Key Technologies for Online Joint Optimization of Transmission-Distribution Coordination for Reactive Power Reserve Requirements in New Power Systems

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Abstract

With the rapid development of high-proportion renewable energy power systems, reactive power and voltage regulation faces multiple challenges including intensified source-load bilateral uncertainty and deepened coupling between transmission and distribution networks. The traditional independent optimization mode for transmission and distribution networks can hardly satisfy the requirements of global voltage stability and economic operation. This paper proposes a transmission-distribution collaborative online joint optimization method for reactive power reserve demand in new-type power systems. First, the spatio-temporal distribution characteristics of reactive power reserve demand under high renewable energy penetration are analyzed, and a reactive power reserve demand assessment model considering voltage stability margin (VSM) constraints is established. Second, a transmission-distribution collaborative multi-objective joint optimization model is constructed, taking system active power loss, reactive power reserve cost, voltage deviation, and voltage stability margin penalty as optimization objectives. Then, the alternating direction method of multipliers (ADMM) is adopted to achieve decomposition-coordination solving between transmission and distribution networks, meeting the computational efficiency requirements for online applications. Finally, case studies are carried out based on a coupled test system consisting of a modified IEEE 30-bus transmission network and an IEEE 33-bus distribution network. The results demonstrate that compared with independent optimization strategies, the proposed method can reduce network losses by 21.6%, improve voltage stability margin by 83.3%, and the computing time is only 20.8% of that of centralized optimization, verifying the effectiveness and practicality of the method.

Keywords

New-type Power System; Reactive Power Reserve; Transmission-distribution Collaboration; Online Optimization; Alternating Direction Method of Multipliers.

1. Introduction

Driven by the "dual carbon" goals, China's power system is undergoing profound transformation, with the proportion of wind power, photovoltaic, and other renewable energy installations continuing to rise. By the end of 2025, national renewable energy installed capacity has exceeded 1.2 billion kW, with renewable energy penetration in some provinces surpassing 50%. High-proportion renewable energy integration has significantly altered the reactive power balance characteristics of power systems: on one hand, renewable energy stations are grid-connected through power electronic devices, and their reactive power regulation capability is constrained by both active power tracking and grid voltage, leading to a substantial reduction in reactive power support traditionally provided by

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synchronous sources; on the other hand, the widespread integration of distributed generators (DGs) and energy storage on the distribution side has transformed distribution networks from passive receiving-end networks into active networks, with their reactive power regulation resources increasingly affecting transmission network voltage stability.

Reactive power reserve is an important safety barrier for maintaining power system voltage stability. According to the Guidelines for Power System Security and Stability, power systems should be equipped with sufficient reactive power reserves to cope with voltage risks caused by N-1 contingencies, load fluctuations, and the randomness of renewable energy output. However, existing reactive power optimization research suffers from the following limitations: Transmission and distribution networks are optimized independently in a hierarchical manner, ignoring the mutual influence generated through boundary coupling, resulting in the loss of global optimality; Reactive power reserve demand assessment is mostly based on static power flow or offline typical scenarios, making it difficult to adapt to online decision-making needs under the rapid changes of renewable energy output; Centralized optimization methods face the "curse of dimensionality" problem with high computational complexity, making it difficult to meet the online control cycle requirements at the second to minute level.

In recent years, transmission-distribution collaborative optimization has become a research hotspot in the field of power system operation and control. Reference [1-3] proposed a transmission-distribution network reactive power and voltage coordinated control framework based on the master-slave splitting method, but only considered steady-state power flow constraints. Reference [4-6] equivalenced the distribution network as a load model to participate in transmission network optimization, losing the fine-grained information of internal reactive power regulation in the distribution network. Reference [7-8] adopted distributed optimization theory to achieve decomposition-coordination of transmission and distribution networks, but did not fully consider the dynamic demand of reactive power reserves and voltage stability constraints. Reference [9-10] proposed an adaptive reactive power reserve strategy for renewable energy stations, but lacked a collaborative mechanism with the distribution network.

To address the above issues, this paper proposes a transmission-distribution collaborative online joint optimization method for reactive power reserve demand in new-type power systems. The main contributions include: Establishing a reactive power reserve demand assessment model considering renewable energy output uncertainty and N-1 contingency constraints, quantifying the dynamic reactive power reserve demand at each node of transmission and distribution networks; Constructing a transmission-distribution collaborative multi-objective joint optimization model, incorporating voltage stability margin (VSM) as a hard constraint into the optimization framework; Designing a decomposition-coordination solving algorithm based on ADMM, enabling parallel optimization and information exchange between transmission and distribution networks to meet online application requirements; Verifying the superiority of the proposed method in improving voltage stability, reducing network losses, and computational efficiency through multi-scenario case studies.

