

Article

Enhanced Load Frequency Control in Multi-Area Hybrid Power Systems Using a 2-DOF Fractional-Order TID Controller with Artificial Ecosystem Optimization

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Abstract

Load frequency control (LFC) plays a critical role in maintaining frequency stability and regulating power transfer between interconnected areas subjected to continuous load variations. In multi-area systems, disturbances tend to propagate through interconnected tie-lines rather than remaining restricted locally, often leading to slower responses and weak coordination when conventional controllers are employed. In this paper, a two-degrees-of-freedom fractional-order differential integration (2DOF FO-TID) controller is proposed to improve both frequency regulation and dynamic interaction. The structure enables independent tuning of tracking and disturbance rejection, allowing greater flexibility in shaping system response. The controller parameters are optimally tuned by the Artificial Ecosystem Optimization (AEO) algorithm. The proposed approach is evaluated on a two-area hybrid thermal power system incorporating an SMES unit within the MATLAB/Simulink (R2022b) environment and compared with PID, FOPID, and TID controllers under identical conditions. The results indicate that, although some conventional controllers provide faster stabilization in one area, their performance in the interconnected area remains slower. In contrast, the proposed controller achieves more robust behavior across both areas, with the settling time of the second area reduced from about 25 s to nearly 11 s without degrading the response of the first area. These results highlight the importance of coordination in multi-area systems and demonstrate that the proposed approach enhances overall system performance and damping compared to conventional methods.

Keywords: load frequency control; artificial ecosystem optimization; multi-area hybrid power systems; fractional order control; metaheuristic optimization; 2DOF FO TID controller



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1. Introduction

For many decades, electrical energy has been an essential factor in supporting technological progress and modern development. The incremental growth of the global population, together with rapid technological advancement, has increased significantly the electricity demand, resulting in a substantial rise in power system load requirements. This trend becomes more evident as system complexity continues to increase. Also, increasing load demand poses significant challenges for control systems, particularly in maintaining stability and dynamic response.

1.1. Literature Review

Advanced control strategies have been extensively studied to improve load frequency control (LFC) performance in interconnected power systems. In recent studies, cascaded and hybrid controller structures have attracted considerable attention due to their effectiveness in improving disturbance rejection and system robustness. For instance, Bhadaseng et al. [1] developed a three-degrees-of-freedom PID–FOPID–FOPD–TID sequential controller, optimized using the LUS-TLBO algorithm for a four-zone hydrothermal system, which showed improved frequency regulation under nonlinear operating conditions. Similarly, Hassan et al. [2] introduced a cascaded two-degree-of-freedom fractional-order master–slave control strategy that combines FOTIDN and FOTDN controllers for hybrid microgrids with renewable energy integration, in which the controller parameters were optimized using the Marine Predators Algorithm. Other hybrid structures have also been explored, such as the 2DOF-PID-TD controller optimized by the Artificial Gorilla Troops Optimizer to improve robustness to load disturbances and nonlinearities [3], and a hybrid cascade controller with a $(1 + PDD^2)(1 + TI)$ structure designed for coordinated LFC–AVR operation [4].

Fractional-order and tilt-based control strategies have also been widely investigated due to their additional tuning flexibility and improved dynamic performance. Mohamed et al. [5] developed a tilt fractional-order integral–derivative controller with a fractional filter (TFOIDFF) optimized using the Artificial Hummingbird Algorithm to mitigate frequency and tie-line power deviations in renewable-energy-based systems. Similarly, a TDn(1 + PI) controller combining tilt–derivative and proportional–integral actions was introduced to enhance LFC performance in a thermal–photovoltaic two-area system, where controller parameters were optimized using a bio-dynamic grasshopper optimization algorithm [6]. In another study, a modified 2DOF-TⁿI^λD^μN controller was proposed to improve frequency stability in hybrid power systems with renewable energy sources, where the controller parameters were tuned using an improved gradient-based optimizer [7]. Even with their greater flexibility, these methods often need complicated adjustments. They may still have difficulty keeping coordinated responses among connected areas when operating conditions change.

In addition to improved controller structures, many metaheuristic optimization algorithms have been used to fine-tune controllers for LFC applications. For instance, Abdel-Hamed et al. [8] employed a 2DOF-PID controller optimized with the Dragonfly Algorithm to manage frequency and tie-line power, while a fractional-order PID controller optimized using the Kangaroo Escape Optimization algorithm was employed to improve convergence behavior and system stability in multi-area interconnected system [9]. Furthermore, several hybrid optimization strategies have been applied to tune complex controller architectures, including the AGTO–EO algorithm for fractional-order hybrid controllers [10], the Owl Search Algorithm for cascaded FOPD–FOPID controllers coordinated with SMES units [11], and hybrid simulated annealing–quadratic interpolation optimization for filtered PID controllers [12].

Energy storage technologies, particularly superconducting magnetic energy storage (SMES), have been incorporated into LFC frameworks to improve system damping and mitigate frequency deviations. Studies have shown that SMES can significantly enhance transient performance and robustness in interconnected systems [13–15]. Nevertheless, the integration of SMES introduces additional dynamic interactions that require more effective coordination strategies within the control framework.

More recently, intelligent and hybrid control frameworks have been proposed to cope with the increasing complexity of modern power systems with high renewable penetration. An ANN-based adaptive controller was presented for decentralized power grids,

including HVDC tie-line modeling and inertia simulation techniques to enhance frequency regulation [16]. In addition, hybrid disturbance-resilient control schemes that combine fractional-order fuzzy regulators with auxiliary PI(1 + DD) controllers have been examined to improve system damping and disturbance rejection in renewable-integrated networks [17]. Other studies have explored advanced PID- and PIDA-based control structures optimized using modern metaheuristic techniques, such as the Catch Fish Optimization Algorithm and hybrid TLBO-based methods, demonstrating improved frequency stability and faster response in interconnected power systems [18–20].

Metaheuristic optimization algorithms have been widely employed for controller parameter tuning in load frequency control problems due to their ability to handle nonlinear and complex optimization landscapes. These algorithms are generally classified into several categories according to their underlying inspiration mechanisms. Figure 1 presents the primary classifications of metaheuristic optimization techniques, with the algorithms utilized in this study highlighted for clarity.

META-HEURISTIC OPTIMIZATION ALGORITHMS								
Evolutionary	Swarm-based			Physics-based	Human-based	Bio-based	System-Based	Math-based
Evolutionary Programming	Particle Swarm Optimization	Grey Wolf Optimizer	Coyote Optimization Algorithm	Simulated Annealing	Culture Algorithm	Invasive Weed Optimization	Germinal Center Optimization	Hill Climbing
Memetic Algorithm	Bacterial Foraging Optimization	Ant Lion Optimizer	Moth Search Algorithm	Multi-Verse Optimizer	Imperialist Competitive Algorithm	Biogeography-Based Optimization	Water Cycle Algorithm	Cross-Entropy Method
Genetic Algorithm	Bees Algorithm	Moth Flame Optimization	Sea Lion Optimization	Wind Driven Optimization	Teaching Learning Based Optimization (TLBO)	Virus Colony Search	Artificial Ecosystem Optimization	Sine Cosine Algorithm
Differential Evolution	Cat Swarm Optimization	Elephant Herding Optimization	Naked Mole-Rat Algorithm	Tug of War Optimization	Brain Storm Optimization	Satin Bowerbird Optimizer		Gradient-Based Optimizer
Flower Pollination Algorithm	Artificial Bee Colony	Whale Optimization Algorithm	Pathfinder Algorithm	Electromagnetic Field Optimization	Queuing Search Algorithm	Earthworm Optimization Algorithm		Arithmetic Optimization Algorithm
Coral Reefs Optimization	Ant Colony Optimization	Dragonfly Optimization	Sailfish Optimizer	Nuclear Reaction Optimization	Search and Rescue Optimization	Wildebeest Herd Optimization		Chaos Game Optimization
	Cuckoo Search Algorithm	Bird Swarm Algorithm	Harris Hawks Optimization	Henry Gas Solubility Optimization	Life Choice-based Optimization	Slime Mould Algorithm		Pareto-like Sequential Sampling
	Firefly Algorithm	Spotted Hyena Optimizer	Manta Ray Foraging Optimization	Atom Search Optimization	Social Ski-Driver Optimization			
	Fireworks Algorithm	Salp Swarm Optimization	Bald Eagle Search	Equilibrium Optimizer	Gaining Sharing Knowledge Algorithm			
	Bat Algorithm	Grasshopper Optimization Algorithm	Sparrow Search Algorithm	Archimedes Optimization Algorithm	Coronavirus Herd Optimization			
	Fruit-fly Optimization Algorithm	Jaya Algorithm	Hunger Games Search	flow direction algorithm	Forensic-Investigation Optimization			
	Social Spider Optimization	Swarm Robotics algorithm	Aquila Optimizer	Quantum Inspired optimization	Battle Royale Optimization			

Figure 1. Classification of metaheuristic optimization algorithms (highlighted algorithms indicate those used in this study).

1.2. Motivation and Contributions

Preserving reliable load frequency control (LFC) in interconnected multi-area power systems remains a challenging issue due to persistent load variations and the dynamic coupling between areas through tie lines. In such systems, disturbances propagate across areas, often leading to unbalanced responses when conventional controllers are used. Although classical controllers such as PID can provide acceptable local performance, maintaining consistent dynamic behavior across interconnected areas remains challenging. Fractional-order control strategies introduce additional flexibility. However, most existing methods focus on improving local performance or optimizing objective functions, while limited emphasis on achieving coordinated responses across areas, especially when energy storage systems such as SMES are involved.

The main contributions of this study are summarized as follows:

1. **Controller Design:** A two-degree-of-freedom fractional order tilt integral derivative (2DOF FO-TID) controller is examined in a multi-area hybrid power system with SMES for load frequency control. This controller design improves response characteristics, such as reducing settling time and overshoots, when compared with conventional controllers.
2. **Inter-Area Coordination:** The proposed method improves the consistency of dynamic responses across interconnected areas. In particular, settling behavior conflicts are reduced and inter-area oscillations following disturbances are effectively suppressed.
3. **AEO-Based Framework:** To locate appropriate parameters of the proposed controller, the Artificial Ecosystem Optimization (AEO) algorithm is employed. The performance is evaluated by comparing with several well-established metaheuristic algorithms under identical operating conditions.
4. **Performance Evaluation:** A comprehensive assessment is evaluated using different performance indices and compared with multiple controllers, ensuring consistency under various error criteria.
5. **Robustness Analysis:** The proposed approach is further examined under sequential load changes, demonstrating stable and robust performance under various operating conditions.

1.3. Paper Structure

The paper structure is outlined as follows. Section 2 shows the mathematical modeling of the two-area load frequency control (LFC) system and explains the nonlinear components considered in the analysis. Sections 3 and 4 show the proposed controller structure and explain the optimization method used for controller parameter tuning. Section 5 discusses the simulation results and focuses on the dynamic controller performance and the system robustness under different operating conditions. Finally, Section 6 summarizes the study's main conclusions and outlines possible paths for future research.

2. Two-Area Hybrid Power System with SMES System Modeling

The power system discussed in this paper consists of two interconnected areas connected by a relatively weak tie-line. Each area contains a hybrid generation unit that includes a steam reheating turbine, a gas turbine and a hydro unit. This configuration represents a practical operating scenario in which the base-load and rapid-response power sources operate simultaneously within the same control area, resulting in complex dynamic interactions that require efficient management.

To enhance transient frequency regulation and overall system performance, a superconducting magnetic energy storage (SMES) unit is incorporated into each area. This unit delivers rapid active power support during disturbances, enhancing the system's dynamic

response. For analytical purposes, the system is linearized around its nominal operating point and represented in the Laplace domain under small-signal load frequency control (LFC) assumptions. Figure 2 represents the hybrid two-area power system with SMES is modeled.

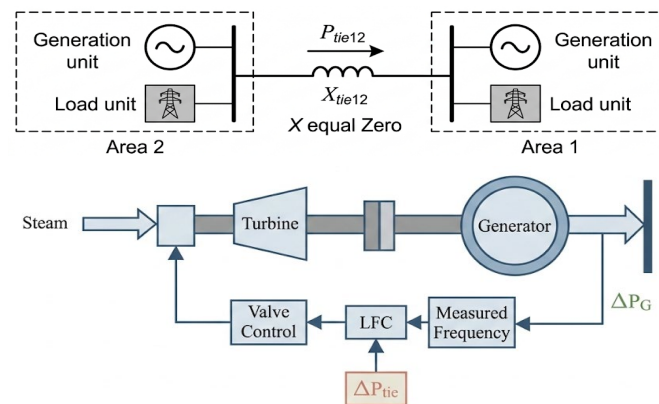


Figure 2. Hybrid Power System Two-Area with SMES schemes.

