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HDE-CGWO-Based Optimal Load Frequency Control for Nonlinear Power Systems

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Abstract

In modern power-system load frequency control (LFC), proportional–integral–derivative (PID) controllers are widely used because of their simple structure and ease of implementation. However, the combined effects of communication delay and nonlinear constraints can degrade control performance. To address this issue, this paper proposes a model-constraint-aware optimal PID tuning method based on a Hybrid Differential Evolution–Chaotic Grey Wolf Optimizer (HDE-CGWO). First, a nonlinear LFC model incorporating data sampling, communication delay, governor deadband (GDB), and generation rate constraint (GRC) is established, and a PID-based LFC model is formulated. Next, an objective function based on the integral of time-weighted absolute area control error (ACE), namely ACE-based integral of time-weighted absolute error (ITAE), is constructed. Accordingly, quasi-opposition-based learning (QOBL), chaotic warm-up, Lévy flight, and differential evolution (DE) are incorporated into the standard Grey Wolf Optimizer (GWO) to develop an HDE-CGWO-based PID design scheme for LFC under sampled-data delay and nonlinear unit constraints. Finally, simulation studies are carried out on a multi-area LFC system. The resulting time-domain responses and statistical results show that, compared with standard GWO in the single-area test, HDE-CGWO reduces the ACE-based ITAE by about 43.3%. In the three-area system, the ACE-based ITAE is reduced by about 3.0% under step disturbances and about 1.4% under random disturbances compared with the warm-up Grey Wolf Optimizer (WGWO), indicating that the proposed method can reduce frequency deviations, attenuate post-disturbance oscillations, and accelerate the dynamic recovery process under the considered disturbance conditions.

Keywords: LFC; PID control; communication delay; nonlinear constraints; HDE-CGWO



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1. Introduction

Frequency is an important indicator of the operating condition and power quality of a power system. The main task of load frequency control (LFC) is to maintain system frequency and tie-line power within prescribed limits under load disturbances [1–4]. With the increasing penetration of renewable energy sources such as wind and photovoltaic power, power-system operating conditions have become more complicated, and frequency regulation associated with renewable energy integration has received increasing attention in recent LFC studies [2,5–8]. Meanwhile, LFC has become increasingly dependent on open communication networks for the transmission of measurement and control signals.

Cyber-attack-driven data availability issues can also affect data-driven LFC strategies under such communication-dependent conditions [9]. Owing to network congestion, protocol processing, and link switching, communication delays can directly deteriorate the dynamic performance and stability of LFC [6,10–12]. In practical implementation, LFC is a typical sampled-data control problem. Simply treating sampling effects as ordinary delays often fails to describe the actual control process accurately [10,13]. In addition, practical generating units exhibit inherent nonlinearities, such as governor deadband (GDB) and generation rate constraint (GRC). If these factors are neglected in system modeling and controller design, the resulting controller parameters may deviate from actual operating conditions [14]. Therefore, establishing an LFC model that simultaneously accounts for communication delay, sampling characteristics, and nonlinear constraints is the first issue addressed in this study. It also provides the basis for subsequent controller design and parameter tuning [6,10,13,14].

For LFC systems with communication delay, sampling effects, and nonlinear constraints, a variety of advanced control approaches have been reported, including sliding mode control, model predictive control, active disturbance rejection control (ADRC), event-triggered control, and robust predictive control [15–21]. Event-triggering LFC schemes have also been extended to deception-attack and random dynamic-triggering conditions [22,23]. Although these methods can improve dynamic performance to some extent, their design procedures are often relatively complicated. Some of them also impose stringent requirements on model accuracy and state availability, which increases implementation difficulty and engineering costs [16–19]. By contrast, PID control remains one of the most widely used strategies in power-system LFC because of its simple structure and the clear physical meaning of its parameters [3,21,24,25]. Since practical power systems are discrete sampled-data systems, the PID control structure is more consistent with LFC implementation and allows sampled feedback signals to be used directly in control computation [6,10,13,26]. Accordingly, the second issue considered in this paper is how to obtain high-quality PID parameters for LFC systems subject to communication delay, sampling effects, and nonlinear constraints, so as to obtain acceptable frequency regulation performance [3,24,26].

Various methods, such as internal model control, particle swarm optimization, whale optimization algorithm, salp swarm algorithm, DE, and hybrid intelligent optimization methods, have been used for tuning PID controllers in LFC [24,27–33]. Since these methods can directly optimize dynamic performance indices, they are well suited to parameter tuning problems [24,27,28]. Compared with these methods, the Grey Wolf Optimizer (GWO) has been widely applied to engineering optimization problems because of its simple structure, small number of parameters, and ease of implementation [34,35]. In the LFC field, Guha et al. first employed standard GWO to tune PI/PID controller parameters in interconnected power systems [36]. They later introduced QOBL and proposed the quasi-oppositional Grey Wolf Optimizer (QOGWO) to improve the quality of the initial population [37]. Following this, Padhy et al. proposed a modified GWO (MGWO) by adjusting the search weights and applied it to AGC controller design in systems with plug-in electric vehicles [38]. Sahoo et al. developed IGWO for tuning fuzzy-aided PID frequency controllers [39]. Beyond the LFC field, Kohli and Arora investigated chaotic GWO for constrained optimization problems [40]. Shangguan et al. further proposed WGWO for LFC problems considering sampling and communication delay [26]. These studies indicate that GWO and its variants are effective tools for LFC parameter tuning [26,36–40]. However, most existing improvements focus on a single aspect, such as initialization strategy, convergence-factor design, or position updating. When sampling, communication delay, GDB, and GRC act simultaneously in an LFC system, the nonlinearity and complexity of PID tuning increase substantially. The interaction among these physical constraints

also makes the search process more susceptible to overly rapid step-size shrinkage and insufficient population diversity in the later stages of iteration [26,37–39]. Therefore, for PID tuning in LFC systems under such complex constraints, further improving GWO to obtain a more suitable optimization algorithm constitutes the third issue addressed in this paper.

Based on the above considerations, this paper proposes a model-constraint-aware HDE-CGWO-based optimal PID tuning method for power-system LFC considering data sampling, communication delay, and unit nonlinear constraints. The main contributions of this work are summarized as follows:

1. A multi-area LFC model considering data sampling, communication delay, GDB, and GRC is established, and a corresponding framework for PID parameter tuning is constructed.
2. For PID tuning under complex constraints, an optimization model with ACE-based ITAE as the objective is formulated. This model enables optimal controller parameter design while retaining the simplicity and implementability of the PID structure.
3. A model-constraint-aware HDE-CGWO tuning framework is developed for PID parameter optimization in sampled-data-delayed LFC systems with GDB and GRC. Based on GWO and warm-up GWO, the proposed method integrates QOBL, chaotic warm-up, Lévy flight, and DE-based local search to improve initialization quality, global exploration, and local refinement. The obtained PID parameters lead to better frequency regulation performance in the tested single-area and three-area systems.

The remainder of this paper is organized as follows. Section 2 establishes a PID-LFC model considering data sampling, communication delay, and nonlinear constraints. Section 3 presents the HDE-CGWO-based controller parameter optimization method. Section 4 gives the simulation studies and discussion. Section 5 concludes the paper.

2. System Modeling and Problem Formulation

2.1. Multi-Area LFC Model with Nonlinear Constraints

To analyze LFC in a multi-area power system, an LFC model that accounts for multiple generating companies (Gencos) and unit nonlinear constraints is first established. Figure 1 shows the LFC structure of area i . The control areas are interconnected through tie-lines, and each area includes n_i Gencos, a generator-load unit, a control unit, renewable-energy sources, and tie-line power exchange dynamics. For the n -th Genco in area i , the participation factor is denoted by $a_{i,n}$, with

$$a_{i,n} = \frac{P_{i,n}^{\text{rate}}}{\sum_{q=1}^{n_i} P_{i,q}^{\text{rate}}}, \quad \sum_{n=1}^{n_i} a_{i,n} = 1 \quad (1)$$

where $P_{i,n}^{\text{rate}}$ is the rated capacity of Genco n in area i . The aggregated mechanical power entering the area-level frequency equation is

$$\Delta P_{m,i}(t) = \sum_{n=1}^{n_i} a_{i,n} \Delta P_{m,i,n}(t) \quad (2)$$

The area-level damping coefficient and equivalent frequency-response inertia coefficient used in the frequency equation are constructed from the unit-level parameters in Table 1 as

$$D_i = \sum_{n=1}^{n_i} a_{i,n} D_{i,n}, \quad M_i = \sum_{n=1}^{n_i} a_{i,n} D_{i,n} T_{p,i,n} \quad (3)$$

Thus, the parameters $D_{i,n}$, $T_{p,i,n}$, $T_{t,i,n}$, $T_{g,i,n}$, and $R_{i,n}$ in Table 1 are used consistently as unit-level Genco parameters. The expression of M_i follows the commonly used first-order power-system frequency-response block. For Genco n in area i , this block can be written as

$$\Delta f_{i,n}(s) = \frac{K_{p,i,n}}{1 + sT_{p,i,n}} \Delta P_{e,i,n}(s), \quad K_{p,i,n} = \frac{1}{D_{i,n}} \quad (4)$$

where $\Delta P_{e,i,n}$ denotes the equivalent net power imbalance acting on the frequency-response block. Rewriting (4) in the time domain gives

$$D_{i,n}T_{p,i,n}\Delta \dot{f}_{i,n}(t) + D_{i,n}\Delta f_{i,n}(t) = \Delta P_{e,i,n}(t) \quad (5)$$

Thus, $D_{i,n}T_{p,i,n}$ is the unit-level equivalent frequency-response inertia contribution, rather than the conventional synchronous-machine inertia constant, and it is aggregated according to the participation factor $a_{i,n}$.

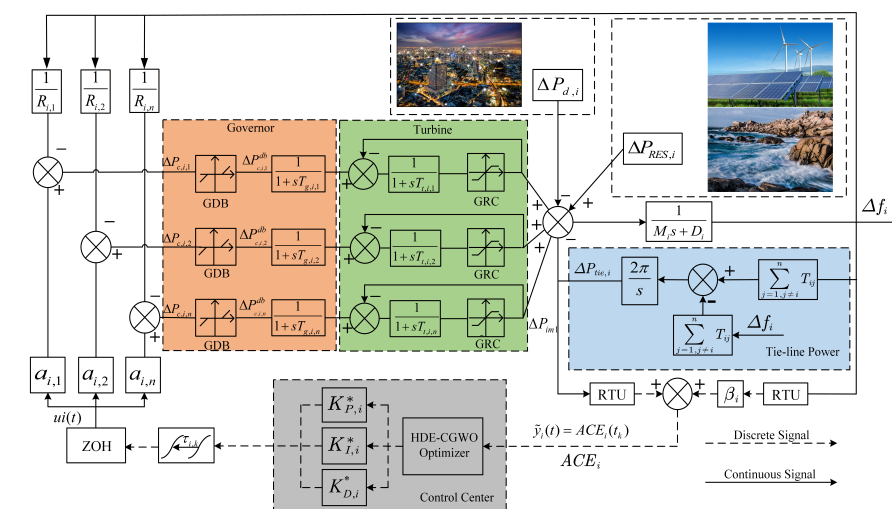


Figure 1. Structural framework of the multi-Genco LFC model of area i .

