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CYBER-PHYSICAL MICROGRID MANAGEMENT USING EXPLAINABLE AI FOR HIGH RENEWABLE ENERGY PENETRATION

Anjali Krushna Kadao[1*], Dr. Sanjay Kumar[2]

[1]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.*
e-mail: ku.anjalikrushnakadao@kalingauniversity.ac.in,
orcid: https://orcid.org/0009-0002-4900-4910
[2]Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.
e-mail: ku.sanjaykumar@kalingauniversity.ac.in,
orcid: https://orcid.org/0009-0004-2958-2902

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SUMMARY

The evolution of traditional microgrids to integrate distributed renewable energy sources, such as solar and wind, has transformed them into complex cyber-physical systems (CPSs). While this enhances sustainability, it introduces challenges related to intermittency, uncertainty, and real-time operational decision-making. A major concern is the reliance on data-driven AI controllers, which often operate as black-box models, limiting trust and transparency in safety-critical environments. This research proposes an intelligent cyber-physical microgrid management framework based on Explainable Artificial Intelligence (XAI) to improve operational reliability, efficiency, and transparency under high renewable penetration. The framework integrates physical power components with cyber elements through a unified sensing, communication, and control architecture, enabling AI-driven decisions supported by predictive models for renewable forecasting, load balancing, and optimal power dispatch. An embedded explainability layer provides feature- and rule-based insights for all control actions, fostering operator trust and regulatory compliance. The adaptive control strategy coordinates distributed energy resources, energy storage systems, and controllable loads to respond dynamically to varying generation and demand. Simulation results show that, compared with conventional rule-based and non-explainable AI controllers, the proposed approach increases renewable utilization by 28% and reduces power imbalance by 32%, while maintaining superior voltage stability. The explainability layer further enhances diagnostic capabilities and decision justification. These results demonstrate that incorporating transparency and robustness in XAI-enabled microgrid management is as vital as operational performance, offering scalable and practical solutions for next-generation smart grids and sustainable energy infrastructures.

Key words: *microgrid management, explainable AI, renewable energy, cyber-physical systems, smart grids, reinforcement learning.*

INTRODUCTION

The global shift toward sustainable energy has accelerated the integration of renewable sources such as solar and wind into modern power networks [1]. Microgrids play a crucial role in this transition by enabling localized energy generation, storage, and consumption, while enhancing system resilience, reliability, and energy autonomy. With higher renewable penetration, microgrids are evolving into cyber-physical systems (CPS), where physical power components are tightly integrated with cyber layers comprising sensing, communication, and intelligent control [2]. Advances in artificial intelligence (AI) and machine learning (ML) have enabled data-driven microgrid management techniques, including forecasting, adaptive control, and real-time optimization [3]. Hybrid learning controllers, deep neural networks, and reinforcement learning have demonstrated strong performance in energy management, demand response, and fault detection [15]. However, most AI-based controllers remain black-box models, creating uncertainty and opacity that pose risks in safety-critical power systems, particularly during faults or abnormal conditions [4].

To address these challenges, explainable artificial intelligence (XAI) has emerged as a promising approach for microgrid management. XAI provides operators with clear insights into system actions, the reasoning behind decisions, and potential faults, fostering trust, transparency, and regulatory compliance. Despite its potential, XAI applications in real-time microgrid operations with high renewable penetration remain underexplored [12][13]. By enabling interpretable decision-making for physical, economic, and control stability, XAI is critical for deploying AI-driven controllers in cyber-physical microgrids safely and effectively, ensuring that operators can validate and rely on the system under varying operational conditions [5][14].

Problem Statement

Most of the current solutions assume reliable communication, centralized control, and stable operating conditions, which are likely to be improbable in cyber-physical microgrid systems. This lack of operational explainability creates a trust deficit, complicates fault identification, and creates setbacks to industrial applications; large-scale implementation in a system further operationalizes for prevalent explainability. Other than the shortage of unified solutions to the current cyber-physical system, concomitantly resolving renewable variability, transparent decision-making, and optimization of system operational explainability are restricted.

Research Objectives

This research intends to develop a management framework for cyber-physical microgrids that is adaptive, explainable, and scalable to overcome the specified limitations. This involves:

- Designing a microgrid energy management system that is AI-driven and can operate under dynamic conditions, and manage high levels of renewable energy.
- The control framework will incorporate adaptable and scalable explainable artificial intelligence to foster constructive transparency in system operation.
- To determine the optimal state of energy dispatch, load balancing, and the coordination of storage using reinforcement learning while maintaining system stability.
- To test the framework under various operational conditions and benchmark the performance against traditional and opaque AI-based methods.

