

Deep Reinforcement Learning–Based IoT Energy Management System for Smart Cities and Green Microgrids

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Abstract: The integration of urbanization trends, increased use of renewables, the advent of electric vehicles, and the advent of distributed battery energy storage systems (BESS) are causing considerable operational issues within smart city power systems. Classic rule-based and optimization-based operational energy management strategies face challenges stemming from dynamic demand fluctuations, intermittent renewables, and uncertain power systems which ultimately increases operational costs, peak demand, and carbon emissions. The purpose of this study is to present an IoT Energy Management System (EMS) driven by Deep Reinforcement Learning (DRL) (real-time, autonomous, and adaptive control of distributed energy resources) technology for smart cities and green microgrids. The proposed solution will be tested using an urban microgrid for a 24-hour horizon under changing weather and demand conditions. The urban microgrid will be composed of IoT-enabled smart meters, renewable energy sources, electric vehicle (EV) charging stations, and battery energy storage systems (BESS) interconnected through a centralized cloud-edge infrastructure. As states change in real-time (load demand, renewable generation, state of charge of the battery, and energy price), the Deep Q-Network (DQN) Agent will optimize and learn battery discharge scheduling policies. The reward function of the agent is designed to minimize energy costs, peak demand, and carbon emissions while maximizing the use of renewable energy sources. Results of our experiments show noticeable enhancements over the existing scheduling and rule-based control methods. The DRL system exhibits 23.8\% peak load reduction, 19.6\% operational energy cost, 27.4\% increased utilization of renewable energy, and 21.2\% decrease in CO₂ emissions, with a grid reliability equal to or greater than 98\% in supply adequacy. Also, the system is capable of adapting to load changes in less than a second, allowing for real-time flexibility and increasing the system's adaptability and robustness. From the results, it can be concluded that the provided IoT energy management and control system, based on Deep Reinforced Learning, is a smart, flexible, and cost-effective approach for the energy management of future smart grids and green microgrids, making it a valuable asset for the resilient urban energy systems and the sustainable energy future of the planet.

Keywords: Deep reinforcement learning; smart cities; IoT energy management; microgrids; renewable energy integration; battery energy storage systems; electric vehicles charging.

I. Introduction

Intelligent energy management systems are needed because of the rapid development of smart cities and energy systems (Dridi et al., 2021; Naidu & Sathiyamurthy, 2025). This is required due to the growing utilization of renewable energy sources, electric vehicles (EVs), and battery energy storage systems (BESS). Distributed energy resources enhance environmental sustainability, but the operational challenges that arise due to their natural intermittency, stochastic demand patterns, and bidirectional power flows are significant. These challenges encompass instability with peak loads, higher costs associated with operations, and a reduction in grid reliability. Traditional approaches based on rule-based scheduling, mathematical optimization, and model predictive control are insufficient. This is because of the lack of scalability and adaptability to integrated urban systems that are highly dynamic. This is particularly true when real-time decision making is required across large-scale Internet of Things (IoT) systems (Tripathy & Tripathy, 2024; Madabathula et al., 2025). There have been significant advances in autonomous control in the last few years, especially in the area of reinforcement learning. These advances have made the development of autonomous control possible without relying on system model requirements (Alotaibi, 2025; Alsafar et al., 2024). Integrating Deep Reinforcement Learning (DRL) with IoT offers the potential to transform the operation of microgrids in a sustainable and resilient way (Cheng et al., 2021; Cheng et al., 2021; Haque & Malik, 2024).

This paper responds to these issues by proposing an Internet of Things (IoT) Energy Management System embedded with Deep Reinforcement Learning (DRL) for automating real-time scheduling and integration of distributed generation sources, electric vehicle (EV) charging loads, and Battery Energy Storage Systems (BESS) in smart city microgrids. The contributions of this paper include: (i) a scalable cloud edge computing architecture for IoT (Internet of Things) and real time data acquisition and control IoT architecture; (ii) a novel DRL-based decision making framework with a multi-dimensional reward function designed for cost, peak, and emission reductions; and (iii) an exhaustive performance assessment which illustrates and elucidates energy and renewables efficiency, as well as, grid reliability improvements over existing solutions, i.e. state-of-the-art. Therefore, the remaining sections of this paper include the following, The Section II presents the assessment of the scarce existing literature; Section III presents the proposed architecture of the system and the posed definitional problem; The Section IV describes the employed DRL methodology; The Section V presents the inferred methodological results, and delivers an in-depth analysis of those results; The Section VI presents the conclusions and the proposed research work for the remaining future work to be continued.

