Adaptive proportional integral control using neural networks for secondary frequency regulation in microgrids

Belkasem Imodane[1], Mohamed Benydir[1], Sana Mouslim[2], Abdellah El Idrissi[1], Mohamed Ajaamoum[1], Brahim Bouachrine[1]
[1]Laboratory of Engineering Sciences and Energy Management (LASIME), Ibn Zohr University, National School of Applied Sciences, Agadir, Morocco
[2]Interdisciplinary Applied Research Laboratory (LIDRA), International University of Agadir Universiapolis, Agadir, Morocco

Article Info

Article history:

Received Sep 4, 2025
Revised Mar 5, 2026
Accepted Apr 20, 2026

Keywords:

Artificial neural network
Frequency regulation
Fuel cell
Grey wolf optimization
Microgrid

ABSTRACT

Microgrids with high renewable energy integration face a challenge in maintaining frequency stability due to the reduced inertia of inverter-based generation and the intermittent nature of these sources. Although primary frequency regulation using virtual synchronous generator (VSG) strategies can provide fast support, it cannot fully bring the system frequency back to its nominal value. This limitation highlights the importance of secondary frequency regulation, which is implemented using proportional integral (PI) controllers. However, fixed parameter PI regulators often fail to adapt effectively to varying loads and fluctuating renewable generation. This paper proposes an adaptive secondary control strategy for microgrids that combines offline optimization with real time learning. Grey wolf optimization (GWO) is first applied offline to determine the optimal PI gains for multiple disturbance scenarios. These datasets are then used to train an artificial neural network (ANN), which updates the PI parameters in real time to achieve adaptive performance. The proposed control is implemented in a hybrid microgrid with a diesel generator, a permanent magnet synchronous generator (PMSG) wind turbine for primary support and a fuel cell for secondary regulation. Simulation results show that the adaptive PI controller improves frequency recovery and reduces steady-state error compared to conventional fixed gain PI.

Corresponding Author:

Belkasem Imodane
Laboratory of Engineering Sciences and Energy Management (LASIME), Ibn Zohr University
National School of Applied Sciences
Agadir 80000, Morocco
Email: b.imodane@uiz.ac.ma

1. INTRODUCTION

Integrating renewable power energy sources into microgrids has now become an effective strategy for achieving global carbon emission reduction objectives while improving energy efficiency and system resilience. By enabling the use of distributed energy resources (DERs), microgrids contribute to sustainable power generation and increased reliability at the local level [1]. However, the process of replacing conventional synchronous machines with inverter-based units also reduces the natural inertia of the system. This loss of inertia makes microgrids more sensitive to frequency fluctuations following disturbances, highlighting the importance of maintaining robust frequency stability [2].

Frequency regulation in inverter-based microgrids is typically achieved through droop control, which allows distributed units to share active power variations without communication [3]. Virtual synchronous generator (VSG) techniques have been introduced to emulate the inertia and damping characteristics of synchronous machines, enabling renewable generators such as permanent magnet synchronous generators (PMSGs) to participate in primary frequency regulation [4], [5]. While droop control methods and VSGs can stabilize short-term deviations, they cannot fully restore frequency to its nominal value due to the inherent droop characteristic and intermittency of renewable sources [6].

To address the limitations of primary regulation, secondary frequency control has been introduced to eliminate steady-state errors. Proportional integral (PI) controllers are the most commonly used due to their simple structure and well-established tuning principles [7], [8]. However, conventional fixed parameter PI controllers struggle to deal with constantly changing operating conditions, and often perform poorly in microgrids experiencing load fluctuations and fluctuating renewable energy generation. Various advanced techniques have been explored to enhance controller performance, including fuzzy PI control, neural network-based adaptive control, model predictive control and robust adaptive strategies [9]–[13]. While these methods achieve significant improvements, each has inherent challenges, fuzzy control requires extensive rule bases, neural networks depend on large training datasets, predictive control is sensitive to model mismatches and adaptive laws require accurate microgrid modelling [14]–[16].

This work proposes an adaptive secondary frequency regulation strategy that combines offline optimization with real time learning. Grey wolf optimization (GWO) is first applied offline to determine the optimal PI parameters for various load and disturbance scenarios. These datasets are then used to train an artificial neural network (ANN), which updates the PI gains in real time. This approach deals with the limitations of fixed PI controllers while avoiding the computational burden of running metaheuristic algorithms in real time.

This article is arranged into several sections. Section 2 presents the proposed model of the system and describes the control design. The secondary frequency regulation approach using ANN is detailed in section 3. Section 4 details the simulation results. Lastly, section 5 presents the conclusions and perspectives.

