

## Article

# Multi-objective Optimization of Accommodation Capacity for Distributed Generation Based on Mixed Strategy Nash Equilibrium, Considering Distribution Network Flexibility

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**Abstract:** The increasing penetration of distributed generation (DG) brings about great fluctuation and uncertainty in distribution networks. In order to improve the ability of distribution networks to cope with disturbances caused by uncertainties and to evaluate the maximum accommodation capacity of DG, a multi-objective programming method for evaluation of the accommodation capacity of distribution networks for DG is proposed, considering the flexibility of distribution networks in this paper. Firstly, a multi-objective optimization model for determining the maximum accommodation of DG by considering the flexibility of distribution networks is constructed, aiming at maximizing the daily energy consumption, minimizing the voltage amplitude deviation, and maximizing the line capacity margin. Secondly, the comprehensive learning particle swarm optimization (CLPSO) algorithm is used to solve the multi-objective optimization model. Then, the mixed strategy Nash equilibrium is introduced to obtain the frontier solution with the optimal joint equilibrium value in the Pareto solution set. Finally, the effectiveness of the proposed method is demonstrated with an actual distribution network in China. The simulation results show that the proposed planning method can effectively find the Pareto optimal solution set by considering multiple objectives, and can obtain the optimal equilibrium solution for DG accommodation capacity and distribution network flexibility.

**Keywords:** distributed generation; accommodation capacity; distribution network flexibility; comprehensive learning particle swarm optimization; mixed strategy Nash equilibrium

## 1. Introduction

Energy consumption has gradually changed from fossil fuels and other traditional energy sources to renewable energy sources, such as wind farms (WF), photovoltaic (PV) energy, and nuclear energy [1–4]. With the reform of the power market in China, distributed WF and PV generation are developing rapidly, and the penetration of distributed generation (DG) in the distribution networks is increasing. When the capacity of DG in traditional medium- and low-voltage distribution networks approaches a high proportion (i.e., high penetration), there are difficulties in ensuring the power balance and the safe operation of distribution networks, and the reliability and power quality for customers [5,6]. On the one hand, the connection of DG into distribution networks helps to alleviate energy supply shortages, reduce network loss, and improve environmental benefits and the voltage quality of the distribution network. On the other hand, due to the randomness and fluctuation of DG,

the connection of DG into distribution networks may cause many problems, such as power quality, relay protection, and flexibility, which will affect the secure and reliable operation of the distribution network [7]. The volatility, intermittency, and unpredictability of renewable energy influence the fluctuation in distribution networks under high penetration of DG, resulting in low efficiency and great investment in distribution network equipment [8]. Improving the flexibility of distribution networks and effectively reducing the adverse impact of the high penetration of DG have become global research hotspots in recent years [9,10].

Many research works have studied the flexibility of distribution networks by considering DG connection. In [11], an intelligent distribution network optimization planning model aiming to minimize comprehensive costs is proposed. The influence of flexible resources and strategies such as operation control means and demand side management on the distribution network planning are comprehensively considered in the proposed model. In [12], a multi-objective optimization dispatching model considering interruptible loads and energy storage is constructed based on the five flexibility indices. It is proven that the optimal dispatching of flexible resources can effectively improve the flexibility of the distribution network, with high penetration of DG, and that the ability of the distribution network to accommodate DG can be assessed with the proposed model. In [13], the flexible planning for power systems with high penetration of renewable energy is reviewed and the quantitative evaluation index system for flexible planning is introduced. Then, the strategies and the key difficulties of flexible coordination planning for power systems are put forward. In [14], a dynamic reconfiguration model for a distribution network is proposed, which aims at improving the accommodation level of DG. Different characteristics of DG in different time periods are considered in the proposed time varying model. In [15], a method for evaluating the accommodation capacity of renewable energy based on the flexibility adequacy of the distribution system is proposed, and the flexibility of various resources in the distribution system is analyzed from the perspective of power regulation range. Energy hub and energy router components that allow exchange of renewable energy sources among energy users are basic technologies that enhance the flexibility of distribution networks with DG. In [16], the Duindam–Stramigioli energy router is studied and applied to realize the energy exchange using standard power electronic converter topologies. The energy hub in [17] is an interface between different energy infrastructures and is used to convert, condition, and store multiple energy carrier systems. Another study [18] presents a decentralized control strategy for the scheduling of the electrical energy activities of a microgrid composed of smart homes connected to a distributor, and the exchange of renewable energy produced by individually owned distributed energy resources. One study [19] presents a distributed power sharing framework among households in microgrids to improve the power reliability and reduce power demands and carbon emissions.

Considering the mass connection of DG, it is necessary to address the uncertainty and fluctuation of DG with optimal planning and scheduling to improve the flexibility of the distribution network. Recent research works on the planning model considering the uncertainty of DG are mainly categorized into two types, namely, planning models based on scenario analysis [20] and models based on uncertainty theories, including robust theory [21,22], stochastic theory [23], and credibility theory [24]. This paper uses the scenario analysis method to generate DG and load scenarios from historical data, which converts the uncertain planning model into the equivalent deterministic planning model. In order to deal with the randomness of DG, both the static and dynamic optimization methods are studied to solve the optimal scheduling problem. Other studies [2,25–27] simulate the fluctuation of DG by subdividing the whole dispatch cycle into short-time-scale dispatch periods. Other studies [28,29] use model predictive control (MPC) [30,31] to realize optimal control of the distribution network with DG.

However, the aforementioned research works mainly consider the impact of flexible resources on the flexibility of the distribution network, such as energy storage systems, demand side response, and superior grids. The evaluation of the distribution network flexibility considering the line capacity

margin has been discussed for optimization of dispatching [12] and distribution reconfiguration [14]. It has not been considered in the optimal planning model for the accommodation of DG.

Compared with previous studies, the main contributions of this paper are:

1. A multi-objective optimal planning model for the accommodation of DG is proposed, which aims to maximize the daily energy supply, minimize the voltage amplitude deviation, and maximize the line capacity margin. The model effectively takes the distribution network flexibility into consideration while achieving multi-objective optimization under the secure operation constraints of the distribution network.
2. The optimal planning problem regarding high-dimensional variables and multi-peak objective functions is solved using the comprehensive learning particle swarm optimization (CLPSO) algorithm. The CLPSO algorithm can obtain the non-inferior solution set of the DG optimal planning problem, which is distributed across the whole Pareto optimal front and shows better diversity.
3. The mixed strategy Nash equilibrium strategy is first applied to decide the optimal planning solution from the non-inferior solutions, which handle the conflicts between multiple objective functions of the optimal planning model more effectively.

