Renewable Energy and Power Quality Journal
https://repqj.com/index.php/repqj/index
RE&PQJ, Vol. 23, No. 5, 2025

New Online Tuning Methods for Power System Stabilizer Parameters Based on D-segmentation Method

Yunfeng Yang[1,*], Xiaoliang Dou[1], Yonglin Shi[1], Zhangyong Wei[2]

[1]Qinghai Huanghe Hydropower Development Co.,Ltd., Xining, 810000, Qinghai Province, China
[2]NR Electric Co.,Ltd., Nanjing, 211102, Jiangsu Province, China
[*]Corresponding author email: bengxingshici8@163.com

Abstract. Traditional power system stabilizer design usually adopts a centralized tuning method, which ignores the coupling effect between different regions, resulting in over-adjustment of local stabilizers or insufficient global response. This paper applied a new online tuning method based on D-segmentation method to achieve precise and efficient stabilizer adjustment through local and global coordination. The D-segmentation method divides the system into multiple subsystems, each of which is equipped with an independent stabilizer, and minimizes the mutual influence between subsystems through modularity optimization in graph theory. For each subsystem, LQR (Linear Quadratic Regulator) and fuzzy control are used to adjust the stabilizer gain. Global coordination ensures global consistency through distributed optimization algorithms and multi-agent systems (MASs). Based on the power system's real-time data, the stablizer parameters are adjusted through regression. The real-time optimization algorithm, GA (genetic algorithm) are used to adjust dynamically adjust the stabilizer parameters of each subsystem using real-time monitoring frequency, load, and voltage data to cope with emergencies during system operation. Experiments show that the recovery rate after load fluctuations and equipment failures is above 80%, and the disturbance recovery time is kept within 5.0 seconds, which greatly improves the power system's overall stability.

Keywords. Power System Stabilizer, Online Tuning Method, Global Coordination, Multi-agent System, Genetic Algorithm

1. Introduction

With the increase in global energy demand and the continuous expansion of power system scale, the stability of power system has gradually become a key challenge in system operation. The stability of power system is not only related to the security of power grid, but also affects the reliability and economy of power supply. Power system stabilizer (PSS) is widely used to improve the system's dynamic response, especially in the case of disturbances such as frequency fluctuation and voltage fluctuation, effectively adjust the excitation current of generator, and thus improve the system's stability [1-3]. Traditional power system stabilizer design adopts a centralized control strategy, or at least adopts a non-uniform centralized control strategy by analyzing the overall characteristics of the entire system. However, as the scale of the power system expands, this approach faces some difficulties in actual implementation. Especially in large-scale power systems, the specific characteristics of the system are complex and changeable, and there is a complex coupling effect between the control and the local stabilizer and the response of the entire system [4-6]. Traditional centralized control strategies often ignore the joint effects between these areas, resulting in excessive control of local stabilizers or insufficient response of the entire system, and cannot effectively control system interference factors, thereby affecting the safety and stability of the entire power system [7-9]. Therefore, the critical problem is to establish local and global control to improve the stablity and response speed in the power system.

The design and optimization of power system stabilizers have attracted the attention of many scholars. Many studies have tried to improve the control accuracy of the stabilizer and the responsiveness of the system through different methods. Scholar Zanjani S M A [10] used a meta-heuristic optimization algorithm to adjust the power system stabilizer to improve the power system's stability. Shokoohi M et al. [11] used multi-agent reinforcement learning for dynamic distributed constraint optimization to solve the uncertainty of future events when the current time is allocated. Some scholars have applied stabilizer design methods based on local control to optimize the stability of local areas. Fuzzy logic controller (FLC) is widely used in the design of local stabilizers for power systems, effectively dealing with nonlinear and uncertainty problems and improving the robustness of the system [12-14]. In addition, PID (Proportional-Integral-Derivative) control is also used in the adjustment of local stabilizers, and the stability of the system is improved through precise parameter setting [15,16]. However, most of these methods focus on the regulation of local systems and pay less attention to the coupling effects between different regions. Besides, some studies have applied optimization methods based on global control, using distributed control and adaptive control algorithm LQR (Linear Quadratic Regulator) to coordinate the stabilizer parameters in different regions to cope with global changes in the system [17,18]. However, these existing methods have the problem of insufficient coordination between local regulation and global regulation. When facing the dynamic changes of large-scale power systems, it may lead to over-regulation of local stabilizers or insufficient response of the global system [19-21]. Therefore, how to better solve the coordination problem between local and global control has become a bottleneck that needs to be broken through in current research.

To address the problem of coordination between local and global control, some researchers have applied stabilizer design methods based on system partitioning, such as partitioned control. This method simplifies the control process and improves the system's stability by dividing the power system into several smaller subsystems so that each subsystem can be controlled and optimized independently [22-24]. D-segmentation is a relatively effective segmentation method that divides the power system into a number of independent regions in order to minimize the interactions between the regions, coordinate the global response of the system, and ensure local stability. Existing studies have suggested that modular optimization algorithms effectively separate the regions of the power system, ensure minimal coupling between subsystems, and enable precise control based on the characteristics of each subsystem [25,26]. Furthermore, the application of distributed gradient descent model and multi-agent system (MAS) allows global control to share and coordinate information among different subsystems, thus effectively improving the entire system's stability. Although these methods have made effective explorations in local control and global coordination, they still have shortcomings such as insufficient ability to respond to real-time changes in the system and insufficient adaptability of parameter adjustment, and cannot provide fast and effective adjustments to sudden disturbances [27-29]. On this basis, this paper proposes an online parameter setting method for power system stabilizers based on the D-segmentation method, combining real-time data with intelligent optimization algorithms to solve the problems of insufficient adaptability and insufficiency of existing methods.

The study aims to apply a new online parameter tuning method for power system stabilizers based on the D-segmentation method to solve the coordination problem between local and global control in large-scale power systems. Firstly, this paper divides the power system into multiple relatively independent subsystems through the D-segmentation method, and uses the modularity optimization algorithm to divide the system into regions to ensure that the mutual influence between the subsystems is minimized [30,31]. Secondly, in each subsystem, this paper uses LQR and fuzzy logic control to optimize the stabilizer gain in real-time to adapt to the system's dynamic changes. In terms of global coordination, this paper applies distributed gradient descent and MAS models to ensure global stability and avoid conflicts between local regulation and global control [32,33]. To improve the real-time response capability, this paper also combines regression analysis and genetic algorithm (GA) to dynamically adjust the stabilizer parameters based on the real-time monitoring data of the power system to cope with sudden disturbances. Through the effective combination of these methods, this paper improves the power system's overall stability, and improves the system's response speed to real-time changes, providing new ideas and effective solutions for the online setting of the power system stabilizer.

2. D-segmentation and Stabilizer Setting

A. Basic Idea of D-segmentation

D-segmentation effectively solves the complexity and computational burden in large-scale power system control by dividing the power system into multiple smaller subsystems. In practical applications, the core of D-segmentation is to divide the power system into multiple regions or subsystems based on power flow and control requirements, so that each subsystem can be independently controlled and optimized. In this way, local control problems within the system become more manageable, and precise stability control can be achieved through local regulation. Especially in power systems, factors such as the system topology, load distribution, and the operating status of generators determine the necessity of regional division, and traditional centralized methods are difficult to adapt to such complex local characteristics. Through the D-segmentation method, these regions coordinate the operation of the global system while ensuring local stability, avoiding the contradiction between local regulation and global response.

