ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Distribution network vulnerability assessment and active distribution network optimization strategy based on grid short circuit capacity change

Junqiu Fan[1,2,], Long Yuan[1], Zhengxiao Yang[1], Yugang Li[1], Yiran Zhou[1], Caike Xie[1,2], Rui Yang[1] and Xiujing Wang[1]*

[1] Guizhou Power Grid Co., Ltd.Guiyang, China, 550002
[2] Guizhou Provincial Key Laboratory of New-Type Power Systems Operation and Control, Guiyang, 550002, China

SUMMARY: *In order to solve the problems of grid stability, security and vulnerability arising from large-scale access to distributed power sources. This paper constructs an assessment method for distribution network vulnerability based on considering the short circuit capacity change. The method is based on analyzing the strength of the electrical connection relationship between nodes, followed by accurately capturing the power system weak links. Then the jellyfish search algorithm is combined with the improved butterfly optimization algorithm to design a multi-objective optimization model for distribution networks based on the consideration of indicators such as active loss, voltage offset and system vulnerability. The results show that this method makes the power system vulnerability and network loss decrease by 30.3% and 37.63%, respectively, and the voltage offset decrease by 33.5%. This study not only provides a reference for the dynamic change of short-circuit capacity and vulnerability analysis of distribution networks, but also provides a reasonable explanation for the optimal design and operational security of active distribution networks.*

KEYWORDS: *active distribution network; distributed power supply; vulnerability assessment; short circuit capacity; multi-objective modeling*

1 Introduction

1.1 Background of the study

Electricity has become the lifeblood of countries' economic development because it is easy to transform and transmit. Since the beginning of the new century, there has been rapid socio-economic development, and the demand for electricity has been increasing. In order to cope with the surge in demand for electricity, the scale of the power grid has been expanding, which has brought about the problem of environmental pollution and the depletion of fossil energy, which has become a problem that needs to be solved urgently [1]. 2020, China put forward the “carbon peak” and “carbon neutral” “dual carbon” goals, promoting environmental protection and environmental protection. In 2020, China proposed the “carbon peak” and “carbon neutral” goals, and advocated an environmentally friendly, low-carbon industrial structure and energy structure [2]. In order to promote the reform of the energy structure and respond positively to the “dual-carbon” strategy, vigorously develop new energy

*fans_edu_gzdx@yeah.net
https://doi.org/10.65102/is2026284 Published: 30 April, 2026

sources, develop new grid technologies, and accelerate the transformation of the power grid has become a major trend in the development of the current power system. Driven by the goal of "dual-carbon", new energy generation technology is developing rapidly, and more and more renewable energy power generation is integrated into the power grid to provide electricity to the load [3]. Renewable energy power generation is usually connected to the distribution grid in the form of distributed generation (DG), which refers to independent power sources installed close to the load center and with a smaller installed capacity, and has the advantages of economy, environmental protection, reliability, low investment, and flexibility compared with traditional power sources [4, 5].

However, the high penetration rate of DG brings great technical challenges to the safe and stable operation of distribution networks. First, the scale access of DG transforms the distribution network from passive to active, which inevitably creates bidirectional currents in the distribution network [6]. Secondly, the output of renewable energy generation is closely related to the natural conditions such as wind speed and light, which leads to the intermittent and uncontrollable output of renewable energy, posing a threat to the safe and stable operation of the distribution network [7, 8]. Finally, the flexible spatial location of DG access to the distribution network and the ability to locally consume the electricity generated have attracted different investors to participate in the operation and control of the distribution network [9]. As a result, the proposed high demand for expansion of the distribution network control system also makes the traditional distribution network scheduling and control mode no longer applicable.

The concept of active distribution grid was formally put forward in the International Conference on Large Power Grids in 2008 [10]. Active distribution grid refers to the distribution grid that can implement active control, active management, active response and other active measures for multiple sources, networks and loads through advanced network communication technology as well as measurement technology, utilizing perfect scheduling and control means [11-14]. As one of the important technical paths to realize orderly grid connection of DG and efficient consumption of renewable energy, active distribution grid technology abandons the passive operation mode of traditional distribution grid, and it coordinates the active and reactive output of multiple types of DG by actively collecting information from various intelligent terminals, so as to realize efficient energy management of active distribution grid [15, 16]. Compared with the traditional distribution network, the active distribution network can better solve the operational security problems such as voltage overrun and power fluctuation brought by the scale access of DG, and at the same time, improve the economy of the operation of the active distribution network and promote the efficient utilization of new energy [17].

In recent years, with the interconnection of power grids, the security and reliability of power systems have become more complex, so power system researchers have proposed the concept of "grid vulnerability" [18]. In a dynamic environment, when the outside world gives a disturbance to the power grid, a chain failure occurs in the power grid, which may eventually lead to the collapse of the power grid, which is a kind of more vulnerable power grid. At present, scholars at home and abroad have made certain research results on the vulnerability of power systems, which can be divided into two directions: structural vulnerability research and state-structural vulnerability research, according to the different perspectives of vulnerability identification [19, 20].

Currently, the most typical structural vulnerability assessment is based on the research of complex network theory, which combines the topology and physical characteristics of the system, and constructs the corresponding vulnerability evaluation indexes based on the basic characteristics (e.g., degree, median), thus realizing the assessment of the structural vulnerability of the system [21]. Bai, H and Miao, S synthesized a variety of influencing factors such as line impedance, power, capacity, peak load and generator capacity, and proposed corresponding vulnerability assessment indexes to provide a more comprehensive assessment of branch circuit vulnerability [22]. Wang, T et al. considered that the simplified network approach of complex networks perfectly fit the concretization of power network topology, so they proposed to establish a structural vulnerability assessment system based on complex networks to assess the vulnerability of nodes or lines of power networks [23]. Liu, B et al. established a chain failure model based on AC currents and weighted network topology, and based on the theory of complex networks, proposed the node electrical mediator to identify the critical nodes of the power grid [24]. Abedi, A et al. considered the impact of reactive power dispatch, losses and voltage distribution on the structural vulnerability of the grid and constructed a two-layer optimization assessment method that reduces the number of reconfigurations and improves the computational efficiency of the algorithms [25]. Wu, D et al. proposed a new electrical dielectric-based vulnerability metric for the grid by considering the direction of the currents, by identifying the key components of the system, and the results showed that compared to the Considering other major electrical properties of the grid (node constraints, line limitations), the change in the direction of the tidal currents has an important impact on the identification of the key elements of the grid, based on which, a comprehensive electrical dielectric vulnerability assessment index is proposed [26]. Bompard, E et al. proposed nodes and edge meshes to assess structural vulnerability on the basis of topological modeling, and considered high edge meshes lines as the key link in the model, but it did not consider the influence of various types of electrical factors in the system [27]. Luo, L et al. proposed a hierarchical structure evolution analysis method to assess the structural vulnerability of the grid from the point of view of the relationship between the hierarchical attributes of the complex network and the vulnerability of the grid [28]. The vulnerability assessment method of grid structure in the above literature mainly originates from the complex network theory, and from the perspective of grid topological structure characteristics and operation state, combining the grid structure, current characteristics, and component electrical quantities to assess the importance of grid lines and nodes, and to identify the important links in the system, which effectively assesses the vulnerability of the grid structure to a certain extent, and conforms to the actual physical background of the power grid.

