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Review Article

Advancements in Automatic Generation Control: Trends in Intelligent Optimization for Modern Power Systems

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Abstract - *Modern power systems are growing increasingly complex with high uncertainty because of the increasing utilization of Renewable Energy Sources (RES). Thus, a power system requires intelligent optimization using Artificial Intelligence (AI) to improve power grid stability. However, there is still a lack of comprehensive reviews that trace the evolution of AI-based algorithms in optimizing Automatic Generation Control (AGC), including their challenges and future directions. Therefore, this paper presents a chronological review of these methods in optimizing AGC from the 2000s to the 2020s. This analysis explains how these AI algorithms have solved challenges in AGC across different eras, each with its own distinct advantages. Generally, AI algorithms in AGC are categorized into three main groups, which are fuzzy logic, metaheuristic algorithms, and machine learning. Fuzzy logic dominated the 2000s because its rule-based control reduced the complexity of mathematical modeling in power systems. Metaheuristic algorithms have dominated AGC studies from the 2010s through the current 2020s because they can obtain optimal AGC controller parameters in high-dimensional search spaces efficiently. Recently, in the 2020s, machine learning techniques have been applied increasingly to optimize AGC. This is because they support model-free learning in power systems with complex parameters that are difficult to model. The integration of RES in the power grid remains one of the main challenges in current AGC studies, which should be focused on by future studies. Thus, this review provides valuable information for future research in AGC to enhance the stability of the power grid.*

Keywords - *Automatic Generation Control, Fuzzy Logic, Evolutionary Algorithm, Swarm Intelligence, Machine Learning.*

1. Introduction

Power systems are designed to generate, transmit, and distribute electrical power. Power systems are becoming more complex as a wide variety of energy sources are used for generating electricity. For example, power generation from Renewable Energy Sources (RES) like solar power is added to the power grid, which creates uncertainty for power stability. This is because these RES depend heavily on environmental factors like sunlight and wind conditions, which are more difficult to predict than traditional energy sources like natural gas or coal. [1, 2] Thus, power output from RES is highly variable and less reliable compared to conventional thermal power plants. [3] Therefore, power system control is critical for ensuring reliable power generation. It involves controlling both active and reactive power to maintain system stability, with the primary objective of generating and delivering power while keeping voltage and frequency at permissible limits. [4] There are two main controls for this system: the Load Frequency Control (LFC), which regulates frequency and real power, while the Automatic Voltage Regulator (AVR) regulates voltage magnitude and reactive power. [5] This review focuses on LFC because frequency control is more challenging, as it is more susceptible to disturbances compared to reactive power control. LFC stabilizes frequency at its nominal level by maintaining equilibrium between generated and consumed power. [6] LFC nowadays uses Automatic Generation Control (AGC) to restore frequency to its nominal value automatically. AGC automatically adjusts generation to counterbalance changes in system load. Furthermore, AGC helps in distributing loads among generators to minimize frequency deviations and maximize economic efficiency in interconnected systems [7]. AGC also automatically controls the power flows between interconnected areas using tie lines while keeping the overall power frequency stable. [8] Thus, the primary objectives of AGC are: (i) maintaining power frequency within permissible limits, (ii) ensuring generators and tie-lines operate within permissible limits, and (iii) sustaining power balance in interconnected power systems. [9] There are many review articles that study various aspects of AGC. For example, articles [10, 11] provided detailed reviews of secondary controllers in AGC, including integer-order, fractional-order, and cascade controllers. However, these papers mainly focus on the controllers themselves and do not explore in depth the AI-based optimization methods used for them. On the other hand, some review articles focus predominantly on a single AI algorithm. For example, articles [12, 13] provided clear explanations about the application of reinforcement learning in AGC. However, other AI algorithms are equally important and should be discussed together as well. There are also review articles that cover both controllers and AI optimization methods in AGC, such as articles [4, 14]. However, these papers provide only a broad overview and lack detailed explanations of the challenges faced by AGC that have driven the evolution and adoption of AI-based optimization techniques in these systems. Since AGC is relying heavily on AI nowadays, as agreed by most researchers, because of the increased complexity in modern power systems, a study of the evolution trend in these AI optimization methods is necessary to predict the future of AGC [15]. Combining the study gaps mentioned above, there is still a lack of a comprehensive review that discusses the complete evolutionary trajectory of AI-based optimization techniques for AGC in a chronologically structured way. Therefore, this provides the primary motivation for this review article, which aims to analyze the evolutionary trends of AI-based optimization methods in AGC.The study of evolution trends is important because reflecting on past challenges and how optimization methods have evolved to address them is essential in any research field.

This helps in identifying promising future research directions in AGC. This leads to the following research questions:

(a) What are the key challenges in AGC that have driven the adoption and evolution of AI-based optimization algorithms in AGC?
(b) What are the strengths and limitations of each AI-based optimization algorithm for AGC?
(c) What are the emerging trends and future research focus in AGC, particularly in AI-based optimization techniques?

Thus, this paper addresses the study gap by focusing on the evolution of AI-based AGC optimization techniques, highlighting their challenges, trends, and future directions, which are absent in previous reviews [10, 11]. Moreover, unlike previous reviews that focused on specific algorithms [12], this study reviews widely used AI algorithms in AGC and explores how evolving power systems have driven their progression. The key novelty and contributions in this work are detailed below:

(d) A trend-based analysis of the challenges faced and the evolution of AI-based optimization algorithms in AGC studies.
(e) A detailed review of the strengths and limitations of each AI-based optimization algorithm for AGC.
(f) A forward-looking perspective on future directions in AGC research using AI optimization.

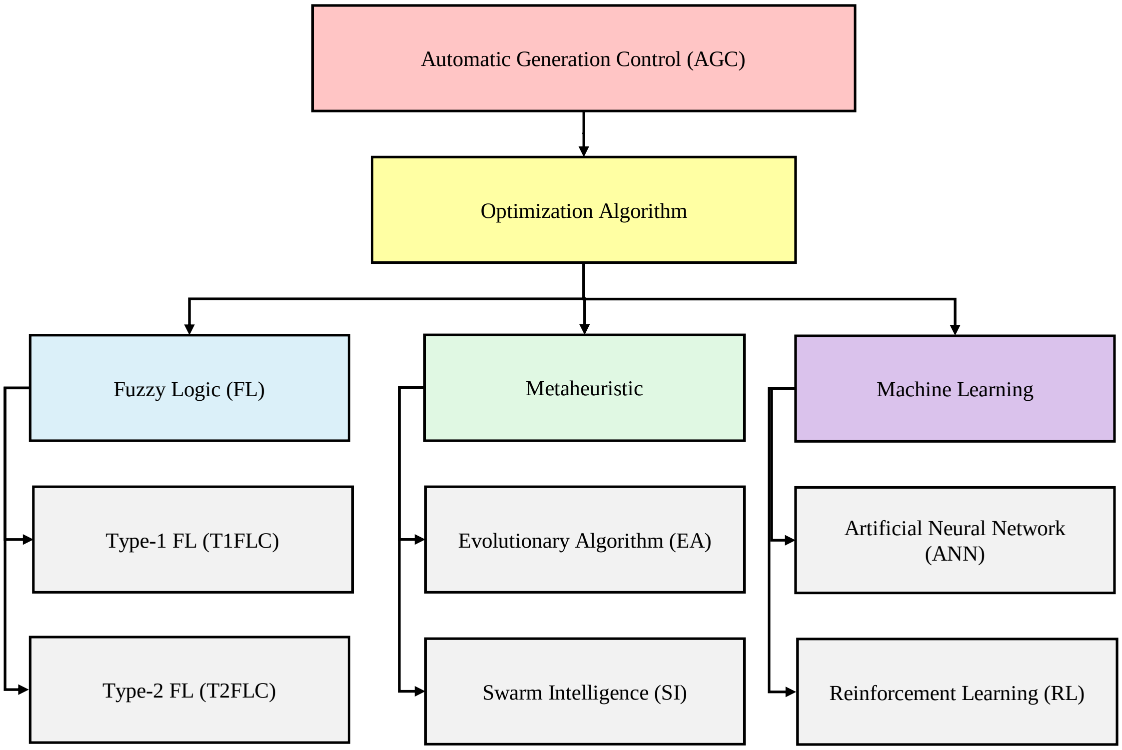


Fig. 1 Overview of the automatic generation control review structure presented in this paper

Therefore, this paper serves as a reference for both newcomers and experienced researchers by providing valuable information on AI optimization methods in AGC.

This information enables researchers to understand and select the appropriate methods or algorithms based on their specific requirements when conducting research on AGC.

As power systems become more complex with higher levels of RES, AI-driven AGC can still be enhanced to improve the overall stability of the power system.

This paper has the following structure: Section 2 reviews the AGC control loop. Section 3 provides an overview of controllers used in AGC. Section 4 presents the methodology for this paper. Section 5 discusses trends in AI-based optimization for AGC. Sections 6, 7, and 8 examine the application of fuzzy logic, metaheuristic algorithms, and machine learning, respectively. Section 9 offers a comparative discussion of the strengths and limitations of these algorithms. Sections 10 and 11 outline limitations and future research directions. Figure 1 provides a comprehensive summary of the optimization algorithms covered in this paper.

2. Control loop of automatic generation control

Before reviewing the optimization algorithms applied in AGC studies, it is crucial to understand the AGC control loop in a power system using synchronous generators, given that system frequency is still mainly determined by these generators.

The operation of AGC relies on the Area Control Error (ACE) in each interconnected area, which includes two components: (i) Δf representing deviation in frequency and (ii) ΔP_{tie} representing deviation in tie-line power. [7] Figure 2 presents the structure of control loops in the AGC system. In general, the AGC system functions through three primary control loops:

2.1. Primary automatic generation control loop

The primary AGC control loop serves as the first response mechanism of the AGC. When there is a variation in user demand, such as an increase in electrical load, the turbine governor adjusts the generator speed based on its speed droop regulation setting to restore the frequency by balancing the power generated and load demand.

The primary control loop provides a rapid response to load changes and helps prevent the power frequency from deviating too far. [7, 8]

2.2. Secondary automatic generation control loop

After the primary control loop is executed, a steady-state frequency error may persist. The secondary control loop corrects this by fine-tuning the speed governor settings to achieve precise frequency regulation.

Most AGC studies focus on designing and optimizing the controller in the secondary loop using AI-based algorithms to restore the frequency back to the reference value without steady-state error in the shortest time. [16]

2.3. Tertiary automatic generation control loop

Once the power system has been stabilized, the tertiary control loop ensures that the load is distributed across all generators economically. This loop adjusts the speed changer settings of the generator to minimize generation costs with economic load dispatch. [5]

3. Controller in automatic generation control

Recent AGC research has focused mainly on secondary control, since the primary control relies on fixed speed regulation, R, which is determined by the design of the synchronous generator. [17, 18].

Secondary control has a critical role because it affects the dynamic response of the system during load changes. Important response characteristics like settling time and oscillation magnitude of frequency deviations would influence the transient stability of the system. [16]

Conventional AGC controllers of secondary AGC control loops are known as secondary controllers and typically rely on mathematical models to regulate system behavior. These controllers do not inherently adapt or learn unless enhanced through AI-based optimization techniques. [1] Commonly used controllers in AGC include integer-order and fractional-order controllers. One of them is the Proportional-Integral-Derivative (PID) controller, which has been reliable and popular since the 1970s. [19, 20] This is due to the simplicity, reliability, and widespread use of PID controllers in industry.

However, optimal selection of controller gains and parameters is essential for AGC controllers to perform effectively. Improper tuning of controller parameters, for example, in a PID controller, may cause the operation of the AGC to become sluggish or even lead to instability.

Traditionally, the tuning of controllers was performed using trial-and-error methods or numerical techniques. However, these methods produce fixed parameters that are only effective under specific operating conditions. [21] To address these limitations, AGC studies have increasingly adopted AI-based optimization methods for the secondary controller.

The flexibility and adaptability of AI make it suitable for optimizing different controllers, even in power systems with high uncertainties [22].

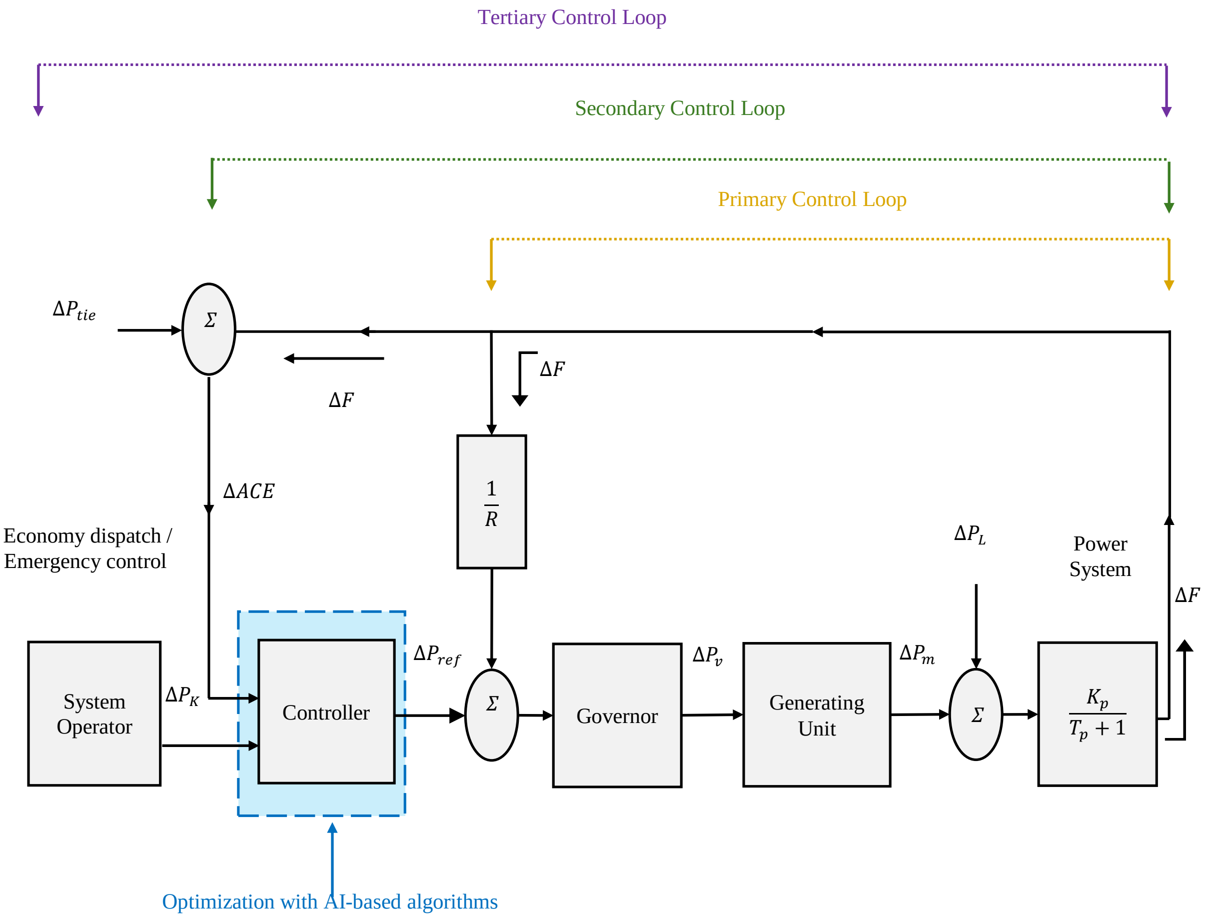


Fig. 2 Schematic diagram of the control loop in automatic generation control

4. Methodology

The evolution trends of AI-based optimization algorithms in AGC were analyzed based on a review of 150 studies published between 2000 and 2025. These include 50 studies from each of the following periods: 2000–2009, 2010–2019, and 2020–2025. The selected articles were published in first Quartile (Q1) journals and primarily come from reputable publishers such as IEEE, Elsevier, and Springer. Priority was also given to highly cited articles. Although priority was given to articles in Q1 journals with high citation count, which may lead to some selection bias, this selection criterion ensures that only high-quality and impactful studies were included in the review and analysis.

5. Artificial Intelligence Optimization

Various AI-based optimization algorithms have been developed for tuning AGC controllers because they provide greater adaptability compared to fixed parameters or numerical methods used in earlier times [23]. The evolution trends of these algorithms were analyzed based on a review of 150 studies published between 2000 and 2025, with 50 studies each in the 2000–2009, 2010–2019, and 2020–2025. These AI-based optimization algorithms are categorized into three main groups: fuzzy logic, metaheuristic algorithms, and machine learning. The distribution of these algorithms is illustrated in Figure 3. The list of articles used to generate the chart in Figure 3 is provided in Appendix 1. Metaheuristic algorithms are further divided into Evolutionary Algorithms (EA) and Swarm Intelligence (SI). The “Hybrid” category in the chart represents studies that combine two or more AI-based optimization techniques.

5.1. 2000s: Rule-Based Simplicity and Limited Computation

In the 2000s, Fuzzy Logic dominated (22 studies) due to its rule-based design, which aligned with the era’s centralized and predictable power systems. It provided intuitive control without requiring complex models or extensive data. At the same time, Evolutionary Algorithms (EA) (10 studies) were preferred over Swarm Intelligence (SI) Algorithms (5 studies), mainly because EA had been developed earlier. Machine learning was mostly limited to Artificial Neural Networks (ANNs), while hybrid approaches (8 studies) experimented with combining two or more algorithms, such as neuro-fuzzy systems. A significant number of studies (10 studies) have no optimization, which relied on numerical methods for optimization.

5.2. 2010s: Rise of Metaheuristics and Renewable Energies

The 2010s saw a shift toward metaheuristic algorithms, particularly Evolutionary Algorithms (21 studies) and Swarm Intelligence (20 studies). These methods gained attention due to the increasing integration of renewable energies and the rise of fractional order controllers, which required fine-tuning. Metaheuristics excelled in optimizing these multi-objective problems with a large search space. Meanwhile, Fuzzy Logic declined (8 studies) as its static rule sets struggled with the growing complexity of modern grids.

However, it remained relevant in Hybrid methods (13 studies), often combined with metaheuristics and ANNs for simplifying power systems with non-linearities. Machine Learning (7 studies) declined due to the lack of high-quality datasets for training ANNs, but Reinforcement Learning (RL), such as Q-learning, began gaining attention for model-free control.

5.3. 2020s: Swarm Intelligence and Machine Learning Grow

Power systems in the 2020s became even more complex, with nearly all grids integrating RES or Energy Storage Systems (ESS). Swarm Intelligence (26 studies) became the dominant optimization technique, surpassing Evolutionary Algorithms (9 studies) because of its excellent balance between exploration and exploitation. Fuzzy Logic (13 studies) saw a resurgence, mainly as part of hybrid approaches (17 studies), where it simplified power system modeling before being fine-tuned with metaheuristic algorithms. Machine learning (15 studies), such as RL, is increasingly studied because it is capable of learning in a model-free environment. This is important because modern power systems are becoming increasingly complex and difficult to model accurately for simulations. Thus, machine learning can adapt well to real-world scenarios in AGC.