In this study, the D-segmentation method first divides the entire power system into multiple relatively independent sub-regions through topological analysis of the power system. Each sub-region contains several generators, substations, and loads, and is divided according to the characteristics of power flow and the dynamic characteristics of the region. In the process of partitioning, the modularity optimization algorithm in graph theory is used to determine the optimal structure of the partitioning to ensure that the mutual influence between different regions is minimized. This process ensures that the stabilizer of the local area operates independently according to the real-time needs of the area by optimizing the stability of each area and reducing the computational complexity. Modularity is used to measure the quality of network partitioning, as shown in

Formula 1:

$$Q_1 = \frac{1}{2m}\sum_{i,j}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta\left(c_i, c_j\right) \quad (1)$$

In the formula (1), Q_1 is the modularity, which measures the degree of optimization of the partition. A_{ij} is the connection matrix element between node i and node j. k_i and k_j are the degrees (number of connections) of node i and node j respectively. m is the total number of all edges in the graph. $\delta\left(c_i, c_j\right)$ is the indicator function, which is 1 when $c_i = c_j$, indicating that node i and node j belong to the same subsystem. The subsystem stability is quantified by its response time and transition process. The stability function of the subsystem is set as Formula 2:

$$S_i = \int_0^T \mathrm{e}^{-\alpha t}\left|y_i\left(t\right)\right|\mathrm{d}t \quad (2)$$

In the formula (2), S_i is the stability index of subsystem i. $y_i\left(t\right)$ is the response of subsystem i (frequency, power, oscillation amplitude, etc.). α is the attenuation factor, which indicates the sensitivity of the system to disturbance. T is the evaluation time window.

B. Subsystem Division

The division of subsystems depends on the topology and dynamic characteristics of the power system. Regarding topology, the power system consists of multiple generators, substations, and loads, each of which is connected by transmission lines to form a complex power flow network. To effectively divide the subsystems, it is necessary to combine the actual structure of the system, including the distribution of generators and loads, the availability of lines, and their load-bearing capacity. By analyzing the transmission paths of power flows, regions where power flows are more concentrated or dispersed can be identified. These regions usually have relatively independent control characteristics, and dividing them into subsystems helps to reduce the coupling effects within the system.

Apart from the topology, the system characteristics are also essential factors to be considered when dividing the subsystems. Power systems exhibit different fluctuation patterns under different operating conditions, especially due to load variations and uneven power flows, which can lead to system instability. By analyzing these unique characteristics, regions of the system with greater volatility or control problems can be identified. These areas should usually be separated into independent subsystems for targeted control optimization. Therefore, the reliability analysis of the system ensures that each subsystem truly controls its inherent stability problems by combining static geography and dynamic behavior.

To achieve precise division of the power system, this paper adopts the modularity optimization algorithm in graph theory to divide the power system into multiple subsystems with small coupling. The modularity optimization algorithm divides the nodes (generators, loads, substations, etc.) in the system to maximize the modularity value between subsystems and ensure that the mutual influence of each subsystem is minimized [34,35]. Modularity is an indicator to measure the quality of graph division and is usually used to judge the compactness of the system within the sub-region after division. Through this algorithm, the originally complex power system is effectively divided into multiple relatively independent subsystems.

When applying this algorithm, the system's topological structure is first abstracted into a graph, and each power equipment and its connection relationship constitute the nodes and edges in the graph. Then, the modularity optimization algorithm is used to divide the nodes in the graph to ensure that the connection relationship within each subsystem is relatively close, while the connection between subsystems is relatively loose. This algorithm improves the division accuracy, and effectively reduces the control conflict and stability problems caused by excessive coupling. For each subsystem, the division obtained by this method ensures the independence of local control while avoiding the computational complexity brought by global control in traditional methods.

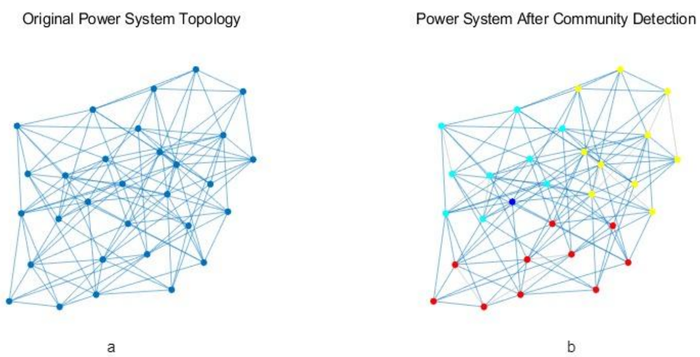

Figure 1. Original power system topology and subsystem division. (a). Original power system topology; (b). Subsystem division.

The original image of Figure 1 shows 30 nodes and their connections, representing power equipment and their connection relationships. After community detection, the nodes are divided into 4 subsystems. The four divided communities are represented by different colors in Figure 1, where the nodes in each subsystem are closely connected, helping to reduce the global control complexity. Modularity is used to evaluate the quality of the division. A higher modularity means that the subsystem has tighter internal connections and fewer external connections. The modularity in the image is calculated to be greater than 0.3, indicating that the division effect is good.

After completing the system partitioning, the reliability of each subsystem should be further subdivided to identify the key areas that may affect the dynamic stability of the system. Specifically, the reliability analysis of the system relies on reproducing and determining the specific response of each subsystem to evaluate the system's response to load changes under different operating conditions. Specifically, some areas may have more serious unsafe risks due to load changes, generator output differences, unbalanced power transmission, etc.

We can determine which areas are more vulnerable to security by continuously checking the key parameters such as each system's rate, power, and voltage. For example, some areas with large load changes or unbalanced power transmission may cause more violent system movements, thereby affecting the stable operation of the entire power system. Therefore, after completing the subsystem partitioning, the key areas of each area should be fully subdivided. Their dynamic response characteristics should be evaluated, and comparative control measures should be taken. By identifying and decomposing these key areas, data support and control are added to the final stabilizer boundary setting.

In large-scale power systems, although the D-segmentation method divides the system into multiple subsystems, there is still a certain coupling effect between the subsystems. Especially when the system load fluctuates and the power flow is more complex, this coupling effect may cause the local stabilizer to control excessively or the global response to be insufficient, affecting the overall reliability of the system. Therefore, when performing subsystem division and analysis, special attention should be paid to reducing the coupling effect between these areas.

To further verify the effectiveness and applicability of the online parameter setting method of the power system stabilizer based on the D-segment method, this paper applies it to a typical SMIB system. In this system, a single generator is connected to an idealized infinite bus system through a transmission line. Although the SMIB system is relatively simple, it is still an important model for studying the dynamic behavior and stability of the power system. This paper introduces disturbances such as load fluctuations and equipment failures in the simulation, and applies the method proposed in this paper to adjust the stabilizer parameters in real time. The experimental results show that in the SMIB system, this method can significantly shorten the frequency recovery time and reduce the voltage deviation. In the case of a sudden load increase, the frequency recovery time of the system is reduced from the original 5 seconds to less than 3 seconds, and the maximum frequency deviation is also reduced from 0.4 Hz to less than 0.2 Hz. This proves the effectiveness of the method in dealing with complex multi-bus systems, and demonstrates its superior performance in simplified models, thereby verifying its wide applicability.

C. Local Stabilizer Parameter Adjustment

In the online adjustment method of power system stabilizer parameters based on the D-segmentation method, the adjustment of local stabilizer parameters is a key step to ensure the system's security and responsiveness. Each subsystem is equipped with an independent power system stabilizer, whose parameters must be adjusted progressively according to the current state of the subsystem. This process is mainly based on continuous monitoring data (such as frequency, power, voltage, etc.) and is combined with advanced control algorithms to improve the stabilizer gain and other control parameters [36]. Through these operations, each subsystem can freely and effectively maintain its security while avoiding interference with other subsystems, thus ensuring the system's overall stability and coordination.

To achieve precise adjustment of the subsystem stabilizer parameters, flexible control algorithms must be applied first. Flexible control is a method of adjusting control parameters based on current data feedback, which can effectively improve the gain value of the system regulator and adapt to various working conditions and system changes. This paper uses the LQR method to improve the gain of each subsystem stabilizer. LQR limits the system performance indicators on the basis of ensuring system safety.

