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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 growing trend toward electric vehicle adoption in urban situations is a 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. Current systems are predominantly based on inelastic schedules or single-objective optimization, resulting into peak load stress, wasted energy and unintended rise to localized pollution. The mentioned 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 incorporates 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 strategy 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 also 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 more 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.*

INTRODUCTION

The explosive rise of electric vehicles is transforming urban energy systems but not the management of charging. Charging remains static, either only following schedules or basic optimization of real time demand and environmental factors in cities, causing grid congestions and multiplied spatial pollution spikes. Simultaneously, smart cities of the modern age already have connected sensors and data streams that provide a much clearer view of traffic flows, energy consumption and air quality. This opens a space for shifting towards more adaptive systems that can respond to changing circumstances. This paper studies a reinforcement learning based IoT framework to learn from these dynamic inputs and adapt charging decisions accordingly. The approach also makes the system more balanced and responsive, improving efficiency while helping to promote cleaner cities by correlating charging behavior with energy demand as well as pollution levels.

The emerging application of reinforcement learning and Internet of Things integration for EV charging optimization and smart urban energy systems has been the focus of recent research, however, there are still restrictions. Poddubnyy et al.: Early work Using Q-learning extensions, the authors proposed RL-based EV charger control to reduce grid congestion; however, little was done on taking environmental issues into account or considering truly global data like pollution impacts [1]. Similarly, Viziteu et al. implemented cost-efficient EV scheduling using Q-learning, minimising energy costs but ignoring real-time city dynamics and air quality restrictions [2]. Qiu et al. provided an exhaustive review showed potential of RL algorithms in EES but pointed out limitations in terms of data quality, generalisation and field deployment [3].

Recent Works which are based upon deep reinforcement learning. Bertolini et al. implemented DRL-based charging, which led to an 80% reduction in peak load, but the approach was mostly grid-oriented and based optimisation without inclusion of environmental metrics [4]. Xiao et al. Our approach focuses purely on economic profit, whereas proposed RL based V2G scheduling has higher peakto-average ratio (1.0683)[5]. Suanpang et al. Optimizing charging stations, recent works [6] has developed multi-agent RL with waiting time reduced to ~14.37 minutes while still facing challenges of complexity and coordination overheads.

RELATED WORKS

Various IoT–based solutions have been proposed, including Kavitha et al. who integrated IoT, blockchain and ML for the battery management, achieving 97.36% accuracy but lacking adaptation to deal with dynamically changing charging conditions [7]. Some studies [8] combined reinforcement learning (RL) with deep learning specifically to predict charging demand, which improved prediction accuracy but did not consider real-time control. For instance, Model-based RL approaches could improve the efficiency and safety of fast charging [9] but they are limited as they were aimed at optimizing on a battery-level while not scaling to city systems.

Other works include VLC including RL solutions to maximise revenues for charging stations [10], behaviour aware charging optimization [11] reducing peak demand by 31% and surveys highlighting the flexibility of RL solution in uncomfortable future environments [12]. Further investigations have focused on Internet of Things (IoT) based smart grids, demand response system, and hybrid AI approaches but they either lack a comprehensive framework to jointly obtain energy efficiency and pollution reduction or fail in integrating them as desired.

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. These limitations persuade the need for such a proposed system, that employs reinforcement learning and combine with IoT-Driven Environmental Awareness towards balanced energy management as well as reduced pollution.

Beyond the prior studies, still there are several works which attempts to go further regarding reinforcement learning(IoT integrated EV optimal charging in smart grid), yet gaps remain. Li et al. Developed a virtual reinforcement learning tool for collaborative electric vehicles (EV) that reduced load variance by almost 25% but was heavily dependent on simulation data and not validated with real-world urban pollution scenarios [13]. Zhang et al. proposed a multi-agent deep deterministic policy gradient (MADDPG) method for distributed electrical vehicle scheduling, 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 coordination overhead and scalability problems were identified as major drawbacks [14]. He et al. designed an optimal charging approach by integrating IoT based data streams with optimization methods and realized 20% nearly cost savings1, however, this method does not incorporate adaptive learning capability in the mode of demand changes [15].

