

Article

Research on Planning and Dispatching Strategy of Grid-Side Energy Storage Power Station Considering Regional Power Grid Interconnection

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Abstract

Energy storage planning and optimal dispatch in real power grids are restricted by high-dimensional nonlinear constraints. The solution process involves a heavy calculation burden. This paper studies the site selection, capacity sizing and optimal dispatch of large-scale grid-side energy storage stations for 220 kV regional power grids. First, a multi-objective optimization model is constructed. It takes two indicators as sub-objectives: total installed capacity of energy storage stations and net load peak–valley difference. Then, a customized improved particle swarm optimization (IPSO) algorithm is designed. This algorithm is improved from the classic gray relationship analysis–particle swarm optimization (GRA–PSO). It targets the site and allocation of electrochemical battery energy storage stations (BESSs) inside interconnected 220 kV regional grids. Unlike the GRA–PSO structure presented in existing studies, this paper reconstructs the gray correlation sequence matching the multi-objective planning demand of regional power grids and introduces differentiated particle velocity constraints based on node load characteristics. By combining gray correlation with PSO, premature convergence and clustered storage layout introduced by traditional PSO can be eliminated. Subsequently, taking the renewable energy accommodation rate and net load peak–valley difference rate as optimization objectives, this paper adopts the walrus optimization algorithm (WOA) to carry out optimal dispatching of BESSs in regional power grids. A fitness-variance early-stop rule is introduced to the WOA for ESS dispatching, cutting redundant iterations while balancing peak-shaving and renewable energy curtailment reduction. Finally, numerical analysis of a case study based on a typical urban 220 kV regional power grid in central Henan Province, China, verifies the effectiveness and reliability of the proposed strategy.

Keywords: grid-side energy storage station; improved particle swarm optimization (IPSO); planning and dispatching; grid-side energy storage stations in regional power grid; walrus optimization algorithm (WOA)



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1. Introduction

In recent years, the large-scale integration of wind and photovoltaic power has significantly improved the penetration of renewable energy in power systems. The strong randomness and volatility of renewable power output present prominent risks to the secure and stable operation of power grids, thereby raising the demand for flexible regulation resources in power systems [1,2]. The large-scale deployment of grid-side energy storage stations (ESSs) has facilitated a novel source–grid–load–storage coordinated operation framework for the development of new power systems with high renewable penetration [3].

As the backbone of provincial transmission networks, 220 kV regional power grids undertake the responsibilities of voltage-level interconnection, urban power supply guarantee, and renewable energy integration [4–6]. However, the large-scale deployment and coordinated dispatch of centralized ESSs in interconnected 220 kV regional grids are simultaneously restricted by grid transmission capacity, system operation security and comprehensive construction costs, resulting in intractable multi-dimensional coupling constraints. Therefore, to mitigate net load fluctuations, reduce peak–valley disparities and enhance the local accommodation capacity of renewable energy generation, targeted research on the optimal layout and real-time economic dispatch of grid-side centralized ESSs in interconnected regional power grids is of great theoretical and practical significance [7].

Most studies on ESS deployment and dispatching focus on distribution networks and microgrids. The solutions proposed in [8–12] take distribution networks and microgrids as research objects, adopting particle swarm optimization (PSO), the genetic algorithm, and the simulated annealing algorithm to optimize storage capacity. However, traditional meta-heuristic algorithms lack engineering-oriented iterative update rules, thus easily generating over-concentrated ESS allocation results. Such a centralized layout fails to adapt to the uneven spatial distribution of node load and renewable output in regional grids, and cannot achieve a decentralized layout matching regional load characteristics. In [13], a Taguchi-tuned PSO approach is presented for the optimal placement and sizing of shunt capacitor banks in unbalanced distribution systems, which reduces the total operation cost and improves the voltage profile. In [14], a two-step approach for improving the voltage profile of a distribution network using the optimal integration of a photovoltaic battery energy storage system is proposed, which limits the voltage deviation from the reference value to less than 1%. However, the research objects of the two aforementioned studies remain limited to distribution systems.

With regard to ESSs dispatching at the distribution network or microgrid level, relevant studies mainly optimize ESSs' charging–discharging schedules to improve renewable energy accommodation, enhance system flexibility and achieve collaborative voltage regulation. In [15], the authors take the impact of the fluctuation of renewable power generation on power systems into account and adopt a multi-dimensional uncertainty set to characterize the stochastic factors of wind power generation. To optimize the dispatching strategy of energy storage batteries, a coupling model is established in [16] to reflect the influence of wind power generation and traditional generating units on the power system's stability. In [17], user-side energy storage and on-load tap changers of power suppliers' transformers in the distribution network are coordinated to achieve voltage regulation. Local droop control and distributed control are applied in [18] to adjust the charging and discharging power for energy storage units in the distribution network, and the extent to which energy storage participates in voltage regulation is designed according to the installed capacity and state of charge (SOC) of the energy storage system.

According to published studies focusing on regional power grids, the transmission network expansion planning problem optimizes the timing, location, and quantity of newly built lines to achieve specific objectives under technical, economic, and environmental

constraints [19]. The dynamic transmission and renewable generation expansion planning problem are solved through robust optimization in [20]. The proposed solution overcomes the scale limitation and computational intractability of such practical engineering problems. In [21], an efficient and accurate model named NC-CUC is proposed to support fast and detailed long-term operation simulations, including unit maintenance optimization, power system investment planning, and reliability assessment. To improve the accommodation capacity of renewable energy generation, the solution proposed in [22] deploys multiple energy storage devices on the transmission network side to address the forced curtailment introduced by the volatility and randomness of renewable energy, as well as the excessive investment costs resulting from single-stage planning. In [23], the relationship between the output range of renewable energy and regulation resources is considered. The proposed solution regards cross-regional transmission channels as flexible regulation resources. Accordingly, a mid- and long-term optimization model is established to realize the preferential accommodation of renewable energy. To minimize the economic cost of thermal power, a short- and mid-/long-term dispatching model is proposed in [24], in which the complementarity among multiple energy sources is considered. For grid-side energy storage systems (ESSs) in power grids, a dispatching method for a compressed air ESS in synchronous condenser operation mode is proposed in [25], by which both active and reactive power flows in power systems can be effectively dispatched. Reference [26] analyzes the economic benefits of different battery types in centralized energy storage stations. It relaxes the nonlinear constraints in the dispatching model into linear expressions, thus transforming the dispatching problem into a mixed-integer linear programming problem. These studies effectively enrich the theoretical framework for regional transmission grid planning and dispatch. However, most of them only focus on standalone grid expansion optimization and source-load coordinated scheduling. They cannot fully explore the collaborative potential of grid-side centralized energy storage in transmission grid regulation.

The power transmitted through cross-regional transmission lines is also of great significance for the optimization of regional power grids. Reference [27] establishes a planning model for interconnected multi-regional power systems that considers ESS planning, transmission expansion, and carbon emission quota trading, and proposes an analytical target cascading algorithm to solve the model in a distributed manner. The scholars in [28] address the accommodation challenges caused by the large-scale integration of variable renewable energy (VRE) into power grids. The proposed solution optimizes energy utilization while ensuring stable and reliable power supply. Reference [29] presents a unified-state variable-based coordination framework for multi-region shared energy storage in long-horizon production simulation, which enables a more reliable assessment of the contribution of shared storage to low-carbon power system operation. In [30], a novel multistage planning-operation model is suggested to tap the flexible potential of HVDC transmission systems and improve renewable penetration. However, the proposed solution cannot be directly applied to 220 kV regional power grids. Combining national and regional policies with resource constraints, a power system coordination planning model is given in [31] to determine the new installed capacity configuration of regional power supplies. Nevertheless, the above studies pay limited attention to the intrinsic coordination mechanism between the power transmission characteristics of cross-regional tie-lines and the flexible regulation capability of grid-side ESSs. Most existing multi-region scheduling schemes optimize tie-line power curves merely from the perspective of power balance and transaction demand, and fail to fully exploit the charge-discharge characteristics of ESSs to suppress tie-line power fluctuations, alleviate transmission congestion and improve the delivery efficiency of cross-regional renewable energy.

Most existing transmission grid-oriented studies only conduct pure power scheduling optimization and grid expansion planning, without integrating grid-side centralized energy storage stations into coordinated optimization frameworks. Furthermore, targeted technical exploration on the joint siting, sizing and scheduling optimization of centralized ESSs for 220 kV regional grids remains inadequate. Few existing works explore two core objectives of regional main grids: peak-shaving performance capability and renewable energy accommodation improvement. The lack of tailored optimal configuration and scheduling strategies for grid-side ESSs hinders the operational performance improvement of 220 kV regional power grids. The case study in this paper is a typical urban 220 kV regional power grid located in central Henan Province, China. Its load and renewable generation characteristics are representative of regional power grids in central Henan.

