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Enhancing Net Frequency Stability in Renewable-Integrated Interconnected Power Systems Using a Novel PSO-BA Optimized Fuzzy-PID Controller

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ABSTRACT

Maintaining frequency stability in modern multi-area interconnected power systems has become increasingly challenging due to growing system complexity, pronounced nonlinear dynamics, and the large-scale integration of renewable energy sources (RESs), which collectively reduce system inertia and introduce stochastic disturbances. To address these challenges, this paper proposes a hybrid intelligent control framework that integrates a Fuzzy-PID controller with an improved Particle Swarm Optimization-Bat Algorithm (PSO-BA) for load frequency control (LFC). The key contribution of the proposed approach lies in the design of a two-stage PSO-BA fusion mechanism, in which the Bat Algorithm is first employed as a pre-optimization stage to enhance population diversity and explore promising regions of the search space, while the Particle Swarm Optimization algorithm subsequently performs efficient parameter refinement with accelerated convergence speed. This sequential hybridization strategy effectively mitigates the premature convergence issues often encountered in conventional PSO-based tuning when optimizing the nonlinear parameters of fuzzy controllers under complex operating conditions. The proposed PSO-BA based Fuzzy-PID controller is evaluated on a two-area interconnected hydro-thermal power system model incorporating practical nonlinearities, including generation rate constraints (GRC), governor deadband (GDB), and renewable energy source integration. Extensive MATLAB/Simulink simulation studies conducted under diverse disturbance scenarios demonstrate that the proposed control scheme achieves superior frequency regulation performance, faster transient response, and enhanced robustness compared with conventional controllers and other metaheuristic-based optimization approaches, thereby highlighting its effectiveness and adaptability for frequency control in renewable-integrated power systems.

1. INTRODUCTION

In the operation of electric power systems, load frequency control (LFC) plays a vital role in regulating frequency deviations within individual control areas and maintaining stable tie-line power exchanges among interconnected regions [1]. With the increasing scale, structural and operational complexity of modern power systems, characterized by a large number of interacting components and control parameters, ensuring system stability, reliability, and operational efficiency has become progressively more challenging [2]. These conditions demand continuous supervision and adaptive control mechanisms capable of responding to dynamic system variations. ver the past decades, a wide range of control strategies has been developed to address LFC-related challenges [1-4]. Among these approaches, intelligent control techniques based on artificial intelligence and fuzzy inference have attracted considerable interest. Representative examples include the Fuzzy Proportional-Integral (FPI) controller introduced in the study [5] and the Fuzzy Proportional-Integral-Derivative (PID) controller presented in [6], both of which were designed to improve control flexibility and robustness. Nevertheless, such controllers may experience performance degradation when applied to large-scale, multi-area interconnected power systems with pronounced nonlinearities and uncertainties.

Another important research direction focuses on the application of metaheuristic optimization algorithms to enhance controller performance. For example, a Genetic Algorithm (GA) was employed in the study [7] to design a robust controller for nonlinear multi-area power systems. Similarly, the authors in the study [8] implemented a PID controller optimized using a hybrid GA-PSO algorithm to improve frequency stability in interconnected power systems.

In addition, $H\infty$ control strategies for autonomous microgrids [9], sliding mode controllers considering communication delays [10], and fractional-order Fuzzy-PID controllers [8] have been proposed to further strengthen frequency regulation performance under complex operating conditions.

In recent years, increasing attention has been directed toward hybrid metaheuristic optimization techniques for LFC applications, aiming to improve convergence reliability and robustness in nonlinear and renewable-integrated power systems. Notably, a hybrid Particle Swarm Optimization–Grey Wolf Optimizer (PSO–GWO) algorithm was proposed to tune a PID-based controller for two-area LFC systems, demonstrating improved convergence behavior and enhanced disturbance rejection capability compared with single-algorithm approaches [11]. Furthermore, the Harris Hawks Optimization (HHO) algorithm has been applied to the LFC of isolated multi-source power generating systems, where its adaptive exploration–exploitation mechanism was shown to enhance frequency regulation performance under high renewable penetration and system uncertainties [12]. These recent studies highlight the growing interest in hybrid and bio-inspired optimization strategies for LFC, while also indicating that achieving an effective balance between global exploration capability and fast convergence remains an open research challenge. The fundamental objective of LFC is to suppress transient frequency deviations in both system frequency and tie-line power exchanges while ensuring that steady-state errors converge to zero [13]. The rapid development of smart grid technologies has significantly transformed traditional power system operations, enabling large-scale data acquisition, decentralized coordination, and real-time control of distributed energy resources [13-14].

However, this transformation also introduces new challenges. Long–term reliance on fossil fuels has contributed to energy crises and environmental pollution [15], thereby accelerating the global transition toward clean and sustainable energy generation [16-19]. Renewable Energy Sources (RESs) play a central role in this transition; nevertheless, their intermittent and non-dispatchable nature significantly reduces system inertia. When integrated through power electronic interfaces, RESs can weaken system damping characteristics,

increasing the likelihood of frequency oscillations and instability. For instance, sudden drops in wind power generation may induce severe frequency deviations, further aggravating the LFC problem [20]. Moreover, system nonlinearities, practical constraints such as governor deadband (GDB) and generation rate constraint (GRC), parameter uncertainties, and communication delays can further deteriorate the performance of conventional control schemes. Although the classical PID controller remains widely adopted due to its simplicity and ease of implementation, its adaptability under nonlinear dynamics and varying operating conditions is often limited.