Table 1. Parameters of the load frequency control (LFC) test system.

Area	Genco n	Rate (MW)	$D_{i,n}$ (pu/Hz)	$T_{p,i,n}$ (s)	$T_{t,i,n}$ (s)	$T_{g,i,n}$ (s)	$R_{i,n}$ (Hz/pu)
Area 1	1	1000	0.0150	0.1667	0.4000	0.08	3.0000
	2	800	0.0140	0.1200	0.3600	0.06	3.0000
	3	1000	0.0150	0.2000	0.4200	0.07	3.3000
Area 2	4	1100	0.0160	0.2017	0.4400	0.06	2.7273
	5	900	0.0140	0.1500	0.3200	0.06	2.6667
	6	1200	0.0140	0.1960	0.4000	0.08	2.5000
Area 3	7	850	0.0150	0.1247	0.3000	0.07	2.8235
	8	1000	0.0160	0.1667	0.4000	0.07	3.0000
	9	1020	0.0150	0.1870	0.4100	0.08	2.9412

As shown in the revised Figure 1, the signal entering the GDB block of Genco n is the equivalent command $\Delta P_{c,i,n}(t)$, which is formed by the participation-weighted supplementary control signal and the governor droop feedback. The GDB output is denoted by $\Delta P_{c,i,n}^{db}(t)$ and is then applied to the first-order governor block. This notation is used consistently in the following equations.

Since both load disturbances and renewable-energy power deviations lead to power imbalance within the area, they are grouped into a unified external disturbance term:

$$w_i(t) = \Delta P_{d,i}(t) - \Delta P_{RES,i}(t) \quad (6)$$

In practical generating units, GDB and GRC directly affect the primary frequency regulation process. Let $u_i(t)$ denote the area-level supplementary control input. According to Figure 1, the equivalent command entering the GDB block of Genco n is

$$\Delta P_{c,i,n}(t) = a_{i,n}u_i(t) - \frac{1}{R_{i,n}}\Delta f_i(t) \quad (7)$$

and the GDB output is described by

$$\Delta P_{c,i,n}^{db}(t) = \mathcal{B}_{i,n}(\Delta P_{c,i,n}(t)) = \begin{cases} \Delta P_{c,i,n}(t) - \kappa_{i,n}^-, & \Delta P_{c,i,n}(t) \leq \kappa_{i,n}^- \\ 0, & \kappa_{i,n}^- < \Delta P_{c,i,n}(t) < \kappa_{i,n}^+ \\ \Delta P_{c,i,n}(t) - \kappa_{i,n}^+, & \Delta P_{c,i,n}(t) \geq \kappa_{i,n}^+ \end{cases} \quad (8)$$

where $\mathcal{B}_{i,n}(\cdot)$ denotes the GDB operator, and $\kappa_{i,n}^-$ and $\kappa_{i,n}^+$ are the lower and upper GDB bounds of Genco n in area i , respectively.

The GRC is introduced to describe the physical limit on the rate of change of the mechanical power of each Genco. Define the saturation operator as

$$\text{sat}_{[r_{i,n}^-, r_{i,n}^+]}(\xi) = \begin{cases} r_{i,n}^-, & \xi < r_{i,n}^- \\ \xi, & r_{i,n}^- \leq \xi \leq r_{i,n}^+ \\ r_{i,n}^+, & \xi > r_{i,n}^+ \end{cases} \quad (9)$$

where $r_{i,n}^-$ and $r_{i,n}^+$ are the lower and upper mechanical power ramp-rate limits of Genco n in area i , respectively.

Based on this formulation, the dynamic equations of area i are written as the following individual equations:

$$\Delta \dot{f}_i(t) = \frac{1}{M_i} \left(\sum_{n=1}^{n_i} a_{i,n} \Delta P_{m,i,n}(t) - D_i \Delta f_i(t) - \Delta P_{tie,i}(t) - w_i(t) \right) \quad (10)$$

$$\Delta \dot{P}_{m,i,n}(t) = \text{sat}_{[r_{i,n}^-, r_{i,n}^+]} \left(\frac{1}{T_{i,n}} (\Delta P_{g,i,n}(t) - \Delta P_{m,i,n}(t)) \right), \quad n = 1, 2, \dots, n_i \quad (11)$$

$$\Delta \dot{P}_{g,i,n}(t) = \frac{1}{T_{g,i,n}} (\Delta P_{c,i,n}^{db}(t) - \Delta P_{g,i,n}(t)), \quad n = 1, 2, \dots, n_i \quad (12)$$

$$\Delta \dot{P}_{tie,i}(t) = 2\pi \sum_{\substack{j=1 \\ j \neq i}}^N T_{ij} (\Delta f_i(t) - \Delta f_j(t)) \quad (13)$$

where $\Delta f_i(t)$ and $\Delta P_{tie,i}(t)$ denote the frequency deviation and tie-line power deviation of area i , respectively. $\Delta P_{m,i,n}(t)$ and $\Delta P_{g,i,n}(t)$ denote the mechanical power deviation and governor output deviation of Genco n in area i , respectively.

For subsequent controller design, define the state vector of area i as

$$x_i(t) = \begin{bmatrix} \Delta f_i(t) & \Delta P_{m,i,1}(t) & \cdots & \Delta P_{m,i,n_i}(t) & \Delta P_{g,i,1}(t) & \cdots & \Delta P_{g,i,n_i}(t) & \Delta P_{tie,i}(t) \end{bmatrix}^T \quad (14)$$

Thus, $x_i(t)$ contains the area-level frequency and tie-line power states, together with the Genco-level turbine and governor states.

Since the GRC and GDB are nonlinear and are applied at the Genco level, the area model in (10)–(13) is expressed compactly as

$$\dot{x}_i(t) = \mathcal{F}_i(x_1(t), x_2(t), \dots, x_N(t), u_i(t), w_i(t)) \quad (15)$$

where $\mathcal{F}_i(\cdot)$ is defined by the multi-Genco dynamics in (10)–(13).

In multi-area LFC, the area control error (ACE) reflects both the local frequency deviation and the tie-line power exchange deviation. It is therefore selected as the system output. The ACE of area i is defined as

$$ACE_i(t) = \beta_i \Delta f_i(t) + \Delta P_{tie,i}(t) \quad (16)$$

Here, β_i is the area frequency-bias coefficient used in the ACE signal. In the present multi-Genco model, it is obtained from the area damping coefficient and the equivalent droop coefficient as

$$\beta_i = D_i + \frac{1}{R_i^{\text{eq}}}, \quad \frac{1}{R_i^{\text{eq}}} = \sum_{n=1}^{n_i} a_{i,n} \frac{1}{R_{i,n}}. \quad (17)$$

Thus, D_i is calculated by (3), and $1/R_i^{\text{eq}}$ is calculated from the participation factors and the Genco-level droop coefficients in Table 1. For the test system considered in this paper, substituting the data in Table 1 gives

$$\beta_1 = 0.3372, \quad \beta_2 = 0.3962, \quad \beta_3 = 0.3572. \quad (18)$$

These values are used in (16) and the output matrix in (19). Let $y_i(t) = ACE_i(t)$. Then

$$y_i(t) = C_i x_i(t), \quad C_i = \begin{bmatrix} \beta_i & \mathbf{0}_{1 \times n_i} & \mathbf{0}_{1 \times n_i} & 1 \end{bmatrix} \quad (19)$$

2.2. Closed-Loop PID-LFC Model with Sampling and Transmission Delay

With the ACE obtained from (16)–(19), the sampling and transmission processes in the practical control loop must be further considered. Let the sampling period be h , and let the corresponding sampling frequency be $f_s = 1/h$. In the numerical studies, $h = 3$ s is used, namely $f_s = 1/3$ Hz, as a conservative sampled-data setting for testing the controller under an unfavorable low-rate measurement/update condition. This value is not chosen from numerical-integration accuracy, but from the intended sampled-data measurement/update interval, and its reliability is checked later through the sampling-delay boundary test. The k -th sampling instant is then given by

$$t_k = kh, \quad k = 0, 1, 2, \dots \quad (20)$$

Accordingly, the feedback output of area i at t_k is

$$y_i(t_k) = C_i x_i(t_k) \quad (21)$$

To account for communication-induced transmission delay, let $\tau_{i,k}$ denote the delay associated with area i . Once the sampled signal reaches the controller, it is held constant until the next control update, that is,

$$\tilde{y}_i(t) = y_i(t_k), \quad t \in [t_k + \tau_{i,k}, t_{k+1} + \tau_{i,k+1}) \quad (22)$$

where $\tilde{y}_i(t)$ denotes the delayed sampled signal available to the controller.

Once the delayed sampled signal is available to the controller, the control action at sampling instant t_k is computed based on the received sampled measurement. For notational simplicity, this received sampled measurement is still written as $y_i(t_k)$ in the following controller equations. Accordingly, a PID control law is used for each area. The controller output of area i at sampling instant t_k is

$$v_i(t_k) = K_{P,i}y_i(t_k) + K_{I,i}h \sum_{m=0}^k y_i(t_m) + K_{D,i} \frac{y_i(t_k) - y_i(t_{k-1})}{h} \quad (23)$$

The derivative term at $k = 0$ is initialized as zero. Define the controller parameter vector and the discrete feedback vector as

$$K_i = \begin{bmatrix} K_{P,i} & K_{I,i} & K_{D,i} \end{bmatrix} \quad (24)$$

$$\xi_i(t_k) = \begin{bmatrix} y_i(t_k) \\ h \sum_{m=0}^k y_i(t_m) \\ \frac{y_i(t_k) - y_i(t_{k-1})}{h} \end{bmatrix} \quad (25)$$

Then (23) can be rewritten as

$$v_i(t_k) = K_i \xi_i(t_k) \quad (26)$$

Under the zero-order hold (ZOH), the control input remains equal to the most recently computed value between two successive updates. Hence,

$$u_i(t) = -v_i(t_k) = -K_i \xi_i(t_k), \quad t \in [t_k + \tau_{i,k}, t_{k+1} + \tau_{i,k+1}) \quad (27)$$

For Genco n in area i , substituting the delayed sampled PID signal in (27) into (7) gives the Genco-level command

$$\Delta P_{c,i,n}(t) = -a_{i,n} K_i \xi_i(t_k) - \frac{1}{R_{i,n}} \Delta f_i(t), \quad n = 1, 2, \dots, n_i \quad (28)$$

and the corresponding GDB output is

$$\Delta P_{c,i,n}^{db}(t) = \mathcal{B}_{i,n}(\Delta P_{c,i,n}(t)), \quad n = 1, 2, \dots, n_i \quad (29)$$

Equations (10)–(13), together with (21), (23) and (27)–(29), constitute the closed-loop PID-LFC model adopted in this paper. In this form, the repeated plant equations are not rewritten, and only the substituted sampled-delay PID command and the resulting GDB input/output relations are added to the plant model.