2.1. Generator–Load Dynamics

In each control area, the generator load block captures the overall electromechanical dynamics and has a direct impact on frequency behavior. By linearizing the swing equation this block was derived, which describes the balance between mechanical input power and electrical output power. The incremental frequency deviation is described by Equation (1) [21]:

$$2H \frac{d(\Delta f)}{dt} = \Delta P_m + \Delta P_{SMES} - \Delta P_L - \Delta P_{tie} - D\Delta f \quad (1)$$

where

- H : equivalent inertia constant
- D : load damping coefficient
- ΔP_m : aggregated mechanical power
- ΔP_{SMES} : injected SMES power
- ΔP_L : load disturbance
- ΔP_{tie} : tie-line power exchange

after Laplace transformation:

$$\Delta f(s) = \frac{1}{2Hs + D} [\Delta P_m(s) + \Delta P_{SMES}(s) - \Delta P_L(s) - \Delta P_{tie}(s)] \quad (2)$$

For compact representation, the generator–load block is expressed as:

$$G_p(s) = \frac{K_p}{T_p s + 1} \quad (3)$$

where:

$$K_p = \frac{1}{D}, \quad T_p = \frac{2H}{D} \quad (4)$$

The dynamic interaction between rotational inertia and load damping within the system is described by the generator–load block. The inertial constant determines the frequency response to sudden disturbances, where the rate of change slows down by higher inertia. In contrast, the damping coefficient influences how effectively frequency deviation are reduced, thus improving the steady-state response under load variations.

2.2. Aggregated Mechanical Power

The total mechanical power within each control area is obtained as the weighted combination of the three generating sources:

$$\Delta P_{m,total} = \alpha_s \Delta P_{m,s} + \alpha_h \Delta P_{m,h} + \alpha_g \Delta P_{m,g} \quad (5)$$

where:

- α_s : steam participation factor
- α_h : hydro participation factor
- α_g : gas participation factor

And:

$$\alpha_s + \alpha_h + \alpha_g = 1 \quad (6)$$

In this study, the adopted participation factors are:

$$\alpha_s = 0.543; \alpha_h = 0.326; \alpha_g = 0.130 \quad (7)$$

These values show that the steam unit contributes roughly 54.35% of the total generation capacity, whereas the hydro and gas units contribute about 32.61%, 13.04%, respectively. This allocation indicates a dominant base-load steam generation supported by hydro and fast-response gas units, thereby ensuring realistic hybrid generation characteristics within each control area. The system parameters are provided in Appendix A.

2.3. Reheat Steam Turbine Unit Modeling

The reheat steam turbine unit is the primary source of baseload generation within each control area and plays a pivotal role in the slow electromechanical system dynamics. A conventional speed regulator (governor) is utilized to regulate the steam valve opening in response to frequency deviations. The governor dynamics are modeled as a first-order system [22]:

$$G_{g,s}(s) = \frac{1}{T_{g,s}s + 1} \quad (8)$$

where $T_{g,s}$ denotes the governor time constant representing actuator and valve delay effects. The mechanical power is produced through a reheat steam turbine consisting of high-pressure and reheated intermediate/low-pressure stages. The reheat process introduces additional thermal energy storage, resulting in a transfer function of the form:

$$G_{t,s}(s) = \frac{1 + K_r T_r s}{1 + T_r s} \quad (9)$$

where T_r is the reheat time constant, and K_r denotes the reheater gain [18,23]. The presence of the numerator term reflects the effect of reheated steam energy transfer between stages, which modifies the transient response characteristics while maintaining minimum-phase behavior.

In addition, steam chest dynamics between the governor valve and turbine blades are represented by:

$$G_{sc}(s) = \frac{1}{T_{sc}s + 1} \quad (10)$$

which accounts for pressure build-up delay in the steam chamber before torque generation. Therefore, the overall reheat steam generating unit transfer function can be formulated as:

$$G_{steam}(s) = \left(\frac{1}{T_{g,s}s + 1} \right) \left(\frac{1 + K_r T_r s}{1 + T_r s} \right) \left(\frac{1}{T_{sc}s + 1} \right) \quad (11)$$

This structure introduces several slow poles related to the thermal–mechanical energy conversion process, making the reheat steam turbine the slowest primary source in the hybrid system. Its large participation factor reflects its role in steady-state power regulation and long-term frequency recovery, while fast transient response is mainly supported by hydro, gas, and SMES units.

2.4. Hydro Turbine Unit

The hydro generating unit represents a medium-speed renewable source whose dynamics are dominated by hydraulic effects rather than thermal energy conversion. Unlike steam turbines, hydro turbines are strongly influenced by water inertia inside the penstock, which gives rise to the so-called water starting time. The governor of the hydro unit is modeled as a first-order actuator [24,25]:

$$G_{g,h}(s) = \frac{1}{T_{g,h}s + 1} \quad (12)$$

where $T_{g,h}$ denotes the governor time constant associated with servo and gate movement dynamics. The hydraulic turbine itself is represented using the classical water starting time model [26]:

$$G_{hydro}(s) = \frac{1 - T_{\omega}s}{1 + 0.5T_{\omega}s} \quad (13)$$

where T_{ω} is the water starting time constant reflecting the inertia of the water column. The presence of the term $1 - T_{\omega}s$ introduces a right-half-plane zero, resulting in non-minimum phase behavior. Physically, this indicates that immediately after gate opening, the water acceleration creates an initial power deviation opposite to the steady-state direction, producing an inverse transient response. As a result, the entire hydro unit model is provided by:

$$G_{hydro,total}(s) = \left(\frac{1}{T_{g,h}s + 1} \right) \left(\frac{1 - T_{\omega}s}{1 + 0.5T_{\omega}s} \right) \quad (14)$$

This non-minimum phase characteristic raises control complexity, especially under inter-area oscillatory conditions. The hydro source responds faster than the steam unit, but it shows more difficult transient behavior due to hydraulic inertia and phase inversion effects.

2.5. Gas Turbine Unit

The gas turbine unit is a quick-response generation source that is mainly used for transient support and load-following applications. Unlike steam and hydro units, gas turbines depend on combustion dynamics and fuel flow control, which leads to much shorter time constants. The governor that controls the fuel valve is modeled as a first-order system [21]:

$$G_{g,g}(s) = \frac{1}{T_{g,g}s + 1} \quad (15)$$

where $T_{g,g}$ denotes the fast actuator time constant related to fuel valve positioning. The fuel and combustion chamber dynamics add extra lead and lag behavior that can be expressed in Equation (16). This representation is commonly used in simplified gas turbine models reported in the literature.

$$G_{fuel}(s) = \frac{1 + T_{fz}s}{1 + T_{fp}s} \quad (16)$$

where T_{fz} and T_{fp} represent the effective fuel system zero and pole constants. Because of rapid combustion processes, these time constants are usually much smaller than those

of steam turbines. Additional mechanical delays from turbine shaft and compressor interactions are represented as:

$$G_{mech}(s) = \left(\frac{1 - T_{mz}s}{1 + T_{mp}s} \right) \left(\frac{1}{T_{m,g}s + 1} \right) \quad (17)$$

where T_{mz} , T_{mp} , and $T_{m,g}$ which characterize the short-time mechanical lag dynamics associated with the turbine–compressor shaft system. Accordingly, the overall transfer function of the gas turbine unit can be expressed as:

$$G_{gas}(s) = \left(\frac{1}{T_{g,g}s + 1} \right) \left(\frac{1 + T_{fz}s}{1 + T_{fp}s} \right) \left(\frac{1 - T_{mz}s}{1 + T_{mp}s} \right) \left(\frac{1}{T_{m,g}s + 1} \right) \quad (18)$$

The gas turbine responds more rapidly than both steam and hydro units, enabling it to effectively limit the initial frequency excursion following a disturbance. Nevertheless, due to its relatively smaller participation factor and reduced inertia contribution, its role is predominantly associated with short-term dynamic support, while sustained steady-state frequency restoration remains largely governed by the larger-capacity generation units.

2.6. Superconducting Magnetic Energy Storage (SMES) Unit

The Superconducting Magnetic Energy Storage (SMES) unit is deployed in each control area to provide rapid active power compensation during transient frequency deviations. In contrast to conventional mechanical generation units, the SMES system retains energy within the magnetic field of a superconducting coil and interfaces with the grid through a power electronic converter, which allows for a nearly instantaneous electromagnetic response. The energy stored in the superconducting coil is expressed in Equation (19). It should be noted that the superconducting coil is assumed to be linear with constant inductance in this study, which allows the use of the above quadratic energy expression [27].

$$E = \frac{1}{2}LI^2 \quad (19)$$

where I is the superconducting current, L is the coil inductance. Due to resistive losses are negligible under superconducting conditions, the SMES system can inject or absorb power with fast response and very high efficiency. Using cascaded lead–lag compensators followed by converter dynamics, the dynamic behavior of the SMES control system is modeled:

$$G_{SMES}(s) = K_{SMES} \left(\frac{1 + T_{l1}s}{1 + T_{p1}s} \right) \left(\frac{1 + T_{l2}s}{1 + T_{p2}s} \right) \frac{1}{T_{conv}s + 1} \quad (20)$$

where K_{SMES} is the SMES gain, T_{l1} , T_{l2} are lead constants, T_{p1} , T_{p2} are lag constants, and T_{conv} represents the converter time constant. This transfer function represents an equivalent series (cascaded) dynamic model of the SMES system and does not necessarily reflect the internal multi-loop control architecture. The converter is modeled as a first-order inertial element as a control-oriented approximation commonly adopted in load frequency control (LFC) studies. In power systems, power electronic converters typically operate at a relatively faster time scale compared to the dominant mechanical dynamics of turbine–governor units. Therefore, the converter delay can be reasonably treated as having a limited impact on the dominant system dynamics, which justifies the use of a simplified first-order representation for system-level frequency response analysis.

This representation is widely used in control-oriented modeling, where the primary objective is to capture the dominant system behavior relevant to frequency control. While this approximation simplifies the representation of converter dynamics, more detailed

converter models may be considered in future studies when higher-frequency effects are of interest.

These Parameters are treated as a tunable parameter within the optimization process. The injected power is dynamically related to the frequency deviation through the transfer function $G_{SMES}(s)$:

$$\Delta P_{SMES}(s) = G_{SMES}(s)\Delta f(s) \quad (21)$$

The lead–lag structure provides phase compensation and bandwidth shaping, allowing the SMES unit to enhance damping and reduce peak frequency deviation. Due to its electromagnetic nature, SMES operates at a relatively fast electromagnetic time scale compared to steam, hydro, and gas turbines, making it effective in suppressing the initial frequency oscillations and improving overall system stability.

2.7. Tie-Line Power Exchange

The tie-line power exchange represents the dynamic coupling between the two interconnected control areas and plays a crucial role in multi-area load frequency control. Physically, the tie-line transfers real power according to the angular displacement difference between the equivalent generators of the two areas. Under small-signal assumptions, the incremental tie line power deviation is given by the following equation:

$$\Delta P_{tie}(s) = \frac{2\pi T_{12}}{s}(\Delta f_1(s) - \Delta f_2(s)) \quad (22)$$

where T_{12} is the synchronizing coefficient of the tie-line, and Δf_1 , Δf_2 are the frequency deviations of Area 1 and Area 2, respectively. The integral term $1/s$ arises from the relationship between rotor angle deviation and frequency deviation, since frequency is the time derivative of the rotor angle. Consequently, tie-line power depends on the accumulated phase angle difference between the areas.

This coupling mechanism gives rise to an inter-area oscillatory mode, as a disturbance in one control area is dynamically transmitted to the other through the tie-line. The magnitude of the synchronizing coefficient defines the strength of this interaction: higher values correspond to stronger electrical coupling and faster power exchange, whereas lower values lead to weaker interconnection and more decoupled system behavior. To reflect practical signal transmission and measurement delays, a first-order lag element is incorporated as:

$$G_{tl}(s) = \frac{1}{T_{tl}s + 1} \quad (23)$$

which captures the effects associated with signal transmission and measurement filtering. Consequently, the inclusion of the tie-line converts the two originally independent control areas into an interconnected multi-variable system, thereby increasing the overall system order and introducing additional inter-area oscillatory modes that must be adequately suppressed by the LFC controller.

The two-area load frequency control (LFC) system considered in this study is implemented in the MATLAB/Simulink (R2022b) environment, as illustrated in Figure 3. In order to enhance the dynamic performance of the system under load disturbances, a two-degree-of-freedom fractional-order TID (2-DOF FO-TID) controller is employed in each control area.

