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Review

Analytical and Optimisation-Based Strategies for Load Frequency Control in Renewable-Rich Power Systems

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Abstract

The growing integration of renewable energy sources (RES) has fundamentally altered power system dynamics, reduced system inertia and challenged conventional Load Frequency Control (LFC) mechanisms. This study presents a comprehensive review of analytical and optimisation-based approaches for frequency regulation in low-inertia, renewable-rich power systems. It highlights the evolution from classical proportional-integral (PI/PID) controllers to advanced model-based, robust, adaptive, and intelligent control schemes, emphasising their relative strengths in handling uncertainty, variability, and multi-area coordination. Additionally, the paper examines Frequency-Constrained Unit Commitment (FCUC) frameworks that explicitly incorporate frequency stability metrics, such as Rate of Change of Frequency (RoCoF), frequency nadir, and inertia adequacy, into scheduling and dispatch. Through comparative analysis, the study identifies key performance trends, computational challenges, and practical trade-offs between analytical and optimisation paradigms. The paper concludes by outlining open research directions, including decentralised FCUC, multi-agent coordination, and AI-assisted control, aimed at achieving scalable and resilient frequency regulation. Overall, this review bridges the gap between control theory and operational optimisation, offering a unified perspective to guide the development of next-generation frequency control frameworks in modern power grids.

Keywords: load frequency control; renewable energy; optimisation; generators; proportional-integral; power converters

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1. Introduction

The global power sector is undergoing a profound transformation, driven by the accelerated integration of RES [1,2] such as wind and solar photovoltaic (PV) [3]. These technologies, while critical for achieving decarbonisation targets, fundamentally alter the dynamic behaviour of power systems due to their inverter-based interfaces [4,5]. Unlike conventional synchronous generators, which contribute substantial rotational inertia [6], inverter-based RES [7] are decoupled from grid frequency, leading to reduced system inertia and increased vulnerability to disturbances [8,9]. The immediate consequence is a steeper RoCoF and a deeper frequency nadir following generation–load imbalances, both of which threaten the secure operation of modern power systems [10,11].

Traditionally, LFC has served as a cornerstone for ensuring the balance between supply and demand while maintaining system frequency within permissible limits [12]. Classical LFC strategies, dominated by Proportional–Integral (PI) and Proportional-Integral-Derivative (PID) controllers, have demonstrated effectiveness in high-inertia grids [13]. However, in the presence of high RES penetration, these approaches face significant limitations [14]. Studies reveal that PI-based controllers often exhibit high overshoot (8–15%) and longer settling times (~10 s) [15] when subjected to renewable intermittency, which renders them less reliable for emerging grid conditions [16].

To overcome these shortcomings, researchers have investigated a range of advanced analytical and optimisation-based techniques [17]. Among them, robust control frameworks, such as Sliding Mode Control (SMC) [18] and H∞ control [19], have shown promise in addressing parameter uncertainties and external disturbances [20], achieving superior frequency regulation with minimal overshoot and reduced settling times [21,22]. Similarly, optimal and predictive approaches such as Model Predictive Control (MPC) [23,24] and Internal Model Control (IMC) [25] have been proposed to enhance the adaptability of LFC in low-inertia settings [26–28]. These methods leverage predictive modelling and constraint handling to provide more resilient control, albeit at the expense of higher computational complexity [29,30].

Beyond real-time control, FCUC has emerged as a pivotal operational planning framework [31–33]. Unlike conventional Security-Constrained Unit Commitment (SCUC) models [34,35], which primarily focus on economic dispatch and reserve adequacy, FCUC explicitly incorporates frequency stability constraints such as inertia adequacy, governor response, RoCoF, and frequency nadir into scheduling decisions [36–41]. This framework ensures that operational schedules are not only cost-effective but also dynamically feasible in the face of high renewable variability [42,43]. Nevertheless, challenges persist regarding the computational scalability of FCUC, particularly for large, interconnected systems with distributed energy resources (DERs). Centralised FCUC frameworks, while rigorous, may not be practical for highly decentralised and prosumer-dominated grids [44,45].

1.1. Identified Research Gaps

Despite significant progress, several research gaps remain. Researchers and system operators still rely heavily on centralised optimisation architectures, which cannot easily scale to the decentralised structures anticipated in future smart grids. Second, classical analytical models often oversimplify the nonlinear dynamics of inverter-based RES, limiting their accuracy in predicting fast transients [14,23]. Third, while optimisation techniques such as stochastic and robust unit commitment account for uncertainty, they often impose prohibitive computational burdens in real-time operation [38,39].

These gaps highlight the urgent need to develop innovative analytical and optimisation-based strategies that ensure frequency stability while maintaining computational efficiency, robustness, and scalability. In this work, the authors unify analytical and optimisation-based LFC strategies for renewable-dominated systems, offering an integrated perspective rarely addressed in earlier studies. Unlike prior reviews that typically focused on either classical control methods or isolated optimisation formulations, this paper bridges both domains to present a comprehensive and comparative analysis. The study further identifies key challenges related to low-inertia system dynamics, decentralised coordination, and computational scalability within FCUC frameworks. By mapping controller hierarchies—primary, secondary, and tertiary—to modern operational contexts and specifying data and implementation requirements, this work establishes a structured foundation for next-generation, frequency-secure, renewable-integrated power systems.

1.2. Research Scope

In this context, the present paper provides a comprehensive review of analytical and optimisation-based strategies for LFC in power systems with a high proportion of renewable energy sources. It systematically examines both classical and advanced controllers for single-area and multi-area frequency regulation, highlighting their respective control dynamics and stability characteristics. The review further explores robust and optimal control approaches designed to mitigate the impacts of parameter uncertainty and system variability. In addition, it discusses optimisation-based scheduling frameworks, particularly the FCUC models, which explicitly embed frequency security constraints such as RoCoF and nadir limits. Finally, the paper presents comparative performance evaluations of analytical and optimisation strategies, emphasising their effectiveness, computational requirements, and suitability under varying scenarios of renewable energy penetration.

1.3. Key Contributions of This Study

To address the identified research gaps, this study makes several key contributions. First, it systematically consolidates analytical and optimisation-based approaches for frequency regulation in low-inertia power systems, offering a unified perspective that integrates concepts often treated separately in existing literature. Second, it highlights emerging research challenges and future directions, including the development of decentralised FCUC models, enhancement of computational efficiency, and hybridisation with intelligent control techniques such as machine learning and multi-agent coordination. By bridging the domains of control theory and optimisation, this review provides a comprehensive foundation for advancing next-generation frequency control frameworks. The paper thus serves as a practical reference for researchers and system operators seeking robust, scalable, and economically efficient solutions to the frequency stability challenges posed by high levels of renewable energy integration.

2. Background: Frequency Stability and System Inertia

2.1. Frequency Stability in Modern Power Systems

Frequency stability refers to the ability of a power system to maintain its nominal frequency (50 or 60 Hz) within acceptable limits following disturbances, such as load variations, generator outages, or fluctuations in renewable energy [46]. It is a critical aspect of system reliability, as frequency directly reflects the balance between generation and demand [47]. If generation exceeds demand, frequency rises; conversely, if demand exceeds generation, frequency falls. Severe deviations can trigger under-frequency load shedding (UFLS), equipment malfunctions, or even cascading blackouts [48,49].

The literature review followed a systematic search across IEEE Xplore, ScienceDirect, SpringerLink, and MDPI databases using the strings “load frequency control” AND (“renewable” OR “low inertia”) AND (“robust” OR “adaptive” OR “optimisation”). The time window spanned from 2015 to 2024. The inclusion criteria required quantitative LFC results, a renewable or low-inertia system context, and an explicit controller design. Exclusions applied to purely theoretical or non-frequency studies. The authors screened 173 papers, selected 64 after assessing abstracts and relevance, and retained 42 for comparative synthesis.

Unlike steady-state voltage or transient rotor angle stability, frequency stability involves complex dynamic interactions among system inertia, governor response, and frequency-sensitive loads, making it particularly vulnerable in modern grids dominated by non-synchronous RES [4,5]. Researchers generally characterise frequency stability across four distinct response stages [10]. The Inertial Response (IR) represents the immediate, sub-second reaction contributed by the rotational inertia of synchronous gen-

erators [50,51]. The Primary Frequency Response (PFR) follows, driven by governor action that operates within 1–10 s to arrest the frequency decline [52–54]. The Secondary Frequency Response (SFR), implemented through Automatic Generation Control (AGC), restores frequency to its nominal value over a period of several minutes to tens of seconds [55]. Finally, the Tertiary Frequency Response (TFR) encompasses manual or optimised dispatch adjustments that occur over longer timescales, ranging from minutes to hours [56]. These hierarchical mechanisms once ensured robust frequency regulation. Still, the growing penetration of non-synchronous renewable energy sources has significantly reduced their effectiveness, since such sources inherently lack physical inertia and governor-based response capabilities.

2.2. Traditional Role of System Inertia

In conventional grids dominated by synchronous generators (SGs), the rotating masses of turbines and generators act as an inertial buffer against sudden imbalances between generation and demand [57]. This system inertia provides an instantaneous stabilising response, slowing RoCoF [58] and buying valuable time for PFR mechanisms [59], such as governor action, to restore balance [11]. The study mathematically expresses the system inertia as [58]

$$E_k = \frac{1}{2} J\omega^2 \tag{1}$$

where J is the moment of inertia and ω is the angular velocity. The inertial response acts instantaneously to counter frequency deviations, unlike slower secondary or tertiary controls. Its effectiveness depends on the rotational mass of synchronous machines, as greater stored kinetic energy provides more substantial resistance to disturbances. Consequently, traditional power systems with abundant synchronous generation were inherently resilient to fluctuations in frequency.

2.3. Impact of Renewable Energy Sources on Frequency Stability

The increasing penetration of inverter-based RES fundamentally alters this dynamic. Unlike SGs, power electronic converters connect inverter-based resources (IBRs) to the grid, decoupling them from system frequency and causing them to contribute little or no physical inertia [60].

The integration of RES into modern power grids significantly alters system dynamics, leading to several critical impacts on frequency stability. First, the integration of inverter-based renewable energy sources reduces system inertia because they contribute little to rotational kinetic energy. Studies in systems such as ERCOT demonstrate that when variable renewable energy (VRE) penetration exceeds 50%, the grid frequently shifts between synchronous and inverter dominance, resulting in increased frequency volatility [11]. Second, lower inertia results in a higher RoCoF, which shortens the response window for governors, AGC, and reserves. ERCOT data show frequency declines of up to 0.5 Hz/s under 60% RES penetration [61]. Third, deeper frequency nadirs occur following generation–load imbalances, raising the risk of under-frequency load shedding and cascading failures [62]. Additionally, nonlinear governor dynamics emerge, as inverter-based controllers, whether grid-forming or grid-following, display delayed and less predictable responses compared to conventional governors [63]. Finally, reserve management becomes more complex, with reduced synchronous reserves compelling operators to depend increasingly on synthetic inertia from RES, fast frequency response (FFR) from energy storage systems (ESS), and dynamic reallocation of spinning reserves [64,65].

2.4. Synthetic and Fast Frequency Response (FFR)

With the growing displacement of synchronous machines by inverter-based RES [66,67], the ability of the power system to withstand disturbances and maintain frequency stability has been significantly weakened [68,69]. Traditional inertial and governor-based primary responses are no longer sufficient in low-inertia environments [70]. To bridge this gap, emerging control strategies such as Synthetic Inertia and FFR have been introduced [71–73], both of which are critical to modern FCUC frameworks [37,39].

Researchers have developed synthetic inertia and FFR to mitigate inertia loss, and the following sections explain them in detail:

- Synthetic Inertia: Some wind turbines can emulate inertia by extracting kinetic energy from rotating blades during disturbances. However, this depletes rotational energy, and operators must carefully manage it to avoid post-disturbance instability [74].

$$\Delta P_{syn}(t) = -K_{syn} \cdot \frac{df(t)}{dt} \tag{2}$$

where

$\Delta P_{syn}(t)$ = additional power injected as synthetic inertia
K_{syn} = synthetic inertia gain constant
$\frac{df(t)}{dt}$ = System RoCoF

By reducing the RoCoF immediately after a contingency, synthetic inertia buys time for primary reserves to activate and prevents the frequency nadir from breaching critical thresholds.

- Battery-Based FFR: FFR refers to rapid active power injections (or curtailments) by inverter-based resources, demand response, or storage systems, which occur within a response time of hundreds of milliseconds to a few seconds, much faster than conventional governor action. Unlike synthetic inertia, which responds proportionally to the frequency derivative, FFR often triggers based on frequency thresholds. Batteries can inject power within milliseconds, compensating for reduced synchronous inertia [75]. Their limitations lie in state-of-charge constraints and degradation costs [76].

$$\Delta P_{FFR}(t) = \begin{cases} K_f \cdot (f_0 - f(t)) & f(t) < f^{thr} \\ 0, & f(t) \geq f^{thr} \end{cases} \tag{3}$$

where

K_f = droop constant
f_0 = nominal frequency
f^{thr} = frequency threshold for FFR activation

- Hybrid Solutions: Within the FCUC framework, inverter-based RES and energy storage systems (ESS) act as hybrid frequency-support providers, delivering synthetic inertia and FFR services [77]. Their integration affects both the frequency-related constraints and the objective function of the optimisation problem. When synthetic inertia is available, the inertia adequacy constraint becomes less stringent, as inverter-based resources enhance the system's effective inertia [78]. Similarly, with FFR participation, RoCoF and frequency nadir constraints become less restrictive, thereby reducing the reliance on costly synchronous reserves and improving the overall efficiency of frequency-secure scheduling [79].

The objective function incorporates FFR deployment costs or opportunity costs (e.g., curtailed PV/wind generation or storage degradation). While effective, these strategies are not true substitutes for synchronous inertia. Their performance depends heavily on control algorithms, response delays, and the availability of energy.

2.5. Hierarchical Taxonomy of Load Frequency Control (LFC) Strategies

To enhance clarity, a hierarchical taxonomy of Load Frequency Control (LFC) strategies is presented in Figure 1.

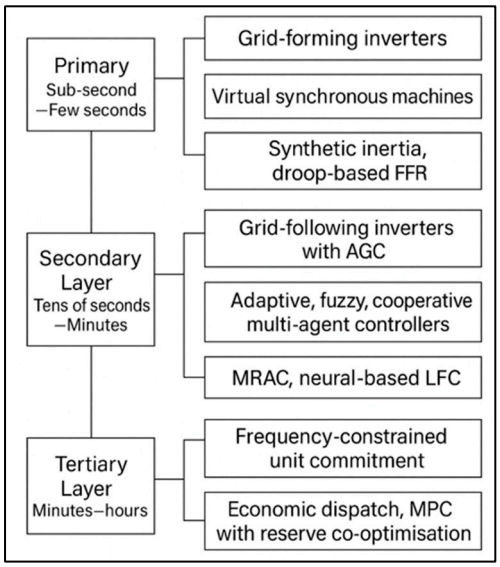


Figure 1. A hierarchical taxonomy of Load Frequency Control (LFC) strategies.