State vulnerability assessment mainly starts from the operating state of the system and realizes the identification of weak links by capturing the physical characteristic quantities of the system.Bompard, E et al. addressed the limitations of the existing current shifting search methods and established a weighted grid shortest transmission path model based on the consideration of the grid branch reactance and the branch load factor, which can effectively identify the vulnerable lines in the grid [29]. Che, Y et al. established a vulnerability assessment index system for the state of power grids by hierarchical analysis (AHP) considering four dimensions: power supply composition, grid structure, grid operation, and important transmission corridors, and combined with artificial neural network (ANN) to constitute a complete assessment system [30]. Pu, C et al. proposed a node centrality metric for the power grid based on topological and electrical characteristics for the chain of faults that may be triggered by localized faults, and evaluated the vulnerability of the grid's operating state in conjunction with intelligent algorithms, which provides clues to ensure the security of the power grid [31]. The state vulnerability assessment mainly starts from the operating state of the system and realizes the identification of weak links by capturing the physical characteristic quantities of the system. The state vulnerability mainly includes transient and steady state [32], and the methods that can be applied to the transient state include the transient energy function method and the extended equal-area law, while the methods that can be applied to the steady state include the risk theory, the stochastic matrix theory and the complex network theory.

At this stage, compared with transmission grids, there are relatively few research results on vulnerability assessment of distribution grids. Vulnerability-related research on distribution networks is mainly reflected in the design of vulnerability assessment systems, vulnerability analysis of coupled systems and exploration of vulnerability assessment methods [33-35]. Luo, L et al. modeled distribution networks as spatial networks based on complexity theory, and an analysis of 14 European distribution networks found that spatial characteristics and geographic constraints significantly affect the overall performance of distribution networks [36]. Sun, P and Dong, Y applied the connectivity of interconnection subnetworks to design a vulnerability assessment system for active distribution networks, and proposed a node vulnerability assessment metric based on shortest path length to identify vulnerable nodes [37]. Li, F et al. studied and analyzed the vulnerability of the coupled system of distribution network and energy system, and proposed a high-dimensional data-driven method for detecting and identifying cyber-physical attacks based on the wave data measured by wave sensors in the distribution network [38]. Liu, N et al. analyzed the vulnerability of the coupled system of distribution network and electric vehicle transportation system based on complex network theory, proposed a hybrid power transfer allocation factor for coupled energy networks, and evaluated the vulnerability of the coupled network by integrating the hybrid power transfer allocation factor and the median [39]. Xu, D et al. proposed a distributed energy management system for distribution grid clusters aggregating wind, light, and biomass microgrids, which optimized the distribution grid coordination using a multi-energy coupling matrix, and used distributed energy sources to evaluate the energy exchanges between microgrid clusters and loads [40]. Wen, J et al. proposed a distribution network vulnerability assessment method based on the ideal solution similarity ranking technique (TOPSIS) for the occurrence of interlocking faults in distribution networks, and established the transfer entropy of electrical dielectrics and power flow to assess the state vulnerability of distribution networks [41]. Tang, L et al. examined the vulnerability of distribution networks using complex network theory and tidal current analysis, and proposed an improved tidal current centrality degree (IPFB) to assess the vulnerability of distribution networks in terms of their topology and operation status [42].

Taken together, the above studies on the vulnerability of distribution networks are all based on the vulnerability study of transmission networks, and the vulnerability study method of transmission networks is improved by combining the characteristics of distribution networks themselves, so as to obtain the vulnerability study method suitable for distribution networks. Although the study of distribution network vulnerability has achieved certain research results, but at the same time there are certain problems, such as for the existing distribution network vulnerability assessment methods, some studies directly adopt the transmission network vulnerability assessment methods, while most other studies do not consider its own characteristics comprehensively enough; in the process of vulnerability assessment, the study of vulnerability assessment model for distribution network is not detailed enough, and so on.

1.2 Status of research

With the development of the power system in the direction of low-carbon intelligence, the research on vulnerability assessment and optimization strategy of active distribution networks has become a hotspot of attention in the academic and engineering communities. In terms of distribution network vulnerability assessment, some researchers proposed an assessment method based on node importance, and electrical distance was introduced to improve the model accuracy. Relevant literature proposes a method for optimal allocation of PV in distribution networks based on node vulnerability assessment, and solves the multi-objective planning model through the MOEA/D algorithm, but the existing research generally ignores the impact of short-circuit capacity changes on the vulnerability of distribution networks. In the application of optimization algorithms, some researchers use jellyfish search algorithm to construct a distribution network model with the goal of minimizing network loss, and there is also literature for butterfly optimization algorithms are prone to fall into the shortcomings of the local optimum, the use of dynamic switching probability and Gaussian variation strategy to enhance the ability of the global optimization search, but a single algorithm to deal with the multi-objective optimization problem still has limitations.

In the study of distributed power supply and energy storage system configuration, some researchers have proposed a distributed power supply optimization configuration method considering load uncertainty, and an energy storage system configuration scheme considering economy and reliability based on multi-objective optimization theory. A two-stage energy storage optimal allocation model is proposed in existing studies, with the first stage using node vulnerability assessment to screen grid weaknesses as energy storage placement nodes, and the second stage using a two-tier optimization method to plan energy storage capacity. However, most of the existing studies consider distributed power sources and energy storage systems individually, lacking a synergistic optimization perspective, and the impact of system vulnerability caused by short-circuit capacity changes is understudied. Although existing studies have made progress in distribution network vulnerability assessment and optimization strategies, there are still problems such as incomplete assessment indexes and limited efficiency of optimization algorithms, etc. In this study, we will propose a vulnerability assessment method for distribution networks based on short-circuit capacity changes. And combined with the improved jellyfish search algorithm and butterfly optimization algorithm, the multi-objective optimization model of active distribution network will be constructed to provide theoretical support for improving the safe and stable operation of active distribution network.

1.3 Contributions and innovations of this study

In this study, the system vulnerability problem caused by short-circuit capacity change in active distribution networks is discussed in depth, and a complete assessment system and optimization scheme are constructed on this basis. In this study, short-circuit capacity change is taken as the core of assessing the vulnerability of distribution networks, and a vulnerability assessment model that is more in line with the physical characteristics of power systems is established. In terms of optimization strategy, this study organically combines the jellyfish search algorithm with the improved butterfly optimization algorithm, and adopts the dynamic switching probability and dynamic Gaussian variation strategy on the improved optimization algorithm. The multi-objective optimization model in this paper comprehensively considers the indicators of active network loss, voltage offset and system vulnerability, which can significantly improve the economy and stability of active distribution networks.

2 Distribution network vulnerability assessment model

2.1 Vulnerability assessment indicators

As a typical complex network system, the vulnerability of the distribution network does not simply depend on the network topology, but is also inextricably linked to the electrical characteristics between nodes. Short-circuit capacity is a key indicator of the strength of the power system, which directly reflects the ability of the system to resist external disturbances. After the access of distributed power supply, the distribution of system short-circuit capacity changes, which makes the strength of the electrical connection between nodes change, and then has an impact on the overall vulnerability of the system. Based on this understanding, we construct a vulnerability assessment index centered on short-circuit capacity change. We define the inter-node electrical distance C_{ij} as:

$$\mathrm{C}_{ij} = \frac{S_{cc,i} \cdot S_{cc,j}}{Z_{ij}} \tag{1}$$

Here $S_{cc,i}$ and $S_{cc,j}$ denote the short-circuit capacity of node i and node j, respectively, and Z_{ij} represents the equivalent impedance between node i and node j. The electrical distance C_{ij} reflects the strength of the electrical connection between the nodes, where a larger value implies a stronger connection and a lower vulnerability of the system on that connection.

On this basis, we define the vulnerability indicator V_i of node i as:

$$V_i = \sum_{j=1}^{n} \frac{1}{C_{ij}} \tag{2}$$

This metric integrates the strength of the electrical connection between node i and all other nodes in the system, and a larger value of V_i indicates that the electrical connection between node i and other nodes is weaker, and the vulnerability of that node is higher.

