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Multi-objective day-ahead resilience improvement method for distribution network with high renewable energy penetration considering uncertainty of load and source sides

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With the increasing integration of a high proportion of renewable energy, the fluctuation characteristics of distributed power generation such as wind and photovoltaic energy affect the safe and stable operation of the power system. Improving the operational resilience of the distribution network is of great significance for ensuring reliable power supply and improving user satisfaction with electricity consumption. In this paper, a multi objective day-ahead resilience improvement method for distribution network is proposed. Firstly, a detailed mathematical model of distribution network and its internal components was established; then, taking into account the economic costs of network loss and wasted renewable power punishment, as well as voltage safety margin indicators, a multi-objective optimization model is given, and the multi-objective optimization problem is transformed into a single objective optimization problem through the weight method. Meanwhile, considering the uncertainty of both source and load sides, a clear equivalence class method is adopted to transform the uncertain optimization problem into a deterministic optimization problem. Due to the existence of nonlinear and non-convex terms in the model, in order to reduce computational complexity, particle swarm optimization (PSO) algorithm is used to achieve the optimal solution. Finally, the effectiveness and feasibility of the proposed method are demonstrated with the modified IEEE-33 node testing system.

KEYWORDS

resilience improvement, distribution network, multi objective optimization, clear equivalence class method, particle swarm optimization (PSO) algorithm

1 Introduction

With the integration of a large number of distributed power sources into the power system, the volatility and fluctuation of photovoltaic and wind power generation have caused serious interference to the safe and stable operation of power system (Liu et al., 2016; Liao et al., 2023). The time-varying characteristics of power demand in the load side increase the burden of reliable operation of the power system. On this condition, actual

operation of the power system needs to withstand a large number of random disturbances. In order to cope with the interference of this random disturbance and ensure the safe operation of the power network, the concept of power system resilience is proposed (Kushal and Illindala, 2021). Power system resilience refers to the ability of the power system to maintain normal operation without collapsing or splitting under continuous random disturbances (Mahzarnia et al., 2020; Lei et al., 2018).

The research on resilience assessment methods for distribution networks is still in its early stages, and there is no unified definition of assessment methods and resilience indicators. Ma et al. (2022) proposed an indicator that reflects the resilience of distribution networks from a temporal perspective; Panteli et al. (2015) designed a toughness evaluation method that considers wind speed level and load capacity; Min et al. (2012) considered the resilience calculation method under the simultaneous action of multiple disaster weather conditions; He et al. (2022) conducted research on urban resilient power grids from several aspects, such as adaptability in response to extreme events; Xu et al. (2021) proposed an operational resilience assessment method for distribution networks with sensitive loads; Yu et al. (2022) evaluated the resilience of each partition of the distribution network through the feeder partitioning method. Although the above references considered different toughness indicators, none of them considered the impact of high permeability distributed power sources. In order to improve the ability of the distribution network to withstand disasters under extreme weather conditions and reduce the severity of system load losses, it is necessary to adopt certain resilience enhancement methods to ensure that normal power as much as possible (Zhou et al., 2018a; Yong et al., 2022) considered the impact of extreme natural disasters and enhanced the resilience of the distribution network by forming initial isolated islands and utilizing demand response technology; Zhou et al. (2021) proposed a method for improving the resilience of AC/DC hybrid distribution networks by line reinforcement and energy storage resource allocation; Tao et al. (2022) proposed a distribution network resilience improvement planning method using stochastic optimization with information gap theory. At present, traditional planning methods such as strengthening high probability fault lines are mostly considered for improving the resilience of distribution networks. Due to limited investment costs, the effectiveness of traditional methods is limited.

Establishing comprehensive quantitative resilience indicator and diversified resilience assessment methods under various extreme events is an important theoretical basis for system resilience analysis. A single resilience indicator can only measure system resilience from a certain aspect and each indicator is interdependent, so resilience assessment should be considered as a multi-attribute decision-making problem with inherent correlation (Ruan et al., 2020). The current research on quantitative indicators of distribution network resilience mainly includes two types: static indicators and dynamic indicators (Su et al., 2022): A static index system based on network topology factors refers to quantitative indicator of distribution network topology resilience that combines network seepage theory and complex network analysis (Chen et al., 2019; Chanda and Seivastava, 2016). Regarding the diversity of static indicators, Bajpai et al. (2018) used Choquet integral to aggregate fuzzy measures of

different resilience indicators, and combined graph theory to obtain the comprehensive values. From the perspective of dynamic indicators, Panteli et al. (2017) proposed quantitative indicator values for toughness triangle and trapezoidal models based on the missing area of function curve under a single extreme event. In response to the uncertainty and complexity of fault scenarios caused by multiple attacks, Monte Carlo simulation (Li et al., 2020) and information entropy method (Zhou et al., 2018b) were used to extract the set of fault scenarios, and probabilistic quantitative indicators such as expected values and probability distributions were used for resilience evaluation (Andersson et al., 2021). A multi-stage mapping evaluation model for distribution networks was established based on the multi-dimensional dynamic characteristics of resilience quantification indicators, and a toughness evaluation index that comprehensively was proposed in Qing et al. (2021), Li et al. (2022), Zhang et al. (2021a) introduces a model for restoring services in unbalanced distribution systems and microgrids dominated by inverters, incorporating constraints on frequency dynamics to enhance load restoration and ensure the system's frequency response performs optimally throughout the restoration phase; in the study presented in Zhang et al. (2021b), a two-phase stochastic mixed-integer linear programming approach is introduced to streamline the preparation and allocation of resources in anticipation of forthcoming extreme weather events, ultimately facilitating swifter and more effective restoration efforts following such events. Despite remarkable results being achieved, the aforementioned method is still limited by computational complexity.