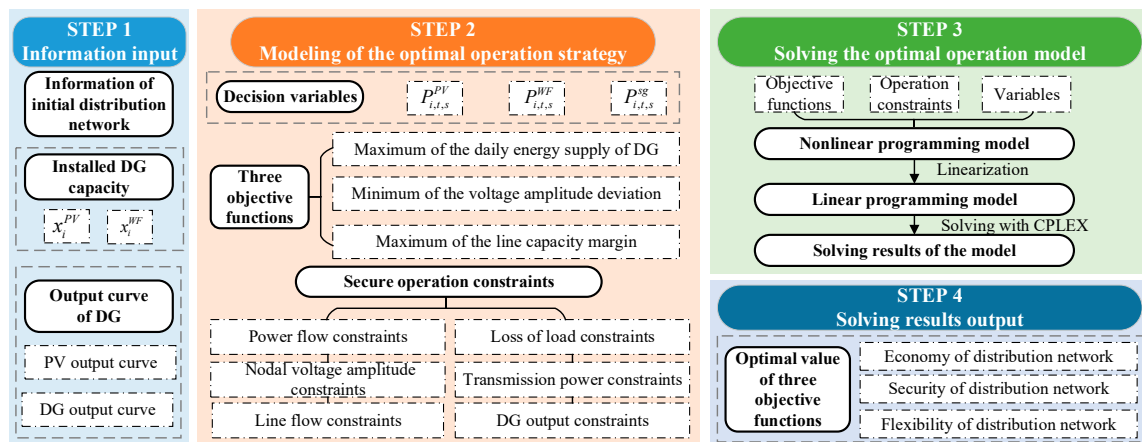
## 2. Multi-Objective Optimization Model for Accommodation Capability of DG, Considering Distribution Network Flexibility

### 2.1. Flexibility of Distribution Network with DG

With the mass connection of DG and the increasing demand for load, the flexibility of urban distribution networks mainly relates to two aspects. On the one hand, the distribution network can quickly adjust and control flexible resources, such as interruptible loads, to flexibly adapt to the connection of DG and loads and ensure secure and economical operation. On the other hand, the distribution network can respond to various possible disturbances to guarantee secure and reliable operation. For example, when WF, PV, and other distributed resources fluctuate, the distribution network should have the ability to guarantee that the renewable resources are fully absorbed. When the distribution network is in normal operation, it should have the ability to effectively deal with various uncertain disturbances and maintain optimal operation status at all times [32]. The flexibility of distribution networks, including DG, is defined as the ability to dispatch flexible resources and respond to various predictable or unpredictable disturbances to the distribution networks, aiming to deal with the uncertainty and fluctuation caused by the connection of DG into the distribution network [12].

### 2.2. Multi-Objective Optimization Model for Accommodation Capability of DG, Considering Distribution Network Flexibility

In order to evaluate the maximum accommodation capacity of DG through optimal programming, this paper proposes a novel multi-objective optimization model for the accommodation capability of DG considering distribution network flexibility. Figure 1 shows the methodology diagrams flows of the multi-objective optimization model. The overall methodology flow includes four steps: information input, modeling, solving, and results output. First, the basic information of the distribution network with DG is input into the model, assuming that the installed DG capacity at each node is determined. Second, the output power of the flexible resources, including PV, WF, and superior grids, is regarded as a real decision variable that impacts the objective functions of the optimal operation model with consideration of the secure operation constraints. Mathematically, the above planning model is a large-scale, nonlinear programming problem, which can be solved with the commercial optimization solver CPLEX (a high-performance mathematical programming solver for linear programming, mixed-integer programming and quadratic programming) after linearization. Finally, the three optimal objective values are output to reflect the economy, security, and flexibility of the distribution network comprehensively.



**Figure 1.** Methodology diagram flows of the multi-objective optimization model. Note: DG = distributed generation.

### 2.2.1. Objective Function of Multi-Objective Optimization Model

In order to accommodate WF as much as possible, the existing accommodation capacity optimization models generally take the maximization of the installed DG capacity as the objective, which may lead to resource waste and uneconomical operation of distribution networks. In addition, the flexibility requirements of distribution network operation should be taken into consideration in the accommodation capability optimization model, so that the distribution network can flexibly adapt to the randomness and fluctuation of distributed generators and loads, and quickly adjust and control flexible resources, such as interruptible loads. Therefore, three indices, namely, the daily energy supply of DG, the voltage amplitude deviation, and the line capacity margin, are considered in the proposed multi-objective optimization model of the accommodation capability of DG.

#### 1. Maximizing the Daily Energy Supply of DG

Regarding whole distribution systems, the daily energy supply of DG reflects the actual consumption of distributed energy by loads of distribution networks in dispatching periods throughout a day. When the distribution system load demand is constant over the dispatching period, maximizing the daily energy supply of DG could minimize the energy purchased from superior grids, therefore reducing the demand for power outside the local distribution system. Thus, the power of flexible resources such as distributed sources could be maximized, which would promote renewable energy and improve the economic level of the distribution network operation.

The objective function  $f_1$  of the energy supply of DG over the daily dispatching period can be represented as:

$$\max f_1 = \sum_{s=1}^S p_s \left( \sum_{t=1}^T \sum_{i \in \Omega_{PV}} P_{i,t,s}^{PV} \Delta t + \sum_{t=1}^T \sum_{i \in \Omega_{WF}} P_{i,t,s}^{WF} \Delta t \right) \quad (1)$$

#### 2. Minimizing the voltage amplitude deviation

The voltage fluctuation is an important index for measuring the power quality of distribution networks [33,34]. The voltage fluctuation phenomenon can be caused by the mass connection of DG in the distribution network, which will cause system insecurity and even partial outages in serious cases. Therefore, it is necessary to consider voltage amplitude deviation in the objective function of the accommodation capability optimization of DG.

The objective function  $f_2$  of the voltage fluctuation can be defined as:

$$\max f_2 = \sum_{s=1}^S p_s \frac{(U_i^N)^2}{\sum_{i \in \Omega_{node}} \left[ \frac{(P_{L,i,t,s} - P_{i,t,s}^{PV} - P_{i,t,s}^{WF})}{I_{k,t,s}^2} - (U_i^N)^2 \right]} \quad (2)$$

### 3. Maximizing the line capacity margin

With the mass connection of newly increased loads and DGs in the distribution network, the fluctuation and randomness of net loads increases, which can easily lead to partial congestion of the lines. The line capacity margin refers to the ratio of the difference between the maximum transmission capacity and the actual transmission capacity at a certain time to the maximum allowable transmission capacity. This mainly reflects the flexible adaptability to randomness and fluctuation for both DG and load, and the power supply transfer capacity to various disturbances in the distribution network. Therefore, the line capacity margin is taken as a flexibility index to evaluate the accommodation capacity of the DG.