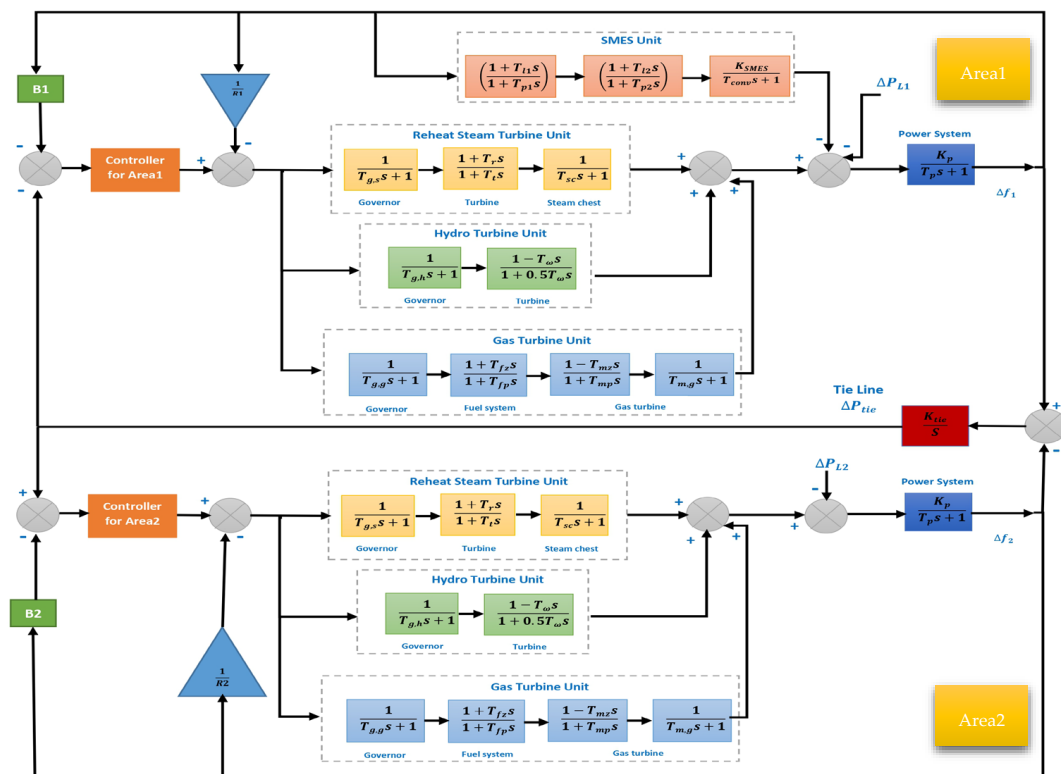


Figure 3. The framework diagram of two-area hybrid power system LFC with SMES.

2.8. Area Control Error (ACE)

In interconnected multi-area power systems, the Area Control Error (ACE) acts as the main feedback signal used in secondary load frequency control. It provides a quantitative measure of the instantaneous power imbalance within a control area by incorporating both the local frequency deviation and the deviation of tie-line power from its scheduled interchange. Its formulation ensures coordinated regulation among interconnected areas while preserving scheduled inter-area power exchange. Mathematically, the ACE for each control area is defined as:

$$ACE_1 = B_1 \Delta f_1 + \Delta P_{tie} \quad (24)$$

$$ACE_2 = B_2 \Delta f_2 - \Delta P_{tie} \quad (25)$$

where Δf_i denotes the frequency deviation of Area i , ΔP_{tie} represents the incremental tie-line power deviation, and B is the frequency bias coefficient of the corresponding area.

The first component of the ACE expression reflects the local frequency control objective, scaled by the frequency bias factor, which determines the sensitivity of the area to its own frequency deviation. The second component enforces adherence to the scheduled tie-line power transfer by correcting deviations in inter-area power exchange. The sign convention ensures that each area responds appropriately to deviations relative to the scheduled interchange.

Physically, ACE represents the net real power mismatch within an area after accounting for interconnection effects. A non-zero ACE indicates that generation does not fully compensate for local load demand and/or that tie-line power flow deviates from its scheduled value. Consequently, the fundamental objective of secondary control is to drive ACE to 0.

Thereby ensuring simultaneous restoration of nominal frequency and scheduled tie-line interchange. The frequency bias coefficient plays a critical role in multi-area coordination, as it determines the proportional contribution of each area to overall frequency

regulation. Proper selection of this coefficient guarantees stable and equitable load sharing among interconnected areas while preventing adverse control interaction.

Accordingly, ACE serves as the principal coupling variable linking local frequency dynamics with inter-area power regulation and forms the essential input for the design of advanced supplementary control strategies in interconnected hybrid power systems

In order to evaluate and optimize the dynamic performance of the proposed controller, several integral-based performance indices are considered. These indices quantify the transient response quality of the interconnected power system under load disturbances. The evaluation focuses on minimizing frequency deviations in both areas as well as tie-line power deviations.

The Integral of Absolute Error (IAE) performance index is defined as:

$$J_{IAE} = \int_0^T (|\Delta f_1(t)| + |\Delta f_2(t)| + |\Delta P_{tie}(t)|) dt \quad (26)$$

The Integral of Squared Error (ISE) index is given by:

$$J_{ISE} = \int_0^T (\Delta f_1^2(t) + \Delta f_2^2(t) + \Delta P_{tie}^2(t)) dt \quad (27)$$

The Integral of Time-Weighted Squared Error (ITSE) criterion places greater weight on errors that persist over time. As a result, slowly decaying deviations contribute more to the performance index, directing the optimization process toward improved damping and reduced settling time.

$$J_{ITSE} = \int_0^T t(\Delta f_1^2(t) + \Delta f_2^2(t) + \Delta P_{tie}^2(t)) dt \quad (28)$$

The proposed objective function in this work is the ITAE criterion, expressed as:

$$J_{ITAE} = \int_0^T t(|\Delta f_1(t)| + |\Delta f_2(t)| + |\Delta P_{tie}(t)|) dt \quad (29)$$

In order that ITAE criterion is highly sensitive to persistent errors over time, ITAE was selected as a primary index for improvement. By weighting error with time, it penalizes long-term oscillations, reduces settling time, and improves overall damping performance. Compared with ISE and IAE, ITAE assigns greater weight to the later stage of the response, thereby reducing slow oscillatory decay, which is particularly important in interconnected multi-area systems with hydro non-minimum phase characteristics.

3. The Proposed 2-DOF FO-TID Controller

3.1. The Fractional Order Theory

Several mathematical formulations have been introduced to define differentiation and integration of non-integer order consistently and rigorously within fractional-order (FO) calculus. The most commonly used definitions are the Grünwald–Letnikov (GL), Riemann–Liouville (RL), and Caputo formulations [28].

Although these definitions differ in structure and interpretation, they are mathematically stable, and each offers particular analytical and practical benefits depending on the requirements of the application. The Grünwald–Letnikov definition, in particular,

formulates the fractional derivative of order α_{th} of a function f within a to t limits as in Equation (30):

$$D^\alpha \Big|_\alpha^t = \lim_{h \rightarrow 0} \frac{1}{h^\alpha} \sum_{r=0}^{\left\lfloor \frac{t-\alpha}{h} \right\rfloor} (-1)^r \binom{n}{r} f(t-rh) \quad (30)$$

where h represents the discretization step size (time increment), and the operator $[\cdot]$ denotes the integer part (floor function) of the preceding argument. Furthermore, the integer variable n must satisfy the constraint $n-1 < \alpha < n$, which ensures the proper definition of the fractional derivative of order α .

The generalized binomial coefficients appearing in the Grünwald–Letnikov formulation are defined as follows [29]:

$$\binom{n}{r} = \frac{\Gamma(n+1)}{\Gamma(r+1)\Gamma(n-r+1)} \quad (31)$$

where Γ denotes the Gamma function, which generalizes the factorial operator to real and complex arguments. It is defined through the classical integral representation as follows:

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt \quad (32)$$

Riemann and Liouville introduced an alternative formulation of the fractional-order (FO) derivative that circumvents the explicit use of discrete summation and limiting processes. Instead, this approach relies on the extension of integer-order (IO) differentiation combined with integral operators to construct the fractional operator in a continuous framework. The Riemann–Liouville fractional derivative is therefore defined through an integral representation followed by integer-order differentiation, and can be expressed as follows [30]:

$$D^\alpha \Big|_\alpha^t = \frac{1}{\Gamma(n-\alpha)} \left(\frac{d}{dt} \right)^n \int_\alpha^t \frac{f(\tau)}{(t-\tau)^{\alpha-n+1}} d\tau \quad (33)$$

An alternative formulation of the fractional-order (FO) derivative was introduced by Caputo. In contrast to the Riemann–Liouville definition, the Caputo approach reformulates the operator in a manner more suitable for physical system modeling. The Caputo fractional derivative is defined as follows:

$$D^\alpha \Big|_\alpha^t = \frac{1}{\Gamma(n-\alpha)} \int_\alpha^t \frac{f^n(\tau)}{(t-\tau)^{\alpha-n+1}} d\tau \quad (34)$$

The general fractional-order (FO) operator $D^\alpha \Big|_\alpha^t$ can be expressed in several equivalent forms, depending on the adopted definition, as follows:

$$D^\alpha \Big|_\alpha^t = \begin{cases} \alpha > 0 \rightarrow \frac{d^\alpha}{dt^\alpha} & \text{FO derivative} \\ \alpha < 0 \rightarrow \int_{t_0}^t dt^\alpha & \text{FO Integral} \\ \alpha = 0 \rightarrow 1 \end{cases} \quad (35)$$

3.2. The Proposed 2DOF FO TID Controller

The proposed controller structure is motivated by the independent advantages reported for fractional-order TID controllers and two-degree-of-freedom control architectures. Observing that existing FO-TID designs are limited to single-degree-of-freedom structures, this work extends the FO-TID concept by incorporating a two-degree-of-freedom frame-

work to enhance the dynamic stability and disturbance rejection capability of the multi-area load frequency control (LFC) system.

Unlike conventional integer-order PID or TID controllers, the proposed structure incorporates fractional-order operators and independent reference weighting parameters. This configuration significantly increases tuning flexibility and enables improved transient performance under load disturbances. The proposed controller is mathematically defined in the Laplace domain as:

$$U(s) = K_T s^{-\lambda} [aR(s) - Y(s)] + K_I s^{-\mu} [R(s) - Y(s)] + K_D \frac{N_D s}{s + N_D} [bR(s) - Y(s)] \quad (36)$$

where K_T , K_I , K_D denote the tilt, integral, and derivative gains, respectively; λ and μ represent the fractional orders of the tilt and integral actions; a and b are the set-point weighting coefficients; N_D is the derivative filter coefficient; and $R(s)$ and $Y(s)$ denote the reference input and system output in the Laplace domain, respectively.

The 2DOF configuration is achieved through the introduction of two independent reference weighting parameters a and b . These parameters allow independent shaping of the proportional (tilt) and derivative actions with respect to the reference signal. This separation provides such of advantages as reducing the overshoot, improving damping characteristics, independent tracking and disturbance rejection tuning and enhanced robustness under load perturbations. Figure 4 shows the proposed controller scheme.

The fractional operators $s^{-\lambda}$ and $s^{-\mu}$ provide additional tuning degrees of freedom compared to classical integer-order controllers. The tilt term $s^{-\lambda}$ improves transient response shaping without aggressive amplification. The fractional integral term $s^{-\mu}$ enhances low-frequency disturbance rejection while avoiding excessive oscillations. By properly selecting λ and μ , the controller achieves reduced peak frequency deviation, faster settling time and improved inter-area oscillation damping.

In the proposed 2-DOF FO-TID controller, the area control error (ACE) is used as the reference signal, while the frequency deviation is introduced separately as the feedback signal. This configuration allows the controller to adjust the tracking behavior and disturbance rejection independently. As a result, the system response becomes smoother, oscillations are reduced, and the overall damping performance is improved.

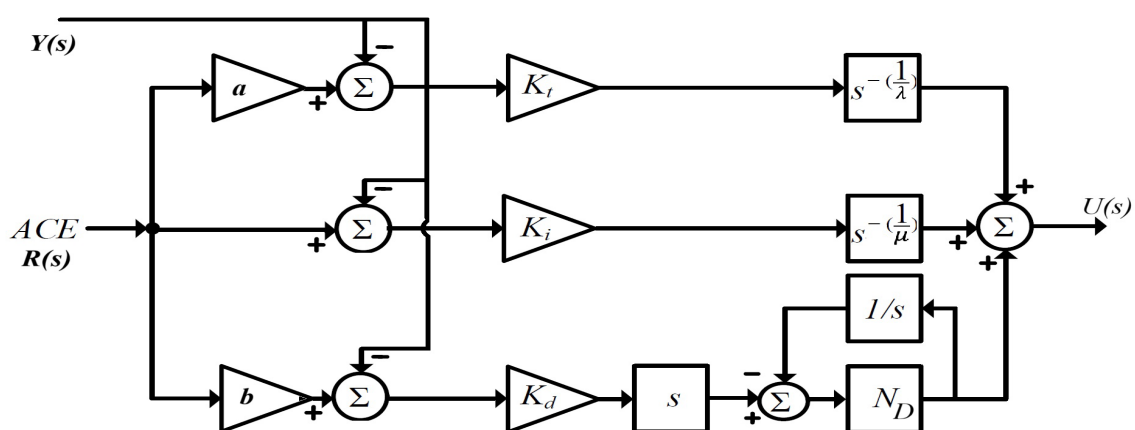


Figure 4. 2DOF FO TID controller scheme.

