
Article

An Improved Voltage Control Method for Distribution Networks Incorporating Adaptive Partitioning and Two-Layer Coordinated Control

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Abstract

The wide integration of volatile renewable energy has intensified voltage regulation challenges in distribution networks. Conventional centralized control approaches are inherently limited by slow response times, heavy reliance on communication, and poor coordination. To address this issue, this paper proposes a voltage optimization method that integrates adaptive partitioning and hierarchical coordination. First, node electrical coupling characteristics are extracted based on the voltage-reactive power sensitivity matrix analysis. The elbow method and K-means clustering are jointly applied to achieve network partitioning, where the optimal number of partitions is automatically determined. On this basis, a hierarchical coordination control architecture is established. The upper level employs scenario-based worst-case dispatch to minimize comprehensive operating costs and voltage deviations, generating reactive power regulation references for distributed generators in each partition. The lower level uses an improved droop control based on the voltage-squared relationship, enabling distributed generators to adjust reactive power in real time according to local voltage deviations, thereby achieving coordination between global optimization and local response. Lastly, simulation results on a modified IEEE 33-bus system demonstrate the effectiveness of the proposed method in eliminating voltage violations, particularly under heavy-load conditions.

Keywords: distribution network; voltage control; adaptive partitioning; droop control

1. Introduction

With the advancement of carbon peaking and carbon neutrality, a new power system dominated by renewable energy is being accelerated. As an important form of clean energy, distributed generation (DG) continues to increase its penetration in distribution networks [1]. However, the integration of high-proportion DG also brings challenges such as power reversal and voltage violations. The volatility and uncertainty of DG output significantly complicate voltage regulation in distribution networks [2–4]. Traditional centralized optimization methods face low computational efficiency and poor adaptability in scenarios with large node numbers and high communication requirements, making it difficult for them to meet real-time regulation needs [5,6]. In this context, achieving coordinated regulation through hierarchical and partitioned control is an effective way to enhance operational flexibility and voltage stability in distribution networks [7,8].

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Research on distribution network partitioning methods has mainly focused on the design and optimization of partition indices. Reference [9] proposed a cluster partition-based two-layer expansion planning method for distribution networks. Reference [10] introduced an IDEC-K clustering method for two-layer optimization configuration of distributed photovoltaic and energy storage systems. Reference [11] proposed an optimal placement and sizing method for distributed PV storage using cluster-based partitioning. Reference [12] developed a cluster partitioning method using K-means clustering for convex optimization in active distribution networks. Reference [13] presented a cluster consensus approach for inherently nonlinear cooperative networks. Reference [14] proposed a hierarchical and partitioned voltage regulation strategy based on HEM sensitivity. Reference [15] proposed a reactive power and voltage optimization method considering the reactive power contribution of photovoltaic clusters. Overall, existing methods have two major limitations. First, the weight settings for evaluating partition quality often rely on experience and lack an objective basis [9,16,17]. Second, the determination of the number of partitions still relies on empirical trial and error or manual intervention, which lacks objectivity and may not reflect the actual electrical coupling of the system [18,19]. To address these issues, this paper proposes a sensitivity-based clustering partitioning method that automatically determines the optimal number of partitions without manual intervention.

Traditional centralized optimal power flow (OPF) approaches solve for all controllable devices in a unified optimization framework without network partitioning and have been widely studied in distribution systems [20,21]. While these methods provide globally optimal solutions, they suffer from high computational burden and poor scalability as the network size increases. More importantly, they lack the ability to respond rapidly to local voltage disturbances due to their reliance on centralized communication. To address these limitations, recent studies have explored two-level control architectures that combine centralized optimization with local feedback. For instance, centralized, distributed, and local control strategies for real-time voltage regulation have been compared [22], but the distributed scheme requires continuous information exchange between physical neighbors, incurring latency and communication overhead. Local VAr droop control has been benchmarked against OPF-based centralized dispatch and feedback optimization controllers [23], yet this single-layer feedback optimization remains model-free and lacks global optimal scheduling, day-ahead dispatch capability, and provable convergence, all of which hinder its practical adoption. Other two-layer control schemes have also been reported for AC microgrids with communication delays [24], for cyber-physical microgrid clusters [25], for cluster synchronization under stochastic networks [26], and for thermostatically controlled loads [27], while a two-level scheme combining centralized OPF with local PI control has been applied to systems with high renewable penetration [28]. More recently, a combined central-local voltage control strategy for inverter-based DGs in active distribution networks has been developed [29], but it treats the entire network as one monolithic region using a piecewise linear local control curve, overlooking subregional voltage characteristics and the nonlinear nature of distribution line coupling. A common drawback across most of these two-level schemes is that the upper-level dispatch and lower-level local control are only loosely coupled: the dispatch plans are determined without explicitly accounting for subsequent local actions, while the local controllers operate independently based on pre-set laws, which may cause conflicts between global optimization and local response. Recent advances in multi-agent reinforcement learning (MARL), such as MAT-Adapt [30], have explored fully distributed coordination of flexible resources. However, their black-box nature hinders interpretability and certification, and the optimization of expected returns does not guarantee constraint satisfaction.

To overcome these limitations, this paper establishes a dual-layer coordinated regulation architecture that leverages the complementary advantages of different time scales.

When minor voltage disturbances occur, the lower-level improved droop control responds immediately to provide fast local voltage support. Meanwhile, the upper-level scenario-based worst-case dispatch generates 24 h reactive power schedules as reference setpoints. The actual reactive power output is determined jointly by the upper-level plan and the droop-based fine-tuning. Furthermore, an inter-partition voltage consistency penalty term is introduced to enhance the coordination between different control regions, and the improved droop control based on the voltage-squared relationship better matches the physical characteristics of distribution lines. The flow of this work is organized as follows. First, a sensitivity-based clustering partitioning method is developed in Section 2, where the elbow method is used to automatically determine the optimal number of partitions without manual intervention. Second, in Section 3, a dual-layer coordinated regulation architecture is established based on the partition results. Then, case study validations are conducted in Section 4, and Section 5 draws the conclusion.

2. Adaptive Partitioning Strategy for Distribution Networks Based on Electrical Coupling Characteristics

This paper proposes an unsupervised clustering adaptive partitioning method based on electrical coupling relationships, laying the structural foundation for subsequent hierarchical coordinated optimization. Based on the distribution characteristics of node electrical features, the optimal number of partitions is automatically identified using the elbow method. This eliminates the need for manual empirical selection of the partition number.

2.1. Partition Feature Extraction and Sensitivity Matrix Construction

Consider the linearization of the distribution network power flow equations near the steady-state operating point. For any node n , its node voltage is

$$P_i = V_i \sum_{j=1}^N V_j (G_{ij} \cos \theta_{ij} + B_{ij} \sin \theta_{ij}) \quad (1)$$

$$Q_i = V_i \sum_{j=1}^N V_j (G_{ij} \sin \theta_{ij} + B_{ij} \cos \theta_{ij}) \quad (2)$$

where P_i and Q_i are the net active and reactive power injected into node i , respectively; V_i and V_j are the voltage magnitudes at nodes i and j ; $\theta_{ij} = \theta_i - \theta_j$ is the voltage phase angle difference between nodes i and j ; $G_{ij} + jB_{ij}$ is the element in the i -th row and j -th column of the node admittance matrix Y_{bus} ; and N is the total number of system nodes.

The voltage at node n after connecting distributed generators is obtained by performing a first-order Taylor expansion on the above equation, yielding the incremental form

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \begin{bmatrix} \Delta \delta \\ \Delta U \end{bmatrix} = \begin{bmatrix} J_{P\theta} & J_{PU} \\ J_{Q\theta} & J_{QU} \end{bmatrix} \begin{bmatrix} \Delta \theta \\ \Delta U \end{bmatrix} \quad (3)$$

From Equation (3),

$$\Delta Q = J_{Q\theta} \Delta \theta + J_{QU} \Delta U \quad (4)$$

During voltage regulation (ΔU is typically less than 10%), the effect of voltage magnitude changes on active power is small, i.e., $\Delta P \approx 0$. Therefore,

$$0 = J_{P\theta} \Delta \theta + J_{PU} \Delta U \quad (5)$$

Rearranging gives

$$\Delta \theta = -J_{P\theta}^{-1} J_{PU} \Delta U \quad (6)$$

Substituting into the ΔQ expression

$$\Delta Q = (-J_{Q0} J_{P0}^{-1} J_{PV} + J_{QV}) \Delta V \quad (7)$$

The equivalent reactive power-voltage sensitivity matrix is defined as

$$S_Q = (-J_{Q0} J_{P0}^{-1} J_{PV} + J_{QV})^{-1} \quad (8)$$

Considering a reactance-dominant grid, i.e., $X > R$, the Q-V coupling remains dominant, and the off-diagonal coupling terms J_{Q0} and J_{PV} are small compared to J_{QV} .

$$\|J_{Q0} J_{P0}^{-1} J_{PV}\| \ll \|J_{QV}\| \quad (9)$$

Therefore, Equation (8) can be approximated as

$$S_Q \approx J_{QV}^{-1} \quad (10)$$

Assume that the number of nodes with controllable voltage in the system is n , and the number of distributed generators is ω . The sensitivity of the reactive power injected by a given distributed generator j to the voltage control of n nodes is solved as

$$S_{ij} = \left(\frac{\partial U_1}{\partial Q_j}, \frac{\partial U_2}{\partial Q_j}, \dots, \frac{\partial U_n}{\partial Q_j} \right), i = 1, 2, \dots, n \quad (11)$$

Since the magnitude of the sensitivity S_{ij} is affected by line impedance and initial voltage levels, a normalized Q-U coupling index matrix C is introduced to ensure fair and consistent coupling analysis.

