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A Two-Stage Fault Reconfiguration Strategy for Distribution Networks with High Penetration of Distributed Generators

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Abstract: In distribution networks with high penetration of distributed generators (DGs), traditional fault reconfiguration strategies often fail to achieve maximum load recovery and encounter operational stability challenges. This paper proposes a novel two-stage fault reconfiguration strategy that addresses both the fault ride-through capability and output uncertainty of DGs. The first stage introduces a rapid power restoration reconfiguration model that integrates network reconfiguration with fault ride-through, enabling DGs to provide power support to the distribution network during faults, thereby significantly improving the recovery rate of lost loads. An AdaBoost-enhanced decision tree algorithm is utilized to accelerate the computational process. The second stage proposes a post-recovery optimal reconfiguration model that uses fuzzy mathematics theory and the transformation of chance constraints to quantify the uncertainty of both generation and load, thereby improving the system's static voltage stability index. Case studies using the IEEE 69-bus system and a real-world distribution network validate the effectiveness of the proposed strategy. This two-stage strategy facilitates short-term rapid load power restoration and enhances long-term operational stability, improving both the resilience and reliability of distribution networks with high DG penetration. The findings of this research contribute to enhancing the fault tolerance and operational efficiency of modern power systems, which is essential for integrating higher levels of renewable energy.

Keywords: distributed generator; network reconfiguration; fault ride-through; uncertainty; decision tree



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1. Introduction

The primary task of a distribution network is to deliver electricity to end-users. As society progresses, users' demands for the quality and reliability of power supply have been steadily increasing. Distributed generators (DGs) provide a broader range of energy sources for distribution networks. However, as the penetration level of DGs increases, maintaining smooth and uninterrupted operation of distribution networks presents significant challenges. Renewable energy devices typically lack the rotational inertia inherent to conventional thermal power units, resulting in a weakened frequency regulation capability of the grid. To address frequency stability issues, grid-forming inverter technologies, such as virtual synchronous generators, virtual impedance control, virtual inertia control, and virtual oscillator control, have been developed [1–3].

The power output of distributed renewable energy sources is inherently volatile, which may lead to local voltage rises or sags, resulting in voltage violations. To mitigate these effects, DGs can be effectively coordinated with other flexibility resources across multiple time scales through mechanisms such as virtual power plants (VPPs) and microgrids [4,5]. This coordination enables aggregated resources to participate as a unified entity in electricity market operations, facilitating optimized dispatch. Furthermore, by deploying energy storage systems, fluctuations in distributed generation output can be smoothed, thereby achieving better power matching between generation and load [6]. In distribution networks with high DG penetration, bidirectional power flows become common, rendering traditional grid protection schemes insufficient. Adaptive protection schemes or novel intelligent algorithms need to be developed to address these new protection challenges [7]. Islanded microgrid technologies offer a promising solution by enabling parts of the distribution system to operate independently from the main grid following a fault [8].

In addition, fault reconfiguration serves as an essential means to ensure supply reliability and maintain smooth, uninterrupted operation of the system. Fault reconfiguration technology refers to an optimization technique whereby, upon a fault occurring in the distribution network, the system's topology is modified to transfer the lost load in non-faulted areas to other feeders or generators that still have power supply capability, enabling rapid restoration of power supply [9].

The integration of a substantial number of DGs into distribution networks has introduced significant challenges to the fault reconfiguration process [10,11]. On one hand, DGs have transformed the distribution network from a traditional single-source structure to a multi-source structure, providing more flexible and diverse recovery options in case of faults. DGs with frequency regulation and voltage stabilization capabilities can support islanded operation of the distribution network during faults, while DGs with fault ride-through capabilities can forcibly remain connected to the grid for a short period to support system power balance [12,13]. On the other hand, the multi-source structure complicates fault reconfiguration, requiring consideration of factors such as power output characteristics and topological constraints. Moreover, the uncertainty of DG output necessitates dynamic adjustments to fault reconfiguration strategies [14].

The issue of fault reconfiguration for distribution networks with DGs has been extensively addressed in the existing literature, with the primary focus on fault ride-through (FRT) characteristics during fault events and the impacts of post-fault uncertainty. In [15], the authors investigate the relationship between fault ride-through characteristics of DGs and their power recovery support capabilities, proposing a multi-stage self-healing method based on the margin capacity of interconnection lines. In [16], the authors analyze the electrical output characteristics of inverter-based DGs during both normal operation and fault ride-through conditions. In [17], the authors propose a fault reconfiguration scheme for distribution networks that coordinates reclosing operations with DGs' LVRT capabilities. However, these studies have primarily focused on analyzing the impact of DGs' fault ride-through characteristics on fault reconfiguration, while offering limited incorporation of this condition within the reconfiguration algorithms themselves.

In [18], the authors emphasize that to ensure the long-term stability of distribution networks, fault reconfiguration strategies must account for dynamic variations in generation and load over multiple time periods. In [19], the authors use C-Vine Copula and conditional probability to characterize the dynamic uncertainty of renewable energy sources. In [20], the authors analyze the impact of the stochastic nature of renewable energy output on system stability, and propose a fault reconfiguration algorithm based on probabilistic power flow. In [21], a fault recovery model based on robust stochastic optimization is proposed to address the uncertainty of DG output. However, the methods still exhibit the following

issues: they rarely account for the uncertainties associated with the output of DGs and load power, leading to lower reliability; and they primarily focus on load shedding and switch operation counts, with less consideration given to the impact on system stability. Additionally, the stability indicators for distribution networks are often nonlinear, making them difficult to handle [22].

In the absence of sufficient operational data and accurate forecasting methods, fuzzy mathematical theory provides an effective approach for analyzing uncertainty, and offers greater applicability in practical scenarios [23,24]. In [25], the authors investigate energy management in multi-energy microgrids using an optimization algorithm integrated with fuzzy decision-making techniques, demonstrating the effectiveness of fuzzy methods in handling uncertain conditions in complex energy systems. In [26], the authors propose a two-stage robust adaptive model, based on a predictive control approach, for the optimal scheduling of integrated energy systems, incorporating fuzzy-inspired uncertainty modeling and adaptive control to balance economy and robustness.

The fault ride-through capability and output uncertainty of DGs exhibit differences in time scales. During the fault recovery process, fault ride-through plays a role in the early stages of the fault, while output uncertainty affects the system's operation after the fault. Few studies simultaneously consider the impacts of both factors and achieve the dual objectives of rapid power restoration and long-term operational stability. Furthermore, due to the inclusion of fault ride-through control and output uncertainty of DGs, fault reconfiguration models tend to be nonlinear and complex. Traditional solution methods may suffer from slow computational speed [27], which makes them less suitable for fast power restoration requirements. To address this, heuristic algorithms, such as decision trees [28] and genetic algorithms [29], are often used to enhance solution speed. Nevertheless, these methods still face challenges, such as the risk of converging to local optima in complex scenarios and the requirements of high quality for training data.

To address the issues outlined above, this paper proposes a two-stage fault reconfiguration strategy that comprehensively considers both the fault ride-through capability and the output uncertainty of DGs, aiming to improve both the short-term power restoration performance and the long-term operational stability of the distribution network system. Specifically, the contributions of this paper are as follows:

1. Establishing a rapid power restoration reconfiguration model, in which different handling strategies are applied to various types of DGs during fault recovery by adding specific constraint conditions, handled based on the Big-M method, that account for the fault ride-through, improving the load recovery percentage for areas that have lost power supply;
2. Proposing a fast solution algorithm for the reconfiguration model based on an AdaBoost-enhanced decision tree, which accelerates the solving process while maintaining the same accuracy;
3. Establishing a post-recovery optimal reconfiguration model by assessing system stability using a linearized static voltage stability index, modeling the uncertainty of DG output and load power based on fuzzy mathematics theory, and applying fuzzy chance constraint transformation to facilitate the model's solution.

The main contents of the subsequent sections are as follows: Section 2 analyzes the role of DGs in distribution network fault recovery, including a classification-based treatment strategy for DGs, which considers fault ride-through capabilities and analysis of uncertainty and stochastic processes, and presents a two-stage fault reconfiguration strategy. Section 3 proposes a rapid power restoration strategy and introduces a fast solution algorithm based on AdaBoost-enhanced decision trees. Section 4 establishes a post-recovery optimal reconfiguration model, incorporating fuzzy representations of

uncertainties and the transformation of fuzzy chance constraints. Section 5 conducts case studies using the IEEE standard system and a real-world distribution network example, comparing multiple algorithms to validate the effectiveness of the proposed approach. Finally, Section 6 concludes the paper.

2. The Impacts of DGs on Distribution Network Fault Recovery

2.1. Analysis of the Support Capability of DGs

2.1.1. Fault Ride-Through Characteristics of DGs

Considering the safety and stability of active distribution networks, DGs should have low-voltage ride-through (LVRT) capability [30]. IEEE 1547-2018 [31] establishes relevant requirements for the fault ride-through capability of DGs, classifying them into three response categories. DGs should have LVRT capability, meaning that when grid disturbances or faults cause voltage drops at the point of common coupling (PCC), DGs should continue to operate without disconnecting from the grid for a specified duration. This helps to prevent cascading failures that could lead to widespread power outages. The requirements for the LVRT capability of DGs are shown in Figure 1.

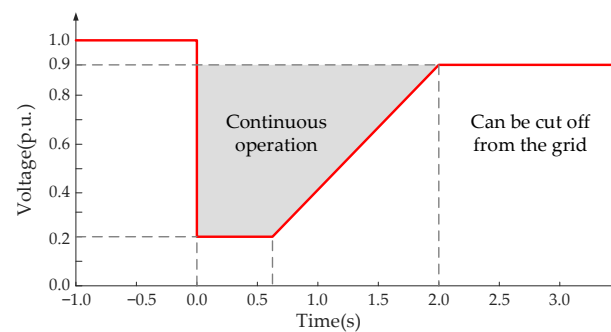


Figure 1. Standard requirements for LVRT capability of DG.