The objective function  $f_3$  of the line capacity margin can be defined as:

$$\max f_3 = \sum_{k=1}^{N_{line}} F_{LMC,k} = \sum_{k=1}^{N_{line}} \frac{\sum_{s=1}^S \sum_{t=1}^T p_s (I_{k,max} - I_{k,t,s})}{I_{k,max}} \times 100\% \quad (3)$$

In Equation (3),  $F_{LMC,k} \geq 0$  indicates that the capacity margin of branch  $k$  is sufficient, and that branch  $k$  can adapt to the fluctuation of loads. Considering the increase of future demands or the drastic fluctuation of DG output, the larger the  $F_{LMC,k}$  is, the better the flexibility of branch  $k$  is. Here,  $F_{LMC,k} < 0$  indicates that the capacity margin of branch  $k$  is insufficient and congestion occurs.

#### 2.2.2. Constraints for the Multi-Objective Optimization Model

Based on the power flow constraints and the guidelines for secure operation of the distribution network, the optimization model should satisfy the following constraints in the process of evaluating the maximum accommodation capacity of DG. It is worth mentioning that the proposed model is a basic model composed of load and DG, and that it can be further improved by integrating models of other active management assets, including distributed energy storage [35,36].

##### 1. Power flow constraints

The distribution network with DG has been developed from a traditional unidirectional power flow network and changed into a bidirectional power flow network. It is necessary to establish active and reactive power flow balance models, considering power flow directions. The power flow constraints are presented as:

$$P_{ij,t,s} = U_{i,t,s} \sum_{j=1}^N U_{j,t,s} (G_{ij} \cos \theta_{ij,t,s} + B_{ij} \sin \theta_{ij,t,s}) = \sum_{(j,k \in \Omega_{line})} P_{jk,t,s} - P_{i,t,s}^{net} \quad (4)$$

$$Q_{ij,t,s} = U_{i,t,s} \sum_{j=1}^N U_{j,t,s} (G_{ij} \sin \theta_{ij,t,s} - B_{ij,t} \cos \theta_{ij,t,s}) = \sum_{(j,k \in \Omega_{line})} Q_{jk,t,s} - Q_{i,t,s}^{net} \quad (5)$$

$$P_{i,t,s}^{net} = P_{i,t,s}^{load} - P_{i,t,s}^{sg} - P_{i,t,s}^{WF} - P_{i,t,s}^{PV} - P_{i,t,s}^{ENS} \quad (6)$$

$$Q_{i,t,s}^{net} = Q_{i,t,s}^{load} - Q_{i,t,s}^{sg} - Q_{i,t,s}^{WF} - Q_{i,t,s}^{PV} - Q_{i,t,s}^{ENS} \quad (7)$$

## 2. Nodal voltage amplitude constraints

The nodal voltage amplitude should meet the requirements of secure operation of the distribution network at any time, which is represented as:

$$U_{i,\min} \leq U_{i,t,s} \leq U_{i,\max} (i \in \Omega_{node}) \quad (8)$$

## 3. Power flow constraints

The power flow of the line should not exceed its maximum capacity, which is represented as:

$$|P_{ij,t,s}| \leq S_{ij} (i, j \in \Omega_{node}) \quad (9)$$

## 4. DG output constraints

The actual output of DG is constrained by the total amount of abandonment power of WF and PV, and the maximum power during the daily dispatching cycle, which are represented as:

$$\begin{cases} (1 - \theta_{WF}) \sum_{s=1}^S p_s \sum_{t=1}^T \overline{P_{t,i,s}^{WF}} \Delta t \leq \sum_{s=1}^S p_s \sum_{t=1}^T P_{t,i,s}^{WF} \Delta t (i \in \Omega_{WF}) \\ (1 - \theta_{PV}) \sum_{s=1}^S p_s \sum_{t=1}^T \overline{P_{t,i,s}^{PV}} \Delta t \leq \sum_{s=1}^S p_s \sum_{t=1}^T P_{t,i,s}^{PV} \Delta t (i \in \Omega_{PV}) \\ P_{t,i,s}^{WF} \leq \overline{P_{t,i,s}^{WF}} (i \in \Omega_{WF}) \\ P_{t,i,s}^{PV} \leq \overline{P_{t,i,s}^{PV}} (i \in \Omega_{PV}) \end{cases} \quad (10)$$

## 5. Loss of load constraints

The loss of load should satisfy the following constraints:

$$0 \leq P_{t,i,s}^{ENS} \leq \lambda P_{t,i,s}^{load} (i \in \Omega_{node}) \quad (11)$$

## 6. Constraints of power from the superior grid

The transmission power from superior grids should satisfy the following constraints:

$$P_{i,t,s}^{sg} > 0 (i \in \Omega_G) \quad (12)$$

In the multi-objective optimization model represented in Equation (13), the decision variables are optimized to achieve the maximum value of each objective function at each dispatching period and under each scenario. The number of the variables reaches  $S \times T \times N_{PV} \times N_{WF} \times N_{sg}$ . Considering the secure operation of the distribution network, equality constraints in Equations (4)–(7) and inequality constraints (i.e., bounding constraints) in Equations (8)–(12) should be satisfied when solving the proposed model.



$$\left\{ \begin{array}{l}
 \max f_1 = \sum_{s=1}^S p_s \left( \sum_{t=1}^T \sum_{i \in \Omega_{PV}} P_{i,t,s}^{PV} \Delta t + \sum_{t=1}^T \sum_{i \in \Omega_{WF}} P_{i,t,s}^{WF} \Delta t \right) \\
 \max f_2 = \sum_{s=1}^S p_s \frac{(U_i^N)^2}{\sum_{i \in \Omega_{node}} \left[ \frac{(P_{L,i,t,s} - P_{i,t,s}^{PV} - P_{i,t,s}^{WF})^2}{I_{k,t,s}^2} - (U_i^N)^2 \right]} \\
 \max f_3 = \sum_{k=1}^{N_{line}} \frac{\sum_{s=1}^S \sum_{t=1}^T p_s (I_{k,max} - I_{k,t,s})}{I_{k,max}} \times 100\% \\
 \text{s.t.} \quad P_{ij,t,s} = \sum_{(j,k \in \Omega_{line})} P_{jk,t,s} - P_{i,t,s}^{net} \\
 Q_{ij,t,s} = \sum_{(j,k \in \Omega_{line})} Q_{jk,t,s} - Q_{i,t,s}^{net} \\
 U_{i,min} \leq U_{i,t,s} \leq U_{i,max} \quad (i \in \Omega_{node}) \\
 |P_{ij,t,s}| \leq S_{ij} \quad (i, j \in \Omega_{node}) \\
 (1 - \theta_{WF}) \sum_{s=1}^S p_s \sum_{t=1}^T \overline{P_{t,i,s}^{WF}} \Delta t \leq \sum_{s=1}^S p_s \sum_{t=1}^T P_{t,i,s}^{WF} \Delta t \quad (i \in \Omega_{WF}) \\
 (1 - \theta_{PV}) \sum_{s=1}^S p_s \sum_{t=1}^T \overline{P_{t,i,s}^{PV}} \Delta t \leq \sum_{s=1}^S p_s \sum_{t=1}^T P_{t,i,s}^{PV} \Delta t \quad (i \in \Omega_{PV}) \\
 P_{t,i,s}^{WF} \leq \overline{P_{t,i,s}^{WF}} \quad (i \in \Omega_{WF}) \\
 P_{t,i,s}^{PV} \leq \overline{P_{t,i,s}^{PV}} \quad (i \in \Omega_{PV}) \\
 0 \leq P_{t,i,s}^{ENS} \leq \lambda P_{t,i,s}^{load} \quad (i \in \Omega_{node}) \\
 P_{i,t,s}^{sg} > 0 \quad (i \in \Omega_G)
 \end{array} \right. \quad (13)$$