To address the aforementioned issues, this paper proposes a multi-objective day-ahead resilience improvement method for distribution networks, considering the uncertainty of both load and source sides. The main innovations of this paper can be summarized as follows:

- (1) In response to the impact of the fluctuation of distributed generation on the safe and stable operation of power systems, this paper introduces a multi-objective day-ahead resilience improvement method. This method comprehensively considers economic costs of network losses, penalties for wind and solar curtailment, and voltage security margin indicators to construct a multi-objective optimization model. By using a weighting method, the multi-objective optimization problem is converted into a single-objective optimization problem, thereby achieving a comprehensive improvement in the resilience of distribution networks.
- (2) Taking into account the uncertainty on both the source and load sides, this paper adopts a clear equivalence class method to transform uncertain optimization problems into deterministic optimization problems. This effectively addresses the issue of how to handle uncertainty factors during the optimization process, improving the accuracy and practicality of the optimization results and reducing the conservativeness of traditional robust optimization methods.

The research framework of this paper is as follows: Firstly, a mathematical model of the distribution network and its internal

components is established in Section 2.1. Based on the analysis of Section 2.1, a multi-objective optimization model is established by comprehensively considering the economic cost of network loss, wasted renewable power punishment, and voltage safety margin indicators. In Section 3, the solution method for the proposed resilience improvement strategy is given. Considering the uncertainty of both source and load ends, the clear equivalence class method is introduced in Section 3.1, which converts uncertain optimization problems into deterministic optimization problems. Considering the nonlinear and nonconvex characteristics of the model, PSO algorithm is used to determine the optimal solution. Finally, the effectiveness and feasibility of the proposed method are demonstrated through a modified IEEE33 node system.

2 Mathematical model for improving the resilience of distribution networks

2.1 Introduction to cloud model

2.1.1 Power supply related constraints

Wind power and photovoltaic power stations can output active power while quickly and continuously compensating for dynamic reactive power. Their participation in distribution network optimization scheduling requires consideration of power factor limitations and inverter capacity constraints, as shown in Equations 1–3.

$$P_{i,t}^{DG} = P_{i,t}^{DG,av} - P_{i,t}^{DG,cut} \quad (1)$$

$$-P_{i,t}^{DG} \tan(\arccos PF_{i,down}^{DG}) \leq Q_{i,t}^{DG} \leq P_{i,t}^{DG} \tan(\arccos PF_{i,up}^{DG}) \quad (2)$$

$$(P_{i,t}^{DG})^2 + (Q_{i,t}^{DG})^2 \leq (S_{i,t}^{DG})^2 \quad (3)$$

Here, $P_{i,t}^{DG,av}$ represents the allowable active power output of renewable energy at node i ; $P_{i,t}^{DG}$ represents the actual renewable energy active power output at node i ; $P_{i,t}^{DG,cut}$ represents the wind and solar power curtailment at node i ; $PF_{i,down}^{DG}$ and $PF_{i,up}^{DG}$ represent power factor maximum and minimum values; $S_{i,t}^{DG}$ represents renewable energy inverter capacity at node i .

2.1.2 Modeling of power consumption on the load side

Some distribution network loads, such as central air conditioning and electric vehicles, have strong controllability and can achieve cross temporal and spatial transfer of electricity consumption, with good peak shaving and valley filling effects. Equation 4 represents the power regulation capacity constraints of controllable loads participating in the coordinated scheduling of multiple flexible resources, while Equation 5 represents that the total electricity consumption of controllable loads remains unchanged during a certain period of time.

$$\begin{cases} P_{i,t}^{Load} = P_{i,t}^{Load,O} \gamma_{i,t}^{DR} \\ Q_{i,t}^{Load} = Q_{i,t}^{Load,O} \gamma_{i,t}^{DR} \\ (1 - \gamma_i^{DR}) \leq \gamma_{i,t}^{DR} \leq (1 + \gamma_i^{DR}) \end{cases} \quad (4)$$

$$\begin{cases} \sum_{t=1}^T P_{i,t}^{Load} \Delta t = \sum_{t=1}^T P_{i,t}^{Load,O} \Delta t \\ \sum_{t=1}^T Q_{i,t}^{Load} \Delta t = \sum_{t=1}^T Q_{i,t}^{Load,O} \Delta t \end{cases} \quad (5)$$

Here, $P_{i,t}^{Load,O}$ and $P_{i,t}^{Load}$ respectively represent the initial active power of controllable load at node i and the active power of load after flexibility transfer; $Q_{i,t}^{Load,O}$ and $Q_{i,t}^{Load}$ are the original reactive power of the controllable load at node i and the reactive power of the load after flexibility transfer; $\gamma_{i,t}^{DR}$ represents shift rate of controllable load at node i . In incentive demand response, the $\gamma_{i,t}^{DR}$ can be determined by the distribution network dispatcher, and controllable load can be dispatched according to instructions; γ_i^{DR} represents power regulation capacity limit of controllable load at node i based on the self-regulation capacity limit of controllable load; Δt represents the time scale of scheduling.

2.1.3 Modeling of energy storage system

To protect the service life of energy storage system (ESS) and prevent excessive charging and discharging, ESS needs to consider its own state of charge and balance constraints [as shown in (Equation 6)] and charging and discharging power constraints [as shown in (Equation 7)] when adjusting the flexibility of charging and discharging.

$$\begin{cases} SOC_{i,t+1} = SOC_{i,t} + \frac{\eta_{i,cha}^{ESS} P_{i,t,cha}^{ESS}}{S_{i,ESS}^{total}} - \frac{P_{i,t,dis}^{ESS}}{\eta_{i,dis}^{ESS} S_{i,ESS}^{total}} \\ SOC_i^{\min} \leq SOC_{i,t} \leq SOC_i^{\max} \end{cases} \quad (6)$$

$$\begin{cases} 0 \leq P_{i,t,cha}^{ESS} \leq P_{i,t,cha}^{ESS,max} \\ 0 \leq P_{i,t,dis}^{ESS} \leq P_{i,t,dis}^{ESS,max} \\ P_{i,t,cha}^{ESS} P_{i,t,dis}^{ESS} = 0 \end{cases} \quad (7)$$

Here, $SOC_{i,t}$, SOC_i^{\min} and SOC_i^{\max} are the state of charging and corresponding limits for ESS at node i ; $P_{i,t,cha}^{ESS}$ and $P_{i,t,dis}^{ESS}$ are the maximum allowable charging and discharging power for ESS at node i . $\eta_{i,cha}^{ESS}$ and $\eta_{i,dis}^{ESS}$ represents the energy storage charging and discharging efficiency at node i , respectively.