3. HDE-CGWO-Based Controller Parameter Optimization

3.1. Optimization Objective and Basic Solution Method

For the closed-loop PID-LFC model established in Section 2, the controller tuning task can be formulated as a constrained optimization problem. Since $ACE_i(t)$ reflects both the frequency deviation and the tie-line power deviation of area i , the ACE-based ITAE is first computed as

$$f_{\text{ITAE}}(X) = \sum_{i=1}^N \int_0^{t_{\max}} t |ACE_i(t)| dt \quad (30)$$

To prevent divergent PID parameters from being selected during numerical optimization, a penalty-based fitness function is further introduced as

$$\min J(X) \quad (31)$$

with

$$J(X) = \begin{cases} f_{\text{ITAE}}(X), & \text{if the closed-loop response is bounded} \\ M_p, & \text{otherwise} \end{cases} \quad (32)$$

subject to

$$\begin{cases} K_{P,\min,i} \leq K_{P,i} \leq K_{P,\max,i}, \\ K_{I,\min,i} \leq K_{I,i} \leq K_{I,\max,i}, \\ K_{D,\min,i} \leq K_{D,i} \leq K_{D,\max,i}, \end{cases} \quad i = 1, 2, \dots, N \quad (33)$$

where N is the number of control areas, and $t_{\max}$ denotes the simulation horizon. $K_{P,i}$, $K_{I,i}$, and $K_{D,i}$ are the proportional, integral, and derivative gains of the PID controller in area i , respectively. In (32), a bounded response means that the simulated closed-loop states and $ACE_i(t)$ remain finite over $[0, t_{\max}]$, and M_p is a large penalty value. In this study, M_p is set to 10^6 . Accordingly, the candidate PID parameter vector to be optimized is denoted by X and written as

$$X = [K_{P1}, K_{I1}, K_{D1}, \dots, K_{PN}, K_{IN}, K_{DN}]^T \quad (34)$$

For any candidate parameter vector X , substituting it into (10)–(13) together with (27)–(29) yields $ACE_i(t)$ for each area. If the corresponding closed-loop response is bounded, $f_{\text{ITAE}}(X)$ is used as the fitness value; otherwise, the penalty value M_p is assigned. Therefore, the problem considered in this paper is to search for a set of PID parameters within the prescribed bounds that minimizes $J(X)$.

To solve this problem, GWO is adopted. The standard GWO is described in detail in [35]. In the present study, the position of each grey wolf represents one set of PID parameters, and the fitness of each individual is evaluated by $J(X)$ obtained from the PID-LFC model and the stability screening rule. Let $X_i(j)$ denote the position of the i -th wolf at iteration j , and let $X_\alpha(j)$, $X_\beta(j)$, and $X_\delta(j)$ denote the current best, second-best, and third-best individuals, respectively. The standard position update can be written as

$$\begin{aligned} D_{\alpha,i} &= |C_1 \odot X_\alpha(j) - X_i(j)|, \\ D_{\beta,i} &= |C_2 \odot X_\beta(j) - X_i(j)|, \\ D_{\delta,i} &= |C_3 \odot X_\delta(j) - X_i(j)| \end{aligned} \quad (35)$$

$$\begin{aligned} X_{1,i} &= X_\alpha(j) - A_1 \odot D_{\alpha,i}, \\ X_{2,i} &= X_\beta(j) - A_2 \odot D_{\beta,i}, \\ X_{3,i} &= X_\delta(j) - A_3 \odot D_{\delta,i} \end{aligned} \quad (36)$$

$$X_i(j+1) = \frac{X_{1,i} + X_{2,i} + X_{3,i}}{3} \quad (37)$$

where $\odot$ denotes element-wise multiplication. The coefficient vectors are defined as

$$A_m = 2ar_{1m} - a, \quad C_m = 2r_{2m}, \quad m = 1, 2, 3 \quad (38)$$

where r_{1m} and r_{2m} are random vectors uniformly distributed over $[0, 1]$. In standard GWO, the convergence factor a is given by

$$a = 2 \left(1 - \frac{j}{j_{\max}} \right) \quad (39)$$

where $j_{\max}$ is the maximum number of iterations.

Although standard GWO is simple and easy to implement, three limitations arise when it is directly applied to the PID tuning problem considered here. First, random initialization may lead to poor-quality initial solutions. Second, the linear decay of the convergence factor is not well suited to the search space shaped by sampling, communication delay, GDB, and GRC, and may cause the algorithm to lose exploration capability too early. Third, the three leader wolves contribute equally to the position update, and no explicit jumping mechanism is provided, which makes the search prone to premature convergence in the later stages.

To overcome these limitations, the proposed HDE-CGWO improves standard GWO in three aspects: population initialization, convergence regulation, and late-stage escape and refinement.

3.2. Improvement Strategies for HDE-CGWO

To address the three limitations discussed above, the proposed HDE-CGWO improves standard GWO from three aspects. The first improvement enhances the quality of the initial population, the second regulates the search process through the convergence factor and dynamic leader weighting, and the third strengthens the late-stage escape and local refinement abilities. These mechanisms are introduced according to the specific difficulties of digital PID-LFC tuning under sampling, communication delay, GDB, and GRC, rather than as an independent stacking of optimization operators.

3.2.1. QOBL-Based Population Initialization

When GWO is used to optimize PID parameters, the distribution of the initial population has a direct influence on the subsequent search process. In standard GWO, the initial individuals are generated randomly. For the LFC tuning problem considered in this paper, however, such a strategy may place some individuals in poor regions of the search space, which degrades the search quality at the early stage. To alleviate this issue, QOBL is introduced during initialization.

Let X_i be the position vector of the i -th individual in the population, and let $x_{i,d}$ denote its d -th component, where $d \in \{1, 2, \dots, 3N\}$. Assume that the search interval of the d -th parameter is $[l_d, u_d]$. Its opposite point, center point, and quasi-opposite point are defined as

$$\bar{x}_{i,d} = l_d + u_d - x_{i,d} \quad (40)$$

$$c_d = \frac{l_d + u_d}{2} \quad (41)$$

$$x_{i,d}^q = c_d + r_{i,d}(\bar{x}_{i,d} - c_d) \quad (42)$$

where $r_{i,d} \in [0, 1]$ is a random number. For each randomly generated set of PID parameters, a corresponding quasi-opposite solution is constructed. Both solutions are then evaluated through the PID-LFC model, and the one with better fitness is retained in the initial population. In this way, the subsequent search starts from a more favorable set of candidate solutions.

3.2.2. Hybrid Convergence Regulation and Dynamic Leader Weighting

To further improve the search process, a warm-up chaotic convergence factor is introduced, and the contributions of the three leader wolves are weighted according to their fitness values. The purpose of these operators is not to build a direct physical mapping between an optimization operator and a single power-system component. Instead, they are introduced because sampling, communication delay, GDB, and GRC jointly make the ACE-based ITAE surface non-smooth and locally flat in some regions. Under this type of search landscape, an overly rapid reduction in the search step may cause the population to stagnate around suboptimal PID gains. To address this issue, a cosine warm-up schedule and a logistic chaotic perturbation are combined to construct the Chaotic Grey Wolf Optimizer (CGWO).

First, the cosine-type convergence baseline is defined as

$$a_0(j) = 2 \cos\left(\frac{\pi}{2} \frac{j}{j_{\max}}\right) \quad (43)$$

Then, the logistic chaotic map is introduced as

$$z_{j+1} = \mu z_j(1 - z_j), \quad 0 < z_j < 1 \quad (44)$$

where $\mu = 4$. Accordingly, the actual convergence factor is written as

$$a(j) = a_0(j) + \eta(z_j - 0.5) \quad (45)$$

where η is the perturbation amplitude, and $\eta = 0.3$ is used in this study. Equation (45) preserves a relatively large search range in the early stage and gradually reduces the step size as the iteration proceeds. The chaotic perturbation helps avoid an overly regular search trajectory. In addition, stagnation is judged from the relative improvement of the current best fitness. The criterion is defined as

$$\rho(j) = \frac{J_{\alpha}(j-1) - J_{\alpha}(j)}{J_{\alpha}(j-1) + 10^{-10}} \quad (46)$$

and the corresponding stagnation condition is

$$\rho(j) < 10^{-3}. \quad (47)$$

If (47) is satisfied for three consecutive iterations, the convergence factor is temporarily enlarged to a random value in $[1.5, 2.0]$ to restore exploration capability. This adaptive adjustment helps the population escape from stagnation regions and continue searching toward better PID parameter regions. A comparison between the standard linear decay and the proposed convergence schedule is shown in Figure 2.

As shown in Figure 2, compared with the linear decay in standard GWO, the proposed convergence factor maintains a larger search range in the early stage and exhibits mild irregular fluctuations during the iterative process. This is helpful for preserving exploration capability under the joint effects of sampling, communication delay, GDB, and GRC, while still keeping a gradual convergence trend in the later stage.

The three leader wolves α , β , and δ correspond to three different sets of PID parameters, and their fitness values are denoted by J_{α} , J_{β} , and J_{δ} , respectively. Their weights are defined as

$$\begin{aligned}
 w_{\alpha} &= \frac{J_{\alpha}^{-1}}{J_{\alpha}^{-1} + J_{\beta}^{-1} + J_{\delta}^{-1}}, \\
 w_{\beta} &= \frac{J_{\beta}^{-1}}{J_{\alpha}^{-1} + J_{\beta}^{-1} + J_{\delta}^{-1}}, \\
 w_{\delta} &= \frac{J_{\delta}^{-1}}{J_{\alpha}^{-1} + J_{\beta}^{-1} + J_{\delta}^{-1}}
 \end{aligned} \tag{48}$$

Accordingly, the position update in (37) is modified as

$$X_i^g(j+1) = w_{\alpha}X_{1,i} + w_{\beta}X_{2,i} + w_{\delta}X_{3,i} \tag{49}$$

With this weighted update, the leader associated with a smaller fitness value exerts a stronger influence on the position update. The hybrid convergence factor regulates the search process, while the dynamic weighting improves the guidance effect of the leading wolves. Together, these two mechanisms alleviate the shortcomings of insufficient early exploration and inaccurate late-stage convergence in standard GWO.

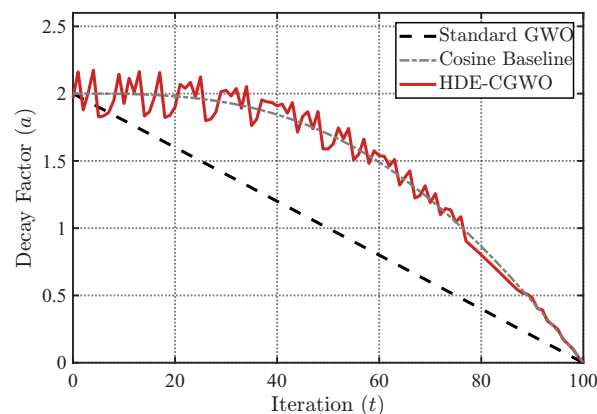


Figure 2. Comparison of the convergence-factor trajectories of standard GWO and HDE-CGWO.