In order to improve the renewable energy accommodation capacity of 220 kV regional main power grids, this paper investigates the siting, sizing and dispatching of centralized electrochemical battery energy storage stations (BESSs). The remainder of this paper is organized as follows. Section 2 establishes the model of regional power grid. Section 3 elaborates on the planning process of BESSs in regional grids. Since traditional PSO tends to fall into local optima and generate centralized storage allocation results, this paper improves the optimization process to realize the fast and accurate siting and sizing of centralized BESSs in 220 kV regional grids. Section 4 designs the dispatching process of BESSs in regional power grids. This paper improves the optimization procedure of the walrus optimization algorithm (WOA) by presetting an early termination condition. The original WOA only adopts the maximum iteration number as the termination criterion, resulting in redundant iterations after convergence. To solve this problem, this paper processes a fitness-variance early-stop judgment rule to eliminate invalid iterative computations. The modified algorithm can converge rapidly and output dispatching results, enabling a rapid response to the actual operational demands of power grids. Section 5 takes a practical urban 220 kV grid in Henan Province, China, as a case study to verify the effectiveness of the proposed solution. Sections 6 and 7 summarize the conclusions, limitations and future research prospects of this paper.

2. Model of Regional Power Grid

In regional power grids, real-time power balance needs to be maintained among the output of thermal power units, renewable power generation, and the transmission power of cross-regional tie-lines. When the system meets the instantaneous power balance constraints and the threshold conditions of grid regulation capability, the capacity margin between the superposed curve of regional load demand and tie-line outgoing power and the lower grid regulation limit characterizes the theoretical maximum renewable energy hosting capacity of the regional power grid. The renewable energy accommodation space in the regional power grid is shown in Figure 1, and relevant parameters can be found in the Nomenclature section.

To establish models of power balance and renewable energy accommodation space for interconnected 220 kV regional power grids, the following engineering assumptions are formulated.

- (1) All thermal units adopt a unified average peak-shaving depth for equivalent aggregation and ignore the discrete start-stop constraints of individual units in the steady-state daily power balance model.
- (2) The minimum technical output of each thermal unit is constrained by $P_{g,i,min}$, and spinning reserve capacity is independently configured outside of the basic load balancing power.

- (3) The ramp power fluctuations of generating units are neglected in the hourly time-scale power balance equation.
- (4) The abandoned power of renewable energy generation is defined as the difference between its theoretical output and the power accommodated by the power grid.
- (5) The model adopts a daily operation simulation framework, and all energy integral terms are calculated over a 0–24 h scheduling horizon.

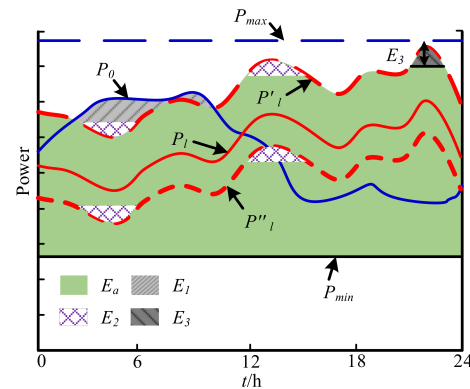


Figure 1. Schematic diagram of renewable energy accommodation space in the regional power grid.

According to Figure 1, the maximum accommodated power of renewable energy generation at time t satisfies

$$\begin{aligned}
 P_a(t) &= P_l(t) + P_{con}(t) - P_s(t) - \sum_{i=0}^{i=I} P_{g,i,min} = P_l(t) + P_{con}(t) - P_s(t) - \sum_{i=0}^{i=I} (P_{g,i,max} - \beta_i P_{g,i,max}) \\
 &= P_l(t) + P_{con}(t) - P_s(t) - (1 - \beta) \sum_{i=0}^{i=I} P_{g,i,max}
 \end{aligned} \quad (1)$$

The averaged peak-shaving depth of all thermal power units can be expressed as

$$\beta = \sum_i \beta_i \cdot P_{g,i,max} / \sum_i P_{g,i,max} \quad (2)$$

where I denotes the number of all conventional thermal generation units in the regional power grid.

Regional power grids are required to maintain stable and reliable operation. The aggregated maximum output of all grid-connected thermal power units is constrained. This upper limit must exceed the instantaneous peak of total system demand, including local load and planned outbound power. Sufficient spinning reserve capacity should be reserved for system emergency response. The corresponding mathematical constraint is established as follows:

$$\sum_{i=0}^{i=I} P_{g,i,max} = \max(P_l(t) + P_{con,plan}(t)) + R_+ \quad (3)$$

Under normal conditions, to maximize the renewable energy accommodation space while guaranteeing adequate grid reserve capacity, the system positive reserve rate can be reduced by shutting down inefficient units and optimizing unit commitment schemes. Meanwhile, units with strong peak-shaving performance are prioritized for operation to provide a sufficient regulation margin against renewable power fluctuations. On this basis, the regulation space E_a for accommodating renewable power fluctuations in the target regional power grid is defined as

$$E_a = \int P_a(t) dt = \int \left[P_l(t) + P_{con}(t) - (1 - \beta) \cdot \sum_i P_{g,i,max} \right] dt \quad (4)$$

When ESSs are deployed in the regional power grid, the corresponding power balance equation is established as

$$P_{con}(t) + P_0(t) + P_S(t) = P_l(t) + P_{con}(t) \quad (5)$$

where P_0 stands for the total renewable energy output of the regional power grid. Accordingly, the net load power $P_{net}(t)$ of the target regional power grid is derived as

$$P_{net}(t) = P_l(t) + P_{con}(t) - P_0(t) - P_S(t) \quad (6)$$

3. Planning Strategy of BESSs in Regional Power Grid

3.1. Optimization Objectives

According to Figure 1, the peak–valley difference in net load reflects the regulation capability of ESSs within the grid, while the required dispatchable capacity characterizes the installation scale and investment cost of ESSs. Thus, to improve power supply reliability and power quality, ESSs are deployed to reduce the peak–valley difference rate and alleviate grid load fluctuations. In this paper, the active net load peak–valley difference rate is employed as the first evaluation index, which is defined as f_1 as follows.

$$\begin{cases} P_{ij}^{net} = P_{ij}^{TS} - P_{ij}^W - P_{ij}^{PV} - P_{ij}^S \\ D_i = (\max(P_{ij}^{net}) - \min(P_{ij}^{net})) / \max(P_{ij}^{net}) \\ f_1 = \sum_{i=1}^{i=N} D_i \end{cases} \quad (7)$$

Meanwhile, the configured capacity of BESSs is adopted as the second evaluation index, which is defined as

$$f_2 = \sum_{i=1}^{i=N} \sum_{j=t_0}^{j=t_0+n\Delta t} P_{ij}^S \cdot \Delta t \quad (8)$$

where Δt stands for the time interval between two adjacent time periods; t_0 and $t_0 + n\Delta t$ are the start and end moments of dispatching BESSs.

By integrating the above two evaluation indexes, the multi-objective function for BESS planning is formulated as

$$\min F = [\lambda_1 f_1 + \lambda_2 f_2] \quad (9)$$

where λ_1 and λ_2 represent weight coefficients that satisfy $\lambda_1 + \lambda_2 = 1$. Notably, λ_1 and λ_2 are not fixed constants. In practical engineering applications, system operators can tune the two weight coefficients according to on-site operation demands. In addition, the total BESS configuration capacity adopted herein only serves as a technical scale constraint to prevent excessively concentrated energy storage layout. Although it is indirectly related to economic benefits, it is not quantified as monetary investment cost in the optimization objective. The proposed multi-objective framework can be further extended to incorporate economic cost terms for practical engineering scenarios, while the core IPSO algorithm remains intact. Furthermore, additional evaluation indexes can be flexibly modified or supplemented according to practical engineering requirements.

3.2. Constraints

During the optimization process, the power balance constraint needs to be primarily satisfied, and the corresponding constraint boundary is derived from (5) as follows:

$$\Delta P_j = P_j^{UP} + P_j^{TE} + \sum_{i=1}^{i=N} P_{ij}^W + \sum_{i=1}^{i=N} P_{ij}^{PV} + \sum_{i=1}^{i=N} P_{ij}^S + \sum_{i=1}^{i=N} P_{ij}^{else} - \sum_{i=1}^{i=N} P_{ij}^{TS} \quad (10)$$

Restricted by their internal battery cells and electrical devices, the charging and discharging power of BESSs must comply with the following constraints.

$$P_{S,\min} \leq P_{S,i,j} \leq P_{S,\max} \quad (11)$$

To guarantee the daily charge–discharge energy balance of BESSs, namely, maintaining a consistent daily SOC, the following constraint should be satisfied on a daily basis.

$$\sum_{j=1}^{j=T} P_{ij}^S \cdot \Delta t = 0 \quad (12)$$

3.3. Planning Strategy of BESSs Based on Improved Particle Swarm Optimization Algorithm

The planning of energy storage stations in power grids is a complex optimization problem featuring multivariate, multi-constraint, nonlinear and non-convex properties. Particle swarm optimization (PSO) exhibits strong global search capability, fast convergence, and high robustness, which renders it well suited for addressing such complex optimization problems. Nevertheless, limited by its inherent structural characteristics, the traditional PSO algorithm encounters slow convergence in the late iteration phase, frequent trapping in local optima, and continuous attenuation of population diversity. These defects make it incapable of satisfying the requirements of high dimensionality, strict constraints and multi-period coupling in complex power grid scenarios.

