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Diverse Control Strategies for Frequency Regulation in Islanded Microgrids: A Systematic Comparison

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***Abstract*— Islanded microgrids are emerging as a cornerstone of modern decentralized power systems, particularly in remote and renewable-rich areas. However, maintaining frequency stability remains a critical challenge due to fluctuating generation, variable load demand, and reduced system inertia. This paper presents a mathematical modelling for analyzing the controllability of system and a systematic comparison of diverse control methods for regulating the frequency in islanded microgrids, encompassing conventional approaches like droop and PID control, advance methods like Model Predictive Control (MPC) and robust control, as well as intelligent techniques including fuzzy logic, neural networks, and deep reinforcement learning. Special emphasis is placed on the inclusion of Hybrid Energy Storage Systems (HESS), combining battery energy storage systems and supercapacitors, to enhance system flexibility and dynamic performance. The study evaluates each control method based on response time, disturbance rejection, implementation complexity, suitability and its mathematical model for HESS-enabled microgrids. The paper concludes by highlighting the superior potential of AI-based control strategies in effectively managing frequency deviations when integrated with HESS, paving the way for resilient and intelligent microgrid operations.**

***Index Terms*— Islanded microgrids, Frequency regulation, Control strategies, Hybrid Energy Storage System (HESS).**

I. INTRODUCTION

With the global transition towards renewable energy and decentralized power generation, islanded microgrids are emerging as a requisite to guarantee uninterrupted supply in remote and grid-isolated regions. Islanded Microgrids typically integrate diverse energy sources ie; solar panels, wind turbines, fuel-based generators and advanced storage systems. However, the intermittent nature of renewables and the absence of a central grid [2] introduce significant challenges, particularly in maintaining frequency and voltage stability.

In this context, various advanced control strategies are developed for ensuring efficient frequency regulation, smooth power sharing, and consistent effectiveness despite the presence of uncertainties and system disturbances. These strategies range from conventional droop-based methods to intelligent controllers [1]-[3] leveraging artificial intelligence, fuzzy logic, sliding mode control, and model predictive control (MPC) [20]. The recent emergence of deep reinforcement learning (DRL) and optimization-based adaptive controllers [6] has further revolutionized frequency control by enabling adaptive, predictive, and decentralized decision-making.

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The growing body of literature reflects a significant research focus on developing robust, intelligent, and communication-efficient control techniques tailored to the evolving architecture of microgrids. The following literature review presents key advancements and diverse methodologies explored in recent studies.

II. Literature Review

Many different control strategies have been proposed for frequency regulation in islanded microgrids. Rosini et al. [8] combined droop and master-slave methods in a decentralized, communication-less approach for PV-storage systems. Xiao Qi et al. [26] introduced smooth switching droop control (SSDC) for flexible, decentralized power management, while Li Yang et al. [24] addressed frequency deviations in multi-area microgrids using robust smoothing control.

AI-based techniques are increasingly applied. El Zoghby et al. [10] integrated green hydrogen storage with AI controllers for improved stability. Abubakr et al. [30] used Harris hawks optimization with virtual inertia for better control under high renewables. Metaheuristic methods like Mayfly-PID [11] and SSAMGO-based hybrid controllers [33] have also enhanced response speed and accuracy.

Fuzzy logic controllers have shown high adaptability. Xu et al. [15] and Shayeghi et al. [16] effectively handled nonlinearities, while Ark Dev et al. [19] proposed a dual-objective SMC-based strategy. Model Predictive Control (MPC) remains popular: adaptive and PSO-tuned MPCs [20, 21], and real-time MPC [22] have demonstrated improved performance.

Hierarchical strategies like those from Chopra et al. [42] and Wang et al. [43] enhanced coordination and power management using cooperative and flow-based control. With lower inertia in renewable-rich systems, virtual inertia methods like that of Hamanah et al. [32] have gained relevance.

Recent developments feature deep reinforcement learning (DRL). Xin Shen et al. [38] proposed QIS-MEAC for adaptive control, while Oboreh-Snapps et al. [39] showcased DRL for effective power sharing. Other notable strategies include impedance-based optimal control [31], robust control under PV uncertainties [25], D-PMU-based secondary control [28], and MIMO control for dynamic conditions [29].

Overall, the literature reflects a shift toward adaptive, decentralized, and intelligent control methods. Hybrid strategies combining predictive, AI-based, and resilient techniques are emerging as key to maintaining frequency stability in complex, renewable-rich microgrid environments.