For node i and DG j , the coupling index C_{ij} is defined as

$$C_{ij} = \frac{|S_{ij}|}{\sum_{k=1}^{N_{DG}} |S_{ik}|} \quad (12)$$

where N_{DG} is the total number of distributed generators.

After obtaining the C matrix, the relative coupling index vector $C_i = [C_{i,1}, C_{i,2}, C_{i,3}]$ for each node is treated as a feature point in an N_{DG} -dimensional space.

2.2. Adaptive Node Partitioning Based on K-Means Clustering

After obtaining the node feature matrix, the classical K-means clustering algorithm is used for automatic node partitioning. This algorithm aims to minimize the sum of squared errors (SSE) and iteratively optimizes to group nodes with similar features into the same partition.

$$SSE(K) = \sum_{k=1}^K \sum_{i \in C_k} \|s_i - \mu_k\|^2 \quad (13)$$

where C_k represents the set of nodes in the k -th partition, and μ_k is the mean of the feature vectors in that region. A smaller SSE indicates higher electrical coupling among nodes within the same partition and better partition quality.

For a given number of partitions K , the K-means clustering analysis process is as follows:

Step 1: Initialization: Randomly select K node feature vectors from N nodes as the initial cluster centers $\mu_{k(0)}$. To mitigate the sensitivity to initial cluster center selection, the K-means algorithm is run multiple times with different random initializations, and the result with the smallest SSE is selected as the final partition.

Step 2: Assignment: Cluster the samples. For the initially selected cluster centers, calculate the Euclidean distance from each node i to each cluster center, and aggregate nodes into the region with the closest distance:

$$C_k^{(t)} = \left\{ i \mid \arg \min_k d_{ik} = k \right\} \quad (14)$$

Step 3: Update: Recalculate the cluster centers after clustering, i.e., the mean of the feature vectors of all nodes in each cluster:

$$\mu_k^{(t+1)} = \frac{1}{|C_k^{(t)}|} \sum_{i \in C_k^{(t)}} s_i \quad (15)$$

Step 4: Convergence check: Repeat Steps 2 and 3 until the cluster centers no longer change significantly.

Finally, the system is divided into K clusters, corresponding to K control regions. For the determination of the number of partitions K, this paper adopts the elbow method to achieve adaptive determination of the optimal K value.

The principle of the elbow method is as follows: as the number of partitions K gradually increases from 2 to the number of nodes N, SSE(K) decreases monotonically. When plotting the curve of SSE as a function of K, an obvious “elbow” inflection point typically appears. This point mathematically represents the optimal balance between the information gain brought by increasing the number of partitions and the increase in model complexity. Therefore, the K value corresponding to the inflection point is the optimal number of partitions that balances partition effectiveness and model complexity.

The inflection point is automatically identified by calculating the mutation point of the SSE decline rate. Let the sequence of SSE decline rates be $\{\Delta_k = \text{SSE}(k) - \text{SSE}(k+1), k \in (2, \dots, N-1)\}$. The inflection point is determined using the robust Kneedle algorithm, which calculates the maximum vertical distance between the normalized SSE curve and its convex hull reference line. This method is fully executed by the algorithm without manual observation or preset thresholds, ensuring objective decision-making. The resulting partition structure serves as a key link in the subsequent upper-level partition coordination and optimization. In this study, ideal measurement conditions without significant noise or data outliers are assumed for the Kneedle algorithm implementation.

3. Hierarchical and Partitioned Voltage Optimization Method for Multi-Device Coordinated Regulation

3.1. Hierarchical and Partitioned Coordinated Regulation Framework for Adaptive Partitioning

Partitioning enables accurate identification of the distributed generator that has the most significant impact on a node's voltage and the shortest regulation distance when a voltage drop occurs in the system, based on real-time electrical coupling relationships. This ensures effective transmission of voltage support commands. Based on the partition results of the current system state, this section proposes a hierarchical voltage optimization method that integrates centralized optimization with local dispatch. The coordinated regulation process is shown in Figure 1.

The proposed hierarchical and partitioned coordinated regulation architecture consists of three parts. First, node electrical coupling characteristics are extracted based on the voltage-reactive power sensitivity matrix. The optimal number of partitions is adaptively determined using the elbow method, and the system is divided into multiple control regions through K-means clustering, laying the structural foundation for subsequent hierarchical regulation. According to the partition results, the upper-level global optimization uses a 24 h dispatch period and employs scenario-based worst-case dispatch to address photovoltaic and load uncertainties. The detailed construction of uncertainty sets and the worst-case scenario-based dispatch formulation are presented in Appendix A. With the objectives of minimizing comprehensive operating costs and voltage deviations, it generates regulation benchmarks for each partition and dispatches reactive power output plans for each distributed generator. The lower-level DG implements improved droop control based on the voltage-squared relationship using local voltage measurements, adjusting reactive power output in real time to achieve fast autonomous voltage support when disturbances occur. The actual reactive power output is determined jointly by the

reactive power output plan from the upper-level optimization and the fine-tuning performed by local droop control based on real-time voltage deviations.

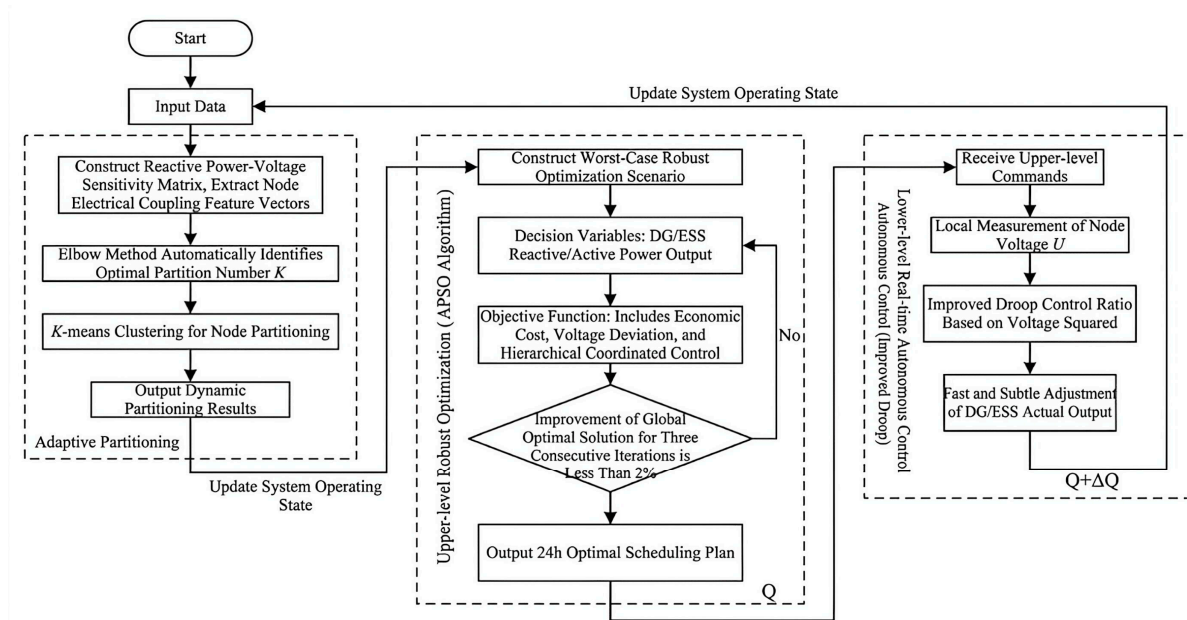


Figure 1. Flowchart of hierarchical and zonal coordinated control.