To overcome the aforementioned issues, this paper develops a targeted modification of the classical GRA–PSO hybrid framework reported in previous studies and designs a differentiated assignment strategy for particle velocity updating during optimization to enhance the algorithm’s overall optimization performance. Compared with the traditional PSO, the main improvements of the proposed algorithm include two core strategies: an adaptive dynamic weight updating method based on gray relational analysis (GRA) and a load characteristic-based differentiated particle velocity updating strategy.

3.3.1. Adaptive Dynamic Weight Updating Method Based on Gray Relational Analysis

The evaluation function of GRA can be expressed as

$$Z(z_0(i), z_y^s(i)) = \frac{\min_y \min_i |z_0(i) - z_y^s(i)| + \zeta \max_y \max_i |z_0(i) - z_y^s(i)|}{|z_0(i) - z_y^s(i)| + \zeta \max_y \max_i |z_0(i) - z_y^s(i)|} \quad (13)$$

where ζ is set to 0.5 in this study. Accordingly, the gray relational degree γ_y between z_0 and z_y can be expressed as

$$\gamma_y(z_0, z_y) = \frac{1}{N} \sum_{i=1}^N Z(z_0(i), z_y(i)) \quad (14)$$

In this paper, the reference sequence $z_0(i)$ and comparison sequence $z_{sy}(i)$ for gray relational calculation are constructed for the multi-objective planning of grid-side energy storage siting and sizing, with the mathematical vector definitions defined below.

Let D_{total}^* denote the globally optimal net load peak–valley difference rate of the regional power grid derived from multi-objective optimization, and N denote the total number of candidate energy storage grid-connected nodes. The ideal target peak–valley difference rate corresponding to node i is proportionally decomposed as

$$z_0(i) = \frac{D_i^{base}}{\sum_{i=1}^N D_i^{base}} D_{total}^*, \quad i = 1, 2, \dots, N \quad (15)$$

where D_i^{base} represents the original net load peak–valley difference rate of node i under a no-energy-storage scenario. The reference sequence vector is constructed as $z_0 = \{z_0(1), z_0(2), \dots, z_0(N)\}$, which acts as the optimal benchmark for evaluating the regulation performance of each grid node.

In the s -th iteration of the IPSO algorithm, particle y generates the energy storage allocation scheme. Accordingly, the actual net load peak–valley difference rate of node i under the corresponding scheme is defined as $D_{s,y}(i)$. The comparison sequence element is formulated as

$$z_{sy}(i) = D_{sy}(i), \quad i = 1, 2, \dots, N \quad (16)$$

The comparison sequence vector of particle y in the s -th iteration is constructed as $z_{sy} = \{z_{sy}(1), z_{sy}(2), \dots, z_{sy}(N)\}$, which reflects the actual real peak-shaving performance of the energy storage allocation scheme corresponding to the current particle.

By substituting the vector elements $z_0(i)$ and $z_{sy}(i)$ into (13) and (14), the gray relational degree γ_y between the ideal benchmark and the actual particle scheme can be derived.

According to the mechanism of the PSO algorithm, a larger inertia weight ω helps enhance the global search ability and facilitates extensive exploration of feasible solutions in the solution space, whereas a smaller inertia weight strengthens the local search performance and enables fine-grained searching in regions.

To further improve the search performance, the comparison sequence of each particle constructed in this study consists of the active net load peak–valley difference rates at all BESS-integrated nodes, while the reference sequence is composed of node-level target peak–valley difference rates decomposed from the overall net load peak–valley difference optimization objective. Based on (13) and (14), the gray relational degrees between the reference sequence and each comparison sequence can be calculated, and the inertia weights of all particles are further updated following the rule below.

$$\omega_y^s = \begin{cases} \gamma_y^s \omega_{\min} + \frac{(\omega_{\max} - \omega_{\min}) \times (F_y^s - F_{\min}^s)}{F_{\text{avg}}^s - F_{\min}^s}, & F_y^s \leq F_{\text{avg}}^s \\ \gamma_y^s \omega_{\max}, & F_y^s > F_{\text{avg}}^s \end{cases} \quad (17)$$

where $\omega_{\min}$ is set to be 0.4, and $\omega_{\max}$ is set to be 0.9.

3.3.2. Differentiated Assignment Method for Particle Updating Velocity Based on Load Characteristics

Traditional PSO algorithms easily induce excessive aggregation of BESSs at adjacent nodes in the optimization of energy storage location and capacity allocation, which cannot satisfy practical engineering application requirements. To address this problem, this paper proposes a differentiated particle velocity updating strategy based on the active load characteristics of individual nodes. With this strategy implemented, all particles abide by the iterative updating rules specified below during the optimization process.

$$v_{y,i,d}^{s+1} = \omega_y^s \times v_{y,i,d}^s + c_1 \times r_1^s \times (p_{i,d}^s - x_{y,i,d}^s) + c_2 \times r_2^s \times (g_{i,d}^s - x_{y,i,d}^s) \quad (18)$$

The $(s + 1)$ -th iteration satisfies

$$x_{y,i,d}^{s+1} = x_{y,i,d}^s + v_{y,i,d}^{s+1} \quad (19)$$

During the optimization process, the schematic diagram of the particle updating procedure is shown in Figure 2.

According to the active load characteristics of each node in the targeted 220 kV regional power grid, this paper limits the particle updating velocity and formulates the following constraints.

$$\begin{cases} v_{\max,i} = \max(p_{ij}^{\text{TS}}) - \min(p_{ij}^{\text{TS}}) \\ 0 \leq v_{y,i,d} \leq v_{\max,i} \end{cases} \quad (20)$$

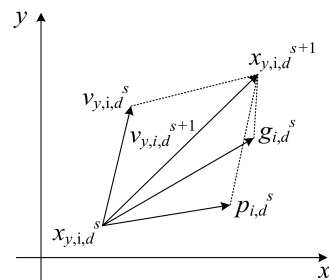


Figure 2. Schematic diagram of particle updating procedure.

3.3.3. Improved PSO Strategy Based on Adaptive Dynamic Weight Updating

Figure 3 displays the flowchart of the proposed improved PSO algorithm. The entire optimization procedure is summarized into following steps. First, two core optimization objectives are formulated in the established model. The first target is the total peak–valley difference rate of the targeted regional power grid, and the second is the configuration capacity of all deployed BESSs. These overall objectives are decomposed into node-level sub-objectives corresponding to each potential energy storage grid-connected node. Subsequently, the optimization objectives of all energy storage nodes generated by each particle are constructed as the reference sequence. During iteration, the real-time optimization results are adopted to form the comparison sequence. The gray correlation coefficients between the reference and comparison sequences are calculated via (13) and (14), and the updated inertia weight ω of each particle is further obtained from (17) to achieve iterative renewal of particle positions. Through continuous iteration optimization, the particle position and update velocities are gradually adjusted, enabling the optimization results to converge to the global optimal solution.

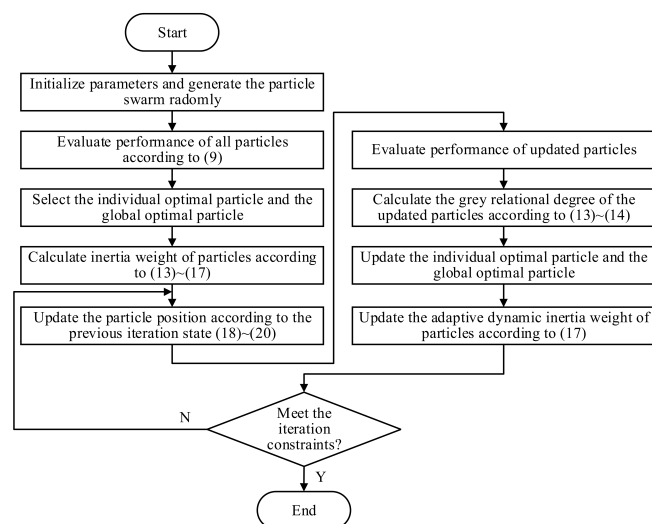


Figure 3. Flow chart of the customized improved PSO algorithm modified from conventional GRA–PSO for regional grid BESS planning.

4. Dispatching Strategy for BESSs in Regional Power Grids

4.1. Optimization Objectives and Constraints

Considering the power supply capability of each 220 kV substation in the actual power grid, the total active net load of the entire regional power grid P_j can be expressed as

$$P_j = \sum_{i=1}^{i=N} (P_{ij}^{TS} - P_{ij}^W - P_{ij}^{PV} - P_{ij}^S - P_{ij}^{else}) \quad (21)$$

where i ranges from 1 to N , and N is the total number of 220 kV substations in the targeted regional power grid; j ranges from 1 to T , and T represents the total time periods within a day; P_{ij}^{else} stands for the total active power of other power sources connected to the i -th 220 kV substation in period j , respectively. Accordingly, the evaluation index of the peak–valley difference rate f'_1 in the power grid can be obtained as follows:

$$f'_1 = (\max(P_j) - \min(P_j)) / \max(P_j) \quad (22)$$

where $\max(P_j)$ and $\min(P_j)$ denote the maximum value and minimum values of the active net load of the targeted regional power grid throughout the time horizon $[1, T]$, respectively.