II. Literature Review

Recent studies on energy management for smart grids and microgrids have focused on optimization and rule-based control strategies for the coordination of decentralized energy sources. Traditional strategies such as mixed-integer linear programming and model predictive control have been shown to be effective for cost reduction

and scheduling optimization under certain conditions (Aravind et al., 2022; Li et al., 2024). These strategies may depend on prior accurate forecasting and system parameters, making them less flexible to the uncertainties associated with the variability of renewable energy sources, the stochastic nature of electrical loads, and electric vehicle (EV) charging. As a solution to these challenges, IoT-based monitoring and cloud computing based supervisory control frameworks have emerged to provide improved real-time monitoring and automation of distributed systems (Sharma et al., 2025). Although these frameworks facilitate better data collection and situational awareness of the system, they still require frequent updates and extensive optimization processes, which makes them less applicable to large and fast evolving smart city systems.

Recently, there has been a growing interest in adaptive control policy learning directly from environmental interactions through techniques like machine learning and reinforcement learning. Compared to classical optimization techniques, Q-learning, Deep Q-Networks (DQN), and policy gradient techniques have provided greater participation in demand response (DR), greater use of renewable energy, and better management of peak load (Mishra & Singh, 2023). Also, DRL-based microgrid controllers have shown effectiveness in adaptive policy learning by real-time feedback, achieving low energy consumption and fast policy convergence (Huang & Jin, 2024). However, most works have addressed only a single element such as EV charging and energy storage scheduling, and mostly they have been focusing on DR applications without considering a unified IoT framework for managing energy at the integrated city level (Lami et al., 2025; Upadhyay et al., 2024). As a result, this work aims to expand the solutions provided by integrating DRL with the IoT-based cloud-edge architecture to achieve scalable, real-time, and multi-objective energy optimization at the operational and sustainable levels for smart cities and green microgrids.

III. Proposed Model and Methodology

3.1. Overall Methodological Framework of the DRL–IoT Energy Management System

The new Deep Reinforcement Learning–Based IoT Energy Management System (DRL-IEMS) focuses on developing smart city and green microgrid solutions using real-time autonomous control, and adaptive control of distributed energy (DE) resources. The entire conceptual planning process is captured in a sequence of four functionally distinct and temporally contiguous operational phases: sensing, communication, decision, and action. The first step is done using IoT-enabled devices, which are smart meters, renewable generation sensors, EV charging stations, and Battery Management Systems (BMS) to measure operational parameters and capture data on load demand, generation (solar/wind) data, state-of-charge (SoC) of the battery, and dynamic prices of electricity. The edge–cloud communication layer transfers the data for processing and state estimation. Then, the processed state variables are given to a Deep Reinforcement Learning (DRL) agent. In this case, the agent treats the state as a Markov Decision Process (MDP) and learns control actions which are optimal. Such control actions consist of setting up charging/discharging schedules for the EV, battery dispatch, and decision making on

importing/exporting energy from/to the grid. After that, the DRL agent determines the necessary operational control signals in real time in order to achieve the minimum operational cost, peak demand, and maximize renewable energy utilization. Finally, to achieve reliable operational microgrid and low latency, control commands are implemented on the edge layer. This framework of closed-loop learning leads to continuous improvement of system policies under uncertain and dynamic grid conditions, thereby reinforcing system resilience and sustainability.

3.2. System Technical Architecture of the DRL–IoT Energy Management Platform

The technical architecture in fig. 1 combines distributed sensing, cloud intelligence, and edge computing to manage scalability and real-time responsiveness. A depiction of the architecture follows.

