

Article

Hierarchical Coordinated Reactive Power Optimization of Wind Farm Clusters Using Environment-Aware Particle Swarm Optimization

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Abstract

Large-scale wind-farm clusters are characterized by intense power fluctuations, various turbine types and time-varying reactive power margins, along with conflicting goals of voltage security and network loss reduction. To address these issues, this paper proposes a hierarchical coordinated reactive power optimization strategy based on an Environment-Aware Particle Swarm Optimization (EAPSO) algorithm. In this study, “environment-aware” specifically refers to operating-condition awareness, including low-load degree, spatial power dispersion, and output imbalance degree of wind turbines. A three-layer framework consisting of cluster level, wind-farm level and unit level is established to coordinate wind-farm reactive power commands, SVG outputs, transformer tap positions, and turbine-level reactive power allocation. A comprehensive disturbance index is constructed from the low-load degree, spatial power dispersion, and output imbalance degree and is then mapped to the initialization strategy, learning factors, and mutation operation of EAPSO. A 24 h offline simulation is conducted using historical operating profiles of a practical large-scale wind-farm cluster in South China. The results show that the proposed strategy reduces the average absolute PCC voltage deviation from 0.013331 p.u. before optimization to 0.004120 p.u. it achieves an average network-loss reduction rate of 3.55%. Compared with Method 1, the transformer tap operation times decrease from 139 to 92, and the cumulative SVG reactive output decreases from 1077.32 Mvar to 208.39 Mvar.

Keywords: wind-farm clusters; reactive power optimization; hierarchical control; EAPSO; multi-objective optimization; static var generator

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1. Introduction

Wind power, especially offshore wind power, has continued to expand rapidly and has become an important component of renewable-dominated power systems. Recent international reports indicate continued growth in both annual wind-power installation and cumulative offshore wind capacity [1–3]. With the increasing scale of offshore wind inte-

gration, wind farms are no longer operated as isolated stations; instead, multiple wind farms are often electrically coupled through collector systems, long submarine cables, reactive power compensation devices, and high-capacity transformers. This development makes voltage regulation and reactive power coordination more difficult, particularly under fluctuating wind-power output and heterogeneous turbine configurations.

Existing studies have laid an important foundation for voltage and reactive power control in wind-farms. For single-wind-farm scenarios, Reference [4] reviewed the progress of active voltage support technologies for wind turbines and emphasized that reactive power capability and multi-device coordination are key to improving grid-friendliness. Reference [5] proposed a master–slave cooperative optimization method considering transient voltage security under high wind power penetration. Reference [6] investigated the reactive power limits of wind farm collector networks using convex inner approximations, highlighting that turbine-level reactive capability should be evaluated together with collector-network losses and voltage constraints. Reference [7] used a nonlinear affine method to realize real-time voltage calculation and optimization. Reference [8] proposed a reactive power substitution control strategy and applied particle swarm optimization to coordinate the reactive power output of wind turbines. Reference [9] developed a model predictive control strategy for wind farms and reactive power compensation devices, showing that predictive control can help restore system parameters to acceptable ranges. Reference [10] further proposed a multi-scenario adaptive model predictive control strategy, considering both voltage deviation and active power loss under different wind power conditions. These studies demonstrate that wind turbines and compensation devices can be coordinated to improve voltage stability. However, their optimization scope is usually limited to a single wind farm or a small number of operating scenarios, and the coordination among multiple wind farms, SVCs, transformer taps, and turbine-level dynamic margins is not fully addressed.

For wind-farm clusters and offshore wind-power systems, Reference [11] proposed a coordinated voltage recovery control method for wind farms based on hierarchical model predictive control, providing a useful reference for hierarchical voltage regulation under voltage-disturbance conditions. Reference [12] further considered reactive power balance in cluster voltage control, providing support for coordinated operation among multiple wind farms. Reference [13] introduced a hierarchical control framework to reduce the computational complexity caused by a large number of wind turbines. Reference [14] designed a two-layer coordinated optimization scheme to regulate both the point of common coupling voltage and the generator terminal voltage. Reference [15] proposed an asynchronous hierarchical Volt/Var control method for offshore wind farms, using wind turbine reactive power capability to increase reactive power reserves. Reference [16] developed a bi-layer coordinated reactive power optimal control strategy to ensure reactive power support while maintaining wind farm voltage security. For offshore wind farms, Reference [17] proposed an adaptive reactive power optimization method based on an improved particle swarm optimization algorithm, jointly considering voltage deviation, active power loss, and reactive power margin. Reference [18] reviewed stability analysis methods and grid-connected control technologies for offshore wind power under weak-grid conditions. Reference [19] developed a coordinated reactive power and voltage control strategy for flexible low-frequency transmission systems of offshore wind farms. Reference [20] established a multi-objective reactive-voltage coordinated control model to balance voltage quality, network loss, and reactive power support capability. These methods provide useful references for coordinated voltage control. Nevertheless, most existing methods either focus on cluster-level or wind-farm-level coordination or adjust optimization parameters according to the iteration process rather than the real-time operating condition of the wind-farm cluster. In addition, the dynamic turbine-level reactive power

margins caused by heterogeneous turbine capacities and time-varying active power outputs are not always incorporated into the allocation process. A comparison between representative studies and the present work is summarized in Table 1.

Table 1. Comparison between existing studies and the proposed method.

Item	References [4–10]	References [11–16]	Reference [17]	References [18–20]	Proposed Method
Scope	Single wind-farm/local grid	Wind-farm clusters/offshore farms	Wind farms/reactive systems	Offshore wind systems	Practical WF cluster
Hierarchy	Single-layer/station-level	Cluster–farm or farm–unit	Single-/two-layer	System-/station-level	Cluster–WF–unit
Turbine margin	Fixed or aggregated	Partly considered, often aggregated	Simplified limits	Aggregated/simplified	Dynamic turbine-level limits
Method	MPC, sensitivity control, PSO	Hierarchical/rule-based control	improved PSO	Multi-objective/coordinated control	IDI-based EAPSO
Benchmark	Selected scenarios	Typical scenarios	Algorithm comparison	Selected offshore cases	24 h profile, comparison, ablation, sensitivity
Limitation	Limited multi-resource coordination	Insufficient turbine-level modeling	Mainly iteration-driven adaptation	Incomplete joint consideration of voltage, loss, equipment, turbine constraints	More field validation needed

Based on the comparison in Table 1, existing studies provide valuable foundations for wind-farm reactive power optimization and hierarchical voltage control. However, three issues remain to be further addressed. First, many studies focus on single wind farms or typical operating scenarios, whereas the coordinated optimization of multiple wind farms, SVGs, and transformer taps at the cluster level remains insufficient. Second, the dynamic relationship between turbine reactive power capability and real-time active power output is not always incorporated into refined unit-level allocation. Third, most improved PSO algorithms adjust parameters mainly according to the iteration process, while the real-time operating condition of wind-farm clusters is seldom used to guide the search behavior.

To address the above issues, this study develops a hierarchical coordinated reactive power optimization strategy for wind farm clusters using an operating-condition-aware particle swarm optimization algorithm, namely EAPSO. The standard hierarchical decomposition is used as the control structure, while the main additions of this study are the incorporation of dynamic turbine-level reactive power margins and the mapping of real-time operating-condition indicators to PSO search strategies. The main contributions are summarized as follows.

First, a three-layer coordination framework consisting of the cluster layer, wind-farm layer, and unit layer is established to coordinate wind-farm reactive power commands, SVG outputs, transformer tap positions, and turbine-level reactive power allocation. Second, the reactive power limits of heterogeneous turbines are dynamically calculated according to turbine type and real-time active power output, which supports refined unit-level allocation. Third, a comprehensive disturbance index is constructed from the low-load degree, spatial power dispersion, and output imbalance degree. This index is mapped to population initialization, learning factors, and mutation operation, enabling the search behavior of PSO to respond to wind-farm operating conditions rather than only to the iteration process. Finally, the proposed strategy is evaluated through a 24 h offline

simulation based on historical operating profiles of a practical wind-farm cluster in South China. The remainder of this paper is organized as follows. Section 2 introduces the hierarchical control structure. Section 3 formulates the optimization model. Section 4 presents the EAPSO algorithm. Section 5 discusses the case study and comparative results. Section 6 concludes the paper and discusses future work.

2. Hierarchical Coordinated Control Structure for Reactive Power of Wind Farm Clusters

2.1. Three-Layer Hierarchical Control Strategy

Aiming at scattered reactive power resources, severe voltage fluctuation and the defects of traditional centralized control, this paper proposes a three-layer hierarchical control strategy (cluster, wind-farm and unit layer). Based on the Automatic Voltage Control (AVC) system, bus voltage, reactive power margin, SVG and main transformer status are collected in real time. Control commands are delivered top-down and operational data are fed back bottom-up, as shown in Figure 1.

(1) Cluster Layer: Calculate the total reactive power demand of the wind-farm cluster according to the voltage deviation of the collection bus and the system operating state.

(2) Wind-Farm Layer: Receive reactive power commands from the cluster layer. Combined with the reactive power regulation capability of each wind farm and the operating state of SVG, the EAPSO algorithm is adopted to optimally allocate reactive power resources and tap positions of main transformers.

(3) Unit Layer: Execute reactive power regulation tasks issued by the wind-farm layer. The EAPSO algorithm is used to determine the optimal reactive power output of doubly fed wind turbines and direct-drive wind turbines.

The three-layer framework decomposes the original high-dimensional mixed continuous–discrete optimization problem into coupled sub-problems with clearer physical meanings. This decomposition facilitates engineering implementation and reduces the search dimension at each layer. Compared with a purely centralized formulation, the proposed structure improves the coordination between cluster-level voltage regulation and unit-level reactive power allocation while avoiding an excessively large decision space in a single optimization problem.

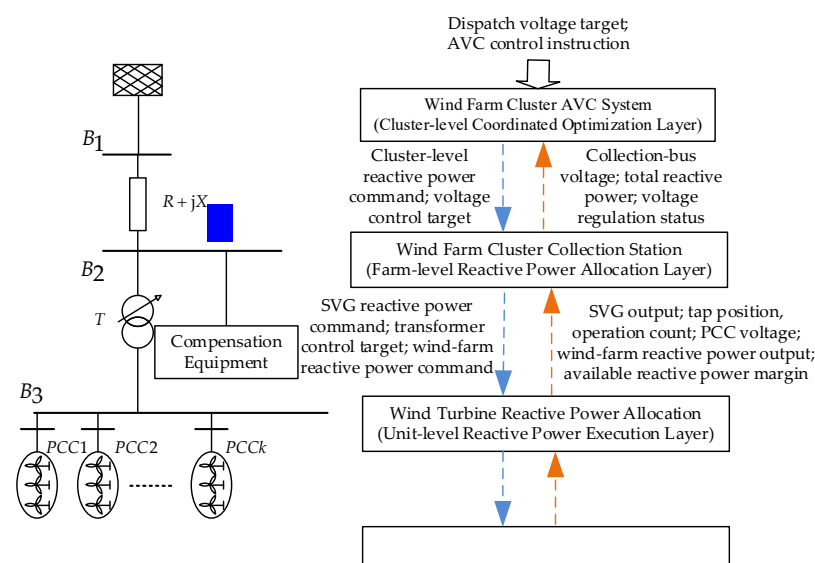


Figure 1. Strategy mechanism for reactive power control of wind-farm clusters.

