Load Frequency Control Enhancement Using Reinforcement Learning Technique

Khaldoon Alfaverh[1*], Laszlo Szamel[1]

1 Department of Electric Power Engineering, Faculty of Electrical Engineering and Informatics, Budapest University of Technology and Economics, H-1521 Budapest, P.O.B. 91, Hungary

* Corresponding author, e-mail: khaldoonalfaverh@edu.bme.hu

Abstract

Microgrids (MGs) face challenges due to load disturbances, the uncertain nature of renewable output power, energy storage system dynamics, and low system inertia. These factors can lead to large frequency deviations, weakening the MG and potentially resulting in a complete blackout. Addressing this, this paper introduces a load frequency control (LFC) method against stochastic power flow from renewable energy sources, leveraging deep reinforcement learning (DRL). A real-time MG test system is employed for simulation purposes. This system is modeled using MATLAB/Simulink, and its performance under various scenarios is analyzed to evaluate the efficacy of the proposed method, contrasting it with existing techniques from the literature. Results indicate that our proposed controller offers a more rapid response and is well-suited for dynamic systems.

Keywords: Load Frequency, Reinforcement learning, Microgrids

1 Introduction

In the realm of microgrid systems, emergency diesel generators (DGs) have traditionally been the primary solution for maintaining power balance, especially during extended outages. However, this reliance on a single DG source introduces significant risk, often unacknowledged, to the end-user. In contrast, the declining costs of photovoltaics and battery energy storage systems (BESS) have sparked significant interest in renewable energy sources for their clean and efficient electricity generation, especially in microgrids and smart grids [1].

MGs typically incorporate Distributed Energy Resources (DERs), including renewable sources like wind and solar power, which are both economical and environmentally friendly [2]. However, these renewable sources are subject to variability due to environmental factors like weather and seasonal changes, leading to power imbalances and frequency deviations in the microgrid system [3].

Maintaining the balance of instantaneous active power in any power system, under both normal and emergency conditions, is crucial. Renewable energy sources integrated into MGs usually have minimal inertia and are electronically interfaced, posing challenges to the stability of islanded MGs with high DER penetration following significant events [4]. Consequently, various frequency control mechanisms have been proposed to address these challenges, including intelligent methods [5]. Nevertheless, the conventional Proportional-Integral-Derivative (PID) control method remains prevalent in practical microgrids due to its simplicity and cost-effectiveness. To accommodate the complexities of microgrids, including variable load demands and intermittent DER outputs, artificial intelligence-based tuning methods for PID controllers, like fuzzy-tuned multistage PID and online particle swarm optimization (PSO), have gained traction [6].

Introducing new units to the microgrid, such as BESS, plug-in hybrid electric vehicles, and Superconducting Magnetic Energy Storage, can enhance MG frequency stability. Particularly, BESS is recognized for its rapid response in mitigating frequency deviations [7]. However, the affordability of high-capacity ESS in low-income regions and the environmental costs of batteries remain concerns.

Recent studies have highlighted the potential of reinforcement learning methods, especially Deep Reinforcement Learning (DRL), in control applications [8]. DRL has demonstrated effectiveness in managing sequential decision-making under uncertainty, marking progress toward autonomous systems with advanced comprehension of the visual world. For instance, DRL has been applied for frequency regulation in microgrids, employing algorithms like Deep Deterministic Policy Gradients (DDPG) for enhancing the adaptive capability of frequency controllers and for multi-scenario emergency control [8].

This paper proposes a centralized, single DRL-based algorithm for load LFC in an islanded MG, aiming to maintain optimal active power flow and limit frequency deviation within safe parameters. This approach simplifies the design compared to multi-agent RL strategies and relies on the DDPG algorithm, suitable for continuous control applications. Our contribution includes establishing a DRL controller based LFC for nonlinear optimization, employing an iterative learning scheme with a simple reward function, and integrating BESS to enhance LFC in an islanded microgrid. This control scheme compensates for frequency deviation caused by DER output uncertainty, demand power fluctuation, and variations in MG internal parameters.