In order to comprehensively assess the node vulnerability, we introduce the short-circuit capacity sensitivity indicator S_i, i.e:

$$\mathrm{S}_i = \frac{\Delta V_i}{\Delta S_{cc,i}} \cdot \frac{S_{cc,i}}{V_i} \tag{3}$$

This metric reflects the extent to which changes in the short-circuit capacity of a node affect its vulnerability, and the larger the value of S_i, the more pronounced is the impact of short-circuit capacity changes on the vulnerability of that node.

Considering that the topological position of a node in the network also has an important impact on the system vulnerability, we introduce the node degree centrality indicator D_i, i.e:

$$D_i = frac\{k_i\}\{n-1\} \tag{4}$$

Here k_i is the degree of node i and n is the total number of nodes in the system. A larger value of D_i means that the node i has more connections in the network and its importance is higher.

In order to consider the above factors together, we construct the node comprehensive vulnerability index CV_i, i.e.:

$$CV_i = \alpha \cdot \frac{V_i}{V_{\max}} + \beta \cdot \frac{S_i}{S_{\max}} + \gamma \cdot \frac{D_i}{D_{\max}} \tag{5}$$

where V_{max}, S_{max} and D_{max} are the maximum value of each indicator for normalization, respectively; α, β and γ are the weight coefficients and satisfy $\alpha + \beta + \gamma = 1$. The overall system vulnerability indicator V_{sys} is defined as:

$$V_{sys} = sum_{i=1}^{n} CV_i \tag{6}$$

2.2 Vulnerability assessment models

This section focuses on constructing a distribution network vulnerability assessment model, which comprehensively considers the physical characteristics of the distribution network, the operational status and the access of distributed power sources. By synthesizing various indicators, it is able to scientifically assess the vulnerability of active distribution networks.

The mathematical expression of the distribution network vulnerability assessment model is:

$$F = \min\left\{ w_1 \cdot V_{sys} + w_2 \cdot P_{loss} + w_3 \cdot \Delta V \right\} \tag{7}$$

where V_{sys} denotes the overall system vulnerability index, P_{loss} is the system active network loss, ΔV represents the node voltage offsets, w_1, w_2 and w_3 are the weighting coefficients, and $w_1 + w_2 + w_3 = 1$. The model constraints are as follows:

$$\begin{cases} P_i - P_{Di} = U_i \sum_{j=1}^{n} U_j \left(G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta_{ij} \right) \\ Q_i - Q_{Di} = U_i \sum_{j=1}^{n} U_j \left(G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta_{ij} \right) \\ U_i^{\min} \le U_i \le U_i^{\max} \\ S_{ij} \le S_{ij}^{\max} \\ P_{DG,i}^{\min} \le P_{DG,i} \le P_{DG,i}^{\max} \\ Q_{DG,i}^{\min} \le Q_{DG,i} \le Q_{DG,i}^{\max} \\ P_{ESS,i}^{\min} \le P_{ESS,i} \le P_{ESS,i}^{\max} \\ SOC_i^{\min} \le SOC_i \le SOC_i^{\max} \end{cases} \tag{8}$$

The system active network loss P_{loss} is calculated as:

$$P_{loss} = \sum_{i=1}^{n} \sum_{j=1}^{n} G_{ij} \left(U_i^2 + U_j^2 - 2U_i U_j \cos\theta_{ij} \right) \tag{9}$$

The node voltage offset ΔV is defined as:

$$\Delta V = \sum_{i=1}^{n} \left| U_i - U_{ref} \right| \tag{10}$$

We find that the short-circuit capacity variation has an important effect on the system vulnerability, and the node short-circuit capacity variation $\Delta S_{cc,i}$ after the distributed power supply access can be expressed as:

$$\Delta S_{cc,i} = \frac{U_i^2}{Z_{DG,i} \| Z_{sys,i}} \tag{11}$$

where $Z_{DG,i}$ is the distributed power equivalent impedance, $Z_{sys,i}$ is the system equivalent impedance, and $\|$ denotes the parallel operation. The node vulnerability index V_i' after considering the short circuit capacity change is:

$$V_i' = \sum\nolimits_{j=1}^{n} \frac{1}{C_{ij}'} = \sum\nolimits_{j=1}^{n} \frac{Z_{ij}}{\left(S_{cc,i} + \Delta S_{cc,i}\right) \cdot \left(S_{cc,j} + \Delta S_{cc,j}\right)} \tag{12}$$

The overall system vulnerability indicator V_{sys} is updated to:

$$V_{sys} = \sum\nolimits_{i=1}^{n} CV_i' = \sum\nolimits_{i=1}^{n} \left(\alpha \cdot \frac{V_i'}{V_{\max}'} + \beta \cdot \frac{S_i'}{S_{\max}'} + \gamma \cdot \frac{D_i}{D_{\max}} \right) \tag{13}$$

This assessment model is characterized by the comprehensive consideration of the electrical characteristics, topology and operation status of the distribution network, especially the inclusion of short-circuit capacity changes in the assessment system, which makes the model more consistent with the physical characteristics of the active distribution network. We achieve a comprehensive assessment by considering system vulnerability, economy and stability simultaneously through a multi-objective optimization approach. The model has strong adaptability and extensibility, and can be applied to different types of distribution network systems by adjusting the weights of each index according to actual needs. This vulnerability assessment model provides a theoretical basis for the optimization strategy of active distribution networks, which can guide the optimal allocation of distributed power sources and energy storage systems and improve the safe and stable operation of the system.

2.3 Vulnerability assessment methodology

This section details the vulnerability assessment method of distribution network based on short-circuit capacity change, which can comprehensively and accurately reflect the vulnerability status of active distribution network through a systematic assessment process and provide scientific basis for the subsequent optimization strategy. The assessment method mainly consists of four key steps: data collection and pre-processing, short circuit capacity calculation and analysis, vulnerability index calculation, and result analysis and application. The assessment process involves collecting basic data of the distribution network, including network topology, line parameters, load distribution, distributed power supply configuration and other information. Specific data items to be collected are distribution network topology data such as the number of nodes, connection relationship, line length, etc., and line parameter data such as impedance parameter, rated capacity, and line type. Load data such as node load size, power factor, load characteristics, etc., distributed power data such as type, capacity, location, output characteristics, etc.; energy storage system data such as capacity, charging and discharging characteristics, initial charge state, etc., and historical operation data such as voltage fluctuations, power flow, short circuit fault records, etc. The data preprocessing stage should standardize the collected data, eliminate abnormal values, and supplement missing data to ensure the accuracy of subsequent calculations. According to the characteristics of the distribution network, suitable typical scenarios are selected for analysis, such as maximum load, minimum load, and maximum output of distributed power sources. Short-circuit capacity is the core indicator for assessing the vulnerability of distribution networks, and its calculation method is as follows:

$$S_{cc,i} = \frac{U_i^2}{Z_{th,i}} \tag{14}$$

Consider the short-circuit capacity of node i changes after the access of distributed power supply as:

$$S'_{cc,i} = \frac{U_i^2}{Z_{th,i} \| Z_{DG,i}} \tag{15}$$

where $Z_{DG,i}$ is the distributed power equivalent impedance of the access node i. The amount of short-circuit capacity change due to distributed power access is:

$$\Delta S_{cc,i} = S'_{cc,i} - S_{cc,i} \tag{16}$$

Based on the short-circuit capacity data, each vulnerability index is calculated, and the electrical distance C_{ij} between nodes, i.e:

$$C_{ij} = \frac{S'_{cc,i} \cdot S'_{cc,j}}{Z_{ij}} \tag{17}$$

Calculate the node vulnerability metric V_i', i.e:

$$V_i' = \sum_{j=1}^{n} \frac{1}{C_{ij}} \tag{18}$$

Calculate the short-circuit capacity sensitivity index S_i', i.e:

$$S_i' = \frac{\Delta V_i}{\Delta S_{cc,i}} \cdot \frac{S'_{cc,i}}{V_i'} \tag{19}$$