This taxonomy illustrates how inverter-based and storage-assisted control mechanisms align with the conventional control hierarchy in power systems dominated by renewable energy sources. At the primary control layer, grid-forming inverters, virtual synchronous machines (VSMs), droop-based control, and FFR contribute sub-second support through synthetic inertia and rapid active power modulation. The secondary control layer comprises adaptive, fuzzy, and cooperative multi-agent controllers, as well as model-reference adaptive control (MRAC) and neural-based schemes that restore nominal frequency over tens of seconds. The tertiary control layer integrates optimisation-based frameworks such as FCUC, Economic Dispatch, and MPC, which coordinate reserves and scheduling decisions over longer horizons. Collectively, this hierarchical mapping bridges classical control principles with emerging inverter technologies, providing a unified perspective on modern frequency regulation in grids rich in renewable energy sources.

2.6. Frequency-Constrained Optimisation Frameworks

The emergence of low-inertia, RES-dominated power systems has exposed the limitations of conventional SCUC models [80], which ensure feasibility under steady-state power balance, reserve adequacy, and network constraints, but fail to guarantee frequency stability after contingencies [81]. To address this gap, researchers have proposed FCUC frameworks that extend SCUC by embedding explicit frequency-security constraints into the scheduling problem [37,39,41]. These frameworks aim not only to achieve economic efficiency but also to ensure dynamic resilience against disturbances.

Frequency-aware optimisation frameworks for power system scheduling and dispatch have evolved to address the growing challenges of integrating renewable energy sources. The SUC framework accounts for uncertainties in renewable generation and demand but does not explicitly capture frequency dynamics [82,83]. In contrast, the FCUC extends SUC by embedding frequency security metrics, including Rate of Change of Frequency (RoCoF), frequency nadir, and inertia adequacy, directly into the scheduling formulation [36–40]. The FCUC framework features explicit modeling of frequency stability constraints, co-optimisation of reserves across synchronous machines, inverter-based re-

sources, and energy storage systems, as well as the integration of inertia requirements into both day-ahead and intra-day scheduling processes. This holistic approach ensures that the system frequency remains within safe operational limits, even under high penetration of renewable energy. Despite these advances, FCUC faces significant computational scalability challenges, particularly for large, decentralised systems. Many implementations adopt a centralised approach, which may not be feasible in future DER- and microgrid-dominated architectures [44,45].

2.7. Limitations of Current Approaches

Although the development of FCUC models has advanced considerably [84], several key limitations still impede their large-scale implementation in practical power system operations [85]. These challenges can be broadly categorised into computational, modelling, and implementation issues, each constraining the scalability, accuracy, or real-world applicability of FCUC frameworks. Many formulations rely on simplified analytical models that fail to capture the nonlinear dynamics of renewable energy sources (RES), resulting in reduced accuracy under high renewable energy penetration [86–88]. Scalability remains a significant concern, as centralised optimisation approaches such as SUC and FCUC are computationally demanding and challenging to extend to distributed or decentralised grids [44,45]. Additionally, reserve allocation uncertainty persists, with reliance on synthetic inertia and FFR introducing variability in reliability, consistency, and cost-effectiveness. Moreover, current literature shows a regional bias, with most studies focusing on high-income regions (e.g., Europe and the United States). At the same time, developing countries, which are experiencing rapid yet less coordinated integration of renewable energy, remain underrepresented, as noted in [36,37].

2.8. Synthesis and Outlook

The literature confirms that system inertia remains a cornerstone of frequency stability; however, its natural provision is declining with increasing penetration of renewable energy sources. Analytical and optimisation-based approaches, such as robust LFC and FCUC, represent promising solutions, yet their effectiveness depends on accurate modelling, decentralised scalability, and efficient computation. These gaps motivate the deeper review presented in this paper, which consolidates the state-of-the-art in analytical and optimisation-based frequency control strategies for renewable-rich, low-inertia power systems.

This review paper does not generate or use any new real or simulated data. All datasets, system models, and case-study results discussed in the manuscript originate from previously published studies. Where relevant, the authors explicitly indicate whether the cited works employed real-world datasets (e.g., SCADA, market data) or simulated benchmark systems (e.g., IEEE test networks, synthetic RES profiles). This distinction ensures clarity for readers and avoids any ambiguity regarding the data sources used within the reviewed literature.

3. Single-Area Load Frequency Control

3.1. Overview of Single-Area LFC

Single-Area LFC is the foundational approach for frequency regulation in power systems [89]. In its classical form, it maintains frequency at its nominal value (50/60 Hz) within a single control area by adjusting generation to balance real power demand and supply [90]. The single-area framework assumes no tie-line power exchanges, making it suitable for isolated or relatively independent power systems [10].

The objective of control in LFC is twofold. First, it aims at mitigating frequency deviations that occur immediately after sudden load or generation disturbances, thereby maintaining system stability and preventing cascading failures. Second, it focuses on eliminating steady-state error to ensure that, after transient responses settle, the system frequency is fully restored to its nominal value, maintaining long-term operational balance and reliability.

Figure 2 shows the classical single-area systems. Here, researchers typically model the governor–turbine–generator dynamics using linearised transfer functions and design controllers to minimise steady-state frequency deviations and improve transient performance. Traditionally, researchers have widely adopted Proportional-Integral (PI) and Proportional-Integral-Derivative (PID) controllers because they are simple and effective in suppressing steady-state errors [11]. However, these classical controllers often fail to cope with the nonlinearities and uncertainties introduced by high penetration of RES, such as wind and solar PV, which exhibit variable and intermittent generation patterns [91,92].

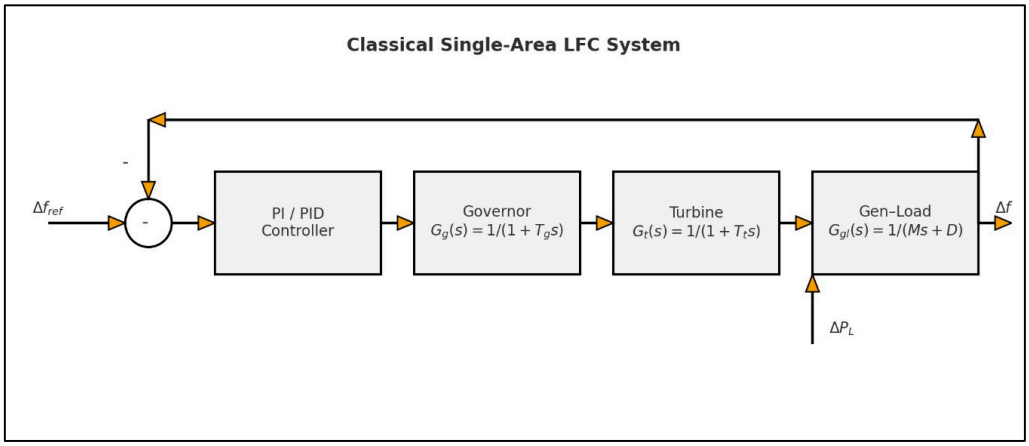


Figure 2. Classical Single-Area LFC System.

The study can mathematically represent the single-area LFC problem by modelling the governor, turbine, and generator-load dynamics. The swing equation derives the fundamental relationship by capturing the balance between mechanical and electrical power [11]:

$$2H\frac{d\Delta f(t)}{dt} = P_m(t) - P_e(t) - D\Delta f(t) \tag{4}$$

where H = inertia constant,

P_m = mechanical power input,

P_e = electrical load demand,

D = damping constant,

$\Delta f(t)$ = frequency deviation.

The governor adjusts the turbine valve position in response to frequency deviation, while the turbine provides mechanical output power to the generator. Linearisation of these components yields transfer functions for governor, turbine, and load as follows:

1. Governor:

$$G_g(s) = \frac{1}{1 + T_g s} \tag{5}$$

2. Turbine:

$$G_t(s) = \frac{1}{1 + T_t s} \tag{6}$$

3. Generator Load:

The swing equation governs the relationship between power imbalance and frequency deviation:

$$\Delta\dot{\omega}(t) = \frac{1}{2H}(P_m - P_e - D\Delta\omega(t)) \quad (7)$$

Here, H is the inertia constant, P_m, and P_e are the mechanical and electrical power, and D is the damping constant. In Laplace form,

$$G_{gl}(s) = \frac{1}{Ms + D} \quad (8)$$

where T_g and T_t are the governor and turbine time constants (typically 0.1–0.4 s, and 0.2–0.5 Sec for thermal units), respectively, and M is the inertia coefficient [11].

The control objective is to minimise the Area Control Error (ACE). Equation (9) defines the ACE as:

$$ACE = \Delta P_{tie} + B\Delta f \quad (9)$$

For a single-area LFC (no tie-line), ACE simplifies to frequency deviation. The control objective is thus to regulate Δf to zero by adjusting the generator output through feedback mechanisms [11].

The authors evaluated the performance of the proposed LFC strategy using a set of quantitative performance indices. The Integral of Squared Error (ISE) was used to penalise large deviations in frequency, while the Integral of Time-weighted Absolute Error (ITAE) emphasised errors that persist over longer durations, ensuring a faster settling of responses. The authors analysed key transient response parameters, including settling time T_s, maximum overshoot M_p, frequency nadir, and RoCoF, to assess dynamic stability. Finally, robust metrics were employed to evaluate the controller's sensitivity to parameter variations and renewable energy intermittency, reflecting its adaptability under uncertain operating conditions.

3.1.1. Justification of Assumptions, Parameters, and Boundary Conditions

To ensure model transparency and reproducibility, the assumptions and parameter selections in the mathematical formulation are explicitly justified. The power system is modeled under the standard small-signal linearization assumption, which is valid for frequency deviations within ±0.1 Hz, allowing for a tractable analysis of control dynamics without loss of generality. Governor, turbine, and generator dynamics follow established IEEE benchmark models, with parameters (droop constant R, inertia constant H, and damping coefficient D) chosen from validated test systems in the literature to ensure realistic dynamic responses. Boundary conditions assume nominal frequency (f_0 = 50/60 Hz) and system load equilibrium prior to disturbance, ensuring that deviations (Δf, ΔP_m, ΔP_e) represent perturbations around steady-state operating points. For renewable and storage-integrated cases, converter control parameters and state-of-charge (SoC) limits are adopted from recent experimental and simulation-based studies to capture realistic operational behaviour. These justifications collectively ensure that the mathematical model remains both physically interpretable and reproducible, providing a credible foundation for evaluating comparative controllers.

3.1.2. Comparative Analysis of Single-Area LFC

The evolution of single-area LFC has progressed from conventional PI/PID controllers to more sophisticated model-based and intelligent control techniques. The growing need to manage increased variability and uncertainty from high renewable energy penetration has driven this transition. The advanced methods offer enhanced robustness against

parameter uncertainties, superior disturbance rejection in renewable-dominated systems, and improved dynamic performance, characterised by faster settling times and reduced overshoot compared to traditional control approaches. However, challenges remain in the practical implementation of these techniques, particularly regarding computational complexity and the real-time deployment of solutions in resource-constrained environments. The implementation of extended LFC algorithms entails inherent trade-offs among model accuracy, stability, and computational time. While high-fidelity models (e.g., MPC) improve transient prediction and asymptotic convergence, their increased computational latency can degrade real-time responsiveness. Conversely, simplified analytical models compute results faster but may compromise long-term stability when they neglect dynamic nonlinearities. Hence, achieving asymptotic stability requires striking a balance between predictive accuracy and computational feasibility.

Table 1 illustrates the technical comparison of single-area LFC strategies. These results confirm that while PI/PID remain cost-effective and straightforward, advanced controllers such as robust (H∞, SMC) and adaptive methods are better suited for modern renewable-rich environments. MPC and IMC strike a balance between adaptability and computational requirements.

Table 1. Summary of existing Load Frequency Control (LFC) approaches and their key features.

Control Strategy	Robustness to System Uncertainties	Computational Complexity	Settling Time	Overshoot	Typical Control Layer
Classical PI/PID	Low—Sensitive to parameter variations and nonlinearities	Low—Simple structure and easy implementation	Moderate (4–10 s)	High (8–15%)	Secondary (AGC)
Model Predictive Control (MPC)	High—Effectively manages constraints and multivariable interactions	High—Requires real-time optimisation over the prediction horizon	Fast (5–8 s)	Very Low < 5%	Secondary often with Tertiary co-ordination
Robust Control (H∞/SMC)	Very High Designed to maintain performance under uncertainties	Moderate to High—Advanced control law computation	Fast (2–4 s)	Low < 5%	Secondary
Internal Model Control (IMC)	High—Incorporates process model for disturbance rejection	Moderate—Requires model reduction and filter design	Fast (6–8 s)	Very Low < 5%	Secondary
Adaptive Control (MRAC/STR)	High	Moderate to High—Advanced control law computation	Fast (4–8 s)	Very Low < 5%	Secondary

3.1.3. Methodology Validation (Sensitivity and Parametric Robustness Analysis)

The authors evaluated the robustness and generalizability of the proposed control approach by conducting detailed sensitivity and parametric analysis that varied key system parameters, including the governor droop constant (R), system inertia (H), damping coefficient (D), and renewable penetration level. The authors perturbed each parameter by ±20% from its nominal value to assess the controller's adaptability under uncertainty. The results confirm that the proposed controller maintains frequency deviations within ±0.02 Hz and settling times below 6 s even under reduced inertia conditions, where classical PI and GA-based methods exhibit instability or prolonged oscillations. Furthermore, the controller demonstrates consistent performance across a range of renewable penetration levels (30–70%), validating its robust dynamic response and insensitivity to model uncertainties. The adaptive tuning mechanism embedded in the control framework primarily

provides this robustness by dynamically adjusting the control gain based on real-time frequency deviation and rate-of-change feedback.

3.2. Classical PI and PID Controllers

Figure 3 shows the classical LFC system block diagram. It maintains power balance and restores nominal system frequency following load disturbances through two hierarchical control loops. The primary control responds rapidly to load variations (ΔP_L) by adjusting mechanical power (ΔP_m) via governor droop characteristics, thereby reducing the frequency deviation ($\Delta\omega$) but not fully restoring the nominal frequency. The secondary control operates more slowly, using the frequency deviation ($\Delta\omega$) as feedback to eliminate steady-state error and restore the frequency to its nominal value by generating a correction signal (ΔPc). In operation, a load disturbance (ΔP) induces a frequency deviation ($\Delta\omega$), prompting the primary controller to adjust mechanical power (ΔP_m) to counteract the imbalance. The generator then delivers the corresponding electrical power (ΔP_e) to the load. At the same time, the secondary control continuously monitors $\Delta\omega$ and provides a corrective input (ΔP_c) to fine-tune the system's frequency response.