2. PROPOSED SYSTEM DESIGN AND MODELING

2.1. Topology of microgrids

The microgrid system comprises several power sources, electronic converters, various loads and the necessary protection and monitoring devices. These elements work together to ensure the system operates safely, shares energy properly, and remains stable under varying operating conditions. Microgrids can generally integrate both conventional synchronous generators and sustainable energy sources connected to inverters, like wind turbines, photovoltaic units, and fuel cells. Depending on the operating mode, they can operate in either grid-connected or island mode [17], [18]. The system under study is based on an islanded microgrid architecture, which is shown in Figure 1.

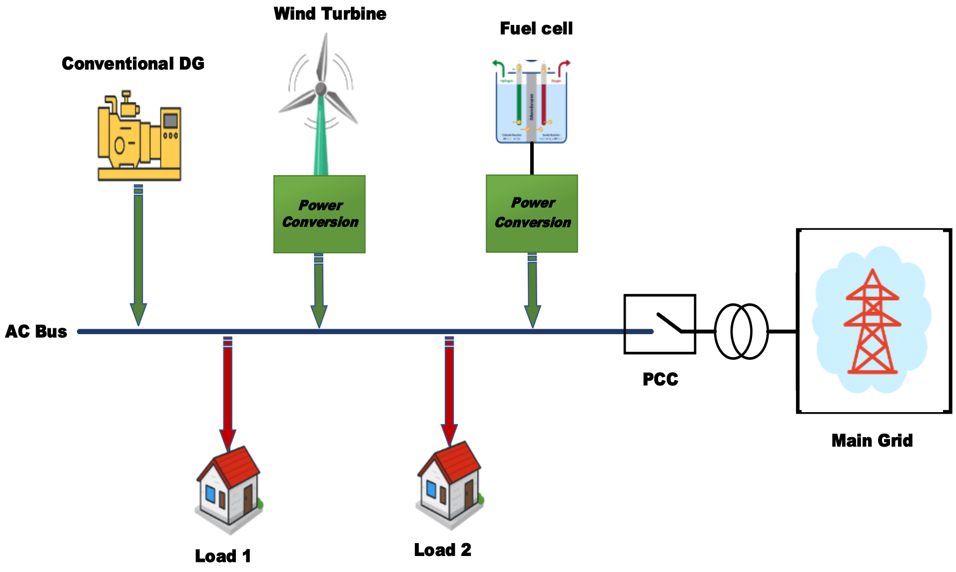

Figure 1. Microgrid system structure

2.2. Droop control strategy

In islanded operation, distributed generators are generally connected in parallel without communication links, which facilitates decentralized power sharing among units [19]. This approach is based on fundamental droop characteristics, where the active power-frequency relationship is defined by (1) and the reactive power-voltage relationship is defined by (2). These droop equations allow for autonomous load sharing while maintaining system stability in microgrids dominated by converters [20]. Here P_0 and Q_0 represent the reference active and reactive powers, while U_{ref} and w_{ref} are the corresponding reference values for voltage and angular frequency. The variables P and Q correspond to the actual active and reactive power outputs of the inverter. The coefficients $\frac{1}{R_m}$ and $\frac{1}{R_n}$ refer to the active and reactive droop constants, respectively, whereas w and U indicate the inverter output frequency and voltage amplitude.

$$w = w_{ref} - \frac{1}{R_m}(P - P_0) \tag{1}$$

$$U = U_{ref} - \frac{1}{R_n}(Q - Q_0) \tag{2}$$

2.3. Secondary frequency regulation approach in microgrid system

In the proposed microgrid, frequency regulation is organized into two levels: primary and secondary. The primary frequency regulation level is supported by the conventional distributed generator as the main source, alongside PMSG, which provides fast inertial and droop-based responses to load disturbances. The secondary frequency regulation level is managed by the fuel cell inverter, which restores the nominal frequency and eliminates the steady-state offset introduced by droop control. In this scheme, only the inverter-side contribution of the fuel cell is taken into account; the hydrogen production process is not modelled. Secondary control operates in a decentralized manner, where the fuel cell measures the frequency at the point of common coupling (PCC) and uses a PI controller to generate the correction signal. The fuel cell voltage can be regulated using a DC-DC boost converter [21], [22].