Calculate the node degree centrality metric D_i, i.e:

$$D_i = \frac{k_i}{n-1} \tag{20}$$

Calculate the node composite vulnerability indicator CV_i', i.e:

$$CV_i' = \alpha \cdot \frac{V_i'}{V'_{\max}} + \beta \cdot \frac{S_i'}{S'_{\max}} + \gamma \cdot \frac{D_i}{D_{\max}} \tag{21}$$

Calculate the overall system vulnerability indicator V_{sys}, i.e:

$$V_{sys} = \sum_{i=1}^{n} CV_i' \tag{22}$$

The determination of weight coefficients α, β and γ can be done by using hierarchical analysis method (AHP) or expert scoring method, which is reasonably set according to the characteristics of different distribution networks. The vulnerability indicators obtained through the calculation can be used to identify the system weak links, and the nodes with higher values of CV_i' are the weak nodes of the system that need to be focused on. Evaluate the overall vulnerability of the system, determine the overall vulnerability level of the system through the V_{sys} value, analyze the impact of distributed power supply access, and compare the change of vulnerability indicators before and after access. Guide the optimization decision, provide the basis for the optimized configuration of distributed power supply and energy storage system.

To verify the effectiveness of the proposed vulnerability assessment method, we take the IEEE33 node system as an example for instance analysis. Table 1 shows the results of system vulnerability assessment under different distributed power access schemes.

From the data in the table, it can be seen that a reasonable distributed power access scheme can effectively reduce the system vulnerability and network loss at the same time. Scenario 3 has the best performance in reducing system vulnerability and network loss, which proves the effectiveness of the proposed vulnerability assessment method. The vulnerability assessment method proposed in this section has the following advantages: it is more in line with the physical characteristics of the active distribution network by considering the short-circuit capacity variation. The integrated consideration of electrical characteristics and topology makes the assessment more comprehensive, the assessment process is systematized and easy to implement, and the assessment results are intuitive and clear to guide practice.

Table 1: Different DG access solution vulnerability assessment results

Plan	DG access node	DG capacity (MW)	System vulnerability	Network loss reduction rate	Max CV value
0	-	-	8.76	-	0.92
1	6, 18	0.8, 1.2	7.43	18.5%	0.78
2	12, 25, 30	0.6, 0.8, 0.6	6.89	22.3%	0.71
3	8, 14, 24, 30	0.5, 0.6, 0.7, 0.5	6.25	25.8%	0.65

3 Active distribution network optimization strategy

3.1 Optimizing the objective function

Constructing an active distribution network optimization objective function is the focus of this study, and we design a multi-objective optimization function that takes into account both economy and stability based on the previous vulnerability assessment. Traditional distribution network optimization often focuses only on economic indicators such as network loss minimization, but with the access of a large number of distributed power sources, system stability becomes equally important. Based on this background, we propose an active distribution grid optimization objective function that considers system vulnerability, i.e:

$$\min F = \min\left(P_{loss} + \alpha \cdot V_{total}\right) \tag{23}$$

where P_{loss} is the system active network loss, V_{total} represents the total vulnerability of the system, and α is the weighting coefficient used to balance the relative importance of economy and stability.

The system active network loss P_{loss} can be calculated by the following equation:

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n} G_{ij}\left(U_i^2 + U_j^2 - 2U_iU_j\cos\theta_{ij}\right) \tag{24}$$

where G_{ij} denotes the conductance between nodes i and j, U_i and U_j are the node voltage amplitudes, and θ_{ij} is the phase angle difference, respectively. The total system vulnerability V_{total} is then evaluated using the evaluation method proposed in the previous sections, i.e:

$$V_{total} = \sum_{i=1}^{n} CV_i' \tag{25}$$

To make the objective function more comprehensive, we also consider the voltage offset index and construct a three-objective optimization function, namely:

$$\min F = \min\left(w_1 \cdot P_{loss} + w_2 \cdot V_{total} + w_3 \cdot \Delta V\right)_e \tag{26}$$

where ΔV is the system voltage offset, w_1, w_2 and w_3 are the weight coefficients and satisfy $w_1 + w_2 + w_3 = 1$. The voltage offset is calculated as:

$$\Delta V = \sum_{i=1}^{n}\left|U_i - U_{ref}\right| \tag{28}$$

U_{ref} is usually taken as 1.0p.u . as the reference voltage value.

The following constraints must be satisfied during the optimization process:

There are in terms of current constraints:

$$\begin{cases} P_i - P_{Di} = U_i \sum\limits_{j=1}^{n} U_j\left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) \\ Q_i - Q_{Di} = U_i \sum\limits_{j=1}^{n} U_j\left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) \end{cases} \tag{29}$$

The voltage constraint is expressed as:

$$U_i^{\min} \le U_i \le U_i^{\max} \tag{30}$$

The voltage constraint is expressed as:

$$S_{ij} \leq S_{ij}^{\max} \tag{31}$$

Distributed power output constraints are included:

$$\begin{aligned} P_{DG,i}^{\min} \leq P_{DG,i} \leq P_{DG,i}^{\max} \\ Q_{DG,i}^{\min} \leq Q_{DG,i} \leq Q_{DG,i}^{\max} \end{aligned} \tag{32}$$

Energy storage system constraints are then available:

$$\begin{aligned} P_{ESS,i}^{\min} \leq P_{ESS,i} \leq P_{ESS,i}^{\max} \\ SOC_{i}^{\min} \leq SOC_{i} \leq SOC_{i}^{\max} \end{aligned} \tag{33}$$

The selection of weight coefficients has a great impact on the optimization results, and Table 2 shows the impact of different weight combinations on the optimization results of the IEEE33 node system. Table 2 shows the effect of different weight combinations on the optimization results of the IEEE33 node system. As can be seen from the table, the optimization results under different weight combinations have their own focuses, with the economic priority scheme having the lowest network loss but other indexes are worse, the stability priority scheme having the smallest vulnerability, the voltage quality priority scheme having the smallest voltage offset, and the balanced optimization scheme having a better balance among the three indexes and the optimal overall index. In practice, the weight coefficients can be flexibly adjusted according to the specific distribution network characteristics and operational requirements to meet the needs of different scenarios. The proposed optimization objective function takes economy and stability into account to achieve multi-objective optimization, introduces vulnerability indicators to enhance the system's ability to resist disturbances, adjustable weight coefficients to adapt to different distribution network characteristics and operational requirements, and a simple objective function form to facilitate the implementation of the project, which provides a theoretical basis for the optimization strategy of the active distribution network and is of great significance in improving the level of safe and stable operation of the system.

Table 2: Effects of different weight combinations on optimization results

Weight combination	$P_{loss}(kW)$	V_{total}	$\Delta V(p.u.)$	Index	Features
$w_1 = 0.8, w_2 = 0.1, w_3 = 0.1$	125.3	6.82	0.187	0.628	Economy
$w_1 = 0.1, w_2 = 0.8, w_3 = 0.1$	142.7	5.46	0.195	0.573	Stability
$w_1 = 0.1, w_2 = 0.1, w_3 = 0.8$	138.5	6.35	0.142	0.612	Voltage quality
$w_1 = 0.33, w_2 = 0.33, w_3 = 0.33$	132.6	5.94	0.165	0.547	Balance

3.2 Optimization Algorithm Design

In this section, for the high-dimensional nonlinear characteristics of the active distribution network optimization problem, this paper designs a hybrid optimization strategy of the jellyfish search (JS) algorithm and the modified butterfly optimization (MBOA) algorithm. This hybrid strategy combines the global search capability of the JS algorithm with the local fine search capability of the MBOA algorithm, and is used to address the limitations of a single algorithm in dealing with complex optimization problems.