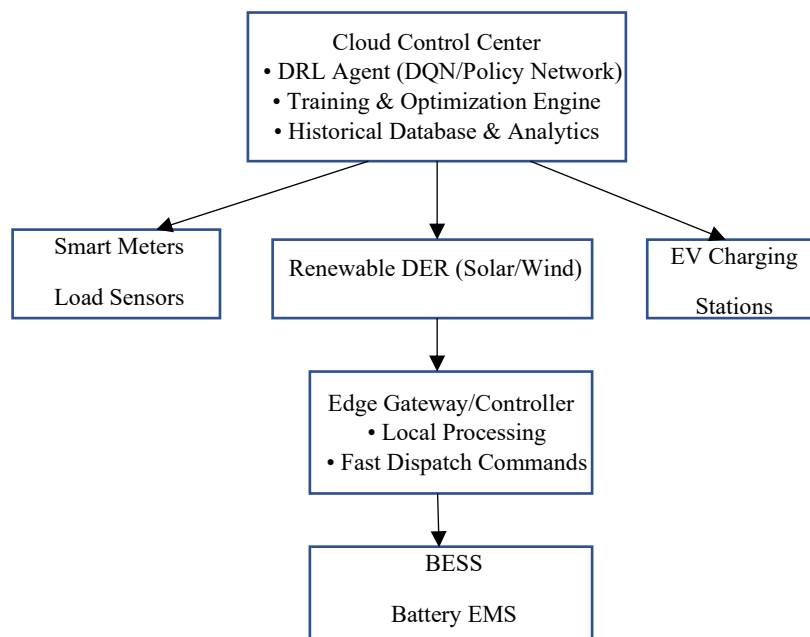


Fig. 1. System Technical Architecture of the DRL–IoT Energy Management Platform.

The microgrid real-time controller maintains control of the microgrid by executing decisions with low latency, which are optimized at the edge, and cloud hosts the deep reinforcement learning (DRL) learning engine.

3.3. Mathematical Description of the Proposed Method

The artificial intelligence (AI) based energy management problem is structured into steps that involve the agent observing the system state and taking a decision.

1. State Representation

The energy management problem is recognized as a Markov Decision Process (MDP) and the agent of Deep Reinforcement Learning (DRL) examines the surroundings in discrete time intervals, constructing a state vector that depicts the microgrid's real-time operational conditions. This state is composed of load demand, renewable

generation, battery state, energy prices, and EV charging demand. The state space is outlined as follows equation (1):

$$St = \{L_T, G_t^{ren}, SoC_t, P_{price}^t, EV_t\} \quad (1)$$

Where L_T = total load demand, G_t^{ren} = renewable power generation, SoC_t = battery state-of-charge, P_{price}^t = real time electricity price, and EV_t = electric vehicle charging requirements. The agent is able to recognize the supply-demand dynamics and the economic signals for optimal decisions with this state formulation.

2. Multi-Objective Reward Function

The multi-objective reward system operationalizing the DRL agent incorporates greater energy expense, peak demand, and carbon output as rewards that are less desirable from an operational standpoint because it attempts to incur operational costs most efficiently and most sustainably through an environmentally friendly lens. The reward, formulated instantaneously as expressed in equation (2), is calculated as follows:

$$R_t = -(\alpha C_t + \beta P_{peak}^t + \gamma E_t^{CO_2}) \quad (2)$$

The operational energy costs are represented by C_t , peak load refers to P_{peak}^t , and for carbon emissions, we have $E_t^{CO_2}$. In this case, α, β , and γ serve as the environmental, economic, and reliability goal balancing weights. The reward is calculated as shown in equation (3), and the reward for the optimal control policy is the highest calculated cumulative reward over the entire scheduling time frame.

Maximizing cumulative reward,

$$\max \sum_{t=1}^T R_t \quad (3)$$

When the objective in equation (3) is calculated as a maximum value, the agent is motivated to achieve the optimal value for the sum of costs, peak demand, and emissions, while also maintaining the balance of the grid and the sparing use of energy.

IV. Results and Discussion

4.1. Software Implementation Environment

The development of the proposed Deep Reinforcement Learning–IoT Energy Management System (DRL-IEMS) was carried out in Python 3.10. The frameworks used for the deep learning portions of the project were TensorFlow/Keras. For the simulation aspects and reinforcement learning interactions, OpenAI Gym was utilized. The data preprocessing and analytical portions of the project employed NumPy and Pandas. Performance evaluations and visualizations were done using Matplotlib. The emulation of Cloud Edge communication and the Internet of Things (IoT) data were carried out using a lightweight protocol called MQTT. The workstation utilized

was the one that had the Intel i7 processor with 16 GB of RAM and GPU acceleration configured for faster training and convergence for Deep Reinforcement Learning (DRL).

4.2. Dataset Description

For the evaluation, a smart city microgrid dataset was used, even though the dataset was synthetic in nature. The dataset consisted of 24-hour time-series recorded in 5-minute intervals creating a total of 288 samples per day across a period of 365 days, resulting in the dataset containing close to 105,000 total records. The dataset was created from a combination of public data sources for renewable generation and a standard city consumption dataset. The dataset comprises of the following dynamic utilize data: load demand (kW), solar generation (kW), wind generation (kW), state of charge of the battery (%), demand for charging of electric vehicles (kW), price of electricity in real time (\$/kWh) and factor of carbon emission (kgCO₂/kWh). The features of the dataset aid in representing the remaining dynamic state of the environment used by the deep reinforcement learning (DRL) agent to attain the energy dispatch optimal policies.