2.1.4 Operation constraints of distribution network

For distribution networks, operational constraints mainly include power flow constraints, power balance constraints, node voltage and current related constraints, and power purchase constraints, which are given as follows. Firstly, the power flow constraint is shown in Equation 8:

$$\begin{cases} P_{ij,t} = g_{ij} U_{i,t}^2 - g_{ij} U_{i,t} U_{j,t} \cos \theta_{ij,t} - b_{ij} U_{i,t} U_{j,t} \sin \theta_{ij,t} \\ Q_{ij,t} = (-b_{ij} - b_{C,ij}) U_{i,t}^2 + b_{ij} U_{i,t} U_{j,t} \cos \theta_{ij,t} - g_{ij} U_{i,t} U_{j,t} \sin \theta_{ij,t} \end{cases} \quad (8)$$

Here, $P_{ij,t}$ and $Q_{ij,t}$ represent the active and reactive power of branch ij , respectively; g_{ij} and b_{ij} represent the conductivity and susceptance of branch ij , respectively; $b_{C,ij}$ represents the ground admittance of branch ij ; $\theta_{ij,t}$ represents the voltage phase difference of nodes i and j ; $U_{i,t}$ and $U_{j,t}$ represent the voltage amplitudes of nodes i and j .

The power balance constraint is shown in Equation 9:

$$\begin{cases} P_{i,t}^{grid} + P_{i,t}^{DG} + P_{i,t}^{ESS} - P_{i,t,dis}^{ESS} - P_{i,t}^{Load} = \sum P_{ij,t} \\ Q_{i,t}^{grid} + Q_{i,t}^{DG} + Q_{i,t}^{ESS} - Q_{i,t}^{Load} = \sum Q_{ij,t} \end{cases} \quad (9)$$

Here, $P_{i,t}^{grid}$ and $Q_{i,t}^{grid}$ represent the active and reactive power provided by the upper level power grid.

Meanwhile, node voltage and branch current constraints should also be satisfied, as shown in Equations 10–12:

$$U_{i,\min} \leq U_{it} \leq U_{i,\max} \tag{10}$$

$$I_{ij,t} \leq I_{ij,\max} \tag{11}$$

$$I_{ij}^2 = \frac{P_{ij}^2 + Q_{ij}^2}{U_i^2} \tag{12}$$

Equation 12 provides the calculation method for line current. As shown in Equation 12, the active power, reactive power flowing through the line, and the node voltage all have an impact on the line current.

Finally, the distribution network is connected to the upper power grid through the root node, and in some scenarios with heavy load, the safe operation of the distribution network can be met by purchasing electricity from the upper network. The purchasing electricity amount constrains are shown in Equation 13:

$$\begin{cases} -P_{i,up}^{grid} \leq P_{i,t}^{grid} \leq P_{i,up}^{grid} \\ -Q_{i,up}^{grid} \leq Q_{i,t}^{grid} \leq Q_{i,up}^{grid} \end{cases} \tag{13}$$

Here, $P_{i,up}^{grid}$ and $Q_{i,up}^{grid}$ represent the active and reactive power limits provided by the upper power grid.

2.2 Objective function for resilience enhancement of distribution networks

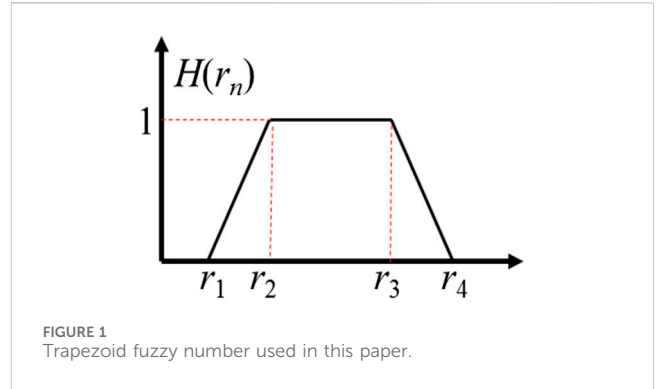
For distribution networks, the common scheduling goal is to minimize network losses. On the other hand, as the proportion of renewable energy access in the distribution network continues to increase, in order to improve the level of renewable energy consumption, waste renewable power penalty fees have been added, as shown in Equation 14:

$$f_1 = \min \sum_{t=1}^T \left(\lambda_{loss} \sum g_{ij} (U_{i,t}^2 + U_{j,t}^2 - 2U_{i,t}U_{j,t} \cos \theta_{ij}) + \lambda_{cut} \sum_{i=1}^I P_{i,t}^{DG,cut} \right) / f_{1,\max} \tag{14}$$

In Equation 14, λ_{loss} represents the penalty cost per unit of network loss; λ_{cut} represents the penalty cost per unit of wind/solar power curtailment; $f_{1,\max}$ represents the maximum value of the objective function f_1 , which can be obtained by ignoring the objective function in Equation 15 (i.e., using a single-objective optimization method). Meanwhile, in this paper, the distribution network can purchase electricity from the upper power grid, so it is believed that there is no shortage of electricity. Therefore, this paper mainly considers the resilience improvement of the distribution network from the perspective of voltage (Xu et al., 2021), and the specific mathematical expression is shown in Equation 15:

$$f_2 = \max \sum_{t=1}^T \left[\frac{4A \cos \alpha (P_{j,t} B \cos \beta + Q_{j,t} B \sin \beta)}{(U_{i,t} \cos \delta)^2} \right] / f_{2,\max} \tag{15}$$