3.3. PID Controller

In this study, the conventional PID controller is employed as a benchmark strategy to provide a fair and consistent comparison with the proposed main controller. Within the load frequency control (LFC) framework, the PID regulator generates an appropriate secondary control signal to attenuate frequency deviations and suppress tie-line power

oscillations following load disturbances. The mathematical representation of the PID controller is given in Equation (37), and its corresponding implementation within the LFC scheme is illustrated in Figure 5a.

$$U(s) = \left[K_p + \frac{K_i}{s} + K_d s \right] R(s) \quad (37)$$

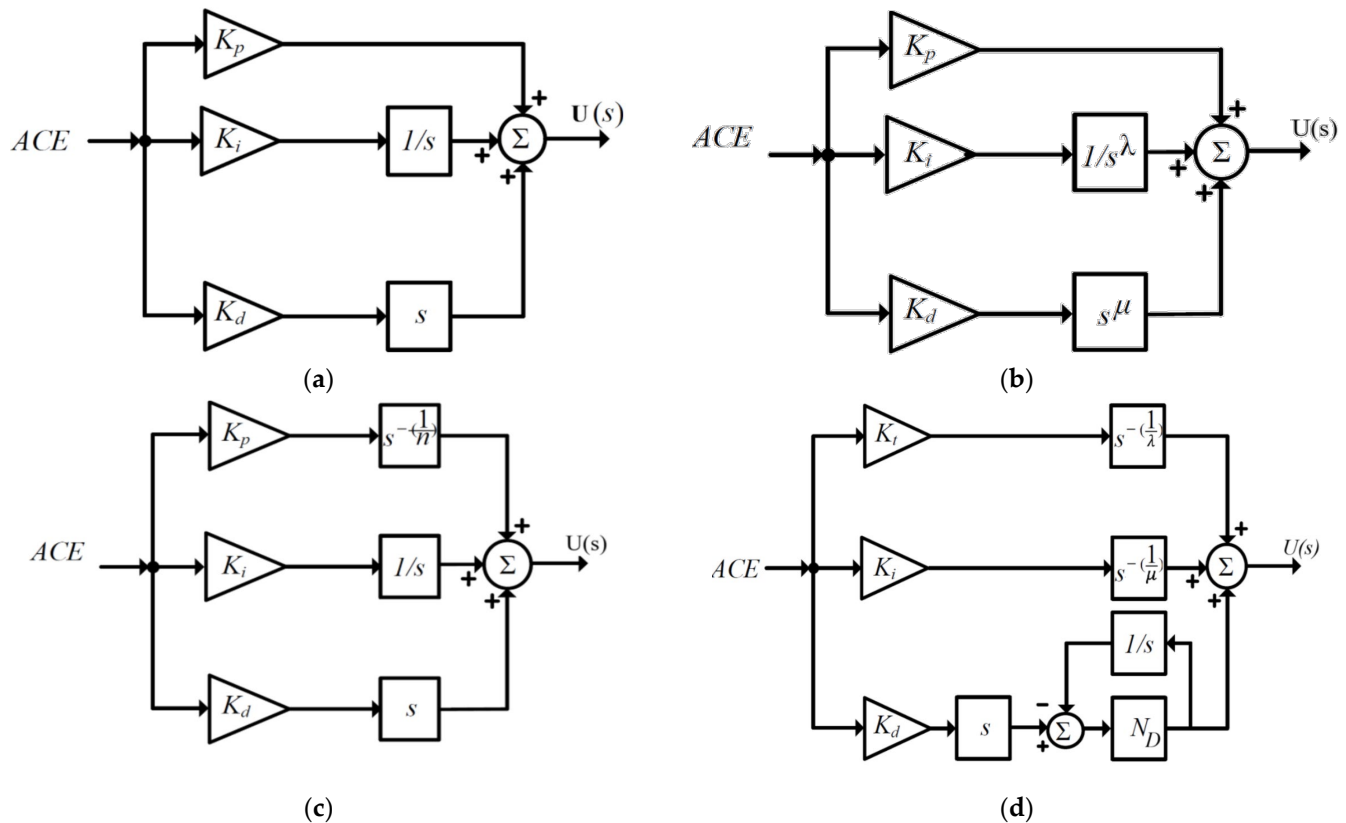


Figure 5. Structures of different control schemes implemented in the LFC system. (a) PID controller; (b) FOPID controller; (c) TID controller; (d) 1DOF FO-TID controller.

3.4. FOPID Controller

This class of controllers has been introduced to enhance the dynamic performance and robustness of the conventional PID structure. Referred to as the fractional-order PID (FOPID) or $PI^\lambda D^\delta$ [31,32], it extends the classical formulation by incorporating two additional fractional orders, λ and δ , associated with the integral and derivative actions, respectively. The controller reduces to the conventional PID when $\lambda = 1$ and $\delta = 1$, as illustrated by the four characteristic points in Figure 5b. It behaves as a PI controller when $\lambda = 1$ and $\delta = 0$, and as a PD controller when $\lambda = 0$ and $\delta = 1$. The transfer function of the FOPID controller is given in Equation (38).

$$U(s) = \left[K_p + K_i s^{-\lambda} + K_d s^\delta \right] R(s) \quad (38)$$

3.5. TID Controller

The TID controller introduces an enhanced feedback structure in which the conventional proportional term is replaced by a compensator characterized by the transfer function $\frac{1}{s} \omega_n$. This component, known as the “Tilt” element, shapes the feedback gain as a function of frequency, thereby improving the frequency-domain characteristics of the control sys-

tem [31]. The transfer function of the TID controller is presented in Equation (39), and its corresponding control configuration is illustrated in Figure 5c.

$$U(s) = \left[K_T s^{-\left(\frac{1}{n}\right)} + K_i s^{-1} + K_d s \right] R(s) \quad (39)$$

The controllers in Figure 5 are shown in their ideal form for structural comparison purposes, while in the actual simulation model, the derivative action is implemented using a filtered form to ensure practical realizability and numerical stability.

4. Optimization Algorithm

The Artificial Ecosystem-Based Optimization (AEO) algorithm is employed in this study to tune the parameters of various controllers, including PID, FOPID, TID, and the proposed 2-DOF FO-TID, for a two-area LFC system integrated with SMES. The obtained results are compared with several well-known metaheuristic algorithms, such as SCA, GWO, QIO, and FDA.

The AEO algorithm, first introduced by Zhao et al. [33], is inspired by energy transfer and nutrient circulation mechanisms observed in natural ecosystems. It is a population-based metaheuristic in which candidate solutions are modeled as interacting organisms classified into three groups: producers, consumers, and decomposers [33,34].

In this framework, producers act as the primary energy source, consumers obtain energy from producers or other consumers, and decomposers recycle nutrients within the system. The interaction among these groups forms the basis of the search mechanism in the AEO algorithm. Figure 6 illustrates the concept of energy transfer in a typical ecosystem.

In the AEO algorithm, the production phase mainly governs the balance between exploration and exploitation. The consumption phase supports exploration, whereas the decomposition phase focuses on exploitation to improve candidate solutions. Typically, the population includes one producer and one decomposer, while the remaining individuals are treated as consumers and classified into predefined categories depending on the problem characteristics.

The energy assigned to each individual is directly related to their level of physical fitness. As shown in Figure 7, producers are highlighted in yellow and decomposers in blue. Based on this distribution, the individual with the lowest fitness (denoted as 1) is given the highest energy level and works as producer [35]. While the best-performing individual (denoted as X9) has the lowest energy level and serves as the decomposer. The remaining individuals operate as consumers: X2 and X5 are herbivores, X3 and X7 are omnivores, and X4 and X6 are carnivores.

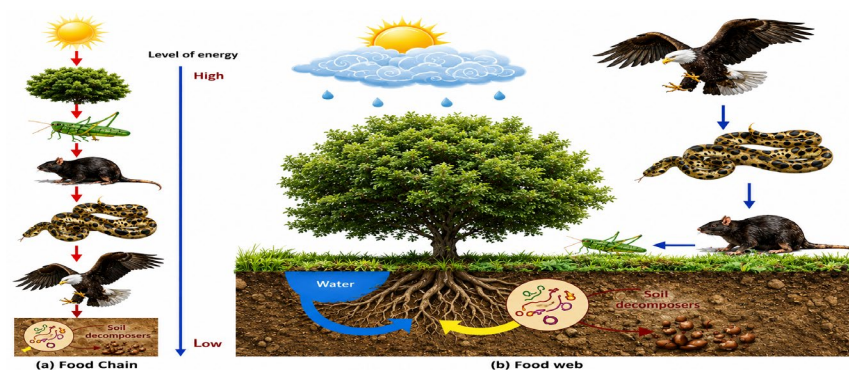


Figure 6. The Ecosystem energy flow.

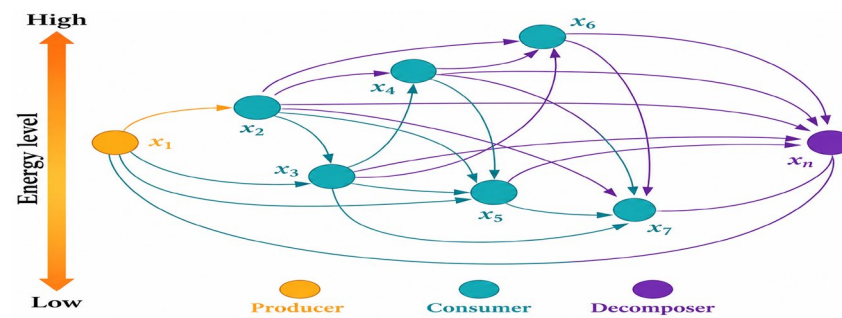


Figure 7. AEO algorithm ecosystem.

To lead the optimization process toward the most suitable solutions, a set of structural rules is considered:

1. A population of candidate solutions where producers, consumers, and decomposers correspond to different individuals within the search space is represented as the ecosystem.
2. The structure of the population is to include one producer and one decomposer, while all other individuals are treated as consumers.
3. Consumers are further categorized into herbivores, carnivores, and omnivores. During the generation of new candidate solutions, and to help maintain population balance and avoid bias toward a specific interaction pattern, each category is selected with equal probability.

4.1. Production Phase

The producer operator is intended to mimic the functional behavior of producers in natural ecosystems within the framework of AEO. In biological systems, producers rely on environmental inputs such as sunlight, water, and nutrients—often recycled through decomposers—to generate energy. Analogously, in AEO, the individual associated with the poorest fitness value assumes the role of the producer and is updated with reference to the predefined search boundaries and the current best-performing solution (i.e., the decomposer).

Following this update mechanism, the remaining individuals within the population adjust their positions accordingly. The production operator subsequently generates a candidate producer by establishing a guided interaction between the current best solution X_n and a randomly selected individual X_{rand} . The mathematical formulation of this updating process is presented in Equations (40)–(42).

$$X_1(t+1) = (1-a)X_n(t) + aX_{rand}(t) \quad (40)$$

$$a = (1 - t/\max_{iter})r_1 \quad (41)$$

$$X_{rand} = r(Ub - Lb) + Lb \quad (42)$$

In the mathematical expressions, the parameters n , $\max_{iter}$, Ub , Lb , and r_1 denote the population size, the maximum number of iterations, the upper and lower search boundaries, and a uniformly distributed random variable within the interval $[0, 1]$ respectively. Furthermore, the coefficients a and r correspond to a linear control parameter and a random vector defined over the range $[0, 1]$.

4.2. Consumption Process

Once the production phase is concluded, the algorithm transitions to the consumption phase, where consumers become active. At this level, a consumer may get energy from

either a producer or another consumer who has a lower energy level. This behavior reflects the hierarchical energy transfer observed in natural ecosystems.

