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Robust Load-Frequency Control of Multi-Area Smart Grid by Combining Neural Network with Real-Time Particle Swarm Optimization

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Abstract: The multi-area power smart grid faces the problem of maintaining stability due to load variations and power exchange through the tie-line, which leads to a significant deviation in the system's frequency. All controllers face the challenge of changing system parameters, which leads to the controller's failure to maintain the system's stability, except the adaptive control, which has the drawback of needing a mathematical system model. The novelty of the presented method lies in facing this challenge by using a combination strategy between an artificial neural network and real-time particle swarm optimization through which the controllers' gains are continuously updated according to the change in system parameters. The proposed method provides additional novelty in immediately deducing the cost function, unlike other real-time methods, which need a long time to evaluate the cost function. In this approach, the parameters of the PID controller are tuned and updated dynamically by real-time monitoring and optimization. Simultaneously, the artificial neural network was trained to predict the optimization cost function for present and next disturbances. Simulation results confirm that the proposed method outperforms the related conventional control techniques. Comparison investigations with recent works show significant enhancement in terms of dynamic performances when the system is subjected to power disturbance equal to 20% of the rated load, which gives about 58%, 45%, and 62% reduction in overshoot, undershoot, and settling time of the frequency deviation in the first area, respectively while giving about 45%, 43%, and 54% reduction in the second area respectively. Also, it exceeds the traditional methods by about 67%, 23%, and 50% in the tie-line power variations, respectively. Furthermore, results demonstrate high robustness and resilience against the system's parameters uncertainty and variations. The robustness was verified by varying the system's inertia and turbine time constant, which increases the reliability and controllability of the modern multi-area smart grid stability.

Keywords: Load frequency control, Multi-area power system, Smart grid, Robust control, Real-time optimization, System parameter uncertainty.

List of nomenclature

Symbol	Description
$\Delta\omega_s$	Frequency deviation
ΔP_{mch}	Mechanical power variation
ΔP_{gn}	Generation power variation
ΔP_{elc}	Load power variation
H_a	Moment of inertia
ΔP_L	Insensitive load variation
D_a	Load-to-frequency ratio
τ_t	Turbine time constant
ΔP_{gov}	Governor power variation
ΔP_{vlv}	Variation of steam power
R_{reg}	Regulation ratio
τ_g	Governor time constant
ACE_a	Area control error

1. Introduction

In interconnected multi-area grids, load-frequency control is essential because it consists of more than a single grid connected by tie-lines supplying or absorbing power. These areas include multiple generating units that meet various load conditions. The dynamic behaviour of the system's power and frequency variations add complexity due to nonlinearity and parameter uncertainty. Effective multi-area operations should balance load and generation to maintain frequency in the desired value and enhance reliability [1]. This balance is important for measuring loads, managing disturbances, and selecting appropriate control schemes. Power systems function on a large scale with nonlinear dynamics requiring fast frequency responses, stability, and automatic generation control. Recent research highlights robust control for enhancing system security is developing, but optimization methods for interconnected systems remain unexplored [2].

Recent literature has extensively reported various innovative schemes and strategies for effective operational methods and controlling techniques essential for optimizing dynamic performance. Most approaches are regarding the single input, single output (SISO) controlling form, incorporating integral, proportional, and derivative (PID) control methods [3]. However, achieving exceptional dynamic performance remains challenging due to system nonlinearity [4]. Despite this, diverse controller implementations are evident in modern applications in various sectors. A comprehensive comparison of these controllers highlights their applications in industrial settings, showcasing differences in features, policies, and optimization attractors [5].

Notably, gaps in the literature on the power swing issue in multiarea systems with input delay are under-researched, revealing a lack. Population-based optimization methods addressing multi-area load frequency control (LFC), especially with embedded renewable generators, are insufficiently explored, underscoring the need for innovative policies to bring transformative changes in conventional controllers [6]. A combination of bald eagle and sparrow searching techniques is used for load frequency control processes that rely heavily on optimization methods, which have recently gained acceptance for sustainable power performance improvements [7]. Genetic algorithms combined with adaptive fuzzy logic control for LFC and load redistribution among generating stations effectively eliminate frequency error signals in multi-source and multi-area power grids [8]. Particle swarm optimization was used in off-line mode to optimize the PID controller parameters of the LFC transmission line [9]. An Ant colony optimization technique is also used to optimize the response of the interconnected power systems and increase reliability with the challenge of governor nonlinearity [10]. The drawback of the methods presented by [7-10] is the implementation of off-time mode adapting techniques, which make them unable to handle uncertainty cases and maintain the system's stability. More efforts were made to improve system performance and increase resiliency, such as using artificial bee colonies for hydro-thermal systems [11]. Also, some work presents the fractional order PID controller to optimize the response of frequency deviation due to load variation [12, 13]. The shortage of this method is that adapting at a specific rated load degrades the response with variable load. The lack of literature on online teaching, learning, or optimizing algorithms for optimal feedback gain selection in LFC also signifies significant methodological gaps. Currently, only the metaheuristic competitive algorithms are effectively used to design LFC systems. The rise of particle swarm optimization (PSO) methodologies opens promising avenues for future research and applications in this vibrant field, and it can be integrated with another stability method, such as Routh Hurwitz's Theory or Flower Pollination Algorithm, for obtaining robust controllers and increasing stability margin [14, 15]. Besides, intelligent techniques, such as neural networks, fuzzy logic, etc., can significantly enhance the performance of smart grids that are integrated with renewable energy [16-18]. Despite their high efficiency, the primary deficiency of the metaheuristic techniques is the constant controllers' parameters due to the offline optimization. Even when real-time optimization is used, the method faces the challenge of evaluating the cost function, which requires a sufficient period.

