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Load Frequency Control of a PV-Thermal Power System with Integrated EV Battery Using the INFO Algorithm

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Abstract: Load frequency control is crucial for keeping the stability of power systems by balancing energy supply and demand in electrical grids, essential for an accurate and fast-acting controller to address sizeable parametric uncertainties. In particular, the growing population of electric vehicles (EVs) requires advanced control and optimization strategies to ensure secure and stable operation. In this paper, the effect of the INFO algorithm on load frequency control is investigated as a new method in the system with renewable energy sources and EV Battery. The novelty of the proposed study lies in the INFO-based optimal tuning of the controller for a PV-thermal system with integrated EV battery and its detailed comparison with several traditional and recent optimization algorithms such as genetic algorithm (GA), firefly algorithm (FA), chess algorithm (CA), flood algorithm (FLA), sinhcosh algorithm (SCHO), artificial rabbits optimization (ARO) and black widow optimization algorithm (BWOA). The obtained results show that the controller optimized with the INFO algorithm provides a robust dynamic response with fast settling time and the lowest overshoot and undershoot values. Compared to the results of other controllers, an average improvement of approximately 30% in system frequency overshoot and approximately 40% in settling time was achieved.

Keywords: automatic generation control (AGC); electric vehicle batteries (EV); INFO algorithm; load frequency control (LFC); renewable energy sources

1 INTRODUCTION

Maintaining grid stability depends on achieving a balance between electricity production and consumption, and this balance is achieved through load frequency control (LFC), which regulates generation to keep the grid frequency within acceptable limits [1].

LFC operates in three stages to respond to demand and supply changes [2]. Primary frequency control automatically kicks in within 15-30 seconds and stabilizes the grid for up to 15 minutes. Secondary control starts after 200 seconds and continues for up to 200 minutes. Tertiary control is initiated by the operator within 15 minutes and addresses long-term imbalances. These stages are based on advanced systems that detect frequency deviations and effectively adjust generation.

However, unlike traditional power systems that include rotating machines, modern power systems incorporate renewable energy sources such as solar power plants and wind turbines. These renewable energy sources require innovative solutions for their integration into LFC systems due to their intermittent and irregular production capacities.

Literature Review

Studies in the literature show that various heuristic methods are used for innovative solutions to LFC problems. For example, in [3], the optimization of the PID controller was conducted using the brown bear optimization technique for a two-area power system that included renewable energy sources. However, with the increase in the integration level of renewable energy sources into the grid, the load frequency control of multi-area interconnected power systems in particular becomes more complex. In [4], the nonlinear constraints of steam turbines were considered and an adaptive model predictive method was proposed for multi-area interconnected power systems. In addition, in [5], the sliding mode method was used considering that the load frequency control in multi-area power systems could be handled in a decentralized structure. More recent studies have focused on examining the effect of changing the controller type on frequency control. As an example, the research in [6] implemented load frequency management using the Walrus optimization algorithm and favored a fractional order PID (FOPID) controller over the conventional PID technique. Enhanced frequency control was shown by the findings.

Research on load frequency management focuses mostly on evaluations done on linked power systems spanning two areas, as opposed to test systems that only cover one region. Studies conducted on two-area test systems have become significant for a better understanding of the influence of power exchange across regions on frequency control.

There is a fundamental test method for two-area linked power systems in load frequency control that was developed in the research in [7], which is cited often in the literature. In the research, the firefly algorithm (FA) was used to improve the PI controller in this two-area system that includes PV and heat production units. Furthermore, the approaches' efficacy was assessed by comparing the acquired findings with the genetic algorithm (GA). This test system has undergone extensive tuning. In [8], for instance, the black widow optimization technique was used to optimize PID controllers. A similar approach was used in [9] to develop PI-(1 + DD) control using the grey wolf optimization (GWO) method. This controller combines proportional, integral, and double derivative functions. The RIME technique described in [10] was also used to optimize the PI controller. Additionally, the PDN-PI controller was fine-tuned using the technique described in [11], which is a hybrid educational competition optimizer. Furthermore, the sea horse optimization technique was used to optimize the PI and PID controllers [12]. Lastly, the sinhcosh optimizer (SCO) algorithm was used to optimize the PI controller in a recent work [13].

This testing system is in addition to the two-area test systems that employ distinct components. In a two-area power system that incorporates wind turbines, for instance, the FOPID controller was tuned using the coot optimization (CO) method in [14]. The controller used in [15] was based on the rank exponent approach. In a two-area system, the PID controller was improved in [16] utilizing GA algorithms and the standard particle swarm optimization (PSO) method. It was also improved in [17] using the bio-dynamic grasshopper optimization algorithm (BDGOA) for a multi-level PI controller. Also, according to [18], the honey badger algorithm (HBA) was used to improve the PID and PI controllers. Furthermore, a two-area power system with heat generating units was enhanced by incorporating a basic electric car battery into the PID controller [19]. Another method was described in [20], which included optimizing a hybrid PID controller with a neural network and including a communication time delay. Last but not least, in a two-area power system with several sources, the whale optimization technique was used to optimize the PI controller [21].

Test systems with additional areas were also considered alongside those with two regions. One example is a three area test system that included thermal, nuclear, and hydro power plants; the PID controller was tuned for this system using the grey wolf optimization (GWO) method [22].

Through the expansion of the number of regions, multi-area test systems have been established. Using a multi area, multi-source test system that incorporates these systems, the PI and PID controllers have been improved using the teaching-learning-based optimization (TLBO) method in the literature, which is relevant due to the growing relevance of electric cars in load frequency management [23].

Managing microgrids is another idea that is taken into account while controlling the load frequency. In this area, researchers have used a variety of optimization strategies in earlier investigations. As an example, the PID controller was optimized in [24] using the microgrid HBA technique. To a similar extent, the artificial rabbits optimization (ARO) method was used to optimize PI and PID controllers in a microgrid in [25]. Furthermore, a microgrid that uses renewable energy sources was controlled using an ARO algorithm that was tweaked using a multi-objective formula in [26]. As a last point, the dandelion optimizer (DO) method was used to optimize a cascaded controller for a microgrid in [27].

This paper proposes a novel method called the INFO algorithm to solve the LFC issue in electric power systems. The INFO algorithm's parameter design allows it to provide an optimization approach with strong global search capabilities [28]. The suggested INFO method for the LFC issue was tested on two-area linked PV-thermal system. The proposed INFO algorithm optimizes the PI controller's gain parameters in the LFC problem. To evaluate the effectiveness of the proposed INFO-based PI controller, its performance was compared with previously published results of GA and FA methods on the same test system.