To address these challenges and further improve convergence reliability observed in recent hybrid optimization-based LFC studies, this work proposes a hybrid control framework that integrates a Fuzzy-PID controller with an enhanced PSO-BA hybrid algorithm [21]. The primary objective of the proposed approach is to optimize controller parameters to suppress frequency oscillations, improve transient response, and enhance adaptability in multi-area interconnected power grids. Comparative simulation results with benchmark controllers, including GA–PI [22], GWO-PID [23] and HHO-FOPID [12], demonstrate that the proposed PSO-BA-based Fuzzy-PID controller achieves superior performance in terms of frequency stability, settling time, and robustness against diverse system disturbances.

2. TWO–AREA POWER SYSTEMS WITH FUZZY–PID CONTROLLER

2.1 Mathematical model of two-area interconnected power system

For large–scale electric power systems, the overall dynamic behavior is commonly represented using linearized power balance equations around a specified operating point. Under typical operating conditions, the system experiences relatively small load perturbations; hence, a linearized model is adequate to capture the essential dynamics relevant to LFC analysis.
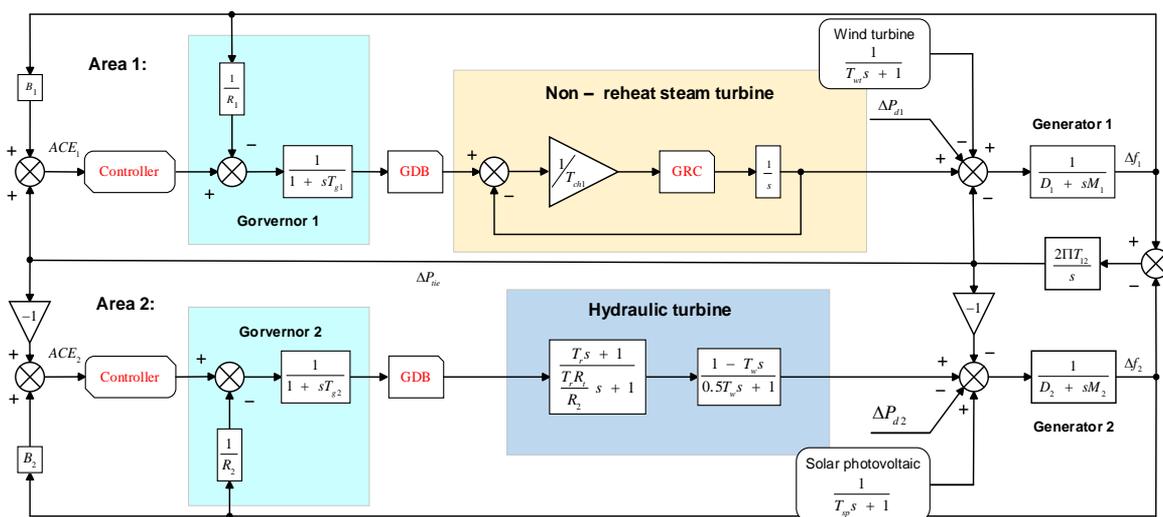

Figure 1. Configuration of the two-area interconnected power system including GRC, GDB, and renewable energy integration

In this work, the considered system consists of two interconnected control areas designed for frequency

regulation.

The configuration includes a two-area interconnected power

system consisting of Area 1 and Area 2. This structure enables the analytical modeling of coordinated frequency dynamics and power exchanges between heterogeneous generation sources, including hydro-thermal units. Figure 1 illustrates the mathematical model of the hydro–thermal system adopted in this research, as referenced in studies [24-26].

The mathematical representation of a power system includes the following major components: the governor model, the turbine model (including both reheat thermal and hydraulic turbines), renewable energy source models (wind turbine and solar PV models), the generator–load model, and the tie-line interconnecting the two control areas.

In the proposed model, the effects of the GDB and the GRC are explicitly considered in order to reflect the inherent nonlinear characteristics and practical operating limitations of real-world power systems.

The RESs incorporated into the system are described using reduced-order dynamic models, which are widely adopted to capture their stochastic nature and time-varying behavior. In particular, the photovoltaic (PV) generation unit is modeled following the approach reported presented in [27], while the wind energy conversion system is formulated based on the framework presented in the study [28].

Within the mathematical formulation of the system, the variables ΔP_{d1} and ΔP_{d2} denote the load demand variations, whereas Δf_1 and Δf_2 correspond to the frequency deviations in each control area of the interconnected power system. The nominal parameters associated with the two-area system configuration are summarized in Table 1.