3.1.1. Objective Function

This paper constructs a multi-objective optimization model that includes operating costs, voltage quality, and coordinated control, incorporating economic costs, voltage quality, and partition coordination into a unified optimization framework. The weighted sum method is used to convert the multi-objective problem into a single-objective optimization problem. The overall objective function is as follows:

$$\min F = \omega_1 (C_{\text{loss}} + C_{\text{grid}} + C_{\text{O\&M}}) + \omega_2 D_v + \omega_3 P_{\text{coord}} \quad (16)$$

where ω_1 , ω_2 , ω_3 are the weight coefficients for comprehensive operating costs, voltage deviation, and the hierarchical coordinated control penalty term, respectively, satisfying $\omega_1 + \omega_2 + \omega_3 = 1$; C_{loss} is the network loss cost; C_{grid} is the cost of purchasing power from the upstream grid; $C_{\text{O\&M}}$ is the operation and maintenance cost; D_v is the voltage deviation penalty term; and P_{coord} is the hierarchical coordinated control penalty term.

(1) Comprehensive Operating Cost

$$\begin{cases} C_{\text{loss}} = c_{\text{loss}} \sum_{t=1}^T \sum_{(i,j) \in \Omega_L} I_{ij}^2(t) R_{ij} \Delta t \\ C_{\text{grid}} = c_{\text{grid}} \sum_{t=1}^T P_{\text{grid}}(t) \Delta t \\ C_{\text{O\&M}} = \sum_{t=1}^T [c_{\text{PV}} P_{\text{PV}}(t) + c_{\text{WT}} P_{\text{WT}}(t) + c_{\text{ESS}} |P_{\text{ESS}}(t)|] \Delta t \end{cases} \quad (17)$$

where c_{loss} is the unit network loss cost coefficient (RMB/kWh); c_{grid} is the electricity purchase price (RMB/kWh); c_{PV} , c_{WT} , and c_{ESS} are the unit operation and maintenance cost coefficients for photovoltaics, wind turbines, and energy storage systems, respectively; $I_{ij}(t)$ is the current amplitude of line ij at time t ; R_{ij} is the line resistance; Ω_L is the set of all branches; Δt is the time interval; T is the dispatch period; $P_{\text{grid}}(t)$ is the active power purchased from the upstream grid at time t ; $P_{\text{PV}}(t)$ and $P_{\text{WT}}(t)$ are the active power outputs of

distributed generators; and $P_{\text{ESS}}(t)$ is the charging/discharging power of the energy storage system (positive for discharging, negative for charging).

(2) Voltage Deviation

To ensure that node voltages do not exceed limits at any time and to minimize voltage fluctuations, a maximum voltage deviation penalty is adopted:

$$D_v = \lambda_v \max_{t \in T, i \in N} \left\{ \begin{aligned} & [\max(0, V_i(t) - V_{\max})]^2, \\ & [\max(0, V_{\min} - V_i(t))]^2 \end{aligned} \right\} \quad (18)$$

where λ_v is the voltage penalty coefficient; $V_i(t)$ is the voltage magnitude of node i at time t (p.u.); and $V_{\max}$ and $V_{\min}$ are the upper and lower voltage safety limits.

(3) Hierarchical Coordinated Control Penalty Term P_{coord}

To enhance the adaptive control capability of the system, a hierarchical coordinated control mechanism is introduced, including the intra-partition droop control deviation penalty P_{droop} and the inter-partition voltage consistency penalty $P_{\text{consensus}}$:

$$\begin{cases} P_{\text{droop}} = \lambda_d \sum_{t=1}^T \sum_{k=1}^{N_{\text{DG}}} [Q_{\text{DG}}^k(t) - Q_{\text{ref}}^k(t) - K_q^k \times (U_{\text{ref}}^2 - U_k^2(t))]^2 \\ P_{\text{consensus}} = \lambda_z \sum_{t=1}^T \sum_{m=1}^M \sum_{i \in Z_m} [U_i(t) - \bar{U}_m(t)]^2 \end{cases} \quad (19)$$

where λ_z is the partition coordination coefficient; M is the number of partitions; Z_m is the set of nodes in the m -th partition; and $\bar{U}_m(t) = 1/|Z_m| \sum_{i \in Z_m} V_i(t)$ is the average voltage of partition m .

The weight coefficients in this article have been determined through multiple experiments and can reflect the relative importance of different optimization objectives. A sensitivity analysis of the weights is provided in Appendix B.

3.1.2. Constraints

To ensure that the optimization results meet practical operational requirements, the constraints considered in this paper include node voltage safety constraints, power flow equation constraints, distributed generator operation constraints, and energy storage system operation constraints.

(1) Node Voltage Safety Constraints

$$V_{\min} \leq V_i(t) \leq V_{\max}, \forall i \in \Omega_N, \forall t \in T \quad (20)$$

where Ω_N is the set of all system nodes; $V_i(t)$ is the voltage magnitude of node i at time t ; and $V_{\max}$ and $V_{\min}$ are the upper and lower voltage safety limits, respectively.

(2) Power Flow Equation Constraints

$$\begin{cases} P_{i,t} = U_{i,t} \sum_{j=1}^n U_{j,t} (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}) \\ Q_{i,t} = U_{i,t} \sum_{j=1}^n U_{j,t} (G_{ij} \sin \theta_{ij,t} - B_{ij} \cos \theta_{ij,t}) \end{cases} \quad (21)$$

where $P_{i,t}$ and $Q_{i,t}$ are the active and reactive power injected into node i at time t , respectively; $U_{j,t}$ is the voltage magnitude of node j at time t ; θ_{ij} is the voltage phase angle difference between nodes i and j at time t ; G_{ij} and B_{ij} are the conductance and susceptance of branch ij , respectively.

(3) Distributed Generator Operation Constraints

The active and reactive power outputs of various full-power converter-based distributed generators (photovoltaics, wind turbines, energy storage converters) are subject to

constraints imposed by their inverter capacity, operating modes, and grid connection standards.

(a) Capacity Constraints

$$P_{DG,i}^2(t) + Q_{DG,i}^2(t) \leq S_{DG,i}^2, \forall i \in \Omega_{DG}, \forall t \in T \quad (22)$$

where $P_{DG,i}(t)$ and $Q_{DG,i}(t)$ are the active and reactive power outputs of DG i at time t , respectively; $S_{DG,i}$ is its converter rated capacity; and Ω_{DG} is the set of all DGs.

(b) Power Factor Constraints

$$\cos \varphi_{i,\min} \leq \frac{P_{DG,i}(t)}{\sqrt{P_{DG,i}^2(t) + Q_{DG,i}^2(t)}} \leq \cos \varphi_{i,\max}, \forall i \in \Omega_{DG}, \forall t \in T \quad (23)$$

where $\cos \varphi_{i,\min}(t)$ and $\cos \varphi_{i,\max}(t)$ are the minimum and maximum allowable power factors for DG i , respectively.

(c) Reactive Power Regulation Range

$$Q_{DG,i}^{\min}(t) \leq Q_{DG,i}(t) \leq Q_{DG,i}^{\max}(t), \forall i \in \Omega_{DG}, \forall t \in T \quad (24)$$

where $Q_{DG,i}^{\min}(t)$ and $Q_{DG,i}^{\max}(t)$ are the lower and upper limits of the time-varying reactive power output after considering the combined constraints, respectively.

(4) Energy Storage System Operation Constraints

(a) Charging/Discharging Power Constraints

$$-P_{ESS,i}^{\text{ch,max}} \leq P_{ESS,i}(t) \leq P_{ESS,i}^{\text{dis,max}}, \forall i \in \Omega_{ESS}, \forall t \in T \quad (25)$$

where $P_{ESS,i}(t)$ is the charging/discharging power of energy storage i at time t (positive for discharging, negative for charging); $P_{ESS,i}^{\text{ch,max}}$ and $P_{ESS,i}^{\text{dis,max}}$ are the maximum charging and discharging power, respectively.