The secondary strategy begins with the calculation of the frequency deviation e_w, which is defined in (3) as the deviation between the nominal frequency and the measured PCC frequency.

$$e_w\,(t) = w_{ref} - w_{pcc}(t) \tag{3}$$

This deviation is analyzed by a PI controller, which then generates a correction signal Δw_{sec} shown in (4).

$$\Delta w_{sec} = K_p e_w(t) + K_i \int_0^t e_w(t)\, dt \tag{4}$$

Here K_p and K_i represent the proportional and integral gains, respectively. Finally, the adjustment is applied as a power correction to the fuel cell droop characteristic, according to (5).

$$P_{fc}(t) = P_{fc,0} + P_{sec}(t) - \frac{1}{R_{fc}}(w_{pcc}(t) - w_{ref}) \tag{5}$$

Where $P_{sec}(t) = \frac{1}{R_{fc}}\Delta w_{sec}$, $P_{fc,0}$ is the reference active power of the fuel cell, P_{sec} is the secondary power correction provided by the PI controller, R_{fc} is its droop coefficient, and P_{fc} is the commanded active power output. In (3) and (5) show how the fuel cell adjusts its power injection in order to eliminate the steady state error caused by droop based primary regulation and to restore the system frequency to its nominal value.

3. ADAPTIVE PROPORTIONAL INTEGRAL CONTROL BASED ON ANN

An ANN-based adaptive secondary frequency controller is proposed in this study. A schematic diagram of the proposed control method is shown in Figure 2. First, the grey wolf optimizer is applied offline under various load disturbances to determine the optimal PI parameters (K_p and K_i) for the secondary controller [23], [24]. The obtained datasets are then used to train an ANN, which learns the non-linear mapping between the system conditions and the optimal controller gains. During real-time operation, the ANN updates the PI parameters online based on the frequency deviation measured at the PCC, thus ensuring adaptive tuning of the secondary controller. In this way, the computational complexity of online optimization is avoided, while ANN ensures rapid adaptation to system changes. The corrected power commands generated by the secondary controller are then applied to the fuel cell inverter, which provides secondary frequency regulation for the microgrid.