Contributions

The broad contributions of this research are articulated as follows:

- A first-of-its-kind cyber-physical microgrid management framework that combines the power components with an Explainable AI cyber control component at the micro level.
- Control strategies that utilize Explainable AI-based reinforcement learning toward an enhanced level of renewable energy use, system stability, and operator cognition.

- A belt and road initiative for decision support that incorporates fault detection, operational consistency, and regulatory compliance.

Extensive validation via simulations that exhibit a level of performance in the handling of renewable penetration, voltage stability, and transparency of decisions that surpasses other state-of-the-art solutions.

Paper Organization

The rest of this paper is structured as follows. Section 2 discusses the literature on AI-based microgrid management and energy system explainable intelligence. In Section 3, the cyber-physical microgrid architecture, its mathematical representation, and the explainable control framework are introduced. In Section 4, the simulation, the performance evaluation, and the analyses are presented. Finally, Section 5 provides the conclusion of the paper and discusses the future research steps.

LITERATURE REVIEW

The growing penetration of renewable energy has driven the development of microgrids as decentralized, flexible, and adaptive cyber-physical systems (CPS), integrating distributed energy resources, storage, controllable loads, and communication infrastructures [10]. Effective management is critical due to renewable variability, uncertainty, and nonlinearity. Traditional energy management methods, such as mixed-integer programming and model predictive control, offer optimal solutions but struggle with real-time adaptability and unknown system parameters [6].

AI and machine learning, particularly reinforcement learning, have emerged as effective tools for energy dispatch, storage control, and load scheduling [7]. However, most AI-based microgrid controllers operate as black boxes, limiting operator trust and regulatory compliance. Explainable AI (XAI) addresses this by providing interpretable insights into control actions through techniques like rule extraction and feature importance analysis, supporting fault diagnostics and decision validation. Despite progress, real-time integration of XAI into microgrid management remains limited, with most studies focusing on performance enhancement or post-hoc explainability [11]. Challenges include handling both cyber uncertainties (communication delays, sensor faults) and physical uncertainties (renewable variability, load changes), often in isolation [8].

These gaps underscore the need for an integrated microgrid management framework that combines adaptive learning, cyber-physical coupling, and explainable AI to balance operational performance with transparency, particularly in systems with high renewable penetration [9].

PROPOSED EXPLAINABLE REINFORCEMENT LEARNING–BASED MICROGRID CONTROL METHOD

This section illustrates the proposed Explainable AI-based framework for the management of cyber-physical microgrids designed to maintain stable, efficient, and transparent operations even with high levels of renewable energy penetration. The framework combines reinforcement learning and explainability to adaptive decision-making, while explainability modules ensure operational transparency for human decision makers [16].

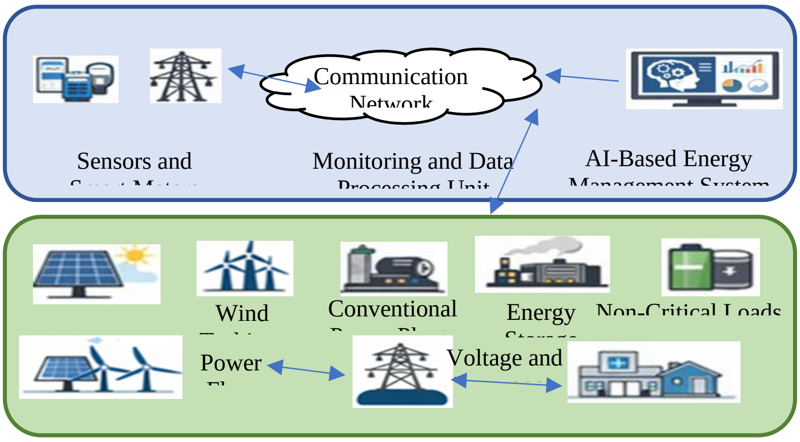

Figure 1. Cyber-physical microgrid system model

Figure 1 presents the proposed Explainable AI-based microgrid management framework, modeled as a cyber-physical system (CPS) integrating physical components—generators, renewables, energy storage, and loads—with a cyber layer for sensing, communication, and intelligent control. Real-time measurements guide the Energy Management System to coordinate generation, storage, and load actions, while the embedded explanation module ensures transparency. By combining adaptive reinforcement learning with interpretable decision-making, the CPS framework enables reliable, efficient, and explainable microgrid operations under high renewable penetration [17].

