Adaptive Load Frequency Control in Islanded Multi-Microgrids Using Hybrid Q-Learning–Differential Evolution Tuned FOPD(1+PI) Controller

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Abstract:

Due to the enhancement of penetration of sustainable energy sources, like wind and solar resources, changing load demands with the increasing in electrical mobility or electrical vehicles, frequency control has critical challenges for microgrids. The discrete nature and unpredictable of energy sources output cause interruption that could not be sufficiently restored by the control system. Hence in this issue we implement the a hybrid optimization that combines Q-Learning with Differential Evolution (QL-DE) method to optimize a Systematic-Fractional Order Proportional-Derivative control technique with (1+PI LFC of networked microgrids using FOPD(1+PI) CONTROLLER. The controller designs the fast response of fractional order dynamics, while the (1+PI) term increase the steady-state accuracy. An QL-DE model has the adaptive learning capability of reinforcement learning, and at the same time it has global search ability (Differential Evolution), which is achieve good performance even in stochastic environment where nonlinear solution function obtain in fitness. Test case is a two-area islanded multi-microgrid system with distributed storage, EVs, and RES. The Simulation result demonstrates to minimize frequency fluctuations, speeds up settling time, and increase system robustness. These results indicate that the FOPD(1+PI) controller utilizing QL-DE is a promising option for dependable frequency regulation in upcoming smart microgrids.

Keywords: FOPD (1+PI) controller, Load frequency control (LFC), Multi-microgrid, optimization technique.

I. Introduction

Microgrids (MGs) rapidly enhancing sustainability, operational flexibility, and reliability, from the reason of the enhanced integration of conventional sources within distribution networks. Such as different environment as apartment complexes, shopping centers, or industrial facilities, it operated as low voltage with various equipment like dispersed generators, storage units, and consumer loads [1]. The microgrid function is distributed in two modes: grid-connected, it is mainly operate the main utility network, and islanded, it operate itself only for outage and disconnection. In both configurations, the frequency stability is required within it limit and also require to maintain balance with supply and demand. In islanded mode the fluctuation more due to less frequency because of less grid support. [2].

To address these challenges and accept frequency stability while systems will safe when the operation will robust and adaptable control systems are essential. The Energy system flexibility has unpredictable, for the reason is continuous increase demand and balance between generation and consumption. Traditionally, popular units have modified and fulfill the requirements else it effect on environment issues [3].

While grid scale energy storage provide a more eco efficient alternatives, their mainstream adoption is short and limited by high infrastructure and capital expenses [4]. Furthermore, electric vehicles (EVs) are one of the option for increasing grid flexibility and environment sustainability. It is adopt not only for emission reduction but also new opportunity in supplementary service and efficient energy balancing [5].

Literature Review: The microgrid Research into microgrid frequency response has increase the momentum from reason is integration of different energy sources and also modern energy system. In the case of disturbances and reduced system inertia the Load frequency control designed for large interconnection power system struggle in microgrid environments [6]. Likewise, even though they are commonly used, traditional proportional-integral-derivative control (PID) have problem to managing the fractal and volatile reason by changing load demands and variable renewable generation [7].

To tackle these challenges, unique control solution such as fractional-order controllers, adaptive intelligence techniques, and model predictive control have been explored. In Fractional-order controllers, provide improve strength and plasticity in adjustment of parameters compared to standard integer-order controllers [8]. For this adjustment of parameter of controller parameters were tuned using the techniques of optimization like as the Grey Wolf Optimizer (GWO), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), from these optimizers can have improved frequency stability and transient response [9]. To improve efficiency of optimization and authenticity should use hybrid technique with evolutionary algorithms help by machine learning or reinforcement learning [10].

In this context, the Q-learning provide adaptive decision for dynamic environment while the Differential Evolution (DE) offers robust global search capabilities. The integration of these two solutions has shown potential in developing controllers that can respond to real-time disturbances while ensuring global optimization [11].

Motivated by these developments, this article applied for islanded microgrid, in optimization framework for a controller, Fractional Order Proportional-Derivative with (1+PI) [FOPD(1+PI)], which employ a mixed Q-Learning–Differential Evolution (QL-DE) approach. A resilient and scalable solution for future smart grid environments is aimed to be delivered by alleviating the challenges posed by system nonlinearities and the variability of renewable energy sources.

Contribution:

- This article gives a novel hybrid optimization technique with actual-tuning a Fractional Order Proportional-Derivative plus (1+PI) [FOPD(1+PI)] controller, which integrates Q-Learning and Differential Evolution (QL-DE).