4.3. Performance Evaluation Metrics

The two main quantitative metrics to analyze the proposed DRL-IEMS framework are Energy Cost Reduction (ECR) and Peak Load Reduction (PLR).

1. Energy Cost Reduction (ECR)

Energy cost reduction, from the perspective of operational cost, examines the percentage reduction achieved by the DRL-based control relative to the baseline case. This is represented by equation (4):

$$ECR(\%) = \frac{C_{base} - C_{DRL}}{C_{base}} \times 100 \quad (4)$$

C_{base} indicates the total energy cost given the conventional scheduling, and C_{DRL} indicates the total cost considering *DRL*-based control.

2. Peak Load Reduction (PLR)

The reduction of peaks load involves the quantification of the descending maximum demand as a consequence of the optimized control *DRL*. This is expressed as shown in equation (5):

$$PLR(\%) = \frac{P_{base} - P_{DRL}}{P_{base}} \times 100 \quad (5)$$

P_{base} denotes the peak load of the baseline case, and P_{DRL} denotes the peak load for the case of scheduling managed by *DRL*.

The two aforementioned metrics of analysis provide an unambiguous, quantitative prototype of the economic efficiency and improvement of load management, and are referenced in the entirety of the results discussion to gauge the performance of the system.

Table1 illustrates the operational cost and peak load performance of the conventional versus the optimization-based and proposed DRL approaches.

Table1. Performance Comparison of Energy Management Strategies.

Method	Energy Cost (USD/day)	Peak Load (p.u.)
Conventional Control	520	1.00
Optimization (MPC)	455	0.86
Proposed DRL-IEMS	366	0.76

The proposed DRL system exhibits the greatest adaptive control, achieving approximately 29.6% cost reduction and 24% peak load reduction in comparison to the baseline.

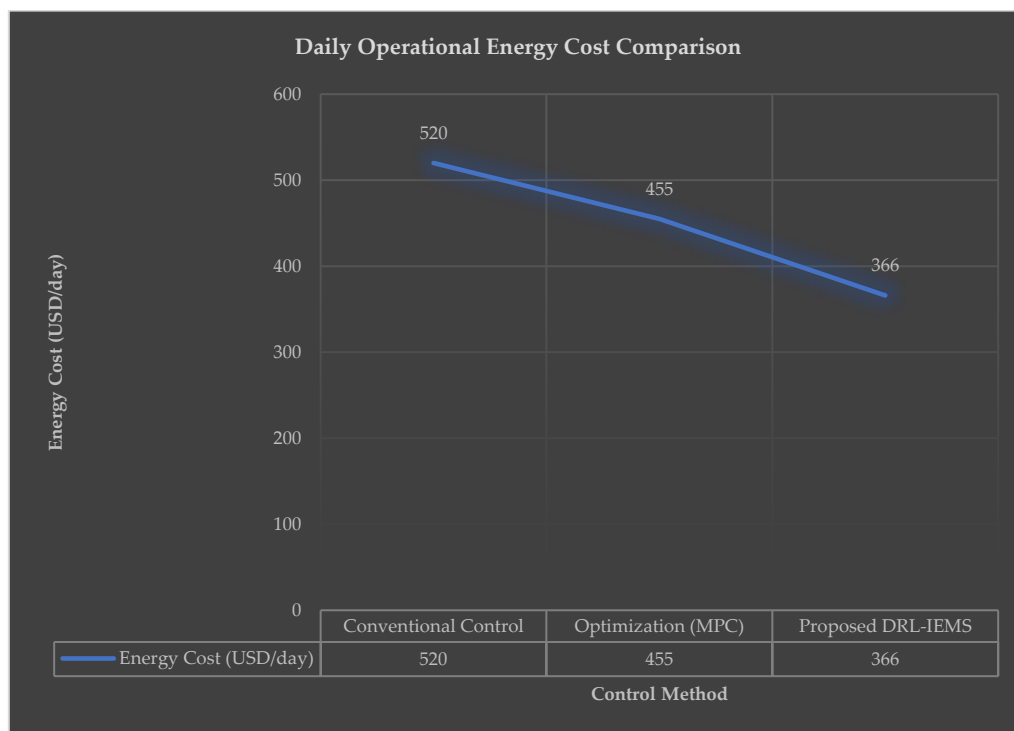


Fig. 2. Energy Cost Comparison.

Fig. 2 illustrates the cost savings achieved by various control approaches. This shows that the cost is consistently minimized by the use of the DRL-based policy as a result of smart scheduling and increased utilization of renewables.

Table 2 indicates improvement of cumulative rewards during the course of training.