The jellyfish search algorithm simulates the group foraging behavior of jellyfish, which has the characteristics of simple implementation and fast convergence. Inside the JS algorithm the position update of individual jellyfish is categorized into three modes: active motion, following motion and time-controlled motion. The active motion is denoted as:

$$X_i^{new} = X_i + \alpha \cdot (-1 + 2 \cdot rand) \cdot (UB - LB) \tag{34}$$

The following motion is denoted as:

$$X_i^{new} = X_i + \beta \cdot \left(X_{best} - X_i \right) \cdot rand \tag{35}$$

where X_{best} is the current optimal position and β is the following intensity parameter.

The time-controlled motion is denoted as:

$$X_i^{new} = LB + rand \cdot (UB - LB) \tag{36}$$

The Butterfly Optimization Algorithm (BOA) simulates the butterfly's foraging and mating behavior, including a global search phase and a local search phase. The standard BOA algorithm is easy to fall into local optimization, so two improvement strategies are proposed:

(1) Dynamic switching probability mechanism, which replaces the original fixed switching probability p with dynamically changing $p(t)$, i.e.:

$$p(t) = p_{\min} + \left(p_{\max} - p_{\min} \right) \cdot \left(1 - \frac{t}{T_{\max}} \right)^2 \tag{37}$$

where t is the current iteration number, $T_{\max}$ is the maximum iteration number, and $p_{\min}$ and $p_{\max}$ are the minimum and maximum switching probabilities, respectively, so that the algorithm performs the global search with a larger probability at the early stage and the posterior search with a larger probability at the later stage.

(2) Gaussian variation strategy, in order to enhance the population diversity, Gaussian variation operation is introduced, i.e:

$$X_i^{new} = X_i + \sigma(t) \cdot N(0,1) \tag{38}$$

where $N(0,1)$ is the standard normal distribution and $\sigma(t)$ is the dynamically varying strength of the variance, i.e:

$$\sigma(t) = \sigma_{\max} \cdot \exp\left(-\gamma \cdot \frac{t}{T_{\max}} \right) \tag{39}$$

where $\sigma_{\max}$ is the maximum variation intensity and γ is the attenuation coefficient.

A hybrid optimization strategy is designed based on the above two algorithms, and the specific steps include the initialization parameters, including the population size, the maximum number of iterations, and the algorithm parameters.

Randomly generate the initial population $X=\left\{X_1, X_2, \ldots, X_N\right\}$, each individual represents a feasible distribution network reconfiguration scheme; calculate the fitness value of each individual, i.e. the value of the objective function is:

$$F\left(X_i\right)=w_1 \cdot P_{loss}\left(X_i\right)+w_2 \cdot V_{total}\left(X_i\right)+w_3 \cdot \Delta V\left(X_i\right) \tag{40}$$

Record the current optimal individual X_{best} and its fitness value F_{best}.

Enter the main loop, for each generation $t=1,2,\ldots,T_{\max}$, compute the current dynamic parameters $p(t)$ and $\sigma(t)$, and generate random numbers $r \in [0,1]$ for each individual X_i in the population, and perform the position of the JS algorithm if $r < p(t)$ Update, generate random number $r_1 \in [0,1]$, if $r_1 < 0.5$, perform active motion update X_i, otherwise perform follow motion update X_i. Otherwise perform position update of MBOA algorithm, perform aroma propagation or visual search to update X_i, and perform Gaussian variation operation on X_i with certain probability. Check whether X_i satisfies the constraints, and correct it if it does not. Calculate the fitness value $F\left(X_i^{new}\right)$ for the new position, and accept the new position $X_i = X_i^{new}$ if $F\left(X_i^{new}\right) < F\left(X_i\right)$. Update the global optimal solution X_{best} and F_{best}, and if the optimal solution does not improve for consecutive k generations, perform a time-controlled motion to reinitialize some individuals. The output optimal solution X_{best} and its fitness value F_{best} is the optimal distribution network reconfiguration scheme.

To verify the effectiveness of the proposed algorithm, it is tested on the IEEE33 node system and Table 3 shows the performance comparison of different algorithms in solving the active distribution network optimization problem. From the table, it can be seen that the proposed JS-MBOA hybrid algorithm outperforms the other algorithms in terms of convergence speed, solution accuracy and stability.The JS-MBOA algorithm converges in only 72 generations on average, and it has a computation time of 24.2 seconds, an optimal solution of 0.521 and a success rate of 94%. This shows that the JS-MBOA hybrid algorithm can effectively solve the active distribution network optimization problem, which provides strong support for the safe and stable operation of distribution networks.

Table 3: Different algorithm performance comparison

Algorithm	Average convergence algebra	Average calculation time	Optimal solution	Success rate
GA	156	42.3s	0.583	82%
PSO	124	36.7s	0.562	85%
JS	98	28.5s	0.547	88%
BOA	112	32.6s	0.554	84%
MBOA	86	26.8s	0.536	91%
JS-MBOA	72	24.2s	0.521	94%

3.3 Optimize strategy implementation

This section details the implementation process of the hybrid algorithm based on jellyfish search and improved butterfly optimization, showing the algorithm parameter setting and optimization result analysis. The specific parameters include the step length control $\alpha = 0.3$

and the following intensity $\beta = 0.6$ of the jellyfish search algorithm, the dynamic switching probability bounds $p_{min} - 0.1, p_{\max} = 0.9$ and Gaussian variance intensity $\sigma = 0.4$, exponential decay coefficient $\gamma = 3$, and the population size and maximum number of iterations are 50 and 150, respectively. For the weighting coefficients, a balanced setting $w_1 = 0.33, w_2 = 0.33, w_3 = 0.33$ is adopted to ensure the comprehensive optimization of economy, system vulnerability and voltage offset. The optimization process adopts multi-dimensional index tracking to record the change of fitness value in each iteration, the use of jellyfish search time to control the motion strategy to prevent local extreme value traps, and the improvement of the butterfly algorithm to balance the global and local exploration capability through dynamic switching probability and Gaussian variance. Table 4 shows the comparative results of the optimization strategy implementation. Tests based on the IEEE-33 node system show that the strategy reduces the active network loss from 165.4kW to 126.4kW, a reduction of 23.6%; the system vulnerability index is reduced from 7.54 to 6.11, and the voltage offset is reduced from 0.198p.u. to 0.163p.u., an overall reduction of 17.7%.

Table 4: Comparison of the implementation results of optimization strategies

Index	Before	After	Rate of change
Good work leads to network loss (kW)	165.4	126.4	-23.6%
System vulnerability	7.54	6.11	-18.9%
Voltage offset (p.u.)	0.198	0.163	-17.7%

Fig. 1 shows the iterative trend of the fitness value during the optimization process, which decreases rapidly at the initial stage and stabilizes after about 100 generations, indicating good convergence of the algorithm. For the weak nodes 14 and 25 of the system, 35% of the energy storage capacity is allocated, which improves the electrical connection weakness and reduces the fault sensitivity. The significant reduction of network loss also brings economic benefits to the operator. The scheme is flexible and adjustable in parameters, applicable to different sizes of distribution networks, supports multi-objective trade-offs, and meets diverse engineering needs. The hybrid algorithm overcomes the shortcomings of a single algorithm, which is easy to fall into local optimization, and the results are stable and reliable as confirmed by multiple tests. Overall, the optimization strategy includes strict parameter configuration, process monitoring and result feedback mechanism, which is effective in reducing system vulnerability, improving economy and guaranteeing voltage quality, and provides a feasible technical solution for the intelligent operation of distribution networks and efficient utilization of distributed resources.