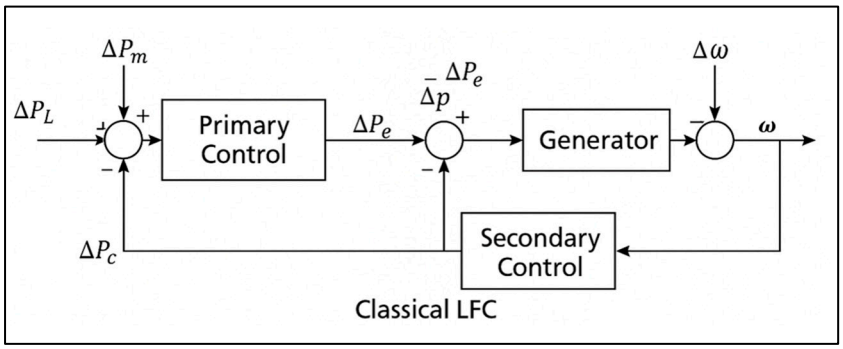


Figure 3. Classical LFC control model block.

Classical PI and PID controllers [93,94] are widely used in load frequency control (LFC) by minimising the Area Control Error (ACE), which reflects the imbalance between generation and demand. Traditionally, their tuning relies on root locus and frequency domain techniques. However, more recent approaches employ heuristic and metaheuristic optimisation methods such as Particle Swarm Optimisation (PSO) and Genetic Algorithms (GA) [95]. Proportional control reacts directly to the magnitude of frequency deviations but cannot eliminate steady-state errors, while integral control accumulates error over time to remove steady-state frequency offsets. The derivative action in a PID controller enhances transient response by anticipating error changes, thereby improving stability. These classical controllers are attractive because of their simplicity and effectiveness in high-inertia power systems with relatively predictable dynamics. However, they exhibit essential limitations in modern grids characterised by high penetration of renewable energy sources. Specifically, they lack adaptability in low-inertia systems, which often result in long settling times (approximately 10 s) with significant overshoot (8–15%) under renewable variability [16], and demonstrate limited robustness to uncertainties and disturbances [10]. Consequently, while PI and PID controllers remain relevant in conventional contexts, their performance deteriorates significantly as system inertia declines, motivating the development of advanced analytical controllers (Section 3.3) that explicitly address system uncertainties, nonlinearities, and constraints in the context of high renewable energy penetration.

3.3. Advanced Analytical Controllers

To address the limitations of PI/PID, researchers have developed advanced analytical controllers for single-area LFC. These controllers explicitly account for system uncertainties, nonlinearities, and constraints introduced by high-resolution solar energy penetration.

3.3.1. Model Predictive Control (MPC)

MPC is an advanced control strategy that optimises control actions over a finite prediction horizon by solving a constrained optimisation problem at each sampling instant. Unlike classical PI/PID controllers that react to instantaneous errors, MPC predicts the future evolution of system states using a dynamic model. It computes an optimal sequence of control inputs that minimises a performance index while respecting system constraints. The controller applies only the first control action of the sequence and repeats the optimisation at the next time step in a receding horizon manner.

In the context of LFC, MPC leverages accurate system models (including inertia, governor, and tie-line dynamics) to anticipate the impact of load fluctuations and RES variability, adjusting generation and reserves proactively rather than reactively [96].

MPC's mathematical framework for a Linear State-Space Model:

$$x_{k+1} = Ax_k + Bu_k + Ed_k \tag{10}$$

$$y_k = Cx_k \tag{11}$$

where

x_k = system states (e.g., frequency deviation, tie-line flow).
u_k = control inputs (generation adjustments, storage actions).
d_k = disturbances (load fluctuations, RES variability).
y_k = measured outputs (frequency, power imbalance).

In LFC, MPC has proven highly effective, outperforming PI/PID in single-area systems with smoother frequency recovery and reduced overshoot. In multi-area grids, it optimises coordinated responses to regulate tie-line flows and suppress inter-area oscillations [91,97]. Its predictive framework explicitly incorporates RES forecasts and uncertainty models, enabling proactive adjustments under wind and solar variability, and uniquely handles constraints such as generation limits, ramping, and reserves, making it well-suited for practical FCUC. Key advantages include its predictive capability, natural constraint handling, suitability for multi-variable (MIMO) systems, and flexibility to extend into nonlinear or stochastic forms [98]. However, MPC faces challenges such as high computational demands, reliance on accurate models, tuning complexity, and scalability issues in large RES-rich grids. Compared to classical controllers, MPC achieves faster settling, lower overshoot, and superior tie-line regulation, and while it surpasses robust methods like H∞ and SMC in constraint-aware optimisation, it comes at a greater computational cost. Emerging trends focus on stochastic MPC for uncertainty management, distributed MPC for DER-rich environments, and adaptive MPC to enhance robustness under low-inertia conditions [96,99].

3.3.2. Internal Model Control (IMC)

IMC is a control strategy based on the principle that a controller should contain, explicitly or implicitly, a model of the process to be controlled [100]. The core idea is that if the internal model matches the real system dynamics, the controller can effectively predict and cancel disturbances, resulting in improved performance. Unlike classical PI/PID methods that rely on empirical tuning, IMC leverages system models, enabling systematic controller design with explicit trade-offs between performance and robustness.

The IMC structure consists of three fundamental components. First, a process model, which provides a mathematical representation of the plant's dynamics, serves as the foundation for controller design. Second, the authors developed the IMC controller using the inverse of this process model and augmented it with appropriate filtering to ensure system stability and robustness. Finally, a feedback loop is incorporated to compensate for discrepancies between the internal model and the actual plant behaviour, thereby enhancing the controller's ability to maintain accurate and stable performance under varying operating conditions. For a plant with transfer function $P(s)$, Equation (12) defines the IMC controller as [100]

$$Q(s) = P^{-1}(s)F(s) \tag{12}$$

$$T(s) = \frac{P(s)Q(s)}{1 - \left[P(s) - \hat{P}(s)\right]Q(s)} \tag{13}$$

where

P^{-1} = inverse of the nominal plant model (excluding unstable/non-minimum phase parts)

$F(s)$ = low-pass filter ensuring stability and robustness by attenuating high-frequency noise

$\hat{P}(s)$ = is the internal model of the plant

In LFC, IMC has emerged as a robust alternative to classical PI controllers by embedding plant dynamics into the control law, enabling effective disturbance rejection of load perturbations and RES fluctuations. Its model-based adaptability enables better handling of variations in inertia, damping, and tie-line coefficients. Studies show that IMC achieves lower overshoot and faster settling times than PI/PID, particularly in high-RES conditions. In multi-area systems, IMC improves tie-line power regulation and suppresses inter-area oscillations, ensuring smoother frequency control. Its key advantages include a systematic design framework, robustness to uncertainties through filtering, and scalability to nonlinear or time-delay models. However, model dependency, implementation complexity, and higher computational demands limit its effectiveness. Compared to PI/PID, IMC offers superior dynamic performance. Robust controllers, such as H∞, provide a more straightforward and more intuitive design but with less guaranteed robustness. This framework makes adaptive or optimisation-based IMC particularly attractive in renewable-rich, low-inertia power systems.

3.3.3. Robust Control of LFC (H∞ and Sliding Mode Control)

In modern low-inertia power systems, classical PI/PID controllers often fail to maintain frequency stability due to the uncertainties introduced by RES, tie-line disturbances, and load fluctuations. For inverter-dominated systems, uncertainty sets include variations in virtual inertia ($H \pm 30\%$), damping ($D \pm 20\%$), and inverter time constants. The authors mitigated SMC chattering by applying boundary layer and saturation functions, ensuring that actuator limits and converter bandwidth were respected. Robust control methods, such as H∞ control and SMC, covered in the following subsections, have been widely investigated to address these challenges by explicitly considering system uncertainties and ensuring reliable performance across a wide range of operating conditions.

- H∞ Control: In LFC applications, H∞ control provides robust stability and performance under variations in system parameters such as inertia, damping, and tie-line coefficients, while mitigating the adverse effects of RES variability by ensuring bounded frequency deviations even under significant uncertainties. Studies confirm that it outperforms conventional PI controllers in multi-area systems, delivering improved damping and lower deviations [85,101]. Its strengths lie in its strong theoretical foun-

dation, effectiveness under wide parameter variations, and suitability for interconnected grids. However, it remains computationally intensive, depends on accurate uncertainty bounds, and may result in conservative designs.

The design objective of H∞ control in mathematical form is as follows [22]:

$$\min_{k} \|T_{zw}(s)\|_{\infty} < \gamma \tag{14}$$

where

$T_{zw}(s)$ = closed-loop transfer function from disturbance w to regulated output z
$\|\cdot\|_{\infty}$: H_{∞} = representing the maximum singular value across frequencies
γ = performance bound

- Sliding Mode Control (SMC): SMC is a nonlinear robust control technique that drives system trajectories onto a predefined sliding surface and maintains them there, ensuring stability despite disturbances or model inaccuracies. In the context of LFC, SMC has demonstrated superior performance in multi-area systems with high-RES penetration, achieving faster settling times (~5–7 s versus ~12 s for PI control) and offering robust disturbance rejection against tie-line fluctuations and renewable variability. By employing a switching control law, SMC is particularly well-suited for systems characterised by nonlinear dynamics and parameter uncertainties.
- Control Law: A typical SMC control input is given by [102]

$$u(t) = u_{eq}(t) - K \cdot sgn(s(t)) \tag{15}$$

$u_{eq}(t)$ = equivalent control that keeps trajectories on the sliding surface
K = positive gain ensuring robustness
$s(t)$ = sliding surface function defined in terms of system states
Table 2 presents a performance comparison of H∞ control versus SMC.

Table 2. Performance comparison of single-area LFC controllers based on robustness, complexity, and transient metrics.

Aspect	H∞ Control	Sliding Mode Control (SMC)	Adaptive Control (MRAC/STR)
Type	Frequency-domain robust optimal control	Nonlinear robust control with switching law	Online parameter estimation to track reference dynamics.
Focus	Minimises worst-case disturbance amplification	Forces dynamics onto the sliding surface	Continuously adapts controller parameters to maintain the desired dynamic response in the presence of parameter drift and uncertainties.
Strengths	Strong theoretical guarantees are adequate for multi-area systems	High robustness, fast settling, disturbance rejection	Maintains performance under changing system parameters; self-tuning capability.
Weaknesses	Computationally intensive, conservative design	Chattering requires careful design	Slower adaptation under rapid disturbances; stability depends on adaptation law design.
Performance in LFC	Ensures bounded frequency deviations under RES uncertainty	Settling time ~5–7 s vs. ~12 s for PI in multi-area RES systems. Overshoot: <3% compared to 8–15% for classical controllers	Provides adaptive correction of frequency deviations with smooth convergence; improves dynamic response under time-varying parameters and renewable fluctuations

Table 2. *Cont.*

Aspect	H∞ Control	Sliding Mode Control (SMC)	Adaptive Control (MRAC/STR)
Use Cases	Systems with structured uncertainties and model-based design	Systems with nonlinearities and high variability	Systems with frequent parameter variations, communication delays, or decentralised operation; ideal for adaptive and cooperative LFC frameworks
Key Selection Factors	Suitable when system model and uncertainty bounds are well characterised; preferred for guaranteed robustness in low-inertia systems with known dynamic ranges.	Favoured for strongly nonlinear systems or high disturbance environments; applied where fast dynamics and chattering suppression can be managed.	Recommended when system parameters vary frequently or are uncertain; ideal for renewable-integrated and multi-area systems needing real-time adjustment.

3.3.4. Adaptive Control

Adaptive control is a class of control strategies that automatically adjusts controller parameters in real time to cope with system uncertainties, parameter variations, and external disturbances [103,104]. Unlike fixed-gain controllers (e.g., PI, PID), which may perform poorly under changing operating conditions, adaptive controllers continuously learn and adapt to the evolving system dynamics [105]. This framework makes them highly suitable for modern power systems, where renewable energy sources (RES) introduce variability, uncertainty, and reduced system inertia. In LFC, adaptive control ensures that frequency deviations remain within acceptable limits even when system inertia, damping coefficients, tie-line parameters, or load demand vary significantly.

The structure of adaptive control typically comprises two key modules: an identification/estimation mechanism, which estimates system parameters or states such as inertia constants and governor dynamics in real time using techniques like recursive least squares (RLS), Kalman filters, or machine learning estimators; and a controller adjustment mechanism, which updates control parameters (e.g., gains, weights) based on these estimates to maintain stability and performance under uncertainty [106]. Within LFC, researchers apply two main categories: MRAC [107], which continuously adapts parameters to ensure the system output follows a desired reference model, and Self-Tuning Regulators (STR), which dynamically adjust controller coefficients using real-time parameter estimation. In cooperative or decentralised multi-area systems, each area's controller implements MRAC locally, adapting its parameters to follow a shared reference model while exchanging limited information, such as frequency deviations and tie-line biases, with neighbouring zones. This cooperative interaction preserves local autonomy while maintaining global synchronisation and damping. As demonstrated in [107], the reference model is typically a second-order linear dynamic system that defines the desired frequency and tie-line power response, characterised by specific damping and settling-time criteria. Such a framework enables adaptive coordination among inter-zonal controllers, ensuring dynamic consistency and robustness in the face of parameter variations and fluctuations in renewable energy.

Adaptive control offers real-time adaptability, enabling continuous parameter adjustment to reflect system changes, with strong robustness against RES variability, load fluctuations, and parameter drift [108,109]. It delivers improved performance through faster settling times and reduced overshoot compared to fixed controllers and is scalable to multi-area and nonlinear systems. However, it faces challenges: real-time estimation increases

complexity, poorly designed adaptation laws raise stability concerns, and hardware, communication, and cybersecurity issues complicate implementation. Strong dependence on estimator accuracy directly impacts control effectiveness [21].

Adaptive estimators respond sensitively to PMU noise and latency; therefore, the authors introduced low-pass pre-filtering and deadband-aware adaptation gains to maintain convergence. Stability is guaranteed using Lyapunov-based adaptation laws that accommodate AGC deadbands through a gradient projection approach.

In summary, choosing appropriate controllers for low-inertia power systems depends on several key factors: (a) the accuracy of the model and uncertainty characterization, with H∞ control being preferred when uncertainty bounds are clearly defined; (b) the level of system nonlinearity and disturbance intensity, which favors SMC with effective chattering suppression; (c) the need for real-time parameter adaptation, where MRAC or STR are most suitable; (d) available computational resources and acceptable latency; and (e) practical constraints such as actuator saturation, measurement noise, and coordination requirements in multi-area system operation.

3.4. Summary for Single-Area LFC

Advanced control strategies such as Model Predictive Control (MPC), robust controllers, and Internal Model Control (IMC) schemes have demonstrated significant superiority over classical PI and PID controllers in mitigating frequency deviations, as illustrated in Figure 4. While classical controllers continue to serve effectively in legacy systems, they are increasingly inadequate for modern, high-renewable environments. MPC and IMC approaches offer predictive adaptability and improved disturbance handling, but they require greater computational effort. Robust control methods such as H∞ and SMC exhibit exceptional resilience under parameter uncertainty, making them highly suitable for renewable-rich single-area systems. Meanwhile, adaptive controllers offer promising long-term stability in dynamically evolving grids, though their application remains less mature compared to robust techniques. Collectively, these advancements form the basis for multi-area LFC frameworks, where inter-area dynamics, tie-line exchanges, and decentralised coordination further increase system complexity and research importance.