III. Mathematical Modelling: Islanded Microgrid

Below mentioned schematic in fig. 1 is a frequency regulation control system for an islanded microgrid using multiple power sources with battery energy storage system and supercapacitors and a proposed advanced control technique. Prior to implementing any control strategy, it is essential to validate the controllability of the system. To facilitate this analysis, the system is represented by a state-space model approach, as described below.

The frequency dynamics of above islanded microgrid is modelled as follows:

$$M\frac{d\Delta f}{dt} + D\Delta f = \Delta P_{DEG} + \Delta P_{BESS} + \Delta P_{SC} + \Delta P_{PV} + \Delta P_{WTG} - \Delta P_{load}$$

Where:

D = damping constant (MW/Hz)

M = Inertia constant (s)

Δf = Frequency deviation

ΔP_{DEG} = Diesel generator output

ΔP_{PV} = PV array output = $G_{PV} \,.\, \Delta\, \varphi$

ΔP_{WTG} = Wind turbine output = $G_{WTG} \,.\, \Delta\, P_W$

ΔP_{BESS} = Battery Energy storage output

ΔP_{SC} = Supercapacitor output

ΔP_{load} = Electrical Load

So, we get [19],

$$M\frac{d\Delta f}{dt} + D\Delta f = \Delta P_{DEG} + \Delta P_{BESS} + \Delta P_{SC} + G_{PV} \,.\, \Delta\, \varphi + G_{WTG} \,.\, \Delta\, P_W - \Delta P_{load} \tag{1}$$

Where,

$\Delta\, \varphi$ = change in PV input

$\Delta\, P_W$ = change in wind power

ΔP_{load} = load change

The state space equation is:

$$x^{\cdot} = Ax + Bu + Ed \tag{2}$$

Where,

$$\text{State vector } x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} \Delta f \\ \Delta P_{DEG} \\ \Delta P_{BESS} \\ \Delta P_{SC} \end{bmatrix},$$

$$\text{Control input } u = \begin{bmatrix} u_1 \\ u_2 \\ u_3 \end{bmatrix} = \begin{bmatrix} \Delta U_{DEG} \\ \Delta U_{BESS} \\ \Delta U_{SC} \end{bmatrix},$$

$$\text{Disturbance Input } d = \begin{bmatrix} d_1 \\ d_2 \\ d_3 \end{bmatrix} = \begin{bmatrix} \Delta\,\varphi \\ \Delta\,P_W \\ \Delta P_{load} \end{bmatrix}$$

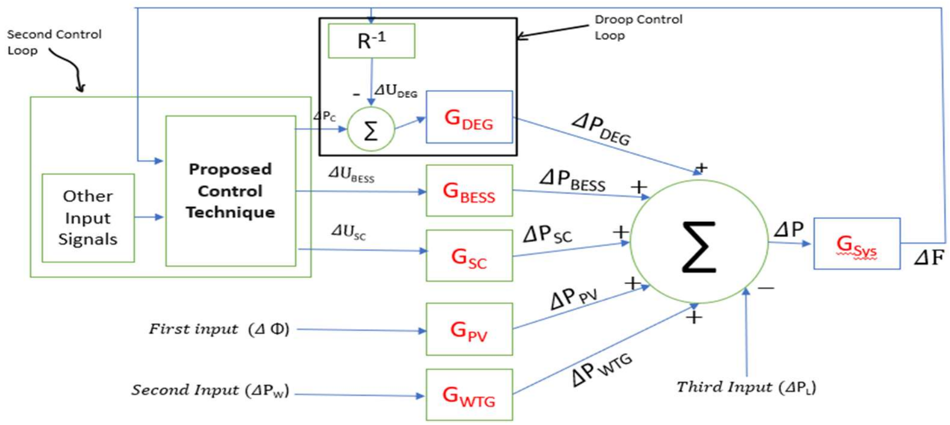

Figure 1: Schematic of Islanded Microgrid

A. Frequency Dynamics

Rewriting (1), we get,

$$\frac{d\Delta f}{dt} = \frac{1}{M}(-D\Delta f + \Delta P_{DEG} + \Delta P_{BESS} + \Delta P_{SC} + G_{PV}\,.\,\Delta\,\varphi + G_{WTG}\,.\,\Delta\,P_W - \Delta P_{load})$$

So, the first state equation becomes:

$$\dot{x}_1 = -\frac{D}{M}x_1 + \frac{1}{M}x_2 + \frac{1}{M}x_3 + \frac{1}{M}x_4 + \frac{G_{PV}}{M}\,.\,d_1 + \frac{G_{WTG}}{M}\,.\,d_2 - \frac{1}{M}d_3 \tag{3}$$