Here, A and B represent the transmission matrix parameters of the distribution network; α represents the complex angle value of parameter A; β represents the complex angle value of parameter B; δ represents the phase angle difference of the voltage at both ends; $f_{2,\max}$ represents the maximum value of the objective function f_2 , which can be obtained by ignoring the objective function Equation 14. The weighting method is a commonly used multi-objective optimization approach that assigns different weights to each objective and then sums these weighted



objectives to form a single objective function. This method is simple, intuitive, and easy to understand and implement. In the paper, considering multiple objectives such as economic cost and voltage security margin, it is reasonable to use the weighting method to transform them into a single-objective optimization problem. It should be noted here that the introduction of $f_{1,\max}$ and $f_{2,\max}$ is to normalize the objective functions, facilitating the subsequent use of allocation factors to convert the multi-objective optimization into a single-objective optimization, ensuring objectivity and accuracy. This paper comprehensively considers network loss and voltage stability, and transforms the multi-objective optimization problem into a single objective optimization problem through the weight method, as shown in Equations 16 and 17:

$$obj = \min (Z_1 f_1 - Z_2 f_2) \tag{16}$$

$$Z_1 + Z_2 = 1 \tag{17}$$

Here, Z_1 and Z_2 represent assignment factors. When system dispatchers pay more attention to network loss, Z_1 can be assigned a larger value. Similarly, when dispatchers are more concerned about the voltage safety of the distribution network, Z_2 can be assigned a larger value. In other words, the objective function f_1 here represents the economic level and f_2 focuses more on the safety aspect. In this paper, the values of Z_1 and Z_2 are set to 0.5, achieving a balance between system safety and economy.

3 Solving algorithm

3.1 Clear equivalence class transformation method

In the power balance constraint Equation 9, both the power consumption on the load side and the output of renewable energy have certain uncertainties and cannot be directly solved. In this section, we first relax the strict power balance constraint into a chance constraint form using fuzzy chance constraints, and then adopt the clear equivalence class method to transform the uncertain optimization problem into a deterministic optimization problem for solution. The specific steps are as follows:

As shown in Figure 1, this paper adopts trapezoidal fuzzy number, in the figure r_1, r_2, r_3, r_4 represent membership parameters and $H(r_n)$ represents membership function. The specific mathematical expression is shown in Equation 18:

With the help of trapezoidal fuzzy number, original strict power constraint Equation 9 can be relaxed as (Equation 19):

$$\begin{aligned} \tilde{P} &= (r_1, r_2, r_3, r_4) \\ r_1 &= \mu_1 P_f, r_2 = \mu_2 P_f \\ r_3 &= \mu_3 P_f, r_4 = \mu_4 P_f \end{aligned} \quad (18)$$

$$\min \text{credit} \left\{ P_{i,t}^{grid} + \tilde{P}_{i,t}^{DG} + P_{i,t,dis}^{ESS} - P_{i,t,cha}^{ESS} - \tilde{P}_{i,t}^{Load} = \sum P_{i,j,t} \right\} \geq r \quad (19)$$

Then, considering the value of confidence level r in this paper is larger than 0.5, (Equation 20) is satisfied and the corresponding proof of sufficiency and necessity can refer to literature (Zhang et al., 2022).

$$(2r_3 - r_4)/2(r_3 - r_4) \geq r \quad (20)$$

According to (Equations 20, 21) can be obtained.

$$(2 - 2r)r_3 + (2r - 1)r_4 \leq 0 \quad (21)$$

Next, the relaxed constraints (Equation 19) be written in a compact form as (Equation 22). Here, x represents decision variables, ς represents trapezoidal fuzzy number.

$$\text{Credit}\{g(x, \varsigma) \leq 0\} \geq r \quad (22)$$

More generally, $g(x, \varsigma)$ can be divided into the sum of several items as (Equation 23), and the two auxiliary functions (Equation 24) and (Equation 25) can be identified.

$$g(x, \varsigma) = \sum_{j=1}^J h_j(x) \varsigma_j + h_0(x), \varsigma_j = (\varsigma_{j1}, \varsigma_{j2}, \varsigma_{j3}, \varsigma_{j4}) \quad (23)$$

$$h_j^+(x) = h_j(x) \vee 0, j = 1, 2, \dots, J \quad (24)$$

$$h_j^-(x) = -h_j(x) \wedge 0, j = 1, 2, \dots, J \quad (25)$$

Here, h_j^+ and h_j^- are nonnegative, and $h_j(x) = h_j^+(x) + h_j^-(x)$. Therefore, (Equation 26) can be derived.

$$\begin{aligned} g(x, \varsigma) &= \sum_{j=1}^J (h_j^+(x) - h_j^-(x)) \varsigma_j + h_0(x) \\ &= \sum_{j=1}^J (h_j^+(x) \varsigma_j + h_j^-(x) \varsigma_j^E) + h_0(x), \varsigma_j^E \\ &= (-\varsigma_{j4}, -\varsigma_{j3}, -\varsigma_{j2}, -\varsigma_{j1}) \end{aligned} \quad (26)$$

According to the addition and multiplication rules of fuzzy programming, (Equation 26) can be written in an expanded form as (Equation 27).

$$g(x, \varsigma)^T = \begin{pmatrix} \sum_{j=1}^J (h_j^+(x) \varsigma_{j1} - h_j^-(x) \varsigma_{j4}) + h_0(x) \\ \sum_{j=1}^J (h_j^+(x) \varsigma_{j2} - h_j^-(x) \varsigma_{j3}) + h_0(x) \\ \sum_{j=1}^J (h_j^+(x) \varsigma_{j3} - h_j^-(x) \varsigma_{j2}) + h_0(x) \\ \sum_{j=1}^J (h_j^+(x) \varsigma_{j4} - h_j^-(x) \varsigma_{j1}) + h_0(x) \end{pmatrix} \quad (27)$$

We substitute (Equation 27) into (Equation 21), and the original chance constraints (Equation 19) can be translated into clear equivalence class model (Equation 28).

$$\begin{aligned} (2 - 2r)(P_{i3,t}^{Load} - P_{i2,t}^{DG}) + (2r - 1)(P_{i4,t}^{Load} - P_{i1,t}^{DG}) + P_{i,t}^{grid} + P_{i,t,dis}^{ESS} \\ - P_{i,t,cha}^{ESS} = \sum P_{i,j,t} \end{aligned} \quad (28)$$

Through the above processing, the uncertain optimization problem is transformed into a deterministic optimization problem for solution.

