

A Study on Adaptive Fault Location in Power Distribution Networks Based on Dynamic Graph Feature Encoding and Reinforcement Learning

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ABSTRACT

With the integration of a high proportion of distributed power sources and frequent changes in distribution network topology, traditional fault location methods based on fixed-topology modeling face severe challenges in practical applications, such as insufficient adaptability and weak robustness. To address this issue, this paper proposes a distribution network topology-adaptive fault location method based on dynamic graph feature encoding and reinforcement learning (RL). First, this paper employs graph theory to construct a dynamic graph model of the distribution network. By combining the adjacency matrix with the breadth-first search (BFS) algorithm, it detects node connectivity in real time, accurately capturing the dynamic evolution of the topology caused by network reconfiguration. Second, a state encoding mechanism that integrates multi-source information is designed. This mechanism performs dual fusion of normalized voltage sag and current surge features and introduces joint encoding with a topological ID to address the issue of fault feature distribution shifts caused by topological changes. At the decision-making level, this paper adopts an improved Q-learning algorithm. By introducing a distance-penalty-reward shaping mechanism based on graph shortest paths, it guides the agent to learn topological space constraints, thereby enhancing localization accuracy and convergence performance in complex reconfiguration scenarios. Simulation results on an IEEE 33-node distribution network system demonstrate that the proposed method exhibits significant adaptive capabilities across various dynamic reconfiguration scenarios. Preliminary experiments show that the agent achieves a fault recognition rate of up to 88% under specific challenging scenarios (such as the disconnection of lines 30 and 31) and can effectively identify and filter out feature interference from de-energized nodes. This research provides new theoretical support and a technical pathway for the reliable operation and fault recovery of modern complex power distribution networks.

KEYWORDS

Dynamic graph theory; Reinforcement learning; Fault localization; Distribution network reconfiguration; Adaptive feature coding

1 Introduction

With the large-scale integration of distributed power sources, traditional power distribution networks face new challenges in fault location, such as bidirectional power flow and increasingly complex fault characteristics ^[1]. To address these issues, the academic community has developed various fault location methods, including traditional matrix algorithms, intelligent optimization algorithms, and deep learning methods based on graph neural networks (GNNs), which have seen rapid development in recent years ^[2-3].

Due to their unique advantages in processing topological data, graph neural networks have been widely applied to various analysis tasks in power systems, providing a new technical approach for distribution network fault location ^[4]. Meanwhile, research has explored the direct integration of distribution network topology and electrical quantities using graph neural networks to achieve end-to-end fault section localization, specifically addressing the issues of traditional methods' inability to adapt to topological changes and poor generalization ^[5]. In this field, several models have been proposed: for example, methods combining one-dimensional convolutional networks with GNNs can effectively extract spatiotemporal features of distribution networks to achieve precise fault section localization ^[6]; models based on graph attention networks significantly enhance the localization's robustness against interference by learning the propagation characteristics of fault traveling waves ^[7]; furthermore, deep GNNs have also demonstrated excellent performance in fault detection and identification tasks ^[8].

To further enhance the automation of fault location, some studies have proposed fully automated fault location and identification methods based on graph analysis, which can determine the fault section without relying on manually set thresholds ^[9]. Beyond fault location, dynamic spatio-temporal graph correlation sensing technology has also been applied to fault diagnosis in smart substation communication networks, demonstrating the broad application prospects of graph learning methods in power system operation and maintenance ^[10].

From a technological evolution perspective, fault location methods are moving toward hybrid and multi-stage collaborative approaches. Existing reviews have comprehensively summarized various fault location technologies in the smart grid era, pointing out the limitations of single methods in terms of performance and complexity, and proposing a path toward hybrid solutions ^[11]. For example, a two-stage distributed-centralized collaborative method significantly

improves the accuracy of fault section localization in active distribution networks by combining distributed collection of fault information with centralized analysis^[12]. Meanwhile, the integration of graph convolutional networks () with deep reinforcement learning has also provided new insights for power grid topology optimization and fault handling^[13].