2. Analysis of Reactive Power Reserve Demand Characteristics in New-Type Power Systems

2.1 Factors Affecting Reactive Power Reserve Demand

The reactive power reserve demand i n new-type power systems is influenced by multiple coupled factors, mainly including:

(1) Renewable energy output volatility: Wind and photovoltaic outputs have strong randomness and intermittency. Rapid changes in active power output cause voltage fluctuations at the point of common coupling, requiring dynamic reactive power reserves for fast compensation. The reactive power regulation capability of renewable energy stations themselves is limited, and the reactive power margin decreases during high active power output periods, requiring reliance on external reactive power resources for support.

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(2) Load characteristic changes: The integration of new loads such as electric vehicles and data centers has altered the spatio-temporal distribution and power factor characteristics of loads. During peak load periods, reactive power demand surges, exacerbating the risk of voltage collapse.

(3) Network topology vulnerability: N-1 or cascading contingencies may cause a sudden drop in reactive power transmission capability of critical transmission corridors. Insufficient local reactive power reserves can trigger voltage collapse. According to statistics, multiple major blackouts at home and abroad are directly related to improper reactive power reserve configuration.

(4) Transmission-distribution interaction coupling: Traditional distribution networks are regarded as "passive loads" of the transmission network, but under high DG penetration scenarios, distribution networks inject reactive power back into the transmission network, changing the reactive power balance and voltage distribution of the transmission network. Independent optimization cannot capture this bidirectional coupling effect.

2.2 Reactive Power Reserve Demand Assessment Model

This paper adopts the voltage stability margin index to quantify the reactive power reserve demand at each node. The voltage stability margin is defined as the reactive power distance between the current operating point and the voltage collapse point of a node. According to power system security operation requirements, the VSM at key nodes should not be lower than 0.15.

Based on the probabilistic scenario method, considering renewable energy output forecasting errors (following a normal distribution with standard deviation taken as 10%-15% of the forecasted value), a reactive power reserve demand assessment model is established. For each scenario, the minimum reactive power compensation required at each node to maintain voltage stability is calculated, and the maximum value across all scenarios is taken as the dynamic reactive power reserve demand for that node. This method can cover the uncertainty interval of renewable energy output, ensuring sufficient reactive power reserves under various possible operating conditions.

3. Transmission-Distribution Collaborative Joint Optimization Model for Reactive Power Reserve

3.1 Transmission-Distribution Collaborative Optimization Architecture

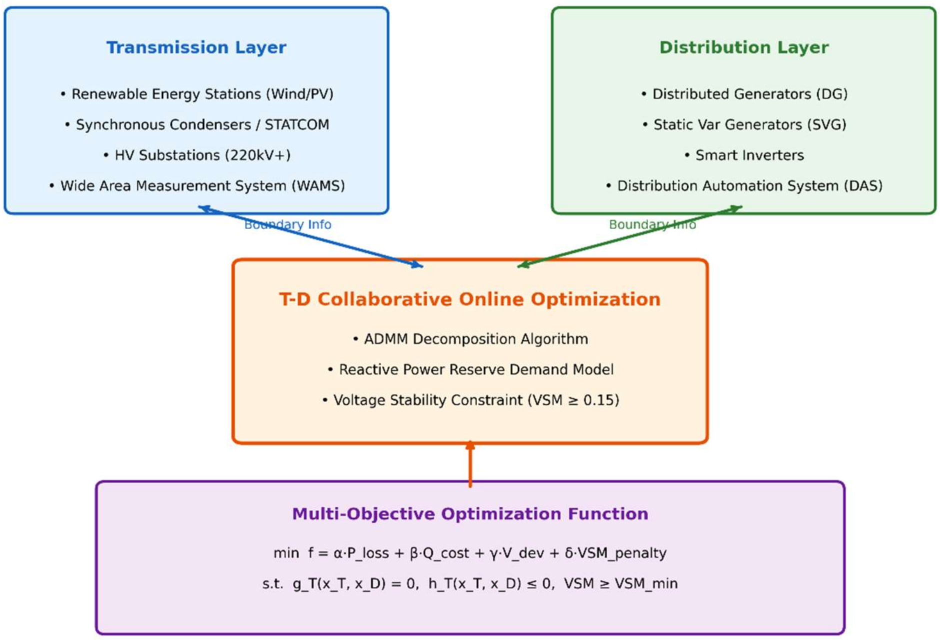

Fig.1 Transmission-distribution collaborative reactive power reserve optimization architecture