In the normal operation region ($U_{DG} \geq 0.9$ p.u.), the DG remains in a grid-connected state. When the voltage drop is relatively minor ($0.2 \text{ p.u.} \leq U_{DG} \leq 0.9 \text{ p.u.}$), the DG continues to operate without disconnecting from the grid, with an output power not less than 80% of that before the disturbance or fault occurred. When the voltage drop point is severe ($U_{DG} \leq 0.2$ p.u.), the DG is disconnected from the system.

During the fault recovery process, the status of the DG may vary with voltage and frequency fluctuations at the PCC. Considering the limitations in the data processing capabilities of equipment and the real-time requirements for generating power restoration schemes, it is necessary to simplify the calculation of the DG's support capacity for engineering purposes.

When a fault causes a voltage drop at U_{DG} , the total output current may exceed the maximum allowable short-circuit current due to the control strategy. To ensure device safety, the DG output power is subject to the following constraint:

$$\begin{cases} P_{DG}^2 + Q_{DG}^2 \leq I_{\max}^2 U_{DG}^2, & U_{DG} > 0.2 \text{ p.u.} \\ P_{DG} = 0, \quad Q_{DG} = 0, & U_{DG} \leq 0.2 \text{ p.u.} \end{cases} \quad (1)$$

where P_{DG} is the active power of the DG; Q_{DG} is the reactive power of DG. $I_{\max}$ is typically 1.2 to 2 times the rated current [32].

2.1.2. Handling Strategies for Different Types of DGs During Fault Recovery

Currently, inverter-based DGs, such as wind and solar DGs, can be categorized into grid-following and grid-forming types based on their grid connection control methods. Both grid-forming DGs and grid-following DGs with fault ride-through capabilities can provide active support to the system during fault recovery. Therefore, different handling strategies should be considered for different types of DGs.

(1) Directly decommissioned type

After fault isolation, if there is no grid-forming DG within the downstream area of the fault point to provide frequency or voltage support, DGs without fault ride-through capability should be decommissioned.

(2) Fault ride-through type

After a fault occurs, grid-forming DGs and grid-following DGs with fault ride-through capabilities begin fault ride-through. If the voltage meets the requirements, the DGs remain connected to the grid; otherwise, they are disconnected.

2.2. Analysis of the Output Uncertainty of DGs

For a distribution system that has just recovered from a fault and is in a relatively fragile state, the uncertainty in both power supply (from DGs) and load demand can exacerbate system instability, posing significant risks. The calculation based on the state of the system at the time of the fault will lead to neglect of the potential power change of the generation and load, and this prediction error will make the reconfiguration result no longer effective. After fault isolation and partial restoration, it is essential to readjust the distribution network to adapt to subsequent operational requirements and enhance its long-term operational capability.

The power output of DGs during a fault recovery period can be predicted using various forecasting methods. However, due to measurement errors during data collection, as well as the inherent limitations of predictive models in addressing complex scenarios, significant deviations may arise between the actual power output of the DG and its predicted value. This deviation can be expressed as follows:

$$\tilde{P}_{DG}^t = \bar{P}_{DG}^t + \Delta_{DG}^t \quad (2)$$

where $\tilde{P}_{DG}^t$ is the actual power value of the DG at time t ; $\bar{P}_{DG}^t$ is the predicted power value of the DG at time t ; and Δ_{DG}^t denotes the deviation between the actual value and the predicted value of the DG.

The deviation between the predicted and actual output values of DGs is commonly described using probability distribution functions. The probability distribution functions for the output deviation of various types of DGs are as follows:

(1) Photovoltaic generation

The probability distribution function for the deviation between the predicted and actual output of a photovoltaic generator can be described by the TLS (t location-scale) distribution, as expressed mathematically below:

$$\phi(\tilde{P}_{pv}^t) = \frac{\Gamma(\frac{v+1}{2})}{\sigma_{pv}\sqrt{v\pi}\Gamma(\frac{v}{2})} \left(\frac{v + \left(\frac{\tilde{P}_{pv}^t - \bar{P}_{pv}^t}{\sigma_{pv}} \right)^2}{v} \right)^{-\frac{v+1}{2}} \quad (3)$$

where $\tilde{P}_{pv}^t$ and $\bar{P}_{pv}^t$ represent the actual and predicted power values of the photovoltaic system at time t , respectively; σ_{pv} and ν are the parameters for the probability distribution of the photovoltaic output deviation; and Γ is the Gamma function.

(2) Wind turbine generation

The probability distribution function for the deviation between the predicted and actual output of a wind turbine generator can be described by the Weibull distribution, with the following mathematical expression:

$$\bar{P}_{wind}^t = \begin{cases} 0, & v_{wind}^t \leq v_{wind,ci} \\ a + bv_{wind}^t, & v_{wind,ci} \leq v_{wind}^t \leq v_{wind,e} \\ P_{wind,e}, & v_{wind,e} \leq v_{wind}^t \leq v_{wind,co} \end{cases} \quad (4)$$

$$a = \frac{P_{wind,e}v_{wind,ci}}{v_{wind,ci} - v_{wind,e}}, \quad b = \frac{P_{wind,e}}{v_{wind,e} - v_{wind,ci}} \quad (5)$$

$$\phi(\tilde{P}_{wind}^t) = \frac{K}{C} \left(\frac{\bar{P}_{wind}^t - a}{bC} \right)^{K-1} \exp \left[- \left(\frac{\bar{P}_{wind}^t - a}{bC} \right)^K \right] \quad (6)$$

where $\tilde{P}_{wind}^t$ and $\bar{P}_{wind}^t$ are the actual and predicted power values of the wind turbine at time t , respectively; v_{wind}^t is the wind speed at time t ; $v_{wind,ci}$, $v_{wind,co}$, and $v_{wind,e}$ are the cut-in, cut-out, and rated wind speeds of the wind turbine, respectively; $P_{wind,e}$ is the rated output power of the wind turbine; K is the shape parameter of the Weibull distribution; and C is the scale parameter.

(3) Conventional DGs

Conventional DGs, such as gas turbines and diesel generators, generally produce stable power output when the fuel supply is sufficient. The power output deviations of such systems are often modeled using a discrete 0–1 probability distribution. In this model, the generator is assumed to either be in normal operation, producing the scheduled power output, or shut down, producing no power. The mathematical expression for this is as follows:

$$P(\tilde{P}_{DG,c}^t = \bar{P}_{DG,c}^t) = p_{normal} \quad (7)$$

where $\tilde{P}_{DG,c}^t$ and $\bar{P}_{DG,c}^t$ are the actual and scheduled power values of the conventional DG at time t , respectively, and p_{normal} is the probability that the generator is operating normally.

2.3. Two-Stage Fault Reconfiguration Strategy for Distribution Networks with DGs

The traditional fault reconfiguration strategy does not consider the changes brought about by DG integration. Firstly, the DG's fault ride-through capability provides additional power support. Secondly, the output uncertainty of DGs will make the restored system potentially unstable. Ignoring these factors will make the reconfiguration result unreliable. In the early stage of the fault, the primary task is to ensure the continuous power supply of important loads. After the fault is completely isolated and the system is restored to stability, the grid-connected DG can be re-connected to the system. At this point in time, the power grid can be reconfigured again to eliminate short-term overload and ensure the long-term stable operation of the system until the faulted line is repaired. It is difficult for existing methods to meet the requirements of load recovery speed and long-term stability at the same time.

The LVRT characteristics exhibit dynamic responses in a matter of seconds, while the output volatility involves longer time scales. Based on the above analysis, to maximize the support capability of DGs in the early stages of a fault and simultaneously consider the

potential long-term stability impacts of their output uncertainty on the system, a staged optimization strategy must be adopted.

In response to the above problems, this paper proposes a two-stage fault reconfiguration strategy, as shown in Figure 2.

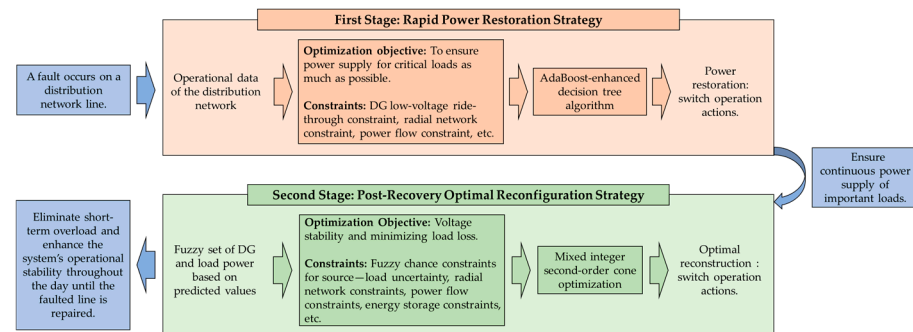


Figure 2. Two-stage fault reconfiguration strategy for distribution network with DGs.

The first stage is a rapid power restoration stage, considering the LVRT capability of DGs and aiming to minimize load shedding, and involves fast optimal calculations. It makes full use of the support capacity of the DG, and provides a very fast solution speed, which can provide a rapid power supply restoration scheme.

The second stage is a post-recovery optimal reconfiguration stage, aiming to optimize system stability and minimize load shedding. It focuses on dealing with the uncertainty of DGs and loads, improving the stability of the distribution network system for a long time.

3. Rapid Power Restoration Strategy

3.1. Rapid Power Restoration Reconfiguration Model Considering FRT Capability of DGs

3.1.1. Objective Function of Rapid Power Restoration Reconfiguration Model

After a fault occurs, we assume that the fault location has already been identified, and that the faulted lines have been isolated from the network. In the rapid power restoration stage following a fault, the system's primary objective is to restore power to the lost loads as quickly as possible by regulating tie switches and fully utilizing DGs and other devices capable of supporting the system's power supply. Thus, the optimization strategy for this stage is focused on ensuring continuous power supply to critical loads, with the objective function formulated as follows:

$$F_1 = \min \sum_{i \in \Omega_{\text{load}}} \omega_i (P_{\text{load},i,0} - P_{\text{load},i}) \quad (8)$$

In Equation (8), ω_i is the priority of load i , where a larger value indicates higher importance of the load; $P_{\text{load},i,0}$ is the pre-fault power of load i ; $P_{\text{load},i}$ is post-fault power of load i ; and Ω_{load} is the set of loads connected to the system.