To clarify the information flow, decision variables, constraints, and interaction among the three layers, the proposed hierarchical coordinated reactive power control framework is summarized in Table 2.

Table 2. Summary of the three-layer coordinated reactive power control framework.

Item	Cluster Layer	Wind-Farm Layer	Unit Layer
Input information	Dispatch voltage command, collection-bus voltage and reactive power, previous operating state	Total reactive power command, PCC voltages, wind-farm reactive power margins, SVG status, and tap positions	Wind-farm reactive power command, turbine active power output, turbine type, and dynamic reactive power limits
Decision variables	Total reactive power demand of the wind-farm cluster	Reactive power commands of wind farms, SVG reactive power outputs, and transformer tap positions	Reactive power outputs of individual wind turbines
Output command	Total reactive power command sent to the wind-farm layer	Reactive power command of each wind farm, SVG output command, and tap-position command	Reactive power command of each wind turbine
Main constraints	Collection-bus voltage limit and total reactive power balance	PCC voltage limits, wind-farm reactive power limits, SVG capacity limits, and transformer tap-position limits	Turbine reactive power limits, turbine terminal voltage limits, and wind-farm reactive power balance
Solver	Voltage–reactive power sensitivity calculation	EAPSO	EAPSO
Update frequency	Dispatch/AVC cycle	Coordinated AVC cycle (60 s is recommended)	Updated after receiving wind-farm-layer commands

2.2. Cluster Layer: Calculation of Total Reactive Power Demand

At the cluster layer, the AVC system calculates the total reactive power demand according to the voltage deviation of the collection bus [21]. The voltage deviation of the collection bus is defined as follows:

$$\Delta V_{B1}(t) = V_{B1,ref}(t) - V_{B1}(t) \quad (1)$$

where $V_{B1,ref}(t)$ is the reference voltage of the collection bus issued by the dispatching system, and $V_{B1}(t)$ is the measured voltage of the collection bus at time (t).

The required reactive power adjustment is calculated as [22]:

$$\Delta Q_{req}(t) = K_{QV}(t) \cdot \Delta V_{B1}(t) \quad (2)$$

where $K_{QV}(t)$ is the voltage–reactive power control sensitivity coefficient, with the unit of Mvar/p.u. It represents the reactive power adjustment required for a unit voltage deviation at the collection bus. When ($Q > 0$) denotes capacitive reactive power injection, a positive $\Delta V_{B1}(t) > 0$ indicates that the collection-bus voltage is lower than its reference value, and additional capacitive reactive power should be provided.

Therefore, the total reactive power command sent to the wind-farm layer can be expressed as follows:

$$Q_{req}(t) = sat[Q_{ctrl}(t-) + K_{QV}(t) \cdot \Delta V_{B1}(t), Q_{req,min}(t), Q_{req,max}(t)] \quad (3)$$

where $Q_{ctrl}(t-)$ is the current total reactive power output of controllable reactive power resources before the new command is issued; $sat[]$ is the saturation function used to prevent the reactive power command from exceeding the available regulation range;

$Q_{req,min}(t)$ and $Q_{req,max}(t)$ are the lower and upper limits of the total reactive power command, respectively.

The current total reactive power output of controllable resources is given by

$$Q_{ctrl}(t-) = \sum Q_{WF,k}(t-) + \sum Q_{SVG,s}(t-) \quad (4)$$

where $Q_{WF,k}(t-)$ is the current reactive power output of the k -th wind farm before optimization, and $Q_{SVG,s}(t-)$ is the current reactive power output of the s -th SVG before optimization.

The upper and lower limits of the total reactive power command are determined by the available reactive power capacities of wind farms and SVGs:

$$\begin{cases} Q_{req,min}(t) = \sum Q_{WF,k,min}(t) + \sum Q_{SVG,s,min} \\ Q_{req,max}(t) = \sum Q_{WF,k,max}(t) + \sum Q_{SVG,s,max} \end{cases} \quad (5)$$

where $\sum Q_{WF,k,max}(t)$ and $\sum Q_{WF,k,min}(t)$ are the maximum and minimum available reactive power outputs of the k -th wind farm at time (t), respectively; $\sum Q_{SVG,s,max}$ and $\sum Q_{SVG,s,min}$ are the maximum and minimum reactive power outputs of the s -th SVG, respectively.

In this study, the voltage–reactive power sensitivity coefficient K_{QV} is obtained from offline power-flow sensitivity analysis. Specifically, a small reactive power perturbation ΔQ_{test} is applied to the controllable reactive power buses, and the corresponding voltage variation in the collection bus ΔV_{B1} is calculated by Newton–Raphson power flow. The voltage–reactive power sensitivity is calculated as follows:

$$S_{VQ}^{off} = \frac{\Delta V_{B1}}{\Delta Q_{test}}, K_{QV}^{off} = \frac{1}{S_{VQ}^{off}} \quad (6)$$

where ΔQ_{test} is set to 5 Mvar. To avoid numerical instability caused by measurement noise, the sensitivity is not updated when $\Delta V_{B1} < 10^{-4}$ p.u. A three-sample moving average filter is used for the measured collection-bus voltage.

$$K_{QV}(t) = \begin{cases} \alpha K_{QV}^{on}(t) + (1-\alpha) K_{QV}^{off}, & |V_{B1}(t)| \geq 10^{-4} \\ K_{QV}(t-\Delta t), & |V_{B1}(t)| < 10^{-4} \end{cases} \quad (7)$$

where K_{QV}^{off} is the offline-calculated sensitivity, $K_{QV}^{on}(t)$ is the sensitivity estimated at the current operating point, and $\alpha = 0.2$. In the 24 h offline simulation, K_{QV}^{off} is used as a fixed sensitivity coefficient. The online filtered update rule is only provided as a practical AVC implementation option and is not used in the reported simulation results.

2.3. Wind-Farm Layer: Collaborative Reactive Power Allocation of Multiple Devices

At the wind-farm layer, the total reactive power command from the cluster layer is allocated among wind farms, SVGs, and transformer tap changers. The decision variables include the reactive power command of each wind farm, the continuous reactive power output of each SVG, and the discrete tap position of each main transformer. The engineering priority is set as wind turbine converters first, SVGs second, and transformer taps last. This priority is implemented through the equipment-operation cost term in the objective function: wind turbine reactive power regulation is not assigned a mechanical switching cost, SVG output variation is penalized as a continuous regulation cost, and transformer

tap operation is assigned a higher equivalent cost. In addition, a reactive power reserve constraint is considered to retain dynamic voltage support capability.

2.4. Unit Layer: Refined Reactive Power Allocation for Wind Turbines

After the reactive power command of each wind farm is determined, the unit layer allocates the command among individual turbines. The decision variable is the reactive power output of each turbine. For DFIG turbines, the reactive power capability is approximated by the stator apparent power limit. For PMSG direct-drive turbines, the capability is approximated by the full-power converter capacity. The reactive power limits are dynamically updated according to turbine type and real-time active power output. When manufacturer-specific capability curves, converter current limits, or grid-code requirements are available, the final reactive power limits should be determined by the intersection of all applicable constraints.

For the i -th DFIG turbine, the reactive power limits are calculated as follows:

$$\begin{cases} Q_{i,DFIG}^{\max}(t) = \sqrt{S_{stator,i}^{rated\ 2} - P_i^2(t)} \\ Q_{i,DFIG}^{\min}(t) = -\sqrt{S_{stator,i}^{rated\ 2} - P_i^2(t)} \end{cases} \quad (8)$$

where $S_{stator,i}^{rated}$ is the rated stator apparent power of the i -th DFIG turbines, in MVA; $Q_{i,DFIG}^{\max}(t)$ and $Q_{i,DFIG}^{\min}(t)$ are the maximum and minimum reactive power outputs of the i -th DFIG turbine, respectively, in Mvar; $P_i(t)$ is the real-time active power output of the i -th turbine, in MW.

For the i -th PMSG direct-drive turbine, the reactive power limits are calculated as follows:

$$\begin{cases} Q_{i,PM}^{\max}(t) = \sqrt{S_{conv,i}^{rated\ 2} - P_i^2(t)} \\ Q_{i,PM}^{\min}(t) = -\sqrt{S_{conv,i}^{rated\ 2} - P_i^2(t)} \end{cases} \quad (9)$$

where $S_{conv,i}^{rated}$ is the rated capacity of the i -th PMSG turbine, in MVA, $Q_{i,PM}^{\max}$ and $Q_{i,PM}^{\min}$ are the maximum and minimum reactive power outputs of the i -th PMSG turbine, respectively, in Mvar.

For the $Q_{j,i}^{\min}$ and $Q_{j,i}^{\max}$ of the i -th turbine in the j -th wind farm, the corresponding DFIG or PMSG formula is selected according to the turbine type. The calculated limits are then incorporated into the unit-layer optimization as box constraints and reserve-margin constraints. In this way, the unit-layer allocation is constrained by both turbine type and real-time active power output.

The main parameters of wind turbines adopted in this paper are listed in Table 3.

Table 3. Main parameters of wind turbines.

Turbine Type	Rated Active Power	Rated Converter/Stator Capacity	Number of Turbines	Voltage Level
DFIG (Doubly fed)	11 MW	12.1 MVA	92	0.69 kV
PMSG (Direct-drive)	6.8 MW	7.6 MVA	37	0.69 kV
PMSG (Direct-drive)	8.3 MW	9.0 MVA	30	0.69 kV

Manufacturer-specific capability curves and converter current limits are unavailable in this study. Therefore, an equivalent apparent-power or converter-capacity model is used.

3. Reactive Power Optimization Model of Wind Power System

In the proposed hierarchical framework, EAPSO is applied at both the wind-farm layer and the unit layer, but the two optimization problems have different decision variables, objectives, and constraints. The wind-farm layer coordinates reactive power allocation among wind farms, SVGs, and transformer tap changers, whereas the unit layer allocates each wind-farm reactive power command among individual turbines. Unless otherwise specified, voltage is expressed in per unit, active and reactive powers are expressed in MW and Mvar, respectively, and transformer tap positions are treated as discrete integer variables.

3.1. Optimization Variables

At the wind-farm layer, the decision variable vector is defined as follows:

$$\mathbf{X}_{WF}(t) = [Q_{WF,1}(t), Q_{WF,2}(t), Q_{WF,3}(t), Q_{SVG,1}(t), Q_{SVG,2}(t), T_1(t), T_2(t), T_3(t)]^T \quad (10)$$

where $Q_{WF,j}(t)$ is the reactive power command of the j -th wind farm; $Q_{SVG,s}(t)$ is the reactive power output of the s -th SVG; $T_k(t)$ is the tap position of the k -th main transformer. $Q_{WF,j}(t)$ and $Q_{SVG,s}(t)$ are bounded continuous variables, while $T_k(t)$ is a discrete integer variable.

At the unit layer, the optimization variable vector for the j -th wind farm is defined as follows:

$$\mathbf{X}_U(t) = [Q_{j,1}(t), Q_{j,2}(t), \dots, Q_{j,N_j}(t)] \quad (11)$$

where $Q_{j,i}(t)$ is the reactive power output of the i -th turbine in the j -th wind farm; N_j is the number of wind turbines in the j -th wind farm. These variables are continuous variables bounded by the dynamic reactive power limits of wind turbines.

3.2. Objective Function

3.2.1. Wind-Farm-Layer

At the wind-farm layer, voltage stability, network loss, and equipment-operation cost are considered. To avoid the dominance of one objective caused by different units and numerical scales, all objective terms are normalized.