3.2.3. Lévy Flight and DE-Based Local Refinement

To alleviate stagnation in the later search stage, Lévy flight and DE are further introduced after the weighted grey-wolf update. Let $p_i \in [0, 1]$ be a random number. If $p_i < p_L$, a Lévy perturbation is applied to $X_i^g(j+1)$, yielding

$$\begin{aligned}
 X_i^L(j+1) &= X_i^g(j+1) \\
 &+ \alpha_L \text{Levy}(\lambda) \odot (X_i^g(j+1) - X_i(j))
 \end{aligned} \tag{50}$$

where α_L is the step-size coefficient, and $\text{Levy}(\lambda)$ is generated by Mantegna's algorithm with distribution parameter λ . In this study, $p_L = 0.1$, $\alpha_L = 0.01$, and $\lambda = 1.5$ are used. The Lévy-flight step is not meant to represent communication delay physically. Its role is algorithmic: the long-tailed perturbation provides occasional larger moves when the delayed sampled-data LFC model with GDB and GRC produces a locally flat or weakly improving fitness region. In this way, frequent short-range moves preserve local search, while occasional long jumps help escape local stagnation regions. Figure 3 compares the Lévy-flight trajectory with a conventional random-search trajectory. The two axes in Figure 3 denote dimensionless normalized parameter-space coordinates.

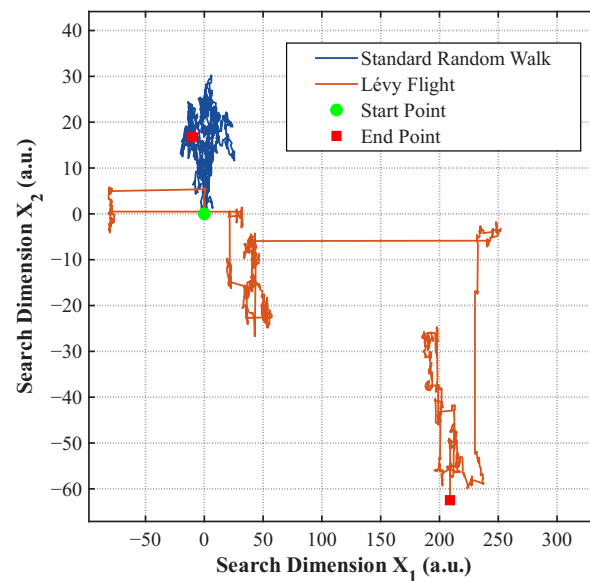


Figure 3. Comparison of Lévy-flight and random-search trajectories in a dimensionless two-dimensional parameter space.

For notational convenience, define the candidate individual after the weighted GWO update and optional Lévy perturbation as

$$X_i^c(j+1) = \begin{cases} X_i^L(j+1), & p_i < p_L, \\ X_i^g(j+1), & \text{otherwise} \end{cases} \quad (51)$$

On this basis, a DE operation is performed. For the i -th individual, three mutually distinct individuals X_{r_1} , X_{r_2} , and X_{r_3} are randomly selected to construct the mutation vector

$$V_i = X_{r_1} + F(X_{r_2} - X_{r_3}) \quad (52)$$

where F is the scaling factor.

The binomial crossover is then expressed as

$$U_{i,d} = \begin{cases} V_{i,d}, & \text{rand}_d \leq CR \text{ or } d = d_{\text{rand}}, \\ X_{i,d}^c(j+1), & \text{otherwise,} \end{cases} \quad d = 1, 2, \dots, 3N \quad (53)$$

where CR is the crossover probability, rand_d is a random number uniformly distributed over $[0, 1]$, and d_{rand} is a randomly selected dimension that ensures at least one component is inherited from the mutation vector. After crossover, the trial vector U_i is obtained.

For any candidate vector Z_i generated by Lévy flight or DE, bound handling is performed by

$$z_{i,d} \leftarrow \min\{\max\{z_{i,d}, l_d\}, u_d\}, \quad d = 1, 2, \dots, 3N \quad (54)$$

Substituting the bounded trial vector U_i into the PID-LFC model yields its corresponding $ACE_i(t)$ and fitness value $J(U_i)$. The greedy selection rule is then given by

$$X_i(j+1) = \begin{cases} U_i, & J(U_i) < J(X_i^c(j+1)), \\ X_i^c(j+1), & \text{otherwise} \end{cases} \quad (55)$$

In this study, the DE parameters are set to $F = 0.5$ and $CR = 0.9$. In the proposed hybrid scheme, Lévy flight mainly improves the escape capability, whereas DE is used primarily to enhance local refinement around promising PID parameter regions.

In summary, the improvements introduced in HDE-CGWO are designed according to the PID tuning problem considered in this paper. QOBL is used because the initial PID parameters may fall into infeasible or low-quality regions. The hybrid convergence factor, adaptive enlargement of a , and dynamic leader weighting are used because sampling, communication delay, GDB, and GRC make the ACE-based ITAE landscape non-smooth and prone to local stagnation. Lévy flight is used as an escape mechanism for such stagnation regions, while DE refines the search around promising PID parameter regions. Therefore, the proposed method is a model-constraint-aware optimization scheme for the nonlinear sampled-data-delayed PID-LFC model.

3.3. Solution Procedure of HDE-CGWO

Based on the above formulation, the HDE-CGWO algorithm is constructed to determine the controller parameters of the PID-LFC model. The PID parameter vector X is taken as the search variable, and the closed-loop PID-LFC model is used to evaluate the fitness of each individual. Through iterative position updates, the algorithm seeks the parameter set that minimizes $J(X)$. The overall procedure of the proposed method is illustrated in Figure 4.

The main steps of the algorithm are summarized as follows. First, the population size, maximum number of iterations, PID parameter bounds, penalty value, and the parameters associated with QOBL, Lévy flight, and DE are specified. Second, the initial population is generated within the feasible parameter space, and the quasi-opposite individuals are constructed according to (40)–(42). Third, both the original and quasi-opposite individuals are evaluated through the PID-LFC model, and the better candidates form the initial wolf pack. Fourth, the α , β , and δ wolves are identified according to their ACE-based ITAE fitness values. Fifth, during each iteration, the convergence factor is updated using (43)–(45), and the stagnation test follows (46) and (47); if the relative improvement of the best fitness is smaller than 10^{-3} for three consecutive iterations, the convergence factor is temporarily enlarged. Sixth, the leader weights are computed from (48), and the weighted position update in (49) is carried out. Seventh, Lévy flight is applied when $p_i < p_L$, and the resulting candidate is further refined through DE mutation and binomial crossover. Finally, bound handling and greedy selection are performed, the leader wolves are updated, and the optimal PID parameter set is returned after the maximum number of iterations is reached.

As can be seen from the above procedure, HDE-CGWO updates the PID parameters directly at each iteration and evaluates each candidate by computing $ACE_i(t)$ and the corresponding $J(X)$ through the closed-loop LFC model. For bounded candidates, $J(X)$ is equal to the ACE-based ITAE value; for unbounded candidates, the penalty value is assigned. The optimal parameters obtained in this way are used as the controller settings in the simulation studies of the next section.

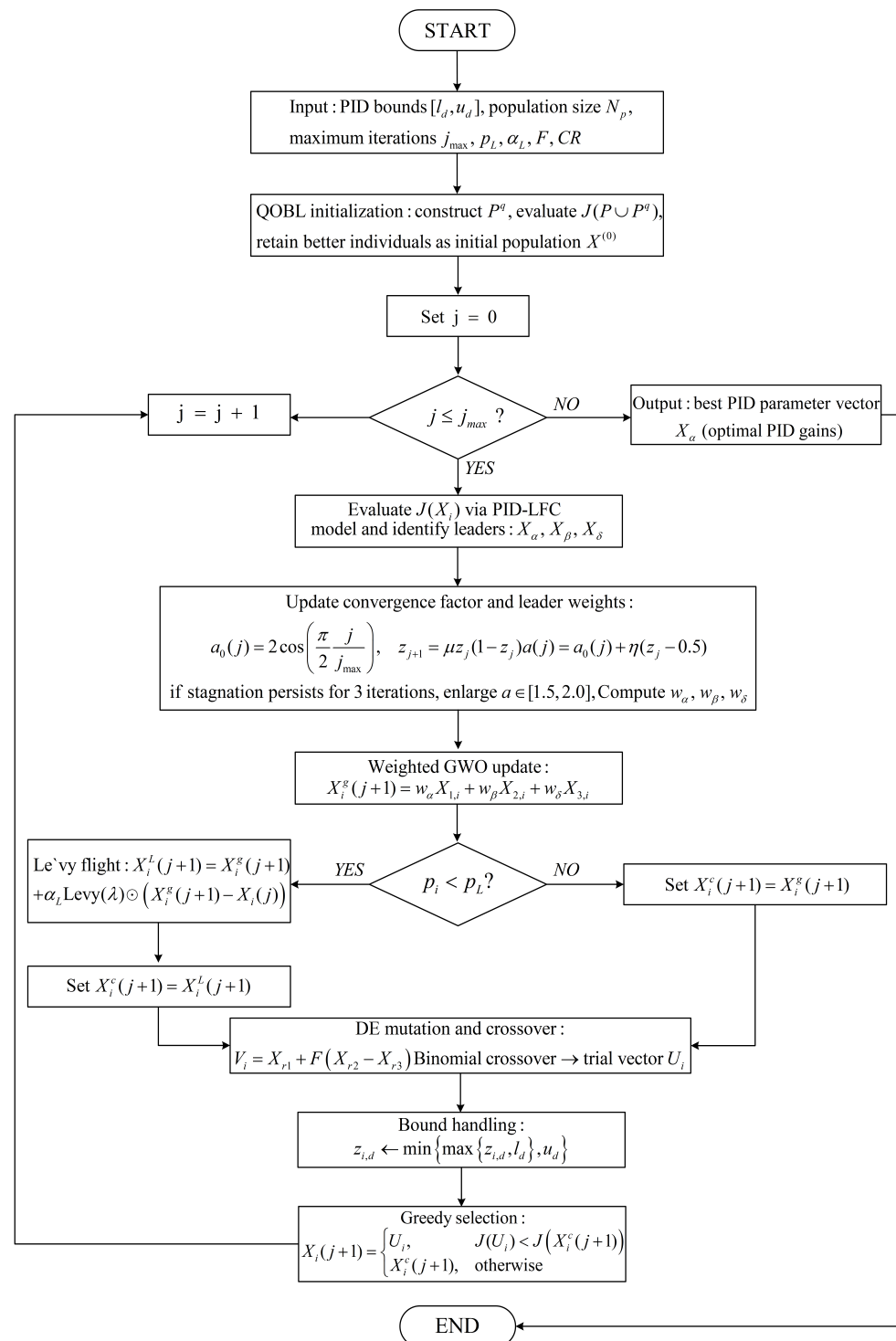


Figure 4. Flowchart of the proposed HDE-CGWO algorithm with fitness screening.