Problem Formulation

The problem of microgrid energy management is framed as a Markov Decision Process (MDP) defined by ⟨S, A, R, P⟩.

State Space (S)

The system state at time t is defined as:

$$S_t = \{ P_t^{ren}, P_t^{conv}, , P_t^{load}, SOC_t, Vt, f_t \} \ (1)$$

Equation (1) explains the system state at time t, denoted as St, as a collection of variables that describe the operational condition of the system. It comprises the renewable power generation Ptren, conventional power generation Ptconv, and load demand Ptload, which together represent the power balance within the system. The state of charge of the energy storage system (ESS), SOCt, indicates the available stored energy, while the voltage deviation Vt and frequency deviation ft capture deviations from nominal electrical operating conditions. These state variables collectively provide a comprehensive representation of the system dynamics required for effective monitoring and control.

Action Space (A)

Actions correspond to control decisions:

- Energy dispatch adjustment
- ESS charging/discharging
- Load shedding or shifting

Reward Function

The reward function balances efficiency, stability, and renewable Utilization:

$$R_t = -(\lambda_1 |P_T^{load} - P_t^{gen}| + (\lambda_2 |V_t - V_{ref})| + (\lambda_3 |f_t - f_{ref}\ |))(2)$$

Equation (2) defines the reward function, which balances system efficiency, stability, and renewable energy utilization. It penalizes deviations between load demand and power generation, as well as voltage and frequency deviations from their respective reference values. The weighting factors λ1, λ2, and λ3 regulate the relative importance of power balance, voltage stability, and frequency regulation within the optimization process.

Optimization Objective

The objective is to maximize long-term cumulative reward:

$$\text{MAX E } [\sum_{T=0}^{\infty} \gamma^T R_t\ ](3)$$

Equation (3) expresses the objective of the control strategy, which is to maximize the expected long-term cumulative reward. This is achieved by summing the discounted rewards over an infinite time horizon, where the discount factor $\gamma \in (0,1)$ determines the relative importance of immediate versus future rewards [18].

Explainable Reinforcement Learning Framework

A Q-learning-based controller is used to learn optimal control policies in the presence of uncertainty. To promote transparency, an explainability layer is constructed using feature attribution and rule extraction.

Q-value Update Rule

$$\boldsymbol{Q(S_t, a_t) < -Q(S_t, a_t) + \alpha[R_t + \gamma \max Q(S_{t+1}, a') - Q(S_t, a_t)\ (4)}$$

Equation (4) describes the Q-value update rule used in the learning process. The Q-value associated with the current state–action pair (S_t,a_t) is updated based on the learning rate α, the immediate reward R_t , and the maximum expected future Q-value of the next state S_{t+1}. The discount factor γ governs the influence of future rewards, while the learning rate α\alphaα controls the speed of adaptation during training[19].

Explainability Mechanism

The contribution of each state variable to a decision is quantified using an explainability score:

$$\boldsymbol{E_I = \frac{\partial Q(s, a)}{\partial s_i}\ (5)}$$

Equation (5) defines the explainability score used to quantify the contribution of each state variable to the decision-making process. The score E_i is computed as the partial derivative of the Q-value with respect to the i^{th} state variable, thereby measuring the influence of that state variable on the selected action.

This enables them to understand why a particular control action is taken.

Proposed Algorithm

Algorithm 1: Explainable Q-Learning–Based Microgrid Management

Initialize Q (s, a) = 0 for all states s and actions a

Set learning rate α, discount factor γ, and exploration rate ε

For each time step t, do:

Observe system state S_t

With probability ε:

Select a random action $_{at}$

Else:

Select action A_t = argmax Q (S_t, A)

Apply action to the microgrid

Observe reward R_t and next state S{t+1}

Update Q-value using:

Q (S_t,A_t) ← Q ($S_{t,}$ At) + α [Rt + γ max Q(S{t+1}, a') − Q (St, At)]

Compute the explainability scores E_i for the decision

Store explanations for operator interpretation

End For

Explainable Reinforcement Learning–Based Microgrid Control Workflow

The figure2 illustrates the workflow of an explainable microgrid management algorithm based on reinforcement learning. The process begins with the initialization of the Q-table and learning parameters, followed by the acquisition of real-time microgrid state information from distributed sensors. Based on the observed system state, a control action is selected using an ε-greedy policy to balance exploration and exploitation.