### 3. Solving Methods for the Multi-Objective Optimization Model Based on the CLPSO Algorithm and Mixed Strategy Nash Equilibrium

#### 3.1. Comprehensive Learning Particle Swarm Optimization Algorithm for Solving the Multi-Objective Optimization Model

To solve the proposed optimization model, which is a multi-objective decision making problem (MODM) [37], the particle swarm optimization algorithm (PSO) is used to obtain the planning results for DG. The PSO algorithm generates the initial particle swarm at random, and then realizes the balance of global and local optimization ability by setting a reasonable velocity parameter and inertia weight parameter [38,39]. The fitness function is used to assess the optimality of different particle solutions, and the optimal solution is obtained through multiple iterations. The PSO algorithm generally solves the single objective optimization problem, which determines only one globally optimal solution, along with determining the particle historical optimal solution in the optimization process. However, the optimization model of accommodation capacity of DG is a multi-objective optimization problem of multiple Pareto non-inferior solutions, which forms the Pareto frontier solution set. Therefore, a new method for determining the optimal particle is needed to ensure the diversity of Pareto non-inferior solutions and avoid falling into the local optimum in the multi-objective optimization model of accommodation capacity of DG. The CLPSO algorithm guides particles to learn from the globally optimal position or from the particle's own historical optimal position through the randomly generated binary sequence  $H$ . Meanwhile, it guides particles to learn from other particles with a certain probability, making better use of the historical information of the global population particles to ensure the comprehensiveness of the algorithm's search [40]. In order to maximize the accommodation capability of DG, the method for updating the connection solution  $i$  of DG with the distribution network in the globally optimal location  $g$  is to randomly select two solutions from the external archives. The binary bidding method is utilized to select the best solution to update the global optimal position. Thus, the temporary global optimization solution can provide the optimal direction

for particles in the CLPSO algorithm process for solving the multi-objective optimization model of accommodation capacity of DG.

### 3.2. Multi-Objective, Non-Cooperative Equilibrium Decision-Making Based on Mixed Strategy Nash Equilibrium for Determining the Optimal Accommodation Capacity of DG

The Pareto frontier set obtained by the proposed CLPSO algorithm is stored in the external archives. Finally, the optimal compromise solution needs to be selected from the external archives as the ultimate maximum accommodation capacity of DG.

The decision regarding the optimal compromise solution is made using multiple attribute decision making (MADM) [41]. Techniques such as simple additive weighting (SAW), analytic hierarchy process (AHP), fuzzy reasoning method [42], and technique for order preference by similarity to ideal solution (TOPSIS) are widely used in solving the MADM problem. SAW, fuzzy reasoning, and AHP methods are greatly affected by subjective factors. Most methods for solving multi-objective optimization problems are based on engineering experience and lack a theoretical basis. TOPSIS is a kind of centralized decision-making method considering both the positive and negative ideal solutions. However, these methods do not consider the distribution trade-off characteristics of the frontier solution set. Therefore, with the help of game theory, the mixed strategy Nash equilibrium is adopted to solve the proposed multi-objective optimization problem in this paper. Three optimization objectives, namely, the maximal daily energy supply of DG, the minimal voltage amplitude deviation, and the maximal line capacity margin, are regarded as non-cooperative decision-making participants. Then, the objective function values in the Pareto frontier solution set can be modeled by the action set of decision-making participants [43]. The optimal compromise solution can be obtained by solving the optimization problem of joint probability distribution in the Pareto frontier action set.

The objective function is normalized first to solve the inconsistency problem of multi-objective dimensions. Then, a multi-objective, non-cooperative equilibrium decision-making model based on mixed strategy Nash equilibrium is established [43] to determine the optimal accommodation capacity of DG, which can be represented as:

$$\begin{aligned} \max \quad & Nash(Y_1, \dots, Y_i, \dots, Y_{S_{ob}}, u_1, \dots, u_i, \dots, u_{S_{ob}}) \\ &= \sum_{i=1}^{S_{ob}} \sum_{j=1}^{S_{es}} \left[ (\omega_i f_{ij}) \left( \prod_{i=1}^{S_{ob}} y_{ij} \right) \right] - \sum_{i=1}^{S_{ob}} u_i \\ \text{s.t.} \quad & \sum_{j=1}^{S_{es}} y_{ij} = 1, i = 1, 2, \dots, S_{ob} \\ & y_{ij} \geq 0, i = 1, 2, \dots, S_{ob}, j = 1, 2, \dots, S_{es} \\ & \sum_{j=1}^{S_{es}} \omega_i f_{ij} y_{ij} \leq u_i, i = 1, 2, \dots, S_{ob} \end{aligned} \quad (14)$$

The overall model of the mixed strategy Nash equilibrium is represented in Equation (14). In the model, the real control variables are the equilibrium solution of objective function  $i$ , (i.e.,  $Y_i = (y_{i1}, \dots, y_{ij}, \dots, y_{iS_{es}})$ ) and the upper limit of the expected value of the objection function  $i$  (i.e.,  $u_i$ ). The two control variables reach  $S_{ob} \times S_{es}$  and  $S_{ob}$ , respectively. The positive control variables  $y_{ij}$  are constrained by equality constraints concerning the sum of equilibrium values of all frontier solution sets and inequality constraints bounded by control variable  $u_i$ . The values of the equality and inequality constraints are  $S_{ob}$  and  $S_{ob} + S_{es}$ , respectively.

The frontier solution with the optimal joint equilibrium represents the joint action with which the decision-making participants can obtain the highest return (i.e., the optimal compromise solution of the connection of DG with the distribution network) [44]. The frontier solution with the optimal joint equilibrium is expressed as:



$$\max(\prod_{i=1}^{S_{ob}} y_{i1}, \dots, \prod_{i=1}^{S_{ob}} y_{ij}, \dots, \prod_{i=1}^{S_{ob}} y_{iS_{es}}) \quad (15)$$

In the optimal connection solution, the distribution network can always operate securely and has better flexibility considering the uncertain output power of DG. The sum of the optimal connected capacity of DG is the maximum accommodation capacity of the DG of the distribution network.

