

## Article

# Research on Secondary Frequency Regulation Strategy for Hybrid Energy Storage Stations in Regional Power Grids

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## Abstract

Aiming at frequency fluctuations caused by high-penetration renewable energy, a coordinated secondary frequency regulation strategy is proposed for hybrid energy storage stations in regional power grid. Hybrid energy storage stations contain electrochemical energy storage stations (EESSs) and compressed air energy storage stations (CAESSs). Complete mathematical models of concerned energy storage stations are constructed, and a multi-objective exponential distribution optimization (MOEDO) algorithm is proposed to optimize regulation cost, automatic generating control (AGC) command tracking and constrain the state of charge (SoC) of energy storage equipment. The proposed strategy rationally distributes secondary regulation instructions for hybrid energy storage stations and thermal power plants. In the end, simulation results on a two-area interconnected power grid are given to verify the effectiveness of proposed strategy. Results reveal that the presented method can effectively suppress frequency deviation and tie-line power oscillation and maintain SoC within a safe operating range.

**Keywords:** compressed air energy storage station; electrochemical energy storage station; hybrid energy storage stations; multi-objective exponential distribution optimization algorithm; secondary frequency regulation; regional power grid



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## 1. Introduction

In recent years, renewable energy penetration in power grids keeps rising. Its inherent volatility and intermittency break the real-time power balance. As a result, traditional thermal units bear heavier frequency regulation pressure under automatic generation control (AGC) [1–3]. Energy storage stations (ESSs) feature fast dynamic response and bidirectional power output. They can compensate the weak regulation capacity of thermal generators well [4,5]. Against this background, an urgent research target for new power systems is explored: how to fully exploit ESS's rapid adjustment ability and coordinate ESSs with conventional units to improve overall AGC frequency regulation performance [6,7].

Published studies on ESS AGC frequency regulation mostly concentrate on fast power support to balance regulation performance and economic cost [8,9]. Researchers set energy

capacity as a core constraint to prolong service time and prevent ESSs from exiting regulation caused by overcharge or overdischarge [10]. However, most existing works only study single energy storage stations, lacking a global coordination framework applicable to multiple storage stations.

Diversified energy storage stations have been widely deployed in China, and they jointly undertake frequency regulation tasks for regional power grids [11,12]. A core challenge lies in globally coordinating the real-time adjustable capacity of all storage devices. Uneven operating states among stations will trigger AGC tracking deviation, redundant charge–discharge cycles and extra operation losses [13–15]. To address such issues, published studies have undertaken a series of explorations. In [16], an adaptive dynamic power allocation model is proposed for multiple ESSs. The suggested solution in [17] put forward a frequency signal decomposition coordination strategy to suppress frequency fluctuation under persistent disturbances. In [18], the flexibility of district cooling systems is verified to help accommodate more renewable power. Reference [19] adopts multi-stage mixed integer linear programming to analyze China’s power decarbonization path towards 2035. The proposed model quantifies the balance among power demand growth, coal capacity reduction and renewable expansion and proves demand response is essential for low-cost carbon reduction. Existing works have realized coordinated control of heterogeneous energy storage stations. However, the computational burden of these algorithms rises sharply with the growth of storage quantity, which brings heavy computing pressure to dispatch centers and limits engineering promotion.

A computable general equilibrium model is established by [20]. The proposed model contains detailed power equipment parameters to evaluate four carbon neutrality paths for China’s power industry. The results show the combination of renewable subsidies, and carbon pricing achieves optimal economic performance. This policy minimizes GDP and social welfare loss while greatly cutting pollutant emissions. Reference [21] proposes a consensus transfer Q-learning algorithm and designs a two-layer power allocation framework to lower calculation load. Reference [22] takes both EESS cycle aging and AGC tracking precision into account and develops a corresponding optimization method. Nevertheless, these algorithms rely on simplified models in optimization, which inevitably sacrifice frequency regulation accuracy.

Few existing papers fully explore the complementary operation advantages of various energy storage devices in regional grids. In fact, different storage stations have completely different dynamic features. This makes it hard to accurately calculate real-time regulation loss and develop global optimal dispatch strategies to reduce total storage operation cost [13,23]. Therefore, it is imperative to design a reasonable power command allocation strategy that effectively coordinates the outputs of multiple ESSs.

Aiming at the above deficiencies, this paper establishes a two-area interconnected grid frequency regulation strategy integrating thermal power units, EESSs and CAESSs. Common multi-objective optimizers have evident defects when solving this multi-timescale hybrid storage optimization model, which is also one of the key issues in this study. In the proposed strategy, a multi-objective optimization model with regulation cost, command tracking accuracy and SoC optimization is considered as evaluation objective. A power distribution strategy based on the MOEDO algorithm is further proposed to solve this multi-objective problem. In the end, the effectiveness and superiority of the proposed coordinated control strategy are verified via numerical simulation based on actual regional power grid operating data.

Main contributions of this paper can be summarized as follows. (1) This paper establishes a coupled electromechanical–electromagnetic hybrid model that fully characterizes the complementary time-scale response features of electrochemical and compressed air

energy storage, including independent charging and discharging frequency support sub-models for CAESS. With the proposed model, the framework for secondary frequency regulation is thus suggested. (2) The fundamental multi-objective mathematical framework refers to classic frequency regulation optimization paradigms in the existing literature, while the customized hybrid energy storage life loss cost term and piecewise SoC balance penalty objective function are newly designed for EESS-CAESS coordinated secondary frequency regulation, representing the scenario-oriented improvement of the multi-objective model. (3) The basic framework of MOEDO has been reported in existing studies. This work introduces exclusive improvements, namely the Information Feedback Mechanism (IFM), adaptive mutation operators and SoC deviation penalty, to tackle the high-dimensional nonlinear multi-timescale constraints of hybrid energy storage AGC dispatch.

## 2. Modeling of Regional Interconnected Power Grid and Frequency Regulation Resources

### 2.1. Static Characteristics of Load-Frequency in Regional Power Grid

According to the static load-frequency characteristic theory, there is a coupling relationship between the active load power and the system frequency, which can be expressed through nonlinear fitting as follows:

$$\begin{cases} P_L = P_{LN} \left[ a_0 + a_1 \left( \frac{f}{f_N} \right) + a_2 \left( \frac{f}{f_N} \right)^2 + \dots + a_n \left( \frac{f}{f_N} \right)^n \right] \\ a_0 + a_1 + a_2 + \dots + a_n = 1 \end{cases} \quad (1)$$

when active power balance is broken in power system, the system load will participate in frequency regulation, which is known as the load regulation effect. To evaluate the magnitude of load regulation effect, the frequency regulation coefficient  $K_L$  is defined as follows:

$$K_L = \frac{\Delta P_L}{\Delta f} \quad (2)$$

Once system frequency deviates, the grid dispatch center calculates power imbalance through regional area control error (ACE). It distributes regulation orders to all adjustable resources and iteratively modifies unit output to recover rated frequency. According to the tie-line power between interconnected regions and power deficit required to compensate for system frequency deviation, the frequency regulation command for regional power grid,  $P_{ACE}$ , can be expressed as follows:

$$P_{ACE} = \Delta P_{tie} + K_L \Delta f \quad (3)$$

### 2.2. Mathematical Model of Thermal Power Generating Unit and Interconnected Tie-Line

Thermal generators are the main equipment undertaking primary frequency regulation currently. The steam flow can be directly controlled by adjusting the main steam valve opening. However, steam cylinder energy storage and steam parameter transfer delay cause a 3–5 s lag in turbine mechanical power. This delay is a key electromechanical coupling constraint and must be considered when designing coordinated frequency regulation schemes. The transfer function can be expressed as follows:

$$\Delta P_m(s) = \frac{(1 + sK_r T_r)}{(1 + T_{ch}s)(1 + sT_r)} \Delta P_v(s) \quad (4)$$

The coupling model between thermal power generator and power grid can be expressed by the following:

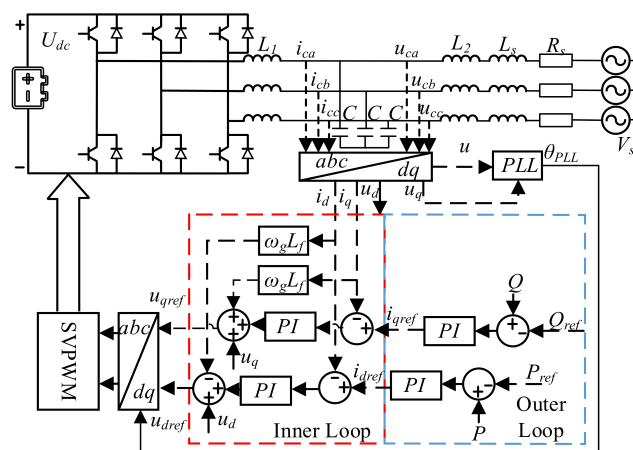
$$\Delta\omega(s) = \frac{K_{ps}}{T_p s + 1} (\Delta P_m(s) - \Delta P_L(s)) \quad (5)$$

Beside thermal generating units, interconnected regional grids are capable of realizing cross-area power mutual support through tie-line interconnections. Controllable power flow delivery enables real-time balancing between power supply and demand across regions and further preserves consistent frequency for the entire bulk power grid. The tie-line power flow of region  $i$ , denoted as  $\Delta P_{tie,i}$ , can be expressed as follows:

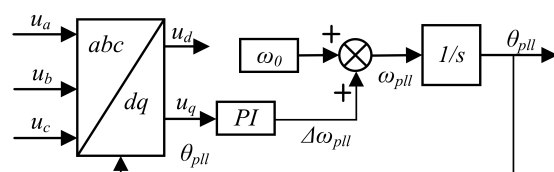
$$\Delta P_{tie,i}(s) = \sum_{j=1}^N \Delta P_{tie}^{ij}(s) = \sum_{j=1}^N T_{i,j} [\Delta f_i(s) - \Delta f_j(s)] \quad (6)$$

### 2.3. Mathematical Model of Electrochemical Energy Storage Stations

Power systems still mainly depend on thermal power for power support, so grid-following control is widely adopted for domestic EESSs. Figure 1 presents its overall control block diagram, and Figure 2 separately draws the internal structure of the phase-locked loop (PLL). In Figure 1, the main circuit parameters include DC-link voltage ( $U_{DC}$ ), power system voltage ( $V_s$ ), LCL filter components ( $L_1$ ,  $C$  and  $L_2$ ), and grid impedance ( $L_s$ ,  $R_s$ ). In the outer control loop,  $Q_{ref}$  and  $P_{ref}$  denote required output reactive and active power of EESS, respective;  $P$  and  $Q$  denote real-time output active power and reactive power, respectively. In the inner control loop,  $i_{dref}$  and  $i_{qref}$  denote current reference for active power control and reactive power control, respectively;  $i_d$ ,  $i_q$  are  $d$ -axis current and  $q$ -axis current, respectively;  $u_d$  and  $u_q$  denote  $d$ -axis voltage and  $q$ -axis voltage, respectively;  $i_{ca}$ ,  $i_{cb}$  and  $i_{cc}$  are real-time output current of three phases;  $u_{ca}$ ,  $u_{cb}$  and  $u_{cc}$  are output voltage of three phases.



**Figure 1.** Control block diagram of grid-following EESSs for regional grid secondary frequency regulation, including outer power control loop and inner current tracking loop.



**Figure 2.** Internal structure block diagram of PLL adopted by grid-following EESS.

As shown in Figure 2, the  $q$ -axis voltage deviation is taken as the error input of PI regulator. The regulator dynamically compensates  $u_q$  and adjusts it to zero to capture accurate grid phase information.