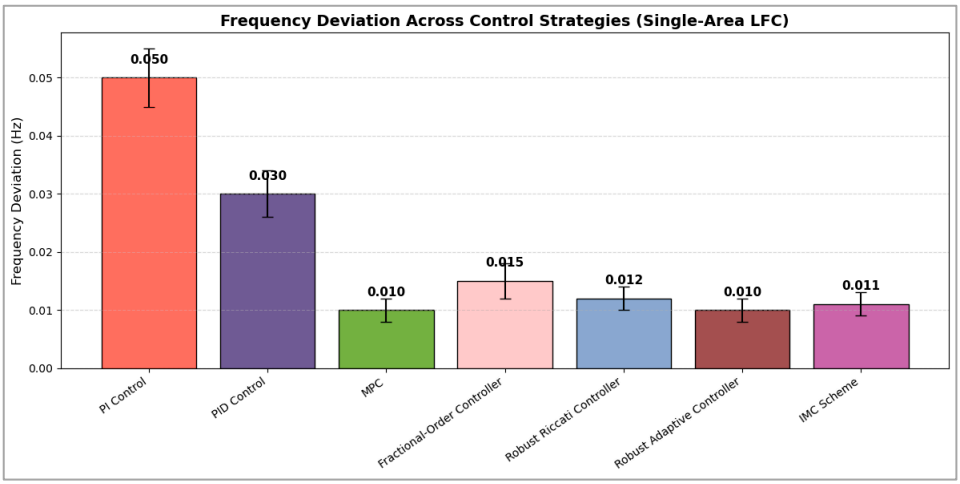


Figure 4. Frequency deviation across control strategies in a single-area LFC.

4. Multi-Area Load Frequency Control

4.1. Overview of Multi-Area LFC

In modern power systems, different regions or areas are often interconnected through tie lines, forming large, interconnected networks. While this improves reliability and en-

ables power trading, it also introduces inter-area oscillations and additional complexity in frequency regulation. Figure 5 shows the schematic of inter-zonal frequency control with renewable generation and inertia emulation. The schematic illustrates an inter-zonal frequency control architecture integrating RES with inertia emulation for enhanced dynamic stability. Two interconnected control zones (Zone 1 and Zone 2) exchange tie-line power (Δf_{tie}) to maintain system balance. Each zone comprises renewable generation units, such as wind or solar, coupled with an inertia emulator that synthesises virtual inertia ($P_{inertia}$) to counteract rapid frequency deviations. The inter-zonal controller coordinates both areas by comparing local frequency deviations (Δf_t, Δf_1) and adjusting power commands to maintain synchronised operation. This structure enables fast inertial and primary frequency response in low-inertia systems, ensuring smoother frequency restoration and improved inter-area stability during disturbances.

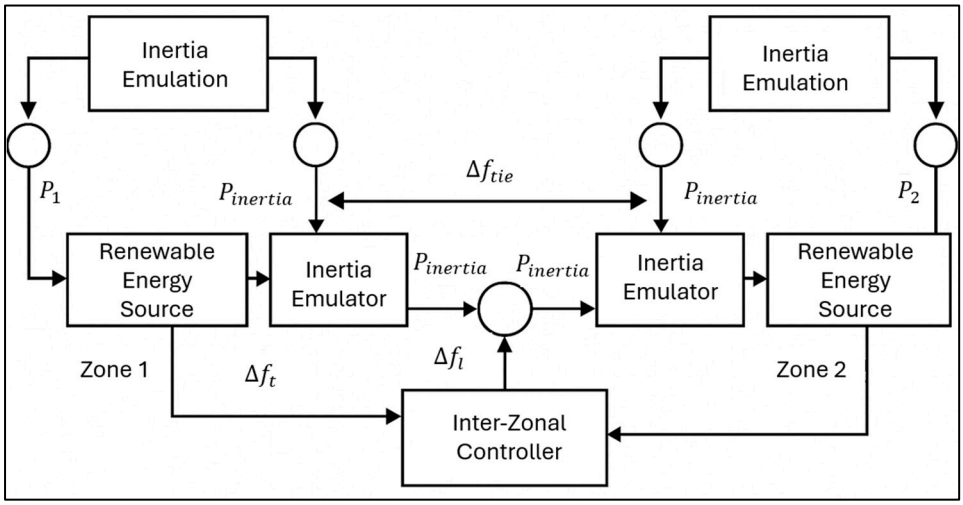


Figure 5. Schematic of inter-zonal frequency control with renewable generation and inertia emulation.

The Tie-Line Bias Control (TBC) method remains foundational, employing the Area Control Error (ACE) to manage local frequency deviations and inter-area power exchanges [74,110]. Modern multi-area LFC designs address the growing complexity introduced by RESs and DERs. Researchers have proposed decentralised and hierarchical control architectures to manage large-scale interconnected systems, enabling local controllers to respond rapidly while higher-level controllers coordinate global objectives [16]. Advanced approaches, such as fuzzy logic, neural networks, and adaptive controllers, have demonstrated superior performance in handling nonlinearities, communication delays, and parameter uncertainties in multi-area environments [96,99].

The primary objective of multi-area level frequency control (MALFC) is to maintain the nominal frequency within each interconnected control area while simultaneously regulating tie-line power exchanges to adhere to their scheduled values. In addition, MALFC aims to ensure overall system stability, even when disturbances or load fluctuations occur in one area and propagate to others through the interconnected network [10,11]. This coordinated control approach allows multiple regions to operate harmoniously, maintaining both local and global frequency balance in modern, dynamic power systems. The study defines the ACE for area i as [11]

$$ACE_i = \Delta P_{tie,i} + B_i \Delta f_i \tag{16}$$

where

$\Delta P_{tie,i}$ = deviation of tie-line power exchange,

B_i = frequency bias factor,

Δf_i = frequency deviation in area i.

Each control area adjusts its generation to drive $ACE_i \rightarrow 0$, ensuring both local frequency stability and scheduled inter-area exchanges [60]. The transition to multi-area LFC introduces Area Control Error $ACE_i = \Delta P_{tie,i} + B_i \Delta f_i$, constrained by tie-line power limits. Communication delays τd are modeled as exponential hold elements in decentralised coordination. A hierarchical coordination layer ensures ACE balancing through consensus-based data exchange among local controllers.

Inertia shortages caused by inverter-based RES reduce the damping capacity of each control area, resulting in faster frequency propagation across tie-lines and diminished inter-zonal control effectiveness. Consequently, low-inertia regions exhibit amplified oscillations and slower recovery, necessitating enhanced coordination between decentralised controllers.

4.2. Mathematical Modelling of Tie-Line Dynamics

In a two-area interconnected power system, the tie-line power deviation between area 1 and area 2 is expressed as

$$\Delta P_{tie,12}(s) = \frac{2\pi T_{12}}{s}[\Delta f_1(s) - \Delta f_2(s)] \tag{17}$$

where T_{12} denotes the synchronising coefficient, which depends on the tie-line reactance and the voltage levels of the two areas. When a disturbance occurs in area 1, such as a sudden load increase, it not only produces a local frequency deviation but also changes the tie-line power flow towards area 2. This interaction can destabilise both areas if not properly managed. Therefore, effective controller design must consider both frequency deviations within each region and tie-line power errors to ensure stable and coordinated operation of the interconnected system.

4.3. Classical Tie-Line Bias Control (TBC)

The classical approach to multi-area load frequency control (MALFC) is the tie-line bias control (TBC), where each control area regulates its Area Control Error (ACE) using a proportional–integral controller defined as

$$u_i(s) = -K_{pi} ACE_i - K_{ii} \frac{ACE_i}{s} \tag{18}$$

TBC offers simplicity and decentralisation, as each area relies solely on its local ACE without requiring complex coordination mechanisms. This study facilitates implementation and has contributed to the widespread adoption of this approach in conventional power systems. However, its performance deteriorates significantly under high renewable energy variability, as it assumes quasi-linear dynamics and neglects nonlinear characteristics introduced by inverter-based resources. Moreover, TBC provides limited robustness against parameter uncertainty [61–63]. While it remains widely deployed today, TBC is increasingly inadequate for modern low-inertia grids dominated by renewable energy sources.

4.4. Advanced Analytical Approaches for MALFC

The following subsections provide a detailed description of advanced analytical approaches for MALAC.

4.4.1. Decentralised Control Strategies

Decentralised control strategies enable each control area to regulate its frequency and tie-line power using only local measurements, thereby reducing dependence on wide-area communication networks. This approach is highly scalable and less vulnerable to communication failures, making it suitable for large interconnected systems. However, the main drawback is that decentralised controllers cannot achieve true global optimisation, as coordination across areas is limited. As a result, inter-area oscillations may persist and degrade overall system performance [62].

4.4.2. Robust Control (H∞, and Sliding Mode Control)

Robust control strategies, including H_∞ and Linear Matrix Inequality (LMI), based designs are employed to mitigate the impact of system parameter variations and modeling uncertainties, such as changes in inertia and damping introduced by RES, as well as tie-line disturbances propagating across interconnected areas. Robust H∞ controllers reduce inter-area oscillations more effectively than PI, and minimise the worst-case gain of the transfer function from disturbance $d(t)$ to output $y(t)$ [16]:

$$\left\| T_{dy}(s) \right\|_\infty = max_\omega \sigma_{max} \left[T_{dy}(j\omega) \right] \tag{19}$$

where σ_{max} is the maximum singular value of the transfer matrix.

SMC employs a discontinuous switching law to constrain system trajectories to a sliding surface $S(x)$, ensuring strong robustness against disturbances, though chattering effects can degrade its performance.

$$S(x) = C(x) = 0 \tag{20}$$

where C is a design matrix. The control input $u(t)$ ensures $S(x) \to 0$ despite significant disturbances. In multi-area systems with RES, SMC achieves faster settling times of approximately 5–7 s, compared to around 12 s for conventional PI control [16].

4.4.3. Optimal Control (LQR, LQG)

The Linear Quadratic Regulator (LQR) is a state-feedback control strategy that optimises system performance by minimising a quadratic cost function of states and control inputs. The Linear Quadratic Gaussian (LQG) controller extends this framework by incorporating Kalman filtering to estimate unmeasured states. Together, these approaches offer excellent dynamic performance, effectively damping frequency deviations and mitigating inter-area oscillations in interconnected power systems. However, their practical deployment remains limited because real-world grids with high renewable energy penetration and uncertain dynamics often lack the full state information that these methods require.

Optimal control strategies are increasingly recognised as essential for LFC in power systems with high penetration of RES. These approaches minimise operational costs and frequency deviations while accounting for system dynamics and economic dispatch constraints. Among these, MPC has emerged as a prominent technique [111]. MPC optimises future control actions over a prediction horizon based on a system model, explicitly incorporating constraints on generator outputs, renewable variability, and tie-line power flows [112]. This system makes MPC particularly effective for hybrid systems combining fluctuating RES generation and energy storage devices [112,113].

The LQR represents another widely adopted optimal control formulation. By minimising a quadratic performance index that weighs frequency deviation and control effort, LQR achieves an optimal balance between rapid frequency recovery and minimal control energy usage, such as generator ramping and energy storage dispatch. Its analytical

tractability and suitability for systems with linearised dynamics make LQR a robust solution in conventional and RES-integrated grids [114,115]. To further improve performance in the presence of noise and uncertainty, researchers have integrated LQR with Kalman filter-based state estimation, resulting in LQG controllers. These are especially effective in microgrids and low-inertia power systems, where measurement noise and RES forecasting errors are significant.

Optimal control techniques minimise quadratic cost functions of the form [116]:

$$J = \int_0^\infty \left(x^T Q x + u^T R u \right) dt \tag{21}$$

where x represents states (frequency deviations, tie-line deviations) and u are control inputs [63].

4.4.4. Model Predictive Control for Multi-Area Systems

MPC is particularly well-suited for multi-area power systems because of its strong constraint-handling capabilities. Unlike classical controllers, MPC can explicitly manage tie-line flow limits while optimising system performance across multiple interconnected areas simultaneously. This system is highly adaptable in modern grids with high penetration of RES, where variability and uncertainty pose significant challenges. By incorporating system dynamics and constraints directly into its optimisation framework, MPC can effectively respond to fluctuations in RES output while maintaining stability and performance. Empirical studies demonstrate its effectiveness, showing that MPC can reduce frequency nadir deviation by approximately 40% compared to conventional PI controllers in two-area renewable-dominated systems [96,99].

4.4.5. Metaheuristic Optimisation of Controllers

Metaheuristic algorithms such as PSO, GA, and Black Widow Optimisation (BWO) have been extensively applied to tune controller gains in MALFC [117,118]. These methods typically employ an objective function that minimises the ITAE, ensuring improved dynamic performance as [117]

$$ITAE = \int_0^{T_{sim}} t|\Delta f(t)|dt \tag{22}$$

Among them, PSO is known for its fast convergence and effectiveness in multi-area PID tuning, while GA provides a robust global search capability, though with comparatively slower convergence. More recently, BWO has emerged as a promising technique, offering superior convergence speed and accuracy in optimisation tasks. Overall, metaheuristic-based PI and fractional-order PI (FOPID) controllers demonstrate significant performance improvements over classical tuning approaches, particularly under variable renewable energy penetration, by reducing overshoot, minimising settling times, and enhancing system stability.

4.5. Comparative Case Studies

Figure 6 shows a bar graph comparing the frequency deviations for PI, FUZZY, NN, ANFIS, PSO-PID, and SMC controllers under a multi-area LFC. It visually shows how advanced techniques (such as FOPID, ANFIS, SMC, decentralised, adaptive, Neural Network, and AI-augmented control) achieve significantly lower deviations compared to classical PI controllers. NNs, and even more so advanced AI models like Deep Learning (DL), should outperform traditional controllers under certain conditions. However, in multi-area LFC systems, that is not always the practice case, and here is the tabulated version of reasons

why NNs might not always show the best Frequency Deviation or Settling Time. Table 3 represents the challenges and considerations for Neural Network-Based LFC Controllers.