- This also merged with the global search capabilities of Differential Evolution with the adaptive decision-making strengths of reinforcement learning. The comprehensive two-area islanded microgrid framework developed includes electric vehicles (EVs), distributed battery storage systems, and renewable energy sources (RES).

- The model provides a realistic environment for assessing frequency stability across different operating and disturbance scenarios. A comparative analysis with traditional controllers demonstrates the effectiveness of the proposed technology by achieving fewer frequency deviations, quicker settling times, and enhanced resilience against uncertainties and external disturbances..

II. Study Framework

The proposed framework configured in Fig. 1. Area 1 integrates hydro generation, a hydrogen electrolyze fuel cell chain, and wind energy resources, whereas Area 2 consists of a battery energy storage unit coupled with solar power. Furthermore, electric vehicles (EVs) are embedded in both areas to enhance grid flexibility and dynamic stability. The dynamic models of wind and solar sources are developed following the methodology reported in [11].

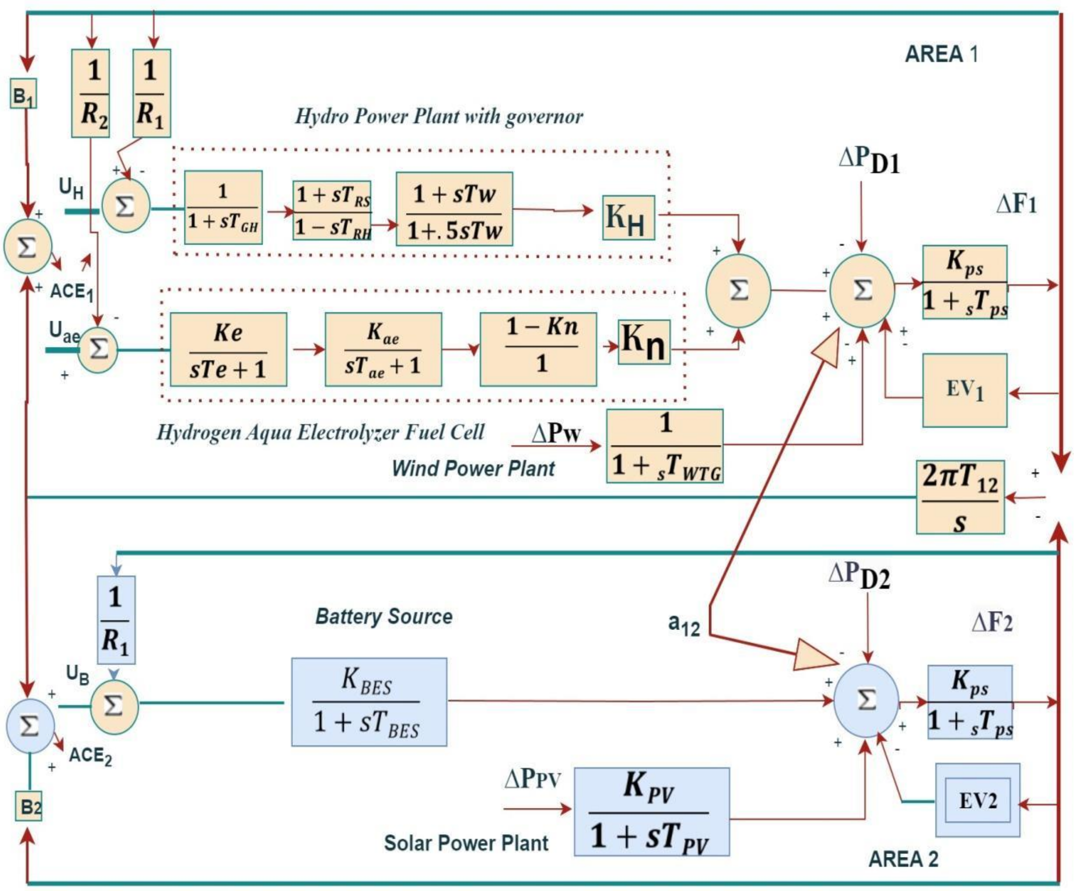

Fig. 1. System under study in two areas with multi sources

Modeling Components:

- **Hydro Power**

The mathematical models of the hydraulic governor and turbine are expressed in Eq.1 and 2 through the following transfer functions [12].

$$G_{HG}(s) = \left[\frac{k_1}{1+st_1}\right]\left[\frac{1+st_r}{1+st_2}\right] \tag{1}$$

$$G_r(s) = \frac{1+st_w}{1+0.5st_w} \tag{2}$$

Here, $t_1,\ t_2,\ t_r, and\ t_w$ correspond to the constants of time of the hydro unit's speed governor, main servo mechanism, reset mechanism, and the water starting time in the penstock, respectively.