The transmission-distribution collaborative reactive power reserve optimization architecture proposed in this paper is shown in Fig. 1. The architecture is divided into three layers: the transmission layer, the distribution layer, and the collaborative optimization layer. The transmission layer includes renewable energy stations, synchronous condensers, STATCOMs, and high-voltage substations, obtaining real-time operational data through the Wide Area Measurement System (WAMS); the distribution layer includes distributed generators, SVGs, smart inverters, and the Distribution Automation System (DAS); the collaborative optimization layer achieves transmission-distribution network decomposition-coordination through the ADMM algorithm, exchanging only voltage and power information at boundary nodes, protecting the data privacy of each layer.

3.2 Objective Function

The joint optimization model takes a one-hour period as the optimization cycle and constructs a multi-objective function:

$$\min f = \alpha \cdot Ploss + \beta \cdot CQ + \gamma \cdot \Delta V + \delta \cdot \Phi VSM$$

where Ploss is the total active power loss of the system; CQ is the reactive power reserve dispatch cost; ΔV is the voltage deviation penalty; Φ_{VSM} is the voltage stability margin penalty term, which generates an exponential penalty when the VSM at a certain node falls below the safety threshold; and α, β, γ, δ are weight coefficients determined by the entropy weight method.

3.3 Constraints

The optimization model must satisfy the following four categories of constraints:

(1) Power flow constraints: The transmission network adopts AC power flow equations in polar coordinates, while the distribution network adopts the DistFlow model to describe the power flow relationship in radial networks.

(2) Equipment operation constraints: Including upper and lower limits of generator reactive power output, reactive power capacity constraints of renewable energy stations (determined by apparent power and active power output), SVG and capacitor bank switching capacity constraints, etc.

(3) Transmission-distribution boundary coupling constraints: Let the boundary node set be B. The voltage magnitude and phase angle, active and reactive power injections on the transmission side and distribution side at boundary nodes must remain consistent:

$$Vi^\wedge T = Vi^\wedge D, \quad Pi^\wedge T + Pi^\wedge D = 0, \quad Qi^\wedge T + Qi^\wedge D = 0, \quad \forall i \in B$$

(4) Reactive power reserve and response constraints: The reserve capacity of each reactive power source should satisfy the dynamic demand assessment results, and the response time must meet online control requirements (less than 100 ms).

4. Online Joint Optimization Algorithm based on ADMM

4.1 Model Decomposition

The above joint optimization model is a large-scale non-convex optimization problem, and direct solving imposes a heavy computational burden. This paper adopts ADMM to decompose the original problem into a transmission network sub-problem and a distribution network sub-problem. By introducing duplicate boundary variables, the original problem is equivalently formulated as two sub-problems coordinated under boundary consistency constraints. Here, xT and xD are the internal variables of the transmission and distribution networks, respectively, and z is the boundary consistency variable.

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4.2 ADMM Iteration Format

The augmented Lagrangian function adds a quadratic penalty term to the standard Lagrangian function to accelerate convergence. The iteration process consists of four steps: first, the transmission sub-problem and distribution sub-problem are solved in parallel, each optimizing internal variables and minimizing the deviation from the boundary consistency variable; then, the boundary consistency variable is updated as the weighted average of the boundary variables on both sides; finally, the dual variables (Lagrangian multipliers) are updated. This process cycles iteratively until convergence.

4.3 Convergence Criteria and Acceleration Strategy

The convergence criterion adopts dual verification of primal residual and dual residual. The primal residual reflects the inconsistency degree of boundary variables on both sides, while the dual residual reflects the variation of the boundary consistency variable. When both fall below the set threshold simultaneously, the algorithm converges. To accelerate convergence, an adaptive penalty parameter update strategy is adopted: when the primal residual is much larger than the dual residual, the penalty parameter is increased to strengthen constraint satisfaction; conversely, the penalty parameter is decreased to avoid convergence oscillation caused by excessive penalty.