### 3.3. Steps for Optimizing the Accommodation Capacity of DG Based on the CPLSO Algorithm and Mixed Strategy Nash Equilibrium

Figure 2 shows the flow chat of the proposed optimization model. To optimize the accommodation capacity of the DG, the Pareto frontier solution set is obtained by CLPSO algorithm first in this paper. Then, the Pareto frontier solution set (i.e., the DG connection solutions) is stored in the external archives. At last, the optimal solution is found from the external archives through the mixed strategy Nash equilibrium. The optimal solution is the final optimization result of the maximum accommodation capacity of the DG of the distribution network. The process for optimizing the accommodation capacity of the DG based on the CPLSO algorithm and mixed strategy Nash equilibrium is as follows:

- Step 1: The Pareto frontier solution set (i.e., the DG connection solutions obtained by CLPSO algorithm) is stored in external archives.
- Step 2: The values of three optimization objective functions are normalized (i.e., maximizing daily power supply of DG, minimizing voltage deviation, and maximizing line capacity margin).
- Step 3: The weight of each object is solved using the entropy weight method.
- Step 4: The multi-objective, non-cooperative equilibrium decision-making model is solved according to Equations (14) and (15), and the optimal compromise solution is obtained.

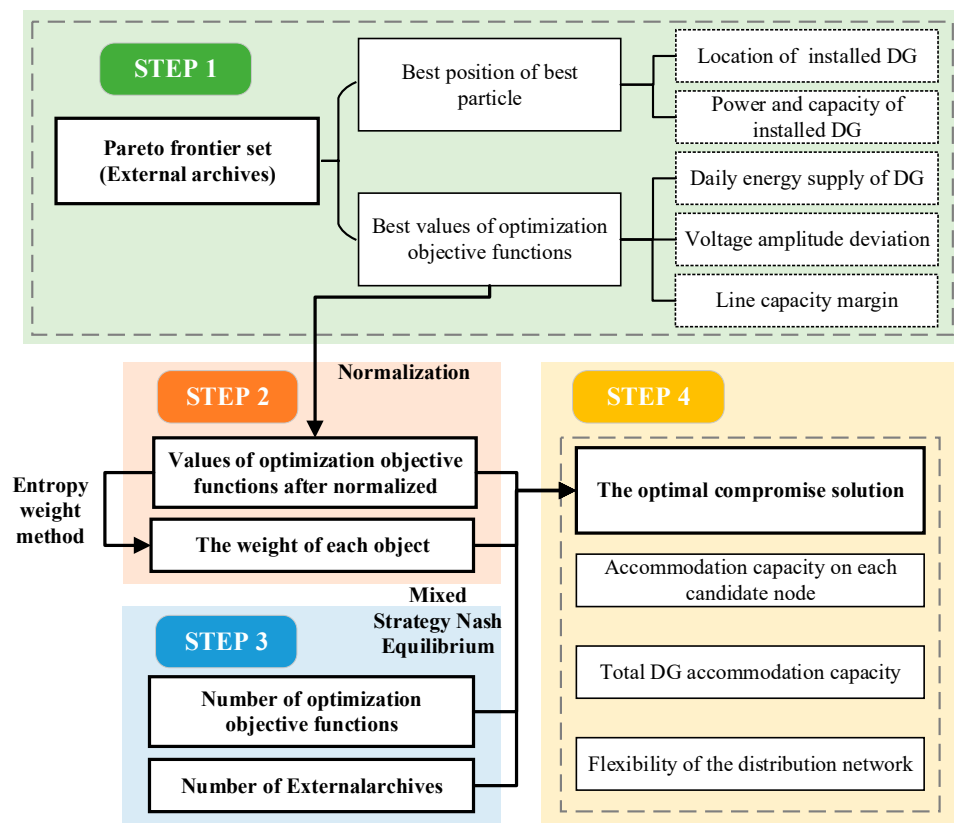
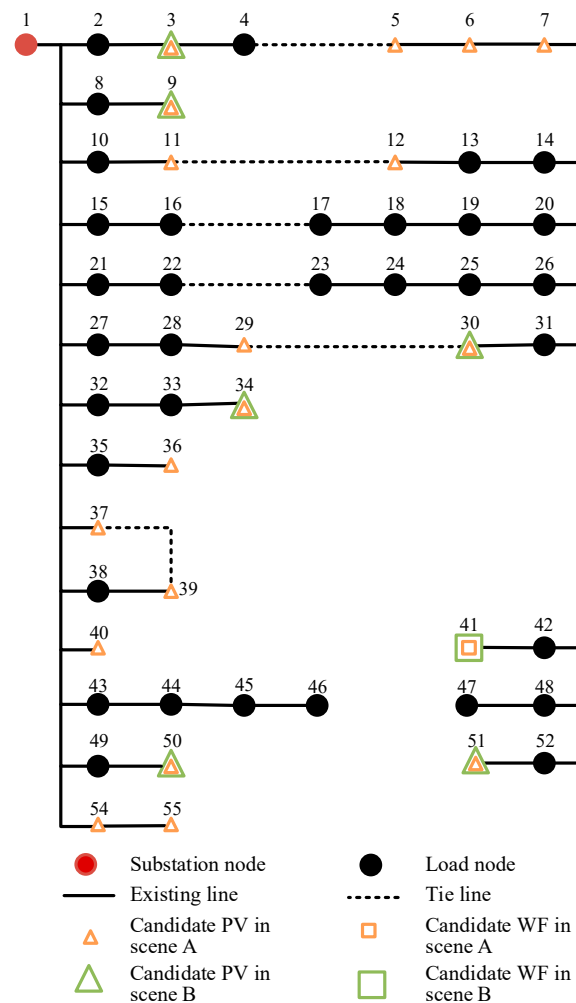


Figure 2. Flow chart of multi-objective optimization of accommodation capacity on distributed generation.

## 4. Numerical Results

### 4.1. Case Descriptions

An actual 20 kV distribution network in China, including two 110-kV substation nodes (i.e., node 1 and node 53, represented by orange solid point), fifty-three 20- kV load nodes, and 53 lines, is used to verify the effectiveness of the proposed model and methods. The total active load of the distribution network is 272.85 MW. The topology of the distribution network is shown in Figure 3, and the dotted lines in Figure 3 represent the tie lines in the distribution system. The voltage fluctuation range of node  $i$  at the dispatching period  $t$  is set to be  $[0.95U_i^N, 1.05U_i^N]$ .



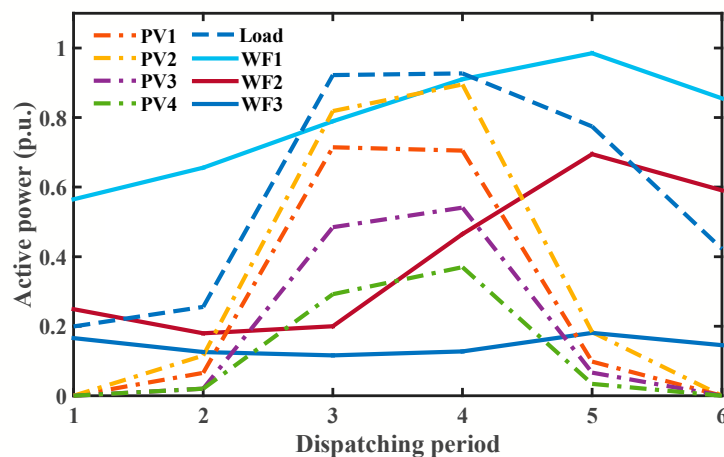
**Figure 3.** Topology of distribution network. Note: PV = photovoltaic energy; WF = wind farms.