The novelty and contribution of this work are to address the challenges that impact maintaining the system's stability, which is affected by varying system parameters and changing the capabilities of exchange power between different areas. This is done by applying real-time particle swarm optimization combined with an artificial neural network. The proposed method also uses a unique process to evaluate the cost function using a trained neural network, which can determine the cost function immediately for each particle publication, unlike the traditional technique, which needs an extended period for comprehensive cost function evaluation. The proposed method can overcome the challenges of parameter uncertainty and system nonlinearity. This is because the controller's gains are updated constantly following the system’s parameter variations, which yield robust control. This paper considers the system's robustness and aims to maintain frequencies within defined limits by continuously adjusting controller gains. Various load and system parameter fluctuations case studies validate system performance and robustness. It is structured as follows: Section 2 represents the concept of LFC, Section 3 details the PSO, Section 4 discusses the real-time PSO approach and the cost function, Section 5 gives details on the investigated system, Section 6 presents simulation results, and Section 7 summarizes the conclusions and future works.

2. Concepts of LFC in multi-area grids

In a multiarea power system, load-frequency control (LFC) manages real power demand changes and maintains frequency for inter- and intra-area exchanges. It uses area and tie-line signals for regulation. Effective LFC enhances system security by preventing power imbalances and fluctuations, ensuring stability, and damping low-frequency oscillations. LFC also balances load and generation by reducing active power losses in tie lines [10, 12]. Power systems experience rapid electrical changes, causing frequency deviations and impacting synchronous machine performance. They strive for high-quality power, adjusting generation to align with demand, which is essential for frequency stability [13].

Gas, hydraulic, or thermal turbines can generate the input mechanical power. The governor observes the variation in generator speed and regulates the turbine's mechanical power output by modifying the state of the turbine's valve, which is called the primary frequency response. The multi-area model can be derived from the per-area model, i.e., the single-area model can be expanded to represent the system model. Accordingly, the generation model can be expressed from the balance electro-mechanical swing equation of the power system [13]:

$$\Delta\omega_s(s) = \frac{\Delta P_{mch}(s)+\Delta P_{gn}(s)-\Delta P_{elc}(s)}{2H_a} \tag{1}$$

Where, ΔP_{mch} , ΔP_{gn} , ΔP_{elc} are the variation of mechanical, generation, and load power, respectively, H_a is the system inertia for individual areas, $\Delta\omega_s$ is the frequency deviation.

The power system contains resistive and inductive loads that may depend on or be independent of line frequency deviation. Therefore, the rate of change in load power can be realized as the aggregate of sensitive and insensitive load variations. The From which the electric load model can be written as follows [9]:

$$\Delta P_{elc}(s) = \Delta P_L(s) + D_a \cdot \Delta\omega_s(s) \tag{2}$$

where ΔP_L is the insensitive load variation, $D_a \cdot \Delta\omega_s$ is the sensitive load variation, and D_a is the rate of change in load to the frequency. The relation between load deviation and frequency variation can be depicted as follows:

$$\Delta P_L(f) = D_a \cdot \Delta\omega_s \tag{3}$$

On the other hand, mechanical energy is supplied through the turbine, which obtains its power by combusting fuel, gas, or any other source. The transfer function of the turbine can be derived as the rate of the change in mechanical output power ΔP_{mch} to the rate of variation in steam valve position ΔP_{vlv} as follows:

$$G_t(s) = \frac{\Delta P_{mch}(s)}{\Delta P_{vlv}(s)} = \frac{1}{1+s\tau_t} \tag{4}$$

Where, τ_t is the time constant of the turbine response.

Furthermore, the output power of the governor $\Delta P_{gov}(s)$ is equal to the difference between the reference power ΔP^* and rate of frequency variation power:

$$\Delta P_{gov}(s) = \Delta P^*(s) - \frac{\Delta\omega_s(s)}{R_{reg}} \tag{5}$$

Where, R_{reg} is the regulated ratio.

Then, the transfer function of the governor can be expressed as:

$$G_{gov}(s) = \frac{\Delta P_{vlv}(s)}{\Delta P_{gov}(s)} = \frac{1}{1+s\tau_g} \tag{6}$$

Where, τ_g is the time constant of the governor's response.