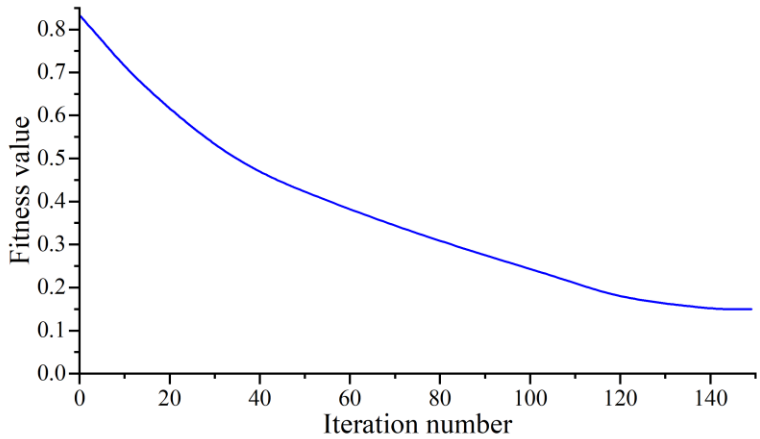

Figure 1: Optimize the trend of the target function iteration

4 Simulation experiment and result analysis

4.1 Experimental design

In order to verify the effectiveness of the distribution network vulnerability assessment method and active distribution network optimization strategy based on the short circuit capacity change of the grid, this paper designs a systematic simulation experiment scheme, which is based on the MATLAB R2023a platform combined with the MATPOWER 7.1 toolbox for the tidal current calculation and system analysis. The experimental environment uses Intel Core i9-12900K processor, 64GB RAM and Windows 11 operating system.

Three typical test systems are selected for the experiments, i.e., the IEEE33 node system, the IEEE69 node system, and a real distribution system (a distribution network under a 110kV/10kV substation in a capital city of a province, containing 87 nodes).The IEEE standard test system is representative and comparable, while the real system is able to validate the methodology's applicability in a complex environment, and the basic parameters of the three test systems are shown in Table 5. Table 5 shows the basic parameters of the three test systems. In order to comprehensively assess the impact of different DG access scenarios on system vulnerability, four typical DG configuration scenarios are designed, as shown in Table 6.

Table 5: Test system basic parameters

System	Point	Branch road	Total load	Reference voltage	Initial network loss
IEEE33	33	32	3.715MW	12.66kV	202.67kW
IEEE69	69	69	3.802MW	12.66kV	224.95kW
Actual distribution network	87	86	5.426MW	10.00kV	312.38kW

Table 6: Design of distributed power source configuration scenarios

Scene	DG type	Capacity ratio	Features
1	Photovoltaic	20% of the total load	Strong intermittency and scattered layout
2	Wind power	15% of the total load	High volatility, concentrated layout
3	Photovoltaic + energy storage	Photovoltaic 15%+ energy storage 10%	Enhanced schedulable
4	Photovoltaic + wind power + energy storage	Photovoltaic 10%+ wind power 10%+ energy storage 10%	Diversified complementary configuration

In order to simulate the load fluctuation characteristics of the actual distribution network, K-means clustering method is used to extract five typical daily load curves from the historical load data, which represent weekdays, weekends, summer peaks, winter peaks, and spring and fall flat peaks, respectively, and 24 hours of load data are selected for each typical day to form 120 load scenarios, and Fig. 2 shows the five typical daily load curves.

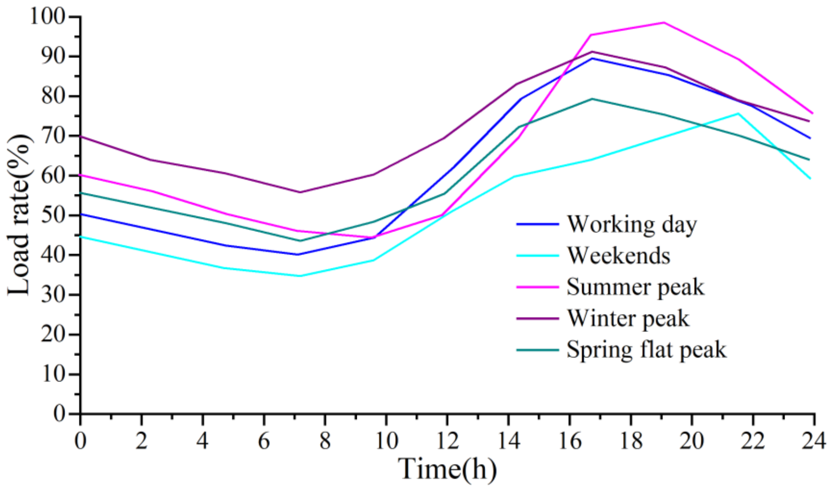

Figure 2: Five typical daily load curves

To accurately calculate the short circuit capacity change, the following steps are used:

(1) Calculate the short-circuit capacity of each node of the original system $S_{cc,i}^{orig} = \frac{U_i^2}{Z_{th,i}^{orig}}$.

(2) Calculate the new equivalent impedance $Z_{th,i}^{new} = Z_{th,i}^{orig} \parallel Z_{DG,i}$ after the access of distributed power.

(3) Calculate the short-circuit capacity after access $S_{cc,i}^{new} = \frac{U_i^2}{Z_{th,i}^{new}}$.

(4) Calculate the amount of short circuit capacity change $\Delta S_{cc,i} = S_{cc,i}^{new} - S_{cc,i}^{orig}$.

Four sets of comparison experiments are designed for the experiments in this paper. Experimental group 1 verifies the impact of short-circuit capacity changes on vulnerability assessment and compares the vulnerability assessment results with and without considering short-circuit capacity changes. Experimental group 2 verifies the impact of different DG access scenarios on system vulnerability and compares the system vulnerability changes under four DG scenarios. Experimental group 3 verifies the effectiveness of the proposed optimization strategy and compares the system vulnerability, network loss and voltage offset before and after optimization. Experimental group 4 verifies the performance of the proposed hybrid algorithm and compares the solving effect of the JS-MBOA algorithm with GA, PSO, JS, BOA and MBOA algorithms.

4.2 Analysis of experimental results

In this section, the results of simulation experiments are analyzed in detail to examine the impact of short circuit capacity variation on the vulnerability of the distribution network. Figure 3 shows the correlation between short-circuit capacity change and node vulnerability in the IEEE33 node system.

From the data in the figure, it can be seen that short-circuit capacity change and node vulnerability indexes show an obvious negative correlation, which means that nodes with increased short-circuit capacity generally have lower vulnerability indexes. This phenomenon is particularly obvious in the node 18-25 region, where the rate of change of short circuit capacity is larger, resulting in the most significant changes in the vulnerability indicators, and these experimental data strongly validate the reliability of short circuit capacity as an important indicator for assessing the vulnerability of distribution networks.