(b) State-of-Charge Constraints

$$SOC_{i,\min} \leq SOC_i(t) \leq SOC_{i,\max}, \forall i \in \Omega_{ESS}, \forall t \in T \quad (26)$$

(c) Cycle Energy Balance Constraints: To ensure sustainable operation of the energy storage system, the state of charge at the beginning and end of the dispatch period must be consistent.

$$SOC_i(t) = SOC_i(0), \forall i \in \Omega_{ESS} \quad (27)$$

3.2. Multi-Device Coordinated Voltage Regulation Optimization Method for Distribution Networks

To solve the high-dimensional, nonlinear, non-convex scenario-based worst-case dispatch model constructed in this paper and achieve fast local voltage support, this section adopts a hierarchical collaborative solution strategy that combines adaptive particle swarm optimization (APSO) with improved droop control. After completing the node clustering and partitioning of the distribution network, the upper layer focuses on global coordination, aiming to minimize comprehensive operating costs and voltage deviations, and formulates day-ahead reactive power dispatch plans for each distributed generator. The lower layer focuses on local response, with each distributed generator autonomously fine-tuning reactive power output in response to local voltage deviations based on the improved droop control law using the voltage-squared relationship.

3.2.1. Upper-Level Partition Optimization Algorithm

This paper uses APSO to solve the upper-level optimization model. The optimization objective is the overall objective function shown in Equation (16), which integrates three components: operating costs, voltage deviation, and hierarchical coordinated control. The model includes nonlinear constraints such as power flow equations, DG output constraints, and energy storage charge–discharge constraints.

In the initialization stage, the sensitivity matrix-based partitioning method is used, combined with the node electrical coupling feature matrix, to make initial particles tend toward high-performance regions within the feasible domain. APSO is an improved algorithm based on classical particle swarm optimization, introducing an adaptive parameter adjustment mechanism. It focuses on global search in the early iteration stages and local optimization in the later stages, avoiding local optima.

The upper-layer optimization performs global optimization based on the adaptive partition results, considering both intra-partition autonomy and inter-partition coordination. It also dispatches the obtained 24 h reactive power output plans for each distributed generator as references for local droop control.

The parameter settings and convergence criteria of the APSO algorithm are summarized in Appendix C.

3.2.2. Local Adaptive Optimization of Reactive Power and Voltage Based on Improved Droop Control

The upper-layer APSO algorithm generates 24 h reactive power output plans for each DG. At the lower layer, power electronic devices such as DGs and ESSs provide reactive power support control through their inverters using locally measured voltage magnitudes. The reactive power output of distributed generators should be adjusted according to node voltage deviation.

$$Q_{DG} = K_q \cdot (U_{ref} - U) \quad (28)$$

where Q_{DG} is the reactive power output of the DG or ESS, U is the measured node voltage, U_{ref} is the reference voltage (1.0 p.u.), and K_q is the droop coefficient.

Traditional droop control approximates the relationship between reactive power output and voltage deviation as linear. However, voltage and reactive power in distribution networks are actually nonlinearly coupled. The linearized voltage-squared difference equation for radial distribution network power flow on branch ji is

$$U_j^2 = U_i^2 + 2(R_{ji}P_{ji} + X_{ji}Q_{ji}) - (R_{ji}^2 + X_{ji}^2) \frac{P_{ji}^2 + Q_{ji}^2}{U_i^2} \quad (29)$$

Neglecting the second-order loss term gives $\Delta(U^2) \approx 2(RP + XQ)$. Therefore, this paper adopts an improved droop control based on the voltage-squared relationship, with the control law:

$$Q_{DG}^{ref} = K_q \cdot (U_{ref}^2 - U^2) \quad (30)$$

Thus, when minor fluctuations occur in the system, the droop control acts immediately without waiting for the upper-layer optimization to recalculate. When the fluctuation exceeds a certain range, the upper-layer optimization updates the reactive power plan in the next dispatch period, forming a closed-loop correction.

4. Case Study

Case 1: IEEE 33-Bus System. The system base voltage is set to 12.66 kV, base power to 10 MVA, and total load to $3.715 + j2.300$ MVA. Distributed photovoltaics are connected at nodes 5 and 18, with maximum active power outputs of 0.5 MW each. A full-power wind turbine is connected at node 33, with a maximum active power output of 0.489 MW.

Energy storage systems are connected at nodes 11 and 18, with a charging/discharging power range of ± 0.2 MW. The system topology is shown in Figure 2.

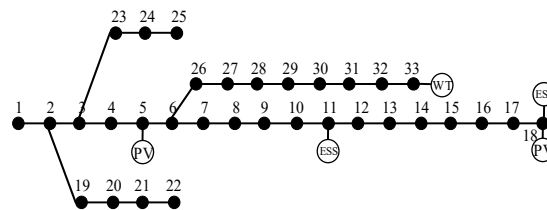


Figure 2. IEEE 33-bus distribution system.

Case 2: 51-Bus Dual-Voltage System. To further validate the scalability of the proposed method, a 51-bus system derived from a real regional distribution network is adopted. As shown in Figure 3, the system consists of two voltage levels: an 11 kV medium-voltage section covering Buses 1 through 33 and a 400 V low-voltage section covering Buses 34 through 51. Five distributed generators are installed across the system, comprising three PV units and one wind turbine with a total capacity of 2.8 MVA.

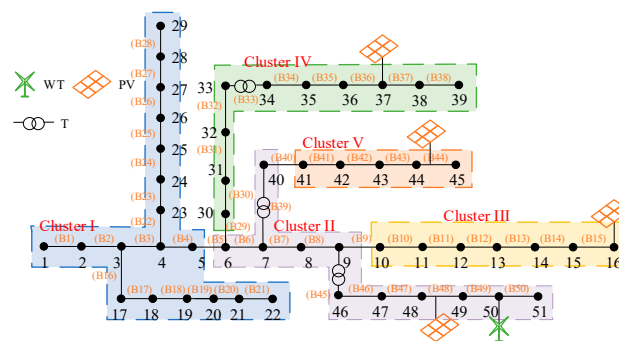


Figure 3. Topology of the 51-bus dual-voltage system.

4.1. Partition Coordination Mechanism

Based on the method proposed in Section 2, node electrical coupling feature vectors are constructed according to the voltage sensitivity matrix, and the optimal number of partitions is adaptively determined using the elbow method. The SSE for $K = 2$ to $K = 6$ is shown in Figure 4.

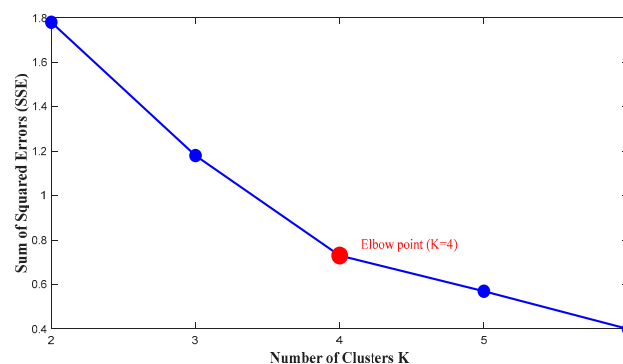


Figure 4. Elbow method for optimal cluster number.

After adaptively determining the optimal number of partitions as 4 using the elbow method, K-means clustering analysis yields the partition results shown in Table 1.

Table 1. K-means clustering results.

Clustering	SSE
1	2, 3, 4, 5, 6, 7, 8, 16, 19, 23, 24, 26, 27, 28, 29, 30
2	25, 31, 32
3	13, 22
4	9, 10, 11, 12, 14, 15, 17, 18, 20, 21, 33

The partition is adaptive in that the optimal number of clusters K is automatically determined by the elbow method without manual intervention. The partition structure is recalculated when the system topology or the representative operating point changes significantly. Based on these partition results, the performance differences between introducing partition coordination and not introducing partition coordination are compared. For the 24 h case study, the partition is performed based on the heavy-load operating point at 18:00, which represents the most critical voltage condition.

As shown in Table 2, the proposed partitioned coordination scheme consistently outperforms the non-partitioned baseline across all evaluated metrics. The maximum voltage deviation is reduced by 3.37%, the average voltage deviation by 2.34%, and the total network loss by 4.16%.

Table 2. Performance comparison between partitioned coordination and non-partitioned schemes.

Index	Non-Partitioned	Partitioned	Advance
Maximum voltage deviation (p.u.)	0.0424	0.0409	3.37%
Average voltage deviation (p.u.)	0.0198	0.0193	2.34%
Loss (MW)	1.3382	1.2825	4.16%
Low-voltage node-hours (>0.04)	2	0	100%

In addition, the proposed method is further applied to the studied 51-nodal system in Case 2. Table 3 compares the non-partitioned and partitioned schemes in this low-voltage network under the same worst-case framework.

Table 3. Performance comparison between partitioned coordination and non-partitioned schemes in the 51-node system.