The output active power and reactive power of EESSs can be expressed as follows:

$$\begin{cases} P_e = \frac{U_t U_g}{X_{line}} \sin(\theta_{pll} - \theta_g) \\ Q_e = \frac{U_t^2}{X_{line}} - \frac{U_t U_g}{X_{line}} \cos(\theta_{pll} - \theta_g) \end{cases} \quad (7)$$

As shown in Figure 1, EESS adopts the following two-layer control structure: outer power PI loop and inner current tracking loop. Considering the first-order inertia response of EESS, the dynamic active power regulation of EESS is as follows:

$$P_e(s) = \frac{1}{T_e s + 1} (K_{pP} + \frac{K_{iP}}{s}) P_{e,ref}(s) \quad (8)$$

Similarly, the dynamic response formula of reactive power under AGC regulating process is established by the following:

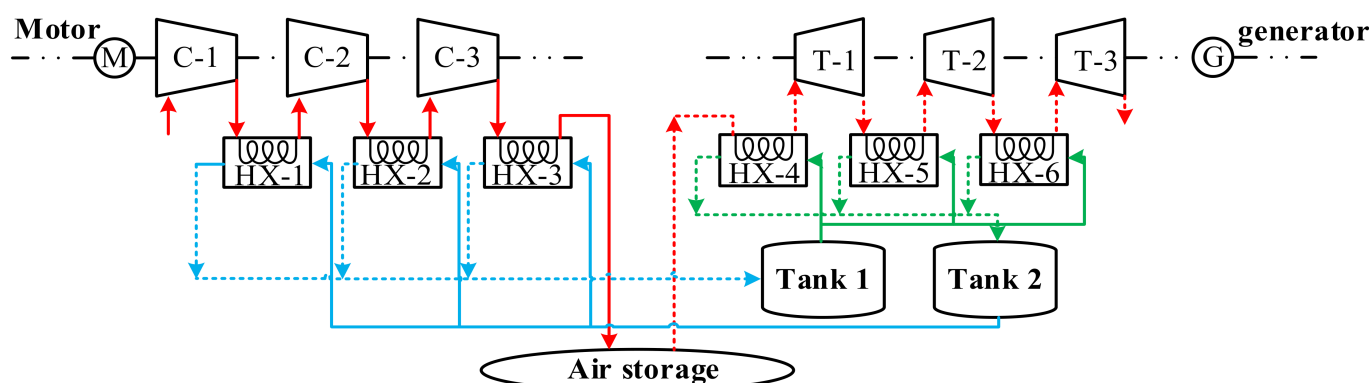
$$\Delta Q_e(s) = \frac{1}{T_e s + 1} (K_{pQ} + \frac{K_{iQ}}{s}) \Delta Q_{e,ref}(s) \quad (9)$$

With above formulas, this subsection includes both steady-state power equations and frequency-coupled dynamic transfer functions, forming a complete mathematical model of EESS in frequency regulation for the two-area interconnected power grid.

#### 2.4. Mathematical Model of Compressed Air Energy Storage Stations

In some regions of China, CAESSs have already been installed in the 220 kV regional power grid. Therefore, CAESS is elected as another form of hybrid energy storage to meet the demand for auxiliary frequency regulation across various time scales.

A CAESS comprises air compressors, air storage chambers, expanders, heat exchangers, throttle valves, electronic control units, and other components. Figure 3 illustrates the structure of a CAESS, where C-1, C-2, and C-3 denote air compressors; T-1, T-2, and T-3 are expanders; HX- $i$  ( $i = 1, 2, 3, 4, 5, 6$ ) are heat exchangers; and tank-1 and tank-2 are the higher and lower temperature tanks, respectively.



**Figure 3.** Schematic structure of CAESS with multi-stage compressors, expanders and heat exchangers for secondary frequency regulation support. The red solid/dashed lines denote high-pressure airflow during compression/expansion stages; the blue lines represent cooling medium flow; and the green lines indicate heating medium flow.

In the energy storage process, CAESS can be employed to handle rapid response with strictly regulated boundaries. CAESS responds to frequency deviations by altering the power for compressor. The frequency support model of CAESS can be expressed as follows:

$$\begin{cases} \Delta P_{CAESS,c} = \frac{1}{T_{cs}+1}(-K_a\Delta f - 2H_c\frac{d\Delta f}{dt}) \\ P_{ac}^{RU} = P_{CAESS,c}^{max} - P_{CAESS,c} \\ P_{ac}^{Rd} = P_{CAESS,c} - P_{CAESS,c}^{min} \\ -P_{ac}^{Rd} \leq \Delta P_{CAESS,c} \leq P_{ac}^{RU} \end{cases} \quad (10)$$

CAESS provides frequency support during power generation through two independent mechanisms. The first one is inertial frequency regulation, which utilizes the rotational inertia of synchronous generators. The second is active power adjustment by changing the air flow into turbines to adjust unit active output. The corresponding frequency support model can be expressed by the following:

$$\begin{cases} \Delta P_{CAESS,r}^m = 2H_{CAESS}\frac{d\Delta f}{dt} \\ \Delta P_{CAESS,r} = \frac{-K_a\Delta f}{(T_{rs}+1)(T_{igs}+1)} \\ P_{ar}^{RU} = P_{CAESS,r}^{max} - P_{CAESS,r} \\ P_{ar}^{Rd} = P_{CAESS,r} - P_{CAESS,r}^{min} \\ -P_{ar}^{Rd} \leq \Delta P_{CAESS,r} \leq P_{ar}^{RU} \end{cases} \quad (11)$$

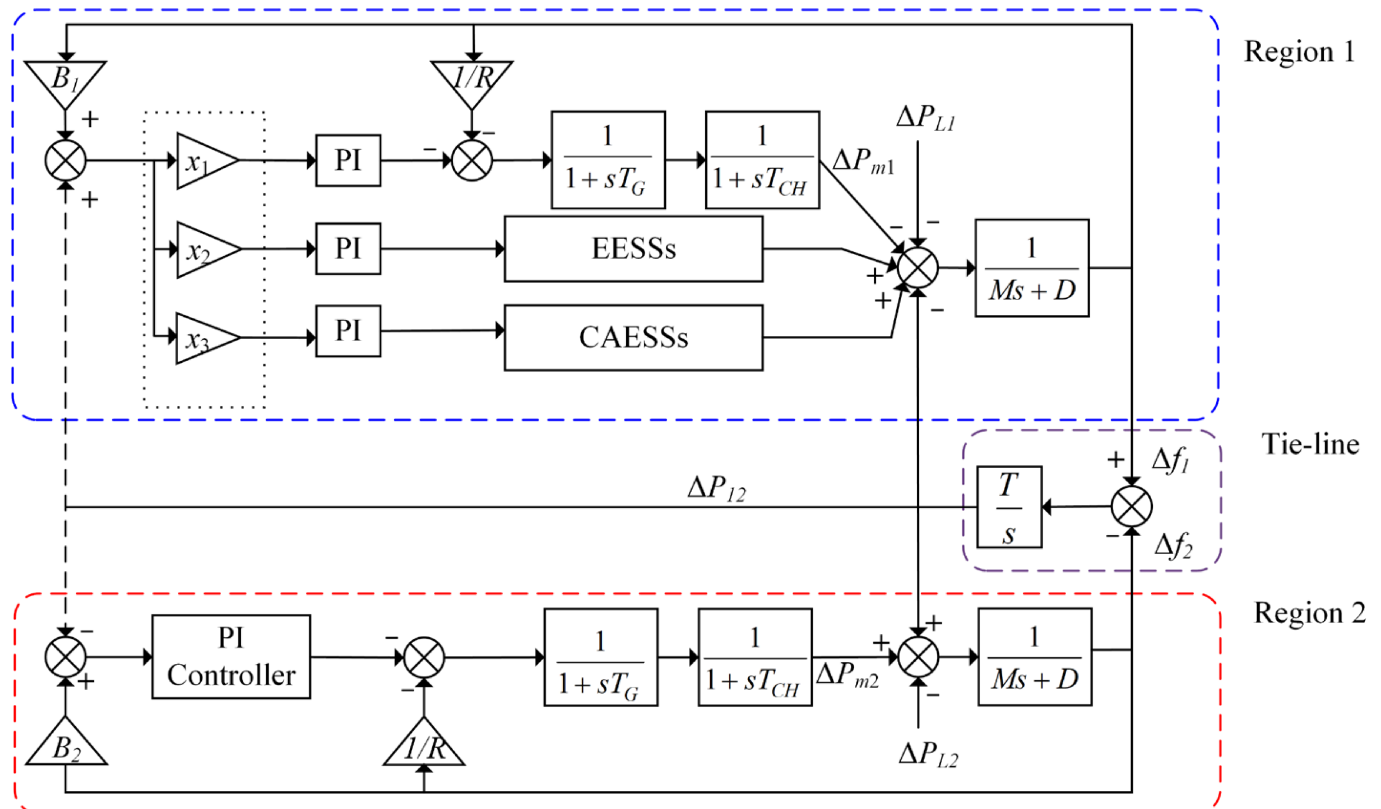
Different from separate independent CAESS or EESS models in the previous literature, this section constructs a fully coupled hybrid dynamic model matching EESS's fast response characteristics, according to which the coordinated secondary frequency regulation framework can be thus established.

This paper adopts first-order inertial transfer functions to describe CAESS frequency response, as the research target focuses on minute-scale AGC secondary frequency fluctuation rather than sub-second internal thermodynamic transients of CAESS. Fine thermodynamic characteristics including air storage pressure dynamic evolution, multi-stage expander nonlinear efficiency and mode-switch power ramp limits are omitted in the simplified model, since their transient variation has negligible impact on the minute-level frequency deviation studied herein. It is noted that fixed ramp hard constraints of CAESS are added in Section 3.1 multi-objective optimization formulas to restrict extreme power switching and partially compensate the simplification of transient ramp dynamics. For ultra-fast primary frequency regulation scenarios, a refined CAESS model coupled with full thermodynamic constraints will be developed in follow-up work.

### 3. Multi-Objective Optimization Modeling and Solution for Secondary Frequency Regulation of Hybrid Energy Storage

The system architecture for coordinated frequency regulation of the two-area interconnected power grid is illustrated in Figure 4, which adopts a heterogeneous interconnection framework to coordinate cross-regional power exchange. Each control area consists of equivalent thermal generating units, diversified energy storage clusters and aggregated load models, with inter-area power interaction realized via tie lines. In Figure 4,  $x_i$  ( $i = 1, 2, 3$ ) denotes the AGC command allocation weights for conventional thermal generating units, CAESSs and EESSs, respectively;  $R$  stands for the droop coefficient of thermal generating unit;  $B_i$  ( $i = 1, 2$ ) is the frequency bias factor of concerned two regions;  $T_G$  and  $T_{CH}$  represent governor time constant and turbine time constant, respectively;  $M$  and  $D$  denote the rotational inertia of equivalent units and damping coefficient of lumped loads, respectively; and  $\Delta P_{Li}$  and  $\Delta P_{mi}$  indicate the turbine power variation in conventional units. As illustrated in the figure,  $x_i$  dictates the participation degree of concerned three frequency regulation

resources in grid frequency regulation process and dominate the overall regulation performance of the system. To simplify the analysis, frequency regulation in region 1 is achieved by thermal generating units, EESSs and CAESSs jointly, while frequency regulation in region 2 is solely undertaken by thermal power units.



**Figure 4.** Coordinated secondary frequency regulation framework of two-area interconnected power grid. Area 1 is equipped with thermal units, EESS and CAESS for joint regulation; area 2 only adopts thermal generating units as frequency modulation resources.

### 3.1. Multi-Objective Function and Optimization Constraints

To analyze the optimization problem with multi-dimensional constraints, the objective function is defined as follows:

$$\begin{cases} \min F = [f_1(x), f_2(x), \dots, f_n(x)] \\ \text{s.t.} \begin{cases} g_j(x) = 0 & j = 1, 2, \dots, J \\ g'_k(x) \leq 0 & k = 1, 2, \dots, K \end{cases} \end{cases} \quad (12)$$

The general multi-objective minimization framework above is a mature existing paradigm, while the four customized objective terms and corresponding hybrid storage operation constraints proposed below are improved and redeveloped for EESS-CAESS joint secondary frequency regulation.

When ESSs provide frequency regulation ancillary services for power grids, the capital cost of rated capacity and energy loss cost are generally taken into consideration. Since this paper focuses on frequency regulation strategies for already commissioned energy storage plants, the initial construction investment cost is excluded from the cost evaluation. For grid frequency regulation scenarios involving frequent switching between charging and discharging power leads to intensive charge–discharge cycles, accelerating degradation and shortening cycle life of both EESSs and CAESSs. To establish a full-life-cycle cost

model of ESSs for ancillary service participation, a quantitative evaluation framework for life consumption based on cycle counts should be formulated. Considering the above technical characteristics, the frequency regulation cost model consists of the following key components:

$$V_{loss,i}(t) = \begin{cases} s_e \cdot \Delta t \cdot P_{c,i}(t) \cdot (1 - \eta_{c,i}), & P_{AGC}(t) < 0 \\ s_e \cdot \Delta t \cdot P_{c,i}(t) \cdot (\frac{1}{\eta_{d,i}} - 1), & P_{AGC}(t) \geq 0 \end{cases} \quad (13)$$

$$V_{life,i}(t) = \begin{cases} \frac{\Delta t \cdot P_{c,i}(t) \cdot \eta_{c,i} \cdot c_{P,i} \cdot P_{rate,i}}{2N_i \cdot E_{rate,i}}, & P_{AGC}(t) < 0 \\ \frac{\Delta t \cdot P_{d,i}(t) \cdot c_{P,i} \cdot P_{rate,i}}{2N_i \cdot E_{rate,i} \cdot \eta_{d,i}}, & P_{AGC}(t) \geq 0 \end{cases} \quad (14)$$

Although EESS and CAESS have fundamentally different degradation mechanisms, cumulative charge–discharge throughput is the dominant factor causing life loss for both under short-cycle AGC secondary frequency regulation scenarios. This paper adopts unified mathematical formula forms only to simplify the analysis and guarantee relative fair comparison of different power allocation schemes. Independent rated cycle values, efficiency and life cost coefficients are assigned to EESS and CAESS separately to distinguish their unique loss characteristics and output differentiated cost results. This simplification will not affect the comparative analysis of frequency modulation performance, so it is acceptable for the core research objective of this paper.