3.2 PSO algorithm

By using the clear equivalence class method, the initial uncertain optimization problem is transformed into a deterministic optimization problem. However, it essentially belongs to mixed integer nonlinear optimization problems, which have a significant computational burden. In order to facilitate the solution, we use the PSO algorithm for fast solution. The specific solution process includes the following steps:

- (1) Establish a high-dimensional solution space for the optimal scheduling of distributed power sources, purchased electricity amount, and energy storage devices.
- (2) Initialize particle swarm parameters. Under the premise of ensuring the stable operation of the distribution network and meeting the constraints, generate appropriate basic parameters such as the number and position of particles, particle motion speed, etc. Set the number of iterations $m = 1$ at the beginning.
- (3) Evaluate the fitness of particles. On the premise of reducing active power loss and improving voltage stability in the distribution network, judge whether the power balance in the distribution network is met.
- (4) Update the velocity and direction of particles in contemporary particle swarm, and continue to search for new particles that meet the conditions for the next-generation.
- (5) Update the number of iterations $m = m+1$, and proceed to step (4).
- (6) Determine whether the particle swarm optimization algorithm converges. Check the fitness in the particle swarm, output the optimal calculation result, terminate the iteration, otherwise continue with the iterative calculation.
- (7) Store the optimal particle data in the solution space matrix established in (1), and obtain the output data of the reactive power compensation device and energy storage device.

To gain a better understanding, the specific solution process is shown in Figure 2.

4 Case study

In this section, an modified IEEE-33 node system is used for case validation. The testing system includes multiple distributed power sources (wind power and photovoltaic), with three energy storage systems. The distribution network is connected to the upper power network through the root node, and during periods of power shortage, electricity can be purchased from the upper power grid

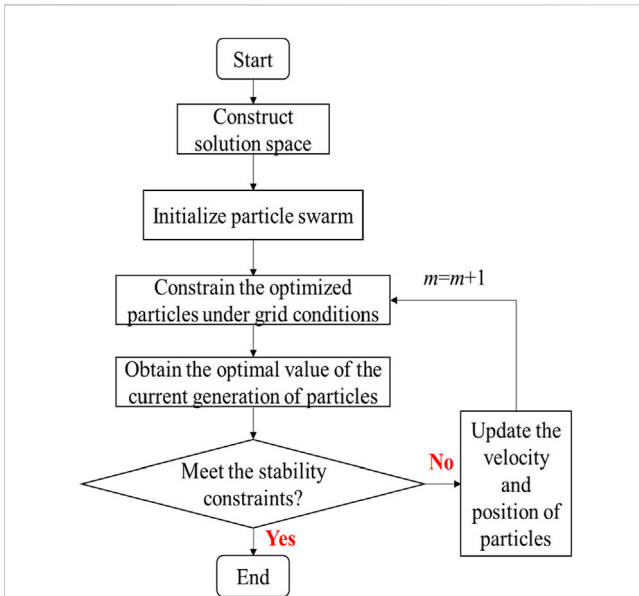


FIGURE 2 Schematic diagram of particle swarm optimization solution.

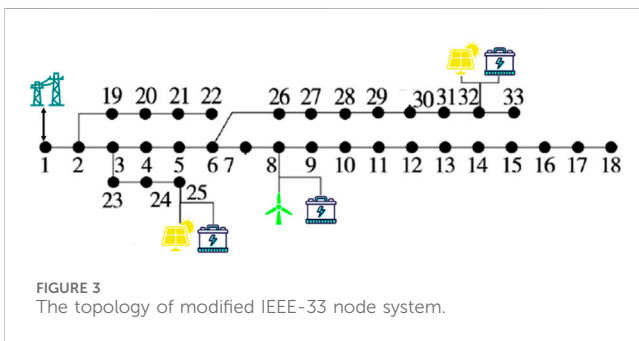


FIGURE 3 The topology of modified IEEE-33 node system.

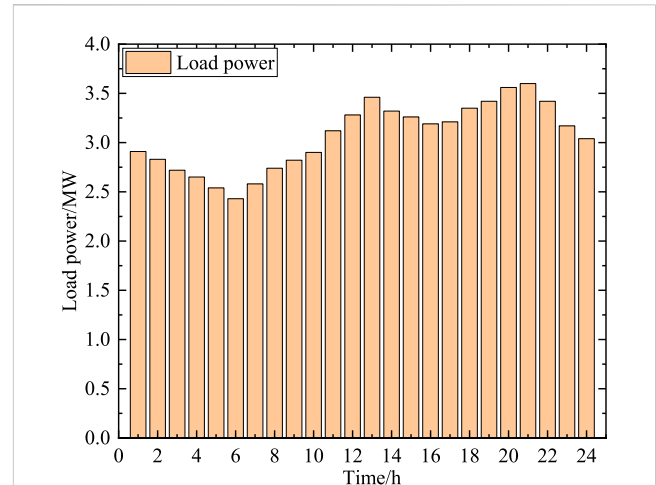


FIGURE 4 Detailed data of load power.

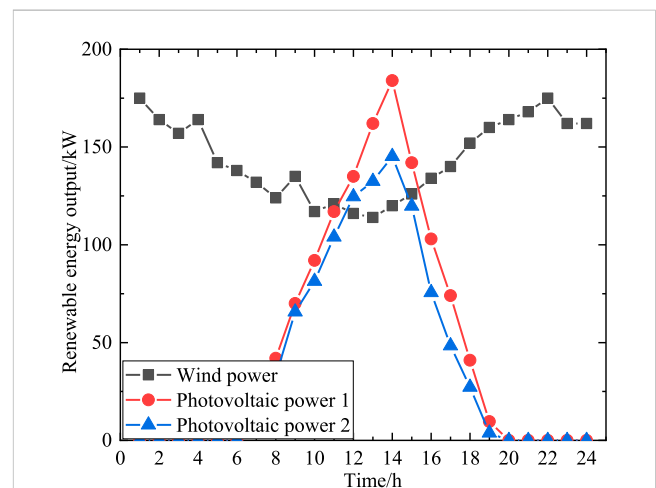


FIGURE 5 Detailed data of renewable energy output.

to meet the demand for electricity supply; similarly, the local distribution network can also choose to sell electricity to the upper power grid to achieve profitability. The topology of modified IEEE-33 node system is shown in Figure 3. Other information including load power and renewable energy output are shown in Figures 4, 5, respectively.