This paper is organized as follows. Section 2 presents the mathematical models and assumptions of the hybrid PV-thermal system integrated with an energy storage system, including electric vehicle (EV) batteries. and explains the optimization process, while Section 3 discusses the results of MATLAB simulations conducted in a two-area interconnected system. Finally, Section 4 concludes the study by highlighting the INFO based controller's robustness and providing recommendations for future work.

2 MATERIAL AND METHOD

Maintaining grid stability depends on achieving a balance between electricity production and consumption, and this balance is achieved through load frequency control (LFC), which regulates generation to keep the grid frequency within acceptable limits [1].

2.1 Power System Model

The study suggests a two-area test system that can be used for LFC analysis and evaluation. The two-area test system consists of a reheat thermal system and a PV system. The PV-thermal power system is modeled in the MATLAB/Simulink program. The two-area interconnected power system containing a PV and thermal unit is used for the designed power system [7-13]. Fig. 1 shows the schematic diagram of the power system under study, including its primary components and their interconnections.

Eq. (1) to Eq. (4). show the mathematical models of the system components, where each component is approached as a first-order transfer function linear model, as is the case for all components in the study system. A PV model is shown in Fig. 2.

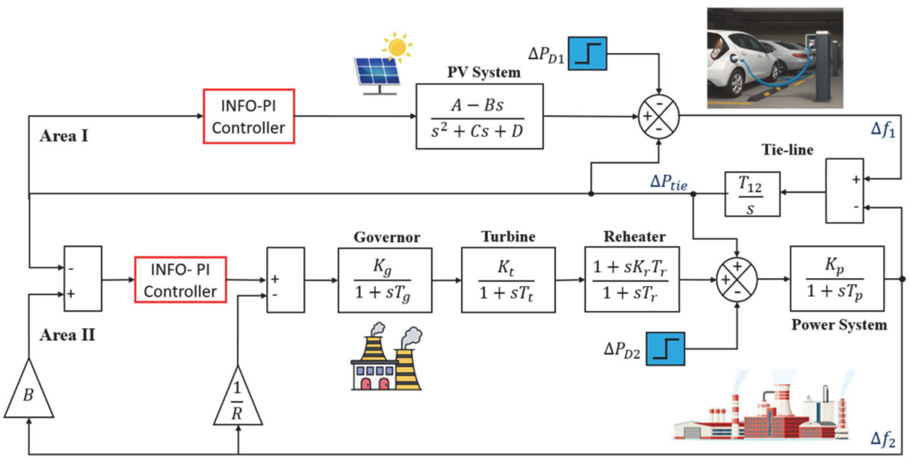

Figure 1 Schematic statement of the two-area test system

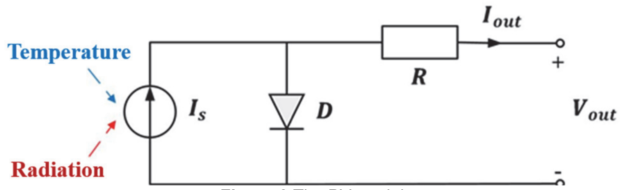

Figure 2 The PV model

According to Fig. 3, the efficiency of a solar panel depends on several factors, such as the intensity of solar radiation and temperature. To increase the performance of the PV system, the MPPT algorithm is utilized. The transfer function expressing the entire PV system including PV panel, MPPT, inverter and filter is represented by the given Eq. (1) [23, 24].

$$G_{\text{PV}} = \frac{\left(A_s + B\right)}{\left(s^2 + C_s + D\right)} \tag{1}$$

where G_{PV} is the transfer function of the PV system. The governor transfer function is given by the following Eq. (2).

$$G_{\text{GVR}} = \frac{K_G}{1 + s\tau_G} \tag{2}$$

where G_{GVR} is the transfer function of the governor, K_G is the gain of the governor, τ_G is the time constant of the governor. The turbine transfer function is given by the following Eq. (3).

$$G_{\text{TRB}} = \frac{K_T}{1 + s\tau_T} \tag{3}$$

where G_{TRB} is the transfer function of the turbine, K_T is the gain of the turbine and τ_T is the time constant of the turbine. The reheater part transfer function is given by the following Eq. (4).

$$G_{\text{RHT}} = \frac{1 + sK_R\tau_R}{1 + s\tau_R} \tag{4}$$

where G_{RHT} is the transfer function of the reheater part, K_R is the gain of the reheater and τ_R is the time constant of the reheater. The power system transfer function is given by the following Eq. (5).

$$G_{\text{PS}} = \frac{1 + K_{\text{PS}}}{1 + s\tau_{\text{PS}}} \tag{5}$$

where G_{PS} is transfer function of the power system, K_{PS} is gain of the power system and τ_{PS} is the time constant of the power system. Area control error (ACE) signal is an important input for the LFC controller, which is responsible for maintaining the balance between system load and system generation. The LFC controller can monitor the ACE signal and adjust the power output of the generators to keep the power system stable and reliable. Mathematically, the ACE signals for Area-1 and Area-2 are as follows

$$ACE_1 = B_1 \cdot \Delta f_1 + \Delta P_{\text{tie}} \tag{6}$$

$$ACE_2 = B_2 \cdot \Delta f_2 + \Delta P_{\text{tie}} \tag{7}$$

where, B_1 and B_2 correspond to the frequency deviation parameters of Area-1 and Area-2. Δf_1 and Δf_2 correspond to the frequency deviation parameters of Area-1 and Area-2. ΔP_{tie} is the tie-line power flow. The LFC mechanism controls the power units by taking the ACE signal into account. The ACE signal is used to match the supply and demand. In other words, the change level of the ACE signal sets the outputs of the generating units and stabilizes the system. This study is inspired by the system parameters in [9, 10].

2.2 Load Frequency Control

The frequency of a power system symbolizes the oscillation number of per second typically operated at 50 Hz or 60 Hz. Any inequality between power production and consumption causes frequency changes, posing a risk of damage to the system and infrastructure. LFC plays a critical role in power system management by operating frequency within acceptable limits. It achieves this by balancing the power generated by the power plants with the load demand, ensuring stable and reliable operation.

Increasing the use of renewable energy sources shows differentiation and uncertainty into power systems, necessitating a development of the conventional LFC framework. These resources are naturally intermittent so if not managed effectively, they can lead to system destabilization. Innovative LFC strategies must adapt to these challenges by incorporating advanced control mechanisms suited to the variable nature of renewable energy. To address these complexities and ensure stability in systems integrating renewable energy sources, the study proposes an updated LFC framework, as shown in Fig. 3.

