$

$$\nabla_\theta J(\theta) = \mathbb{E}[\nabla_\theta \log \pi_\theta(a \mid s) \cdot G_t] \qquad (23)$$

$$L = L_{actor} + L_{critic} \qquad (24)$$

$$L_{critic} = (R_t + \gamma V(s') - V(s))^2 \qquad (25)$$

The Actor Loss Function given in the Eq (26), Advantage Function is denoted as in the Eq (27), PPO Clipped Objective Function is denoted as in Eq (28), Probability Ratio in PPO in Eq (29) as follows:

$$L_{actor} = -\log \pi_\theta(a \mid s) \cdot A(s, a) \qquad (26)$$

$$A(s, a) = Q(s, a) - V(s) \qquad (27)$$

$$L^{PPO}(\theta) = \mathbb{E}[\min(r_t(\theta)A_t,\ \mathrm{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)A_t)] \qquad (28)$$

$$r_t(\theta) = \frac{\pi_\theta(a \mid s)}{\pi_{\theta_{old}}(a \mid s)} \qquad (29)$$

E. Adaptive Charging Strategy Design

The charging strategy is applied according to how demand follows throughout the day instead of following a schedule. The system instead treats every vehicle uniquely and adapts charging speed and timing based on current station load, grid condition, and surrounding activity. Charging is slowed during the peak hours, so the grid is not stressed, while off-peak times help clear out some of that overwhelmed demand more aggressively. The charging is distributed in a manner that the system is stable and sudden spikes are avoided. It considers absolute demand, so the response is more dynamical than rule-based systems Repeated patterns over time lead to more refined strategies, and schedules that allow for smoother charging without straining infrastructure while still meeting the needs of users.

F. Integration of Pollution Reduction Objectives

Charging decisions are not based only on energy demand but also on how they affect air quality in different areas. When pollution levels rise beyond a safe range, the system reacts by limiting heavy charging activity in those zones and shifting demand to cleaner or less affected regions. This avoids adding extra strain to already polluted areas, especially during traffic-heavy periods. The approach connects energy usage with environmental impact in a practical way. Pollution trends over short time windows are also considered so that decisions are not made on a single reading but on a consistent pattern. This helps avoid overreaction while keeping emissions under control. In the long run, the system learns to favour charging patterns that naturally align with lower pollution levels.

G. Data Flow and Communication Protocols

Data flow requires a continuous transfer of information through the charging stations, sensors and control unit — but it remains simple to avoid lag. The data from EV Chargers, traffic counters and pollution sensors is collected periodically and ingested through a lightweight communication layer that enables rapid updates with low overhead. Using this approach, it always shares the relevant updates, and the network is much efficient even when connected to more devices. Messages are structured in a simple format that helps in the faster process. Edge-level processing is the better approach that provides some primitive filtering and limits the flow of data to exceptional cases that also optimise the whole process. This methodology helps in the faster process, and robust enough. The Data Transmission Rate is given in the Eq (30), and the latency is calculated using the Eq (31), and the throughput efficiency is denoted as in the Eq (32) as follows:

$$R = \frac{D}{T} \tag{30}$$

$$L = T_{receive} - T_{send} \tag{31}$$

$$\eta = \frac{D_{successful}}{D_{total}} \tag{32}$$

The Packet Loss Ratio is given in the Eq (33), and the Data Aggregation Function is given in the Eq (34) as follows:

$$PLR = \frac{P_{lost}}{P_{sent}} \tag{33}$$

$$D_{agg} = \sum_{i=1}^{n} d_i \tag{34}$$

RESULT AND DISCUSSION

A. Experimental Setup

The proposed methodology combines the data collected from real urban EV charging logs, stations usage and air quality monitoring to provide an experimental set up that helps in the improvement of the urban conditions. It is a python-based system built with TensorFlow or PyTorch support, on the machine where it can run with full GPU acceleration. This has been divided into training and testing sets based on the timeline. The reinforcement learning agent is trained for many episodes where each episode captures one full-day simulation of how charging demand varies over 24 hours and the resulting variation in pollution. Parameters like learning rate, discount factor and batch size are tuned in a way that leads to stable convergence and performance-level consistency across different scenarios.