The multi-area system is usually controlled by the proportional, integral, and derivative (PID) controllers, which are standard controllers used in several applications. They evaluate the distinction between the actual process quantity and the required set value. The controller's performance depends on the fine-tuning of its parameters. They are essential to enhance the dynamic response and reduce the steady-state error [10]. The transfer function of this controller is:

$$G_c(s) = \frac{K_i+K_p s+K_d s^2}{s} \tag{7}$$

The controlling signal $\widehat{u_c}$ that maintains the system's frequency is the response of the PID controller to the area-controlling error ACE_a:

$$\widehat{u_c}(s) = -G_c(s) \cdot ACE_a(S) \tag{8}$$

$$ACE_a(s) = B_a \cdot \Delta\omega_r \tag{9}$$

Where, B_a is the based frequency.

The multiarea controller faces many challenges, such as frequency deviations, parameter uncertainty, and variable power demands. The work aims to develop adaptive controllers for real-time optimization, increasing the PID controller's ability and robustness.

3. Particle swarm optimization

Particle swarm optimization (PSO) is a stochastic algorithm inspired by bird flocks, where individuals balance their movements between personal bests and the global best founded by the search particles. It begins with a random population of particles' positions that learn from their own experiences, and the best particle is called the best. During iterations, particles update their positions based on local information, considering their personal best, best local, and best global positions. The particle velocities are adjusted to reflect the best particle in the local and global parameters for collective attraction. The PSO algorithm involves particles in a D-dimensional search space, each with a position and velocity updated according to performance evaluated at the global best. As the particles travel through the search space, they explore various regions randomly. Its simplicity and effective convergence have led it to be used in optimization problems, including online adaptation for dynamic environments. Particularly, PSO benefits for controlling issues can be exploited in load-frequency control in fluctuating load conditions [15].

For h-dimensional space, let the position x_i and velocity v_i for i^{th} domain is expressed as:

$$x_i = x_{i,1}, x_{i,2}, \ldots . x_{i,h} \tag{10}$$

$$v_i = v_{i,1}, v_{i,2}, \ldots . v_{i,h} \tag{11}$$

Then, the local and global best positions in the i^{th} search domain are;

$$P_i^{best} = x_{i,1}^{pbest}, x_{i,2}^{pbest}, \ldots . x_{i,h}^{pbest} \tag{12}$$

$$G_i^{best} = x_1^{gbest}, x_2^{gbest}, \ldots . x_h^{gbest} \tag{13}$$

Then, the particle position and velocity are updated for each search process, which is evaluated by summing the previous velocity with the distance from P_i^{best} to G_i^{best} as in:

$$v_{i,h}^{(k+1)} = W \cdot v_{i,h}^{(k)} + C_1 \cdot \delta_1 \cdot \left(P_i^{best(k)} - x_{i,h}^{(k)}\right) + C_2 \cdot \delta_2 \cdot \left(G_i^{best(k)} - x_{i,h}^{(k)}\right) \tag{14}$$

$$W = W_{max} - (W_{max} - W_{min}) \cdot \frac{iter.no.}{\max iter.} \tag{15}$$

$$x_{i,h}^{(k+1)} = x_{i,h}^{(k)} + v_{i,h}^{(k+1)} \tag{16}$$

Where, $v_{i,h}^{(k)}$ is the velocity of the particle (i) in the domain (h) at iteration (k); W is the weighted inertia coefficient; C_1 and C_2 are the learning parameters; δ_1 and δ_2 are random numbers [0 to1]; $x_{i,h}^{(k)}$ is the particle position at the current iteration; P_i^{best} and G_i^{best} are the best local and global particle positions.

4. Online PSO and cost function

In real-time applications, PSO is adapted as an online PSO, allowing it to respond to dynamic environments by continuously updating parameters and learning from operational data. This adaptability helps manage disruptions like load or control structure changes rather than parameter variation [14, 16]. Online PSO features learning from experiences, adaptability, and enhanced solution quality. This work modified a special PSO algorithm to run at real-time optimization of the controller gains according to system situations. The particles and optimization iterations are reduced to 20 and 50, respectively, to reduce the computation time and speed the optimum decision. Discrete-time optimization models a parallel multi-agent system where controllers communicate through delays in negative feedback. The strategy focuses on reducing the overshoot of frequency deviation and enhancing resilience against unforeseen events. Achieving that goal depends on the choice and effectiveness of the cost function; it should represent a comprehensive evaluation of the total error in system frequency. Real-time optimization faces the limitation of operation time for each particle at a specific iteration, so ordinary cost functions can't be used. Instead, the rate of change in frequency deviation can be evaluated in terms of sign and magnitude for each particle in the searching domain. A simple separate Neural Network (NNT) was trained by a large amount of data extracted for various operation conditions that can easily decide whether the particle moves toward the best local or global position. The utilized training data is evaluated offline using an integral time absolute error (ITAE) cost function. The inputs of the NNT are the

Table 1. Power systems' parameters

Symbol	Descriptions	Area 1	Area 2
1/Reg (MW/Hz)	Regulating ratio	0.0431	0.0787
Ba (Hz/MW)	Base frequency	19.6	13.8
Da	load/freq. rate of change	0.7	0.85
Ha	Total inertias	4.2	6.1
τ_g (s)	Governor time const.	0.3	0.52
τ_t (s)	Turbine time constant	0.47	0.54
K	Synchronizing factor	3.1	
F (Hz)	Systems' frequency	50	
LD (pu)	Load Disturbance	0.2	

magnitude of the area control error and the rate of change in frequency deviation. The validation data confirms that the cost function evaluated by the NNT has a high degree of accuracy, which can be successfully adopted in the optimization process. This evaluation of the coat function required less than a few milliseconds. The PSO setting coefficients are modified by trial and error to get efficient optimization results: W_{min}=0.4, W_{max}=0.9, C_1=1.5, C_2=1.5, no. of particles=20, no. of iterations=50. The proposed technique performs better than the previous methods due to the real-time optimization process.