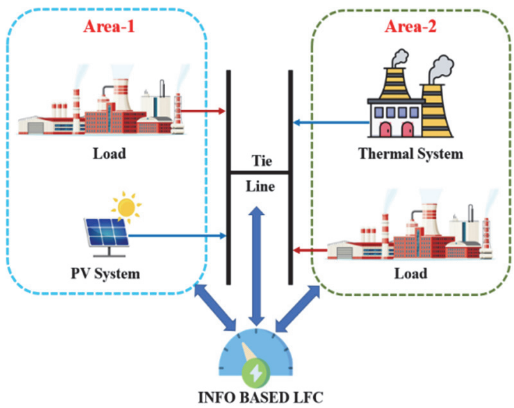

Figure 3 The LFC model

PI and PID controllers are widely used in LFC systems due to their simple applicability. These controllers are set to achieve optimal performance by adjusting parameters to ensure stable frequency responses and fast settling times within the expected range. The setting process requires careful consideration of power system dynamics and performance standart to prevent instability or oscillations.

2.3 Gain Scheduling Control

The adaptive control technique that adjusts the values of the variables according to the changing operating conditions of the systems is called gain planning control. It is particularly effective for managing systems with nonlinear, time-varying dynamics, or scenarios where control changes with operating conditions. One of the advantages of gain scheduling is its simplicity compared to other control methods. It also allows controller parameters to be quickly adjusted in response to changes in system dynamics. A typical block diagram representation of the method is shown in Fig. 4. In this diagram, the setting variables can include measured signals, control signals, or external inputs.

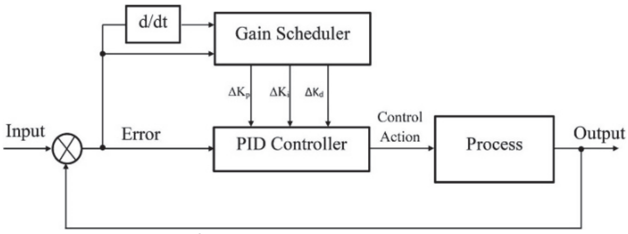

Figure 4 Gain scheduling controller block diagram

The controller parameters are decided using a gain scheduling algorithm, which is designed to automatically set the controller for various operating conditions. Whereas classical setting methods have been widely used, optimization techniques used in ANN are progressively adopted owing to their ease of application, faster convergence, and improved performance [27]. In the following part of this paper, two similar algorithms are discussed.

2.4 INFO Algorithm

The INFO algorithm is a population-based optimization technique designed to address multi-dimensional directional problems using weighted averages of vectors [28]. The algorithm begins with a population of N_p solution vectors, each with D-dimensions, randomly initialized within the search space.

The optimization process of the INFO algorithm is structured into three key stages: rule updating, vector combining (merging), and local search.

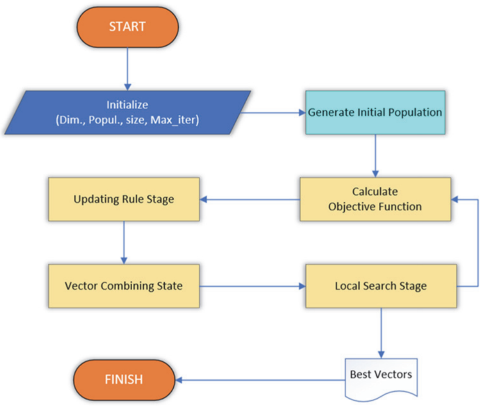

Figure 5 The flowchart of INFO algorithm

2.4.1 Rule Updating Stage

This stage's purpose is to preserve the population's diversity throughout the iterative optimization operation. New solution vectors are generated by leveraging the weighted mean of existing vectors, utilizing two primary components:

Mean-Based Rule (MBR): The MBR engages a weighted mean approach, attributing on a set of randomly selected vectors to compute a new solution. With an initial random solution, the MBR iteratively adjusts the solution by using information derived from the weighted mean of the selected vectors.

Convergence Acceleration (CA): The CA focuses on enhancing convergence speed and improving the general performance of algorithm, enabling the attainment of optimal results efficiently.

The updating rule for generating new vectors is indicated mathematically, summarizing these principles and guiding the optimization process effectively.

$$\text{MeanRule} = r \cdot \text{WM1}_l^g + \text{WM2}_l^g,\ l = 1,\ 2,\ 3,\ n,\ N_p \tag{8}$$

$$\begin{aligned}\text{WM1}_l^g &= \delta \cdot \\ &\cdot \frac{\left(\omega_1\left(x_{a1}-x_{a2}\right)+\omega_2\left(x_{a1}-x_{a3}\right)+\omega_3\left(x_{a2}-x_{a3}\right)\right)}{\left(\omega_1+\omega_2+\omega_3+\varepsilon\right)}+ \\ &+\varepsilon \cdot \text{rand},\ l=1,\ 2,\ 3,\ \ldots,\ N_p\end{aligned} \tag{9}$$

$$\begin{aligned}\omega_1 &= \cos\left(\left(f\left(x_{a1}\right)-f\left(x_{a2}\right)\right)+\pi\right)\cdot \\ &\cdot\exp\left(-\left|\frac{\left(f\left(x_{a1}\right)-f\left(x_{a2}\right)\right)}{\omega}\right|\right)\end{aligned} \tag{10}$$

$$\begin{aligned}\omega_2 &= \cos\left(\left(f\left(x_{a1}\right)-f\left(x_{a3}\right)\right)+\pi\right)\cdot \\ &\cdot\exp\left(-\left|\frac{\left(f\left(x_{a1}\right)-f\left(x_{a3}\right)\right)}{\omega}\right|\right)\end{aligned} \tag{11}$$

$$\begin{aligned}\omega_3 &= \cos\left(\left(f\left(x_{a2}\right)-f\left(x_{a3}\right)\right)+\pi\right)\cdot \\ &\cdot\exp\left(-\left|\frac{\left(f\left(x_{a2}\right)-f\left(x_{a3}\right)\right)}{\omega}\right|\right)\end{aligned} \tag{12}$$

$$\omega = \max\left(f\left(x_{a1}\right), f\left(x_{a2}\right), f\left(x_{a3}\right)\right) \tag{13}$$

The INFO algorithm uses wavelet functions to combine translations and expansions of the mother wavelet, producing effective fluctuations that are used to evaluate the weight of the vectors. The weighted mean calculation for three vectors (x_{a1}, x_{a2}, x_{a3}) is presented in Eq. (9) to Eq. (12), with Eq. (9) providing the general calculation. The fitness functions ($f(x_{a1})$, $f(x_{a2})$, $f(x_{a3})$) and the weight functions (ω_1, ω_2, ω_3) are used in the calculation of the weighted mean.