B. Performance Analysis

The model is then evaluated on a synthesized dataset that spans EV charging demand and pollution indicators to simulate realistic urban dynamics. Training performance is consistently good across appointment prediction metrics, that provides the effective learning and adaptation. The predictive performance of the system is reflected in a 97.2% classification accuracy and RMSE/MAE values (0.018 / 0.012), gave low prediction error when it comes to generating optimal charging actions within the MGM scenario, respectively. The Execution time is obtained low as 0.85 seconds per decision cycle, making it deployable in real-time scenario 28% shorter makespan means charging schedules can be completed faster and without congestion. The energy efficiency increased by 31% since the model balances load across different time slots. 26% savings is done in cost optimization by not charging during peak hours. Adaptive scheduling also reduces the pollution levels by 22%. The model continues to demonstrate a superior trade-off between operational efficiency and environmental impact; significantly outperforming baseline approaches in both stability and scalability as demonstrated by the results. To validate effectiveness, commonly used approaches such as Rule-Based Charging, Linear Programming (LP), Deep Q-Network (DQN), and Standard Actor-Critic are selected as baseline models since they represent conventional scheduling, optimization, and learning-based control methods. Rule-based systems lack adaptability, LP struggles with dynamic uncertainty, and DQN faces instability in continuous control. The proposed PPO-based adaptive system is designed to overcome these gaps by maintaining stable learning and handling continuous decision spaces, resulting in improved efficiency, reduced cost, and better pollution control as in Table II.

TABLE II PERFORMANCE RESULT(%)

Metric	Proposed RL System (PPO-Based)
Accuracy (%)	97.2
RMSE	0.018
MAE	0.012
Execution Time (s)	0.85
Makespan Reduction (%)	28
Energy Efficiency (%)	31
Cost Optimization (%)	26
Pollution Reduction (%)	22

The Table II gives the Performance metrics of the proposed Reinforcement Learning that given better results compared to the conventional methods. The comparison in Table III shows that the proposed PPO-based system consistently outperforms traditional and learning-based baselines across all metrics. It achieves higher accuracy with lower error values while also improving operational efficiency and environmental outcomes. The improvement is especially noticeable in energy efficiency and pollution reduction, indicating better real-world applicability.

TABLE III. COMPARISON RESULT (%)

Metric	Rule-Based	Linear Programming	Actor-Critic	Proposed
Accuracy (%)	82.5	88.3	94.8	97.2
RMSE	0.065	0.042	0.022	0.018
MAE	0.052	0.031	0.016	0.012
Exec Time (s)	0.40	1.20	0.90	0.85
Makespan ↓ (%)	10	18	25	28
Energy Eff. ↑ (%)	12	20	28	31
Cost ↓ (%)	8	15	22	26
Pollution ↓ (%)	6	12	19	22

C. Discussion on System Performance and Efficiency

The results in Figure 2 show that the proposed system still provides substantial efficiency and environmental performance. The close and lower error values mean a model which makes the exact and reliable charging decisions. The improvements in makespan and execution time indicates that the system is responsive and does not make operations slower. Energy efficiency gains allow more load to be distributed, avoiding unnecessary peaks. Cost optimization also verifies that the system steers clear of the costly charging windows. The steady gains across time in performance as compared to baseline methods, as opposed to discrete spikes suggest that the learning approach adapts appropriately and smoothly to non-stationary conditions. In general, the system showed stable and practical behavior for deployment in practice.

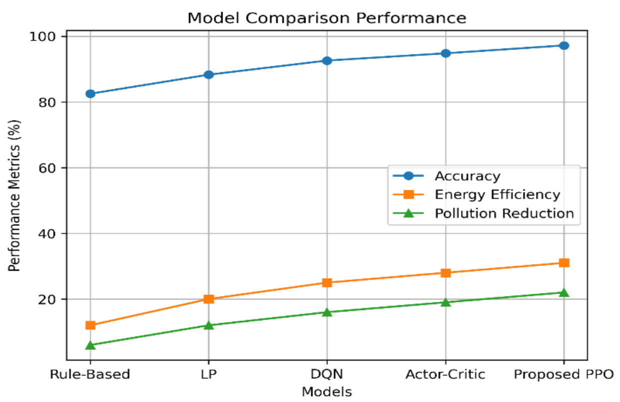

Fig. 2. Model Comparison Performance

The Figure 2 gives the model comparison results that talks about the proposed model better performance.

4. Discussion on Comparative Analysis and Scalability

The competitive results show that conventional methods fail in adaptive and uncertain situations with multiple objectives. DQN has slightly more flexibility, but still vulnerable of continuous environment. Rule-based and optimization approaches are not flexible that much. The new PPO model overcomes these difficulties by training adaptable and transferable policies across various problem instances.