Furthermore, to promote the renewable energy accommodation capacity of the regional power grid and optimize system economic performance, the renewable generation curtailment rate is adopted as the second evaluation index f'_2 , which is formulated as

$$f'_2 = \frac{\sum_{j=1}^T P_j^{Cu}}{\sum_{j=1}^T (P_j^{Cu} + P_j^{WP220})} \quad (23)$$

Thus, the multi-objective evaluation function for the dispatching stage can be constructed as follows.

$$\min F' = [\lambda'_1 f'_1 + \lambda'_2 f'_2] \quad (24)$$

where λ'_1 and λ'_2 satisfy $\lambda'_1 + \lambda'_2 = 1$. For theoretical analysis convenience, both λ'_1 and λ'_2 are set to 0.5. In practical power dispatching scenarios, dispatchers can tune these two weight coefficients according to on-site operational objectives.

Notably, the renewable energy curtailment rate serves only as a technical indicator for evaluating renewable energy accommodation capability, rather than accounting for monetary loss quantification or arbitrage revenue optimization. The proposed dispatching framework can be embedded with additional economic dimensions to meet practical demands, while the procedure of the improved WOA algorithm remains unchanged. Furthermore, flexible modification and supplement of other evaluation indicators can be implemented according to actual engineering requirements.

During the optimization process of BESS dispatching, the power balance, energy balance, and charge–discharge power limits of the regional power grid must be strictly satisfied as essential constraints. Therefore, the constraints defined by (10)–(12) are still applicable throughout the optimization process. In addition, to extend the service life of electrochemical batteries, the daily charge–discharge cycle is limited to a maximum of twice in this study. The upper and lower bounds of SOC (SOC_{max}, SOC_{min}) and daily charge–discharge cycle constraints adopted in this model comply with the actual operation specifications of grid-side electrochemical energy storage stations in China, representing standardized operational limits for electrochemical batteries.

4.2. Charging/Discharging Optimization Strategy of BESSs Based on WOA

WOA is a novel meta-heuristic optimization algorithm with excellent comprehensive optimization performance. Its optimization workflow consists of five stages: the initialization stage, exploration stage, migration stage, exploitation stage and termination stage [32].

In the initialization stage, the walrus population size is set to N and the maximum iteration number is set to G . The population matrix is formulated as

$$\mathbf{X}' = \begin{bmatrix} X'_1 \\ \vdots \\ X'_i \\ \vdots \\ X'_N \end{bmatrix}_{N \times M'} = \begin{bmatrix} x'_{1,1} & \dots & x'_{1,d} & \dots & x'_{1,M'} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x'_{i,1} & \dots & x'_{i,d} & \dots & x'_{i,M'} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ x'_{N,1} & \dots & x'_{N,d} & \dots & x'_{N,M'} \end{bmatrix}_{N \times M'} \quad (25)$$

The position information of each walrus is evaluated by (22). The fitness of each individual is

$$\mathbf{F}' = \begin{bmatrix} F'_1 \\ \vdots \\ F'_i \\ \vdots \\ F'_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} F'(X'_1) \\ \vdots \\ F'(X'_i) \\ \vdots \\ F'(X'_N) \end{bmatrix}_{N \times 1} \quad (26)$$

Then, in the exploration stage, the algorithm evaluates the existence of superior solutions by generating coordinates of new trial solutions, which is formulated as

$$x'^1_{i,d} = x_{i,d} + \text{rand}'^1_{i,d} \times (SW_d - I^1_{i,d} \times x'_{i,d}) \quad (27)$$

After evaluating the generated trial solutions, the algorithm identifies and updates the current optimal solution following the rule below:

$$X'^{p_1}_i = \begin{cases} X'_i & , F'_i < F'_i \\ X'_i & , \text{others} \end{cases} \quad (28)$$

where $X'^{p_1}_i$ denotes the updated position of the i -th walrus after this stage.

In the migration stage, if the population perceives that new habitats (i.e., new regions in the search space) provide superior survival conditions in terms of multi-objective evaluation metrics, the entire population migrates to more favorable positions in accordance with the rule below.

$$x'^2_{i,d} = \begin{cases} x'^{p_1}_{i,d} + \text{rand}^2_{i,d} \times (x'_{k,d} - I^2_{i,d} \times x'^{p_1}_{i,d}) & , F'_k < F'^{p_1}_i \\ x'^{p_1}_{i,d} + \text{rand}^2_{i,d} \times (x'^{p_1}_{i,d} - x'_{k,d}) & , \text{others} \end{cases} \quad (29)$$

$$X'^{p_2}_i = \begin{cases} X'^2_i & , F'^2_i < F'^{p_1}_i \\ X'^{p_1}_i & , \text{others} \end{cases} \quad (30)$$

where X'^2_i and $X'^{p_2}_i$ are the newly generated position and updated position of the i -th walrus after this stage, respectively.

Once the algorithm obtains a new solution, it proceeds to the exploitation stage. With the obtained solution as the center, the WOA establishes a dynamically adjustable search region. If superior solutions capable of improving the objective function value are identified within this region, the solution set update is updated accordingly. The mathematical expression of the above process is given as

$$x'^3_{i,d} = x'^{p_2}_{i,d} + \left(l^s_d + \left(u^s_d - \text{rand}^3_{i,d} \times l^s_d \right) \right) \quad (31)$$

$$\begin{cases} l_d^s = l_d^s \\ u_d^s = u_d^s \end{cases} \quad (32)$$

$$X_i^{p3} = \begin{cases} X_i^{p3} & , F_i^{p3} < F_i^{p2} \\ X_i^{p2} & , \text{else} \end{cases} \quad (33)$$

where $x_{i,d}^{p3}$, $x_{i,d}^{p2}$, $\text{rand}_{i,d}^{p3}$, $x_{k,d}^{p3}$, F_i^{p2} , F_i^{p3} , X_i^{p3} and X_i^{p2} denote the newly updated parameters in this stage; l_d and u_d represent the lower and upper bounds of the d -dimensional value of walruses, respectively; and l_d^s and u_d^s represent the allowable lower and upper bounds of the d -dimensional walrus position variables, respectively. Specifically, the d -dimensional variables correspond to the output power constraints of thermal power units or BESSs.

In accordance with the WOA framework presented in [32], the traditional WOA typically adopts the maximum iteration number as the termination condition. Nevertheless, in practical engineering scenarios, this mechanism results in excessive resource consumption and redundant iterative calculations. To address this issue, this study defines the termination condition as zero variance of fitness values obtained in the latest 20 iterations, which is expressed as follows:

$$\begin{cases} S_{avg} = \sum_{i=n_{fit}-20}^{n_{fit}} S_i / 20 \\ S_{fit} = \sum_{i=n_{fit}-20}^{n_{fit}} (S_i - S_{avg})^2 / 20 \end{cases} \quad (34)$$

As illustrated in (34), the proposed criterion eliminates redundant iterations when the population fitness remains stable over 20 consecutive iterations and reduces the risk of insufficient global search. Although larger threshold values can further shorten the computational time, they increase the likelihood of generating suboptimal BESS dispatching schemes and degrade grid regulation performance. The complete optimization flow chart for BESS dispatching in the regional power grid is shown in Figure 4.

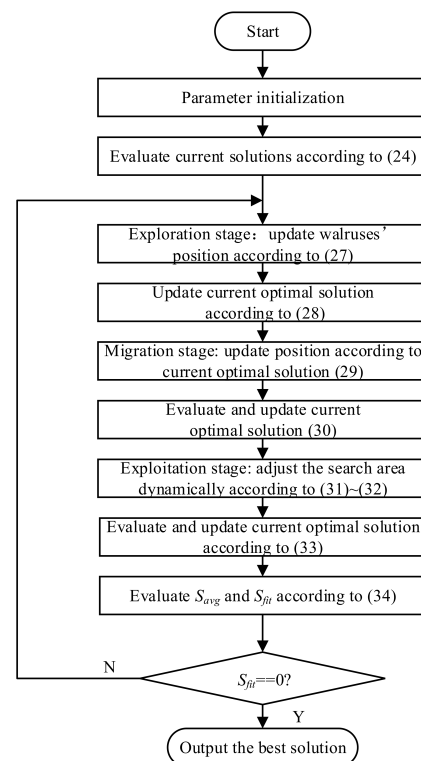


Figure 4. Flow chart of dispatching process of BESSs in regional power grid based on WOA.

5. Case Study

This study selects a typical urban 220 kV regional power grid in central Henan Province, China, as the research object. The input datasets adopt field-measured daily maximum load and renewable generation curves. The selected test day reflects the most severe annual operating condition, characterized by extreme net load fluctuations and serious power supply–demand imbalance. Accordingly, superior optimization performance verified under this extreme scenario can fully validate the adaptability and effectiveness of the proposed joint planning and dispatching strategy for general daily operating scenarios with milder load fluctuations. This study primarily focuses on the improvement of two meta-heuristic algorithms rather than full-year multi-scenario simulations. Therefore, only one typical daily scenario is adopted for numerical verification, which corresponds to the annual worst-load operating condition. Such a selection avoids redundant repeated simulations and improves computational efficiency. Figure 5 presents the topology of the studied 220 kV regional power grid, which comprises 28 load nodes of 220 kV substations, six load nodes of 500 kV substations, three generator nodes of 220 kV substations and two generator nodes of 500 kV substations.