$$\mathrm{WM2}_l^g = \delta \cdot \frac{\left(\omega_1\left(x_{bs}-x_{bt}\right)+\omega_2\left(x_{bs}-x_{\omega s}\right)+\omega_3\left(x_{bt}2-x_{\omega s}3\right)\right)}{\left(\omega_1+\omega_2+\omega_3+\varepsilon\right)} + \varepsilon \cdot \mathrm{rand},\ l = 1, 2, 3, \ldots, N_p \tag{14}$$

$$\omega_1 = \cos\left(\left(f\left(x_{bs}\right)-f\left(x_{bt}\right)\right)+\pi\right) \cdot \exp\left(-\left|\frac{\left(f\left(x_{bs}\right)-f\left(x_{bt}\right)\right)}{\omega}\right|\right) \tag{15}$$

$$\omega_2 = \cos\left(\left(f\left(x_{bs}\right)-f\left(x_{\omega s}\right)\right)+\pi\right) \cdot \exp\left(-\left|\frac{\left(f\left(x_{bs}\right)-f\left(x_{\omega s}\right)\right)}{\omega}\right|\right) \tag{16}$$

$$\omega_3 = \cos\left(\left(f\left(x_{bt}\right)-f\left(x_{\omega s}\right)\right)+\pi\right) \cdot \exp\left(-\left|\frac{\left(f\left(x_{bs}\right)-f\left(x_{bt}\right)\right)}{\omega}\right|\right) \tag{17}$$

$$\omega = f\left(x_{\omega s}\right) \tag{18}$$

In the INFO algorithm, the objective function $f(x)$ is used to evaluate the fitness of solution vectors. Integers are selected from the range $[1, N_p]$ and denoted by a_1, a_2, a_3, and l, where $a_1 \neq a_2 \neq a_3 \neq l$. The three best solutions of the g-th generation are represented by x_{bs}, x_{bt} and $x_{\omega s}$, which denote the best, better, and worse solutions, respectively. To perform a global search of the solution space, the algorithm uses weight functions that are determined by a random number r between 0 and 0.5. The CA technique plays a vital role in the updating rule operator by selecting the best vector as the current vector for global search. The best solution is described as the vector that is nearest to the global optima, and the CA technique assists the vectors in moving towards the improved direction [23].

$$\mathrm{CA} = \mathrm{rand} \cdot \frac{\left(\left(x_{bs}-x_{a1}\right)\right)}{\left(f\left(x_{bs}\right)-f\left(x_{a1}\right)+\varepsilon\right)} \tag{19}$$

2.4.2 Vector Combining (Merging)

Vector combining, also referred to as merging, is a vital step in the INFO algorithm that facilitates diversity and exploration in the search space. In these steps, candidate solutions (vectors) are combined using weighted averages, increasing the best features from different solutions. This operation helps the algorithm to navigate towards promising intervals of the solution space while retaining enough variation to avoid early convergence. The weights designated during this step are dynamically adjusted based on the fitness of individual solutions and make sure that high-quality candidates contribute more significantly to the combined vector.

2.4.3 Local Search

The local search step in the INFO algorithm focuses on purifying the solutions got from the merging process. By performing a more detailed search in the neighbourhood of promising candidate solutions, the algorithm improves its ability to converge to an optimal solution. This step typically involves perturbing the solution within a defined neighbourhood and evaluating its performance, ensuring improvements in fitness. The local search balances the algorithm's global search with focused exploitation, letting it to fine-tune solutions and achieve higher accuracy in complex optimization problems.

2.5 PI Controller with INFO Algorithm

In order to develop the control strategy for the analyzed power system, the structure of the PI controller used is shown in Fig. 6.

The equation representing the PI controller is shown as follows:

$$G_{\mathrm{controller}}(s) = K_p + \frac{K_I}{s} \tag{20}$$

The controller gains in this study will be optimized by the proposed INFO algorithm. The objective function is the integral of the time times absolute error (ITAE) of the frequency deviations in the areas and the tie-line power variation. The ITAE objective function is used to determine the best controller gains, as shown in Eq. (21). ITAE reduces the error during the initial transient response and prevents larger errors. This criterion is suitable for techniques that require fast response and settling time or control optimization. ITAE is more suitable if improvement in response speed and reduction of settling time are required.

$$J = \int_0^{\infty} t\left(\left|\Delta f_1\right| + \left|\Delta f_2\right| + \left|\Delta P_{\mathrm{tie}}\right|\right) \mathrm{d}t \tag{21}$$

where J is the objective function of the LFC problem. It is focused to minimize the J. However, the optimal values of K_P and K_I, which are the gain parameters of the PI controller, must be within the lower and upper limit range defined as the variable constraint.

$$K_I^{min} \leq K_I \leq K_I^{max},\ K_P^{min} \leq K_P \leq K_P^{max} \tag{22}$$

When solving the optimization problem, the variable constraints are taken into account, with the minimum and maximum limits being set between the range of [−2, 2] as given in [29].

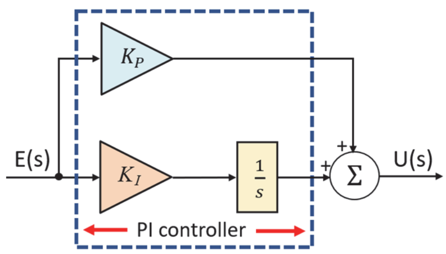

Figure 6 The structure of the PI controller

3 EXPERIMENTAL RESULTS and DISCUSSION

The suggested INFO-based PI controller has been applied to a two-area interconnected power system containing a PV and thermal unit, as depicted in Fig. 1. In the INFO algorithm, the minimization function is derived from the ACE obtained from the controller entry, ensuring convergence to the desired solution. Using an offline gain scheduling control method, the algorithm optimizes the controller gains.

The considered system is developed in MATLAB/SIMULINK program and INFO algorithm is implemented using a special MATLAB script (.m file). The developed model is simulated in a separate program (using initial population and controller parameters) to analyze the dynamic behaviour of the system under load disturbances. The objective function that analyses the system performance is located in the .m file and is used in the optimization process. This analysis is updated for the number of population individuals. Based on the objective function values, the INFO algorithm iteratively updates the population for the next generation.

The system's performance was tested under four different scenarios:

Scenario 1: The response of the INFO-based PI controller was compared to that of GA-tuned and FA-tuned PI controllers.

Scenario 2: Load disturbances in both areas were introduced, and the system's performance was evaluated under these conditions.