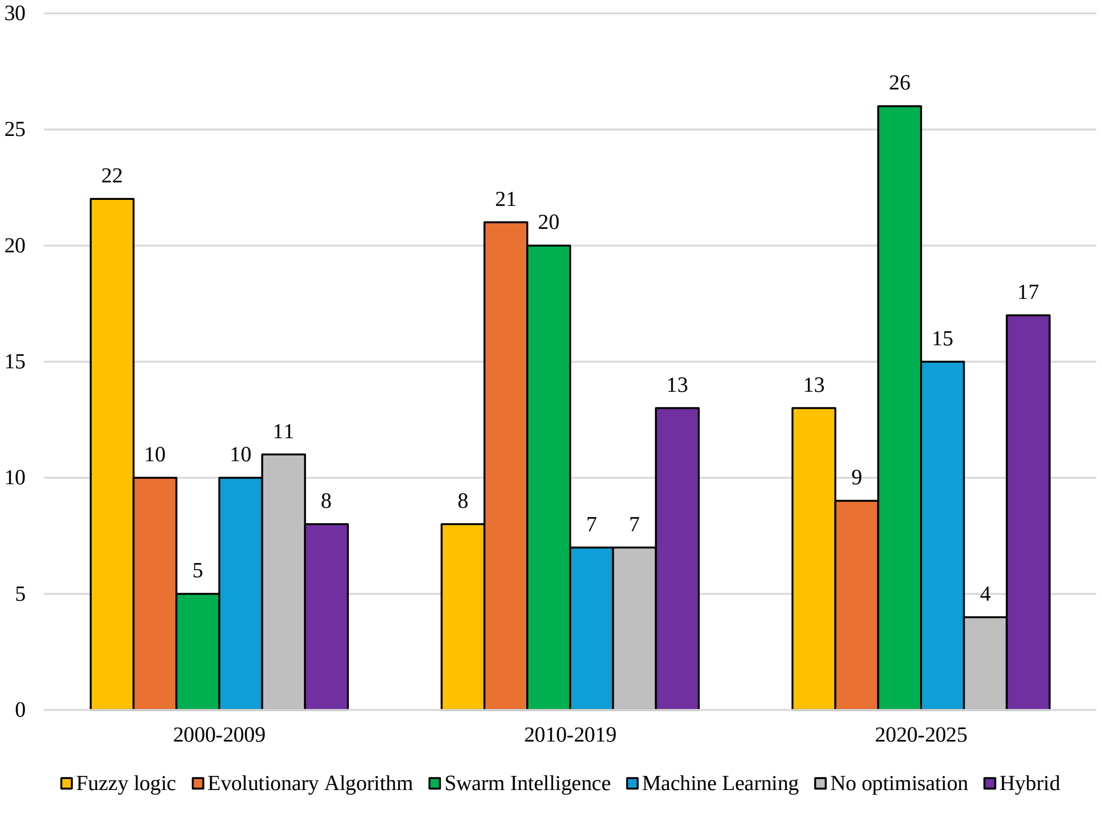


Fig. 3 Distribution of AI-based optimization algorithms in automatic generation control studies from the 2000s to 2020s

6. Fuzzy Logic (FL)

In the 1990s, researchers discovered that power system control efforts could be minimized by applying symbolic, rule-based methods. This realization encouraged the use of fuzzy logic in AGC, allowing the system to make decisions through qualitative and symbolic reasoning. A Fuzzy Logic Controller (FLC) is a rule-driven control approach that replicates human reasoning by utilizing if-then rules to address nonlinear, complex, and uncertain system behaviors. Unlike conventional controllers, which rely on precise mathematical models, FLCs use a set of rules and linguistic terms to define control strategies [24]. There are two main types of fuzzy logic used in AGC studies: Type-1 Fuzzy Logic (T1FLC) and Type-2 Fuzzy Logic (T2FLC). A fuzzy-tuned PID or FOPID controller is commonly referred to as FPID or FFOPID, respectively. Figure 4 shows a typical schematic of a fuzzy-tuned PID in AGC. FL systems in AGC typically take multiple inputs, such as frequency deviation and its rate of change. These inputs are transformed into fuzzy values or linguistic variables. Fuzzy logic system then infers the control output based on these inputs, and a defuzzification process determines the controller parameters, such as the gains of P, I, or D [25].

6.1. Type-1 Fuzzy Logic (T1FLC)

Type-1 Fuzzy Logic Control (T1FLC) has been applied in AGC research since the 1990s [26, 27]. In the 2000s, researchers found that tuning a PID controller using a mathematical model was not easy because nonlinear behaviors exist in the AGC, such as Governor Dead Band (GDB) and Governor Rate Constraint (GRC).

Therefore, fuzzy logic was applied because it can handle nonlinear systems better by mimicking human reasoning without relying on mathematical models. Standalone fuzzy logic controllers, which map load deviations directly to control actions, have gained popularity in AGC [23], [28-33]. Fuzzy logic was also applied to tune the parameters of FUZZY-PI (FPI) [34-38] and FUZZY-PID (FPID) [39-46] controllers for AGC interconnected power systems. Additionally, fuzzy logic is integrated with Artificial Neural Networks (ANN) to become neuro-fuzzy systems, which use data and ANN to define fuzzy rules and membership functions for AGC [47, 48].

In the 2010s, fuzzy logic was increasingly integrated into hybrid algorithms with other metaheuristic techniques. This is because power systems became more complex with diverse power sources, and tuning using only fuzzy logic became difficult due to the large number of fuzzy rules required. Therefore, fuzzy logic is used to simplify nonlinearities while metaheuristic algorithms search for optimal controller parameters. For example, FPID controllers were optimized using Differential Evolution (DE) [49], Bat Algorithm (BA) [50], Imperialist Competitive Algorithm (ICA) [51], and Teaching Learning Based Optimization algorithm (TLBO). [52] Furthermore, fuzzy logic was employed to tune Fractional Order PI (FOPI) controllers in interconnected systems. [53]. Additionally, neuro-fuzzy systems continued to be applied in AGC studies incorporating GRC [54, 55].

In the 2020s, fuzzy logic remained widely used in combination with metaheuristic algorithms, particularly in more complex systems such as hybrid power systems incorporating RES and ESS. This is because fuzzy logic was proven to be effective in simplifying the modeling of power systems. Several studies [56-61] employed FPID controllers in power systems with RES and Energy Storage Systems (ESS). Hybrid algorithms where metaheuristic algorithms were combined with fuzzy logic included Genetic Algorithm (GA), Sine Cosine Algorithm (SCA) [62], and Moth Swarm Algorithm (MSA) [63].

Additionally, the application of fuzzy logic in cascaded controllers such as fuzzy-PID-FOPID was explored, with tuning achieved using the Artificial Hummingbird Algorithm (AHA) [64]. The integration of Deep Reinforcement Learning (DRL) with neuro-fuzzy controllers has also emerged as a promising approach for AGC in systems involving ESS and Electric Vehicles (EVs) [65].

Overall, fuzzy logic has demonstrated its usefulness, especially in simplifying power systems with nonlinearities to make tuning of controller parameters easier. However, uncertainties in systems with RES can affect the performance of T1FLC. This is because their membership functions need to be precisely defined and may not capture uncertainties from incomplete information in real-world systems. As a result, Type-2 Fuzzy Logic Controllers (T2FLC) were introduced for AGC to address these limitations.

6.2. Type-2 Fuzzy Logic (T2FLC)

The limitations of T1FLC in capturing the uncertainties of modern power systems have driven research into T2FLC for AGC. T2FLC enhances system performance by employing three-dimensional membership functions [66]. Unlike T1FLC, which uses fixed membership values, T2FLC incorporates uncertainty directly into the membership functions.

These are defined by Upper-Membership- Function (UMF), a Lower-Membership-Function (LMF), and a Footprint of Uncertainty (FOU), which is the area between the UMF and LMF [66]. Figure 5 shows a comparison of T1FLC and T2FLC membership functions. The gray area in Figure 5(b) represents the FOU, which provides flexibility in handling uncertain or imprecise data. While T1FLC maps an input to a single value (e.g., 0.6), T2FLC maps it to a range of values (e.g., [0.5, 0.7]), thereby better reflecting uncertainty in real-world conditions.

By doing so, T2FLC is better suited for modeling the dynamic and uncertain behavior of complex power systems, especially those with RES. The application of T2FLC in AGC began in the 2010s when there was an increasing integration of RES in the power system. For instance, a T2 fuzzy PID controller tuned with Symbiotic Organism Search (SOS) showed improved results with lower settling time and lower oscillation compared to T1FLC in an interconnected power network [25]. More recently, T2FLC has been extended to fractional order controllers in the 2020s, such as the Fuzzy Fractional Order PD-PI controller (FFOPD-PI) tuned with the Cheetah Optimizer (CO) [66, 67]. These studies focus on Microgrid (MG) applications during islanded operation, where load fluctuations and the intermittency of RES are the main challenges. The T2FLC shows superior performance compared to conventional T1FLC by achieving lower Integral Time Absolute Error (ITAE) in frequency deviation. T2FLC also exhibits higher robustness to system uncertainties, as confirmed by sensitivity analysis.

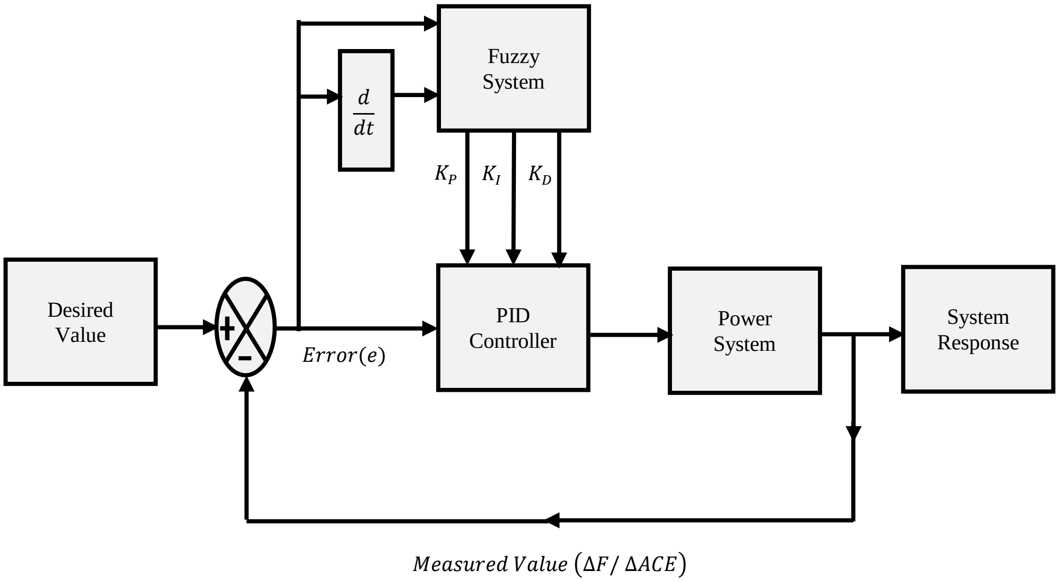
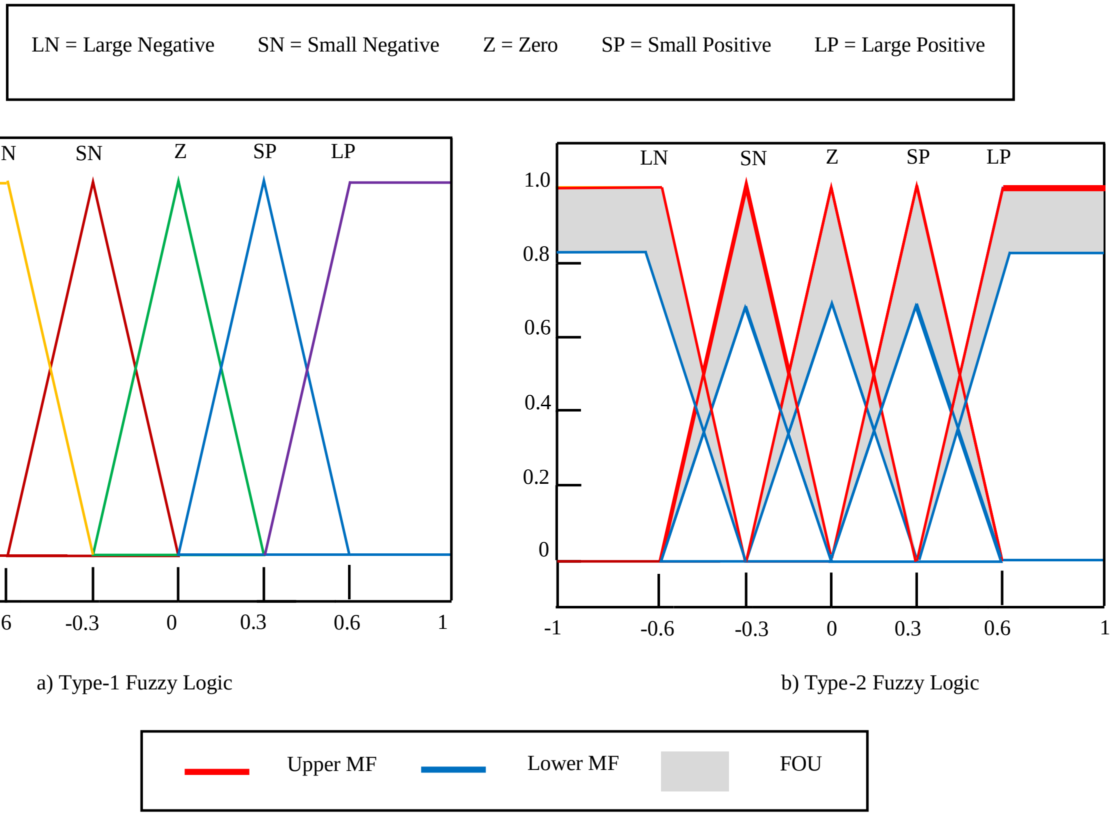


Fig. 4 Schematic diagram of a fuzzy logic-tuned PID controller in automatic generation control

From the review and analysis of T1FLC and T2FLC, fuzzy logic can be recognized as an effective method for handling nonlinearities in AGC [60]. A major advantage of T2FLC is its capability to model and integrate uncertainties associated with environmental inputs. This allows T2FLC to model signal noise and variability caused by the integration of RES, which is a significant improvement over T1FLC [25]. However, designing the UMF, LMF, and FOU of a T2FLC is significantly more complex than defining a single crisp membership function in a T1FLC. Moreover, there is no standardized method for selecting the shape or width of the FOU [66]. Therefore, optimizing a controller in AGC using T2FLC would require more effort. A major challenge in both T1FLC and T2FLC lies in their difficulties in designing suitable membership functions and rule bases for different power systems. This problem becomes more apparent as power systems grow increasingly complex with the integration of RES. The required number of fuzzy rules grows exponentially with the increase in inputs, especially as the number of generating units rises. For example, if the input to a fuzzy system has five membership functions (as shown in Figure 5), a system with two inputs would require $5^2 = 25$ rules, while a four-input system requires $5^4 = 625$ rules. Thus, the high number of rules required greatly increases design complexity [60]. Although modern processors can handle the large computational load from fuzzy rules, designing a large fuzzy rule base still requires extensive domain expertise to define the membership functions properly. The lack of a standardized framework for selecting parameters in fuzzy logic, like input variables and membership functions, can result in poor performance in AGC, especially in large, interconnected power networks. Therefore, the major limitation of applying for an effective FLC in AGC is its heavy dependence on expert knowledge to be designed accurately and function properly as intended. Therefore, recent research has focused on integrating fuzzy controllers with other AI algorithms to overcome the challenges of Fuzzy Logic Design in AGC. Fuzzy logics are combined with an Artificial Neural Network (ANN) to create an Adaptive Neuro-Fuzzy Inference System (ANFIS). ANNs are widely applied to set the rules of fuzzy sets using real-world grid data. This greatly improves the adaptability of the FLC in complex systems [47].

Additionally, fuzzy logic is combined with various metaheuristic algorithms such as GA [32, 44], PSO [45, 46, 59], TLBO [52, 56], SAMBA [50], SCA [62], and MSA [63]. These algorithms help to find the optimal parameters for fuzzy rules, such as the width of the membership function, based on current system dynamics. This enables fuzzy controllers to adapt dynamically under various operating conditions. FL is also combined with Deep Reinforcement Learning (DRL) to simplify the state-action space and accelerate the learning process of the DRL agent [65]. Therefore, other AI algorithms can help in designing rules for fuzzy logic to make it adaptable to the current power system. All in all, fuzzy logic is useful in optimizing the AGC controller for better handling of uncertainties in the power system. Looking ahead, fuzzy logic is expected to continue integrating with other AI algorithms as a hybrid algorithm for optimizing AGC controllers. Although fuzzy logic faces challenges in rule designing, it remains a valuable tool for simplifying nonlinearities like GRC and GDB that exist in the generators. Furthermore, fuzzy logic can be combined with machine learning techniques in the future to learn and map daily load disturbance patterns using fuzzy sets. This can help adjust generation proactively and reduce power output fluctuations throughout the day.



a) Type-1 Fuzzy Logic

b) Type-2 Fuzzy Logic

Fig. 5 Comparison of the Membership Function of Type-1 and Type-2 Fuzzy Logic Control

Moreover, future researchers can explore more on T2FLC as computational power improves and advanced AI algorithms become more accessible. It is expected that designing the UMF, LMF, and FOU of T2FLC will become easier. T2FLC has strong potential to replace T1FLC in future AGC applications, offering better representation of uncertainties in modern power systems. Table 1 summarizes the T1FLC and T2FLC applied in the AGC from the 2000s to 2020s, along with a brief description including their key strengths and limitations of the discussed controllers.

Table 1. Summary of fuzzy logic applications in automatic generation control (2000s–2020s)

Algorithm	Year	Controller	System	Description	Literature
Type-1 FLC	2000s	- Standalone - PID - SMC - Neuro-fuzzy	- Thermal	-Membership functions were manually defined. -Effective even without mathematical models. -Fixed membership functions lack adaptability.	[28-31, 33, 39-43]
	2010s	- PID - FOPI-FOPD - Neuro-fuzzy	- Thermal - Thermal with ESS	-Combined fuzzy logic with metaheuristic. -Can model out non-linearities in power systems. -Lack of application in a hybrid energy system.	[49, 51 ,52-55]
	2020s	- SMC - PID - FOPID - PID-FOPID	- Thermal - Hybrid with RES and ESS	-Application in a power grid with RES and ESS. - Used for simplification of the power system	[56, 57, 58, 59, 62, 63-65, 68, 69]

				- Definition of rules struggled with uncertainties	
Type-2 FLC	2000s	- N/A	- N/A	- Not under research in this era	N/A
	2010s	- PIDN	- Thermal	- Includes uncertainty in membership functions - Provide a better approximation of systems. - Outperform T1FLC with lower settling time.	[25]
	2020s	- PD-PI - FO-T2FLC	- Hybrid with RES and ESS	- Consider varying weather conditions for RES. - Improved robustness and flexibility in control. - Improved adaptability to dynamic operating conditions.	[66, 67]

7. Metaheuristic Algorithms

By the late 20th century, increased computing power enabled researchers to explore population-based and stochastic search techniques for solving high-dimensional and nonlinear problems. This led to the rise of metaheuristic algorithms, which are frequently applied within engineering, scheduling, control systems, and power system optimization. Metaheuristic algorithms are high-level problem-solving techniques that can efficiently explore and exploit the search space to obtain sufficiently good solutions to optimization problems. Unlike conventional optimization methods, they do not require gradient information and can handle nonlinear, complex, and multi-objective problems. Furthermore, metaheuristic algorithms are stochastic, which enables them to explore unique search paths in each run. Although the final results may vary slightly, the results typically converge to a common near-optimal solution [70]. As mentioned before, power systems in the real world are highly nonlinear and subject to constraints such as GDB and GRC. Thus, conventional trial-and-error or numerical methods struggle to include these constraints in the mathematical model. As a result, metaheuristic algorithms have gained popularity for tuning secondary controllers into AGC, especially for integer- and fractional-order controllers. These algorithms can efficiently determine optimal controller parameters even in a high-dimensional and large search space. [71]. A common example of a PID controller tuned using a metaheuristic algorithm in an AGC study is illustrated in Figure 6.