Index	Non-Partitioned	Partitioned	Advance
Maximum voltage deviation (p.u.)	0.0682	0.0529	22.4%
Average voltage deviation (p.u.)	0.0315	0.0248	21.3%
Loss (MW)	1.3382	1.2825	8.3%
Low-voltage node-hours (>0.04)	9	1	88.9%

The partitioned approach reduces the maximum voltage deviation from 0.0682 p.u. to 0.0529 p.u., an improvement of 22.4%, and lowers the average voltage deviation from 0.0315 p.u. to 0.0248 p.u., corresponding to a 21.3% reduction. The total network loss decreases from 1.3382 MW to 1.2825 MW, achieving a saving of 8.3%. More significantly, the low-voltage node-hours exceeding the 0.04 p.u. threshold drop from 9 to 1, representing an 88.9% reduction, which confirms the effectiveness of the partition mechanism in mitigating voltage violations in low-voltage networks with high line impedance.

In the medium-voltage network, the relatively low line impedance limits regional voltage deviations, and the partition coordination yields correspondingly modest gains. In the low-voltage system, however, the higher line impedance amplifies both the voltage deviations and the coordination effect. These more pronounced improvements indicate that the partition coordination is particularly effective in scenarios where voltage

regulation is more challenging and the need for regional coordination is stronger. In medium-voltage networks with relatively low line impedance, the voltage deviations across different regions are moderate, and the benefits of partition coordination are inherently limited.

In addition, a detailed comparison with centralized optimization without partitioning is provided in Appendix D.

4.2. Hierarchical Control Effect

Based on the adaptive partition structure, distributed generators within each partition achieve coordinated regulation using the setpoints dispatched by the upper-layer optimization as benchmarks, combined with fine-tuning through improved droop control.

When droop control is introduced, if minor fluctuations occur in system load or photovoltaic output, DGs can respond quickly using droop characteristics, avoiding the time required to wait for optimization algorithm recalculation. This improves system robustness and fast-response performance. The final control strategy possesses both the global optimality of optimal dispatch and the local fast-response capability of droop control.

A comparison is made between the optimization results with droop local control and those without droop. The comparison of maximum voltage deviation is shown in Figure 5. Meanwhile, after adding droop control, the total network loss is reduced by 7.09%, optimizing power flow through more reasonable reactive power distribution and reducing line losses.

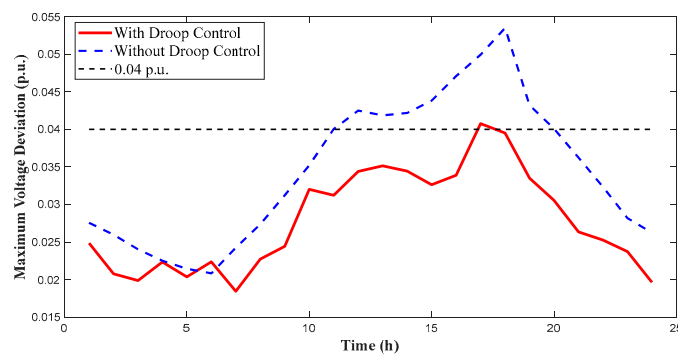


Figure 5. Comparison of maximum voltage deviation with and without droop control.

Under a heavy-load scenario of 1.4 times the base load, comparative tests between linear droop and improved droop control are conducted, with results shown in Table 4.

Table 4. Performance comparison between linear droop control and improved droop control.

Index	Linear Droop Control	Improved Droop	Advance
Voltage standard deviation (p.u.)	0.0106	0.0094	11.31%
Low-voltage node-hours	124	91	26.61%

The low-voltage node-hours count the total number of bus-hour instances where the voltage magnitude exceeds the 0.04 p.u. deviation limit, i.e., $V < 0.96$ or $V > 1.04$ p.u., over the 24 h horizon. The total possible bus-hours is $33 \times 24 = 792$.

When using improved droop control, the voltage standard deviation is reduced by 11.31%, significantly improving voltage stability and achieving more balanced voltage distribution. The improved droop control based on the voltage-squared relationship is used to achieve regional voltage autonomy. An inter-partition voltage consistency penalty

term is added to the objective function to minimize the variance of the average voltage across partitions. The upper-layer APSO algorithm simultaneously optimizes the device outputs within each partition and the coordination relationships between partitions.

In terms of response speed, the lower-level improved droop control responds to voltage deviations immediately (millisecond level) without waiting for upper-level recalculation, which is particularly beneficial for mitigating fast voltage fluctuations caused by intermittent renewable generation.

4.3. Control Performance for Different R/X Ratio Distribution Networks

In many voltage regulation studies, a common simplification is to regulate voltage solely via reactive power Q , while keeping active power P at its forecasted value. However, for distribution networks with high R/X ratios, both P and Q can affect the voltage profile. The proposed Q-V control framework can be easily extended into a PQ-V scheme by taking PQ, instead of only Q , as decision variables of DG outputs with an identical apparent power limit given in Equation (22). Hereby, the performance of the two control schemes is compared for different R/X ratio conditions. This sensitivity analysis is conducted under a light load, i.e., $0.6 \times$ base load, condition to avoid voltage violations that would otherwise complicate the interpretation.

Case 1: Original network for $R/X \approx 1.5$. The original IEEE 33-bus network has an R/X ratio around 1.5, which represents the medium-voltage distribution system with comparable line resistance and reactance.

The results are given in Table 5 and Figure 6. As shown, taking only the Q-V control scheme, the maximum voltage deviation is around 0.0297 p.u., which is well below the 0.04 p.u. safety limit. Co-optimization of P and Q further reduces the maximum deviation to 0.0285 p.u., while the average voltage deviations remain comparable. In addition, network losses are also similar.

Thus, in the original network with a moderate R/X ratio, regulating Q alone is sufficient to achieve satisfactory voltage regulation performance.

Table 5. Performance comparison under different decision variable sets in the original network ($R/X \approx 1.5$).

Network	Decision Variables	Network Loss (MW)	Maximum Voltage Deviation (p.u.)	Average Voltage Deviation (p.u.)
Original Network	Q	0.7876	0.0297	0.0119
Original Network	P&Q	0.8364	0.0285	0.0122

At this moderate R/X condition, the Q-V coupling still dominates voltage behavior, and the cross-coupling term is relatively small compared to J_{QV} . Therefore, as a practical engineering approximation, $S_{VQ} \approx J_{QV}^{-1}$ was adopted to construct the electrical coupling features for partitioning. This simplification is widely used in medium-voltage distribution system analysis and is acceptable for the target system of this study. For the target system of this study, the approximation is justified and yields partition results that are consistent with the full sensitivity matrix, as validated in Appendix A.

Case 2: High resistance condition with $R/X \approx 7.5$. The resistance values of all branches are multiplied by 5 to create this condition. For networks with high R/X ratios, active and reactive power controls are coupled in their voltage regulation effects, and the assumption in Equation (8) no longer applies. The proposed control framework, however, can be readily extended to co-optimize both P and Q under the apparent power constraint in Equation (22). A comparative study is accordingly conducted between the Q-based and PQ-incorporated schemes.

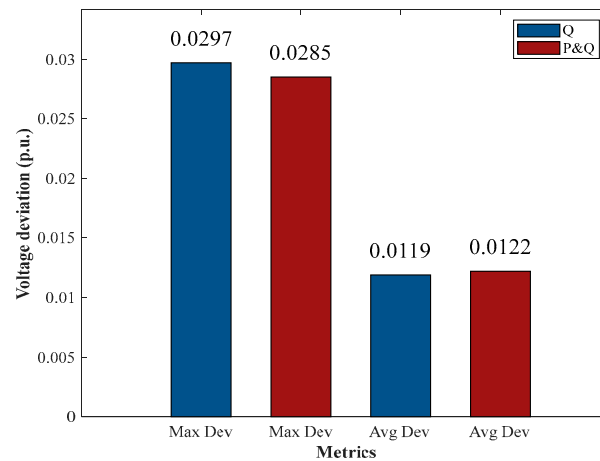


Figure 6. Comparison of voltage deviation (maximum and average) under different control strategies in the original network ($R/X \approx 1.5$).

Table 6 and Figure 7 show the optimization results. When only Q is optimized, the voltage quality deteriorates severely, with the maximum deviation reaching 0.0928 p.u., far exceeding the safety limit. However, when both P and Q are co-optimized, the maximum voltage deviation is reduced to 0.0396 p.u., bringing it back within the acceptable range. The network loss also decreases substantially from 4.0377 MW to 1.2579 MW, with a reduction of 68.8%.