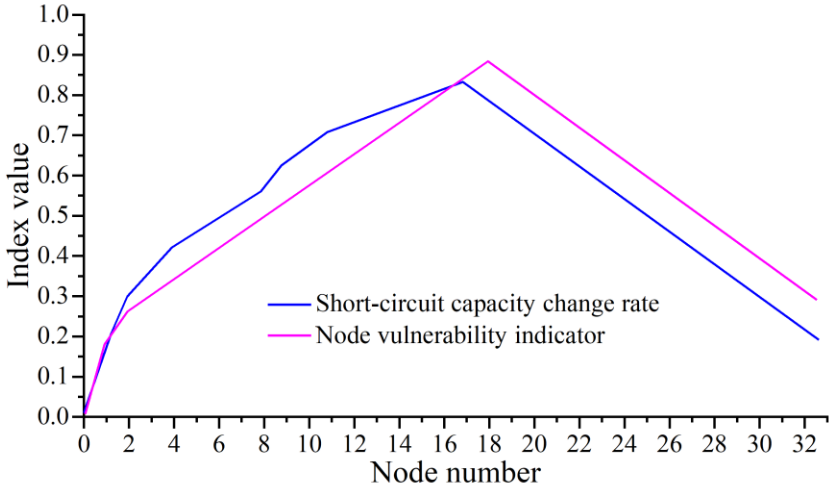

Figure 3: Short-circuit capacity variation and node vulnerability

Figure 4 shows the improvement of each index before and after optimization, and Table 7 shows the comparison results of system performance indexes under different DG access scenarios. From the figure, it can be seen that compared with the multiple complementary configuration scheme, the optimized configuration scheme has significant improvement in each index, and the system vulnerability, network loss improvement rate and voltage offset improvement rate are increased by 8.5, 12.3 and 8.8 percentage points, respectively, and these experimental results strongly prove the effectiveness and practical value of the proposed optimization strategy. As can be seen from the table, the multiple complementary configuration (Scenario 4) performs better than the single energy access scheme, with the system fragility, network loss and voltage offset reduced by 21.8%, 25.28% and 24.7%, respectively. After the optimized configuration, the indicators are further improved, the system fragility is reduced to 6.11, which is 30.3% lower than the original system, the network loss is reduced to 126.40kW, which is 37.63% lower, and the voltage offset is reduced to 0.143p.u., which is 33.5% lower, which are sufficient proof that the diversified complementary energy configurations can effectively improve the system stability and economy.

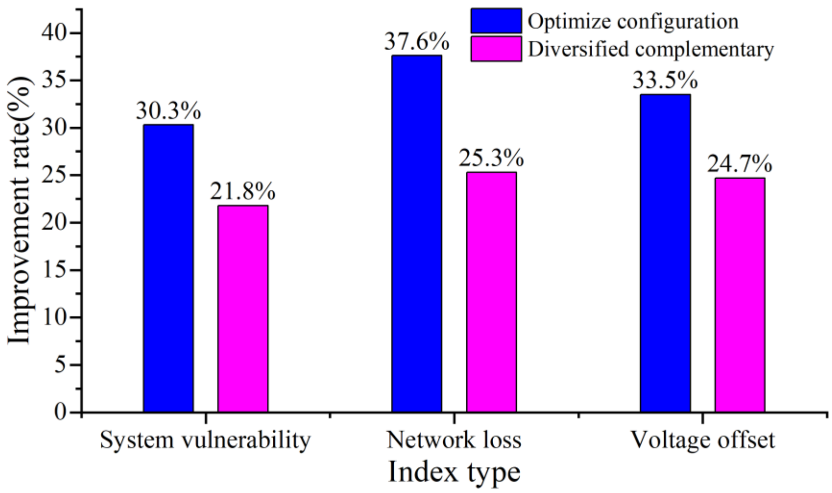

Figure 4: Optimize the strategy effect comparison diagram

Table 7: Different DG access scenario system can be used

Scene	System vulnerability	Network loss	Network loss reduction rate	Voltage offset	Max node vulnerability
Primal	8.76	202.67kW	-	0.215p.u.	0.92(Node 18)
1	7.85	172.34kW	14.96%	0.187p.u.	0.85(Node 18)
2	7.92	176.52kW	12.90%	0.192p.u.	0.87(Node 18)
3	7.23	158.76kW	21.67%	0.175p.u.	0.79(Node 25)
4	6.85	151.43kW	25.28%	0.162p.u.	0.73(Node 14)
Optimization	6.11	126.40kW	37.63%	0.143p.u.	0.65(Node 14)

The test results for IEEE69 node system and real distribution network also show that the optimization strategy has good applicability in different scales of distribution networks, and the optimized configuration scheme reduces the system vulnerability by 28.7%, the network loss by 34.2%, and the voltage offset by 31.5% in the test of real distribution network, which is a significant effect. Moreover, by comparing and analyzing the system performance under different load scenarios, it is found that the proposed optimization strategy is more effective under high load scenarios, and the improvement rate of system vulnerability reaches 33.8% under the summer peak load scenario, and 27.5% under the spring and autumn peak scenarios, which indicates that the optimization strategy can play a greater role in the case of higher system pressure. The experimental results fully prove that the distribution network vulnerability assessment method based on short circuit capacity change can accurately reflect the system vulnerability. The hybrid optimization strategy combining the jellyfish search algorithm and the improved butterfly optimization algorithm can effectively reduce the system vulnerability and improve the economy and voltage quality, which provides a strong support for the safe and stable operation of the active distribution network, and at the same time provides new ideas and directions for the subsequent research.

5 Conclusion

This paper systematically studies the problem of distribution network vulnerability assessment and optimization after large-scale grid integration of distributed power sources. This study proposes a vulnerability assessment method for distribution networks based on short-circuit capacity change, and establishes a vulnerability assessment system that is more in line with the physical characteristics of the power system. The study shows that there is a significant negative correlation between short-circuit capacity change and node vulnerability, and the node vulnerability index decreases significantly when the short-circuit capacity is increased. In this paper, a hybrid optimization strategy of jellyfish search algorithm and improved butterfly optimization algorithm is developed, which balances global and local search capacity through dynamic switching probability mechanism. The experimental data show that the JS-MBOA hybrid algorithm has obvious advantages over traditional optimization methods in terms of convergence speed, solution accuracy and stability.

In this paper, a multi-objective optimization model is designed to achieve the synergistic optimization of distribution network security, economy and power quality by considering the key indexes such as system vulnerability, active network loss and voltage offset. Verified by IEEE standard test system and real distribution network cases, the optimized configuration scheme reduces system vulnerability, network loss and voltage offset, and comprehensively improves the system operation performance index. The above research results are of great practical significance for improving the security, economy and reliability of active distribution networks, and provide new ideas and methods for constructing a more resilient and efficient modern distribution network.

Funding

This work was supported by China Southern Power Grid Science and Technology Projects Research on Online Monitoring of Short-circuit Parameters of Active Distribution Network Based on Domestic Non-fault Disturbance Measurement Technology（GZKJXM20240672）

References

[1] Yang, Y., & Lo, K. (2024). China's renewable energy and energy efficiency policies toward carbon neutrality: A systematic cross-sectoral review. Energy & Environment, 35(1), 491-509.

[2] Li, P., Sun, W., Zhang, Z., He, Y., & Wang, Y. (2022). Forecast of renewable energy penetration potential in the goal of carbon peaking and carbon neutrality in China. Sustainable Production and Consumption, 34, 541-551.

[3] Eltamaly, A. M., Mohamed, Y. S., El-Sayed, A. H. M., & Elghaffar, A. N. A. (2019). Impact of distributed generation (DG) on the distribution system network. Annals of the Faculty of Engineering Hunedoara, 17(1), 165-170.

[4] Adefarati, T., & Bansal, R. C. (2016). Integration of renewable distributed generators into the distribution system: a review. IET Renewable Power Generation, 10(7), 873-884.

[5] Rehman, N., Mufti, M. U. D., & Gupta, N. (2024). Power flow analysis in a distribution system penetrated with renewable energy sources: a review. International Journal of Ambient Energy, 45(1), 2305701.

[6] Perera, D., Meegahapola, L., Perera, S., & Ciufo, P. (2014). Characterisation of flicker emission and propagation in distribution networks with bi-directional power flows. Renewable Energy, 63, 172-180.

[7] Dorostkar-Ghamsari, M. R., Fotuhi-Firuzabad, M., Lehtonen, M., & Safdarian, A. (2015). Value of distribution network reconfiguration in presence of renewable energy resources. IEEE Transactions on Power Systems, 31(3), 1879-1888.

[8] Ghiani, E., & Pisano, G. (2018). Impact of renewable energy sources and energy storage technologies on the operation and planning of smart distribution networks. In Operation of distributed energy resources in smart distribution networks (pp. 25-48). Academic Press.

[9] Zhu, L., Lv, X., & Liang, Q. (2024, June). Tidal Flow Assessment Algorithm for Microgrid Distribution Network Integration. In 2024 6th International Conference on Energy Systems and Electrical Power (ICESEP) (pp. 995-999). IEEE.