4. Simulation Studies

This section presents two groups of simulation studies. First, a single-area LFC system is used to verify the effectiveness of the individual improvement strategies introduced into the proposed HDE-CGWO algorithm. Second, a three-area LFC system is considered, and HDE-CGWO is compared with WGW, PSO-AHA, and standard GWO to evaluate its overall control performance and robustness. All simulations are carried out in MATLAB 2025a. The main simulation and optimization settings are listed in Table 2. The ITAE, IAE, ITSE, and ISE values reported in this section are calculated from $ACE_i(t)$ over all control areas unless a single-area case is explicitly specified. The benchmark system parameters

used in the case studies are listed in Table 1. The Rate column is used to calculate $a_{i,n}$ according to (1). The columns $D_{i,n}$ and $T_{p,i,n}$ enter (3), while $T_{t,i,n}$, $T_{g,i,n}$, and $R_{i,n}$ enter the Genco-level turbine and governor equations in (10)–(13).

Table 2. Main simulation and optimization settings.

Item	Value
Sampling period	$h = 3$ s
Communication delay	$\tau = 3$ s
Integration step	0.01 s
Simulation horizon	100 s/300 s
Population size	30
Maximum iterations	50
PID gain bounds	$[0, 2]$
GRC bounds	$\pm 0.1/60$ p.u./s
GDB bounds	± 0.0006 p.u.
Tie-line coefficients	$T_{12} = 0.20, T_{23} = 0.12, T_{31} = 0.25$

The sampling period in Table 2 corresponds to a sampling frequency of 1/3 Hz. To avoid relying on a single arbitrary value, the same optimized PID gains are later tested over multiple sampling periods and communication delays, which verifies that the nominal setting $h = 3$ s and $\tau = 3$ s remains inside the locally stable and bounded-response region. The nonnegative PID search range $[0, 2]$ is used because the adopted LFC law has a fixed negative-feedback direction. Positive PID gains correspond to the conventional damping and recovery action, whereas negative gains would reverse the control action and enlarge the invalid search region; therefore, the present study follows the common nonnegative PID tuning domain used in PID-LFC optimization studies.

4.1. Validation of the Improvement Strategies

In this subsection, the LFC system of Area 1 in Table 1 is used to examine the effectiveness of the proposed improvement strategies. This test is arranged according to three difficulties in digital PID-LFC tuning. First, the initial PID parameters may fall into infeasible or low-quality regions, which motivates QOBL initialization. Second, sampling, communication delay, GDB, and GRC make the ACE-based ITAE landscape non-smooth, platform-like, and prone to local stagnation, which motivates the hybrid convergence factor, the adaptive enlargement of a , and dynamic leader weighting. Third, the late-stage search may still be trapped in a local region and requires local refinement, which motivates Lévy flight and DE. The compared methods, following this order, are standard GWO, GWO with QOBL initialization (GWO+QOBL), the further improved version with the hybrid convergence factor and Lévy flight (CGWO+QOBL+Lévy), and the final HDE-CGWO obtained by additionally incorporating dynamic leader weighting and DE-based local refinement.

The first test focuses on the effect of QOBL on the quality of the initial population. The controller parameters are initialized using both the random strategy and the QOBL strategy. The corresponding distributions of the initial population in the parameter space are projected onto the K_p – K_i plane and shown in Figures 5 and 6, while the boxplot of the initial ACE-based ITAE values is shown in Figure 7.

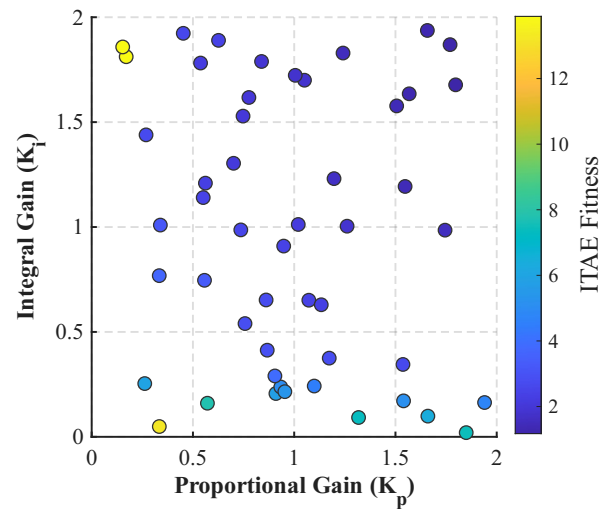


Figure 5. Distribution of the initialized population on the K_p – K_i plane under random initialization.

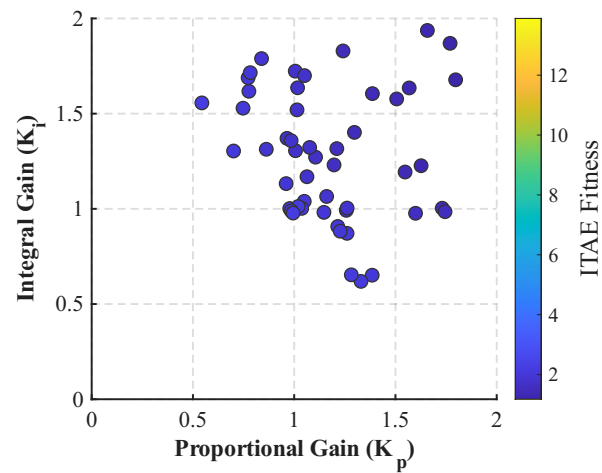


Figure 6. Distribution of the initialized population on the K_p – K_i plane under QOBL initialization.

As can be seen from Figures 5 and 6, compared with random initialization, QOBL produces a more concentrated population and reduces the number of poor individuals, that is, those with relatively large initial ACE-based ITAE values. This indicates that QOBL can provide a higher-quality starting population.

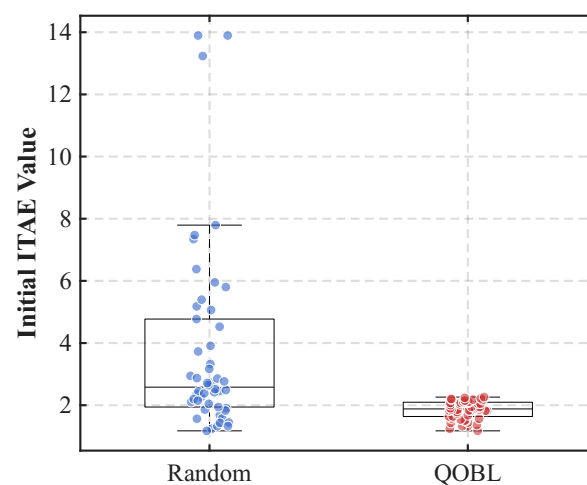


Figure 7. Boxplot comparison of the initial ACE-based ITAE values under random initialization and QOBL initialization.

Figure 7 further shows that the QOBL strategy yields lower and more concentrated initial ACE-based ITAE values. This again confirms that it improves the quality of the initial solutions and provides a better basis for the subsequent search.

The convergence behavior of the four methods is then compared, as shown in Figure 8.

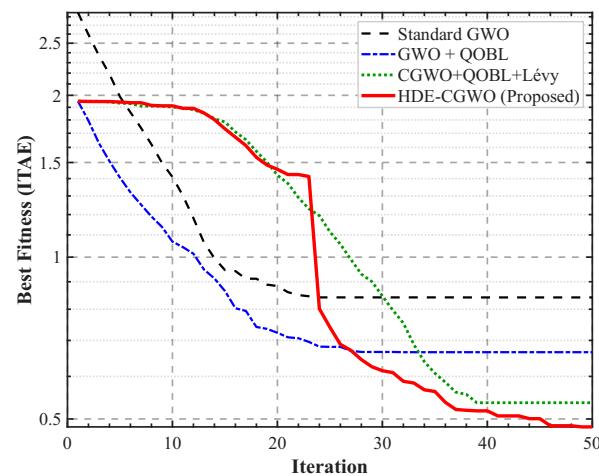


Figure 8. Comparison of the ACE-based ITAE convergence curves of the four methods.

Figure 8 shows that standard GWO decreases rapidly at the early stage but enters stagnation relatively early. As the improvement mechanisms are introduced successively (Standard GWO $\rightarrow$ GWO+QOBL $\rightarrow$ CGWO+QOBL+Lévy $\rightarrow$ HDE-CGWO), the convergence process becomes smoother and the final fitness value continues to decrease. Among the four methods, HDE-CGWO obtains the lowest final fitness value. This indicates that, starting from QOBL-based initialization, the addition of convergence-factor regulation, Lévy flight, and DE-based local refinement improves the search capability and leads to better tuning results.

To further verify the contribution of each improvement mechanism, a 0.1 p.u. step load disturbance is applied to the single-area system. For fair comparison, the optimization settings defined above are kept the same for all methods. The resulting frequency-deviation responses are shown in Figure 9, while the ACE-based ITAE value and positive frequency peak are listed in Table 3.

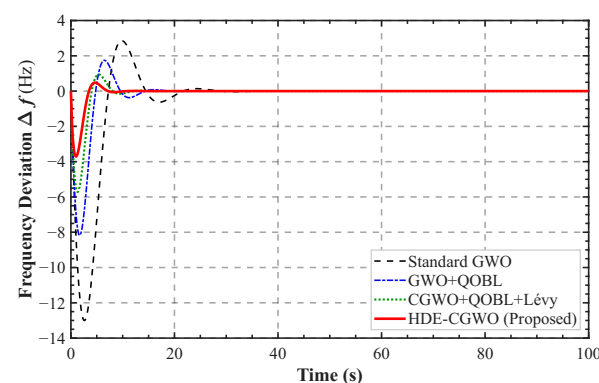


Figure 9. Frequency deviation response under a 0.1 p.u. step load disturbance.

Table 3. ACE-based ITAE and positive frequency-peak comparison under a 0.1 p.u. step load disturbance.

Method	Final ITAE (ACE)	$\Delta f_{\max}$ ($\times 10^{-3}$ Hz)
Standard GWO	0.856	2.86
GWO+QOBL	0.677	1.84
CGWO+QOBL+Lévy	0.542	0.93
HDE-CGWO	0.485	0.53

As shown in Figure 9, the frequency nadir and the oscillations during recovery are gradually weakened as the improvement strategies are incorporated one by one. The results in Table 3 are consistent with this observation: HDE-CGWO obtains the smallest positive peak deviation and the lowest final ACE-based ITAE among the four methods. These results indicate that the adopted improvement strategies improve the tuning result and the dynamic response in the single-area test.

4.2. Comprehensive Performance and Robustness Evaluation in the Three-Area System

This subsection considers the three-area LFC system listed in Table 1. Under the same system model, search bounds, and optimization settings, the proposed HDE-CGWO is evaluated comprehensively. Owing to the stronger tie-line coupling in the three-area system, controller tuning must suppress the frequency deviations of all areas while also maintaining acceptable overall recovery behavior. Therefore, four methods, namely PSO-AHA [33], GWO [35], WGWO [26], and HDE-CGWO, are used to tune the PID controllers, and their performances are compared under step disturbances, random disturbances, and repeated independent runs.