2 System Description and Modeling

2.1 Description of the Proposed Microgrid System

2.1.1 Problem Formulation:

LFC in MGs primarily focuses on mitigating grid frequency deviations by adjusting distributed sources to restore MG frequency to its nominal value. Due to the small inertia of most DERs in an

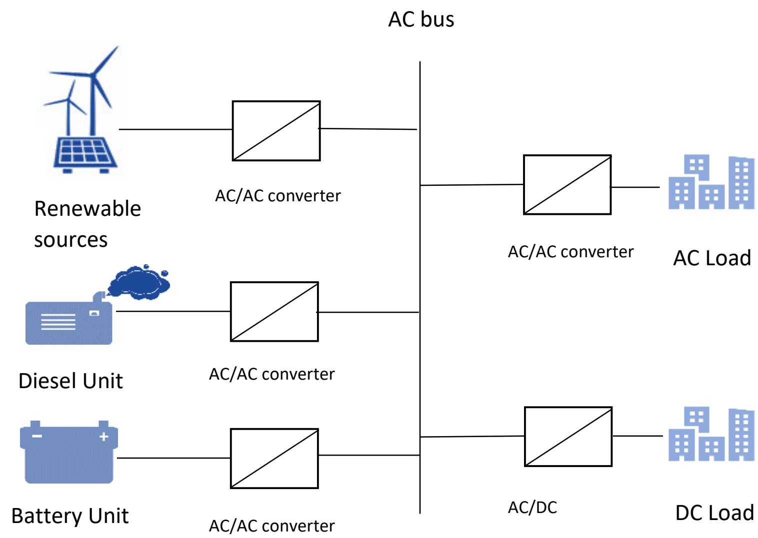

Figure 1 Isolated Microgrid

MG, system indices are significantly impacted by load fluctuations and intermittent DER output. Effective integration of Energy Storage Systems (ESSs) is crucial for maintaining power balance and enhancing MG reliability, particularly during outages. Figure 1 illustrates an isolated MG, encompassing components like DG, photovoltaic and wind systems, and ESS.

This study aims to develop a novel intelligent controller for LFC in stand-alone MGs, addressing the challenges of dynamic modeling in systems with diverse generation units. Most research focuses on static models, which inadequately describe backup components and power supply units in MGs. In optimizing resources and managing demands, a Distribution Management System (DMS) is crucial for real-time monitoring and control of the MG. Our control operation model, shown in Figure 6, replaces centralized secondary control and primary-level droop mechanism with a singular loop control. The Reinforcement Learning (RL) agent inputs frequency deviation and load changes, outputting control signals to the diesel generator and BESS. Subsequent performance testing involves integrating other units like PV, wind, and stochastic load.

2.1.2 Model of Diesel Power System:

This model uses a first-order transfer function for the diesel engine's turbine-governor, with saturation limits indicating engine capacity, as depicted in the accompanying figure. The diesel engine, directly connected to the MG, provides inertia response and damping. Conventional automatic generation control is employed for frequency regulation, with models reacting directly to RL agent signals.

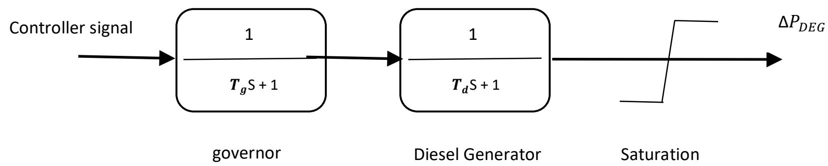

Figure 2 Diesel Model

2.1.3 Model of Battery Energy Storage System (BESS):

BESS offers fast-controllable power for frequency regulation, countering deviations caused by intermittent renewable generation and variable loads. An equivalent transfer function model, as shown in figure 3, is used to analyze BESS influence, focusing on the effectiveness of the RL control method. BESS capacity is set at ±0.50 p.u.

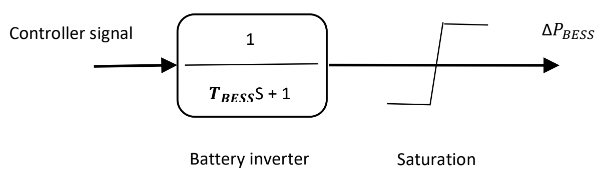

Figure 3 Battery Model

2.1.4 Model of Wind System with Output Power:

Wind Turbine Generators (WTGs) face nonlinear output power changes due to variable wind speeds and directions. Instead of forecasting WTG output, the RL agent is trained with random load changes within a specified range, fitting all stochastic output scenarios. The transfer function model of the WT is displayed in Figure 4.