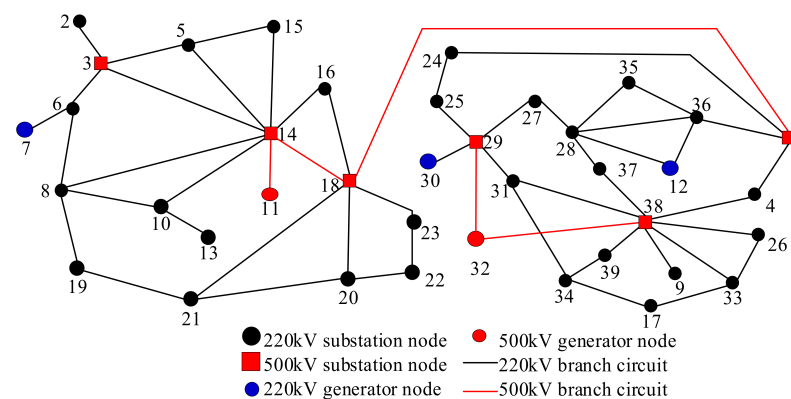


Figure 5. Topology of an actual 220 kV regional power grid in China.

5.1. Verification on Planning Strategy Based on Improved PSO Algorithm for BESSs

Figure 6 illustrates the field-measured total load power curve, wind power curve, and photovoltaic generation curve of the regional power grid on the annual peak-load day. It can be seen that two peak power consumption periods occur throughout on the day, i.e., at 00:00–07:00 and 17:00–23:00.

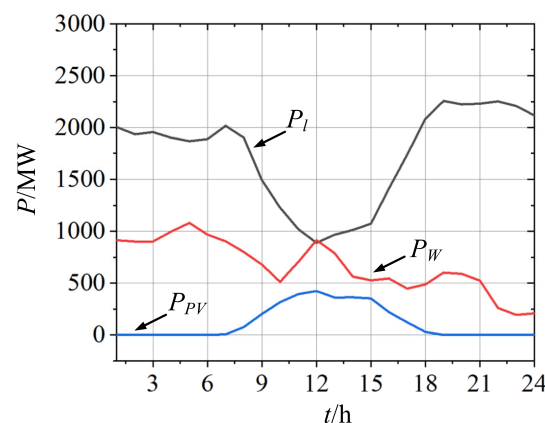


Figure 6. Curves of total load, wind power generations and photovoltaic generation of the maximum load day in the 220 kV regional power grid.

According to the optimization workflow illustrated in Figure 3, the key parameters of the improved IPSO algorithm are configured as listed in Table 1.

Table 1. Preset key parameters for IPSO.

Parameters	Value
Number of iterations	300
Population size	100
$\omega_{\max}$	0.9
$\omega_{\min}$	0.4
λ_1	0.5
λ_2	0.5
Scale of Pareto solution	100

Figure 7 presents the variation in inertia weight for the traditional PSO algorithm. It can be observed that the inertia weight of all particles decreases monotonically with the increase in iteration numbers. Nevertheless, this method ignores individual characteristic differences among particles and fails to dynamically adjust the inertia weight adaptively according to the real-time optimization status.

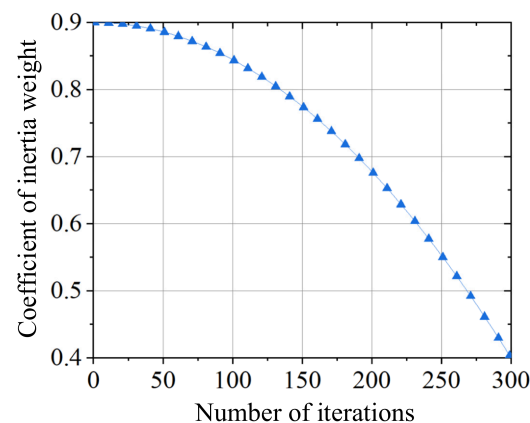


Figure 7. Variation in weight coefficients in the optimization process of the traditional PSO algorithm. The blue triangle indicates the inertia weight of the traditional PSO algorithm.

In accordance with the solution procedure illustrated in Figure 3, Figure 8 demonstrates the variations in the adaptive inertia weight and gray correlation degree of a single particle within the first 50 iterations. As specified in the algorithm procedure, a higher gray correlation degree implies that the particle is closer to the optimal objective, thereby requiring a larger inertia weight to retain its current moving direction. As depicted in Figure 8, the customized improved PSO algorithm, developed based on the conventional GRA-PSO framework in this study, enables the adaptive inertia weight to correlate with individual particle characteristics and vary synchronously with the gray correlation degree. This mechanism effectively guides the particle position updating throughout the optimization process.

Figure 9 compares the multi-objective evaluation function F_1 iteration curves of the traditional PSO and the improved PSO algorithms. As illustrated in Figure 9a, the optimal values of the evaluation function F_1 obtained by the traditional PSO and the proposed improved PSO are 1.54 and 1.12, respectively. The 27.3% reduction in the F_1 value verifies that the improved PSO provides superior global convergence accuracy, whereas the traditional PSO is susceptible to local optimal trapping. Figure 9b presents the iterative comparison results of the two algorithms within the first 40 iterations, demonstrating that the proposed IPSO algorithm achieves faster early-stage convergence speed.

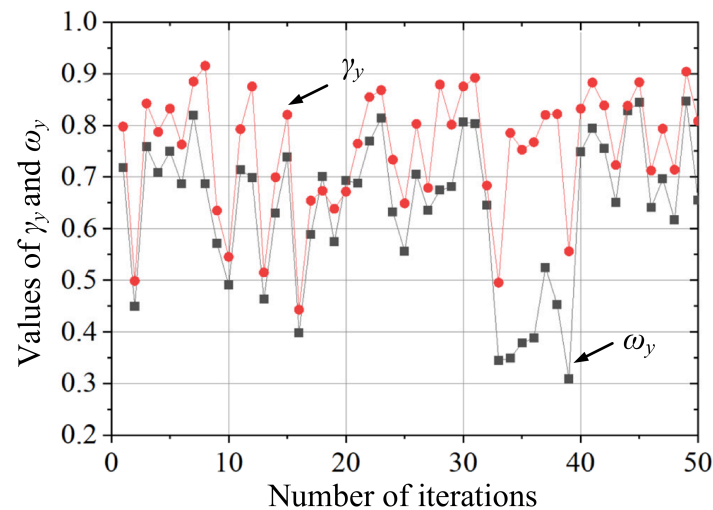


Figure 8. Variation in weight coefficients in the optimization process of the proposed improved PSO algorithm. The grey squares and red circles represent the value of ω_y and γ_y , respectively.

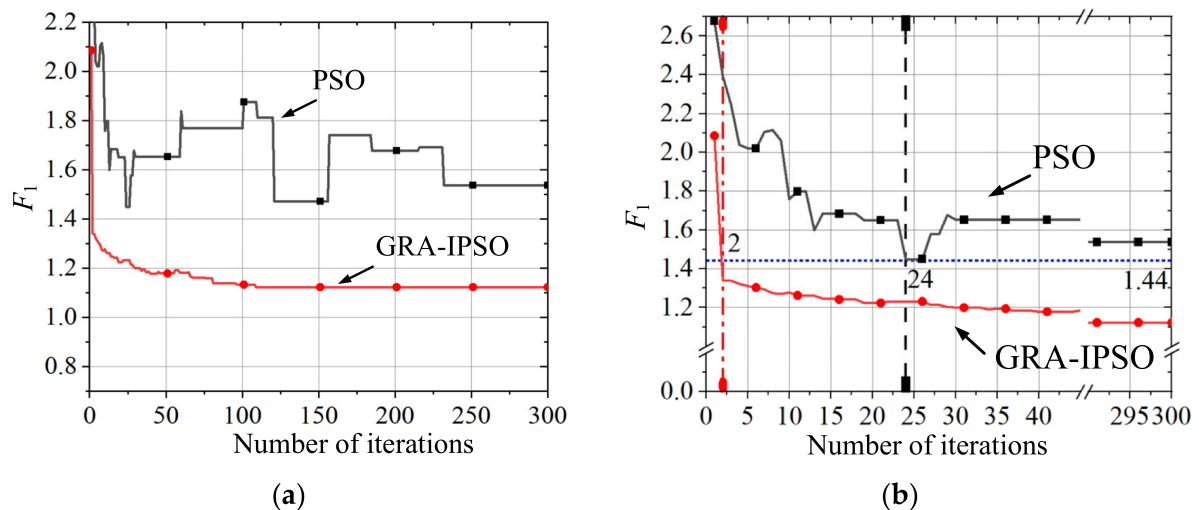


Figure 9. Comparison of the iteration process of the traditional PSO algorithm and the improved PSO algorithm. (a) Comparison of the whole iteration process. (b) Comparison of the first 40 iterations. The grey squares and red circles represent the iteration data of PSO and GRA-IPSO, respectively. The blue dashed line indicate the optimal solution generated by PSO. The black dashed line represent the iteration number when PSO generates its optimal solution. The red dashed line represent the iteration number when GRA-IPSO generates the same final optimization result as PSO.