Scenario 3: The impact of variations in solar radiation on the system's behaviour was analyzed.

Scenario 4: The system's response was studied with the integration of EV batteries into the grid.

System performance was evaluated based on key metrics, including frequency deviation (Δf_1 and Δf_2), power flow deviations across the tie-line during disturbances (ΔP_{tie}) and the ITAE.

In a simplified test system (single-area), the INFO algorithm efficiently updated the controller gains to their optimal values. Starting from a random initialization, the algorithm iteratively adjusted the search scaling factor and employed weighted vector averaging to enhance the population's uniformity. By leveraging exponential functions to calculate the search scaling factor, the INFO algorithm achieves superior performance in exploring the search space compared to other optimization methods. The algorithm concludes the optimization process by combining vectors during the vector combination phase and refining the solution in the local search phase, ensuring the ideal solution is attained.

Controller gain limits were set as follows: $K_P^{min} = -2$, $K_I^{min} = -2$, $K_P^{max} = 2$ and $K_I^{max} = 2$. The proposed INFO algorithm was independently executed 30 times. As a result of these independent runs, the best ITAE values obtained for Case 1 and Case 2 are 2.844 and 2.847, respectively.

The statistical results for Case 1 are as follows: (Best = 2.844, Worst = 2.981, Average = 2.903 and Std = 0.036). The statistical results for Case 2 are as follows: (Best = 2.847, Worst = 2.995, Average = 2.924 and Std = 0.047).

3.1 Case 1. 10% Load Disturbance in Area-2

In Scenario 1, the functionality of a PI controller optimized using the INFO algorithm was analysed under a 10% load disturbance in Area-2 of the interconnected power grid. The implementation metrics, including settling time, overshoot and undershoot, were compared against controllers tuned using GA and FA algorithms. The controller gains were optimized as shown in Tab. 1.

Table 1 The controller gains

Cases	Methods	K_{P1}	K_{I1}	K_{P2}	K_{I2}
Case 1	GA	−0.5663	−0.4024	−0.5127	−0.7256
	FA	−0.8811	−0.5765	−0.7626	−0.8307
	INFO	−0.3117	−0.0261	−1.9898	−0.8694
Case 2	GA	−0.5663	−0.4024	−0.5127	−0.7256
	FA	−0.8811	−0.5765	−0.7626	−0.8307
	INFO	−0.4115	−0.3505	−2.0000	−0.2733
Case 3	INFO	−0.8380	−0.2343	−2.0000	0.0470
Case 4	INFO	−0.0110	−0.0101	−2.0000	−1.2168

Table 2 Analysis results

Methods	Parameter	Case 1				Case 2			
		Area-1	Area-2	Tie-Line	ITAE	Area-1	Area-2	Tie-Line	ITAE
FA Algorithm	Overshoot (M^+)	0.158	0.124	0.047	7.426	0.169	0.149	0.039	7.426
	Undershoot (M^-)	0.315	0.230	0.048		0.321	0.271	0.049	
	Settling Time (s)	17.500	15.440	17.520		14.130	17.230	15.760	
GA Algorithm	Overshoot (M^+)	0.1637	0.157	0.057	12.124	0.190	0.150	0.043	12.124
	Undershoot (M^-)	0.2966	0.243	0.049		0.300	0.296	0.055	
	Settling Time (s)	14.850	18.550	16.220		16.850	15.550	15.020	
INFO Algorithm (proposed)	Overshoot (M^+)	-	0.064	0.043	2.844	0.0190	-	0.023	2.847
	Undershoot (M^-)	0.111	0.187	0.014		0.173	0.231	0.021	
	Settling Time (s)	8.940	9.973	5.013		5.540	10.400	8.070	

According to Tab. 2, while the FA algorithm yields an ITAE value of 7.426 and the GA algorithm 12.124, the proposed INFO algorithm provides the best objective function values in both cases, with ITAE values of 2.844 and 2.847. The proposed INFO algorithm also achieves the fastest settling time (s) and the lowest overshoot (M^+) and undershoot (M^-) performance in Cases 1 and 2 compared with the other methods.

Fig. 7 shows the frequency deviation in Area-1 for Case 1. The INFO algorithm experienced a smaller undershoot of 0.111 Hz compared to the other algorithms, and did not experience any overshoot. The INFO algorithm reached a quick settlement of 8.94 seconds, making the system stable.

Fig. 8 shows the frequency deviation in Area-2 for Case 1. The INFO algorithm peaked at 0.187 Hz as an undershoot, which is a smaller value than the other algorithms, and again made a small overshoot compared to the others, and settled in a short time of 9.973, making the system stable.

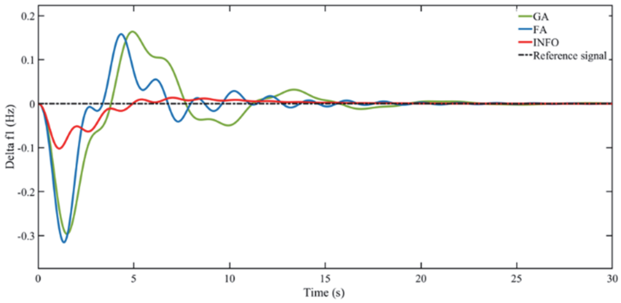

Figure 7 Change of delta f_1 / Hz

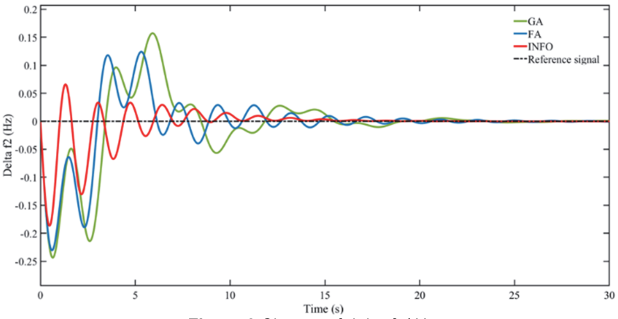

Figure 8 Change of delta f_2 / Hz

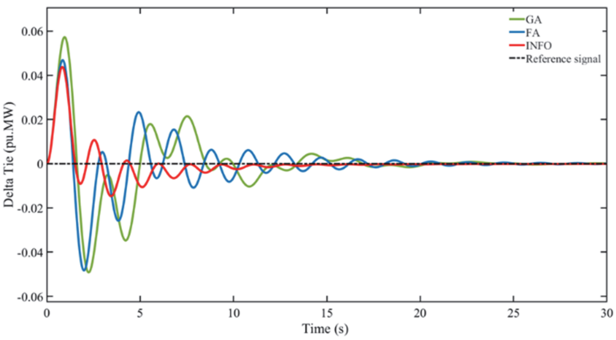

Figure 9 Change of delta Tie / pu.MW

Fig. 9 shows the power flow change in the connection line that provides power flow between areas for Case 1. Although the INFO algorithm shows a peak overshoot value of 0.043 pu.MW, which is close to the FA algorithm, it shows a small undershoot value of 0.014 pu.MW and stabilizes the system by damping the oscillation in a short time of 5.013 seconds.