Different foraging behaviors of animals can be mathematically modeled using the Lévy flight coefficient, which is widely used to enhance the exploration capability of optimization algorithms. Accordingly, the consumption phase is described with Lévy flight in (43) and (44).

$$C = \frac{1}{2} \frac{v_1}{|v_2|} \quad (43)$$

$$v_1 \sim N(0, 1), v_2 \sim N(0, 1) \quad (44)$$

where $N(0, 1)$ represents a Gaussian distribution with a mean of zero and unit standard deviation. This consumption coefficient enables each consumer to obtain energy through different hunting strategies. When a consumer is randomly assigned as an herbivore, it is restricted to consuming only the producers. Under these conditions, the consumption behavior of the herbivore is mathematically formulated as follows:

$$X_i(t+1) = X_i(t) + C (X_i(t) - X_1(t)), \quad i \in [2, \dots, n] \quad (45)$$

If a consumer is randomly categorized as a carnivore, they will outperform another consumer with a higher energy level. In this case, the carnivorous behavior is modeled mathematically as shown in Equation (46).

$$X_i(t+1) = X_i(t) + C (X_i(t) - X_j(t)), \quad i \in [3, \dots, n] \\ j = \text{randi}([2i-1]) \quad (46)$$

If an omnivore is selected within an ecosystem, it may consume either a high-energy consumer or a producer. This interaction differs from the feeding behavior observed in herbivores and carnivores. The mathematical formula corresponding to this case is shown in Equation (47).

$$X_i(t+1) = X_i(t) + C (r_2 (X_i(t) - X_1(t)) + (1-r_2)(X_i(t) - X_j(t))), \quad i \in [3, \dots, n] \\ j = \text{randi}([2i-1]) \quad (47)$$

In Equation (47), r_2 represents a random variable that is uniformly distributed within the interval $[0, 1]$. Individual positions are updated either by random selection or via a consumption factor applied to less successful individuals. The ability of algorithm to approach the global optimal solution is enhanced through this mechanism.

4.3. Decomposition Process

This phase presents a key element in the AEO structure. In analogy with natural ecosystems, inactive producers or consumers are broken down by decomposers, releasing nutrients that support the regeneration and sustainability of the producer population.

The mathematical representation of the decomposition operator is presented in Equations (48)–(51).

$$X_i(t+1) = X_n(t) + D (eX_n(t) - hX_i(t)), \quad i \in [1, \dots, n] \quad (48)$$

$$D = 3u, \quad u \sim N(0, 1) \quad (49)$$

$$e = r_3 \text{randi}([1 \ 2]) - 1 \quad (50)$$

$$h = 2r_3 - 1 \quad (51)$$

In Equation (48), the decomposition factor D is introduced along with the weighting factors e and h to mathematically describe the decomposition mechanism. The position of the i_{th} individual, denoted as X_i , is determined based on the parameters D , e , and h , with reference to the position of the best individual X_n .

The AEO algorithm commences by randomly initializing the population. During each iteration, the initial search agent updates its position according to Equation (40), whereas the remaining individuals update their positions with equal probability using Equations (45)–(47). The newly developed solution is accepted if it improves the value of the objective function in the previous iteration. Subsequently, each individual is optimized using the decomposition factor described in Equation (48). The iterative procedure continues until the predefined maximum number of iterations is attained or a specified termination criterion is satisfied. The flowchart of the AEO algorithm is provided in Figures 8 and 9 illustrates the proposed AEO-based control framework.

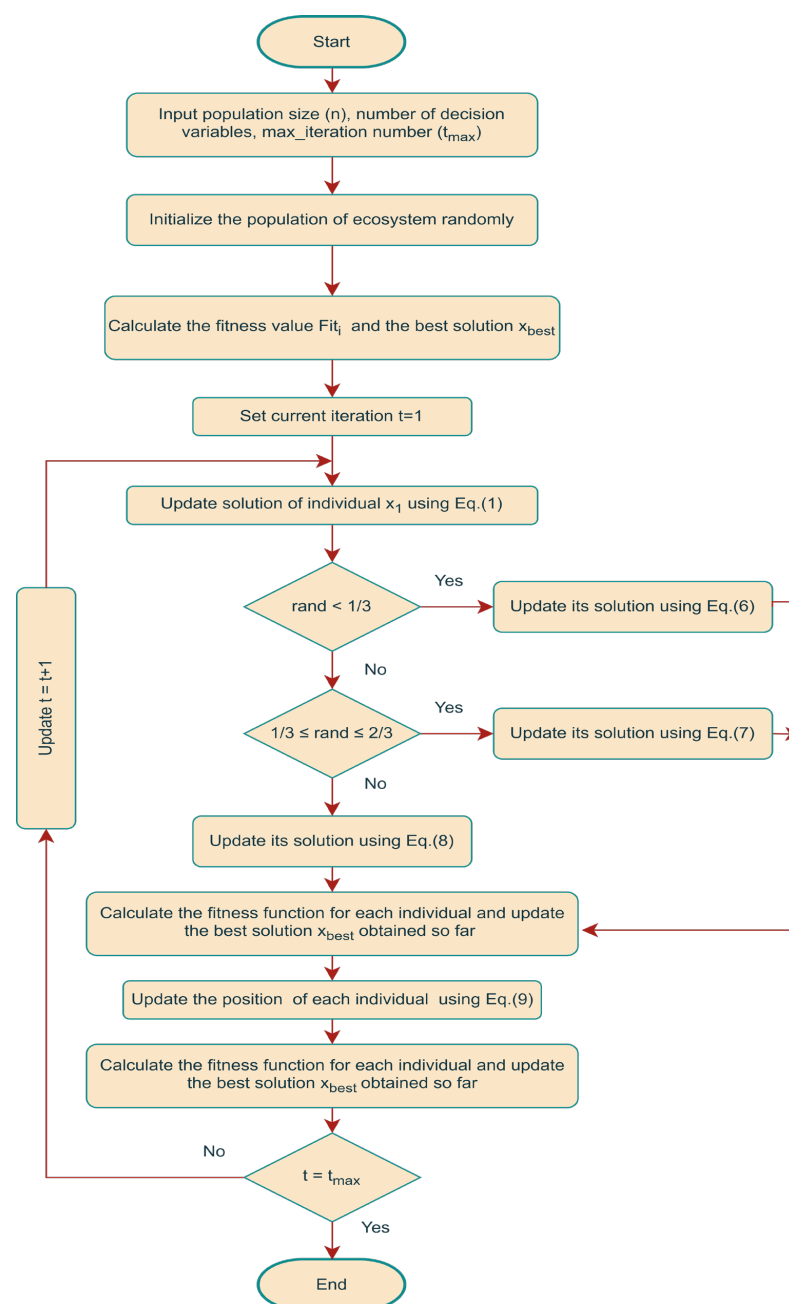


Figure 8. AEO algorithm flowchart.

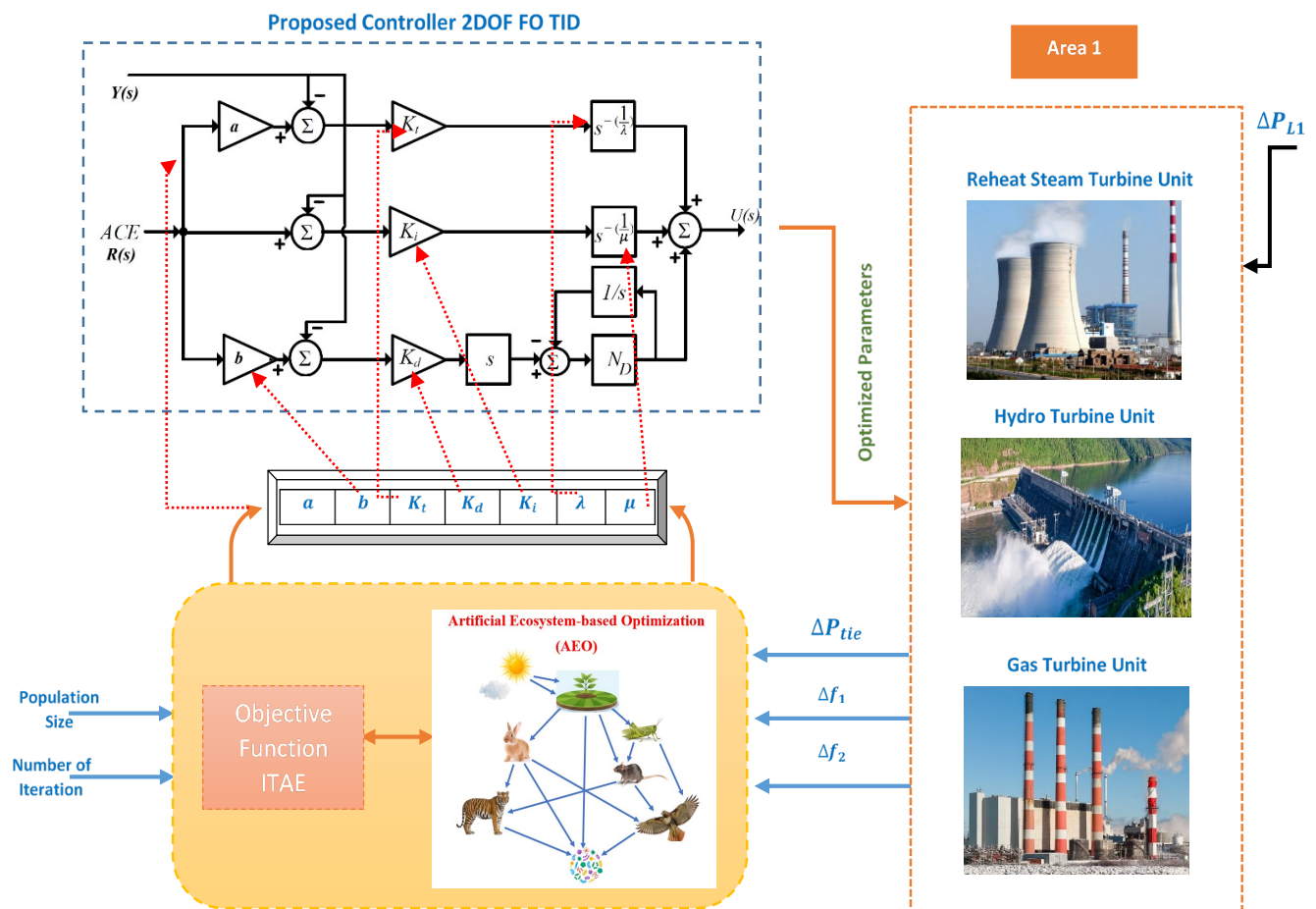


Figure 9. 2DOF FO TID parameters tuned by AEO algorithm.

5. Results

This section presents the simulation results obtained to evaluate the performance of the proposed control strategy in the two-area load frequency control (LFC) system. The controller parameters are optimally tuned using the Artificial Ecosystem Optimization (AEO) algorithm within the MATLAB/Simulink (R2022b) environment. To provide a comprehensive assessment, the proposed controller is examined under different operating scenarios and compared with several well-established controllers. The system performance is analyzed in terms of frequency deviations in both areas (Δf_1 and Δf_2) and tie-line power deviation (ΔP_{tie}) in order to assess the disturbance rejection capability and dynamic stability of the interconnected power system.

5.1. Performance Comparison of Controllers Optimized by the AEO Algorithm

A comparative evaluation of different controllers optimized using the Artificial Ecosystem Optimization (AEO) algorithm is presented in this section for the considered two-area load frequency control (LFC) system. The comparison includes conventional and fractional-order controllers, namely PID, FOPID, and TID, 1DOF FO TID in addition to the proposed 2DOF FO-TID controller. To ensure a fair assessment, the parameters of all controllers are tuned using the same optimization algorithm under identical operating conditions. The optimized controller parameters are summarized in Table 1, while the corresponding dynamic performance indices are reported in Table 2. The system responses are analyzed in terms of frequency deviations in both control areas and the tie-line power exchange in order to assess disturbance rejection capability and overall system stability.

As shown in Tables 1 and 2, the proposed AEO-2DOF FO-TID controller provides the more coordinated dynamic response among the examined controllers. Although some controllers achieve slightly faster local settling in the frequency response of Area 1 (Δf_1), this improvement is accompanied by considerably slower recovery in Area 2 (Δf_2). For instance, the AEO-PID and AEO-TID controllers achieve settling times of 3.03 s and 4.12 s in Δf_1 , respectively; however, the corresponding settling times in Δf_2 exceed 22 s, indicating weaker dynamic coordination between the interconnected areas. Figure 10 shows the dynamic responses of the interconnected two-area power system under a load disturbance using different controllers.