Table 1. System parameters used in the two-area interconnected power system model [24]

Area with Reheat Turbine	Value	Area with Reheat Turbine	Value
$M_1(p.u.s)$	10	$T_w(s)$	10
$D_1(p.u./Hz)$	1	$T_r(s)$	1
$T_{ch1}(s)$	0.3	$R_t(s)$	0.3
$T_{g1}(s)$	0.1	$R_2(Hz/p.u.)$	0.05
$R_1(Hz/p.u.)$	0.05	$T_{sp}(s)$	1.8
$B_1(p.u./Hz)$	21	$T_{wt}(s)$	1.5
$T_1(p.u./rad)$	22.6	$GDB(\%)$	0.06
		$GRC(pu/min())$	0.1

To maintain frequency stability in each control area, the Area Control Error (ACE) is introduced as the primary control signal, with the objective of regulating it toward zero. Any variation in load demand within a specific area leads to deviations in system frequency and simultaneously induces power exchanges between interconnected areas through the tie-line.

The ACE is formulated as a linear combination of the tie-line power deviation and the local frequency deviation. Therefore, for the *i-th* control area, the ACE can be expressed in (1).

$$ACE_i(t) = \sum_{j=1}^{N}(\Delta P_{ij}(t) + B_i \Delta f_i(t)) \quad (1)$$

where:
- N - Denotes the total number of areas interconnected with area i th;
- ΔP_{ij} - Represents the deviation of tie-line power flow between areas i th and j th;
- Δf_i - Denotes the frequency deviation in the i th area;
- B_i - Denotes the frequency bias factor of area i th.

The simulation parameters of the two-area interconnected power system are provided in Table 1.

2.2 Architecture of the proposed Fuzzy–PID controller

The structural framework of the proposed Fuzzy–PID controller is presented in Figure 2.
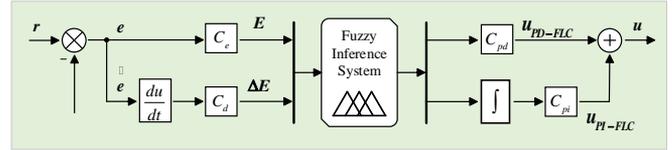

Figure 2. Architecture of the proposed Fuzzy-PID controller

The Fuzzy-PID controller is designed to enhance the frequency regulation performance of multi-area interconnected power systems by incorporating human-like reasoning into the conventional PID control framework. The controller processes two input signals: the instantaneous control error E and its rate of change ΔE. Based on these inputs, a fuzzy inference system (FIS) generates the control signal u, which is subsequently applied to the governor to regulate the generator output power.

In each control area, the Fuzzy-PID controller receives two main input variables: the ACE and its rate of change (ΔACE). The ACE represents the mismatch between the generated power and the load demand while explicitly accounting for the tie-line power deviations among interconnected areas. By simultaneously considering both ACE and ΔACE, the controller is capable of responding not only to the magnitude of the frequency deviation but also to its dynamic trend. This dual-input structure allows the Fuzzy-PID controller to mitigate frequency oscillations more effectively and to shorten the system settling time compared with controllers relying solely on instantaneous error information.

To ensure that the input signals fall within the effective operating range of the fuzzy inference system, appropriate scaling factors are introduced to normalize ACE and ΔACE into the interval $[-1, 1]$. Similarly, the output signal u is rescaled before being applied to the governor. This normalization process enhances numerical robustness and facilitates a consistent interpretation of the linguistic variables across different operating conditions.

The normalized input variables ACE and ΔACE are represented by five triangular membership functions, namely NB, NS, ZE, PS, and PB, as illustrated in Figure 3. Triangular membership functions are selected due to their piecewise linear formulation, which results in low computational complexity and ensures a continuous and smooth input–output mapping within the fuzzy inference process. Moreover, triangular membership functions offer high interpretability and ease of tuning, since their parameters directly correspond to intuitive linguistic regions, while requiring fewer parameters than Gaussian or bell-shaped functions. As widely recognized in classical fuzzy control theory, this combination of simplicity, numerical robustness, and sufficient approximation capability makes triangular membership functions well suited for real-time control applications such as LFC [29].
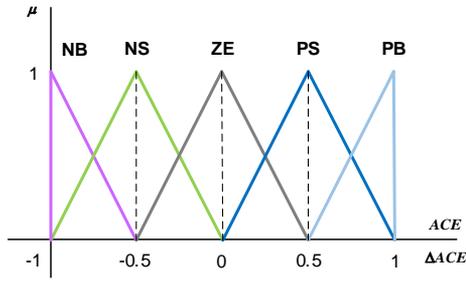
Figure 3. Input (ACE, ΔACE) membership functions

For the output control signal u, singleton-type membership functions are employed, as illustrated in Figure 4. In this representation, each output linguistic term is associated with a single crisp value, which significantly reduces the computational complexity of the defuzzification process while maintaining a smooth and continuous nonlinear input–output mapping. Owing to their numerical efficiency and ease of implementation, singleton output membership functions are widely adopted in fuzzy control systems, particularly in applications requiring fast computation and real-time operation.
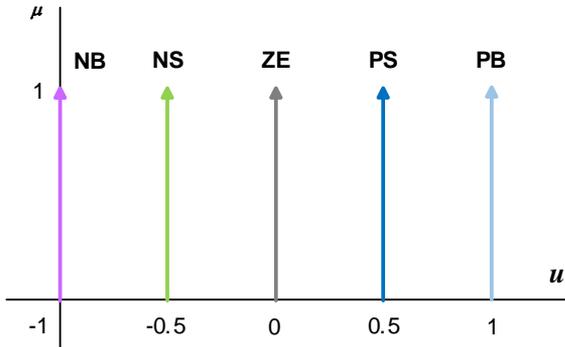