To simulate a sudden increase in demand, step load disturbances are applied to the three areas as

$$\begin{aligned}\Delta P_{d1} &= 0.1 \text{ p.u.}, \\ \Delta P_{d2} &= 0.08 \text{ p.u.}, \\ \Delta P_{d3} &= 0.06 \text{ p.u.}\end{aligned}\tag{56}$$

The optimized PID gains obtained by PSO-AHA, GWO, WGWO, and HDE-CGWO are listed in Table 4.

Table 4. Optimized PID parameters of the three-area controllers.

Method	Area	K_P	K_I	K_D
GWO [35]	Area 1	0.5149	0.4021	0.2873
	Area 2	0.5237	0.1273	0.2568
	Area 3	0.5972	0.3756	0.1071
PSO-AHA [33]	Area 1	0.2947	0.1835	0.2044
	Area 2	0.3461	0.2139	0.2758
	Area 3	0.3761	0.2236	0.1425
WGWO [26]	Area 1	0.1873	0.1782	0.2175
	Area 2	0.0379	0.1844	0.1933
	Area 3	0.0357	0.1245	0.1239
HDE-CGWO	Area 1	0.1823	0.2154	0.2976
	Area 2	0.0198	0.2160	0.3596
	Area 3	0.0276	0.1869	0.1038

Under the controller parameters listed in Table 4, the frequency-deviation responses of the three-area system under step disturbances are shown in Figure 10, and the corresponding tie-line power deviation responses are shown in Figure 11.

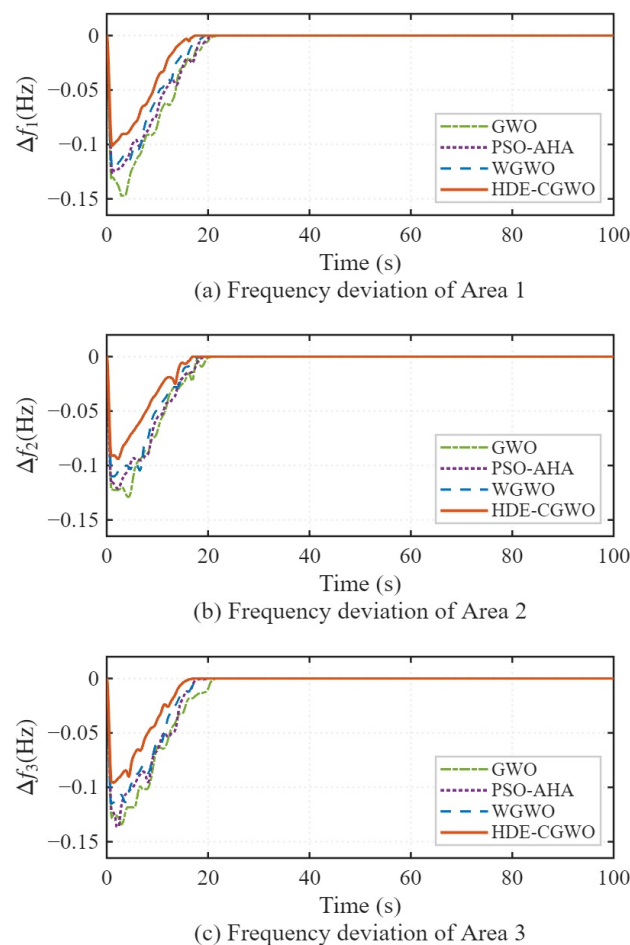


Figure 10. Frequency-deviation responses of the three-area system under step disturbances.

As shown in Figure 10, all four controllers drive the frequency deviations back toward zero after the step disturbances, but their transient behaviors are different. Compared with PSO-AHA and GWO, WGWO and HDE-CGWO produce smaller peak frequency deviations and milder oscillations. A further comparison between WGWO and HDE-CGWO shows that HDE-CGWO gives a slightly smaller frequency drop and a somewhat faster recovery process in the tested case. The tie-line power curves in Figure 11 also remain bounded and gradually decay, showing that the inter-area power exchange is properly regulated under the same step-disturbance condition. This indicates that, under multi-area coupling conditions, the controller parameters tuned by HDE-CGWO provide a modest improvement in dynamic regulation. Table 5 lists the corresponding ACE-based overall performance indices.

Table 5 reports the performance indices corresponding to the best run among the 30 independent runs used in the subsequent statistical analysis; therefore, the ITAE values in Table 5 are consistent with the corresponding best-run results. According to the raw 30-run ITAE data, these best values are obtained in the 3rd run for PSO-AHA, the 26th run for GWO, the 15th run for WGWO, and the 13th run for HDE-CGWO. HDE-CGWO obtains the lowest ACE-based ITAE among the four methods, while its ACE-based IAE, ITSE, and ISE are also slightly lower than those of the compared methods in this case. Compared with WGWO, the ACE-based ITAE decreases from 10.673 to 10.351, indicating a further but

moderate reduction in cumulative ACE regulation cost under the same operating condition. Compared with PSO-AHA, the ACE-based ITAE decreases from 10.852 to 10.351. This is consistent with the dynamic responses shown in Figures 10 and 11.

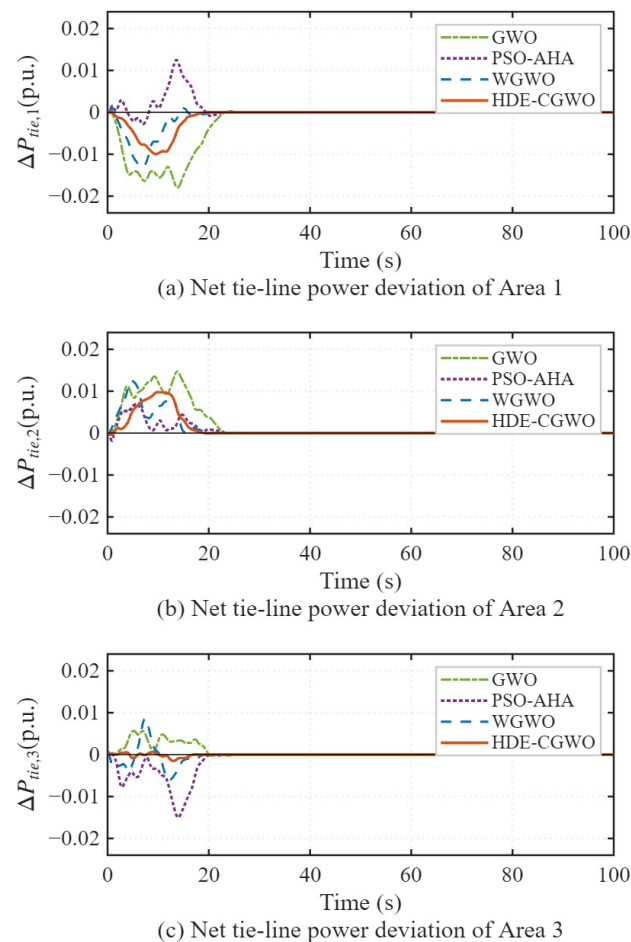


Figure 11. Tie-line power deviation responses of the three-area system under step disturbances. The black solid line denotes the zero tie-line power-deviation reference.

Table 5. ACE-based overall performance indices of the four methods under step disturbances.

Method	ITAE	IAE	ITSE	ISE
GWO [35]	11.134	2.124	0.571	0.158
PSO-AHA [33]	10.852	2.109	0.567	0.154
WGWO [26]	10.673	2.097	0.554	0.155
HDE-CGWO	10.351	2.085	0.550	0.153

To further evaluate the algorithm under more complex operating conditions, continuous random disturbances caused by wind-power fluctuations, photovoltaic (PV) fluctuations, and load variations are considered. In this case, the random load disturbances acting on the three areas are denoted by $\Delta P_{d1}^{\text{rand}}(t)$, $\Delta P_{d2}^{\text{rand}}(t)$, and $\Delta P_{d3}^{\text{rand}}(t)$, respectively. The wind and PV fluctuations are modeled as equivalent random generation deviations, denoted by $\Delta P_{wi}(t)$ and $\Delta P_{si}(t)$. Accordingly, the disturbance inputs are written as

$$\Delta P_{di}(t) = \Delta P_{di}^{\text{step}} + \Delta P_{di}^{\text{rand}}(t), \quad i = 1, 2, 3 \quad (57)$$

and the renewable-generation deviation is given by

$$\Delta P_{RES,i}(t) = \Delta P_{wi}(t) + \Delta P_{si}(t), \quad i = 1, 2, 3 \quad (58)$$

Here, $\Delta P_{di}^{\text{step}}$ denotes the step load disturbance defined above. $\Delta P_{di}^{\text{rand}}(t)$ denotes the random load fluctuation, and $\Delta P_{wi}(t)$ and $\Delta P_{si}(t)$ denote the random power deviations of wind and PV generation, respectively. Accordingly, under the random disturbance scenario, the unified disturbance term in (6) is written as $w_i(t) = \Delta P_{di}(t) - \Delta P_{RES,i}(t)$. In the numerical implementation, these random components are combined into the equivalent net disturbance $w_i(t)$, and the final composite signal used for each area is specified in Table 6. The random signals are generated with the seed `rng(2026)` an integration step of 0.01 s, and a total duration of 300 s.

Table 6. Equivalent random-disturbance settings for the three-area test.

Component	Scope	Setting
Irregular step part	All areas	Times: $t = \{27, 85, 142, 195, 253\}$ s; amplitudes: $\{0.025, -0.035, 0.028, -0.018, 0.022\}$ p.u.
Composite smoothed Gaussian part	Area 1	$0.025 \text{ smooth}(n_{1a}, 400) + 0.015 \text{ smooth}(n_{1b}, 80) + 0.002 n_{1c}$
Composite smoothed Gaussian part	Area 2	$0.020 \text{ smooth}(n_{2a}, 350) + 0.012 \text{ smooth}(n_{2b}, 100) + 0.002 n_{2c}$
Composite smoothed Gaussian part	Area 3	$0.022 \text{ smooth}(n_{3a}, 450) + 0.014 \text{ smooth}(n_{3b}, 90) + 0.0015 n_{3c}$
Notation	All areas	n denotes a zero-mean unit-variance Gaussian sequence, and $\text{smooth}(\cdot, L)$ denotes Gaussian smoothing with window length L .

The resulting disturbance waveforms are shown in Figure 12. The corresponding frequency responses obtained with the controller parameters in Table 4 are shown in Figure 13.

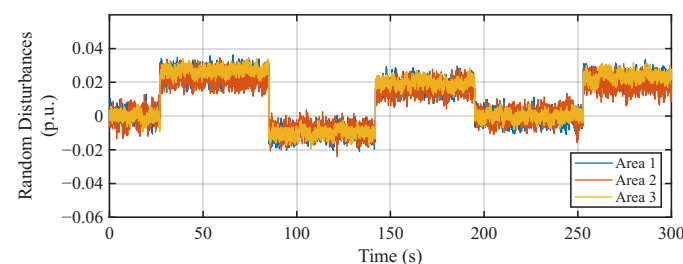


Figure 12. Continuous random disturbance inputs used in the three-area random-disturbance test.