Table 2 summarizes the system performance indexes under three distinct simulation scenarios. In Scenario 1, no BESS is deployed in the power grid. In Scenario 2, the BESS layout scheme is optimized by the standard PSO. In Scenario 3, the BESS layout scheme is optimized by the proposed IPSO.

Table 2. Comparison of system performance.

Scenarios	Total Peak–Valley Difference Rate of Net Load (MW)	Improvement
No BESSs	29.5	–
Optimized by PSO	25.7	12.88%
Optimized by improved PSO	23.70	19.66%

Figure 10 compares the BESS layout optimization results obtained by the two algorithms. The comparison is based on nodal net load peak–valley profiles in Figure 10a. As revealed in Figure 10b, the traditional PSO allocates BESSs predominantly to nodes with drastic net load peak–valley fluctuations. In addition, the configured capacity of some nodes exceeds the actual demand, leading to unreasonable BESS distribution and insufficient configuration at nodes with mild net load fluctuations. In contrast, the proposed IPSO algorithm adopts a differentiated particle velocity updating strategy. It deploys an adequate BESS capacity for nodes with severe peak–valley differences while achieving a distributed and balanced layout, thereby effectively reducing power regulating line losses.

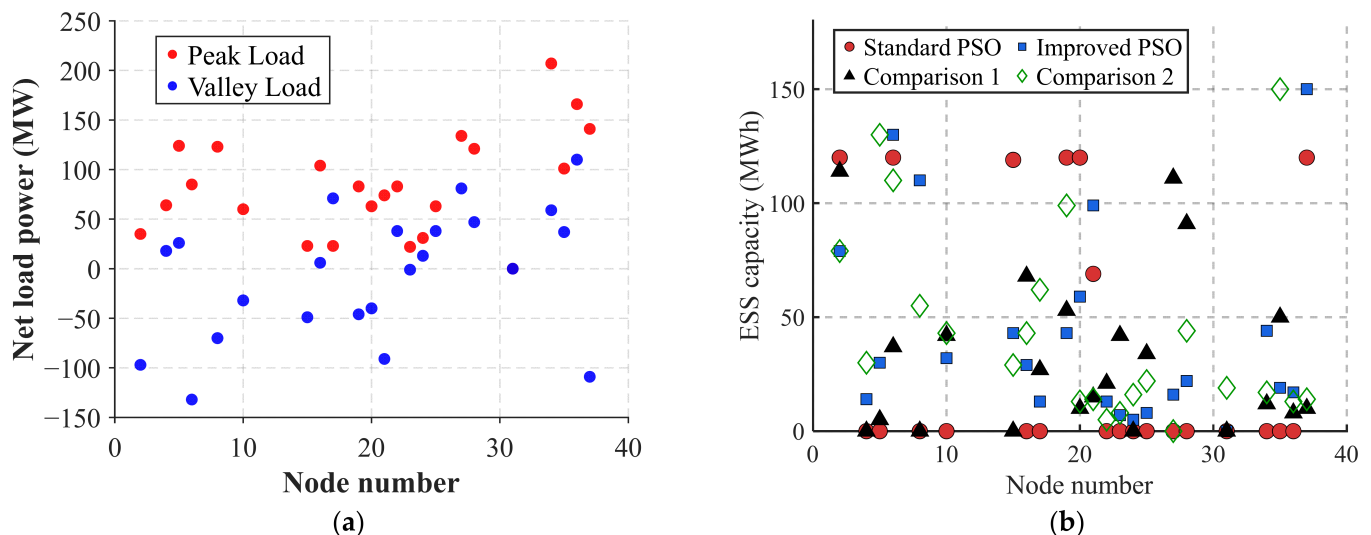


Figure 10. Comparison of optimization results of the standard PSO algorithm and the improved PSO algorithm. (a) Peak value and valley value of net load power of each node. (b) Comparison of optimization results.

As quantified in Figure 10b, the total optimized BESS capacity configured by the standard PSO is 788 MWh, while the corresponding capacity determined by the IPSO reaches 984 MWh. Despite the slight increase in total energy storage capacity, the overall net load peak–valley difference in the entire grid decreases from 25.6 MW to 23.7 MW, demonstrating the superior peak-shaving capability of the proposed algorithm. To further analyze the sensitivity between the BESS configuration scale and peak-shaving performance, two intermediate iterative solutions are selected for auxiliary comparison and denoted as Comparison 1 and Comparison 2 in Figure 10b. The layout scheme of Comparison 1 adopts a total EES capacity of merely 751 MWh, but the system-wide net load peak–valley difference remains as high as 25.12 MW. In contrast, the layout scheme of Comparison 2 requires a larger total BESS capacity of 1017 MWh, but it only achieves a moderate reduction in peak–valley difference to 24.07 MW. The results indicate that the blind expansion of energy storage capacity fails to deliver effective peak-shaving improvement. Instead, the proposed IPSO algorithm achieves a favorable trade-off between rational BESS layout rationality and systemic peak-shaving benefits.

To further compare the optimization performance of the two algorithms, Figure 11 compares the net load fluctuations of Node 2 and Node 6 (as illustrated in Figure 5) under three operating conditions: no BESS deployment, traditional PSO-optimized deployment, and IPSO-optimized deployment. The comparison results verify that the proposed IPSO algorithm exhibits superior performance in suppressing the net load fluctuations at individual nodes compared with the traditional PSO algorithm.

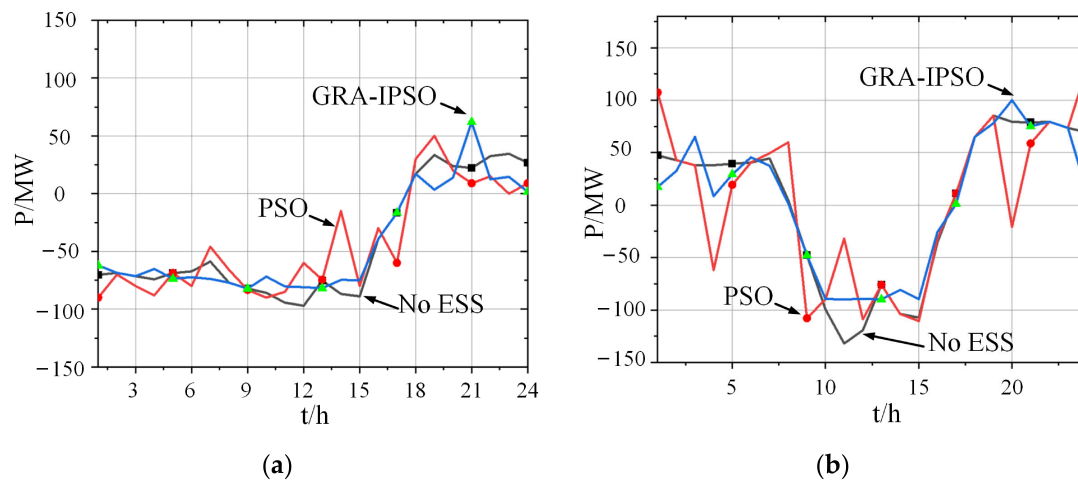


Figure 11. Comparison of net load fluctuation of specific node. (a) Comparison for Node 2. (b) Comparison for Node 6. The red line with red circles, blue line with green triangles, and black line with black squares denote net load fluctuation after PSO optimization, net load fluctuation after GRA-IPSO optimization and without ESS, respectively.

5.2. Verification on Dispatching Strategy Based on WOA for ESSs

This study uses the typical daily operating curve of the target regional power grid as the test case. Table 3 lists key operational data. Based on the optimal BESS allocation results in Section 5.1, the total schedulable capacity of BESSs in this regional power grid is set to 1000 MWh.

Table 3. Key operating data of 220 kV regional power grid.

Time Period	1	2	3	4	5	6	7	8	9	10	11	12
	13	14	15	16	17	18	19	20	21	22	23	24
Total net load (MW)	1345	1340	1310	1291	1293	1384	1442	1385	1162	1042	830	790
Wind power generation (MW)	824	922	984	1134	1285	1452	1570	1578	1537	1538	1514	1463
Photovoltaic generation (MW)	313	274	269	304	355	299	277	235	208	159	334	549
Power of tie-line (MW)	477	336	299	348	266	262	305	272	239	104	63	45
	0	0	0	0	0	0	1	15	48	66	83	93
	89	67	58	42	21	4	0	0	0	0	0	0
	906	894	895	848	799	890	945	881	788	781	482	293
	370	562	629	700	832	998	1021	1072	1081	1198	1215	1206

The weight coefficients in (22) are set to $\lambda'_1 = \lambda'_2 = 0.5$. The key WOA parameter settings are listed in Table 4. The BESS dispatching scheme is performed using the typical daily operation data of the target regional power grid.

Table 4. Preset key parameters for WOA.