A 10% rising in load was applied in Area-1, and the matching performance indices, including ITAE values, frequency deviations, tie-line power flows, and settling times, are presented in Tab. 2. From Tab. 2, it is evident that INFO outperforms GA and FA by achieving the minimum ITAE value. Additionally, INFO demonstrates superior performance with shorter settling times and lower peak overshoots and undershoots.

3.2 Case 2. 10% Load Disturbance in Both Areas

In Scenario 2, the INFO-tuned PI controller was tested for robustness under simultaneous 10% step load changes in both areas. Fig. 10 to Fig. 12 and Tab. 2. summarize the results, showing enhanced system stability and faster response times. The controller gains were optimized as shown in Tab. 1.

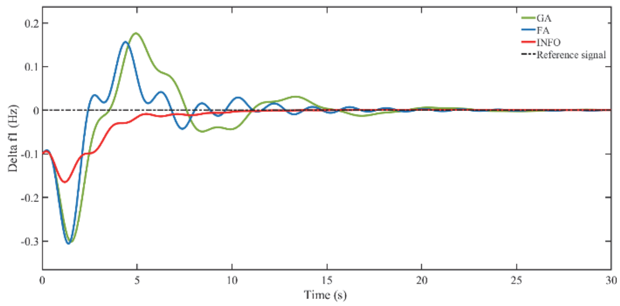

Figure 10 Change of delta f_1 / Hz

Fig. 10 shows the frequency deviation in Area-1 for Case 2. The INFO algorithm experienced a smaller undershoot of 0.1729 Hz compared to the other algorithms, and did not experience any overshoot. The INFO algorithm reached a quick settlement in 5.54 seconds, making the system stable.

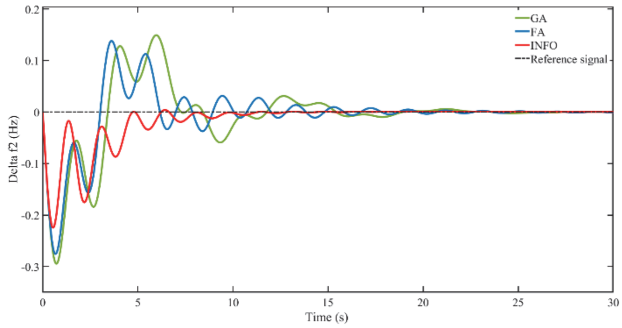

Figure 11 Change of delta f_2 / Hz

Fig. 11 shows the frequency deviation in Area-2 for Case 2. The INFO algorithm peaked at 0.1887 Hz as an undershoot, which is a smaller value than the other algorithms, and again made a small overshoot compared to the others, and settled in a short time of 10.4 seconds, making the system stable.

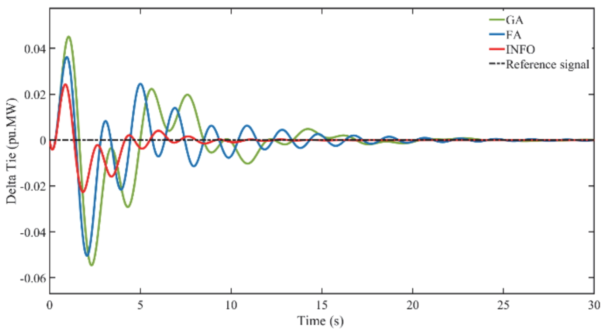

Figure 12 Change of delta Tie / pu.MW

Fig. 12 shows the power flow change in the tie-line that provides power flow between areas for Case 2. The proposed INFO algorithm showed a very small overshoot peak value like 0.0235 pu.MW and again showed a small undershoot value like 0.0214 pu.MW, and dampened the oscillation in a short time like 10.87 seconds, thus making the system stable.

In Area-2, a 10% load increase was introduced, and Tab. 2. summarizes the associated performance metrics, including ITAE values, frequency deviations, tie-line power fluctuations, and settling times. As shown in Tab. 2. INFO surpasses GA and FA by achieving the lowest ITAE value. Moreover, INFO delivers better performance with reduced settling times and smaller peak overshoots.

3.3 Case 3. Impact of Solar Radiation Variations

This case analyzed the sensitivity of the INFO-tuned PI controller to sudden fluctuations in solar radiation caused by factors such as cloud movements and sunrise/sunset. The controller gains were optimized as shown in Tab. 1.

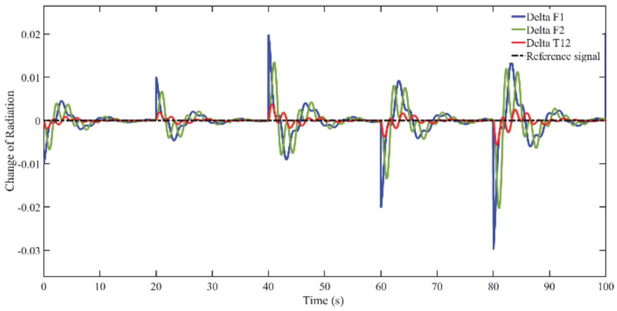

Figure 13 Change of solar radiation

Fig. 13 shows how the sudden changes in solar radiation experienced in a time interval of 100 seconds for Case 3 caused production fluctuations. Since the solar source production unit was connected to Area-1, the frequency deviations experienced here were more severe and reached a maximum of 0.03 Hz. The INFO-tuned controller quickly reduced these deviations, effectively restoring system stability, demonstrating its adaptability and sensitivity.

3.4 Case 4. Integration of EV Batteries

The final case examined the role of EV batteries in improving system stability. EV batteries, connected to Area-1, provided energy during sudden load increases, reducing oscillations and improving the tie-line power flow. The controller gains were optimized as shown in Tab. 1.