Therefore, in high R/X networks, co-optimizing both P and Q yields significantly better voltage quality and lower network losses. It is worth noting that the proposed control framework can be readily extended to cover such operating conditions. Although the main manuscript focuses on Q-only control for the moderate R/X ratio network, the transition from Q-only regulation to P&Q co-optimization is smooth and natural within our formulation. This demonstrates the flexibility and potential of the proposed framework for voltage optimization across a wide range of distribution system configurations.

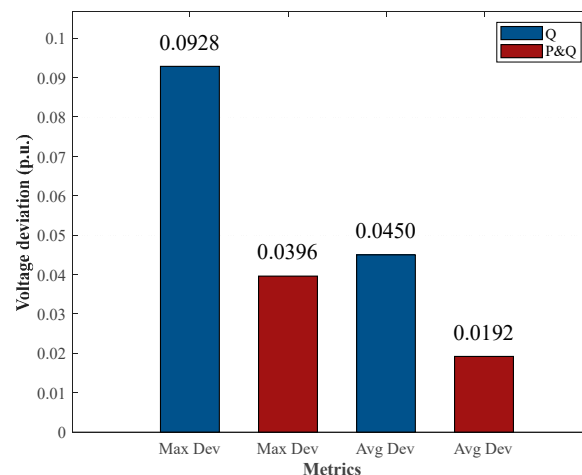


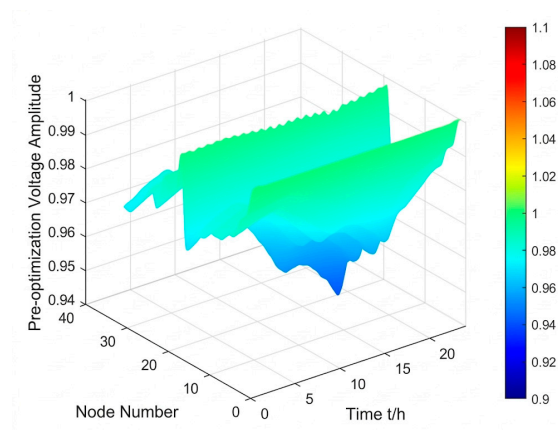
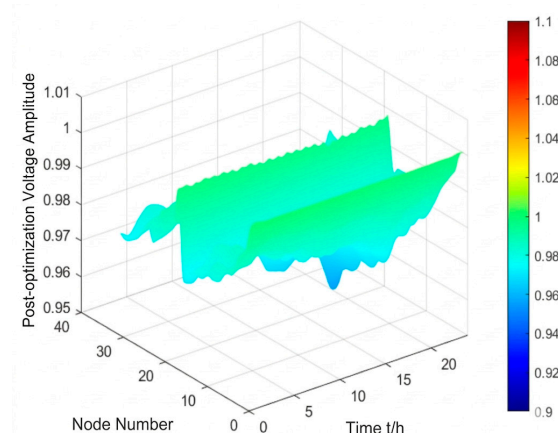
Figure 7. Comparison of voltage deviation (maximum and average) under different control strategies in the high R/X network ($R/X \approx 7.5$).

Table 6. Performance comparison under different decision variable sets in the high R/X network ($R/X \approx 7.5$).

Network	Decision Variables	Network Loss (MW)	Maximum Voltage Deviation (p.u.)	Average Voltage Deviation (p.u.)
High R/X Network	Q	4.0377	0.0928	0.0450
High R/X Network	P&Q	1.2579	0.0396	0.0192

4.4. Comprehensive Optimization Effect

Case 1: Analyzing from the overall perspective of the entire network voltage distribution on the 33-bus system, the voltage profiles before and after optimization using the proposed Q-only adaptive partitioning-based hierarchical and partitioned regulation strategy with improved droop control are shown in Figures 8 and 9. Before optimization, the system voltage shows significant dispersion and instability. The dark blue areas represent regions where node voltages deviate greatly from the rated value, with some node voltages falling below the safety lower limit of 0.95 p.u., indicating a clear risk of voltage violation.

**Figure 8.** Voltage profile before optimization.**Figure 9.** Voltage profile after optimization.

After optimization using the proposed strategy, all node voltages are strictly controlled within the safe range of [0.96, 1.01] p.u., with more concentrated and uniform voltage distribution. To further illustrate the effect of the optimization strategy on critical weak nodes, the voltage variation at node 18 is shown in Figure 10. Before optimization, the voltage severely drops below 0.95 p.u. during peak load periods, posing a low-voltage

safety hazard. After optimization, the voltage remains stable in the range of [0.96, 1.00] p.u. throughout the entire 24 h period, maintaining qualified levels even during peak load periods.

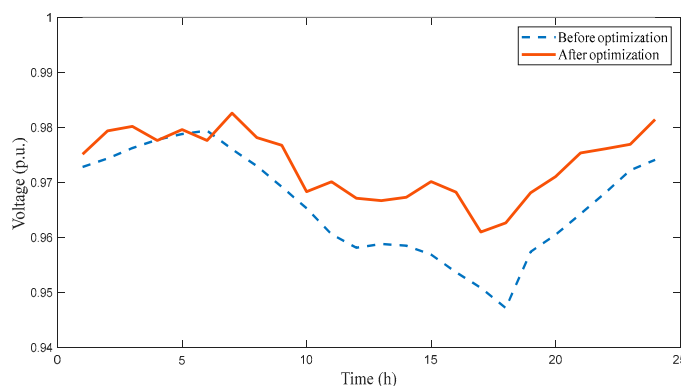


Figure 10. Comparison of voltage at Bus 18.

After optimization using the proposed strategy, all node voltages are strictly controlled within the safe range of [0.96, 1.01] p.u., with more concentrated and uniform voltage distribution. To further illustrate the effect of the optimization strategy on critical weak nodes, the voltage variation at node 18 is shown in Figure 8. Before optimization, the voltage severely drops below 0.95 p.u. during peak load periods, posing a low-voltage safety hazard. After optimization, the voltage remains stable in the range of [0.96, 1.00] p.u. throughout the entire 24 h period, maintaining qualified levels even during peak load periods.

Case 2: To further validate the generality of the proposed method, the same strategy is then applied to a more complex 51-bus system with dual-voltage levels.

Due to the high line impedance in the 400 V low-voltage network, voltage drops are more significant and voltage deviations are larger than those in the 11 kV network. Therefore, the voltage regulation focus of this case study is placed on the low-voltage side (Buses 34–51).

Before optimization, as exhibited in Figure 11, the voltage distribution on the 400 V side exhibits significant dispersion. The voltage ranges from 0.896 p.u. to 1.147 p.u., with Bus 45 experiencing severe undervoltage and Bus 50 experiencing significant overvoltage, indicating clear voltage violation risks at both ends.

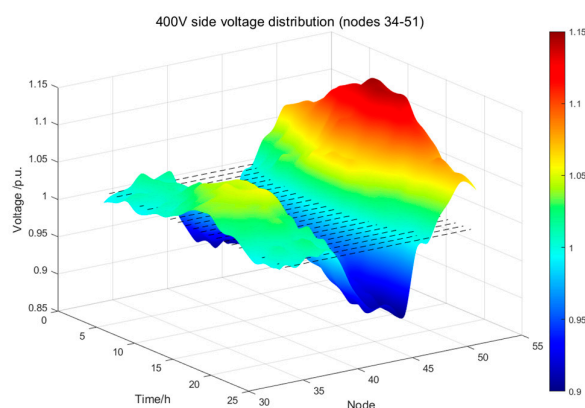


Figure 11. Voltage profile of the 400 V low-voltage side before optimization.

After applying the proposed hierarchical partitioned voltage regulation strategy, as given in Figure 12, all node voltages are strictly controlled within the safe range of [0.95, 1.05] p.u. The voltage distribution becomes significantly more concentrated and uniform.

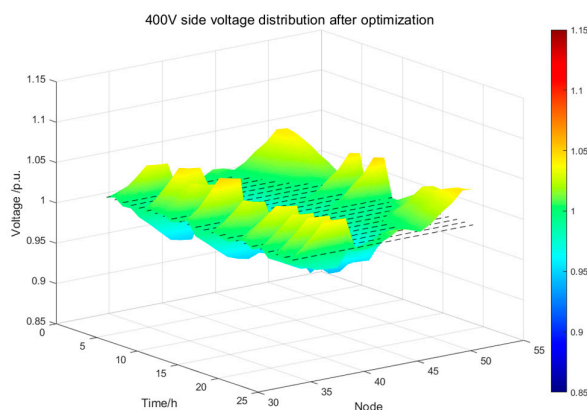


Figure 12. Voltage profile of the 400 V low-voltage side after optimization.