Figure 4. Output (u) membership functions

Table 2. The fuzzy logic rules [21, 24]

	ΔACE	NB	NS	ZE	PS	PB
	NB	NB	NB	NB	NS	ZE
	NS	NB	NB	NS	ZE	PS
ACE	ZE	NS	NS	ZE	PB	PB
	PS	NS	ZE	PS	PB	PB
	PB	ZE	PB	PS	PB	PS

The fuzzy rule base presented in Table 2 is constructed according to Mamdani-type heuristic fuzzy control and approximate reasoning principles, where control rules are formulated using qualitative knowledge of system behavior to establish a linguistic relationship between ACE, ΔACE, and the control output u. The rule table is designed to be symmetric around the ZE operating point and to satisfy a monotonic relationship between the input variables and the control action, ensuring balanced responses to positive and negative disturbances while avoiding rule conflicts during transitions between adjacent operating regions. By jointly considering the magnitude of ACE and its rate of change, the resulting rule base provides effective damping of frequency deviations and robust control performance under varying operating conditions, as commonly adopted in classical fuzzy control design [29-30].

3. PSO-BA OPTIMIZATION TECHNIQUES

In this work, a hybrid optimization strategy based on Particle Swarm Optimization and the Bat Algorithm (PSO-BA), originally proposed in the study [21], is employed. The hybrid approach is implemented within a two-stage pre-optimization framework, in which an auxiliary optimization process is introduced prior to the main PSO procedure in order to improve global search capability and accelerate convergence.

In the first stage, the BA is executed as a pre-optimization mechanism to explore the search space and generate a set of high-quality candidate solutions. Owing to its frequency-tuning and loudness-based random movement, BA is capable of maintaining population diversity and performing effective global exploration, albeit with relatively slow convergence. Instead of directly optimizing the controller parameters to termination, BA is only run for a limited number of iterations to identify promising regions of the search space and extract elite solutions.

In the second stage, the PSO algorithm performs the main optimization process using the BA-generated solutions to initialize the particle swarm. Specifically, the elite solutions obtained from the BA stage are used to initialize the positions of a portion of the PSO particles, while the remaining particles are randomly initialized within the predefined bounds. This strategy enhances the diversity and quality of the initial swarm, thereby reducing sensitivity to random initialization and mitigating the risk of premature convergence to local optima.

The PSO algorithm, inspired by the social behavior of birds and fish, offers fast convergence but often suffers from premature convergence and limited global search capability in complex, high-dimensional problems. The position and velocity of the *i-th* particle at iteration *t* are updated as follows:

$$v_i(t+1) = \omega . v_i(t) + c_1 . r_1\big(pBest_i - x_i(t)\big) + c_2 . r_2\big(gBest - x_i(t)\big) \tag{2}$$

$$x_i(t+1) = x_i(t) + v_i(t+1) \tag{3}$$

where, $v_i(t)$ and $x_i(t)$ denote the velocity and position of the *i*-th particle at iteration t, respectively; ω is the inertia weight controlling the influence of the previous velocity; c_1 and c_2 are the cognitive and social acceleration coefficients; and r_1 and r_2 are uniformly distributed random numbers in the interval [0, 1].

Conversely, the BA, although exhibiting a relatively slower convergence rate due to its random movement controlled by frequency and loudness parameters, is capable of achieving a more effective trade-off between exploration and exploitation, while requiring lower computational effort [31].

By integrating the fast exploitation capability of PSO with the adaptive exploration mechanism of BA, the proposed hybrid PSO–BA algorithm achieves improved convergence speed, higher solution accuracy, and enhanced robustness in optimizing the parameters of the Fuzzy-PID controller.

In this work, the hybrid PSO-BA algorithm is implemented using the parameter settings summarized in Table 2. Based on these parameters, the PSO-BA approach efficiently determines the optimal scaling factors $\big(C_e, C_d, C_{pd}, C_{pi}\big)$ as well as the membership-function parameters of the Fuzzy–PID controller. The optimization process is driven by the Integral

of Time-multiplied Absolute Error (ITAE) performance index, which has been widely recognized as an effective criterion in control system optimization. Unlike conventional integral-based indices such as IAE, ISE, and ITSE, which may result in longer settling times and less satisfactory transient performance [32-33], the literature indicates that the ITAE criterion is generally more effective than other commonly used performance evaluation criteria.

In this study, the ITAE index is employed to evaluate the time-weighted absolute frequency deviations and tie-line power deviations, thereby offering a comprehensive assessment of overall system performance. Accordingly, the ITAE-based objective function is formulated as:

$$J = \int_0^{t_{sim}} (\alpha|\Delta f_1(t)| + \beta|\Delta f_2(t)| + |\Delta P_{tie}(t)|).t\,dt \quad (4)$$

where:
- α and β are two positive weight coefficients. These factors can strongly affect control quality regarding the frequency deviations for each control-area.
- t_{sim} denotes the simulation time range.