- **Hydrogen aqua Electrolyzer Fuel Cell**

One promising option to lessen dependency on fossil fuels for the production of power is through hydrogen. Hybrid power systems employ Energy Storage Systems (ESS) combining hydrogen electrolyzers and fuel cells (HAFC) to enhance frequency regulation and maintain transient response. In this setup, excess renewable energy is utilized to generate hydrogen, which is stored and subsequently transformed into electrical energy using fuel cells [13].

The mathematical models of the hydrogen aqua electrolyzer fuel cell are expressed in Eq.3 through following transfer function [14].

$$\Delta P_{HAFC} = \left[\left(\frac{k_f}{st_f+1} * \frac{k_{ae}}{st_{ae}+1}\right) + k_n\right] * \Delta f_n \tag{3}$$

Where $$k_n = \frac{P_T}{P_{wind}+P_{PV}} \tag{4}$$

k_f *and* t_f = constants of gain and time of fuel cell

k_{ae} *and* t_{ae} =constants of gain and time of aqua electrolyzer

- **Wind Power**

The performance of a turbine is described by the output coefficient Cp is expressed in Eq.6, which depends on the tip speed ratio (λ) and the blade pitch angle (β). The tip speed ratio λ is defined as Eq.5 [15].

$$\lambda = \frac{r_{blade} * \omega_{blade}}{v_{\omega}} \tag{5}$$

Where

r_{blade} *and* ω_{blade} = blade radius and angular velocity of the blades

$$C_p = (0.44 - 0.0167\beta)\, sin\, sin\left(\frac{\pi(\lambda-3)}{15-0.3\beta}\right) - 0.0184(\lambda - 3)\beta$$

(6)

The mathematical models of the wind turbine are expressed in Eq.7 through following transfer function.

$$G_{WTG}(s) = \frac{k_{wtg}}{1+st_{wtg}} \tag{7}$$

- **Solar Power**

The photovoltaic power output using the expression is expressed in Eq.8.

$$P_{PV} = \eta S\varphi[1 - 0.005(T + 25)] \tag{8}$$

Where

η = efficiency of conversion of PV cell (10%)

S = array angle of PV (4084 m^2)

φ = irradiation of solar in kW/ m^2

T = environment temperature (25ºC)

The mathematical models of the solar system are expressed in Eq.9 through following transfer function.

$$G_{PV}(s) = \frac{k_{pv}}{1+st_{pv}} \tag{9}$$

- **Electric Vehicles**

The rapid penetration of electric vehicles (EVs) in modern power networks highlights their potential as active participants in grid support, primarily through plug-in battery functionalities. When coordinated as a fleet, EVs can act as ancillary service providers within smart grids, contributing to frequency regulation and overall system stability. In this study, a two-area interconnected hybrid energy system incorporating EVs is employed as the testbed to examine their role in enhancing dynamic stability under load fluctuations. The EV model, developed using transfer function representation, is illustrated in Fig. 2 and follows the methodology reported in [16]. Within this framework, the load frequency control (LFC) signal ΔU governs the charging–discharging operations of EVs to support frequency control.