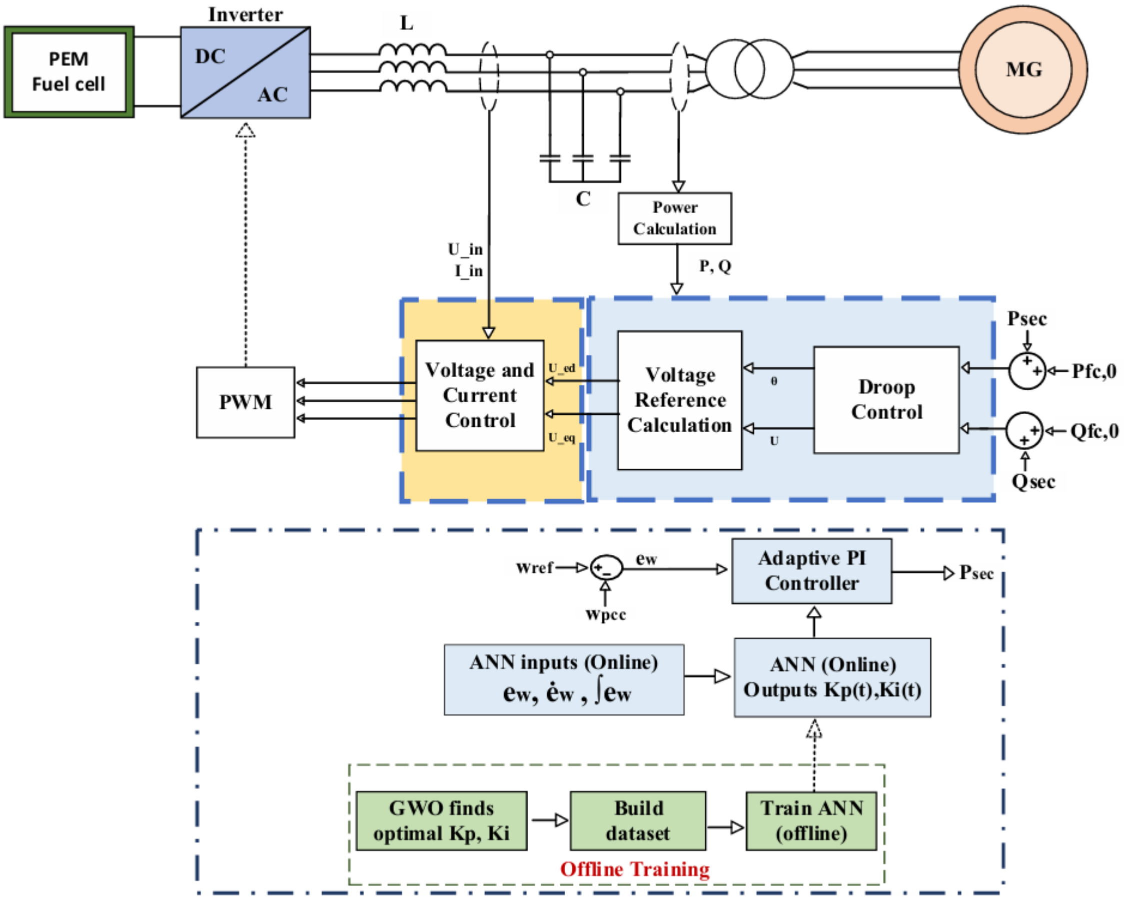

Figure 2. Adaptive secondary frequency control block for microgrid based on ANN

3.1. Artificial neural network model

ANNs are non-linear models capable of learning complex relationships between inputs and outputs, making them suitable for adaptive control in microgrids [25]. The input layer has three neurons that correspond to the frequency error $e_w(t)$, its derivative $\dot{e}_w(t)$, and its integral $\int_0^t e_w(t)\,dt$. The network has two hidden layers, the first hidden layer has 12 neurons, while the second has 8, as shown in Figure 3. This configuration was chosen after preliminary validation in order to obtain a good compromise between accuracy and computational efficiency. The output layer has two linear neurons that provide time-varying PI gains in the form of a column vector y, as shown in (6).

$$y(t) = \left[K_p(t), K_i(t)\right]^T \tag{6}$$

The flowchart in Figure 4 illustrates the application of the grey wolf optimizer for PI controller tuning in secondary frequency control. The process begins with the initialization of a population of candidate PI gains (K_p, K_i) within predefined limits. Each candidate is then evaluated using integral of time-weighted absolute error (ITAE) criterion for frequency error e_w, and the three best solutions are designated as leaders α, β, δ. If the stopping condition is not satisfied, the convergence coefficients a, A, and C are updated, and all wolves adjust their position according to the leaders while respecting the parameter limits. The new population is re-evaluated, the leaders are updated, and the process is repeated until the iteration limit is reached or the target performance is reached. The algorithm then produces the best solution, providing the optimal PI gains for the system.

