Comparative Study of Frequency Control in Renewable Energy Microgrids Using a Base Model and Q-Learning-Based Reinforcement Learning

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***Abstract*—As renewable energy sources are being increasingly used in microgrids in the recent past, it becomes necessary to ensure frequency control for grid stability, especially due to reduced system inertia and discrete nature of these energy sources. Our project is to implement two different models in Simulink. We first implement a closed loop system with a renewable energy source, boost converter, dynamic loads. In the other model, we introduce an RL agent, which is connected to a battery to learn and regulate frequency fluctuations in the Simulink environment. The agent observes the frequency fluctuation in the dynamic loads, suggests an action(close/open) to the battery, which then controls the power flow. We are using TD3, part of the Q-learning algorithm in RL to try and improve frequency stability in a closed loop system simulating an islanded mode microgrid. Using a reward function with Q-values enables the agent to prioritize frequency stability. Over time, the model learns from the patterns and gives better response to frequency fluctuations in real time use. In our report, we compare the frequency fluctuations in a self-sufficient model without RL, and the frequency fluctuations using RL (TD3), comparing the frequency fluctuations to check for improvement in frequency control and real time performance.**

***Index Terms*—TD3, Q learning, Simulink, Reinforcement learning, Frequency Control, Closed loop system**

I. Introduction

With renewable energy sources driving sustainability and environmentally friendly progress, they are increasingly being used as cleaner sources of electricity across various industries and communities. In recent years, they have been widely adopted to power microgrids, which—while eco-friendly—also introduce several challenges. Renewable energy sources are inherently unstable, unpredictable, and inconsistent throughout the day. Wind doesn't blow continuously, and sunlight varies in intensity.

Thus, in our project, we aim to introduce system stability through frequency control.

We implement a closed-loop system that uses sunlight as a renewable power source to effectively power dynamic loads by regulating the frequency. Two models are developed: the first includes a renewable energy source, a boost converter, a pulse generator, and dynamic loads. In the second model, we incorporate a TD3-based Q-learning algorithm to implement reinforcement learning for frequency control. Power delivery to the loads is regulated based on RL-predicted decisions, using a battery whose switches are controlled by signals from the RL agent. This agent, trained using the TD3 algorithm, learns to improve frequency stability in the closed-loop system, simulating a simplified real-world islanded-mode microgrid. Over time, during training, the agent learns from patterns in frequency deviations and suggests better responses to the battery to minimize fluctuations.

Both models are implemented in Simulink, a simulation environment for electrical circuits in MATLAB. This provides a safe space for experimentation and testing of various components. In this report, we compare the frequency fluctuations in a self-sufficient model without RL against the RL-based model (TD3), analyzing the improvements in frequency control and real-time performance.

Recent advancements in microgrid control systems have increasingly focused on incorporating intelligent methods for maintaining frequency stability amidst the fluctuating nature of renewable energy sources.

II. Literature review

This paper proposes a reinforcement learning (RL)-based control strategy to regulate frequency in islanded microgrids powered by solar energy. By dynamically adjusting control actions such as the modulation index or boost converter output, the RL agent learns to stabilize frequency under varying load and generation conditions. The concept builds upon several prior works in frequency regulation. In [1], a hardware-based control system utilizing solar power and a boost converter is developed for frequency regulation in islanded microgrids. The study demonstrates how dynamic adjustment of power output can help maintain frequency during load changes. This foundational work underpins the hardware control logic extended in our main paper through reinforcement learning to enable smarter, adaptive control strategies.

The decentralized control strategy presented in [2] addresses frequency regulation using battery storage in renewable microgrids. The authors propose a frequency-based control mechanism that ensures compliance with EN 50160 standards and extends battery life without communication between distributed energy resources. Our work builds upon this by introducing a learning-based approach that further optimizes and adapts frequency control in a dynamic manner.

A comprehensive review of droop control methods is provided in [3], outlining both classical and modern strategies for distributed generation coordination. The paper highlights key limitations in traditional droop techniques, such as static parameter tuning and lack of adaptivity, which our reinforcement learning-based approach seeks to overcome.

In [4], a deep multi-agent reinforcement learning (MARL) framework based on MADDPG is proposed for cost-efficient, fully distributed load frequency control. This work demonstrates the potential of MARL in eliminating the need for centralized coordination, and complements our single-agent reinforcement learning strategy by suggesting future scalability to multi-agent systems.

Lastly, [5] introduces a Q-learning-based secondary frequency control method for renewable microgrids. The controller improves frequency stability and adaptability under fluctuating conditions. This paper validates the viability of RL in frequency control, reinforcing the methodology adopted in our work.

