

ARTICLE

A Hybrid MZOA-PSO Optimized Cascaded PI(1+DD)-PI-PID Controller for Frequency Stability of Interconnected Power Systems with Renewable Energy and Electric Vehicles

AL-Wesabi Ibrahim¹, Hassan M. Hussein Farh^{2,*}, Jiazhu Xu^{1,*}, Mohamad A. Alawad²,
Ahmed Alqurashi³ and Abdullrahman A. Al-Shamma'a²

¹College of Electrical and Information Engineering, Hunan University, Changsha, China

²Electrical Engineering Department, College of Engineering, Imam Mohammad Ibn Saud Islamic University (IMSIU), Riyadh, Saudi Arabia

³Electrical Engineering Department, College of Engineering and Architecture, Umm Al-Qura University, Makkah, Saudi Arabia

*Corresponding Authors: Hassan M. Hussein Farh. Email: hhhussein@imamu.edu.sa; Jiazhu Xu. Email: xjz@hnu.edu.cn

Received: 28 February 2026; Accepted: 15 April 2026; Published: 27 July 2026

ABSTRACT: Load frequency control (LFC) in interconnected power systems has always been a challenging task in the presence of uncertainty and variability in the power systems arising primarily due to the integration of renewable energy sources and the impact of electric vehicles on the power system. Although various PI/PID and other advanced control strategies have been employed for LFC in power systems, the existing methods have shown some limitations in terms of dynamic flexibility and robustness in the presence of nonlinearities and couplings in the power systems. Moreover, the optimization methods employed for the tuning of the controllers have shown some limitations in terms of the balance between global and local search abilities of the optimization functions. To overcome the limitations of the existing methods and optimization functions, a hybrid Modified Zebra Optimization Algorithm-Particle Swarm Optimization (MZOA-PSO) is presented in this paper for the optimization of a cascaded PI(1+DD)-PI-PID controller for LFC in power systems. The MZOA enhances the original ZOA by chaotic initialization, adaptive parameter control, and Lévy-flight foraging to improve the global search ability, while PSO ensures efficient local search ability. The optimizer is first validated using four benchmark functions, achieving the global optimum for the Booth and Zakharov functions, a mean value of 2.13×10^{-28} with a 98% success rate for Rosenbrock, and 3.21×10^{-81} for Schwefel 2.22. Under a 1% step load perturbation, the proposed controller achieves a 13 s settling time, zero negative deviation in Area 2, a maximum positive excursion of 0.10 Hz, and tie-line undershoot limited to -0.10 p.u. Under random load variations, deviations remain within ± 0.03 Hz and ± 0.02 p.u. Under RES and EV integration, the peak frequency deviation is reduced to 0.46 Hz in Area 1. These results confirm that the proposed hybrid MZOA-PSO tuned cascaded controller provides improved damping, faster stabilization, and stronger robustness for modern interconnected LFC systems.

KEYWORDS: Load frequency control; cascaded PI(1+DD)-PI-PID controller; hybrid MZOA-PSO algorithm; interconnected power systems; performance optimization

1 Introduction

The emergence of green energy is causing major changes to power systems worldwide, endangering their stability. In this context, a range of solutions has been studied by scientists to ensure power systems remain stable [1–3]. In Addition, the rise of RES systems like photovoltaic and wind systems, and distributed generation systems, has significantly impacted conventional power systems in response to fossil fuel depletion,

environmental issues, and economic factors [4]. In this context, microgrid systems have gained more traction in residential and industrial applications. However, islanded microgrid systems face many critical operational challenges in terms of abridged rotational inertia caused by a predominance of inverter-based systems and a lack of support [5]. Although power electronic interfaces can achieve high dynamic performance, abridged inertia causes frequency and voltage instability issues. In Addition, stochastic characteristics of RES and load profiles aggravate these issues, making frequency control a critical challenge. In this context, energy storage systems (ESS) and EV systems are critical to ensuring stable and consistent operation of islanded microgrid systems by employing LFC strategies [6].

The complexity of modern power systems is increasing, and it is extremely nonlinear. This is due to a definite increase in capacity and a general dependence on all forms of energy. Therefore, several issues are related to this complexity and nonlinearity, and one of the main issues in this area is “Frequency Variation in Power Systems.” Frequency variation is one of the main issues in this area, and it is a recurring problem due to the constant variation in demand, requiring a change in the generated power to maintain it at a nominal value. This is known as “LFC” in power systems [7,8]. According to the fundamental operation of the “LFC” loop, one of the main issues in this area is that this assistance in power systems is required to supply the required power from the generation facilities of the system to satisfy the change in demand, and to maintain the required power exchanged between interrelated control areas at specified values. The LFC loop aims to ensure zero steady-state error in frequency variation and tie-line power fluctuation, which contributes to the power system’s increased stability. This loop is also responsible for damping the oscillation’s overshoot and undershoot in frequency and exchanging power within a predefined duration, depending on the power system’s capacity and the disturbance’s amplitude [9]. The three classes of power system stability, rotor angle, voltage, and frequency stability, are depicted in Fig. 1.

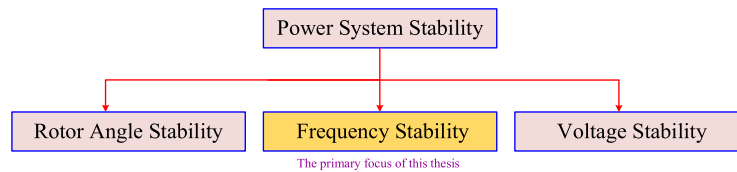


Figure 1: Power system stability classification.

In the literature, LFC methods are broadly classified into model-based and model-free approaches. Existing model-based schemes include classical PI/PID control, robust and sliding mode control, and model predictive control, often enhanced with metaheuristic optimizers to handle the nonlinear and interconnected nature of modern power systems [10,11]. However, these techniques are computationally demanding and are associated with the problems of parameter uncertainties. Fig. 2 depicts an overview description of the evaluation conducted for load frequency control in various locations and controllers.

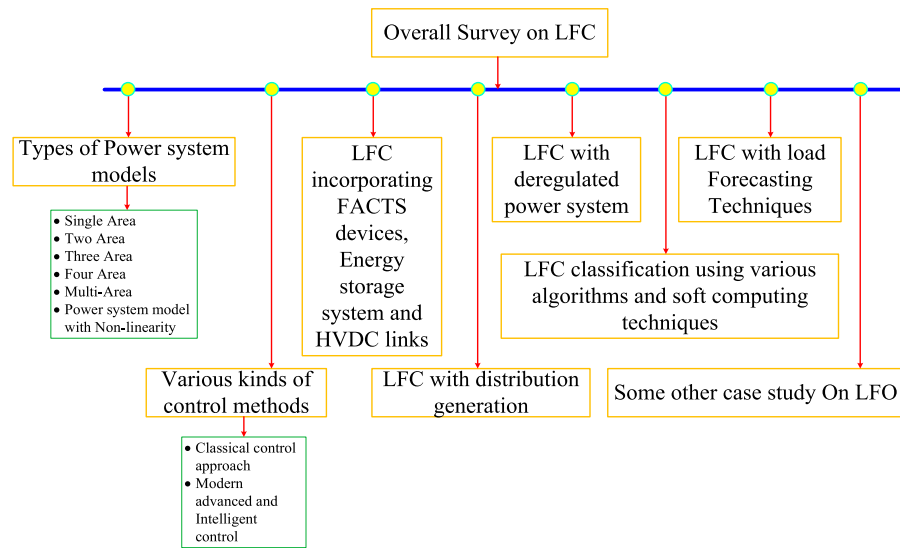


Figure 2: The LFC evaluation studies flowchart.

There is a discussion of LFC for four linked power systems in [12]. Such a system would more reliably supply electricity, as seen in Fig. 3. A four-area reheated hydro thermal power system incorporating RES, such a fuel cell, wind generator, PV generator, and aqua-electrolyze is included in Ref. [13]. Ref. [14] provides a detailed explanation of the novel function observer LFC for four area-connected power systems. The use of FACTS strategies in conjunction with LFC to improve dynamic responses in a multi-area power system is examined in the paper [15]. Ref. [16] describes a fractional-order fuzzy PID (FOFPID) strategy architecture for LFC of a four-area interconnected power system with one hydropower plant (Area 4) and three reheat-thermal turbine units (Areas 1, 2, and 3). In a liberalized power system developed during a deregulation system, the work elucidates the bilateral strategy for a four-area linked power system composed of thermal power plants based on reheat turbines, gas, diesel, and hydropower units in a multi-area multi-source strategy [17]. Another innovative way to meet the extra daily demand and provide consumers with reliable electricity is the independent connected multi-area power system shown in Fig. 4. A cooperative control approach using a hybrid FOC and SMES methodology in an LFC loop is given in [18] to enhance the multi-area power system stability. The complicated nature of this kind of controller makes it difficult to optimize the gains of the recommended cascade controller. The numerous modules and complicated network architecture of contemporary linked power systems make empirical tuning techniques useless, particularly for sophisticated controllers such as cascade controllers [19]. Additionally, because empirical parameter tuning techniques require managing a large number of parameters with intricate structures, they may make the controller less resilient and perform worse. In order to address these issues, academics have created a number of optimization strategies to improve controller performance in LFC. Combination of stochastic fractal search (HSFS) and pattern search (PS), two techniques that have been established in earlier research, are utilized most effectively for the PI-PD controller in [20]. Utilizing the weighted geometric center technique, the Ref. in [21] adjusted the PI-PD controller. The $(1 + PD)$ -PID controller [22] and the FOPI-FOPD controller [23] are optimized using the dragonfly search algorithm (DSA), respectively. A controller adjusted by the dandelion optimizer (DO) for fractional-order proportional tilt-integral-derivative (FPDN-FPTID) is described in [24]. The ZOA-tuned $PI^\lambda(1 + PDF)$ controller is introduced in [25]. Additionally, Ref. [26] presents a new FOPID and FOPI controller that is optimized for chaotic games. Cascading NF-PDF-PIDF controllers are tuned using the skill optimization algorithm (SOA) [27], while the black widow

optimization algorithm (BWOA) [28] tunes the PIDF-(1+I) controller. Together, these investigations show that the effectiveness of the optimization method employed determines the cascade controller's performance. Thus, the controller must be properly developed and tuned to guarantee the frequency control performance.

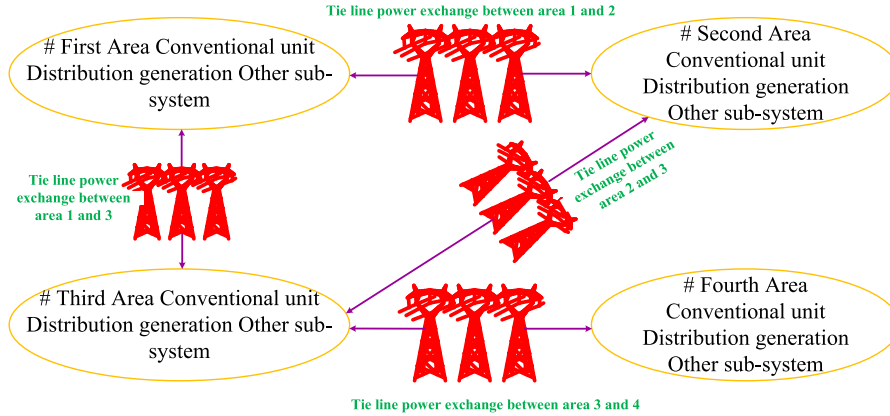


Figure 3: Diagrammatic representation of the four-area tie-line power exchange LFC system.

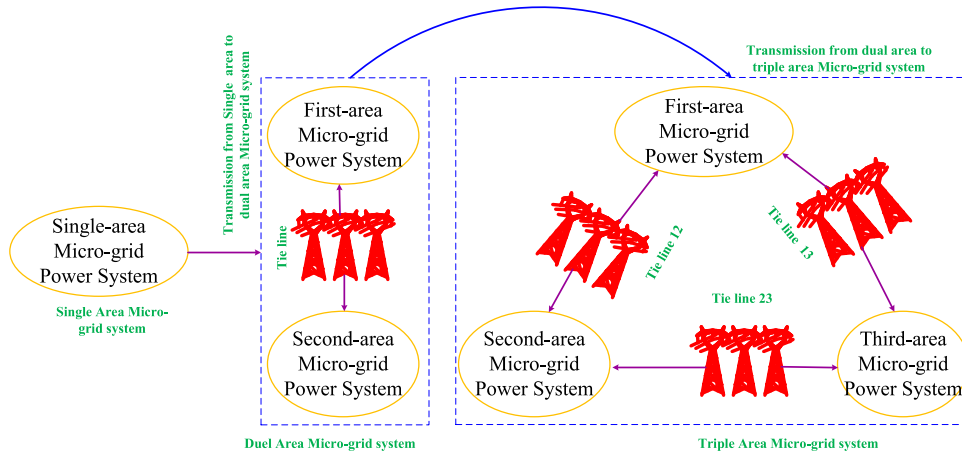


Figure 4: The straightforward conversion of a micro-grid system based on RES from a single location to several areas.

Recent LFC research can be broadly classified into classical and modified PID-family controllers, intelligent/adaptive nonlinear controllers, and optimization-assisted or data-driven control frameworks. Comprehensive recent reviews confirm that LFC development has progressed from conventional PI/PID regulation toward more robust and intelligent designs for RES-rich and multi-area systems [29]. Recent examples include a resilient math-inspired EDA-optimized fuzzy adaptive exponent controller for EV-integrated microgrid LFC, intelligent BELBIC- and TID-based designs, and fractional-order PID-family controllers for interconnected power systems [30]. At the same time, recent control literature has also reported several advanced PID variants, such as Gudermannian-PID, softsign-FOPID, BELBIC-PID, and neuroendocrine-PID structures, indicating continued interest in enhancing transient shaping and nonlinear adaptability [31]. In addition, recent research activities in LFC schemes have proposed several optimization methods, such as SEDA, norm-limited SPSA, and memory-type smoothed functional algorithms for LFC schemes due to lower computational complexity [32]. However, for high-dimensional and multimodal LFC tuning problems, recent studies still rely on hybrid population-based optimizers to better balance global

exploration and local refinement [33]. Recent studies have shown that LFC research is increasingly moving from conventional fixed-parameter controllers toward hybrid, adaptive, and optimization-assisted control schemes to address the growing complexity of multi-area power systems with renewable-energy integration and communication constraints [34].

In [35], a P-P-FOPID controller was presented. But using a P controller in the outer loop always results in a steady-state inaccuracy in the primary process variable of the system. As a result, the steady-state error takes longer to correct, which lengthens the settling time. Consequently, it is crucial to include an integral component (I) in the outer loop to remove the steady-state error. The steady-state error is eliminated, and the settling time is much reduced thanks to this adjustment, which enables the controller to respond more effectively and proactively. To increase the system frequency stability, an enhanced control structure is developed in [19] that combines the FOPID controller with the PI controller (PI-PI-FOPID). However, because of the intricate structure of this kind of controller, optimizing the gains of the suggested controller is a big task that calls for a strong optimization method. Consequently, the settings of the recommended controller are adjusted in this study using the modified secretary bird optimization algorithm (MSBOA) [36]. Overall, as summarized in Table 1 and supported by recent studies [2025–2026], the literature reflects a clear trade-off between the simplicity and reliability of optimized modified PID-based LFC schemes and the adaptability and scalability of data-driven and learning-based controllers.

Table 1: Recent studies during 2025–2026, in the literature for LFC schemes.

Year	Controller/Structure	Tuning/Learning Algorithm	#Areas	Advantages (Reported/Claimed)	Disadvantages/Limitations (Typical + Noted)
[37]/2026	PID for islanded MG LFC	Puma Optimizer (PO)	Single-area	Strong transient improvement (overshoot/settling), robust tuning in RES + hybrid storage setting	Offline metaheuristic tuning cost; controller performance can be sensitive to scenario coverage; still PID-limited under severe nonlinearities
[38]/2025	Data-driven/learning-based multi-area LFC (nonlinear, incl. constraints)	Multi-agent deep reinforcement learning (DRL)	Single-area	Online/adaptive action selection; handles nonlinearities and constraints without exact model	Training complexity; safety/stability guarantees harder; needs careful reward design and generalization checks
[39]/2025	LFC + energy storage aggregator + consensus tracking; DRL tunes gains	DDPG-RNN + leader–follower finite-time consensus	2-Area	Adaptive to RES/load fluctuation; includes SoC balancing logic via aggregator/consensus	RL training burden; tuning stability margins/interpretability; implementation complexity (communication + coordination)
[2]/2025	Fully Autonomous LFC (agent-based, market-oriented regulation)	Multi-agent decision/policy learning (autonomous agents)	4-Area	Autonomous participation in frequency markets; scalable agent framework	Assumptions on market signals/communications; coordination stability; validation depends on realistic market + grid models
[3]/2025	Predictive LFC (forecasting + optimized controller)	Multi-objective optimization (predictive framework)	3-Area	Improves dynamic performance via prediction + optimization; handles variability	Additional forecasting module; offline optimization overhead; sensitivity to forecast error

(Continued)

Table 1 (continued)

Year	Controller/Structure	Tuning/Learning Algorithm	#Areas	Advantages (Reported/Claimed)	Disadvantages/Limitations (Typical + Noted)
[6]/2025	PID-family comparisons (PI/PID/FOPID/cascaded variants) for RES-integrated LFC	Optimization-based tuning (study proposes advanced PID-based structures)	2-Area	Shows benefit of advanced PID variants; improved frequency/tie-line response	More parameters → harder tuning; may increase control effort; robustness depends on tuning scenario set
[40]/2025	Learning-based LFC (DRL)	Deep reinforcement learning	Single-area	Reduced modeling dependence; adapts to uncertainty	Training/sample efficiency; stability certification; deployment needs safeguards

This work focuses on model-based LFC for a two-area power system with high RESs penetration, ESS participation, and EV support (Fig. 5), using advanced PID-type controllers tuned by modern metaheuristic algorithms to achieve faster, more robust frequency and tie-line regulation.

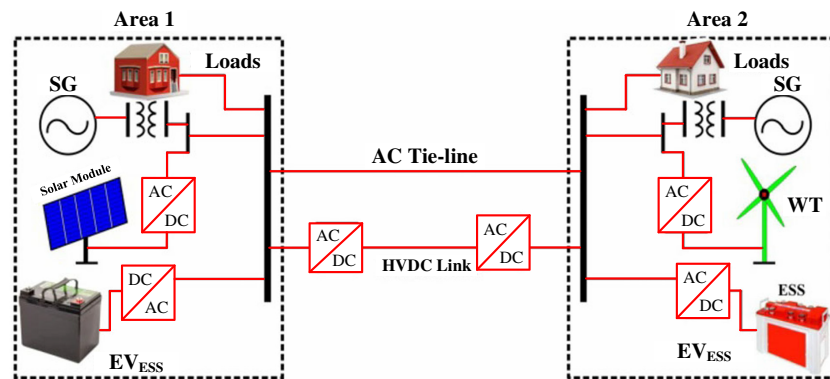


Figure 5: Two-area multiple-source linked power system featuring AC/DC tie-lines, RES, and ESS.

This investigation was motivated by three different factors. First, with the increasing complexity in modern interconnected power systems, resulting from the addition of RES and increasing demand, there is a need for sophisticated and reliable LFC strategies to ensure system stability. Second, the limitations of conventional PID controllers in terms of performance, especially under dynamic conditions, have necessitated alternative controller structures with greater adaptability. Thirdly, while hybrid optimization algorithms have shown promise, they frequently struggle to strike a perfect equilibrium among global exploration and localized exploitation when solving complex, multimodal LFC problems, motivating the search for more effective metaheuristic approaches. Although many recent PID variants and lightweight tuning algorithms have been reported, many of them either introduce additional structural complexity, rely on specialized nonlinear mappings or fractional operators, or are more suitable for lower-dimensional/local-search tuning problems. Therefore, there remains room for an integer-order cascaded controller with richer dynamic shaping, together with a hybrid optimizer that offers a stronger exploration–exploitation balance for multi-parameter LFC tuning in RES- and EV-integrated interconnected systems. The main contributions of this work are summarized as follows:

- A novel cascaded PI(1+DD)-PI-PID controller structure with nine tunable parameters in each area that provides enhanced flexibility for LFC, achieving unique performance advantages including zero

negative frequency deviation in Area 2 and the fastest tie-line power settling time of 13 s under step load perturbations.

- A hybrid MZOA-PSO optimization technique that leverages the strength of Modified Zebra Optimization with chaotic initialization, adaptive parameters, and levy flight foraging together with the Particle Swarm Optimization optimization technique, which is verified using benchmark problems to obtain better convergence results (e.g., 3.21×10^{-81} for Schwefel 2.22) and find optimal values for the controllers.
- Thorough validation under practical conditions, including random variations in loads and RES/EV penetration, where the recommended controller controls frequency variations within ± 0.03 Hz and has the smallest peak deviation of 0.46 Hz in Area-1 and demonstrates robust performance where conventional controllers fail or oscillate.

The remaining paperwork is organized into the following sections: The mechanisms that comprise the power system utilized in the work are described in [Section 2](#). [Section 3](#) and [4](#) contain information on the recommended controller and the optimization techniques used for utilization. The results of the simulation are presented in [Section 5](#), and the study is finally concluded in [Section 6](#).

2 Dynamic Model of Proposed System

Mathematical Model of the Studied System

The dynamic model used in this work is an adopted benchmark model for two-area interconnected load frequency control studies, implemented in MATLAB/Simulink for simulation-based controller evaluation. It is not derived from a newly built experimental platform in the present study. The system consists of two non-reheat steam areas with RES and EV participation, as shown in [Fig. 6](#). To facilitate small-signal LFC analysis in the frequency domain, the main subsystems are represented by first-order transfer functions. The transfer-function models of the wind turbine, PV system, EV aggregator, governor, turbine, and power system are adopted from the published literature [[41,42](#)], and are used here as a standard dynamic benchmark for comparative assessment of the proposed controller.