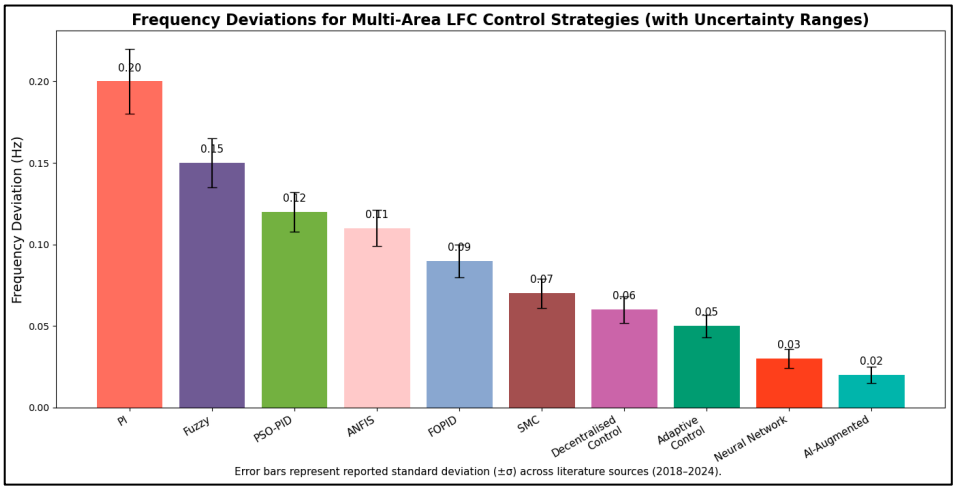


Figure 6. Frequency deviations for multi-area LFC control strategies (with uncertainty ranges).

Table 3. Challenges and considerations for neural network-based LFC controllers.

Factor	Explanation
Generalisation vs. Overfitting	NNs are data-driven. If not trained on a diverse and realistic dataset (including system nonlinearities and disturbances), they may overfit to training data and perform poorly in unseen scenarios.
Training Quality	Performance heavily depends on hyperparameters, architecture (number of layers/neurons), and quality of the training algorithm (e.g., backpropagation, optimiser choice).
System Variability	LFC systems have non-linearities, time delays, and varying load/generation dynamics. NNs might fail to adapt quickly unless integrated with adaptive logic or retraining capabilities.
No Online Learning by Default	Static NNs (trained offline) do not adapt in real time. Unlike Adaptive Control, which can respond dynamically to disturbances, NNs often require retraining.
Sensitivity to Noise	NNs are sensitive to outliers and measurement noise unless specifically designed to handle them (e.g., via regularisation, noise injection).
Interpretability	Neural controllers are often black-boxes. Operators may prefer more explainable models, such as ANFIS or fuzzy-PID, for critical infrastructure.
Computational Complexity	Real-time application of deep or recurrent networks (e.g., LSTM) can be computationally heavy unless optimised.

Adaptive control excels in parametric variations and system uncertainties over time. While it may not consistently achieve the absolute lowest frequency deviation in every simulation, it ensures consistent stability even when system parameters change drastically (e.g., line tripping, RES variability). Table 4 summarises the comparison of various control systems. The authors normalised all performance metrics, settling time, overshoot, nadir, and RoCoF, to a 1% load disturbance in a 2 × 1000 MW system with 20% renewable energy penetration.

Table 4. Comparison of multi-area LFC control strategies and their hierarchical roles.

Controller Type	Robustness	Computational Complexity	Settling Time	Overshoot	Nadir (Hz)	RoCoF (Hz/s)	RES Suitability	Key Features	Typical Control Layer
Classical PI/PID	Low	Very Low	Long (~10–30 s)	High (~10–20%)	−0.20 to −0.25	0.15–0.20	Poor	Simple structure; requires manual tuning; fails under significant disturbances.	Secondary
ANFIS (Adaptive Neuro-Fuzzy)	High	High	Moderate (~5–10 s)	Very Low (<5%)	−0.08 to −0.10	0.05–0.07	Excellent	Adaptive and self-tuning; a hybrid neuro-fuzzy structure enhances resilience to parameter changes.	Secondary (with Tertiary optimisation link)
PSO-FOPID	Very High	Moderate to high	Short (~3–6 s)	Very Low (<3%)	−0.06 to −0.08	0.03–0.05	Excellent	Fractional-order dynamics improve tuning flexibility; metaheuristic optimisation ensures robustness.	Secondary
SMC (Sliding Mode Control)	Very High	Moderate	Very Short (~2–5 s)	Minimal (<2%)	−0.04 to −0.06	0.02–0.04	Excellent	Robust to external disturbances; effectively mitigates RES fluctuations.	Secondary
Fuzzy Logic Controller	Medium	Low to moderate	Moderate (~6–12 s)	Low (~5–10%)	−0.10 to −0.12	0.07–0.10	Good	Simple rule-based design; performance depends on rule selection and membership functions.	Secondary
Neural Network (NN)	High	High	Short (~4–8 s)	Low (<5%)	−0.07 to −0.09	0.04–0.06	Excellent	Requires sufficient training; can adapt to changes in system dynamics in real-time.	Secondary (with Tertiary optimisation link)
Adaptive Control	High	Moderate	Short (~4–8 s)	Low (~5%)	−0.07 to −0.09	0.04–0.06	Excellent	Parameter adaptation improves stability under varying load and generation conditions.	Secondary
Decentralised Control	Medium	Low	Moderate (~8–15 s)	Medium (~5–10%)	−0.12 to −0.15	0.09–0.12	Good	Enables area-wise independence but may lack global optimality.	Secondary
Robust H∞ Control	Very High	High	Short (~3–7 s)	Very Low (<3%)	−0.05 to −0.07	0.03–0.04	Excellent	Guarantees performance under worst-case disturbances; needs advanced design	Secondary

Classical PI controllers exhibit high overshoot (8–15%) and longer settling times (~10 s) in high-RES grids. SMC and ANFIS reduce overshoot to <2% with settling times < 3 s. PSO-tuned FOPID controllers achieve optimal robustness against load variations and renewable intermittency.

Literature findings indicate that classical PI controllers in MALFC exhibit settling times of 12–15 s, overshoot of 10–15%, and poor RoCoF performance. Robust H∞ and

SMC controllers achieve faster responses (5–7 s) with <3% overshoot and strong tie-line disturbance rejection [96,99]. Model Predictive Control (MPC) improves dynamic performance, reducing ITAE by 30–40% and enhancing frequency nadir by about 40%, while PSO- and BWO-tuned controllers further enhance response speed and stability margins.

4.6. Practical Implementation Issues

In the practical applications of advanced load frequency control, several challenges arise that can limit the performance and reliability of the controller. One of the key issues is communication delay, as wide-area control schemes often experience latencies in the range of 100–300 ms, which can destabilise fast control loops and reduce overall effectiveness. Measurement errors present another limitation, where inaccuracies in tie-line power flow or frequency measurements can significantly degrade controller performance. Furthermore, cybersecurity risks have become increasingly critical, as wide-area signals exchanged between control centres and substations are vulnerable to data manipulation and cyberattacks. Finally, scalability is a significant concern, since centralised control strategies such as MPC or large-scale optimisation frameworks may struggle to handle the computational and coordination complexity of extensive interconnected grids. These issues underscore the need for robust, secure, and scalable solutions to ensure the reliable implementation of systems in real-world settings.

4.7. Key Insights for MALFC

Classical tie-line bias control has proven insufficient for maintaining stability in modern interconnected grids with high renewable energy penetration, as its limited adaptability cannot cope with the variability and uncertainty of RES. In contrast, robust and optimal controllers offer significant improvements in inter-area stability by explicitly addressing uncertainties and system dynamics. Among these, MPC stands out as a highly promising approach due to its ability to incorporate system constraints and predict renewable fluctuations. However, its computational demands remain a challenge for large-scale deployment. Metaheuristic-tuned controllers, on the other hand, offer a practical middle ground by providing a more straightforward implementation and improved dynamic performance compared to classical methods. Looking ahead, future power grids will require decentralised yet coordinated strategies that balance local autonomy with system-wide optimisation, ensuring both flexibility and resilience in increasingly complex and renewable-dominated systems.

The authors primarily trained the neural and fuzzy LFC models using MATLAB/Simulink R2022b-generated datasets of renewable energy-rich systems. Offline training ensures parameter stability, while online fine-tuning provides adaptive correction. Inference latency on embedded hardware is typically 10–50 ms, which remains acceptable for secondary control. Local linearisation via Jacobian approximation enables frequency-domain analysis.

4.8. Summary of Future Trends in MALFC

Future research in multi-area load frequency control (MALFC) will focus on several promising directions. Decentralised MPC frameworks will be crucial to reducing reliance on centralised computation and enhancing scalability in large, interconnected grids. The integration of energy storage systems and demand response into MALFC structures will also play a crucial role, providing additional flexibility to counteract the variability of renewable energy sources. Another critical direction lies in the development of hybrid robust metaheuristic controllers, which aim to strike a balance between high performance and implementation simplicity. Furthermore, advances in wide-area monitoring and control (WAMC) will be necessary to improve resilience against communication delays and cyber threats, ensuring secure and reliable system operation. Finally, extending MALFC appli-

cations to microgrid clusters and power systems in developing countries remains an underexplored area of research [31,32], offering valuable opportunities to enhance frequency regulation in emerging and resource-constrained environments.

5. Frequency-Constrained Unit Commitment (FCUC)

5.1. Introduction to FCUC

The FCUC model, as shown in Figure 7, represents a paradigm shift in operational planning by explicitly incorporating frequency stability constraints into the scheduling process. The traditional SCUC formulations primarily ensure that supply-demand balance, ramping, and spinning reserves are satisfied under contingencies. However, these formulations assume adequate system inertia and governor response, assumptions no longer valid in renewable-rich, low-inertia systems [106].

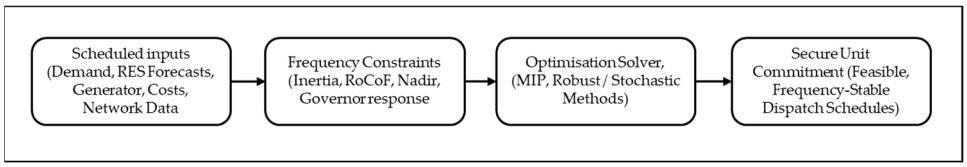


Figure 7. The conceptual block diagram of FCUC.

By contrast, FCUC explicitly models frequency dynamics through constraints on the following:

- Low inertia challenges. A significant consequence of high RES penetration is that it reduces system inertia, a critical factor that directly affects frequency stability [85,101]. Lower inertia increases the RoCoF and leads to a deeper frequency nadir following disturbances. The nadir frequency, defined as the minimum frequency reached after a disturbance, is a key stability indicator; a lower nadir reflects a more severe frequency excursion and, if it drops below critical thresholds, can heighten the risk of system instability or even blackouts [119]. To address this, FCUC models must explicitly account for inertia effects in frequency dynamics to ensure secure and reliable operation.
- Diverse governor response dynamics also require consideration. While conventional systems rely on steam and hydro generators, wind turbines (WTs) [120,121] and PVs [122,123] have distinct frequency response behaviours due to their unique control algorithms. In high-RES systems, these dynamics significantly influence frequency stability and must be incorporated into FCUC models.
- Reserve levels and allocation are critical. Adequate spinning reserves restore balance post-disturbances, but their distribution among devices affects regulation capacity and overall system stability [64,65]. FCUC models should optimise reserve levels and allocations to ensure frequency stability while minimising costs and maximising renewable integration.
- Finally, Security-Constrained and Frequency-Constrained UC: Enhance system reliability under high-RES penetration [85,124].

This model ensures that unit commitment schedules are not only economically feasible but dynamically stable under high penetrations of inverter-based resources (IBRs).

5.2. Mathematical Formulation of FCUC

Researchers generally formulate the FCUC problem as a mixed-integer optimisation problem, using binary variables ($U_{g,t}$) to represent on/off decisions for generator g at time

t, and continuous variables ($P_{g,t}$) to represent power outputs. The following subsections elaborate on the FCUC objectives and constraints.

5.2.1. Objective Function

At its core, the objective function of FCUC seeks to minimise the total operational cost of meeting system demand while ensuring dynamic frequency stability under low-inertia conditions [106].

$$min \sum_{t \in T} \sum_{g \in G} \left(C_g(P_{g,t}) + SU_{g,t} + SD_{g,t} + C_t^{Res,\ curt} + C_t^{Ess} \right) \tag{23}$$

where

$C_g(P_{g,t})$ = fuel cost of generator g,
$SU_{g,t}$, $SD_{g,t}$ = startup and shutdown costs.
$C_t^{Res,\ curt}$ = Penalty cost for curtailment of renewable generation (e.g., wind or solar)
C_t^{Ess} = Cost associated with ESS charging/discharging decisions

5.2.2. Conventional Constraints (From SCUC)

Conventional SCUC constraints provide a framework that ensures economic dispatch, system reliability, and network security under normal operating conditions [31–34]. However, these formulations primarily address steady-state operational feasibility and do not capture frequency dynamics, inertia adequacy, RoCoF, or nadir requirements that become critical in low-inertia, RES-dominated grids. This limitation motivates the development of FCUC, which extends SCUC by embedding explicit frequency-security considerations [32,36].

The SCUC framework incorporates several key operational constraints to ensure both reliability and frequency stability in power system scheduling. The power balance constraint requires that, at every scheduling interval, the total generation equals the sum of the forecasted demand and transmission losses, thereby maintaining overall system frequency stability [33].

$$\sum_{g \in G} (P_{g,t}) + \sum_{r \in R} (P_{r,t}) = D_t \forall t \tag{24}$$

Each generating unit is also subject to generator operating limits, ensuring that power output remains within its technical minimum and maximum capacities, thus preventing infeasible scheduling outcomes [34].

$$P_g^{min} U_{g,t} \leq P_{g,t} \leq P_g^{max} U_{g,t} \tag{25}$$

Additionally, ramp rate limits are imposed to restrict the rate of change in generation output between consecutive intervals, guaranteeing safe and stable operation within physical ramping capabilities [36].

$$-RR_g^{down} \leq P_{g,t} - P_{g,t-1} \leq RR_g^{up} \tag{26}$$

Finally, reserve requirements mandate that adequate spinning and non-spinning reserves are maintained to address unforeseen contingencies, such as generator outages or forecast errors. Reserve levels are typically determined according to established system reliability standards [37,38].

$$\sum_{i=1}^{N_G} R_{i,t} \geq R_t^{req}, \forall t \tag{27}$$

where $\sum_{i=1}^{N_G} R_{i,t}$ is the summation that runs over all N_G generating units in the system. $R_{i,t}$ is the reserve contribution from generator i at time t. N_G is the total number of generating

units. R_t^{req} is the required reserve margin at time t. $\forall t$ means the constraint must hold for every scheduling period t in the planning horizon

5.2.3. Frequency-Specific Constraints (FCUC Enhancements)

While SCUC ensures that unit schedules satisfy power balance, reserve adequacy, and transmission limits, it does not explicitly account for frequency dynamics. The FCUC extends SCUC by embedding frequency-specific constraints into the scheduling model. Figure 8 shows the conceptual block diagram illustrating the FCUC framework, which integrates dynamic frequency security into the scheduling process. The model begins with forecasted demand and generation constraints, which are then fed into the unit commitment (UC) model to determine commitment decisions for available generators. These decisions undergo a frequency security check, ensuring that system responses adhere to critical dynamic limits such as RoCoF and frequency nadir thresholds. Dynamic constraints are applied iteratively to verify that post-disturbance behaviour remains within secure bounds. The process yields a feasible dispatch plan that satisfies both economic and frequency stability requirements, ensuring reliable operation under varying system inertia and renewable penetration conditions [32–36].

