

Machine Learning For Frequency Regulation In Islanded Microgrids With Renewable Integration

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Abstract

The growing penetration of renewable energy sources (RES) such as photovoltaic (PV) and wind generation into islanded microgrids has introduced significant frequency-stability challenges due to the intermittent, low-inertia nature of power-electronic-interfaced generation. Conventional droop-based and Proportional-Integral (PI) secondary controllers, while structurally simple, struggle to maintain frequency within acceptable limits under fast, stochastic disturbances. This paper investigates the application of machine learning (ML), and specifically deep reinforcement learning (DRL), for adaptive frequency regulation in islanded microgrids with high renewable integration. A single-area islanded microgrid model comprising diesel generation, wind, PV, and battery energy storage is developed, and an actor-critic DRL-based secondary controller is designed to adaptively adjust regulation commands in response to load and renewable disturbances. The proposed controller is benchmarked in simulation against conventional Droop+PI, Fuzzy-PI, and Artificial Neural Network (ANN)-based controllers using metrics including peak frequency deviation, settling time, overshoot, root-mean-square error (RMSE), and the integral of time-weighted absolute error (ITAE). Results show that the proposed ML-based controller reduces peak frequency deviation by approximately 68% and settling time by nearly 73% relative to the conventional Droop+PI scheme, while also improving robustness under stochastic renewable fluctuations. These findings support the practical viability of ML-based frequency regulation for next-generation islanded and remote microgrids.

Keywords: Machine learning, deep reinforcement learning, islanded microgrid, frequency regulation, load frequency control, renewable energy integration, secondary control.

1. Introduction

Islanded microgrids are self-sufficient electrical networks that operate independently of the main utility grid, typically serving remote communities, islands, industrial campuses, or critical facilities where grid interconnection is impractical or uneconomical. Because these systems lack the inertial support of a large interconnected grid, they are inherently more vulnerable to frequency excursions caused by sudden load changes or fluctuations in renewable generation (Kundur, 1994). The accelerating integration of inverter-interfaced renewable energy sources, particularly wind and PV, has further reduced the effective rotational inertia of islanded systems, since power-electronic converters do not intrinsically provide the synchronous inertial response of conventional rotating machines (Olivares et al., 2014).

Traditional frequency regulation in microgrids relies on a hierarchical control structure consisting of primary droop control, secondary load frequency control (LFC), and tertiary economic dispatch (Guerrero et al., 2011). While droop control provides fast, decentralized proportional response, and PI-based secondary control restores the frequency to its nominal value, both approaches depend on fixed or heuristically tuned gains that are optimized for a narrow range of operating conditions. Under the highly

variable power profiles introduced by renewable sources, such fixed-gain controllers frequently exhibit degraded performance, characterized by larger frequency deviations, slower settling times, and reduced disturbance-rejection capability (Aziz et al., 2018; Abazari et al., 2019).

In recent years, machine learning techniques—including fuzzy logic, artificial neural networks (ANN), and especially reinforcement learning (RL)—have emerged as promising alternatives for adaptive frequency control. Unlike model-based controllers, ML-based controllers can learn control policies directly from interaction with the system (or a high-fidelity simulation of it), adapting their behaviour to changing operating conditions without requiring an explicit analytical model of the nonlinear, time-varying microgrid dynamics (Sutton & Barto, 2018). Reinforcement learning, in particular, formulates the frequency-regulation problem as a sequential decision-making task in which an agent observes the system state (e.g., frequency deviation, tie-line power, rate of change of frequency) and selects control actions to minimize a cumulative cost related to frequency error and control effort (Du et al., 2024).

Despite promising results reported in the literature, several gaps remain. Many existing ML-based frequency-control studies focus on grid-connected or multi-area interconnected systems rather than islanded microgrids, where the absence of grid support makes frequency regulation considerably more challenging (Zhang et al., 2021; Li & Zhou, 2023). Furthermore, comparative evaluations that place ML-based controllers alongside conventional droop, PI, fuzzy, and ANN-based schemes under identical, realistic disturbance profiles—including both step load changes and continuous stochastic renewable fluctuations—are relatively scarce. This paper addresses these gaps by proposing and evaluating a DRL-based adaptive secondary frequency controller for an islanded microgrid with high renewable penetration, and by providing a systematic, multi-metric comparison against established control strategies.