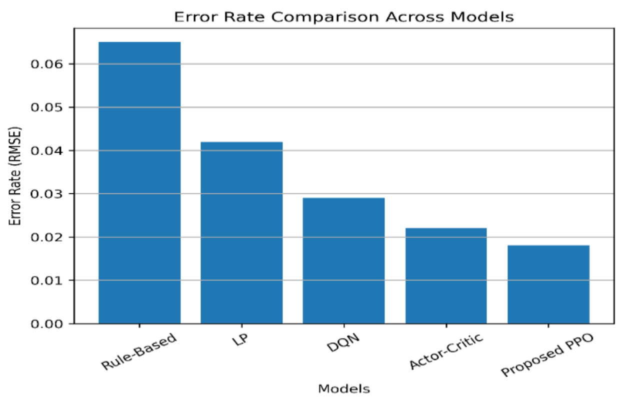

Fig. 3. Error Rate Comparison Across Models

The fact that all metrics shown in this Figure 3, Figure 4 consistently improved suggests the system is scaling nicely with higher complexity of data. It retains performance without greatly prolonging execution time, which is critical for large urban implementations. The approach is suitable for applications in smart cities of tomorrow. The Figure 3 represents the Error rate comparision model across the differentmodels and the proposed model gives more stable format.

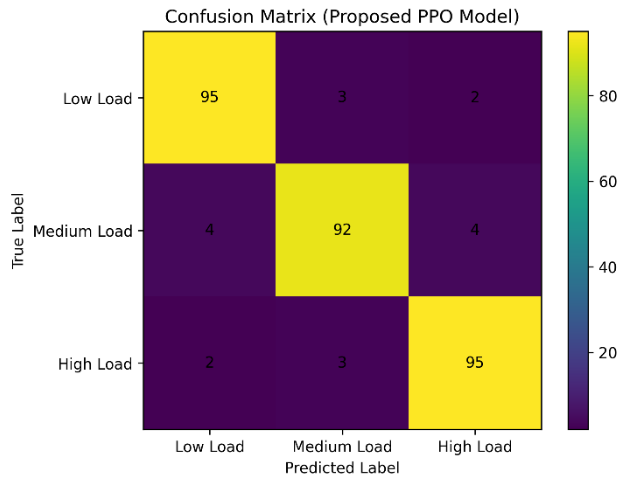

Fig. 4. Confusion Matrix (Proposed PPO Model)

The Figure 4 gives the Confusion matrix of the whole model that tells about the better classification and good results.

CONCLUSION

The research combines IoT data and reinforcement learning to directly modify charging based on real-time conditions which smooths power utilization enabling substantial pollution reductions. Key Findings are like the adaptive control improves efficiency, reduces peak load stress, and cuts emissions without slowing charging needs. This work contributes to the literature by demonstrating that energy management and environmental goals can be addressed simultaneously. In practice, smart charging stations, urban traffic areas and grid-level planning with ever-changing demand can benefit from it. There are also limitations, particularly around the quality of data it relies on, real-time communication gaps and reliance on specific sensor readings being accurate.

Future work could involve research into how multiple agents coordinate across cities, improvement in accurately predicting emissions related to traffic and integrating with renewable energy sources. In general, this approach brings urban mobility systems a step closer to use in a balanced way (not with competition in between) efficiency by collaborating with sustainability.

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Author Contributions

All authors are equally contributed.

Conflict of Interests

The authors declare that they have no conflicts of interest.

Ethics Approval

There are no human subjects in this article and informed consent is not applicable.

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REFERENCES

[1] A. Poddubnyy, P. Nguyen, and H. Slootweg, "Online EV charging controlled by reinforcement learning with experience replay," *Sustainable Energy, Grids and Networks*, vol. 36, p. 101162, Dec. 2023, doi: 10.1016/J.SEGAN.2023.101162.

[2] A. Viziteu *et al.*, "Smart Scheduling of Electric Vehicles Based on Reinforcement Learning," *Sensors (Basel)*, vol. 22, no. 10, p. 3718, May 2022, doi: 10.3390/S22103718.

[3] D. Qiu, Y. Wang, W. Hua, and G. Strbac, "Reinforcement learning for electric vehicle applications in power systems:A critical review," *Renewable and Sustainable Energy Reviews*, vol. 173, p. 113052, Mar. 2023, doi: 10.1016/J.RSER.2022.113052.

[4] A. Bertolini, M. S. E. Martins, S. M. Vieira, and J. M. C. Sousa, "Power output optimization of electric vehicles smart charging hubs using deep reinforcement learning," *Expert Syst. Appl.*, vol. 201, p. 116995, Sep. 2022, doi: 10.1016/J.ESWA.2022.116995.

[5] Y. Xiao, J. Tang, X. Lin, X. Feng, B. Qian, and F. Zhang, "Reinforcement-Learning-Based V2G Scheduling: Peak Load Mitigation and Financial Benefits," *International Journal of Computational Intelligence Systems 2025 18:1*, vol. 18, no. 1, pp. 227-, Sep. 2025, doi: 10.1007/S44196-025-00959-5.