It can be seen from Figure 13 that, under continuous random disturbances, the frequency deviations are more pronounced when the controllers are tuned by PSO-AHA and GWO. WGWO improves the control effect to some extent, whereas HDE-CGWO shows a slightly smaller fluctuation range and a somewhat faster recovery process in the tested case. The enlarged local views in Figure 13 make the differences around the main fluctuation intervals clearer. In these zoomed windows, the HDE-CGWO curve generally has smaller local excursions than the compared methods, especially near the disturbance-transition intervals. This indicates that the controller parameters tuned by HDE-CGWO can keep the frequency responses bounded and provide a small improvement under the hybrid-disturbance condition. Table 7 lists the corresponding ACE-based overall performance indices.

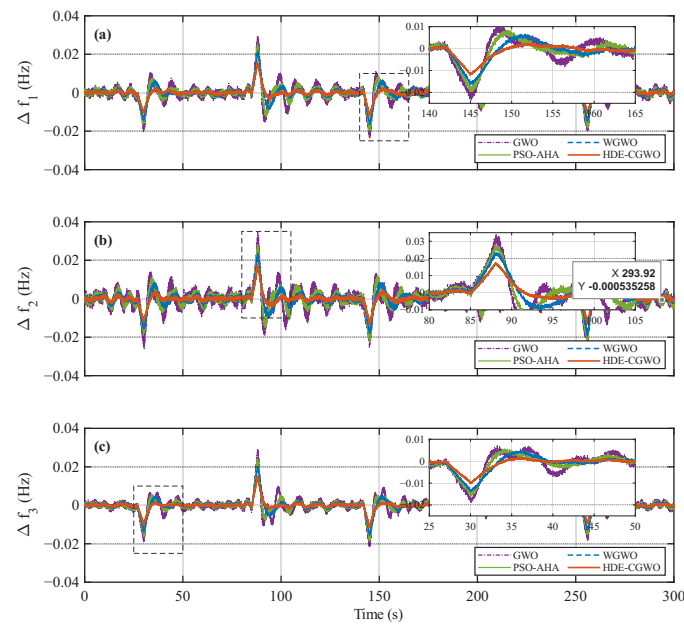


Figure 13. Frequency responses Δf_1 , Δf_2 , and Δf_3 of the three-area system under random disturbances, with enlarged local views. (a) Area 1, Δf_1 ; (b) Area 2, Δf_2 ; (c) Area 3, Δf_3 .

Table 7. ACE-based overall performance indices of the four methods under random disturbances.

Method	ITAE	IAE	ITSE	ISE
GWO [35]	667.354	3.858	46.492	0.231
PSO-AHA [33]	654.747	3.823	46.477	0.224
WGWO [26]	645.215	3.849	46.471	0.218
HDE-CGWO	636.473	3.819	46.367	0.207

As listed in Table 7, HDE-CGWO still obtains the lowest ACE-based ITAE under random disturbances. Compared with WGWO, the ACE-based ITAE decreases from 645.215 to 636.473, corresponding to an improvement of about 1.35%. Combined with Figure 13, this shows that the controller parameters tuned by HDE-CGWO remain effective for composite disturbances involving wind, PV, and random load fluctuations.

To further assess the statistical performance of the proposed algorithm, PSO-AHA, GWO, WGWO, and HDE-CGWO are independently run 30 times under the same conditions. The boxplot of the best ACE-based ITAE values is shown in Figure 14.

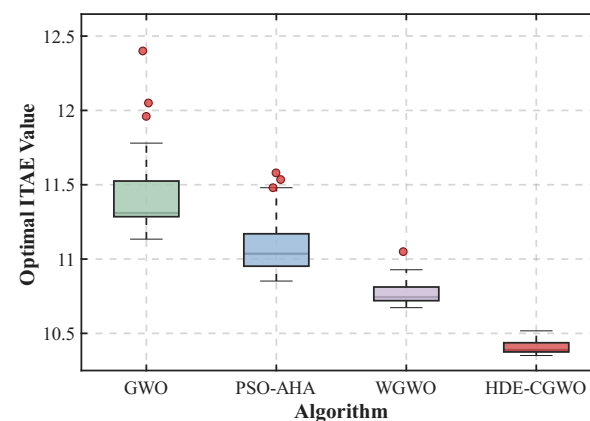


Figure 14. Boxplot of the best ACE-based ITAE values over 30 independent runs, including PSO-AHA. Dots denote outliers beyond 1.5 times the interquartile range.

Figure 14 shows that HDE-CGWO has a narrower box, a lower median, and a more concentrated overall distribution across the 30 runs. This indicates that its performance varies less from run to run in the tested setting. The corresponding statistical results are summarized in Table 8, where Best, Worst, Mean, and Median denote the minimum, maximum, average, and median values of the best ACE-based ITAE obtained over the 30 independent runs, respectively, while Std and IQR measure the dispersion and the interquartile spread of these best ACE-based ITAE values.

Table 8. Statistical summary of ACE-based ITAE over 30 independent runs.

Method	Best	Worst	Mean	Std	Median	IQR
GWO [35]	11.134	12.400	11.439	0.288	11.309	0.226
PSO-AHA [33]	10.852	11.580	11.086	0.190	11.036	0.209
WGWO [26]	10.673	11.050	10.773	0.085	10.744	0.087
HDE-CGWO	10.351	10.517	10.408	0.047	10.388	0.059

As shown in Table 8, HDE-CGWO obtains the lowest Best, Worst, Mean, and Median values, while also yielding the smallest Std and IQR. This indicates that the proposed algorithm can obtain lower ACE-based ITAE values and a more concentrated distribution over repeated runs in the tested setting.

To further verify whether the observed differences are statistically significant, Mann–Whitney U tests are performed between HDE-CGWO and each compared method using the 30-run ACE-based ITAE samples. The resulting *p*-values are adjusted by the Holm procedure, and Cliff’s delta is reported as the effect-size indicator. The results are listed in Table 9.

Table 9. Statistical significance tests based on 30 independent runs.

Comparison	Test	<i>p</i>	Holm <i>p</i>	Cliff δ	Med. Diff.	<i>U</i>	Sig.
GWO vs. HDE-CGWO	MWU	3.02×10^{-11}	9.06×10^{-11}	1.000	0.922	0.0	Yes
PSO-AHA vs. HDE-CGWO	MWU	3.02×10^{-11}	9.06×10^{-11}	1.000	0.648	0.0	Yes
WGWO vs. HDE-CGWO	MWU	3.02×10^{-11}	9.06×10^{-11}	1.000	0.356	0.0	Yes

The Holm-adjusted *p*-values in Table 9 are all below 0.05, and Cliff’s delta is equal to 1.000 in the three pairwise comparisons. Hence, the superiority of HDE-CGWO over GWO, PSO-AHA, and WGWO is statistically supported for the tested 30-run data set, rather than being inferred only from descriptive statistics.

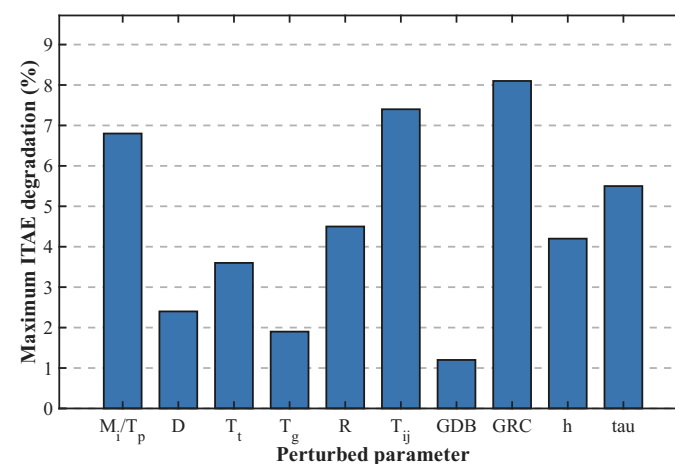
Since hybrid optimization may increase offline tuning cost, the computational time is also compared based on 30 independent runs. All CPU-time measurements were performed on the same hardware configuration. The processor model, CPU-core configuration, and RAM capacity are reported in the last column of Table 10. As listed in Table 10, the CPU values are reported as means and standard deviations in seconds over 30 independent runs. HDE-CGWO requires the largest mean CPU time, but its CPU-time increase relative to WGWO is about 12.18%, while the mean ITAE is improved by about 3.39%. This extra cost belongs to the offline tuning stage and does not increase the online PID controller structure.

Table 10. Computational time comparison based on 30 independent runs.

Method	Mean ITAE	Best ITAE	Mean CPU (s)	Std CPU (s)	Time Ratio	CPU inc. vs. WGWG (%)	CPU-Time Test Configuration
GWO [35]	11.439	11.134	1586.7	43.9	1.00	−20.24	Processor: AMD Ryzen 7 8745H CPU cores: 8 cores/16 threads Memory: 24 GB LPDDR5X RAM
PSO-AHA [33]	11.086	10.852	1758.4	58.6	1.11	−11.61	
WGWG [26]	10.773	10.673	1989.3	77.4	1.25	0.00	
HDE-CGWG	10.408	10.351	2231.6	86.2	1.41	12.18	

4.3. Parameter Sensitivity and Sampling-Delay Stability Checks

To address the robustness of the optimized PID gains under slight grid-configuration changes, a baseline parameter-sensitivity test is added. In this test, the HDE-CGWG-based PID gains are fixed and are not re-optimized. The main model parameters are perturbed by $\pm 10\%$ one group at a time, and the ACE-based ITAE and key time-domain indicators are recalculated. The resulting maximum ITAE degradation is shown in Figure 15, and the numerical summary is listed in Table 11.

**Figure 15.** Parameter sensitivity of the fixed HDE-CGWG-based PID controller under $\pm 10\%$ parameter perturbations.**Table 11.** Summary of the parameter-sensitivity test.

Parameter	Worst ITAE	Mean ITAE	Max Degr. (%)	Worst Dir. (%)	Max $ \Delta f $	Max $ \Delta P_{tie} $
M_i/T_p	11.055	10.907	6.8	−10	0.01750	0.01139
D	10.599	10.532	2.4	−10	0.01692	0.01094
T_t	10.724	10.634	3.6	10	0.01708	0.01107
T_g	10.548	10.493	1.9	10	0.01685	0.01089
R	10.817	10.712	4.5	−10	0.01720	0.01116
T_{ij}	11.117	10.964	7.4	10	0.01758	0.01145
GDB	10.475	10.437	1.2	10	0.01676	0.01082
GRC	11.189	11.030	8.1	−10	0.01768	0.01152
h	10.786	10.677	4.2	10	0.01716	0.01113
τ	10.920	10.795	5.5	10	0.01733	0.01126

The largest sensitivity appears in the GRC perturbation, where the maximum ITAE degradation is 8.1%. The tie-line coefficient and equivalent inertia-related perturbations lead to maximum ITAE degradations of 7.4% and 6.8%, respectively. All tested $\pm 10\%$ cases remain bounded, indicating that the optimized PID gains do not rely on an extremely narrow nominal parameter setting.