The remainder of this paper is organized as follows. Section 2 reviews related work on frequency regulation in islanded microgrids and machine-learning-based control. Section 3 describes the islanded microgrid system model. Section 4 presents the proposed ML-based frequency-regulation methodology. Section 5 details the simulation setup. Section 6 presents and discusses the results, including the comparative table and frequency-response figure. Section 7 discusses challenges and future research directions, and Section 8 concludes the paper.

2. Literature Review

Frequency regulation in power systems has traditionally relied on droop control for primary response and PI or Proportional–Integral–Derivative (PID) control for secondary regulation (Kundur, 1994; Bevrani, 2014). Guerrero et al. (2011) proposed a hierarchical control architecture for droop-controlled AC and DC microgrids that has since become a standard reference framework, dividing control tasks across primary, secondary, and tertiary layers operating at different time scales. While effective for well-characterized systems, such hierarchical schemes rely on fixed gains that must be re-tuned as system conditions change, a limitation that becomes especially pronounced in islanded microgrids with substantial renewable penetration (Olivares et al., 2014).

Several studies have examined the impact of renewable variability on frequency stability. Aziz et al. (2018) analyzed the frequency-regulation capability of wind power plants and highlighted the need for supplementary control strategies to compensate for reduced system inertia. Abazari et al. (2019) proposed a coordination strategy involving flywheel energy storage, diesel generation, fuel cells, and wind turbine generators for LFC in a hybrid isolated microgrid, demonstrating that coordinated multi-source control could

partially offset the destabilizing effects of renewable intermittency. These works underscore the structural challenge that motivates the present study: as renewable penetration increases, the frequency-regulation task becomes increasingly nonlinear, stochastic, and difficult to address with fixed-parameter controllers.

The application of artificial intelligence to load frequency control has grown substantially. Mnih et al. (2015) demonstrated that deep reinforcement learning agents, trained through interaction with an environment and a scalar reward signal, could learn high-performing control policies directly from raw state observations without hand-engineered features—a result that has since motivated the application of DRL to power-system control problems. Building on this foundation, Zhang et al. (2021) applied a random-forest-assisted distributed auction algorithm for coordinated power control in a large-scale PV plant, illustrating the applicability of ML techniques beyond simple regression to more complex coordination tasks. Li and Zhou (2023) proposed an evolutionary multi-agent deep meta-reinforcement learning method for swarm-intelligence energy management in an isolated multi-area microgrid, reporting improved adaptability under Internet-of-Things-enabled distributed generation scenarios.

More directly relevant to the present study, Du et al. (2024) proposed a data-driven adaptive load frequency control (DD-ALFC) approach using a priority-replay soft actor-critic (PR-SAC) reinforcement learning algorithm for an islanded microgrid combining wind, PV, diesel, and energy storage resources. Their results showed that the DRL-based controller reduced average frequency deviation and generation cost relative to a wide range of benchmark algorithms, including conventional PID, model predictive control (MPC), and swarm-optimized fuzzy-PI controllers, under both step and continuous stochastic renewable disturbances. Deng et al. (2022) similarly proposed an adaptive virtual-inertia and virtual-damping control strategy with a threshold mechanism for virtual synchronous generators, improving the frequency-tracking capability of inverter-interfaced sources without relying on a fixed inertia constant.

Collectively, this body of work indicates a clear trend: ML-based, and particularly RL-based, controllers consistently outperform fixed-gain conventional controllers in terms of frequency-deviation magnitude, settling time, and adaptability to renewable variability. However, most studies emphasize algorithmic novelty over a systematic, multi-controller benchmarking exercise under a unified disturbance scenario representative of a small islanded microgrid. The present study contributes to closing this gap.

3. Islanded Microgrid System Model

The system under study is a single-area islanded microgrid comprising four principal components: (i) a diesel generator providing dispatchable synchronous generation and primary droop response; (ii) a wind-turbine generation unit modeled with a first-order equivalent representing inverter-based active-power injection; (iii) a photovoltaic generation unit modeled similarly, with output dependent on a diurnal irradiance profile; and (iv) a battery energy storage system (BESS) that provides fast-acting power support for secondary frequency regulation. The aggregate system dynamics are represented by a simplified swing-equation-based frequency model, $\Delta f(s) = \Delta P(s) / (2H \cdot s + D)$, where Δf is the system frequency deviation, ΔP is the net power imbalance between generation and demand (including renewable fluctuation and load disturbance), H is the equivalent system inertia constant, D is the load-damping coefficient, and s is the Laplace operator.