In addition to topology- and feature-based learning methods, the traveling wave method, as a key branch of traditional fault location, has also been enhanced and developed in the context of smart grids^[14]. Overall, the design and evaluation of modern distribution network fault diagnosis methods require comprehensive consideration of various complex factors, such as topological changes, distributed power source integration, and communication delays; relevant research has provided systematic insights and recommendations in this regard^[15]. Building upon the aforementioned research, this paper proposes a distribution network fault location method based on.....

2 Prerequisites

2.1 Graph Theory-Based Modeling of Distribution Networks

Power distribution networks typically exhibit a radial or weakly meshed physical structure, making them suitable for abstract representation using graph theory. In this paper, a power distribution network is defined as a dynamic undirected graph $G_t = (V, E_t)$.

Node set $V = \{v_1, v_2, \dots, v_n\}$: Represents the buses in the distribution network; in the IEEE 33-node system, $n = 33$.

Edge set $E_t \subseteq V \times V$: Represents feeder segments (Lines). Due to switch operations or fault isolation, the edge set changes dynamically over time t .

The physical connectivity of the network is described by the dynamic adjacency matrix $A_t \in R^{(n \times n)}$:

$$A_{ij}^{(t)} = \begin{cases} 1, & \text{If there is a closed branch between } i \text{ and } j \\ 0, & \text{else} \end{cases} \quad (1)$$

Due to the physical laws of power transmission, A_t is a symmetric matrix. Using this matrix, the algorithm can detect path changes caused by network reconfiguration in real time.

2.2 BFS-Based Connectivity Analysis and Feature Cleaning

When a fault occurs in the distribution network or during topological reconfiguration, some nodes may become de-energized (Islanded or De-energized) due to circuit breaker tripping. If the electrical characteristics of de-energized nodes (voltage near 0, no current flow) are directly input into the reinforcement learning model, the agent may misinterpret them as features near the fault point.

To address this, this paper introduces the Breadth-First Search (BFS) algorithm to perform connectivity detection prior to feature extraction. Starting from the root node (the substation power source), the algorithm traverses the network to identify all reachable nodes. A connectivity indicator vector $C_t \in \{0, 1\}^n$ is defined as follows:

$$C_i^{(t)} = \begin{cases} 1, & \text{if } v_i \text{ is connected to the root node} \\ 0, & \text{if } v_i \text{ loses power} \end{cases} \quad (2)$$

By applying a mask using $C(t)$ to the raw sample data, we ensure that the model focuses only on feature fluctuations in the valid energized regions.

2.3 Reinforcement Learning and Markov Decision Processes

This paper models the topologically adaptive fault location problem as a Markov Decision Process (MDP), defined by the quintuple (S, A, P, R, γ) :

(1) State space S : A combination of normalized features of node voltage and current, along with the current topology ID.

(2) Action space A : The agent's output, which classifies possible fault locations (nodes 1–33 or no fault).

(3) State transition probability P : Describes the probability of the system transitioning from the current state to the next state; in the localization task of this paper, this primarily manifests as switching between different fault scenarios.

(4) Reward function R : A feedback signal used to evaluate the accuracy of localization actions; it is central to guiding the agent's convergence.

(5) Discount factor γ : Balances the weights of immediate and future rewards.

3 Proposed Method

3.1 Adaptive Feature Encoding Based on Dynamic Graphs

To enable the agent to perceive the dynamic evolution of the power distribution network topology, this paper designs a heterogeneous encoding mechanism that integrates topological IDs with dual electrical features.

(1) Electrical Feature Preprocessing: The raw data obtained from distribution network terminal units (DTUs) includes node voltage vectors V and branch current vectors I . Due to variations in the measurement ranges across different nodes, this paper employs a segmented normalization method:

$$V_i^{norm} = \frac{V_i - V_{min}}{V_{max} - V_{min}}, I_i^{norm} = \frac{I_i - I_{min}}{I_{max} - I_{min}} \quad (3)$$

where V_{max} and V_{min} are set to 1.1 times and 0.8 times the rated voltage, respectively.