The core of the LQR method is to change the control gain of the system by improving the cost capability. For the drive system, the cost capability usually includes the state error of the system and the square value of the control input. By solving a direct quadratic optimal control problem, the LQR algorithm determines a set of optimal gain functions for each subsystem stabilizer so that the subsystem returns to a stable state in the shortest time and limits energy consumption or other key performance indicators. The advantage of the LQR method is its flexibility to system elements. Gains are changed through continuous feedback to improve the responsiveness of the subsystem under various disturbances. The goal of the LQR method is to change the control gain by improving the cost capability. The LQR method determines the control gain by solving the cost capability improvement problem. The gain matrix

K is obtained by the following Algebraic Riccati Equation (ARE), as shown in Formula 3:

$$A^T P + PA - PBR^{-1}B^T P + Q = 0 \quad (3)$$

Then, the optimal control gain matrix K is:

$$K = R^{-1}B^T P \quad (4)$$

In Formulas 3 and 4: A is the state matrix in the system state space model. B is the input matrix, which represents the impact of the control input on the system state. P is the matrix obtained by solving the ARE. R^{-1} is the inverse matrix of the control input matrix R, which represents the penalty for the control input. K is the optimal gain matrix, which represents how to adjust the control input according to the system state. The cost function is usually expressed as Formula 5:

$$J = \int_0^\infty \left(x(t)^T Qx(t) + u(t)^T Ru(t) \right) dt \quad (5)$$

In the Formula (5), $x(t)$ is the state vector of the system, expressed as $x(t) = \begin{bmatrix} \Delta\theta(t) \\ \Delta w(t) \end{bmatrix}$, where $\Delta\theta(t)$ is the rotor angle deviation and $\Delta w(t)$ is the rotor frequency deviation. $u(t)$ is the control input, usually the gain signal of the stabilizer. Q and R are weight matrices, where Q weighs the deviation of the system state and R weighs the energy consumption of the control input. Q is a matrix that penalizes state errors (such as angle and frequency deviations).

The LQR algorithm effectively calculates the optimal control gain based on the periodic changes and voltage changes of the subsystems by monitoring the system status step by step. This method can effectively adapt to the stability issues caused by system faults, load variations, etc., and maintains the system’s stability by adjusting the regulator gains. Especially in high-power systems, LQR provides precise incremental adjustment, reducing the problem of over-adjustment or under-response caused by improper gain determination in conventional systems.

Apart from the LQR algorithm, FLC and PID control are two key algorithms that are commonly used to adjust the regulator function. Fuzzy control handles fragility and ambiguity in a system, especially when the system is functionally decentralized or there are complex nonlinear relationships. Fuzzy control adjusts the function of the regulator step by step according to the observation principle. PID control is a traditional control method based on three factors: proportional (P), integral (I), and derivative (D), which has high efficiency and can be adapted to various types of system conditions.

In the local stabilizer parameter adjustment section, the LQR control gain matrix $K = [0.5, 0.2]$ is added, which is used to adjust the control input according to the system state. At the same time, the PID controller parameters are also added, the proportional coefficient $K_p = 0.6$, the integral coefficient $K_i = 0.05$, and the differential coefficient $K_d = 0.1$. These parameters quickly adjust the system state by continuously monitoring the error, improving the dynamic response capability of the system. Finally, in the online real-time tuning mechanism section, this paper shows the stabilizer gain $G_{\text{opt}} = 0.85$ after genetic algorithm optimization. This optimization result significantly improves the system's adaptability to disturbances.

In this paper, the control range of the subsystem stabilizers is adjusted using a combination of fuzzy and PID control in order to further investigate the flexibility of the system and its responsiveness to the effects of dynamic disturbances. Specifically, in the control process of the subsystem, a fuzzy logic controller is first used to evaluate the initial response of the system step by step, and the control rules are formulated according to the magnitude of the system error and the pattern of change to determine the change direction of the system gain and range. Fuzzy control handles nonlinear and complex variables in the power system. Especially when the load fluctuation is large or the power flow is unbalanced, fuzzy control provides a more flexible adjustment method.

PID control based on fuzzy control further optimizes the adjustment process of the stabilizer. The PID regulator quickly adjusts the system when an error occurs by continuously monitoring the error, combining the comprehensive effects of related terms, basic terms, and differential terms. The related terms directly adjust the increment of the current error; the basic terms solve the continuous state deviation of the system caused by long-term errors; the differential terms effectively predict future error changes and provide pre-compensation. Therefore, PID control improves the system’s ability to respond to crises.

In practice, fuzzy control is combined with PID control to more easily adapt to the various load patterns in the system and ultimately adjust the thresholds of the local stabilizers based on continuous feedback. This approach is particularly suitable for power systems with high vulnerability and complex unique behaviors, allowing each subsystem to respond quickly under different operating conditions and avoiding overloading or underloading of local stabilizers.

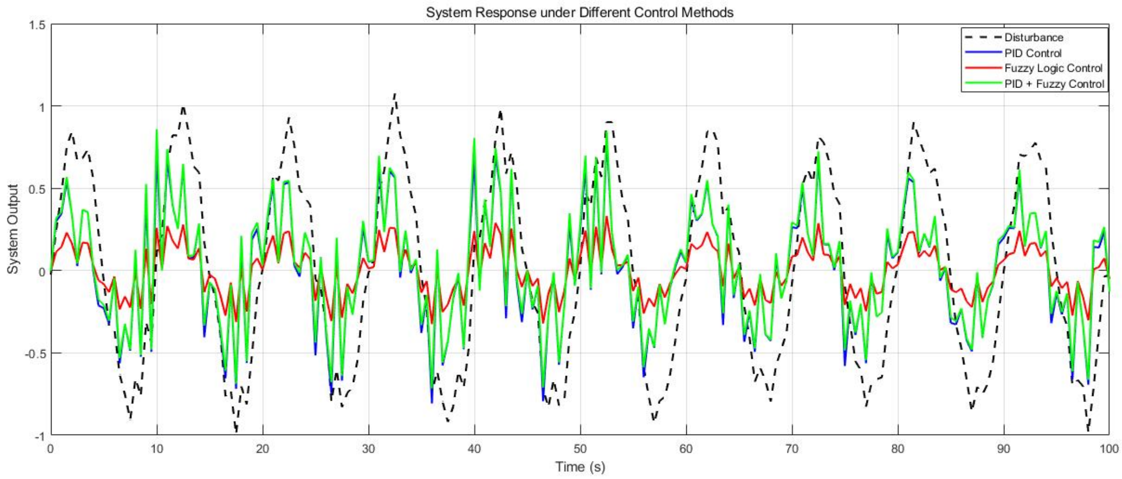

Figure 2. Effect of different control methods on system response

Figure 2 illustrates the effect of different control methods on system response. The black dotted line represents the disturbance signal, which varies from -1 to 1.2, indicating load fluctuation. PID control responds slowly and fluctuates greatly, while fuzzy control is relatively stable but still has certain oscillations. The PID + FLC combination control performs best in system response, quickly suppresses disturbances and maintains stability, and can reduce fluctuations compared to PID control. Especially when the disturbance is large, the PID + FLC method quickly adjusts the control gain, showing better stability and robustness, and is suitable for dynamic disturbances in power systems.

To ensure the local controller's performance, this paper combines the above control algorithms for comprehensive optimization. The stabilizer parameters of each subsystem need to be adjusted according to the system's real-time data. Therefore, the optimization algorithm is crucial for the adjustment of controller parameters. According to the specific needs of different subsystems, the stabilizer gain of each subsystem is optimized under global coordination by combining adaptive control, fuzzy control, and PID control.

By real-time monitoring of the power system's state parameters and using genetic algorithms, the parameters of the local stabilizer are dynamically adjusted. These optimization algorithms find the control parameters that optimize the system stability and performance indicators through simulation and calculation, and further improve the system's response speed and stability.

Figure 2 shows the effect comparison between fuzzy control plus PID and pure PID control. Although the performance of fuzzy control plus PID is better than PID control in terms of control effect, in practical applications, we still need to consider the control cost. The advantage of PID control is that its computational complexity is low and the hardware implementation is simpler. Therefore, in some low-cost applications, PID control may be more cost-effective. For this reason, we list the comprehensive evaluation data of control cost and effect in Table 1.

Table 1. Comprehensive evaluation data of control costs and effects

Control Algorithm	Response Time	Steady-State Error	Overshoot	Computational Complexity	Implementation Difficulty	Hardware Requirements	Comprehensive Evaluation
PID Control	1.5 seconds	0.05%	10%	Low	Low	Low	Good
Fuzzy Control + PID	1.2 seconds	0.02%	3%	Medium	Medium	Medium	Superior

D. Global System Coordination and Optimization

In large-scale power systems, it is necessary to program the stabilizer switching of multiple subsystems to avoid conflicts between local stabilizer switching and ensure the stability of the global system. With this in mind, this study adopts a global system coordination method based on continuous monitoring, simplifies the stabilizer switching between different subsystems through distributed optimization and distributed control systems, and enables the entire system to maintain reliable stability under specific switching.