In fact, internal parameters settings of EESS aging model and CAESS aging model are completely different. This paper uses fixed rated cycle times in the aging model. This method reduces iterative calculation load and facilitates intuitive comparison of AGC tracking performance, but it neglects the nonlinear coupling aging effect between discharge depth (DOD) and operating temperature under frequent charge–discharge cycles. For lithium-ion energy storage, uneven internal temperature distribution produces regional capacity fading, and cycle loss presents obvious nonlinear correlation with DOD and ambient temperature [24,25]. For CAESS, recurrent temperature and flow fluctuation during frequent AGC charging/discharging will induce cumulative thermal fatigue of heat storage equipment, which cannot be quantified by fixed cycle counts [26]. The DOD-temperature coupled nonlinear aging formulas proposed in the above studies can be embedded into this loss equation in future research to realize accurate degradation quantification under actual AGC operating conditions. Moreover, the proposed life calculation framework is highly adjustable, and researchers and field engineers can set dynamic cycle correction coefficients according to the actual operating temperature and discharge depth of energy storage equipment in practical projects.

The cost of thermal generating units in frequency regulation process can be expressed as follows:

$$f(P_G(t)) = (aP_G(t)^2 + bP_G(t) + c)c_{coal} + \mu c_{co2}P_G(t)\Delta t + \gamma P_G(t)\Delta t \quad (15)$$

The total frequency regulation cost can be calculated by the following:

$$\begin{cases} C_1 = c_1 + f(P_G(t)) \\ c_1 = V_{loss}(t) + V_{life}(t) \end{cases} \quad (16)$$

Modern power grids adopt tie-line bias control as the core frequency regulation method. Its core target is to eliminate regional frequency deviation and tie-line power fluctuation or restrict them within allowable ranges. This measure ensures stable dynamic operation of the whole power grid. Control accuracy is negatively correlated with deviation amplitude, which characterizes the dynamic regulation performance of the AGC system.

Although the synchronization mechanism maintains uniform system frequency across all control areas, random local load fluctuations, intermittent output of renewable energy and response delay of frequency regulation resources lead to minor dynamic frequency discrepancies between adjacent regions. Accordingly, frequency deviation suppression and power balance level should be covered as indices for evaluation. Above evaluation indices are therefore formulated as follows:

$$\min C_2 = \sum_{t=1}^T (\Delta f_1^2(t) + \Delta f_2^2(t)) \quad (17)$$

$$\min C_3 = \sum_{t=1}^T \Delta P_{tie}^2(t) \quad (18)$$

It can be observed that smaller values of  $C_2$  and  $C_3$  correspond to superior AGC optimization performance.

Moreover, when energy storage participates in AGC dispatch, its *SoC* should be maintained within the ideal operating range. This arrangement enables the energy storage device to deliver optimal frequency regulation performance while extending its service life. The objective function for *SoC* control is formulated as follows:

$$\min C_4 = \begin{cases} 0 & \text{if } 40\% < SoC_{avg} < 60\% \\ |SoC_{avg} - 0.5| - 0.1 & \text{if } SoC_{avg} \leq 40\% \text{ or } SoC_{avg} \geq 60\% \end{cases} \quad (19)$$

According to (19), the evaluation index  $C_4$  is set to 0 if *SoC* remains within the ideal interval of 40% to 60%; otherwise, it is equal to the absolute deviation from this range.

Thus, the multi-objective function for frequency regulation is formulated as follows:

$$\min F = [C_1, C_2, C_3, C_4] \quad (20)$$

To guarantee stable system operation, the model is subject to power balance constraints, output limit constraints of frequency regulation resources, and ramp-up/ramp-down constraints. Crucially, these constraints are formulated to reflect the distinct physical limitations of hybrid components. Power balance constraint is expressed as follows:

$$P_T + P_e + P_{CAESS} + P_L = P_{tie} \quad (21)$$

Meanwhile, all aforementioned power values shall not exceed the maximum capacity limit of their respective components. Furthermore, the ramp rate constraints of spinning frequency regulation resources are formulated as follows:

$$P_{k,t} + P_{k,t}^{Ru} - P_{k,t-1} - P_{k,t-1}^{Rd} \leq \alpha_k^{dn}, \quad k \in \{T, CAESS\} \quad (22)$$

$$P_{k,t-1} + P_{k,t-1}^{Ru} - P_{k,t} - P_{k,t}^{Rd} \leq \alpha_k^{un}, \quad k \in \{T, CAESS\} \quad (23)$$

The above ramp rate constraints are designed to distinguish different response limits of regulation resources. Thermal units and CAESSs are limited by mechanical inertia, while EESSs supported by power electronics realizes ultra-fast adjustment. For CAESSs, heat exchange and gas expansion procedures restrict its response speed. Its adjustable speed is higher than thermal generators but much lower than EESSs. These specific constraints for thermal generating unit and CAESSs are formulated to prevent mechanical stress.

To balance the cycle life and frequency regulation margin of EESSs as well as the safe gas storage allowance of CAESSs, the allowable *SoC* variation range for both types of storage plants is set as [20%, 80%]. To ensure the reliable long-term coordinated operation

of concerned two types of ESSs, the SoC at initial and final dispatching instants should be equal and satisfies:

$$SoC_e(0) = SoC_e(T + 1) \quad (24)$$

$$SoC_{CAESS}(0) = SoC_{CAESS}(T + 1) \quad (25)$$

### 3.2. Optimization Based on Multi-Objective Exponential Distribution Optimization Algorithm

To reasonably allocate output power of various frequency regulation resources within the regional power grid, MOEDO algorithm is suggested in this paper to optimize the power allocation coefficients of each regulation resource shown in Figure 4.

Standard multi-objective algorithms often struggle with the conflicting time-scale characteristics (milliseconds for EESS vs. seconds/minutes for CAES) and complex non-linear constraints in hybrid systems. Traditional non-dominated sorting genetic algorithm II (NSGA-II) lacks effective inheritance of historical elite solutions and converges slowly under coupled multi-timescale constraints; multi-objective particle swarm optimization (MOPSO) introduces extra archive maintenance overhead and reduces Pareto diversity during optimization. The original EDO cannot adapt to hybrid storage operation limits without information feedback links. Therefore, the proposed MOEDO is not merely a direct extension but incorporates specific improvements, such as the Information Feedback Mechanism (IFM) and adaptive mutation operators, to enhance the search capability for the Pareto front in this specific high-dimensional space. As a multi-objective optimization method extended from the exponential distribution optimizer, MOEDO is suitable for optimizing complex engineering problems featuring high dimensionality, nonlinearity and multiple constraints [27].

The overall implementation procedure of MOEDO algorithm is divided into five stages: population initialization, intermediate population generation via exponential distribution optimization (EDO) operators, offspring population construction relying on IFM, selection based on non-dominated sorting and crowding distance, and iteration termination judgment.

Step 1: initialization. The algorithm first specifies the population size  $N$ , decision-space dimension  $d$ , the maximum iteration number  $Max\_time$ . Each decision variable is limited within the feasible range  $[l_b, u_b]$ . The initial population is generated by the following:

$$X_{winners_{v,w}} = l_b + rand \times (u_b - l_b) \quad (26)$$

Then, construct and initialize a matrix, namely **memoryless**, which is equal to the initial population.

Step 2: intermediate population generation via EDO operators. First, individuals in  $X_{winners}$  are sorted in accordance with the merit of objective function values obtained by (15)~(19). The guided solution  $X_{guid}^{time}$  is generated by the following:

$$X_{guide}^{time} = \frac{X_{best1} + X_{best2} + X_{best3}}{3} \quad (27)$$

Define rate parameter of exponential distribution  $\lambda$  and standard deviation of exponential distribution  $\sigma$  as follows:

$$\delta = \mu = \frac{\mathbf{memoryless}_v + X_{guid}}{2}, \lambda = \frac{1}{\mu} \quad (28)$$

Related adaptive parameters are defined as follows:

$$f' = 2rand - 1, a' = (f')^{10}, b' = (f')^5, d' = \frac{Max\_time - time}{Max\_time}, c' = d' \times f' \quad (29)$$

This step implements the adaptive mutation operator controlled by coefficient  $a'$ . Its core function is to dynamically switch between global exploration ( $a' \geq 0.5$ ) and local exploitation ( $a' < 0.5$ ) in each individual update, balancing early wide-range search and late precise convergence to avoid premature local optima.

This step includes two search modes determined by adaptive coefficient  $a'$  as follows:

- (1) Local search is activated when  $a' < 0.5$ . The position update rule is shown in (30).
- (2) Global search is activated when  $a' \geq 0.5$ . The update formula is given in (31). The adaptive coefficient  $a'$  acts as the switching threshold for two search modes. When a larger value of  $a'$  is generated, the algorithm carries out global exploration to fully expand the feasible search space; when a smaller value of  $a'$  is obtained, local exploitation is adopted to precisely converge to the Pareto optimal front.

All newly generated candidate individuals are processed within boundary constraints and then stored into **memoryless** matrix.

$$\begin{cases} V_v^{time+1} = (\mathbf{memoryless}_i - \sigma^2) + bX_{guide}^{time} & \text{if } X_{winners,v} = \mathbf{memoryless}_v \\ V_v^{time+1} = (\mathbf{memoryless}_i - \sigma^2) + \log(\phi)X_{winners,v} & \text{otherwise} \end{cases} \quad (30)$$

$$V_i^{time+1} = X_{winners,i} + (1-2c)\left(\frac{1}{M}\sum_{j=1}^N X_{winners} - X_{rand1}\right) + (2c-1)\left(\frac{1}{M}\sum_{j=1}^N X_{winners} - X_{rand2}\right) \quad (31)$$

The fitness values are compared according to (15)~(18) item by item. Inferior individuals in the original  $X_{winners}$  are replaced by superior counterparts to obtain the temporary intermediate population output by this stage.

Step 3: offspring population construction relying on IFM. This step is the implementation step of the Information Feedback Mechanism (IFM). Select the historical elite individual  $x_k^{t'}$  from the  $t'$ -th parent population  $X_t$ , where  $f_k^{t'}$  denotes its objective function value. New population is constructed by combining offspring solutions and attached population in accordance with following rule:

$$\begin{cases} \partial_1 = \frac{f_k^{t'}}{f_v^{t'+1} + f_k^{t'}}, \partial_2 = \frac{f_i^{t'+1}}{f_i^{t'+1} + f_k^{t'}} \\ x_i^{t'+1} = \partial_1 u_v^{t'+1} + \partial_2 x_k^{t'} \\ Y_{t'+1} = \{x_v^{t'+1}\} \end{cases} \quad (32)$$

The function of IFM is to extract high-quality historical elite solutions from previous iterations and fuse them into new offspring individuals, which inherits superior objective information and accelerates the Pareto front convergence speed under multi-timescale hybrid energy storage constraints.

Step 4: selection based on non-dominated sorting and crowding distance. Combine the parent population  $X_t$  and offspring population  $Y_{t+1}$  to generate the mixed population as follows:

$$Z_t = X_t \cup Y_{t+1} \quad (33)$$

Perform fast non-dominated sorting on  $Z_t$  to divide it into multiple Pareto fronts:

$$F_w = \{F_1, F_2, F_3, \dots, F_l\} \quad (34)$$

Add individuals layer by layer into the candidate set  $S_t$  until its size reaches  $N$ . If number of individuals in  $S_t$  equals  $N$ ,  $S_t$  is directly adopted as the new parent population. If the number of individuals in  $S_t$  exceeds  $N$ , all individuals of the first  $l-1$  fronts are fully retained. Then, individuals are selected from the last front  $F_l$  in descending order of

crowding distance to supplement the population size to  $N$ , and the new parent population is finally generated.