3.1.2. Constraints of Rapid Power Restoration Reconfiguration Model

The rapid power restoration reconfiguration model must satisfy the following constraints:

(1) DG output power constraint

The constraint on the DG's output described in Equation (1) is a piecewise function, which is handled using the Big-M method in this paper:

$$\begin{cases} P_{\text{DG}}^2 + Q_{\text{DG}}^2 \leq I_{\text{max}}^2 U_{\text{DG}}^2 \\ -M\alpha_{\text{on}} \leq P_{\text{DG}}^2 + Q_{\text{DG}}^2 \leq M\alpha_{\text{on}} \\ \alpha_{\text{on}} \leq U_{\text{DG}}/0.2 \end{cases} \quad (9)$$

α_{on} is a binary variable, where a value of 1 indicates that the DG is connected to the grid, and 0 indicates that the DG is disconnected; and M is a sufficiently large positive constant. In this paper, M was calibrated as the upper limit of the DG output power.

For DGs using a virtual impedance control strategy, they are handled by introducing the auxiliary binary variables α_{z1} and α_{z2} :

$$\begin{cases} Z_{DG} = \alpha_{z1}Z_0 + \alpha_{z2}Z_{\text{virtual}} \\ \alpha_{z1} + \alpha_{z2} = 1 \\ 0.9\alpha_{z1} + 0.2\alpha_{z2} \leq U_{DG} \leq \alpha_{z1} + 0.9\alpha_{z2} \end{cases} \quad (10)$$

where Z_{DG} is the additional impedance in series with the DG, Z_0 is the impedance of the DG during normal operation, and Z_{virtual} is the virtual additional impedance of the DG.

(2) Radial network constraint

The distribution network should maintain radial operation, ensuring that the reconfigured network does not form unintended islands. In this paper, a description method based on the non-connectivity condition of the power supply loop is adopted [33]. Compared to the conventional spanning tree model, this method offers a reduced scale and complexity.

$$\begin{cases} \sum_{l=1}^L y_l = N_b - 1 \\ \sum_{m=1}^{M_h} y_{hm} \leq M_h - 1, h = 1, 2, \dots, H \end{cases} \quad (11)$$

where l is the branch index of the distribution network; L is the total number of branches; N_b is the number of nodes; y_l is a binary variable representing the status of the l -th branch, where 1 indicates that the branch is closed and 0 indicates that the branch is open; M_h is the number of branches in the h -th power supply loop; H is the total number of power supply loops; and y_{hm} is a binary variable representing the status of the m -th branch in the h -th power supply loop.

(3) Other constraints

Other constraints are provided in Appendix A, including power flow constraints using second-order cone relaxation, line operational safety constraints to prevent line overloads, voltage constraints to prevent overvoltage at nodes, and energy storage output constraints.

3.2. Fast Solution Algorithm for Rapid Power Restoration Reconfiguration Model

3.2.1. Fast Solution Algorithm Based on Decision Trees

For the power restoration model established above, conventional mathematical optimization methods may struggle to meet the real-time solution requirements. To overcome this challenge, this paper proposes a fast solution algorithm based on decision trees. This method based on decision trees has the characteristics of rapid computation speed and strong interpretability, while also exhibiting excellent adaptability to a wide range of operating conditions [34]. The workflow of the proposed method is shown in Figure 3.

The fast algorithm based on decision trees consists of two main components: the “knowledge base” and the “inference machine”. The “knowledge base” is a collection of instances, each containing the system’s operational state, fault details, and corresponding restoration plans. The “inference machine” is trained on the “knowledge base” samples by a decision tree generation algorithm. It can quickly infer the power restoration operation solutions based on fault characteristics.

The instances in the “knowledge base” are derived from the calculation results of the proposed power restoration optimization model or manually set and verified reasonable

solutions. The inference machine model is constructed using a decision tree algorithm improved by AdaBoost.

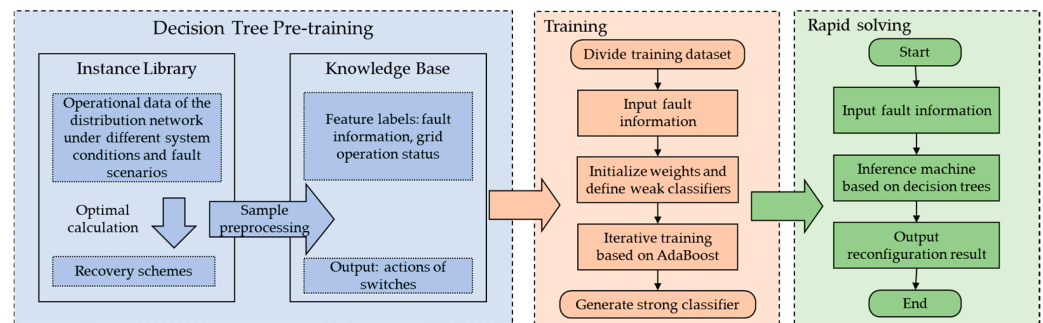


Figure 3. Flow chart of fast solution algorithm for power restoration strategy based on decision trees.

3.2.2. Steps of Solution Algorithm

The steps of the solution algorithm based on decision trees are as follows:

(1) Establishment of the instance library

Distribution network operation data are collected under different system conditions and fault scenarios, and reconfiguration problems are solved using optimization models to build the instance library for training. The feature labels for the instance library are selected as generation and load power, line status (on/off), energy storage status, and fault information. The solution, which is the output of the decision tree, corresponds to the switching actions of each connection switch.

(2) Construction of the knowledge base sample set

The feature labels serve as the classification criteria for the decision tree. To enhance the decision tree's accuracy, normalization and other preprocessing steps are applied to the feature labels in the instance library. For Boolean data (e.g., switch status), the value of 1000 represents a closed line, to mitigate the difference in magnitude between this and continuous data (e.g., power). For continuous data, normalization is performed using the rated values as the benchmark. Finally, the corresponding power restoration solution for each fault is added, completing the knowledge base sample set.

(3) Training of the inference machine based on the decision tree

The sample set of the knowledge base is divided into 70% for training and 30% for testing. The specific training algorithm is described in Section 3.2.3. After training, the decision tree inference machine for power restoration is generated. When a system fault is detected, the inference machine first processes the fault information and grid operation data according to the knowledge base standards. Then, the inference machine retrieves and infers the power restoration solution based on the trained decision tree, ultimately providing the recovery strategy.

3.2.3. AdaBoost-Enhanced Decision Tree

Ordinary decision tree training often employs algorithms like CART [34], but decision trees trained using CART typically serve as weak classifiers, and may lack accuracy when handling new fault scenarios. To address this issue, we propose an improved decision tree algorithm based on AdaBoost.

AdaBoost is capable of combining multiple weak classifiers into a strong classifier by following a specific rule [35]. It works by iteratively adjusting the weights of different samples, focusing more on those misclassified by previous iterations, thereby improving the overall decision accuracy. The specific process is outlined below:

- (1) Assume there are n training samples, where the i -th sample has a feature label X_i and a decision result Y_i . Set the initial weight of each sample as $D_{0,i} = 1/n$.
- (2) Iteratively train decision trees based on the CART algorithm to obtain m weak classifiers. In the CART algorithm, the Gini index is used as the criterion for node splitting [36].

At each iteration, the sample weights are updated, and the weight of the weak classifier in the current iteration is computed. Let E_j be the error rate of the weak classifier in the j -th iteration. The weight W_j of the classifier and the sample weights $D_{j,i}$ are updated as follows:

$$W_j = 0.5 \ln\left(\frac{1 - E_j}{E_j}\right) \quad (12)$$

$$D_{j,i} = \begin{cases} D_{j-1,i} e^{W_j / Z_j}, & \text{If the classification is correct} \\ D_{j-1,i} e^{-W_j / Z_j}, & \text{If the classification is incorrect} \end{cases} \quad (13)$$

where Z_j is the normalization factor.

- (3) After m iterations, m weak classifiers are generated. The final strong classifier is obtained by summing them with weights W_j . In this paper, the number of AdaBoost iteration rounds is 30 [37,38].

4. Post-Recovery Optimal Reconfiguration Strategy

During the rapid power restoration stage, DGs are allowed to operate under low voltage for a short period. However, prolonged operation in this fault ride-through state is not sustainable, as it poses the risk of overload and can undermine the long-term stability of the system. During the period when the faulted line has been isolated but not fully repaired (which typically ranges from several hours to a few days), the uncertainty of the output of DGs and load power fluctuations may also affect the stability of the system. Therefore, it is necessary to perform further optimal reconfiguration of the post-recovery system to ensure that it can operate safely and reliably over the long term.

4.1. DG and Load Uncertainty Models

4.1.1. Fuzzy Representation of Uncertainty Parameters

In Section 2.2, the probability distribution function for the output of DGs has been modeled. Similarly, the probability distribution function for load demand power can be described using the same approach.

$$\begin{cases} \tilde{P}_{\text{load}}^t = \bar{P}_{\text{load}}^t + \Delta_{\text{load}}^t \\ \phi(\tilde{P}_{\text{load}}^t) = \frac{1}{\sqrt{2\pi}\sigma_{\text{load}}} \exp\left[-\frac{(\tilde{P}_{\text{load}}^t - \bar{P}_{\text{load}}^t)^2}{2\sigma_{\text{load}}^2}\right] \end{cases} \quad (14)$$

where $\tilde{P}_{\text{load}}^t$ and $\bar{P}_{\text{load}}^t$ represent the actual and predicted power values of the load at time t , respectively, and Δ_{load}^t denotes the deviation between the actual and predicted load power. σ_{load} is the parameter for the normal distribution function describing the load power deviation.