B. Diesel Generator Power Response

The diesel generator output follows the governor-turbine system, often modelled as a first-order system:

$$\frac{d\Delta P_{DEG}}{dt} = -\frac{1}{T_{DEG}}\Delta P_{DEG} + \frac{K_{DG}}{T_{DG}}u_{DEG}$$

Which becomes,

$$\dot{x}_2 = -\frac{1}{T_{DEG}}x_2 + \frac{K_{DEG}}{T_{DEG}}u_1 \tag{4}$$

C. BESS Dynamics (slower first-order response)

BESS is slower than SC, also modelled as a first-order lag:

$$\frac{d\,\Delta P_{BESS}}{dt} = -\frac{1}{T_{SC}}\Delta P_{BESS} + \frac{K_{BESS}}{T_{BESS}}u_{BESS}$$

Which becomes,

$$\dot{x}_3 = -\frac{1}{T_{BESS}}x_3 + \frac{K_{BESS}}{T_{BESS}}u_2 \tag{5}$$

D. Supercapacitor Power Dynamics (first-order response)

Supercapacitor responds quickly and is often modelled as a first-order lag:

$$\frac{d\,\Delta P_{SC}}{dt} = -\frac{1}{T_{SC}}\Delta P_{SC} + \frac{K_{SC}}{T_{SC}}\,u_{SC}$$

Which becomes,

$$\dot{x}_4 = -\frac{1}{T_{SC}}x_4 + \frac{K_{SC}}{T_{SC}}\,u_3 \tag{6}$$

Rewriting (3) to (6) in state space form in (2), we get [19],

$$\begin{bmatrix}\dot{x}_1\\ \dot{x}_2\\ \dot{x}_3\\ \dot{x}_4\end{bmatrix} = \begin{bmatrix} -\frac{D}{M} & \frac{1}{M} & \frac{1}{M} & \frac{1}{M} \\ 0 & -\frac{1}{T_{DEG}} & 0 & 0 \\ 0 & 0 & -\frac{1}{T_{BESS}} & 0 \\ 0 & 0 & 0 & -\frac{1}{T_{SC}} \end{bmatrix} \begin{bmatrix} x_1\\ x_2\\ x_3\\ x_4\end{bmatrix} + \begin{bmatrix} 0 & 0 & 0 \\ \frac{K_{DG}}{T_{DG}} & 0 & 0 \\ 0 & \frac{K_{BESS}}{T_{BESS}} & 0 \\ 0 & 0 & \frac{K_{SC}}{T_{SC}} \end{bmatrix} \begin{bmatrix} u_{DG}\\ u_{BESS}\\ u_{SC}\end{bmatrix}$$

$$+ \begin{bmatrix} \frac{G_{PV}}{M} & \frac{G_{WTG}}{M} & -\frac{1}{M} \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta\,\varphi \\ \Delta\,P_W \\ P_{load}\end{bmatrix}$$

The output equation (ie; frequency deviation):

$$y = Cx + Du,\ \text{with}\ C = \begin{bmatrix}1 & 0 & 0 & 0\end{bmatrix},\ D = 0$$

The parameter values for the aforementioned equations can be determined through iterative trial-and-error procedures, ensuring that the system remains controllable. Once a suitable set of parameters guaranteeing controllability is identified, an appropriate control technique can be implemented for frequency regulation in the islanded microgrid.

IV. Performance Analysis of Different Control Strategies

Table I and Table II highlights 12 control strategies focusing on some performance parameters such as response time, disturbance rejection, implementation and computational complexity, suitability, implementation process and its mathematical model for regulating the frequency of islanded microgrid.

TABLE I: COMPARATIVE ANALYSIS OF CONTROL STRATEGIES IN ISLANDED MICROGRIDS

Control Strategy	Response Time	Disturbance Rejection	Implementation & Computational Complexity	Suitability	References
'Conventional Droop Control'	Moderate	Low	Low – Easy to implement in real-time	Suitable for small-scale MGs with moderate accuracy needs	[7]-[10]
'PI/PID Control'	Moderate	Moderate	Low – Computationally simple	Suitable for systems with linear or mildly nonlinear dynamics	[11]-[13]
'Fuzzy Logic Control (FLC)'	Moderate–High	High	Moderate – Depends on rule base size	Good for uncertain or nonlinear microgrids	[14]-[16]
'Sliding Mode Control (SMC)'	High	Very High	Moderate to High – Requires fast switching	Effective for fast dynamics and highly disturbed systems	[17]-[19]
'Model Predictive Control (MPC)'	Moderate	Very High	High – Optimization at each step	Suitable for systems with sufficient computational resources	[20]-[22]
'H-infinity Robust Control'	Moderate	Very High	High – Complex control law design	Ideal for high-reliability and uncertain environments	[23]-[25]