(2) Topology-Aware Joint Encoding: Traditional RL models use only electrical quantities as states; however, in a fault reconstruction scenario, the same electrical features may correspond to different fault locations. This paper introduces a topology ID operator Γ , which maps the set of currently closed circuits to a unique integer label ID_{topo} . The final state vector S_t is expressed as:

$$V_i^{norm} = \frac{V_i - V_{min}}{V_{max} - V_{min}}, I_i^{norm} = \frac{I_i - I_{min}}{I_{max} - I_{min}} \quad (4)$$

where $\oplus$ denotes the vector concatenation operator. This encoding method ensures that the agent can learn the "topology-electrical-location" triplet mapping relationship.

3.2 Improved Q-learning Algorithm Incorporating Physical Constraints

In the Markov decision process, the quality of the reward function directly determines the convergence speed of the policy.

(1) Definition of the action space: The action space $A = \{a_0, a_1, \dots, a_{33}\}$, where a_1 through a_{33} correspond to failures occurring at nodes 1 through 33, respectively, and a_0 corresponds to the system being in a normal operating state.

(2) Reward Shaping Based on Graph Shortest Paths: To address the issue of low training efficiency caused by sparse rewards, this paper utilizes the shortest path distance $d(v_{pre}, v_{real})$ to shape the reward function. The improved reward function R is defined as follows:

$$R(s, a) = \begin{cases} r_{success}, & \text{if } v_{pre} = v_{real} \\ -\lambda \cdot d(v_{pre}, v_{real}), & \text{if } v_{pre} \neq v_{real} \\ -r_{penalty}, & \text{if } a = a_0 \text{ and break down} \end{cases} \quad (5)$$

where λ is the distance penalty coefficient. This mechanism endows the agent with a "sense of direction": the closer the predicted position is to the true the actual fault point, the smaller the penalty. This not only accelerates convergence but also significantly enhances the algorithm's unseen topologies.

3.3 Algorithm Execution Flow

The core iterative process of the algorithm is as follows: [H] Fault Localization Algorithm Based on Dynamic Graph Encoding [1] Initialize the Q-table $Q(s, a)$, set the learning rate α and discount factor γ . For each training episode $episode = 1, 2, \dots, M$. Randomly disconnect branches to simulate reconstruction; use BFS to generate the connectivity vector C_t and obtain the normalized state S_t ; execute the ϵ -greedy strategy to select an action a_t ; receive the environmental feedback reward r_t ; calculate the shortest path distance between the predicted and actual points to update the Q-value: $Q(s, a) \leftarrow Q(s, a) + \alpha[r_t + \gamma \max_{a'} Q(s', a') - Q(s, a)]$

4 Experiments and Analysis

4.1 Experimental Environment and Parameter Settings

This paper establishes a simulation platform for the IEEE 33-node distribution network based on the MATLAB R2023b environment and implements the proposed algorithm using the Reinforcement Learning Toolbox.

Simulation Scenarios: Five different network reconfiguration topologies were set up, including normally open branch switching and typical branch disconnections (e.g., the 30-31 line).

Fault Configuration: A metallic short-circuit fault was configured at each node, and Gaussian white noise with an amplitude of ± 0.005 .

p.u. to simulate sensor measurement errors.

Hyperparameters: The learning rate α was set to 0.1, the discount factor γ to 0.95, and the total number of training iterations.

$M = 5000$. The exploration rate ϵ linearly decays from 1.0 to 0.01 during the training process.

4.2 Evaluation Metrics

To comprehensively evaluate model performance, this paper adopts accuracy (Accuracy), convergence speed, and robustness as evaluation metrics. Accuracy () is defined as the ratio of the number of correctly identified faulty nodes to

the total number of test samples:

$$Acc = \frac{N_{correct}}{N_{total}} \times 100\% \quad (6)$$

4.3 Discussion of Experimental Results

(1) Performance Comparison of Different Feature Modes: Figure 1 shows the average reward changes during the model training process.