In practical distribution network engineering, parameters for the probability distribution function of DGs' output and load power are often difficult to obtain accurately, due to factors such as sustained faults, which can affect subsequent processing. To address this issue, fuzzy mathematics theory provides an operational method with good accuracy [21]. The triangular membership function, known for its computational efficiency and

applicability in real-time systems, is used to describe the output of DGs and load power, as follows:

$$\mu(\tilde{P}_i^t) = \begin{cases} \frac{\tilde{P}_i^t - k_{i,1}^t \bar{P}_i^t}{\bar{P}_i^t - k_{i,1}^t \bar{P}_i^t}, & k_{i,1}^t \bar{P}_i^t \leq \tilde{P}_i^t \leq \bar{P}_i^t \\ \frac{k_{i,2}^t \bar{P}_i^t - \tilde{P}_i^t}{k_{i,2}^t \bar{P}_i^t - \bar{P}_i^t}, & \bar{P}_i^t \leq \tilde{P}_i^t \leq k_{i,2}^t \bar{P}_i^t \\ 0, & \text{other} \end{cases} \quad (15)$$

where $\tilde{P}_i^t$ is the actual output of the i -th DG at time t , and $\bar{P}_i^t$ is the predicted output of the i -th DG at time t . $k_{i,1}^t$ denote the positive scaling factors, and $k_{i,2}^t$ denote the negative scaling factors; they satisfy $0 < k_{i,1}^t < 1$, $k_{i,2}^t > 1$.

The triangular membership function parameters for each device can be derived through statistical fitting of the predicted data and actual measurement data. Taking photovoltaic generation as an example, the procedure is as follows:

First, a photovoltaic output forecasting model is used to obtain a time series of power fluctuation data at a specified time granularity (e.g., every 15 min). Next, the actual PV output power measurements at corresponding time points are collected, and the relative difference k_i^t between the actual measurement and predicted values is calculated. Then, the frequency distribution of k_i^t is obtained through statistical analysis. Finally, based on the frequency distribution of k_i^t , a triangular membership function is fitted to represent the uncertainty in the photovoltaic output.

Additionally, if the probability distribution function of the DG or the load power can be accurately described, the triangular membership function can also be directly fitted to the probability distribution function.

4.1.2. Transformation of Fuzzy Chance Constraints

Due to the incorporation of uncertainty, the deterministic model established in Section 3 for the rapid power restoration reconfiguration model requires revision. Specifically, the constraint conditions involving random variables, such as the output of DGs and load power (e.g., Equation (A13)), should be reformulated as fuzzy chance constraints:

$$\begin{cases} \text{Cr}\{\tilde{P}_{\text{load},j,t} + \sum_{k \in \Omega_{j,z}} P_{jk,t} - (\tilde{P}_{\text{DG},j,t} + P_{m,j,t} + P_{\text{ess},j,t}) - \sum_{i \in \Omega_{j,f}} (P_{ij,t} - r_{ij} I_{ij,t}^{\text{sqr}}) \leq 0\} \geq \alpha \\ \text{Cr}\{\tilde{Q}_{\text{load},j,t} + \sum_{k \in \Omega_{j,z}} Q_{jk,t} - (\tilde{Q}_{\text{DG},j,t} + Q_{m,j,t}) - \sum_{i \in \Omega_{j,f}} (Q_{ij,t} - x_{ij} I_{ij,t}^{\text{sqr}}) \leq 0\} \geq \alpha \end{cases} \quad (16)$$

where $\tilde{P}_{\text{DG},j,t}$ and $\tilde{Q}_{\text{DG},j,t}$ are the actual active and reactive power of the DG at node j at time t ; $\tilde{P}_{\text{load},j,t}$ and $\tilde{Q}_{\text{load},j,t}$ are the actual active and reactive power of the load at node j at time t ; $I_{ij,t}^{\text{sqr}}$ is the square of the current flowing through the line ij at time t ; $P_{m,j,t}$ and $Q_{m,j,t}$ are the active and reactive power outputs of the main grid at node j at time t ; $P_{\text{ess},j,t}$ is the charging and discharging power of the energy storage at node j at time t (discharge is positive); $\text{Cr}\{\cdot\}$ denotes the confidence level of the event that the load power is less than the power output of the source; and α is the confidence level of this event, and since the system optimal reconfiguration strategy aims to ensure reliable load supply, a higher value is chosen (e.g., $\alpha = 90\%$).

Based on the principle of fuzzy chance constraint equivalence transformation [25], when $\alpha > 0.5$, Equation (16) can be transformed as follows:

$$\begin{cases} \sum_{k \in \Omega_{j,z}} P_{jk,t} - \sum_{i \in \Omega_{j,f}} (P_{ij,t} - r_{ij} I_{ij,t}^{\text{sqr}}) - P_{m,j,t} - P_{\text{ess},j,t} + (2 - 2\alpha) \bar{P}_{\text{load},j,t} + (2\alpha - 1) k_{\text{load},2}^t \bar{P}_{\text{load},j,t} - (2 - 2\alpha) \bar{P}_{\text{DG},j,t} - (2\alpha - 1) k_{\text{DG},1}^t \bar{P}_{\text{DG},j,t} \leq 0 \\ \sum_{k \in \Omega_{j,z}} Q_{jk,t} - \sum_{i \in \Omega_{j,f}} (Q_{ij,t} - x_{ij} I_{ij,t}^{\text{sqr}}) - Q_{m,j,t} + (2 - 2\alpha) \bar{Q}_{\text{load},j,t} + (2\alpha - 1) k_{\text{load},2}^t \bar{Q}_{\text{load},j,t} - (2 - 2\alpha) \bar{Q}_{\text{DG},j,t} - (2\alpha - 1) k_{\text{DG},1}^t \bar{Q}_{\text{DG},j,t} \leq 0 \end{cases} \quad (17)$$

where $\bar{P}_{DG,j,t}$ and $\bar{Q}_{DG,j,t}$ are the predicted active and reactive power of the DG at node j at time t ; and $\bar{P}_{load,j,t}$ and $\bar{Q}_{load,j,t}$ are the predicted active and reactive power of the load at node j at time t .

By following the above steps, the uncertainty optimization is transformed into a deterministic optimization problem under a specific confidence level, thereby reducing the solving complexity.

4.2. Optimization Objective of Post-Recovery Optimal Reconfiguration Model

The uncertainty of generation and load leads to increasing power imbalances and voltage violations at nodes, which pose significant safety risks to the distribution networks [39]. Through optimal reconfiguration, the voltage distribution can be improved, thereby enhancing system stability. To address this, the optimization objective based on the static voltage stability index L_{ij} is given by the following:

$$L_{ij} = \frac{4[(x_{ij}P_{ij} - r_{ij}Q_{ij})^2 + (r_{ij}P_{ij} + x_{ij}Q_{ij})U_i^2]}{U_i^4} \quad (18)$$

where r_{ij} and x_{ij} are the resistance and reactance of branch ij ; P_{ij} and Q_{ij} are the active and reactive power flowing into node j ; U_i is the voltage at node i ; and the voltage stability is indicated by L_{ij} , where a value less than 1 signifies stability, and the closer it is to 0, the better the system's voltage stability. For distribution networks with multiple branches, the maximum value of L_{ij} across all lines is selected as the overall voltage stability indicator for the system.

Equation (18) is nonlinear and requires simplification. In practical applications of distribution networks, the voltage magnitudes and phase angles at both ends of the line are approximately equal. Therefore, $x_{ij}P_{ij}$ and $r_{ij}Q_{ij}$ can be considered approximately equal [40], allowing Equation (18) to be simplified as follows:

$$\tilde{L}_{ij} = 4(r_{ij}P_{ij} + x_{ij}Q_{ij}) - U_i^2 \quad (19)$$

where $\tilde{L}_{ij}$ less than 0 indicates voltage stability, and the smaller the value, the better the voltage stability.

The quadratic voltage terms in Equation (19) can be handled using second-order cone relaxation. Thus, the optimization objective F_{2_1} is given by the following:

$$F_{2_1} = \min \sum_{t=1}^T \tilde{L}_{ij,t} \quad (20)$$

where $\tilde{L}_{ij,t}$ represents the static voltage stability index of line ij at time t , and T is the number of scheduling periods.

To ensure the supply of critical loads, the optimization objective minimizing load shedding F_{2_2} is given by the following:

$$F_{2_2} = \min \sum_{t=1}^T \sum_{i \in \Omega_{load}} \omega_i (P_{load,i,t,0} - P_{load,i,t}) \Delta T \quad (21)$$

ΔT denotes the length of each scheduling period, which depends on the granularity of the power forecast for the source and load. $P_{load,i,t,0}$ and $P_{load,i,t}$ are the predicted and actual power of load i at time t , respectively.

Since the multiple objective functions in the proposed optimal reconfiguration model have different dimensions and magnitudes, normalization is required for each objective function:

$$F'_i = \frac{F_{i,\max} - F_i}{F_{i,\max} - F_{i,\min}} \quad (22)$$

where F'_i is the normalized value of the objective; and $F_{i,\max}$ and $F_{i,\min}$ are the maximum and minimum values of the objective i , respectively.

After normalization, the linear weighted sum is applied to obtain the fault reconfiguration objective function F_2 , which comprehensively considers the system's long-term voltage stability and load shedding:

$$F_2 = \min(\omega_1 F'_{2,1} + \omega_2 F'_{2,2}) \quad (23)$$

where ω_1 and ω_2 represent the weights of the two optimization objectives. In this paper, ω_1 is set to 0.4 and ω_2 is set to 0.6. Furthermore, the impact of different weight values on the optimization results is shown in Section 5.3.

4.3. Constraints of Post-Recovery Optimal Reconfiguration Model

The power flow constraints, radial network constraints, and other conditions of the post-recovery optimal reconfiguration model are fundamentally similar to those in the rapid power restoration reconfiguration model. The key distinction lies in the need to account for the power variations of DGs, loads, and energy storage devices over different time periods, where these variables are associated with distinct time instances. Additionally, some constraints must be transformed into fuzzy chance constraints, as detailed in Section 4.1.2.