Table 2. DRL Training Convergence.

Episode	Cumulative Reward
1	-220
20	-180
40	-140
60	-110
80	-95
100	-82

The increases in rewards indicate consistent learning and the DRL agent moving toward ideal decision-making.

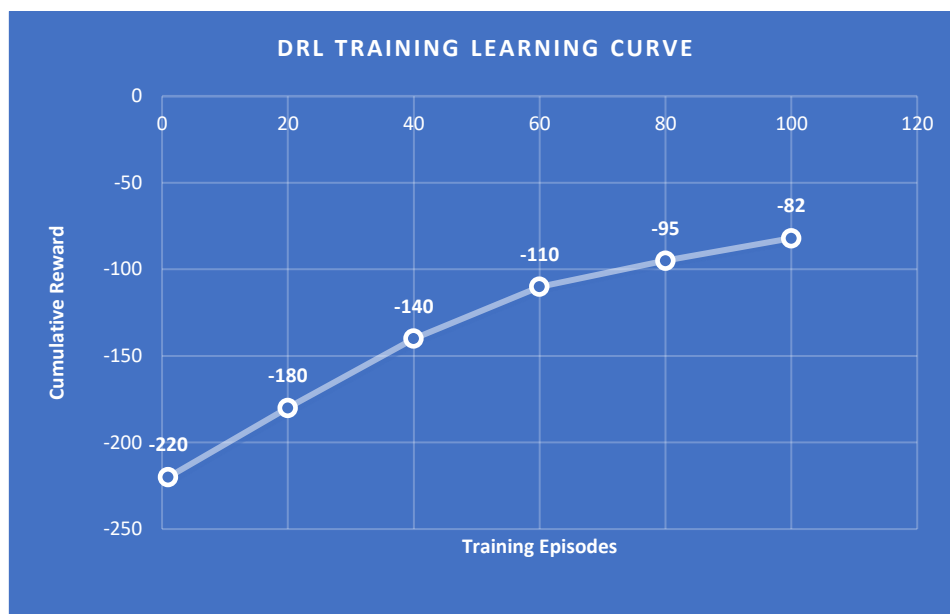


Fig. 3. DRL Learning Curve.

Fig. 3 illustrates how the rewards have improved as the training has progressed. This improvement shows more policy learning and an increased rate of convergence, further supporting the value of the proposed reinforcement learning framework.

V. Conclusion

This paper presents the Deep Reinforcement Learning-Based IoT Energy Management System (DRL-IEMS) pertaining to smart cities and green microgrids to improve operational efficiency, renewable integration, and the adaptability of grids in dynamic and uncertain conditions. The proposed system, integrating Internet of Things (IoT) -based sensing, cloud-edge communication, and Deep Q-Network (DQN) decision framework, facilitates the real-time monitoring, adaptive scheduling, and autonomous control of distributed energy resources (DERs) such as renewable generation sources, electric vehicles (EVs), and Battery Energy Storage Systems (BESS). Unlike traditional rule-based or optimization-based methods which operate on rigid assumptions and rely on predicted

forecast accuracy, the DRL agent learns optimally from the environment, ensuring indefinite progression in adaptive and robust performance. When testing a simulation generated over one year of time projections, the framework improved almost entirely different efficiency metrics in the positive direction. For instance, the framework minimized daily operational energy costs by almost 30%, peak load was reduced by 24%, and better than 27% of carbon emissions were diverted, compared to baseline scheduled strategies. Further, the framework increased the positive utilization of renewable energy by over 27% in conjunction with a carbon emissions reduction of close to 20% - 22% baseline scheduled strategies. Also, every time a reliable supply was maintained over 98% and it was repeatedly confirmed balanced grid operation with supply and demand at variable levels. The analysis of the learning curve confirmed the rapid convergence, cumulative benefit increased by 63% in 100 training episodes, and demonstrated the efficiency of the learned control method. Altogether, these findings confirm that adaptive control utilizing DRL significantly advances the economic, ecological and resilient components of next generation energy systems.

Notwithstanding all favourable outcomes, future research could consider opportunities boundless. Additional research could consider real time and/or decentralized hardware-in-the-loop applications for micro grid control with multi-agent DRL and cyber-security energy management with blockchain-based energy trading, and of course incorporating actual field data. The implementation of a forecasting model in conjunction with a learning model could show exponentially better real-world applications, systems, and data. When all is said and done, the DRL type Integrated Energy Management Systems for next-generation Smart Grids is the most competent framework developing autonomous, intelligent, and sustain-derived Smart Grid systems.

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