The Pseudocode of the proposed hybrid PSO–BA optimization algorithm

Stage 1: BA Pre-Optimization

1. Initialize bat population
2. Initialize algorithm parameters
3.   Frequencies $f_i \sim U(f_{min}, f_{max})$, velocities $v_i(0) = 0$, loudness A_i, pulse rate r_i
4. Evaluate the fitness function $J(x_i(0))$; set global best x^*
5. For $t = 1$: maximum pre – iteration
6.   For $i = 1$: pre – population size
7.   Update frequency:
8. $f_i(t) = f_{min} + (f_{max} - f_{min})\beta, \beta \sim U(0,1)$
9.   Update velocity:
10. $v_i(t + 1) = v_i(t) + (x_i(t) - x^*)f_i(t)$
11.   Update position:
12. $\tilde{x}_i = x_i(t) + v_i(t + 1)$
13.   If $rand() > r_i(t)$ then
14. $\tilde{x}_{i-new} = \tilde{x}_{i-old} + \varepsilon A^t$
15.   Apply bounds to $\tilde{x}_i$
16.   If $J(\tilde{x}_i) < J(x_i(t))$ & $rand() < A_i$
17. $x_i(t + 1) = \tilde{x}_i$
18.   Reduce r_i & increase A_i
19.   Update global best x^*
20.   End for
21. End for
22. Select elite solutions x_e from BA population

Stage 2: PSO main Optimization

23. Initialize PSO particle positions:
24. First N_e particles from BA elites
25. Remaining $N - N_e$ particles randomly
26. Initialize velocities $v_i(0) \sim U(v_{min}, v_{max})$
27. Set personal best $pBest_i$; determine global best $gBest$
28. For $t = 1$: maximum iteration
29.   For $i = 1$: population size
30.   For $d = 1$: dimension
31.   Update velocity

32. $v_{i,d}(t + 1) = \omega v_{i,d}(t) + c_1 r_1 \left(p_i - x_{i,d}(t)\right) + c_2 r_2 \left(g - x_{i,d}(t)\right)$
33.   Apply velocity bounds
34.   Update position
35. $x_{i,d}(t + 1) = x_{i,d}(t) + v_{i,d}(t + 1)$
36.   Apply position bounds
37.   End for
38.   Update p_i & g
39.   End for
40.   End for
41. End for

The parameter settings of the PSO-BA algorithm reported in Table 3 are determined following a two-step strategy that combines literature-based guidelines with limited preliminary tuning. First, the initial values of the PSO and BA parameters are selected within commonly recommended ranges reported in classical studies on particle swarm optimization and bat algorithm, ensuring stable convergence behavior and avoiding numerically unstable configurations [34-36]. Subsequently, a small number of preliminary trials are conducted on a nominal operating scenario to fine-tune these parameters with respect to convergence speed and solution robustness. Once selected, the final parameter set is kept fixed for all simulation scenarios to guarantee fairness and reproducibility of the comparative results.

Table 3. Parameters of the PSO-BA algorithm

Parameter	Symbol	Value
Swarm size	$Npar$	50
Inertia weight factor	ω	0.72
Learning coefficients	c_1, c_2	2.43, 2.62
Random distribution function	r	0.01
Maximum frequency searching	f_{max}	2
Minimum frequency searching	f_{min}	1.25

For the PSO component, the inertia weight ω controls the influence of the previous velocity and thus regulates step persistence and trajectory stability, while the learning coefficients c_1 and c_2 quantify the relative contributions of the cognitive term (attraction toward the particle's personal best $pBest_i$) and the social term (attraction toward the global best $gBest$) [34-35]. Accordingly, c_1 primarily affects individual exploration, whereas c_2 strengthens collective convergence; in this study, $c_1 = 2.43$ and $c_2 = 2.62$ lie within commonly accepted PSO stability ranges and slightly emphasize social learning to accelerate convergence once promising regions have been identified. For the BA pre-optimization stage, the frequency parameter f (bounded by f_{min} and f_{max}) scales the velocity update and thus controls the effective step size and exploration range, while the loudness A and pulse emission rate r jointly regulate the transition between exploration and exploitation. In accordance with the standard BA mechanism, when a newly generated solution improves the current one and satisfies the acceptance condition, the loudness A is gradually reduced, whereas the pulse emission rate r is increased, enabling a progressive shift from global exploration to local exploitation [36]. Since the BA is employed only for a limited number of iterations to generate diverse yet competitive initial candidates, its parameters are chosen to enhance population diversity and identify promising regions prior to initializing the subsequent PSO swarm.

4. NUMERICAL SIMULATION RESULTS AND DISCUSSION

This section aims to assess the performance of the proposed control approach that integrates the PSO-BA optimization algorithm with a Fuzzy-PID controller for the LFC problem in a two-area interconnected power system. Particular attention is given to the influence of RESs on overall system dynamics. The complete system model is implemented in MATLAB/Simulink, as depicted in Figure 1, and its stability characteristics and control accuracy are systematically evaluated under various assumed operating scenarios.

Following the control strategy described in the previous section, the PSO-BA algorithm, based on the objective function defined in Eq. (4), is employed to determine the optimal scaling factors, presented in Table 4, and the optimized membership-function parameters of the Fuzzy-PID controller, illustrated in Figures 5 and 6.