5. Investigated multi-area system

The discussed power system in this work involves two unequal grids with interconnection tie-lines depicted in Fig. 1. This scheme has been extensively adopted in various studies for designing and analyzing the LF control. In a stable operation, the governor decreases its speed if the demand for power increases. This will lead to opening the turbine's valve to increase the input torque. The regulation coefficient (1/Reg) refers to the ratio frequency variation to the output power deviation. The parameters of the two systems are listed in Table 1. The ACE_a is essentially evaluated, its value can be extracted for two areas from Eq. (15) by adding the term of the power difference between the two areas ΔP_{12}. The ACE and the rate of change in ACE are the inputs of the NNT, which estimates the cost function. Simultaneously, the ACE is utilized as input of the PID controller. The controller's gains (K_p, K_i, and K_d) The PSO algorithm continuously updates the ACE values during online optimization. To achieve the function of LF control, the value of this procedure is accomplished for both areas. Eq. (17) and Eq. (18) can express the ACEs of the first and second areas. As control theory expects, the required operating of large multi-area smart grids is to conserve the tie-line power and frequency variations within prelimited values even in load variations; this is imposed by reducing the ACE value to zero.

$$ACE_{a1} = \Delta P_{12} + B_{a1} \cdot \Delta F_{a1} \tag{17}$$

$$ACE_{a2} = \Delta P_{21} + B_{a2} \cdot \Delta F_{a2} \tag{18}$$

Where ΔF_{a1}& ΔF_{a2} are the frequency deviations in the first and second systems, respectively, ΔP_{12} & ΔP_{21} are the variations in power between the two areas, B_{a1} and B_{a2}, are the frequency biases.

6. Simulation results and analysis

The dynamic performance of the interconnected power grid under diverse sudden load disturbances is investigated by the MATLAB/SIMULINK program. The proposed system is evaluated under various initial conditions and step load settings with the same dynamic real-time control strategy. The simulation results were validated through several key approaches that assess the effectiveness, robustness, and adaptability of the proposed online PSO-PID multi-area control strategy. A comparison with previous related works was done to validate the proposed method's effectiveness. Because of the different parameters used in each work, the system commonly used in the literature was adopted, and the control methods presented in [9-12] were reorganized in the same context as those adopted by the authors of those works, as follows:

- PSO-PID: This is closest to the proposed method. Our system's PID controllers' parameters were optimized using the presented procedure in [9] at off-time, and the cost function was integral time absolute error ITAE; the obtained response is identical to that obtained in [9] when the system was subjected to a 20% disturbance.
- ACO-PID: In this method, the system's controllers were optimized using the ant colony optimization technique with the IATE cost function, as adopted in [10] precisely. The results were better than those obtained using the PSO method for area 2 but degraded in area 1.
- ABC-PID: The system structure used in [11] is very close to our system but consists of hydro-thermal units, and the parameters differ from our system parameters. Then, we used the ant colony optimization method to manipulate our system

using the same settings utilized by the authors, such as (colony size=50, number of foods=20, limit=100, max. cycle=3000). The response is identical to that obtained in the work.

- FOPID: The structure of the power system analyzed in [12] is a hybrid power system that slightly differs from ours. We used the part of thermal unit transfer functions and optimized the orders of the fractional-order PID controller using the Aquila optimizer algorithm. The response is identical to that obtained by the authors.

Results demonstrate that the proposed controller significantly minimizes frequency deviations following load disturbances at 10 and 50 seconds in both Area 1 and Area 2, as shown in Fig. 2 and 3, which outperform conventional control methods by reducing overshoot, undershoot, and settling time. Similarly, Fig. 4 highlights the improved performance in tie-line power variation, where the real-time PSO-PID controller achieves superior dynamic response, ensuring smooth power exchange between interconnected areas. Table 2 summarizes the comparison dynamic response between the proposed and recent methods' showing the overshoot (**O$_{sh}$**), undershoot (**U$_{sh}$**), and settling time (**t$_s$**) for the first and second areas' frequency deviations and tie-line power deviations. Also, each method's integral absolute error (**ITAE**), obtained for a 50-second operation period, is listed.