(1) Voltage Stability Objective

$$F_V^{WF} = \frac{[V_{B1}(t) - V_{B1,ref}]^2}{(\Delta V_{B1,max})^2} + \frac{1}{n} \sum_{j=1}^n \frac{[V_{PCC,j}(t) - V_{PCC,j,ref}]^2}{(\Delta V_{PCC,max})^2} \quad (12)$$

where $V_{PCC,j}(t)$ is the PCC voltage of the j -th wind farm, $V_{PCC,j,ref}$ is the corresponding PCC voltage reference; n is the number of wind farms within the cluster; $\Delta V_{B1,max}$ and $\Delta V_{PCC,max}$ are the maximum allowable voltage deviations.

(2) Network Loss Objective

$$F_L^{WF} = \frac{P_{loss}(t)}{P_{loss,0}(t)} \quad (13)$$

where $P_{loss}(t)$ is the active power loss after optimization; $P_{loss,0}(t)$ is the active power loss before optimization.

The active power loss is calculated as follows:

$$P_{\text{loss}}(t) = \sum_{(i,m) \in \Omega_l} g_{im} [V_i^2(t) + V_m^2(t) - 2V_i(t)V_m(t)\cos\theta_{im}(t)] \quad (14)$$

where Ω_l is the set of system branches, g_{im} is the conductance of branch $i-m$, $V_i(t)$ and $V_m(t)$ are the voltage magnitudes at both ends of the branch, and $\theta_{im}(t)$ is the voltage angle difference between bus i and bus m .

(3) Equipment-Operation Cost Objective

The equipment-operation cost objective is used to reflect the regulatory priority of “wind turbine converters first, SVGs second, and transformer tap changers last”. Since wind turbine reactive power regulation does not involve mechanical switching costs, no additional operation penalty is assigned to wind turbines. SVG output variation is included as the continuous reactive power regulation cost, while transformer tap operation is assigned a higher equivalent cost.

$$F_A^{\text{WF}} = \frac{1}{S} \sum_{s=1}^S \frac{|Q_{\text{SVG},s}(t) - Q_{\text{SVG},s}(t-1)|}{Q_{\text{SVG},s}^{\text{max}} - Q_{\text{SVG},s}^{\text{min}}} + \gamma_T \frac{1}{K} \sum_{k=1}^K \frac{|T_k(t) - T_k(t-1)|}{T_k^{\text{max}} - T_k^{\text{min}}} \quad (15)$$

where S is the number of SVGs, K is the number of main transformers, and γ_T is the equivalent cost coefficient of transformer tap operation.

In this study, γ_T is set to 10. This value is selected to make one transformer tap movement equivalent to a relatively large continuous SVG regulation cost after normalization. Since the main transformer has a tap range of $(525 \pm 8 \times 1.25\%)$, one tap movement corresponds to $\frac{1}{16}$ of the full tap range. With $\gamma_T = 10$, the normalized cost of one tap movement is approximately $10/16 = 0.625$, which is much larger than a small SVG output adjustment. Therefore, the optimizer tends to use wind-turbine reactive power and SVG continuous regulation before changing transformer taps, unless the voltage or reactive power tracking constraints cannot be effectively satisfied by converter-based resources alone.

To examine the influence of γ_T on the utilization of SVGs and transformer tap changers. As shown in Table 4, a short sensitivity comparison was carried out under the same 24 h operating profile. The results show that a smaller γ_T leads to more frequent transformer tap operations and lower SVG utilization, whereas a larger γ_T suppresses tap actions but increases SVG reactive power output. When $\gamma_T = 10$, the proposed method achieves a balanced compromise between reducing mechanical tap operations and avoiding excessive SVG regulation. Therefore, $\gamma_T = 10$ is adopted in the following simulations.

Table 4. Sensitivity comparison of the transformer tap operation cost coefficient γ_T .

γ_T	Average PCC Voltage Deviation/p.u.	Average Loss Reduction/%	Total Tap Operation Times	Cumulative SVG Output/Mvar
1	0.00405	3.57	126	162.48
10	0.00412	3.55	92	208.39
20	0.00418	3.50	71	276.84

Through Equation (15), the engineering priority described in Section 2.3 is embedded into the optimization objective. The optimizer tends to use wind turbine reactive power first, then SVG output, and finally transformer tap adjustment when necessary.

Therefore, the wind-farm-layer objective function is expressed as follows:

$$F_{WF} = w_V F_V^{WF} + w_L F_L^{WF} + w_A F_A^{WF} + F_{pen}^{WF} \quad (16)$$

where w_V , w_L , and w_A are the weighting coefficients of voltage stability, network loss, and equipment-operation cost, respectively. The weighting coefficients satisfy the following condition: $w_V + w_L + w_A = 1, w_V \geq 0, w_L \geq 0, w_A \geq 0$.

To reduce arbitrariness in weight selection, the order relation analysis method, also known as the G1 method, is adopted. The indicators are first ranked according to their engineering priority. In this study, voltage regulation is regarded as the primary objective, followed by network-loss reduction and equipment-operation cost. The adjacent importance ratios are set as $r_2 = 1.4, r_3 = 1.2$, and the final normalized weights are listed in Table 5. To further examine the influence of the objective-function weights, a weight-sensitivity analysis is conducted in Section 5.3.1.

Table 5. Weighting coefficients of the objective function.

Objective Term	Symbol	Weight
Voltage deviation	w_V	0.433
Active power loss	w_L	0.309
Equipment-operation cost	w_A	0.258

3.2.2. Unit-Layer

After the wind-farm-layer reactive power command $Q_{WF,j}(t)$ is determined, the unit layer allocates this command to individual turbines in the j -th wind farm. To avoid introducing additional weighting coefficients, the unit-layer objective function is formulated as the direct summation of normalized reactive power allocation deviation and turbine terminal voltage deviation.

$$F_{U,j} = F_{Q,j}^U + F_{V,j}^U + F_{pen,j}^U \quad (17)$$

where $F_{Q,j}^U$ is the reactive power allocation deviation term, $F_{V,j}^U$ is the turbine terminal voltage deviation term.

The reactive power allocation deviation term is defined as follows:

$$F_{Q,j}^U = \frac{[\sum_{i=1}^{N_j} Q_{j,i}(t) - Q_{WF,j}(t)]^2}{[|Q_{WF,j}(t)| + \varepsilon]^2} \quad (18)$$

where $Q_{WF,j}(t)$ is the reactive power command assigned to the j -th wind farm by the wind-farm layer, and ε is a small positive constant used to avoid division by zero.

The turbine terminal voltage deviation term is defined as follows:

$$F_{V,j}^U = \frac{1}{N_j} \sum_{i=1}^{N_j} \frac{[V_{WT,j,i}(t) - V_{WT}^{\text{ref}}]^2}{(\Delta V_{WT}^{\text{max}})^2} \quad (19)$$

where $V_{WT,j,i}(t)$ is the terminal voltage of the i -th wind turbine in the j -th wind farm, V_{WT}^{ref} is the reference value of turbine terminal voltage, and $\Delta V_{WT}^{\text{max}}$ is the maximum allowable deviation of turbine terminal voltage.

The penalty function is defined as follows:

$$F_{pen} = \lambda_V G_V + \lambda_Q G_Q + \lambda_R G_R + \lambda_{PF} G_{PF} \quad (20)$$

where G_V , G_Q , G_R , and G_{PF} denote the penalty terms for voltage violation, reactive power tracking error, reactive reserve margin violation, and power-flow non-convergence, respectively. The final fitness function is as follows:

$$F_{fit} = F + F_{pen} \quad (21)$$

The penalty coefficients used in this study are summarized in Table 6, reflecting the prioritization of constraint violations during optimization.

Table 6. Penalty coefficient settings.

Penalty Item	Symbol	Value
Voltage violation	λ_V	10^4
Reactive tracking error	λ_Q	10^3
Reactive reserve violation	λ_R	10^3
Power-flow non-convergence	λ_{PF}	10^6

3.3. Constraint Conditions

The wind-farm cluster optimization should satisfy the AC power-flow equations. The active and reactive power balance equations are given as follows [23]:

$$\begin{cases} P_i = V_i \sum_{m=1}^{N_b} V_m (G_{im} \cos \theta_{im} + B_{im} \sin \theta_{im}) \\ Q_i = V_i \sum_{m=1}^{N_b} V_m (G_{im} \sin \theta_{im} - B_{im} \cos \theta_{im}) \end{cases} \quad (22)$$

where P_i and Q_i are the active and reactive power injected at each node; V_i and V_m are the voltage amplitudes of each node; G_{im} and B_{im} are the self-conductance for nodes i and m ; θ_{im} is the phase angle difference between nodes i and m ; N_b is the number of buses. The AC power flow is solved by the Newton–Raphson method with a convergence tolerance of 10^{-6} p.u. on a 100 MVA base.

The wind-farm-layer control variable constraints are expressed as follows [24]:

$$\begin{cases} Q_{WF,j}^{\min}(t) \leq Q_{WF,j}(t) \leq Q_{WF,j}^{\max}(t), & j = 1, 2, \dots, J \\ Q_{SVG,s}^{\min} \leq Q_{SVG,s}(t) \leq Q_{SVG,s}^{\max}, & s = 1, 2, \dots, S \\ T_k^{\min} \leq T_k(t) \leq T_k^{\max}, & T_k(t) \in Z, \quad k = 1, 2, \dots, K \end{cases} \quad (23)$$

The total reactive power output at the wind-farm layer should track the total reactive power demand issued by the cluster layer within an allowable tolerance:

$$\left| \sum_{j=1}^J Q_{WF,j}(t) + \sum_{s=1}^S Q_{SVG,s}(t) - Q_{req}(t) \right| \leq \Delta Q_{tol} \quad (24)$$

where ΔQ_{tol} is the allowable tracking error of the total reactive power command, which is set to 5 Mvar in this study.

The unit-layer control variable constraints are expressed as follows:

$$Q_{j,i}^{\min}(t) \leq Q_{j,i}(t) \leq Q_{j,i}^{\max}(t), \quad i = 1, 2, \dots, N_j \quad (25)$$

The total reactive power output of all turbines in the j -th wind farm should satisfy the reactive power command issued by the wind-farm layer within an allowable tolerance:

$$\left| \sum_{i=1}^{N_j} Q_{j,i}(t) - Q_{WF,j}(t) \right| \leq \Delta Q_{WF,j}^{\text{tol}} \quad (26)$$

where $\Delta Q_{WF,j}^{\text{tol}}$ is the allowable tracking error of the unit-layer reactive power command for the j -th wind farm, which is set to 1 Mvar in this study.

To retain sufficient dynamic reactive power support capability, the turbine reactive power reserve constraint is expressed as follows:

$$Q_{j,i}^{\min}(t) + \Delta Q_{\text{res},j,i}(t) \leq Q_{j,i}(t) \leq Q_{j,i}^{\max}(t) - \Delta Q_{\text{res},j,i}(t) \quad (27)$$

$$\Delta Q_{\text{res},j,i}(t) = 0.1[Q_{j,i}^{\max}(t) - Q_{j,i}^{\min}(t)] \quad (28)$$

where $\Delta Q_{\text{res},j,i}$ is the reserved reactive power margin of the i -th turbine in the j -th wind farm.