Population-based metaheuristic algorithms are the most commonly used approaches in AGC studies. These algorithms refine a set of candidate solutions iteratively to search for an optimal solution. They explore the search space using strategies modeled after natural processes, such as natural evolution and swarm intelligence. These mechanisms help to balance exploration (diversifying search) and exploitation (refining solutions) when searching. Some of the earliest metaheuristic algorithms in AGC studies include Simulated Annealing (SA) [72] and Tabu Search (TS) [73]. The process of controller tuning using metaheuristic algorithms is generally similar across different methods and can be referenced in Figure 6. The iterative process of metaheuristics begins with population initialization, where random solutions (e.g., P, I, D gains of a PID controller) are generated. Next, the fitness of each solution is calculated with a fitness function based on performance metrics. Common performance metrics in AGC studies include the integral of absolute or squared error for frequency deviation or ACE in the power system. Some studies also evaluate the fitness value using metrics such as settling time or peak power deviation after disturbances [25].

The algorithm then iteratively generates new populations of candidate solutions using operators such as crossover (in evolutionary algorithms) or swarm movements (in swarm intelligence algorithms). This process is repeated to eliminate weak solutions and create stronger ones with higher fitness values based on the objective function. This iterative process continues until the termination condition is fulfilled or the optimal solution is achieved. The optimal solution usually represents the most suitable secondary controller parameters of the power system under study [74].

Evolutionary Algorithms (EAs) and Swarm Intelligence (SI) are two major categories of metaheuristic algorithms that are widely applied in AGC studies. These two algorithms differ mainly in their population update mechanisms. The EA relies on genetic variation, where the fittest solutions reproduce through crossover and mutation to create new offspring [72]. In contrast, the solutions in SI algorithms move and adapt to new positions in the search space based on simple rules of interaction and information sharing [41]. SI algorithms typically converge faster than EA but may fall more easily into local optima. Both of these algorithms require careful selection of parameters such as crossover probabilities for EA and inertia weight for SI. Despite some differences, all metaheuristic algorithms aim to find optimal solutions and are sometimes combined into hybrid algorithms to leverage their strengths. The following section discusses how EA and SI are applied in AGC studies.

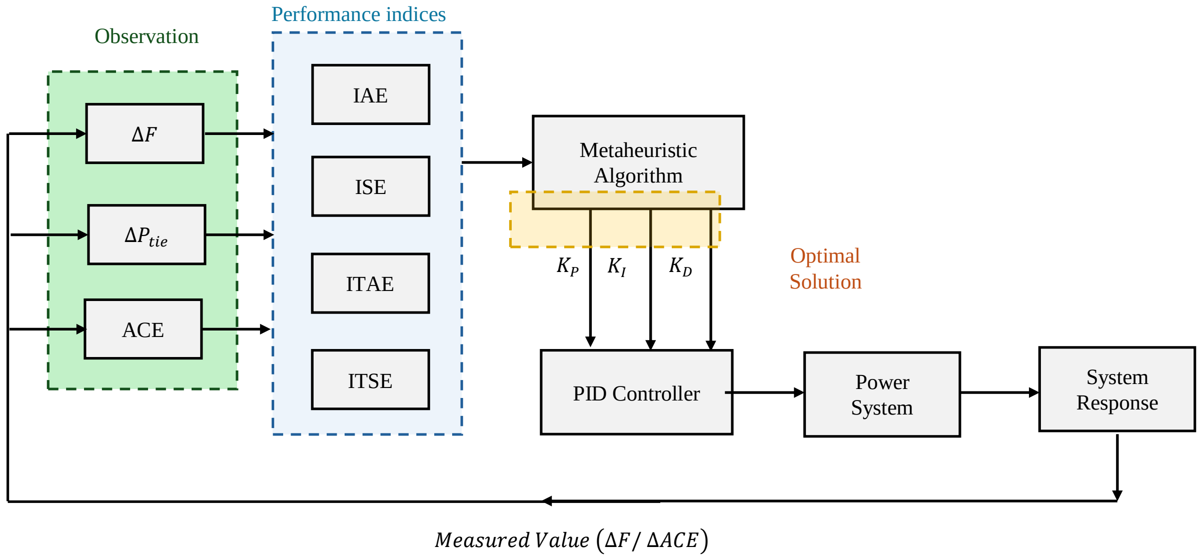


Fig. 6 Schematic diagram of metaheuristic-tuned PID controller in automatic generation control

7.1. Evolutionary Algorithms (EA)

EAs belong to a family of global optimization strategies that draw inspiration from the processes of natural evolution. In biological terms, a population of candidate solutions undergoes processes such as natural or artificial selection, recombination, and mutation. EA represented candidate solutions as chromosomes with each of them encoding a set of parameters (e.g., PID controller gains). In each generation, chromosomes with higher fitness values are selected as parents, and their information is exchanged through crossover to produce new offspring. The crossover between two parents is illustrated in Figure 7. Some of the offspring undergo mutation to introduce random changes to enhance diversity. Over successive generations, the population evolves toward better solutions with higher fitness value. This process continues until termination criteria are reached, and the final solution is the chromosome with the highest fitness value [75, 76].

7.1.1. Evolutionary Algorithms (EA) in the 2000s

Researchers found that one of the main challenges in the traditional tuning of AGC controllers (e.g., PID) is the difficulty in optimizing multiple competing criteria simultaneously.

For example, AGC requires balancing objectives like minimizing frequency deviation and settling time while keeping the control action within a tolerant level to prevent aggressive actions that cause oscillations. Thus, EAs are selected for AGC studies because they are suitable for multi-objective problems. EAs can explore solutions with trade-offs among conflicting objectives by using a high population of candidate solutions. Genetic Algorithm (GA) was the most researched EA to optimize controllers for AGC studies in the 2000s. The primary advantage of GA is its ability to obtain optimal controller parameters quickly and effectively in AGC studies. It has been used to optimize PI [74, 75, 76] and PID [72, 77, 78] controllers' gain in AGC. GA also helped to reduce the design effort in tuning fuzzy membership functions [31, 32, 44].

However, GA can struggle with problems that involve a large number of variables, as GA generally performs better with a smaller state space [14]. Additionally, GA is primarily designed for combinatorial problems with a discrete solution search space, which can reduce its effectiveness for continuous optimization tasks in AGC applications [74].

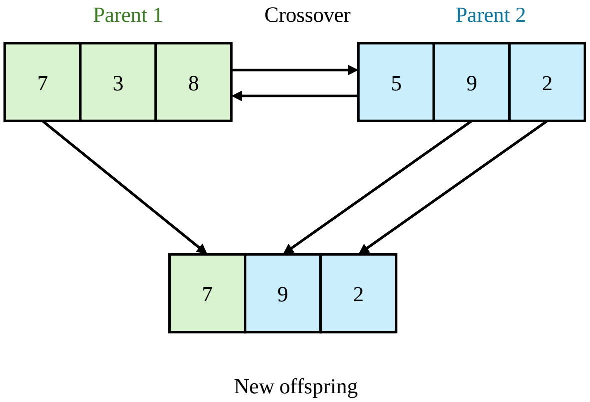


Fig. 7 Crossover in evolutionary algorithms

7.1.2. Evolutionary Algorithms (EA) in the 2010s

Researchers in the 2010s focused on improving EA by addressing the limitations of GA. As mentioned before, one of the key limitations is that GAs often lack effective mechanisms for continuous search spaces. This contrasts with the fact that the controller parameters in AGC are mostly continuous. Moreover, efforts were made to reduce the number of algorithmic operators in EAs to minimize the burden of hyperparameter tuning.

One of the new EAs developed is Differential Evolution (DE), which differs from GA in how it generates new solutions. DE creates a new population of candidate solutions by combining existing solutions with mutant vectors. This method enables better exploration in continuous spaces. DE has proven effective in optimizing PI [79] and PID [80-82] controllers for AGC with improved performance compared to the Bacteria Foraging Optimization Algorithm (BFOA).

Moreover, DE was used in [49] to optimize fuzzy PID within a complex power grid, which includes GRC, Thyristor Controlled Series Compensator (TCSC), and capacitors. Although DE shows promising results in AGC studies, its performance depends on selecting appropriate parameters such as crossover probability and differential weight [14]. Thus, the hyperparameter tuning of DE requires additional effort.

In addition to GA and DE, another EA related to genetic evolution is the Backtracking Search Optimization Algorithm (BSOA). BSOA uses selection, mutation, and crossover, but differs from GA by employing a memory-based mutation step inspired by DE. This step utilizes historical information to guide offspring generation and help solutions converge faster. BSOA was employed in [83, 84] to optimize the PID controller parameters and achieved improved robustness compared to the Firefly Algorithm (FA).

As seen in GA, DE, and BSOA, these algorithms require tuning of operator hyperparameters, which can be labor-intensive. This led to the development of algorithms that do not rely on crossover or mutation to generate new solutions. One such algorithm is the Harmony Search Algorithm (HSA), which was used in [85, 86] to optimize a PID controller in power systems with GRC and GDB constraints. HSA stores past solutions in a harmony memory and reuses good solutions instead of relying on random mutations. HSA is easier to tune compared to other EAs because it has crossover, mutation, and selection operators. This also reduces the computation time of HSA.

Another widely used Evolutionary Algorithm (EA) in AGC studies is the Teaching Learning-Based Optimization (TLBO) algorithm. TLBO employs a population-based approach to iteratively converge towards the optimal solution. TLBO was utilized in AGC to optimize PID [87], Proportional-Integral-Double Derivative (PIDD) [88], Sliding Mode Control (SMC) [89], and a Fuzzy PID [52] controller in a multi-source power system. TLBO consistently outperformed GA, DE, BFOA, and PSO in these studies, with faster convergence and reduced overshoot.

The Jaya Algorithm is another EA that requires no parameter tuning besides the initial population size. The Jaya algorithm is known for its simple structure and rapid convergence rate. It has been used to tune an integral controller [90] in an integrated wind power system and a PIDN controller [71] in a two-area interconnected system. These studies found that the Jaya Algorithm outperformed PSO with fuzzy logic, FA, Cuckoo Search (CS), Bat Algorithm (BA), Salp Swarm Algorithm (SSA), and Particle Swarm Optimization (PSO).

Apart from parameter-free designs, new EAs in the 2010s also explored novel evolution strategies for improved exploration. One such algorithm is the Differential Search Algorithm (DSA), which explores the solution space through a stochastic walking pattern similar to Brownian motion. DSA was applied in [25, 91] to optimize a PID in a multi-area network incorporating GDB. Unlike GA and DE, DSA uses a migration operator that simulates species traveling to new environments. It outperformed GA, DE, and HSA for achieving faster settling time and lower overshoot. Similar to DSA, the Biogeography-Based Optimization (BBO) algorithm generates new solutions through migration rather than crossover. Migration allows high-quality solutions to share their features with poorer solutions without disrupting the inherent structure of the solutions. BBO was applied in article [92] for optimizing gains of the PI and PID controllers of a hybrid thermal power system with RES. Findings show that PID controllers optimized using BBO achieve shorter settling times, smaller overshoots, and reduced oscillation magnitudes. Another EA with a different solution-generation mechanism is the Imperialist Competitive Algorithm (ICA).

ICA refines solutions by converging toward stronger imperialists and assimilating weaker ones. This guided assimilation helps ICA avoid local optima more effectively than some other EAs. ICA was applied in [93] to optimize a PID controller in an interconnected power system, outperforming GA and ANN compared in response speed when restoring frequency deviations. ICA was also applied in [51] to tune a PI controller with fuzzy logic and in [53] to tune a fuzzy FOPI-FOPD controller, showing better performance compared to PSO, BFOA, GA, and FA. The 2010s marked a transition from conventional GA to more specialized EAs with enhanced exploration capabilities in continuous spaces and reduced dependence on parameter tuning.

These new EAs also employ more advanced exploration strategies, such as the migration operator in DSA and BBO. These exploration strategies help to explore the increasingly large search space caused by the complexities of modern power systems with RES. Most studies show improvement in settling time of frequency deviation or ACE after optimization using these EAs. However, achieving a balance between exploration and exploitation remains a challenge for these new EAs, which may produce suboptimal solutions due to inefficient exploration of the solution space when searching for solutions.

7.1.3. Evolutionary Algorithms (EA) in the 2020s

During the 2020s, the rise of hybrid power systems with RES and ESS led to an increase in generation units and a larger solution search space. As a result, EAs have focused on improving exploration and exploitation to find optimal solutions efficiently. An improved version of GA, known as Non-dominated Sorting Genetic Algorithm II (NSGA-II), was developed for optimizing AGC with multiple conflicting objectives to minimize cost and power losses.

NSGA-II improves standard GA by ranking solutions with dominance and preserving solution diversity with crowding distance. NSGA-II was used in the article [94, 95] to tune a PID and fractional-order controller and outperform classical GA. DE and TLBO remain relevant in the 2020s. For instance, articles [96, 97] used DE to optimize a PD-PI controller with fuzzy logic for damping and inertia coefficient tuning in virtual synchronous generators within low-inertia microgrids with high-RES penetration. Additionally, article [56, 98] employed TLBO to tune a PID with fuzzy logic in a hybrid power network equipped with flexible AC transmission system components. Results show that the TLBO-based controller achieved faster frequency deviation settling times compared to those optimized using PSO.

More recently, new EAs have emerged for AGC optimization. The Archimedes Optimization Algorithm (AOA), inspired by the buoyancy principle, employs a mathematically defined movement strategy, making it well-suited for continuous search spaces in complex AGC problems.

AOA was applied in [99] to optimize a 2DOF-TIDN controller and [100] to optimize a FOID-FOPIDN controller for microgrids. Results show that the controller optimized using AOA had shorter settling times in terms of power deviation compared to GA, Jaya, and PSO. The Growth Optimization (GO) algorithm is another EA inspired by the learning and reflection mechanisms of human development.

It has two phases, which are a learning phase and a reflection phase. Solutions improve based on past experience in the learning phase and are refined using feedback in the reflection phase. This two-phase mechanism enhances the balancing of exploration and exploitation. GO applied in [101] to tune the cascaded FOPID-TID controller in a power system with Virtual Inertia Control (VIC) from Electric Vehicle (EV) Lithium-Ion Batteries.

Despite continued research in AGC, the usage of EAs has declined in the 2020s compared to SI algorithms. This is because SI algorithms typically require fewer algorithm-specific parameters and feature simpler population update mechanisms. However, EAs are becoming similar to SI algorithms since both use population-based solutions, which allow them to be combined to create hybrid algorithms. EAs still have another limitation, which is their reliance on an accurate simulation model. This is because the optimal parameters are obtained based on the simulation result. However, the optimal parameters may not be reliable if the simulation model differs from the real system.

Therefore, a robustness test is needed to evaluate the sensitivity of the EAs. Furthermore, future AGC studies could benefit from hybridizing EAs with machine learning algorithms. This hybrid approach can help solve the problem of inaccurate modeling in simulations. This is because controllers tuned using EAs can learn online using machine learning algorithms and adapt to real-world power systems when deployed. Table 2 summarizes the different types of GAs applied in AGC from the 2000s to the 2020s, along with key strengths, limitations, and a brief description of the discussed controllers.

Table 2. Summary of evolutionary algorithm applications in automatic generation control (2000s–2020s)

Algorithm	Controller	Power System	Description	Literature
2000s				
Genetic Algorithm (GA)	- PI - PID - FLC	- Thermal	- Widely used in AGC to find solutions quickly and effectively - Struggles with large and continuous state spaces	[31, 32, 44, 74, 75, 76-78]
2010s				
Differential Evolution (DE)	- PID - FOPID - Fuzzy PID	- Thermal - Hybrid with ESS	- Better exploration in the continuous search space - Performance depends on control parameters.	[49, 79, 80]
Backtracking Search Optimization (BSOA)	- PID	- Thermal	- Employs a memory-based mutation step. - Complex mutation strategy increases tuning effort.	[83, 84]
Harmony Search Algorithm (HSA)	- PID	- Thermal	- Reuses good past solutions via harmony memory.	[85, 86]

			- Harmony memory leads to slower convergence in complex problems.	
Teaching-Learning-Based (TLBO)	- PID - SMC - Fuzzy PID	- Thermal	- Parameter-free, which leads to less tuning and faster convergence. - Poor exploration in highly constrained problems.	[52, 87-89]
Differential Search Algorithm (DSA)	- PID	- Thermal	- Migration, inspired by Brownian motion. - Random-walk patterns may slow exploitation.	[25, 91]
Biogeography-Based Optimization (BBO)	- I - PI - PID	- Hybrid with RES	- Migration-based with simple parameter tuning - Lacks crossover in reproduction, reducing diversity.	[962
Jaya Algorithm	- I - PID	- Hybrid with RES	- Parameter-free and faster convergence - Risk of premature convergence in a multimodal task.	[71, 90]
Imperialist Competitive (ICA)	- PID - Fuzzy PI - Fuzzy FOPI	- Thermal	- Avoids local optima via guided assimilation. - High computational cost for large empires requires testing on RES	[51, 53, 93]
2020s				
Non-dominated Sorting GA-II (NSGA-II)	- FOPID	- Hybrid with RES	- Designed to handle multiple conflicting objectives - Rank solutions with non-dominated sorting.	[94, 95]
DE and TLBO (Continued Use)	-Fuzzy PID	- Hybrid with RES and ESS	- Applied with a virtual synchronous generator - Applied in a power system with FACTS and SMES	[56, 96, 97]
Archimedes Optimization (AOA)	-2DOF-TIDN	- Hybrid with RES	- Rigorous movement for continuous spaces. - Requires careful parameter tuning.	[99, 100]
Growth Optimization (GO)	-FOPID-TID	- Hybrid with RES and EVs	- A two-phase approach enhances the exploration-exploitation balance. - Requires higher computational power	[101]

7.2. Swarm Intelligence (SI)

Swarm Intelligence (SI) is a metaheuristic algorithm inspired by the cooperative behavior of decentralized natural systems, like bird flocks and ant colonies.

These algorithms rely on interactions among agents to navigate the search space and move toward an optimal solution. The process begins with a swarm of randomly distributed agents.

Different from the crossover operator in the EA, each agent in SI updates its position based on local and global information, typically guided by personal best and global best-known solutions, as shown in Figure 8. Exploration mechanisms, such as random movements, help maintain diversity and prevent early convergence. The algorithm repeats until it reaches a terminating criterion like reaching the maximum number of iterations [41, 102].