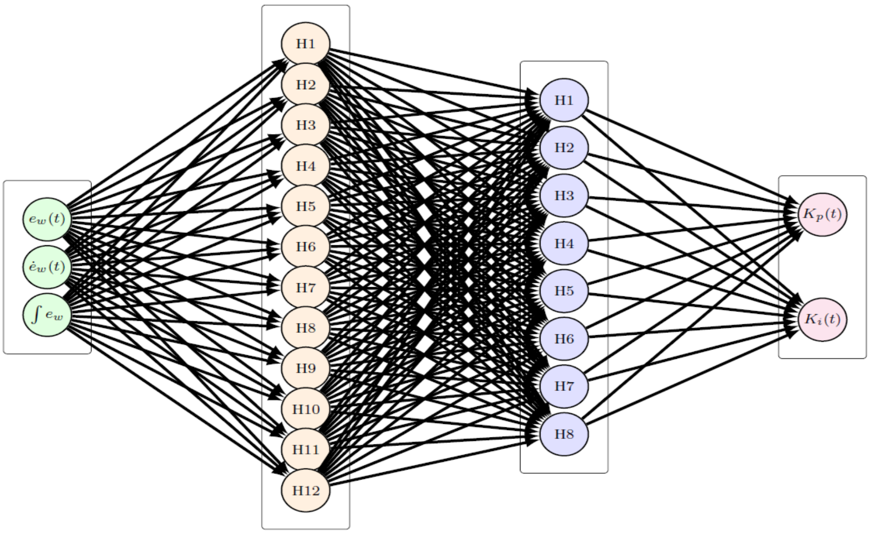

Figure 3. Architecture of the ANN implemented model

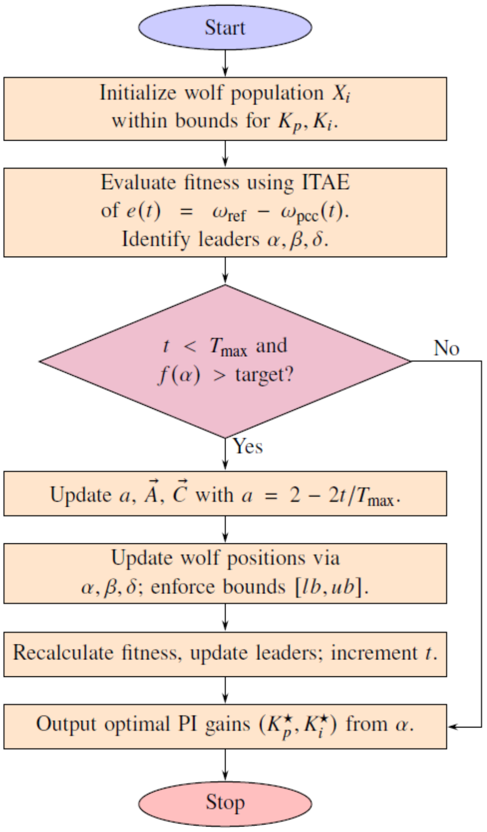

Figure 4. GWO model recognition flowchart

4. RESULTS AND DISCUSSION

This study focuses on evaluating secondary frequency control in a microgrid environment by analyzing a conventional PI controller and a proposed adaptive PI control strategy in comparison with each other. The aim is to determine which approach is more effective at maintaining frequency stability under different operating conditions. Two representative scenarios are investigated, a variable load profile with fixed power generation sources, and a fixed load with variable power input from a PMSG. These cases are chosen to demonstrate the performance, robustness, and adaptability of the proposed controller in response to demand-side and supply-side fluctuations.

In Figure 5, when the load increased at t =0.5 s from 85 kW to 95 kW, then decreased at t =2.5 s to return to 85 kW in the first scenario, the conventional PI controller produced a frequency nadir of approximately 49.992 Hz, with an overshoot of nearly 0.010 Hz and a recovery time of 0.5 seconds. In this case, the adaptive PI controller achieved an improved nadir of 49.994 Hz, a reduced overshoot of 0.006 Hz, and a faster recovery time of approximately 0.4 seconds. In Figure 6, the load remained at 85 kW, while the PMSG contribution decreased from 10 kW to 5 kW at t =0.5 s and from 5 kW to 0 kW at t =2.5 s. With PI control, the nadir frequency reached approximately 49.985 Hz, with an overshoot of 0.015 Hz and a recovery time of 0.6 seconds. The adaptive controller improved the nadir frequency to 49.987 Hz, limited the overshoot to 0.010 Hz, and reduced the recovery time to 0.5 seconds. Similar behavior under load disturbances has been reported for adaptive and intelligent secondary control strategies [26], [27].

Even though the differences observed are still relatively small because the applied disturbances are modest ±10 kW, the results clearly indicate that the adaptive PI controller provides superior performance compared to the fixed PI controller. Specifically, the adaptive approach achieves a more effective reduction in frequency deviations, minimizes overshoot, and shortens recovery times after disturbances. This observation is consistent with recent studies on online parameter adaptation [28]–[30]. These improvements demonstrate the ability of the adaptive mechanism to adjust controller parameters in real time, enhancing the dynamic response of the microgrid. These results confirm that online parameter adaptation is a valuable strategy for enhancing the robustness and reliability of secondary frequency control, even under moderate changes in load or generation.