Data Type	Value
Iteration number	300
Population size	500
Total capacity of ESSs	1000 MWh
Charging/discharging power limits of ESSs	500 MW
SOC_{max}	0.8
SOC_{min}	0.2

Figure 12 compares the iteration curves of the original WOA and the improved WOA proposed in this study. The original WOA runs iterations until the preset maximum iteration number, even after locating the optimal solution. This mechanism wastes computing resources and slows down dispatching response speed. By adopting the early termination criterion in Equation (34), the iteration can stop in advance. The total iteration count drops from 300 to 99. When the threshold is set to 1, 3, or 5, the algorithm terminates even faster. However, the final multi-objective evaluation values rise to 0.81, 0.82 and 0.80, respectively. These increased thresholds lead to suboptimal solutions.

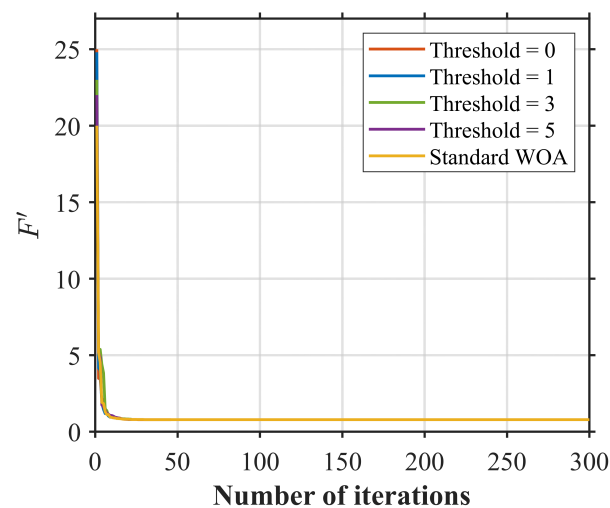


Figure 12. Comparison of the iteration process of the WOA and the improved WOA proposed in this paper.

Figure 13 illustrates the optimized scheduling results. The charge and discharge intervals of BESSs are coordinated in line with local time-of-use electricity prices. During the low-price off-peak window of 9:00–15:00, the storage system executes charging operations. Discharging is scheduled for the high-price peak period of 16:00–24:00. The total utilized energy storage capacity reaches 434 MWh. Prior to optimization, the wind and solar curtailment rate stands at 29.28%, and the peak–valley difference rate of active net load is 66.02%. After the proposed optimization strategy is implemented, the curtailment rate falls to 27.93%, and the active net load peak–valley difference rate declines to 59.73%. Within this regional grid structure, the renewable power generation output remains high while the local electricity load stays low. Surplus renewable power exceeds the available charging capacity of BESSs. This condition brings challenges to peak regulation and local renewable energy accommodation. Moreover, massive power delivery to the external 220 kV power grid via tie-lines further reduces the accommodation potential of on-site renewable energy generation.

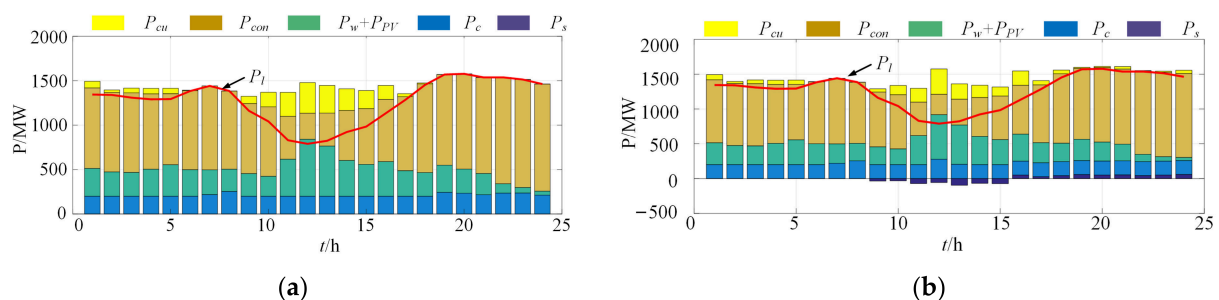


Figure 13. Comparison of regulation effects with ESSs participating in regional power grid regulation. (a) No ESS is dispatched. (b) ESSs are dispatched by the WOA.

Table 5 compares the evaluation indexes calculated via (24). The results demonstrate that the ESS dispatching scheme optimized by the WOA effectively mitigates load fluctuations and improves the renewable energy accommodation rate.

Table 5. Comparison of dispatching results.

Items	Without ESSs	ESSs Dispatched by WOA	Improvement Percentage
Active net load peak–valley difference rate	66.02%	59.73%	9.53%
Wind and photovoltaic power curtailment rate	29.28%	27.93%	4.61%

To further verify the performance of the proposed dispatching strategy, this study adjusts the operation scenario as follows. The electricity price valley window is set to 11:00–14:00 for BESS charging, and the electricity price peak window is set to 16:00–24:00 for BESS discharging. The corresponding energy storage dispatching curve under this scenario is illustrated in Figure 14a. The utilized energy storage capacity reaches 558 MWh, the wind–solar curtailment rate is 30.97%, and the peak–valley difference rate of the active net load is 51.79%. Under this time-of-use price setting, partial peak-shaving and renewable energy accommodation performance decline to secure the operation revenue of the energy storage systems.

Without considering the time-of-use price factor, the energy storage dispatching curve is provided in Figure 14b. In this scenario, the configured energy storage capacity is 240 MWh, the wind–solar curtailment rate is 30.78%, and the peak–valley difference rate of the active net load is 51.97%. Restricted by the state-of-charge (SOC) limits and the daily charge–discharge energy balance constraints of the energy storage systems, the full regulation potential of BESSs cannot be exploited during the heavy renewable curtailment period (10:00–15:00). As a result, the renewable energy accommodation rate barely improves relative to the benchmark case without energy storage, while the peak-shaving capability of energy storage remains satisfactory.

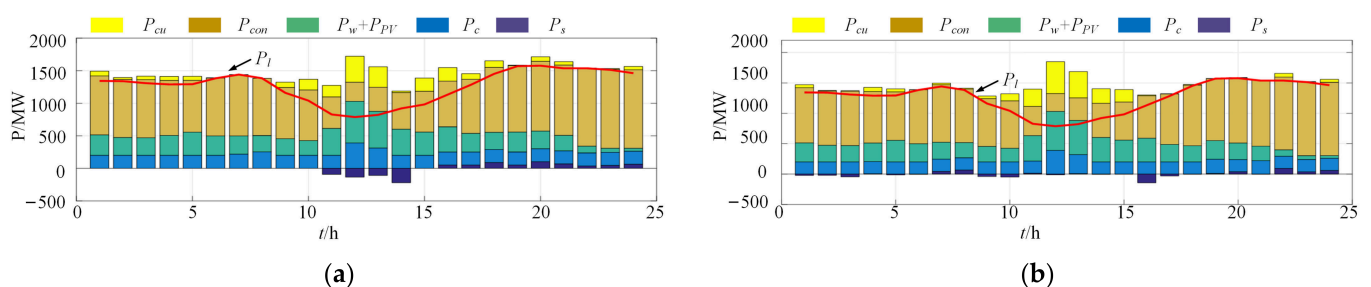


Figure 14. Dispatching results under different scenarios. (a) The electricity price valley period is set from 11:00 to 14:00 and the peak period is set as 16:00–24:00. (b) Time-of-use electricity is not considered.

In conclusion, the BESS scheduling strategy for regional power grids optimized by the improved WOA with the proposed early termination criterion can effectively improve new energy accommodation and flatten net load fluctuations, while delivering fast computational response.

6. Conclusions

This paper conducts systematic research on planning and operation dispatching methods for BESSs in regional power grids. Electrochemical energy storage has become the dominant new energy storage technology in China. Thus, the joint planning and

dispatching strategy targeting BESSs proposed in this study is applicable to most actual power grid operation scenarios nationwide. Furthermore, the multi-objective optimization framework used in both planning and dispatching stages exhibits strong generality. After replacing the operational characteristic constraints for different energy storage devices, the IPSO planning algorithm and improved WOA dispatching algorithm can be extended to compressed air energy storage, flywheel energy storage and other energy storage forms. The main contributions of this study are summarized as follows.

- (1) Targeted improvements are made to the existing GRA-PSO hybrid framework, forming an adaptive improved PSO algorithm for BESS planning in regional power grids. The algorithm dynamically adjusts inertia weights via gray relational analysis and sets differentiated velocity bounds based on nodal load features. This design improves the convergence accuracy, convergence speed, and rationality of energy storage capacity distribution. Compared with the standard PSO, the multi-objective evaluation index drops from 1.54 to 1.12, marking a 27.3% reduction. Meanwhile, the system-wide net load peak–valley difference rate declines from 25.70% to 23.70%, bringing a 19.66% overall optimization enhancement.
- (2) The walrus optimization algorithm (WOA) is improved and applied to ESS dispatching in regional power grids. An early termination criterion is embedded into the improved WOA to enhance system regulation performance and achieve fast computational responses. Case studies demonstrate that the iteration number is reduced by a range of 67% to 69.7% compared with the original WOA adopting fixed maximum iterations.
- (3) Based on the practical 220 kV power grid structure and operational data of a city in China, simulation verifications are performed to validate the effectiveness and accuracy of the proposed algorithms. Correspondingly, the optimal energy storage configuration scheme and scheduling strategy are obtained.
- (4) Each improved meta-heuristic can be independently deployed for grid-side energy storage planning and dispatching. The proposed method exhibits good generalization capability for regional grids with different voltage levels and various energy storage types.