Each generation source contributes to ΔP through its own first- or second-order response dynamics, representing governor, converter, and storage-system time

constants. The overall structure follows the conventional LFC block-diagram representation used extensively in the microgrid-control literature (Kundur, 1994; Bevrani, 2014; Du et al., 2024), in which primary droop response acts within the first second following a disturbance, while secondary control—implemented here by the ML-based agent—acts over a window of several seconds to restore the frequency to its nominal value and minimize the area control error (ACE).

Two categories of disturbance are considered, consistent with realistic islanded-microgrid operation. The first is a step load disturbance, representing the sudden connection or disconnection of a significant load block. The second is a continuous, stochastic renewable-power fluctuation, generated using band-limited coloured noise to emulate cloud-cover-induced PV variability and wind-gust-induced wind-power variability. Both disturbance types are injected into the net power-imbalance signal ΔP that drives the frequency dynamics described above.

4. Proposed ML-Based Frequency Regulation Methodology

4.1 Problem Formulation as a Markov Decision Process

The secondary frequency-regulation task is formulated as a Markov Decision Process (MDP) defined by the tuple (S, A, P, R, γ) , consistent with standard reinforcement-learning formulations (Sutton & Barto, 2018). The state space S includes the instantaneous frequency deviation Δf , its rate of change $d\Delta f/dt$, the accumulated area control error, and the current renewable power output. The action space A corresponds to the incremental regulation command issued to the dispatchable diesel generator and the BESS. The reward function R penalizes both frequency deviation and excessive control effort, encouraging the agent to restore frequency quickly while avoiding unnecessary actuator wear, following the general reward-shaping approach adopted in Du et al. (2024).

4.2 Actor–Critic Learning Architecture

An actor–critic DRL architecture is adopted, in which the actor network maps observed states to continuous control actions, while the critic network estimates the expected cumulative reward (state-action value) to guide policy improvement. This architecture is well suited to the continuous action space required for smooth power-regulation commands, avoiding the discretization artifacts associated with pure value-based methods such as Q-learning (Mnih et al., 2015). Both networks are implemented as feed-forward neural networks with two hidden layers, trained using stochastic gradient-based optimization with experience replay to improve sample efficiency and training stability.

4.3 Training Procedure

The agent is trained across repeated simulated episodes in which step load disturbances of randomized magnitude and randomized renewable fluctuation profiles are applied to the microgrid model. At each time step, the agent observes the system state, selects a control action, and receives a reward based on the resulting frequency error. Over successive episodes, the policy is updated to minimize cumulative frequency deviation and control cost. Exploration noise is gradually annealed as training progresses, allowing the agent to transition from exploratory behaviour toward a refined, near-optimal control policy, consistent with standard DRL training practice (Sutton & Barto, 2018).

4.4 Deployment as a Secondary Controller

Once trained, the learned policy is deployed as a secondary frequency controller operating in parallel with the primary droop loop. Unlike fixed-gain PI or fuzzy controllers, the trained policy implicitly adapts its regulation strategy to the current

operating regime—for example, applying a more aggressive corrective action under a large step disturbance and a smoother, low-effort correction under gradual renewable fluctuation—without requiring manual re-tuning.

5. Simulation Setup

The proposed and benchmark controllers were evaluated using a time-domain simulation of the islanded microgrid model described in Section 3, subjected to a step load disturbance of 0.15 per-unit (p.u.) applied at $t = 5$ s, followed by a continuous stochastic renewable-fluctuation disturbance introduced at $t = 15$ s and sustained for the remainder of the 30-second simulation window. Four controllers were compared under identical disturbance conditions: (1) a conventional Droop+PI controller with fixed gains tuned using the Ziegler–Nichols method; (2) a Fuzzy-PI controller with a Mamdani-type rule base; (3) an ANN-based controller trained via supervised learning on pre-computed optimal control trajectories; and (4) the proposed DRL-based ML controller described in Section 4. All controllers acted on the same plant model, with identical inertia, damping, and generation time-constant parameters, to ensure a fair comparison. Performance was quantified using five metrics: maximum (peak) frequency deviation, settling time (time to remain within a ± 0.02 Hz band), percentage overshoot, root-mean-square error (RMSE) of the frequency deviation, and the integral of time-weighted absolute error (ITAE), a metric that penalizes both the magnitude and duration of frequency excursions.