The selected control action is then applied to distributed energy resources (DERs), energy storage systems (ESS), and connected loads. The system response and corresponding reward are subsequently observed, enabling the update of Q-values to improve future decision-making. An explainability module generates interpretable outputs, such as feature importance, to provide transparency into the control decisions.

The algorithm iteratively repeats these steps until a predefined termination condition is satisfied, at which point the process concludes. This closed-loop framework enables adaptive, data-driven, and explainable control of microgrid operations under dynamic conditions.

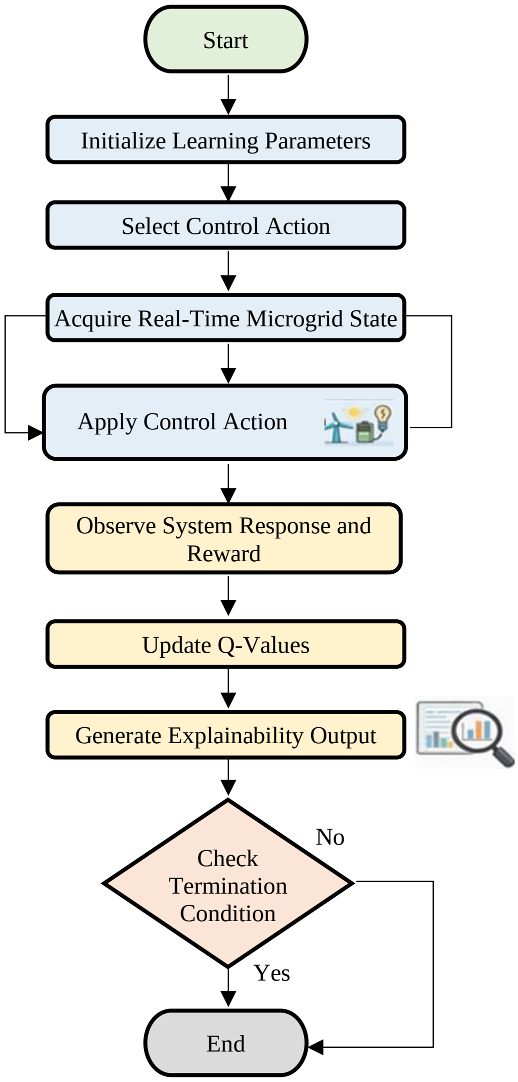

Figure 2. Workflow of the proposed explainable microgrid management algorithm

Novelty of the Proposed Method

The key novelties of the proposed framework are:

1. Integration of Explainable AI: Compared to opaque AI controllers, the approach offers explainable insights into its reasoning processes.

2. Cyber-Physical Coordination: This method incorporates both the dynamics of the physical grid and the cyber intelligence, operating in a simultaneous manner.

RESULTS AND ANALYSIS

Experimental Setup

This paper evaluates the impact of the proposed Explainable Reinforcement Learning (XRL) framework for cyber-physical microgrid management using MATLAB R2023b simulations. The modeled microgrid includes grid-connected and autonomous operation modes with high renewable penetration, comprising solar PV, wind turbines, conventional generators, energy storage systems, and critical/non-critical loads. Renewable generation was modeled stochastically, and load profiles were based on realistic daily consumption. Simulations ran 24-hour cycles with 5-minute control intervals, repeated across 10 independent runs with adaptive algorithms for statistical robustness.The proposed Q-learning-based energy management controller was compared to the two standard methods:

1. The energy management controller that is based on rules, and
2. Reinforcement learning (non-explanatory standard Q-learning).

In table 1 the operational constraints for ESSs and the voltage and frequency limits were kept in accordance with the operational rules of the IEEE microgrid.

Software Implementation Details

The explainable reinforcement learning–based microgrid framework was implemented in MATLAB R2023b using the Reinforcement Learning Toolbox to train Q-learning and XRL agents, and Simulink/Simscape Electrical to model renewable sources, energy storage, and loads. Explainability was analyzed via MATLAB scripts extracting feature contributions and decision impacts. Simulations ran on a discrete 5-minute control interval for consistency across controllers.