Table 4. Optimal Fuzzy–PID scaling factors obtained by PSO–BA

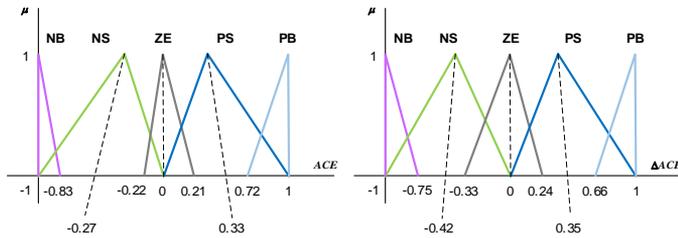| Coefficient	C_e	C_d	C_{pd}	C_{pi}
Value	807.27	135.2	674.81	723.5

Figure 5. Input (ACE, ΔACE) membership functions PSO-BA tuning
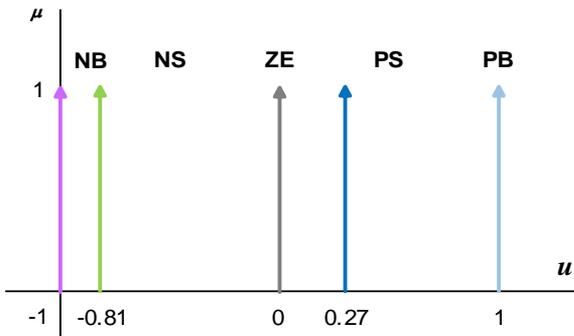
Figure 6. Output (u) membership functions PSO-BA tuning

To assess the performance of the proposed model, multiple simulation scenarios are designed based on the mathematical representation of the two-area interconnected power system, incorporating the Fuzzy-PID controller optimized via the PSO-BA algorithm. These scenarios simultaneously consider load demand variations and fluctuations in renewable energy generation, thereby enabling a thorough evaluation of the controller's dynamic response and robustness under realistic operating conditions.

The effectiveness of the proposed control strategy is subsequently benchmarked against several established approaches, including the GA-PI controller, the GWO-PID scheme, and the HHO-FOPID.

Three numerical simulation scenarios are considered to evaluate the system response under different load disturbance conditions:

- Scenario 1: Step load disturbances of $\Delta P_{d1} = \Delta P_{d2} = 0.03(pu)$ are applied simultaneously to both control areas, while a pulse-type disturbance of $\Delta P_{pv} = \Delta P_{wt} = 0.03(pu)$ is assumed for the RESs.
- Scenario 2: Larger step load disturbances of $\Delta P_{d1} = \Delta P_{d2} = 0.05(pu)$ are imposed on both areas, accompanied by pulse disturbances in the renewable generation, with $\Delta P_{pv} = \Delta P_{wt} = 0.05(pu)$.
- Scenario 3 (Random Load Fluctuations): Random load variations are applied to represent realistic and time-varying operating conditions. As shown in Figure 7, the load profile comprises irregular step-like changes with varying magnitudes over time, and is used to assess the robustness of the proposed control strategy under stochastic load disturbances.
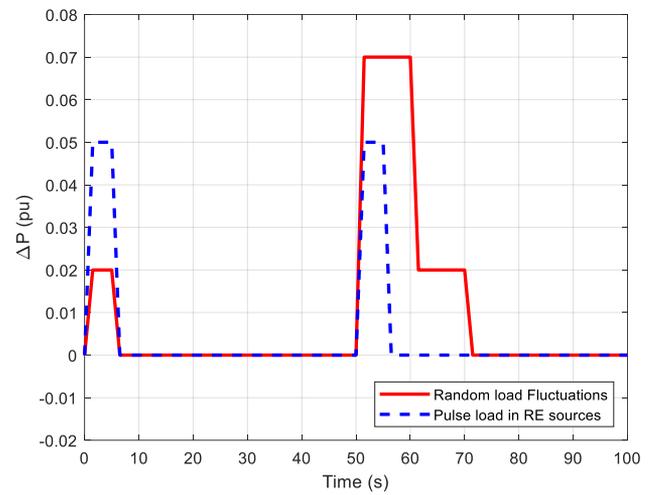
Figure 7. Random load fluctuations and renewable pulse disturbances

The simulation results illustrated in Figures 8 and 9 indicate that the proposed hybrid control strategy achieves superior frequency regulation performance in the two-area interconnected power system. The corresponding frequency deviation responses confirm that the PSO-BA-based Fuzzy-PID controller provides enhanced transient behavior by effectively attenuating both the amplitude and persistence of frequency oscillations.

Compared with the conventional PID controller, which often exhibits noticeable steady-state deviations and relatively long settling times, the proposed hybrid intelligent control approach delivers improved regulation performance and stronger adaptability under complex and varying operating conditions. By integrating Particle Swarm Optimization (PSO) with the Bat Algorithm (BA) to tune the parameters of the Fuzzy-PID controller, the hybrid control scheme achieves superior performance across multiple frequency regulation performance indices.