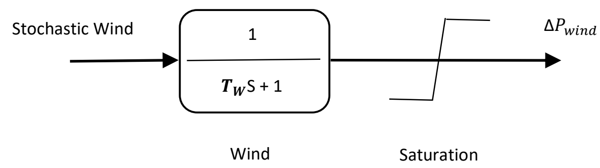

Figure 4 Wind Model

2.1.5 Model of Solar System with Output Power Figure:

PV array output is similarly volatile, dependent on solar irradiation and temperature. The transfer function model for the PV array is detailed below in figure 5.

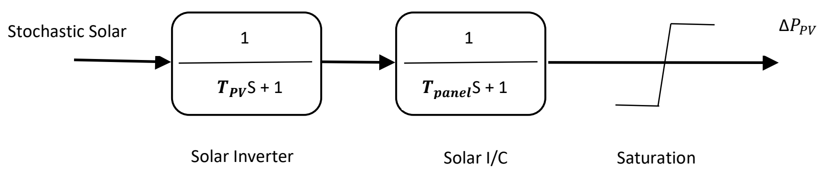

Figure 5 Solar Model

Table 1 Table of System Parameters

symbol	*value*	*Unit*	*Capacity*
T_g	1000	DG	0.50
T_d	2000	BESS	0.50
T_{BESS}	20		
T_W	600		
T_{PV}, T_{panel}	200		
2H	100		
D	200		

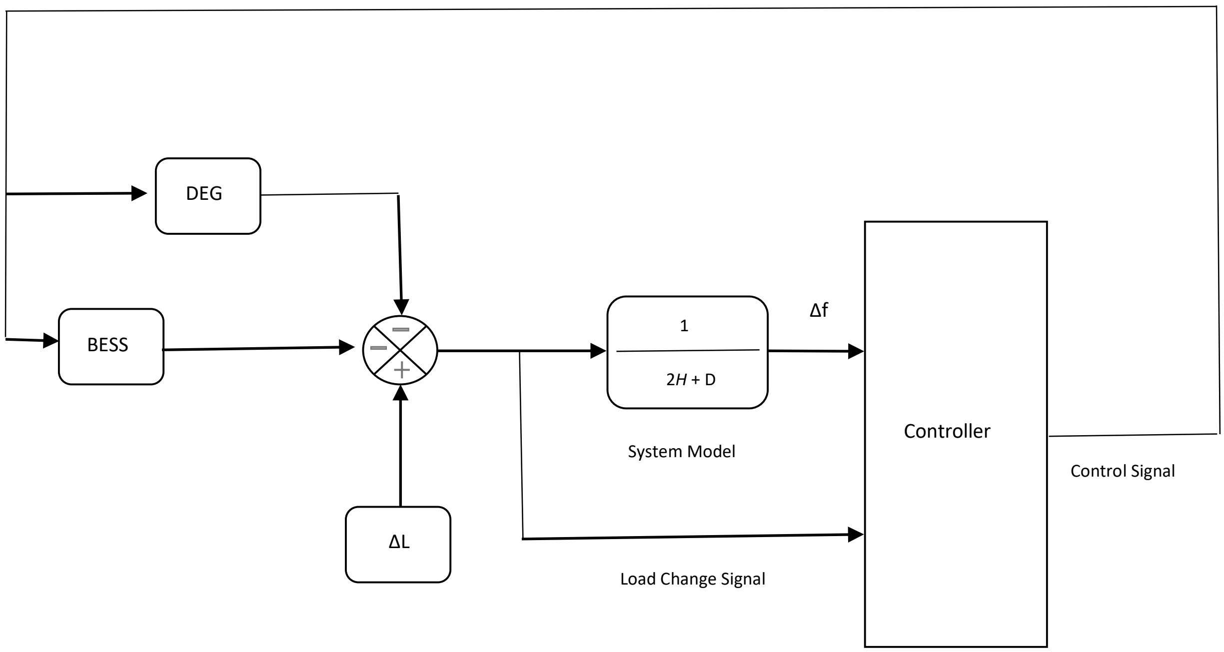

Figure 6 Base System Model

2.2 Deep RL Controller - Deep Deterministic Policy Gradient Method:

Frequency regulation remains an active research area, with the challenge of handling large-scale information from distributed units. We propose a deep learning approach with a single DDPG agent, described as an actor-critic, model-free, online, off-policy reinforcement learning method. This method is optimal for continuous action spaces and maximizes long-term rewards.

2.3 Agent Creation and Training Algorithm:

The DDPG agent is created with actor and critic representations, based on the model environment. Actor approximates a deterministic function, while the critic implements a Q-value function for continuous actions. Agent training involves updating actor and critic models at each time step, with parameters detailed in table 2.