Step 5: iteration termination judgment. Repeat aforementioned step 2~step 4, until the number of iterations meets the termination condition. In the end, the algorithm terminates and outputs the final Pareto optimal solution set.

After solving the Pareto optimal solution set, it needs to select a compromise power allocation scheme as the final output. The optimizer calculate the fuzzy membership value of each solution for every objective via (35). Then, Equation (36) is used to compute the comprehensive normalized satisfaction.

$$h_v = \begin{cases} 1 & C_i \leq C_{\min,i} \\ \frac{C_{\max,v} - C_v}{C_{\max,v} - C_{\min,v}} & C_{\min,v} < C_i < C_{\max,v} \\ 0 & C_i > C_{\max,v} \end{cases} \quad (35)$$

$$h = \frac{1}{M_{obj}} \sum_{v=1}^{M_{obj}} h_v \quad (36)$$

According to above steps, the adaptive mutation operator runs in Step 2 for dynamic search mode switching; the Information Feedback Mechanism (IFM) is executed in Step 3 to reuse historical elite information. These two improvements coordinate to enhance the optimization performance of MOEDO for high-dimensional constrained frequency regulation models.

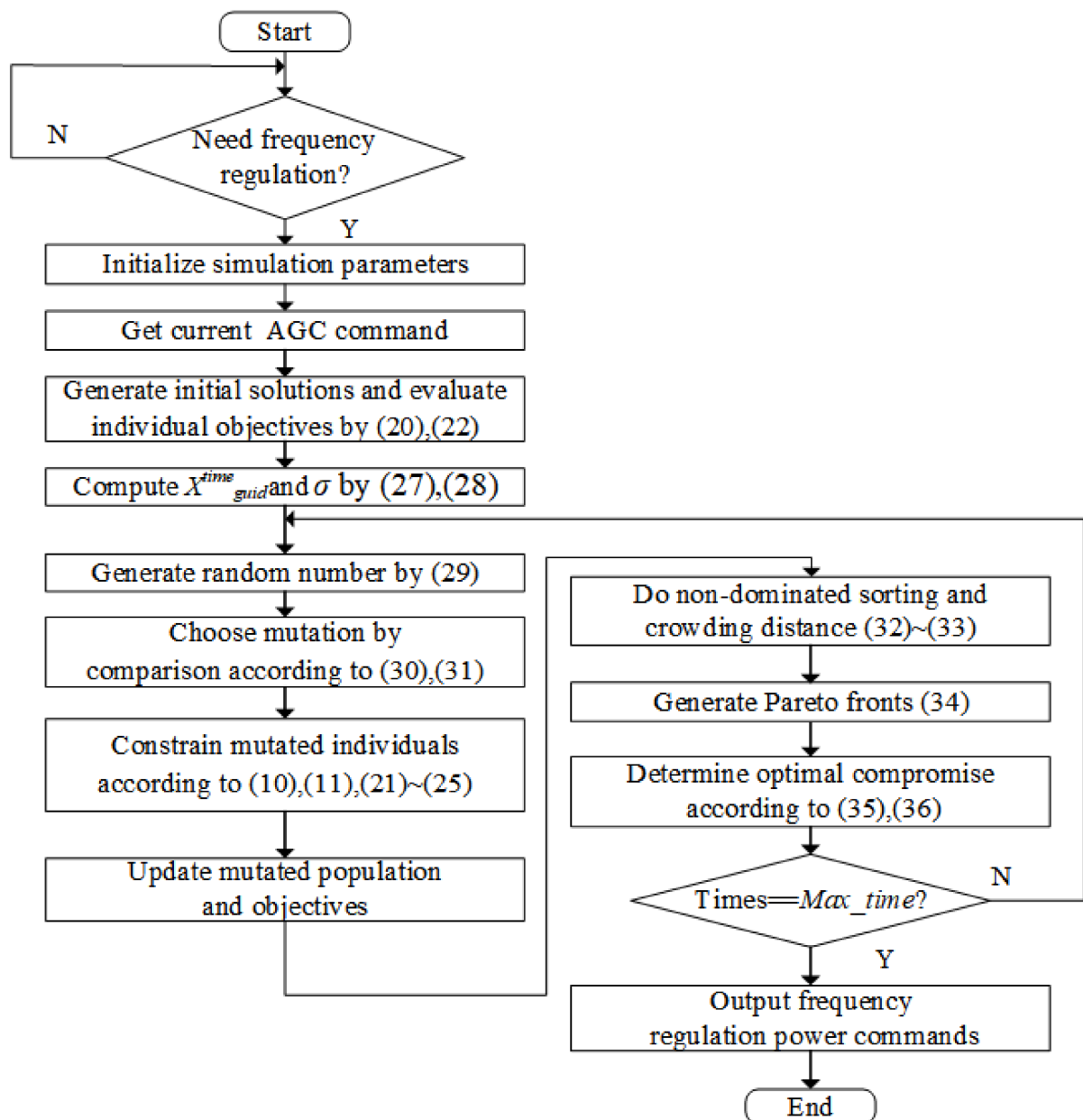
### 3.3. Implementation of the Optimization Process for Frequency Regulation

The AGC center first calculates the total secondary frequency regulation demand and inputs the value into the MOEDO algorithm. The optimizer generate  $M$  feasible search points to construct the initial solution set. Each point corresponds to a group of power allocation coefficients  $[x_1, x_2, x_3]$  for thermal units, EESSs and CAESSs, satisfying the constraint  $x_1 + x_2 + x_3 = 1$ .

Taking the time-series dataset of real-time operating parameters, the electromechanical transient model of the two-area interconnected power grid is established. Parallel numerical simulations are carried out for the sets of frequency regulation resource allocation coefficient vectors in the feasible region  $X_0$  that satisfy operational constraints. The electromechanical transient response dataset is acquired, and multiple objective evaluation indices including frequency deviation integral, tie-line power fluctuation and equipment regulation cost are obtained.

According to the evaluation results, the multi-objective Pareto frontier optimization is implemented. Adopting the elitist preservation strategy and adaptive crossover and mutation operators, the iteration mechanism dynamically optimizes the combinations of allocation coefficients until the convergence criterion is met. The flow chart of entire process is shown as Figure 5.

It should be noted that the basic framework of MOEDO has been proposed in existing research, and this paper does not innovate the original exponential distribution optimization framework. Instead, targeted improvements including IFM, adaptive mutation operators and SoC deviation penalty are embedded to adapt to hybrid energy storage multi-timescale optimization.

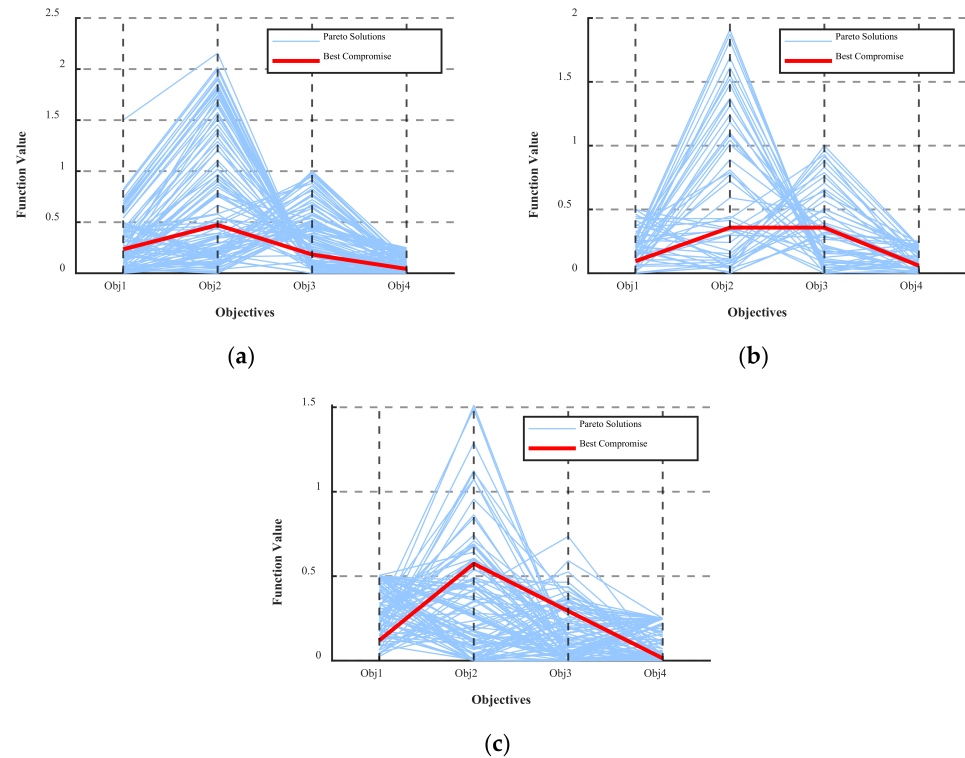


**Figure 5.** Flow chart of entire optimization process.

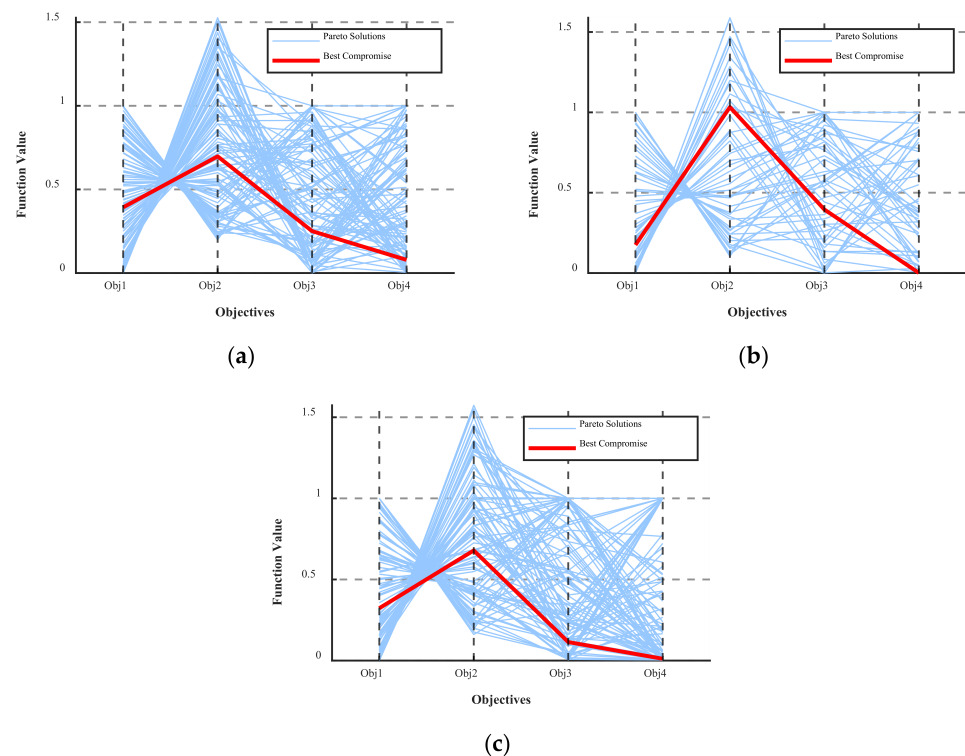
### 3.4. Comparison with Existing Optimization Algorithms

In order to compare the performance of proposed MOEDO with existing optimization method, MOPSO and NSGA-II are selected as bench mark algorithms. The open-source code implementations of MOPSO and NSGA-II are adopted for comparative experiments.