The voltage constraints include the collection-bus voltage constraint, PCC voltage constraints, and turbine terminal voltage constraints [25]:

$$\begin{cases} V_{B3}^{\min} \leq V_{B3}(t) \leq V_{B3}^{\max} \\ V_{\text{PCC},j}^{\min} \leq V_{\text{PCC},j}(t) \leq V_{\text{PCC},j}^{\max}, & j = 1, 2, \dots, J \\ V_{\text{WT}}^{\min} \leq V_{\text{WT},j,i}(t) \leq V_{\text{WT}}^{\max}, & i = 1, 2, \dots, N_j \end{cases} \quad (29)$$

According to the grid-connection requirements of offshore wind farms, the voltage at the point of connection is constrained within 0.97–1.07 p.u. for wind farms connected to 220 kV and below public grids, while the voltage adaptability range of wind turbines is taken as 0.90–1.10 p.u. In addition, the voltage of the collection/common bus is constrained within 0.95–1.05 p.u.

4. Solution of Reactive Power Optimization Model

Traditional PSO generally uses fixed or iteration-dependent parameters [26]. When applied to wind-farm clusters with strongly fluctuating output and time-varying reactive power margins, such parameter settings may lead to slow convergence or premature convergence. Existing improved PSO methods, such as adaptive PSO and chaotic PSO, can enhance search performance, but their parameter adjustment is usually driven by the iteration process rather than by the real-time operating condition of the optimization object [27–29]. To address this limitation, EAPSO introduces an explicit mapping from wind-farm operating-condition indicators to PSO search strategies. Specifically, the comprehensive disturbance index is used to guide population initialization, learning-factor adjustment, and mutation operation. This design enables the search process to respond to the complexity of the current operating condition.

4.1. Environment-Aware Particle Swarm Optimization (EAPSO) Algorithm

4.1.1. Feature Extraction of Operating Environment

To establish the connection between the algorithm and the dynamic operating environment, it is first necessary to quantitatively characterize the real-time state of the wind farm. The EAPSO algorithm extracts the following three basic environmental features and constructs comprehensive environmental evaluation indicators, comprehensively characterizing the working condition characteristics of the optimized object.

(1) Load Rate (LF)

The load rate reflects the current active power output level of the wind-farm cluster and is defined as follows:

$$LF(t) = \frac{\sum_{i=1}^N P_i(t)}{\sum_{i=1}^N P_{rated,i}} \quad (30)$$

where N is the total number of turbines in the wind-farm cluster, $P_{rated,i}$ is the rated capacity of the i -th turbine.

(2) Spatial Power Dispersion (PD)

The spatial power dispersion index reflects the dispersion of active power outputs among turbines at the same time instant. The normalized active power output of the i -th turbine is defined as follows:

$$p_i(t) = \frac{P_i(t)}{P_{rated,i}} \quad (31)$$

The mean and standard deviation of normalized turbine outputs are

$$\begin{aligned} \bar{p}(t) &= \frac{1}{N} \sum_{i=1}^N p_i(t) \\ \sigma_p(t) &= \sqrt{\frac{1}{N-1} \sum_{i=1}^N [p_i(t) - \bar{p}(t)]^2} \end{aligned} \quad (32)$$

The spatial power dispersion index is then defined as follows:

$$PD(t) = \frac{\sigma_p(t)}{\max(\bar{p}(t), \varepsilon_p)} \quad (33)$$

where ε_{PD} is a safeguard term used to avoid a near-zero denominator under low-output conditions, set to 0.02 in this study.

(3) Output Imbalance Degree (OI)

The output imbalance degree is used to describe the output difference among wind turbines at the same time instant.

$$OI(t) = \frac{\max_i p_i(t) - \min_i p_i(t)}{\bar{p}(t) + \varepsilon_{OI}} \quad (34)$$

where ε_{OI} is a safeguard term under low-output conditions and can generally be selected to be 0.02. Compared with $PD(t)$, which measures statistical dispersion around the average output, $OI(t)$ emphasizes the range of output imbalance among turbines.

To link the algorithm with operating conditions, the above indicators are combined into a comprehensive disturbance index:

$$IDI(t) = w_{LF} [1 - LF(t)] + w_{PD} PD(t) + w_{OI} OI(t) \quad (35)$$

where w_{LF} , w_{PD} and w_{OI} are the weighting coefficients of the low-load degree, spatial power dispersion rate, and output imbalance degree, respectively, satisfying $w_{LF} + w_{PD} + w_{OI} = 1$. A larger $IDI(t)$ indicates that the wind-farm cluster is operating under more complex conditions, such as low load, big spatial differences in turbine outputs, or severe output imbalance.

To avoid determining the environmental-feature weights in (IDI) purely by subjective experience, the G1 method is also adopted to determine w_{LF} , w_{PD} , and w_{OI} . Considering that unit-level reactive power allocation is most directly affected by the difference

between heavily loaded and lightly loaded turbines. A larger OI usually indicates a more uneven distribution of turbine reactive power margins, making it more difficult to satisfy both wind-farm reactive power tracking and turbine terminal voltage constraints. PD reflects the overall spatial dispersion, whereas $(1-LF)$ mainly affects the overall level of available turbine reactive power capability. Therefore, the weights used in this paper should be interpreted as engineering weights based on operating experience and data inspection; the importance order can be set as follows:

$$OI > PD > (1-LF) \quad (36)$$

The weights are then calculated according to the relative importance ratios between adjacent indicators and normalized. The adjacent importance ratios are set as $r_2 = 1.2, r_3 = 1.2$, and the final weighting coefficients of $IDI(t)$ are listed in Table 7.

Table 7. Weighting coefficients of the comprehensive disturbance index.

Environmental Feature	Symbol	Weight
Low-load degree	w_{LF}	0.275
Spatial power dispersion	w_{PD}	0.330
Output imbalance degree	w_{OI}	0.395

4.1.2. Intelligent Population Initialization Strategy

The initial population affects both convergence speed and search diversity.

(1) Diversity Factor

To quantify the required distribution breadth of the initial population, the diversity factor is defined as follows:

$$\alpha_d = 0.5 + 0.5IDI \quad (37)$$

This design limits the value of α_d to the range [0.5, 1.0]. A larger $IDI(t)$ results in a wider initial distribution, which increases global exploration under complex operating conditions.

(2) Hierarchical Initialization Method

Based on the diversity factor, this paper designs a hierarchical initialization strategy comprising three types of particles, balancing solution diversity and quality.

The initial population is generated as follows:

$$\mathbf{X}_0 = [x_1^0, x_2^0, \dots, x_M^0] \quad (38)$$

where M is the number of particles; x_1^0 is the zero-increment benchmark particle. The zero-vector particle is used only as a benchmark particle representing the initial uncompensated or zero-increment control state. x_2^0 is the central particle, with its optimization variables set to the geometric center of the feasible region, representing the average compensation level and offering a stable, viable starting search point; $x_i^0, i \in [3, 4, \dots, M]$ are environmental particles, whose positions are influenced by the environmental diversity factor. For the k -th dimension variable of the i -th particle, its initial value is determined by the following:

$$x_{i,k}^0 = x_{\min,k} + \alpha_d \cdot r_{i,k} (x_{\max,k} - x_{\min,k}) \quad (39)$$

where $x_{\min,k}$ and $x_{\max,k}$ are the lower and upper bounds of the k -th dimension variable, respectively; $r_{i,k} \in [0,1]$ is a random number.

For infeasible particles generated during initialization or iteration, a repair-and-penalty strategy is adopted. First, each variable is projected onto its lower and upper bounds. Second, discrete transformer tap positions are rounded to the nearest feasible integer value. Third, if the reactive power tracking constraint is violated, the continuous reactive power variables are proportionally adjusted within their remaining available margins. Residual violations are included in the penalty term of the objective function.

To handle infeasible particles generated during initialization or iteration, a repair-and-penalty strategy is adopted, as detailed in Algorithm 1.

Algorithm 1. Initialization, constraint repair, and penalty handling of EAPSO.

Input: variable bounds, feasible transformer tap set, reactive power command, population size, and IDI.

Step 1: Calculate the initialization diversity factor α_d according to IDI.

Step 2: Generate a benchmark particle using the current operating state.

Step 3: Generate a central particle using the midpoint of variable bounds.

Step 4: Generate the remaining particles within the IDI-adjusted search range.

Step 5: Round transformer tap variables to the nearest feasible integer positions.

Step 6: Project continuous variables onto their corresponding lower and upper bounds.

Step 7: Calculate the reactive power tracking error.

Step 8: If the tracking error exceeds the tolerance, adjust continuous reactive variables proportionally according to the remaining reactive power margins.

Step 9: Check variable bounds and transformer tap integer feasibility again.

Step 10: Solve the AC power flow.

Step 11: Calculate penalties for voltage violation, reactive tracking error, reserve margin violation, and power-flow non-convergence.

Step 12: Calculate the final fitness value.

Output: Repaired particle and its fitness value.

4.1.3. Parameter Self-Adaptive Adjustment Law Based on the Environmental Feature Mapping

The core of EAPSO lies in dynamically mapping environmental features to algorithm parameters, achieving “environment-adaptive” adjustment of the search strategy.

Inertia weight ω is adjusted adaptively: a larger value enhances global exploration under complex conditions, while a smaller value in later iterations benefits local fine search.

$$\omega(t) = \omega_{\min} + (\omega_{\max} - \omega_{\min}) \text{IDI} - (\omega_{\max} - \omega_{\min}) \left(1 - \frac{t}{T_{\max}}\right) \quad (40)$$

where $\omega_{\max}$ and $\omega_{\min}$ are the preset upper and lower bounds of the inertia weight, respectively.

The learning factors are adaptively adjusted according to the spatial power dispersion $PD(t)$ and the output imbalance degree $OI(t)$. A larger $OI(t)$ indicates stronger output differences among turbines and requires enhanced individual search capability. A larger $PD(t)$ indicates a more dispersed active power distribution within the wind-farm cluster and requires enhanced group-coordinated search capability. The learning factors are defined as follows:

$$\begin{cases} c_1(t) = \text{clip}[c_{1,\text{base}} + (c_{1,\text{max}} - c_{1,\text{base}})OI(t) - (c_{1,\text{base}} - c_{1,\text{min}})PD(t), c_{1,\text{min}}, c_{1,\text{max}}] \\ c_2 = \text{clip}[c_{2,\text{base}} + (c_{2,\text{max}} - c_{2,\text{base}})PD(t) - (c_{2,\text{base}} - c_{2,\text{min}})OI(t), c_{2,\text{min}}, c_{2,\text{max}}] \end{cases} \quad (41)$$

where $c_{1,\text{base}}$ and $c_{2,\text{base}}$ are the benchmark values of the learning factors; $c_{1,\text{min}}$, $c_{1,\text{max}}$, $c_{2,\text{min}}$ and $c_{2,\text{max}}$ the lower and upper bounds of the learning factors, and $\text{clip}()$ denotes the clipping function.

4.1.4. Environment-Aware Mutation Operation

To maintain population diversity and reduce the risk of premature convergence, EAPSO introduces an adaptive mutation operation. The mutation probability depends on both the comprehensive disturbance index and the iteration stage:

$$p_m = \text{clip}\left[p_{m,\text{min}} + (p_{m,\text{max}} - p_{m,\text{min}})\left(0.5IDI + 0.5\left(1 - \frac{t}{T_{\text{max}}}\right)\right), p_{m,\text{min}}, p_{m,\text{max}}\right] \quad (42)$$

where $p_{m,\text{min}}$ and $p_{m,\text{max}}$ are the minimum and maximum mutation probabilities, respectively, t is the current iteration number, and T_{max} is the maximum iteration number. This setting increases mutation probability under complex operating conditions and early iterations, while gradually reducing mutation in later local-search stages.