Table 2 DRL Algorithm

Algorithm
• Initialize the critic $Q(S,A)$ with random parameter values $\boldsymbol{\theta_Q}$, and initialize the target critic with the same random parameter values: $\boldsymbol{\theta_{Q'}} = \boldsymbol{\theta_Q}$

- Initialize the actor $\boldsymbol{\mu(S)}$ with random parameter values $\boldsymbol{\theta_{\mu}}$ and initialize the target actor with the same parameter values**:** $\boldsymbol{\theta_{\mu'}} = \boldsymbol{\theta_{\mu}}$
- **For** each training time step **Ts**
  1. For the current observation $\boldsymbol{S}$, select action $\boldsymbol{A = \mu(S) + N}$, where $\boldsymbol{N}$ is stochastic noise from the noise model.
  2. Execute action $\boldsymbol{A}$. Observe the reward $\boldsymbol{R}$ and next observation $\boldsymbol{S'}$.
  3. Store the experience $\boldsymbol{(S, A, R, S')}$ in the experience buffer.
  4. Sample a random mini-batch of $\boldsymbol{M}$ experiences $(\boldsymbol{S_i}, \boldsymbol{A_i}, \boldsymbol{R_i}, \boldsymbol{S'_i})$ from the experience buffer.
  5. If $\boldsymbol{S'_i}$is a terminal state, set the value function target $\boldsymbol{y_i}$ to , $\boldsymbol{R_i}$. Otherwise, set it to

     $\boldsymbol{y_i = R_i + \gamma Q'(S'_i, \mu'(S'_i|\theta_{\mu})|\theta_{Q'})}$

     The value function target is the sum of the experience reward $\boldsymbol{R_i}$ and the discounted future reward. To specify the discount factor **γ**, use the DiscountFactor option.

     To compute the cumulative reward, the agent first computes a next action by passing the next observation $\boldsymbol{S'_i}$ from the sampled experience to the target actor. The agent finds the cumulative reward by passing the next action to the target critic.
  6. Update the critic parameters by minimizing the loss $\boldsymbol{L}$ across all sampled experiences

     $$\boldsymbol{L = \frac{1}{M}\sum_{i=1}^{M} (y_i - Q(S_i, A_i|\theta_Q))^2}$$
  7. Update the actor parameters using the following sampled policy gradient to maximize the expected discounted reward.

     $$\boldsymbol{\Delta_{\theta_{\mu}} J \approx \frac{1}{M}\sum_{i=1}^{M} G_{ai}\, G_{\mu i}}$$

     $\boldsymbol{G_{ai} = \Delta_A Q(S_i, A|\theta_Q)}$ **where** $\boldsymbol{A = \mu(S_i|\theta_\mu)}$

     $\boldsymbol{G_{\mu i} = \Delta_{\theta_{\mu}} \mu(S_i|\theta_{\mu})}$

     For the current observation $\boldsymbol{S}$, select action $\boldsymbol{A = \mu(S) + N}$, where $\boldsymbol{N}$ is stochastic noise from the noise model. To configure the noise model, use the NoiseOptions option.

Here, $\boldsymbol{G_{ai}}$ is the gradient of the critic output with respect to the action computed by the actor network, and $\boldsymbol{G_{\mu i}}$ is the gradient of the actor output with respect to the actor parameters. Both gradients are evaluated for observation $\boldsymbol{S_i}$.

8. Update the target actor and critic parameters depending on the target update method.

2.4 Agent Implementation:

The RL Agent block connects to signals for action (fed to the plant), observation (including load and frequency changes), and reward (penalizing larger frequency deviations). A custom reset function randomizes load changes.