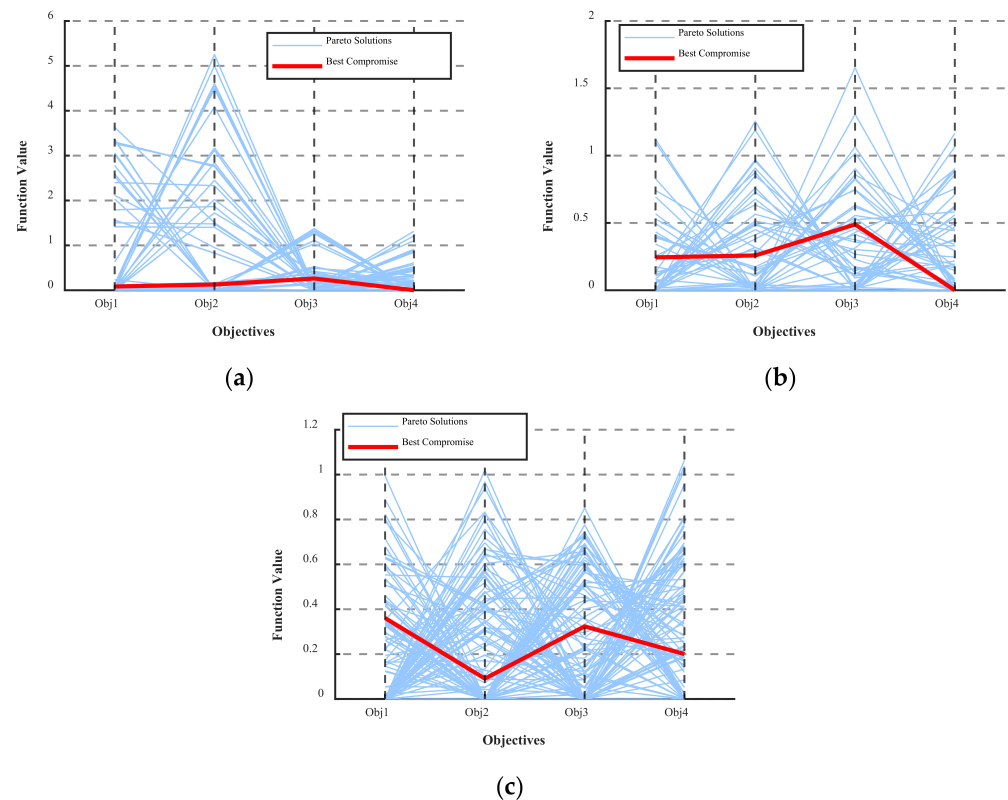
All algorithms share population size = 50, max iterations = 100 and 10 independent runs. MOPSO and MOEDO adopt archive size 100 (not applicable to NSGA-II). MOPSO uses linearly decaying inertia weight 0.9–0.4 with  $c_1 = c_2 = 2.0$ ; NSGA-II uses simulated binary crossover and mutation noise of 0.1. Comparison metrics include HV and single-objective optimum. Figures 6–8 plot the average of optimal compromise solutions from 10 repeated simulations to eliminate randomness.



**Figure 6.** Comparison on optimization results for Test Function I. The red line is averaged optimal compromise solutions over 10 independent runs with unified algorithm parameters. (a) Optimization results via MOEDO; (b) optimization results via MOPSO; (c) optimization results via NSGA-II.



**Figure 7.** Comparison on optimization results for Test Function II. The red line is averaged optimal compromise solutions over 10 independent runs with unified algorithm parameters. (a) Optimization results via MOEDO; (b) optimization results via MOPSO; (c) optimization results via NSGA-II.



**Figure 8.** Comparison on optimization results for Test Function III. The red line is averaged optimal compromise solutions over 10 independent runs with unified algorithm parameters. (a) Optimization results via MOEDO; (b) optimization results via MOPSO; (c) optimization results via NSGA-II.

Combined with the actual research object and application scenario of this paper, three test functions are constructed in this work. The decision variables of all test functions are defined as  $[x_1, x_2, x_3]$ ,  $x_i \in [0, 1]$ . The number of objective functions of all test functions are set as four. The objective function of Test Function I is expressed as follows:

$$\begin{cases} \min f_1(x) = |x_1 - 0.5| + x_2^2 \\ \min f_2(x) = 2x_2 + x_3 \\ \min f_3(x) = |x_1 - x_2| \\ \min f_4(x) = (x_3 - 0.5)^2 \end{cases} \quad (37)$$

The comparison of multi-objective solution referring to Test Function 1 is shown in Figure 6. As shown in the figure, MOEDO effectively alleviates multi-objective conflicts for this test model and delivers superior trade-off results on objective 3 and 4 compared with MOPSO. However, its convergence precision on objective 1 and 2 is inferior to NSGA-II and requires further optimization.

The objective function of Test Function II is expressed as follows:

$$\begin{cases} g(x) = 1 + \frac{1}{2}(x_2 + x_3) \\ \min f_1(x) = x_1 \\ \min f_2(x) = g(x)(1 - \sqrt{\frac{x_1}{g(x)}}) \\ \min f_3(x) = 2|x_2 - 0.5| \\ \min f_4(x) = 4(x_3 - 0.5)^2 \end{cases} \quad (38)$$

The comparison of multi-objective solution referring to Test Function II is shown in Figure 7. As shown in the figure, simulation results reveal that the MOEDO algorithm can maintain favorable multi-objective trade-off balance on the Test Function II, yet its absolute

convergence accuracy is inferior to NSGA-II. Specifically, it fails to reach the extreme values obtained by NSGA-II in objective 4 (0.0787) and objective 1 (0.3931). Compared with MOPSO, although MOEDO exhibits slightly weaker optimization performance on objective 3, it delivers more robust comprehensive performance for objective 1 and objective 2.

The objective function of Test Function III is expressed as follows:

$$\left\{ \begin{array}{l} g(x) = 100[3 + \sum_{i=1}^3 ((x_i - 0.5)^2 - \cos(20\pi(x_i - 0.5)))] \\ \min f_1(x) = \frac{0.5x_1x_2x_3(1 + g(x))}{50} \\ \min f_2(x) = \frac{0.5x_1x_2(1 - x_3)(1 + g(x))}{50} \\ \min f_3(x) = \frac{0.5x_1(1 - x_2)(1 + g(x))}{50} \\ \min f_4(x) = \frac{0.5(1 - x_1)(1 + g(x))}{50} \end{array} \right. \quad (39)$$

The comparison of multi-objective solution referring to Test Function III is shown in Figure 8. Simulation results show that MOEDO delivers excellent overall trade-off performance on the Test Function III. It achieves an ultra-low objective 3 value, vastly surpassing NSGA-II and MOPSO. However, compared with other two methods, MOEDO's absolute precision for several single objectives can be further improved.

From the overall simulation results of three test sets, MOEDO shows stable optimization capacity and excellent multi-objective equilibrium for various multi-objective problems. It efficiently prevents local optimum trapping in complex engineering and high-dimensional scenarios. While it occasionally underperforms NSGA-II on the extreme precision of single objectives, its Pareto set quality and overall trade-off performance far exceed MOPSO. MOEDO balances convergence and diversity well, proving its reliable potential for practical complex engineering optimization tasks.

According to above analysis, MOEDO achieves fast convergence and wide Pareto coverage, and Section 3.5 further verifies its lower iteration cost compared with other existing optimization algorithms.

### 3.5. Analysis on Computational Complexity and Convergence Properties of MOEDO

The time complexity of MOEDO is analyzed by decomposing five execution stages, with population size  $N$ , objective number  $M_{obj}$ , decision variable dimension  $d$ , maximum iteration *Max-time*.

- (1) Population initialization:  $O(N \cdot d)$ , only generating random feasible individuals with negligible overhead.
  - (2) EDO intermediate population generation:  $O(N \cdot d)$ , exponential distribution search operators adopt linear position update without matrix inversion.
  - (3) IFM offspring construction: extra complexity  $O(N \cdot M_{obj})$  compared with basic EDO, caused by historical elite objective value fusion calculation.
  - (4) Non-dominated sorting and crowding distance screening: consistent with mainstream multi-objective algorithm at  $O(M_{obj} \cdot N^2)$ , which dominates overall computational overhead.
  - (5) Fuzzy compromise solution:  $O(N \cdot M_{obj})$  for normalization and satisfaction calculation.
- The overall time complexity of single iteration is  $O(M_{obj} \cdot N^2)$ , same order as classical NSGA-II. The improved IFM only introduces linear extra complexity independent of decision dimension. Compared with MOPSO, whose achieve maintenance typically  $O(N \cdot \log(N))$ , MOEDO achieves lower complexity under large population.

So, the adaptive mutation operator does not increase the complexity order, but only adds lightweight random parameter judgment during individual update.

The convergence performance is quantified by the following two core indicators: hypervolume (HV) of Pareto front and convergence iteration threshold. The original EDO suffers slow convergence when facing multi-timescale constraints between EESS and CAESS, due to weak historical information inheritance. The embedded IFM transmits elite objective information from historical iterations to new offspring, accelerating the HV growth rate in early iterations. The adaptive mutation operator adjusts global/local search weight with iteration decay factor, avoiding premature convergence to local Pareto suboptimal fronts.

#### 4. Case Study

In order to evaluate the effectiveness of proposed auxiliary secondary frequency regulation method, a case study is carried out based on the field frequency regulation data of a typical operating day in a certain area of China. The 120 min AGC time series plotted in Figure 9 corresponds to typical daily normal steady operation, representing the most common regular working condition of the studied regional grid, without extreme load surge or generator tripping disturbance. In the concerned region, the base power is set to 1000 MW and the nominal frequency is 50 Hz. The rated capacity of EESSs in the region is 200 MWh and the capacity of CAESSs is 800 MWh, and their maximum charging and discharging power are both 100 MW. The AGC command is shown in Figure 9. Other key parameters in the case study are listed in Tables 1–3.

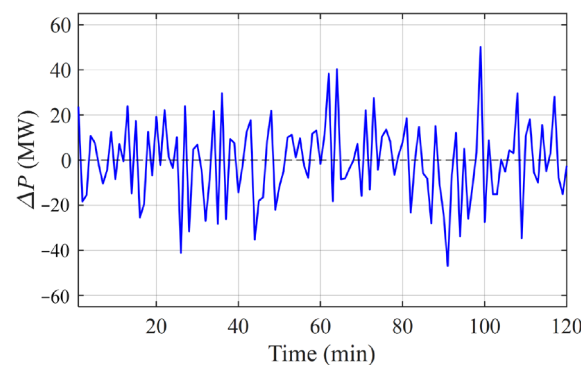


Figure 9. AGC command in the concerned case study.

Table 1. Key parameters for thermal generating units in concerned region.

| Items                                                       | Values | Items                                          | Values     |
|-------------------------------------------------------------|--------|------------------------------------------------|------------|
| $a$ ( $\text{kg} \cdot (\text{MW}^2 \cdot \text{h}^{-1})$ ) | 0.226  | $\mu$ ( $\text{kg}/\text{kW} \cdot \text{h}$ ) | 0.75       |
| $b$ ( $\text{kg} \cdot (\text{MW} \cdot \text{h}^{-1})$ )   | 30.42  | $\gamma$ (RMB/MWh)                             | 83.5       |
| $c$ ( $\text{kg} \cdot \text{h}^{-1}$ )                     | 786.80 | $C_{\text{co2}}$ (RMB/T)                       | 80         |
| $C_{\text{coal}}$ (RMB/T)                                   | 700    | $P_{\text{min}}$ (MW)                          | 60         |
| $P_{\text{max}}$ (MW)                                       | 200    | Regulation dead band (Hz)                      | $\pm 0.02$ |
| Ramp-up/down rate (MW/min)                                  | 2.5    | Response delay (s)                             | 30         |

Table 2. Key parameters for EESSs participate in frequency regulation in concerned region.

| Items                        | Values | Items                      | Values |
|------------------------------|--------|----------------------------|--------|
| $SoC_{\text{max}}$           | 0.8    | $SoC_{\text{min}}$         | 0.2    |
| Ramp-up/down rate (MW/min)   | 100    | Response delay (s)         | 0.2    |
| Cost of dispatching (RMB/kW) | 2500   | Cost of capacity (RMB/kWh) | 5000   |
| Cycling life (times)         | 2000   | Efficiency                 | 90%    |

**Table 3.** Key parameters for CAESSs participate in frequency regulation in concerned region.

| Items                          | Values | Items                               | Values |
|--------------------------------|--------|-------------------------------------|--------|
| Rated charging power (MW)      | 90     | Rated discharging power (MW)        | 100    |
| Total storage capacity (MWh)   | 800    | Minimum storage capacity (MWh)      | 160    |
| Ramp-up rate (MW/min)          | 9      | Ramp down rate (MW/min)             | 10     |
| Charging/discharging delay (s) | 8      | Electricity selling price (RMB/MWh) | 398.23 |
| Initial SoC                    | 0.5    | Efficiency                          | 70%    |

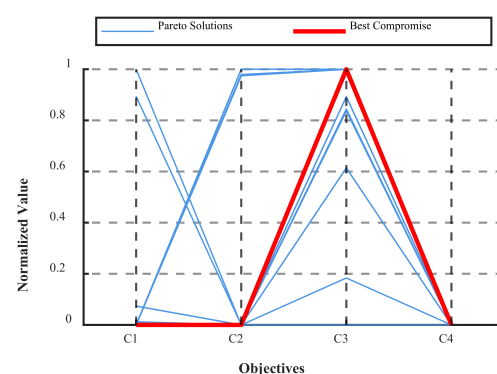
Notes: The simulation platform adopts 0.06 s electrical transient calculation step, and the AGC command updating cycle is set to 60 s, which is longer than the 8 s charging/discharging delay of CAESS. The time scale matching ensures the whole delay characteristic can be fully captured in a single control period, so the response performance of CAESS will not be overestimated.