To further illustrate the voltage improvement at the device level, two representative buses on the 400 V side are selected for detailed analysis: Bus 45, which experiences the lowest voltage of 0.896 p.u., and Bus 50, which experiences the highest voltage of 1.147 p.u. As shown in Figure 13, before optimization, the voltage at Bus 45 remains continuously below 0.95 p.u. during 12:00–18:00, with the lowest value reaching approximately 0.896 p.u., indicating a clear low-voltage risk.

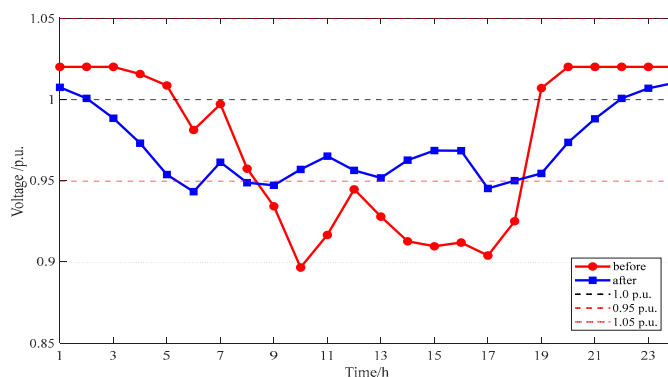


Figure 13. Voltage comparison at Bus 45 before and after optimization.

Similarly, as shown in Figure 14, the voltage at Bus 50 exceeds 1.05 p.u. during the peak DG output period, around 10:00–16:00, with a maximum of 1.147 p.u., indicating a significant overvoltage risk. After applying the proposed optimization strategy, the minimum voltage at Bus 45 is raised above 0.94 p.u., and the maximum voltage at Bus 50 is suppressed below 1.05 p.u. Both undervoltage and overvoltage violations are effectively eliminated, demonstrating the dual effectiveness of the proposed method in undervoltage support and overvoltage suppression on the 400 V low-voltage side.

The results demonstrate that the proposed method achieves consistent performance improvements on the larger 51-bus system. Importantly, all voltage violations on the 400 V side are eliminated, validating the scalability and effectiveness of the proposed method for distribution networks with multiple voltage levels.

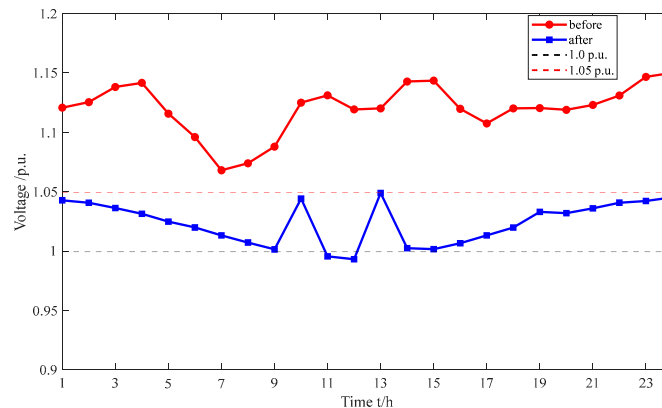


Figure 14. Voltage comparison at Bus 50 before and after optimization.

5. Conclusions

To address the issues of intensified voltage fluctuations and increased operational uncertainty in distribution networks caused by high-proportion DG integration, this paper proposes a voltage optimization method that integrates adaptive partitioning with hierarchical coordination. The main contributions include: (1) a sensitivity-based clustering partitioning method that automatically determines the optimal number of partitions without manual intervention; (2) a dual-layer coordinated regulation architecture combining upper-level scenario-based worst-case dispatch with lower-level improved droop control based on the voltage-squared relationship. The proposed voltage control framework can be readily extended to incorporate active/reactive power coordination to cover high R/X ratio distribution networks. Simulation results on the modified IEEE 33-bus and regional 51-bus systems demonstrate the effectiveness of the proposed method.

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Appendix A. Scenario-Based Worst-Case Dispatch Modeling Details

Seven typical scenarios are constructed to represent the main uncertainty realizations of PV generation and load demand, as shown in Table A1. The PV output scaling factor ξ_{PV} ranges from 0.2 (extreme overcast) to 1.6 (extreme sunny), while the load scaling factor ξ_L ranges from 1.0 to 1.6. It should be noted that PV capacity and cost are treated as static

parameters in this approach, with uncertainty considered only through short-term weather-driven output variations.

Table A1. Typical uncertainty scenarios.

Scenario	Description	ξ_{PV}	ξ_L	Probability
S ₁	Normal	1.0	1.0	0.5
S ₂	Cloudy	0.4	1.0	0.15
S ₃	Extreme overcast	0.2	1.0	0.05
S ₄	Sunny	1.3	1.0	0.10
S ₅	Extreme sunny	1.6	1.0	0.05
S ₆	High load	1.0	1.3	0.10
S ₇	Extreme high load	1.0	1.6	0.05

The PV output and load demand for each scenario s are defined as

$$P_{PV}^s(t) = \xi_{PV,s} \cdot P_{PV}^0(t)$$

$$P_L^s(t) = \xi_{L,s} \cdot P_L^0(t)$$

where $P_{PV}^0(t)$ and $P_L^0(t)$ are the forecasted PV output and load demand at time t , respectively. $s \in S = \{1, \dots, 7\}$ indexes the seven discrete scenarios defined in Table A1. The worst-case dispatch is formulated as a min–max optimization problem over this discrete scenario set S :

$$\min_x \max_{s \in S} J(x, s)$$

where x represents the decision variables. S is the set of seven uncertainty scenarios defined in Table A2. $J(x, s)$ is the objective function value under scenarios. The maximization operator selects the worst-case scenario from the finite set S , which is then minimized by the optimization.

To address the potential over-conservativeness of the worst-case dispatch, an uncertainty budget parameter $\Gamma \in [0, 1]$ can be introduced to adjust the conservativeness level. When $\Gamma = 1$, the optimization considers the full worst-case scenario ($\xi_{PV} = 0.2$, $\xi_L = 1.6$ at all hours), yielding the most conservative but also the most robust solution. When $\Gamma = 0$, the optimization only considers the nominal scenario (S₁), yielding the least conservative solution. Intermediate values of Γ represent a trade-off between robustness and economy. The worst-case scenario under a given budget Γ can be defined as

$$\xi_{PV}^\tau(t) = 0.2 + (1.0 - 0.2) \cdot (1 - \tau)$$

$$\xi_L^\tau(t) = 1.0 + (1.6 - 1.0) \cdot \tau$$

When $\Gamma = 1$, this reduces to $\xi_{PV} = 0.2$ and $\xi_L = 1.6$ (the full worst case). When $\Gamma = 0$, this reduces to $\xi_{PV} = 1.0$ and $\xi_L = 1.0$ (the nominal case). In this study, $\Gamma = 1$ is adopted as the default setting to ensure system security under the most severe conditions, while acknowledging that Γ can be tuned by operators according to their risk preference.

Appendix B. Sensitivity Analysis of Weight Coefficients

The objective function in Equation (16) combines three terms with different physical units and orders of magnitude. To evaluate the impact of the weight coefficients on the optimization results, a sensitivity analysis was conducted by varying ω_2 from 0.1 to 0.7 while keeping $\omega_3 = 0.2$ and $\omega_1 = 1 - \omega_2 - \omega_3$. Table A2 presents the results.

Table A2. Sensitivity analysis of weight coefficients.

ω_1	ω_2	ω_3	Economic Term	Fitness
0.7	0.1	0.2	1.6792	1.6879
0.6	0.2	0.2	1.4392	1.4480
0.5	0.3	0.2	1.1994	1.2082
0.4	0.4	0.2	0.9595	0.9683
0.3	0.5	0.2	0.7196	0.7284
0.2	0.6	0.2	0.4798	0.4885
0.1	0.7	0.2	0.2399	0.2486

As ω_2 increases (giving more importance to voltage quality), the total fitness decreases, indicating that the proposed method achieves good voltage quality even with moderate weight settings. The selected weights ($\omega_1 = 0.4$, $\omega_2 = 0.4$, $\omega_3 = 0.2$) provide a reasonable trade-off between economic efficiency and voltage quality.

Appendix C. Adaptive Particle Swarm Optimization (APSO) Implementation Details

The parameters of the APSO algorithm used in this study are summarized in Table A3.

Table A3. Algorithm parameter settings.