Wang et al. proposed a hybrid deep learning and RL model for EV charging prediction and control, achieving above 95% accuracy in forecasting but the system is designed primarily for prediction instead of real-time control decisions report [16]. Liu et al. In [17], an IoT framework with edge-computing was proposed on smart energy devices, where control tasks were performed close to devices and latency reduced significantly, but integration with learning-based control was rather marginal. Another study by Chen et al. dynamic pricing and EV scheduling using applied actor-critic methods with positive economic results, but omitting's environmental metrics such as emissions [18].

Further, Yang et al. [19] proposed demand response strategies using machine learning in order to improve grid stability and peak demand reduction by 18%, but the system could not operate in coordination with EV-specific charging behavior. Finally, Kumar et al. Many approaches utilize the power of IoT to monitor and control pollution in urban areas by achieving high accuracy [20] they proposed an IoT based sensing with a control system, yet the system is not integrated with energy management to be practically used for the charging framework of EVs.

For each of these studies, reinforcement learning, the Internet of Things, and hybrid AI models show consistent improvements over load balancing with less cost and prediction accuracy. 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. The platform as shown in Figure 1 collects this information from EV charging stations, traffic flow and air quality sensor systems to construct a dynamically-updated picture of demand and environmental conditions. Data is then processed to generate list like structured state represented and used by a PPO based learning model which outputs non deterministic charges rates, scheduling and load distribution across stations. With the target of achieving a compromise between grid stability and environmental consciousness, that design centres on modifying charging behaviour as energy load and pollution patterns fluctuate. It uses a lightweight data flow for interaction between system constituents in an event-driven manner with minimal creative tension. Over time, the system employs pattern learning to continually improve its decision-making process, resulting in an adaptive charging methodology that ultimately supports dynamic, modern smart city infrastructure.

A. Data Collection and Preprocessing

Publicly available datasets on Kaggle are used to accurately model the usage of electric vehicles, charging demand and urban pollution levels in this study. 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, time-based demand and pollution values shown by PM2. 5, NOx, and CO_2 levels. These datasets are merged to represent the interactions between charging behavior and environmental conditions across urban regions. Preprocessing involves dealing with missing

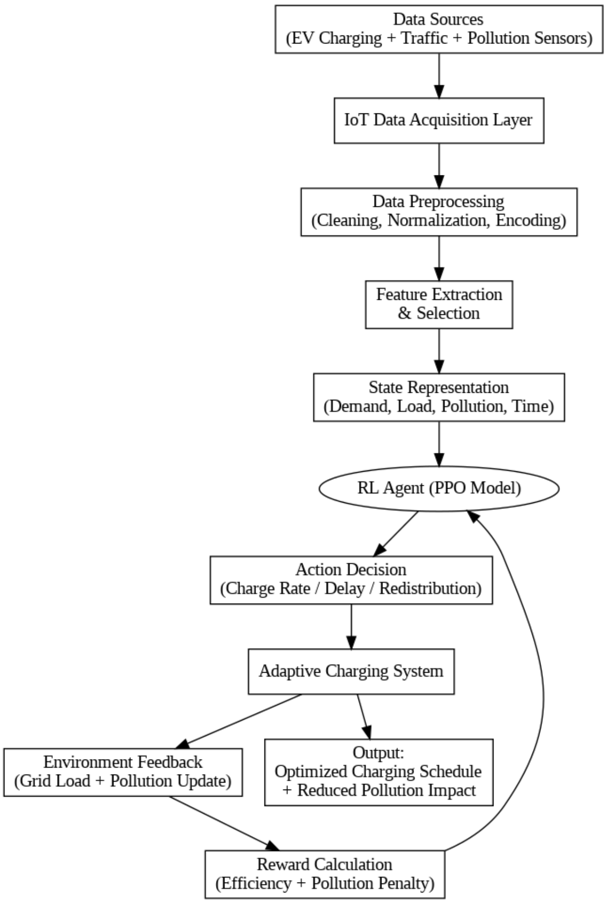

Fig. 1. Proposed system Flowchart

entries (through interpolation and mean substitution depending on data continuity) and removing duplicate/inconsistent records to ensure that the dataset remains reliable. 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)