The critical operation and economic parameters of thermal generating units participating in AGC frequency regulation are summarized in Table 1, including coal consumption coefficients, ramp constraints and response delay indicators of thermal units.

Different from slow-response thermal units, EESSs feature ultra-fast power adjustment capability. The core technical parameters of EESSs such as power ramp limit, cycle life and efficiency are listed in Table 2.

CAESSs are adopted to undertake long-duration frequency regulation tasks. Table 3 presents the rated power, storage capacity and dynamic response parameters of the CAESS equipment in the test regional grid.

One randomly picked AGC power commands are extracted from Figure 9. Figure 10 illustrates corresponding Pareto fronts for these AGC commands and the total AGC command is 20 MW. All results are converted to two-dimensional projections for comparison. The optimization model includes four mutually conflicting objectives. The optimal compromise solution obtained by fuzzy set evaluation is highlighted with red line in the figure. The coordinate of this compromise solution demonstrates balanced performance across concerned four objectives. According to (19), to maintain sufficient residual capacity of energy storage, this state-of-charge constraint severely prunes the solution set generated by the MOEDO algorithm.

**Figure 10.** Pareto optimal front under four objective for randomly selected AGC command. For clear visualization, all evaluation indicators are normalized.

However, we should point out that a fixed benchmark electricity price of 398.23 RMB/MWh is adopted purely to reduce optimization dimensionality and facilitate focused, intuitive analysis of the proposed algorithm's superiority in this case study, and this kind of simplification is widely adopted in secondary frequency regulation research [28]. Nevertheless, this static price hypothesis ignores hourly spot price fluctuation and the opportunity cost of energy storage sacrificing peak-valley arbitrage income to reserve capacity for frequency regulation service,

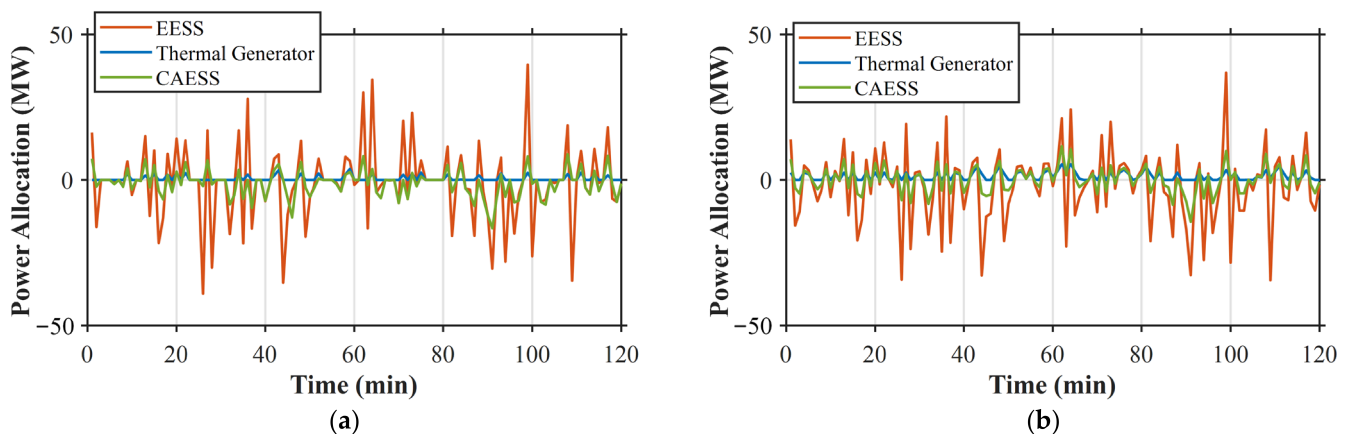
which inevitably leads to overly optimistic economic evaluation results. The time-series electricity and opportunity modeling framework in [24] can be introduced into the objective function for subsequent refined market economic analysis. Meanwhile, the established optimization framework retains full flexibility, and scholars and engineering practitioners can import real local hourly electricity data and calculate corresponding opportunity costs according to actual market conditions for customized economic assessment.

The performance of presented strategy is compared with traditional proportional allocation (TPA) strategy for frequency regulation. The dispatching capacity for the  $i$ -th type of frequency resource is expressed as follows:

$$\begin{cases} \Delta P_i = \alpha_i \Delta P \\ \alpha_i = \frac{K_i \Delta P_{ava,i}}{\sum_{i=1}^3 (K_i \Delta P_{ava,i})} \end{cases} \quad (40)$$

where  $\Delta P_i$  and  $\Delta P$  are frequency regulation instructions for the  $i$ -th type of resource and total frequency regulation requirement in the power grid, respectively;  $\alpha_i$  and  $K_i$  are frequency regulation participation factor, participation weight coefficient, and real-time available capacity for frequency regulation of  $i$ -th type of resource, respectively. In the case study,  $K_i$  is set as 1.2, 2.0 and 1.4 for thermal generating unit, EESSs, and CAESSs, respectively.

According to the optimization result, frequency regulation commands for three types of frequency regulation resources are shown in Figure 11. As compared by Figure 11a,b, under proposed control framework, EESSs are fully utilized for their fast response capability to improve the regulating accuracy according to AGC command, while CAESSs undertake continuous secondary frequency regulation tasks by virtue of their long-duration regulation capacity.



**Figure 11.** Power regulation commands allocated to thermal generating units, EESSs and CAESSs under proposed MOEDO and traditional TPA. (a) Power allocation generated by MOEDO; (b) power allocation generated by TPA.

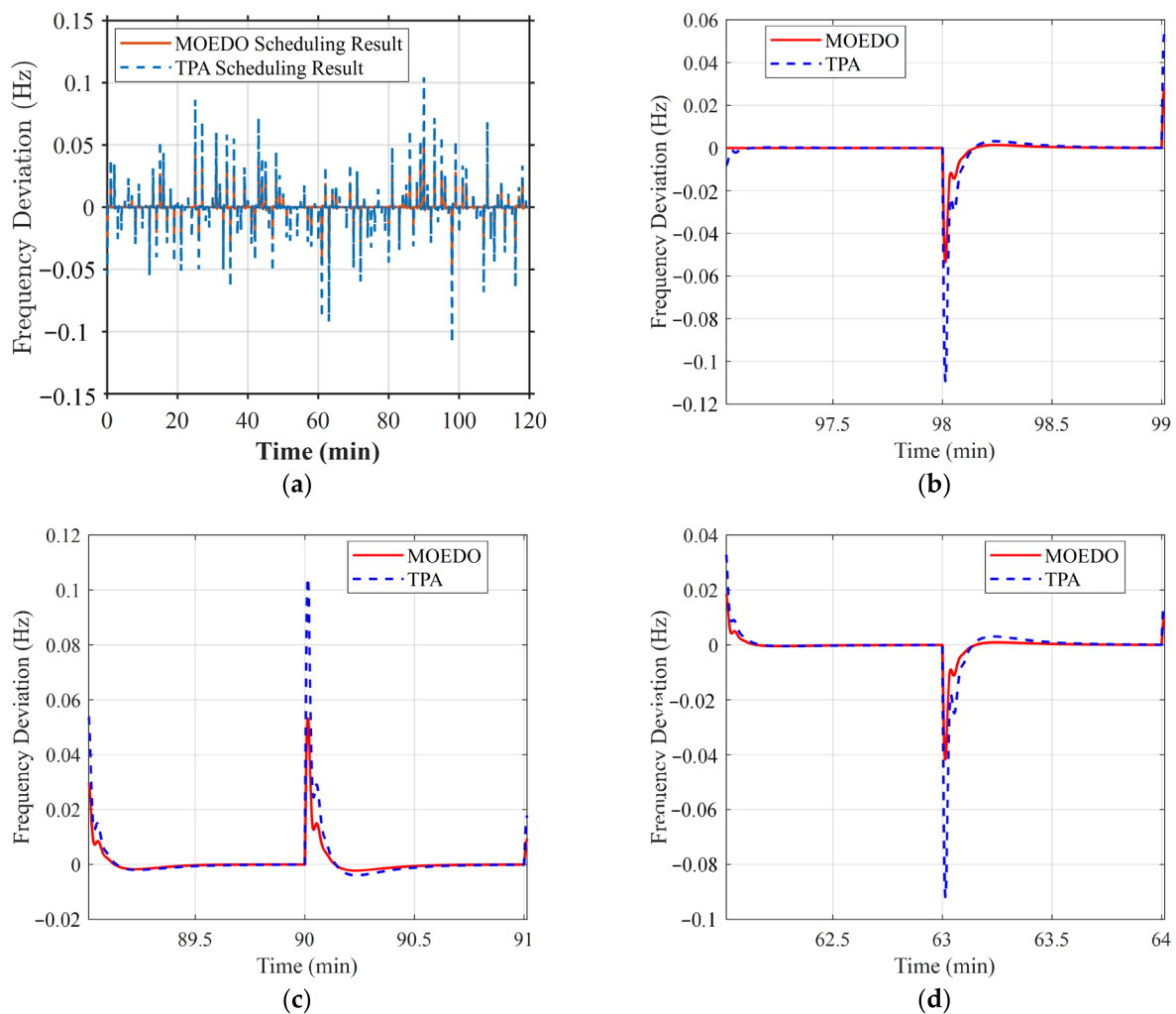
Referring to proposed MOEDO, the observed distribution is the result of the MOEDO algorithm resolving the inherent conflicts among the four objectives ( $C_1$  to  $C_4$ ). From the physical mechanism perspective, the algorithm prioritizes fast-adjustment resources to reduce frequency deviation index  $C_1$  in (17). Dynamic Formulas (8) and (11) verify that EESS owns a much smaller time constant than CAESS. Therefore, the optimizer distributes more regulation power to EESS during transient disturbance.

The algorithm balances regulation cost  $C_2$  and SoC equilibrium index  $C_4$  via cost-benefit trade-off analysis. Even though EESS has higher unit dispatch cost, the model still allocates more power to EESS to prevent deep discharge of CAESS. The core reason is that

keeping storage SoC within the ideal range can eliminate the penalty of  $C_4$ . The model slightly sacrifices economic efficiency to guarantee long-term available regulation capacity of CAESS. As shown in Figure 11a, under MOEDO, the maximum charging command of the EESS reaches 38.9 MW and the maximum discharging command reaches 39.6 MW. In Figure 11b, under the conventional TPA scheduling strategy, the maximum charging command of the EESS is 32.7 MW, and the maximum discharging command is 35.8 MW.

Finally, the final optimal solution is selected from the Pareto front using the fuzzy membership, which is defined as (35) and evaluates the satisfaction degree of each objective. The solution with the maximum comprehensive satisfaction  $h$  is chosen as the final output.

A 120 min simulation of secondary frequency regulation power allocation is carried out on the two-area frequency regulation system shown in Figure 4. Comparison is shown in Figure 12.



**Figure 12.** Comparison of frequency deviations under TPA and MOEDO. MOEDO achieves lower peak frequency fluctuations than TPA. (a) The overall view of simulation from 0 min to 120 min. (b) Transient response at 98 min. (c) Transient response at 90 min. (d) Transient response at 63 min.

A 120 min AGC disturbance simulation is carried out to compare the TPA and the proposed MOEDO strategy. The MOEDO method obviously reduces overall frequency deviation of the two-area interconnected grid. Several typical time points with severe frequency fluctuation are compared below.

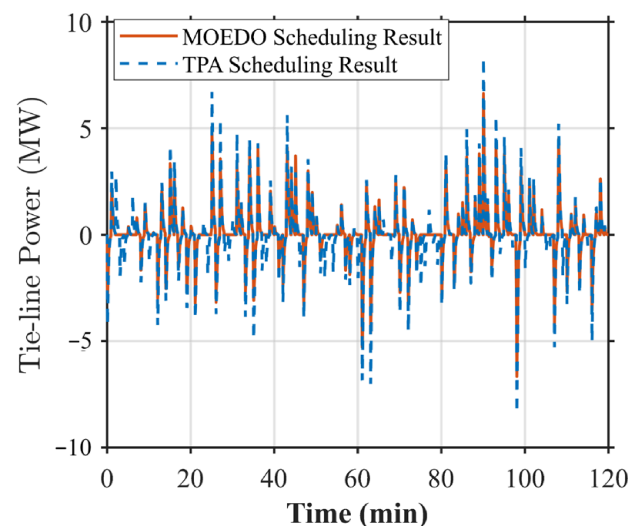
- (1) At 98 min, the frequency deviation is  $-0.109$  Hz under TPA control, and drops to  $0.053$  Hz with MOEDO, a reduction of  $0.056$  Hz.