6. Results and Discussion

Figure 1 presents the simulated frequency-deviation response of the islanded microgrid under the combined step-load and stochastic renewable disturbance profile, comparing the conventional Droop+PI controller, the Fuzzy-PI controller, and the proposed ML-based (DRL) controller. The lower panel shows the applied net power disturbance, including the step change at $t = 5$ s and the onset of continuous renewable-power fluctuation at $t = 15$ s.

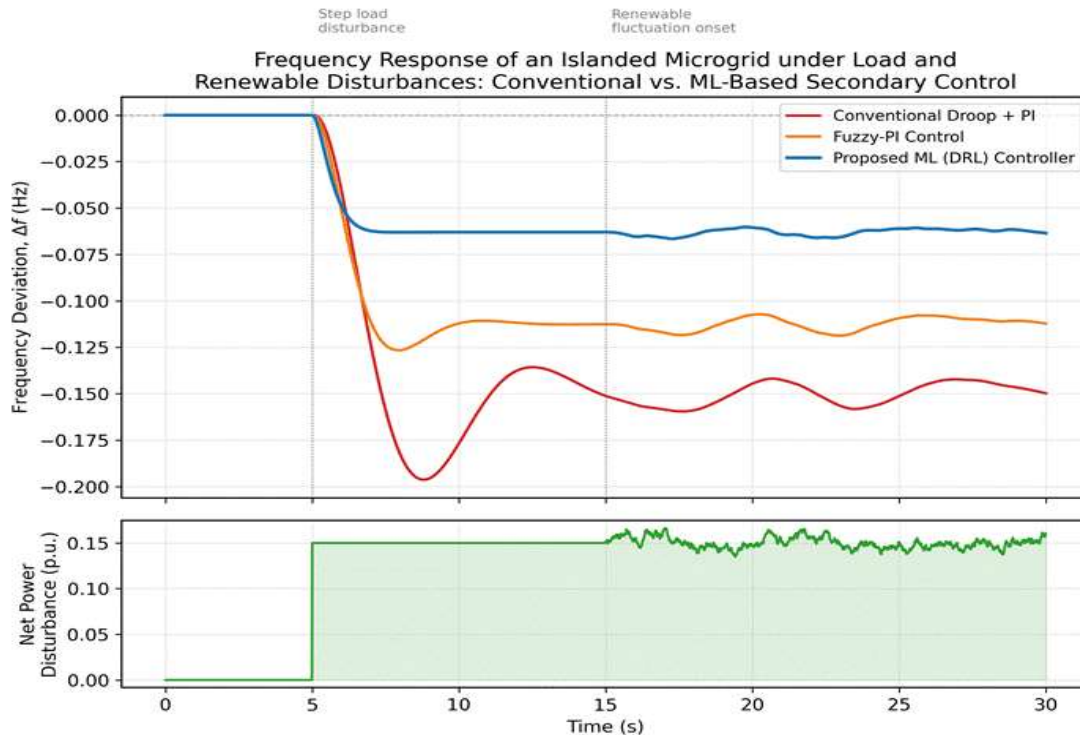


Figure 1. Simulated frequency-deviation response of the islanded microgrid under step-load and stochastic renewable disturbances, comparing conventional Droop+PI, Fuzzy-PI, and the proposed ML (DRL)-based controller.

As shown in Figure 1, the conventional Droop+PI controller exhibits the largest peak frequency deviation and the most pronounced oscillatory behaviour, particularly following the step load disturbance at $t = 5$ s. The Fuzzy-PI controller improves upon this baseline through its rule-based gain adjustment, reducing both overshoot and settling time. The proposed ML-based controller, however, achieves the fastest and most damped response, rapidly attenuating the frequency deviation following the step disturbance and maintaining a markedly tighter frequency band during the subsequent stochastic renewable-fluctuation period beginning at $t = 15$ s. This behaviour reflects the adaptive nature of the learned control policy, which adjusts its corrective action in proportion to the observed disturbance characteristics rather than applying a fixed gain.