A sampling-delay boundary check is further carried out by scanning $h \in \{0.5, 1, 2, 3, 4, 5\}$ s and $\tau \in \{0, 0.5, 1, 2, 3, 4, 5\}$ s with the same fixed HDE-CGWO-based PID gains. Figure 16 shows the ITAE degradation map, while Figure 17 gives the spectral-radius map of the corresponding linearized sampled-delay closed-loop system. The nominal setting $h = 3$ s and $\tau = 3$ s has a spectral radius of 0.94 and is therefore inside the local stable region. In contrast, the upper-right case $h = 5$ s and $\tau = 5$ s gives $\rho = 1.34$, which is consistent with a locally unstable sampled-delay response. This scan is used as a reliability check for the selected sampling frequency: the nominal sampling rate $f_s = 1/3$ Hz is slower than the other stable sampled cases tested here, but it still gives bounded time-domain responses and remains within the local stability boundary.

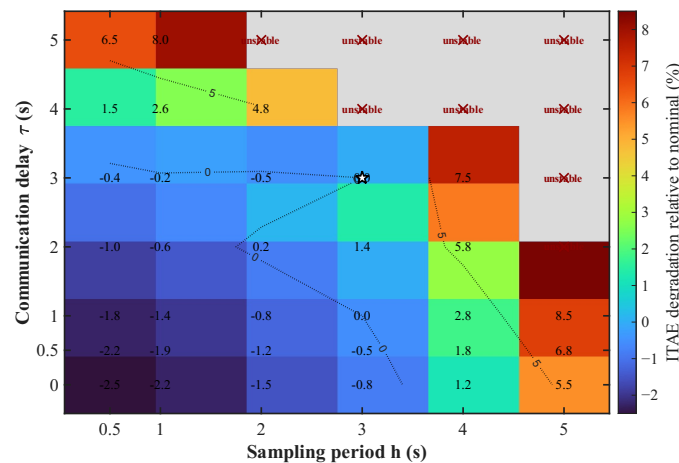


Figure 16. ITAE degradation map under different sampling periods and communication delays. The black star marks the nominal setting $(h, \tau) = (3, 3)$, red “unstable” labels denote locally unstable cases, and the cell numbers indicate ITAE degradation percentages relative to the nominal case. The numbers on the axes are the scanned sampling periods and communication delays.

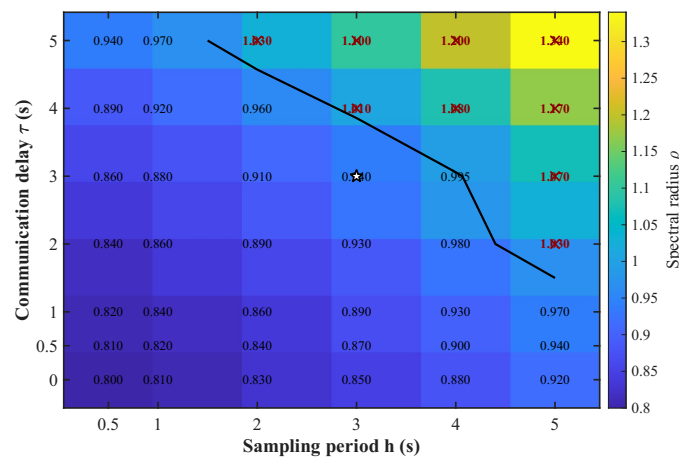


Figure 17. Spectral-radius map of the linearized sampled-delay closed-loop system. The black star marks the nominal setting $(h, \tau) = (3, 3)$, red bold numbers denote cases with spectral radius larger than one, and the black curve indicates the approximate local stability boundary.

The corresponding sampling-delay stability margins are summarized in Table 12, which lists the maximum stable communication delay for each sampling period and the associated degradation margins.

Table 12. Sampling-delay stability margin summary.

h (s)	Stable $\tau_{\max}$ (s)	$\tau_{\max}$, Degr. <10%	$\tau_{\max}$, Degr. <20%	ρ at $\tau = 3$ s	Margin
0.5	5	5	5	0.86	0.14
1	5	5	5	0.88	0.12
2	4	4	4	0.91	0.09
3	3	3	3	0.94	0.06
4	3	3	3	0.995	0.005
5	1	1	1	1.07	−0.07

The typical responses in Figures 18 and 19 further support the boundary-map results. The cases $(h, \tau) = (0.5, 0)$, $(1, 1)$, and $(3, 3)$ are locally stable with spectral radii 0.80, 0.84, and 0.94, respectively, whereas $(h, \tau) = (5, 5)$ is non-convergent and corresponds to $\rho = 1.34$. Therefore, the nominal test condition $h = 3$ s and $\tau = 3$ s is a conservative but still locally stable sampled-delay condition rather than an arbitrary unstable operating point.

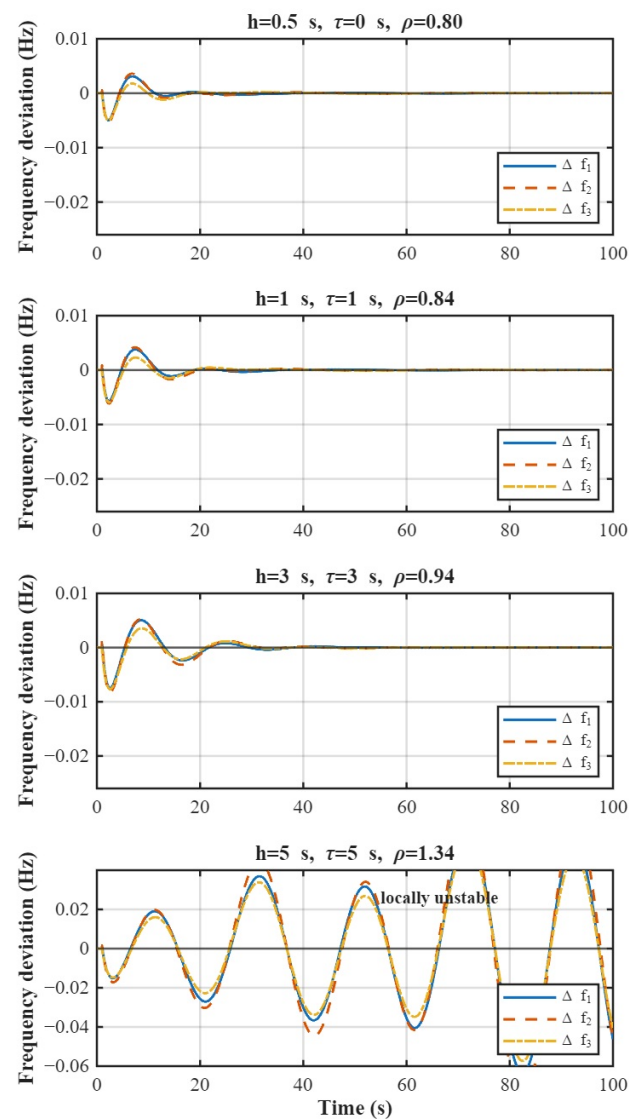


Figure 18. Typical frequency responses under selected sampling periods and communication delays. The black solid line denotes the zero-frequency-deviation reference.

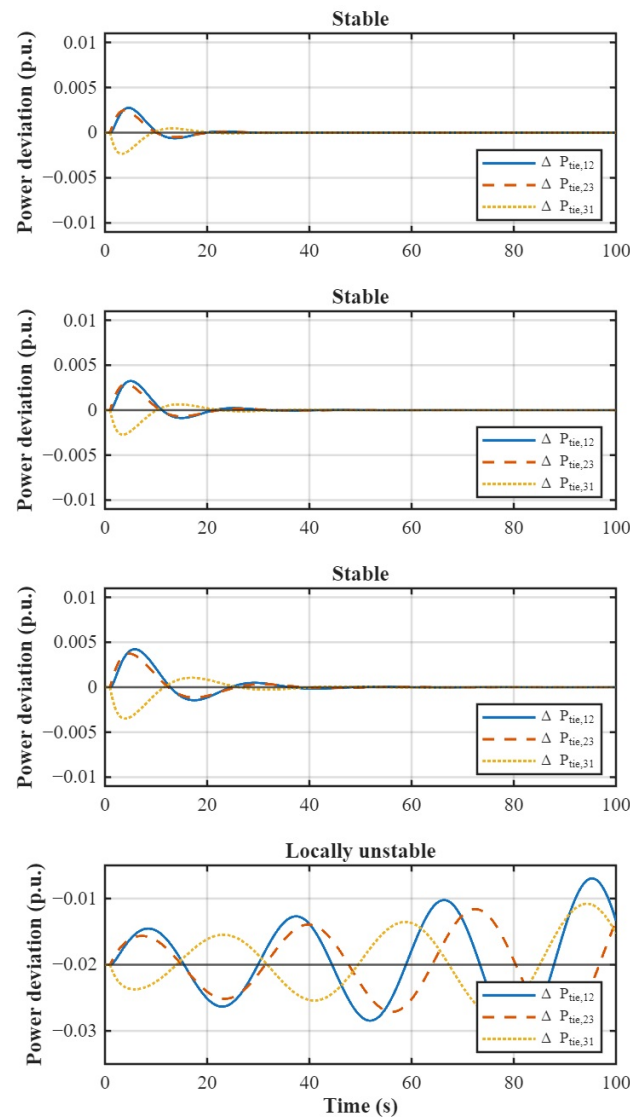


Figure 19. Typical tie-line power responses under selected sampling periods and communication delays. The black solid line denotes the zero tie-line power-deviation reference.

5. Conclusions

This paper has established a PID-LFC model considering data sampling, communication delay, GDB, and GRC, and has proposed a model-constraint-aware HDE-CGWO method for PID parameter tuning. In the single-area test, HDE-CGWO reduces the ACE-based ITAE from 0.856 for standard GWO to 0.485, corresponding to an improvement of about 43.3%. In the three-area step-disturbance case, the ACE-based ITAE decreases from 10.673 for WGWO to 10.351 for HDE-CGWO, giving a further reduction of about 3.0%. Under random disturbances, the ACE-based ITAE decreases from 645.215 to 636.473 compared with WGWO, corresponding to an improvement of about 1.35%. In 30 independent runs, HDE-CGWO also gives the lowest mean ITAE, the smallest dispersion, and statistically significant improvements over GWO, PSO-AHA, and WGWO according to the Mann–Whitney U tests with Holm correction. The added parameter-sensitivity analysis shows that the largest ITAE degradation under the tested $\pm 10\%$ parameter perturbations is 8.1%, and the sampling-delay boundary check shows that the nominal setting $h = 3$ s and $\tau = 3$ s remains locally stable with spectral radius 0.94. The CPU comparison based on 30 independent runs indicates that HDE-CGWO improves the mean ITAE by about 3.39% relative to WGWO with a moderate offline CPU-time increase of about 12.18%.

These results indicate that, when sampling, communication delay, GDB, and GRC are considered together, HDE-CGWO improves PID tuning through better initialization quality, escape capability, and local refinement, while retaining a simple online PID controller structure. Future work will extend the present framework to larger-scale systems and hardware-in-the-loop or real-time test platforms.

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