For particles selected for mutation, their positions are updated as follows:

$$\mathbf{x}_{\text{new}}^t = \mathbf{x}_{\text{old}}^t + \Delta(\mathbf{x}_{\text{max}} - \mathbf{x}_{\text{min}}) \odot \mathbf{d} \quad (43)$$

where $\Delta = 0.1 + 0.3IDI$ is the mutation amplitude; $\mathbf{d} \in [-1, 1]$ is the mutation direction vector, with each component randomly sampled to ensure randomness and diversity in exploration. $\odot$ denotes element-wise multiplication.

4.2. Control Flow

Figure 2 shows the control flow of the hierarchical coordinated reactive power strategy. The cluster-level AVC receives the dispatching voltage command and collects operating data from the wind-farm cluster. The total reactive power demand is calculated according to the collection-bus voltage deviation and the available reactive power range. The wind-farm layer then uses EAPSO to determine wind-farm reactive power commands, SVG outputs, and transformer tap positions. The unit layer further allocates the wind-farm reactive power command among individual turbines according to their dynamic reactive power limits. After the control commands are executed, voltage, reactive power, SVG status, tap position, and turbine operating data are fed back to the upper layers for the next control cycle. The hierarchical coordinated reactive power optimization is executed as shown in Algorithm 2, the underlying EAPSO process is depicted in Figure 3

Algorithm 2. EAPSO-based hierarchical reactive power optimization.

Step 1: Collect voltage, active power, reactive power, SVG status, transformer tap positions, and turbine operating data.

Step 2: Calculate the cluster-level reactive power command using voltage–reactive power sensitivity.

Step 3: Calculate $LF(t)$, $PD(t)$, $OI(t)$ and $IDI(t)$

Step 4: Initialize the EAPSO population according to $IDI(t)$.

Step 5: Evaluate the wind-farm-layer objective function.

Step 6: Update particle velocity and position.

Step 7: Update ω , c_1 , c_2 , and mutation probability according to operating-condition indicators.

Step 8: Apply mutation.

Step 9: Set $t = t + 1$. If $t \geq T_{\max}$, output the optimal solution; otherwise, repeat Steps 5–8.

Step 10: Send wind-farm reactive power commands, SVG commands, and transformer tap commands to the lower layer.

Step 11: For each wind farm, repeat the EAPSO procedure at the unit layer to allocate reactive power among turbines.

Step 12: Execute commands and update feedback data.

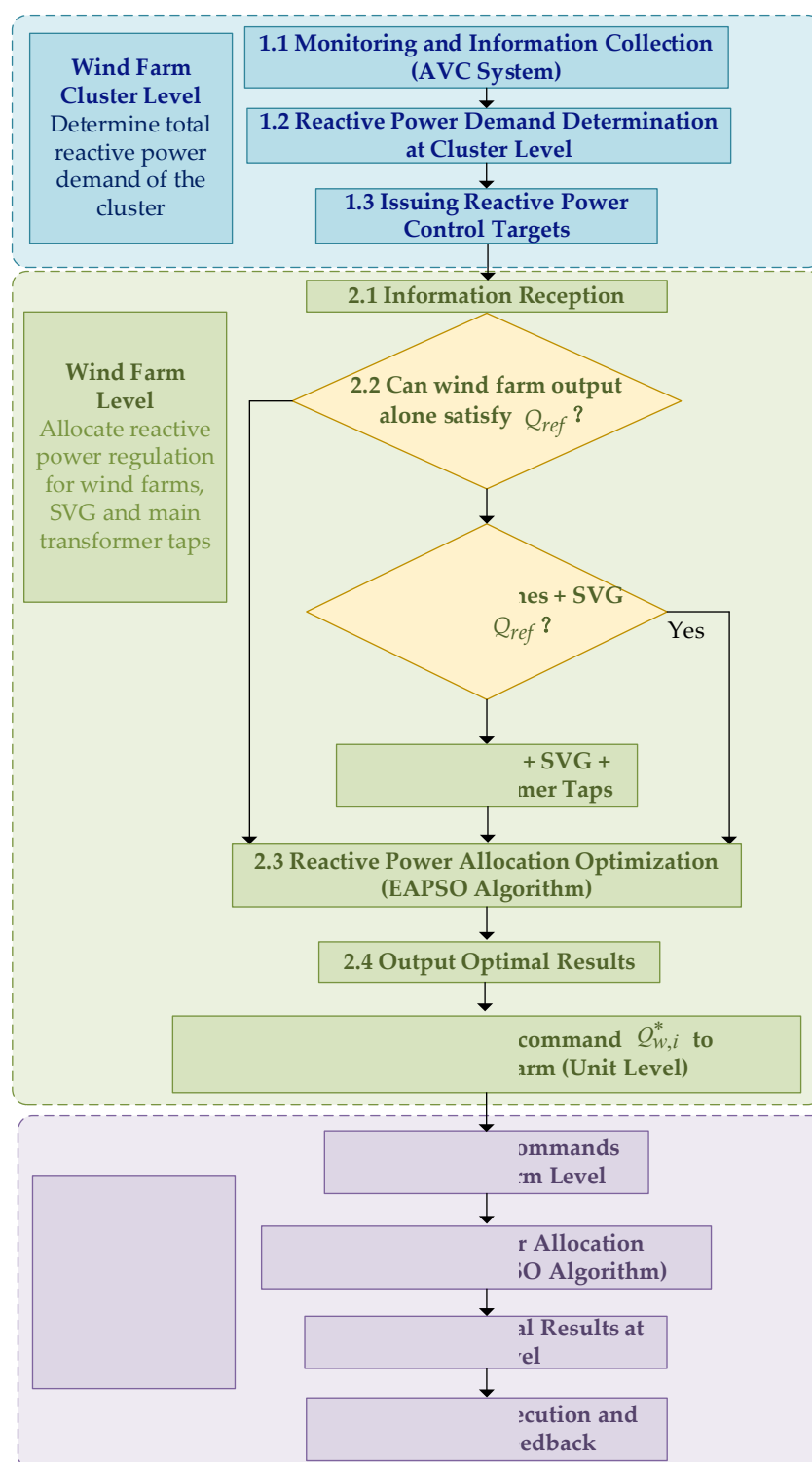
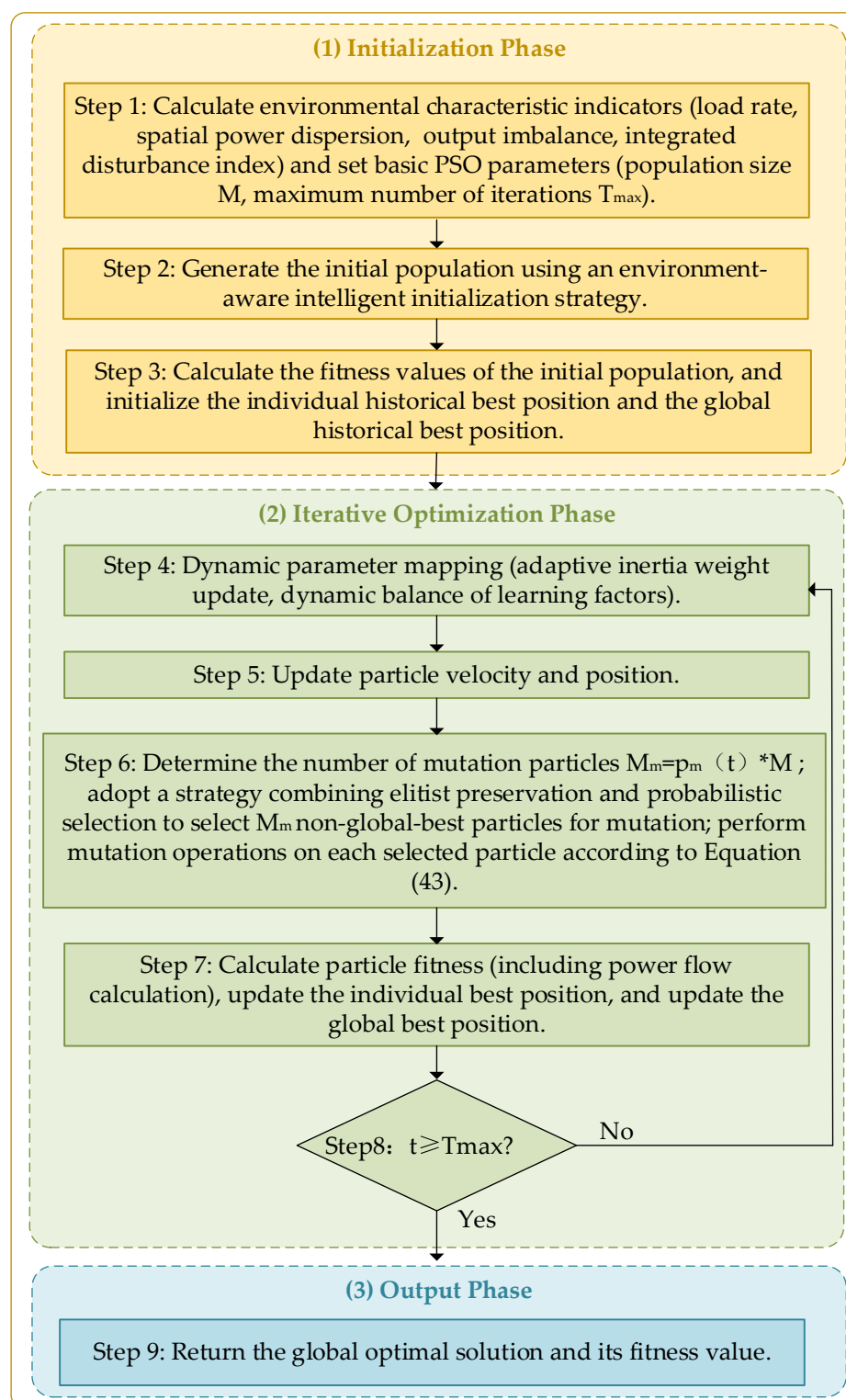


Figure 2. Flowchart of reactive power hierarchical coordinated control for wind-farm clusters.**Figure 3.** Flowchart of EAPSO.

5. Case Study

5.1. Test System Configuration

A practical large-scale wind-farm cluster in South China is used as the test system. Figure 4 illustrates the system structure of the wind-farm cluster, which consists of three wind farms, 159 wind turbines, two SVGs, and three main transformers, with a total in-

stalled capacity of 1515.6 MW. The wind farm cluster is connected to the upper-level grid through submarine cables, step-up transformers, and a common grid-connection system. The voltage target issued by the dispatching system is set to 1.0 p.u. The case study is established based on the topology, equipment capacities, and historical operating profiles of a practical engineering system and is used to verify the applicability of the proposed hierarchical coordinated reactive power optimization strategy. The internal collection topologies and collection voltage levels of the three wind farms are different. Wind Farm 1 contains seven collection feeders, with five to six wind turbines connected to each feeder. The turbines on each feeder are connected through 66 kV submarine cables. Wind Farm 2 contains nine collection feeders, with five to six wind turbines connected to each feeder, and the turbines are also connected through 66 kV submarine cables. Wind Farm 3 contains nineteen collection feeders, with three to four wind turbines connected to each feeder, and the turbines are connected through 35 kV submarine cables. Each wind turbine is equipped with a box-type transformer. The terminal voltage of each turbine is first stepped up by its box-type transformer to the corresponding collection voltage level of the wind farm and then connected to the submarine cable collection system of its feeder. The feeders are collected at the wind-farm booster station, then further stepped up by the main transformers and connected to the common grid-connection system of the wind-farm cluster.