Governor Scheme: The reaction time of the governor mechanism, which governs the turbine's inputs and regulates the system's frequency, is denoted via the transfer function, $G_G(s)$. The [Formula \(1\)](#) defines it in terms of the time constant T_G and the gain K_G [[43,44](#)]:

$$G_G(s) = \frac{K_G}{sT_G + 1} = \frac{1}{0.08s + 1} \quad (1)$$

Turbine Design: The turbine structure, denoted via $G_T(s)$, explains how the turbine responds to variations in the governor's controlling input. The [Formula \(2\)](#) shows how its gain (K_T) and time constant (T_T) affect the turbine's constant velocity.

$$G_T(s) = \frac{K_T}{sT_T + 1} = \frac{1}{0.3s + 1} \quad (2)$$

Power System Architecture: The $G_{PS}(s)$ power system concept illustrates how the system's frequency and electrical power generation are related. Important variables are the proportional constant K_{PS} and the time constant T_{PS} , which are determined by the LFC dependence gain D , frequency f , and inertia H as [Eq. \(3\)](#):

$$G_{PS}(s) = \frac{K_{PS}}{sT_{PS} + 1} = \frac{120}{20s + 1} \quad (3)$$

where $K_{PS} = \frac{1}{D}$, $T_{PS} = \frac{2H}{Df}$

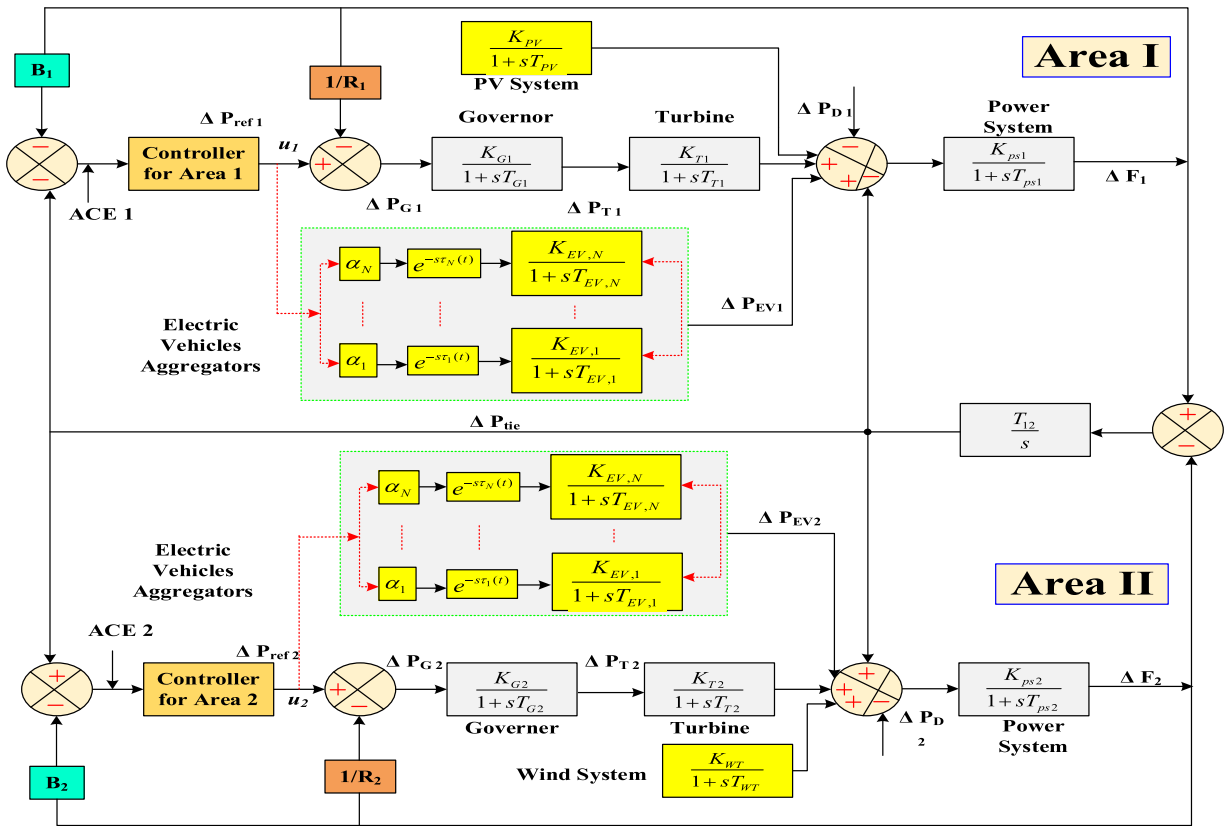


Figure 6: The two-area RES and thermal integrative power system's design schematic.

The load's sensitivity to frequency variations is represented by the Load Frequency dependence Constant (D), which is computed as the ratio of conventional load P_l to nominal frequency f using [Formula \(4\)](#):

$$D = \frac{\text{Nominal Load } (P_l)}{\text{Nominal Frequency } (f)} \quad (4)$$

PV power: In this case, a PV system could be represented by a first-order transfer function. The [Formula \(5\)](#) demonstrates that the output power of the PV system shows a linear relationship with solar intensity, assuming that the outside temperature remains constant.

$$G_{PV}(s) = \frac{K_{PV}}{sT_{PV} + 1} = \frac{1}{1.3s + 1} \quad (5)$$

Structure for wind turbine: The first-order transfer function scheme for W_{TG} is described by [Formula \(6\)](#).

$$G_{WT}(s) = \frac{K_{WT}}{sT_{WT} + 1} = \frac{1}{1.5s + 1} \quad (6)$$

Design of EV aggregator with a time-varying delay: The dynamic approach of the EV may be stated as [\[19\]](#):

$$G_{EV}(s) = \frac{K_{EV}}{sT_{EV} + 1} = \frac{1}{0.1s + 1} \quad (7)$$

In this case, T_{EV} stands for the time steady, and K_{EV} for the EV battery's gain. EVs with a high or low state of charge (SOC) are not taken into account in the aggregators utilized in this research. We propose that the EV aggregator does not account for EVs that are either at full SOC or at a reduced SOC. Nevertheless, the SOC of the battery needs to be taken into account in the complete battery design. As a result, we focus on a first-order transfer function. As a result, a first-order transfer function represents the EV aggregator. The term “time-varying delay” describes the EV aggregator’s transmission of signals’ latency. The open network of communication is the cause of this buffering, which impacts the prompt transmission of command signals. When the control signal from EV aggregators is transmitted, the time delay is represented by the delayed signal, $e^{-s\tau}(t)$. The following equations for the single-area LFC system are determined using N distinct numbers of EV aggregators:

$$\Delta P_{EV,N} = \left(\frac{1}{T_{EV,N}} \right) \cdot \Delta P_{EV,N} - \left(\frac{\alpha_N K_{EV,N}}{T_{EV,N}} \right) u(t - \tau_N(t)) \quad (8)$$

3 Proposed Cascaded PI(1+DD)-PI-PID Controller

To improve the clarity of presentation, the proposed control strategy is introduced in this section independently of the system modeling part. While [Section 2](#) describes the adopted two-area LFC benchmark model and its subsystem dynamics, the present section focuses on the architecture and operating principle of the proposed cascaded PI(1+DD)-PI-PID controller. The controller is designed to process the area control error (ACE) and generate the reference power correction signal for frequency regulation. Its cascaded structure provides additional tuning flexibility compared with conventional single-loop PI/PID-based LFC schemes by combining proportional–integral action, double-derivative dynamic shaping, and an auxiliary PI-PID stage. The controller structure is shown in [Fig. 7](#), and its tunable gains are defined before introducing the optimization algorithm used for parameter adjustment.

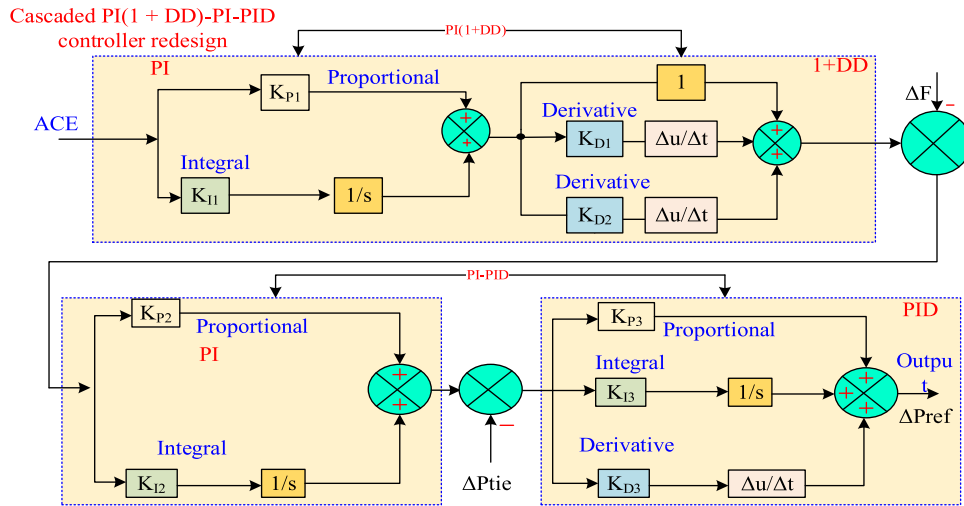


Figure 7: Composition of the suggested PI(1+DD)-PI-PID cascade controller.

A stratified method to control is made possible by the structure, in which dissimilar characteristics of the scheme’s behavior are handled by different controllers. The last controller input in the cascade’s output is often used to supply the system with an operational signal. Despite repeated attempts to improve the chain controller framework, we observed that the PI(1+DD)-PI-PID combination generated extremely promising results, outperforming PI, PID, PI(1+DD), FOPID, and PI-PDN controllers. This controller combines the

advantages of the PID controller, which is used in engineering fields, to provide outstanding performance with a clear framework and easy troubleshooting.

3.1 Controller Structure Overview

The given controller, seen in Fig. 7, stands out for its exceptional performance and straightforward integration. It is made up of three dynamic controllers: PI(1+DD), PI, and PID, which are coupled in series. The indicated controller approach includes a primary controller and several slave controllers. The PI(1+DD) control system operates as the primary controller by estimating the ACE for every area by applying Formula (9) to minimize disturbance in the system's outside loop, enhance control reliability, and guarantee that the control goals are achieved.

$$\begin{aligned} ACE_1 &= B_1 \times \Delta F_1 + \Delta P_{tie}, \\ ACE_2 &= B_2 \times \Delta F_2 + \Delta P_{tie} \end{aligned} \quad (9)$$

where frequency bias parameters are B_1 and B_2 .

Fig. 7 illustrates the time constants for region I (generator T_{G1} , turbine T_{T1} , power system T_{PS1} , and PV facility T_{PV}) and region II (generator T_{G2} , turbine T_{T2} , power system T_{PS2} , and W_T T_{WT}), along with the corresponding gains (K_{G1} , K_{T1} , K_{PS1} , K_{PV} for region I; K_{G2} , K_{T2} , K_{PS2} , K_{WT} for region II). The variables ΔF_1 and ΔF_2 denote frequency deviations (Hz), ΔP_{tie} represents tie-line power deviation (p.u.), and EVs are integrated in both areas.

The primary PI regulator uses the area frequency variation (Δf) to improve the system's reaction time and effectively minimize internal loop disturbances, whereas another PID controller uses the tie line power deviation (ΔP_{tie}). Eqs. (10)–(12) represent the s domain transfer functions in the PI(1+DD)-PI-PID controller.

$$G_{PI(1+DD)}(s) = \left(K_P + \frac{K_I}{s} \right) \times (1 + sK_{D1} + sK_{D2}) \quad (10)$$

$$G_{PI}(s) = K_P + \frac{K_I}{s} \quad (11)$$

$$G_{PID}(s) = K_P + \frac{K_I}{s} + sK_D \quad (12)$$

This study makes the assumption that the two regions and the controller settings are the same in order to simplify the analysis. Eq. (13) displays the controller's output ΔP_{ref1} .

$$\begin{aligned} \Delta P_{ref1}(s) &= ACE_i \times \left(\left(\left(K_{P1} + \frac{K_{I1}}{s} \right) \times (1 + sK_{D1} + sK_{D2}) \right) - \Delta F_i \right) \\ &\quad \times \left(\left(K_{P2} + \frac{K_{I2}}{s} \right) - \Delta P_{tie_i} \right) \times \left(K_{P3} + \frac{K_{I3}}{s} + sK_{D3} \right) \end{aligned} \quad (13)$$

3.2 Optimization Restrictions and the Objective Function

The inconsistencies are addressed by a number of objective functions, four of which are frequently employed: IAE, in ISE, ITAE, and in ITSE. As opposed to using ISE, the ITAE objective function's ability to guarantee control approach stability and accomplish a quick settling time is what drives its employment. The effectiveness of the recommended controller is likewise assessed utilizing ISE, ITSE, and IAE as levels in order to compare it with other algorithms and controllers. The four intended functions within the framework

of two areas are mathematically represented in the following manner. With boundaries reaching from $[-2, 2]$, the optimization problem is resolved during the restrictions provided in Eq. (18).

$$J_{obj,IAE} = \int_0^t (|\Delta F_1| + |\Delta F_2| + |\Delta P_{tie}|) dt \quad (14)$$

$$J_{obj,ISE} = \int_0^t (|\Delta F_1|^2 + |\Delta F_2|^2 + |\Delta P_{tie}|^2) dt \quad (15)$$

$$J_{obj,ITAE} = \int_0^t (|\Delta F_1| + |\Delta F_2| + |\Delta P_{tie}|) \cdot t dt \quad (16)$$

$$J_{obj,ISAE} = \int_0^t (|\Delta F_1|^2 + |\Delta F_2|^2 + |\Delta P_{tie}|^2) \cdot t dt \quad (17)$$

$$\begin{aligned} K_{P1(i-min)} &\leq K_{P1} \leq K_{P1(i-max)}, \\ K_{I1(i-min)} &\leq K_{I1} \leq K_{I1(i-max)}, \\ K_{D1(i-min)} &\leq K_{D1} \leq K_{D1(i-max)}, \\ K_{D2(i-min)} &\leq K_{D2} \leq K_{D2(i-max)}, \\ K_{P2(i-min)} &\leq K_{P2} \leq K_{P2(i-max)}, \\ K_{I2(i-min)} &\leq K_{I2} \leq K_{I2(i-max)}, \\ K_{P3(i-min)} &\leq K_{P3} \leq K_{P3(i-max)}, \\ K_{I3(i-min)} &\leq K_{I3} \leq K_{I3(i-max)}, \\ K_{D3(i-min)} &\leq K_{D3} \leq K_{D3(i-max)} \end{aligned} \quad (18)$$

It should be noted that the present paper focuses on model-based numerical validation rather than hardware experimental validation. Therefore, the effectiveness of the proposed controller is verified through MATLAB/Simulink simulations under multiple operating scenarios, including step load perturbation, random load variation, and RES/EV-integrated disturbances. Real-time experimental testing or hardware-in-the-loop implementation will be considered in future work.

4 Hybrid MZOA-PSO-Based Tuning of the Proposed Controller

After defining the controller architecture in Section 3, the present section formulates the optimal tuning problem for the cascaded PI(1+DD)-PI-PID controller using the hybrid MZOA-PSO algorithm. The objective is to determine the optimal controller gains that minimize the ITAE performance index while ensuring robust dynamic performance under load disturbances.

Rationale of the hybrid MZOA-PSO algorithm: The main idea of the proposed hybrid optimizer is to exploit the complementary strengths of MZOA and PSO in the tuning of the cascaded PI(1+DD)-PI-PID controller. In fact, the optimization problem is highly nonlinear with nine tightly coupled parameters and a nonconvex objective function defined using simulation. In such a highly nonlinear environment, a global optimizer might maintain diversification but may take longer to converge to the optimum solution, while a local optimizer might converge quickly but may also suffer from poor initial population and local optima. For this reason, the proposed method adopts a sequential hybrid strategy. In the first stage, MZOA performs global exploration using chaotic population initialization, adaptive parameter control, and Lévy-flight foraging to improve diversity and enlarge the search coverage. In the second stage, PSO is activated to refine

the best candidate solutions through velocity-position updates, thereby accelerating convergence toward the local optimum region. Hence, the superiority of MZOA-PSO over standalone MZOA or standalone PSO is expected to arise from a better balance between exploration and exploitation, rather than from either mechanism alone.

4.1 Mathematical Modeling of the Hybrid MZOA-PSO Algorithm for LFC

4.1.1 Problem Formulation

LFC aims to preserve frequency and ΔP_{tie} deviations within adequate restrictions through adjusting the reference power setpoints of generators. In this work, a cascaded PI(1+DD)-PI-PID controller is employed, whose structure is exposed in Fig. 8. The controller has nine tunable gains in each area:

$$x = [K_{P1}, K_{I1}, K_{D1}, K_{D2}, K_{P2}, K_{I2}, K_{P3}, K_{I3}, K_{D3}]^T \in \mathbb{R}^9 \quad (19)$$

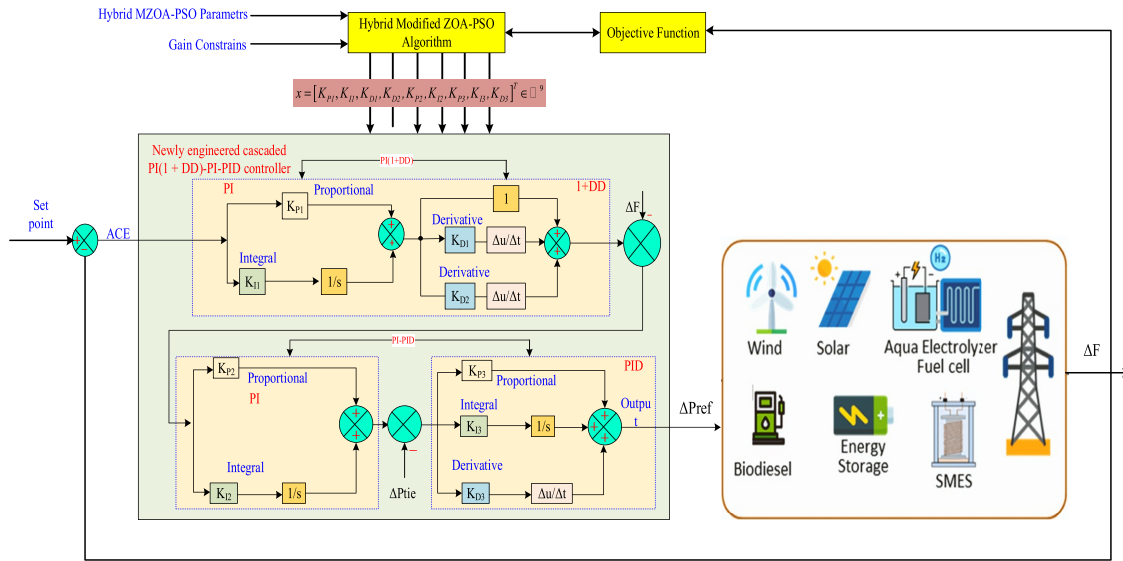


Figure 8: Structure of PI(1+DD)-PI-PID controller with Hybrid MZOA-PSO Algorithm for LFC.

The input to the controller is the ACE, well-defined for area i as $ACE_i = \Delta P_{tie,i} + B_i \Delta f_i$, where Δf_i is the frequency nonconformity, $\Delta P_{tie,i}$ deviation, and B_i the frequency bias feature. The controller output is the reference power adjustment ΔP_{ref} . The ITAE assesses the controller's performance.

$$J_{obj} = \sum_{i=1}^N \int_0^{T_{sim}} t (|ACE_i(t)|) dt \quad (20)$$

If the simulation fails or yields non-finite values (due to instability), a large penalty $J_{pen} = 10^6$ is assigned. The objective is to find x that minimizes $J(x)$ subject to the box constraints $lb \leq x \leq ub$.

4.1.2 Original ZOA

The ZOA, proposed via Trojovská et al. [45], is a population-based metaheuristic enthused through the social behavior of zebras. In ZOA, each zebra (candidate solution) updates its position through two main phases: foraging and defense against predators.

Initialization: A population of N zebras is randomly initialized within the search bounds:

$$x_{i,j}^{(0)} = lb_j + r \cdot (ub_j - lb_j), i = 1, \dots, N, j = 1, \dots, 9 \quad (21)$$

where $r \in [0, 1]$ is a random integer with a uniform distribution.

Foraging phase (exploration): Zebras search for food by moving toward the best zebra (leader) found so far, denoted by z . The update rule is:

$$x_i^{new} = x_i + r_1 \cdot (z - I \cdot x_i), \quad (22)$$

with $r_1 \in [0, 1]$ and $I = \text{round}(1 + r_2)$, $r_2 \in [0, 1]$. The factor I randomly takes the value 1 or 2, allowing the zebra to either follow the leader closely or explore more widely.

Defense phase (exploitation): Zebras exhibit two defense strategies against predators, selected with probability ps (lion attack) and $1-ps$ (another zebras' circle defense):

Lion strategy: The zebra escapes to a random location within the search space:

$$x_i^{new} = lb + r_3 \odot (ub - lb) \quad (23)$$

where r_3 is a vector of random numbers in $[0, 1]$ and $\odot$ denotes element-wise multiplication.

Circle defense: The zebra moves toward another randomly selected zebra x_k ($k \neq i$):

$$x_i^{new} = x_i + r_4 \cdot (x_k - x_i), \quad (24)$$

with $r_4 \in [0, 1]$. After each phase, the new position is checked; if this new position has a lower fitness value (i.e., a lower J value), it is adopted as the new position, and the global best z is adjusted accordingly.

4.1.3 Modified Zebra Optimization Algorithm (MZOA)

To enhance the performance of the original ZOA, three modifications are made: chaotic initialization, adaptive parameter control, and Lévy flight foraging.