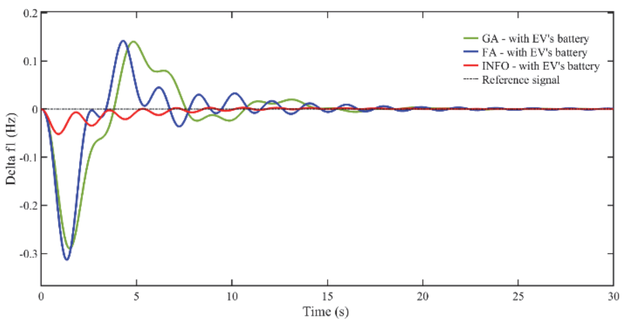

Figure 14 Change of delta f_1 / Hz

Fig. 14 shows the frequency deviation in Area-1 for Case 4. In the system connected to EV batteries, the INFO algorithm experienced an undershoot well below 0.1 Hz and did not experience an overshoot. The INFO algorithm reached a settlement in less than 5 seconds, making the system stable.

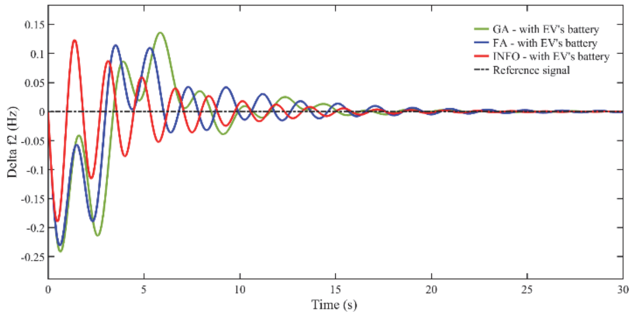

Figure 15 Change of delta f_2 / Hz

Fig. 15. shows the frequency deviation in Area-2 for Case 4. In the system with EV batteries connected, the INFO algorithm experienced an undershoot below 0.2 Hz. The INFO algorithm reached a settlement in less than 10 seconds, making the system stable.

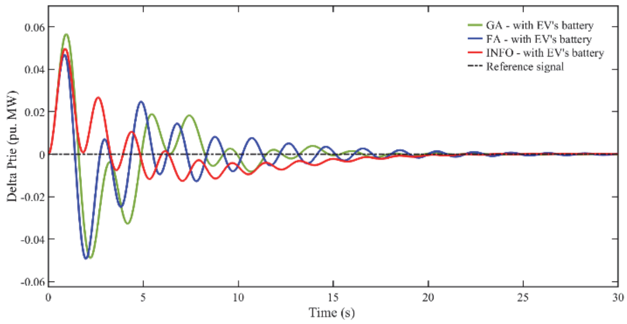

Figure 16 Change of delta Tie / p.u, MW

Fig. 16 shows the power flow change in the connection line that provides power flow between areas for Case 4. In the system with EV batteries connected, the INFO algorithm showed an overshoot peak value of 0.05 pu.MW below the others, and also showed an undershoot value of less than 0.02 pu.MW, making the system stable.

The integration of EV batteries plays a crucial role in damping oscillations, enhancing frequency stabilization, and enabling faster recovery to steady-state conditions. INFO-tuned PI controllers consistently outperformed GA and FA approaches, demonstrating superior dynamic response and robustness. Additionally, the PV and EV batteries, with their exceptionally small time constants, significantly improve the system's dynamic performance by minimizing frequency deviations and reducing tie-line power fluctuations in interconnected power systems.

3.5 Case 5. Comparison with Recent Metaheuristic Algorithms

In this case study, the proposed INFO-based PI controller was comprehensively compared with several recently reported optimization algorithms, namely the chess algorithm (CA) (2025) [29], flood algorithm (FLA) (2025) [30], sinhcosh optimizer (SCHO) (2025) [13], artificial rabbits optimization (ARO) (2024) [31] and black widow optimization algorithm (BWOA) (2022) [8]. The performance of these algorithm-based PI controllers was evaluated on the test system shown in Fig. 1 under a 0.1 p.u. load disturbance introduced in Area 2.

The corresponding PI gain parameters obtained by each algorithm are presented in Tab. 3.

Table 3 The controller gains

Methods	Year	K_{P1}	K_{I1}	K_{P2}	K_{I2}
INFO	-	−0.3117	−0.0261	−1.9898	−0.8694
CA	2025	−0.4687	−0.0923	−1.9942	−0.9399
FLA	2025	−0.4660	−0.0918	−2.0000	−0.9358
SCHO	2025	−0.4758	−0.0931	−2.0000	−0.9339
ARO	2024	−0.4098	−0.3474	−2.0000	−0.2737
BWOA	2022	−0.6671	−0.5477	−2.0000	−0.8470

Using the gain parameters given in Tab. 3, the load frequency control performance of the two-area test system was tested. The resulting objective function (ITAE) values are presented in Tab. 4 for comparative evaluation.

Table 4 The controller gains

Methods	Year	ITAE
INFO	-	2.8444
CA	2025	3.0573
FLA	2025	3.0570
SCHO	2025	3.0602
ARO	2024	3.1254
BWOA	2022	3.7547

According to Tab. 4, the proposed INFO-based PI controller, with an ITAE value of 2.8444, provides the best performance among the recently published methods.

The frequency response analyses (Δf_1, Δf_2 and ΔP_{tie}) of the proposed INFO-based PI controller and the other recent methods are illustrated in Fig. 17 to Fig. 19.

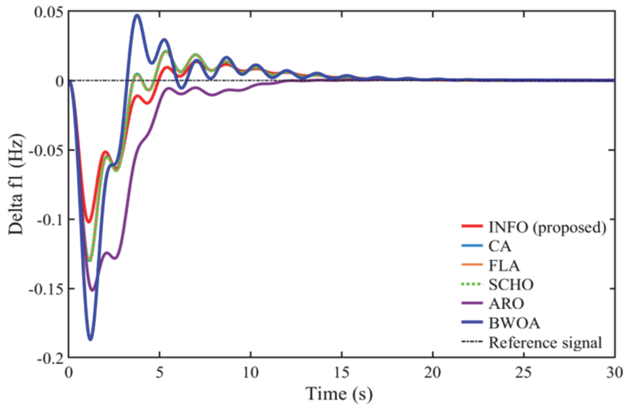

Figure 17 Change of delta f_1 / Hz

According to Fig. 17, the proposed INFO-based PI controller yields the smallest undershoot in the frequency response of Area 1 under the 0.1 p.u. load change in Area 2, ensuring a smoother and more stable frequency regulation.