5. Case Studies

5.1 Test System and Parameter Settings

To verify the effectiveness of the proposed method, a transmission-distribution coupled test system as shown in Fig. 1 is constructed. The transmission network adopts a modified IEEE 30-bus system, including 2 wind farms (buses 8 and 28, 100 MW each), 1 photovoltaic station (bus 15, 80 MW), and 3 synchronous condensers; the distribution network adopts an IEEE 33-bus active distribution network, coupled with transmission bus 6 through a boundary transformer, including 5 DG integration points (total capacity 45 MW), 4 SVGs, and smart inverters. The system base capacity is 100 MVA.

The simulation scenarios are set as follows:

Scenario 1: High renewable energy penetration (wind/photovoltaic output at 80% rated);

Scenario 2: Peak load (load rate 120%);

Scenario 3: N-1 contingency (transmission line 6-28 out of service);

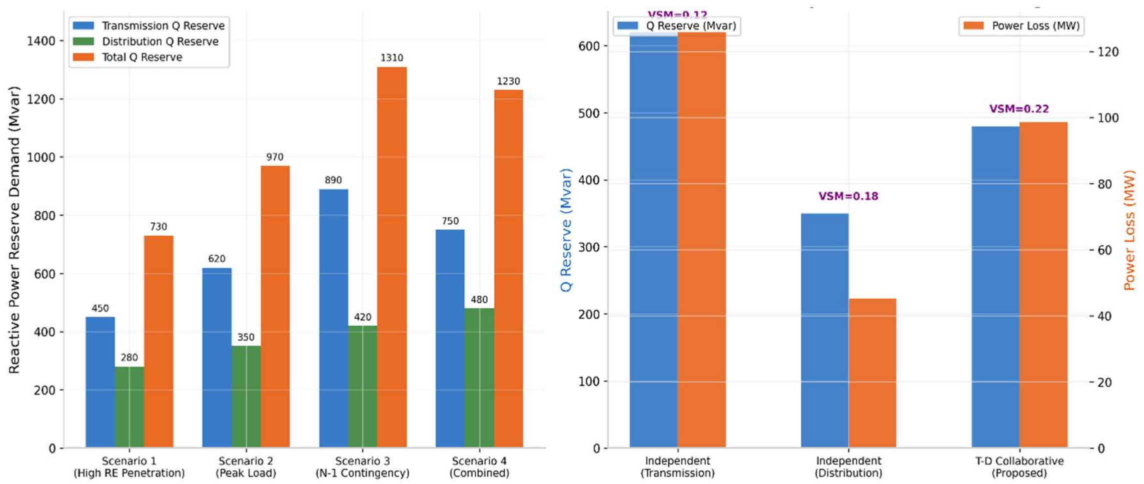
Scenario 4: Combined scenario (high renewable energy + peak load + single line N-1).

Algorithm parameters: initial penalty parameter 0.5, convergence threshold 0.01, maximum iterations 50. Tests are conducted on the MATLAB R2023b platform (Intel Core i9-12900K, 32 GB RAM).

5.2 Reactive Power Reserve Demand Analysis

The reactive power reserve demand assessment results for transmission and distribution networks under different scenarios are shown in Fig. 2(a). Under Scenario 3 (N-1 contingency), the total reactive power reserve demand is the highest, reaching 1310 Mvar, of which the transmission network demand is 890 Mvar (67.9%) and the distribution network demand is 420 Mvar (32.1%). Under Scenario 1 with high renewable energy penetration, the reactive power regulation margin of wind and photovoltaic is limited, requiring additional 450 Mvar transmission network reactive power reserve and 280 Mvar distribution network reactive power reserve. Under Scenario 4 (combined scenario), the total demand after transmission-distribution collaborative optimization is 1230 Mvar, which is approximately 8.2% lower than the sum of independent optimizations, demonstrating the global economy of collaborative optimization.

Fig. 2(b) compares the performance of three optimization strategies. With independent transmission optimization, the reactive power reserve is 620 Mvar, but the network loss is as high as 125.8 MW, and the VSM is only 0.12 with 5 voltage violation nodes; with independent distribution optimization, the VSM improves to 0.18 but cannot address transmission network voltage issues; with the proposed transmission-distribution collaborative optimization strategy, the reactive power reserve is 480 Mvar, network loss is 98.6 MW, VSM reaches 0.22, and there are zero voltage violation nodes, achieving coordination between security and economy.