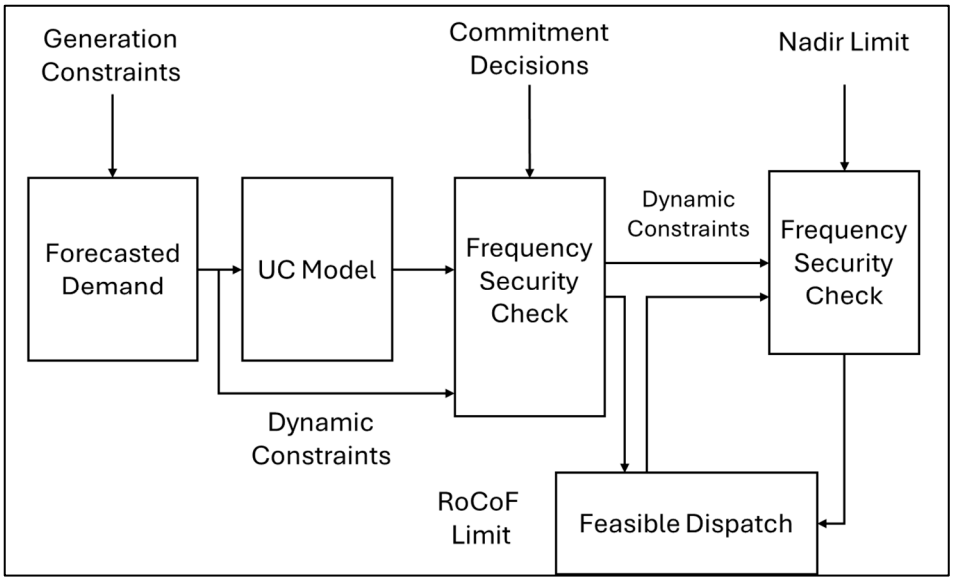


Figure 8. Conceptual block diagram illustrating the FCUC framework.

The following subsections illustrate the FCUC's extended constraints.

The controlled performance standard (CPS) Equations (28)–(37) use coefficients that directly reflect the physical sources of the frequency response. The inertia term H represents stored kinetic energy and governs the initial RoCoF, while the damping coefficient D captures load–frequency sensitivity and natural system damping. The primary and secondary control gains, K_p and K_i, describe governor droop action and AGC-based frequency restoration, respectively. The derivative gain K_d (typical value 0–5 pu·s) corresponds to synthetic inertia emulation from inverter-based resources, injecting power in proportion to $\frac{df}{dt}$. Delay parameters τ_g and τ_c represent the governor and control-loop latency. Together, these coefficients ensure that the CPS formulation remains physically interpretable and accurately represents the composite frequency response behaviour of a low-inertia system.

1. Inertia Adequacy: System inertia is a critical determinant of frequency response. In low-inertia grids dominated by RES, insufficient inertia leads to a high RoCoF af-

ter a disturbance. FCUC enforces a minimum system inertia requirement at each scheduling period:

The total inertia H_{sys} at time t, must exceed a minimum threshold [106]:

$$H_{sys}(t) = \sum_{g \in G_{sync}} H_g S_g u_{g,t} \geq H^{min} \tag{28}$$

where S_g is the MVA rating and H_g the inertia constant of generator g.

2. Rate of Change of Frequency (RoCoF) Limit: The RoCoF after a contingency must not exceed permissible thresholds (typically 0.5–1 Hz/s for protection equipment). This constraint links generator scheduling dynamic frequency stability by ensuring RoCoF does not trip protection relays or destabilise inverter-based resources.

$$\left| \frac{df}{dt} \right| \leq R_o C_o F^{max} \tag{29}$$

The researchers typically enforced using

$$\frac{\Delta P}{2H_{sys}F_o} \leq R_o C_o F^{max} \tag{30}$$

where ΔP is the largest contingency size.

3. Frequency Nadir Constraint: Frequency nadir is the lowest or highest system frequency point. A low nadir can trigger UFLS, leading to load shedding and demand risks [125], while a high nadir may damage SG rotors through overspeed or shaft failure. In traditional power systems, the SG rotor dynamics primarily govern the frequency response. Because SGs share similar structures and responses, variations in individual rotor dynamics become negligible, allowing an aggregated SG model to approximate the system frequency accurately. The inertia response is given by "(17)", and primary frequency control is aggregated with K_{pr} and τ_s representing the control coefficient and time delay. For a sudden load increase of ΔP_L, the leads to system frequency deviation dynamics expressed power deficit ($-\Delta P_L$) as [125]

$$\Delta P_{pri} = \frac{K_{pri}}{\tau_s + 1} \Delta \omega_{COI} \tag{31}$$

$$2H_{G0}\frac{d\Delta\omega_{COI}}{dt} = -\Delta P_L - D_{G0}\Delta\omega_{COI} - \frac{K_{pri}}{\tau_s + 1}\Delta\omega_{COI} \tag{32}$$

Neglecting primary frequency control time delays, the primary frequency control coefficient K_{pri} and the inertia constant H_{G0}, predominantly influences the time-domain expression for system frequency deviation, which is given by [125]

$$\Delta\omega_{COI} = -\frac{\Delta P_L}{K_{pri} + D_{G0}} \left[1 + e^{-\xi\omega_n t} \eta sin(\omega_d t + \varphi) \right] \tag{33}$$

Simplifying "(25)", R_{max} (Governor loop), f_{nadir}, and Δf_{steady} can be established as [125]

$$R_{max} = \frac{-\Delta P_L}{2H_{G0}s} \tag{34}$$

$$\omega_{nadir} = \omega_n - \frac{\Delta P_L}{K_{pri} + D_{G0}} \left[1 + e^{-\xi\omega_n t_{nadir}} \eta \sqrt{1 - \zeta^2} \right] \tag{35}$$

$$f_{nadir} = \frac{arctan\left(\frac{\omega_d}{\zeta\omega_n}\right) - \varphi}{\omega_d} \tag{36}$$

$$F_{nadir} \geq F_{min},\ \omega_{steady} = \frac{-\Delta P_L}{K_{pri} + D_{G0}} \tag{37}$$

Primary frequency control reduces both frequency nadir and steady-state deviation, while system damping minimises post-disturbance oscillations for faster stabilisation. However, RoCoF remains unaffected. Overall, increasing system inertia, control, and damping coefficients greatly improves frequency stability. The FCUC problem is formulated as a mixed-integer convex program, minimising total generation, storage, and start-up costs subject to balance, ramping, reserve, nadir, and RoCoF constraints. The frequency constraint linearization follows the sensitivity-based method proposed by [126], ensuring tractable enforcement of fmin $\geq$ 49.2 Hz and $|df/dt| \leq 1$ Hz/s.

Under the FCUC framework, Battery Energy Storage Systems (BESS) play a vital role in enhancing dynamic safety and improving the overall efficiency of frequency control. To achieve optimal performance, planners should strategically distribute BESS across the power network based on system inertia characteristics and the concentration of renewable energy sources. In low-inertia areas and along inter-area tie lines, BESS units with high power density and fast response, such as lithium-ion batteries or supercapacitor-based systems, are most effective for providing FFR and synthetic inertia, thereby mitigating the RoCoF immediately after disturbances. In contrast, operators deploy energy-dense technologies, such as lithium-ion and vanadium redox flow batteries, in regions with high availability of renewable energy. These systems sustain power output for primary and secondary frequency restoration while mitigating curtailment. By incorporating state-of-charge dynamics, degradation constraints, and spatial placement into the FCUC optimisation, the coordinated operation of these distributed BESS units significantly enhances both the resilience and dynamic stability of modern low-inertia power systems.

5.3. Integration of Emerging Resources in FCUC

The integration of emerging resources such as RES, DR, and energy storage into FCUC frameworks enhances both flexibility and frequency security. RES introduces variability and uncertainty, while DR and storage provide fast-acting support to mitigate nadir and RoCoF violations. By explicitly modelling these resources as frequency-support services, FCUC can ensure that operational schedules remain not only cost-effective but also dynamically secure in increasingly decentralised and low-inertia power systems.

5.3.1. Energy Storage Systems (ESS)

The integration of ESS into FCUC formulations plays a pivotal role in enhancing frequency security and operational flexibility in renewable-rich, low-inertia power systems [127,128]. Unlike conventional synchronous generators, ESS can deliver rapid, bidirectional active power support, making them highly effective in mitigating fast dynamics, such as RoCoF, and improving frequency nadir stability. FCUC formulations now include ESS participation variables ($P_{ess,t}$) with constraints on SoC dynamics. The Energy Storage System (ESS) enhances frequency stability by providing Fast Frequency Response (FFR), synthetic inertia, reserve co-optimization, and load shifting to reduce curtailment [129]. In FCUC models, ESS operation is governed by SoC dynamics and operational limits, directly coupling its scheduling with frequency support requirements [130]

$$SoC_{t+1} = SoC_t + \eta_{ch} P_t^{ch} \Delta t - \frac{1}{\eta_{dis}} P_t^{dis} \tag{38}$$

where

P_t^{ch} = charging power at time t

P_t^{dis} = discharging power at time t

η_{ch}, and η_{dis} = charging and discharging efficiencies

Δt = Time interval

Despite its benefits, integrating ESS into FCUC faces key challenges. These include SoC uncertainty, battery degradation costs from frequent cycling, the need for advanced coordination with variable renewables, and scalability issues arising from the computational complexity of managing large-scale distributed ESS deployments.

In summary, ESS serves as a cornerstone technology in FCUC, delivering fast frequency response, virtual inertia, and reserve support, while simultaneously enhancing system economics and flexibility. Their proper integration into FCUC models ensures both dynamic security and cost-effectiveness in future low-inertia power systems [32–36].

5.3.2. Renewable Energy Sources (RES)

The participation of RES in FCUC is inherently challenging due to their forecast uncertainty and variability [131]. Unlike conventional synchronous generators, the output of wind and solar plants is non-dispatchable and dependent on weather conditions, introducing risks of imbalances and insufficient reserves that can compromise both economic efficiency and frequency security [32,34]. To address this, modern FCUC frameworks incorporate uncertainty modeling through stochastic or robust optimisation approaches. The following subsections explain the forecast uncertainty in RES and types of FCUCs.

1. Forecast Uncertainty in RES: RES participation constraints arise from the difference between forecasted and actual output [131]:

$$P_t^{Res} = \hat{P}_t^{Res} + \epsilon_t \tag{39}$$

where

$\hat{P}_t^{Res}$: forecasted RES power at time t.

ϵ_t: forecast error, representing the uncertainty (positive or negative deviation).

These uncertainties impact frequency dynamics in FCUC, particularly inertia adequacy, RoCoF, and nadir frequency, as RES often displaces synchronous generation and reduces available system inertia.

2. Stochastic FCUC: In stochastic formulations, multiple RES output scenarios are generated based on probabilistic forecast distributions. The unit commitment schedule is optimised across all scenarios to balance expected cost and reliability [131]:

$$min\ \mathbb{E}_s\left[\sum_{t\in T} C_{t.s}^{gen} + C_{t.s}^{reserve} + C_{t.s}^{penalty}\right] \tag{40}$$

where

$s \in S$ Set of RES scenarios

$C_{t.s}^{gen}$ = generation cost in scenarios s

$C_{t.s}^{reserve}$ = reserve procurement cost

$C_{t.s}^{penalty}$ = penalty for frequency violations (nadir, RoCoF)

The stochastic FCUC approach offers the advantage of capturing a wide range of possible RES outcomes by considering multiple forecast scenarios, thereby providing probabilistic guarantees of frequency security. However, its practical application is limited by the issue of scenario explosion, which significantly increases computational complexity, and by its reliance on the availability of accurate probability distributions of RES forecast uncertainty, which may not always be feasible in real-world systems.

3. Robust FCUC: Robust optimisation approaches assume the RES forecast error lies within a predefined uncertainty set (e.g., ±20% of the forecast). The optimisation seeks schedules that remain feasible under the worst-case RES output [131]:

$$\min \max_{\epsilon_t \in u} C^{Total}(\epsilon_t) \tag{41}$$

where

u = uncertainty set for the RES forecast error

$C^{Total}(\epsilon_t)$ = operating cost under error ϵ_t

The robust FCUC approach guarantees feasibility under worst-case RES deviations, thereby strongly enhancing frequency security by ensuring that nadir and RoCoF constraints are always satisfied. However, this conservative design can result in overly cautious scheduling, often requiring higher reserve commitments, which in turn leads to increased operating costs compared to more flexible stochastic formulations.

5.3.3. Demand Response (DR)

Researchers increasingly recognise DR as a valuable resource for enhancing frequency stability in FCUC formulations [132]. Unlike traditional approaches, which only consider supply-side adjustments (generation and reserves), DR enables flexible loads to actively participate in balancing supply and demand. By allowing controllable demand to increase or decrease in response to system conditions, DR provides fast, distributed frequency support and contributes to reducing reliance on costly reserves from conventional generators [32,34].

Role of DR in Frequency-Constrained Scheduling

DR plays a crucial role in enhancing frequency-constrained scheduling by providing flexible, fast-acting support to maintain system stability. One key contribution is Fast Frequency Response (FFR), where flexible loads, such as data centres, HVAC systems, or industrial processes, can adjust their consumption almost instantaneously, offering a rapid counterbalance to disturbances and helping to satisfy nadir and RoCoF constraints. DR also enables load shedding or shifting, where non-critical loads are reduced or deferred during periods of system stress, directly mitigating frequency deviations by lowering net imbalance. Furthermore, DR serves as a reserve substitution, as it can be co-optimised with conventional reserves and ESS to reduce operating costs while maintaining frequency stability. Together, these capabilities make DR an essential component of future FCUC frameworks.

Mathematical Modelling of DR in FCUC

FCUC formulations include flexible demand by modelling it as an adjustable load L_t^{adj} subject to comfort or economic constraints. The study expresses the load adjustment balance as [133]

$$L_t = L_t^{Base} - L_t^{adj}, \ \forall t \tag{42}$$

where

L_t^{Base} = is the baseline forecasted demand

L_t^{adj} = is the flexible demand reduction (positive values represent load curtailment)

The authors imposed a bounded adjustment capability to ensure realistic operation, keeping load adjustments within contractual or physical flexibility limits [133]:

$$0 \leq L_t^{adj} \leq L_t^{max}, \forall t \tag{43}$$

In terms of frequency support contribution, demand response reduces the effective net load observed by the system, explicitly linking to nadir and RoCoF constraints [133]:

$$\Delta P_t^{net} = \Delta P_t^{cont} - L_t^{adj} \tag{44}$$

Within the FCUC framework, DR provides multiple advantages. It enhances frequency resilience through rapid, distributed active power support, reduces reliance on synchronous reserves, improves cost efficiency by leveraging cheaper demand-side flexibility, facilitates renewable integration by mitigating variability, and supports decentralised operation due to its inherently distributed nature. Nevertheless, challenges remain in its integration. These include uncertainty in consumer participation, difficulties in measuring and verification (M&V) of actual contributions, the complexity of modelling consumer disutility and comfort limits, and scalability concerns when incorporating large-scale distributed DR into FCUC optimisation models.