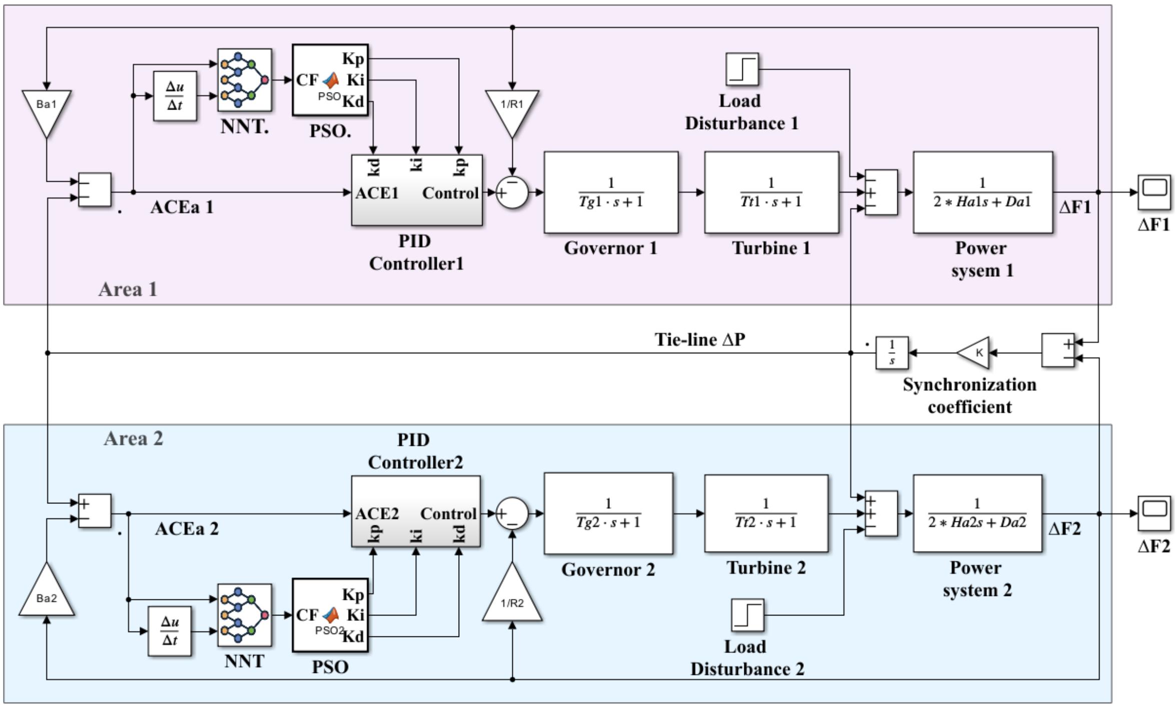

Figure. 1 Power system model

Table 2 Comparison of transient response coefficients

Method	ΔF$_{a1}$ (p.u.)			ΔF$_{a2}$ (p.u.)			ΔP$_{tie}$ (p.u.)			ITAE
	O$_{sh}$	U$_{sh}$	t$_s$ (s)	O$_{sh}$	U$_{sh}$	t$_s$ (s)	O$_{sh}$	U$_{sh}$	t$_s$ (s)	
Off-line PSO-PID [9]	2.4	8.4	23.5	5.2	12.1	24.5	39.4	20.2	36.3	1.732
ACO-PID [10]	4.6	9.1	28.4	4.2	12.6	21.3	37.2	24.2	36.5	1.841
ABC-PID [11]	2.2	8.8	25.1	2.9	12.8	19.6	39.3	24.3	40.5	1.563
FOPID [12]	3.2	8.9	20.7	5.6	12.5	29.5	39.4	24.4	37.1	1.689
Proposed On-line PSO-PID	1.9	4	13.3	2.3	7.2	15.6	12.7	8.1	20.3	1.329
Percentage enhancing (%)	**58**	**45**	**62**	**45**	**43**	**54**	**67**	**23**	**50**	**≈22**