[10] McDonald, J. (2008). Adaptive intelligent power systems: Active distribution networks. Energy Policy, 36(12), 4346-4351.

[11] Zhou, H., Chen, S., Lai, J., Lu, X., Yu, C., Hu, W., ... & Zhou, D. (2018). Modeling and synchronization stability of low-voltage active distribution networks with large-scale distributed generations. IEEE Access, 6, 70989-71002.

[12] Ponnaganti, P., Pillai, J. R., & Bak-Jensen, B. (2018). Opportunities and challenges of demand response in active distribution networks. Wiley Interdisciplinary Reviews: Energy and Environment, 7(1), e271.

[13] Lin, C., Wu, W., Zhang, B., Wang, B., Zheng, W., & Li, Z. (2016). Decentralized reactive power optimization method for transmission and distribution networks accommodating large-scale DG integration. IEEE Transactions on Sustainable Energy, 8(1), 363-373.

[14] Xing, H., Fan, H., Sun, X., Hong, S., & Cheng, H. (2018). Optimal siting and sizing of distributed renewable energy in an active distribution network. CSEE journal of power and energy systems, 4(3), 380-387.

[15] Zhao, J., Wang, H., Wu, Q., Hatziargyriou, N. D., & Shen, F. (2020). Optimal generator start-up sequence for bulk system restoration with active distribution networks. IEEE Transactions on Power Systems, 36(3), 2046-2057.

[16] Sekhavatmanesh, H., & Cherkaoui, R. (2020). A multi-step reconfiguration model for active distribution network restoration integrating DG start-up sequences. IEEE Transactions on Sustainable Energy, 11(4), 2879-2888.

[17] Al Kaabi, S. S., Zeineldin, H. H., & Khadkikar, V. (2013). Planning active distribution networks considering multi-DG configurations. IEEE Transactions on Power Systems, 29(2), 785-793.

[18] Arianos, S., Bompard, E., Carbone, A., & Xue, F. (2009). Power grid vulnerability: A complex network approach. Chaos: An Interdisciplinary Journal of Nonlinear Science, 19(1).

[19] Saleh, M., Esa, Y., & Mohamed, A. (2018). Applications of complex network analysis in electric power systems. Energies, 11(6), 1381.

[20] Bose, D., Chanda, C. K., & Chakrabarti, A. (2020). Vulnerability assessment of a power transmission network employing complex network theory in a resilience framework. Microsystem Technologies, 26(8), 2443-2451.

[21] Beyza, J., Ruiz-Paredes, H. F., Garcia-Paricio, E., & Yusta, J. M. (2020). Assessing the criticality of interdependent power and gas systems using complex networks and load flow techniques. Physica A: Statistical Mechanics and its Applications, 540, 123169.

[22] Bai, H., & Miao, S. (2015). Hybrid flow betweenness approach for identification of vulnerable line in power system. IET Generation, Transmission & Distribution, 9(12), 1324-1331.

[23] Wang, T., Cheng, H., & Wang, X. (2020). A link addition method based on uniformity of node degree in interdependent power grids and communication networks. Physica A: Statistical Mechanics and its Applications, 560, 125112.

[24] Liu, B., Li, Z., Chen, X., Huang, Y., & Liu, X. (2017). Recognition and vulnerability analysis of key nodes in power grid based on complex network centrality. IEEE Transactions on Circuits and Systems II: Express Briefs, 65(3), 346-350.

[25] Abedi, A., Hesamzadeh, M. R., & Romerio, F. (2021). An ACOPF-based bilevel optimization approach for vulnerability assessment of a power system. International Journal of Electrical Power & Energy Systems, 125, 106455.

[26] Wu, D., Ma, F., Javadi, M., Thulasiraman, K., Bompard, E., & Jiang, J. N. (2017). A study of the impacts of flow direction and electrical constraints on vulnerability assessment of power grid using electrical betweenness measures. Physica A: Statistical Mechanics and its Applications, 466, 295-309.

[27] Bompard, E., Pons, E., & Wu, D. (2013). Analysis of the structural vulnerability of the interconnected power grid of continental Europe with the Integrated Power System and Unified Power System based on extended topological approach. International Transactions on Electrical Energy Systems, 23(5), 620-637.

[28] Luo, L., Han, B., & Rosas-Casals, M. (2016). Network hierarchy evolution and system vulnerability in power grids. IEEE Systems Journal, 12(3), 2721-2728.

[29] Bompard, E., Napoli, R., & Xue, F. (2010). Extended topological approach for the assessment of structural vulnerability in transmission networks. IET generation, transmission & distribution, 4(6), 716-724.

[30] Che, Y., Jia, J., Zhao, Y., He, D., & Cao, T. (2019). Vulnerability assessment of urban power grid based on combination evaluation. Safety science, 113, 144-153.

[31] Pu, C., Wu, P., & Xia, Y. (2019). Vulnerability assessment of power grids against link-based attacks. IEEE Transactions on Circuits and Systems II: Express Briefs, 67(10), 2209-2213.

[32] Jin, M., Lavaei, J., & Johansson, K. H. (2018). Power grid AC-based state estimation: Vulnerability analysis against cyber attacks. IEEE Transactions on Automatic Control, 64(5), 1784-1799.

[33] Yang, L., & Teh, J. (2023). Review on vulnerability analysis of power distribution network. Electric Power Systems Research, 224, 109741.

[34] Hakimollahi, H., Ramezani, M. R., Karati, A. A. M., & Amraei, N. (2017, April). Studies of seismic vulnerability assessment and improvement in Tehran Province electricity distribution network. In 2017 Conference on Electrical Power Distribution Networks Conference (EPDC) (pp. 51-54). IEEE.

[35] Darestani, Y. M., Shafieezadeh, A., & DesRoches, R. (2017). Effects of adjacent spans and correlated failure events on system-level hurricane reliability of power distribution lines. IEEE Transactions on Power Delivery, 33(5), 2305-2314.

[36] Luo, L., Pagani, G. A., & Rosas-Casals, M. (2016). Spatial and performance optimality in power distribution networks. IEEE Systems Journal, 12(3), 2557-2565.

[37] Sun, P., & Dong, Y. (2020, November). On vulnerability analysis of nodes against cross-domain cascading failures propagation in active distribution network cyber-physical system. In 2020 7th International Conference on Dependable Systems and Their Applications (DSA) (pp. 355-363). IEEE.

[38] Li, F., Xie, R., Yang, B., Guo, L., Ma, P., Shi, J., ... & Song, W. (2019). Detection and identification of cyber and physical attacks on distribution power grids with pvs: An online high-dimensional data-driven approach. IEEE Journal of Emerging and Selected Topics in Power Electronics, 10(1), 1282-1291.

[39] Liu, N., Hu, X., Ma, L., & Yu, X. (2021). Vulnerability assessment for coupled network consisting of power grid and EV traffic network. IEEE transactions on smart grid, 13(1), 589-598.

[40] Xu, D., Zhou, B., Chan, K. W., Li, C., Wu, Q., Chen, B., & Xia, S. (2018). Distributed multienergy coordination of multimicrogrids with biogas-solar-wind renewables. IEEE Transactions on Industrial Informatics, 15(6), 3254-3266.

[41] Wen, J., Lin, S., Qu, X., & Xiao, Q. (2023). A TOPSIS-based vulnerability assessment method of distribution network considering network topology and operation status. IEEE Access, 11, 94358-94370.

[42] Tang, L., Han, Y., Zhou, S., Zalhaf, A. S., Yang, P., Wang, C., ... & Lu, C. (2025). Identification and vulnerability assessment of critical components in distribution networks under high penetration rate conditions. Energy, 318, 134864.