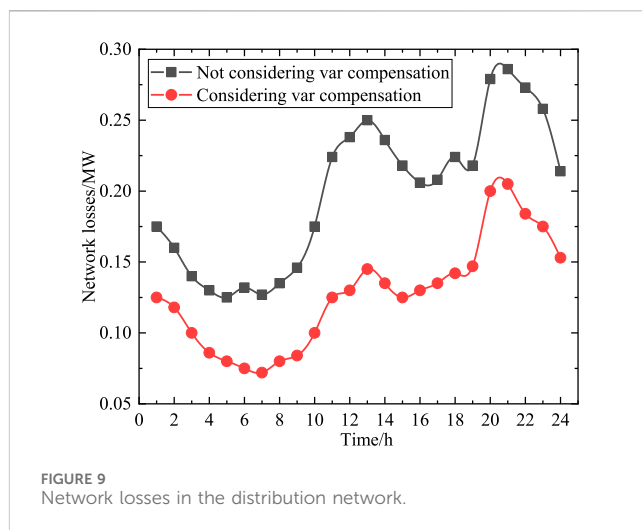
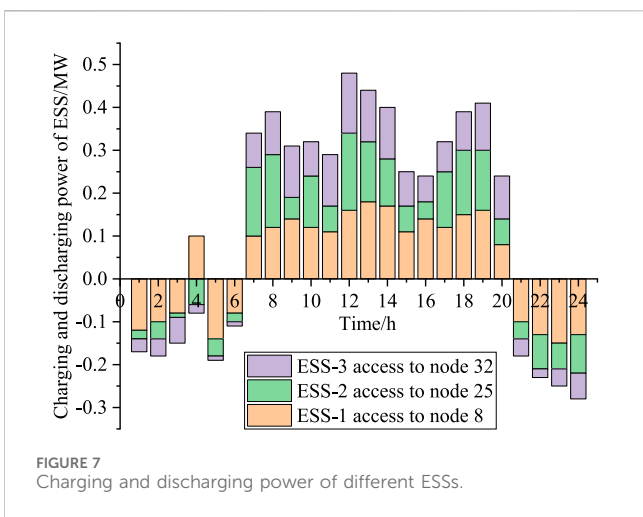
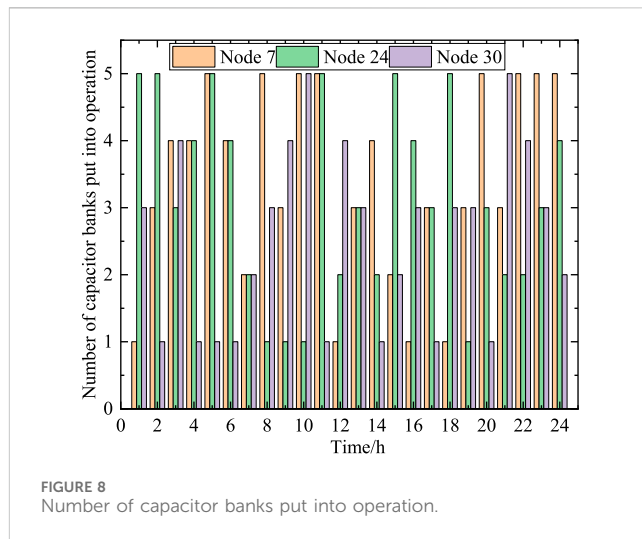
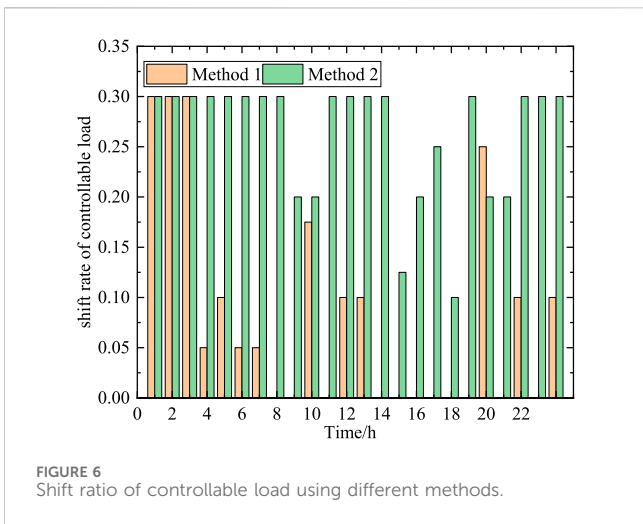
The reconstruction of distribution networks is currently widely adopted to reduce network losses. In order to more intuitively demonstrate the effectiveness of the proposed method, two comparative cases are set up for analysis:

Method 1: The Multi objective day ahead resilience improvement method for distribution network proposed in this paper considers the coordinated scheduling of multiple flexible resources.

Method 2: The method proposed in Zhang et al. (2022) adopts a dynamic reconfiguration strategy for the distribution network.