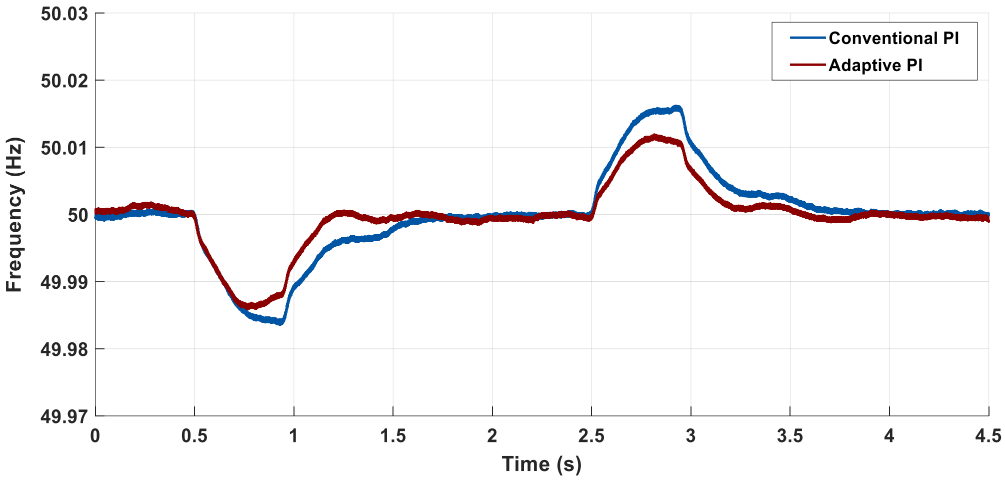

Figure 5. Frequency response under variable load with fixed power source

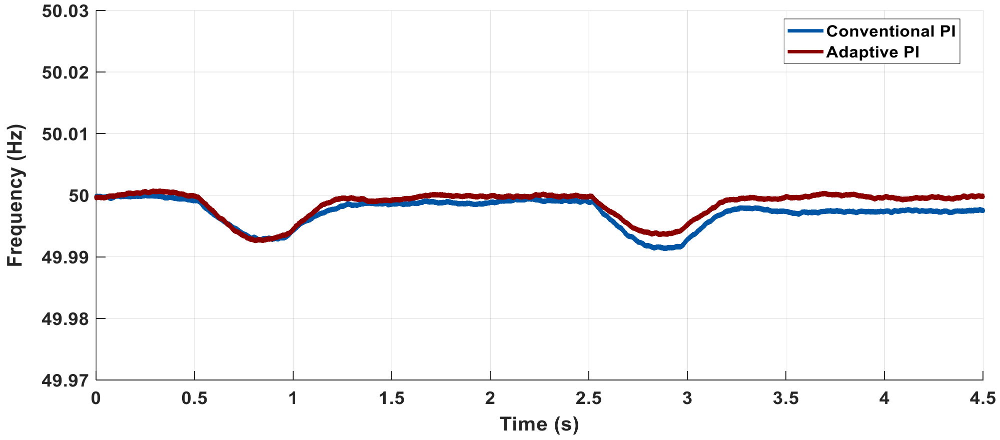

Figure 6. Frequency response under fixed load with variable power sources

5. CONCLUSION

This work proposed an adaptive secondary frequency control strategy for microgrids, combining offline GWO with an ANN to overcome the limitations of fixed-parameter PI controllers. Simulation results under load variations and fluctuating renewable generation, represented in this study by PMSG output, confirmed that the adaptive controller consistently achieved lower frequency nadirs, reduced overshoots, and enabled faster recovery compared to conventional PI, demonstrating improved system stability. These results demonstrate the effectiveness of online parameter adaptation in improving secondary frequency regulation and confirm its potential for application in practical microgrid environments. This approach will be extended to larger hybrid systems in future research, supported by real time or hardware in the loop (HIL) validation, and explore integration with prediction methods and adaptive power sharing techniques.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Belkasem Imodane	✓	✓	✓	✓	✓	✓			✓	✓	✓			
Mohamed Benydir		✓	✓	✓	✓	✓				✓	✓			
Sana Mouslim				✓	✓	✓				✓		✓		
Abdellah El Idrissi			✓			✓				✓				
Mohamed Ajaamoum		✓					✓			✓		✓	✓	
Brahim Bouachrine		✓					✓			✓		✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors confirm that there are no financial or personal interests that could have affected the objectivity of the research reported in this paper.

DATA AVAILABILITY

Data availability is not applicable to this study since no new data were generated or analyzed.

REFERENCES

[1] J. Heidary, M. Gheisarnejad, H. Rastegar, and M. H. Khooban, “Survey on microgrids frequency regulation: modeling and control systems,” *Electric Power Systems Research*, vol. 213, 2022, doi: 10.1016/j.epsr.2022.108719.
[2] S. Saha, M. I. Saleem, and T. K. Roy, “Impact of high penetration of renewable energy sources on grid frequency behaviour,” *International Journal of Electrical Power & Energy Systems*, vol. 145, 2023, doi: 10.1016/j.ijepes.2022.108701.
[3] G. Shahgholian, M. Moradian, and A. Fathollahi, “Droop control strategy in inverter-based microgrids: A brief review on analysis and application in islanded mode of operation,” *IET Renewable Power Generation*, vol. 19, no. 1, 2025, doi: 10.1049/rpg2.13186.
[4] W. Sang, W. Guo, S. Dai, C. Tian, S. Yu, and Y. Teng, “Virtual synchronous generator, a comprehensive overview,” *Energies*, vol. 15, no. 17, 2022, doi: 10.3390/en15176148.
[5] M. Abuagreb, M. F. Allehyani, and B. K. Johnson, “Overview of virtual synchronous generators: existing projects, challenges, and future trends,” *Electronics*, vol. 11, no. 18, 2022, doi: 10.3390/electronics11182843.
[6] J. Liu, Y. Miura, and T. Ise, “Comparison of dynamic characteristics between virtual synchronous generator and droop control in inverter-based distributed generators,” *IEEE Transactions on Power Electronics*, vol. 31, no. 5, pp. 3600–3611, 2016, doi: 10.1109/TPEL.2015.2465852.
[7] Z. Lian, C. Wen, F. Guo, P. Lin, and Q. Wu, “Decentralized secondary control for frequency restoration and power allocation in islanded AC microgrids,” *International Journal of Electrical Power & Energy Systems*, vol. 148, 2023, doi: 10.1016/j.ijepes.2022.108927.
[8] M. A. E. Mohamed, K. Jagatheesan, and B. Anand, “Modern PID/FOPID controllers for frequency regulation of interconnected power system by considering different cost functions,” *Scientific Reports*, vol. 13, no. 1, 2023, doi: 10.1038/s41598-023-41024-5.