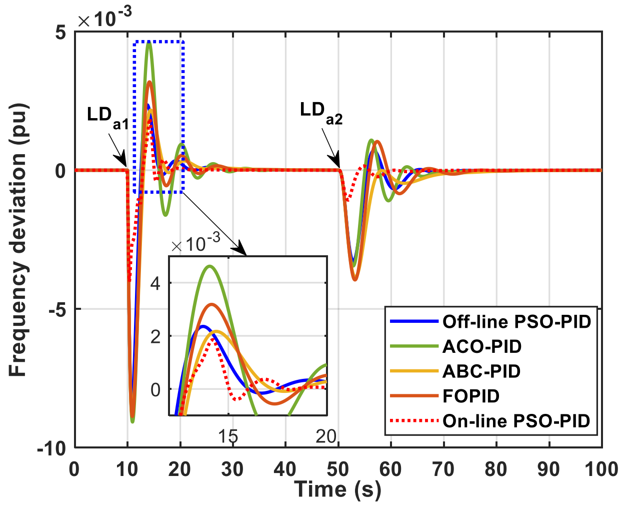

Figure. 2 Aera 1 frequency control response

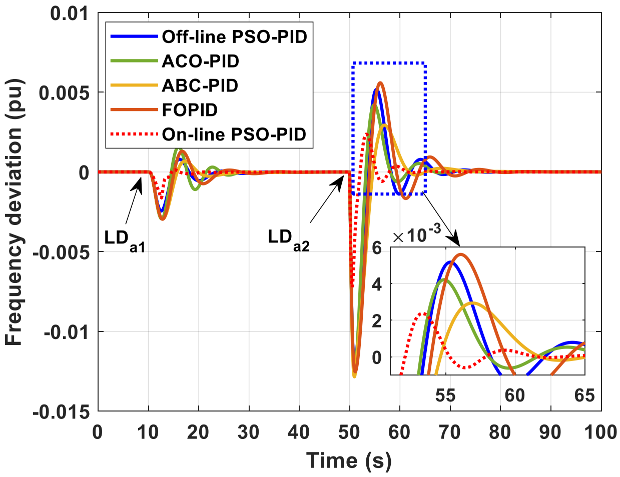

Figure. 3 Aera 2 frequency control response

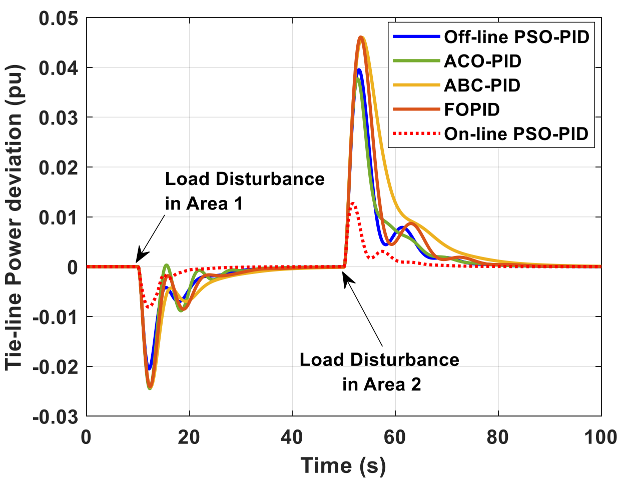

Figure. 4 Power variation in the tie-line

Figs. 5 and 6 demonstrate the adaptive nature of the online PSO-based controller, with real-time updates to PID parameters in response to load

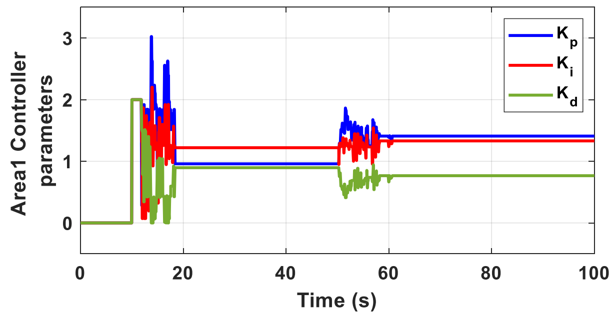

Figure. 5 Real-time controller's parameters optimization of Area 1

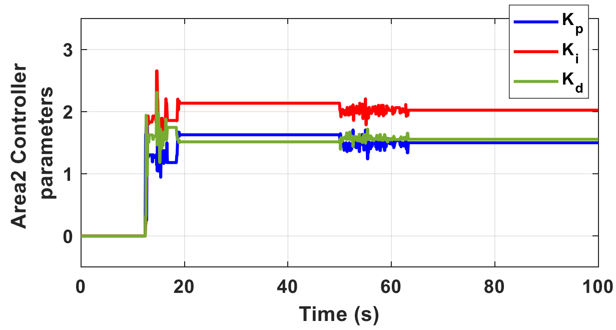

Figure. 6 Real-time controller's parameters optimization of Area 2

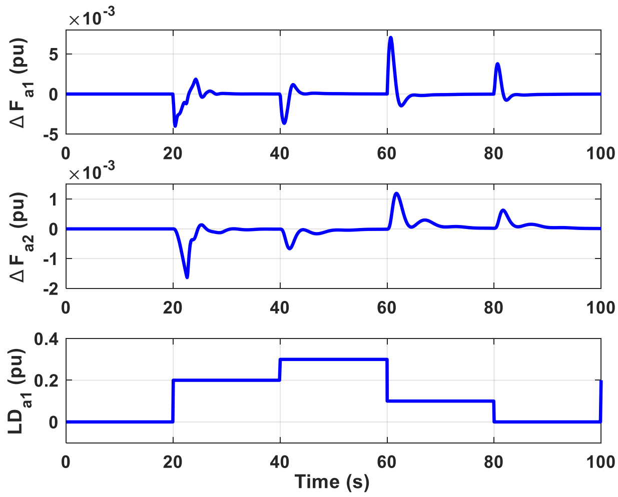

Figure. 7 Frequency response of Area 1 under various load disturbances

variations, showcasing its ability to maintain optimal performance under varying conditions. The proposed control method is tested under varying load disturbances occurring at different times in both areas. Fig. 7 and Fig. 8 show that the system successfully mitigates the frequency deviations and stabilizes the grid after disturbances at 20, 40, 60, and 80 seconds. Under multiple disturbances, the dynamic response validates the controller's effectiveness in real-world scenarios, illustrated by the real-time updating of the

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PID controller parameters. This adjustment is the success key when the system experiences load variations, ensuring the controller parameters are always at the optimum values for any given condition.