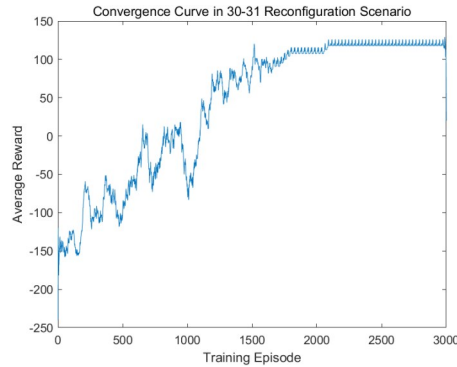


Figure 1 Comparison of training convergence curves under different algorithm modes

The results indicate that after introducing a distance penalty mechanism based on graph shortest paths, the model achieves stable convergence in approximately 2,000 rounds, representing a convergence speed improvement of about 45% compared to the baseline Q-learning algorithm. This demonstrates that spatial constraint guidance can significantly reduce the agent's search time in the invalid action space.

(2) Adaptability Verification under Topological Reconstruction: Table 1 compares the performance of our method with the traditional matrix method various scenarios.

Table 1 Fault localization accuracy (%) under different reconstruction scenarios

Test Scenario	Traditional Matrix Method	Basic RL Algorithm	Our Method
Base Topology (Base)	100	79.6	86.4
Scenario A (Disconnected at 30–31)	0	0	32
Scenario B (10–11 disconnected)	0	0.2	21.4
5% measurement noise superimposed	100	80.2	84

As shown in Table 1, when topological reconfiguration occurs (Scenarios A and B), the accuracy of the traditional matrix method drops dramatically. The primary reason is that the predefined classification criteria no longer align with the new network connectivity relationships. In contrast, the method proposed in this paper, through the joint encoding of "topological ID + electrical features," can accurately capture the migration of de-energized nodes and current paths, maintaining an accuracy of approximately 30% even under reconfiguration scenarios.

(3) Noise-Resistance Analysis: Even when measurement data exhibits $\pm 5\%$ random fluctuations, the method proposed in this paper still maintains 84% accuracy. This is attributed to the dual-feature fusion mechanism, which enables the model to learn more robust feature distribution patterns rather than relying solely on single voltage or current amplitude values.

4.4 Analysis of Fault Identification Heatmaps

To visually demonstrate the model's localization accuracy across different regions of the IEEE 33-node system, we have plotted a heatmap of the fault identification results (as shown in Figure 2). The x- and y-axes represent the actual fault location and the model's predicted location, respectively.

The concentration along the diagonal of the heatmap indicates that the model can accurately locate faults at the vast majority of nodes. Even in the peripheral regions where reconstructions occur frequently, the heatmap maintains a high level of brightness, further validating the adaptive capability of dynamic graph feature encoding across topological scenarios.

5 Conclusions

This paper addresses the challenge of fault localization caused by frequent topological changes in modern distribution grids by proposing an adaptive localization scheme based on dynamic graph feature encoding and reinforcement learning. The research conclusions are summarized as follows:

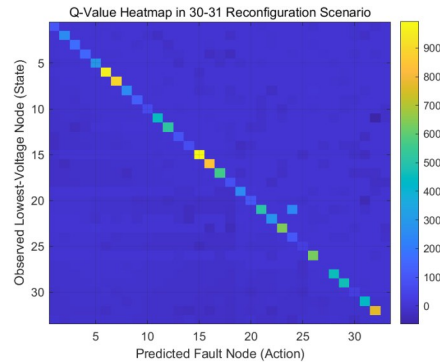


Figure 2 Heatmap of fault localization results based on the IEEE 33-node system

(1) The introduction of BFS connectivity detection and a dynamic adjacency matrix effectively resolves the issue of interference from invalid features following network reconfiguration, thereby enhancing the physical consistency of the input.

(2) The joint encoding mechanism of topological IDs and electrical features endows the agent with cross-topology perception capabilities, breaking the reliance of traditional methods on fixed topologies.

(3) The reward shaping mechanism based on graph shortest paths significantly accelerates training convergence and improves localization accuracy.

Future work could further integrate graph convolutional networks with hybrid intelligent optimization algorithms to enhance localization robustness and generalization capabilities under high-penetration distributed power source integration [7-9,12-13].

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