Moreover, in accordance with the hierarchical dispatching and management system of the State Grid Corporation of China, provincial power companies serve as equivalent transmission system operators and are responsible for the operation of 220 kV, 330 kV and 500 kV transmission networks. The 500 kV grid undertakes inter-provincial power transmission tasks, while the 220 kV regional transmission grid adopted in this paper acts as a typical intra-provincial research carrier for method verification. The core mathematical models and solution strategies proposed in this paper have no inherent voltage-level limitations. By updating the grid topology, load data, and renewable power parameters, the integrated ESS planning and dispatching strategy can be directly applied to 330 kV and 500 kV transmission networks under provincial operation. This further validates the generalization performance of the proposed method.

7. Limitations and Future Work

This paper constructs a joint optimization model for grid-side BESS planning and dispatching. This model excludes the cycle degradation mechanism of lithium iron phosphate (LFP) batteries. Such simplification reduces the computational burden of high-dimensional transmission grid optimization but ignores capacity degradation losses. Such losses are generated by frequent charge–discharge cycles. According to the industrial LFP degradation model proposed in [31], battery aging loss is highly correlated with daily cycle times, depth of discharge (DOD) and SOC fluctuation range.

Moreover, this manuscript only adopts technical quantitative indicators for planning and dispatching optimization, without introducing monetized economic objectives. The constructed multi-objective system provides good expandability. Economic metrics including BESS investment costs, peak–valley arbitrage benefits, and curtailment loss can be embedded into the existing model framework without modifying the proposed algorithms.

In future research, the piecewise capacity degradation function will be embedded into the multi-objective optimization constraints for both the IPSO planning stage and WOA dispatching stage. The full-life-cycle replacement cost of energy storage attributable to battery degradation will be incorporated into the objective function, achieving collaborative optimization among peak-shaving performance, renewable energy accommodation, and battery aging loss.

Furthermore, full-life-cycle monetary economic constraints, including BESS construction investment and renewable energy curtailment loss costs, will be integrated into the joint optimization framework. This enables the coordinated optimization of technical operational performance and economic benefits for grid-side BESSs. In addition, the charge–discharge cycle constraint in Section 4.1 can be further refined by correlating cycle times with degradation loss, thereby deriving a more economical long-term BESS operation scheme.

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Conflicts of Interest: P.Y., W.X., Y.S., Y.Z., C.C., R.W. and W.P. are employed by NARI Technology Co., Ltd. Authors Q.W. and Y.D. are employed by Nanchang University. Author S.R. worked for his master’s degree at Nanchang University from Sep. 2023 to Jun. 2025. Mr Ren is now employed by State Grid Zhejiang Electric Power Co., Ltd. Ultra High Voltage Branch. All authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as potential conflicts of interest.

Nomenclature

ESSs	Energy storage stations
PSO; IPSO	Particle swarm optimization; improved particle swarm optimization
GRA	Gray relational analysis
WOA	Walrus optimization algorithm
SOC	State of charge
NCCUC	Network-constrained unit commitment suggested in [21]
$P_{max}; P_{min}$	Maximum output power of thermal power plant units; minimum output power of thermal power plant units
$P_l; P'_l; P''_l$	Load power; the sum of load power and tie-line export power; the sum of load power and tie-line input power
$E_0; E_1; E_2; E_3$	Renewable energy consumption space; total curtailment energy of renewable energy generation; peak-shaving and valley filling by energy storage stations; positive reserve of conventional generation units

$P_a(t); P_l(t); P_{con}(t); P_S(t)$	Consumable power of renewable energy generation at time t ; total load power within the regional power grid at time t ; power transmission through regional tie-lines at time t (power delivery is defined as positive and power reception as negative); discharging power of ESSs (discharging power is defined as positive and charging power as negative)
$\beta; \beta_i; P_{g,i,max}; P_{g,i,min}$	Averaged peak-shaving depth of conventional thermal generating units; peak-shaving depth of the i -th conventional thermal generating unit; the maximum output power of i -th thermal generating unit; the minimum output power of i -th conventional thermal generating unit
$P_{con,plan}(t); R_+$	Planned power transmission through tie-lines; positive reserve capacity considering the participation of renewable energy for power balance consideration
$P_0(t); P_{net}(t)$	Power generated by renewable energy generation at time t ; net load power of regional power grid at time t
$P_{ij}^{net}; P_{ij}^{TS}; P_{ij}^W; P_{ij}^{PV}; P_{ij}^S$	Active net load power; active load power; output power of wind power generations; output power of photovoltaic generations; discharging power of ESSs
$i; j$	Number of nodes; number of time periods
D_i	Peak–valley difference rate of active net load at node i over the time period $[1, T]$
$f_1; f_2$	Evaluation indexes for D_i and configured capacity of ESSs in planning process, respectively
$P_j^{up}; P_j^{TE}; \Delta P_j; P_j$	The total active power injected into 220 kV regional power grid from power grids above 220 kV voltage level during period j ; the total power supplied by 220 kV regional power grid to other regional power grids at voltage levels of 220 kV and below; total power loss within the regional power grid; total active net load power of the entire regional power grid
$P_{S,min}; P_{S,i,j}; P_{S,max}$	Lower limitation of total charging/discharging active power of ESSs; discharging power of ESS in node i at time j ; upper limitation of total charging/discharging active power of ESSs
$Z; Z_0(i); z_{sy}(i)$	The gray relational coefficient; the reference sequence; the comparison sequence of particle y in the s -th iteration
$M; \xi;$	The number of particles in the particle swarm and $y \in [1, M]$; the distinguishing coefficient
$\omega; \omega_y^s; \omega_{min}; \omega_{max}$	Inertia weight coefficient; the inertia weight of particle y in the s -th iteration; the minimum value of inertia weight coefficient; the maximum value of inertia weight coefficient
$F_y^s; F_{avg}^s; F_{min}^s$	The objective function value of particle y in the s -th iteration; the average value of objective function of particle swarm in the s -th iteration; the minimum objective function value of the particle swarm in the s -th iteration
$c_1; c_2$	Learning factors in (16)
$p_{i,d}^s$	The d -dimensional component of node i in the personal best particle at the s -th iteration, with $d \in [1, T \times N]$
$r_1^s; r_2^s$	Random numbers at the s -th iteration within the range of (0,1)
$v_{y,i,d}^s; g_{i,d}^s; x_{y,i,d}^s$	The d -dimensional velocity updating component of node i in particle y at the s -th iteration; the corresponding d -dimensional component of node i in the global best particle at the s -th iteration; the corresponding d -dimensional position component of node i in particle y at the s -iteration
$v_{y,i,d}^{s+1}; x_{y,i,d}^{s+1}$	Updating velocity and position of the d -dimensional component corresponding to node i in particle y at the $(s + 1)$ -th iteration, respectively

$f_1'; f_2'$	Evaluation indexes for peak–valley difference rate and curtailment rate of renewable energy generation in dispatching process, respectively
$P_j^{Cu}; P_j^{WP220}$	Total curtailed active power of all renewable generations; total actual generated active power of renewable generations in regional power grids
$\lambda_1'; \lambda_2'$	Weight coefficients for multi-objective evaluation in dispatching process
$X; M'; X'_i; x'_{i,d}$	The walrus population; total dimension number of each walrus in WOA optimization process; the position of i -th walrus; the value of the d -th dimension of the i -th walrus ($1 < d < M$)
F'_i	The objective function value evaluated by the i -th walrus individual
$x'_{i,d}{}^1; rand_{i,d}{}^1$	The newly generated value of the d -th dimension of the i -th walrus in the exploration stage; a random number uniformly distributed within interval [0,1] during the exploration stage
$SW_d; I_{i,d}{}^1$	The d -th dimensional value of the optimal walrus individual; an integer randomly selected between 1 and 2 in the exploration stage
$x'_{i,d}{}^2; x_{i,d}'{}^p{}^1$	The newly generated d -dimensional population of the i -th walrus in the migration stage; the d -dimensional value of the i -th walrus transmitted from the exploration stage to the migration stage
$rand_{i,d}{}^2; x'_{k,d}{}^2; I_{i,d}{}^2$	A random number within the range [0,1] in the migration stage; the d -dimensional value of the randomly selected k -th walrus ($k \neq i$); an integer randomly chosen between 1 and 2 in current stage
$F'_k; F'_i{}^p{}^1; F'_i{}^2$	The objective function value of the k -th walrus; the objective function value of the i -th walrus passed into current stage; multi-objective evaluation result of the i -th walrus in this stage
$N_{fit}; S_i; S_{avg}; S_{fit}$	The current iteration number; fitness value of current iteration; average fitness of the latest 20 iterations; the variance of latest 20 iterations' fitness

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