Moreover, the robustness of the proposed technique is examined against parameter uncertainties, such as power system inertia and turbine time constants. Firstly, the system's inertia was varied by steps: +100%, +50%, -50%, and -100% of its nominal value. The system adapts through continuous optimization of the controller parameters, as shown in Figs. 9 and 10, ensuring optimal performance under different uncertainty conditions. Secondly, the turbine time constant varies by steps: +20%, +10, -10%, and -20% of its nominal values.

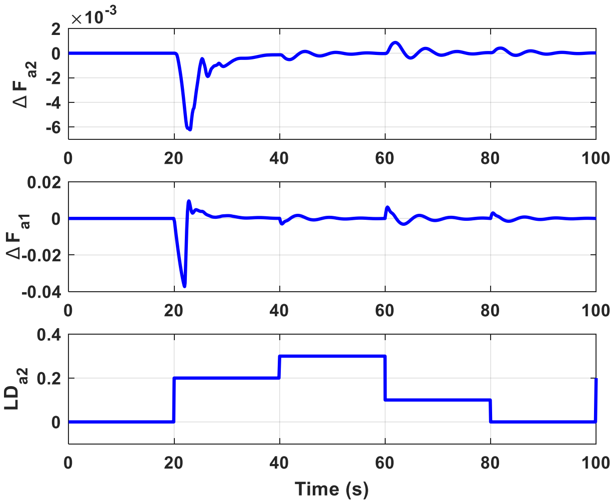

Figure. 8 Frequency response of Area 2 under various load disturbances

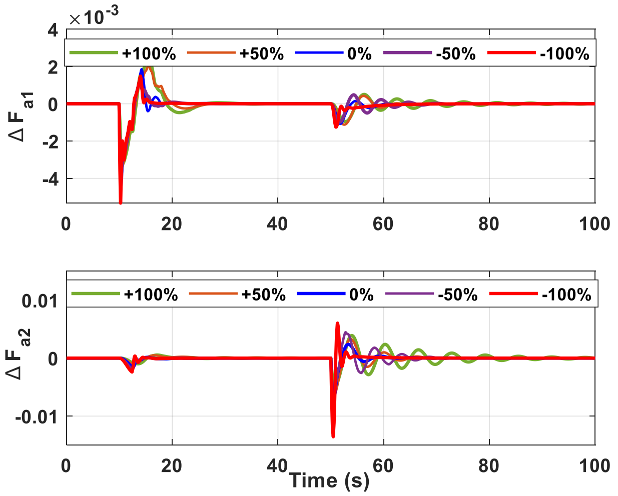

Figure. 9 Frequency deviation under inertia variation

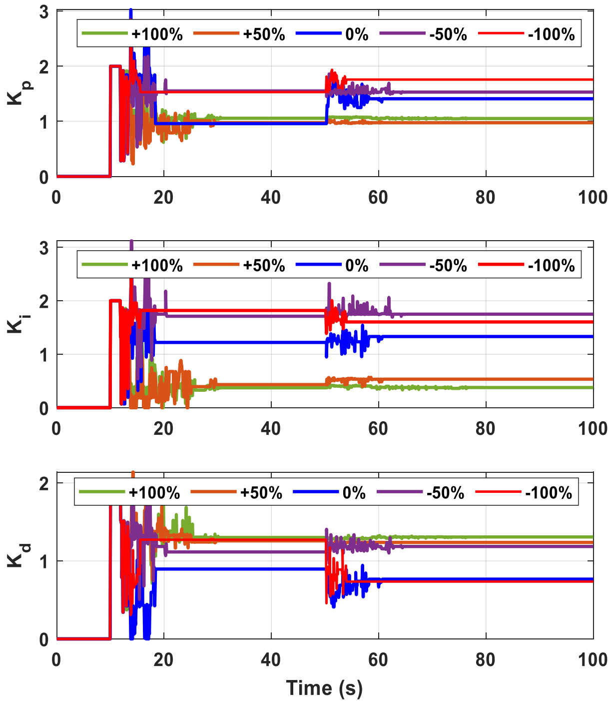

Figure. 10 Real-time controller's parameters optimization under inertia variation

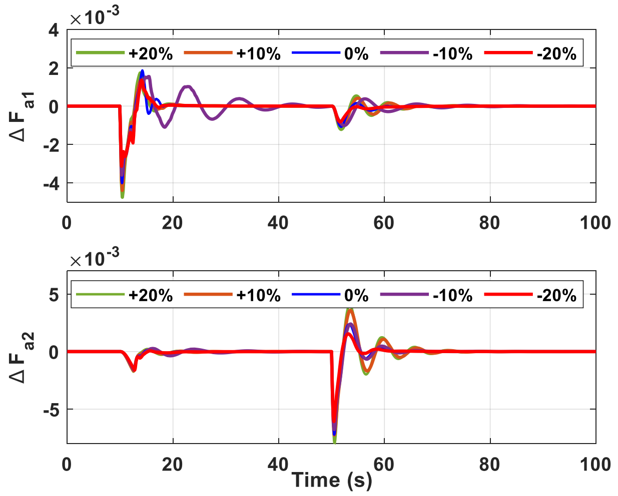

Figure. 11 Frequency deviation under variation of turbine time constant

Results demonstrate that the controller preserves the system's stability even when the turbine time constant varies significantly, as shown in Figs. 11 and 12. Notably, high variation in a turbine or governor time constants may cause unstable response and denigrating controllers. Finally, investigating the ACE for both areas, as depicted in Fig. 13, can provide additional confirmation.