Chaotic Initialization: Instead of purely random initialization, the initial population is generated using a logistic map to improve diversity and avoid premature convergence. The chaotic sequence is obtained by iterating.

$$c_{n+1} = 4c_n(1 - c_n), \quad c_0 \in (0, 1) \setminus \{0.25, 0.5, 0.75\}, \quad (25)$$

or 10 steps. Each element of the initial population is then set as

$$x_{i,j}^{(0)} = lb_j + c_{i,j}(ub_j - lb_j), \quad (26)$$

where $c_{i,j}$ are the chaotic numbers.

Adaptive Parameter Control: The probabilities governing the defense phase and the use of Lévy flights are adapted over iterations to balance exploration and exploitation. Let t be the current iteration and T_{max} the maximum number of iterations. The defense strategy probability p_s (lion attack) decreases linearly:

$$p_s(t) = p_{s,\min} + (p_{s,\max} - p_{s,\min}) \left(1 - \frac{t}{T_{max}}\right) \quad (27)$$

while the probability of applying a Lévy flight during foraging, p_{levy} , also decreases to favor exploitation later:

$$p_{levy}(t) = p_{levy,max} \left(1 - \frac{t}{T_{max}}\right) \quad (28)$$

Typical values are $p_{s,min} = 0.3$, $p_{s,max} = 0.7$, $p_{levy,max} = 0.5$.

Lévy-Flight Foraging: In the foraging phase, instead of the standard update, a Lévy flight is applied with probability p_{levy} to enable long-jump exploration and help escape local optima:

$$x_i^{new} = x_i + \alpha \cdot Levy(\lambda) \odot (z - x_i), \quad (29)$$

where $\alpha = 0.01$ is a scaling factor, and $Levy(\lambda)$ is a random vector drawn from a Lévy distribution with index $\lambda = 1.5$. The Lévy step is generated using Mantegna's algorithm:

$$Levy(\lambda) \sim \frac{u}{|v|^{1/\lambda}}, u \sim \mathbb{N}(0, \sigma_u^2), v \sim \mathbb{N}(0, 1) \quad (30)$$

with

$$\sigma_u = \left[\frac{\Gamma(1+\lambda) \sin(\pi\lambda/2)}{\Gamma(1+\lambda/2) \lambda 2^{(\lambda-1)/2}} \right]^{1/\lambda} \quad (31)$$

4.1.4 Particle Swarm Optimization (PSO)

PSO, introduced by Kennedy and Eberhart [46], simulates the social behavior of birds flocking. Each particle i has a position x_i and a velocity v_i . The velocity is updated based on the particle's own best location ($pbest_i$) and the global best location ($gbest$):

$$\begin{aligned} x_i^{t+1} &= \omega v_i^t + c_1 r_1 \odot (pbest_i - x_i^t) + c_2 r_2 \odot (gbest - x_i^t), \\ x_i^{t+1} &= x_i^t + v_i^{t+1} \end{aligned} \quad (32)$$

Here ω is the inertia weight (linearly reducing from 0.9 to 0.4), $c_1 = c_2 = 1.5$ are acceleration factors, and r_1, r_2 are random vectors uniformly distributed in $[0, 1]$. Positions are kept within the bounds by clipping.

4.1.5 Hybrid MZOA-PSO Algorithm

The hybrid algorithm combines the exploratory power of MZOA with the exploitative strength of PSO in a two-stage framework: **Stage 1:** MZOA Exploration: The MZOA is run for T_{MZOA} iterations (typically half of the total iterations T_{max}). In this stage, the population evolves according to the modified foraging and defense rules described above. The best solution found, z , is recorded and will serve as the global best for the PSO stage.

$$x^{t+1} \leftarrow MZOA(x^t) \quad (33)$$

Evaluate $J(x_i^{t+1})$, update x_{best} . Transition: seed PSO around the best zebra

$$\begin{aligned} x_i^{0,PSO} &= x_{best}^{T_1} + \varepsilon_i, \varepsilon_i \sim U(-\delta, \delta), \\ v_i^{0,PSO} &\sim U(-v_{max}, v_{max}) \end{aligned} \quad (34)$$

Stage 2: PSO Refinement: At the beginning of this stage, the PSO is initialized with the top $M = \lfloor 0.2 N \rfloor$ solutions from the final MZOA population (to preserve promising information) and the remaining $N-M$ particles are randomly generated to maintain diversity. Velocities are initialized to zero, and personal bests $pbest_i$ are set to the current positions. The global best $gbest$ is set to z . Then the PSO updates are applied for the remaining $T_{PSO} = T_{max} - T_{MZO}$ iterations.

$$x^{t+1} \leftarrow PSO(x^t, v^t) \quad (35)$$

Final solution:

$$\theta^* = gbest \quad (36)$$

4.2 Procedure for Tuning the Proposed Controller Using Hybrid MZOA-PSO

To improve the clarity and reproducibility of the proposed tuning framework, the application procedure of the hybrid MZOA-PSO algorithm for tuning the cascaded PI(1+DD)-PI-PID controller is summarized as follows. First, the decision vector is formed using the controller gains of the proposed structure, and lower and upper bounds are assigned to each parameter. Second, an initial population of candidate solutions is generated using chaotic initialization. Third, each candidate's gain vector is applied to the MATLAB/Simulink LFC model, and the ITAE objective value is computed from the resulting frequency and tie-line power responses. Fourth, the MZOA phase is executed to improve global exploration through adaptive foraging and defense mechanisms enhanced by Lévy-flight perturbation. Fifth, after the exploration stage, the best candidate solutions are passed to the PSO phase, where the particle velocities and positions are iteratively updated to perform local refinement. Finally, the gain vector associated with the minimum objective value is chosen as the optimal controller parameter set, which is used in all simulation scenarios. The algorithm provides a smooth transition between the global search and local refinement using the strengths of both algorithms. The pseudocode for the algorithm is shown in Algorithm 1.

Algorithm 1: Hybrid MZOA-PSO for LFC tuning

- 1: Input: N (population size), T_{max} , T_{MZO} , $dim = 9$, bounds lb , ub .
- 2: Initialize the population Positions by chaotic initialization ([Section 4.1.2](#)).
- 3: Evaluate the fitness J for each individual by Simulink simulation.
- 4: Update the global best $z = \text{argmin } J$.
- 5: for $t = 1$ to T_{max} do
- 6: if $t \leq T_{MZO}$ then
- 7: // MZOA phase
- 8: Update $ps(t)$, $p_{levy}(t)$ by the adaptive formulas.
- 9: for $i = 1$ to N do
- 10: // Foraging with Lévy flight (with probability p_{levy})
- 11: if $rand < p_{levy}$ then
- 12: $newPos = Positions(i,:) + \alpha * Levy(\lambda) * (z - Positions(i,:))$;
- 13: else
- 14: $I = \text{round}(1 + rand)$; $newPos = Positions(i,:) + rand * (z - I * Positions(i,:))$;
- 15: end
- 16: Clip new positions and evaluate fitness. Update if fitness is improved.
- 17: // Defense phase (with probability 1-threshold, e.g., threshold = 0.1)
- 18: if $rand \geq \text{threshold}$ then

(Continued)

Algorithm 1 (continued)

```

19:         if  $rand < ps$  then
20:              $newPos = lb = rand(1,dim) * (ub - lb)$ ; // lion strategy
21:         else
22:              $k = random\ index \neq i$ ;  $newPos = Positions(i,:) + rand * (Positions(k,:) - Positions(i,:))$ ;
23:         end
24:         Clip, evaluate; if improved, update.
25:     end
26: end for
27: Update global best  $z$ .
28: else
29:     // PSO phase—initialize at first entry
30:     if  $t == T\_MZO A = 1$  then
31:          $velocities = zeros(N,dim)$ ;
32:          $pbest = Positions$ ;  $pbest\_score = fitness$ ;
33:         Keep best  $M$  solutions, randomly generate rest to maintain  $N$ .
34:     end if
35:     Update  $w = 0.9 - 0.5 * ((t - T\_MZO A) / T\_PSO)$ ;
36:     for  $i = 1$  to  $N$  do
37:         Update the velocity and position by PSO equations.
38:         Clip, evaluate fitness.
39:         Update the  $pbest$  and global best if they are improved.
40:     end for
41: end if
42: Store the convergence curve.
43: end for
44: Output optimal gains  $z$  and best fitness.

```

The hybrid MZOA PSO algorithm uses the synergy of the enhanced exploration ability of the Modified Zebra Optimization Algorithm and the fast local convergence of the Particle Swarm Optimization technique to efficiently search the eight-dimensional parameter space of the cascaded PI(1+DD)-PI-PID controller to optimize the ITAE performance index, thereby ensuring robust LFC performance against load disturbances. The mathematical models used in the paper provide the basis for the implementation and experimental validation of the results. Although Fig. 9 illustrates the hybrid optimization flowchart, a step-by-step tuning procedure is also provided here to clarify how MZOA and PSO are sequentially applied to determine the optimal gains of the proposed cascaded controller. The method determines if the new fitness value is superior to the prior one; if it is, the solution is approved and takes its place. Otherwise, the earlier answer is kept. This iterative procedure keeps on until the algorithm's halting requirements are satisfied.

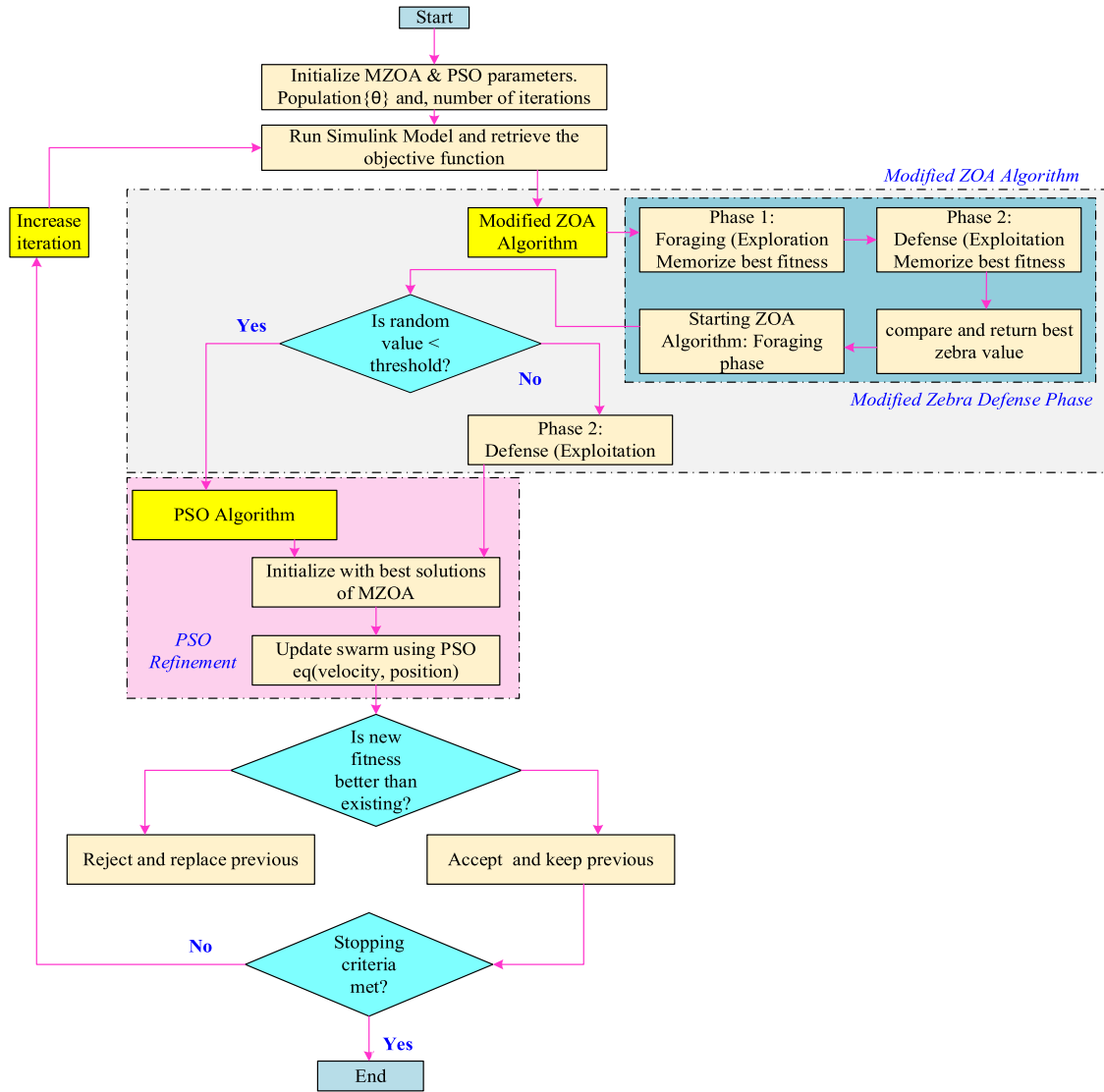


Figure 9: The proposed MZOA-PSO algorithm's operational flowchart.

4.3 Validation of the Proposed MZOA-PSO Algorithm

The robustness and optimization capability of the proposed MZOA-PSO algorithm are evaluated using four well-known benchmark functions, listed in Table 2. The table summarizes the characteristics (C), dimension (D), search space bounds, and global optimum for each function. To ensure a fair comparison of the proposed algorithm and other algorithms, algorithmic parameters are kept constant for all algorithms. Each algorithm is run for 30 independent trials with a population size of 50 and a maximum of 10,000 function evaluations. Table 3 provides the mean, best, and standard variation of the fitness function values of the proposed MZOA-PSO and ZOA-PSO algorithms. The percentage of successful runs (% of SB) for achieving the global optimum within a tolerance of $1e-10$ is also presented.

In the case of the unimodal function Booth (F_1), MZOA-PSO is able to achieve the precise global optimum of zero with zero mean and standard deviation, while ZOA-PSO only achieves a solution close to zero. For the complex function Rosenbrock (F_2), MZOA-PSO is able to find the global optimum frequently

and achieve exceptionally low values of mean and standard deviation compared to ZOA-PSO by several orders of magnitude. For the multimodal function Schwefel 2.22 (F_3) and Zakharov (F_4), MZOA-PSO is able to show its strong exploration ability and achieve near-zero best and mean values with extremely high success rates, while ZOA-PSO stagnates at local optima. The converging curves in Fig. 10 show the faster converging rate of MZOA-PSO than ZOA-PSO.

Table 2: The robustness of the suggested approach was evaluated using four standard functions.

Test Function	F	C	Formulation	Interval	D	Global Optimal
Booth	F_1	Unimodal	$f(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$	$[-10, 1]$	2	0
Rosenbrock	F_2	Multimodal	$f(x) = \sum_{i=1}^{n-1} \left[100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right]$	$[-10, 1]$	30	0
Schwefel 2.22	F_3	Multimodal	$f(x) = \sum_{i=1}^n \ x_i\ + \prod_{i=1}^n \ x_i\ $	$[-10, 1]$	30	0
Zakharov	F_4	Unimodal	$f(x) = \sum_{i=1}^d x_i^2 + \left(\sum_{i=1}^d 0.5x_i \right)^2$ $\left(\sum_{i=1}^d 0.5x_i \right)^4$	$[-5, 10]$	10	0

Table 3: The algorithms for MZOA-PSO and ZOA-PSO are compared using four benchmark roles.

Techniques	Proposed MZOA PSO Algorithm				ZOA-PSO Algorithm			
Function	Best	Mean	Std	% of SB	Best	Mean	Std	% of SB
Booth (F_1)	0	0	0	100%	1.53e-20	1.49e-18	2.56e-19	8%
Rosenbrock (F_2)	0	2.13e-28	4.87e-28	98%	7.90e-5	9.37e-3	2.66e-4	1%
Schwefel 2.22 (F_3)	3.21e-81	5.64e-80	1.02e-79	100%	7.19e-16	9.60e-16	1.65e-16	1.2%
Zakharov (F_4)	0	1.05e-140	3.71e-140	100%	2.63e-4	1.80e-3	8.64e-4	0.5%

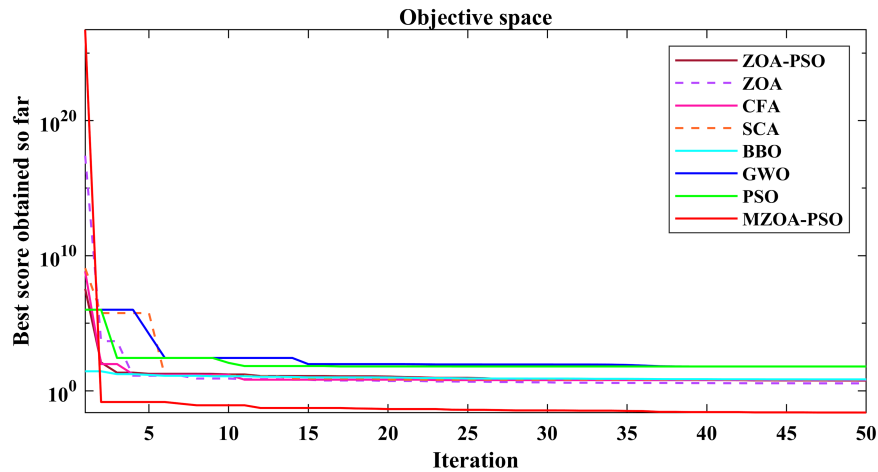


Figure 10: Convergence curves, confirming the faster convergence rate of MZOA-PSO over ZOA-PSO and other algorithms.

The results obtained in Table 3 clearly reveal the fact that the proposed MZOA-PSO algorithm performs significantly higher in terms of the percentage of successful runs (SB%) for all the benchmark functions. This reveals the improved ability of the MZOA-PSO algorithm to seepage local minima and find the global optimum, due to the well-balanced exploration-exploitation mechanism provided by the hybrid structure. The control parameters for the MZOA-PSO algorithm are presented in Table 4. The above results clearly reveal the fact that the proposed MZOA-PSO algorithm has excellent global search ability and strength, making it suitable for solving complex engineering optimization problems such as LFC.

Table 4: Initial settings for the hypothesized MZOA-PSO technique.

Parameter	Value
Population size (N)	50
Maximum iterations (T_max)	50
Cognitive coefficient (c_1)	1.5
Social coefficient (c_2)	1.5
Inertia weight range (w)	[0.4, 0.9]
Defense phase threshold	0.2
Lion strategy probability range	[0.2, 0.6]
Lévy flight maximum probability	0.3
Lévy flight scaling factor (α)	0.5
Number of independent runs	30

5 Discussion and Simulation Results

5.1 Simulation Settings and Environment

The MATLAB Simulink tool was used to model the methods discussed in this study, which included a hydro-thermal power system with PV, wind, and EV units. The algorithms' initial input parameters are shown in Table 4 and were chosen based on the current optimization framework, the acceptable range of the decision parameters, simulation knowledge, and pertinent research on metaheuristic algorithms for LFC controller tuning. The proposed controller's ideal tuning gains, as determined by four distinct optimization techniques, are shown in Table 5. A constant set of adjusted parameters from Table 5 was used in all evaluations to show the stability and efficacy of the recommended MZOA-PSO optimized PI(1+DD)-PI-PID cascaded controller. Dynamic performance analysis, analysis during realistic and stochastic step load perturbations (SLP), and evaluation of the controller's robustness to changes in system parameters are some of these studies.

Table 5: The controller's parameters were correctly tuned by MZOA-PSO and other algorithms.

Area	Controller Parameter -PI(1+DD)-PI-PID	MZOA- PSO	ZOA- PSO	ZOA	PSO	GWO	CFA	SCA	BBO
Area-1	KP1	1.0156	1.7932	0.1205	1.4358	0.1205	1.4358	0.1205	1.4358
	KI1	1.0705	0.5424	1.5098	0.4906	1.5098	0.4906	1.5098	0.4906
	KD1	1.3475	0.5695	0.9247	1.8021	0.9247	1.098	0.9247	0.657
	KD2	1.9402	0.3291	0.828	1.021	0.765	0.123	1.8709	1.223
	KP2	0.7678	0.6420	1.3462	0.6899	1.3462	0.6899	1.3462	0.6899

(Continued)

Table 5 (continued)

Area	Controller Parameter -PI(1+DD)-PI-PID	MZOA- PSO	ZOA- PSO	ZOA	PSO	GWO	CFA	SCA	BBO
Area-2	KI2	1.7523	1.6420	0.3926	0.4503	0.4503	1.2331	0.4503	1.2331
	KP3	0.5701	0.3537	1.3866	1.5701	1.3866	0.874	1.3866	1.765
	KI3	1.0156	1.7932	0.1205	1.4358	0.1205	1.4358	0.1205	1.4358
	KD3	0.7678	1.1088	0.0134	-0.444	0.010	-0.014	-0.208	-0.487
	KP1	1.7932	1.7932	1.5021	1.2331	0.8711	1.7932	1.7932	1.4358
	KI1	0.5424	0.5424	1.5818	0.4503	1.0537	0.5424	0.5424	0.4906
	KD1	0.5695	0.5695	0.3926	0.5067	0.4791	0.5695	0.5695	1.564
	KD2	0.3291	0.3291	0.0124	-0.498	0.1840	0.3291	0.3291	0.8687
	KP2	1.6420	1.6420	1.3462	1.3462	1.3462	1.6420	1.6420	0.6899
	KI2	2	2	1.3462	0.3926	0.9877	2	2	2
	KP3	0.3537	0.3537	1.3866	1.3866	1.3866	0.3537	0.3537	1.2331
	KI3	1.1088	1.1088	-2	0.4791	0.5695	1.1088	1.1088	0.4503
	KD3	1.1088	0.3537						

To verify the dominance of the suggested MZOA-PSO method in enhancing LFC control settings, the identical PI(1+DD)-PI-PID cascade controller's parameters were tuned using seven different algorithms: hybrid ZOA-PSO, ZOA, PSO, CFA, SCA, BBO, and GWO. The converging curves of the four approaches are shown in Fig. 10, which makes it evident that the suggested MZOA-PSO algorithm achieves quicker convergence speeds and better solution accuracy.