To analyze the influence of the number of DG connection nodes on the accommodation capacity and flexibility of the distribution network, two scenes with different DG connection nodes are set up, as shown in Table 1. Table 1 shows that only node 41 is a WF node, and there are more PV nodes in scene A than in scene B. The maximum accommodation capacity of DG in the distribution network in this area (i.e., the maximum connection capacity of DG) is calculated by the proposed CLPSO algorithm and mixed strategy Nash equilibrium. The basic parameters of the CLPSO algorithm used in this paper are as follows: the number of particles is set to 30; each acceleration factor is 1.494; the upper and lower limit of inertia weight are set to 0.7 and 0.2, respectively; and the maximum number of iterations is set to 100.

**Table 1.** The configuration scenes of DG connection nodes.

DG Type	Accommodation Nodes in Scene A	Accommodation Nodes in Scene B
PV	3, 5, 6, 7, 9, 11, 12, 29, 30, 34, 36, 37, 39, 40, 50, 51, 54, 55	3, 9, 34, 36, 50, 51
WF	41	41

Considering the uncertainties of DG, three typical WF output scenarios and four typical PV output scenarios are generated based on measured data. Each scenario is divided into six dispatching periods. The standardized output curve of each dispatching period is shown in Figure 4.

**Figure 4.** The typical output scenarios of WF and PV in different dispatching periods.

#### 4.2. Simulation Results

Seven external archival solutions for the maximum accommodation capacity of DG are obtained by the proposed CLPSO algorithm, and the objective function values of each solution are standardized. The proposed method is implemented in CPLEX and solved using the YALMIP (an optimization solution tool which relies on external solvers for the low-level numerical solution of optimization problem) toolbox on a PC with a Core i5 3570 CPU and 4GB of RAM. The running time using the proposed CLPSO algorithm in the basic case is 58504.2 s, which is acceptable in the optimal planning problem. In order to visually display the distribution of three objective functions corresponding to external archives, the Pareto frontier solution set of three-dimensional objective function space is drawn, as shown in Figure 5. It can be seen from Figure 5 that the solution set in the external archives is distributed at the Pareto optimal frontier, the distances between the external archives are large, and the congestion degree is low. It can be concluded that the external archive solution set obtained by the proposed CLPSO algorithm contains a variety of decision-making solutions that fully consider the mutual dominance of the three objective functions presented in this paper. The optimal compromise solution could fully weigh the interests of each objective function and achieve the comprehensive optimum.

The weights of the three objective functions calculated by the entropy weight method are 0.3143, 0.3661, and 0.3196, respectively. The difference of the weights of the three objective functions is not significant, which means that the information entropy provided by each objective function in the proposed optimization model is comparable and the economy and flexibility of the distribution network operation after the connection of DG can be considered comprehensively.

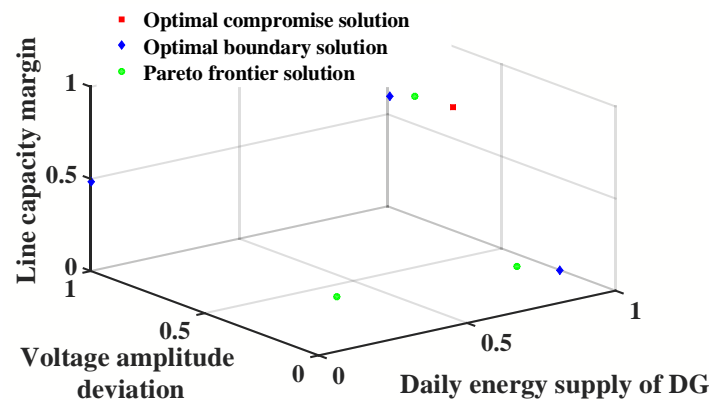


Figure 5. The distribution map of objective functions of external archives.

The normalized function values of each optimal boundary solution and the optimal solutions with Nash equilibrium decision-making and TOPSIS are presented in Table 2. In Table 2, the line capacity margin is the least among the seven Pareto frontier solutions in the optimal solution for the maximizing daily energy supply of DG. The daily energy supply of DG is least in the optimal solution for minimizing nodal voltage amplitude deviation. This means that there is a game relationship among the three objectives. The optimal solution obtained with the mixed strategy Nash equilibrium decision-making, which is a type of decentralized decision-making method, is the same as that obtained with TOPSIS, which is a type of centralized decision-making method. The result shows that the directions along which the particle swarms search to find the optimal solutions for the two methods are consistent. Moreover, because the three objectives are regarded as non-cooperative decision-making participants in a competitive relationship, the proposed mixed strategy Nash equilibrium decision-making model is more suitable for finding the optimal compromise solution and corresponding DG connection solution for the distribution network in this paper.

Table 2. The optimal boundary solutions and compromise solutions of the multi-objective optimization model.

Objective	Daily Energy Supply of DG	Voltage Amplitude Deviation	Line Capacity Margin	The Optimal Solution (Mixed Strategy Nash Equilibrium Decision-Making)	The Optimal Solution (TOPSIS Method)
Daily energy supply of DG	1.000	0.000	0.5821	0.7996	0.7996
Voltage amplitude deviation	0.2442	1.000	0.456	0.4508	0.4508
Line capacity margin	0.000	0.4867	1.000	0.8582	0.8582

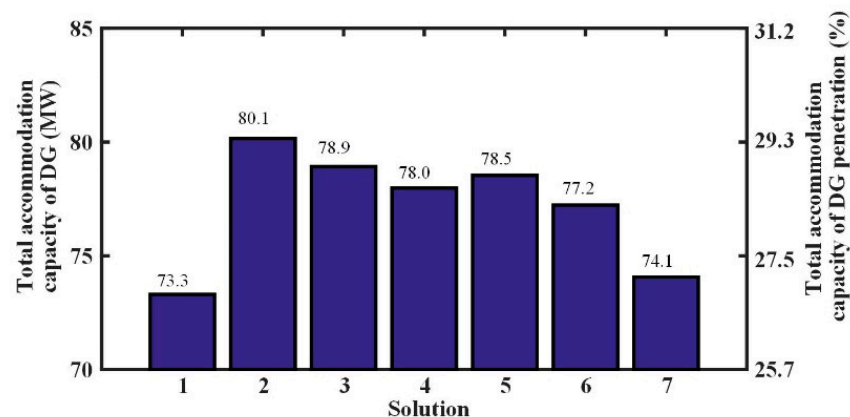
Note: TOPSIS = Technique for order preference by similarity to ideal solution.