- (2) Around 90 min, the deviation decreases from 0.103 Hz to 0.054 Hz, with a decrement of 0.049 Hz by proposed MOEDO control.
- (3) Nearby 63 min, the frequency fluctuation falls from  $-0.091$  Hz to  $-0.042$  Hz, reduced by 0.049 Hz with proposed MOEDO control.

It should be clarified that the comparison in this case focuses on the practical engineering gain of power allocation schemes under AGC operating signals, while the inherent optimization performance of MOEDO against state-of-the-art multi-objective optimizers (NSGA-II, MOPSO) is independently analyzed in Section 3.4 via standard benchmark functions. The two sets of comparison systems serve different research purposes: the benchmark function test reflects pure algorithm optimization capacity, whereas TPA comparison quantifies the performance improvement brought by the optimized scheduling scheme relative to widely deployed basic industrial dispatch strategies. In the future, we will carry out complete comparative simulations of NSGA-II and MOPSO under multiple disturbance conditions to further enrich engineering verification results.

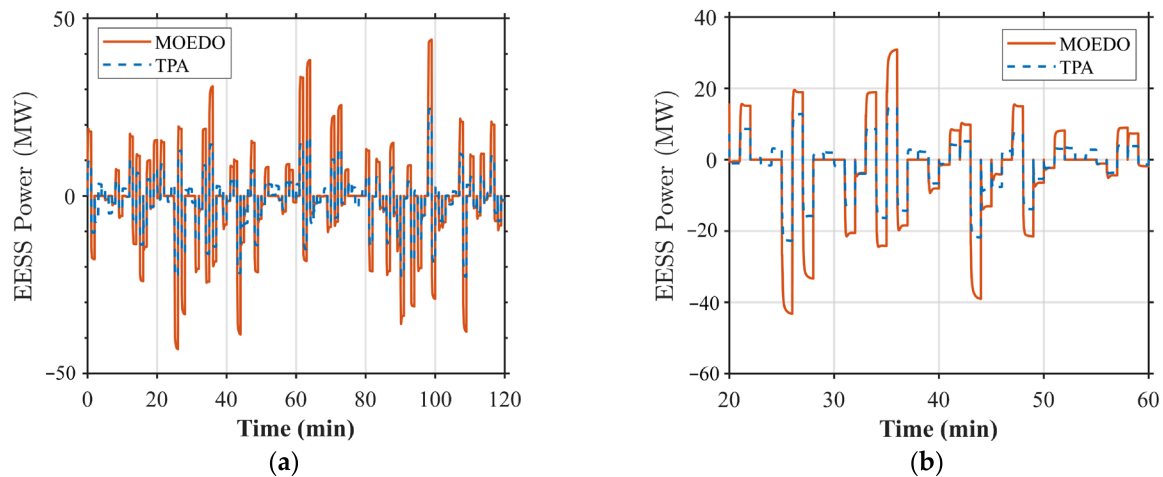
As a result, the proposed method effectively mitigates the peak values of frequency fluctuations.

Figure 13 shows the power exchange of tie-line between concerned two regions. The simulation results of power interaction results in Figure 13 show a trend similar to that of the frequency deviation results illustrated in Figure 12a. It can be seen that the overall power exchange across regions is effectively suppressed. Under the TPA control, the maximum tie-line power exchange reaches approximately 8.3 MW, whereas the maximum power deviation is limited to below 6.2 MW with the MOEDO algorithm-based control strategy. At timestamps around 63 min, 90 min and 98 min, the power exchange is reduced by roughly 1.3 MW compared with TPA control.



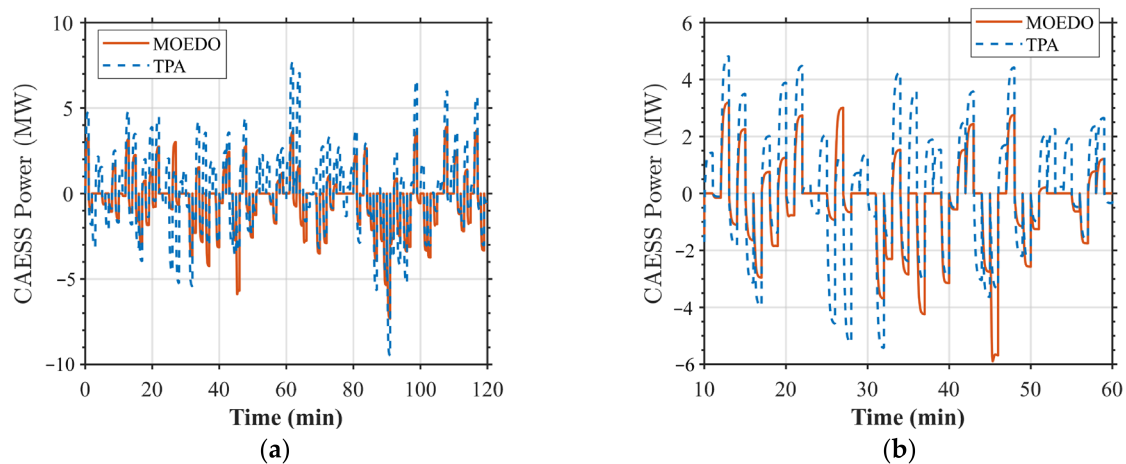
**Figure 13.** Cross-area tie-line power transmission comparison between TPA and MOEDO. MOEDO reduces the maximum tie-line swing.

Figure 14 illustrates the comparison on power response of EESSs when responding to AGC commands. As observed from the figure, the power output of EESSs under TPA control is evidently lower than that under the MOEDO algorithm-based allocation strategy. The power allocation scheme of the proposed strategy can fully exploit the power delivery capability of EESSs. Benefiting from the fast response characteristic of EESSs and system frequency fluctuations are further reduced.



**Figure 14.** EESSs active power output curves under two allocation strategies. MOEDO makes full use of EESSs fast response capability. (a) The overall view of simulation from 0 min to 120 min; (b) enlarged view within 20 min to 60 min.

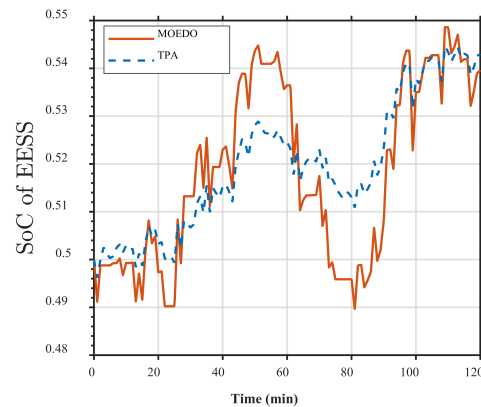
Meanwhile, a portion of the regulation power is assigned to CAESSs, corresponding responding curve is shown in Figure 15. This arrangement allows EESSs to rapidly provide power support while mitigating its cycle aging loss. Therefore, the proposed allocation strategy achieves a favorable trade-off between frequency regulation rapidity and economic efficiency.



**Figure 15.** CAESSs active power output curves under TPA and MOEDO. MOEDO avoids excessive CAESSs output and frequency oscillation. (a) The overall view of simulation from 0 min to 120 min; (b) enlarged view within 10 min to 60 min.

Figure 15 shows the power deviation curve of CAESSs. Under TPA control, CAESSs undertake a large share of the regulation power output. Restricted by its ramp rate limits, severe system frequency fluctuations are triggered. By contrast, the output of CAESSs is appropriately reduced under the proposed MOEDO algorithm strategy. Subject to the constraint of maintaining the health state of electrochemical energy storage, the reduced CAESSs output effectively to stabilize the system frequency.

The corresponding variation in SoC of EESSs is shown in Figure 16. Under proposed MOEDO control, EESSs are dispatched more frequently, accompanied by larger SoC variations. Nevertheless, the SoC variation in EESSs is incorporated as one of the optimization objectives in MOEDO. As a result, even though EESSs undertake a larger share of frequency regulation duties, the system avoids excessive reliance on their regulation capability.



**Figure 16.** SoC variation curve of EESSs under TPA and MOEDO. MOEDO keeps SoC within required operating range.

Table 4 quantitatively summarizes the overall performance of TPA and MOEDO across all metrics requested by the reviewer, including frequency deviation metrics, settling behavior, tie-line fluctuation, total regulation expense, EESS SoC operating range and computational consumption. With respect to the comparison in Table 4, remarks are given as following.

**Table 4.** Performance comparison between TPA and MOEDO.

| Performance Category | Evaluation Index                          | TPA              | MOEDO            | Perform   |
|----------------------|-------------------------------------------|------------------|------------------|-----------|
| Frequency stability  | Maximum absolute frequency deviation (Hz) | 0.1092           | 0.0535           | Reduced   |
|                      | RMS frequency deviation (Hz)              | 0.0054           | 0.0026           | Reduced   |
|                      | Average settling time (s)                 | 37.9             | 32.1             | Shortened |
|                      | Maximum settling time (s)                 | 49.7             | 49.7             | Equal     |
| Tie-line oscillation | Max tie-line power deviation (MW)         | 8.3703           | 6.2317           | Reduced   |
|                      | RMS tie-line fluctuation (MW)             | 1.3753           | 1.0810           | Reduced   |
|                      | Tie-line peak-to-peak swing (MW)          | 16.6911          | 14.2332          | Reduced   |
| Economic index       | Total 120 min regulation cost (RMB)       | 11289.43         | 11751.23         | Increased |
| EESS safety          | EESS SoC operating range                  | [0.4962, 0.5446] | [0.4897, 0.5486] | Increased |
| Computation cost     | Single AGC command optimization time      | 3.2ms            | 2.9s             | Increased |
|                      | 120 min AGC commands optimization time    | 0.48s            | 356s             | Increased |

- (1) Settling time refers to the minimum time when frequency deviation stays within  $\pm 0.02$  Hz without exceeding the threshold afterwards.
- (2) The regulation cost growth of MOEDO is caused by Pareto compromise: more fast-response EESS power is dispatched to suppress transient frequency shock.
- (3) Calculation time is measured on MATLAB R2024b with i7-12700H processor.
- (4) The estimated regulation cost is derived solely from the preset costs and simulation results, and is intended exclusively for evaluating the proposed solution algorithm.

It can be observed from Table 4 that MOEDO achieves prominent suppression on frequency deviation and inter-area power oscillation. Though the total regulation cost rises slightly, the EESS SoC is always constrained in the preset ideal interval without overcharge/overdischarge risks. For real-time scheduling, the single-step computation

delay of MOEDO is far less than the 60 s AGC dispatch window, which satisfies the online operation requirement of regional power grids.

## 5. Conclusions and Future Work

This paper investigates the coordinated secondary frequency regulation strategy of different types of ESSs in regional power grids and proposes a joint frequency regulation strategy for EESSs and CAESSs based on the MOEDO algorithm. First, according to the frequency response characteristics of generators, loads and tie lines, an electromechanical-electromagnetic hybrid simulation model of a two-area power system integrated with dual energy storage systems is established. Then, considering the comprehensive requirements of frequency regulation economy, system dynamic stability and energy storage service life, a multi-objective evaluation function is constructed to minimize the integral of frequency deviation, tie-line power fluctuation and frequency regulation cost. Meanwhile, multiple operational constraints including *SoC* and power ramp rate are embedded during the optimization process. The Pareto optimal solution set is obtained and the optimal commands are selected. Main technical contributions can be summarized as follows.

1. A two-area grid hybrid model with two kinds of energy storage is established. The model reflects the complementary fast and long-time regulation features of EESS and CAESS. The coordinated secondary frequency framework can be thus achieved.
2. Four target functions and supporting operation constraints for joint EESS-CAESS frequency regulation. The *SoC* deviation penalty is suggested for dispatching.
3. IFM and adaptive mutation operators are added to the optimizer, which overcomes the solve slow convergence problems under multi-timescale nonlinear constraints.

Simulation results show that the proposed strategy can effectively suppress the overall frequency fluctuation of the power grid. It fully exploits the frequency regulation capability of energy storage while guaranteeing its operational economy. The effectiveness of multi-energy-storage coordinated frequency regulation in improving grid dynamic performance and operational economy is verified. More discussion is given as following for further application of proposed solution.