The Fuzzy-PID controller is systematically constructed with clearly defined input membership functions and a rational rule base, thereby enhancing its flexibility and adaptive capability when dealing with nonlinear and time-varying system dynamics. Comparative analyses with GA-PI, GWO-PID, and the HHO-FOPID control structure further demonstrate that the

PSO-BA-based Fuzzy-PID strategy provides improved frequency regulation performance, enhanced system stability, and faster dynamic response in the multi-area power system.

and optimization techniques often struggle to satisfy the increasingly stringent requirements on stability, adaptability, and reliability imposed by contemporary power grids.
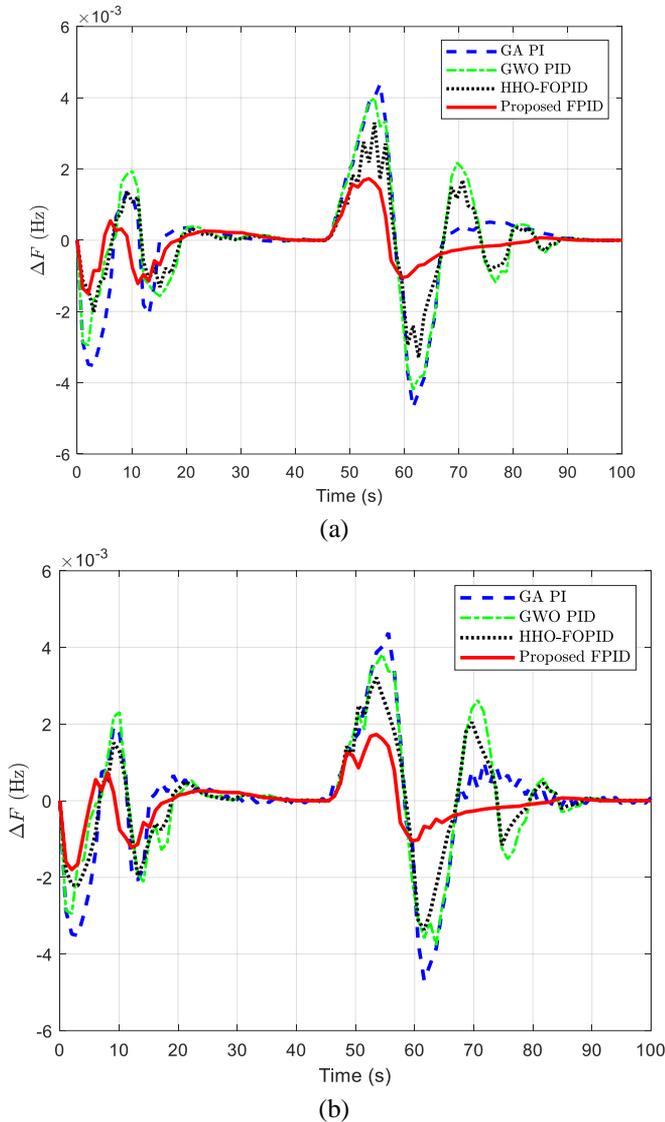

(a)

(b)

Figure 8. Dynamic frequency responses of the two control areas under Scenario 1: (a) Area 1 and (b) Area 2

Under Scenario 3, which involves random load fluctuations, the dynamic frequency responses of both control areas are presented in Figure 10. It can be observed that the proposed PSO-BA-based Fuzzy-PID controller consistently exhibits smaller peak frequency deviations, improved oscillation damping, and faster recovery to steady-state conditions compared with the GA-PI, GWO-PID, and HHO-FOPID controllers. In both Area 1 and Area 2, the proposed controller demonstrates enhanced robustness against stochastic and time-varying disturbances, effectively suppressing frequency oscillations induced by irregular load variations. These results confirm that the proposed control strategy maintains stable and reliable frequency regulation performance even under non-deterministic operating conditions, highlighting its suitability for practical power systems with high levels of uncertainty.