In the power-flow model, each collection feeder is represented by equivalent branch models according to the actual electrical connection sequence. The submarine cables between adjacent wind turbines on each feeder are modeled using the unit-length impedance parameters of the corresponding voltage level. Each box-type transformer is represented by an equivalent two-winding transformer model, with its low-voltage side connected to the wind turbine terminal and its high-voltage side connected to the corresponding 35 kV or 66 kV collection line. Since the original geographical coordinates, real bus names, and exact cable routes are subject to engineering confidentiality restrictions, the releasable system structure, equipment parameters, and statistical results are provided in the manuscript. The main equipment parameters of the wind-farm cluster are listed in Table 8.

Table 8. Main equipment parameters of the wind-farm cluster.

Equipment	Parameter	Value	Unit
Box transformer	Rated capacity	12.1	MVA
	Rated voltage	66/0.69	kV
	Connection group	Dyn11	—
	Short-circuit impedance	9.23	%
	No-load loss	9.17	kW
Main transformer	Rated capacity	550	MVA
	Rated voltage	$525 \pm 8 \times 1.25\%/66/10$	kV
	Connection group	YNyn0d11	—
	Short-circuit impedance	18.10	%
	No-load loss	171.54	kW
SVG1	Rated capacity	± 240	Mvar
	Rated voltage	35	kV
SVG2	Rated capacity	± 200	Mvar
	Rated voltage	35	kV
500 kV submarine cable	Resistance	0.01216	Ω/km
	Reactance	0.07464	Ω/km
	Capacitance	14.35	nF/km
	Length	50	km

220 kV submarine cable	Resistance	0.035	Ω/km
	Reactance	0.09	Ω/km
	Capacitance	14.5	nF/km
	Length	75.7	km
66 kV submarine cable	Resistance	0.0977	Ω/km
	Reactance	0.1274	Ω/km
	Capacitance	14.72	nF/km
35 kV submarine cable	Resistance	0.16	Ω/km
	Reactance	0.135	Ω/km
	Capacitance	15.21	nF/km

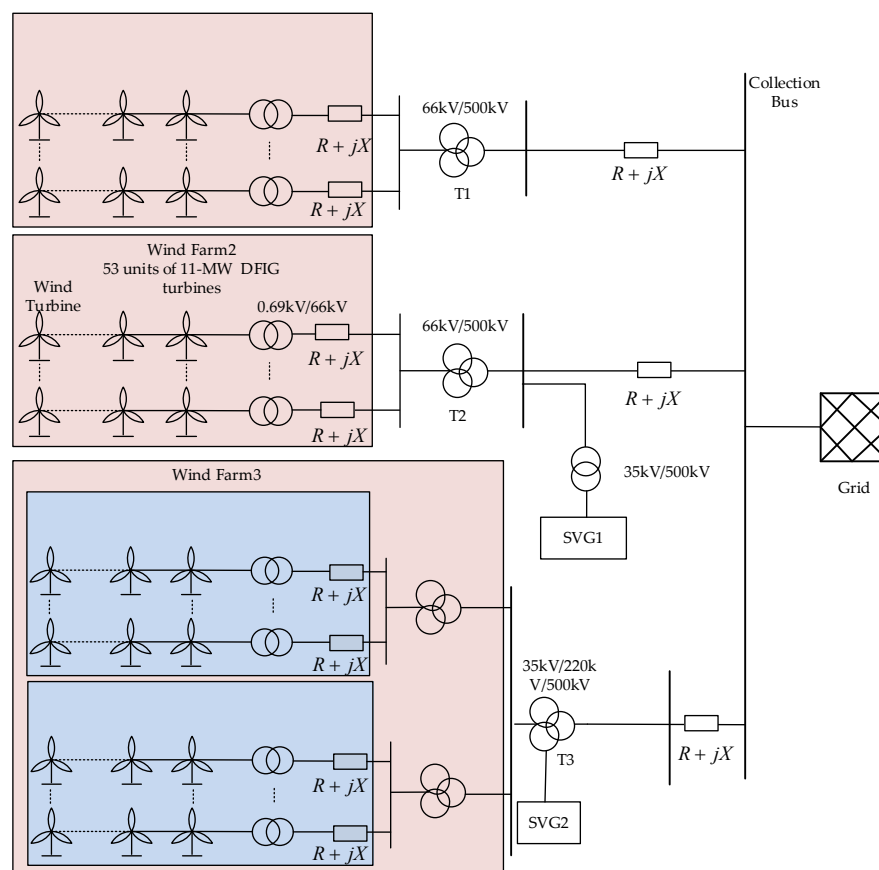


Figure 4. System structure of the wind-farm cluster.

5.2. Simulation Scenarios

The 24 h simulation is conducted as an offline engineering case study. At each time interval, the active power output of each turbine is used as the main operating input. Due to engineering confidentiality restrictions, the pre-optimization turbine-level reactive power records and complete SCADA/AVC records cannot be released. Therefore, the turbine reactive power outputs before optimization are initialized as 0 Mvar in the offline baseline. This baseline should be interpreted as a zero-reactive-power initialization case rather than a fully verified historical plant operating state. The 24 h total active power output curve and the comprehensive disturbance index are shown in Figures 5 and 6, respectively.

To evaluate the algorithmic performance under a representative complex operating condition, the 20:00 operating instant is selected for detailed comparison because it corresponds to a high *IDI* value in the 24 h profile. This instance reflects a condition with relatively strong spatial dispersion of turbine outputs and uneven reactive power regula-

tion margins. The active power output distribution of all turbines at 20:00 is shown in Figure 7. The core parameter settings of EAPSO are listed in Table 9.

All simulations are performed in MATLAB R2023b (The MathWorks, Inc., Natick, MA, USA) on a personal computer equipped with an Intel Core i7-12700 CPU, 32 GB RAM, and Windows 11 64-bit operating system. All computations are implemented in serial mode without GPU acceleration or parallel computing. All stochastic optimization algorithms use the same random seed sequence, with seeds set from 1 to 30, to ensure fairness in repeated-run statistics and algorithm comparison.

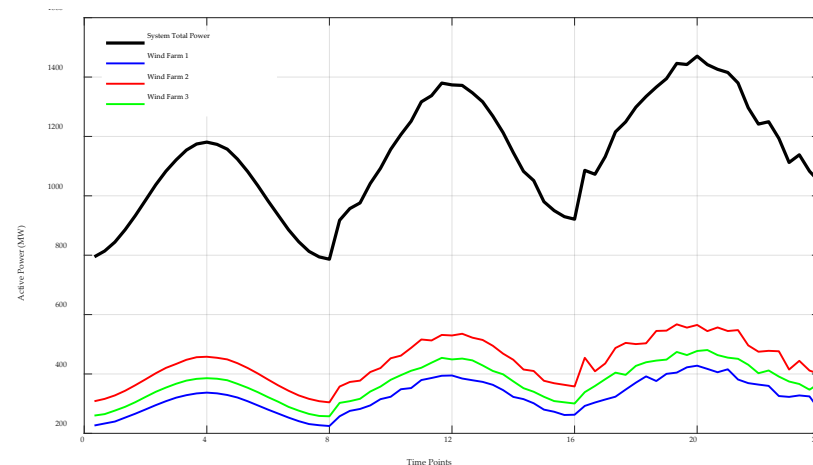


Figure 5. Total active power output of the wind-farm cluster.

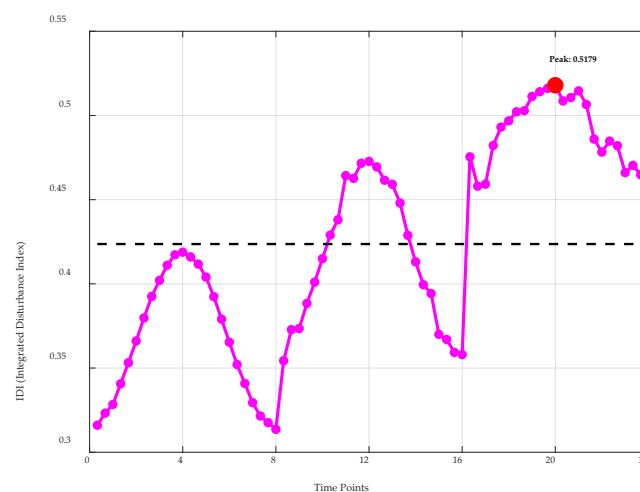


Figure 6. Variation in Comprehensive Disturbance Index (IDI) over time.

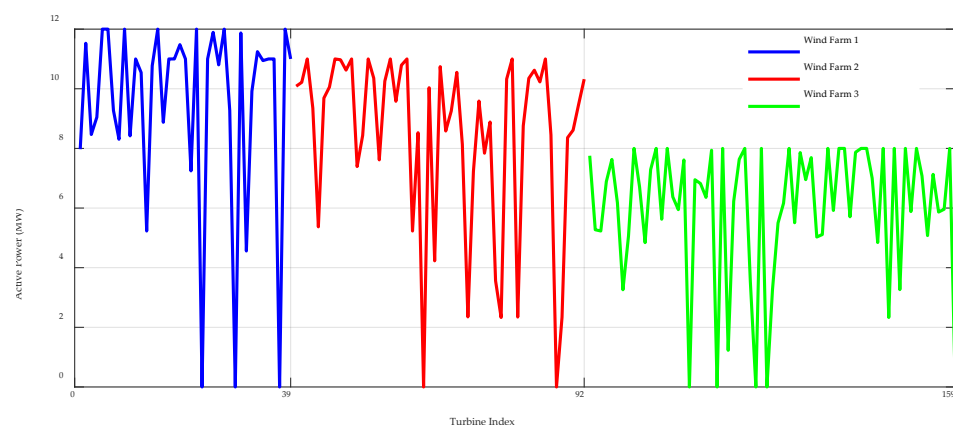


Figure 7. Active power output distribution of all wind turbines at 20:00.**Table 9.** Core parameter settings of the EAPSO algorithm.

Parameter	Symbol	Value
Population size	M	50
Maximum iterations	$T_{\max}$	100
Maximum inertia weight	$\omega_{\max}$	0.9
Minimum inertia weight	$\omega_{\min}$	0.4
Base cognitive factor	$c_{1,base}$	2
Base social factor	$c_{2,base}$	2
Lower bound of learning factor	$c_{\min}$	1.5
Upper bound of learning factor	$c_{\max}$	2.5
Minimum mutation probability	$p_{m,\min}$	0.02
Maximum mutation probability	$p_{m,\max}$	0.2
PD safeguard	ε_{PD}	0.02
OI safeguard	ε_{OI}	0.02
Seed policy	-	Seeds 1–30
Convergence tolerance	ϵ_{PF}	10^{-6}

5.3. Analysis of Simulation Results

5.3.1. Performance Analysis of Hierarchical Coordinated Reactive Power Optimization

To evaluate the effectiveness of the proposed two-layer EAPSO-based hierarchical coordinated reactive power control strategy, four comparative methods are designed in terms of topological structure, optimization algorithm and unit allocation rule:

Method 1: Centralized optimization without a hierarchical structure, where the EAPSO algorithm is adopted to uniformly solve the reactive power optimization problem of the entire wind-farm cluster.