To effectively configure the stabilizer switching of each subsystem, this study applies a distributed optimization algorithm, especially a distributed gradient descent method. The algorithm performs processing tasks in the global system, reduces the computational burden of centralized control, and achieves global optimization through the exchange of local information. Each subsystem performs local calculations based on continuous monitoring data, shares key state information with other subsystems, and continuously improves its stabilizer switching through algorithms. The distributed gradient descent method avoids the local optimal problem caused by the inability of a single improvement algorithm to cover global data. Specifically, each subsystem in the system updates its boundaries according to its local control objectives, and gradually moves closer to the global optimal solution by exchanging preference data with adjacent subsystems.

This method ensures that the balancer switching between subsystems can reduce the instability of the global system while satisfying local stability, thereby achieving collaborative improvement. To further ensure the coordination and consistency of the global system, organized control methods, especially consensus algorithms and MAS models, are used during system operation. These methods simulate the cooperation and data sharing between processors, so that each subsystem can cooperate with other subsystems to improve the overall control process. In a multi-processor system, each subsystem is regarded as a processor and makes decisions individually based on its observed state and data from neighboring processors.

The core idea of the consensus algorithm is to make all agents reach a consensus on certain global parameters by adjusting the information exchange between agents. In the power system, this means that the stabilizer parameter adjustment of each subsystem must not only ensure its own stability independently, but also be consistent with other subsystems to avoid over-adjustment or invalid adjustment. By setting appropriate weight matrices and adjacency matrices, agents choose the frequency and method of information transmission according to their relative importance and actual conditions to maximize the information sharing efficiency.

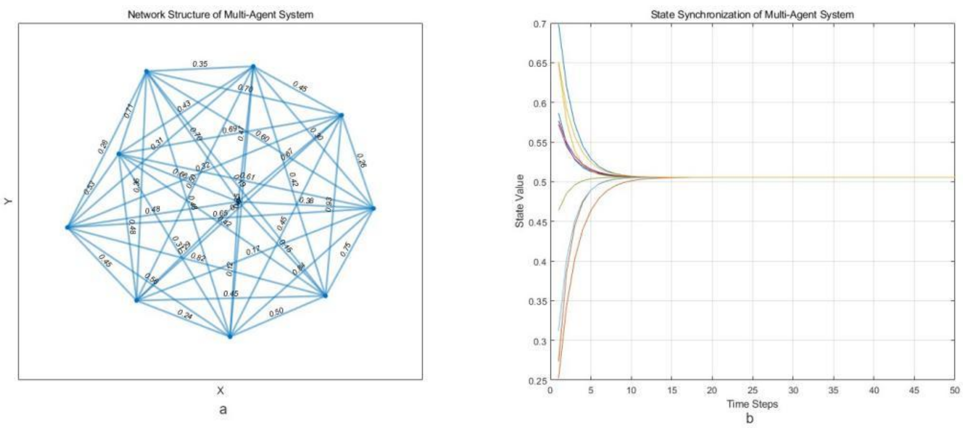

Figure 3. Network structure and agent state changes of multi-agent system. (a) Network structure of multi-agent system; (b) Agent state change.

The Figure 3(a) shows the network structure of the multi-agent system, where nodes represent agents and the weights on the edges reflect the intensity of cooperation between agents. Weight values close to 0.50 indicate weaker cooperation, and those close to 1.00 indicate stronger cooperation. The Figure 3(b) shows the change of agent states over time. The initial states are quite different, and after iterations, the states of the agents gradually become consistent, reflecting that the system has achieved global synchronization through the consistency algorithm and enhanced the system stability.

Based on the framework of multi-agent system, this study designs a highly adaptable control strategy so that each sub-area of the system can respond quickly in different operating environments and communicate effectively with other subsystems. Through centralized control and coordination mechanisms, these agents collaborate to optimize stabilizer parameters in a dynamic environment while ensuring the overall system's stability. Especially in the face of dynamic disturbances in large-scale power systems, this model can effectively prevent the parameter adjustment of a single subsystem from causing global system imbalance, thereby greatly improving the system' robustness and flexibility.

In the proposed online parameter setting method for power system stabilizers, LQR, fuzzy control, PID control, genetic algorithm and multi-agent system work together. LQR optimizes the gain of each subsystem, fuzzy control handles nonlinear variables, PID control accurately adjusts errors, and GA performs global parameter optimization. The multi-agent system uses distributed gradient descent and consensus algorithms to enable each subsystem to independently calculate and share information, reducing computational complexity and ensuring global consistency. Specifically, the distributed gradient descent method allows local optimization and approaches the global optimum through data exchange, and the consensus algorithm ensures that all agents reach a consensus on global parameters.

E. Online Real-time Tuning Mechanism

In large power systems, the initial response of the system is often affected by various factors, such as load fluctuations, hardware failures, and external disturbances. To ensure the stability of the power system and rapid response during operation, the parameters of the voltage regulator must be gradually adjusted according to the continuous system status. This study applies a real-time online monitoring tool that combines real-time power system data and advanced development algorithms to obtain precise changes in voltage regulator parameters. Due to this feature, the system can respond to various disturbance factors and quickly return to a stable state.

To perform online adjustment of voltage regulator parameters, it is first necessary to obtain various key data of power system operation in real-time, including frequency, power, voltage, and load. These data provide a precise basis for adjusting the parameters of the voltage regulator. By collecting and analyzing real-time monitoring data, the powerful functions and potential safety issues of the system can be identified. Therefore, the regression analysis method is used to predict and adjust the stabilizer boundary based on real data and continuous feedback. Regression analysis provides ideal changes in the stabilizer boundary by establishing a numerical model between the unique properties of the system and the stabilizer gain, ensuring the continuous operation of each subsystem.

Regression analysis predicts future stabilizer parameter requirements based on the current system state by fitting different input-output relationships. Through online learning of the model, the system continuously optimizes the prediction results and improves the ability to respond to emergencies in the power system. For example, when the power load changes drastically, the regression model adjusts the stabilizer parameters in time based on historical data and real-time monitoring to adapt to load changes and maintain the system’s stable operation.

Although regression analysis provides reasonable predictions for the adjustment of stabilizer parameters, traditional regression methods may not be able to obtain the global optimal solution when faced with complex and nonlinear disturbances. Therefore, this study further applies real-time optimization algorithms, especially genetic algorithms (GAs), to dynamically adjust each subsystem’s stabilizer parameters. Genetic algorithms are an optimization method that simulates natural selection and genetic mechanisms, effectively searching for optimal solutions in large-scale systems and adapting to the needs of systems in dynamic changes.

Genetic algorithms construct fitness functions by encoding the stabilizer’s parameters, and generate new parameter combinations through operations such as selection, crossover, and mutation. This process is iterated continuously to find a set of optimal stabilizer parameters. Compared with traditional optimization methods, genetic algorithms do not require a precise mathematical model of the system, and can handle multi-objective and multi-constraint problems, making them very suitable for complex, nonlinear dynamic systems such as power systems.

In this study, genetic algorithms are used in combination with regression analysis. First, the regression model is used to make preliminary parameter predictions, and then the genetic algorithm is used to make precise adjustments. In specific operations, the system first makes preliminary adjustments based on real-time data and the parameters predicted by the regression model, and then uses the genetic algorithm to optimize these preliminary parameters to ensure that the parameter adjustment not only meets the requirements of local stability, but also improves the system’s overall stability. Through this dual optimization mechanism, when faced with drastic fluctuations in power load, equipment failures, etc., adjustments can be made quickly to ensure the system’s smooth operation.