7.2.1. Swarm Intelligence (SI) in the 2000s

Similar to EA, SI algorithms began gaining attention in the 2000s for optimizing controller parameters in AGC studies. They are well-suited for handling optimization problems with multiple objectives. Particle Swarm Optimization (PSO) is a fundamental SI algorithm that served as a foundational reference for the development of other SI algorithms. PSO mimics the cooperative movement of birds and fish, where each individual updates its position using its own past performance and shared information of the group to guide the search toward an optimal solution [41]. PSO is one of the most widely used SI algorithms because it is easy to implement and requires minimal parameters. It updates the candidate solution based on their velocity and position within the search space. This position is affected by factors such as the inertia coefficient, cognitive coefficient, and social coefficient of the algorithm. PSO offers a simpler framework with faster convergence in continuous search spaces when compared to

GA [14]. PSO was applied to optimize the gains of integer-order controllers in AGC studies [103]. In the late 2000s, PSO was also hybridized with Fuzzy Logic Systems To Tune Fuzzy PID (FPID) controllers [41, 45, 46]. However, PSO is prone to becoming trapped in local optima, especially in high-dimensional problems [14]. To overcome this limitation, it is essential to tune the inertia coefficient and acceleration coefficient of the algorithm to maintain robust performance across different AGC problems.

Another SI algorithm used in the 2000s is the Bacterial Foraging Optimization Algorithm (BFOA), which is inspired by the natural behavior of *Escherichia coli* (E. coli) bacteria in search of nutrients. Since PSO tends to get trapped in local optima, BFOA introduced an elimination and dispersal process, where some bacteria are randomly removed and relocated to new positions in the search space. This mechanism enhances global exploration and prevents stagnation. BFOA was used in AGC studies for optimizing the integral gain of controllers [104], with results showing faster convergence compared to GA.

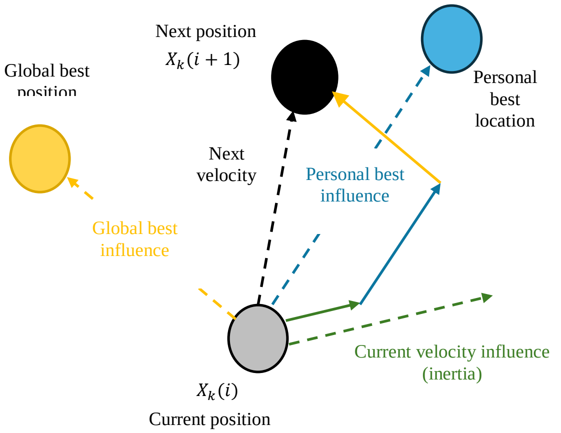


Fig. 8 Adaptive movement in swarm intelligence

7.2.2. Swarm Intelligence (SI) in the 2010s

During the 2010s, SI algorithms experienced rapid growth, with many new techniques inspired by collective behaviors in nature aimed at improving exploration capabilities and preventing premature convergence. The number of published articles on AGC using SI algorithms increased significantly, surpassing those focusing on EA in the field of metaheuristic optimization. PSO remained widely used and extended to applications in complex power systems with ESS and Flexible AC Transmission System (FACTS) devices. For example, PSO was applied in [105] to tune the integral controller of an AGC system integrated with a Battery Energy Storage System (BESS). Additionally, it was used to optimize an integral controller in AGC with a thyristor-controlled capacitor [106]. These studies show that PSO is still a reliable SI algorithm for AGC studies in the 2010s. The Bacterial Foraging Optimization Algorithm (BFOA) also remained relevant. BFOA was used to tune PID parameters for AGC in nonlinear systems in [107]. Furthermore, hybrid approaches combining BFOA and PSO were introduced in [108, 109] to improve the exploration efficiency of both algorithms. The hybrid BFOA-PSO algorithm outperformed conventional PSO, BFOA, and GA in tuning Fractional-Order PID (FOPID) controllers, as shown in these articles.

In addition to PSO and BFOA, other SI algorithms were developed to address PSO limitations, particularly its tendency toward premature convergence. One such algorithm is the Artificial Bee Colony (ABC), which is inspired by the foraging strategies of honeybees [14]. ABC exhibited superior exploration in large search spaces with its triple search mechanism. The employed and onlooker bees conduct local searches to refine solutions, while scout bees explore the search space to identify new potential solutions. Therefore, ABC is more effective in exploring large search spaces compared to PSO. ABC was used in [110, 111] to optimize the PID and TID controllers in an interconnected power system.

Another popular SI algorithm is the Ant Colony Optimization (ACO). ACO mimics this behavior using artificial ants that navigate a solution space and update a pheromone matrix to guide future ants toward optimal solutions. ACO is particularly suitable for optimizing controllers in dynamic environments due to pheromone evaporation, which allows adaptation to changing conditions, though at the cost of slower convergence. In [112], ACO was used for optimizing PID in a multiple-area power system, which requires adaptation to varying conditions. The PID optimized using ACO had reduced peak overshoot and settling time in comparison with the traditional PID. A similar algorithm to ACO is the Fruit Fly Optimization Algorithm (FFA), where agents mimic the food-searching behavior of fruit flies. FFA was used in [83] for tuning a PID controller, and results showed that the FFA-tuned controller exhibited lower overshoot compared with the Backtracking Search Optimization Algorithm (BSA).

Several SI algorithms inspired by predatory hunting behaviors also emerged with enhancements in balancing exploration and exploitation. These include the Grey Wolf Optimization (GWO), Bat Algorithm (BA), and Ant Lion Optimizer (ALO). These algorithms mimic the collective hunting strategies of predators, which allow them to trap prey and optimize solutions in a search space. Hunting-based algorithms have a structured leader-follower mechanism, ensuring a balance between exploration and exploitation, helping them to avoid local optima [14]. BA was used in [52, 113] to optimize a PI controller and in [122] for a cascaded PD–PID controller for AGC with GRC, while ALO was used in [115] for tuning the PID parameters of a hybrid thermal system with GRC. GWO was used in [116, 117] for tuning the PID controller in an interconnected system incorporating solar power. Besides improving the exploration-exploitation trade-off, newer SI algorithms were developed to handle higher-dimensional optimization tasks, such as tuning fractional-order controllers in AGC, which involve a larger number of parameters. Among these are the Firefly Algorithm (FA) and the Moth Swarm Algorithm (MSA). FA is inspired by the flashing patterns of fireflies. A key advantage of FA is that fireflies naturally form subgroups, enhancing multimodal optimization during exploration and exploitation [14]. This has led to its application in several studies, such as tuning PID controllers [118, 119], 2-DOF-FOPID controllers [120], and 2-DOF-PIDD controllers [121] for an interconnected power system with GRC. FA has outperformed PSO and ABC in these applications. On the other hand, MSA is inspired by the navigational behavior of moths, utilizing Lévy flights for exploration and phototaxis for exploitation. This makes it highly efficient in high-dimensional search spaces. MSA applied in [122] to tune a PID in a power system with RES like wind power, which involves a very large state-action search space.

The trend in the 2010s indicates a shift toward enhancing the exploration-exploitation balance of SI algorithms through adaptive mechanisms, such as the leader–follower structure in GWO and Lévy flights in MSA. Furthermore, new algorithms such as FA have been developed to enable multimodal optimization in high-dimensional AGC design problems. These advancements have significantly improved the reliability of the SI algorithm in AGC optimization.

7.2.3. Swarm intelligence (SI) in the 2020s

In the 2020s, SI algorithms continue to be among the most widely used methods in AGC research, often appearing more frequently than EA techniques. During this period, SI methods have been applied to controller optimization in hybrid energy systems and microgrids equipped with energy storage. The integration of diverse energy sources increases system complexity, leading to controller parameters with varying dimensions. As a result, SI algorithms are preferred for handling the nonlinear and increasingly high-dimensional optimization challenges in AGC. These emerging challenges also motivate the development of newer algorithms with improved exploration and exploitation balance.

Predator-Prey and Hunting-Based SI Algorithms are applied in AGC due to their aggressive exploitation mechanics. These include African Vulture Optimization Algorithm (AVOA) [123], Aquila Optimizer (AO) [129, 130], Marine Predators Algorithm (MPA) [136-138], Gazelle Optimization Algorithm (GOA) [72, 134], and Selfish Herd Optimization (SHO) [130]. For example, the scavenging mechanism in AVOA improves the convergence speed for obtaining optimal controller parameters, outperforming FA and GWO when applied to multi-area systems with RES [123]. Moreover, MPA uses Lévy-flight exploration to refine the parameters of cascaded controllers, such as cascaded PD-P-PID [137], cascaded 2DOF FOTIDN-FOTDN [126], and cascaded FO-3DOF controllers [128] in hybrid energy systems. Results show that MPA minimizes ITAE faster than PSO. Similarly, the gazelle-inspired evasion strategies in the GOA help the algorithm to explore the parameters faster for fuzzy sliding mode controllers compared to GWO [69, 129]. These SI algorithms are particularly well-suited for RES-dominated grids due to their effectiveness in refining solutions under dynamic conditions.

Another category of SI algorithms is Marine-Inspired Algorithms, such as the Tunicate Search Algorithm (TSA) [131], Coot Algorithm (CA) [132], and Quasi-Opposition Sea Horse Optimization (CQOSHO) [133]. These algorithms use group coordination for adaptive exploration. TSA optimizes TFOPID controllers in hybrid systems by utilizing its jet propulsion mechanics and collaborative swarming behavior to optimize parameters for different types of generator controllers [131]. The CA utilizes coot flocking to tune cascade FOPID-FOPD controllers in RES/EV-integrated grids [132]. On the other hand, CQOSHO combines seahorse movement with quasi-opposition learning to improve exploration efficiency, thus reducing computational costs in AGC applications [133]. These algorithms had high adaptability to different multi-dimensional problems, making them ideal for grids with EV variability and intermittent RES.

Furthermore, there are SI Algorithms inspired by the flocking behavior of birds. These algorithms include the Sparrow Search Optimization (SSO) [134], Salp Swarm Algorithm (SSA) [135-147], Bird Swarm Algorithm (BSA) [148], Mayfly Optimization Algorithm (MOA) [139], Lyrebird Optimization Algorithm (LOA) [145] and Artificial Hummingbird Algorithm (AHA) [67], which balance exploration-exploitation through hierarchical foraging and vigilance. For example, the SSO algorithm accelerates convergence in cascaded (1+PI)-PID controllers [139]. Next, BSA's multi-modal foraging optimizes 2DOF-TID controllers, reducing undershoots and settling times compared to PSO [138]. SSA has been proposed for tuning a cascade optimal FO controller [137], a cascade FOTID [135], and a cascaded 3DOF-FOPIDN-MPC [136] for multi-area power systems with ESS, while AHA's territorial flight optimizes fuzzy PID-FOPID controllers in RES-integrated grids [67]. These algorithms are well-suited for multi-area systems with cascaded control architectures, which utilize the hierarchical search in these algorithms.

Nature-Foraging and Plant-Based Algorithms, such as the Dandelion Optimizer (DO) [22], Artificial Rabbit Optimization (ARO) [141], and Dung Beetle Optimization (DBO) [142], prioritize exploration through dispersal mechanics. DO's seed-spreading avoids local optima in optimizing the cascaded FPDN-FPTID for a multi-area microgrid [22], while ARO's rabbit-inspired hopping optimizes the parameters of a cascade PI-FOPD [141] in a three-area power network, with lower oscillation compared to FA, PSO, and GWO. DBO is combined with the fusion osprey algorithm for optimizing the Cascaded Extended Sliding Mode Control (CE-SMC) in a power system with ESS [142].

In addition to the development of new algorithms, several conventional SI algorithms have been hybridized with other AI algorithms, like fuzzy logic and EA, to enhance their optimization capabilities. For example, PSO is being used for optimizing parameters of a fuzzy PID controller [59, 143, 144] and a fuzzy controller with Type-2 fuzzy logic in [145]. These studies with hybrid algorithms have shown significantly better performance compared to conventional FPID controllers. Furthermore, a combination of PSO with a Deep Artificial Neural Network control strategy was introduced in [146] to optimize AGC in a power grid with Vehicle-To-Grid (V2G). These hybrid algorithms have shown improvements in settling time and overall frequency regulation, validating their effectiveness in maintaining stable microgrid operations. Furthermore, hybrid algorithms that combine SI algorithms with Math-Enhanced Algorithms have also been developed, such as the Quasi-Opposition Improved Pathfinder Algorithm (QO-PFA) [147] and Aquila-Sine Cosine Fusion (AO-SCA) [124, 148]. The QO-FPA merged biological inspiration with mathematical rigor and used an opposition-based learning to accelerate convergence in a hybrid power system with a type-2 fuzzy tilt controller [147]. The QO-PFA has a lower ITAE than the PFA and PSO algorithms. AO-SCA combines Aquila's exploitation with sine-cosine exploration for fault-resilient PID tuning [124]. These hybrid algorithms improve convergence speed and reduce computational cost, thereby enhancing their reliability in real-time AGC applications. Future researchers can further investigate the application of hybrid algorithms combined with SI algorithms.

From the trend of SI algorithms in the 2020s, it can be observed that most controllers are cascaded, which introduces even larger search spaces than single controllers. Therefore, while many new algorithms have emerged, most of them aim to further improve the exploration-exploitation mechanism compared to algorithms from the 2010s and 2000s to address this challenge. For example, the MPA algorithm introduces a phased search, where early iterations favor Lévy flights (exploration), and later phases prioritize local exploitation using Brownian motion. These mechanisms with self-adaptive step size help to refine solutions dynamically. Newer SI algorithms also reduce reliance on manual hyperparameter tuning. For instance, DBO auto-adjusts search intensity using tangent functions for adaptive step sizes. Table 3 summarizes the SI applied in AGC from the 2000s to the 2020s. Although SI algorithms have shown promising results in AGC studies, they still face challenges such as a tendency to fall into local optima. Most SI algorithms in this review are standalone algorithms without hybridization with other algorithms. Therefore, hybrid approaches (e.g., AO-SCA) can help overcome these limitations by combining the exploration and exploitation strengths of different methods, which increases diversity in the search population. Thus, future AGC studies could explore multi-algorithm frameworks to enhance the performance of SI algorithms.

Generally, metaheuristic algorithms, including EA and SI, can obtain near-optimal solutions for controller parameters. However, they require longer computational time to achieve high-quality optimization, especially in large solution spaces. This is because evaluating the fitness value of a solution in AGC requires applying its parameters to the controller, running simulations, and measuring time-domain response metrics such as overshoot, undershoot, and settling time. The total simulation time is approximately equal to the population number per generation multiplied by the number of iterations, making it computationally intensive. This challenge is further amplified by the addition of RES in the power grid, which expands the solution space. This issue is especially critical for real-time control, where optimization algorithms must generate solutions within a short computational time [149].

Additionally, metaheuristic algorithms may produce suboptimal solutions when system parameters and operating conditions differ from those in simulations. This is because the optimal solutions obtained are designed for specific operating conditions. Thus, the effectiveness of metaheuristic algorithms relies on accurate system models [150]. Metaheuristic algorithms also struggle with online adaptation in real-world power systems due to this limitation. For instance, PID controllers optimized using metaheuristic algorithms are designed for specific conditions. These parameters cannot be easily adapted to system variations if real-world power system behavior deviates from the simulation models. This limitation has led to research on model-free machine learning algorithms, which do not require precise system models for AGC optimization.

Table 3. Summary of Swarm Intelligence (SI) applications in automatic generation control (2000s–2020s)

Category	Algorithm	Controller	System	Description	Literature
2000s					
Bio-Inspired	- PSO - BFOA	- PI - PID - FPID	- Thermal	- Faster convergence than GA - May be trapped in local optima	[41, 45, 46, 103, 104]
2010s					
Foraging-Based	- ABC - ACO	- PI - PID	- Thermal	- Role-based search balances exploration and exploitation.	[110, 151]

		- SMC	- Microgrid with RES	- Slower convergence.	
Attraction-Based	- FA - MSA - FFA	- PID - 2-DOF-FOPID	- Thermal	- High-dimensional optimization using Lévy flights. - Sensitive to parameter tuning.	[83, 118, 120, 121]
Predator-Prey-	- ALO - BA - GWO	- 2-DOF-PIDD - PID - PD–PID	- Thermal - Hybrid with RES	- Flexible to continuous problems. - Adaptive boundary shrinking enhances exploitation	[50, 114, 115, 116]
2020s					
Predator-Prey	- AVOA - AO - MPA - COA - GOA - SHO	- PID - PD-P-PID - FOTIDN-FOTDN - FOPD-FOPI - Fuzzy SMC	- Thermal - Hybrid with RES - Hybrid with RES, ESS, EVs	- Balances exploration and exploitation with phased search. - Fast convergence in dynamic environments through exploration. - Strong local refinement through boundary shrinking.	[123-128]
Marine-Inspired	- TSA - CA - CQOSHO	- TFOPID - FOPID-TID - FOPID-FOPD	- Thermal - Hybrid with RES, ESS, EVs	- Highly adaptable to dynamic load and non-linearity. - Low computational cost in hybrid systems.	[136-138]
Bird-Inspired	- SSO - SSA - BSA - MOA - LOA - AHA	- FOTIDN-FOTDN - (1+PI)-PID - FOPID-PID - Fuzzy PID-FOPID	- Thermal - Hybrid with RES - Hybrid with RES, ESS	- Hierarchical foraging balances exploration and exploitation. - Effective in multi-modal, high-dimensional spaces.	[139-145]
Nature-Foraging	- DO - ARO - DBO	- CE-SMC - FPDN-FPTID - PI-FOPD	- Hybrid with RES - Microgrid with EVs	- Auto-adjust search intensity using tangent functions. - Requires less parameter tuning.	[23, 146, 147]
Math-Enhanced	- QO-PFA - AO-SCA	- PID - Fuzzy TID	- Hybrid with RES, ESS	- Faster convergence with the hybrid algorithm. - Reduce computational costs and randomness	[124, 147]

8. Machine learning

Researchers worldwide have increasingly focused on machine learning algorithms for AGC since the 1990s, due to their data-driven characteristics and suitability for real-time power system control. Machine learning algorithms like Artificial Neural Networks (ANNs) and Reinforcement Learning (RL) are model-free learning algorithms. Therefore, they are independent from physical models, making them well-suited for AGC studies as power systems are getting more complex to be modeled accurately [12].

8.1. Artificial neural network (ANN)

Although integer-order controllers have provided robust AGC performance since the 1990s, researchers have recognized their limitations in adapting to uncertainties in power systems, such as varying inertia in the generators. Thus, researchers have looked for adaptive controllers that are capable of learning from experience to generate optimal control action in AGC. As a result, Artificial Neural Networks (ANNs) were studied and applied in AGC studies in the late 1990s [111, 112].

ANNs are inspired by the human nervous system and can adapt by adjusting their internal parameters through learning, unlike conventional controllers that rely on predefined mathematical models.

This makes them well-suited for nonlinear, time-dependent systems like AGC [154]. In AGC studies, ANNs are typically trained using supervised learning, where the network learns from historical frequency or power data (inputs) to generate the corresponding control actions (outputs) for the power generator. Figure 9 shows a typical ANN structure in AGC, which includes the input, hidden, and output layers.

Inputs for ANN in AGC typically include frequency and tie-line deviations or ACE in the system, while the output is the control signal or power reference (ΔP_{ref}) for the generator. ANNs are considered adaptive nonlinear controllers because they use learning rules to adjust the weights of synaptic connections to continuously learn from past states and improve AGC performance over time.

During the 2000s, researchers explored ANN-based AGC in multiple areas of power systems. Studies in [154-156] applied ANNs to AGC in an interconnected power network with a synchronous generator using steam and hydro turbines. ANN-based controllers were also integrated with an H_2/H_∞ controller in [167, 168] for AGC in deregulated power systems. Additionally, ANNs were utilized in [159] for AGC in power systems incorporating ESS. ANN-based AGC controllers continued to be studied in the 2010s, with applications in a hydrothermal power system with GRC [160]. These studies highlighted the effectiveness of ANNs in handling nonlinearities and system constraints. Deep Learning (DL) is a subcategory of ANN that applies neural networks with many hidden layers to learn hierarchical features based on large datasets. DL has been explored for AGC applications since the 2020s.