Method 2: A hierarchical framework is adopted. EAPSO is used at the wind-farm layer, and reactive power is proportionally allocated according to the reactive power limit of each wind turbine at the unit layer.

Method 3: The strategy proposed in Reference [30] is applied. The improved genetic algorithm is adopted at the wind-farm layer, and the proportional allocation rule is retained for wind turbines.

Method 4: The proposed two-layer EAPSO strategy, in which EAPSO is used at both the wind-farm layer and the unit layer.

For fairness, all methods use the same 24 h operating profiles; each 5 min simulation interval is independently executed 30 times with random seeds from 1 to 30. The same seed sequence is used for all stochastic algorithms, and the population size, maximum iteration number, objective function, constraints, and power-flow solver are kept identical. For each independent run, the average PCC voltage deviation, average loss reduction rate, and average runtime over all time intervals are first calculated. Then, the mean and standard deviation are calculated based on the 30 independent runs.

(1) Active Power Loss Optimization Performance

The active power loss-reduction rate is defined as follows:

$$\eta_{\text{loss}} = \frac{P_{\text{loss},0} - P_{\text{loss}}}{P_{\text{loss},0}} \times 100\% \quad (44)$$

Tables 10 and 11 and Figure 8 present the active power loss optimization results. The results show that Method 4 achieves the best loss-reduction performance. Compared with the pre-optimization case, Method 4 reduces the average active power loss by approximately 1.014 MW, outperforming the other three methods. Its average loss-reduction rate is 3.55%, with a maximum value of 5.59%, and the minimum value remains above 2.50%. Method 1 has a negative loss-reduction value at a few sampling instants, indicating that centralized optimization may locally deteriorate the loss term. This is mainly because its larger mixed continuous–discrete search space makes it more prone to local optima under the same population size and iteration number. In addition, since the objective function simultaneously considers voltage deviation, network loss, and equipment-operation cost, the optimizer may prioritize voltage security under strict operating conditions, leading to local deterioration of the loss term. Method 3 shows a larger standard deviation in the loss-reduction rate, indicating that its results are more sensitive to operating-condition changes and the stochastic search process, possibly because the reference method does not explicitly use *IDI* to map operating conditions to algorithm parameters.

Table 10. Statistical results of absolute active power loss.

Index	Before Optimization	Method 1	Method 2	Method 3	Method 4
Average loss (MW)	26.862	26.374 ± 0.184	26.311 ± 0.162	26.392 ± 0.171	25.848 ± 0.126
Maximum loss (MW)	42.998	41.814 ± 0.236	41.600 ± 0.211	41.187 ± 0.225	40.667 ± 0.173
Minimum loss (MW)	13.481	13.186 ± 0.092	13.101 ± 0.086	13.417 ± 0.095	13.070 ± 0.064
Average loss reduction (MW)	—	0.488 ± 0.067	0.551 ± 0.059	0.470 ± 0.073	1.014 ± 0.081

Table 11. Statistical results of active power loss reduction rate.

Index	Method 1	Method 2	Method 3	Method 4
Average reduction rate (%)	1.6914 ± 0.2186	1.9671 ± 0.1764	1.4381 ± 0.2419	3.5506 ± 0.1427
Maximum reduction rate (%)	3.1563 ± 0.2842	3.4192 ± 0.2517	4.3506 ± 0.3028	5.5934 ± 0.2265
Minimum reduction rate (%)	−0.1490 ± 0.0631	1.1853 ± 0.0946	0.0012 ± 0.0415	2.4958 ± 0.1083
Standard deviation	0.8179 ± 0.0542	0.5526 ± 0.0418	1.1927 ± 0.0675	0.8994 ± 0.0526

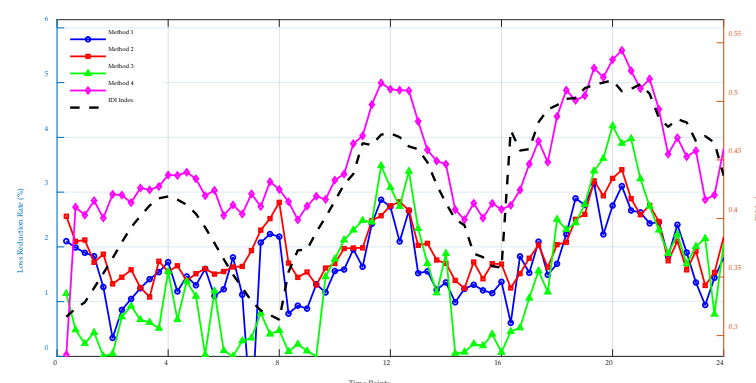


Figure 8. Comparison curves of active power loss reduction rate.

(2) Voltage Regulation Performance

Figure 9 and Table 12 show the PCC voltage-regulation performance. In Table 12, a voltage-deviation exceedance is defined as the condition in which the absolute PCC voltage deviation exceeds the engineering control band of 0.015 p.u., namely

$|V_{PCC} - V_{ref}| > 0.015 \text{ p.u.}$. Before optimization, the average absolute PCC voltage deviation is 0.013331 p.u., and the maximum deviation reaches 0.038583 p.u. After optimization, all methods reduce the PCC voltage deviation; the proposed Method 4 eliminates all voltage-deviation exceedances under the engineering control band of 0.015 p.u. Before optimization, the maximum exceedance magnitude reaches 0.023583 p.u., with an estimated exceedance duration of 30 min. Method 1 and Method 3 reduce the number of exceedances but still show residual voltage-deviation exceedances. Method 2 further reduces the exceedance frequency, while Method 4 achieves zero exceedance, indicating that the proposed two-layer EAPSO strategy provides more effective PCC voltage regulation.

Table 13 presents the operation and output statistics of reactive power regulation devices. Taking Method 1 as the baseline, Method 4 reduces transformer tap operation times from 139 to 92. The cumulative SVG reactive output is reduced from 1077.32 Mvar to 208.39 Mvar. The results indicate that the proposed strategy can preferentially utilize the reactive power regulation capability of wind turbines and reduce the dependence on SVGs and transformer tap changers, thereby decreasing equipment-operation intensity.

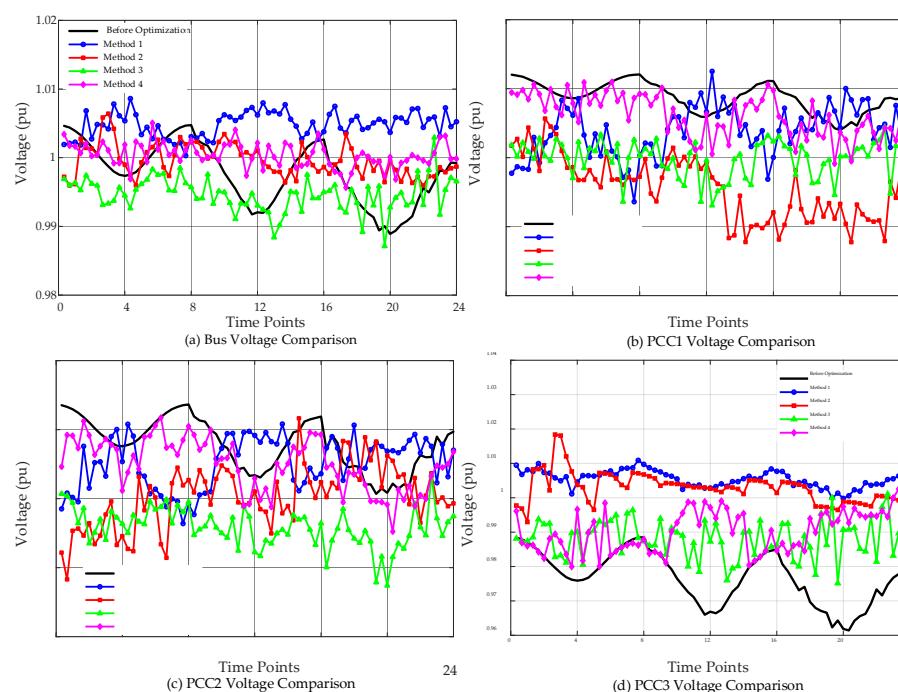


Figure 9. Comparison of voltage regulation performance of different methods.

Table 12. Statistical results of absolute PCC voltage deviation and voltage deviation exceedance.

Index	Before Optimization	Method 1	Method 2	Method 3	Method 4
Average value (p.u.)	0.013331	0.006180 ± 0.000318	0.004289 ± 0.000236	0.006137 ± 0.000407	0.004120 ± 0.000190
Maximum value (p.u.)	0.038583	0.024762 ± 0.001126	0.018470 ± 0.000853	0.021240 ± 0.001038	0.012524 ± 0.000614
Minimum value (p.u.)	0.000708	0.000028 ± 0.000011	0.000122 ± 0.000035	0.0000132 ± 0.000009	0.000013 ± 0.000006
Standard deviation (p.u.)	0.004473	0.003293 ± 0.000184	0.003278 ± 0.000171	0.004017 ± 0.000209	0.002845 ± 0.000143
Number of voltage deviation exceedances	6	2.13 ± 0.57	0.23 ± 0.43	1.07 ± 0.52	0.00 ± 0.00

Maximum exceedance magnitude (p.u)	0.023583	0.009762 ± 0.001126	0.003470 ± 0.000853	0.006240 ± 0.001038	0
Estimated exceedance duration (min)	30	10.65 ± 2.85	1.15 ± 2.15	5.35 ± 2.60	0.00 ± 0.00
Affected location	PCC buses of wind farms	PCC buses of wind farms	PCC buses of wind farms	PCC buses of wind farms	None

Table 13. Operation statistics of reactive power compensation devices.

Method	Total Tap Operation Times	Cumulative Reactive Power of Wind Farms (Mvar)	Cumulative Reactive Power of SVG (Mvar)
Method 1	139.0 ± 6.31	7818.45 ± 216.37	1077.32 ± 42.68
Method 2	96.3 ± 4.76	5028.42 ± 168.54	256.46 ± 19.63
Method 3	113.5 ± 5.12	6491.46 ± 187.29	261.32 ± 18.91
Method 4	91.7 ± 4.18	4088.35 ± 132.47	208.39 ± 15.74

(3) Statistical Significance Test for the Complete 24 h Hierarchical Strategy

To further verify whether the performance improvement of the proposed hierarchical EAPSO strategy is statistically significant over the complete 24 h operating profile, Wilcoxon signed-rank tests are conducted based on the 30 independent runs. For each run, the average PCC voltage deviation, average loss-reduction rate, and average reactive-power tracking error over all 24 h intervals are first calculated. Then, paired Wilcoxon signed-rank tests are performed between the proposed Method 4 and each comparative method. The significance level is set to 0.05.

As shown in Table 14, Method 4 shows statistically significant improvements over Method 1, Method 2, and Method 3 in most performance indices. In particular, the improvements in active power loss, loss-reduction rate, maximum PCC voltage deviation, and cumulative SVG reactive output are significant at the ($p < 0.001$) level. For the average PCC voltage deviation and transformer tap operation times, the differences between Method 4 and Method 2 are also statistically significant, with ($p = 0.004$) and ($p = 0.001$), respectively. These results indicate that the performance improvement of the proposed two-layer EAPSO strategy is not only reflected in the mean values but is also statistically significant over repeated 24 h simulations.

Table 14. Wilcoxon signed-rank test results of Method 4 compared with other methods over the complete 24 h simulation.