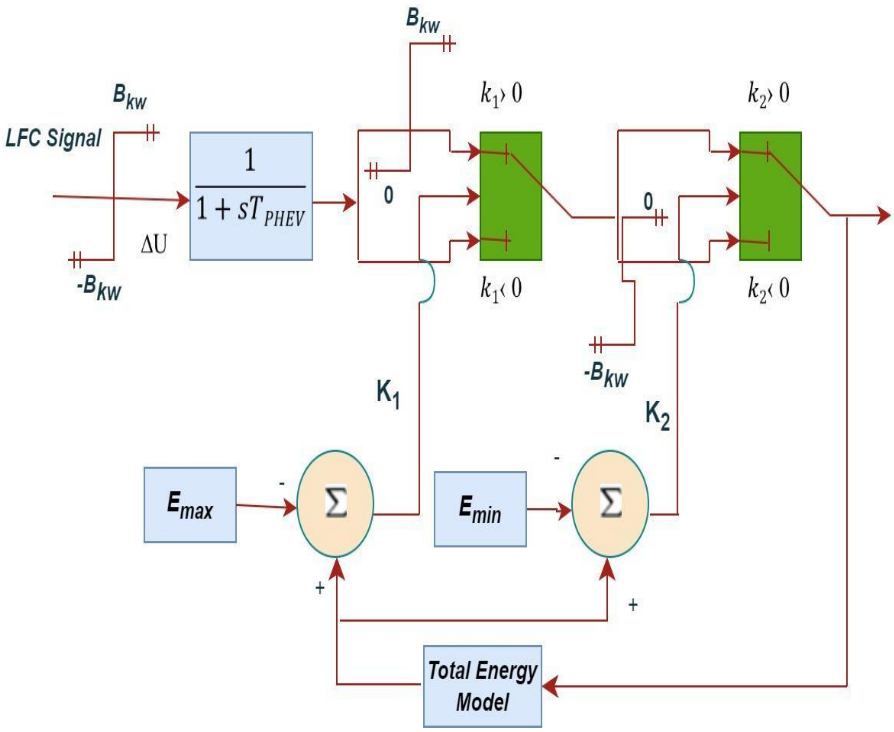

Fig. 2. Frequency control EV system model

Battery storage capacity is denoted as ±B kW, and the instantaneous energy level E is constrained within specified operational limits, E_{min} and E_{max}, corresponding to 80% and 90% of the total capacity, respectively. The control boundaries for energy management are characterized by the parameters K_1 and K_2, defined as follows in Eq.10.

$$k_1 = E - E_{max}\ ,\ k_2 = E - E_{min} \tag{10}$$

II. Proposed Methodology

To improve frequency stability in islanded multi-microgrid systems that integrate distributed storage, electric vehicles, and renewable energy sources, a new hybrid Q-Learning–Differential Evolution (QL-DE) methodology is presented for the right intonation of a Fractional-Order Proportional Derivative controller with a (1+PI) configuration (FOPD(1+PI)).This approach effectively addresses the complex uncertainties and nonlinear dynamics inherent in such systems, delivering superior adaptive Load Frequency Control performance.

Controller Design:

The proposed controller Fig. 3, integrates the rapid response characteristic of fractional-order PD control with the integral action provided by a (1+PI) component. Its transfer function is expressed in Eq.11:

$$C(s) = k_p + k_i\left(\frac{1+\alpha}{s}\right) + k_d s^{\mu} \tag{11}$$

Where

k_p, k_i, k_d = gains of proportional, integral and derivative

μ= fractional derivative ($0<\mu\leq 1$)

α = integral gain scaling parameter

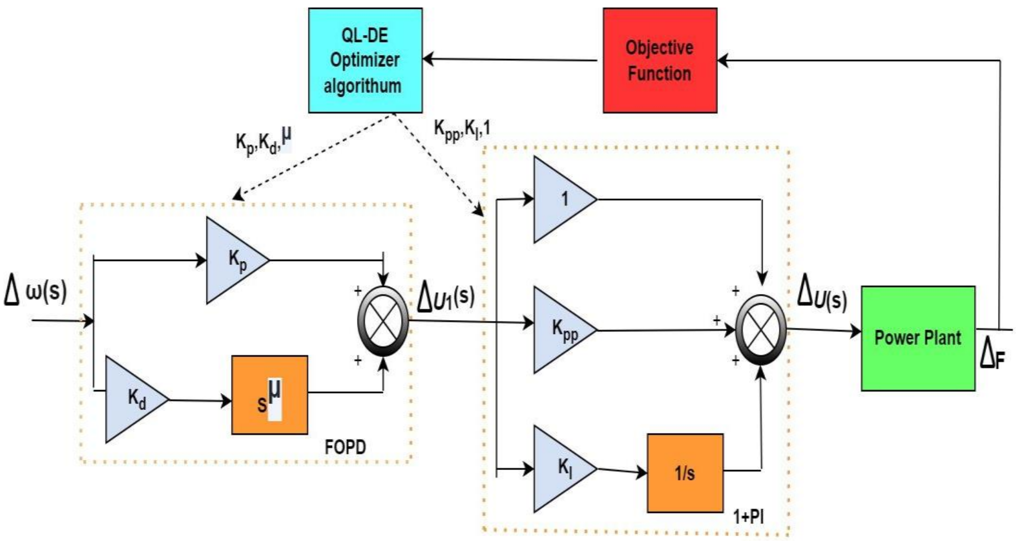

Fig.3. Controller model

The fractional order PD with integral action provided (1 + PI) controller significantly improve system stability and dynamic response during rapid reference tracking under variable conditions. It optimizes control accuracy, suppresses oscillations, and improves efficiency, ensuring robust and reliable performance in process control systems [17].

$$G_{FOPD(1+PI)}(s) = \frac{\Delta I(s)}{\Delta\omega(s)} = \left(k_p + k_d s^{\mu}\right) * \left(1 + k_{pp} + \frac{k_i}{s}\right)$$

(12)

Optimization Framework:

The hybrid QL-DE algorithm merges the global optimization strength of Differential Evolution (DE) with the adaptive learning feature of Q-Learning (QL). In this approach, DE produces new candidate solutions for tuning controller parameters, while QL refines the learning policy according to the reward signal, which is defined as the inverse of frequency deviation.