Through analysis, the renewable energy consumption rate of the proposed method is 93.86%, while the renewable energy consumption rate of method 2 is 87.12%. This also demonstrates the advantages of the proposed method. The

proposed method can fully utilize the flexibility of the source and load sides, economically and efficiently improve the level of renewable energy consumption, while avoiding the damage to mechanical equipment caused by the traditional distribution network reconstruction strategy. Figure 6 shows the shift ratio of controllable load using different methods. By observing Figure 6, it can be obtained that during the periods of 1: 00–5: 00 and 19: 00–24: 00, when wind power output is high, the shift rate of controllable loads is higher. Increasing the load power consumption during these periods can effectively reduce the wind abandonment rate. On the other hand, compared to Method 2, the proposed method has a lower controllable load shift rate because ESSs participate in scheduling, avoiding frequent adjustments to the user’s electricity consumption behavior, which is beneficial for improving the user’s electricity consumption experience. In fact, ESS has the highest flexibility in power system scheduling. ESS has a dual identity, and when the energy storage device is discharged, it can be considered as a power source; when the energy storage



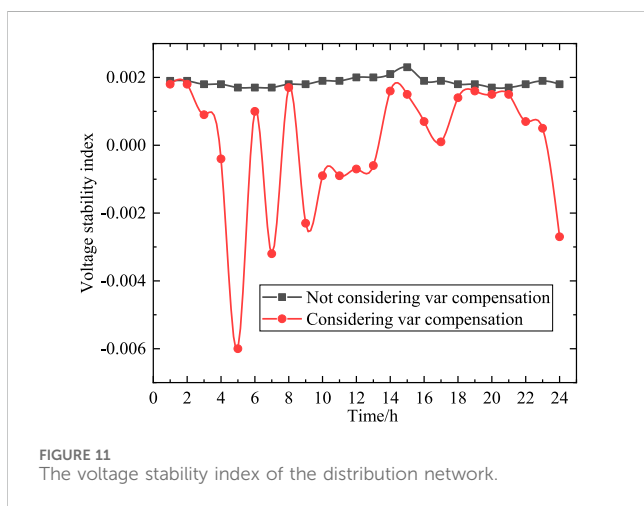
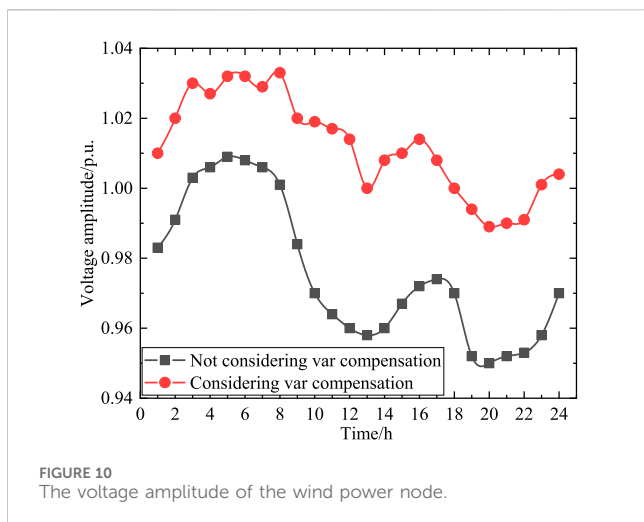
device is charged, it can be considered as a load. The participation of ESS in power system scheduling will significantly improve the scheduling flexibility of the system. Figure 7 shows the charging and discharging power of different ESSs. During periods of high output of renewable energy, ESSs are used to charge and store renewable energy that cannot be absorbed by power grid. During peak load periods, ESSs release power to meet the load electricity demand, reduce the demand for electricity from the upper power grid, and thus reduce overall operating costs.

Meanwhile, the optimization scheduling strategy proposed in this paper not only considers active power, but also reactive power. By implementing reactive power compensation, the voltage level of nodes can be improved, and the operational risks caused by unstable renewable energy output can also be reduced. A certain number of capacitor banks are installed in the distribution network. Each group of capacitors has a capacity of 200 MVar and is equipped with 5 sets of capacitors at nodes 7, 24, and 30. The number of capacitor banks put into operation during the dispatch process of the distribution network is shown in Figure 8.

The network loss during 24 h are shown in Figure 9. From Figure 9, it can be seen that by using the reactive power

compensation equipment obtained from the optimization results, the network losses in the distribution network can be obtained. Adding reactive power compensation equipment can reduce network losses of the distribution network by approximately 1 MW at each time period. The voltage amplitude of the wind power node is also shown in Figure 10. As shown in Figure 10, while ensuring the safe, economic and stable operation of the distribution network, capacitor banks put into operation also increases the voltage amplitude of wind power generation nodes, ensuring the reliability of power supply.

Voltage stability is an important index of the resilience of power systems. After calculating the values of node voltage and current in the network, the voltage stability index can be obtained. The voltage stability index of the distribution network are shown in Figure 11. From Figure 11, it can be seen that the voltage stability of the entire distribution network is significantly improved after the addition of reactive power compensation devices and energy storage devices. After the participation of compensation devices, the voltage stability fluctuations tend to flatten out, and the value of voltage stability index fluctuate between 0.001 and 0.002. Compared to the drastic



fluctuations in voltage stability of the distribution network before the participation of compensation equipment, the quantitative index of voltage stability fluctuate between -0.006 and 0.002 . From the perspective of voltage stability, compensation equipment has a significant effect on improving the resilience of the distribution network.

Comparisons with some commonly used methods are also added, including the reactive power compensation voltage control method (Method A) (Win et al., 2015), dynamic reconfiguration of distribution networks (Method B) (Luo et al., 2024), load demand response method (Method C) (Rabiee et al., 2019), a multi-objective method based on stochastic optimization (Method D) (Xie et al., 2021), and a multi-objective optimization algorithm based on the box-type robust model (Method E) (Melgar-Dominguez et al., 2022). The relevant calculation results are shown in Table 1 below.