In modern power systems, the growing penetration of RESs, driven by the global transition toward clean energy, poses additional challenges for frequency regulation due to their intermittent characteristics and the associated reduction in system inertia. Under such conditions, conventional control
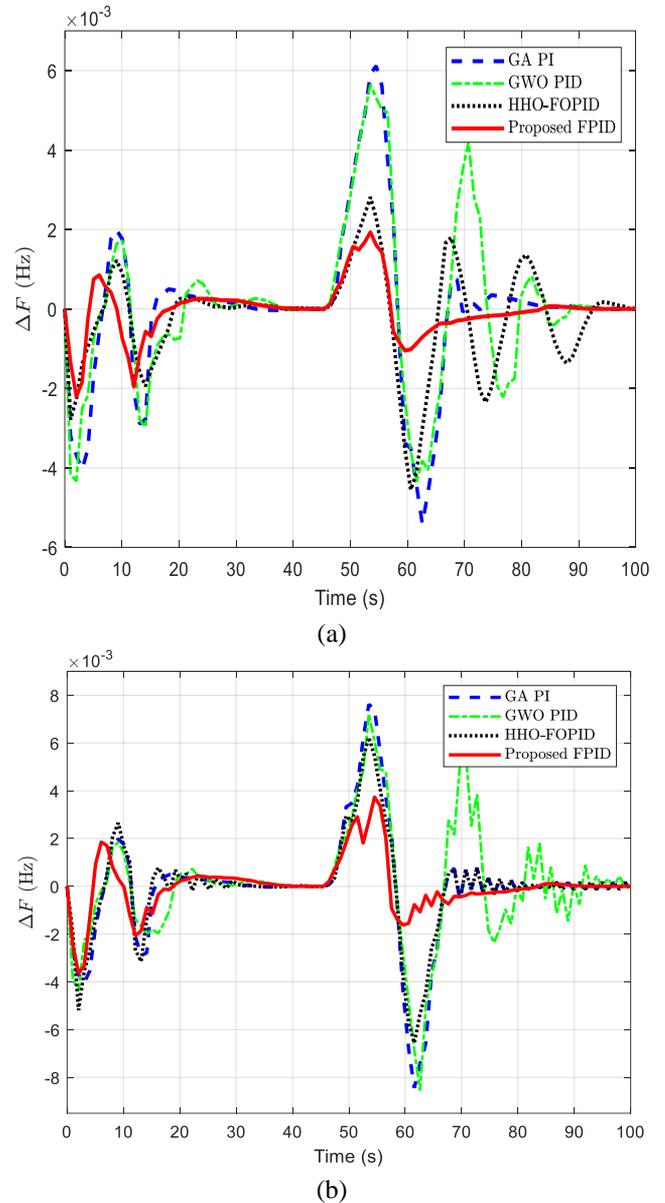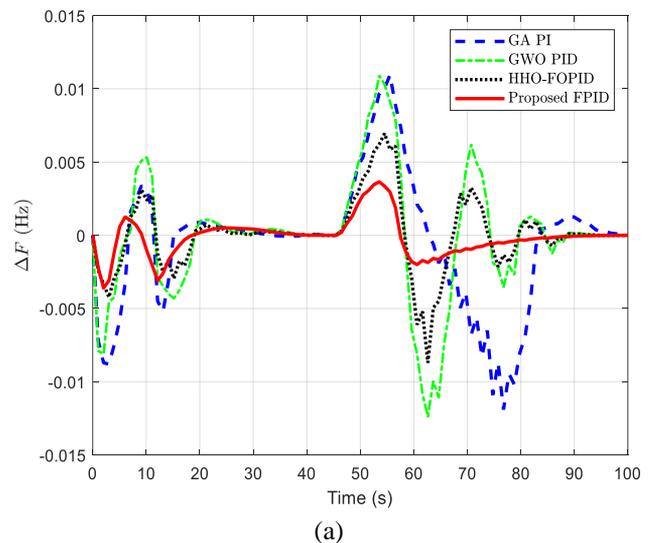

(a)

(b)

Figure 9. Dynamic frequency responses of the two control areas under Scenario 2: (a) Area 1 and (b) Area 2
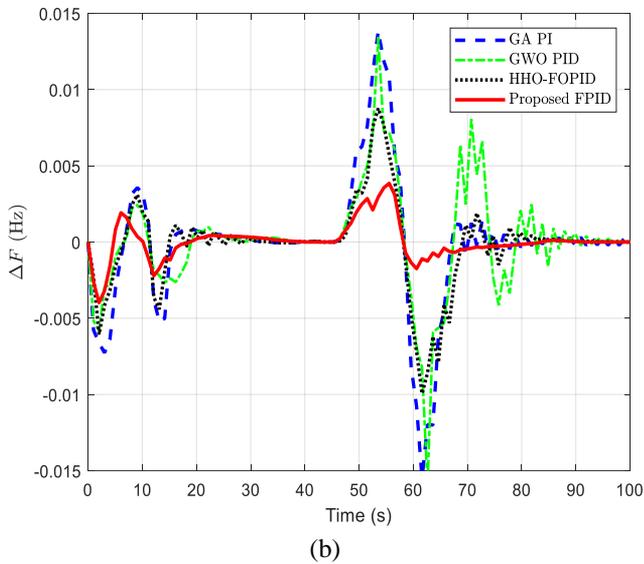

(a)

(b)

Figure 10. Dynamic frequency responses of the two control areas under Scenario 3: (a) Area 1 and (b) Area 2

5. CONCLUSIONS AND FUTURE WORK

This study presents and validates a hybrid intelligent control framework aimed at improving frequency regulation performance in multi-area interconnected power systems. Its main contribution lies in the integration of a Fuzzy-PID controller with an enhanced PSO-BA-based parameter optimization scheme. By combining the fast convergence characteristics of the PSO algorithm with the strong global exploration capability of the BA, the resulting hybrid optimization strategy achieves improved convergence behavior and superior optimization performance compared with the individual algorithms.

Extensive numerical simulations conducted under realistic operating conditions, including load disturbances and intermittent renewable energy fluctuations, consistently confirm the effectiveness of the PSO-BA-based Fuzzy-PID controller. The obtained results demonstrate notable improvements in key performance indicators, such as peak frequency deviation, oscillation damping, and dynamic settling behavior, when compared with conventional PID controllers and other metaheuristic-based control schemes. Moreover, the carefully designed fuzzy inference structure, incorporating expert-defined rule bases and well-calibrated membership functions, significantly enhances adaptability, robustness, and resilience in the presence of nonlinear and time-varying dynamics inherent in modern power systems.

Overall, this hybrid control framework provides an effective and structurally flexible solution for frequency stability enhancement in interconnected multi-area power networks with high renewable energy penetration. Future research will focus on extending the optimization framework toward multi-objective formulations, integrating advanced control strategies such as Model Predictive Control and Adaptive Neural Control, and performing comprehensive validations on higher-order and more realistic interconnected power systems that account for communication delays and cyber–physical security constraints.

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