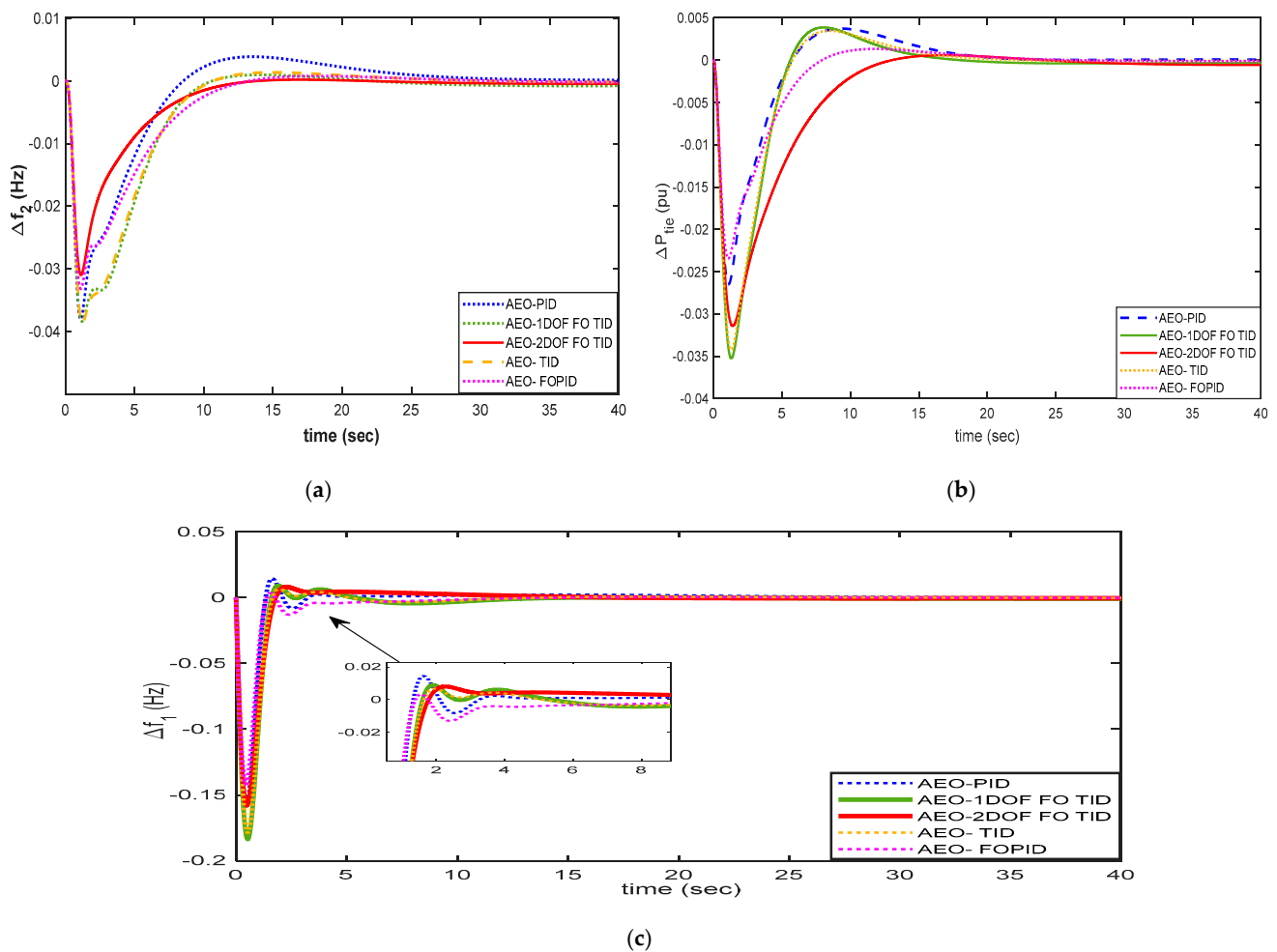


Figure 10. Dynamic responses of the interconnected two-area power system under a load disturbance for different controllers: (a) frequency deviation in area1; (b) frequency deviation in area 2; (c) tie-line power deviation.

In contrast, the proposed AEO-2DOF FO-TID controller achieves a more consistent stabilization pattern across the interconnected system, with settling times of 6.02 s for Δf_1 and 11.14 s for Δf_2 . This improved interaction reflected by balanced response between the two control areas and more effective suppression of oscillations between the two regions. In addition, the proposed controller scored the lowest ITAE value among all structures examined, this result indicates that the improved dynamic behavior results not only from parameter tuning but also from the structural advantages of the 2DOF-FO design.

Table 1. Optimized controller parameters obtained using the AEO algorithm.

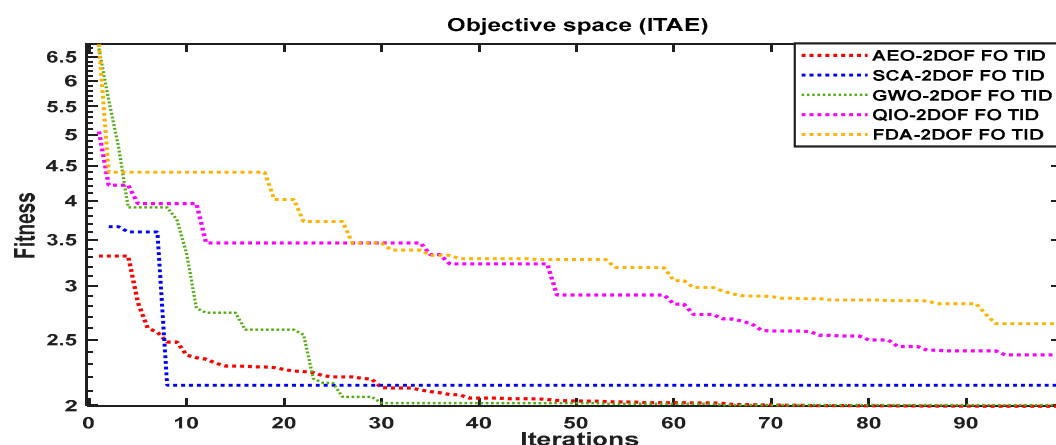
Controller	K_P	K_T	K_I	K_D	λ	μ	a	b	N
AEO-2DOF FO TID	-	1.4922	0.4977	0.0323	0.718	0.799	0.336	0.1553	10
AEO-1DOF FO TID	-	1.492	0.3964	0.1049	0.7495	0.7989	-	-	10
AEO-TID	-	0.4965	1.493	0.0386	-	-	-	-	1.672
FOPID	2.731	-	1.482	0.399	0.874	0.948	-	-	-
AEO-PID	2.962	-	1.4947	0.26843	-	-	-	-	-

Table 2. Dynamic performance comparison of controllers under the ITAE criterion.

Controller	Peak Δf_1 (Hz)	Peak Δf_2 (Hz)	Peak ΔP_{tie} (pu)	Settling Time Δf_1 (s)	Settling Time Δf_2 (s)	Settling Time ΔP_{tie} (s)	Best Fitness
AEO-2DOF FO TID	0.1578	0.03095	0.03141	6.0179	11.141	23.611	2.0627
AEO-1DOF FO TID	0.1834	0.0383	0.03521	4.629	22.367	15.76	2.4131
AEO-TID	0.1788	0.0386	0.0342	4.124	22.635	16.498	2.194
AEO-FOPID	0.149	0.0362	0.0258	39.59	24.30	34.334	1.6086
AEO-PID	0.149	0.0363	0.0257	3.03367	25.446	18.365	2.426

5.2. Optimization Algorithm Comparison for Tuning the Proposed 2DOF FO-TID Controller

The evaluation of different optimization algorithms effectiveness is further through a comparative analysis of their ability to tune the parameters of the proposed controller. The Artificial Ecosystem Optimization (AEO) algorithm is compared with different well-known metaheuristic algorithms, such as Grey Wolf Optimization (GWO), the Sine Cosine Algorithm (SCA), the Quadratic Interpolation Optimization (QIO), and the Flow Direction Algorithm (FDA). For a fair comparison, all algorithms are implemented under identical conditions (100 iterations, and a population size of 50) and employ the same objective function. The comparison is carried out based on the obtained fitness values, convergence characteristics, and the resulting dynamic performance of the LFC system. The convergence behavior of the considered algorithms is illustrated in Figure 11, while the optimized controller parameters and corresponding performance indices are summarized in Tables 3 and 4.

**Figure 11.** Convergence curves of different optimization algorithms 2DOF FO-TID controller.

Under the ITAE performance criterion, the parameters of the proposed 2DOF FO-TID controller were tuned using the considered optimization algorithms in order to evaluate their effectiveness in solving the controller tuning problem. As observed from Table 4, the GWO algorithm achieves the smallest numerical fitness value (2.008), while the proposed AEO algorithm provides a very close objective value of 2.0627. Despite this slight difference

in the fitness value, the dynamic responses obtained using the AEO algorithm demonstrate improved consistency and faster settling performance across the interconnected system. Figure 12 shows the dynamic responses of the two-area power system using a 2DOF FO-TID controller optimized by different algorithms.

Table 3. Optimized controller parameters obtained by multi-algorithms.

Algorithm	K_T	K_I	K_D	λ	μ	a	b
<i>AEO</i>	1.4922	0.4977	0.0323	0.718	0.799	0.336	0.1553
<i>SCA</i>	1.46	0.5	0.0368	0.75	0.8	0.35	0.1806
<i>GWO</i>	1.5	0.5	0.0276	0.75	0.8	0.35	0.1089
<i>QIO</i>	1.435	0.4351	0.0443	0.7277	0.769	0.3372	0.2257
<i>FDA</i>	1.5	0.5	0.0232	0.75	0.8	0.278	0.11

Table 4. Dynamic performance comparison of algorithms under the ITAE criterion.

Algorithm	Peak Δf_1 (Hz)	Peak Δf_2 (Hz)	Peak ΔP_{tie} (pu)	Settling Time Δf_1 (s)	Settling Time Δf_2 (s)	Settling Time ΔP_{tie} (s)	Best Fitness
<i>AEO</i>	0.1578	0.03095	0.03141	6.0179	11.141	23.611	2.0627
<i>SCA</i>	0.1297	0.02777	0.03037	10.898	20.992	24.168	2.0944
<i>GWO</i>	0.1692	0.0327	0.03247	8.856	18.441	23.333	2.008
<i>QIO</i>	0.1452	0.0301	0.0322	9.855	11.912	23.7886	2.4942
<i>FDA</i>	0.1219	0.0274	0.031	11.891	20.112	25.008	2.6375

To further support these results, a statistical comparison based on multiple independent runs is presented in Table 5. The table reports the best, mean, and standard deviation of the ITAE values for each algorithm, along with the corresponding settling time metrics. The results indicate that GWO achieves the lowest ITAE value, while FDA provides the smallest standard deviation but with relatively slower dynamic response. In contrast, AEO achieves a lower mean ITAE with competitive standard deviation and significantly reduced settling times, confirming the consistency and effectiveness of the obtained responses.

Table 5. Statistical Comparison of Optimization Algorithms.

Algorithm	Run 1	Run 2	Run 3	Best ITAE	Mean ITAE	Std Deviation	Best Settling Time Δf_1 (s)	Best Settling Time Δf_2 (s)
<i>AEO</i>	2.080	2.0627	2.121	2.0627	2.088	0.030	6.0179	11.141
<i>SCA</i>	2.0944	2.103	2.181	2.0944	2.131	0.043	10.898	20.992
<i>GWO</i>	2.230	2.131	2.008	2.008	2.119	0.091	8.856	18.441
<i>QIO</i>	2.4942	2.520	2.610	2.4942	2.541	0.048	9.855	11.912
<i>FDA</i>	2.650	2.6375	2.690	2.6375	2.659	0.027	11.891	20.112

In particular, the settling time of the frequency deviation in Area 1 (Δf_1) is reduced to 6.02 s when the controller parameters are tuned using AEO, whereas the settling times obtained using SCA, QIO, GWO, and FDA range between approximately 8.86 s and 11.89 s. A similar trend can be observed in the frequency response of Area 2 (Δf_2), where the AEO-based tuning achieves faster stabilization compared with most of the other examined algorithms.

Regarding the tie-line power deviation (ΔP_{tie}), the proposed algorithm maintains a competitive stabilization performance while avoiding the slower responses observed in some of the other optimization methods. Since the ITAE criterion imposes stronger penalties on errors that persist for longer durations, the reduced settling times achieved by

the AEO-based tuning indicate more effective suppression of late-time oscillations. Overall, the obtained results demonstrate that the proposed AEO algorithm provides a reliable and effective tuning strategy for the 2DOF FO-TID controller, leading to improved dynamic performance of the interconnected LFC system.