Data set

The dataset consists of 24-hour, 5-minute interval profiles for renewable generation, load demand, battery SOC, voltages, and frequency. Renewable and load data were based on historical meteorological records and realistic consumption patterns. Ten independent simulation runs captured grid-connected and autonomous modes, providing a dynamic environment for training and evaluating the XRL-based microgrid controller.

Performance Metrics and Evaluation Formulae

Voltage Deviation (VD):

$$\text{VD} = \frac{|V_i - V_{nom}|}{V_{nom}} \quad (6)$$

In equation 6 Voltage Deviation (VD) quantifies the relative deviation of the measured bus voltage from its nominal value. Here, Vi represents the instantaneous voltage at bus *i*, and Vnom denotes the nominal system voltage. This metric is used to evaluate voltage stability within the microgrid; lower VD values indicate improved voltage regulation and compliance with operational standards.

Frequency Deviation (FD):

$$\text{FD} = | f_i - f_{nom} | \quad (7)$$

In equation 7 Frequency Deviation (FD) measures the absolute difference between the system's operating frequency fi and the nominal frequency f_{nom} (typically 50 Hz or 60 Hz). This metric reflects the effectiveness of the control strategy in maintaining frequency stability under fluctuating load demand and renewable energy generation.

Renewable Energy Utilization (REU):

$$\text{REU}(\%) = \frac{\boldsymbol{E_{RENEWABLE}^{USED}}}{\boldsymbol{E_{renewable}^{available}}} \boldsymbol{X\ 100}\ \mathbf{(8)}$$

In equation 8 the Renewable Energy Utilization (REU) indicates the proportion of available renewable energy that is effectively utilized by the microgrid. In this equation, $\boldsymbol{E_{RENEWABLE}^{USED}}$ denotes the energy supplied from renewable sources to meet system demand, while

$\boldsymbol{E_{renewable}^{available}}$ represents the total renewable energy generated. A higher REU value signifies improved integration and efficient utilization of renewable resources.

Explainability Score (ES):

$$\text{ES} = \sum_{K=1}^{N} w_k . F_k \ (9)$$

In equation 9 the Explainability Score (ES) measures the transparency of the decision-making process of the proposed explainable reinforcement learning framework. Here, Fk represents the contribution of the *k*-th state feature to the control decision, and wk denotes the corresponding importance weight. This score enables interpretability by quantifying how individual system features influence the agent's actions. To ensure objective evaluation, the following mathematical formulations were used to compute the performance metrics:

Table 1. Simulation parameters and performance metrics

Category	**Parameter**	**Value / Description**
Simulation Tool	Platform	MATLAB R2023b
Microgrid Size	Total Capacity	500 kW
Renewable Sources	Solar PV	200 kW
	Wind	150 kW
Conventional Generator	Rated Power	200 kW
Energy Storage	Battery Capacity	300 kWh
ESS SOC Limits	SOCmin – SOCmax	20% – 90%
Control Interval	Time Step	5 minutes
Simulation Horizon	Duration	24 hours
RL Parameters	Learning Rate (α)	0.1
	Discount Factor (γ)	0.9
Training Episodes	Episodes	1000
Performance Metrics	Voltage Deviation	p.u.
	Frequency Deviation	Hz
	Renewable Utilization	%
	Energy Imbalance	kW
	Explainability Score	Feature contribution