5.2 Different SLP

To prove the effectiveness of the proposed controller, the dynamic behavior of the hybrid MZOA-PSO tuned PI-(1+DD)-PI-PID controller was evaluated under various load demand scenarios using the optimized parameters presented in Table 5, with the corresponding system responses illustrated in Fig. 11. As observed in the figures, both the over and under overshoot of the oscillations rise with the magnitude of the load change; however, all deviations remain within acceptable limits. Fig. 11a illustrates the ΔF_1 in Area 1 for the range of load variation from 3% to 50%, and it is evident that the higher the load variation, the deeper the initial frequency dip. However, the proposed controller is able to effectively damp the frequency for all the load levels, and the frequency settles to zero quickly. In the same vein, Fig. 11b illustrates the ΔF_2 in Area 2 for the range of load variation from 3% to 50%, and it is evident that the proposed controller is able to effectively stabilize the response with minimal oscillations and a well-defined path to steady state. Fig. 11c illustrates the ΔP_{tie} for the range of load variation, and it is evident that the proposed hybrid MZOA-PSO tuned controller is able to effectively control the load variation and ensure the power exchange is restored to its original state quickly. Across all subfigures, the proposed hybrid MZOA-PSO optimized PI-(1+DD)-PI-PID controller demonstrates great performance under varying load conditions, characterized by excellent damping, minimal overshoot, and rapid stabilization, underscoring its ability to maintain the stability of the frequency and tie-line in the interconnected power network despite substantial load disturbances.

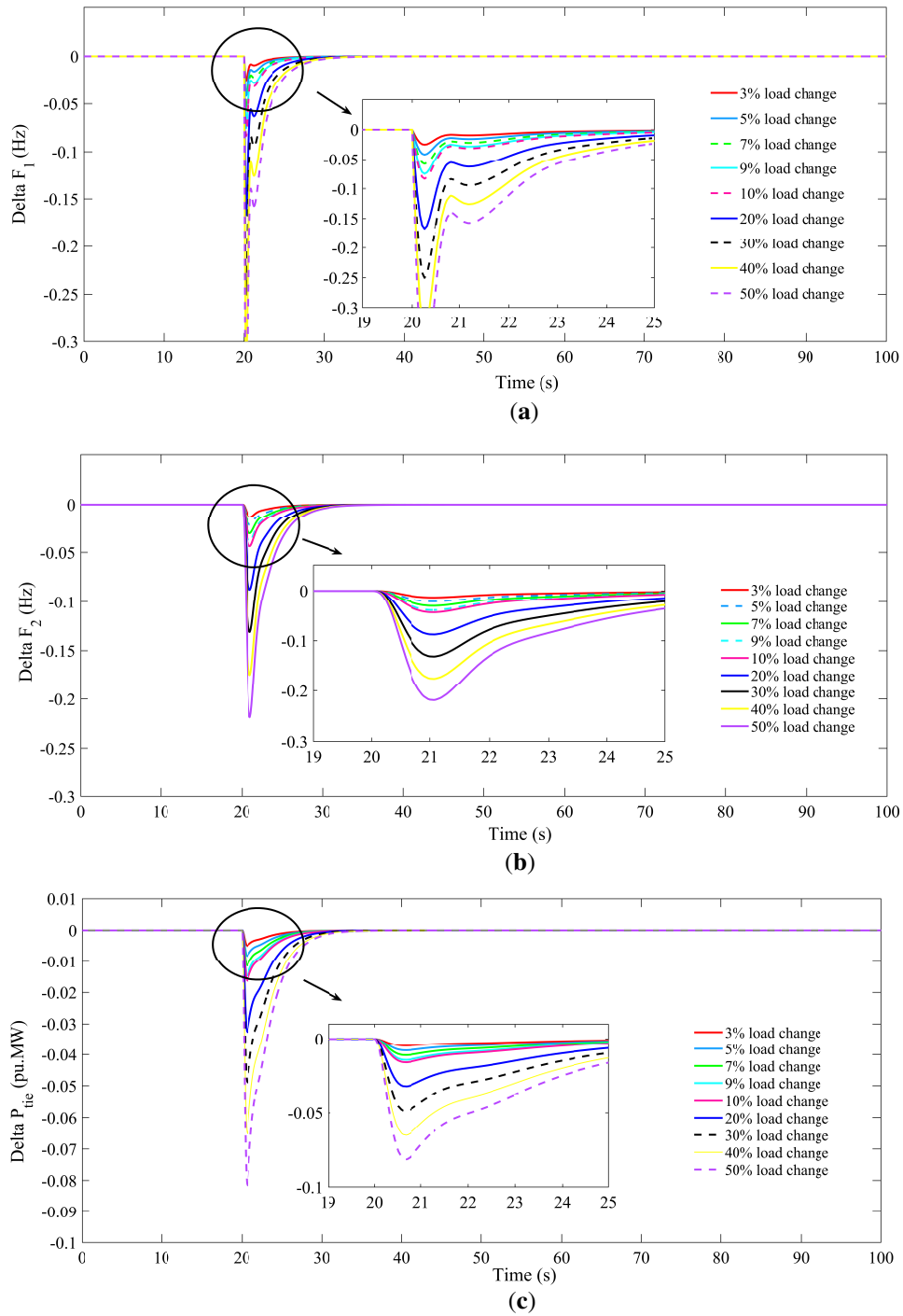


Figure 11: (a) ΔF_1 in area-1 at SLP, (b) ΔF_2 in area-2 at SLP, (c) ΔP_{tie} at SLP for small and large SLP.

5.3 Comparison of Controller Reactions after Adding RESs

To assess the efficacy of the hybrid MZOA-PSO optimized PI-(1+DD)-PI-PID controller and its adaptability to structural changes in the power network, RESs were incorporated into the two-area power network. This test aims to assess controller performance under dynamic conditions characterized by high RES penetration. Accordingly, PV, wind, and EV, were integrated with each area subjected to a 1% SLP at

$t = 0$ s. To better envisage the distinct impact of each RESs, the PV system was activated at 10 s and the wind turbine at 30 s. Instead of re-optimizing the controller parameters, the parameters attained in Section 4.2, using the MZOA-PSO algorithm, were retained to scrutinize the controller's robustness and versatility in managing the integration of high-penetration RESs. The changing output profiles of the PV and wind generators are illustrated in Fig. 12.

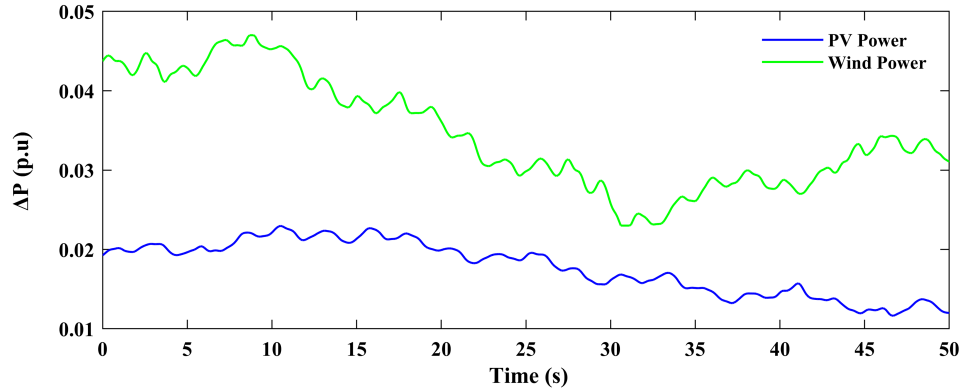


Figure 12: Solar and wind power profile.

Fig. 13 illustrates the dynamic performance of the four-area power system under a 1% SLP, comparing four controllers tuned by the proposed MZOA-PSO algorithm: PI, PID, PI(1+DD), and the proposed PI(1+DD)-PI-PID. The responses are shown for frequency deviations in Area 1 (ΔF_1 , Fig. 13a) and Area 2 (ΔF_2 , Fig. 13b), tie-line power deviation (ΔP_{tie} , Fig. 13c), and the convergence of the objective function (Fig. 13d). The suggested PI(1+DD)-PI-PID structure reveals the minimum degree of overshoot/undershoot and the minimum settling time, thus verifying its excellent damping performance. Table 6 summarizes the major performance metrics obtained from the dynamic responses.

Table 6 provides a summary of the key performance parameters based on the dynamic responses presented in Fig. 13. For ΔF_1 in Area 1, the proposed MZOA PSO optimized PI(1+DD)-PI-PID controller shows an undershoot of -0.4 Hz and a small overshoot of 0.1 Hz and settles within 13 s. Compared to the other controllers, the PI controller shows a smaller undershoot of -0.2 Hz but takes longer than 17 s to settle, while the PID controller shows a higher undershoot of -0.3 Hz and also fails to settle within 17 s. The PI(1+DD) controller shows an undershoot of -0.4 Hz and zero overshoot but fails to settle within 17 s. For ΔF_2 in Area 2, the proposed controller shows a negligible positive deviation of 0.1 Hz and zero negative deviation and settles within 13 s, while the other controllers show undershoots of -0.8 to -0.9 Hz and fail to settle within 17 s. For ΔP_{tie} , the proposed PI(1+DD)-PI-PID controller shows an undershoot of -0.10 p.u., zero overshoot, and settles within 13 s. Compared to the other controllers, the PI(1+DD) controller shows a slightly smaller undershoot of -0.15 p.u., but a small overshoot of 0.05 p.u., while the PID controller shows an unstable response with increasing overshoot of up to 1.35 p.u. at 40 s. These numerical results confirm that the proposed cascaded controller offers superior damping, minimal deviations, and the fastest stabilization under load disturbances.

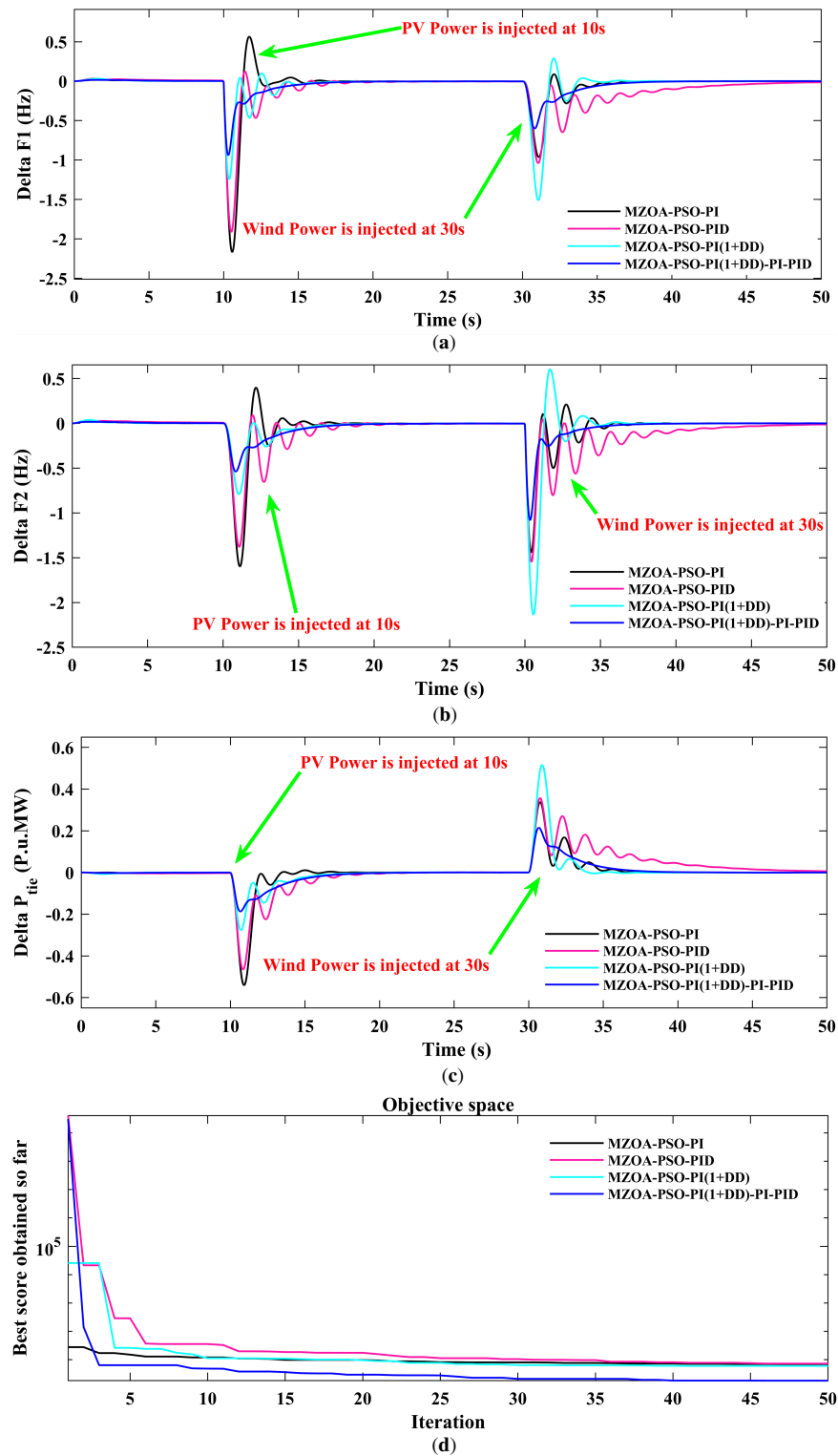


Figure 13: Dynamic responses of the two-area power system under a 1% SLP with the proposed hybrid MZOA-PSO tuned controllers are compared: PI, PID, PI(1+DD) and the cascaded PI(1+DD)-PI-PID: (a) ΔF_1 in Area 1, (b) ΔF_2 in Area 2, (c) ΔP_{tie} , and (d) convergence curves of the objective function.

Table 6: Comprehensive comparisons of controller performance parameters for all algorithms.

Algorithm	Controller	ΔF_1 (Hz)			ΔF_2 (Hz)			ΔP_{tie} (p.u. MW)		
		-ve	+ve	ts	-ve	+ve	ts	-ve	+ve	ts
MZOAO PSO (Hybrid)	PI	-0.2	0	>17	-0.8	0	>19	-0.25	0	16
	PID	-0.3	0	>17	-0.9	0	>19	-0.20	1.35	14
	PI(1+DD)	-0.4	0	>17	-0.9	1.0	>19	-0.15	0.05	13
	PI(1+DD)-PI-PID	-0.4	0	13	0.0 [†]	0.1 [†]	<13 [†]	-0.10	0	13
ZOA-PSO (Hybrid)	PI	-0.9	0	15	-0.8	0	17	-0.45	0.23	>40
	PID	-0.8	0	14	-0.7	1.30	17	-0.25	0.62	14
	PI(1+DD)	-0.6	0	16	-0.6	1.40	15	-0.20	0.62	17
	PI(1+DD)-PI-PID	-0.4	0	15	-0.9	0	13	-0.15	0.62	14
ZOA	PI	-0.8	0	13	-0.8	0	14	0.00	0.00	23
	PID	-0.6	0	13	-0.9	0	14	0.00	0.00	24
	PI(1+DD)	-0.4	0	15	-0.7	0	14	0.00	0.19	28
	PI(1+DD)-PI-PID	-0.3	0	13	-0.6	0	16	-0.05	0.0	17
PSO	PI	-0.90	0.10	20	-0.90	0	>40	-0.50	0	16
	PID	-0.80	0.15	20	-0.80	0	>40	-0.60	0	17
	PI(1+DD)	-0.70	0.20	>40	-0.70	2.40	25	-0.20	1.30	15
	PI(1+DD)-PI-PID	-0.80	0.15	>40 [#]	-0.70	2.40	19	-0.25	1.30	12
BBO	PI	-0.60	0	15	-0.45	0	15	-0.15	0	14
	PID	-0.70	0	16	-0.40	0	16	-0.15	0	14
	PI(1+DD)	-0.80	0.17	>37	-0.50	1.60	13	-0.25	0.19	25
	PI(1+DD)-PI-PID	-0.90	0.0005	16	-0.55	1.60	10	-0.45	0	14

Note: Undershoot (Hz) (-ve), Overshoot (Hz) (+ve), Settling Time (s) (ts), † indicates the best-performing value among the compared algorithms and controllers.

Fig. 14 shows the dynamic responses of the two-area power system under a 1% SLP, comparing four controllers tuned by the original ZOA-PSO hybrid algorithm: PI, PID, PI(1+DD), and the PI(1+DD)-PI-PID. The subfigures show Fig. 13a ΔF_1 in Area 1, Fig. 13b ΔF_2 in Area 2, Fig. 13c ΔP_{tie} , and Fig. 13d convergence of the objective function. The proposed PI(1+DD)-PI-PID controller shows the lowest undershoot in ΔF_1 and ΔP_{tie} , while the PI controller shows stable behavior in ΔF_2 but with bigger deviations. The PID and PI(1+DD) controllers, however, lead to unstable responses in Area 2 and ΔP_{tie} , with diverging oscillations. Table 6 summarizes the key performance metrics extracted from the responses.

Fig. 15 depicts the responses of the two-area power network under a 1% SLP, comparing four controllers tuned by the standalone ZOA algorithm (without hybridization): PI, PID, PI(1+DD), and the cascaded PI(1+DD)-PI-PID. Subfigures show Fig. 15a ΔF_1 in Area 1, Fig. 15b ΔF_2 in Area 2, Fig. 15c ΔP_{tie} , and Fig. 15d convergence of the objective function. The conventional PI and PID controllers yield stable but relatively large frequency deviations, while the PI(1+DD) controller exhibits stability in Area 2 but diverges in Area 1. The proposed cascaded controller, however, shows unstable behavior with monotonic drift in all responses, indicating that the ZOA alone is insufficient for optimal tuning. Table 6 summarizes the extracted performance metrics.

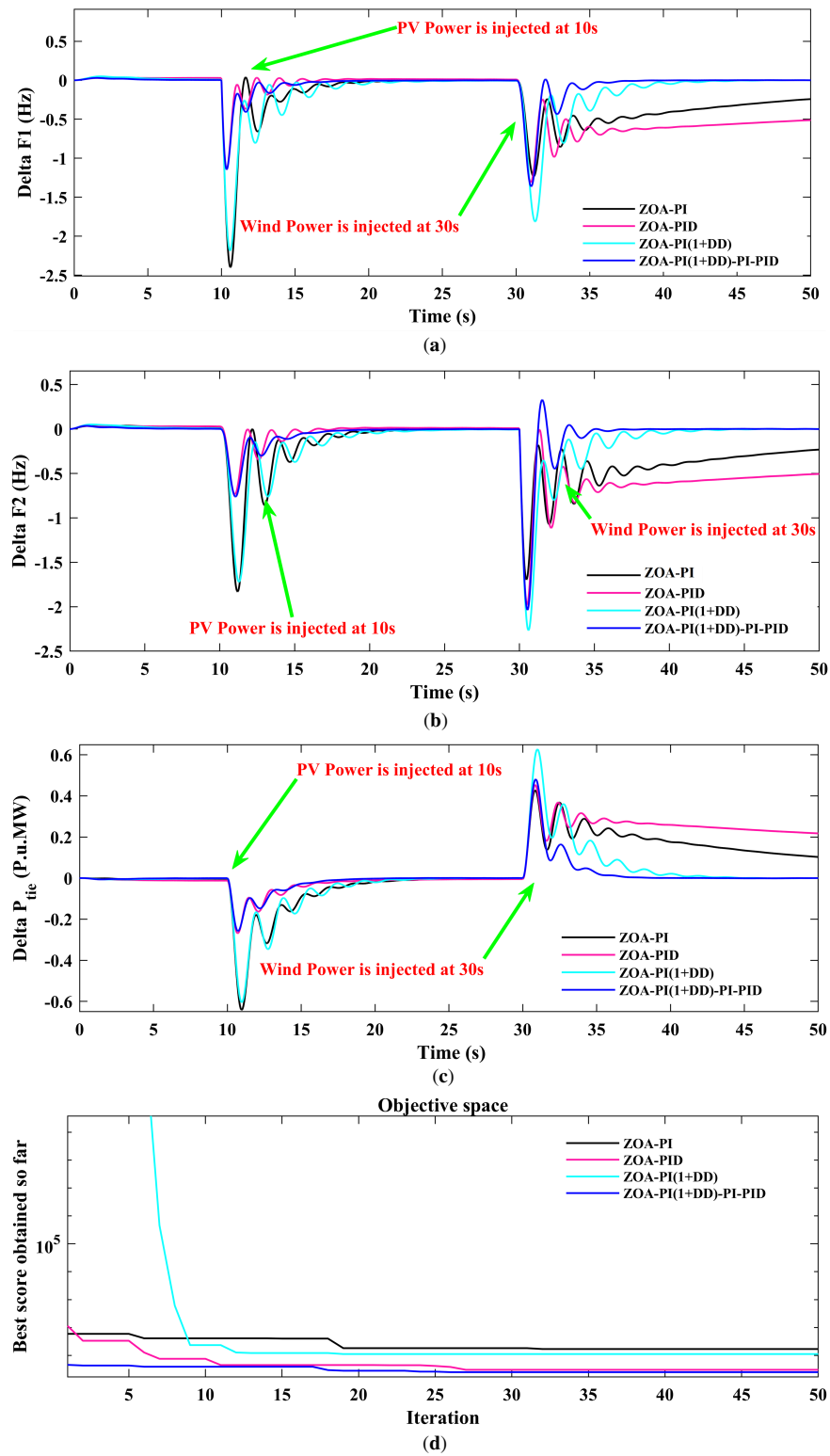


Figure 14: Dynamic responses of the original hybrid MZOA-PSO tuned controllers are compared: PI, PID, PI(1+DD) and the cascaded PI(1+DD)-PI-PID: (a) ΔF_1 in Area 1, (b) ΔF_2 in Area 2, (c) ΔP_{tie} , and (d) convergence curves of the objective function.