The resulting model, which considers the uncertainty of the DG output, is a mixed-integer second-order cone optimization problem, and can be solved using solvers such as Gurobi.

5. Case Study

5.1. Case Study Model Description

In this study, two systems are used to analyze the performance of algorithms: an IEEE 69-bus distribution network with high penetration of DGs (as shown in Figure 4), and a certain 11-bus distribution network project (as shown in Figure 5). The DG penetration rates in these two systems are approximately 65% and 60%, respectively, and all connected DG units are equipped with fault ride-through capability. The specific parameters of the two systems, as well as the variations in power generation and load, are detailed in Appendix B.

In these cases, the faulty line exits operation. A variety of different fault cases were set up, as shown in Tables 1 and 2.

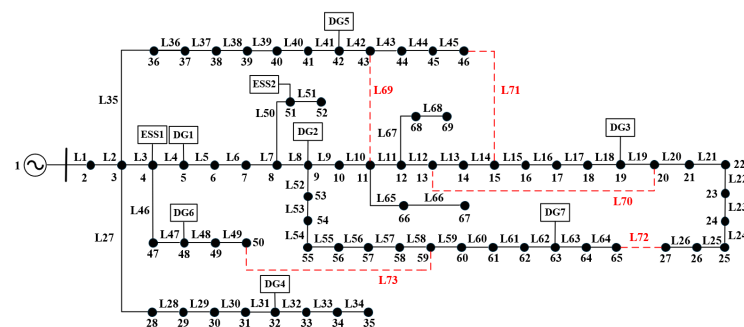


Figure 4. An IEEE 69-bus distribution network with DGs.

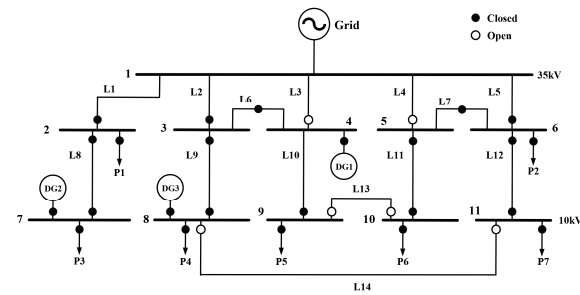


Figure 5. A real-world 11-bus distribution network.

Table 1. The fault cases of the 69-bus system.

Case Number	Faulty Line
1	L3
2	L10
3	L5 and L18
4	L38 and L64
5	L48; DG6 fault ride-through operation
6	L62; DG7 fault ride-through operation

Table 2. The fault cases of the 11-bus system.

Case Number	Faulty Line
1	L2
2	L9
3	L3 and L10
4	L4; DG1 fault ride-through operation

In Table 1, Case 1 simulates a fault occurring at the beginning of a branch line, resulting in the largest power outage area. Case 2 simulates a fault occurring in the middle section of a branch line, near a tie switch, which causes multiple power outage areas. Cases 3 and 4 simulate situations where multiple lines fail simultaneously. Cases 5 and 6 simulate line faults with DGs operating in fault ride-through mode. In Table 2, Cases 1–3 simulate single and multiple fault cases, while Case 4 simulates a line fault with a DG operating in fault ride-through mode.

5.2. Analysis of Calculation Results for the Rapid Power Recovery Stage

Based on the model and fault instance library established above, calculations for the first stage of rapid power recovery were performed. The results are shown in Tables 3 and 4.

Table 3. Load recovery results of 69-bus system.

Case Number	Reconfiguration Operation	Load Recovery Percentage		
		Primary Load	Secondary Load	Tertiary Load
1	L69 is closed	100%	100%	90.57%
2	L71 is closed	100%	100%	100%
3	L69 and L72 are closed	100%	100%	81.33%
4	L69 and L72 are closed	100%	100%	100%
5	L73 is closed	100%	100%	93.04%
6	L72 is closed	100%	100%	95.48%

Table 4. Load recovery results of 11-bus system.

Case Number	Reconfiguration Operation	Load Recovery Percentage		
		Primary Load	Secondary Load	Tertiary Load
1	L11 is closed	100%	100%	100%
2	L14 is closed	100%	100%	100%
3	L12 and L13 are closed	100%	100%	100%
4	L11 is closed	100%	100%	100%

From the results in Tables 3 and 4, it can be observed that the proposed algorithm successfully provides reasonable reconfiguration operations for different fault scenarios. The reconfiguration schemes differ across the various fault cases, indicating that the proposed algorithm is capable of analyzing different fault scenarios and providing tailored recovery solutions.

In all cases, the algorithm restores the power supply to all primary and secondary loads, ensuring that the most critical loads are prioritized for recovery. When the fault is relatively mild (e.g., Case 2 and Case 4 in Table 3), the algorithm restores power to all loads, as the system's damage is limited and the available resources are sufficient. However, in more severe fault scenarios (e.g., Case 1 and Case 3 in Table 3), the restoration of tertiary loads cannot be fully achieved. As the fault severity increases, the recovery rate for tertiary loads gradually decreases.

This demonstrates that the algorithm adapts to the severity of the fault and dynamically seeks to maximize load restoration, while dealing with the limitations imposed by the faulted lines. It is important to clarify that under more extreme fault conditions, the recovery rate for tertiary loads may be significantly lower, and even the restoration of primary and secondary loads might not reach 100%.

5.3. Analysis of Calculation Results for the Post-Recovery Optimal Reconfiguration Stage

The post-recovery optimal reconfiguration model in the second stage is solved using the Gurobi solver, with the calculation results presented in Tables 5 and 6. Loss of load refers to the total accumulated load shedding across all time periods. The worst $\tilde{L}_{ij}$ refers to the maximum $\tilde{L}_{ij}$ of all nodes in all periods (24 h) after reconfiguration, which can characterize the stability of the system.

Table 5. The results of the 69-bus system reconfiguration.

Case Number	Reconfiguration Operation	The Worst $\tilde{L}_{ij}$	Loss of Load (MWh)
1	L69 is closed	−0.8898	1.4664
2	L69 is closed	−0.9264	0.4602
3	L72 and L73 are closed	−0.9479	1.2070
4	L69 and L72 are closed	−0.9251	0.6349

Table 6. The results of the 11-bus system reconfiguration.

Case Number	Reconfiguration Operation	The Worst $\tilde{L}_{ij}$	Loss of Load (MWh)
1	L11 is closed	−0.9984	0
2	L14 is closed	−0.9919	0
3	L12 and L13 are closed	−0.9919	0

For the 11-bus system, the power supply is sufficient, and no load loss can be realized after the optimal reconfiguration. The value of the worst $\tilde{L}_{ij}$ is small, meaning that the voltage stability of the system is relatively high. For the 69-bus system, there is still some load loss after the optimal reconfiguration, but the stability of the system is also guaranteed.

Taking Case 1 as an example, the static voltage stability index curves for each node at different times are shown in Figure 6.

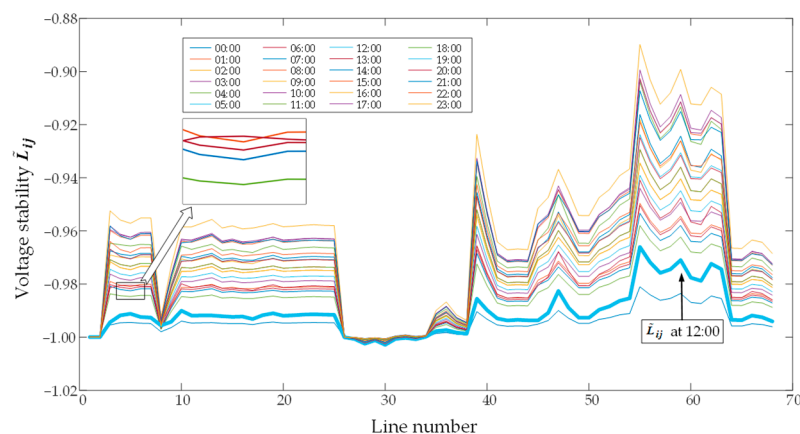


Figure 6. $\tilde{L}_{ij}$ change diagram of reconstructed system under L3 line fault.

In Figure 6, the different curves represent the static voltage stability index of each line in the distribution network at various times throughout a day. The topology of the network remains unchanged during the period shown in the figure, which explains the general similarity in the trends of the curves. However, due to random fluctuations in the output of DGs, the curves at different times exhibit differences. For example, the variation in Line 5 from 5:00 to 8:00, marked in the figure, highlights the effect of DG output fluctuations on voltage stability.

Throughout the day, the output of DGs and load variations cause the voltage stability index to fluctuate. During long-term operation, the value of $\tilde{L}_{ij}$ consistently meets the requirements (less than 0). Specifically, at 12:00, the value of $\tilde{L}_{ij}$ is relatively small, indicating that the load pressure is lower at this time. This can be considered a special case during long-term system operation. Using the power value of the source and load at this time for reconfiguration may result in a relatively large deviation.

These observations highlight the ability of the proposed algorithm to maintain voltage stability under varying conditions, ensuring that the system can recover efficiently from faults while keeping voltage fluctuations within acceptable limits.

In the proposed post-recovery optimal reconfiguration algorithm, the value of weight settings may affect the optimization result. Using the 69-bus system in Case 3 as an example, the results with different weight settings of voltage stability and load shedding are as follows.

As shown in Table 7, the impact of different weight settings on the optimal reconfiguration is minimal, as there is a certain positive relationship between the static voltage stability index and the load shedding amount: the more stable the system, the smaller the load shedding.

It is important to note that α should remain at a relatively high value to adequately account for the variability in DG output and load. Experiments with different values of α , including 80% and 90%, showed that the outcomes, such as load shedding and voltage stability, remained largely unchanged. This suggests that as long as α is sufficiently large, the specific value does not substantially impact the final results.

Table 7. The results with different weight settings of voltage stability and load shedding.