Table 3 shows the solutions of the mixed strategy Nash equilibrium decision-making with different  $u_i$ . It shows that the change in values of parameter  $u_i$  does not influence the final optimal solution for the mixed strategy Nash equilibrium decision-making, which demonstrates the robustness and adaptability of the proposed decision-making method.

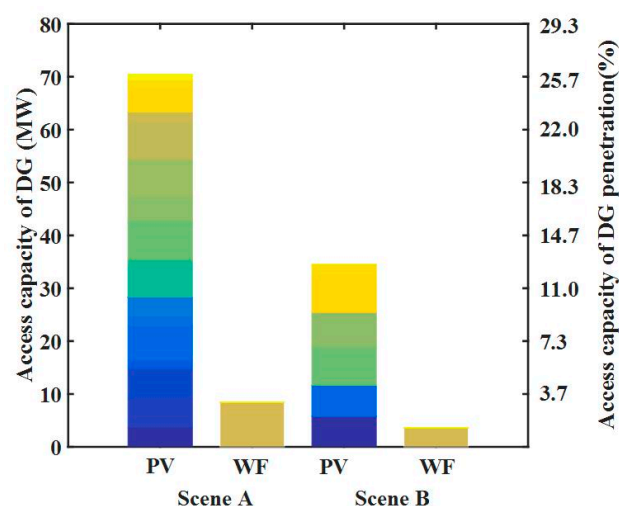
The total DG accommodation capacities of seven Pareto frontier solutions are shown in Figure 6. The optimal compromise solution (i.e., solution 3) has a 78.9-MW DG accommodation capacity on the premise of obtaining joint optimal values of multiple objectives. Its DG accommodation capacity is the second largest, following solution 2. Furthermore, the penetration of DG in solution 3 is 28.9%, showing that the distribution network in solution 3 has a better accommodation capacity for DG.

**Table 3.** Solutions of the mixed strategy Nash equilibrium decision-making method with different  $u_i$ .

Number of Case	Upper Limit of the Expected Value ( $u_1, u_2, u_3$ )	Objective Function Value of Nash Equilibrium Decision-Making	Number of Optimal Solutions
1	(0.5,0.5,0.5)	−0.8094	3
2	(0.5,0.7,0.7)	1.2094	3
3	(0.7,0.7,0.7)	−1.4094	3
4	(0.5,0.7,0.9)	−1.4094	3
5	(1.0,1.0,1.0)	−3.000	-

**Figure 6.** The total accommodation capacity of DG corresponding to the Pareto frontier solution set.

The specific PV and WF accommodation capacities of each node to be built under two different scenes are shown in Figure 7. In scene A, the number of DG nodes to be built is large and the distribution is scattered. Thus, the total DG accommodation capacity of the distribution network in this area could be maximized on the premise of ensuring the flexibility of the distribution network, in which several nodes do not need to connect large-capacity DG equipment. In scene B, the actual accommodation capacity of the PV nodes to be built is larger and more centralized than for the corresponding nodes in scene A.

**Figure 7.** The DG accommodation capacity of each node under two scenes.

The optimal compromise solutions for DG accommodation capacity under two scenes are shown in Table 4. It can be seen from Table 4 that when the number of DG connection nodes in the distribution network is reduced, the fitness of each objective function and the total DG accommodation capacity

of the optimal compromise solution of the DG configuration are reduced simultaneously. This is because of the limitation of the line capacity; the DG capacity of a single node is limited and the reduction of the connection nodes directly leads to the reduction of the total accommodation capacity. Thus, the dispatchable DG power is also reduced accordingly. At the same time, more decentralized DG connection nodes can provide voltage support and alleviate the pressure of power transmission. The fitness function value of the line capacity margin which represents the average of all line capacity margin values is 58.1% for scene A. It is higher than that for scene B, indicating that the planning strategy of DG, having more connection nodes and more dispersed distribution, can help to improve the flexibility of the distribution network.

**Table 4.** Optimal compromise solutions under two scenes.

	Scene A	Scene B
Daily energy supply of DG	476.8 MW·h	282.0 MW·h
Voltage amplitude deviation	0.347	0.257
Line capacity margin	58.1%	58.7%
Total accommodation capacity of DG	78.9 MW	38.2 MW

Because of the distinct renewable energy consumption requirements at different stages in different regions, it is necessary to carry out sensitivity analysis for abandonment rates of PV and WF in the proposed optimization model. Table 5 presents the sensitivity analysis results considering abandonment rates of PV and WF, namely 10% (Case 1), 30% (Case 2), and 50% (Case 3), which include the fitness of each objective function and the total DG accommodation capacity of the optimal compromise solution.

**Table 5.** Sensitivity analysis results considering different abandonment rates.

Permissible Abandonment Rate	Case 1 (10%)	Case 2 (30%)	Case 3 (50%)
Daily energy supply of DG	532.5 MW·h	604.0 MW·h	644.4 MW·h
Voltage amplitude deviation	0.0933	0.0965	0.1027
Line capacity margin	56.5%	57.0%	57.1%
Total accommodation capacity of DG	20.5 MW	27.7 MW	31.6 MW

It can be seen from Table 5 that with the increase of permissible abandonment rate, the total accommodation capacity of DG increases after optimization. At peak load stages, the distribution network can use more renewable energy, and the power transmission pressure of the lines in the distribution network is reduced. Eventually, the line capacity margin index increases from 56.5% to 57.1%.

Take scenario 1 and scenario 12 as examples. Figure 8 shows the voltages of node 41, considering different abandonment rates for all dispatching periods. Scenario 1 is composed of PV scenario 1 and WF scenario 1, while complex scenario 12 is composed of PV scenario 4 and WF scenario 3. When the permissible abandonment rate is 50%, the total accommodation capacity of DG reaches the maximum value of 31.6 MW. Under complex scenario 1, the high output power of WF at dispatching periods 3 and 4, which are load peak stages, can provide adequate voltage support. The bigger accommodation capacity of WF at node 41 will cause higher nodal voltage amplitude, even exceeding the rated voltage. Under scenario 12, the WF output power at load peak stages is lowest and the output level of PV is also low, which makes it difficult to support the nodal voltage of node 41 at a distance. In case 3, although the total accommodation capacity of DG is maximal, the voltages of node 41 for dispatching periods 3 and 4 are 19.9961 kV and 19.9964 kV, respectively, which are still lower than the rated voltage.

Figure 9 represents the voltage of node 5 under all scenarios. It shows that the magnitude of nodal voltage is influenced by the types of scenarios. Under scenario 10, the power of PV, whose output characteristic is consistent with that of load, is the largest, while the power of WF, whose output characteristic is different to that of load, is the smallest. Hence, the value of the nodal voltage at each



dispatching period is closest to 20 kV. Under scenario 4, the output of PV is smallest and that of PV is largest, causing the maximum voltage amplitude deviation among all scenarios.