Observing the above table, it can be seen that the method proposed in this paper achieves a balanced effect across various indicators. Compared with Method A, the proposed method reduces network losses by 27.6% while the calculation time is only half of that of Method A. This is mainly because Method A adjusts voltage by regulating steady-state reactive power, introducing integer variables such as the switching status and number of capacitor banks, which

further increases computational complexity. Additionally, Method A adjusts voltage from the perspective of reactive power balance, whereas renewable energy integration is more often regulated through active power, leading to a lower renewable energy absorption rate under Method A. Similarly, Method B enhances the reliability and resilience of distribution network operation through dynamic reconfiguration, but it introduces a large number of 0–1 variables to describe the switching status of lines, especially for large-scale distribution networks with numerous lines, resulting in extremely high computational complexity. Method C guides orderly electricity consumption through demand response strategies, encouraging loads to consume more electricity during periods of high renewable energy output to improve renewable energy absorption rates. However, it should be noted that when load power consumption increases, the power transmission demand on distribution network lines also increases, leading to an increase in system network losses. Compared with the proposed method, Method C increases network losses by 53.9%. Meanwhile, for the load side, as China still uses a long-term fixed time-of-use electricity pricing mechanism, to assist in renewable energy absorption, the load side needs to increase electricity consumption during periods of higher electricity prices, requiring the system to provide additional compensation, which increases system operating costs. From the perspective of uncertainty handling, this paper adopts a fuzzy chance-constrained method to deal with uncertainty. Fuzzy chance-constrained programming does not require precise modeling of the probability distribution of random variables, but instead uses fuzzy sets to describe uncertainty. This reduces the need for a large amount of historical data, thereby simplifying data collection and processing. Method D requires generating a large number of scenarios to simulate uncertainty, while fuzzy chance-constrained programming directly handles uncertainty through fuzzy sets and chance constraints without generating numerous scenarios, thus reducing computational effort. Fuzzy chance-constrained programming can convert uncertainty into deterministic constraints and obtain decision-making solutions by solving optimization problems under these constraints. This process is relatively straightforward and efficient, avoiding the complex scenario combinations and optimization solutions that may be involved in scenario-screening-based stochastic optimization algorithms. Method E ensures that decisions are valid under all possible uncertainty scenarios by setting a boundary for uncertainty (i.e., a box set). This method often leads to overly conservative decisions because it ignores the diversity and probability distribution of uncertainty in actual situations. In contrast, fuzzy chance-constrained programming allows decisions to satisfy constraints within a certain confidence level, thereby reducing the conservativeness of decisions.

To quantitatively describe the impact of Z_1 and Z_2 on the objective functions, Figure 12 presents the results of voltage fluctuation and total operating cost under different weight factors. Observing the figure below, it can be found that there is an approximately linear increasing relationship between the average voltage fluctuation rate and Z_1 . The larger the value of Z_1 , the better the system's economy and the lower the total operating cost. For system decision-makers, during periods of heavy load or significant fluctuations in renewable energy, reducing the value of Z_1 can provide a larger margin of safety for voltage stability. In

TABLE 1 Comparison of indicators under different methods.

Indicators	The proposed method	Method A	Method B	Method C	Method D	Method E
Network loss/MW	2.564	3.272	3.254	3.945	3.254	4.187
Average voltage fluctuation rate/%	3.10	3.25	3.78	3.69	3.12	3.15
Renewable energy consumption rate/%	96.7	92.5	93.2	95.7	94.8	93.2
Total operating cost/\$	11324.6	13526.4	12784.9	13785.9	12056.3	14152.6
Total calculation time/s	32.8	61.8	57.4	33.5	297.6	32.7

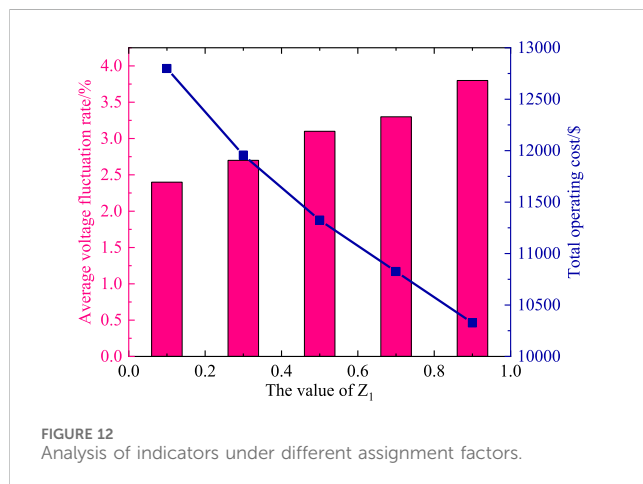


FIGURE 12 Analysis of indicators under different assignment factors.

conventional scenarios, such as light load conditions where the risk of voltage instability is lower, increasing the value of Z_1 can be considered to achieve better economic efficiency.

5 Conclusion

In this paper, a multi objective day-ahead resilience improvement method for distribution network is proposed. Firstly, a detailed mathematical model of distribution network and its internal components was established; then, taking into account the economic costs of network loss and wasted renewable power punishment, as well as voltage safety margin indicators, a multi-objective optimization model is given, and the multi-objective optimization problem is transformed into a single objective optimization problem through the weight method. Through case analysis of the IEEE-33 node testing system, the following conclusions can be drawn:

- (1) Adding ESSs and reactive power compensation devices into the distribution network to mitigate the impact of such random interference, keeping the node voltage around 3% of the rated voltage, ensuring that nodes do not experience significant fluctuations, and improving the resilience of the distribution network.
- (2) The clear equivalence class method and PSO algorithm are used to model and solve the 33 node distribution system. In the established distribution network resilience improvement model, by comparing the active power loss, the data showed

that the network losses in the distribution network decreased by approximately 0.03 MW during each time period.

- (3) In the calculation results, the voltage stability index of the distribution network fluctuates smoothly within the range of 0.001–0.002, ensuring the safe and stable operation of the distribution network.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

TG: Conceptualization, Methodology, Software, Writing–original draft, Writing–review and editing. YZ: Conceptualization, Methodology, Validation, Writing–original draft, Writing–review and editing. YT: Writing–original draft, Writing–review and editing. XC: Conceptualization, Investigation, Software, Supervision, Writing–original draft, Writing–review and editing. YC: Conceptualization, Data curation, Methodology, Validation, Writing–original draft, Writing–review and editing. WG: Conceptualization, Formal Analysis, Validation, Writing–original draft, Writing–review and editing.

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Conflict of interest

Authors TG, YZ, and YT were employed by State Grid Liaoning Electric Power Co., Ltd. Authors XC, YC, and WG were employed by Electric Power Technology Collaboration.

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