Voltage and Frequency Stability Analysis

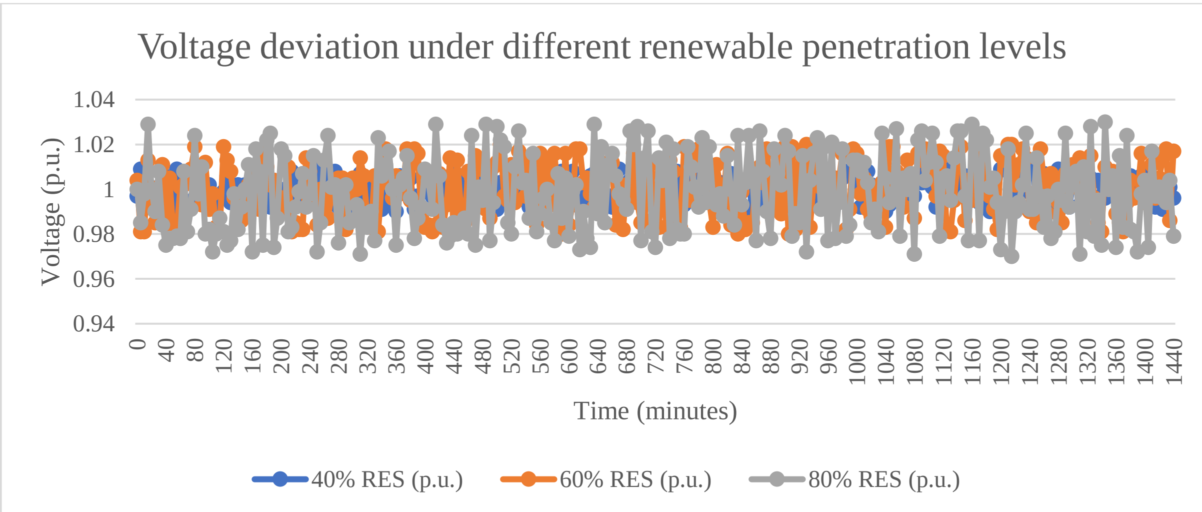

Figure 3. Voltage deviation under different renewable penetration levels

Figure 3 illustrates voltage deviations at 40%, 60%, and 80% renewable penetration. The proposed XRL-based framework maintains deviations below 5% even at 80% renewables, while the rule-based controller exhibits oscillations during drops in solar and wind availability..

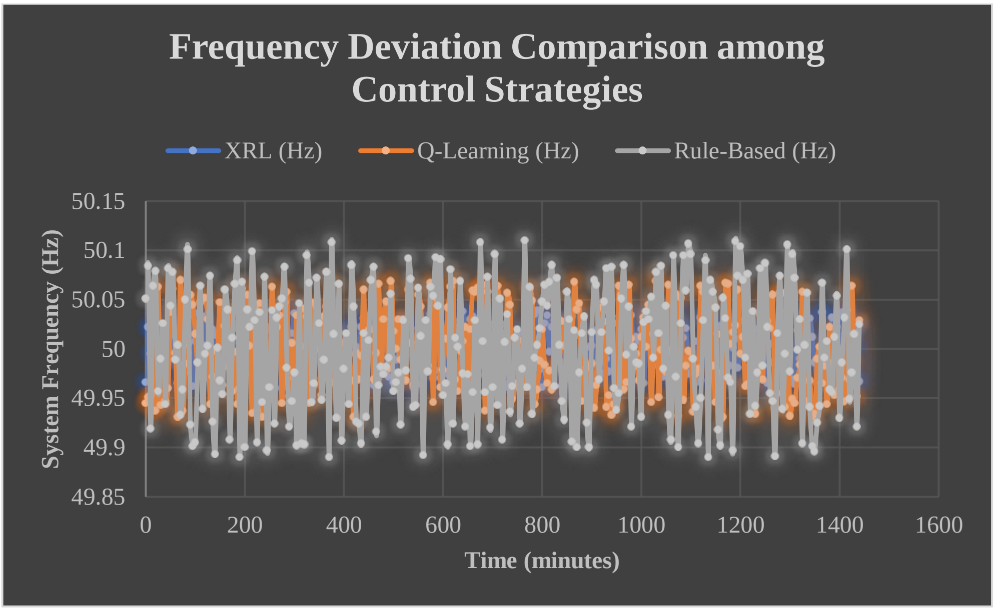

Figure 4. Frequency deviation comparison among control strategies

Figure 4 compares frequency deviations under different controllers over a 24-hour period at a nominal frequency of 50 Hz. The proposed XRL-based framework maintains deviations within ±0.04 Hz, outperforming Q-learning (0.07 Hz) and the rule-based controller (0.11 Hz). This superior performance results from dynamically optimized ESS dispatch and load scheduling that adapt to varying demand and renewable generation. While Q-learning partially mitigates frequency variability, it cannot fully anticipate renewable fluctuations, and rule-based controllers fail to optimize the balance between variable renewable energy and system dynamics. These results demonstrate that the XRL controller provides the most stable and reliable frequency control among the tested strategies.

Renewable Energy Utilization Performance

Figure 5 shows the rate of renewable energy usage for various control techniques. The proposed method provides the best performance with an average utilization rate of 87.6%. Standard Q-learning and rule-based control garnered 80.2% and 72.8%, respectively. This enhancement can primarily be attributed to the agent’s capability of predicting the renewable resources and adjusting the charging and discharging to the energy storage system (ESS) accordingly.