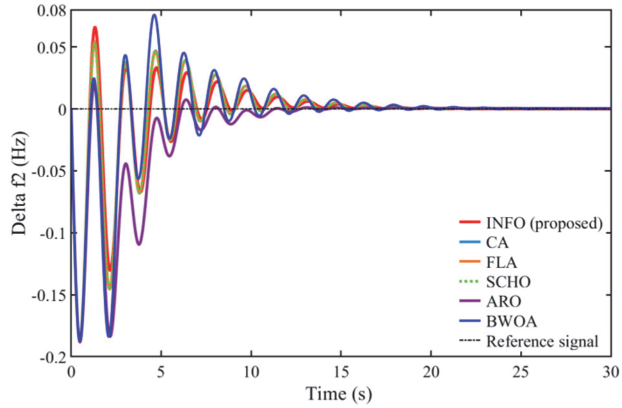

Figure 18 Change of delta f_2 / Hz

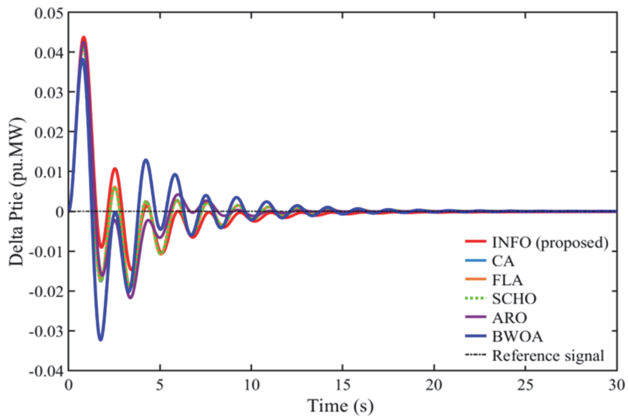

Figure 19 Change of delta Tie / pu.MW

According to Fig. 19, the proposed INFO-based PI controller effectively utilizes the tie-line power exchange to maintain frequency stability under the 0.1 p.u. load change in Area 2.

To enable a clearer comparison of the controllers' performance, the time-domain performance indices, namely settling time, overshoot, and undershoot, are presented in Tab. 5.

Table 5 The controller gains

Parameters		INFO (proposed)	CA [29]	FLA [30]	SCHO [13]	ARO [31]	BWOA [8]
Δf_1	Overshoot (M^+)	0.111	0.130	0.129	0.131	0.151	0.186
	Undershoot (M^-)	-	0.021	0.021	0.021	0.001	0.047
	Settling Time (s)	8.940	9.056	9.066	9.101	9.308	10.549
Δf_2	Overshoot (M^+)	0.187	0.197	0.196	0.196	0.198	0.198
	Undershoot (M^-)	0.064	0.054	0.054	0.053	0.052	0.076
	Settling Time (s)	9.973	13.549	13.618	13.583	14.135	14.135
ΔP_{tie}	Overshoot (M^+)	0.014	0.019	0.019	0.019	0.022	0.032
	Undershoot (M^-)	0.043	0.042	0.042	0.042	0.042	0.038
	Settling Time (s)	5.013	5.201	5.136	5.137	4.011	4.585

According to Tab. 5, when examining the frequency response of Area 1, the proposed INFO method achieves an undershoot value of 0.111, which is 14.6%, 14.0%, 15.3%, 26.5% and 40.3% lower than those of the CA, FLA, SCHO, ARO and BWOA methods, respectively. The proposed INFO approach provides the best overshoot performance with a value of 0.000. In terms of settling time, INFO attains 8.940 s, corresponding to improvements of 1.3%, 1.4%, 1.8%, 4.0% and 15.3% compared with CA, FLA, SCHO, ARO and BWOA, respectively.

For the frequency response of Area 2, the proposed INFO method yields an undershoot value of 0.187, which is 5.1%, 4.6%, 4.6%, 5.6% and 5.6% lower than those of the CA, FLA, SCHO, ARO and BWOA techniques, respectively. INFO produces an overshoot of 0.064, which is about 15.8% lower than BWOA, while being approximately 18.5%, 20.8% and 23.1% higher than CA/FLA, SCHO and ARO, respectively. The settling time of INFO is 9.973 s, providing improvements of 26.4%, 26.8%, 26.6%, 29.4% and 29.4% over CA, FLA, SCHO, ARO and BWOA, respectively.

For the tie-line power deviation, the proposed INFO method achieves an undershoot value of 0.014, which is 26.3%, 26.3%, 26.3%, 36.4% and 56.2% lower than those of CA, FLA, SCHO, ARO and BWOA, respectively. INFO yields an overshoot of 0.043, which is approximately 2.4% higher than CA, FLA, SCHO, and ARO, and 13.2% higher than BWOA. The settling time of INFO is 5.013 s, which is about 3.6%, 2.4% and 2.4% faster than CA, FLA and SCHO, respectively; however, it is approximately 25% and 9.3% longer than ARO and BWOA, respectively.

4 CONCLUSION

This study proposed an INFO-based approach for tuning PI controller parameters in interconnected power systems with high penetration of renewable energy sources and energy storage units. The robustness of the proposed optimization strategy has been validated under different operating conditions and load disturbances, demonstrating its capability to preserve satisfactory dynamic performance.

The proposed INFO-based PI controller achieves ITAE values of 2.844 (Case 1) and 2.847 (Case 2), providing approximately 61% and 76% lower ITAE values than the FA and GA methods, respectively. In terms of overshoot performance, the proposed INFO algorithm yields values of 0, 0.064, and 0.041 for Δf_1, Δf_2 and ΔP_{tie} in Case 1, corresponding to reductions of 100%, 48%, and 13% compared with FA and 100%, 59%, and 28% compared with GA. Regarding undershoot performance, the INFO algorithm provides values of 0.111, 0.189, and 0.019 for Δf_1, Δf_2 and ΔP_{tie} in Case 1, resulting in reductions of approximately 65%, 18%, and 60% relative to FA and about 63%, 22%, and 61% relative to GA. In terms of settling time, the INFO algorithm achieves 8.940 s, 13.470 s, and 10.870 s for Δf_1, Δf_2 and ΔP_{tie} in Case 1, which correspond to reductions of approximately 49%, 13%, and 38% compared with FA and about 40%, 27%, and 33% compared with GA. These results confirm that the INFO-tuned PI controller provides superior damping characteristics, lower overshoot and undershoot, and faster stabilization of system frequency and tie-line power compared with GA and FA based designs.

Additionally, comparative analyses against recent methods (CA, FLA, SCHO, ARO and BWOA) demonstrate that the proposed INFO method continues to exhibit superior performance.

Despite these promising results, this work has certain limitations. The investigation is restricted to a two-area interconnected system and selected disturbance scenarios, without explicitly considering large-scale uncertainties, communication delays, or measurement noise.

Future research will focus on extending the INFO-based design to more complex multi-area structures and validating its performance through hardware-in-the-loop (HIL) applications in renewable-integrated power systems.

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