The additional layers improve feature extraction and learning, making DL well-suited for capturing complex features in power systems and learning optimal actions. The authors in [161] used DL to model the difference of output power between the AGC command and the actual output, thereby reducing errors in the power deviations. Similarly, studies in [17] and [162] applied deep learning for smart AGC, focusing on coordinating an ESS in a hybrid power system.

Both ANN and DL can adapt to changing grid conditions without requiring precise mathematical models. However, as supervised learning methods, they require substantial training data to generalize well, which is not always readily available. Furthermore, ANNs are usually trained offline on historical or simulated data. Thus, they function as fixed input-output mappings and do not adapt to real-time changes unless retrained. This limitation presents challenges in power grids with high-RES, where operating conditions may change unpredictably. Moreover, an ANN trained on past data may fail to generalize to novel scenarios in the power system.

Therefore, researchers have integrated ANNs with other AI techniques in AGC studies to overcome these limitations. One of them is the Adaptive Neuro-Fuzzy Inference System (ANFIS), which combines ANN and fuzzy logic to enhance interpretability and adaptability. ANFIS has been studied since the 2000s [47, 48] and continued to be explored in the 2010s [54, 55]. The ANFIS controller uses the rule-based decision-making of fuzzy logic while retaining the learning capabilities of ANNs.

Deep Reinforcement Learning (DRL), which integrates deep learning with Reinforcement Learning (RL), has gained popularity in AGC research during the 2020s [146]. DRL solves the limitation of conventional deep learning, which is typically trained offline and lacks real-time adaptability. By integrating deep neural networks into reinforcement learning frameworks, DRL retains the strong feature-learning capabilities of DL while enabling online adaptation through continuous learning from rewards. Various DRL algorithms, such as Deep Q-Network (DQN) [163] and Twin Delayed Deep Deterministic Policy Gradient (TD3) [164], are currently being researched for AGC.

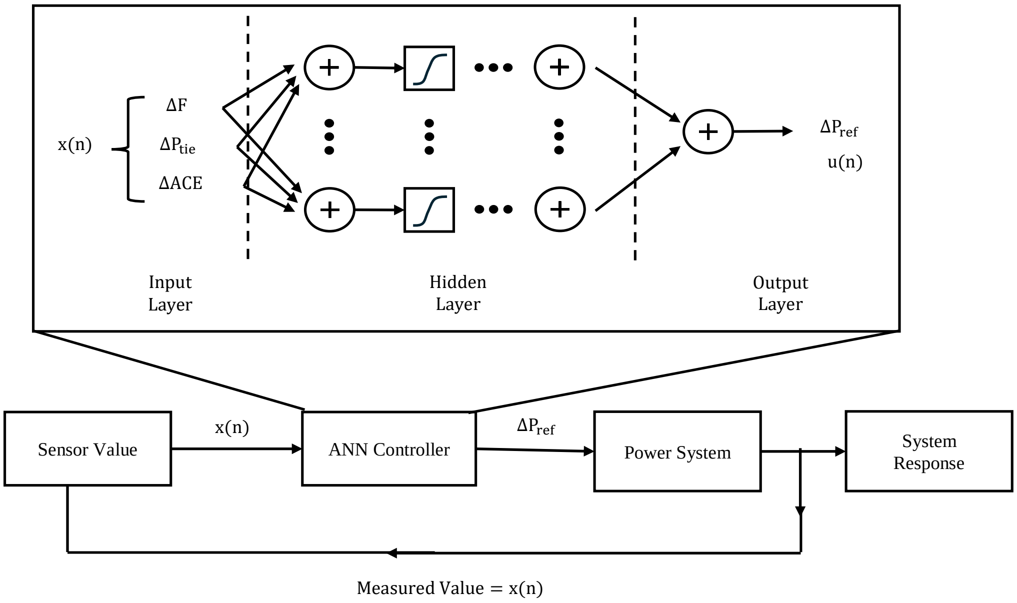


Fig. 9 Architecture of an artificial neural network-based secondary controller for automatic generation control

8.2. Reinforcement Learning

Reinforcement Learning (RL) is a model-free machine learning algorithm under research for AGC. Unlike the supervised learning approach in ANN and DL, RL enables an agent to learn by interacting with the environment to learn a policy with the highest cumulative rewards [165]. The agent observes the system's state at each time step and selects actions according to its policy. It then receives feedback in the form of rewards and iteratively updates its policy to enhance decision-making [166].

A typical RL structure for AGC is shown in Figure 10 [12]. In this framework, the RL controller acts as the agent, while the power system serves as the environment. The system state typically includes frequency (Δf) and tie-line power (ΔP_{tie}) deviations. The action of the agent is the control signal (ΔP_{ref}) sent to the generators. After executing an action, the new state of the environment is observed by the agent to compute a reward, and the control policy is gradually improved. RL algorithms can be further categorized into two groups: value-based methods that approximate the value function [167] and policy-based methods that learn the optimal policies directly.

8.2.1. Value-based Methods

Early RL primarily relied on value-based methods due to their simplicity and lower computational requirements. Value-based RL methods, such as Q-Learning (QL), have been widely applied in AGC studies. Value-based methods estimate the expected return of a state or action using state values $V(s)$or state–action values $Q(s,a)$, which are updated using the Bellman Equation [12]. These methods learn an optimal policy by iteratively updating $V(s)$ or $Q(s,a)$ to maximize expected returns, rather than directly learning a policy. These values are stored in a Q-table, which keeps memory and computational requirements low. Q-Learning (QL) is one of the earliest RL algorithms applied to AGC. This is because researchers are looking for a model-free learning method with a simple structure that can run efficiently on processors with low computational power. Q-learning uses state–action values (Q-values) in a Q-table to evaluate how good an action is in a specific state. These Q-values are updated iteratively based on the reward obtained and the maximum expected Q-value for the subsequent state. The learning mechanism of QL is simple and does not require neural networks or gradient computation. Q-learning has been applied to AGC since the early 2000s in [165, 168], demonstrating its effectiveness in handling systems with complex dynamics. During the 2010s, Q-learning was used in [169] to optimize AGC performance with multiple goals like minimizing generation cost and error. Additionally, an improved version of Q-learning, known as Hierarchical Q-Learning (HQL), was introduced in [170] to enhance the convergence speed of QL. This method decomposes the problem into smaller subtasks with their own Q-table. This method reduces convergence time by nearly 50%. There are some limitations to conventional Q-learning, which include its poor scalability to continuous or high-dimensional state spaces. Q-learning relies on state discretization, which causes approximation errors in continuous environments. This makes it unsuitable for power systems that require high sensitivity. For example, discretizing input states can cause the agent to overlook minor power deviations. This could result in sustained frequency deviations that go uncorrected. Moreover, Q-learning depends on a Q-table, which becomes impractically large in environments with large state spaces, especially when the power system becomes larger and more complex.

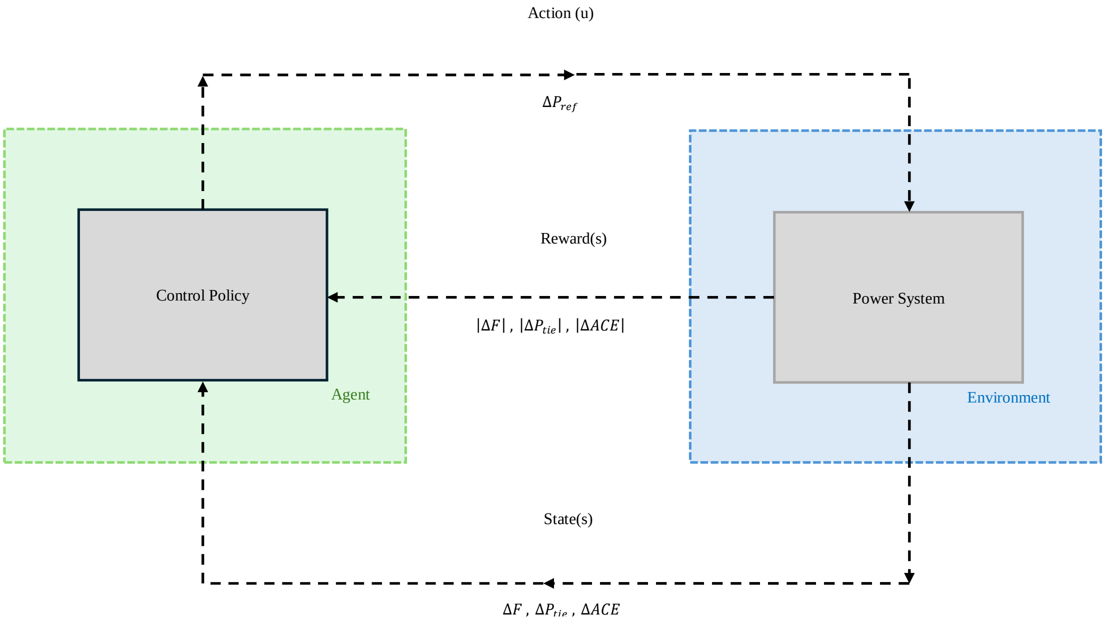


Fig. 10 Schematic diagram of a reinforcement learning agent for automatic generation control

To overcome these challenges, researchers integrated Deep Learning (DL) with RL, forming Deep Reinforcement Learning (DRL) to mitigate the curse of dimensionality. In the 2010s, [171] introduced Deep Q-Learning (DQN), which combines Q-learning with Deep Neural Networks. DQN enables the direct processing of continuous state inputs without discretization. Additionally, DQN approximates Q-values using a neural network, making it effective for high-dimensional inputs, especially in RES-integrated systems. By the 2020s, DQN was applied to AGC in hybrid energy systems [163], achieving lower frequency deviation compared to PID, Fuzzy Logic Control (FLC), and conventional Q-learning.

Another major limitation of Q-learning is the tendency to overestimate Q-values. This happens when the learned Q-values are higher than the true values. This happens because the Q-learning update relies on the maximum expected Q-value for the subsequent state, causing estimation errors to accumulate. Thus, Double Q-Learning (DQL) is introduced in AGC, which uses two separate Q-tables that are updated alternatively to reduce overestimation. In the 2020s, [23] proposed an Optimistic Initialized Double Q-learning (OIDQ) to manage frequency instability in power systems due to large-scale electric vehicles. Although DQL reduces overestimation of Q-values, it may sometimes lead to underestimation bias. To counter this, [167, 172] proposed Maxmin Q-learning for AGC in large-scale renewable energy systems. Maxmin Q-learning employs multiple Q-tables and computes the state-action value as the minimum of the maximum Q-values across these estimators. Thus, Maxmin Q-learning helps in balancing overestimation and underestimation in conventional Q-learning. Double Deep Q-Learning (DDQL) is another variant of Q-learning that combines the advantages of DQN and DQL. DDQL was used in [173] for AGC in multi-area hybrid energy systems. This approach solves the overestimation issues in Q-learning while stabilizing the learning process in RES-integrated systems with continuous state spaces. Besides these limitations, researchers also found that conventional Q-learning lacks efficiency while learning because it updates Q-values based on a single time step. Therefore, multi-step reinforcement learning methods, such as Q(λ)-learning, were developed. The Q-values in Q(λ)-learning are updated with reward from multiple time steps with an eligibility trace(λ). Q(λ)-learning is applied for AGC in the 2010s [174] and 2020s [175], which enables faster and more efficient learning by including multiple past actions in a single update step.

Although Deep Reinforcement Learning (DRL) methods such as DQN were introduced to address the limitations of value-based algorithms in handling continuous state spaces, these methods still struggle with continuous action spaces. The reliance of value-based RL on discrete actions can lead to inefficiencies and a loss of precision, especially when precise power control is required. Additionally, value-based RL selects actions based on predicted Q-values, which can be inaccurate due to the unknown true target values. These limitations have led to the development of policy-based RL methods.

8.2.2. Policy-based Methods

Policy-based RL methods were developed to overcome the limitations of value-based methods in a continuous action space. Policy-based RL methods focus on optimizing policies directly without relying on explicit value estimation. However, value functions are still used to enhance learning in some policy-based algorithms, such as those with Actor-Critic frameworks. These algorithms combine both value-based and policy-based learning for greater stability and efficiency in learning, especially in complex and continuous power control tasks.

The Actor-Critic framework is a model-free RL approach that combines policy optimization (Actor) with value function estimation (Critic). The Actor updates its policy using policy gradients, whereas the Critic evaluates the action from the Actor based on the value function. This structure helps accelerate learning and reduces noise in policy updates. One of the algorithms using the Actor-Critic framework is Deep Deterministic Policy Gradient (DDPG). DDPG is designed for continuous action spaces and is an off-policy algorithm. In DDPG, the actor network learns a deterministic policy while the critic network evaluates Q-values to assist the actor in improving the policy. DDPG was used in [176] during the late 2010s and in [21] during the 2020s to enable continuous control actions in AGC of hybrid power systems, effectively managing frequent load perturbations caused by wind power. However, DDPG tends to overestimate Q-values, potentially leading to learning suboptimal policies.

Twin Delayed Deep Deterministic Policy Gradient (TD3) enhances DDPG by solving the issues of Q-value overestimation in DDPG. TD3 is an Actor-Critic algorithm and introduces three key improvements: (1) employing two critic networks to prevent overestimation in values, (2) updating the actor network less frequently than the critic to ensure accurate Q-value estimation before policy updates, and (3) adding small noise to the next action before feeding it into the target Q-network to discourage reliance on sharp, unrealistic action values. Article [164] integrates TD3 with Model Predictive Control (MPC) in a multi-layered control approach for AGC in large-scale Electric Vehicle (EV) systems. Similarly, article [18] applies TD3 for AGC while considering the economic benefits of power systems integrated with RES and ESS.

Beyond DDPG and TD3, authors in [177] further improved the Actor-Critic algorithm by introducing a greedy Actor-Critic framework combined with experience replay using data. It uses high-value demonstration data to guide multi-agent learning. This approach reduces unproductive exploration in the early training phase and accelerates convergence toward a high-performance policy in two-area AGC systems with hybrid energy sources.

Although DDPG and TD3 have significantly improved the performance of AGC in continuous action spaces, both algorithms still rely on deterministic policies. These algorithms suffer from poor exploration and may lead to a suboptimal policy. Additionally, deterministic algorithms struggle to adapt to stochastic environments in real-world applications. This limitation caused the development of the Soft Actor-Critic (SAC) algorithm. SAC trains a stochastic policy by including an entropy term in the expected reward function of the Actor during training. This entropy mechanism encourages exploration and helps prevent premature convergence. As a result, the actor network simultaneously maximizes both reward and entropy during training. SAC was applied in [65, 178] to optimize AGC in islanded microgrids with better robustness compared to DDPG. Although RL and DRL are becoming increasingly popular in AGC studies, the number of research articles on RL-based AGC remains limited compared to studies using metaheuristic algorithms. Therefore, future researchers should address this gap and explore RL-based approaches further, as data-driven machine learning is becoming an important trend in the 2020s. RL and DRL could also be combined with other AI techniques, such as metaheuristic algorithms. This hybrid algorithm could leverage the model-free adaptability of RL along with the strong optimization capabilities of metaheuristic methods. However, RL still faces challenges in balancing exploration and exploitation, which can lead to convergence to local optimal and suboptimal solutions. Moreover, RL models require rigorous pretraining before online deployment to ensure reliable performance [16]. Table 4 summarizes the machine learning algorithms applied in AGC from the 2000s to the 2020s.

Table 4. Summary of machine learning applications in automatic generation control (2000s–2020s)

Algorithm	Year	System	Description	Literature
Artificial Neural Network (ANN)	2000s 2010s	- Hybrid with ESS	- Adaptable to nonlinear systems without a precise model. - Requires large training datasets; offline training limits real-time adaptability.	[154-158, 160]
Deep Learning (DL)	2020s	- Hybrid with RES and ESS	- Improving feature extraction and learning with hidden layers. - Requires large training datasets, and offline training limits real-time adaptability	[17, 161, 162]
Q-Learning (QL)	2000s 2010s	- Hybrid with RES	- Converges faster and is less computationally intensive. - Poor scalability to high-dimensional states and tends to overestimate Q-values.	[165, 168, 170]
Deep Q-Learning (DQN)	2010s 2020s	- Hybrid with RES	- Directly processes continuous state, avoiding discretization. - DQN is limited to discrete action spaces and prone to Q-value overestimation.	[163, 171, 179]
Double Q-Learning (DQL)	2020s	-Hybrid with RES and EVs	- Uses two Q-value estimators that are updated alternately to reduce overestimation. - Sometimes leads to underestimation bias of Q-value	[23]
Maxmin Q-Learning	2020s	- Hybrid with RES and EVs	- Employs multiple Q-estimators, balancing overestimation and underestimation. - Overly conservative updates may lead to slower exploration.	[167, 172]
Double Deep Q-Learning (DDQL),	2020s	- Hybrid with RES	- Mitigated overestimation issues while stabilizing Q-learning with a neural network. - Training two deep neural networks is computationally heavy.	[173]
Multi-step Q-learning, Q(λ)	2010s 2020s	- Hybrid with RES	- Uses multi-step returns for quicker and more efficient learning. - Longer steps may increase update variance, require careful tuning of λ, and step count.	[174, 180]
DDPG	2010s 2020s	- Hybrid with RES	- Directly outputs continuous actions with policy gradients. - May suffer from Q-value overestimation and require careful tuning of hyperparameters.	[21, 176]

TD3	2020s	- Hybrid with RES, ESS, and EVs	- Twin critical updates reduce overestimation and better handle noisy environments. - Additional networks increase computational difficulty.	[18, 164]
Soft Actor-Critic (SAC)	2020s	- Microgrid with RES	- Balances exploration and exploitation effectively with an entropy mechanism. - Requires careful parameter tuning and high computational power.	[65, 178]

9. Discussion

This review paper presents a detailed review of AI-based optimization algorithms for AGC, covering their advantages, disadvantages, challenges, and evolutionary trends from the 2000s to the 2020s. Unlike existing review papers that may select articles randomly with potential bias, this work primarily includes studies published in Q1 journals from reputable publishers. This ensures that high-quality articles are reviewed to reflect developments by established researchers in the field accurately.

Moreover, this review provides a detailed chronological analysis of each AI algorithm in different eras. This work distinguishes clearly between outdated and recent studies based on their eras, unlike previous reviews. This enables readers to trace historical progress and identify emerging directions. Therefore, this review serves as a reliable and comprehensive reference for AI-driven AGC research. Based on the review of AGC studies from the 2000s to the 2020s, Table 5 summarizes the general strengths and limitations of various AI-based optimization algorithms. Besides the advantages and drawbacks of these algorithms, several trends have emerged over the years:

(i) Integer and fractional-order controllers remain the most widely used controllers in AGC studies. Cascaded controllers have become increasingly prevalent, particularly in the 2020s, because of the growing complexity in power systems with RES and ESS. Cascade controllers improve the flexibility and robustness of the control action, while their tuning has become more feasible with the optimization from AI algorithms.

(ii) Fuzzy logic continues to be widely used in AGC studies. It is often combined with other AI algorithms to assist in simplifying and modeling nonlinear systems. The hybrid of fuzzy logic and neural networks shows strong potential for future AGC research, as they can learn fuzzy sets based on data acquired by the network.