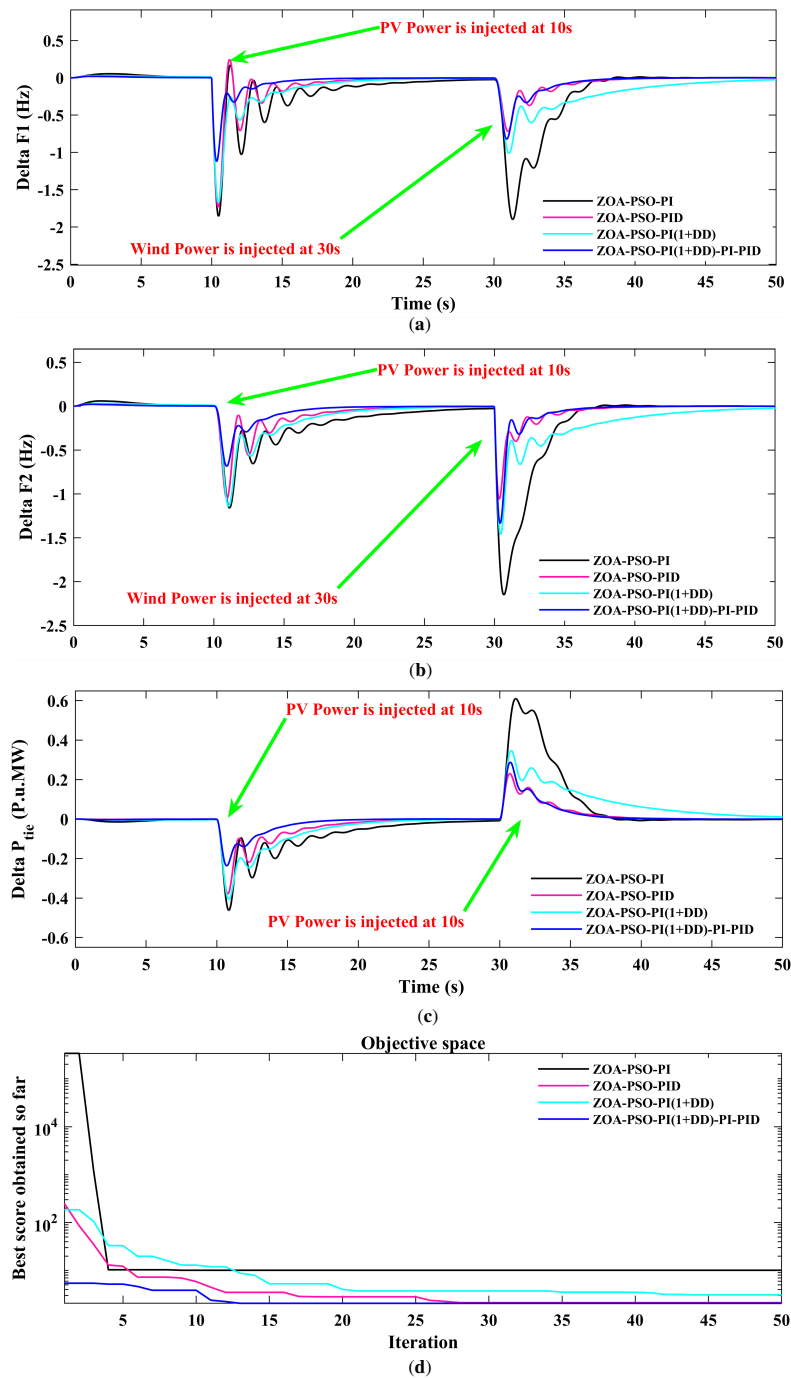


Figure 15: Dynamic responses of the original ZOA tuned controllers are compared: PI, PID, PI(1+DD) and the cascaded PI(1+DD)-PI-PID: (a) ΔF_1 in Area 1, (b) ΔF_2 in Area 2, (c) ΔP_{tie} , and (d) convergence curves of the objective function.

Fig. 16 demonstrates the responses of the two-area power network under a 1% SLP, comparing four controllers tuned by the standalone PSO algorithm: PI, PID, PI(1+DD), and the cascaded PI(1+DD)-PI-PID. Subfigures show Fig. 16a ΔF_1 in Area 1, Fig. 16b ΔF_2 in Area 2, Fig. 16c ΔP_{tie} , and Fig. 16d convergence of the objective function. The PSO-tuned PI and PID controllers exhibit stable but oscillatory responses, with noticeable secondary oscillations following the initial disturbance. The PI(1+DD) and the proposed

cascaded controller, however, demonstrate unstable behavior in Area 2 and tie-line power, with growing oscillations that indicate inadequate tuning by the standalone PSO. Table 6 summarizes the extracted performance metrics.

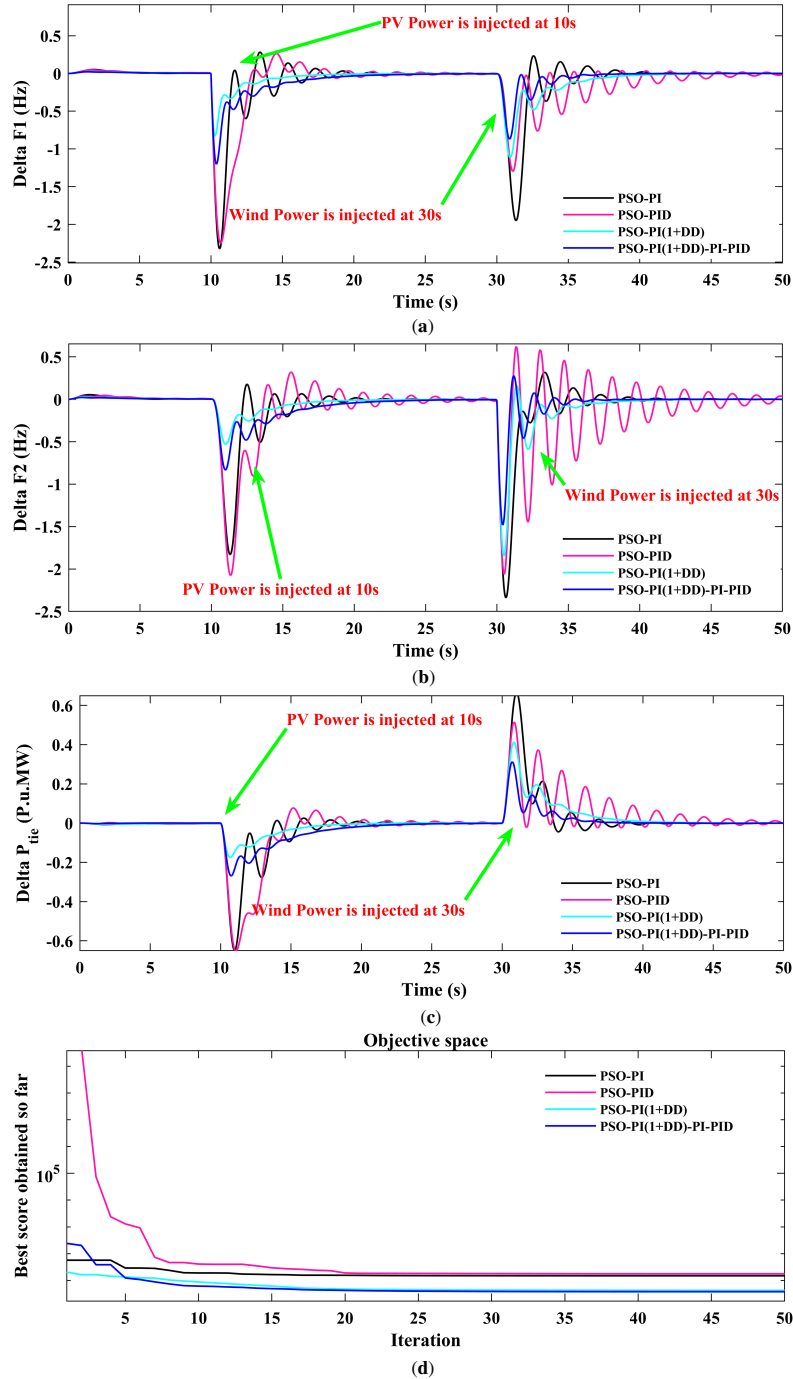


Figure 16: Dynamic responses of the original PSO tuned controllers are compared: PI, PID, PI(1+DD) and the cascaded PI(1+DD)-PI-PID: (a) ΔF_1 in Area 1, (b) ΔF_2 in Area 2, (c) ΔP_{tie} , and (d) convergence curves of the objective function.

Fig. 17 depicts the responses of the two-area power network during a 1% SLP, comparing four controllers tuned by the BBO algorithm: PI, PID, PI(1+DD), and the cascaded PI(1+DD)-PI-PID. Subfigures

show Fig. 17a ΔF_1 in Area 1, Fig. 17b ΔF_2 in Area 2, Fig. 17c ΔP_{tie} , and Fig. 17d convergence of the objective function. The BBO-optimized PI and PID controllers demonstrate stable responses with well-damped oscillations and rapid settling in both frequency and ΔP_{tie} . The PI(1+DD) controller has a slower oscillatory decay in ΔF_2 with a small offset, whereas the cascaded controller has initial damping characteristics followed by increased oscillation in ΔF_2 and a negative drift in tie line power after 20 s, indicating instability of the BBO tuned parameters. Table 6 shows the extracted performance metrics.

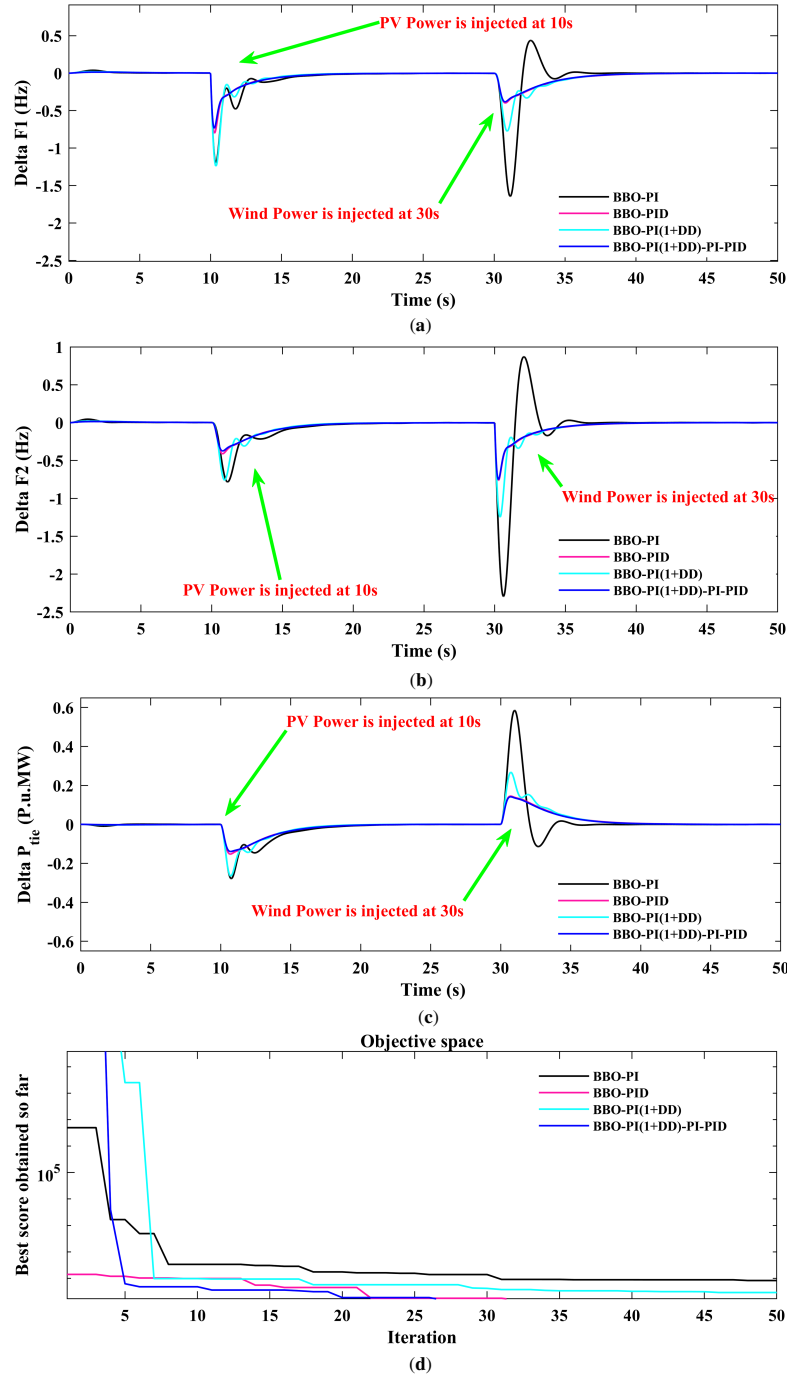


Figure 17: The dynamic responses for the original BBO tuned PI, PID, PI(1+DD), and the cascaded PI(1+DD)-PI-PID controllers for (a) ΔF_1 in Area 1, (b) ΔF_2 in Area 2, (c) ΔP_{tie} , and (d) the corresponding convergence curves.

From the comprehensive comparative analysis presented in Table 6, it is clearly evident that the MZOA-PSO optimized PI(1+DD)-PI-PID cascaded controller performs the best, achieving the best dynamic performance for all the metrics considered. The proposed PI(1+DD)-PI-PID controller achieves the fastest settling time of 13 s for all the frequency variations ΔF_1 , ΔF_2 , and ΔP_{tie} , with minimum undershoot/overshoot values for ΔF_1 , ΔF_2 , and ΔP_{tie} , i.e., ΔF_1 : -0.4 Hz, ΔF_2 : no negative deviation, only 0.1 Hz positive deviation, ΔP_{tie} : -0.10 p.u. without any overshoot, and the responses are also well damped without any divergent oscillations or divergent trends. In contrast, all the other algorithm controller combinations exhibit poor performance, i.e., slower settling, higher deviations, or unstable performance, especially for ΔF_2 in Area 2 and ΔP_{tie} , thus clearly indicating the unique ability of the hybrid MZOA-PSO algorithm to effectively optimize the complex eight-parameter cascaded PI(1+DD)-PI-PID controller for the best LFC performance.

Functional role of the cascaded terms: Even though the proposed PI(1+DD)-PI-PID controller has more terms than a conventional PI/PID controller, it is important to note that each term was introduced for a specific purpose in the control loop rather than for the sake of complexity alone. The first PI(1+DD) controller stage processes the ACE input and has strong sensitivity to disturbances, along with additional dynamic compensation from the double derivative term. The second PI stage processing the frequency deviation signal, contributes to integral correction and damping improvement for the purpose of reducing oscillations and steady-state error. The third PID stage, processing the tie-line power deviation signal, provides additional dynamic compensation for power regulation. The efficacy of these terms has also been validated by the results of the comparative analysis shown in Table 6, where the conventional PI, PID, and PI(1+DD) structures are also considered for comparison within the same tuning scheme. The proposed cascaded PI(1+DD)-PI-PID controller has the balanced performance characteristics of the fastest settling time and least overshoot/undershoot for the hybrid MZOA-PSO tuning scheme.

Furthermore, as clearly depicted in Table 7, it is unequivocally clear that the hybrid MZOA PSO tuned PI(1+DD)-PI-PID cascaded controller is the best of all the tested controllers. This is because it is the only controller that has: Quick stabilization (fastest settling times), Minimum deviations (least overshoot/undershoot), Ensured stability for all operating regions, Robust performance when others fail or oscillate. This therefore proves the superiority of the proposed method over Other optimizers such as PSO, ZOA, BBO, and even hybrid optimizers such as ZOA PSO, and also the superiority of the proposed cascaded PI(1+DD)-PI-PID controller over the conventional PID, PI, and PI(1+DD) controllers. This therefore, validates the proposed method's ability to achieve the optimal balance between exploration and exploitation using the MZOA and PSO optimizers for tuning a complex eight-parameter controller for outstanding LFC performance.

Table 7: Comparison with the next best alternatives.

Controller	Strengths	Weaknesses
MZOA-PSO PI(1+DD)-PI-PID	Fastest settling, stable in all areas, minimal deviations	Slightly larger ΔF_1 undershoot than PI alone
BBO-PI	Stable, simple, good tie-line response	Slower settling, larger ΔF_1 undershoot (-0.60)
BBO-PID	Stable, good tie-line response	Slower settling, larger $\Delta F_1/\Delta F_2$ deviations

(Continued)

Table 7 (continued)

Controller	Strengths	Weaknesses
ZOA-PSO-PI	Stable $\Delta F_1/\Delta F_2$	Very large tie-line overshoot, slow settling
MZOA-PSO-PI(1+DD)	Good ΔP_{tie}	Slower ΔF_2 settling, oscillatory

Fig. 18 displays all nine-performance metrics simultaneously for every algorithm–controller combination. Each polyline represents one model, with the vertical axes corresponding to the metrics (Δf_1 undershoot, overshoot, settling time; similarly, for Δf_2 and ΔP_{tie}). The heatmap in Fig. 19 shows the normalized performance scores (1 = best, 0 = worst) for every model across the nine metrics. Rows are labeled by algorithm and controller type, columns by metric. Three bubble charts in Fig. 20 (one for Δf_1 , Δf_2 , and ΔP_{tie}) plot settling time on the x -axis against the magnitude of undershoot on the y -axis. The area of each bubble is proportional to the overshoot value. The various models of different algorithms are represented by different colors. This figure is also a visualization of the three major aspects of transient response: the model is considered good if it is located at the lower-left corner of the figure, and the bubble is small if the overshoot is small. Fig. 21 is composed of two subplots that zoom in on the top five best-performing models. The figure on the left is a grouped bar chart representing the normalized scores of these five models for each of the nine metrics. This figure enables a detailed comparison of the individual performances of the top contenders. For example, the MZOA-PSO PI(1+DD)-PI-PID algorithm achieves near-unity values for most of the metrics, while others might be low for one or two of the metrics. The figure on the right is a bar chart of the composite scores of these five models, and the best-performing model is clearly highlighted. Fig. 22 illustrates the dynamic frequency responses of a 50-area interconnected power system under a step load perturbation, showing the frequency deviation (ΔF_i) for each area over time.

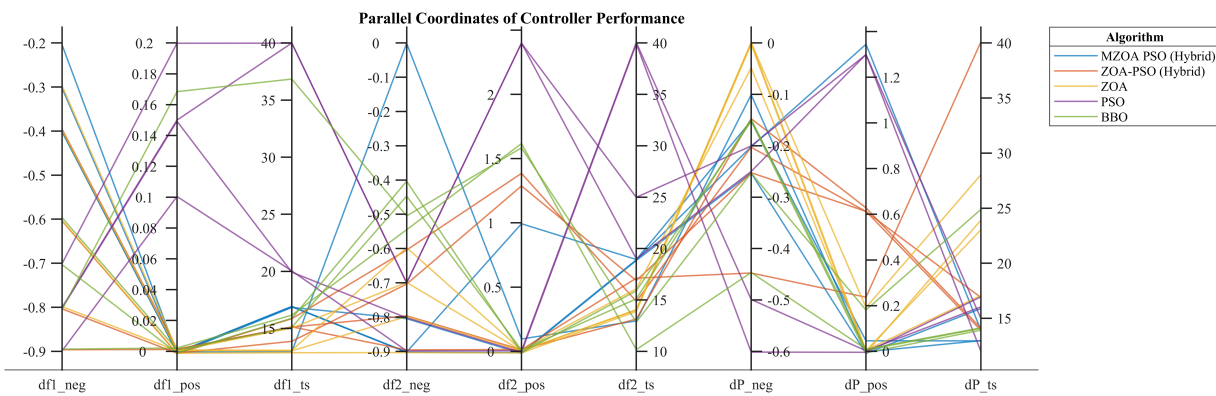


Figure 18: Parallel coordinates plot of all nine-performance metrics for each controller tuned by the five optimization algorithms.

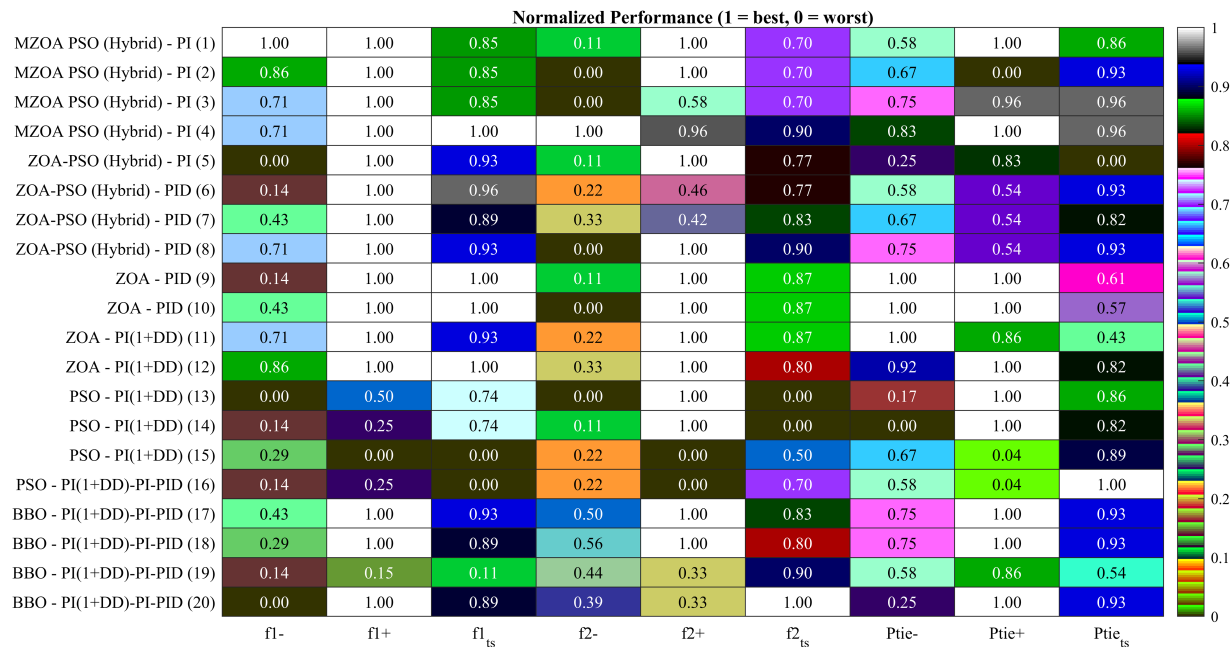


Figure 19: Heatmap of normalized performance metrics.