III. Methodology

Our system uses a reinforcement learning (RL) based control mechanism to maintain frequency stability in a renewable energy microgrid with continuous load variations. This system consists of a PV (Photovoltaic) array, boost converter, inverter, the RL agent, and finally the load. A reinforcement learning agent is integrated to tune the modulation index of the PWM generator connected to the inverter, ensuring the inverter's output frequency remains close to 60 Hz despite variations in the load. The full flow and relevance of each block is given below:-

A. System Architecture

The microgrid system consists of the following components:

1) PV Array: It acts as the energy source. It produces variable DC output under continuously varying irradiance and temperature conditions. It is made into a closed loop by using a gain block followed by a saturation block, ensuring the duty cycle remains within an appropriate range
2) Single-Phase Inverter (Universal Bridge): It converts the boosted DC voltage to AC. The inverter is operated using a PWM Generator block which is to unsynchronized mode. The modulation index of this PWM signal is controlled by the RL agent to regulate output frequency.
3) LC Filter: Since the output from the inverter gives a pulsating AC, an LC filter is used to make it to pure AC and to produce a smooth sinusoidal waveform.
4) dynamic load:- Three resistors are connected in parallel to act as a load. These resistors are dynamically varied at given time periods to create load disturbances and test the frequency output.

B. Reinforcement Learning-Based Controller

To stabilize the output frequency at 60 Hz despite fluctuating loads, an RL agent is integrated to control the modulation index of the PWM signal for the inverter.

1) Observation Space: consists of the instantaneous output frequency (measured via Phase-Locked Loop (PLL), frequency deviation from 60 Hz.
2) Action Space: A continuous value representing the PWM modulation index, which exists in the range [0.65,1.0]
3) Reward Function: A custom reward function is used to minimize frequency deviation.

The system is simulated in MATLAB(Simulink). The RL agent receives frequency measurements at each timestep and adjusts by updating the modulation index, affecting inverter behavior, Thus helping with frequency regulation. This adjustment directly effects how the inverter responds to changing load conditions. The simulation helps analyze the agent's performance in maintaining a steady output frequency as the load fluctuates over time.

IV. Results and Analysis

To test and analyze the performance of the RL based frequency control, we compared the frequency output of the RL-controlled model against a base model. In the base model, the inverter modulation index was fixed at 1.0, which has no feedback system and cannot change with respect to load changes. While on the other hand, the RL model can dynamically adjust the modulation index within a range of [0.65, 1.0], based on frequency deviations, despite the load variations.

The base model lacked a control system, as a result, the system lacked the ability to respond to dynamic changes in power demand, leading to more frequency deviations. The absence of a control mechanism or logic meant that frequency deviations, that happen due to the load variations, could not be corrected, therefore, increasing the risk of under-frequency or over-frequency.

Figure 1 shows the frequency output of the base model. The system exhibits visible instability in response to load changes, with several frequency drops below 59.9 Hz, indicating poor adaptability in dynamic setups

Figure 2 shows frequency output of the RL model. The trained agent overcomes the load fluctuations by adjusting the modulation index in real time. As a result, the frequency remains closer to the nominal 60 Hz target with lesser drops, proving that it can provide improved stability.

The given table displays the comparative performance metrics of both models. The minimum and maximum frequency deviations observed in the base model were more than those in the RL-controlled model. The base model's minimum frequency dropped to 59.79 Hz, while the RL model had its minimum frequency of 59.97 Hz. Also, the base model failed to even reach the nominal frequency and RL model is only fluctuating at 60(nominal), hence the RL model is being