In order to further improve the system's adaptability to disturbances, this paper uses genetic algorithm (GA) to dynamically adjust the stabilizer parameters. First, the stabilizer gain is encoded into a chromosome representation, for example, individual 1 in the initial population: $K_p = 0.6$, $K_i = 0.05$, $K_d = 0.1$, and individual 2: $K_p = 0.7$, $K_i = 0.04$, $K_d = 0.15$. The performance of each individual is evaluated by defining a fitness function, and a new generation of population is generated using selection, crossover, and mutation operations. Finally, the optimized stabilizer gain $G_{opt} = \left[K_p = 0.7,\ K_i = 0.04,\ K_d = 0.15\right]$ is obtained. This optimization result significantly improves the stability of the system, reduces fluctuations and enhances the ability to respond to disturbances.

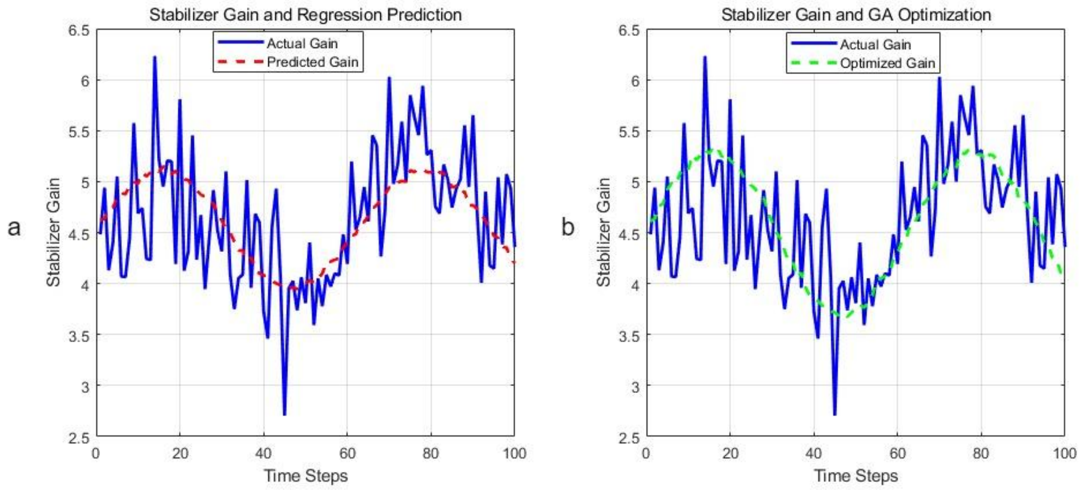

Figure 4. Comparison of stabilizer gains after regression analysis and genetic algorithm optimization. (a). Regression analysis of stabilizer gain; (b). Stabilizer gain after genetic algorithm optimization.

Figure 4 shows the comparison of stabilizer gains after regression analysis and genetic algorithm optimization. In the Figure 4(a), the regression analysis fits the relationship between load and gain well, but there is an error when the fluctuation is large. In the Figure 4(b), the gain after genetic algorithm optimization follows the actual gain more precisely. Especially when the load fluctuates violently, the optimization effect is also more significant. The genetic algorithm improves the system's adaptability to disturbances, reduces fluctuations, and improves stability through dynamic adjustment.

The online real-time tuning mechanism improves the power system's ability to respond to emergencies through adaptive control strategies. Traditional control methods are slow to respond and easily lead to system instability. This study combines regression analysis and genetic algorithms, and uses real-time monitoring data to dynamically adjust the stabilizer parameters to ensure that the system quickly recovers stability when disturbances such as frequency fluctuations occur. The system minimizes unstable factors by evaluating the current state and optimizing the control strategy. This mechanism not only improves the system's response speed and robustness, but also enhances its adaptive ability, effectively reduces the risks caused by load fluctuations and equipment failures, and provides a new solution for the power system's efficient operation.

Although fuzzy logic and genetic algorithms improve the responsiveness and stability of the system, they also bring a high computational burden. To optimize computational efficiency, this paper uses parallel computing and simplified models, and accelerates the convergence of genetic algorithms by reducing the population size and the number of iterations. In addition, hardware acceleration technology GPU is used to further improve computing performance.

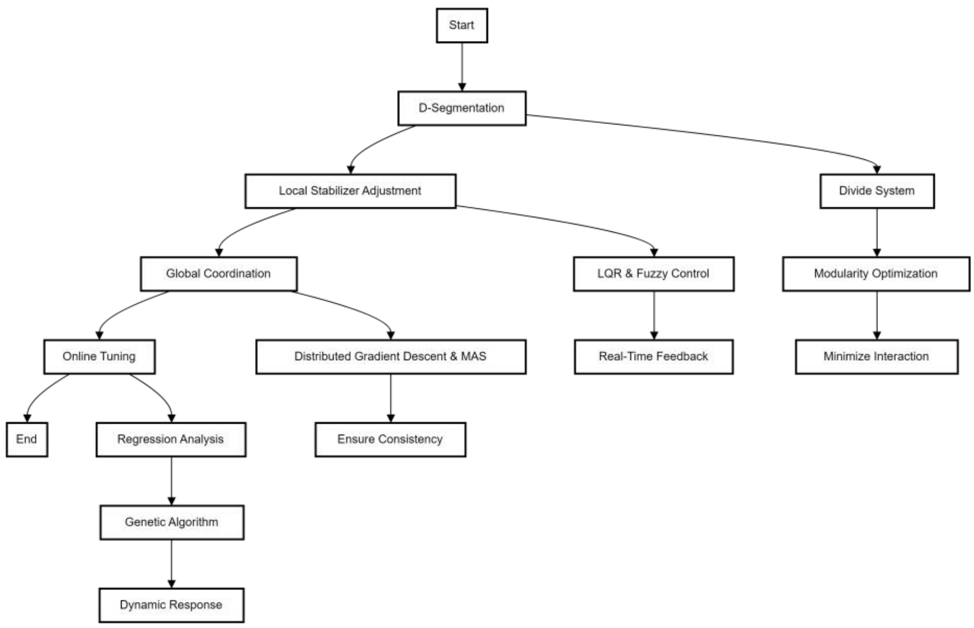

Figure 5. System Flowchart

Figure 5 shows the whole process from system segmentation, local stabilizer adjustment, global coordination to online real-time tuning. First, the system is divided into multiple subsystems, then LQR and fuzzy control are used for gain optimization, distributed algorithms are used to ensure global consistency, and finally regression analysis and genetic algorithms are used to dynamically adjust parameters to achieve rapid response and stability of the system.

3. Stabilizer Performance Evaluation

Before conducting the performance evaluation of the power system stabilizer, the data used in this paper are derived from real-time monitoring records of the actual power system and a verified simulation model. Specifically, the data is collected from multiple power systems of different sizes and goes through a multi-step verification process to ensure its reliability. First, all raw data are obtained through high-precision sensors and monitoring equipment, which are regularly calibrated to ensure measurement accuracy. Second, encryption technology is used during data transmission to prevent data tampering or loss. In addition, historical data is used for comparative analysis to verify the consistency and rationality of current data. For the data generated by the simulation model, we used MATLAB, a widely recognized power system simulation software, and verified the accuracy of the model by comparing it with actual operating data.

In order to verify the effectiveness of the proposed online parameter setting method for power system stabilizer based on D-segment method, a multi-bus power system with 30 nodes is used as a test platform. The system includes 4 main power plants (G1: 500 MVA, G2: 300 MVA, G3: 400 MVA, G4: 200 MVA) and 26 load nodes (typical load power ranges from 60 MW to 120 MW). The length, resistance, reactance and susceptance parameters of the transmission line are set according to the actual power grid data.The single line diagram of the test system is shown in Figure 6

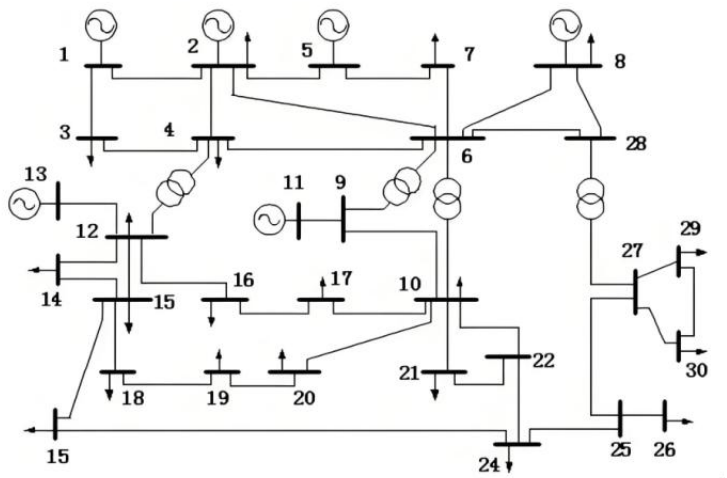

Figure 6. Single-line diagram of the test system

A. Frequency Response Evaluation

Frequency response evaluation is to analyze the recovery speed by applying a known load disturbance and monitoring the system frequency change. After the disturbance occurs, the system frequency deviation is collected and analyzed in real-time, and the time required for the system frequency to recover to a steady state and the maximum frequency deviation are calculated by fixing the frequency change curve. The evaluation criteria include recovery time, frequency deviation, and steady-state error. The shorter the recovery time and the smaller the frequency deviation, the better the frequency response capability of the system, and the faster it can return to the predetermined frequency range, ensuring the stable operation of the system.