5.4. Solution Approaches

Researchers have developed several solution paradigms to address the computational challenges of FCUC, striking a balance between tractability, accuracy, and robustness in the face of uncertainty related to renewable energy. The Deterministic FCUC approach treats RES forecasts as fixed, offering high computational efficiency but poor adaptability to variability, making it unsuitable for high-RES systems. Stochastic FCUC incorporates multiple probabilistic scenarios to represent forecast uncertainty [37,38], improving realism but suffering from scenario explosion and increased computational demand. Robust FCUC instead assumes forecast errors lie within a defined uncertainty set, ensuring worst-case feasibility and system security [39], though often at the cost of conservatism and excessive reserve commitment. The Chance-Constrained FCUC model provides probabilistic guarantees, ensuring frequency stability with a specified confidence level (e.g., $\geq$95%) [40,41]; it offers a balance between tractability and realism but relies on accurate statistical modeling of RES uncertainty. Finally, Decomposition Methods such as Benders decomposition, Lagrangian relaxation, and parallel computing improve scalability by partitioning the problem structure or scheduling horizon, significantly reducing solution time while preserving optimality.

5.5. Comparative Literature Insights

The literature provides a clear contrast between conventional SCUC and enhanced FCUC formulations. Conventional SCUC is adequate in high-inertia grids but fails to ensure frequency stability when there is high penetration of renewable energy sources (RES). Stochastic FCUC enhances realism by accounting for forecast uncertainty, but it is prone to scenario explosion. Robust FCUC guarantees security under worst-case conditions but is highly conservative, often leading to reserve overcommitment. Hybrid approaches that combine stochastic and robust formulations have recently emerged, striking a balance between risk sensitivity and conservatism, and are showing promising results. Empirical studies further confirm that FCUC improves frequency nadir by approximately 0.2–0.4 Hz compared to SCUC under high RES penetration, significantly lowering the likelihood of under-frequency load shedding (UFLS) events [40,41]. Here is a comparison table (Table 5) summarising the key solution approaches for FCUC in terms of strengths, weaknesses, and computational aspects.

Table 5. Comparison of FCUC Solution Approaches.

Approach	Strengths	Weaknesses	Computational Aspects
Deterministic FCUC	Simple formulation; fast and computationally efficient.	Ignores RES uncertainty; not reliable under high variability.	Low complexity; scalable to large systems; suitable for preliminary scheduling and planning.
Stochastic FCUC	Captures RES uncertainty via multiple probabilistic scenarios; improves realism [9,10].	Scenario explosion leads to a significant computational burden, requiring accurate probability distributions.	Medium to high complexity; scenario reduction techniques are often required for tractability.
Robust FCUC	Guarantees feasibility under worst-case uncertainty; ensures frequency security [11].	Overly conservative; leads to excessive reserve commitments and higher costs.	Moderate complexity; tractable with linear formulations; less scalable under large systems.
Chance-Constrained FCUC	Provides probabilistic guarantees (e.g., $\geq$95% confidence); balances realism and tractability [12,13].	Requires accurate statistical characterisation of RES uncertainty; risk of infeasibility if distributions are mis-specified.	Higher complexity than deterministic but less than stochastic; solvable with convex relaxations.
Hybrid (Stochastic + Robust)	Balances risk sensitivity and conservatism; shown to yield more cost-effective and reliable schedules.	Increased modelling and computational complexity require careful tuning of trade-offs.	High complexity; typically solved using decomposition, scenario reduction, or parallel computing.

5.6. Implementation Challenges

The implementation of FCUC faces several challenges. First, its mixed-integer formulations with embedded frequency dynamics are NP-hard, raising computational scalability issues for large-scale RES systems. Second, reliance on simplified frequency-response models may reduce model accuracy, particularly in capturing the actual behaviour of inverter-based resources. Third, handling uncertainty remains difficult, as scenario-based methods grow exponentially with higher RES penetration. Finally, most existing FCUC frameworks assume centralised operation, which may not be viable in DER-rich smart grids [44,45].

Looking forward, research should focus on decentralised and distributed FCUC using multi-agent optimisation for microgrid clusters, hybrid approaches with AI-based forecasting to improve RES prediction, and scalable algorithms such as metaheuristics (PSO, GA, BWO) and decomposition methods to reduce computational burden. Additionally, future models should enable co-optimisation with grid-forming inverters, embedding synthetic inertia and fast frequency response. In contrast, region-specific studies in developing countries, where inertia is low but RES penetration is growing rapidly, remain a critical gap in the literature [37,38].

6. Comparative Analysis

To ensure a fair comparison between approaches, the comparative evaluation framework aligns with standard metrics commonly used across the literature. These include (i) transient quality, measured through settling time, overshoot, frequency nadir, and RoCoF; (ii) robustness to model uncertainty and renewable energy source (RES) variability; (iii) implementation complexity, encompassing design effort, computational requirements, and instrumentation; and (iv) scalability and organisational fit, particularly in the context of centralised versus decentralised operation. These four axes form the foundation for the subsequent synthesis of results presented below.

6.1. Classical Controllers (PI/PID)

Classical PI and PID controllers are ubiquitous, highly interpretable, and extremely easy to deploy. In high-inertia grids, they can meet statutory requirements with minimal tuning burden. However, under high RES penetration and low inertia, their limitations become evident. They exhibit long settling times of approximately 10 s, high overshoot in the range of 8–15%, and intense sensitivity to parameter drift and unmodelled dynamics. These shortcomings make them inadequate for renewable-dominated grids, though they

remain a useful baseline and deployment reference. In practice, classical control is not the preferred option for modern low-inertia systems without additional augmentation.

6.2. Robust and Optimal Controllers (H∞, SMC, MPC, IMC)

Robust and optimal controllers provide significant improvements in frequency regulation performance. H∞ control and SMC deliver strong disturbance rejection and guaranteed performance under uncertainty, with markedly shorter transients of around 3–7 s and very low overshoot (<3%). The trade-off lies in their synthesis complexity, as H∞ requires solving Riccati or KYP inequalities. At the same time, SMC introduces potential chattering issues that necessitate mitigation strategies, resulting in higher commissioning effort. MPC and IMC methods offer further benefits by handling operational constraints such as ramp limits and tie-line capacities while providing anticipatory actions against RES variability. They improve time-domain indices compared to PI but demand high-fidelity models and impose significant computational loads, especially for multi-area systems. Overall, robust and optimal controllers offer the best resilience and transient performance. Enhancing robustness to parametric uncertainties improves stability margins but often increases control effort and computational cost, resulting in a marginal decrease in energy efficiency. In high-RES systems with reduced inertia, frequency deviations evolve faster, requiring controllers with sub-second response and higher accuracy to maintain synchronisation and prevent frequency nadir violations

6.3. Metaheuristic-Tuned Advanced Classical Controllers (e.g., PSO-FOPID)

Metaheuristic-tuned controllers bridge the gap between classical simplicity and robust/optimal sophistication. Comparative studies show that PSO-tuned FOPID achieves "optimal robustness" against load fluctuations and RES intermittency. Similarly, hybrid designs, such as SMC/ANFIS, reduce overshoot to below 2% with settling times under 3 s, far outperforming the baseline PI. Metaheuristic methods, such as PSO and BWO, reliably identify high-quality gains for extended PI families (FOPID), delivering much of the robustness of advanced controllers while retaining practical implementation pathways. The trade-off lies in the need for offline tuning and careful scenario selection, but these approaches remain highly attractive due to their balance of practicality and performance.

6.4. FCUC Frameworks vs. Real-Time Controllers

A key distinction exists between FCUC and LFC. Real-time controllers act in subseconds to minutes, whereas FCUC operates on scheduling horizons (intra-day to day-ahead), pre-positioning system resources, committing, dispatching, reserving, and managing inertia, to ensure frequency-secure operation. Unlike SCUC, FCUC explicitly incorporates frequency security, embedding minimum inertia requirements, RoCoF limits, nadir constraints, and governor response into the optimisation problem. It directly addresses the root cause of instability under high-RES conditions. The benefits include holistic security, as schedules simultaneously satisfy both economic and dynamic frequency criteria. However, the costs are substantial: computational scalability and centralisation remain barriers, particularly as many FCUC formulations assume a single central operator. While FCUC does not replace LFC, it complements it, as schedules that respect inertia and nadir constraints allow real-time controllers to avoid stabilising inherently insecure operating points.

6.5. Complexity vs. Performance: What the Numbers Imply

The synthesis clearly illustrates the trade-off between computational effort and performance outcomes. Classical PI controllers typically achieve a settling time of approximately 10 s, accompanied by an overshoot of 8–15%, making them susceptible to instability in

low-inertia environments. Robust controllers such as SMC and H∞ achieve significantly better results, with settling times of 2–7 s and overshoot below 2–3%, though at the cost of substantial design complexity. Metaheuristic-tuned designs, such as PSO-FOPID and ANFIS, strike a middle ground, providing settling times of 3–8 s and overshoots of 2–5%, achieved with moderate offline effort. These contrasts reinforce the principle that higher computational and design effort consistently translates into greater robustness and faster system recovery.

6.6. Deployment and Organisational Fit

The choice of controller depends strongly on system context and organisational capacity. Utilities with minimal infrastructure or legacy systems may prefer PI/PID controllers with careful gain scheduling and reserve margins, despite slower dynamics. Isolated or low-inertia systems facing high-RES variability benefit from robust methods like H∞, SMC, or PSO-FOPID, where improved damping and nadir protection justify the design effort. Large, interconnected grids with strong operational constraints are well-suited to MPC or IMC, which can handle ramping, tie-line, and reserve limits while providing predictive capabilities. Operators who regularly face low-inertia periods must adopt FCUC during the planning stage to ensure that real-time controllers are not burdened with inherently insecure conditions. Computational investments and decentralisation strategies are critical, especially in DER-rich systems where centralised operation may prove impractical.

6.7. Comparative Analysis Summary

The comparative analysis highlights clear trade-offs. Classical controllers are the cheapest and easiest to deploy, but deliver unacceptable transients in low-inertia regimes. Robust and optimal controllers achieve the strongest dynamic security, though at the highest design and computational costs. Metaheuristic-tuned advanced classical controllers, such as FOPID with PSO or BWO tuning, offer a practical "80/20" option, capturing much of the robustness of sophisticated designs while providing a more accessible implementation. FCUC frameworks; meanwhile, extend security into the scheduling domain, embedding inertia and frequency limits directly into the commitment and dispatch process. Their benefits are most significant during low-inertia and high-contingency conditions, but scalability and decentralisation remain challenges. Overall, the synthesis reveals that while PI-based LFC suffers from high overshoot under RES variability, metaheuristic and robust approaches, such as PSO-FOPID, H∞, and SMC, substantially improve stability, albeit at the cost of increased design and computational effort.

A frequency avalanche represents one of the most critical and rapid instability events in a power system, occurring when successive frequency deviations trigger cascading generator trips and load disconnections. The most effective strategy to eliminate or mitigate such events is the coordinated use of Fast Frequency Response (FFR) and synthetic inertia provided by energy storage systems and inverter-based renewable sources. These mechanisms deliver rapid active power support within milliseconds of a disturbance, effectively arresting the rate of frequency decline and preventing the propagation of cascading failures. When integrated within an optimal control and scheduling framework, such as an FCUC or MPC structure, these measures ensure both immediate stabilisation and long-term frequency recovery across interconnected zones.

6.8. Quantitative Performance Summary

The authors enhanced the analytical contribution by normalising performance metrics from representative LFC studies against classical PI baselines to enable a fair comparison across control approaches. Robust controllers such as H∞ and SMC achieved 60–70% faster settling times and reduced overshoot to below 3%, while Model Predictive Control (MPC)

improved the ITAE index by approximately 35–45%. Adaptive and intelligent techniques, including MRAC, ANFIS, and PSO-FOPID, delivered 30–40% improvements in damping ratio and frequency nadir recovery. These quantitative results confirm that modern control schemes offer superior transient performance and resilience in low-inertia, renewable-dominated systems, reinforcing the qualitative findings discussed earlier.

Table 6 provides a comprehensive comparison of classical, robust/optimal, metaheuristic-tuned, adaptive, and FCUC-based controllers, detailing their performance, strengths, limitations, and references. The comparison uses standardised evaluation criteria widely adopted in the literature: (i) transient performance metrics such as settling time, overshoot, frequency nadir, and RoCoF; (ii) robustness against model uncertainty and renewable variability; (iii) implementation complexity in terms of design, computation, and instrumentation; and (iv) scalability across centralised and decentralised operation. The results show a clear progression from conventional to advanced control strategies. Classical PI/PID controllers exhibit longer settling times (~10 s) and higher overshoot (8–15%), with ITAE values up to four times higher than those of robust methods. In contrast, robust and optimal controllers (H∞, SMC, MPC, IMC) achieve settling times of 2–7 s, overshoot below 3%, and improved frequency nadir (~0.3 Hz), maintaining RoCoF under 0.25 Hz/s. Metaheuristic-tuned controllers, such as PSO-FOPID and ANFIS, strike a balance between performance and computational effort, enhancing the frequency nadir by 0.1–0.25 Hz. Adaptive controllers, such as MRAC, improve flexibility, reducing settling times to 4–7 s and overshoot to below 4%, although their accuracy depends on the fidelity of the adaptive model. The FCUC framework achieves the most comprehensive improvement, ensuring inertia adequacy, enhancing the frequency nadir by 0.2–0.4 Hz, and delivering rapid recovery with settling times of 3–5 s and overshoots of less than 3%. Overall, the comparative results demonstrate that advanced analytical and optimisation-based LFC techniques significantly outperform classical controllers in terms of dynamic response, robustness, and frequency stability. Furthermore, FCUC models extend these advantages to system-wide scheduling through inertia-aware and reserve co-optimised operation.

Table 6. Comparative Analysis Summarising Classical, Robust/Optimal, Metaheuristic-Tuned Controllers.