- **Differential Evolution (DE)**

An evolutionary computation that operates on a population of another approach and is characterized by Eq.13, 14 and 15:

Mutation:

$$v_i = x_{r1} + F * (x_{r2} - x_{r3})$$

(13)

Crossover:

$$u_{ij} = \{v_{ij}, if\ randj\ \leq CR\ \ x_{ij}, otherwise\}$$

(14)

Selection:

$$x_i^{t+1} = \{u_i, if\ J_{u_i} < J_{x_i}\ x_i, otherwise\ \}$$

(15)

- **Q-Learning**

Q-Learning enhances Differential Evolution (DE) by adaptively tuning the parameters F, CR, and the exploration-exploitation trade-off in response to environmental feedback. The update mechanism for Q-values is expressed as in Eq.16:

$$Q(s,a) \leftarrow Q(s,a) + \alpha[r + \gamma max Q(\acute{a}, \acute{s}) - Q(s,a)]$$

(16)

Where

s = current state (controller performance class)

a= action (parameter tuning)

α = learning rate

γ = Discount factor

r = reward (inverse of objective function value)

Work Flow: The complete implementation process is depicted in Fig. 1. The simulation starts by initializing the system model alongside the QL-DE optimizer. Controller parameters are tested within the simulation, with their effectiveness measured by the ITAE criterion. The optimizer then iteratively adjusts these parameters to reduce the objective function. The flowchart of the QL-DE optimizer is shown in Fig. 4.

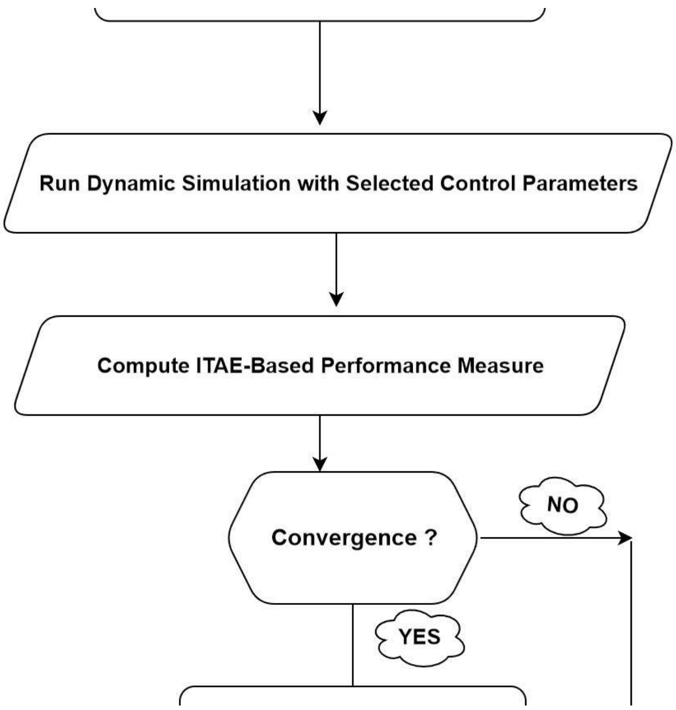

Fig. 4. Flow of QL-DE

Objective Function: The control approach aims to enhance dynamic response and decrease frequency deviation. The Integral of Time-weighted Absolute Error (ITAE) criterion in Eq. 17 is used to assess the performance:

$$J = \int_0^t \quad r * |\Delta f(r)| dt$$

(17)

This goal guarantees a quick system response while minimizing overshoot. In more complex scenarios, additional multi-objective criteria, including control effort u(t) and rate of change, may also be incorporated in Eq.18:

$$J = \omega_1 \int_0^t \quad r * |\Delta f(r)| dt + \omega_2 \int_0^t \quad u(r)^2 dt$$

(18)

Where

J = composite objective function

$\Delta f(r)$= frequency deviation (Hz)

$u(t)$ = control effort (actuation signal)

ω_1 , ω_2 = weighting factors between response time and control energy

III. Simulation

To validate the effectiveness of the proposed QL-DE–tuned FOPD (1+PI) controller, two test scenarios were created on a two-area islanded multi-microgrid system:

• Case 1: Area-1 subjected to a step load disturbance illustrated in Fig. 5.