‘Artificial Neural Networks (ANN)’	High	High	High – Training and inference overhead	Suitable for adaptive control in nonlinear and variable environments	[26]-[28]
‘Multi-Agent Systems (MAS)’	Moderate	High	Moderate to High – Depends on coordination complexity	Best for distributed MGs with multiple DERs and storage systems	[29]
‘Adaptive Control’	High	High	Moderate – Needs parameter update mechanisms	Good for systems with time-varying parameters or configurations	[30]-[31]
‘Virtual Inertia Control’	Low–Moderate	Moderate	Moderate – Needs power electronics integration	Highly suitable for inverter-dominated microgrids	[32]-[33]
‘Reinforcement Learning-Based Control’	Moderate–High	High–Very High	Very High – Needs continuous learning or offline training	Promising for dynamic, uncertain environments with complex dynamics	[34]-[39]
‘Hierarchical Control Structures’	Varies (Layer-dependent)	Very High	Moderate to High – Depends on hierarchy depth	Best for complex MGs with multiple objectives and control layers	[40]-[43]

TABLE II: IMPLEMENTATION PROCESS AND MATHEMATICAL MODELS OF DIFFERENT CONTROL STRATEGIES

Sr. No.	Control Strategy	Implementation Process	Mathematical Model	Nomenclatures	
1	**Conventional Droop Control**	- Based on frequency-active power (P–f) and voltage-reactive power (Q–V) relationships. - Linear droop characteristics: $\Delta f = -k_f \cdot \Delta P \Delta V = -k_v \cdot \Delta Q$. - Implemented at primary control level for decentralized power sharing.	$\omega = \omega^* - G_P(s)(P_C - P^*)$, $E = E^* - G_Q(s)(Q_C - Q^*)$ [7]	ω	Instantaneous system frequency (Hz)
				ω^*	Nominal frequency (Hz)
				$G_P(s)$	Active Power Droop Controller (Hz/W)
				P_C	Measured active power (W)
				P^*	Nominal active power (W)
				E	Measured voltage (V)
				E^*	Nominal voltage (V)
				$G_Q(s)$	Reactive Power Droop Controller (V/VAR)
				Q_C	Measured reactive power (VAR)
				Q^*	Nominal reactive power (VAR)
2	**PI/PID Control**	- Classical feedback control - Applied to maintain frequency and/or voltage setpoints - Requires tuning of gains (Ziegler-Nichols, etc.).	$u(t) = K_p \cdot e(t) + K_i \cdot \int e(t)dt + K_d \cdot de(t)/dt$	u(t)	Control signal output
				e(t)	Error signal (e.g., frequency deviation)
				K_p	Proportional gain
				K_i	Integral gain
				K_d	Derivative gain
				$\int e(t)dt$	Integral of error
				de(t)/dt	Derivative of error
3	**Fuzzy Logic Control (FLC)**	- Input: frequency error and rate of change. - Rule base (IF–THEN) controls power flow from HESS - Defuzzification method (e.g., centroid) converts fuzzy output to control signal. - No need for exact mathematical model.	$u(t) = \Sigma(w_i \cdot \mu_i(e, \dot{e}))$	u(t)	Control output
				e	Error input
				$\dot{e}$	Change in error
				μ_i	Membership function of rule i
				w_i	Weight of fuzzy rule i
4	**Sliding Mode Control (SMC)**	- Define sliding surface s(t) based on system error - Control law switches based on sign of s(t): $u(t) = u_{eq} - K \cdot sign(s(t))$		s(t)	Sliding surface
				e(t)	Error
				$\dot{e}(t)$	Rate of change of error