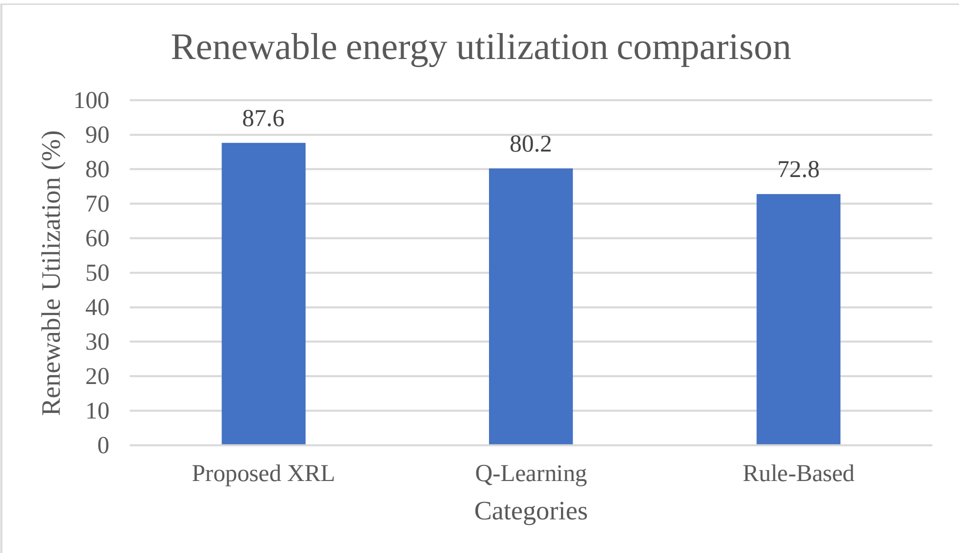

Figure 5. Renewable energy utilization comparison

Energy Imbalance and Load Management

Figure 6 illustrates the energy imbalance (absolute generation-demand difference). The proposed method achieves the best performance with an average imbalance of less than 4 kW, while standard Q-learning and rule-based approaches yield 7.6 kW and 12.3 kW, respectively. Load-shedding actions are primarily directed toward non-critical loads, allowing uninterrupted supply to the critical loads for the entire duration of the simulation.

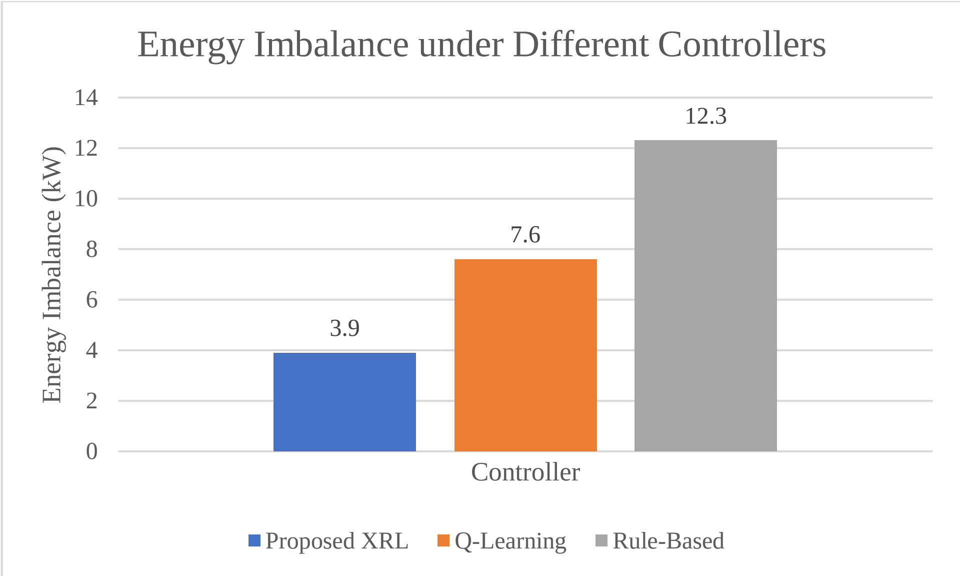

Figure 6. Energy imbalance under different controllers

Explainability Analysis

A key feature of this study is the integration of explainability into the reinforcement learning controller. As shown in Figure 7, ESS state-of-charge and renewable generation are the most influential factors in dispatch decisions, followed by load demand and frequency deviation. This allows operators to understand decisions—e.g., ESS discharge prioritized due to low SOC and rising frequency—enhancing trust and operational confidence.