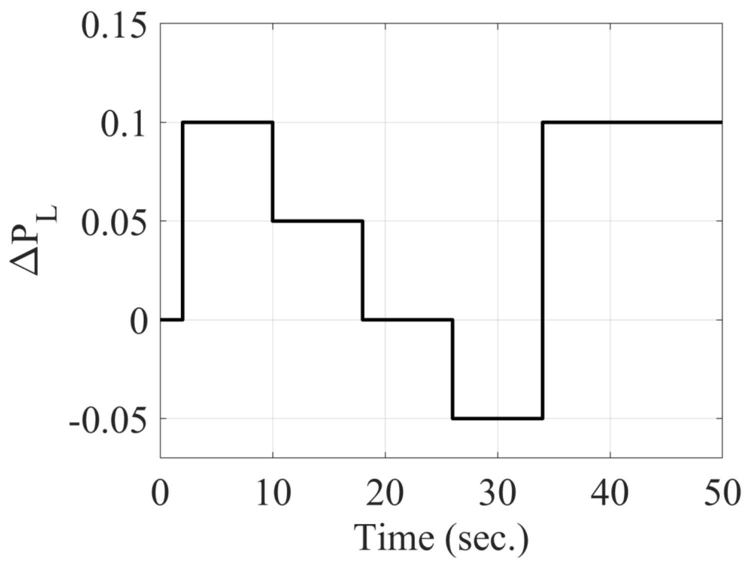

Fig. 5. Load perturbation for case-1

• Case 2: Area-2 subjected to a step load disturbance illustrated in Fig. 6.

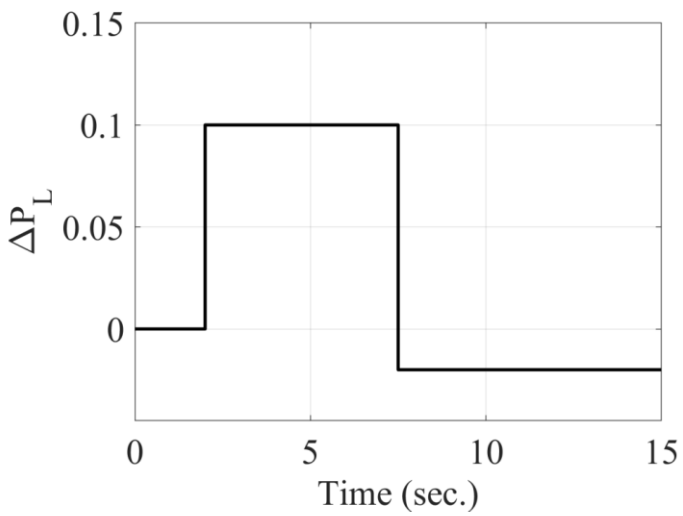

Fig. 6. Load perturbation for case-2

In both cases, the performance metric was defined in terms of frequency deviations (Δf_1 and Δf_2), which were minimized using the formulated optimization problem expressed in Fig. 7 and 8. The fitness function integrated both transient and steady-state characteristics, ensuring balanced controller performance across dynamic operating conditions.

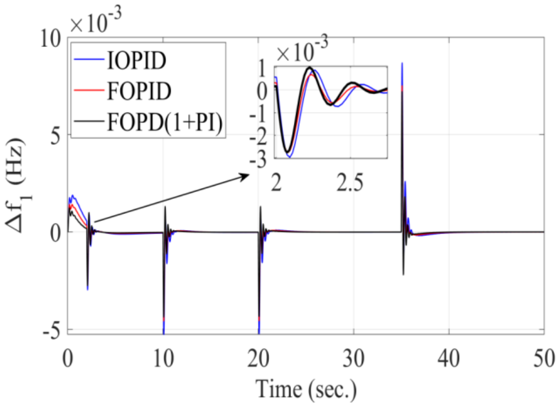

Fig.7.Δf_1 for case-1

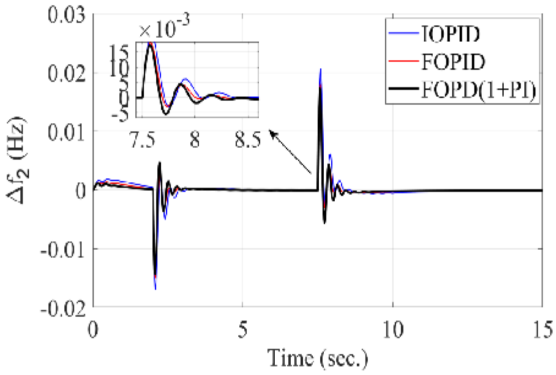

Fig.8.Δf_2 for case-2

Simulation results demonstrate that the proposed controller effectively suppresses frequency deviations under both disturbance scenarios. The QL-DE optimized FOPD (1+PI) controller exhibits faster transient recovery and reduced overshoot compared to conventional PID and FOPID controllers. Moreover, the steady-state deviations are significantly minimized, confirming the superior robustness of the proposed strategy against renewable intermittency and load fluctuations.