1. The MOEDO framework has good scalability for large-scale complex power grids, because it adopts population iterative optimization. Nevertheless, massive multi-area grid models with dozens of storage stations will bring huge computational pressure restricted by its  $O(M_{obj}, N^2)$  dominant complexity. In follow-up research, parallel computing or model order reduction can be integrated into the algorithm to reduce the computational overhead caused by nondominated sorting and guarantee real-time dispatch performance.
2. The current model adopts deterministic simulation relying on historical load and power prediction data, without considering renewable output uncertainty. To adapt high-renewable power grids, we can expand the model into stochastic or robust optimization. This new form evaluates regulation cost and frequency deviation under multiple random scenarios, which requires embedding probabilistic prediction modules at the input layer of the algorithm. In addition, unified comparison conditions with model predictive control and deep reinforcement learning-based frequency regulation strategies will be established for further horizontal verification. Future work will also add multiple daily measured AGC datasets and synthetic severe extreme disturbance simulation cases, and complete formal mathematical convergence derivation of MOEDO.
3. The proposed model can be further improved to adapt electricity market operation by adding market income items into objective functions. At present, the optimiza-

tion target only minimizes regulation cost and frequency fluctuation. For market scenarios, we can reset the objective as profit maximization. It balances the income from frequency regulation auxiliary service and the aging loss cost of EESS and CAESS. Corresponding cost coefficients need to be redefined according to real-time market prices.

4. This paper adopts a simplified fixed cycle counting model to focus on comparing control performance. Future research can replace this formula with the following two refined aging models: (i) zonal electrothermal coupling degradation model for lithium EESS [25]; (ii) variable-temperature thermal fatigue loss model for CAESS [26]. In addition, a high-fidelity CAESS model integrating air tank pressure dynamics, multi-stage expander nonlinear efficiency and mode-switch ramp thermodynamic constraints will be built for short-time-scale primary frequency regulation simulation. The two refined models can accurately quantify cycle aging loss caused by frequent AGC charge and discharge cycles.

An obvious limitation of the current work should be clearly clarified: all performance analysis and verification results in this paper are purely derived from offline numerical simulation, and the proposed coordinated frequency regulation strategy has not been tested and verified in practical applications. There exists a certain gap between the simulation environment and the actual complex operation conditions of power grids (such as uncertain renewable fluctuation, equipment communication delay and on-site control hardware constraints), which may cause deviation between simulated results and on-site practical effects.

Correspondingly, real-world engineering verification should be taken as an important follow-up research direction. The project team will cooperate with provincial power dispatching departments and energy storage station operators to collect long-term measured AGC operation data of actual EESS and CAESS projects. A hardware-in-the-loop (HIL) real-time simulation test platform will be built to reproduce real grid disturbance scenarios. So, the proposed MOEDO strategy can be comprehensively verified under on-site practical working conditions to further improve its engineering practicability.

The research outcomes of this paper can provide theoretical support and engineering solutions for the refined secondary frequency control of power grids with high penetration of new energy.

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## Nomenclature

|                                                     |                                                                                                                                                                                                                             |
|-----------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| AGC; ACE                                            | Automatic generation control; area control error                                                                                                                                                                            |
| ESS; EESS; CAESS                                    | Energy storage station; electrochemical energy storage station; compressed air energy storage station                                                                                                                       |
| IFM                                                 | Information feedback mechanism                                                                                                                                                                                              |
| EDO; MOEDO                                          | Exponential distribution optimization; multi-objective exponential distribution optimization                                                                                                                                |
| TPA                                                 | Traditional proportional allocation                                                                                                                                                                                         |
| SoC                                                 | State-of-charge                                                                                                                                                                                                             |
| $f; f_N$                                            | Actual frequency; rated frequency                                                                                                                                                                                           |
| $P_L; P_{LN}$                                       | Actual total active load power; active load power at rated frequency                                                                                                                                                        |
| $P_T; P_e; P_{tie}$                                 | Output active power of thermal generating units; charging/discharging power of EESSs; power transmission through regional tie-line                                                                                          |
| $a_0 \sim a_n$                                      | Proportion coefficients of each load component                                                                                                                                                                              |
| $K_L; \Delta f; \Delta P_L$                         | Frequency regulation coefficient; changes in frequency; changes in load power                                                                                                                                               |
| $\Delta P_{tie}$                                    | Variation in power transmission through regional tie-line                                                                                                                                                                   |
| $\Delta P_m; \Delta P_v$                            | Change in input power of the generator; change in valve position of gas turbine                                                                                                                                             |
| $T_{ch}; K_r; T_r$                                  | Inertia coefficient of the steam turbine; reheat factor of thermal power generator; reheat period of the thermal power generator                                                                                            |
| $\Delta \omega; K_{ps}; T_p; \Delta P_L(s)$         | The change in angular velocity of generator, which is related to the variation in grid frequency; gain coefficient of grid power-frequency characteristic; power-frequency conversion coefficient; the change in load power |
| $i; T_{ij}; \Delta f_i$                             | The number of concerned region; synchronization coefficient of the tie line between regions $i$ and $j$ ; frequency deviation of the $i$ -th region                                                                         |
| $P_e; Q_e$                                          | Active power and reactive power of EESS                                                                                                                                                                                     |
| $U_t; U_g$                                          | Voltage amplitude at the common coupling point; voltage amplitude of AC grid                                                                                                                                                |
| $\theta_{pll}; \theta_g$                            | Angle at the common coupling point; angle of AC grid                                                                                                                                                                        |
| $X_{line}$                                          | Equivalent impedance of power line                                                                                                                                                                                          |
| $T_e; \Delta P_{e,ref}; K_{pP}; K_{iP}$             | Delay constant of EESS; active power reference generated by AGC; proportional coefficient of PI controller in active power control loop; integral coefficient of PI controller in active power control loop                 |
| $\Delta Q_{e,ref}; K_{pQ}; K_{iQ}$                  | Reactive power reference generated by AGC; proportional coefficient of PI controller in reactive power control loop; integral coefficient of PI controller in reactive power control loop                                   |
| C-1; C-2; C-3                                       | Air compressors in CAESS                                                                                                                                                                                                    |
| T-1; T-2; T-3                                       | Expanders in CAESS                                                                                                                                                                                                          |
| HX- $i$ ( $i = 1 \sim 6$ )                          | Heat exchangers in CAESS                                                                                                                                                                                                    |
| Tank-1; tank-2                                      | Higher temperature tank in CAESS; lower temperature tank in CAESS                                                                                                                                                           |
| $\Delta P_{CAESS,c}; T_c; K_a; H_{ac}$              | Regulation of active power in charging process of CAESS; time coefficient for regulating compressor; deviation coefficient of frequency modulation; inertia time coefficient of CAESS                                       |
| $P_{CAESS,c}; P_{CAESS,c}^{min}; P_{CAESS,c}^{max}$ | Charging power of CAESS; minimum constraint of charging power; maximum constraint of charging power                                                                                                                         |
| $P_{ac}^{RU}; P_{ac}^{RD}$                          | Upper backup power during the regulation process; lower backup power during the regulation process                                                                                                                          |

|                                                                                               |                                                                                                                                                                                                                                                                                 |
|-----------------------------------------------------------------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| $\Delta P_{CAESS,r}^m; \Delta P_{CAESS,r}; P_{CAESS,r}; P_{CAESS,r}^{min}; P_{CAESS,r}^{max}$ | Active power support provided by rotor inertia; regulation of active power in generating process; actual output active power of CAESS; minimum constraint of output power of CAESS; maximum constraint of output power of CAESS                                                 |
| $T_r; T_{igve}; H_{CAESS}$                                                                    | Emission delay of CAESS turbine; Adjustment time constant of valve opening; inertia time coefficient of synchronous grid-connected generator in CAESS                                                                                                                           |
| $F; x; f_i(x) (i = 1, 2, \dots, n)$                                                           | Multi-objective function; solution sets; evaluation indices                                                                                                                                                                                                                     |
| $g_i(x); g'_k(x)$                                                                             | Corresponding constraints during optimization in (12)                                                                                                                                                                                                                           |
| $V_{loss,i}; V_{life,i}$                                                                      | Energy loss cost of $i$ -th EESS; life degradation cost of $i$ -th EESS                                                                                                                                                                                                         |
| $s_e; c_{p,i}$                                                                                | On-grid electricity price; unit power cost of the $i$ -th EESS                                                                                                                                                                                                                  |
| $P_{c,i}(t); P_{d,i}(t); P_{rate,i}$                                                          | Charging power of $i$ -th EESS at moment $t$ ; discharging power of $i$ -th EESS at moment $t$ ; rated power of $i$ -th EESS                                                                                                                                                    |
| $\eta_{c,i}; \eta_{d,i}$                                                                      | Charging efficiency of $i$ -th EESS; discharging efficiency of $i$ -th EESS                                                                                                                                                                                                     |
| $E_{rate,i}; N_i$                                                                             | Rated capacity of $i$ -th EESS; allowable cycle number under full charge and full discharge condition for the $i$ -th EESS                                                                                                                                                      |
| $a; b; c$                                                                                     | Coal consumption coefficients of thermal generating units in (15)                                                                                                                                                                                                               |
| $\mu; c_{coal}; c_{CO2}; \gamma$                                                              | Carbon emission coefficient; coal cost coefficient; carbon capture cost; unit wear coefficient                                                                                                                                                                                  |
| $T$                                                                                           | Entire evaluation period                                                                                                                                                                                                                                                        |
| $C_1; C_2; C_3; C_4$                                                                          | Total frequency regulation cost; evaluation index corresponding to frequency deviation suppression; evaluation index corresponding to power balance level among concerned regions; evaluation index corresponding to SoC                                                        |
| $C_i (i = 1 \sim 4)$                                                                          | Value of $i$ -th evaluation index                                                                                                                                                                                                                                               |
| $SoC_{avg}$                                                                                   | Averaged SoC during frequency regulation                                                                                                                                                                                                                                        |
| $\alpha_{T,r}^{um}; \alpha_{T,r}^{dn}; \alpha_{CAESS,r}^{um}; \alpha_{CAESS,r}^{dn}$          | Ramp-up constraint of thermal generating units; ramp-down constraint of thermal generating units; ramp-up constraint of CAESSs; ramp-down constraint of CAESSs                                                                                                                  |
| $SoC_e; SoC_{CAESS}; SoC(0); SoC(T+1)$                                                        | SoC of EESS; SoC of CAESS; SoC value at initial dispatching instant; SoC value at final dispatching instant                                                                                                                                                                     |
| $M; d; Max\_time$                                                                             | Population size; decision-space dimension; maximum iteration number                                                                                                                                                                                                             |
| $rand; v; w$                                                                                  | A uniformly distributed random number within [0,1]; individual index; variable index                                                                                                                                                                                            |
| $X_{guid}^{time}; time$                                                                       | Guided solution; current iteration index                                                                                                                                                                                                                                        |
| $X_{best1}; X_{best2}; X_{best3}$                                                             | Best fitness values in current solution                                                                                                                                                                                                                                         |
| $f'; c'; d'$                                                                                  | Random adjustment factor; generation decay coefficient; exploration fusion coefficient                                                                                                                                                                                          |
| $a'; b'$                                                                                      | Exploitation weight coefficients calculated by (29)                                                                                                                                                                                                                             |
| $\Phi$                                                                                        | A uniformly distributed random number generated once within (0,1)                                                                                                                                                                                                               |
| $X_{rand1}; X_{rand2}$                                                                        | Two distinct individuals selected randomly from current population according to (31)                                                                                                                                                                                            |
| $\partial_1; \partial_2$                                                                      | Adaptive fusion weights                                                                                                                                                                                                                                                         |
| $u_v^{t'+1}$ and $f_v^{t'+1}; Y_{t+1}$                                                        | Temporary generated $v$ -th individual; Objective function value in step 2 referring to $u_v^{t'+1}$ ; offspring population                                                                                                                                                     |
| $C_{min,i}; C_{max,i}$                                                                        | Minimum value of the $i$ -th evaluation index; maximum value of the $i$ -th evaluation index                                                                                                                                                                                    |
| $h; M_{obj}$                                                                                  | Normalized satisfaction degree of individuals in Pareto solution sets; the number of objective function                                                                                                                                                                         |
| $\Delta P_i; \Delta P; \alpha_i; K_i; \Delta P_{ava,i}$                                       | Frequency regulation instruction for the $i$ -th regulating resource; total frequency regulation requirement; frequency regulation participation factor; participation weight coefficient; real-time available capacity for frequency regulation of $i$ -th regulating resource |

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