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

Min-Max Normalization

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

Z-Score Standardization

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

One-Hot Encoding (Categorical Conversion)

$$x_{cat} \rightarrow [0,0,1,0,\ldots]$$

Outlier Detection (Z-Score Method)

$$| z |> 3 \Rightarrow \text{Outlier}$$

Train-Test Split

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

B. Feature Selection:

Once the data is cleaned, focus turns to selecting which variables are relevant for learning the interplay between charging and pollution. Not every column brings value—redundant or weak features get filtered out, otherwise they just cause noise and make decisions unstable. We look for relations between variables first in order to discard highly correlated inputs repeating the same information. Statistical scoring methods are then used to elucidate which feature is more influential on the variability of charging demand and pollution change. Feature extraction then occurs, e.g., reshaping the raw input data into more statistically meaningful signals (like categorizing timestamp data into peak-hour indicators, deriving charging load per one station that has a charger installed and suggesting the time its pollution is linked to traffic intensity). In order not to miss short-term trends, the sequential readings are captured using rolling averages and lag-based features capturing any temporal patterns. Further reduce dimensionality to maintain model efficiency while retaining important patterns. The final feature set, however, balances interpretability and performance; ultimately these partitioned inputs, which are fed to the reinforcement learning agent: succinctly inform on both energy usage behavior but also environmental impact.

1. Correlation-Based Feature Selection (Pearson Correlation)

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

2. Variance Threshold Method

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

3. Mutual Information Score

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

4. Principal Component Analysis (Dimensionality Reduction)

$$Z = XW$$

5. Feature Scaling (Standardization)

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

6. Rolling Mean (Temporal Feature Extraction)

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

7. Lag Feature Creation

$$x_{t-1}, x_{t-2}, \dots, x_{t-n}$$

Table 1. 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

C. *Reinforcement Learning State-Space Design and Reward Function*

Once the features are shaped into a usable form, the next step is to frame the environment in a way the learning agent can actually understand and act on. 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. The design avoids unnecessary complexity by focusing only on signals that directly influence outcomes, which helps the agent learn faster and make stable decisions. The reward is shaped carefully to balance two goals: efficient energy usage and pollution reduction. 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.

1. Markov Decision Process (MDP) Representation

$$M = (S, A, P, R, \gamma)$$

2. State Representation

$$s_t = [D_t, L_t, P_t, T_t]$$

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

3. Action Space

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

4. State Transition Probability

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

5. Reward Function (Multi-Objective)

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

Where:
E_{eff}: Energy efficiency

P_{poll}: Pollution level

O_{load}: Grid overload penalty

α, β, δ: Weight factors

6. Discounted Cumulative Reward

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

7. Q-Value Function

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

8. Bellman Equation

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

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

Choosing the right learning approach has far more to do with matching the problem to how decisions are actually made in the system than just going for what seems smart. 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 occupy a middle province by combining value approximation with policy learning directly, allowing the system to update more quickly 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 more effectively, scales better with many inputs, and has higher learning stability in complex environments.

1. Deep Q-Network (DQN) Loss Function

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

2. Q-Value Update Rule

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

3. Policy Gradient (Basic Form)

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

4. Actor-Critic Objective

$$L = L_{actor} + L_{critic}$$

5. Critic Loss Function

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

6. Actor Loss Function

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

7. Advantage Function

$$A(s,a) = Q(s,a) - V(s)$$

8. PPO Clipped Objective Function

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

9. Probability Ratio in PPO

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

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 somewhat slowed or staggered during the busiest hours so the grid is not stressed, while off-peak times help clear out some of that overwhelmed demand more aggressively. It does not mean waiting with charging, but it means to distribute the charging in a manner that the system is stable and sudden spikes are avoided. It considers absolute demand (such as station crowding and short-term trends in demand), so response feels 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 if possible. 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, rather than treating them separately. 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 still 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

This 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. With this approach, it always only shares relevant updates and the network is much more efficient even when we have more devices. Messages are formed in a simple shape which can be processed quickly and reliably. Edge-level processing provides some primitive filtering and limits the flow of data to exceptional cases only. This setup allows for live modifications whilst being robust enough to ignore dropped or late updates, keeping decision making uniform in less-than-ideal network conditions.