[9] D. L. S. Nagasri and R. Marimuthu, “Review on advanced control techniques for microgrids,” *Energy Reports*, vol. 10, pp. 3054–3072, Nov. 2023, doi: 10.1016/j.egyr.2023.09.162.

[10] K. Keerthana and C. Sreekumar, “Relative performance evaluation of novel controllers used for reducing frequency drifts in power systems,” in *2022 IEEE 19th India Council International Conference (INDICON)*, 2022, pp. 1–5, doi: 10.1109/INDICON56171.2022.10040074.

[11] H. K. Shaker, H. E. Keshta, M. A. Mosa, and A. A. Ali, “Adaptive nonlinear controllers based approach to improve the frequency control of multi islanded interconnected microgrids,” *Energy Reports*, vol. 9, pp. 5230–5245, 2023, doi: 10.1016/j.egyr.2023.04.007.

[12] B. Singh, A. Slowik, and S. K. Bishnoi, “Review on soft computing–based controllers for frequency regulation of diverse traditional, hybrid, and future power systems,” *Energies*, vol. 16, no. 4, 2023, doi: 10.3390/en16041917.

[13] A. E. Karkevandi, M. J. Daryani, and O. Usta, “ANFIS-based intelligent PI controller for secondary frequency and voltage control of microgrid,” in *2018 IEEE PES Innovative Smart Grid Technologies Conference Europe (ISGT-Europe)*, 2018, pp. 1–6, doi: 10.1109/ISGTEurope.2018.8571748.

[14] D. Razmi and T. Lu, “A literature review of the control challenges of distributed energy resources based on microgrids (MGs): past, present and future,” *Energies*, vol. 15, no. 13, 2022, doi: 10.3390/en15134676.

[15] J. S. Gomez, D. Saez, J. W. S. -Porco, and R. Cardenas, “Distributed predictive control for frequency and voltage regulation in microgrids,” *IEEE Transactions on Smart Grid*, vol. 11, no. 2, pp. 1319–1329, 2020, doi: 10.1109/TSG.2019.2935977.

[16] R. K. Jha, B. K. Shah, and A. Patel, “Advanced control strategies for resilient voltage and frequency regulation in smart grids,” *Journal of Electrical Engineering and Automation*, vol. 6, no. 1, pp. 1–18, 2024, doi: 10.36548/jeea.2024.1.001.

[17] K. Twaisan and N. Barışçı, “Integrated distributed energy resources (DER) and microgrids: modeling and optimization of DERs,” *Electronics*, vol. 11, no. 18, 2022, doi: 10.3390/electronics11182816.

[18] A. J. Albarakati *et al.*, “Microgrid energy management and monitoring systems: a comprehensive review,” *Frontiers in Energy Research*, vol. 10, 2022, doi: 10.3389/fenrg.2022.1097858.

[19] S. G. Ndeh, B. J. Ebot, A. F. Akawung, N. D. Khan, and T. Emmanuel, “Decentralized droop control strategies for parallel-connected distributed generators in an AC islanded microgrid: a review,” in *2023 7th International Conference on Green Energy and Applications (ICGEA)*, 2023, pp. 83–90, doi: 10.1109/ICGEA57077.2023.10126012.

[20] Q. Salem, R. Aljarrah, M. Karimi, and A. Al-Quraan, “Grid-forming inverter control for power sharing in microgrids based on P/f and Q/V droop characteristics,” *Sustainability*, vol. 15, no. 15, 2023, doi: 10.3390/su151511712.

[21] F. P. Priya, K. Latha, and K. Ramya, “Analysis and implementation of feedback linearisation controller for fuel cell-fed boost converter,” *International Journal of Electronics*, vol. 112, no. 2, pp. 370–389, 2025, doi: 10.1080/00207217.2024.2302339.

[22] F. Mumtaz, N. Z. Yahaya, S. T. Meraj, N. S. S. Singh, M. S. Rahman, and M. S. H. Lipu, “A high voltage gain interleaved DC-DC converter integrated fuel cell for power quality enhancement of microgrid,” *Sustainability*, vol. 15, no. 9, 2023, doi: 10.3390/su15097157.

[23] O. Can, A. Ozturk, H. Eroğlu, and H. Kotb, “A novel grey wolf optimizer-based load frequency controller for renewable energy sources integrated thermal power systems,” *Electric Power Components and Systems*, vol. 49, no. 15, pp. 1248–1259, 2021, doi: 10.1080/15325008.2022.2050450.

[24] A. H. Sule, A. S. Mokhtar, J. J. B. Jamian, U. U. Sheikh, and A. Khidrani, “Grey wolf optimizer tuned PI controller for enhancing output parameters of fixed speed wind turbine,” in *2020 IEEE International Conference on Automatic Control and Intelligent Systems (I2CACIS)*, 2020, pp. 118–122, doi: 10.1109/I2CACIS49202.2020.9140171.