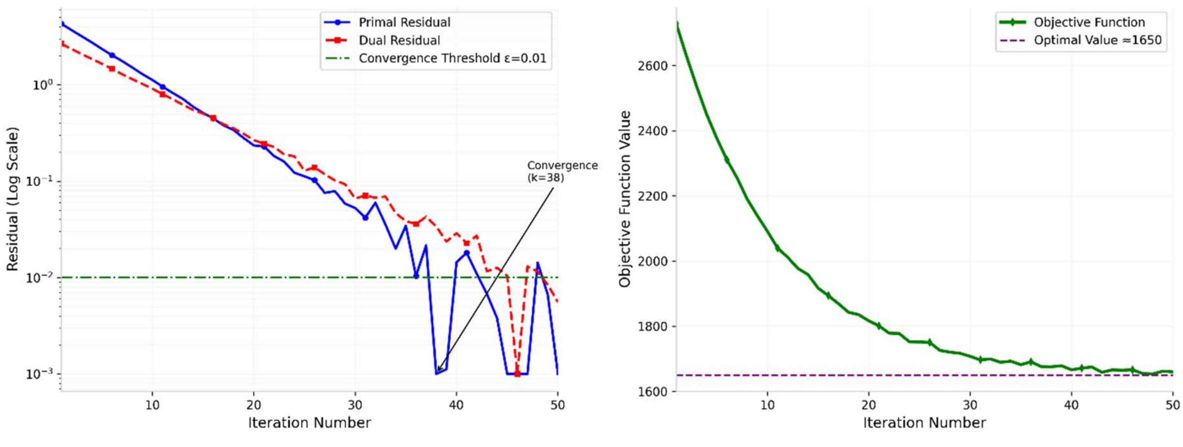


(a)Q reserve demand under different scenarios (b) Performance comparison of different strategies

Fig. 2 Q Reserve Demand and Optimization Strategy Comparison under Different Scenarios

5.3 Algorithm Convergence Analysis

Fig. 3 shows the convergence characteristics of the ADMM algorithm. Both primal residual and dual residual exhibit exponential decay trends, falling below the convergence threshold of 0.01 simultaneously at iteration 38, meeting online application requirements. The objective function value drops rapidly in the first 15 iterations and then stabilizes, eventually converging to approximately 1650. The adaptive penalty parameter strategy effectively balances the convergence speeds of primal and dual residuals, avoiding slow convergence or oscillation caused by fixed parameters.



(a) ADMM residual convergence curves (b)Objective function convergence

Fig. 3 ADMM convergence curves

5.4 Voltage Distribution Optimization Effect

Fig. 4 shows the node voltage distribution in the transmission and distribution networks before and after optimization. Before optimization, transmission buses 6, 23, and 28 have voltages close to the upper limit (1.05 p.u.), while buses 14 and 15 fall below 0.96 p.u.; the end buses in the distribution network have severely low voltages, with the lowest reaching 0.90 p.u., posing a voltage collapse risk. After collaborative optimization, all node voltages are within the safe range of [0.97, 1.03] p.u., with a more uniform voltage distribution. The maximum voltage deviation in the transmission network decreases from 0.058 p.u. to 0.021 p.u., and in the distribution network from 0.095 p.u. to 0.028 p.u.