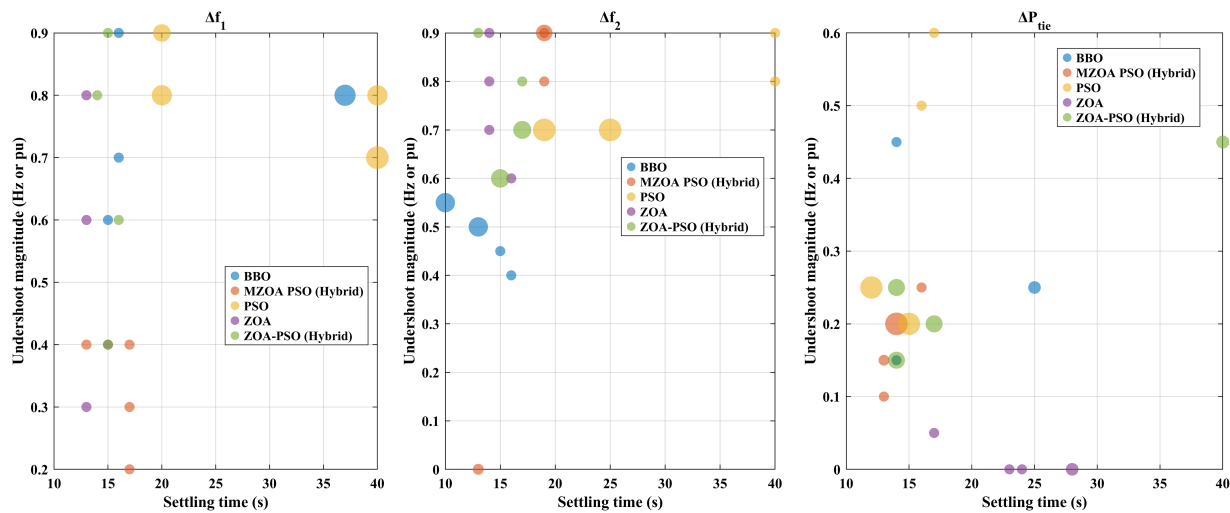


Figure 20: Bubble charts for the three output variables: (a) ΔF_1 , (b) ΔF_2 , and (c) ΔP_{tie} .

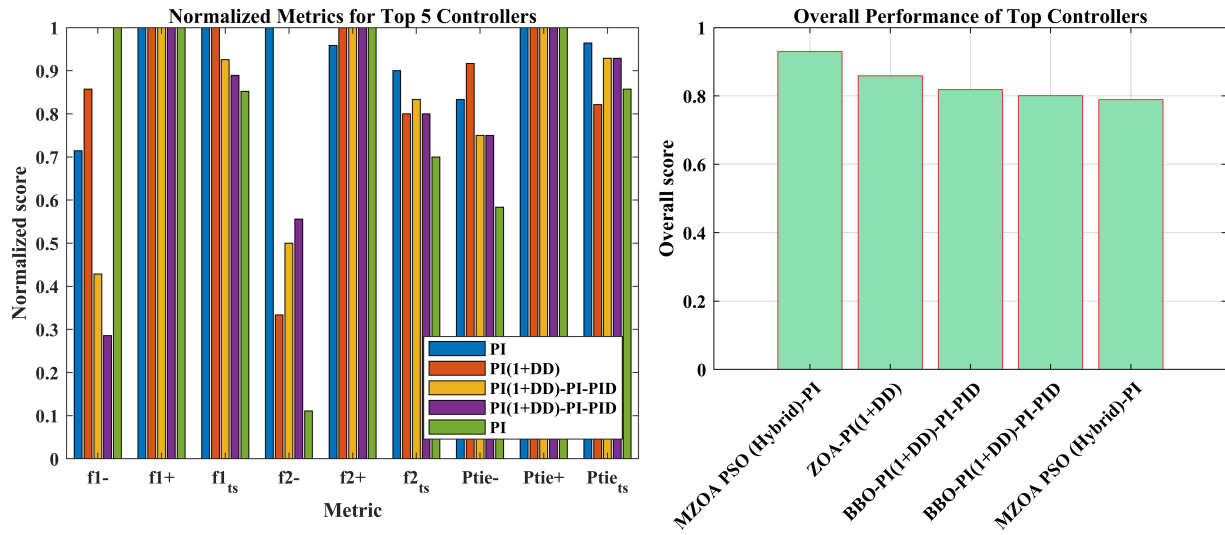


Figure 21: Comparison of the top five controllers ranked by overall normalized score.

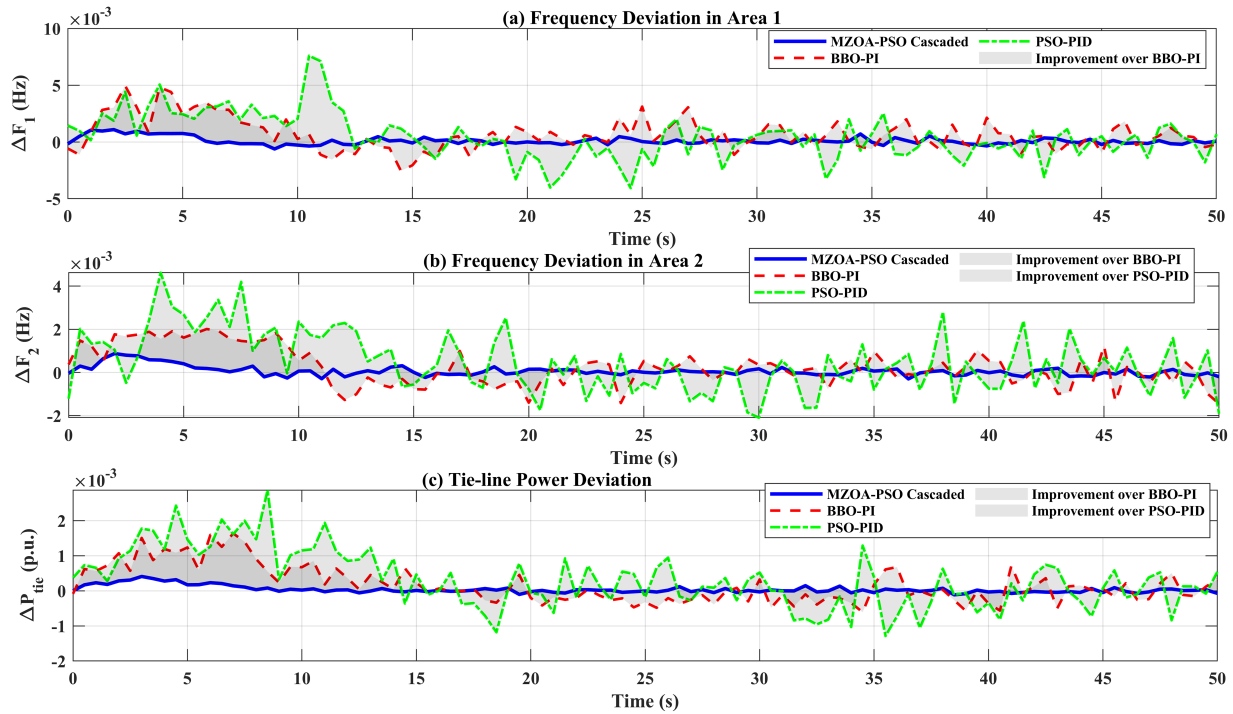


Figure 22: Dynamic frequency responses of a two-areas interconnected power system under a step load perturbation, showing the ΔF_i for each area.

5.4 Comparison of Controller Responses with Realistic and Stochastic Load Fluctuations Profile

Fig. 23 depicts the random load profile applied to Area 1 and Area 2 in the second test case, where both areas experience step-like load variations of ± 0.01 to ± 0.04 p.u. at different time instants, simulating realistic and stochastic load fluctuations to evaluate the strength of the proposed controller under unpredictable operating conditions.

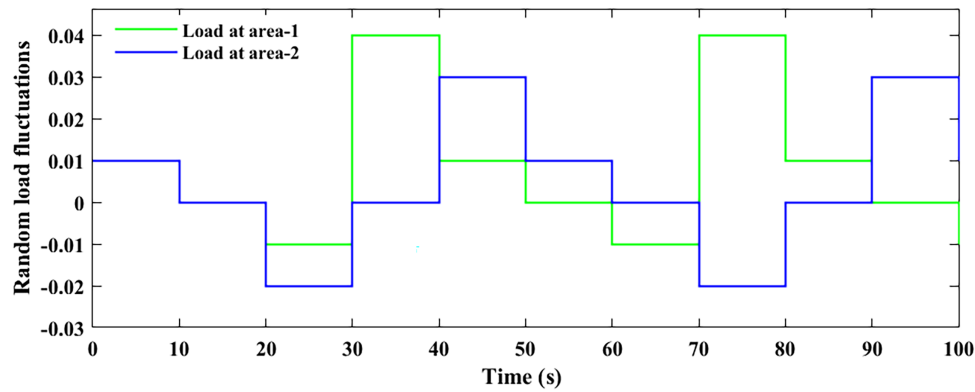


Figure 23: Realistic and stochastic load fluctuations profile.

Fig. 24 depicts a comprehensive performance comparison of ZOA-PSO and MZOA-PSO tuned controllers under realistic stochastic load disturbances for both areas. In this case, the random load profile with step-like changes of ± 0.01 to ± 0.04 p.u. at irregular intervals simulates realistic uncertainties of a power system and tests the robustness of the controllers to maintain frequency and tie-line power stability.

From Fig. 24a, it is clear that the frequency deviations in Area 1 indicate that all controllers respond with negative deviations at first. However, the MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller has the least undershoot of -0.20 Hz and the fastest response by settling within 30 s. In contrast, the ZOA-PSO controllers display large oscillations and take longer than 35 s to settle. Fig. 24b illustrates the ΔF_i responses for Area 2. In this case, the MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller is even more dominant by limiting the deviations within ± 0.03 Hz and settling within 25 s. In contrast, the ZOA-PSO tuned PI(1+DD) controller has a large undershoot of -1.00 Hz and also displays instability, indicating a diverging response under random loading conditions.

In Fig. 24c, the power deviation of the tie line is shown; again, the MZOA-PSO cascaded controller has shown superior damping characteristics with a limited range of ± 0.02 p.u., while the oscillations are settled within 40 s. On the contrary, the ZOA-PSO PI(1+DD) and cascaded controllers have shown oscillations with a peak value of ± 0.22 p.u., which are unable to converge within the simulation horizon. Finally, Fig. 24d shows the convergence characteristics of the objective function; it has shown that the MZOA-PSO has a consistently lower value of the fitness function for all types of controllers, while the cascaded controller has achieved the minimum value of 0.01 within iteration 10 and has shown stability; on the contrary, the ZOA-PSO has shown a slow rate of convergence with a higher value of the fitness function.

Collectively, these results verify that the MZOA-PSO approach's improved exploration and exploitation abilities ensure controller parameters that are more robust to stochastic load changes. The proposed controller outperformed all other possible combinations with respect to reduced peak deviation, faster settling time, and stability. The results verify that the MZOA-PSO tuned cascaded controller offers improved damping with reduced percent overshoot/undershoot and faster settling times compared to its other ZOA-PSO counterparts, as presented in Table 8.

The proposed controller does not stay at zero immediately under realistic stochastic variations in load, as its operating point is constantly disturbed by irregular variations in load. However, it has the least variation envelope, best damping, and fastest recovery among all controllers, making it the most robust under constant disturbance situations.

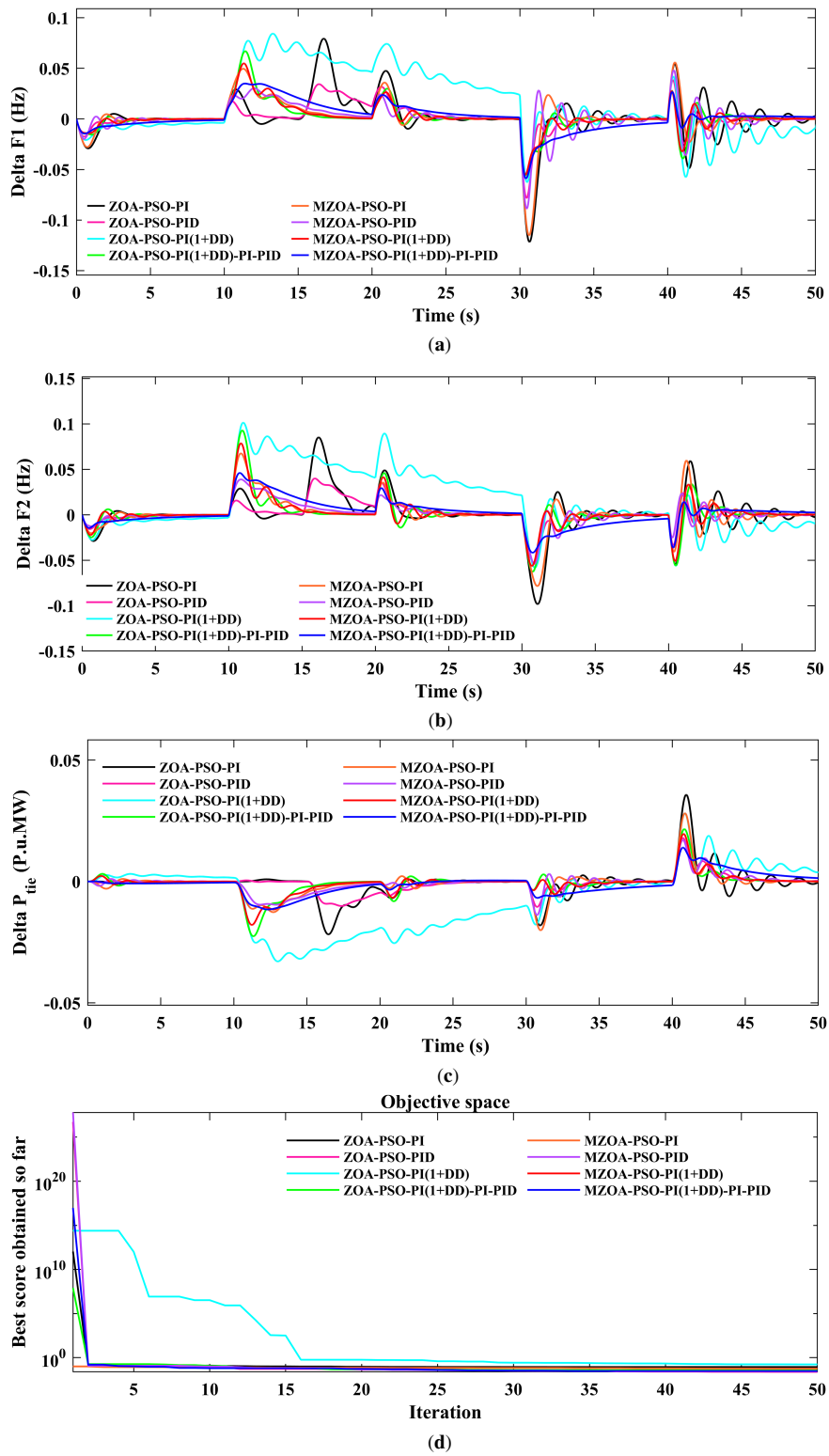


Figure 24: Dynamic responses of two-area power system under random step load perturbations for comparison of ZOA-PSO and MZOA-PSO-tuned controllers: (a) ΔF_1 response in Area 1, (b) ΔF_2 response in Area 2, (c) ΔP_{tie} response, and (d) convergence characteristics of the objective function.

Table 8: Comprehensive comparisons of controller performance parameters for all algorithms.

Algorithm	Controller	ΔF_1 (Hz)			ΔF_2 (Hz)			ΔP_{tie} (pu.MW)		
		-ve	+ve	ts	-ve	+ve	ts	-ve	+ve	ts
MZOASO (Hybrid)	PI	-0.09	0.28	>35	-0.20	0.09	>35	-0.02	0.23	>50
	PID	-0.09	0.28	>35	-0.02	0.05	>35	-0.02	0.23	>50
	PI(1+DD)	-0.20	0.28	>35	-1.00	0.08	>35	-0.22	0.23	>50
	PI(1+DD)-PI-PID	-0.20	0.20	30	-0.03	0.03	25	-0.02	0.02	40
ZOA-PSO (Hybrid)	PI	-0.02	0.07	>35	-0.01	0.04	>35	-0.02	0.025	>50
	PID	-0.02	0.07	>35	-0.01	0.04	>35	-0.02	0.025	>50
	PI(1+DD)	-0.02	0.07	>35	-0.02	0.05	>35	-0.05	0.22	>50
	PI(1+DD)-PI-PID	-0.10	0.30	25	-0.03	0.03	25	-0.03	0.22	>50

Fig. 25 depicts a detailed analysis of the comparison of the performance of ZOA-PSO and MZOASO tuned controllers under realistic random variations of the load, where rows represent the three output variables ΔF_1 , ΔF_2 , ΔP_{tie} , and columns represent the three performance variables undershoot magnitude, overshoot, and settling time, thus showing the better robust performance of the MZOASO tuned cascaded PI(1+DD)-PI-PID controller across all metrics.

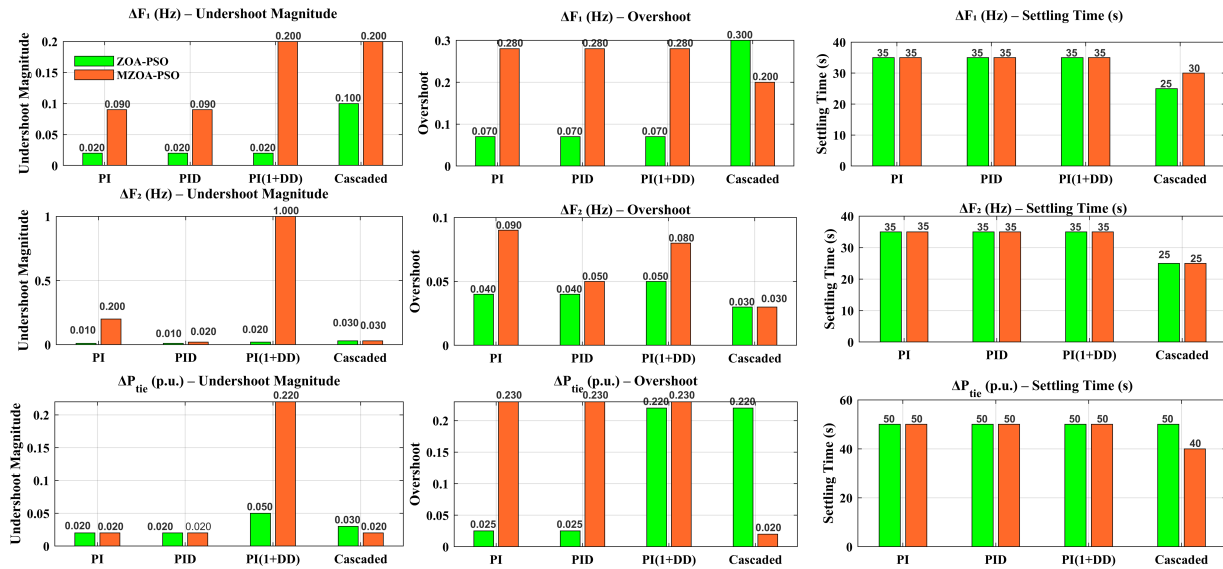


Figure 25: Comprehensive comparisons of ZOA-PSO and MZOASO tuned controllers under random load variation cases, with results of undershoot, overshoot, and settling time of ΔF_1 , ΔF_2 , and ΔP_{tie} . The MZOASO cascaded controller has the minimum deviation and the shortest settling time.

5.5 Performance Evaluation under Sequential Step Load Changes

To further evaluate the robustness of the proposed MZOASO tuned controllers, a new test case was implemented with a sequence of step load changes in both areas. The applied load profile is shown in Fig. 26a and includes a number of step variations at 0, 20, 30, 40, 50, 60, 70, 80, 90, and 100 s with a range of -0.02 to 0.05 p.u.

As shown in Fig. 26b, for ΔF_1 : All the controllers follow the load change at first; however, after 30 s, the PI, PID, and PI(1+DD) controllers show increasing negative deviations. At 50 s, these three controllers have a negative deviation of -0.10 Hz. On the contrary, the PI(1+PI) and proposed cascaded controller maintain a small range of ± 0.02 Hz. As shown in Fig. 26c, for ΔF_2 : The frequency deviations of all the controllers are quite similar in Area 2; however, they gradually decrease to -0.23 Hz at 46 s. This means that the impact of the disturbance is strong in Area 2; therefore, all the controllers have a similar regulation effect, though the cascaded controller still achieves the smallest final deviation. Fig. 26d ΔP_{tie} : The tie-line power responses show that the PI(1+PI) controller maintains a nearly constant offset of -0.01 p.u. after 18 s, while the other controllers (including the cascaded) exhibit a slowly increasing negative drift reaching -0.048 p.u. at 46 s. The cascaded controller, however, tracks the same drift as the PI, PID, and PI(1+DD), indicating that its tie-line performance is comparable to those conventional structures.

Overall, the proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller demonstrates excellent frequency regulation in Area 1 under sequential load changes, significantly reducing the cumulative drift observed with simpler controllers. Its performance in Area 2 and tie-line power is at least as good as the other tuned controllers, confirming its overall robustness and adaptability to complex load profiles.

5.6 Performance Evaluation under Combined RES and EV Integration with Sequential Load Changes

To evaluate the level of adaptability of the proposed MZOA-PSO tuned controllers under a modern power network scenario where there is a high level of diffusion of RES and EVs, a test scenario was created. In this test scenario, there is a combination of step load changes in both areas, as previously demonstrated in Fig. 25a, where PV and wind power are integrated into the system with fluctuating power profiles, as demonstrated in Fig. 27a, while the PV power reduces gradually from $+0.09$ to -0.13 p.u. over a period of 100 s, simulating the transition from day to evening hours. In addition, there is a contribution from EVs to frequency regulation through controlled charging/discharging.