(iii) Metaheuristic algorithms remain dominant in AGC studies because they provide optimization in problems with high-dimensional and large state spaces. Many recent studies propose new EA and SI variants that offer improved exploration-exploitation balance. These algorithms can optimize the parameters of a controller within a short time. However, they still face challenges because they rely on accurate system models to optimize simulations and obtain optimal solutions.

(iv) Machine learning is gaining attention in the 2020s as researchers are looking for model-free algorithms that are capable of optimizing power plants despite system uncertainties. RL allows power systems to develop effective control policies through online interaction with the system. Future research could focus more on policy-based RL due to its ability to optimize continuous action and state spaces, which provides significant advantages for AGC control problems.

(v) Hybrid algorithms will remain a key research area in AGC. Hybrid algorithms have become increasingly common with rising computational power. For example, combinations of machine learning and metaheuristic algorithms are still underexplored. Machine learning models can approximate real-time grid dynamics such as load demand and power generation during online learning, while metaheuristic algorithms may optimize controller parameters using the data learned. Therefore, hybrid algorithms can greatly improve the adaptability of AI algorithms in AGC.

Table 5. Strengths and limitations of optimization algorithms in automatic generation control studies.

Algorithm	Advantages	Disadvantages	Literature
FL	- Handles nonlinearity well - Does not require an explicit model	- Difficult to tune membership functions. - Not adaptive to varying system dynamics.	[64, 65, 67, 181]
EA	- Global optimization, multiple objectives - No gradient information required.	- Requires many iterations to converge. - Requires exact and accurate modeling.	[56, 77, 78, 96]
SI	- Global optimization, multiple objectives - Faster convergence rate compared to EA.	- Requires exact and accurate modeling. - Prone to local optima in complex problems.	[137, 139, 147, 140]

ANN	- Can model complex and nonlinear systems. - Learning from data, reducing the need for manual tuning.	- Requires high-quality training data. - Trained offline, lacks adaptability to dynamic conditions.	[155, 157, 158, 160]
VBRL[a]	- Model-free learning. - RL can continuously learn online.	- Struggle with continuous action spaces. - May have errors in state-action value predictions.	[173, 170, 179, 182]
PBRL [b]	- Works well in a continuous environment. - Directly optimizes policy in high-dimensional problems.	- High computational and resource cost - Requires careful parameter tuning for neural networks.	[18, 164, 65, 176]

[a] VBRL refers to value-based reinforcement learning

[b] PBRL refers to policy-based reinforcement learning

10. Limitations

This review provides a comprehensive review of AI-based optimization methods based on their trend, advantages, and disadvantages, which are beneficial for future researchers. However, several limitations in this review paper can be addressed in future review papers on AGC.

10.1. Fixed Sample Size per Decade

This review used a fixed sample size of exactly 50 articles per decade (2000–2009, 2010–2019, and 2020–2025). Although the sample size for each decade was kept equal to ensure balanced historical representation, this approach may still introduce selection bias. This is because the volume of AGC-related publications has a notable rise recently because of the rapid increase in RES, which demand more efficient AGC systems. As a result, the 50 papers selected for 2020-2025 represent only highly cited works and a small fraction of the available literature. This fixed sample size may miss emerging AI trends that have attracted attention primarily in the 2020s.

10.2. Insufficient Analysis of Hybrid Approaches

Although hybrid algorithms are identified as one of the rapidly growing trends, especially in the 2020s, they are not analyzed as a distinct category in this paper. Most hybrid approaches are described only by referencing their individual components. For example, a “GA-tuned fuzzy-PID” is discussed either under genetic algorithms or under fuzzy logic, rather than being examined as a true hybrid method on its own.

Consequently, this review provides only a general overview of hybrid algorithms and does not explore which specific hybrid pairings dominate in each era or why certain combinations consistently outperform others. Future reviews could examine these hybrid algorithms in greater depth and discuss the advantages of integrating different AI algorithms.

10.3. Insufficient Quantitative Comparison

This review provides qualitative and quantitative comparisons of different algorithms across various eras to highlight important evolution trends. However, this paper does not include a quantitative benchmark to compare the families of AI algorithms directly. Performance metrics such as convergence speed, computational time, and memory requirements are compared and summarized, but not analyzed using the same benchmark. Future reviews could extend this work by normalizing and comparing these metrics using actual data extracted from individual papers. This data could be presented in unified comparison tables or figures to provide a more detailed quantitative comparison as references for the future AGC.

Although this review paper has limitations, it still serves as an important reference by clearly mapping the historical trends, patterns, and challenges of various AI algorithms. It can provide motivation for the next generation of review and benchmarking studies in AGC. Future reviews on AGC could include a larger sample size, focus more on hybrid approaches, and compare these algorithms with benchmark performance metrics to produce more reliable analyses.

11. Future Directions

Besides the limitations mentioned in this review paper, there are several research gaps and recommended areas for further investigation in AGC that have been identified from the review of AGC literature.

11.1. Impact of Renewable Energy Sources (RESs)

The addition of RESs in power systems nowadays reduces system inertia, making frequency control more challenging. Additionally, RESs introduce uncertainties due to weather fluctuations. While many studies have considered the impact of RESs, future research should focus on the incorporation of virtual inertia through energy storage devices to enhance grid stability and improve power system flexibility [183].

11.2. Challenges in Electric Vehicle Integration

The increasing adoption of Electric Vehicles (EVs) has introduced new challenges for AGC systems. EV charging increases load demand variability and uncertainty, as charging patterns can vary over time and across locations. Additionally, new technology known as Vehicle-to-Grid (V2G) enables EVs to function as both energy consumers and suppliers with bidirectional power flow. Thus, future research on optimizing V2G integration could enhance grid flexibility and improve AGC performance [184].

11.3. Research Opportunities in Energy Storage System (ESS)

Energy Storage Systems (ESS) are essential for balancing energy supply and demand by reducing fluctuations in power from RES. Therefore, ESS technologies such as supercapacitors, superconducting magnetic energy storage, and lithium-sulfur batteries should be further explored [185]. However, ESS still faces problems like high production costs and requires optimal battery sizing. Additionally, key factors such as state of charge and ramp rate limitations must be considered to enhance the effective deployment of ESS. [186].

11.4. Cybersecurity Vulnerabilities

The growing dependence on digital control systems in modern power grids has made AGC vulnerable to cybersecurity threats. Cyberattacks like Denial-of-Service (DoS) attacks that target AGC network infrastructure, control platforms, and data processing tools could pose significant risks. Future research should aim to develop robust cybersecurity frameworks to strengthen the robustness of power systems against these threats [187].

11.5. Challenges in the Integration of Machine Learning Algorithms

Although machine learning algorithms like reinforcement learning are becoming increasingly popular, there are challenges in integrating them into existing AGC systems. These algorithms often require modifications to the system architecture, which increases implementation complexity. Furthermore, they demand high computational resources for efficient deployment of machine learning-based AGC systems.

12. Conclusion

This paper offers an in-depth review of the latest trends and developments in AI-based optimization techniques for enhancing secondary control in AGC systems. It explores various AI algorithms, including fuzzy logic, metaheuristic algorithms, and machine learning approaches. A review of past research shows that ANN and fuzzy logic were broadly used in the 2000s for AGC controllers because they do not require explicit mathematical models and can capture nonlinear characteristics of the power system. Power systems became more complex in the 2010s with the increasing integration of RES, leading to more generation units and parameters that require optimization. As a result, many AGC studies have shifted toward metaheuristic algorithms, which are well-suited for optimization problems with large search spaces. Metaheuristic algorithms have remained popular in the 2020s, especially SI algorithms. At the same time, machine learning algorithms such as RL are increasingly studied for AGC. This shift is driven by the growing complexity and uncertainty introduced by RES and ESS, which make accurate modeling difficult. Thus, machine learning offers a promising alternative as a model-free algorithm that is capable of learning from data and adapting to system uncertainties in real time. This study also evaluates the strengths and limitations of various AI-based optimization algorithms in AGC to provide direction for future research. Despite the potential of these AI algorithms, they still face challenges in real-world implementation, such as computational complexity, limited data availability, and concerns regarding system reliability.

Future AGC studies should focus more on testing the feasibility of AI-based algorithms for optimizing AGC, integrating RES, ESS, and electric vehicles to enhance grid flexibility and stability. Beyond its academic value, this review provides useful information for power system planners and operators. The historical trends and comparative findings presented in this paper can assist engineers and regulators in decision-making when upgrading AGC systems. System operators can use these insights to justify budgets and schedules for transitioning from older fixed-parameter controllers to modern AI-optimized controllers. Additionally, operators can refer to this review to identify the technical specifications required for AGC upgrades over the next five to ten years. In summary, this review not only supports researchers in this field but also serves as a reference for engineers and operators in selecting effective solutions for modern AGC systems.

Ethics and Conflicts of Interest

This study was conducted in accordance with standard ethical guidelines. All methods, analyses, and results were carried out responsibly, with honesty, transparency, and academic integrity. This work does not pose any risk to individuals or the environment. The author(s) declare that there is no conflict of interest regarding the publication of this paper.

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References

[1] Muhammad Majid Gulzar et al., "Load Frequency Control Progress: A Comprehensive Review on Recent Development and Challenges of Modern Power Systems," *Energy Strategy Reviews*, vol. 57, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[2] Thavamani Jeyaraj, Arul Ponnusamy, and Dhamodharan Selvaraj, "Hybrid Renewable Energy Systems Stability Analysis Through Future Advancement Technique: A Review," *Applied Energy*, vol. 383, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[3] Nishant Thakkar, Deepa Kaliyaperumal, and V. Ravikumar Pandi, "Trend and Evolution in Muti-Microgrid Systems: A Bibliometric Analysis and Literature Review," *Results in Engineering*, vol. 25, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[4] Ming Kuang et al., “A Review of Control Strategies for Automatic Generation Control in Power Systems with Renewable Energy,” *Progress in Energy*, vol. 6, no. 2, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Dillip Kumar Mishra et al., *Power System Frequency Control: Modeling and Advances*, 1st ed., Academic Press, 2023. [Google Scholar] [Publisher Link]

[6] Jiawen Li, and Yuanyuan Cheng, “Deep Meta-Reinforcement Learning-based Data-Driven Active Fault Tolerance Load Frequency Control for Islanded Microgrids Considering Internet of Things,” *IEEE Internet of Things Journal*, vol. 11, no. 6, pp. 10295-10303, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Leonard L. Grigsby, *Power System Stability and Control*, 2nd ed., CRC Press, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[8] Ritu Verma et al., “A State of Art Review on the Opportunities in Automatic Generation Control of Hybrid Power System,” *Electric Power Systems Research*, vol. 226, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[9] Samuel Lalngaihawma et al., “Enhancing Grid Stability Through Virtual Inertia Control in Automatic Generation Control of a Multi Area System,” *Energy Reports*, vol. 13, pp. 2764-2789, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[10] Naladi Ram Babu et al., “A Comprehensive Review of Recent Strategies on Automatic Generation Control/Load Frequency Control in Power Systems,” *Archives of Computational Methods in Engineering*, vol. 30, no. 1, pp. 543-572, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[11] Mohammed Wadi et al., “Load Frequency Control in Smart Grids: A Review of Recent Developments,” *Renewable and Sustainable Energy Reviews*, vol. 189, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[12] Rasananda Muduli, Debashisha Jena, and Tukaram Moger, “A Survey on Load Frequency Control using Reinforcement Learning-based Data-Driven Controller,” *Applied Soft Computing*, vol. 166, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[13] Noer Fadzri Perdana Dinata et al., “Designing an Optimal Microgrid Control System using Deep Reinforcement Learning: A Systematic Review,” *Engineering Science and Technology, an International Journal*, vol. 51, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Sanjeev Kumar Bhagat et al., “A Review on Various Secondary Controllers and Optimization Techniques in Automatic Generation Control,” *Archives of Computational Methods in Engineering*, vol. 30, no. 5, pp. 3081-3111, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Muhammad Inshal Shahzad et al., “From Classical to AI-Driven Load Frequency Control: Addressing Smart Grid Challenges with Renewable Energy Sources and EVs Integration,” *Renewable and Sustainable Energy Reviews*, vol. 226, 2026. [CrossRef] [Google Scholar] [Publisher Link]

[16] Shuai Wang et al., “A Comprehensive Review on the Development of Data-Driven Methods for Wind Power Prediction and AGC Performance Evaluation in Wind-Thermal Bundled Power Systems,” *Energy and AI*, vol. 16, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Linfei Yin, and Yi Xiong, “Long-Term Deep Reinforcement Learning for Real-Time Economic Generation Control of Cloud Energy Storage Systems with Varying Structures,” *Engineering Applications of Artificial Intelligence*, vol. 138, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[18] Javier Cardo-Miota et al., “Deep Reinforcement Learning-based Strategy for Maximizing Returns from Renewable Energy and Energy Storage Systems in Multi-Electricity Markets,” *Applied Energy*, vol. 388, pp. 1-15, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[19] J. Nanda, and B.L. Kaul, “Optimal Controller for Automatic Generation Control,” *IFAC Proceedings Volumes*, vol. 10, no. 1, pp. 429-433, 1977. [CrossRef] [Google Scholar] [Publisher Link]

[20] H. Glavitsch, and J. Stoffel, “Automatic Generation Control,” *International Journal of Electrical Power and Energy Systems*, vol. 2, no. 1, pp. 21-28, 1980. [CrossRef] [Google Scholar] [Publisher Link]

[21] Junaid Khalid et al., “Efficient Load Frequency Control of Renewable Integrated Power System: A Twin Delayed DDPG-based Deep Reinforcement Learning Approach,” *IEEE Access*, vol. 10, pp. 51561-51574, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] A. Elsawy Khalil et al., “A Novel Cascade-Loop Controller for Load Frequency Control of Isolated Microgrid Via Dandelion Optimizer,” *Ain Shams Engineering Journal*, vol. 15, no. 3, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Lei Xi et al., “A Novel Automatic Generation Control Method based on the Large-Scale Electric Vehicles and Wind Power Integration into the Grid,” *IEEE Transactions on Neural Networks and Learning Systems*, vol. 35, no. 5, pp. 5824-5834, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[24] Ho Jae Lee, Jin Bae Park, and Young Hoon Joo, “Robust Load-Frequency Control for Uncertain Nonlinear Power Systems: A Fuzzy Logic Approach,” *Information Sciences*, vol. 176, no. 23, pp. 3520-3537, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[25] Jyoti Ranjan Nayak, Binod Shaw, and Binod Kumar Sahu, “Application of Adaptive-SOS (ASOS) Algorithm based Interval Type-2 Fuzzy-PID Controller with Derivative Filter for Automatic Generation Control of an Interconnected Power System,” *Engineering Science and Technology, an International Journal*, vol. 21, no. 3, pp. 465-485, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[26] Seyed Mohammad T. Bathaee, and Mehdi Jafari Harandi, “Decentralized Load Frequency Control of Multi-Area Power Systems using Combined Variable Structure and Fuzzy Logic Controller,” *IFAC Proceedings Volumes*, vol. 30, no. 25, pp. 493-498, 1997. [CrossRef] [Google Scholar] [Publisher Link]

[27] C.S. Chang, and Weihui Fu, “Area Load Frequency Control using Fuzzy Gain Scheduling of PI Controllers,” *Electric Power Systems Research*, vol. 42, no. 2, pp. 145-152, 1997. [CrossRef] [Google Scholar] [Publisher Link]

[28] Ali Feliachi, and Dulpichet Rerkpreedapong, “NERC Compliant Load Frequency Control Design using Fuzzy Rules,” *Electric Power Systems Research*, vol. 73, no. 2, pp. 101-106, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[29] C. Srinivasa Rao, S. Siva Nagaraju, and P. Sangameswara Raju, “Automatic Generation Control of TCPS based Hydrothermal System Under Open Market Scenario: A Fuzzy Logic Approach,” *International Journal of Electrical Power and Energy Systems*, vol. 31, no. 7-8, pp. 315-322, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[30] M.K. El-Sherbiny, G. El-Saady, and A.M. Yousef, “Efficient Fuzzy Logic Load-Frequency Controller,” *Energy Conversion and Management*, vol. 43, no. 14, pp. 1853-1863, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[31] Y.L. Karnavas, and D.P. Papadopoulos, “AGC for Autonomous Power System using Combined Intelligent Techniques,” *Electric Power Systems Research*, vol. 62, no. 3, pp. 225-239, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[32] Pingkang Li, and Xiuxia Du, “Decision Table Looking up Approach for Fuzzy Logic Control of Multi-Area AGC Systems,” *IFAC Proceedings Volumes*, vol. 38, no. 1, pp. 279-284, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[33] Meng Xiangping et al., “Fuzzy Sliding Mode Load Frequency Control of Multiarea Interconnected Power Systems,” *IFAC Proceedings Volumes*, vol. 34, no. 22, pp. 452-457, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[34] İlhan Kocaarslan, and Ertuğrul Çam, “Fuzzy Logic Controller in Interconnected Electrical Power Systems for Load-Frequency Control,” *International Journal of Electrical Power and Energy Systems*, vol. 27, no. 8, pp. 542-549, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[35] Ertuğrul Çam, “Application of Fuzzy Logic for Load Frequency Control of Hydroelectrical Power Plants,” *Energy Conversion and Management*, vol. 48, no. 4, pp. 1281-1288, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[36] Ertuğrul Çam, and İlhan Kocaarslan, “Load Frequency Control in Two Area Power Systems using Fuzzy Logic Controller,” *Energy Conversion and Management*, vol. 46, no. 2, pp. 233-243, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[37] Xiangjun Li, Yu-Jin Song, and Soo-Bin Han, “Frequency Control in Micro-Grid Power System Combined with Electrolyzer System and Fuzzy PI Controller,” *Journal of Power Sources*, vol. 180, no. 1, pp. 468-475, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[38] Ertuğrul Çam, and İlhan Kocaarslan, “A Fuzzy Gain Scheduling PI Controller Application for an Interconnected Electrical Power System,” *Electric Power System Research*, vol. 73, no. 3, pp. 267-274, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[39] A. Demiroren, and E. Yesil, “Automatic Generation Control with Fuzzy Logic Controllers in the Power System Including SMES Units,” *International Journal of Electrical Power and Energy Systems*, vol. 26, no. 4, pp. 291-305, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[40] Saravuth Pothiya, and Issarachai Ngamroo, “Optimal Fuzzy Logic-based PID Controller for Load-Frequency Control Including Superconducting Magnetic Energy Storage Units,” *Energy Conversion and Management*, vol. 49, no. 10, pp. 2833-2838, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[41] V. Mukherjee, and S.P. Ghoshal, “Comparison of Intelligent Fuzzy based AGC Coordinated PID Controlled and PSS Controlled AVR System,” *International Journal of Electrical Power and Energy Systems*, vol. 29, no. 9, pp. 679-689, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[42] H. Shayeghi, H.A. Shayanfar, and A. Jalili, “Multi-Stage Fuzzy PID Power System Automatic Generation Controller in Deregulated Environments,” *Energy Conversion and Management*, vol. 47, no. 18-19, pp. 2829-2845, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[43] E. Yeşil, M. Güzelkaya, and İ. Eksin, “Self Tuning Fuzzy PID Type Load and Frequency Controller,” *Energy Conversion and Management*, vol. 45, no. 3, pp. 377-390, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[44] H. Shayeghi, A. Jalili, and H.A. Shayanfar, “Robust Modified GA based Multi-Stage Fuzzy LFC,” *Energy Conversion and Management*, vol. 48, no. 5, pp. 1656-1670, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[45] H. Shayeghi, A. Jalili, and H.A. Shayanfar, “Multi-Stage Fuzzy Load Frequency Control using PSO,” *Energy Conversion and Management*, vol. 49, no. 10, pp. 2570-2580, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[46] S.P. Ghoshal, “Optimizations of PID Gains by Particle Swarm Optimizations in Fuzzy based Automatic Generation Control,” *Electric Power Systems Research*, vol. 72, no. 3, pp. 203-212, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[47] S.H. Hosseini, and A.H. Etemadi, “Adaptive Neuro-Fuzzy Inference System based Automatic Generation Control,” *Electric Power Systems Research*, vol. 78, no. 7, pp. 1230-1239, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[48] Kamel Sabahi, Mohammad Teshnehlab, and Mahdi Aliyari shoorhedeli, “Recurrent Fuzzy Neural Network by using Feedback Error Learning Approaches for LFC in Interconnected Power System,” *Energy Conversion and Management*, vol. 50, no. 4, pp. 938-946, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[49] Saroj Padhan, Rabindra Kumar Sahu, and Sidhartha Panda, “Automatic Generation Control with Thyristor Controlled Series Compensator Including Superconducting Magnetic Energy Storage Units,” *Ain Shams Engineering Journal*, vol. 5, no. 3, pp. 759-774, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[50] Mohammad Hassan Khooban, and Taher Niknam, “A New Intelligent Online Fuzzy Tuning Approach for Multi-Area Load Frequency Control: Self Adaptive Modified Bat Algorithm,” *International Journal of Electrical Power and Energy Systems*, vol. 71, pp. 254-261, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[51] Yogendra Arya, “Automatic Generation Control of Two-Area Electrical Power Systems via Optimal Fuzzy Classical Controller,” *Journal of the Franklin Institute*, vol. 355, no. 5, pp. 2662-2688, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[52] Binod Kumar Sahu et al., “Teaching-Learning based Optimization Algorithm based Fuzzy-PID Controller for Automatic Generation Control of Multi-Area Power System,” *Applied Soft Computing*, vol. 27, pp. 240-249, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[53] Yogendra Arya, “A New Optimized Fuzzy FOPI-FOPD Controller for Automatic Generation Control of Electric Power Systems,” *Journal of the Franklin Institute*, vol. 356, no. 11, pp. 5611-5629, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[54] S. Baghya Shree, and N. Kamaraj, “Hybrid Neuro Fuzzy Approach for Automatic Generation Control in Restructured Power System,” *International Journal of Electrical Power and Energy Systems*, vol. 74, pp. 274-285, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[55] Swasti R. Khuntia, and Sidhartha Panda, “Simulation Study for Automatic Generation Control of a Multi-Area Power System by ANFIS Approach,” *Applied Soft Computing*, vol. 12, no. 1, pp. 333-341, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[56] Ashok Kumar Mohapatra et al., “Modeling of Flexible AC Transmission System Devices and Fuzzy Controller for Automatic Generation Control of Electric Vehicle-Injected Power System,” *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 7, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[57] Mohammed Kh. Al-Nussairi et al., “Design of a Two-Area Automatic Generation Control using a Single Input Fuzzy Gain Scheduling PID Controller,” *International Journal of Intelligent Engineering and Systems*, vol. 15, no. 6, pp. 443-455, 2022. [CrossRef] [Google Scholar]