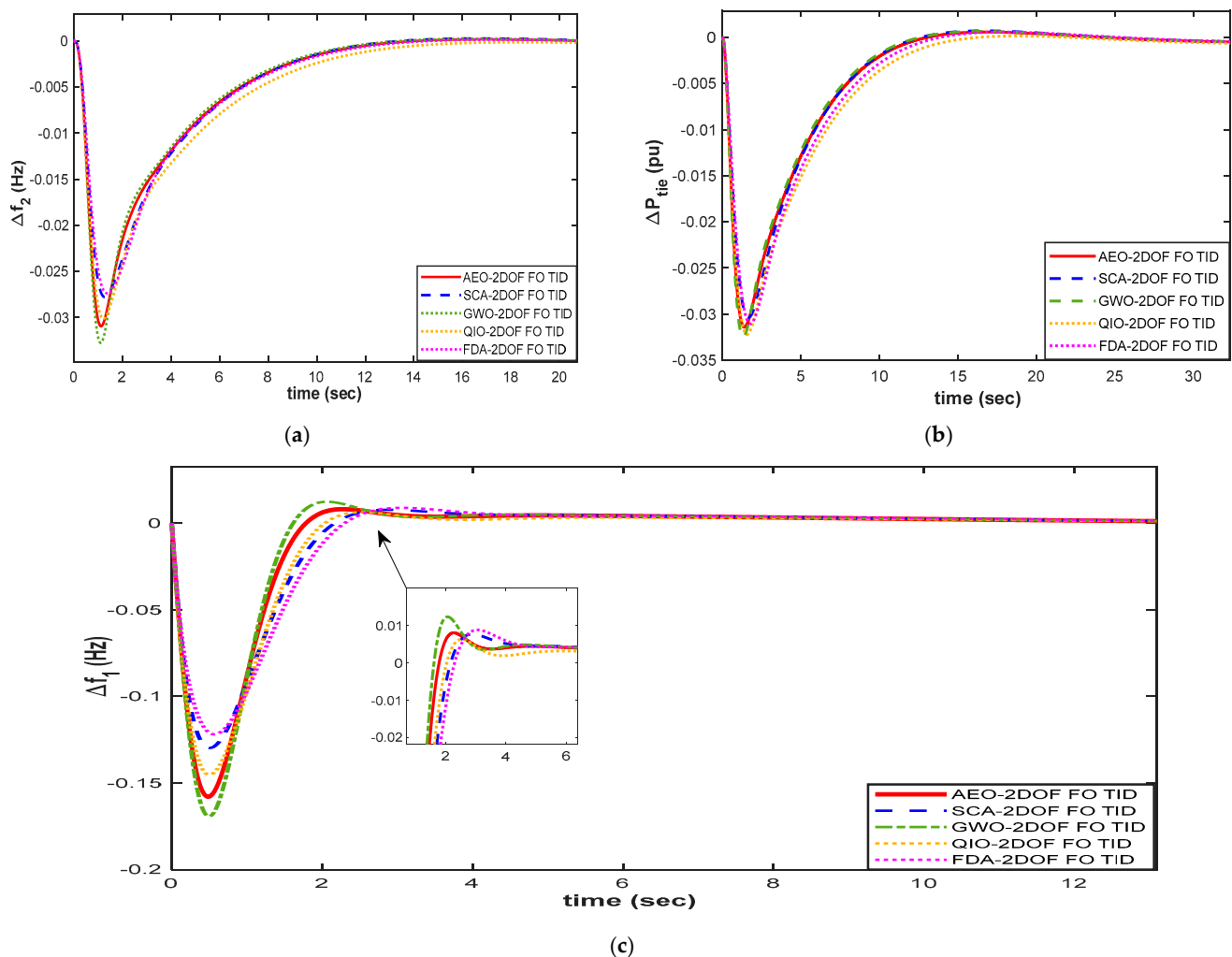


Figure 12. Dynamic responses of the two-area power system using a 2DOF FO-TID controller optimized by different algorithms: (a) frequency deviation in area1; (b) frequency deviation in area2; (c) tie-line power deviation.

5.3. Influence of Objective Functions on Controller Performance

To evaluate the influence of different performance indices on the tuning process, four objective functions ITAE, IAE, ITSE, and ISE were employed to optimize the parameters of the proposed 2DOF FO-TID controller. The resulting system responses, including the frequency deviations in both areas and the tie-line power deviation, are illustrated in Figure 13, while the corresponding quantitative results are summarized in Table 6.

The results clearly show that the selection of the objective function has a noticeable impact on the transient behavior of the LFC system. Among the investigated criteria, the ITAE-based tuning leads to the fastest overall stabilization. In particular, the settling time of Δf_1 is reduced to approximately 6.02 s, which is significantly shorter than the settling times obtained using IAE, ITSE, and ISE. A similar observation can be made for the frequency response of Area 2, where the ITAE criterion restores the system to steady state in about 11.14 s, whereas the other objective functions require longer recovery times.

The ISE criterion although may result in slightly lower peak deviations in certain cases, this advantage does not necessarily reflect superior dynamic performance. In contrast, slower reduction in oscillations compared to those achieved under ITAE-based tuning shown by the responses obtained using IAE, ITSE, and ISE. This can be explained by the formulation of the ITAE index, this can be explained by the formulation of the ITAE index, where errors that persist over time are given greater weight, resulting in a faster suppression of long-term deviations.

Table 6. Dynamic performance comparison of different objective functions.

Objective Function	Peak Δf_1 (Hz)	Peak Δf_2 (Hz)	Peak ΔP_{tie} (pu)	Settling Time Δf_1 (s)	Settling Time Δf_2 (s)	Settling Time ΔP_{tie} (s)	Best Fitness
ITAE	0.1578	0.03095	0.03141	6.0179	11.141	23.611	2.0627
IAE	0.1576	0.03057	0.03038	9.59740	19.66	24.117	0.4496
ITSE	0.165	0.0312	0.03046	8.930	18.289	24.087	0.0458
ISE	0.1392	0.0278	0.0295	8.526	12.883	23.562	0.0339

Overall, ITAE stands out as the most appropriate tuning criterion for the proposed 2DOF FO-TID controller, as it enables faster frequency recovery and enhances dynamic coordination between interconnected areas within the LFC system.

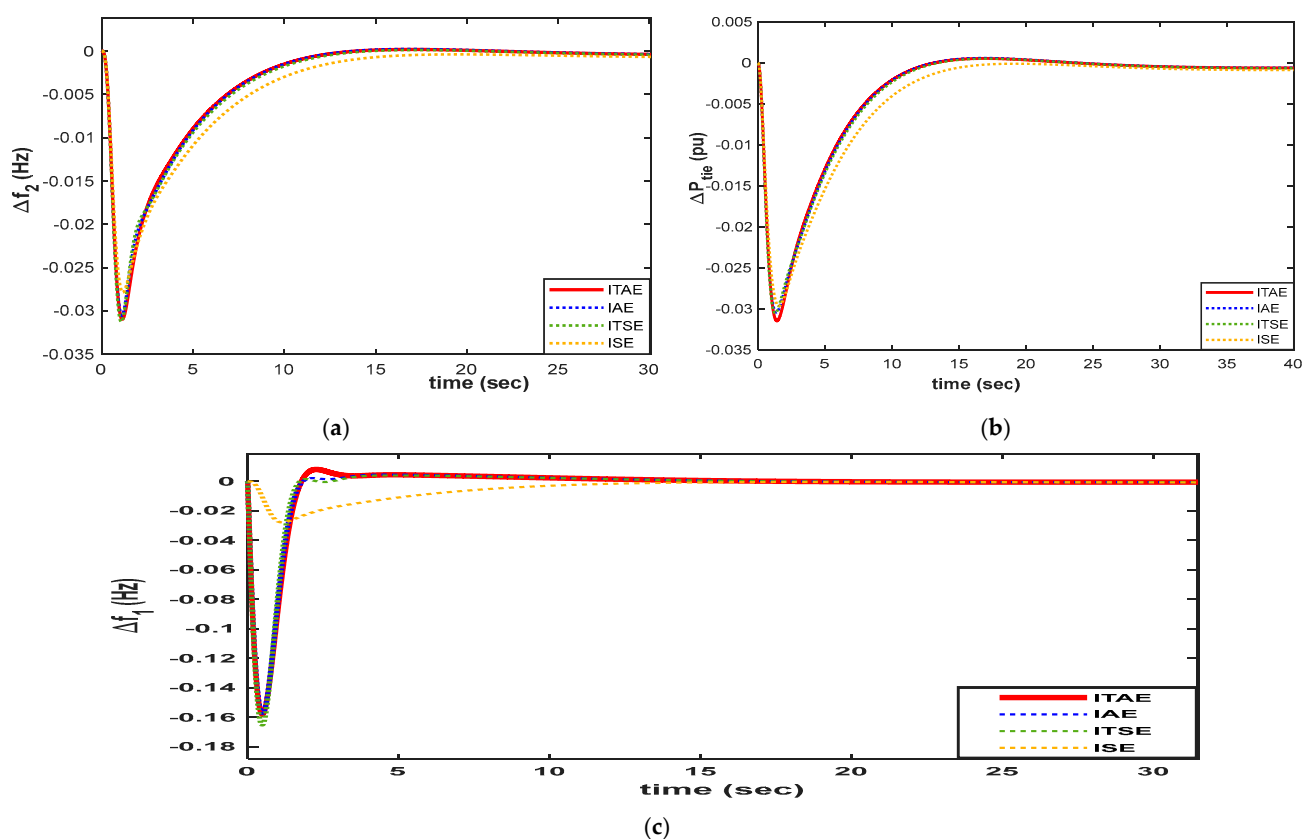


Figure 13. Dynamic responses under different objective functions: (a) frequency deviation in area1; (b) frequency deviation in area2; (c) tie-line power deviation.

5.4. Dynamic Response Under Sequential Load Disturbances

In this scenario, the perturbations rejection capability and dynamic performance of the two-area interconnected power system are evaluated by applying a sequence of step load disturbances in Area 1 at different time instants. During this case study, Area 2 initially operates under nominal conditions while the load perturbations are introduced only in

Area 1. Specifically, a positive load disturbance of $\Delta PL_1 = 0.01$ pu is applied at $t = 10$ s, followed by a negative load variation of $\Delta PL_1 = -0.01$ pu at $t = 60$ s. Finally, a larger disturbance of $\Delta PL_1 = 0.015$ pu is introduced at $t = 100$ s.

These load variations introduce a temporary imbalance between generation and demand in Area 1, resulting in frequency deviations. Owing to the dynamic coupling between the two areas through the tie-line, the disturbance is transferred to Area 2, producing corresponding variations in both system frequencies and the tie-line power exchange.

It should be noted that step load disturbances are used in this study as standard test signals in load frequency control (LFC) analysis to evaluate system dynamic performance under sudden imbalance conditions. These inputs are not intended to represent exact real-world disturbance profiles, but rather to provide a consistent and widely adopted benchmark for controller design and comparison.

From the obtained results, the classical PID controller exhibits relatively larger frequency deviations and slower recovery after the disturbances. The FOPID and TID controllers provide improved damping characteristics and slightly reduced deviations compared with the PID controller. In contrast, the proposed 2DOF FO-TID controller demonstrates a more consistent dynamic response under all disturbance scenarios. The oscillations following each disturbance are effectively attenuated, and the system variables smoothly return toward their nominal operating conditions. Furthermore, the tie-line power deviation remains well regulated, confirming appropriate power sharing between the interconnected areas. Overall, the results demonstrate that the proposed control structure provides reliable dynamic performance and strong disturbance rejection under successive load variations. Figure 14 illustrates the dynamic responses of the interconnected system in terms of Δf_1 , Δf_2 , and ΔP_{tie} under sequential load disturbances for the PID, FOPID, TID, and the proposed 2DOF FO-TID controllers.

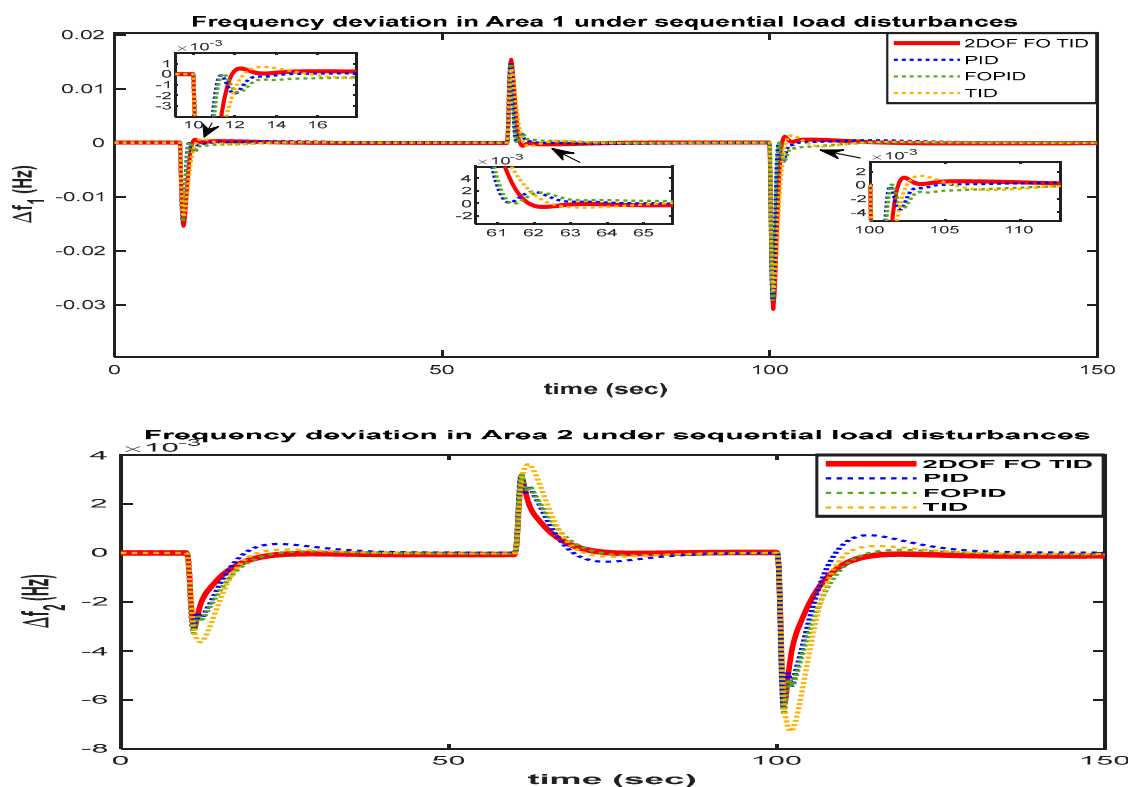


Figure 14. Cont.