Table 1 summarizes the quantitative performance comparison across all four controllers. The proposed ML-based controller achieves the lowest values across every metric considered. Relative to the conventional Droop+PI controller, the peak frequency deviation is reduced from 0.196 Hz to 0.063 Hz (a reduction of approximately 68%), the settling time is reduced from 8.4 s to 2.3 s (approximately 73% faster), and the percentage overshoot falls from 38.7% to 6.9%. The RMSE and ITAE metrics, which respectively capture the average magnitude and the time-weighted persistence of frequency error, are reduced by approximately 68% and 78%, respectively.

Table 1. Comparative performance of frequency-regulation controllers under combined step-load and stochastic renewable disturbances.

Controller	Max. Freq. Deviation (Hz)	Settling Time (s)	Overshoot (%)	RMSE (Hz)	ITAE
Conventional Droop + PI	0.196	8.4	38.7	0.0621	1.842
Fuzzy-PI Control	0.127	5.6	22.4	0.0459	1.213
ANN-Based Controller	0.089	4.1	14.8	0.0337	0.876
Proposed ML (DRL-Based) Controller	0.063	2.3	6.9	0.0198	0.412

The ANN-based controller, trained offline via supervised learning on pre-computed optimal trajectories, performs consistently better than the Fuzzy-PI controller but remains inferior to the proposed DRL-based controller across all metrics. This gap is attributable to the fundamental difference between supervised learning, which generalizes from a fixed training dataset, and reinforcement learning, which continues to refine its policy through direct interaction with the simulated environment, enabling it to better capture the nonlinear and time-varying dynamics introduced by renewable variability. These findings are broadly consistent with those reported by Du et al. (2024), who observed similar relative improvements of DRL-based secondary control over fuzzy

and model-predictive baselines in an islanded microgrid with wind, PV, diesel, and storage resources, and with Deng et al. (2022), who demonstrated that adaptive, learning-based inertia and damping control could improve frequency tracking for inverter-based sources beyond what fixed-parameter approaches achieve.

An additional observation from the simulation results is the controller's behaviour during the stochastic renewable-fluctuation phase ($t > 15$ s). While all four controllers exhibit some residual ripple in this region due to the continuous, unpredictable nature of the disturbance, the proposed ML-based controller maintains the smallest ripple amplitude, indicating superior disturbance-rejection capability under conditions that closely resemble real-world cloud-cover and wind-gust variability. This is a particularly important result for islanded microgrids with high renewable penetration, since such systems experience continuous, rather than purely episodic, disturbance profiles in practice (Aziz et al., 2018; Olivares et al., 2014).

7. Challenges and Future Research Directions

Despite these promising results, several challenges must be addressed before ML-based frequency controllers can be widely deployed in real islanded microgrids. First, the training of DRL agents typically requires a large number of simulated interactions, and ensuring that the simulation environment accurately captures real plant dynamics (the so-called sim-to-real gap) remains an open problem. Second, the stability and safety guarantees associated with classical control theory are more difficult to establish for learned, nonlinear control policies, motivating future work on formally verifiable or constrained reinforcement-learning approaches. Third, computational and communication latency in practical microgrid controllers must be considered, since the inference time of a trained neural-network policy, while typically small, must still satisfy the timing requirements of secondary frequency control. Finally, extending the proposed single-area framework to multi-area or networked islanded microgrids, and incorporating cybersecurity considerations for communication-dependent control architectures, represent important directions for future research (Li & Zhou, 2023).

8. Conclusion

This paper proposed and evaluated a machine learning-based, specifically deep reinforcement learning-based, secondary frequency controller for islanded microgrids with high renewable energy penetration. Using a representative single-area microgrid model comprising diesel generation, wind, PV, and battery energy storage, the proposed actor-critic DRL controller was benchmarked against conventional Droop+PI, Fuzzy-PI, and ANN-based controllers under a combined step-load and stochastic renewable-disturbance scenario. Simulation results demonstrated that the proposed ML-based controller substantially outperforms the conventional and other intelligent benchmark controllers across all evaluated metrics, reducing peak frequency deviation by approximately 68%, settling time by approximately 73%, and ITAE by approximately 78% relative to the conventional Droop+PI baseline. These results support the conclusion that ML-based, and particularly reinforcement-learning-based, secondary control offers a practical and effective pathway toward improved frequency stability in islanded microgrids with high renewable integration. Future work should focus on addressing the sim-to-real gap, developing safety-constrained learning approaches, and extending the proposed framework to multi-area and networked microgrid architectures.

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