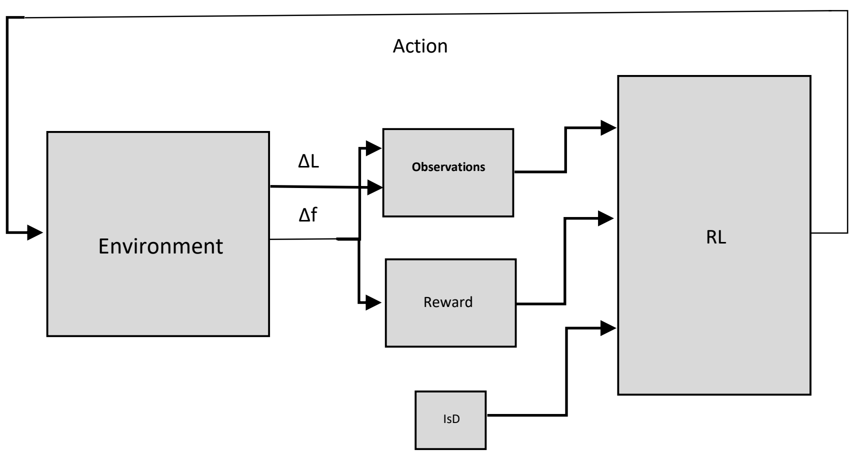

Figure 7 DRL model.

This model as shown above figure 7, contains an RL Agent block, which connected to the following signals: (i) The action signal that is fed to the plant where the DEG and the BESS regulate their output power in order to compensate for any load change. (ii) The observation input signal consists of: ΔL, the change in load and Δf, the change in frequency along with the integral of Δf which provides the steady-state features (the agent has been trained with different observations scenarios, only with the integral part the agent was able to handle the steady state error in more efficient way) (iii) Reward Signal R = -1 * |Δf|, in which the agent takes higher penalty for the larger frequency deviation. (iv) Logical input signal for stopping the simulation is set to zero. Finally, a custom reset function that randomizes load change at each training episode in which the disturbance signal generated using the uniformly distributed random generator within the interval - 0.3 to 0.3 per unit.

3 Result and Discussion

The DDPG supplementary controller tried to mitigate frequency fluctuation by adapting to the stochastic disturbances of load demand, Wind, and PV. It is also evident that by adopting the DDPG supplementary controller, the frequency fluctuation takes less time to be damped and the best robust LFC performance is achieved as detailed below.

3.1 Scenario 1:

In this case, under the islanded grid mode, we set the diesel installed capacity to 25% and the battery installed capacity to 0%. As shown in figure 9, the load demand has been increased at t=60[s] by 0.07 p.u and decreased at t=90 [s] by 0.05 pu. Both units can upgrade the execution of the microgrid. However, the battery has much faster control over the active and reactive power compared to the diesel unit. At t=60[s], the frequency deviation in is almost 0.0058 and -0.003 at t=90[s] as shown in figure 8. The power percentage of these two units is shown in Fig 10 and Fig 11.

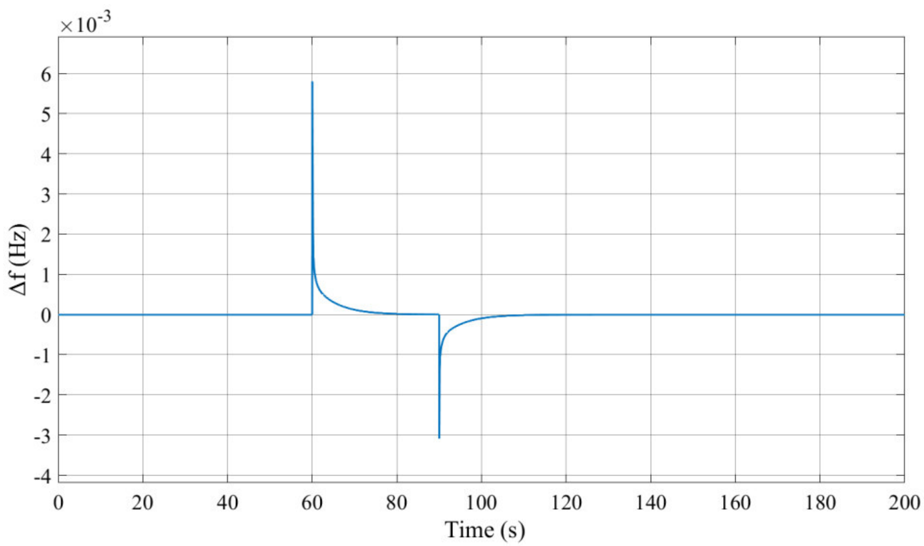

Figure 8 frequency deviation of scenario 1.