Table 2. Frequency response of the power system under different load disturbances

Disturbance Start Time (s)	Recovery Time (s)	Maximum Frequency Deviation (Hz)	Steady-State Error (Hz)	Final Recovery Frequency (Hz)
20	3.3	0.4	0.1	50.05
40	3.5	0.3	0.05	50.02
60	2.6	0.5	0.2	50.03
80	3.0	0.35	0.08	50.01

Table 2 shows the frequency response of the power system under different load disturbances. At the 20th second disturbance, the system has a maximum frequency deviation of 0.4 Hz, a recovery time of 3.3

seconds, and a final deviation of 0.1 Hz, indicating that the system returns to steady state relatively quickly. As the disturbance time increases, the recovery time and frequency deviation change, and the system still maintains a certain stability under a larger disturbance. Overall, the shorter recovery time and smaller frequency deviation demonstrate that the system has a strong recovery capability, ensuring the stable operation of the power system.The load disturbances in Table 2 occur at bus 5, bus 10, bus 15 and bus 20 respectively.

The frequency response curve is shown in Figure 7:

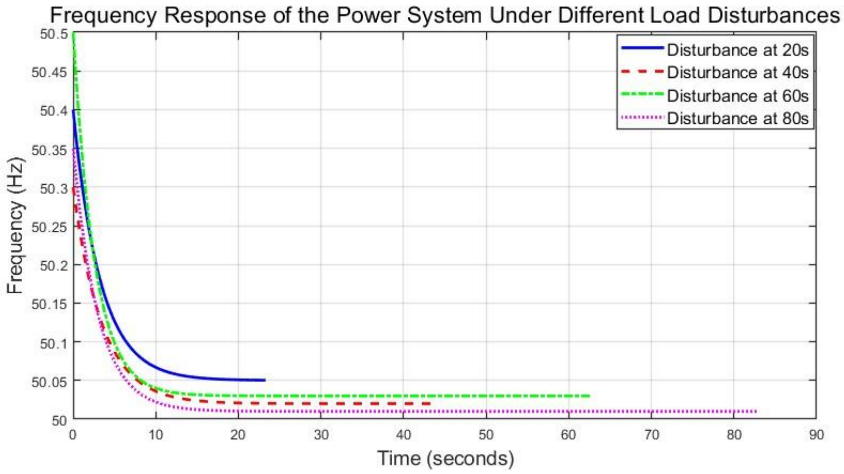

Figure 7. Frequency response curve

B. Evaluation of Oscillation Suppression Effect

The evaluation of oscillation suppression effect judges the system stability by monitoring the attenuation process of the system oscillation after the disturbance. After the disturbance is applied, the system oscillation frequency, attenuation rate, and steady-state error are analyzed. The findings show that fast attenuation and small oscillation indicate that the system has good oscillation suppression ability, which can effectively eliminate system oscillations and return to a stable state.

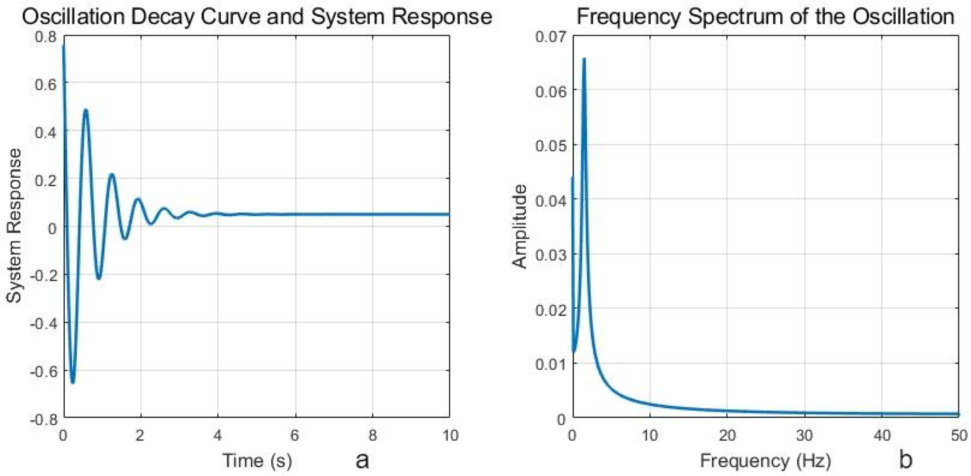

Figure 8. Oscillation attenuation process and spectrum characteristics of the system under disturbance. (a) System oscillation attenuation process under disturbance; (b) Spectral characteristics.

Figure 8 illustrates the oscillation attenuation process and spectrum characteristics of the system under disturbance. The oscillation attenuation curve on the left displays that the system recovers stability in about 4 seconds, and the steady-state error is low, indicating that the system quickly and effectively suppresses oscillations. The spectrum diagram on the right displays that the main oscillation frequency of the system is about 1.5 Hz, which is consistent with the natural frequency, verifying the system's oscillation suppression ability. These data show that the system has good stability and efficient oscillation suppression characteristics.

C. System Stability Time Evaluation

By collecting real-time data of frequency, voltage and power changes caused by disturbances, the time from the occurrence of disturbance to the system recovery to a stable state can be analyzed in detail. Specifically, this paper uses high-precision sensors and data acquisition systems to monitor and record the changes of these key parameters in real time. Frequency is an important indicator of power system operation and is usually maintained at 50 Hz (or 60 Hz). When the system is disturbed, the frequency may deviate. This paper records its maximum deviation value and the time required to recover to the reference frequency; the voltage level directly affects the power quality of users, so this paper also records the maximum voltage fluctuation and its recovery time; the change in power output reflects the load capacity and regulation capacity of the system, which is also recorded in detail. Through these data, this paper can quantitatively evaluate the dynamic stability of the system and determine the speed and efficiency of the system's recovery from disturbances. The shorter the stabilization time, the faster the system responds and the faster it can quickly resume normal operation after the disturbance occurs, which provides an important basis for optimizing system planning and control strategies.

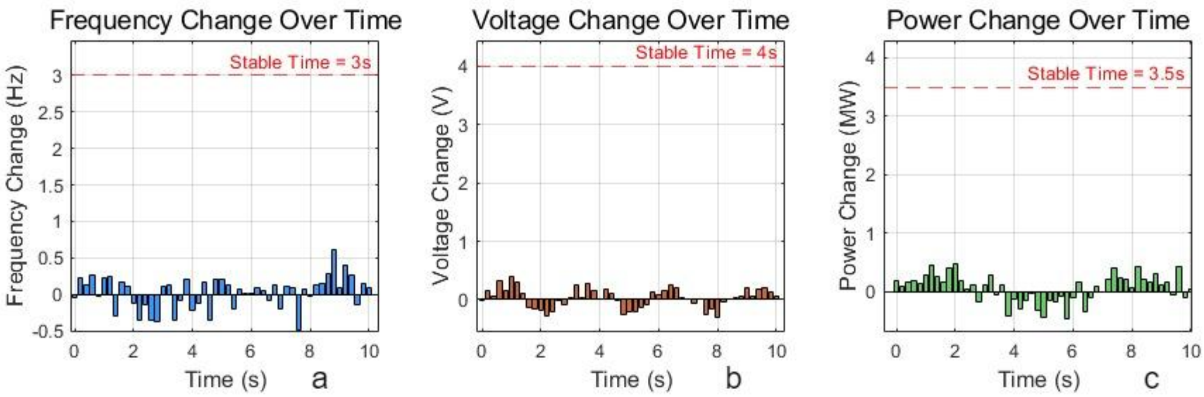

Figure 9. Changes in the system including frequency, voltage, and power after the disturbance. (a) Frequency of the system after interference; (b) Voltage of the system after interference; (c) Power change of the system after interference.