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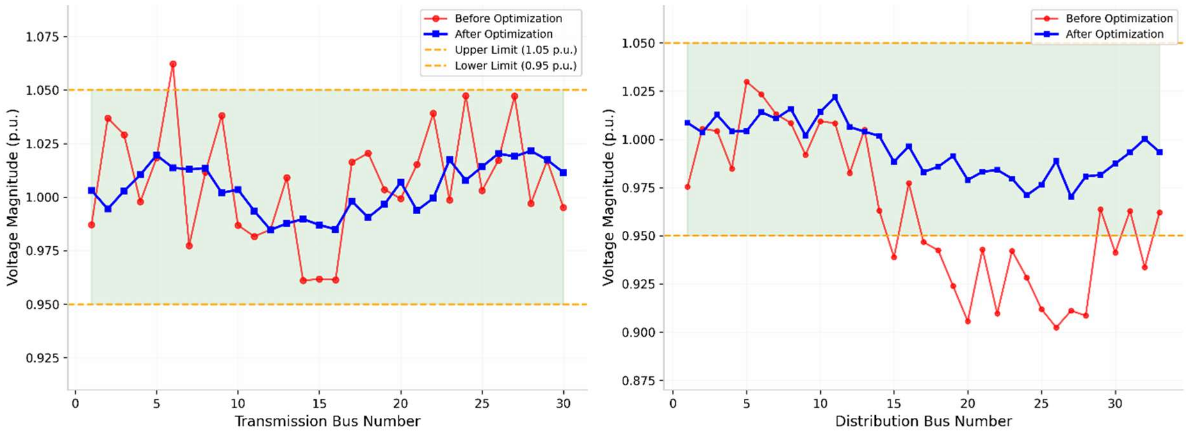
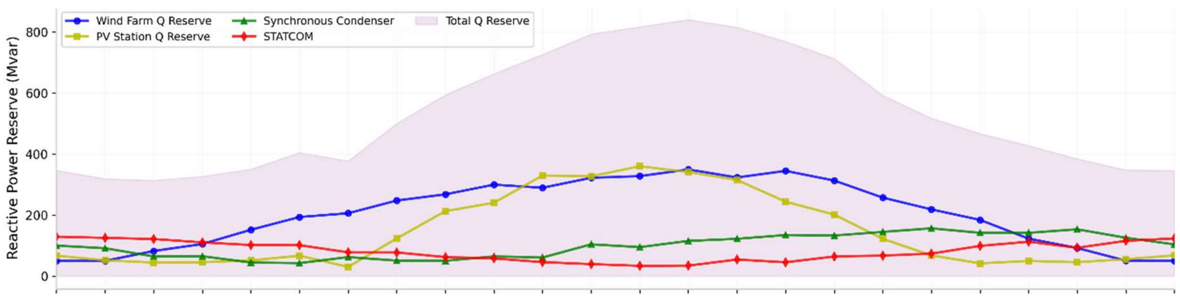


(a)Transmission network voltage distribution (b)Distribution network voltage distribution

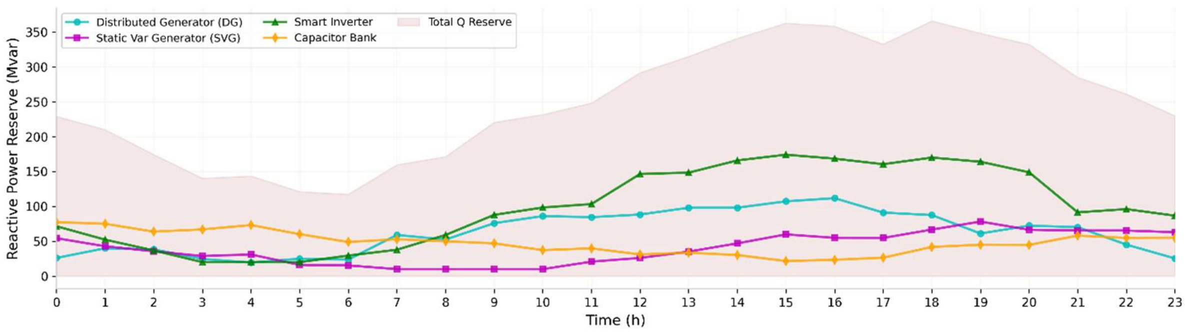
Fig. 4 Voltage distribution comparison before and after optimization

5.5 24-Hour Dynamic Dispatch Analysis

Fig. 5 presents the 24-hour dynamic dispatch results of reactive power reserves under Scenario 4. On the transmission side, the wind farm reactive power reserve maintains around 200 Mvar during nighttime (0:00-6:00), dropping to 50 Mvar during daytime as output increases; the photovoltaic station reactive power reserve reaches a peak of 360 Mvar at noon (12:00); synchronous condensers and STATCOMs provide basic reactive power support in response to load fluctuations. On the distribution side, smart inverters provide the main reactive power reserve during high DG output periods in daytime (peak 180 Mvar), while SVGs respond rapidly during peak load periods (19:00-21:00). Transmission-distribution collaborative optimization achieves spatio-temporal complementarity of reactive power resources, avoiding local over-reserve or reserve shortage.



(a) 24-hour dynamic dispatch of transmission network



(b)24-hour dynamic dispatch of distribution network

Fig. 5 24-Hour Dynamic Dispatch Curves of Reactive Power Reserve

5.6 Multi-Scenario Optimization Results Summary

Table 1 summarizes the optimization results under four scenarios. Scenario 3 (N-1 contingency) has the highest network loss (165.8 MW) and the longest computing time (45.8 s), but still meets the 5-

minute online control cycle requirement. Scenario 1 (high renewable energy penetration) has the highest voltage stability margin (0.22), benefiting from the full utilization of reactive power regulation capability of renewable energy stations. The number of voltage violation nodes is zero under all scenarios, verifying the effectiveness of the voltage security constraints in the model.