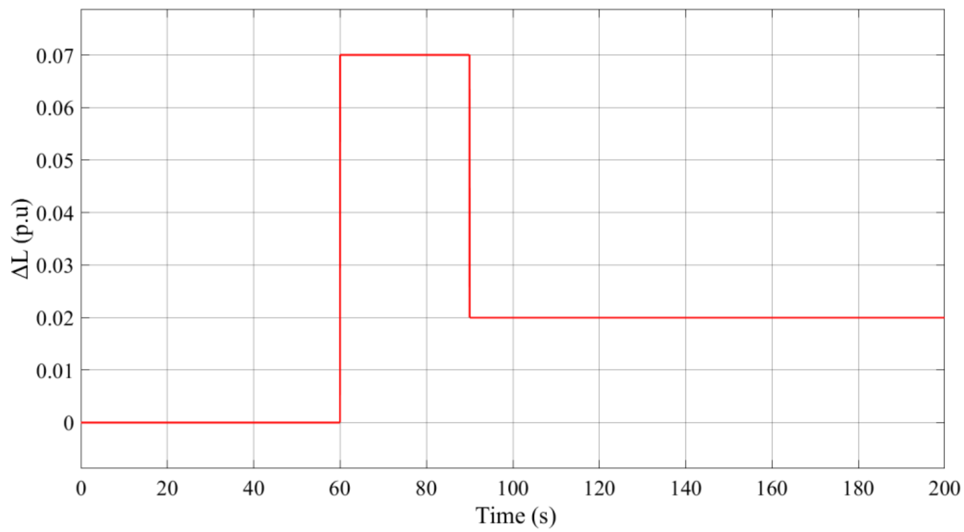

Figure 9 the change in load demand of scenario 1.

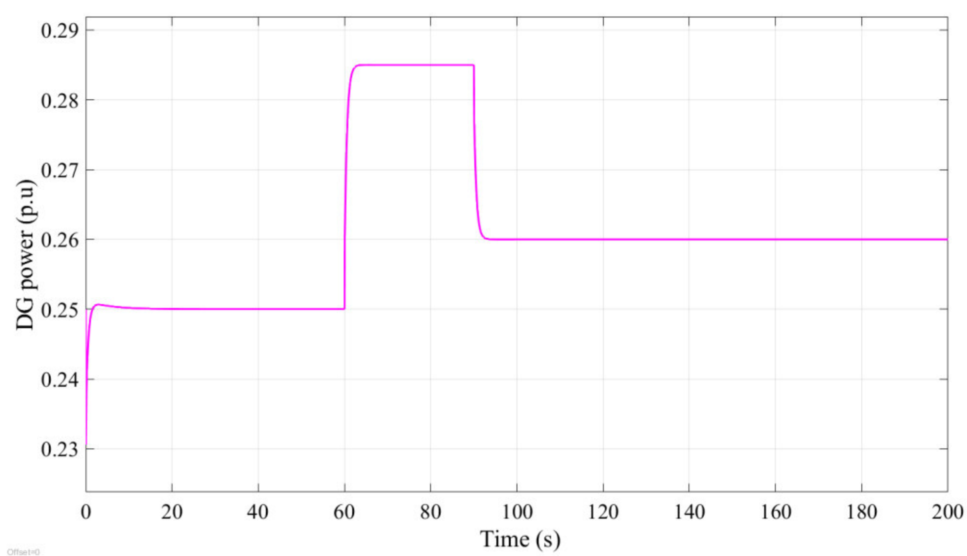

Figure 10 diesel power of scenario 1.

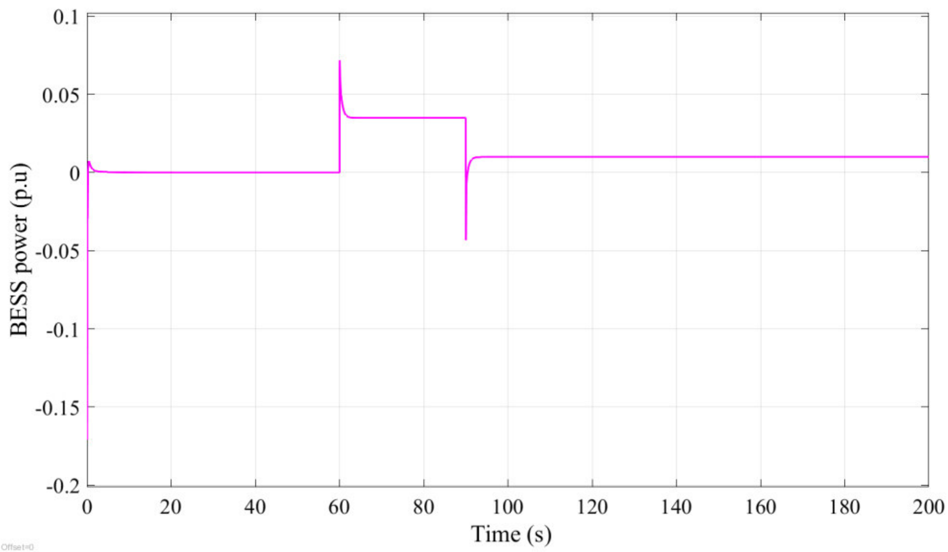

Figure 11 the power of the battery of scenario 1.