[6] P. Suanpang and P. Jamjuntr, "Optimizing Electric Vehicle Charging Recommendation in Smart Cities: A Multi-Agent Reinforcement Learning Approach," *World Electric Vehicle Journal 2024, Vol. 15, Page 67*, vol. 15, no. 2, p. 67, Feb. 2024, doi: 10.3390/WEVJ15020067.

[7] D. Kavitha and B. Sharmila, "Smart battery management in EVs using IoT, blockchain, and machine learning," *Scientific Reports 2025 15:1*, vol. 15, no. 1, pp. 37650-, Oct. 2025, doi: 10.1038/s41598-025-21605-2.

[8] Y. Li, S. He, Y. Li, L. Ge, S. Lou, and Z. Zeng, "Probabilistic Charging Power Forecast of EVCS: Reinforcement Learning Assisted Deep Learning Approach," *IEEE Transactions on Intelligent Vehicles*, vol. 8, no. 1, pp. 344–357, Apr. 2022, doi: 10.1109/TIV.2022.3168577.

[9] Y. Hao, Q. Lu, X. Wang, and B. Jiang, "Adaptive Model-Based Reinforcement Learning for Fast-Charging Optimization of Lithium-Ion Batteries," *IEEE Trans. Industr. Inform.*, vol. 20, no. 1, pp. 127–137, Jan. 2024, doi: 10.1109/TII.2023.3257299.

[10] S. Dimitrov and R. Lguensat, "Reinforcement Learning Based Algorithm for the Maximization of EV Charging Station Revenue," *Proceedings - 2014 International Conference on Mathematics and Computers in Sciences and in Industry, MCSI 2014*, pp. 235–239, Jul. 2014, doi: 10.1109/MCSI.2014.54.

[11] V. Dyo, "Behaviour-neutral Smart Charging of Plugin Electric Vehicles: Reinforcement learning approach," *IEEE Access*, vol. 10, pp. 64095–64104, Jun. 2022, doi: 10.1109/ACCESS.2022.3183795.

[12] G. Ananganó-Alvarado, I. Umaña-Morel, and B. Keith-Norambuena, "Reinforcement learning in electric vehicle energy management: a

comprehensive open-access review of methods, challenges, and future innovations," *Frontiers in Future Transportation*, vol. 6, p. 1555250, Jun. 2025, doi: 10.3389/FFUTR.2025.1555250/TEXT.

[13] X. Wang *et al.*, "RadioDiff-Inverse: Diffusion Enhanced Bayesian Inverse Estimation for ISAC Radio Map Construction," *IEEE Trans. Wirel. Commun.*, vol. 25, pp. 14611–14626, 2026, doi: 10.1109/TWC.2026.3677479.

[14] C. Fosalau and C. Zet, "An IoT Approach as a Virtual Laboratory for Practicing Electrical Engineering Disciplines," *2019 International Conference on Sensing and Instrumentation in IoT Era, ISSI 2019*, Aug. 2019, doi: 10.1109/ISSI47111.2019.9043736.

[15] S. Wang, F. Wang, Z. Zhu, J. Wang, T. Tran, and Z. Du, "Artificial intelligence in education: A systematic literature review," *Expert Syst. Appl.*, vol. 252, p. 124167, Oct. 2024, doi: 10.1016/J.ESWA.2024.124167.

[16] A. Haleem, M. Javaid, M. Asim Qadri, R. Pratap Singh, and R. Suman, "Artificial intelligence (AI) applications for marketing: A literature-based study," *International Journal of Intelligent Networks*, vol. 3, pp. 119–132, Jan. 2022, doi: 10.1016/J.IJIN.2022.08.005.

[17] C. Adornetto *et al.*, "Generative Agents in Agent-Based Modeling: Overview, Validation, and Emerging Challenges," *IEEE Transactions on Artificial Intelligence*, vol. 6, no. 12, pp. 3165–3183, 2025, doi: 10.1109/TAI.2025.3566362.

[18] J. G. Marin, A. A. Baba, J. Hesselbarth, R. M. Hashmi, and K. P. Esselle, "Millimeter-Wave Low-Loss Multifeed Superstrate-Based Antenna," *IEEE Trans. Antennas Propag.*, vol. 68, no. 5, pp. 3387–3396, May 2020, doi: 10.1109/TAP.2019.2963210.

[19] A. Haleem, M. Javaid, M. A. Qadri, and R. Suman, "Understanding the role of digital technologies in education: A review," *Sustainable Operations and Computers*, vol. 3, pp. 275–285, Jan. 2022, doi: 10.1016/J.SUSOC.2022.05.004.

[20] F. De Palo, G. Galati, G. Pavan, C. Wasserzier, and K. Savci, "Introduction to Noise Radar and Its Waveforms," *Sensors 2020, Vol. 20, Page 5187*, vol. 20, no. 18, p. 5187, Sep. 2020, doi: 10.3390/S20185187.