[25] A. S. I. Hilaiwah, H. A. A. A. Allah, B. A. Abbas, and T. Sutikno, “Live to learn: learning rules-based artificial neural network,” *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 21, no. 1, pp. 558–565, 2021, doi: 10.11591/ijeecs.v21.i1.pp558-565.

[26] A. A. Raslan *et al.*, “Optimized non-integer with disturbance observer frequency control for resilient modern airport microgrid systems,” *Fractal and Fractional*, vol. 9, no. 6, 2025, doi: 10.3390/fractalfract9060354.

[27] E. Alipour, A. Dejamkhooy, M. Hosseinpour, and A. Vahidnia, “Enhanced frequency control of a hybrid microgrid using RANFIS for partially shaded photovoltaic systems under uncertainties,” *Scientific Reports*, vol. 14, no. 1, 2024, doi: 10.1038/s41598-024-73233-x.

[28] Y. Shi, Y. Cheng, B. Xie, and J. Su, “An adaptive control strategy for microgrid secondary frequency based on parameter identification,” *Global Energy Interconnection*, vol. 6, no. 5, pp. 592–600, 2023, doi: 10.1016/j.gloei.2023.10.006.

[29] M. Negahban, M. V. Ardalani, M. Mollajafari, E. Akbari, M. Talebi, and E. Pouresmaeil, “A novel control strategy based on an adaptive fuzzy model predictive control for frequency regulation of a microgrid with uncertain and time-varying parameters,” *IEEE Access*, vol. 10, pp. 57514–57524, 2022, doi: 10.1109/ACCESS.2022.3178739.

[30] K. Nosrati, V. Skiparev, A. Tepljakov, E. Petlenkov, and J. Belikov, “Intelligent frequency control of AC microgrids with communication delay: An online tuning method subject to stabilizing parameters,” *Energy and AI*, vol. 18, 2024, doi: 10.1016/j.egyai.2024.100421.

BIOGRAPHIES OF AUTHORS

Belkasem Imodane is a Ph.D. student in Electrical Engineering at the University of Ibn Zohr, Agadir. He graduated as an embedded systems engineer in 2021 from the National School of Applied Sciences, Agadir, Morocco. Subsequently, he joined the research group at the Laboratory of Engineering Sciences and Energy Management (LASIME), University of Ibn Zohr, Agadir, Morocco. His research focuses on renewable energies for his doctoral thesis. He can be contacted at email: b.imodane@uiz.ac.ma.

Mohamed Benydir is a Ph.D. candidate and substitute teacher specializing in Electrical Engineering at the High School of Technologies in Agadir (EST Agadir), originates from Agadir, Morocco. His research, integral to his national doctoral thesis, is primarily focused on renewable energy, engineering science, and energy management. He can be contacted at email: mohamed.benydir@edu.uiz.ac.ma.

Sana Mouslim is a professor at the Polytechnic School of Agadir, Universiapolis–International University of Agadir, Morocco. She earned her Ph.D. in Electrical Engineering, specializing in automation and renewable energy, from the National School of Applied Sciences (ENSA) of Agadir. Her research focuses on the control and optimization of DC-DC converters for photovoltaic applications, including the development of advanced control strategies to improve the performance and efficiency of power electronic systems. She can be contacted at email: sana.mouslim@uiz.ac.ma.

Abdellah El Idrissi is a Ph.D. student in Engineering Sciences at Ibn Zohr University (UIZ), Agadir, Morocco, and a member of the Laboratory of Engineering Sciences and Energy Management (LASIME) at the High School of Technologies of Agadir (ESTA). His doctoral research focuses on renewable energy systems for hydrogen production, emphasizing the optimization of solar-powered electrolyzes through advanced control strategies and the integration of power electronics. He can be contacted at email: abdellah.elidrissi@edu.uiz.ac.ma.

Mohamed Ajaamoum is a professor Ph.D. at the Department of Electrical Engineering, High School of Technology of Agadir, Ibn Zohr University, Agadir, Morocco. His research interests are in photovoltaic systems, fuzzy control, neural network, renewable energy technologies, system modeling, and power electronics. He can be contacted at email: m.ajaamoum@uiz.ac.ma.

Brahim Bouachrine is professor Ph.D. at the Department of Electrical and Energy Engineering, High School of Technologies of Guelmim (ESTG), Ibn Zohr University, Morocco. His research interests are in renewable energy: photovoltaic and wind energy systems, photovoltaic emulator, hybrid MPPT control, system modeling, and power electronics. He can be contacted at email: b.bouachrine@uiz.ac.ma.