ω_1/ω_2	Reconfiguration Operation	Worst $\tilde{L}_{ij}$	Loss of Load (MWh)
0.1/0.9	L72 and L73 are closed	−0.9479	1.2070
0.4/0.6	L72 and L73 are closed	−0.9479	1.2070
0.9/0.1	L72 and L73 are closed	−0.9479	1.2070

5.4. Analysis of Comparison with Other Methods

5.4.1. Comparison of Reconfiguration Results of Different Methods

The conventional mathematical optimization method, ordinary decision trees, and AdaBoost-enhanced decision trees were used to calculate the fault cases of the 69-bus system, in order to verify the correctness and effectiveness of the proposed method. The weak classifier generation method with improved decision trees adopted the same CART algorithm as the ordinary decision trees method. All methods used the Gini index as the node splitting criterion; the relevant training parameters were set in the same way, and the fault sample set used for training was also the same. The conventional mathematical optimization method was solved using the Gurobi 10.0.2 solver. The reconfiguration results of the three methods are shown in Table 8.

Table 8. Comparison of the reconfiguration results of the different algorithms.

Case Number	Reconfiguration Results of Conventional Mathematical Optimization	Reconfiguration Results of Ordinary Decision Trees	Reconfiguration Results of AdaBoost-Enhanced Decision Trees
1	L69 is closed	L69 is closed	L69 is closed
2	L71 is closed	L71 is closed	L71 is closed
3	L69 and L72 are closed	L70 and L73 are closed	L69 and L72 are closed
4	L69 and L72 are closed	L71 and L72 are closed	L69 and L72 are closed
5	L73 is closed	L73 is closed	L73 is closed
6	L72 is closed	L72 is closed	L72 is closed

By comparing the results of the above three methods, it can be observed that the improved AdaBoost decision tree algorithm is consistent with the reconfiguration results obtained from conventional mathematical optimization, while the ordinary decision tree algorithm exhibits noticeable deviations. For example, in Case 4, the AdaBoost-enhanced decision tree method produces the same optimal switching strategy as the mathematical solver, ensuring almost full load recovery. In contrast, the ordinary decision tree method yields a suboptimal configuration that causes a large portion of the network to disconnect from the main power source, resulting in lower load restoration and potential voltage instability.

In Case 3, while all three methods produce feasible solutions that allow the system to operate under acceptable conditions, only the mathematical optimization method and the AdaBoost-enhanced decision tree method generate optimal configurations. The ordinary decision tree algorithm, due to its limited learning capacity and the absence of adaptive weighting for decision nodes, can only provide a suboptimal switching configuration, which leads to higher load losses and reduced overall performance.

5.4.2. Comparison of Load Recovery Speed of Different Methods

In the process of load recovery, the speed of load recovery depends on the calculation speed of the different methods. The 69-bus system was chosen for comparing the computa-

tion speed of the different algorithms, due to its larger scale. In addition, a new fault case was added (Case 7), in which L3 and L8 line are faulty.

The conventional mathematical optimization algorithm and the AdaBoost-enhanced decision tree algorithm were applied to calculate the results for the different fault cases of the 69-bus system. The conventional mathematical optimization method was solved using the Gurobi 10.0.2 solver. The computation times for both methods under identical fault cases are presented in Table 9.

Table 9. Comparison of the solving time of the different algorithms.

Case Number	Solving Time of Conventional Mathematical Optimization (s)	Solving Time of AdaBoost-Enhanced Decision Trees (s)
1	25.6861	0.2426
2	23.5707	0.2815
3	27.7653	0.2328
4	24.3391	0.3042
5	22.9184	0.2436
6	25.5102	0.2761
7	Non-convergence	0.2591

By comparing the solving times of the two algorithms in Table 5, it is evident that the AdaBoost-enhanced decision tree algorithm offers significantly faster computation. In Cases 1–6, the solving time of the conventional mathematical optimization method ranges from approximately 22 to 28 s, while the AdaBoost-enhanced decision tree algorithm completes the calculation in around 0.23 to 0.30 s, representing a reduction of about 90% in solving time. The AdaBoost-enhanced decision tree algorithm can rapidly retrieve power restoration solutions by learning from historical fault scenarios and system operating conditions, thereby avoiding the time-consuming process of solving complex mixed-integer nonlinear programming problems.

In practical engineering applications, minimizing the outage duration is critical, and fault reconfiguration decisions are typically required within a few seconds. The proposed fast-solving algorithm is therefore more aligned with real-time operational requirements.

Notably, in Case 7, where the faulty line is special, the conventional mathematical optimization approach fails to converge, due to increased model complexity. In contrast, the AdaBoost-enhanced decision tree algorithm still produces a feasible solution in this case. Although the generated solution requires further validation through power flow analysis, it nonetheless provides a viable reconfiguration scheme. This demonstrates the practical advantage of the proposed algorithm in handling complex or atypical fault scenarios.

5.4.3. Comparison of Algorithm Methods, Considering Different Factors

In the proposed two-stage fault reconfiguration strategy in this paper, the fault ride-through characteristics and output uncertainty of DGs are taken into account, allowing for the achievement of a higher load restoration ratio and better system stability. It is necessary to compare the proposed method with traditional methods that do not consider these factors, so as to demonstrate the advantages of the proposed method.

(1) The factor of DG fault ride-through

Case 5 and Case 6 of the 69-bus system and Case 4 of 11-bus system were used to analyze the impact of DG fault ride-through on the algorithm results. The load recovery results with and without considering fault ride-through are shown in Figure 7.

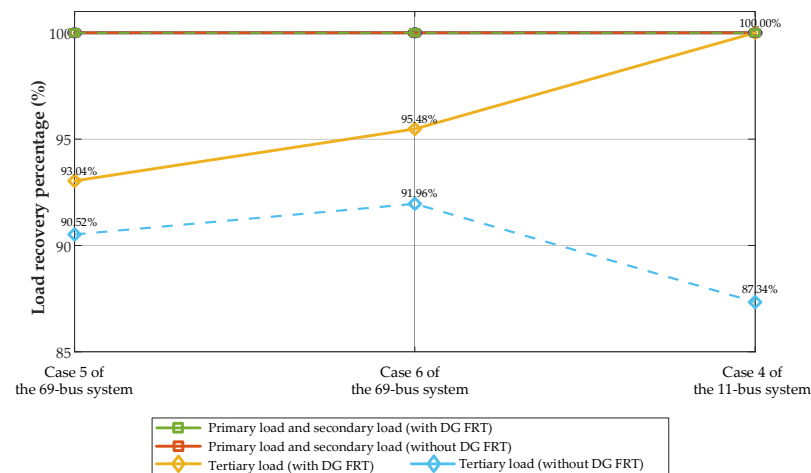


Figure 7. Comparison of load recovery results with/without considering FRT.

In Figure 7, the load recovery percentage of the method that does not consider the DG FRT capability is lower than that of the proposed method, which incorporates this factor. The case study results show that the proposed strategy achieves a higher load recovery rate, particularly in fault scenarios where DG disconnection is likely to occur.

For example, in Case 4 of the 11-bus system, the proposed method successfully restores all three levels of load. In contrast, the method without considering DG FRT restores only 87.34% of the tertiary load, resulting in a reduction of approximately 13%. Similarly, in the 69-bus system, Case 5 and Case 6 show that the tertiary load recovery rate in the method without considering DG FRT is about 4% lower than that of the proposed method.

It is worth noting that the 11-bus system has relatively limited resources and fewer available nodes for reconfiguration. Therefore, the observed gap in load recovery rate is more significant, which highlights the advantage of the proposed method in resource-constrained systems. These results demonstrate that by leveraging the FRT capability of DGs, the proposed strategy can significantly enhance the load recovery capability, particularly in smaller-scale or less redundant distribution networks.

(2) The factor of the uncertainty of DGs and loads

To demonstrate the necessity of considering the factor of the uncertainty of DGs and loads, a comparative calculation was performed for the 69-bus system without considering DG uncertainty (by assuming it to be a constant value for the calculation). In the optimal calculation without considering uncertainty, the power of source and load was set to a constant value. To avoid the influence of specific value choices, the power of source and load values at four typical times were selected for the calculation: 4:00, 10:00, 12:00, and 16:00. The worst case was chosen for comparison. The results are shown in Table 10.

Table 10. Comparison of optimal reconfiguration results with and without considering uncertainty.

Case Number	Considering Uncertainty		Without Considering Uncertainty	
	Worst $\tilde{L}_{ij}$	Loss of Load (MWh)	Worst $\tilde{L}_{ij}$	Loss of Load (MWh)
1	−0.8898	1.4664	−0.8898	1.4664
2	−0.9264	0.4602	−0.9264	0.4712
3	−0.9479	1.2070	−0.8425	1.5457
4	−0.9251	0.6349	−0.9251	0.7266

In Case 2, 3, and 4, when the uncertainty of DGs and loads is not considered, the load loss is higher. This suggests that fluctuations in DG power may lead to a larger net load power (the difference between the load and DG power), causing load loss. Therefore, the optimal reconfiguration strategy must account for the uncertainty of DGs and loads.

As for the static voltage stability index, in Case 3, the $\tilde{L}_{ij}$ with consideration of uncertainty is smaller, indicating better system stability. Additionally, the largest deviation from the results occurs at 12:00. At 12:00, the DG output is highest, and the supply pressure is relatively low, so the scheme given at this time may not be optimal for other time periods.

In summary, considering uncertainty in the optimal reconfiguration can reduce load loss and improve the stability of the system in post-recovery long-term operation.

In terms of load loss, the results of Case 2, 3, and 4 show that the method considering uncertainty achieves lower load loss compared to the method that does not. Specifically, in Case 3, the load loss is reduced by approximately 22% when uncertainty in DG output and load demand is taken into account. Incorporating uncertainty into the optimization process enables the strategy to better anticipate and adapt to such variations, resulting in more effective load restoration.