Sr. No.	Control Strategy	Implementation Process	Mathematical Model	Nomenclatures	
		- Ensures robustness by driving states to sliding surface. - Chattering can be reduced by using saturation or boundary layer techniques.	$s = c_1 \cdot e + c_2 \cdot \dot{e}$, $u = -K \cdot \mathrm{sign}(s)$	c_1, c_2	Sliding surface coefficients
				K	Switching gain
				sign(s)	Sign function
5	**Model Predictive Control (MPC)**	- Predicts future behavior over a prediction horizon - Solves optimization problem: minimize cost function J subject to constraints. - Outputs optimal control signal for HESS. - Requires accurate system model and computational resources.	Minimize: $\Sigma(x_k^T \cdot Q \cdot x_k + u_k^T \cdot R \cdot u_k)$, Subject to: $x_{k+1} = A \cdot x_k + B \cdot u_k$	x_k	System state at time k
				u_k	Control input at time k
				Q	State cost matrix
				R	Control cost matrix
				A, B	State-space system matrices
				N	Prediction horizon
6	**H-infinity Control**	- Minimizes worst-case effect of disturbances on system output - Formulated as an optimization problem in frequency domain:	Minimize max ‖T_{zw}(s)‖_∞	Tzw(s)	Transfer function from w to z
				$\lVert\cdot\rVert_\infty$	Infinity norm (maximum gain)
7	**Artificial Neural Networks (ANN)**	- Trained with historical data to map inputs (e.g., load, Δf) to output control signals - Structure: Input layer – Hidden layer(s) – Output layer. - Can approximate nonlinear control laws - Needs supervised training (backpropagation).	$y = f(W_2 \cdot f(W_1 x + b_1) + b_2)$	x	Input vector
				y	Output vector
				W_1, W_2	Weight matrices
				b_1, b_2	Bias vectors
				f	Activation function
8	**Multi-Agent System (MAS)**	- Agents (e.g., DEG, BESS, SC controllers) make decisions based on local data and communication. - Follows consensus or auction algorithms. - Requires distributed computation and communication protocols.	$u_i = f_i(x_i, x_j, ..., x_n)$	u_i	Control output from agent i
				x_i	Local state of agent i
				x_j	Neighbor agent state
				f_i	Local decision function
9	**Adaptive Control**	- Online estimation of plant parameters - Gains are adjusted in real time using model reference adaptive control (MRAC) / self-tuning regulators (STR) - Suitable for systems with time-varying behavior.	$\theta' = \gamma \cdot e(t) \cdot \phi(t)$	θ	Adaptive parameter vector
				γ	Adaptation gain
				e(t)	Error signal
				φ(t)	Regressor or feature vector
10	**Virtual Synchronous Machine (VSM)**	- Emulates inertia of synchronous generator: $J \cdot d\omega/dt + D \cdot (\omega - \omega_{ref}) = P_m - P_e$ - Implemented in converter controls to mimic swing equation. - Enhances frequency stability.	$J \cdot d\omega/dt = P_m - P_e$	J	Virtual inertia constant
				ω	System frequency
				P_m	Input (mechanical) power
				P_e	Output (electrical) power
11	**Reinforcement Learning (RL)**	- Agent interacts with environment (microgrid), receives reward based on action - Learns control policy π(s) → a to maximize cumulative reward. - Uses Q-learning, DDPG, or PPO algorithms. - Requires exploration and training time.	π^* = argmax_π E[Σ $\gamma^t \cdot r_t$]	π	Control policy
				π*	Optimal policy
				r_t	Reward at time t
				γ	Discount factor
				E[·]	Expectation operator
12	**Hierarchical Control Structure**	- Typically 3-layered: **Primary** (droop, current control) **Secondary** (voltage/frequency restoration via PI or MPC) **Tertiary** (energy management, power flow optimization) - Each level has its own model and timescale.	Primary: Droop (P–f, Q–V) Secondary: Integral/PI Control Tertiary: Optimization-based dispatch (economic/environmental)	Primary	Fast local control using droop (P–f, Q–V)
				Secondary	Restoration using PI control
				Tertiary	Optimization-based dispatch

V. CONCLUSION

In the context of HESS-enabled islanded microgrids, various control strategies have been explored to ensure effective frequency regulation under dynamic load and generation conditions. Conventional methods such as droop control and PI/PID controllers offer simplicity and ease of implementation but are often limited in their ability to respond rapidly to disturbances or adapt to nonlinear system dynamics. Advanced techniques like Sliding Mode Control (SMC), H-infinity robust control, Model Predictive Control (MPC) provide superior disturbance rejection and dynamic performance, albeit at the cost of increased implementation complexity and computational demand. Hierarchical and multi-agent control structures enhance scalability and coordination but require sophisticated communication infrastructure.

Among these methods, Artificial Intelligence (AI)-based techniques, especially Artificial Neural Networks (ANN) and Reinforcement Learning (RL) have shown great potential because of their ability to learn system dynamics, handle uncertainties, and enhance performance in real time. These methods excel in handling the nonlinear, multi-variable nature of microgrid dynamics and offer high disturbance rejection with rapid response times. Despite their high implementation complexity, the adaptability, self-learning capability, and potential for autonomous operation position AI-based control techniques as superior solutions for managing frequency deviations in HESS-integrated systems. Their deployment paves the way for intelligent, resilient, and future-ready microgrid operations capable of maintaining stability even under highly uncertain and variable conditions.

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