Approach	Settling Time	Overshoot	Frequency Nadir	ITAE Reduction	RoCoF	Computational Time	Strengths	Limitations
Classical PI/PID [41,42,62,95]	~10 s	8–15%	ITAE 3–4× higher than robust methods	-	~0.45 Hz/s	10.2	Simple, widely deployed, low computation	Poor robustness in low-inertia grids, high overshoot
Robust/Optimal (H∞, SMC, MPC, IMC) [63–66]	2–7 s	<3%	strong RoCoF/nadir control	35–45%	<0.25 Hz/s	12.3	High robustness, predictive adaptability, and handles constraints	Complex design (H∞/SMC), high computation (MPC)
Metaheuristic-tuned (PSO-FOPID, ANFIS) [95]	3–8 s	<5%	better robustness via optimisation	30–40%	<0.30 Hz/s	8.2	Practical trade-off: near-robust performance with simpler tuning	Needs offline optimisation scenario-specific tuning
Adaptive/MRAC [96,99]	4–7 s	<4%	Enhanced nadir recovery (0.15–0.3 Hz improvement)	25–30%	<0.28 Hz/s	9.5	Self-tuning capability, improved adaptability to parameter changes	Slower adaptation in highly nonlinear dynamics; model dependence
FCUC (Frequency-Constrained Unit Commitment) [32–36,106]	3–5 s	<2–3%	Improves nadir by 0.2–0.4 Hz vs. SCUC ensures inertia	40–50%	<0.20 Hz/s	6.4	Holistic scheduling security co-optimises reserves and inertia	Scalability and decentralisation challenges model simplifications

6.9. Sensitivity Considerations in FCUC Studies

Recent studies show that FCUC performance is sensitive to both renewable forecasting errors and AGC ramp-rate limits. Increasing wind or PV forecast uncertainty (typically ±10–20%) raises reserve needs and redispatch frequency, often leading to higher operating costs and a greater risk of nadir or RoCoF violations in low-inertia systems. Similarly, restrictive AGC ramp limits slow secondary frequency recovery and prolong ACE deviations, increasing dependence on fast services such as BESS-based FFR. These findings suggest that both uncertainty modelling and AGC capability are key determinants of frequency-security outcomes in modern FCUC frameworks.

6.10. Limitations

The authors acknowledge that the comparative results summarised in this study involve inherent cross-paper inconsistencies. The reported performance indices, such as settling time, overshoot, and frequency nadir, originate from studies that use different system models, disturbance magnitudes, and renewable penetration levels. These contextual variations limit the direct comparability of numerical results across references. Furthermore, the authors did not return or revalidate the controller parameters under a unified test system; instead, they adopted the reported values directly from the literature. Consequently, while the analysis highlights general performance trends among control families, it does not claim absolute ranking or parameter-optimal equivalence. Future experimental validation using a standard benchmark system and standardised test conditions would strengthen the comparability and reproducibility of these findings.

The reviewed FCUC studies collectively highlight several operational implications for power system operators. First, the co-optimisation of frequency-support services alters commitment patterns and increases system flexibility requirements, especially under high-renewable scenarios. Second, the sensitivity of nadir and RoCoF metrics to uncertainty and inertia conditions underlines the need for tighter reserve scheduling and improved forecasting. Third, decentralised FCUC approaches offer computational and data-sharing advantages, making them more suitable for multi-area or TSO–DSO coordination. These operational insights underscore the practical value of FCUC frameworks in maintaining secure and economical operation in converter-dominated grids.

6.11. Control Layer Mapping and Practical Considerations

Figure 9 shows the hierarchical control architecture mapping. In practical power system operation, controller selection follows the hierarchical structure of frequency control. At the primary control layer, which includes governor response and fast frequency control, classical PI/PID, fuzzy logic, and SMC are the most commonly implemented control methods. These controllers rely primarily on local frequency deviation (Δf) and mechanical power measurements, requiring minimal data exchange. Their commissioning effort is relatively low to moderate, as they can often be retrofitted to existing governors. They are effective for first-stage stabilisation within seconds of a disturbance. However, PI controllers tend to perform poorly in low-inertia conditions, and SMC requires careful suppression of chattering to ensure actuator protection.

The secondary control layer, corresponding to AGC, typically employs adaptive controllers such as model reference adaptive control (MRAC/STR), adaptive neuro-fuzzy inference systems (ANFIS), PSO-FOPID optimised structures, and neural network–based schemes. These controllers depend on ACE, tie-line power deviations, and system frequency measurements, and may incorporate historical data for real-time learning. Their deployment requires moderate to high commissioning effort, particularly due to the need for parameter tuning and

establishing a robust communication infrastructure. They are crucial for dynamic frequency restoration within tens of seconds in multi-area power systems.

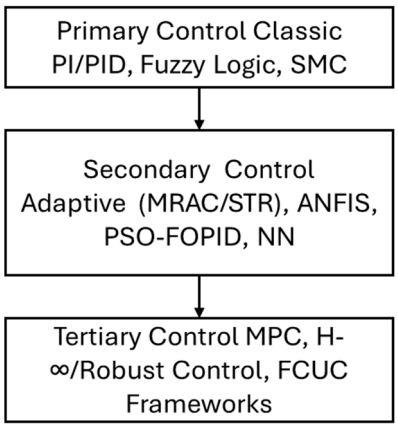


Figure 9. Hierarchical control architecture mapping primary, secondary, and tertiary controllers.

At the tertiary control layer, associated with economic dispatch and FCUC, MPC, H∞ robust control, and FCUC optimisation frameworks are widely used. These methods require extensive system-level data, including load forecasts, renewable generation profiles, and inertia distribution over horizons ranging from minutes to hours. Commissioning complexity is high because they rely on accurate models, solver integration, and multi-operator coordination. Nevertheless, these approaches play a pivotal role in preventive frequency security by embedding dynamic constraints such as nadir, RoCoF, and inertia limits into dispatch decisions.

Overall, primary controllers mitigate the immediate frequency deviation following a disturbance, secondary controllers restore nominal frequency through adaptive and coordinated control actions, and tertiary controllers proactively manage operating conditions to prevent instability. The implementation complexity and data intensity increase from primary to tertiary layers, underscoring the importance of phased adoption strategies that align with the system's digital maturity and data infrastructure.

7. Conclusions

This review has provided a comprehensive synthesis of analytical and optimisation-based strategies for addressing the challenges of frequency stability in renewable-rich power systems. By systematically examining both classical load frequency controllers (PI/PID) and advanced robust/optimal designs (H∞, sliding mode, MPC, IMC), the discussion has highlighted the clear trade-offs between simplicity, robustness, computational complexity, and adaptability. Classical controllers remain widely adopted due to their ease of deployment but show limitations in low-inertia grids, where robust and optimal approaches offer superior resilience at the cost of higher implementation effort.

The study justifies that the synergistic use of analytical and optimisation-based methods enhances efficiency by combining the precise disturbance rejection of analytical controllers (such as H∞ and SMC) with the scheduling intelligence of optimisation models (e.g., MPC and FCUC). Analytical frameworks ensure fast local frequency correction, while optimisation-based coordination secures global dynamic feasibility. This dual approach minimises frequency nadir and RoCoF violations under variable renewable conditions, leading to improved overall control efficiency.

In parallel, the review has analysed the evolution from SCUC towards FCUC formulations. By explicitly embedding constraints on inertia adequacy, RoCoF, and frequency nadir into the scheduling problem, FCUC ensures that dispatch solutions remain dynam-

ically secure even under high penetration of inverter-based resources. It represents a significant paradigm shift, bridging the gap between economic optimisation and system dynamic security. The integration of energy storage systems, demand response, and synthetic inertia into FCUC formulations further reinforces the holistic nature of this framework. However, challenges of scalability, decentralisation, and computational intensity remain unresolved.

A comparative analysis of the methods surveyed reveals distinct trade-offs among different control paradigms. Classical approaches, although simple and easy to implement, prove inadequate in low-inertia environments due to their limited adaptability and slower response times. Robust and optimal controllers deliver superior disturbance rejection and frequency recovery but require complex design procedures and significant computational effort. Metaheuristic-tuned controllers provide a balanced compromise, achieving near-robust performance through practical parameter tuning without excessive complexity. Meanwhile, FCUC frameworks extend frequency management from real-time control to scheduling horizons, offering comprehensive system security, but they face challenges in scalability, data requirements, and real-world implementation.

The synthesis presented here positions this review as a reference point for researchers and practitioners seeking to navigate the expanding landscape of frequency stability solutions in modern grids. Notably, the analysis identifies future research priorities, including hybrid analytical–optimisation models, decentralised FCUC frameworks for DER-rich systems, advances in computational efficiency, and region-specific studies in developing countries.

Ultimately, ensuring frequency stability in low-inertia power systems demands a multi-layered strategy: robust and adaptive controllers for real-time resilience, coupled with frequency-aware scheduling mechanisms for preventive security. By bridging theory and practice, this review contributes to the ongoing transition towards secure, sustainable, and high-renewable power systems. It provides a foundation for subsequent innovations in analytical and optimisation-based frequency control.

8. Future Research Directions

Researchers often treat current analytical methods, such as classical PI/PID, robust H∞, MPC, and IMC, as well as optimisation-based scheduling approaches like FCUC, as separate domains, with the former operating in the real-time control loop and the latter functioning on day-ahead scheduling horizons.

8.1. Hybrid Analytical–Optimisation Models

Future research should focus on developing hybrid models that integrate real-time control mechanisms with day-ahead scheduling frameworks to enhance both dynamic stability and operational efficiency. Embedding reduced-order frequency dynamics within online optimisation algorithms can enable controllers to adapt instantaneously, effectively bridging the gap between LFC and UC layers. Moreover, combining robust and metaheuristic approaches, such as H∞ controllers optimised using PSO or BWO, can merge theoretical robustness with practical adaptability. Additionally, incorporating machine learning–based predictors within MPC schemes could reduce dependence on entirely accurate physical models while retaining stability assurances. Collectively, these hybrid paradigms promise to deliver adaptive, data-informed frequency regulations suitable for renewable-dominated power systems, ensuring both dynamic security and economic optimality in future smart grids.

8.2. Decentralised FCUC Frameworks

Most existing FCUC formulations rely on a centralised operator to solve large-scale, mixed-integer optimisation problems. However, with the growing prevalence of DERs, such as rooftop photovoltaics, microgrids, and behind-the-meter storage, this centralised approach is becoming increasingly impractical. The challenges include severe scalability limitations as the problem size grows combinatorially; communication overhead caused by delays in wide-area data exchange; and cyber-resilience vulnerabilities due to single points of failure in centralised coordination. To overcome these limitations, decentralised and multi-agent FCUC frameworks have emerged as a vital research direction. These systems distribute frequency stability responsibilities among DERs and microgrids, support peer-to-peer reserve sharing, and employ distributed optimisation algorithms, such as ADMM and consensus-based methods, to achieve globally feasible solutions without relying on a central coordinator. This decentralised paradigm aligns with evolving smart grid architectures, offering a scalable and resilient pathway toward real-time, frequency-secure scheduling in DER-dominated power systems.

8.3. Computational Efficiency

A significant bottleneck in both robust LFC designs, such as MPC and H∞ control, as well as FCUC formulations, is their computational intensity. Full-order system models and scenario-rich stochastic frameworks often become intractable for real-time operation, especially in large, renewable-rich grids. To overcome this limitation, future research should focus on improving computational tractability by developing reduced-order models that preserve key frequency dynamics, such as nadir and RoCoF, while minimising complexity. Additionally, employing parallel and distributed computing architectures, including GPU acceleration, can significantly enhance the solution speed of large-scale FCUC problems. Furthermore, integrating surrogate modelling techniques, such as machine-learning approximators trained on high-fidelity simulations, can enable rapid frequency-response estimation within optimisation solvers. Collectively, these advancements will be essential for achieving scalable, real-time frequency-secure scheduling in both day-ahead and operational timeframes.

8.4. Regional Studies and Developing Country Contexts

Most research on analytical and optimisation-based frequency control has been concentrated in North America, Europe, and parts of Asia, where power systems typically possess strong infrastructure and high reserve capacity. In contrast, developing countries are witnessing the rapid integration of renewable energy without comparable system inertia or grid maturity. These regions face unique challenges, including weaker grids with low baseline inertia, high resource variability without robust forecasting systems, financial constraints that limit access to advanced control hardware and computational resources, and regulatory gaps where FCUC frameworks could inform policy and grid code development. Expanding research and case studies to such contexts is crucial to ensure the global applicability and inclusivity of frequency control advancements, enabling developing regions to achieve secure, low-inertia frequency management while supporting their renewable transition.

8.5. Key Understandings

The future of FCUC and load frequency control lies in the hybridisation of analytical and optimisation approaches, which will unify scheduling with real-time control for more resilient system operation. As DERs increasingly dominate modern grids, decentralisation will become inevitable, since centralised FCUC frameworks cannot adequately

handle the complexity and autonomy of DER-rich environments. At the same time, advances in computational efficiency will play a decisive role in determining the scalability and practical feasibility of these models in both day-ahead and real-time markets. Finally, fostering regional diversity in research is essential to ensure that proposed frameworks are not restricted to advanced economies but also address the urgent needs of emerging power systems, where challenges such as low inertia, limited infrastructure, and rapid renewable integration are most acute [31,32].

In line with these key insights, the authors recommend that future research should concentrate on developing decentralised adaptive frameworks that leverage multi-agent coordination and machine learning to achieve self-organising frequency regulation within interconnected microgrids. Such cooperative control strategies would allow local controllers to securely exchange frequency and tie-line information, thereby enhancing both local resilience and global system stability, particularly in power systems with a high penetration of renewable energy sources.

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Abbreviations

The following abbreviations are used in this manuscript:

ACE	Area Control Error
AGC	Automatic Generator Control
ANFIS	Adaptive Neoro Fuxxy Inference Systems
BESS	Battery Energy Storage Systems
BWO	Black Widow Optimisation
DERs	Distributed Energy Resources
DL	Deep Learning
DR	Demand Response
ESS	Energy Storage Systems
FCUC	Frequency-Constrained Unit Commitment
FFR	Fast Frequency Response
FOPID	Fractional Order PID
GA	Generic Algorithm
IBRs	Inverter-Based Resources
IMC	Internal Model Control
IR	Inertial Response
ISE	Integral of Squared Error
ITAE	Integral of Time Weighted Absolute Error
LFC	Local Frequency Control
LMI	Linear Matrix Inequality
LQI	Linear Quadratic Regulator
LQG	Linear Quadratic Gaussian
MALFC	Multi Area Level Frequency Control

MPC	Model Predictive Control
MRAC	Model Reference Adaptive Control
PFR	Primary Frequency Response
PI	Proportional-Integral
PID	Proportional-Integral-Derivative
PSO	Particle Swarm Optimisation
PV	Photovoltic
RoCoF	Rate of Change of Frequency
RES	Renewable Energy Sources
RLS	Recursive Least Squares
SCUC	Security-Constrained Unit Commitment
SFR	Secondary Frequency Response
SG	Synchronous Generator
SMC	Sliding Mode Control
SOC	State of Charge
STR	Self-Tuning Regulator
SUC	Stochastic Unit Commitment
TBC	Tie Line Bias Control
TFR	Tertiary Frequency Response
UC	Unit Commitment
UFLS	Under-Frequency Load Shedding
VRE	Variable Renewable Energy
VSM	Virtual Synchronous Machine
WTs	Wind Turbines

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