As for the static voltage stability index $\tilde{L}_{ij}$, it is also improved when uncertainty is considered. In Case 3, the index increases by about 12.5%, suggesting that the system operates under more stable conditions during post-recovery operation. It is also observed that the largest deviation in the voltage stability index occurs at 12:00, when the DG output is at its peak. At 12:00, the supply pressure is relatively low, and the reconfiguration scheme selected for that moment may not be optimal across other time periods, due to the dynamic nature of DG output and load.

In summary, considering uncertainty in DGs and loads during fault reconfiguration not only reduces load loss, but also enhances post-recovery voltage stability. This demonstrates the necessity of incorporating uncertainty into the reconfiguration strategy to ensure the long-term reliable operation of the distribution system.

5.5. Analysis of the Practicality of the Proposed Method

The aforementioned comparisons between the proposed method and other approaches have demonstrated its advantages in terms of computational speed, accuracy, load restoration, and system stability. In addition, the proposed two-stage reconfiguration strategy exhibits strong engineering applicability in real-world scenarios.

Taking the power supply company of a certain city in China as an example, we investigated the current fault reconfiguration process used by the operator, and identified several practical challenges they face during real-time fault restoration. These are summarized as follows:

1. Limited adaptability of current reconfiguration schemes

In existing practice, maintenance staff predefine several reconfiguration schemes during system planning. When a fault occurs, one of these fixed schemes is selected after manual verification, regardless of real-time system conditions. This rigid approach limits flexibility and responsiveness. The method proposed in this paper can automatically generate reconfiguration strategies based on real-time operational data, and considers multiple optimization objectives, thus offering dynamic adaptability.

2. Slow computation and infeasibility under complexity

Under certain scenarios with high DG penetration and complex network topology, existing methods often fail to provide timely or feasible solutions, especially with limited on-site computational capacity. Our proposed AdaBoost-enhanced decision tree algorithm

significantly improves computational efficiency while ensuring optimality, enabling rapid decision-making in field environments.

3. Neglect of DG support capabilities

The existing strategy does not take into account the FRT capabilities of DGs. As DGs become more prevalent, this omission leads to underutilization of available resources. Our model explicitly considers the FRT capabilities of DGs, allowing them to actively support the system during fault recovery.

4. Lack of consideration of post-fault operational risks

The current approach focuses only on the immediate restoration of important loads, without evaluating the potential risks that may arise during subsequent operation. In contrast, our second-stage reconfiguration model considers the uncertainties in both DG output and load demand using fuzzy-based modeling, and ensures post-recovery voltage stability, contributing to long-term secure system operation.

6. Conclusions

This paper proposes a two-stage fault reconfiguration strategy for distribution networks with high penetration of DGs, considering the fault ride-through capability and output uncertainty of DGs. The results from the case studies demonstrate the following:

1. The proposed rapid power restoration reconfiguration model takes into account different types of DG behaviors during fault recovery, including the fault ride-through capability of DGs. After a fault occurs, it can effectively leverage the DGs' support capability for distribution networks and improve the load recovery percentage, thereby enhancing the restoration of lost load.
2. In the rapid power restoration strategy, the AdaBoost-enhanced improved decision tree algorithm offers faster computation speeds than traditional optimization methods, enhancing its ability to meet fault response requirements in practical engineering applications.
3. In the post-recovery optimal reconfiguration strategy, the reconfiguration model simultaneously considers load restoration and system stability as optimization objectives, and accounts for the uncertainty of DGs' output and load power, in order to enhance the long-term operational stability of the system.

The strategy proposed in this paper focuses primarily on fault reconfiguration within the distribution networks. It does not yet consider the issue of island operation after the failure of external power sources. The DG grid-connected control strategy does not analyze factors such as voltage–frequency control. Fault reconfiguration is typically based on static models, while distributed generators exhibit strong dynamic characteristics. The adaptability of more complex uncertainty models to the reconfiguration problem remains to be further validated. Future research will address and expand upon these aspects.

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Appendix A

Appendix A.1

The constraints of the first stage (fast power restoration) of the strategy model are as follows:

(1) Power flow constraints

$$\begin{cases} P_{s,j} + \sum_{i \in \Omega_{j,f}} \alpha_{ij}(P_{ij} - r_{ij}I_{ij}^2) = P_{load,j} + \sum_{k \in \Omega_{j,z}} \alpha_{jk}P_{jk} \\ Q_{s,j} + \sum_{i \in \Omega_{j,f}} \alpha_{ij}(Q_{ij} - x_{ij}I_{ij}^2) = Q_{load,j} + \sum_{k \in \Omega_{j,z}} \alpha_{jk}Q_{jk} \end{cases} \quad (A1)$$

$$U_j^2 = U_i^2 - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) + (r_{ij}^2 + x_{ij}^2)I_{ij}^2 \quad (A2)$$

$$(U_i I_{ij})^2 = P_{ij}^2 + Q_{ij}^2 \quad (A3)$$

$$\begin{cases} P_{s,j} = P_{m,j} + P_{DG,j} + P_{ess,d,j} - P_{ess,c,j} \\ Q_{s,j} = Q_{m,j} + Q_{DG,j} \end{cases} \quad (A4)$$

where α_{ij} is the line switch status variable; $P_{s,j}$ and $Q_{s,j}$, and $P_{load,j}$ and $Q_{load,j}$, are the active and reactive power of the power source and load at node j , respectively; $P_{m,j}$, $P_{DG,j}$, $P_{ess,d,j}$, and $P_{ess,c,j}$ are the active power outputs of the main grid, DG, energy storage discharge, and energy storage charge at node j , respectively; $Q_{m,j}$ and $Q_{DG,j}$ represent the reactive power outputs of the main grid and DG at node i ; and $\Omega_{j,f}$ and $\Omega_{j,z}$ are the parent and child node sets of node j .

The above power flow constraints form a non-convex model. The 0–1 variable α_{ij} in Equation (A1) is linearized using the Big-M method. Additionally, variables U_i^{sqr} and I_{ij}^{sqr} are introduced, and second-order cone relaxation (as shown in Equation (A5)) is applied to transform Equations (A1) to (A3) into a mixed-integer second-order cone programming model.

$$\begin{cases} U_j^{sqr} = U_j^2, I_{ij}^{sqr} = I_{ij}^2 \\ -\alpha_{ij}M \leq P_{ij} \leq \alpha_{ij}M \\ -\alpha_{ij}M \leq Q_{ij} \leq \alpha_{ij}M \\ -\alpha_{ij}M \leq I_{ij}^{sqr} \leq \alpha_{ij}M \end{cases} \quad (A5)$$

$$\begin{cases} P_{s,j} + \sum_{i \in \Omega_{j,f}} (P_{ij} - r_{ij}I_{ij}^{sqr}) = P_{load,j} + \sum_{k \in \Omega_{j,z}} P_{jk} \\ Q_{s,j} + \sum_{i \in \Omega_{j,f}} (Q_{ij} - x_{ij}I_{ij}^{sqr}) = Q_{load,j} + \sum_{k \in \Omega_{j,z}} Q_{jk} \end{cases} \quad (A6)$$

$$\begin{cases} U_j^{sqr} \leq M(1 - \alpha_{ij}) + U_i^{sqr} + (r_{ij}^2 + x_{ij}^2)I_{ij}^{sqr} - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) \\ U_j^{sqr} \geq -M(1 - \alpha_{ij}) + U_i^{sqr} + (r_{ij}^2 + x_{ij}^2)I_{ij}^{sqr} - 2(r_{ij}P_{ij} + x_{ij}Q_{ij}) \end{cases} \quad (A7)$$

$$\left\| \begin{matrix} 2P_{ij} \\ 2Q_{ij} \\ I_{ij}^{sqr} - U_i^{sqr} \end{matrix} \right\| \leq I_{ij}^{sqr} + U_i^{sqr} \quad (A8)$$

(2) Line operation safety constraints

$$\begin{cases} 0 \leq I_{ij}^{\text{sqr}} \leq I_{ij,\text{max}}^2 \\ 0 \leq P_{ij} \leq P_{ij,\text{max}} \\ 0 \leq Q_{ij} \leq Q_{ij,\text{max}} \end{cases} \quad (\text{A9})$$

where $I_{ij,\text{max}}$, $P_{ij,\text{max}}$, and $Q_{ij,\text{max}}$ are the maximum allowable current, active power, and reactive power that can flow through the line ij , respectively.

(3) Node voltage constraints

For nodes without DG connections, the node voltage must remain within the allowable range. For nodes with DG connections, the voltage can operate in a low-voltage condition.

$$\begin{cases} U_{\text{ref}} = 1 \\ U_{i,\text{min}}^2 \leq U_{i,\text{other}}^{\text{sqr}} \leq U_{i,\text{max}}^2 \\ U_{i,\text{DG}}^{\text{sqr}} \leq U_{i,\text{max}}^2 \end{cases} \quad (\text{A10})$$

where U_{ref} is the reference node voltage magnitude; and $U_{i,\text{min}}$ and $U_{i,\text{max}}$ are the minimum and maximum allowable voltage magnitudes at node i , respectively.

(4) Energy storage operation constraints

$$\begin{cases} C_{i,\text{min}}^{\text{soc}} \leq C_i^{\text{soc}} + \frac{\eta_{c,i} P_{\text{ess},c,i} \Delta T - P_{\text{ess},d,i} \Delta T / \eta_{d,i}}{E_{\text{ess}}} \leq C_{i,\text{max}}^{\text{soc}} \\ 0 \leq P_{\text{ess},c,i} \leq u_{c,i} P_{\text{ess},c,i,\text{max}} \\ 0 \leq P_{\text{ess},d,i} \leq u_{d,i} P_{\text{ess},d,i,\text{max}} \\ u_{c,i} + u_{d,i} = 1 \end{cases} \quad (\text{A11})$$

where C_i^{soc} denotes the state of charge of the energy storage at node i ; $C_{i,\text{min}}^{\text{soc}}$ and $C_{i,\text{max}}^{\text{soc}}$ are the minimum and maximum states of charge at node i , respectively; $\eta_{c,i}$ and $\eta_{d,i}$ are the charging and discharging efficiencies at node i ; $P_{\text{ess},c,i}$ and $P_{\text{ess},d,i}$ are the charging and discharging power at node i ; $P_{\text{ess},c,i,\text{max}}$ and $P_{\text{ess},d,i,\text{max}}$ represent the maximum charging and discharging power at node i ; and $u_{c,i}$ and $u_{d,i}$ represent the charging and discharging states at node i .