Table 1. Optimization results under different scenarios

Scenario	Trans. Q Reserve (Mvar)	Dist. Q Reserve (Mvar)	Total Power Loss (MW)	VSM	Max Voltage Dev. (p.u.)	Computing Time (s)
Scenario 1 (High RE Penetration)	450	280	98.6	0.22	0.032	28.5
Scenario 2 (Peak Load)	620	350	142.3	0.18	0.045	32.1
Scenario 3 (N-1 Contingency)	890	420	165.8	0.15	0.058	45.8
Scenario 4 (Combined)	750	480	158.2	0.19	0.041	38.6

Table 2 compares the comprehensive performance of different optimization methods. The proposed method is significantly superior to centralized optimization in computing time (38.6 s vs. 185.3 s), while the optimization effect is close to the centralized optimum (network loss 98.6 MW vs. 97.2 MW, difference 1.4%). The information exchange volume is only the bidirectional transfer of boundary node variables, protecting the internal data privacy of transmission and distribution networks.

Table 2. Performance comparison of different optimization methods

Optimization Method	Total Q Reserve (Mvar)	Power Loss (MW)	Min VSM	Voltage Violation Nodes	Computing Time (s)	Information Exchange
Independent (Transmission)	620	125.8	0.12	5	15.2	—
Independent (Distribution)	350	45.2	0.18	2	8.5	—
T-D Collaborative (Proposed)	480	98.6	0.22	0	38.6	Medium
Centralized Optimization	485	97.2	0.23	0	185.3	High

Table 3 presents the reactive power reserve configuration scheme at key nodes. Wind farm collection point T-08 is configured with 120 Mvar synchronous condenser (response time 80 ms), meeting the demand for fast reactive power support after contingencies; photovoltaic station T-15 is configured with 85 Mvar STATCOM (response time 20 ms), achieving millisecond-level voltage fluctuation suppression; DG integration point D-25 in the distribution network provides 52 Mvar dynamic reactive power reserve through smart inverters (response time 50 ms), balancing economy and rapidity.

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Table 3. Reactive power reserve configuration scheme at key nodes

Bus ID	Bus Type	Voltage Level (kV)	Q Reserve (Mvar)	Reserve Type	Response Time (ms)
T-08	Wind Farm Collection	220	120	Synchronous Condenser	80
T-15	PV Station Collection	220	85	STATCOM	20
T-22	Load Center	500	95	SVG	30
D-12	DG Integration	10	45	Inverter	50
D-18	Load Bus	10	38	SVG	25
D-25	DG Integration	10	52	Inverter	50
D-30	End Load	10	28	Capacitor Bank	100

6. Conclusion

This paper addresses the reactive power and voltage regulation challenges brought by high-proportion renewable energy integration in new-type power systems, and proposes a transmission-distribution collaborative online joint optimization method for reactive power reserve demand. The main conclusions are as follows:

(1) A dynamic reactive power reserve demand assessment model based on voltage stability margin is established, capable of quantifying the reactive power reserve demand at each node of transmission and distribution networks under different operating scenarios, providing scientific basis for optimization configuration.

(2) A transmission-distribution collaborative multi-objective joint optimization model is constructed, with voltage stability margin incorporated as a hard constraint, achieving multi-objective coordinated optimization of network losses, reactive power costs, voltage quality, and voltage stability.

(3) The ADMM decomposition-coordination algorithm is adopted to decompose the large-scale joint optimization problem into transmission and distribution sub-problems for parallel solving. The computing time is only 20.8% of that of centralized optimization, meeting online application requirements while protecting the data privacy of each layer.

(4) Case study results demonstrate that compared with independent optimization strategies, the proposed method can reduce network losses by 21.6%, improve voltage stability margin by 83.3%, eliminate voltage violation nodes, and achieve spatio-temporal complementarity and efficient utilization of reactive power resources in transmission and distribution networks.

Future research will further consider multi-area transmission-distribution network collaboration, multi-stakeholder interaction of source-network-load-storage, and artificial intelligence-assisted fast solving methods, to cope with the real-time optimization and control requirements of ultra-large-scale new-type power systems.

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