[58] K. Iyswarya Annapoorani et al., “Fuzzy Logic-based Integral Controller for Load Frequency Control in an Isolated Micro-Grid with Superconducting Magnetic Energy Storage Unit,” *Materials Today: Proceedings*, vol. 58, pp. 244-250, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[59] M.A. Abdel Ghany et al., “Improving the Frequency Response of a Multi-Generation Power System using Adaptive Variable Structure Fuzzy Controller,” *Electric Power Systems Research*, vol. 232, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[60] Mohamed Barakat, “Optimal Design of Fuzzy-PID Controller for Automatic Generation Control of Multi-Source Interconnected Power System,” *Neural Computing and Applications*, vol. 34, no. 21, pp. 18859-18880, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[61] Zixiang Shen, and Guo Chen, “Robust $H\infty$ Control for LFC of Discrete T-S Fuzzy MAPS with DFIG and Time-Varying Delays,” *Journal of Computational and Applied Mathematics*, vol. 457, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[62] Prakash Chandra Sahu, “Impact and Integration of Electric Vehicles on Renewable Energy based Microgrid: Frequency Profile Improvement by A-SCA Optimized FO-Fuzzy PSS Approach,” *Green Energy and Intelligent Transportation*, vol. 4, no. 2, pp. 1-19, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[63] Dillip Khamari et al., “A mMSA-FOFPID Controller for AGC of Multi-Area Power System with Multi-Type Generations,” *Sustainable Computing: Informatics and Systems*, vol. 44, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[64] R.V.R.F, and P.F.A, “NERC Standards based Cascaded FO Controller for Frequency Regulation in Restructured Model with Flow Resources,” *Heliyon*, vol. 10, no. 6, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[65] Reza Sepehrzad et al., “An Applied Deep Reinforcement Learning Approach to Control Active Networked Microgrids in Smart Cities with Multi-Level Participation of Battery Energy Storage System and Electric Vehicles,” *Sustainable Cities and Society*, vol. 107, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[66] Siavash Shirali, Saeed Zolfaghari Moghaddam, and Mortaza Aliasghary, “An Interval Type-2 Fuzzy Fractional-Order PD-PI Controller for Frequency Stabilization of Islanded Microgrids Optimized with CO Algorithm,” *International Journal of Electrical Power and Energy Systems*, vol. 164, pp. 1-10, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[67] Shu-Rong Yan et al., “A Fractional-Order Multiple-Model Type-2 Fuzzy Control for Interconnected Power Systems Incorporating Renewable Energies and Demand Response,” *Energy Reports*, vol. 12, pp. 187-196, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[68] Maloth Ramesh et al., “A Novel Fuzzy Assisted Sliding Mode Control Approach for Frequency Regulation of Wind-Supported Autonomous Microgrid,” *Scientific Reports*, vol. 14, no. 1, pp. 1-28, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[69] Benazeer Begum et al., “Application of an Intelligent Fuzzy Logic based Sliding Mode Controller for Frequency Stability Analysis in a Deregulated Power System using OPAL-RT Platform,” *Energy Reports*, vol. 11, pp. 510-534, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[70] Sanjiv Kumar Jain et al., “Interrelated Solar and Thermal Plant Autonomous Generation Control Utilizing Metaheuristic Optimization,” *Energies*, vol. 16, no. 8, pp. 1-21, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[71] Sasmita Padhy, and Sidhartha Panda, “A Hybrid Stochastic Fractal Search and Pattern Search Technique based Cascade PI-PD Controller for Automatic Generation Control of Multi-Source Power Systems in Presence of Plug in Electric Vehicles,” *CAAI Transactions on Intelligence Technology*, vol. 2, no. 1, pp. 12-25, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[72] S.P. Ghoshal, “Application of GA/GA-SA based Fuzzy Automatic Generation Control of a Multi-Area Thermal Generating System,” *Electric Power Systems Research*, vol. 70, no. 2, pp. 115-127, 2004. [CrossRef] [Google Scholar] [Publisher Link]

[73] Issarachai Ngamroo, “An Optimization Technique of Robust Load Frequency Stabilizer for Superconducting Magnetic Energy Storage,” *Energy Conversion and Management*, vol. 46, no. 18-19, pp. 3060-3090, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[74] A. Demiroren, and H.L. Zeynelgil, “GA Application to Optimization of AGC in Three-Area Power System after Deregulation,” *International Journal of Electrical Power and Energy Systems*, vol. 29, no. 3, pp. 230-240, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[75] K.S.S. Ramakrishna, and T.S. Bhatti, “Automatic Generation Control of Single Area Power System with Multi-Source Power Generation,” *Proceedings of the Institution of Mechanical Engineers, Part A: Journal of Power and Energy*, vol. 222, no. 1, pp. 1-11, 2008. [CrossRef] [Google Scholar] [Publisher Link]

[76] A. Demirören, S. Kent, and T. Günel, “A Genetic Approach to the Optimization of Automatic Generation Control Parameters for Power Systems,” *European Transactions on Electrical Power*, vol. 12, no. 4, pp. 275-281, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[77] Z.M. Al-Hamouz, and H.N. Al-Duwaish, “A New Load Frequency Variable Structure Controller using Genetic Algorithms,” *Electric Power Systems Research*, vol. 55, no. 1, pp. 1-6, 2000. [CrossRef] [Google Scholar] [Publisher Link]

[78] Ranjit Roy, S.P. Ghoshal, and Praghnesh Bhatt, “Evolutionary Computation based Four-Area Automatic Generation Control in Restructured Environment,” *2009 International Conference on Power Systems*, Kharagpur, India, pp. 1-6, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[79] Umesh Kumar Rout, Rabindra Kumar Sahu, and Sidhartha Panda, “Design and Analysis of Differential Evolution Algorithm based Automatic Generation Control for Interconnected Power System,” *Ain Shams Engineering Journal*, vol. 4, no. 3, pp. 409-421, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[80] P.K. Hota, and B. Mohanty, “Automatic Generation Control of Multi Source Power Generation Under Deregulated Environment,” *International Journal of Electrical Power and Energy Systems*, vol. 75, pp. 205-214, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[81] Abdelmoumène Delassi, Salem Arif, and Lakhdar Mokrani, “Load Frequency Control Problem in Interconnected Power Systems using Robust Fractional $PI^{\lambda}D$ Controller,” *Ain Shams Engineering Journal*, vol. 9, no. 1, pp. 77-88, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[82] Banaja Mohanty, Sidhartha Panda, and P.K. Hota, “Differential Evolution Algorithm based Automatic Generation Control for Interconnected Power Systems with Non-Linearity,” *Alexandria Engineering Journal*, vol. 53, no. 3, pp. 537-552, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[83] Satya Dinesh Madasu, M.L.S. Sai Kumar, and Arun Kumar Singh, “Comparable Investigation of Backtracking Search Algorithm in Automatic Generation Control for Two Area Reheat Interconnected Thermal Power System,” *Applied Soft Computing*, vol. 55, pp. 197-210, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[84] Ragini et al., “Automatic Generation Control for a Two Area Power System using Backtracking Search Algorithm,” *2015 International Conference on Energy, Power and Environment: Towards Sustainable Growth (ICEPE)*, Shillong, India, pp. 1-6, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[85] Chandan Kumar Shiva, and V. Mukherjee, “Design and Analysis of Multi-Source Multi-Area Deregulated Power System for Automatic Generation Control using Quasi-Oppositional Harmony Search Algorithm,” *International Journal of Electrical Power and Energy Systems*, vol. 80, pp. 382-395, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[86] Chandan Kumar Shiva, and V. Mukherjee, “A Novel Quasi-Oppositional Harmony Search Algorithm for Automatic Generation Control of Power System,” *Applied Soft Computing*, vol. 35, pp. 749-765, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[87] A.K. Barisal, “Comparative Performance Analysis of Teaching Learning based Optimization for Automatic Load Frequency Control of Multi-Source Power Systems,” *International Journal of Electrical Power and Energy Systems*, vol. 66, pp. 67-77, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[88] Rabindra Kumar Sahu, Tulasichandra Sekhar Gorripotu, and Sidhartha Panda, “Automatic Generation Control of Multi-Area Power Systems with Diverse Energy Sources using Teaching Learning based Optimization Algorithm,” *Engineering Science and Technology, an International Journal*, vol. 19, no. 1, pp. 113-134, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[89] Banaja Mohanty, “TLBO Optimized Sliding Mode Controller for Multi-Area Multi-Source Nonlinear Interconnected AGC System,” *International Journal of Electrical Power and Energy Systems*, vol. 73, pp. 872-881, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[90] Chittaranjan Pradhan, and Chandrashekhar N. Bhende, “Online Load Frequency Control in Wind Integrated Power Systems using Modified Jaya Optimization,” *Engineering Applications of Artificial Intelligence*, vol. 77, pp. 212-228, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[91] Dipayan Guha, Provas Kumar Roy, and Subrata Banerjee, “Study of Differential Search Algorithm based Automatic Generation Control of an Interconnected Thermal-Thermal System with Governor Dead-Band,” *Applied Soft Computing*, vol. 52, pp. 160-175, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[92] Asadur Rahman, Lalit Chandra Saikia, and Nidul Sinha, “Automatic Generation Control of an Interconnected Two-Area Hybrid Thermal System Considering Dish-Stirling Solar Thermal and Wind Turbine System,” *Renewable Energy*, vol. 105, pp. 41-54, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[93] Hamed Shabani, Behrooz Vahidi, and Majid Ebrahimpour, “A Robust PID Controller based on Imperialist Competitive Algorithm for Load-Frequency Control of Power Systems,” *ISA Transactions*, vol. 52, no. 1, pp. 88-95, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[94] Xiaotong Ji et al., “Multi-Objective Design of Fractional Frequency-Load Control for Hydro-Thermal System Considering Nonlinear Models and Uncertainty,” *Ain Shams Engineering Journal*, vol. 15, no. 12, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[95] Yand Yang et al., “Optimising PID Controllers for Multi-Area Automatic Generation Control with Improved NSGA-II,” *CAAI Transactions on Intelligence Technology*, vol. 10, no. 4, pp. 1135-1147, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[96] Youssef Awda, and Maad Alowaifeer, “Adaptive Optimization of Virtual Synchronous Generator based on Fuzzy Logic Control and Differential Evolution,” *Ain Shams Engineering Journal*, vol. 15, no. 4, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[97] Jagan Mohana Rao Chintu, Rabindra Kumar Sahu, and Sidhartha Panda, “Adaptive Differential Evolution Tuned Hybrid Fuzzy PD-PI Controller for Automatic Generation Control of Power Systems,” *International Journal of Ambient Energy*, vol. 43, no. 1, pp. 515-530, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[98] Ark Dev et al., “Teaching Learning Optimization-based Sliding Mode Control for Frequency Regulation in Microgrid,” *Electrical Engineering.*, vol. 106, no. 6, pp. 7009-7021, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[99] K. Peddakapu et al., “Optimized Controllers for Stabilizing the Frequency Changes in Hybrid Wind-Photovoltaic-Wave Energy-based Maritime Microgrid Systems,” *Applied Energy*, vol. 361, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[100] K. Peddakapu et al., “Assessment of Energy Storage and Renewable Energy Sources-based Two-Area Microgrid System using Optimized Fractional Order Controllers,” *Journal of Energy Storage*, vol. 86, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[101] Wessam A. Hafez et al., “Improved Fractional Order Control with Virtual Inertia Provision Methodology for Electric Vehicle Batteries in Modern Multi-Microgrid Energy Systems,” *Journal of Energy Storage*, vol. 106, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[102] Praghnesh Bhatt, Ranjit Roy, and S.P. Ghoshal, “Comparative Performance Evaluation of SMES–SMES, TCPS–SMES and SSSC–SMES Controllers in Automatic Generation Control for a Two-Area Hydro–Hydro System,” *International Journal of Electrical Power and Energy Systems*, vol. 33, no. 10, pp. 1585-1597, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[103] V. Mukherjee, and S.P. Ghoshal, “Application of Capacitive Energy Storage for Transient Performance Improvement of Power System,” *Electric Power Systems Research*, vol. 79, no. 2, pp. 282-294, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[104] Janardan Nanda, S. Mishra, and Lalit Chandra Saikia, “Maiden Application of Bacterial Foraging-based Optimization Technique in Multiarea Automatic Generation Control,” *IEEE Transactions on Power Systems*, vol. 24, no. 2, pp. 602-609, 2009. [CrossRef] [Google Scholar] [Publisher Link]

[105] Nidhi Gupta, and Narendra Kumar, “Particle Swarm Optimization based Automatic Generation Control of Interconnected Power System incorporating Battery Energy Storage System,” *Procedia Computer Science*, vol. 132, pp. 1562-1569, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[106] Kazem Zare, Mehrdad Tarafdar Hagh, and Javad Morsali, “Effective Oscillation Damping of an Interconnected Multi-Source Power System with Automatic Generation Control and TCSC,” *International Journal of Electrical Power and Energy Systems*, vol. 65, pp. 220-230, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[107] E.S. Ali, and S.M. Abd-Elazim, “BFOA based Design of PID Controller for Two Area Load Frequency Control with Nonlinearities,” *International Journal of Electrical Power and Energy Systems*, vol. 51, pp. 224-231, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[108] Sidhartha Panda, Banaja Mohanty, and P.K. Hota, “Hybrid BFOA–PSO Algorithm for Automatic Generation Control of Linear and Nonlinear Interconnected Power Systems,” *Applied Soft Computing*, vol. 13, no. 12, pp. 4718-4730, 2013. [CrossRef] [Google Scholar] [Publisher Link]

[109] Mahmut T. Özdemir et al., “Tuning of Optimal Classical and Fractional Order PID Parameters for Automatic Generation Control based on the Bacterial Swarm Optimization,” *IFAC-PapersOnLine*, vol. 48, no. 30, pp. 501-506, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[110] Haluk Gozde, M. Cengiz Taplamacioglu, and İlhan Kocaarslan, “Comparative Performance Analysis of Artificial Bee Colony Algorithm in Automatic Generation Control for Interconnected Reheat Thermal Power System,” *International Journal of Electrical Power and Energy Systems*, vol. 42, no. 1, pp. 167-178, 2012. [CrossRef] [Google Scholar] [Publisher Link]

[111] Arman Oshnoei et al., “Automatic Generation Control Incorporating Electric Vehicles,” *Electric Power Components and Systems*, vol. 47, no. 8, pp. 720-732, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[112] K. Jagatheesan et al., “Performance Evaluation of Objective Functions in Automatic Generation Control of Thermal Power System using Ant Colony Optimization Technique-Designed Proportional–Integral–Derivative Controller,” *Electrical Engineering*, vol. 100, no. 2, pp. 895-911, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[113] M. Elsisi et al., “Bat Inspired Algorithm based Optimal Design of Model Predictive Load Frequency Control,” *International Journal of Electrical Power and Energy Systems*, vol. 83, pp. 426-433, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[114] Puja Dash, Lalit Chandra Saikia, and Nidul Sinha, “Automatic Generation Control of Multi Area Thermal System using Bat Algorithm Optimized PD–PID Cascade Controller,” *International Journal of Electrical Power and Energy Systems*, vol. 68, pp. 364-372, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[115] More Raju, Lalit Chandra Saikia, and Nidul Sinha, “Automatic Generation Control of a Multi-Area System using Ant Lion Optimizer Algorithm based PID Plus Second Order Derivative Controller,” *International Journal of Electrical Power and Energy Systems*, vol. 80, pp. 52-63, 2016. [CrossRef] [Google Scholar] [Publisher Link]