Appendix A.2

Compared to the first stage, the constraints of the second stage (post-recovery optimal reconfiguration) of the strategy model take into account multiple time periods. The constraints are as follows:

(1) Power flow constraints

$$\begin{cases} U_{j,t}^{\text{sqr}} = U_{j,t}^2, I_{ij,t}^{\text{sqr}} = I_{ij,t}^2 \\ -\alpha_{ij} M \leq P_{ij,t} \leq \alpha_{ij} M \\ -\alpha_{ij} M \leq Q_{ij,t} \leq \alpha_{ij} M \\ -\alpha_{ij} M \leq I_{ij,t}^{\text{sqr}} \leq \alpha_{ij} M \end{cases} \quad (\text{A12})$$

$$\begin{cases} P_{s,j,t} + \sum_{i \in \Omega_{j,f}} (P_{ij,t} - r_{ij} I_{ij,t}^{\text{sqr}}) = P_{\text{load},j,t} + \sum_{k \in \Omega_{j,z}} P_{jk,t} \\ Q_{s,j,t} + \sum_{i \in \Omega_{j,f}} (Q_{ij,t} - x_{ij} I_{ij,t}^{\text{sqr}}) = Q_{\text{load},j,t} + \sum_{k \in \Omega_{j,z}} Q_{jk,t} \end{cases} \quad (\text{A13})$$

$$\begin{cases} U_{j,t}^{\text{sqr}} \leq M(1 - \alpha_{ij}) + U_{i,t}^{\text{sqr}} + (r_{ij}^2 + x_{ij}^2) I_{ij,t}^{\text{sqr}} - 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) \\ U_{j,t}^{\text{sqr}} \geq -M(1 - \alpha_{ij}) + U_{i,t}^{\text{sqr}} + (r_{ij}^2 + x_{ij}^2) I_{ij,t}^{\text{sqr}} - 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) \end{cases} \quad (\text{A14})$$

$$\left\| \begin{array}{c} 2P_{ij,t} \\ 2Q_{ij,t} \\ I_{ij,t}^{\text{sqr}} - U_{i,t}^{\text{sqr}} \end{array} \right\| \leq I_{ij,t}^{\text{sqr}} + U_{i,t}^{\text{sqr}} \quad (\text{A15})$$

$$\begin{cases} P_{s,j,t} = P_{m,j,t} + P_{\text{DG},j,t} + P_{\text{ess},d,j,t} - P_{\text{ess},c,j,t} \\ Q_{s,j,t} = Q_{m,j,t} + Q_{\text{DG},j,t} \end{cases} \quad (\text{A16})$$

$P_{s,j,t}$ and $Q_{s,j,t}$, and $P_{\text{load},j,t}$ and $Q_{\text{load},j,t}$, are the active and reactive power of the power source and load at node j at time t , respectively; $P_{m,j,t}$, $P_{\text{DG},j,t}$, $P_{\text{ess},d,j,t}$, and $P_{\text{ess},c,j,t}$ are the active power outputs of the main grid, DG, energy storage discharge, and energy storage charge at node j at time t , respectively; $P_{ij,t}$ and $Q_{ij,t}$ represent the active and reactive power flowing from node i to node j at time t ; $I_{ij,t}$ represents the current flowing through line ij at time t ; and $U_{i,t}$ denotes the voltage magnitude at node j at time t .

(2) Line operation safety constraints

$$\begin{cases} 0 \leq I_{ij,t}^{\text{sqr}} \leq I_{ij,\text{max}}^2 \\ 0 \leq P_{ij,t} \leq P_{ij,\text{max}} \\ 0 \leq Q_{ij,t} \leq Q_{ij,\text{max}} \end{cases} \quad (\text{A17})$$

where $I_{ij,\text{max}}$, $P_{ij,\text{max}}$, and $Q_{ij,\text{max}}$ are the maximum allowable current, active power, and reactive power that can flow through the line ij , respectively.

(3) Node voltage constraints

$$\begin{cases} U_{\text{ref}} = 1 \\ U_{i,\text{min}}^2 \leq U_{i,t}^{\text{sqr}} \leq U_{i,\text{max}}^2 \end{cases} \quad (\text{A18})$$

where U_{ref} is the reference node voltage magnitude; and $U_{i,\text{min}}$ and $U_{i,\text{max}}$ are the minimum and maximum allowable voltage magnitudes at node i , respectively.

(4) Energy storage operation constraints

$$\begin{cases} C_{i,t}^{\text{soc}} = C_{i,t-1}^{\text{soc}} + \frac{\eta_{c,i} P_{\text{ess},c,i,t} \Delta T - P_{\text{ess},d,i,t} \Delta T / \eta_{d,i}}{E_{\text{ess}}} \\ 0 \leq P_{\text{ess},c,i,t} \leq u_{c,i,t} P_{\text{ess},c,i,\text{max}} \\ 0 \leq P_{\text{ess},d,i,t} \leq u_{d,i,t} P_{\text{ess},d,i,\text{max}} \\ u_{c,i,t} + u_{d,i,t} = 1 \\ C_{i,\text{min}}^{\text{soc}} \leq C_{i,t}^{\text{soc}} \leq C_{i,\text{max}}^{\text{soc}} \end{cases} \quad (\text{A19})$$

where $C_{i,t}^{\text{soc}}$ denotes the state of charge of the energy storage at node i at time t ; $P_{\text{ess},c,i,t}$ and $P_{\text{ess},d,i,t}$ are the charging and discharging power at node i at time t ; and $u_{c,i,t}$ and $u_{d,i,t}$ represent the charging and discharging states at node i at time t .

Appendix B

Appendix B.1. IEEE 69-Bus Distribution Network System with DGs

Table A1 lists the access nodes and parameters of the distributed power sources. In addition, the maximum allowable short-circuit current I_{max} of DGs is 1.2 times the rated current.

Table A2 lists the energy storage access nodes and parameters.

The total load of the system is 3 802 kW + j2 695 kVar, and the load weights of each node are shown in Table A3.

Table A1. Parameters of DGs in the IEEE 69-bus system.

Equipment	Connected Node	Rated Active Power (kW)	Equipment	Connected Node	Rated Active Power (kW)
DG1	5	800	DG5	42	200
DG2	9	400	DG6	48	100
DG3	19	250	DG7	63	800
DG4	32	250			

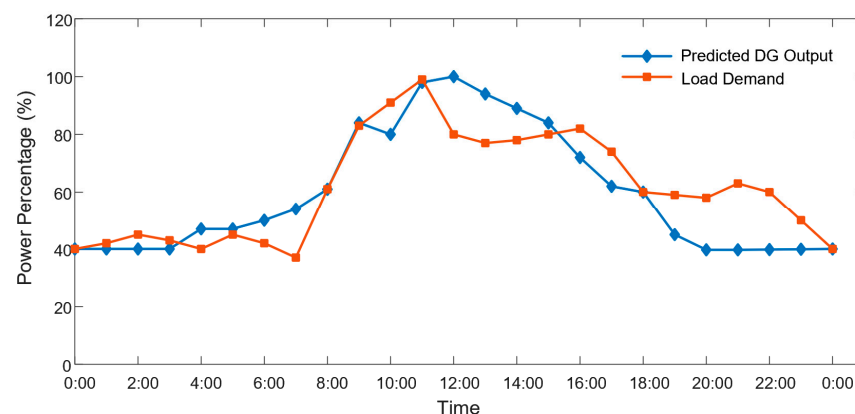
Table A2. Parameters of energy storage devices in the IEEE 69-bus system.

Equipment	Connected Node	Capacity (MWh)	Upper Limit of Charging and Discharging Power (MW)	Charging and Discharging Efficiency
Energy storage 1	4	1.2	0.45/0.45	90%/90%
Energy storage 2	51	1	0.3/0.3	90%/90%

Table A3. Parameters of loads in the IEEE 69-bus system.

Type of Load	Connected Nodes	Weight Factor
Primary load	6, 8, 21, 51	100
Secondary load	12, 17, 33, 42, 49, 64	10
Tertiary load	The rest of the nodes	1

Figure A1 shows the power prediction curves of DGs and loads in one day, where the ordinate refers to the DG output power as a percentage of the rated power, and the load demand power as a percentage of the maximum demand. The fuzzy triangle membership parameters of DGs, $k_{i,1}^t$ are $k_{i,2}^t$, 0.92 and 1.08, respectively, and the fuzzy triangle membership parameters of loads, $k_{i,1}^t$ $k_{i,2}^t$, are 0.95 and 1.05, respectively.

**Figure A1.** DG and load power forecasting curves.

Appendix B.2. 11-Bus Distribution Network System with DGs

The system voltage level is 10 kV, and the power forecast of DGs and loads in one day is the same as that of system 1.

Table A4 lists the access nodes and parameters of the distributed power sources. In addition, the maximum allowable short-circuit current I_{max} of DGs is 1.2 times the rated current.

Table A4. Parameters of DGs in the 11-bus system.

Equipment	Connected Node	Rated Active Power (MW)
DG1	4	4
DG2	7	10.6
DG3	8	5

Table A5 lists the load weights of each node.

Table A5. Parameters of loads in the 11-bus system.

Equipment	Connected Node	Power (MW)	Weight Factor
P1	2	2.14 MW + j0.35 MVar	100
P2	6	1.89 MW + j0.96 MVar	100
P3	7	4.29 MW + j1.34 MVar	100
P4	8	5.93 MW + j4.27 MVar	10
P5	9	6.34 MW + j4.71 MVar	1
P6	10	4.16 MW + j1.35 MVar	1
P7	11	7.85 MW + j2.23 MVar	1

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