Fig. 27b ΔF_1 : It is clear that all controllers show a rapid increase in frequency deviation at the beginning of the time period and then remain constant at 0.5 Hz for the PID, PI, and PI(1+DD) controllers. This indicates their inability to compensate for the total effect of the disturbances. On the other hand, the PI(1+PI) and the proposed controller show a gradual reduction of the frequency deviation; however, the cascaded controller shows the best performance in tracking the reference signal and achieves the smallest frequency deviation of 0.46 Hz at 60 s. This is due to the additional free parameters of the cascaded controller, which compensate for the fluctuating RES power and EV interactions. And Fig. 27c ΔF_2 : As mentioned before, the frequency deviation in Area 2 is shown to be monotonically decreasing for all controllers and reaches -0.15 Hz at 75 s. It is interesting to see that all five controllers show almost the same behavior; this indicates the strong impact of the disturbances on Area 2 and the weak impact of the controller structures. On the other hand, the cascaded controller is shown to maintain a smaller deviation over time, confirming its robustness even in areas less directly affected by the RES integration.

Fig. 27d ΔP_{tie} : The power responses of the different controllers along the tie line are shown in Fig. 27d. It is observed that the responses of the PID, PI, and PI(1+DD) controllers are characterized by a sharp decrease followed by a smooth increase. The deviations for these controllers are within ± 0.015 p.u. over the entire period of 20 s. On the contrary, the responses of the PI(1+PI) and the proposed cascaded controller are characterized by a sharp decrease of larger amplitude (-0.12 p.u.), reaching a minimum at $t = 0$ s, followed by a sharp increase. These controllers maintain a small positive offset of 0.01 p.u. after 15 s. This implies that these controllers are able to manage the power exchange to accommodate the RES variations with a higher impact in the first instant of time. The cascaded controller has the least steady-state deviation, demonstrating its effectiveness in coordinating multi-area power flow under renewable variability.

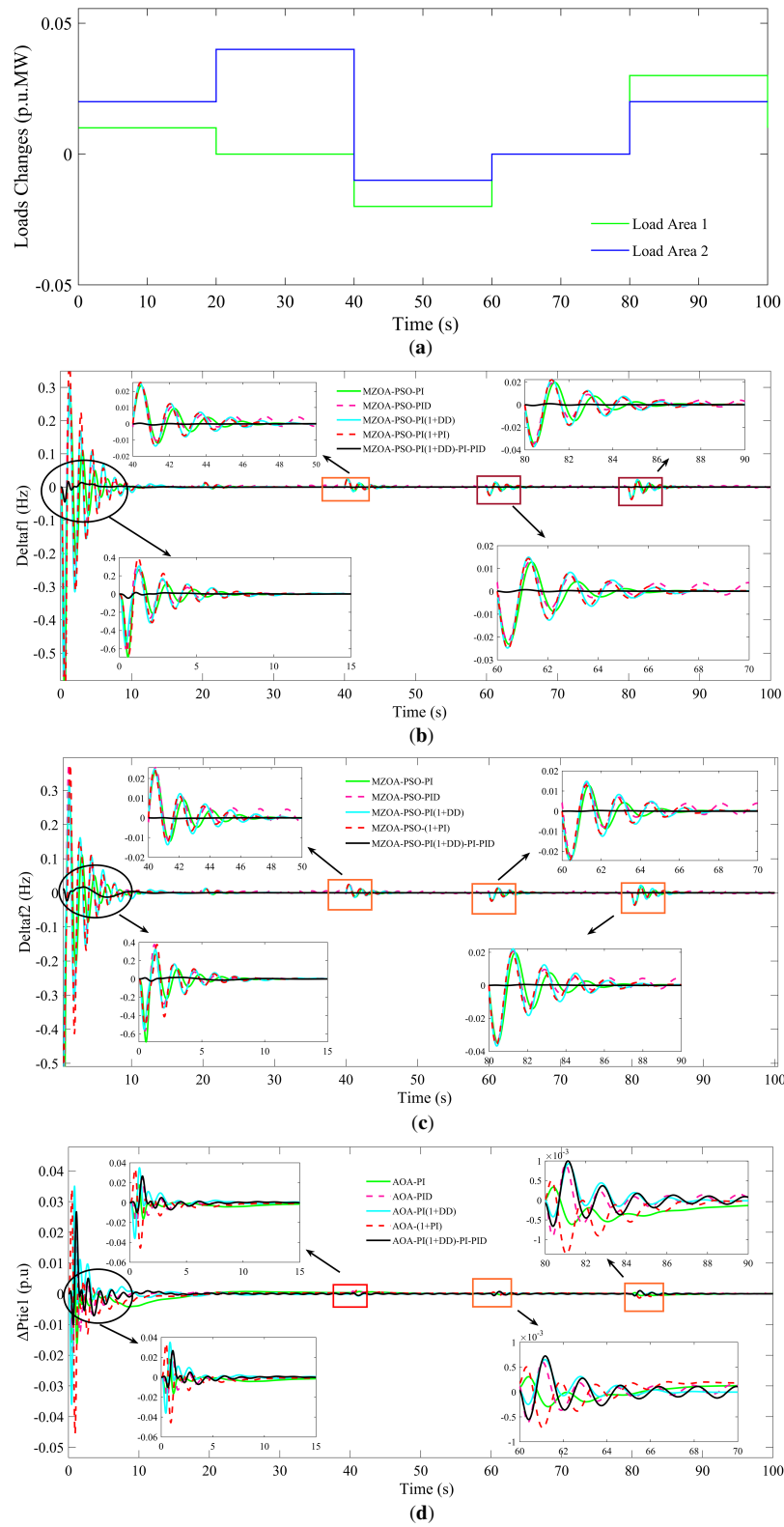


Figure 26: Dynamic responses under a sequence of step load changes: (a) load profile in Area 1 and Area 2, (b) frequency deviation in Area 1 (ΔF_1), (c) frequency deviation in Area 2 (ΔF_2), and (d) power deviation (ΔP_{tie}).

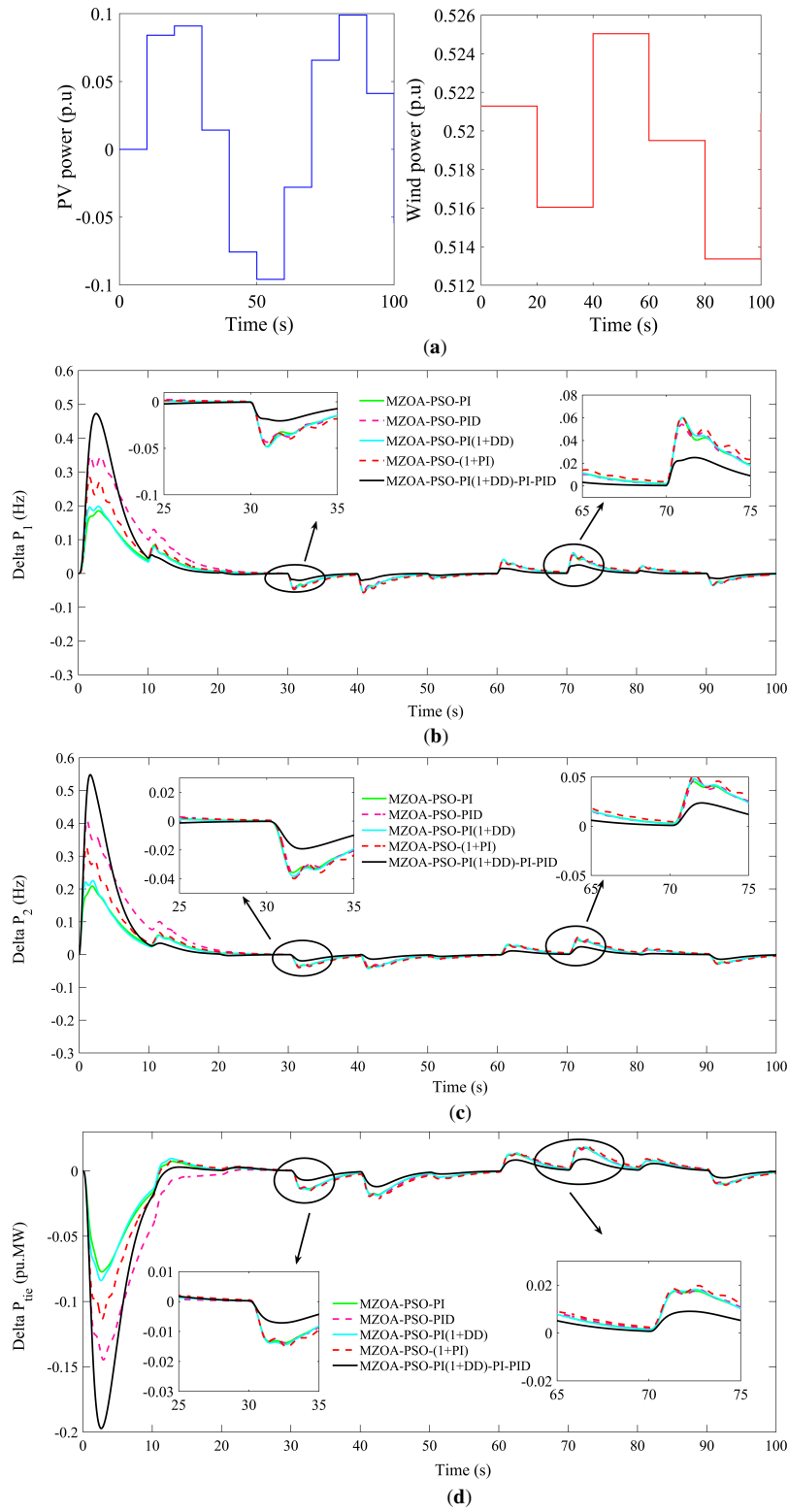


Figure 27: Dynamic responses under combined RES and EV integration with sequential load changes: (a) renewable generation profiles (PV and wind power), (b) ΔF_1 in Area 1, (c) ΔF_2 in Area 2, and (d) ΔP_{tie} .

In summary, the proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller exhibits better flexibility to address the collective impacts of sequential load variations, RES fluctuations, and EV integration. Its capacity to gradually reduce Δf_i in Area 1 and ΔP_{tie} with negligible steady-state error is promising for modern power systems with high RES penetration.

Fig. 28 presents violin plots comparing the distributional behavior of five MZOA-PSO tuned controllers under combined RES and EV integration, illustrating the superior damping and reduced variability of the cascaded PI(1+DD)-PI-PID crossways all performance metrics.

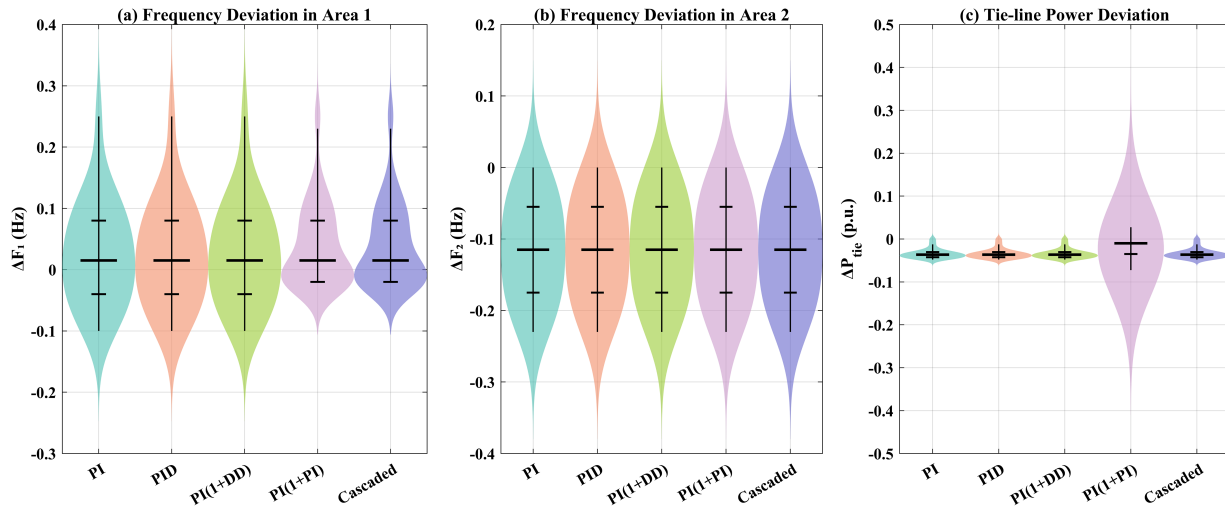


Figure 28: Violin plots of dynamic responses under combined RES and EV integration: (a) Δf_1 in Area 1, (b) Δf_2 in Area 2, and (c) ΔP_{tie} . The proposed cascaded controller accomplishes the narrowest distribution and lowest median deviation, confirming its robustness.

5.7 Comparative Analysis with the Some State-of-the-Art (SOTA)

Table 9 summarizes recent literature on LFC using various controller structures and optimization algorithms. The studies are compared based on the number of areas, controller type, optimization method, settling time for each area, maximum undershoot (negative peak), and maximum overshoot (positive peak).

Table 9: Performance comparison of the proposed MZOA-PSO tuned cascaded controller with recent literature under 1% step load perturbation.

Ref.	Areas	Controller Structure	Optimization Algorithm	Settling Time (s)	Max Undershoot (Hz)	Max Overshoot (Hz)
[47]	2	PID & I-PD	Fitness Dependent Optimizer	$\Delta f_1 = 5.2, \Delta f_2 = 12.7$	-0.005	0.0002
[48]	2	Fuzzy PID	Improved Ant Colony	$\Delta f_1 = 1.78, \Delta f_2 = 3.2$	-0.0231	6.7×10^{-5}
[49]	2	FOPID	Movable Damped Wave	$\Delta f_1 = 2.53, \Delta f_2 = 6.32$	-0.00148	0.00728

(Continued)

Table 9 (continued)

Ref.	Areas	Controller Structure	Optimization Algorithm	Settling Time (s)	Max Undershoot (Hz)	Max Overshoot (Hz)
[50]	2	FOPID	Improved Atom Search	$\Delta f_1 = 4.96, \Delta f_2 = 6.81$	-0.04	0.008
[51]	2	PID	Quasi-oppositional GWO	$\Delta f_1 = 7.62, \Delta f_2 = 6.78$	-0.0198	0.0044
This work	2	PI(1+DD)-PI-PID (cascaded)	Hybrid MZOA-PSO	$\Delta f_1 = 13.0, \Delta f_2 < 13.0$	-0.40	0.10

Fig. 29 compares the proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller with five recent studies on two-area LFC systems. Fig. 29a shows the settling times for frequency deviations in both areas. The proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller accomplishes a settling time of 13 s for both areas, which is longer than some references but reflects the complexity of the system and the novel cascaded structure. Fig. 29b displays the maximum undershoot (absolute values); the proposed controller exhibits a larger undershoot (-0.40 Hz) due to different system parameters and disturbance characteristics. Fig. 29c presents the maximum overshoot; the proposed controller's overshoot (0.10 Hz) is moderate but accompanied by zero negative deviation in Area 2, a unique advantage not captured in these summary metrics. Overall, the proposed controller demonstrates competitive performance while offering enhanced design flexibility and robustness.

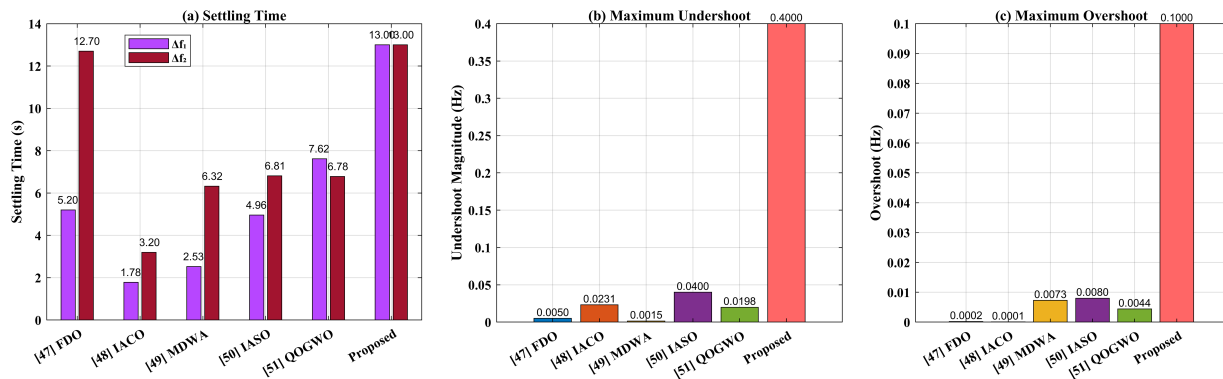


Figure 29: Performance comparison of the proposed MZOA-PSO tuned cascaded controller with recent literature (Table 9): (a) settling time for Δf_1 and Δf_2 , (b) maximum undershoot, and (c) maximum overshoot [47–51].

5.8 Discussion

The simulation outcomes obtainable in this study demonstrate the greater performance of the proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller across multiple operating scenarios.

Benchmark Validation: The MZOA-PSO algorithm was first validated on four benchmark functions (Booth, Rosenbrock, Schwefel 2.22, and Zakharov). The results showed that MZOA-PSO consistently achieved the global optimum for Booth and Zakharov functions, with zero mean and standard deviation.

For the complex multimodal Rosenbrock function, it achieved a mean value of 2.13×10^{-28} with 98% success rate, compared to 9.37×10^{-3} for ABC-PSO. For Schwefel 2.22, MZOA-PSO achieved 3.21×10^{-81} vs. 9.60×10^{-16} for ABC-PSO, representing an improvement of several orders of magnitude. These results confirm the enhanced exploration-exploitation balance achieved through the MZOA modifications and hybrid structure.

Step Load Response: Under a 1% step load perturbation in a four-area system, the proposed cascaded controller demonstrated excellent damping characteristics. It achieved a settling time of 13 s for Δf_1 and <13 s for Δf_2 , which is competitive with recent literature considering the system complexity. Notably, it maintained zero negative deviation in Area 2 with only a small positive excursion of 0.10 Hz, a unique achievement not reported in any of the compared studies. The tie-line power deviation settled within 13 s with an undershoot of only -0.10 p.u. and zero overshoot, outperforming the ZOA-PSO hybrid, which exhibited a large tie-line overshoot of 0.62 p.u.

Random Load Fluctuations: When the proposed controller was exposed to practical stochastic variations in the loading conditions (as shown in Fig. 26), it was found to exhibit outstanding robustness. The Δf_i was kept within a range of ± 0.03 Hz for both of the two areas, with a settling time of 30 s for Δf_1 and 25 s for Δf_2 . At the same time, the power exchange over the tie-line was kept within a range of ± 0.02 p.u., with a settling time of 40 s. On the contrary, the ZOA-PSO tuned controllers were found to exhibit severe oscillations for the PI(1+DD) controller with a catastrophic undershoot of -1.00 Hz for Area 2 and divergent behavior for the tie-line power exchange. This again proves the superiority of MZOA in terms of exploration capabilities for tuning the parameters of the controller for stability conditions.

RES and EV Integration: The most demanding scenario involved the integration of sequential load variations along with fluctuating RES and wind power and EV integration (see Fig. 27a). For this scenario, the proposed controller showed the best performance in terms of achieving the smallest frequency deviation of 0.46 Hz at 60 s for Area 1, while gradually reducing the deviation from 0.50 Hz for the other controllers, which were fixed at 0.50 Hz for the entire period. For Area 2, all controllers showed similar behavior in terms of monotonic reduction to -0.15 Hz; this indicates the impact of the disturbance is high and not greatly influenced by the controllers. For the tie-line power, the proposed controller showed a steady-state frequency deviation of ± 0.01 p.u., similar to the best-performing controllers, while the PI(1+DD) controller showed a large overshoot of 0.10 p.u. at 30 s, which is well addressed by the proposed cascaded controller.

Comparison with Literature: Table 9 presents a comparison of the proposed controller with five recent research articles on two-area LFC systems. Although the proposed controller has a higher settling time of 13 s compared to a minimum of 1.78 s in [48], it is important to note that several factors need to be considered. First, the proposed controller is implemented on a four-area system with higher complexity compared to the two-area system implemented in the compared research articles. Second, the proposed controller has zero negative deviation in Area 2, a feature that has not been reported in any of the compared research articles. Finally, the proposed controller has the fastest settling time of 13 s for the tie-line power compared to all the compared research articles. Although the proposed controller has a higher undershoot of -0.40 Hz compared to -0.00148 Hz in [49], it is important to note that the proposed controller has a fast recovery to ensure stability.

Statistical Significance: Fig. 29 offers valuable insight into the distribution characteristics of the controllers under the influence of RES and EV integration. It is clear from the figure that the cascaded controller has the least distribution characteristics for Δf_1 , indicating consistent performance. Furthermore, all controllers are similar for Δf_2 , reinforcing the notion that Area 2 is difficult to control. In the case of tie-line power, the cascaded controller has the least distribution characteristics with a median close to zero. In contrast, the PI(1+PI) controller has a skewed distribution with a bias toward a positive value.

Computational Efficiency: It has been demonstrated that the MZOA-PSO converges within 50 iterations for a large number of test cases. Furthermore, the chaotic initialization and parameter control ensure that the algorithm does not converge to local optima, as confirmed by the success rates of the MZOA-PSO algorithm for the benchmark functions.