3.2 Scenario 2:

In this case, under the islanded grid mode too. As shown in figure 9, the load demand has been decreased at t=60[s] by 0.15 p.u and decreased at t=90 [s] by 0.2 pu. Again, the battery has much faster control over the active and reactive power compared to the diesel unit. At t=60[s], the frequency deviation in is almost -0.0135 and -0.0235 at t=90[s] as shown in figure 8. The power percentage of these two units is shown in Fig 10 and Fig 11.

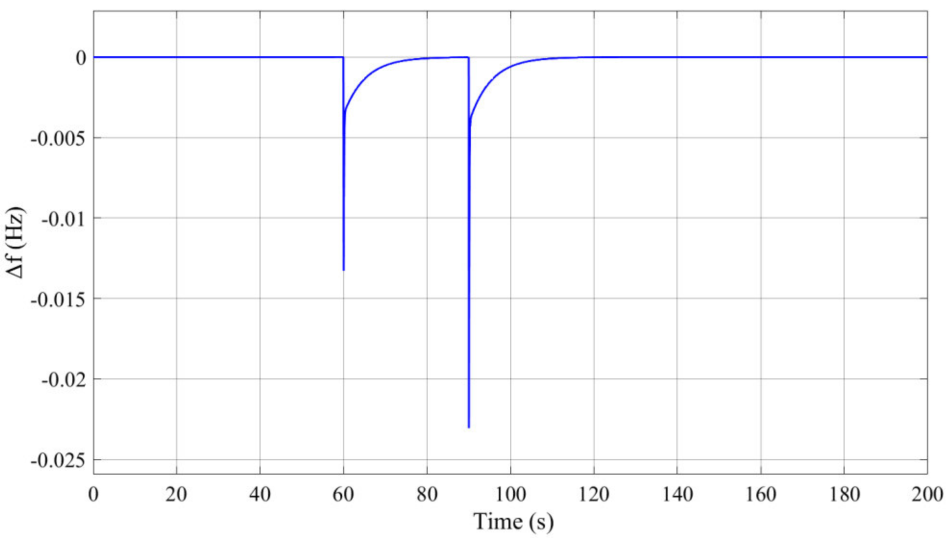

Figure 12 frequency deviation of scenario 2.

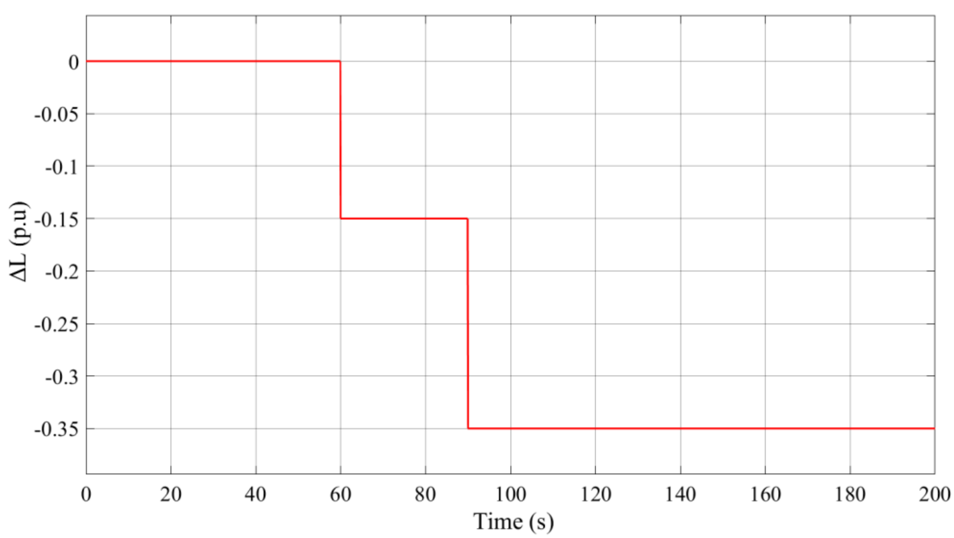

Figure 13 load change of scenario 2.