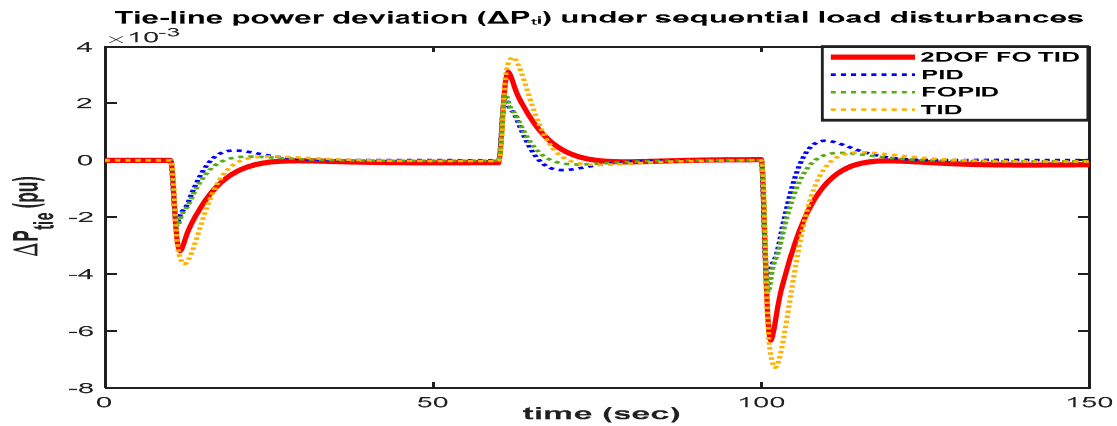


Figure 14. Dynamic responses of Δf_1 , Δf_2 , and ΔP_{tie} under sequential load disturbances in Area 1 for PID, FOPID, TID, and the proposed 2DOF FO-TID controllers.

5.5. Robustness Analysis Under Variations in System Parameters

To examine the impact of hydro system parameter variations, a sensitivity analysis was conducted by modifying the water starting time constant (T_w) by $\pm 20\%$ of its nominal value. The dynamic responses are shown in Figure 15, and the results are summarized in Table 7.

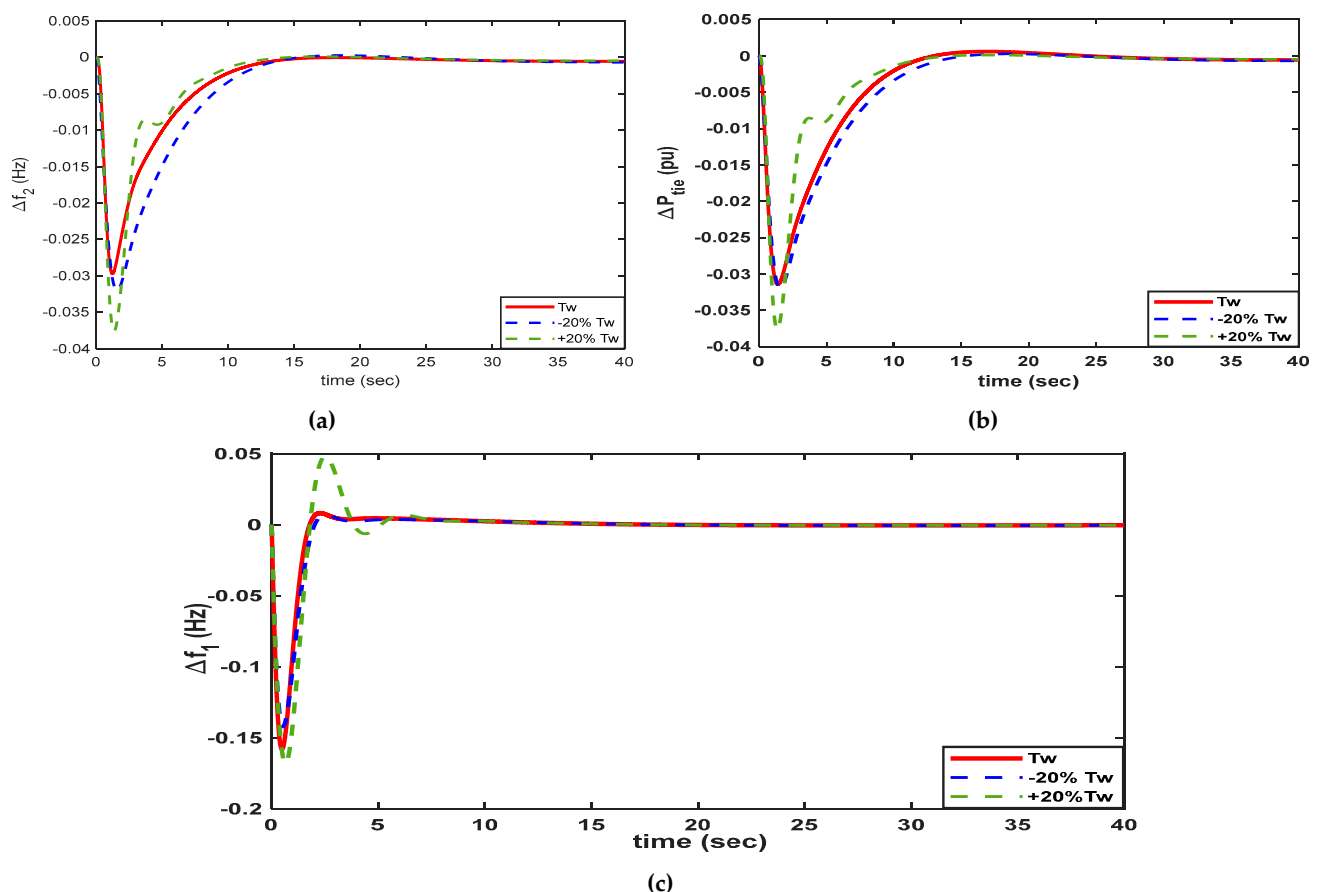


Figure 15. Dynamic responses under different Water Starting Time Constant (T_w): (a) frequency deviation in area1; (b) frequency deviation in area2; (c) tie-line power deviation.

The results indicate that the proposed 2DOF FO-TID controller maintains stable and well-damped performance under all variations. For the nominal case, the settling times are about 6.02 s for Δf_1 and 11.14 s for Δf_2 . When T_w is reduced, a slightly smoother response

is observed, while increasing T_w results in a more oscillatory behavior with marginally longer settling times. In terms of peak deviations, lower values are obtained when T_w is reduced, whereas higher peaks appear when T_w is increased. Despite these changes, the controller effectively limits frequency deviations and preserves overall system stability.

Table 7. Sensitivity Analysis of Water Starting Time Constant (T_w).

Case	Peak Δf_1 (Hz)	Peak Δf_2 (Hz)	Peak ΔP_{tie} (pu)	Settling Time Δf_1 (s)	Settling Time Δf_2 (s)	Settling Time ΔP_{tie} (s)	Best Fitness
Case 1 (Nominal)	0.1578	0.03095	0.03141	6.0179	11.141	23.611	2.0627
Case 2 (−20%)	0.1421	0.0297	0.0320	7.615	11.637	37.385	2.3659
Case 3 (+20%)	0.1678	0.0375	0.04008	8.931	14.21	37.037	2.2168

6. Conclusions

This paper investigated an enhanced control strategy for a two-area load frequency control (LFC) system using a two-degree-of-freedom fractional-order TID (2DOF FO-TID) controller tuned via the Artificial Ecosystem Optimization (AEO) algorithm. The effectiveness of the proposed approach has been demonstrated through extensive simulation studies, including comparisons with conventional PID, TID, and 1-DOF fractional-order controllers, as well as evaluations using different optimization algorithms and various performance indicators. The results indicate that the proposed controller achieves more balanced dynamic behavior across interconnected regions compared to traditional control structures. Although certain controllers exhibit faster local responses, they are associated with significantly slower recovery in the interconnected area. In contrast, improved inter-area coordination is obtained with the proposed 2DOF FO-TID controller, together with faster attenuation of frequency oscillations, resulting in smoother restoration of both system frequency and tie-line power exchange.

The comparative analysis of optimization algorithms indicates that reliable tuning performance is achieved by AEO for the proposed controller. Although some algorithms produce slightly lower fitness values, the dynamic responses obtained using AEO-based tuning are more consistent, with shorter settling times, confirming its effectiveness in identifying practically suitable controller parameters. In addition, the evaluation of different objective functions demonstrates that ITAE represents the most appropriate tuning criterion. Faster suppression of long-duration oscillations and improved overall system stability are achieved with ITAE-based tuning compared with IAE, ITSE, and ISE.

To further support these findings, a statistical comparison based on multiple independent runs was conducted and summarized in Table 5, where the best, mean, and standard deviation of the ITAE values are reported together with the corresponding settling time metrics. The results show that GWO achieves the lowest ITAE value, while FDA provides the smallest variation, whereas AEO demonstrates competitive average performance along with improved settling time characteristics.

A sensitivity analysis was carried out by varying the water starting time constant (T_w) by $\pm 20\%$ of its nominal value. The results, shown in Figure 15 and summarized in Table 7, indicate that the proposed 2DOF FO-TID controller maintains stable performance under all cases. While slight changes in peak values and settling times are observed, the overall system response remains well-damped, confirming the robustness of the controller against variations in hydro system parameters.

Overall, the results indicate that improved disturbance rejection and enhanced dynamic coordination in interconnected LFC systems are achieved by combining the 2DOF fractional-order control structure with AEO-based tuning. These findings suggest that effective support for frequency regulation in modern interconnected power networks can be provided by the proposed approach. Future work on this study may expand upon by investigating the performance of the proposed controller in more complex environments, including the integration of renewable energy, communication delays, and uncertainties of system parameters.

It should be noted that the simulation scenarios considered in this study are limited to step load disturbances, which are commonly used in load frequency control analysis. Although such disturbances provide a clear evaluation of system dynamic performance, they do not explicitly represent the stochastic variations associated with renewable energy sources such as wind and photovoltaic systems. Therefore, incorporating random and continuously varying load profiles to better capture renewable energy fluctuations is considered as a potential direction for future work.

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Abbreviations

The following abbreviations are used in this manuscript:

LFC	Load Frequency Control
AGC	Automatic Generation Control
AVR	Automatic Voltage Regulator
SMES	Superconducting Magnetic Energy Storage
ACE	Area Control Error
PID	Proportional–Integral–Derivative
PIDF	Proportional–Integral–Derivative with Filter
FOPID	Fractional-Order Proportional–Integral–Derivative
PIDA	Proportional–Integral–Derivative–Acceleration
TID	Tilt–Integral–Derivative
2DOF FO TID	Two-Degree-of-Freedom Fractional Order Tilt–Integral–Derivative
ANN	Artificial Neural Network
ITAE	Integral of Time-weighted Absolute Error
IAE	Integral of Absolute Error
ISE	Integral of Squared Error
ITSE	Integral of Time-weighted Squared Error
AEO	Artificial Ecosystem Optimization
GWO	Grey Wolf Optimization
SCA	Sine Cosine Algorithm
TLBO	Teaching–Learning-Based Optimization
AGTO	Artificial Gorilla Troops Optimizer
QIO	Quadratic Interpolation Optimizer
FDA	Flow Direction Algorithm

Appendix A

Table A1. Table of System Parameters.

Parameter	Description	Value
Generator–Load Parameters		
K_P	Generator–load gain	68.9655
T_P	Generator–load time constant	11.49
The Reheat steam Parameters		
$T_{g,s}$	Steam governor time constant	0.06
T_r	Reheat time constant	3.06
T_t	Turbine time constant	10
T_{sc}	Steam chest time constant	0.3
α_s	Participation factor	0.543478
Hydro Unit Parameters		
$T_{g,h}$	Hydro governor time constant	0.2
T_ω	Water starting time	1.1
α_h	Participation factor	0.326084
Gas Unit Parameters		
$T_{g,g}$	Gas governor time constant	0.05
T_{fz}	Fuel zero constant	0.6
T_{fp}	Fuel pole constant	1.1
T_{mz}	Mechanical zero constant	0.01
T_{mp}	Mechanical pole constant	0.239
$T_{m,g}$	Final mechanical lag	0.2
α_g	Participation factor	0.130438

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