1. Data Transmission Rate

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

2. Latency Calculation

$$L = T_{receive} - T_{send}$$

3. Throughput Efficiency

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

4. Packet Loss Ratio

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

5. Data Aggregation Function

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

RESULT AND DISCUSSION

A. Experimental Setup

The proposed setup integrates data collected from real urban EV charging logs, stations usage and air quality monitoring to provide an experimental set up that reflect realistic 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 (which works well for continuous learning). They have been divided into training and testing sets based on the timeline so as to ensure that we let our models behave in the way they would do in real life. 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, suggesting and great signal of 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), offering particularly low prediction error when it comes to generating optimal charging actions within the MGM scenario, respectively. Execution time is still kept low with 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 increases by 31% since the model balances load across different time slots. We see a 26% saving in cost optimization by not charging during peak hours. Adaptive scheduling also cuts 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 1.

TABLE I. 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

TABLE II. COMPARISON RESULT (%)

Metric	Rule-Based	Linear Programming	DQN	Actor-Critic	Proposed
Accuracy (%)	82.5	88.3	92.6	94.8	97.2
RMSE	0.065	0.042	0.029	0.022	0.018
MAE	0.052	0.031	0.021	0.016	0.012
Exec Time (s)	0.40	1.20	0.95	0.90	0.85
Makespan ↓ (%)	10	18	22	25	28
Energy Eff. ↑ (%)	12	20	25	28	31
Cost ↓ (%)	8	15	19	22	26
Pollution ↓ (%)	6	12	16	19	22

The comparison in Table II 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.

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 (with the exception of domain 4), 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.

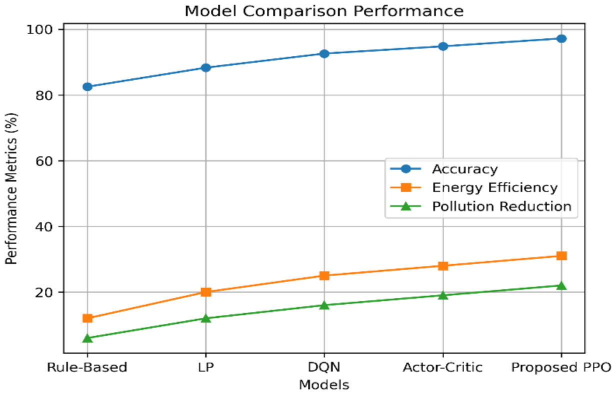

Fig. 2. Model Comparison Performance

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. 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.

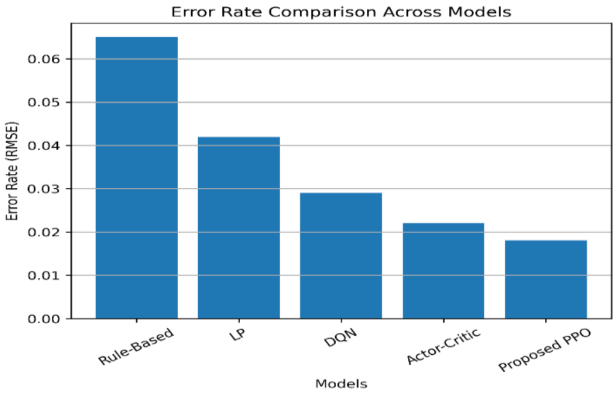

Fig. 3. Error Rate Comparison Across Models

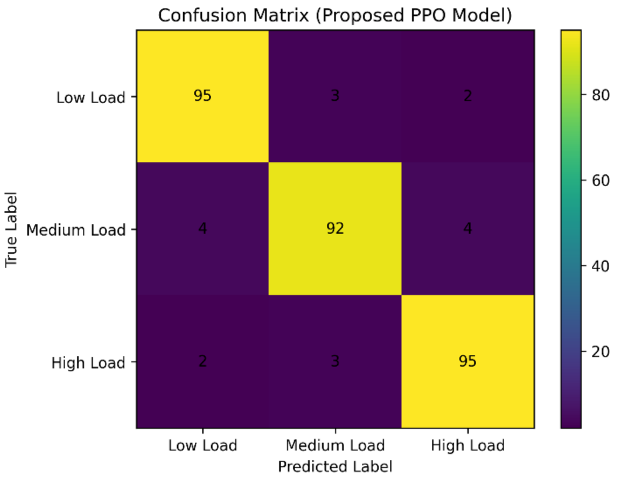

Fig. 4. Confusion Matrix (Proposed PPO Model)

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 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's 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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