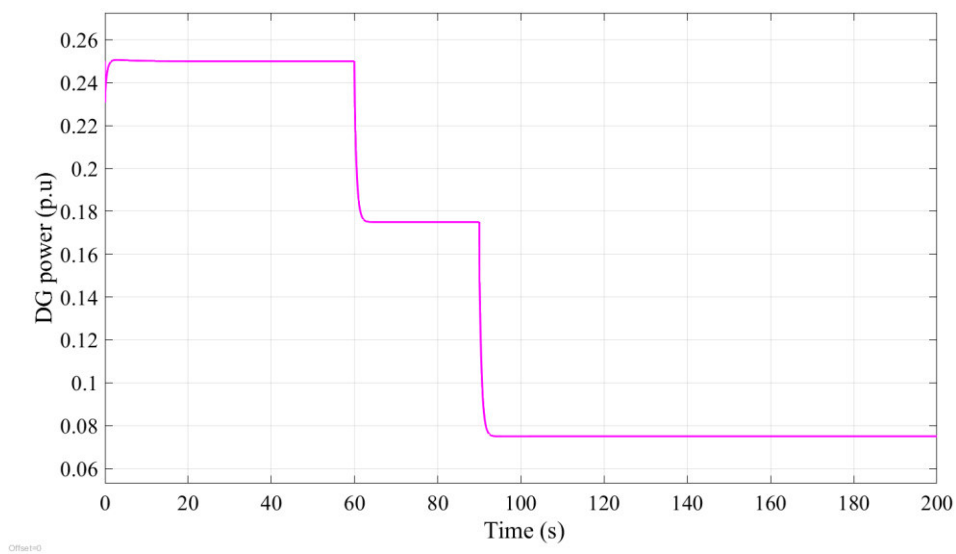

Figure 14 diesel power scenario 2.

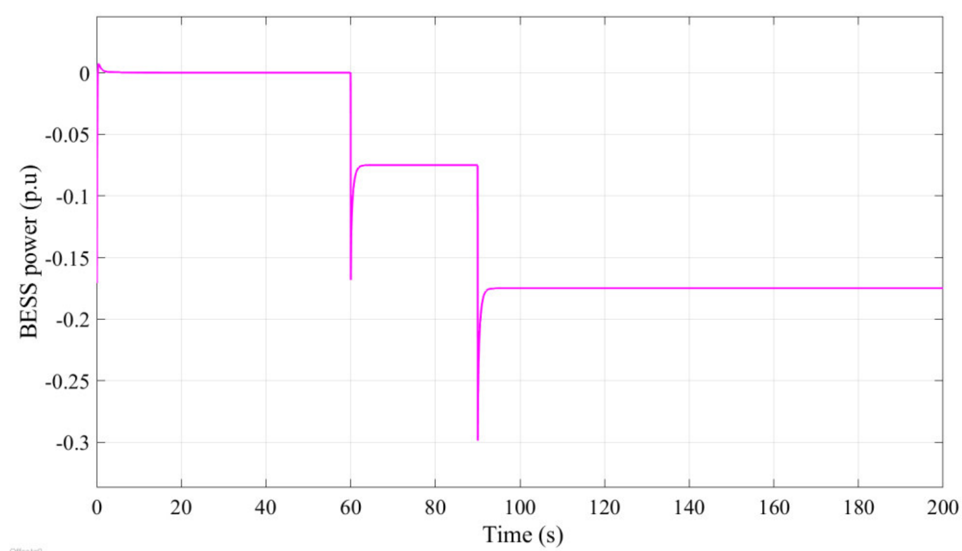

Figure 15 battery power of scenario 2.

Figure 16 training window of the DRL agent.

Conclusions

Microgrids face challenges due to load disturbances, the uncertain nature of renewable output power, energy storage system dynamics, and low system inertia. These factors can lead to large frequency deviations, weakening the MG and potentially resulting in a complete blackout. Addressing this, this paper introduces LFC method against stochastic power flow from renewable energy sources, leveraging DRL. A real-time MG test system is employed for simulation purposes. This system is modeled using MATLAB/Simulink, and its performance under various scenarios is analyzed to evaluate the efficacy of the proposed method, contrasting it with existing techniques from the literature. Results indicate that our proposed controller offers a more rapid response and is well-suited for dynamic systems.

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