[116] Yatin Sharma, and Lalit Chandra Saikia, “Automatic Generation Control of a Multi-Area ST – Thermal Power System using Grey Wolf Optimizer Algorithm based Classical Controllers,” *International Journal of Electrical Power and Energy Systems*, vol. 73, pp. 853-862, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[117] Manoj Kumar Debnath, Ranjan Kumar Mallick, and Binod Kumar Sahu, “Application of Hybrid Differential Evolution–Grey Wolf Optimization Algorithm for Automatic Generation Control of a Multi-Source Interconnected Power System using Optimal Fuzzy–PID Controller,” *Electric Power Components and Systems*, vol. 45, no. 19, pp. 2104-2117, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[118] K. Naidu et al., “Application of Firefly Algorithm with Online Wavelet Filter in Automatic Generation Control of an Interconnected Reheat Thermal Power System,” *International Journal of Electrical Power and Energy Systems*, vol. 63, pp. 401-413, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[119] Rabindra Kumar Sahu, Sidhartha Panda, and Saroj Padhan, “A Hybrid Firefly Algorithm and Pattern Search Technique for Automatic Generation Control of Multi Area Power Systems,” *International Journal of Electrical Power and Energy Systems*, vol. 64, pp. 9-23, 2015. [CrossRef] [Google Scholar] [Publisher Link]

[120] Sanjoy Debbarma, Lalit Chandra Saikia, and Nidul Sinha, “Automatic Generation Control using Two Degree of Freedom Fractional Order PID Controller,” *International Journal of Electrical Power and Energy Systems*, vol. 58, pp. 120-129, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[121] Sanjoy Debbarma, Lalit Chandra Saikia, and Nidul Sinha, “Robust Two-Degree-of-Freedom Controller for Automatic Generation Control of Multi-Area System,” *International Journal of Electrical Power and Energy Systems*, vol. 63, pp. 878-886, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[122] Gaber Magdy et al., “SMES based a New PID Controller for Frequency Stability of a Real Hybrid Power System Considering High Wind Power Penetration,” *IET Renewable Power Generation*, vol. 12, no. 11, pp. 1304-1313, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[123] Arindita Saha et al., “Optimization of Dual-Stage Controllers in Renewable Energy Sources-based Interconnected Power Systems Through Refinement of the African Vultures Optimization Algorithm,” *Ain Shams Engineering Journal*, vol. 15, no. 11, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[124] Sadeq D. Al-Majidi et al., “A Robust Automatic Generation Control System based on Hybrid Aquila Optimizer-Sine Cosine Algorithm,” *Results in Engineering*, vol. 25, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[125] Deepak Kumar Gupta et al., “Fractional Order PID Controller for Load Frequency Control in A Deregulated Hybrid Power System using Aquila Optimization,” *Results in Engineering*, vol. 23, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[126] Amira Hassan et al., “Optimal Cascade 2DOF Fractional Order Master-Slave Controller Design for LFC of Hybrid Microgrid Systems with EV Charging Technology,” *Results in Engineering*, vol. 25, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[127] Abdelkader Halmous et al., “Design A New Cascade Controller PD-P-PID Optimized by Marine Predators Algorithm for Load Frequency Control,” *Soft Computing*, vol. 27, no. 14, pp. 9551-9564, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[128] Vivek Patel, Dipayan Guha, and Shubhi Purwar, “Optimized Cascade Fractional-Order 3DOF-Controller for Frequency Regulation of a Hybrid Power System using Marine Predators Algorithm,” *International Journal of Numerical Modelling: Electronic Networks, Devices and Fields*, vol. 36, no. 5, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[129] Debodyuti Upadhaya et al., “Optimal Power Flow and Grid Frequency Control of Conventional and Renewable Energy Source using Evolutionary Algorithm based FOPID Controller,” *Renewable Energy Focus*, vol. 53, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[130] Sonali R. Nandanwar et al., “Synergistic Control for Enhancing Frequency Stability in Grid-Integrated Network with Decentralized Renewable Energy Resources, Energy Storage, and Electric Vehicles,” *Cleaner Engineering and Technology*, vol. 20, pp. 1-11, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[131] Muhammad Majid Gulzar, Daud Sibtain, and Muhammad Khalid, “Innovative Design for Enhancing Transient Stability with an ATFOPID Controller in Hybrid Power Systems,” *Journal of Energy Storage*, vol. 99, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[132] Hiramani Shukla, and More Raju, “Combined Frequency and Voltage Regulation in an Interconnected Power System using Fractional Order Cascade Controller Considering Renewable Energy Sources, Electric Vehicles and Ultra Capacitor,” *Journal of Energy Storage*, vol. 84, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[133] Prabhat Kumar Vidyarthi, Ashiwani Kumar, and Saurav Raj, “Chaos Quasi-Opposition Sea-Horse based Modified New Tilt Controller Designed for Multi-Area Deregulated AGC using Deep Learning Against Cyber-Attacks,” *Chaos Solitons and Fractals*, vol. 188, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[134] Wei Wang et al., “Flexible Heat and Power Load Control of Subcritical Heating Units based on Energy Demand-Supply Balance,” *Energy*, vol. 313, pp. 1-38, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[135] Yogendra Arya et al., “LFC Performance Advancement of Two-Area RES Penetrated Multi-Source Power System Utilizing CES and A New CFOTID Controller,” *Journal of Energy Storage*, vol. 87, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[136] Muhammad Majid Gulzar et al., “A New Optimal 3° Of Freedom Fractional Order Proportion Integral Derivative Controller with Model Predictive Controller for Frequency Regulation in High Penetrated Renewable based Interconnected System,” *Computers and Electrical Engineering*, vol. 119, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[137] Sandeep Rangi, Sheilza Jain, and Yogendra Arya, “Utilization and Performance Comparison of Several Hesss with Cascade Optimal-FOD Controller for Multi-Area Multi-Source Power System Under Deregulated Environment,” *Journal of Energy Storage*, vol. 94, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[138] Sanjeev Kumar Bhagat, Lalit Chandra Saikia, and Naladi Ram Babu, “Application of an Optimal Tilt Controller in a Partial Loading Schedule of Multi-Area Power System Considering HVDC Link and Virtual Inertia,” *ISA Transactions*, vol. 146, pp. 437-450, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[139] Tirumalasetty Chiranjeevi et al., “Impact of HVDC Link and Electric Vehicle on Multi-Area Power System using MOA Optimized I-TD2N Controller,” *Results in Engineering*, vol. 25, pp. 1-8, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[140] Amit Sharma, and Navdeep Singh, “Load Frequency Control of Connected Multi-Area Multi-Source Power Systems using Energy Storage and Lyrebird Optimization Algorithm Tuned PID Controller,” *Journal of Energy Storage*, vol. 100, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[141] Arindita Saha et al., “Evaluation of Renewable and Energy Storage System-based Interlinked Power System with Artificial Rabbit Optimized PI(FOPD) Cascaded Controller,” *Ain Shams Engineering Journal*, vol. 15, no. 2, pp. 1-16, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[142] Xuehan Li et al., “Improving Frequency Regulation Ability for a Wind-Thermal Power System by Multi-Objective Optimized Sliding Mode Control Design,” *Energy*, vol. 300, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[143] J.C. Vinitha, Geetha Ramadas, and P. Usha Rani, “PSO based Fuzzy Logic Controller for Load Frequency Control in EV Charging Station,” *Journal of Electrical Engineering and Technology*, vol. 19, no. 1, pp. 193-208, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[144] D.V. Doan, K. Nguyen, and Q.V. Thai, “Load-Frequency Control of Three-Area Interconnected Power Systems with Renewable Energy Sources using Novel PSO~PID-Like Fuzzy Logic Controllers,” *Engineering, Technology and Applied Science Research*, vol. 12, no. 3, pp. 8597-8604, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[145] Ahmed Mohammed Attiya Soliman, Mostafa Bahaa, and Mohammed A. Mehanna, “PSO Tuned Interval Type-2 Fuzzy Logic for Load Frequency Control of Two-Area Multi-Source Interconnected Power System,” *Scientific Reports*, vol. 13, no. 1, pp. 1-14, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[146] Prasantini Samal et al., “Load Frequency Control in Renewable based Micro Grid with Deep Neural Network based Controller,” *Results in Engineering*, vol. 25, pp. 1-22, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[147] Ashok Kumar Mohapatra et al., “Design and Modelling of an AI Governed Type-2 Fuzzy Tilt Control Strategy for AGC of a Multi-Source Power Grid in Constraint to Optimal Dispatch,” *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 7, pp. 1-15, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[148] Rasmia Irfan et al., “Robust Operating Strategy for Voltage and Frequency Control in a Non-Linear Hybrid Renewable Energy-based Power System using Communication Time Delay,” *Computers and Electrical Engineering*, vol. 123, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[149] Rabindra Kumar Sahu, Sidhartha Panda, and Saroj Padhan, “Optimal Gravitational Search Algorithm for Automatic Generation Control of Interconnected Power Systems,” *Ain Shams Engineering Journal*, vol. 5, no. 3, pp. 721-733, 2014. [CrossRef] [Google Scholar] [Publisher Link]

[150] Satya Dinesh Madasu, M.L.S. Sai Kumar, and Arun Kumar Singh, “A Flower Pollination Algorithm based Automatic Generation Control of Interconnected Power System,” *Ain Shams Engineering Journal*, vol. 9, no. 4, pp. 1215-1224, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[151] Hisham Alghamdi et al., “A Novel Intelligent Optimal Control Methodology for Energy Balancing of Microgrids with Renewable Energy and Storage Batteries,” *Journal of Energy Storage*, vol. 90, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[152] Françoise Beaufays, Youssef Abdel-Magid, and Bernard Widrow, “Application of Neural Networks to Load-Frequency Control in Power Systems,” *Neural Networks*, vol. 7, no. 1, pp. 183-194, 1994. [CrossRef] [Google Scholar] [Publisher Link]

[153] D.K. Chaturvedi, P.S. Satsangi, and P.K. Kalra, “Load Frequency Control: A Generalised Neural Network Approach,” *International Journal of Electrical Power Energy Systems*, vol. 21, no. 6, pp. 405-415, 1999. [CrossRef] [Google Scholar] [Publisher Link]

[154] H.L. Zeynelgil, A. Demiroren, and N.S. Sengor, “The Application of ANN Technique to Automatic Generation Control for Multi-Area Power System,” *International Journal of Electrical Power and Energy Systems*, vol. 24, no. 5, pp. 345-354, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[155] Yusuf Oysal, “A Comparative Study of Adaptive Load Frequency Controller Designs in A Power System with Dynamic Neural Network Models,” *Energy Conversion and Management*, vol. 46, no. 15-16, pp. 2656-2668, 2005. [CrossRef] [Google Scholar] [Publisher Link]

[156] Aysen Demiroren, Neslihan S. Sengor, and H. Lale Zeynelgil, “Automatic Generation Control by using ANN Technique,” *Electric Power Components and Systems*, vol. 29, no. 10, pp. 883-896, 2001. [CrossRef] [Google Scholar] [Publisher Link]

[157] H. Shayeghi, and H.A. Shayanfar, “Application of ANN Technique based on μ-synthesis to Load Frequency Control of Interconnected Power System,” *International Journal of Electrical Power and Energy Systems*, vol. 28, no. 7, pp. 503-511, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[158] H. Shayeghi, H.A. Shayanfar, and O.P. Malik, “Robust Decentralized Neural Networks based LFC in a Deregulated Power System,” *Electric Power Systems Research*, vol. 77, no. 3-4, pp. 241-251, 2007. [CrossRef] [Google Scholar] [Publisher Link]

[159] Demirören, “Automatic Generation Control for Power System with SMES by using Neural Network Controller,” *Electric Power Components and Systems*, vol. 31, no. 1, pp. 1-25, 2003. [CrossRef] [Google Scholar] [Publisher Link]

[160] Lalit Chandra Saikia et al., “Automatic Generation Control of a Multi Area Hydrothermal System using Reinforced Learning Neural Network Controller,” *International Journal of Electrical Power and Energy Systems*, vol. 33, no. 4, pp. 1101-1108, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[161] Guangyu Chen et al., “Accurate Identification and Confidence Evaluation of Automatic Generation Control Command Execution Effect based on Deep Learning Fusion Model,” *Engineering Applications of Artificial Intelligence*, vol. 131, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[162] Peng Chen et al., “A Novel Load Frequency Control Strategy for Renewable Energy Power System by Coordinating Energy Storage and Thermal Power,” *Journal of Energy Storage*, vol. 108, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[163] Quan Lu, Wenxuan Huang, and Linfei Yin, “Decomposition Prediction Fractional-Order Active Disturbance Rejection Control Deep Q Network for Generation Control of Integrated Energy Systems,” *Applied Energy*, vol. 377, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[164] Peixiao Fan et al., “A Multi-Layer Intelligent Control Strategy for Multi-Regional Power System with Electric Vehicles: A Deep Reinforcement Learning Approach,” *Journal of Energy Storage*, vol. 103, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[165] T.P. Imthias Ahamed, P.S. Nagendra Rao, and P.S. Sastry, “A Reinforcement Learning Approach to Automatic Generation Control,” *Electric Power Systems Research*, vol. 63, no. 1, pp. 9-26, 2002. [CrossRef] [Google Scholar] [Publisher Link]

[166] Lihui Xie et al., “Automatic Generation Control Strategy for Integrated Energy System based on Ubiquitous Power Internet of Things,” *IEEE Internet of Things Journal*, vol. 10, no. 9, pp. 7645-7654, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[167] Lei Xi et al., “A Novel Controllable Bias Reinforcement Learning Method for Distributed Automatic Generation Control Integrated with Large-Scale Electric Vehicles,” *Electric Power Systems Research*, vol. 232, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[168] T.P. Imthias Ahamed, P.S. Nagendra Rao, and P.S. Sastry, “A Neural Network based Automatic Generation Controller Design through Reinforcement Learning,” *International Journal of Emerging Electric Power Systems*, vol. 6, no. 1, pp. 1-31, 2006. [CrossRef] [Google Scholar] [Publisher Link]

[169] Huaizhi Wang et al., “Multiobjective Reinforcement Learning-based Intelligent Approach for Optimization of Activation Rules in Automatic Generation Control,” *IEEE Access*, vol. 7, pp. 17480-17492, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[170] T. Yu et al., “Stochastic Optimal Generation Command Dispatch Based on Improved Hierarchical Reinforcement Learning Approach,” *IET Generation, Transmission and Distribution*, vol. 5, no. 8, pp. 789-797, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[171] Linfei Yin, Tao Yu, and Lv Zhou, “Design of a Novel Smart Generation Controller based on Deep Q Learning for Large-Scale Interconnected Power System,” *Journal of Energy Engineering*, vol. 144, no. 3, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[172] Rasananda Muduli, Debashisha Jena, and Tukaram Moger, “Application of Reinforcement Learning-based Adaptive PID Controller for Automatic Generation Control of Multi-Area Power System,” *IEEE Transactions on Automation Science and Engineering*, vol. 22, pp. 1057-1068, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[173] Jing Zhang et al., “A Load Frequency Control Strategy based on Double Deep Q-Network and Upper Confidence Bound Algorithm of Multi-Area Interconnected Power Systems,” *Computers and Electrical Engineering*, vol. 120, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[174] Tao Yu et al., “Stochastic Optimal Relaxed Automatic Generation Control in Non-Markov Environment based on Multi-Step Q(λ) Learning,” *IEEE Transactions on Power Systems*, vol. 26, no. 3, pp. 1272-1282, 2011. [CrossRef] [Google Scholar] [Publisher Link]

[175] Peng Xin et al., “Temporal Difference Learning with Multi-Step Returns for Intelligent Optimal Control of Dynamic Systems,” *Neurocomputing*, vol. 622, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[176] Ziming Yan, and Yan Xu, “Data-Driven Load Frequency Control for Stochastic Power Systems: A Deep Reinforcement Learning Method with Continuous Action Search,” *IEEE Transactions on Power Systems*, vol. 34, no. 2, pp. 1653-1656, 2019. [CrossRef] [Google Scholar] [Publisher Link]

[177] Lei Xi et al., “Research on the Multi-Area Cooperative Control Method for Novel Power Systems,” *Energy*, vol. 313, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[178] Yuemin Zheng et al., “Load Frequency Active Disturbance Rejection Control for Multi-Source Power System based on Soft Actor-Critic,” *Energies*, vol. 14, no. 16, pp. 1-17, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[179] Sundaravelu Lakshmi, and Anandraj Manonmani, “Optimizing Thermal Power Plant Efficiency through Washout Filter based Proportional Integral Derivative Controller,” *Heliyon*, vol. 11, no. 4, pp. 1-17, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[180] Lei Xi et al., “A Multi-Step Unified Reinforcement Learning Method for Automatic Generation Control in Multi-Area Interconnected Power Grid,” *IEEE Transactions on Sustainable Energy*, vol. 12, no. 2, pp. 1406-1415, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[181] Zhihong Huo et al., “Adaptive Event-Triggering Mechanism based Takagi-Sugeno Fuzzy Automatic Generation Controller Design for Offshore Wind Power System,” *Ocean Engineering*, vol. 302, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[182] Linfei Yin, and Da Zheng, “Hybrid Modeling with Data Enhanced Driven Learning Algorithm for Smart Generation Control in Multi-Area Integrated Energy Systems with High Proportion Renewable Energy,” *Expert Systems with Applications*, vol. 261, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[183] Farhan Ullah et al., “A Comprehensive Review of Wind Power Integration and Energy Storage Technologies for Modern Grid Frequency Regulation,” *Heliyon*, vol. 10, no. 9, pp. 1-24, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[184] Ye Yang et al., “Review of Vehicle to Grid Integration to Support Power Grid Security,” *Energy Reports*, vol. 12, pp. 2786-2800, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[185] Wei Hown Tee, Chin Kim Gan, and Junainah Sardi, “Benefits of Energy Storage Systems and its Potential Applications in Malaysia: A Review,” *Renewable and Sustainable Energy Reviews*, vol. 192, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[186] Dina A. Elalfy et al., “Comprehensive Review of Energy Storage Systems Technologies, Objectives, Challenges, and Future Trends,” *Energy Strategy Reviews*, vol. 54, pp. 1-27, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[187] Guangdou Zhang et al., “Data-Driven Load Frequency Cooperative Control for Multi-Area Power System Integrated with VSCs and EV Aggregators Under Cyber-Attacks,” *ISA Transactions*, vol. 43, pp. 440-457, 2023. [CrossRef] [Google Scholar] [Publisher Link]

Appendix 1

The following lists the articles used to create the chart showing the distribution of AI-based optimization algorithms in automatic generation control studies from the 2000s to the 2020s in Figure 3.

Algorithm	**2000-2009**	**2010-2019**	**2020-2025**
Fuzzy Logic	[24, 28, 29-48]	[25, 49-55]	[58-70]
Evolutionary Algorithm	[31, 32, 44, 72, 73, 74, 75-78]	[25, 49, 51, 52, 53, 71, 79-93]	[56, 94-101]
Swarm Intelligence	[41, 45, 46, 103, 104]	[50, 83, 105-122]	[123-148]
Machine Learning	[47, 48, 154, 155, 156, 157, 158, 159, 165, 168]	[54, 160, 169, 170, 171, 174, 176]	[17, 18, 21, 23, 65, 161, 162, 163, 164, 167, 172, 173, 175, 177, 178]
Hybrid	[31, 32, 41, 44-48]	[25, 49-55, 59, 83, 108, 109, 119]	[56, 59, 62-66, 96, 97, 124, 143-148]

Therefore, the distribution of AI algorithms in AGC can be observed from these articles.

- *Fuzzy Logic dominated in the 2000s,*
- *Evolutionary Algorithms dominated in the 2010s, and*
- *Swarm Intelligence dominated in 2020.*

Further analysis of this distribution is provided in Section 5, where Artificial Intelligence Optimization is explained in detail.