These results confirm that the presented

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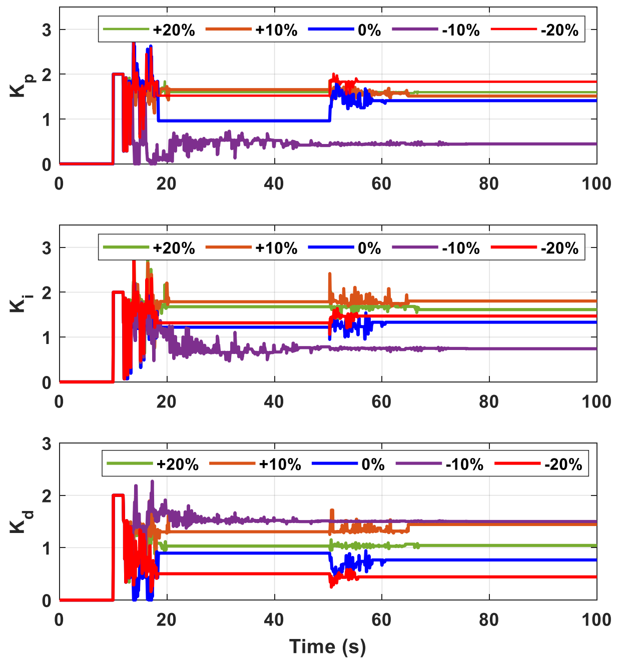

Figure. 12 Real-time controller's parameters optimization under variation of turbine time constant

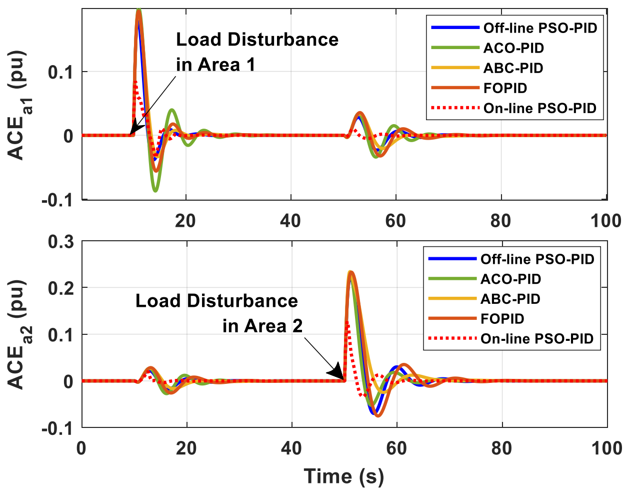

Figure. 13 Area control errors

controller enhances the response and stability of the multi-area LFC and ensures robustness and adaptability in real-world applications. This comprehensive investigation demonstrates the effectiveness of the presented real-time PSO-PID control strategy in solving the LFC problem in the presence of uncertainties. Furthermore, results show that this approach leads to superior dynamic performance because it has a less integrated absolute error and faster settling time than traditional controllers. Nevertheless, when the system parameters are changed significantly, the sensitivity analysis highlights that the proposed control strategy may lose some effectiveness in achieving optimal performance.

7. Conclusion and future work

This paper proposes an LFC technique based on real-time PSO combined with artificial NNT to address the challenge of parameter uncertainty. The method significantly improved the dynamic response and robustness of the interconnected power grids. The simulation results detect that this approach effectively enhances the tie-line power and frequency performances of overshoot, undershoot, and settling, outperforming conventional control techniques. This adaptability behaviour of the controllers, offered by continuous tuning of PID parameters via the real-time PSO algorithm, enables the system to respond effectively to load variations and preserve stability across interconnected areas. The results show significant enhancement in dynamic performances, which give about 58%, 45%, and 62% reduction in overshoot, undershoot, and settling time for the first area, respectively, while giving about 45%, 43%, and 54% reduction in the second area respectively. Also, it outperformed the traditional by about 67%, 23%, and 50%, respectively. Furthermore, the proposed controller's robustness is confirmed under variations of system parameters, such as uncertainties in system inertia and turbine time constants. The method shows strong resilience by maintaining stable operation despite significant parameter variations. The proposed method offers a practical and reliable solution for improving multi-area smart grids' stability and dynamic performance. Its real-time optimization facility handles system uncertainties, making it an excellent candidate for future power grid control applications. However, further investigation is recommended to explore the proposed method's capability in larger multi-area grids.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Fadhil and Fatima; methodology, Fadhil; software, Fadhil; validation, Fadhil and Mohammed; formal analysis, Fadhil; investigation, Fatima; resources, Mohammed; data curation, Fatima; writing—original draft preparation, Fadhil; writing—review and editing, Fadhil; visualization, Fatima; supervision, Fadhil; project administration, Fadhil; funding acquisition, Fatima and Mohammed.

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