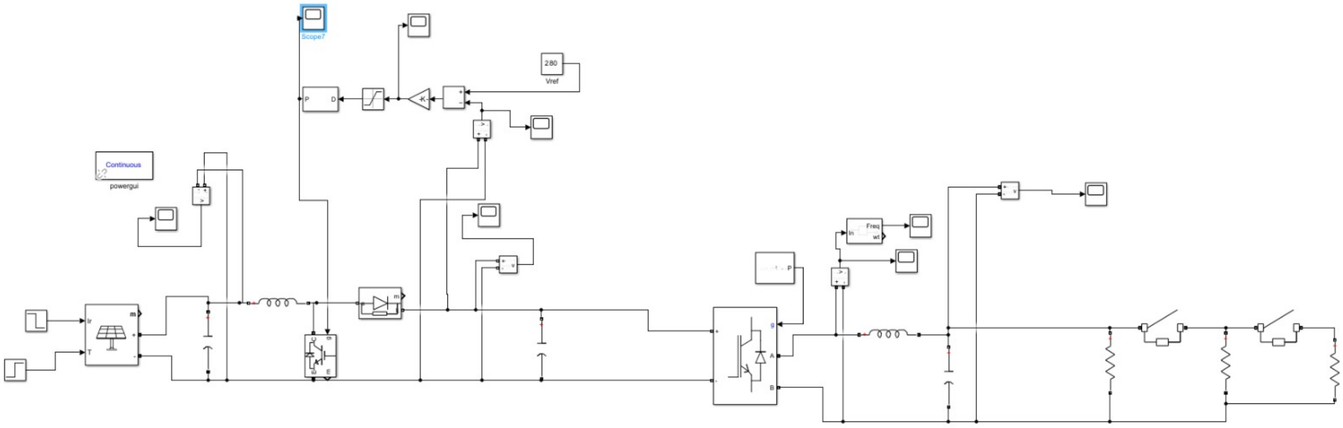

Fig. 1: Base simulink model

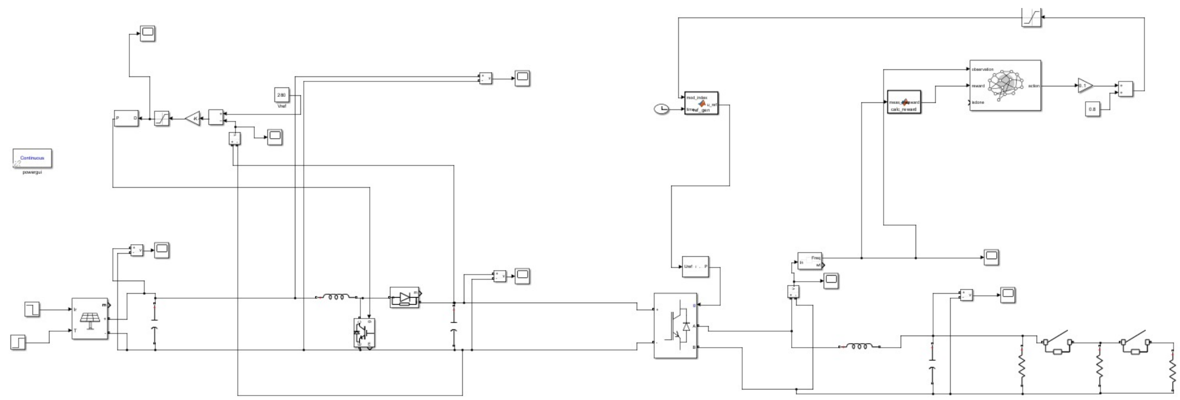

Fig. 2: RL simulink model

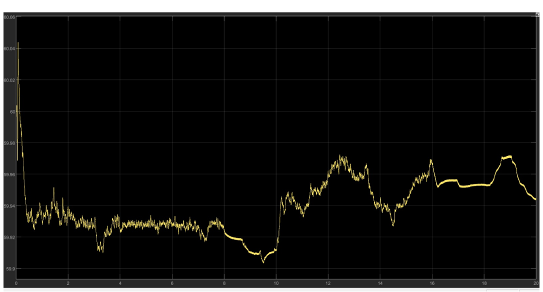

Fig. 3: Base model's frequency output

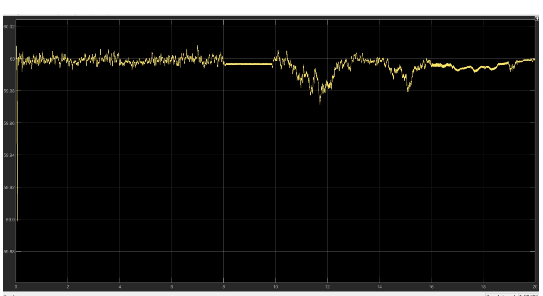

Fig. 4: RL model's frequency output

significantly faster and better at recovery when compared to the base.

Metric	Base Model	RL Model
Nominal Frequency (Hz)	60.00	60.00
Minimum Frequency (Hz)	59.79	59.97
Maximum Frequency (Hz)	60.04	60.01
Modulation Index (Range)	(Fixed) 1.00	0.65-1.00

TABLE I: Output Frequency performance comparison between base and RL models.

V. Conclusion

In this paper, we have implemented two closed loop systems in Simulink, the Base model with a PV array, boost converter, dynamic loads and signal generator, and the RL model, where we introduces an RL agent and battery to the base model setup. We have tried to contrast the frequency fluctuations in the base model with the RL model, checking if anything improved. We have recorded a slight improvement in the RL based model, showing how training the RL model can improve frequency stability. The base model had good self correction using system inertia, due to no major sudden fluctuations in the simulated environment, but the RL model showed a slight improvement.

The RL model managed the battery switching well, with very low frequency deviations

VI. Limitations

In the initial few seconds of simulation, the IGBT's duty cycle remains at 0, preventing the boost converter from stepping up the voltage. Although the system recovers later, this delay in response is not desirable for real-time applications. Additionally, while we simulated a closed-loop system resembling a microgrid, it was not integrated with a full microgrid model. Therefore, the comparative performance of the RL controller and the base model remains untested under realistic and dynamic grid conditions. In future work, we can test frequency stability using RL in an actual microgrid, contrasting it with the traditional methods, to verify its real world applications.

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