Performance Index	Method 4 vs. Method 1	Method 4 vs. Method 2	Method 4 vs. Method 3
Average active power loss/MW	$p < 0.001$	$p < 0.001$	$p < 0.001$
Average loss-reduction rate/%	$p < 0.001$	$p < 0.001$	$p < 0.001$
Average PCC voltage deviation/p.u.	$p < 0.001$	$p = 0.004$	$p < 0.001$
Maximum PCC voltage deviation/p.u.	$p < 0.001$	$p < 0.001$	$p < 0.001$
Total transformer tap operation times	$p < 0.001$	$p = 0.001$	$p < 0.001$
Cumulative SVG reactive output/Mvar	$p < 0.001$	$p < 0.001$	$p < 0.001$

(4) Runtime and Real-Time Feasibility Analysis

As shown in Table 15, on the serial MATLAB platform, the average runtime of EAPSO is 45.83 s, the maximum runtime is 56.42 s, and the 95th percentile is 52.88 s. This indicates that the proposed method satisfies the requirement of a 60 s coordinated AVC cycle. Since all computations in this study are implemented in serial mode without GPU acceleration or parallel computing, the computation time can be further reduced in engineering applications by parallelizing particle fitness evaluation, using fast power-flow

solvers, and adopting rolling optimization. For a stricter 30 s control cycle, further research on parallel acceleration and model reduction is required.

Table 15. Runtime statistics of EAPSO over the complete 24 h simulation based on 30 independent runs.

Statistic	Runtime (s)
Mean	45.83
Standard deviation	3.94
Minimum	38.76
Maximum	56.42
95th percentile	52.88

(5) Weight-Sensitivity Analysis

To analyze the influence of objective-function weights on optimization results, five weight combinations are tested under the same 24 h operating profile. As shown in Table 16, the objective-function weights have a clear influence on the optimization results. Increasing w_V reduces PCC voltage deviation but increases tap operations and SVG output. Increasing w_L enhances loss optimization but leads to larger voltage deviation. Increasing w_A reduces equipment operation but weakens voltage regulation and loss reduction. The G1-based weight combination adopted in this paper achieves a balanced compromise among voltage deviation, loss reduction, and equipment operation. The small standard deviations in 30 independent runs also indicate good stability of this weight combination.

Table 16. Sensitivity analysis of objective-function weights.

w_V	w_L	w_A	Average PCC Voltage Deviation/p.u.	Average Loss Reduction/%	Tap Operations	Cumulative SVG Output/Mvar
0.50	0.30	0.20	0.00391 ± 0.00018	3.42 ± 0.16	103.2 ± 5.21	231.72 ± 17.84
0.433	0.309	0.258	0.00412 ± 0.00019	3.55 ± 0.14	91.7 ± 4.18	208.39 ± 15.74
0.35	0.40	0.25	0.00483 ± 0.00023	3.86 ± 0.18	97.5 ± 4.66	224.18 ± 18.37
0.40	0.25	0.35	0.00445 ± 0.00021	3.21 ± 0.15	76.3 ± 3.82	189.64 ± 14.92
0.60	0.25	0.15	0.00376 ± 0.00017	3.18 ± 0.17	121.0 ± 6.03	263.45 ± 20.16

5.3.2. Performance Evaluation of the EAPSO Algorithm

To further evaluate the algorithmic performance of EAPSO, the high-disturbance operating condition at 20:00 is selected for comparison. The hierarchical structure, objective function, constraints, population size, maximum iteration number, power-flow solver, and input operating data are kept identical, and only the optimization algorithm is replaced. Since the algorithms are stochastic, each algorithm is independently executed 30 times. As shown in Table 17, EAPSO achieves the lowest average voltage deviation, the smallest reactive power tracking error, and the highest average loss-reduction rate. All simulations were performed on a MATLAB platform. Table 18 further shows that the average computation time of EAPSO is 48.57 s, which is lower than those of standard PSO and adaptive PSO and close to that of chaotic PSO and DE-PSO. Therefore, EAPSO improves optimization quality while maintaining acceptable computation time, making it more suitable for a 60 s coordinated AVC cycle.

Table 17. Optimization effects of different algorithms under the high-disturbance condition at 20:00.

Algorithm	Average Voltage Deviation/p.u.	Maximum Voltage Deviation/p.u.	Loss Reduction Rate/%	Reactive Power Tracking Error/Mvar
Standard PSO	0.00784 ± 0.00053	0.01896 ± 0.00126	3.12 ± 0.34	4.86 ± 0.58
Adaptive PSO	0.00691 ± 0.00046	0.01672 ± 0.00104	3.48 ± 0.29	3.74 ± 0.43
Chaotic PSO	0.00637 ± 0.00039	0.01541 ± 0.00088	3.76 ± 0.27	3.18 ± 0.36
DE-PSO	0.00586 ± 0.00037	0.01452 ± 0.00091	4.12 ± 0.30	2.63 ± 0.31
EAPSO	0.00492 ± 0.00028	0.01231 ± 0.00061	4.87 ± 0.22	1.36 ± 0.18

Table 18. Average running time of different algorithms under the high-disturbance condition at 20:00.

Algorithm	Mean/s	Std./s	Best/s	Worst/s
Standard PSO	55.82	2.76	51.34	61.08
Adaptive PSO	56.91	3.05	52.10	63.44
Chaotic PSO	49.37	1.89	46.21	53.02
DE-PSO	51.84	2.36	48.62	56.39
EAPSO	48.57	1.42	46.18	51.26

5.3.3. Ablation Study of EAPSO

To analyze the contribution of each improved component in EAPSO, an ablation study is further conducted under the high-disturbance condition at 20:00. Table 19 presents the settings of the ablation. All methods adopt the same hierarchical structure, optimization model, population size, maximum iteration number, and constraint-handling method, and only the corresponding improved module is removed. As shown in Table 20, the complete EAPSO obtains the best overall performance among the tested variants. Removing adaptive parameter adjustment results in the most evident deterioration, indicating that the mapping between operating-condition indicators and PSO parameters is important under high-disturbance conditions. Removing environment-aware initialization or mutation operation also degrades the optimization results, suggesting that these two components contribute to initial population quality and population diversity, respectively. The loss-reduction metric in the ablation study is calculated using the same definition as in Section 5.3.2.

Table 19. Settings of the EAPSO ablation study.

Method	Environment-Aware Initialization	Adaptive Parameters	Mutation Operation
EAPSO-Init	No	Yes	Yes
EAPSO-Param	Yes	No	Yes
EAPSO-Mutation	Yes	Yes	No
EAPSO	Yes	Yes	Yes

Table 20. Results of the EAPSO ablation study under the high-disturbance condition at 20:00.

Method	Average Voltage Deviation/p.u.	Maximum Voltage Deviation/p.u.	Loss Reduction Rate/%	Reactive Power Tracking Error/Mvar
EAPSO-Init	0.00572 ± 0.00034	0.01405 ± 0.00082	4.31 ± 0.31	2.44 ± 0.27
EAPSO-Param	0.00612 ± 0.00041	0.01478 ± 0.00096	4.18 ± 0.35	2.91 ± 0.33
EAPSO-Mutation	0.00548 ± 0.00031	0.01362 ± 0.00076	4.42 ± 0.28	2.08 ± 0.24
EAPSO	0.00492 ± 0.00028	0.01231 ± 0.00061	4.87 ± 0.22	1.36 ± 0.18

6. Conclusions

This paper proposes a hierarchical coordinated reactive power optimization method based on an Environment-Aware Particle Swarm Optimization algorithm to address voltage control, reactive power allocation, and equipment coordination problems in large-scale offshore wind-farm clusters under complex operating conditions. The main conclusions are as follows.

1. A hierarchical coordinated reactive power optimization framework combining the cluster layer, wind-farm layer, and unit layer is established. The framework integrates cluster-level total reactive power demand calculation, wind-farm-level coordination of SVGs and transformer tap changers, and unit-level dynamic reactive power allocation into the same optimization system. Compared with centralized reactive power optimization, the proposed hierarchical structure reduces the search dimension of the mixed continuous–discrete optimization problem and improves its implementability in practical AVC systems. In the case system, the three wind farms have different feeder numbers, turbine numbers, collection voltage levels, and submarine cable structures, which verifies the applicability of the proposed hierarchical method to complex offshore wind-farm cluster topologies.
2. A comprehensive disturbance index, IDI, is constructed and introduced into the adaptive parameter mechanism of EAPSO. IDI consists of the low-load degree, spatial power dispersion, and output imbalance degree and is used to describe the complexity of the operating condition of the wind-farm cluster. By mapping IDI to population initialization, learning factor adjustment, and mutation probability setting, EAPSO can adaptively adjust its search behavior under different operating conditions. The ablation study shows that environment-aware initialization, adaptive parameter adjustment, and mutation operation all contribute to improving optimization performance, among which adaptive parameter adjustment has the most significant influence under high-disturbance conditions. Compared with Standard PSO, Adaptive PSO, Chaotic PSO, and DE-PSO, EAPSO achieves lower voltage deviation, smaller reactive power tracking error, and higher loss reduction rate under the high-disturbance condition.
3. Simulation results based on a 24 h operating profile of a practical offshore wind-farm cluster show that the proposed method effectively improves voltage quality, reduces network loss, and decreases equipment operation. The proposed two-layer EAPSO method reduces the average PCC voltage deviation to 0.00412 p.u. and achieves an average loss reduction rate of 3.55%. Meanwhile, the number of transformer tap operations is reduced to 92, and the cumulative SVG reactive power output is reduced to 208.39 Mvar. The real-time feasibility analysis shows that the average runtime of EAPSO over the complete 24 h simulation is 45.83 s, and the maximum runtime is 56.42 s, satisfying the requirement of a 60 s coordinated AVC cycle.

Several limitations should be noted. First, the case study is based on one practical offshore wind-farm cluster, and the proposed method still needs to be further validated under more topologies, different installed capacities, and different grid-strength conditions. Second, due to engineering data confidentiality restrictions, the complete turbine-level time-series data, exact feeder connectivity, and raw SCADA/AVC records cannot be publicly released, which limits full reproducibility. Third, the dynamic reactive power capability of wind turbines is described using an equivalent capacity constraint, and detailed manufacturer-specific converter capability curves are not included. Future work will focus on validation using more wind-farm clusters, field AVC testing, robustness analysis under extreme events, detailed converter capability modeling, and parallel acceleration.

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Data Availability Statement: The original engineering data used in this study are subject to confidentiality restrictions because they contain detailed topology, equipment, and operating information of a practical offshore wind-farm cluster. Therefore, the raw SCADA/AVC records, exact feeder connectivity, real bus names, complete bus/branch tables, full turbine-level time-series data, and executable simulation input files cannot be publicly released. The information provided in the manuscript, including the releasable system structure, main equipment parameters, cable parameters, algorithm parameters, aggregated operating profiles, and statistical simulation results, is intended to support technical understanding and partial verification. However, the reported results cannot be independently reproduced exactly from the published material alone.

Conflicts of Interest: Author Xipeng Cai was employed by the company China Southern Power Grid. And Yihua Zhu and Chao Luo were employed by State Key Laboratory of HVDC, Electric Power Research Institute, China Southern Power Grid (China). The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare that this study received funding from Science and Technology Project of China Southern Power Grid. The funder was not involved in the study design, collection, analysis, interpretation of data, the writing of this article or the decision to submit it for publication.

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