Parameter	Value	Description
npop	100	Population size
maxIter	100	Maximum number of iterations
nVar	120	Number of decision variables
$\omega_{\max}$	0.9	Maximum inertia weight
$\omega_{\min}$	0.4	Minimum inertia weight

The improvement rate is calculated as

$$\frac{J_{iter-2} - J_{iter}}{J_{iter-2}} \times 100\%$$

where J_{iter} is the global best fitness value at iteration $iter$. This criterion ensures that the algorithm stops when further iterations are unlikely to produce significant improvements, thereby balancing solution quality and computational efficiency.

Appendix D. Performance Comparison

The comparison is performed on the modified IEEE 33-bus system under the same scenario-based worst-case dispatch framework. Table A4 summarizes the results.

Table A4. Performance comparison between the proposed method and centralized optimization without partitioning.

Index	Centralized Without Partitioning	Proposed Method	Improvement
Maximum voltage deviation (p.u.)	0.0466	0.0399	14.50%
Average voltage deviation (p.u.)	0.0199	0.0191	3.71%
Network loss (MW)	1.3507	1.2654	6.31%

As shown in Table A4, the proposed method outperforms the centralized approach in all key performance indicators. Specifically, the proposed method reduces network losses by 6.31% and improves the maximum voltage deviation by 14.50%.

References

- Shi, J.C.; Hu, S.N.; Fu, R.; Zhang, Q. Convex optimization and PV inverter control strategy-based research on active distribution networks. *Energies* **2025**, *18*, 1793.
- Meng, L.; Yang, X.; Zhu, J.; Wang, X.; Meng, X. Network partition and distributed voltage coordination control strategy of active distribution network system considering photovoltaic uncertainty. *Appl. Energy* **2024**, *362*, 122846.
- Song, G.; Wu, Q.; Jiao, W.; Lu, L. Distributed coordinated control for voltage regulation in active distribution networks based on robust model predictive control. *Int. J. Electr. Power Energy Syst.* **2025**, *166*, 110529.
- Meng, L.Z.C.; Yang, X.Y.; Guo, W.H.; Li, S.; Wei, C. A two-layer voltage coordination control strategy for active distribution network considering photovoltaic uncertainty and network partitioning. *IEEJ Trans. Electr. Electron. Eng.* **2025**. <https://doi.org/10.1002/tee.70226>
- Han, D.; Deng, W.; Zhao, Z.; Pei, W.; Xiao, H. Coordinated optimization of active distribution network and multi-microgrids considering voltage robustness and economic efficiency: A distributed model predictive control method. *IET Gener. Transm. Distrib.* **2025**, *19*, e70130.
- Song, Y.; Wang, C.L.; Sun, S.M.; Cheng, Y.; Yu, P. Cluster partition-based two-layer expansion planning of grid-resource-storage for distribution networks. *Front. Energy Res.* **2024**, *12*, 1390073.
- Li, P.; Zhang, C.; Wu, Z.; Xu, Y.; Hu, M.; Dong, Z. Distributed adaptive robust voltage/VAR control with network partition in active distribution networks. *IEEE Trans. Smart Grid* **2020**, *11*, 2245–2256.
- Wu, X.Y.; Zhang, L.Y.; Xu, Y.; Wang, S.; Guerrero, J.M. Hierarchical and distributed control of AC and DC microgrid clusters interconnected by flexible DC distribution network. *CSEE J. Power Energy Syst.* **2025**, *12*, 825–836.
- Liao, J.L.; Lin, J.; Wu, G.L. Two-layer optimization configuration method for distributed photovoltaic and energy storage systems based on IDEC-K clustering. *Energy Rep.* **2024**, *11*, 5172–5188.
- Liu, X.; Zhao, P.; Qu, H.B.; Liu, N.; Zhao, K.; Xiao, C. Optimal placement and sizing of distributed PV-storage in distribution networks using cluster-based partitioning. *Processes* **2025**, *13*, 1765.
- Zheng, F.; Meng, X.; Wang, L.; Zhang, N. Operation optimization method of distribution network with wind turbine and photovoltaic considering clustering and energy storage. *Sustainability* **2023**, *15*, 2184.
- Develer, Ü.; Cihan, O.; Akar, M. Cluster consensus for inherently nonlinear cooperative networks. *Int. J. Robust. Nonlinear Control* **2024**, *34*, 1921–1938.
- Askarzadeh, A.; Fadaeinedjad, R. Optimal allocation of energy storage systems, wind turbines and photovoltaic systems in distribution network considering flicker mitigation. *Appl. Energy* **2022**, *319*, 119253.
- Wan, D.; Mo, W.H.; Li, J.H.; Yang, C.; Wu, J.; Zhou, Q.; Gong, Y. Two-layer cooperative optimization of flexible interconnected distribution networks considering electric vehicle user satisfaction degree. *Electronics* **2023**, *12*, 4582.
- Yu, H.; Zhao, H.; Li, K.; Zhu, X.; Huangfu, X.; Fan, J.; Li, C.; Li, J. Carrying capacity evaluation of distribution network for distributed photovoltaic cluster considering user-side demand response. *Electr. Power Constr.* **2023**, *44*, 122–131.
- Lu, X.Q.; Lai, J.G. Two-layer cooperative control for multiple converter-network clusters. *IEEE Trans. Circuits Syst. II Express Briefs* **2021**, *68*, 682–686.
- Yang, T.; Lai, J.G.; Yu, C.; Wang, X.; Xiao, Q. Distributed two-layer predictive control of AC microgrid clusters with communication delays. *IEEE Trans. Smart Grid* **2025**, *16*, 1.
- Yang, T.; Lai, J.G. Brain-like distributed two-layer SoC balancing control of cyber-physical microgrid clusters. *IEEE Trans. Ind. Cyber-Phys. Syst.* **2025**, *3*, 567–576.
- Zhang, C.; Wei, J.C.; Wang, F.; Liang, Y. Cluster synchronization of stochastic two-layer networks with infinite distributed delays via delayed pinning impulsive control. *Int. J. Adapt. Control Signal Process.* **2024**, *38*, 2093–2105.
- Frank, S.; Rebennack, S. Optimal power flow: A bibliographic survey I: For mutations and deterministic methods. *Energy Syst.* **2016**, *7*, 221–258.
- Farivar, M.; Low, S.H. Branch flow model: Relaxations and convexification—Part I. *IEEE Trans. Power Syst.* **2013**, *28*, 2554–2564.
- Zhan, S.; Paterakis, N.G.; van den Akker, W.; van der Molen, A.; Morren, J.; Slootweg, H. Distributed online feedback optimization for real-time distribution system voltage regulation. *arXiv* **2024**, arXiv:2405.02487.
- Ortmann, L.; Hauswirth, A.; Caduff, I.; Dörfler, F.; Bolognani, S. Experimental validation of feedback optimization in power distribution grids. *Electr. Power Syst. Res.* **2020**, *189*, 106782.
- Cao, J.; Jin, Y.L.; Zheng, T.; Xu, J.J.; Si, Y.Q. A decentralized robust voltage control method for distribution networks considering the uncertainty of distributed generation clusters. *Power Syst. Prot. Control* **2023**, *51*, 155–166.

25. Sun, M.; Zhou, Z.; Dui, M.; Huang, J.; Wang, R.; Xiao, C. Multiple stakeholder partition-based interactive-game voltage control for distribution networks. *Processes* **2025**, *13*, 1523.
26. Kang, T.Y.; Liu, K.Y.; Li, Z. Hierarchical coordinated voltage control strategy for medium and low voltage distribution networks based on photovoltaic inverter regulation. *High Volt. Eng.* **2024**, *50*, 1225–1234.
27. Lai, J.M.; Yin, Y.; Yin, X.; Du, Y.F. Multi-mode coordinated control strategy for AC-DC microgrids based on hybrid transformer interconnection. *Power Syst. Prot. Control* **2025**, *53*, 15–27.
28. Nowak, S.; Wang, L.; Metcalfe, M.S. Two-level centralized and local voltage control in distribution systems mitigating effects of highly intermittent renewable generation. *Int. J. Electr. Power Energy Syst.* **2020**, *123*, 106252.
29. Zhang, Z.; Li, P.; Ji, H.; Zhao, J.; Xi, W.; Wu, J.; Wang, C. Combined central-local voltage control of inverter-based DG in active distribution networks. *Appl. Energy* **2024**, *372*, 123813.
30. Wu, H.; Qiu, D.; Zhang, L.; Sun, M. Adaptive multi-agent reinforcement learning for flexible resource management in a virtual power plant with dynamic participating multi-energy buildings. *Appl. Energy* **2024**, *374*, 123998.

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