Comparative Evaluation: To establish the generality of the proposed approach, the optimization problem was solved using three metaheuristic algorithms: QL-DE, Particle Swarm Optimization (PSO), and Genetic Algorithm (GA). The parameters of algorithms are expresses in Table No.1.Each algorithm was executed independently 30 times with a population size of 20 and a maximum of 500 iterations, ensuring statistical reliability expressed in Table No.2.

Algorithms	Parameters
PSO	ω=0.53,c1=1.49,c2=1.49
GA	Crossover rate=0.8, mutation rate=0.2
QLDE	α_Q = 0.3,γ=0.95, CR= ϵ_0 =0.9, F=0.6

Table 1. Parameters of Algorithms

Controller	IOPID			FOPID			FOPD (1+PI)		
Algorithms	ISE	`t_{s1}	t_{s2}	ISE	t_{s1}	t_{s2}	`ISE	t_{s1}	t_{s2}`
PSO	$9.00*e^{-5}$	2.66	2.61	$8.66*e^{-5}$	2.43	2.4	$8.651*e^{-5}$	2.37	2.083
GA	$8.83*e^{-5}$	2.59	2.37	$8.4*e^{-5}$	2.48	2.15	$8.227*e^{-5}$	2.39	1.93
QLDE	$8.34*e^{-5}$	2.53	2.22	$8.17*e^{-5}$	2.32	2.06	$8.067*e^{-5}$	2.03	1.89

Table 2. Comparative evolution

The comparative results highlight that:

- The QL-DE–based controller consistently achieved the lowest frequency deviations, outperforming PSO and GA across both test cases.

- In terms of dynamic response, QL-DE reduced the settling time by nearly 12% compared to FOPID and by 20% compared to IOPID, confirming its effectiveness in achieving faster system stabilization.

- QL-DE also demonstrated superior resilience, maintaining frequency stability under large perturbations, whereas conventional methods exhibited delayed recovery and larger oscillations.

These findings clearly establish the hybrid reinforcement learning–evolutionary framework as a robust solution for frequency regulation in renewable-dominated islanded microgrids. By integrating adaptive intelligence with global search capability, QL-DE ensures both fast transient response and steady-state accuracy, making it a promising candidate for deployment in next-generation smart grid control architectures.

IV. Conclusion

To strengthen load frequency control (LFC) in isolated multi-microgrids, this study proposed a multi-stage fractional-order control strategy. The approach effectively addressed issues arising from high renewable energy penetration and reduced system inertia. The proposed FOPD(1+PI) controller was optimized using the QL-DE algorithm, yielding superior performance over traditional PID and FOPID controllers. According to simulation results, the QL-DE-tuned FOPD(1+PI) controller offers quicker response times, reduced frequency fluctuations, and enhanced system stability. Notably, the proposed technique decreased settling time by as much as 12% and 20% when compared to the FOPID and IOPID controllers, respectively.

Furthermore, a comparative analysis revealed that QL-DE outperforms PSO and GA in optimizing controller parameters, leading to the best possible system performance across various operating conditions. The proposed approach bolsters the resilience of multi-microgrid systems by integrating adaptive tuning mechanisms with sophisticated fractional-order control, ensuring consistent and reliable operation even amidst dynamic load variations and renewable energy intermittency.

V. References

1) Mohajery, R., Shayeghi, H., and Bizon, N. "Frequency Control of an Islanded Microgrid with Electric Vehicles Using a Fractional-Order Controller." *International Journal of Technical and Physical Problems of Engineering (IJTPE)*, vol. 16, no. 58, 2024, pp. 365–373.

2) Jalilian, M., Rastgou, A., Kharrati, S., and Hosseini-Hemati, S. "Frequency Stability of Hybrid Power System in the Presence of Superconducting Magnetic Energy Storage and Uncertainties." *Journal of Operation and Automation in Power Engineering*, vol. 11, no. 4, 2023, pp. 230–239.

3) Salari, A., Ahmadi, S. E., Marzband, M., and Zeinali, M. "Fuzzy Q-Learning-Based Approach for Real-Time Energy Management of Home Microgrids Using Cooperative Multi-Agent System." *Sustainable Cities and Society*, vol. 95, 2023, p. 104528.