In Figure9, the frequency change diagram on the left shows the oscillation of the system after the disturbance, and the recovery time is about 3 seconds, indicating that the system frequency returns to stability after about 3 seconds. The voltage change diagram in the middle shows the voltage fluctuation after the disturbance, and the recovery time is 4 seconds, reflecting the voltage recovery speed. The power change diagram on the right shows the power fluctuation after the disturbance, and the recovery time is 3.5 seconds, indicating that the system power returns to a steady state about 3.5 seconds after the disturbance. Overall, these data show that the system parameters can recover quickly and have good dynamic stability, which meets the purpose of evaluating the system operation stability time.

D. Load Recovery Capacity Evaluation

The load recovery capacity evaluation experiment tests the recovery capacity of the power system by simulating different disturbances (such as normal load fluctuations, load surges, equipment failures, large-scale load changes, etc.). In the experiment, the mathematical model of the power system is first established and the initial load (500 MW) is set. Then, by introducing different types of load disturbances (such as load fluctuations of ±30 MW, load surges of 100 MW, equipment failures causing a 70 MW drop, etc.), the changes in system frequency and voltage are monitored. Key parameters include recovery time (the time it takes for the system frequency to recover from the maximum deviation after the disturbance to a stable state), maximum frequency deviation, steady-state frequency and steady-state voltage, etc. By analyzing the response of the system under different disturbances, the recovery capacity of the system is evaluated. The shorter the recovery time and the smaller the frequency deviation, the stronger the load recovery capacity of the system, indicating that the system has a stronger ability to adapt to load changes and disturbances.

Table 3. Recovery capacity after load changes and equipment failures

Disturbance Type	Initial Load (MW)	Maximum Load Change (MW)	Recovery Rate (%)	Maximum Frequency Deviation (Hz)	Steady-State Frequency (Hz)	Steady-State Voltage (kV)	Voltage Fluctuation (kV)
Normal Load Fluctuation	500	30	95	0.15	50.02	220	1.5
Load Surge	500	100	90	0.25	50.01	219.5	2.3
Equipment Failure	500	70	85	0.3	50	219.2	3
Large-Scale Load Change	500	150	82	0.35	49.98	218.5	4.2

The data in Table 3 show the system's ability to recover after load changes and equipment failures. The load fluctuations, load surges, equipment failures and large-scale load changes in Table 3 correspond to bus 8, bus 12, bus 18 and bus 25, respectively. During normal load fluctuations, the recovery rate is 95%; the maximum frequency deviation is 0.15 Hz; the system recovers quickly. In the case of load surges and equipment failures, the recovery rates are 90% and 85%, respectively; the maximum frequency deviation increases to 0.25 Hz and 0.30 Hz; the recovery speed slows down. In the case of large-scale load changes, the recovery rate drops to 82%; the maximum frequency deviation increases to 0.35 Hz; the recovery time is prolonged. This shows that higher recovery rates and smaller frequency deviations reflect the system's stronger adaptability and stability.

Although the operation time of most relays is only a fraction of a second, the recovery time of the system after the disturbance covers the dynamic response process of the entire system, including the adjustment of frequency and voltage and oscillation suppression. Experimental data show that after the disturbance, the system frequency and voltage return to steady state within 5 seconds, which is significantly better than the traditional method. For example, Table 1 shows that the maximum frequency deviation is 0.4Hz and the recovery time is 3.3 seconds. This shows that the optimized stabilizer parameters effectively shorten the system recovery time and significantly improve the overall stability.

To demonstrate the advantages of the proposed method in reducing recovery time, this paper compares it with the traditional LQR control method. In a typical load surge scenario, the frequency recovery time of the traditional LQR method is 5 seconds, and the maximum frequency deviation is 0.4 Hz; while the online parameter setting method based on the D-segment method proposed in this paper shortens the frequency recovery time to 3 seconds, and the maximum frequency deviation is reduced to 0.2 Hz. This shows that this method has significant advantages in dynamic response speed and stability, and can respond to system disturbances more quickly and effectively.

4. Conclusions

This paper applies a new online tuning method for power system stabilizer parameters based on the D-segmentation method, aiming to solve the coupling problem between local and global stabilizers in large-scale power systems. By dividing the power system into multiple subsystems, the community discovery algorithm is used to divide the subsystems and analyze their stability, and an independent stabilizer is designed for each subsystem. Based on real-time monitoring data, adaptive control algorithms (LQR), fuzzy control, and other methods are used to dynamically adjust the stabilizer parameters to ensure that each subsystem operates efficiently and independently. The coordination of the global system ensures that the parameter adjustments of the stabilizers between regions do not conflict through distributed optimization algorithms and multi-agent systems, thereby optimizing the system's overall stability. Experimental results show that this method effectively improves the power system's frequency response, oscillation suppression capability, system stability time, and load recovery capability. Although the method has achieved remarkable results in improving the power system's stability, it still faces the problems of real-time data processing delay and computational complexity in large-scale systems. Future research can consider further optimizing the real-time performance of the algorithm and exploring more efficient parameter adjustment mechanisms to cope with more complex dynamic disturbances of the power system. Although the stabilizer parameter solution method based on the D-segment method significantly improves the system stability, it still has some limitations. The accurate partitioning of complex systems and the delay of real-time data processing. In addition, the effectiveness and robustness of the control strategy in the face of extreme disturbances still need to be further verified.

Consent to Publish

The manuscript has not been published before, and it is not being reviewed by any other journal. The authors have all approved the content of the paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author, upon request.

Conflicts of Interest

The authors affirm that they do not have any financial conflicts of interest.

References

[1] Z.S. Hasan, D.H. Al-Mamoori. Studies enhancement of transient stability by single machine infinite bus system and setting purpose genetic algorithm. Indonesian Journal of Electrical Engineering and Computer Science, 2022, 25(2), 648-655. DOI: 10.11591/ijeecs.v25.i2.pp648-655

[2] Y. Yan, M.Q. Liu, S.Z. Li, C.D. Li, K. Li, et al. Distributed low-carbon operational optimization model of an integrated energy system based on ladder carbon trading and integrated demand response. International Journal of Green Energy, 2024, 21(6), 1324-1344. DOI: 10.1080/15435075.2023.2251048

[3] A. Kumar, O. Singh. Recent strategies for automatic generation control of power systems with diverse energy sources. International Journal of System Dynamics Applications (IJSDA), 2021, 10(4), 1-26. DOI: 10.4018/IJSDA.20211001.oa8

[4] R.N. Mishra, D.K. Chaturvedi, P. Kumar. Recent philosophies of AGC techniques in deregulated power environment. Journal of The Institution of Engineers

(India), Series B, 2020, 101(3), 417-433. DOI: 10.1007/s40031-020-00463-8

[5] V.L. Narayanan. Reinforcement learning in wind energy-a review. International Journal of Green Energy, 2023, 21(9), 1945-1968. DOI: 10.1080/15435075.2023.2281329

[6] H. Jazayeri, M. Heshmati. Integrating Reinforcement Learning and Game Theory for Enhancing Supply Chain Optimization. International Journal of Industrial Engineering and Construction Management (IJIECM), 2024, 2(1), 54-71.