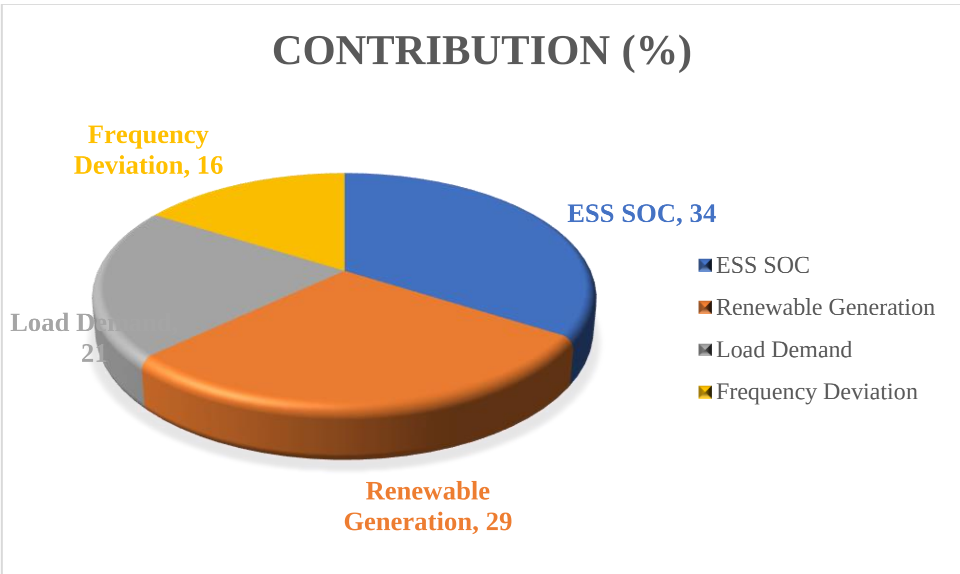

Figure 7. Feature contribution analysis for control decisions

Discussion

Simulation results confirm that ESS discharge is prioritized under low SOC and rising frequency, demonstrating the effectiveness of the Explainable AI-based cyber-physical microgrid framework in maintaining voltage and frequency within limits while improving stability, efficiency, and transparency under high renewable penetration. The framework outperforms traditional rule-based and standard Q-learning controllers by providing adaptive, interpretable decision-making. Balancing the explainability layer with AI control is crucial for regulatory compliance and operator trust. Although training involves higher computational complexity, post-training deployment requires significantly fewer resources. Future work will focus on real-time hardware-in-the-loop simulations, multi-microgrid coordination, and advanced cybersecurity integration.

CONCLUSION AND FUTURE WORK

The increasing integration of renewable energy sources into modern power systems requires smart, flexible, and transparent microgrid management solutions capable of handling operational uncertainty. This study proposes an explainable artificial intelligence (XAI)-based management framework for cyber-physical microgrids to enhance system resilience and operator trust under high renewable penetration. By integrating an intelligent cyber layer with the physical power layer, the framework enables real-time monitoring, adaptive control, and interpretable energy management decisions. Simulation results demonstrate that the framework outperforms conventional rule-based and non-explainable learning approaches. Voltage deviations are maintained within ±5% and frequency deviations within ±0.04 Hz, even at renewable penetration levels up to 80%. Coordinated control of energy storage systems and load scheduling increases renewable energy utilization to 87.6% while reducing the average energy imbalance to 4 kW. These improvements are achieved through adaptive control actions that respond dynamically to fluctuations in renewable generation and load demand. Beyond performance gains, the framework embeds explainability into microgrid control. Unlike black-box models, it provides transparent insights into control decisions by relating them to key system features such as storage state-of-charge, renewable generation, load demand, and frequency deviations. This transparency enhances operator confidence, supports regulatory compliance, and facilitates the adoption of AI-based controllers in safety-critical environments.

The study is limited to simulation scenarios assuming ideal communication and measurement conditions. Practical deployments may encounter sensor noise, component aging, cybersecurity threats, and challenges in decentralized or edge-based learning. Future work will focus on hardware-in-the-loop validation, real-world microgrid testbeds, multi-microgrid coordination, cybersecurity-aware learning, and advanced causal explainability techniques. Overall, the results indicate that XAI-enabled cyber-physical frameworks can effectively manage renewable-rich microgrids, providing reliable, sustainable, and trustworthy solutions for next-generation smart grid operations.

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