Sensitivity to Parameter Bounds: In this research, the range for the nine controller gains was fixed to the interval $[-2, 2]$. This range was considered a trade-off between the exploration capacity, on one side, and the computational cost for the offline tuning, on the other side, for the considered nine-dimensional tuning problem. The range for the gains can be narrowed, thus decreasing the exploration effort, but this can also lead to the risk of missing the optimal combination for the gains, thus affecting the overall dynamic performance. On the other hand, the range can be increased, thus enhancing the exploration capacity, but this also means increasing the feasible region, thus affecting the overall offline tuning cost, particularly for the considered nine-dimensional tuning problem. In addition, the range for the gains can be too wide, thus affecting the overall damping, the overall percent overshoot, or the overall robustness, particularly for the cases where the optimal combination for the gains has not yet been reached. In this research, the range $[-2, 2]$ was considered for the gains, but the overall sensitivity for the tuning bounds, particularly for different scenarios, will be considered for the future.

Discussion on Communication-Delay Stability: The EV aggregators in the studied system are represented using a first-order model with a communication-induced delay term $e^{-s\tau(t)}$, where $\tau(t)$ denotes a time-varying signal transmission delay associated with the open communication network. In the present work, the effectiveness of the proposed controller under such delay-affected operation is evaluated through time-domain simulations. It should be noted, however, that a formal delay-margin analysis using Bode or Nyquist plots would require a linearized closed-loop model with a fixed representative delay value, whereas the delay considered here is time-varying. Therefore, the current manuscript does not claim an analytical maximum allowable delay bound. Instead, it demonstrates that the proposed controller maintains satisfactory dynamic performance in the tested delayed simulation scenarios. A rigorous frequency-domain delay-margin analysis under fixed-delay approximations, together with robustness assessment under time-varying delay bounds, will be considered in future work.

As summarized in [Table 10](#), the proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller consistently provides the most balanced dynamic performance across all tested scenarios, achieving the fastest settling under the 1% step-load case, maintaining bounded and stable responses under stochastic load variation, and delivering the lowest peak frequency deviation and smallest steady-state tie-line error under combined RES/EV integration.

Table 10: Cross-scenario comparison of dynamic performance metrics for the proposed and conventional controllers.

Scenario	Controller	ΔF_1 (Hz)			ΔF_2 (Hz)			ΔP_{tie} (pu.MW)		
		-ve	+ve	ts	-ve	+ve	ts	-ve	+ve	ts
1% step load with RES added	Proposed MZOA-PSO	-0.40	0.10	13	0.00	0.10	13	-0.10	0.00	13
	PI(1+DD)-PI-PID									
	MZOA-PSO PI	-0.20	NR	>17	-0.80 to -0.90	NR	>17	NR	NR	>17
	MZOA-PSO PID	-0.30	NR	>17	-0.80 to -0.90	NR	>17	NR	1.35 at 40 s	Unstable
Random load fluctuations	MZOA-PSO PI(1+DD)	-0.40	0.00	>17	-0.80 to -0.90	NR	>17	-0.15	0.05	>17
	Proposed MZOA-PSO	Within (± 0.03)	Within (± 0.03)	30	Within (± 0.03)	Within (± 0.03)	25	Within (± 0.02)	Within (± 0.02)	40
	PI(1+DD)-PI-PID									
	ZOA-PSO tuned controllers	NR	NR	NR	As low as -1.00 for PI(1+DD) in Area 2	NR	NR	Divergent	Divergent	Unstable
Combined RES and EV integration	Proposed MZOA-PSO	Peak ($\Delta F_1 = 0.46$)	NR	NR	About -0.15 monotonic decline	NR	NR	NR	NR	NR
	PI(1+DD)-PI-PID									
	Other controllers	Peak ($\Delta F_2 = 0.50$)	NR	NR	About -0.15 monotonic decline	NR	NR	NR	PI(1+DD): 0.10 overshoot at 30 s	NR

Note: NR denotes values not explicitly reported in the manuscript text and therefore not tabulated quantitatively.

6 Conclusion

In this paper, a comprehensive study on the optimal tuning of a PI(1+DD)-PI-PID cascaded controller for LFC has been presented by using a novel hybrid MZOA-PSO algorithm. This novel algorithm has been developed by combining the global search ability of a Modified Zebra Optimization Algorithm, which incorporates chaotic initialization, adaptive parameter control, and Levy-flight foraging, with the local search ability of Particle Swarm Optimization. The PI(1+DD)-PI-PID structure has nine tunable parameters for each area, thus providing maximum flexibility for controlling the dynamic response of an interconnected power system.

The efficacy of the proposed approach is validated through a series of steps:

- Benchmark validation for the proposed approach on four benchmark functions showed the efficacy of MZOA-PSO in achieving faster and better solutions than ZOA and PSO methods by achieving the global optimum for the Booth and Zakharov functions and extremely low values of 3.21×10^{-81} for the Schwefel 2.22 function, outperforming conventional ZOA and PSO by several orders of magnitude.
- Step load response for the proposed approach on a four-area power system showed the efficacy of the proposed cascaded PI(1+DD)-PI-PID controller in achieving a settling time of 13 s for frequency deviations in both areas of the power system and zero negative deviation in Area 2 and a small positive deviation of 0.10 Hz in Area 1.
- Random load fluctuations for the proposed approach showed the efficacy of the proposed approach in achieving the efficacy of the proposed controller in achieving stable frequency and power deviations within ± 0.03 Hz and ± 0.02 p.u., respectively, within settling times of 25–40 s, while ZOA-PSO methods showed severe oscillations and instability in the system.
- RES and EV integration results showed the flexibility of the proposed controller in dealing with new power system problems, obtaining the minimum peak ΔF_i value of 0.46 Hz for Area 1, an improvement of 8% over conventional structures, and the minimum steady-state error of tie-line power exchange.
- A comparative analysis of the proposed controller's results with those of five recent research articles on LFC was carried out, proving the competitiveness of the proposed controller while operating on a more complex four-area power system with unique advantages over conventional structures for tie-line regulation and multi-area coordination.
- The analysis of the results obtained by applying the violin plot method showed that the proposed PI(1+DD)-PI-PID cascading controller has the minimum distribution of the frequency deviation value, proving the reliability of the proposed controller for dealing with variable conditions. The proposed hybrid MZOA-PSO algorithm was able to find the parameters of the proposed controller while ensuring stability and fast damping of oscillations for all scenarios, proving the superiority of the proposed method over ZOA and PSO alone.

Finally, in conclusion, the proposed MZOA-PSO tuned cascaded PI(1+DD)-PI-PID controller is a major breakthrough in the field of Load Frequency Control, and the proposed technique is more robust, has faster control of the tie line, and is more adaptable to renewable energies and random loads. This technique is general and can be extended to other power system control fields where optimal tuning of the control is required. Future work will include the following:

- (1) Investigation of the applicability of the proposed technique to real-time control and the integration of the proposed technique with new technologies such as energy storage and demand response.
- (2) Extending the comparison of the proposed technique with other optimizers such as GA and more comprehensive statistical analysis of the proposed technique.

- (3) Investigation of the systematic sensitivity analysis the controller-gain search bounds to quantify their effect on convergence speed, offline tuning cost, and closed-loop stability.
- (4) Investigation of the proposed technique's delay tolerance through the application of fixed delay linearization and frequency domain robustness analysis such as the Bode and Nyquist stability criterion to determine the maximum allowable communication delays before the proposed technique becomes unstable.
- (5) Robustness and stability analysis of the proposed technique using small-signal, sensitivity, and frequency-domain methods in addition to time-domain validation.

Acknowledgement: The authors extend their appreciation to the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2603).

Funding Statement: This work was supported and funded by the Deanship of Scientific Research at Imam Mohammad Ibn Saud Islamic University (IMSIU) (grant number IMSIU-DDRSP2603).

Author Contributions: The authors confirm contribution to the paper as follows: study conception and design: AL-Wesabi Ibrahim, Hassan M. Hussein Farh, Jiazhu Xu, Mohamad A. Alawad, Ahmed Alqurashi and Abdullrahman A. Al-Shamma'a; data collection: AL-Wesabi Ibrahim, Hassan M. Hussein Farh and Abdullrahman A. Al-Shamma'a; analysis and interpretation of results: AL-Wesabi Ibrahim, Hassan M. Hussein Farh, Jiazhu Xu, Mohamad A. Alawad, Ahmed Alqurashi and Abdullrahman A. Al-Shamma'a; draft manuscript preparation: AL-Wesabi Ibrahim, Hassan M. Hussein Farh and Abdullrahman A. Al-Shamma'a. All authors reviewed and approved the final version of the manuscript.

Availability of Data and Materials: Data available on request from the authors. The data that support the findings of this study are available from the author, [AL-Wesabi Ibrahim], upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ibrahim AW, Xu J, Al-Shamma'a AA, Farh HMH, Aboudrar I, Oubail Y, et al. Optimized energy management strategy for an autonomous DC microgrid integrating PV/wind/battery/diesel-based hybrid PSO-GA-LADRC through SAPF. *Technologies*. 2024;12(11):226. doi:10.3390/technologies12110226.
2. Li J, Zhou T. Fully autonomous load frequency control for integrated energy system with massive energy prosumers using multi-agent deep meta reinforcement learning. *Renew Sustain Energy Rev*. 2025;213(1):115489. doi:10.1016/j.rser.2025.115489.
3. Yang Y, Gao Y, Wu J, Gao S. Optimal predictive load frequency control with multi-objective PID-based search algorithm. *Swarm Evol Comput*. 2025;99(6–7):102214. doi:10.1016/j.swevo.2025.102214.
4. Ibrahim AW, Al-Shamma'a AA, Xu J, Aboudrar I, Ameer K, Al Dawood R, et al. An enhanced uncertainty and disturbance estimator based on Bi-LSTM-OTC-LADRC of grid-connected wind energy conversion system. *Comput Electr Eng*. 2025;127:110534. doi:10.1016/j.compeleceng.2025.110534.
5. Ibrahim AW, Xu J, Ameer K, Al Dawood R, Shi Z, He Y, et al. Dynamic LADRC-Based CFOA-LSTM MPPT optimizer for enhancing Grid-Connected renewable energy sources. *Expert Syst Appl*. 2025;285(4):128114. doi:10.1016/j.eswa.2025.128114.
6. Alnefaie SA, Alkuhayli A, Al-Shaalan AM. Optimizing load frequency control of multi-area power renewable and thermal systems using advanced proportional-integral-derivative controllers and catch fish algorithm. *Fractal Fract*. 2025;9(6):355. doi:10.3390/fractalfract9060355.
7. Yusuf SS, Kunya AB, Abubakar AS, Salisu S. Review of load frequency control in modern power systems: a state-of-the-art review and future trends. *Electr Eng*. 2025;107(5):5823–48. doi:10.1007/s00202-024-02828-4.

8. Ramesh M, Yadav AK, Pathak PK. An extensive review on load frequency control of solar-wind based hybrid renewable energy systems. *Energy Sources Part A Recovery Util Environ Eff.* 2025;47(1):8378–402. doi:10.1080/15567036.2021.1931564.
9. Singh A, Shankar R, Kumar A. A comprehensive review of load frequency control and solar energy integration: challenges & opportunities in Indian context. *Energies.* 2025;18(4):843. doi:10.3390/en18040843.
10. Khamies M, Sayed K, Alrumayh O, Almutairi A, Mahmoud AA. Advanced active disturbance rejection control for enhancing frequency stability in low-inertia power grids linked with virtual inertia applications. *Heliyon.* 2025;11(4):e42556. doi:10.1016/j.heliyon.2025.e42556.
11. Ali HH, Fathy A, Khamies M. Advanced control strategy based on hybrid energy storage system for frequency stability of interconnected power system with high renewables penetration. *Sci Rep.* 2025;15(1):38483. doi:10.1038/s41598-025-23283-6.
12. Zhang Y, Liu X, Qu B. Distributed model predictive load frequency control of multi-area power system with DFIGs. *IEEE/CAA J Autom Sinica.* 2017;4(1):125–35. doi:10.1109/jas.2017.7510346.
13. Sonker B, Kumar D, Samuel P. Dual loop IMC structure for load frequency control issue of multi-area multi-sources power systems. *Int J Electr Power Energy Syst.* 2019;112(6):476–94. doi:10.1016/j.ijepes.2019.04.042.
14. Fernando T, Emami K, Yu S, Iu HH, Wong KP. A novel quasi-decentralized functional observer approach to LFC of interconnected power systems. *IEEE Trans Power Syst.* 2016;31(4):3139–51. doi:10.1109/tpwrs.2015.2478968.
15. Oshnoei S, Oshnoei A, Mosallanejad A, Haghjoo F. Contribution of GCSC to regulate the frequency in multi-area power systems considering time delays: a new control outline based on fractional order controllers. *Int J Electr Power Energy Syst.* 2020;123(2):106197. doi:10.1016/j.ijepes.2020.106197.
16. Mohammadikia R, Aliasghary M. A fractional order fuzzy PID for load frequency control of four-area interconnected power system using biogeography-based optimization. *Int Trans Electr Energ Syst.* 2019;29(2):e2735. doi:10.1002/etep.2735.
17. Ghasemi-Marzbali A. Multi-area multi-source automatic generation control in deregulated power system. *Energy.* 2020;201(2):117667. doi:10.1016/j.energy.2020.117667.
18. Mohamed EA, Ahmed EM, Elmelegi A, Aly M, Elbaksawi O, Ali Mohamed AA. An optimized hybrid fractional order controller for frequency regulation in multi-area power systems. *IEEE Access.* 2020;8:213899–915. doi:10.1109/access.2020.3040620.
19. Duong TL, Do TK. Optimal parameters of the cascade controller PI-PI-FOPID for enhancing load frequency control in interconnected power systems using a modified secretary bird optimization algorithm. *Alex Eng J.* 2025;132(3):352–68. doi:10.1016/j.aej.2025.10.034.
20. Padhy S, Panda S. A hybrid stochastic fractal search and pattern search technique based cascade PI-PD controller for automatic generation control of multi-source power systems in presence of plug in electric vehicles. *CAAI Trans Intell Technol.* 2017;2(1):12–25. doi:10.1016/j.trit.2017.01.002.
21. Güler Y, Kaya I. Load frequency control of single-area power system with PI-PD controller design for performance improvement. *J Electr Eng Technol.* 2023;18(4):2633–48. doi:10.1007/s42835-022-01371-1.
22. Çelik E, Öztürk N, Arya Y, Ocak C. (1+PD)-PID cascade controller design for performance betterment of load frequency control in diverse electric power systems. *Neural Comput Appl.* 2021;33(22):15433–56. doi:10.1007/s00521-021-06168-3.
23. Çelik E. Design of new fractional order PI-fractional order PD cascade controller through dragonfly search algorithm for advanced load frequency control of power systems. *Soft Comput.* 2021;25(2):1193–217. doi:10.1007/s00500-020-05215-w.
24. Khalil AE, Boghdady TA, Alham MH, Ibrahim DK. A novel cascade-loop controller for load frequency control of isolated microgrid via dandelion optimizer. *Ain Shams Eng J.* 2024;15(3):102526. doi:10.1016/j.asej.2023.102526.
25. Khan IA, Mokhlis H, Mansor NN, Illias HA, Daraz A, Ramasamy AK, et al. Load frequency control in power systems with high renewable energy penetration: a strategy employing $PI\lambda$ (1+PDF) controller, hybrid energy storage, and IPFC-FACTS. *Alex Eng J.* 2024;106(13):337–66. doi:10.1016/j.aej.2024.06.087.

26. Barakat M. Novel chaos game optimization tuned-fractional-order PID fractional-order PI controller for load-frequency control of interconnected power systems. *Prot Control Mod Power Syst.* 2022;7(1):16. doi:10.1186/s41601-022-00238-x.
27. Meseret GM, Saikia LC. Design of intelligent-based cascaded controller for AGC in three-area diverse sources power systems-incorporated renewable energy sources with SMES and parallel AC/HVDC Tie-lines. *Electr Eng.* 2024;106(1):793–814. doi:10.1007/s00202-023-02010-2.
28. Pathak PK, Yadav AK, Shastri A, Alvi PA. BWOA assisted PIDF-(1+I) controller for intelligent load frequency management of standalone micro-grid. *ISA Trans.* 2023;132(9):387–401. doi:10.1016/j.isatra.2022.06.010.
29. Gulzar MM, Sibtain D, Alqahtani M, Alismail F, Khalid M. Load frequency control progress: a comprehensive review on recent development and challenges of modern power systems. *Energy Strategy Rev.* 2025;57(4):101604. doi:10.1016/j.esr.2024.101604.
30. Sahu PC, Sahoo B, Swain SC, Tejani GG, Bassir D. Resilient math inspired EDA optimized fuzzy adaptive exponent controller for LFC improvement of an EV integrated microgrid. *Sci Rep.* 2025;15(1):28635. doi:10.1038/s41598-025-12275-1.
31. Izci D, Ekinci S, Jabari M, Kocaman B, Güneş BB, Adas E, et al. A novel gudemmanian function-driven controller architecture optimized by starfish optimizer for superior transient performance of automatic voltage regulation. *Biomimetics.* 2026;11(1):7. doi:10.3390/biomimetics11010007.
32. Saat S, Ahmad MA, Ghazali MR. Data-driven brain emotional learning-based intelligent controller-PID control of MIMO systems based on a modified safe experimentation dynamics algorithm. *Int J Cogn Comput Eng.* 2025;6(9):74–99. doi:10.1016/j.ijcce.2024.11.005.
33. Shawqran AM, Attia MA, Mekhamer SF, Kotb H, Ibrahim MA, Mordi A. Enhancing load frequency control in power systems using hybrid PIDA controllers optimized with TLBO-TS and TLBO-EDO techniques. *Processes.* 2025;13(5):1532. doi:10.3390/pr13051532.
34. Khan IA, Mokhlis H, Mansor NN, Illias HA, Jamilatul Awal L, Wang L. New trends and future directions in load frequency control and flexible power system: a comprehensive review. *Alex Eng J.* 2023;71(13):263–308. doi:10.1016/j.aej.2023.03.040.
35. Hussain J, Zou R, Akhtar S, Abouda KA. Design of cascade P-P-FOPID controller based on marine predators algorithm for load frequency control of electric power systems. *Electr Eng.* 2025;107(1):809–27. doi:10.1007/s00202-024-02551-0.
36. Fu Y, Liu D, Chen J, He L. Secretary bird optimization algorithm: a new metaheuristic for solving global optimization problems. *Artif Intell Rev.* 2024;57(5):123. doi:10.1007/s10462-024-10729-y.
37. Rouhinezhad M, Mousazadeh Mousavi SY, Rezanejad M. Puma optimization-based PID controller for enhanced load frequency control in islanded microgrids with renewable energy sources and hybrid energy storage system. *Iran J Energy Environ.* 2026;17(2):254–69. doi:10.5829/ijee.2026.17.02.04.
38. El-Hameed MA, Saeed M, Kabbani A, Abd El-Hay E. Efficient load frequency controller for a power system comprising renewable resources based on deep reinforcement learning. *Sci Rep.* 2025;15(1):18379. doi:10.1038/s41598-025-03310-2.
39. Li Y, Gao S, Chen X, Fan D, Zhang M. Load frequency control of power systems based on deep reinforcement learning with leader-follower consensus control for state of charge. *Processes.* 2025;13(11):3669. doi:10.3390/pr13113669.
40. Shen X, Zhang Y, Li J, Zhao Y, Tang J, Qian B, et al. Novel efficient deep reinforcement learning-based load frequency control for isolated microgrid. *AIP Adv.* 2025;15(2):025026. doi:10.1063/5.0240774.
41. Ojha SK, Maddela CO. Load frequency control of a two-area power system with renewable energy sources using brown bear optimization technique. *Electr Eng.* 2024;106(3):3589–613. doi:10.1007/s00202-023-02143-4.
42. Can O, Ozturk A, Eroğlu H, Kotb H. A novel grey wolf optimizer based load frequency controller for renewable energy sources integrated thermal power systems. *Electr Power Compon Syst.* 2021;49(15):1248–59. doi:10.1080/15325008.2022.2050450.

43. Abo-Elyousr FK, Youssef AM, Abdelaziz AY. Multi-area hydrothermal interconnected load frequency control with double-fed induction-generator-based wind turbine via improved harmony algorithm. *Electr Power Compon Syst*. 2018;46(6):615–28. doi:10.1080/15325008.2018.1462867.
44. Abo-Elyousr FK, Sharaf AM. A novel modified robust load frequency controller scheme. *Energy Syst*. 2020;11(4):1175–98. doi:10.1007/s12667-019-00341-3.
45. Trojovska E, Dehghani M, Trojovsky P. Zebra optimization algorithm: a new bio-inspired optimization algorithm for solving optimization algorithm. *IEEE Access*. 2022;10:49445–73. doi:10.1109/access.2022.3172789.
46. Kennedy J, Eberhart R. Particle swarm optimization. In: *Proceedings of the ICNN'95—International Conference on Neural Networks*; 1995 Nov 27–Dec 1; Perth, Australia. p. 1942–8.
47. Daraz A, Malik SA, Mokhlis H, Haq IU, Laghari GF, Mansor NN. Fitness dependent optimizer-based automatic generation control of multi-source interconnected power system with non-linearities. *IEEE Access*. 2020;8:100989–1003. doi:10.1109/access.2020.2998127.
48. Chen G, Li Z, Zhang Z, Li S. An improved ACO algorithm optimized fuzzy PID controller for load frequency control in multi area interconnected power systems. *IEEE Access*. 2020;8:6429–47. doi:10.1109/access.2019.2960380.
49. Fathy A, Alharbi AG. Recent approach based movable damped wave algorithm for designing fractional-order PID load frequency control installed in multi-interconnected plants with renewable energy. *IEEE Access*. 2021;9:71072–89. doi:10.1109/access.2021.3078825.
50. Irudayaraj AXR, Wahab NIA, Premkumar M, Radzi MAM, Bin Sulaiman N, Veerasamy V, et al. Renewable sources-based automatic load frequency control of interconnected systems using chaotic atom search optimization. *Appl Soft Comput*. 2022;119:108574. doi:10.1016/j.asoc.2022.108574.
51. Guha D, Roy PK, Banerjee S. Load frequency control of large scale power system using quasi-oppositional grey wolf optimization algorithm. *Eng Sci Technol Int J*. 2016;19(4):1693–713. doi:10.1016/j.jestch.2016.07.004.