4) Soofi, M., Jalilvand, A., Delavari, H., Mobayen, S., and Su, C.-L. "Prescribed Performance Control Strategy for an Isolated Multi-Agent DC Microgrid." *IEEE Transactions on Smart Grid*, 2024.

5) Malek, S., Khodabakhshian, A., and Hooshmand, R. "A New Robust Load Frequency Controller for Electric Vehicle Aggregators." *Journal of Operation and Automation in Power Engineering*, vol. 11, no. 2, 2023, pp. 83–93.

6) Chupradit, S., Widjaja, G., Mahendra, S., Ali, M., Tashtoush, M., Surendar, A., Kadhim, M., Oudah, A., Fardeeva, I., and Firman, F. "Modeling and Optimizing the Charge of Electric Vehicles with Genetic Algorithm in the Presence of Renewable Energy Sources." *Journal of Operation and Automation in Power Engineering*, vol. 11, no. 1, 2023, pp. 33–38.

7) Mishra, D., Maharana, M. K., Kar, M. K., and Nayak, A. "A Modified Differential Evolution Algorithm for Frequency Management of Interconnected Hybrid Renewable System." *International Journal of Power Electronics and Drive Systems*, vol. 14, no. 3, 2023, pp. 1711–1721.

8) Ding, Z., Li, L., Wang, X., Yu, T., and Xia, Y. "Vibration-Based FRP Debonding Detection Using a Q-Learning Evolutionary Algorithm." *Engineering Structures*, vol. 275, 2023, p. 115254.

9) Dkhil, A., Hamed, J., Amairi, M., Chetoui, M., and Trabelsi, H. "Robust Fractional PI Controller Design for Stand-Alone Microgrid Under Load Variation: An Optimization-Based Approach." *International Journal of Renewable Energy Research (IJRER)*, vol. 13, no. 4, 2023, pp. 1526–1537.

10) Shukla, R. R., Garg, M. M., and Panda, A. K. "Driving Grid Stability: Integrating Electric Vehicles and Energy Storage Devices for Efficient Load Frequency Control in Isolated Hybrid Microgrids." *Journal of Energy Storage*, vol. 89, 2024, p. 111654.

11) Pan, I., and Das, S. "Kriging Based Surrogate Modeling for Fractional Order Control of Microgrids." *IEEE Transactions on Smart Grid*, vol. 6, no. 1, 2014, pp. 36–44.

12) Khadanga, R. K., Kumar, A., and Panda, S. "Frequency Control in Hybrid Distributed Power Systems via Type-2 Fuzzy PID Controller." *IET Renewable Power Generation*, vol. 15, no. 8, 2021, pp. 1706–1723.

13) Khan, I. A., Mokhlis, H., Mansor, N. N., Illias, H. A., Daraz, A., Ramasamy, A., Marsadek, M., and Afzal, A. R. "Load Frequency Control in Power Systems with High Renewable Energy Penetration: A Strategy Employing PIλ (1+PDF) Controller, Hybrid Energy Storage, and IPFC-FACTS." *Alexandria Engineering Journal*, vol. 106, 2024, pp. 337–366.

14) Irudayaraj, A. X. R., Wahab, N. I. A., Umamaheswari, M. G., Radzi, M. A. M., Sulaiman, N. B., Veerasamy, V., Prasanna, S., and Ramachandran, R. "A Matignon's Theorem Based Stability Analysis of Hybrid Power System for Automatic Load Frequency Control Using Atom Search Optimized FOPID Controller." *IEEE Access*, vol. 8, 2020, pp. 168751–168772.

15) Abualigah, L., Abusaleem, A., Ikotun, A. M., Zitar, R. A., Alsoud, A. R., Khodadadi, N., Ezugwu, A. E., Hanandeh, E. S., and Jia, H. "Arithmetic Optimization Algorithm: A Review and Analysis." *Metaheuristic Optimization Algorithms*, 2024, pp. 73–87.

16) Padhy, S., Panda, S., and Mahapatra, S. "A Modified GWO Technique Based Cascade PI-PD Controller for AGC of Power Systems in Presence of Plug In Electric Vehicles." *Engineering Science and Technology, an International Journal*, vol. 20, no. 2, 2017, pp. 427–442.

17) Padhy, S., and Panda, S. "Application of a Simplified Grey Wolf Optimization Technique for Adaptive Fuzzy PID Controller Design for Frequency Regulation of a Distributed Power Generation System." *Protection and Control of Modern Power Systems*, vol. 6, no. 1, 2021, pp. 1–16.

18) Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M., and Gandomi, A. H. "The Arithmetic Optimization Algorithm." *Computer Methods in Applied Mechanics and Engineering*, vol. 376, 2021, p. 113609.