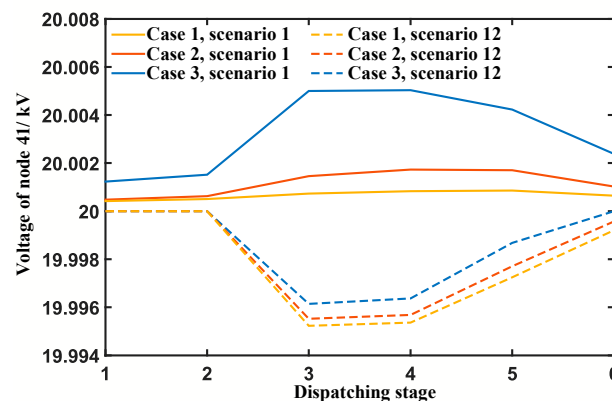


Figure 8. Voltage of node 41 considering different abandonment rates.

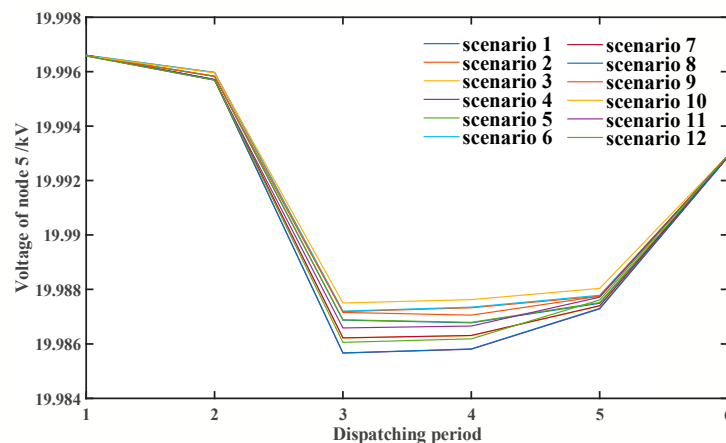


Figure 9. Voltage of node 5 under all scenarios.

## 5. Conclusions

A multi-objective optimization model for the maximum accommodation capacity of DG considering flexibility of the distribution network is proposed in this paper, aiming at maximizing the daily energy supply of DG, minimizing the voltage amplitude deviation, and maximizing the line capacity margin. The CLPSO algorithm is used to solve the multi-objective optimization model and the mixed strategy Nash equilibrium is applied to determine the optimal compromise solution, with the optimal joint equilibrium value in the Pareto solution set obtained by the CLPSO algorithm. The optimal compromise solution decides the maximum accommodation capacity of the DG with the equilibrium of each objective function considered. An actual 20-kV distribution network in China is used to verify the effectiveness and practicality of the proposed method. The simulation results show that the proposed method can effectively find the Pareto optimal solution set under multi-objective optimization and obtain the optimal balanced solution of the accommodation capacity of the DG and the flexibility of the distribution network.

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## Nomenclature

### (1) Indices and Sets

$i, j$	Index for nodes.	$s$	Index for scenarios.
$ij$	Index for branch from node $i$ to node $j$ .	$t$	Index for time periods.
$k$	Index for branches.	$\Omega_{PV}$	Node set of PV generation.
$\Omega_{WF}$	Node set of WF generation.	$\Omega_{node}$	Set of all nodes.
$\Omega_{Line}$	Branch set of distribution network.	$\Omega_G$	Set of power nodes.

### (2) Parameters

$S$	Number of WF and PV output scenarios.	$p_s$	Occurrence probability of scenario $s$ .
$T$	Number of periods in the daily scheduling period.	$\Delta t$	Length of unit scheduling period.
$U_i^N$	Rated voltage of node $i$ .	$N_{line}$	The total number of branches.
$I_{k,max}$	Maximum transmission current of branch $k$ .	$N_{PV}, N_{WF}$	The total number of PVs and WFs.
$U_{i,min} U_{i,max}$	The lowest and highest allowed voltage magnitudes of node $i$ .	$G_{ij}, B_{ij}$	The corresponding elements of node admittance matrix.
$\theta_{WF}, \theta_{PV}$	Maximum abandonment rate of WF and PV in an allowable daily dispatching period of the distribution system.	$S_{ij}$	Upper limit of power flow through branch $i-j$ .
$\lambda$	Maximum loss of load rate.	$\overline{P}_{t,i,s}^{WF}, \overline{P}_{t,i,s}^{PV}$	Maximum output of WF and PV of node $i$ at the dispatching period $t$ .
$u_i$	Upper limit of the expected value of objective function $i$ .	$Y_i$	Equilibrium solution of objective function $i$ .
$f_{ij}$	Normalized function value of frontier solution $j$ for objective function $i$ .	$\omega_i$	Importance weight of objective function $i$ .
$S_{es}$	Number of Pareto frontier solution set in external archives.	$S_{ob}$	Number of objective functions.

### (3) Variables

$P_{i,t,s}^{PV}$	Actual power of PC in dispatching period $t$ under scenario $s$ .	$P_{i,t,s}^{WF}$	Actual power of distributed wind farm generation at dispatching period $t$ under scenario $s$ .
$P_{L,i,t,s}$	Active load of node $i$ at dispatching period $t$ under scenario $s$ .	$I_{k,t,s}$	Current of branch $k$ at dispatching period $t$ under scenario $s$ .
$F_{LMC,k}$	Capacity margin of branch $k$ .	$P_{ij,t,s}, Q_{ij,t,s}$	The active and reactive power flowing through branch $i-j$ at dispatching period $t$ under scenario $s$ .
$U_{i,t,s}$	Voltage amplitude of node $i$ at dispatching period $t$ under scenario $s$ .	$\theta_{ij,t,s}$	Power factor angle.
$P_{i,t,s}^{net}, Q_{i,t,s}^{net}$	Net active and reactive power of node $i$ at dispatching period $t$ under scenario $s$ .	$P_{i,t,s}^{load}, Q_{i,t,s}^{load}$	Actual active and reactive power of node $i$ at dispatching period $t$ under scenario $s$ .
$P_{i,t,s}^{sg}, Q_{i,t,s}^{sg}$	Active and reactive power injected from the superior grid to node $i$ at dispatching period $t$ under scenario $s$ .	$Q_{i,t,s}^{WF}, Q_{i,t,s}^{PV}, Q_{i,t,s}^{ENS}$	Reactive power of the wind farm, photovoltaic farm, and non-supplied load of node $i$ at dispatching period $t$ under scenario $s$ .
$P_{t,i,s}^{ENS}$	Energy not supply at node $i$ at dispatching period $t$ under scenario $s$ .	$P_{i,t,s}^{tran}$	Transmission power from superior grids to power node $i$ at dispatching period $t$ under scenario $s$ .
$P_{t,i,s}^{load}$	Load power at node $i$ at dispatching period $t$ under scenario $s$ .	$y_{ij}$	Equilibrium value of frontier solution set $j$ for objective function $i$ .

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