[7] B. Hirchoua, I. Mountasser, B. Ouhbi, B.B. Frikh. CONTINUOUS EVOLUTIONARY DEEP REINFORCEMENT LEARNING ENVIRONMENT: AUGMENTED TRANSFER LEARNING-BASED GENETIC ALGORITHM. Journal of Data Intelligence, 2022, 3(3), 333-349. DOI: 10.26421/JDI3.3-3

[8] N.A. Orka, S.S. Muhaimin, M.N.S. Shahi, A. Ahmed. Artificial intelligence-based online control scheme for the regulations of interconnected thermal power systems. Arabian Journal for Science and Engineering, 2023, 48(11), 15153-15176. DOI: 10.1007/s13369-023-07995-3

[9] V. Lopes, F.M. Carlucci, P.M. Esperança, M. Singh, A. Yang, et al. Manas: multi-agent neural architecture search. Machine Learning, 2023, 113(1), 73-96. DOI: 10.1007/s10994-023-06379-w

[10] S.M.A. Zanjani, M. Mahdavian, M.A. Honarvar, M. Riahinasab, A. Fattollahi. A Review on Improving Power System Stability Using Meta-Heuristic Optimization Algorithms for Power System Stabilizer Tuning. Signal Processing and Renewable Energy, 2024, 8(1), 15-56. DOI: https://oiccpress.com/spre/article/view/7907

[11] M. Shokoohi, M. Afsharchi, H. Shah-Hoseini. Dynamic distributed constraint optimization using multi-agent reinforcement learning. Soft Computing, 2022, 26(8), 3601-3629. DOI: 10.1007/s00500-022-06820-7

[12] S.M. Padmaja, A. Kumar, L. Dhanesh, V.V. Kamesh, H. Geetha, et al. Stability and Reliability Analysis for Multiple WT Using Deep Reinforcement Learning. Electric Power Components and Systems, 2023, 52(2), 308-321. DOI: 10.1080/15325008.2023.2220313

[13] T. Yacine Trad, K. Choutri, M. Lagha, F. Khenfri. Collaborative Multi-Agent Deep Reinforcement Learning Approach for Enhanced Attitude Control in Quadrotors. International Journal of Computing and Digital Systems, 2025, 17(1), 1-13. DOI: 10.12785/ijcds/1571033189

[14] K. Peddakapu, M.R. Mohamed, P. Srinivasarao, A.S. Veerendra, D.J.K. Kishore, et al. Review on automatic generation control strategies for stabilising the frequency deviations in multi-area power system. International Journal of Ambient Energy, 2021, 43(1), 5571-5594. DOI: 10.1080/01430750.2021.1969272

[15] M. Maheedhar, T. Deepa. A behavioral study of different controllers and algorithms in real-time applications. IETE Journal of Research, 2022, 70(2), 1657-1681. DOI: 10.1080/03772063.2022.2153089

[16] M. Gautam. Deep Reinforcement learning for resilient power and energy systems: Progress, prospects, and future avenues. Electricity, 2023, 4(4), 336-380. DOI: 10.3390/electricity4040020

[17] N.R. Nkosi, R.C. Bansal, T. Adefarati, R.M. Naidoo, S.K. Bansal. A review of small-signal stability analysis of DFIG-based wind power system. International Journal of Modelling and Simulation, 2022, 43(3), 153-170. DOI: 10.1080/02286203.2022.2056951

[18] A.P. Arunkumar, S. Kuppusamy, S. Muthusamy, S. Pandiyan, H. Panchal, et al. An extensive review on energy management system for microgrids. Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, 2022, 44(2), 4203-4228. DOI: 10.1080/15567036.2022.2075059

[19] D. Voumick, P. Deb, M.M. Khan. Operation and control of microgrids using IoT (internet of things). Journal of Software Engineering and Applications, 2021, 14(8), 418-441. DOI: 10.4236/jsea.2021.148025

[20] A. Abedini, G. Shahgholian, B. Fani. Power system dynamic stability improvement using PSS equipped with microcontroller. International Journal of Smart Electrical Engineering, 2021, 10(2), 67-76. DOI: 10.30495/ijsee.2021.683681

[21] A. Tiguercha, A.A. Ladjici, S. Saboune. Multi-area optimal adaptive under-frequency load shedding control based on ANFIS approach. Electrical Engineering, 2024, 106(3), 3573-3587. DOI: 10.1007/s00202-023-02156-z

[22] M.J. Mahmoodabadi. Moving least squares approximation-based online control optimised by the team game algorithm for Duffing-Holmes chaotic problems. Cyber-Physical Systems, 2020, 7(2), 93-113. DOI: 10.1080/23335777.2020.1811385

[23] Y. Prajapati, V. Kamat, J. Patel, R.K. Kher. A Comprehensive Survey on Use of Soft Computing and Optimization Techniques for Load Frequency Control. Journal of Electrical and Electronic Engineering, 2020, 8(2), 64-70. DOI: 10.11648/j.jeee.20200802.13

[24] S.O. Bade, A. Meenakshisundaram, O.S. Tomomewo. Current Status, Sizing Methodologies, Optimization Techniques, and Energy Management and Control Strategies for Co-Located Utility-Scale Wind–Solar-Based Hybrid Power Plants: A Review. Eng, 2024, 5(2), 677-719. DOI: 10.3390/eng5020038

[25] N. Zhang, H.Y. Jia, Q.C. Hou, Z.Y. Zhang, X.Cai, et al. Data-driven security and stability rule in high renewable penetrated power system operation. Proceedings of the IEEE, 2022, 111(7), 788-805. DOI: 10.1109/JPROC.2022.3192719

[26] N. Hakimuddin, I. Nasiruddin, T.S. Bhatti, Y. Arya. Optimal automatic generation control with hydro, thermal, gas, and wind power plants in 2-area interconnected power system. Electric Power Components and Systems, 2020, 48(6-7), 558-571. DOI: 10.1080/15325008.2020.1793829

[27] W.K. Ibrahim, F.S. Abdullah, F.A. Ali. Comparative Analysis of Fuzzy Logic, PID, and FOPID Controllers in DC Microgrid Voltage Regulation for Power Plants: Integrating Renewable Energy Sources. Journal of Advanced Research in Applied Mechanics, 2024, 128(1), 50-61. DOI: 10.37934/aram.128.1.5061

[28] M.G.M. Almihat, J.L. Munda. Review on recent control system strategies in Microgrid. Edelweiss Applied Science and Technology, 2024, 8(6), 5089-5111. DOI: 10.55214/25768484.v8i6.3116

[29] A. Fakhar, A.M.A. Haidar, M.O. Abdullah, N. Das. Smart grid mechanism for green energy management: a comprehensive review. International Journal of Green Energy, 2023, 20(3), 284-308. DOI: 10.1080/15435075.2022.2038610

[30] G. Kodeeswara Kumaran, P. Rajesh, S. Kumaravel, G. Irusapparajan. Two-area power system stability analysis by frequency controller with UPFC synchronization and energy storage systems by optimization approach. International Review of Applied Sciences and Engineering, 2023, 14(2), 270-284. DOI: 10.1556/1848.2022.00538

[31] Q. Wang, Y.S. Hao. Routing optimization with Monte Carlo Tree Search-based multi-agent reinforcement learning. Applied Intelligence, 2023, 53(21), 1-16. DOI: 10.1007/s10489-023-04881-1

[32] T. Madiba, R.C. Bansal, N.T. Mbungu, M. Bettayeb, R.M. Naidoo, et al. Under-frequency load shedding of

microgrid systems: a review. International Journal of Modelling and Simulation, 2022, 42(4), 653-679. DOI: 10.1080/02286203.2021.1964061
[33] W. Aribowo. A novel improved sea-horse optimizer for tuning parameter power system stabilizer. Journal of Robotics and Control (JRC), 2023, 4(1), 12-22. DOI: 10.18196/jrc.v4i1.16445
[34] S. Ekinci, D. Izci, B. Hekimoglu. Implementing the Henry gas solubility optimization algorithm for optimal power system stabilizer design. Electrica, 2021, 21(2), 250-258. DOI: 10.5152/electrica.2021.20088
[35] D. Butti, S.K. Mangipudi, S. Rayapudi. Model order reduction based power system stabilizer design using improved whale optimization algorithm. IETE Journal of Research, 2023, 69(4), 2144-2163. DOI: 10.1080/03772063.2021.1886875
[36] A.H. Abd El-Kareem, M. Abd Elhameed, M.M. Elkholy. Effective damping of local low frequency oscillations in power systems integrated with bulk PV generation. Protection and Control of Modern Power Systems, 2021, 6(4), 1-13. DOI: 10.1186/s41601-021-00219-6