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A new fault location method for distribution networks using sparse measurements

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ABSTRACT

In response to the growing demand to improve reliability and quality of power supply, distributed monitoring devices are gradually being implemented in distribution networks. On the other hand, utilities are demanding more accurate and reliable fault location systems to reduce the economic impact of power outages. This paper presents a novel method that takes full advantage of all available measurements to provide an accurate fault location. The developed method first uses an iterative state estimation based algorithm to find the nearest node to the fault location. It then examines all lines connected to the selected node and locates the fault. The performance of the proposed method is studied by simulation tests on a real 13.8 kV, 134-node distribution system under different fault scenarios. The results verify the accuracy of the algorithm and its robustness even under uncertain measured data. The method robustly handles measurement errors, and is applicable to any distribution network with laterals, load taps and heterogeneous lines.

Introduction

Power distribution networks, because of their geographical dispersion in urban and rural areas, can be significantly affected by faults arising from different sources such as adverse weather conditions, bird contacts, vegetation growth and equipment failure. Over 80% of customer service interruptions are owing to faults on distribution networks; thus, in order to minimize outage times and improve the continuity of supply, distribution network automation has been applied to enhance the reliability, efficiency, and quality of power supply. In this context, fault management can be stated as the core of distribution network automation. As one of the main building blocks of the fault management, fault location enables fast service restoration and narrows down the search area to find the fault point.

Considerable studies have been devoted to the development of practical methods of fault location, thereby reducing the average outage time and hence improving the reliability. These studies can be categorized into two main groups. The first group, also known as outage mapping, are a combination of techniques applied to narrow down the search area by using various available data sources like customer outage calls, weather data or fault indicator signals to estimate the most likely affected area [1–3]. The second group utilize field measurements to locate the fault and can be classified into impedance based algorithms [4–7], methods based on traveling waves [8–11], artificial intelligence based methods [12,13] and algorithms based on sparse voltage measurements [14–18].

Because of their simplicity and practical feasibility, impedance based algorithms are the most widely used type of fault location methods. However, due to the branched nature of distribution networks, these algorithms are prone to multiple location estimation problem. Installation of fault indicators can solve the multiple estimation problem [19], but increases the implementation cost. Other solutions such as injection of two sinusoidal signals with different frequencies [20] or fault diagnosis based on the fault current patterns [6] would be more cost effective. Traveling wave based methods produce accurate results for networks with small configurations and very limited number of laterals and branches [10,11]. However, in distribution systems with a large number of laterals and load taps, these methods often require very high frequency sampling rate to identify the exact fault location. Methods based on artificial intelligent systems, such as neural networks, despite their accuracy and simplicity, require large training data and retraining following a change in the distribution system topology [21].

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Recent advances in metering and communication systems, and the advent of Intelligent Electronic Devices (IEDs) such as power quality meters, digital protective relays and digital fault recorders have greatly improved monitoring and protection of modern distribution networks and have provided new opportunities to enhance fault location methods. Accordingly, another class of fault location methods has been proposed trying to benefit from the sparse voltage measurements, provided by IEDs, in addition to the voltage and current measured at the upstream substation in order to overcome some of the aforementioned problems in the previous algorithms [14–18].

The fault location method proposed in [16], first estimates fault current by summing fault current contributions from all sources. It then injects the calculated current at all system nodes to calculate the change in three phase voltages at all measurement nodes. Finally, comparing the measured values with calculated values, the method identifies the faulted node. This work has a simple procedure; however, its approximate estimate of fault current affects the accuracy of the results. Authors in [18], propose a method with the same principles, but instead of estimating the change in voltages, they estimate the fault currents and identify the faulted node by comparing the estimated currents. The proposed method has acceptable results with or without synchronization of the measured values, though, it requires a large number of meters.

The fault location methods proposed in [14,17] are based on the fact that each fault causes voltage sags with different characteristics at different nodes. Therefore, knowing the voltage sag magnitudes at certain measurement nodes, it would be possible to locate the faulted node. The algorithm assumes the fault at each node throughout the network and calculates voltage sags using a load flow program. It then determines the faulted node by comparing how well the calculated values for each node match the measured values. The proposed methods successfully find the nearest node to the fault without synchronization of the measured values, but they cannot identify the actual location of the fault.

The method presented in [15] follows the same principles. For each node, the method first employs a set of short circuit analysis to estimate fault resistance. It then applies the estimated resistance and explores the similarity between the measured and calculated voltage sags to find the faulted node. In the next step, the algorithm considers the lines connected to the selected node, moves the fault along these lines and locates the fault. The method is accurate and can identify the exact fault location; however, using three iterative stages for estimation of fault resistance, identification of faulted node and exact fault location increases the computational burden, especially for large networks.

Despite the shortcomings mentioned, all of the previously mentioned works provide acceptable results. However, since all of these methods rely on indices defined based on measured voltages, they would be very sensitive to measurement inaccuracies. Therefore, whilst all of the previously proposed algorithms use measurements only to define their indices, the main idea of this work is to incorporate all measured values into calculations through a state estimation based algorithm to improve both the accuracy and reliability of the results even under uncertain conditions. Each time a fault is detected, the developed method identifies the nearest node to fault location using an iterative state estimation based algorithm. It then examines all lines connected to the selected node and finds the exact fault location. The method has been tested by simulation studies on a 134-node, real, radial distribution network. The results verify accuracy and robustness of the method for different fault types, positions, and resistances even when there are measurement and load estimation errors.

The rest of the paper is organized as follows: the concept of Branch-current-based State Estimation (BSE) is described in Section 'Branch-current-based state estimation'. Section 'The algorithm' presents the outline and a detailed description of the proposed fault location method. Case study is given in Section 'Case study' where the performance of the proposed method is evaluated and Section 'Conclusion' concludes the paper.

Branch-current-based state estimation

State estimation is the process of determining the most likely state of a system by using its mathematical model and a set of measurements, which may include any combination of current, voltage and power measurements.

The measurements relate to system states by a set of nonlinear functions:

$$z = h(x) + e \tag{1}$$

where $h(x)$ is the vector of nonlinear functions, x is the vector of system states, and e is the vector of measurement errors.

Branch-current-based state estimation [22,23], commonly used in distribution networks, is developed based on the weighted least squares method and uses branch currents as state variables:

$$x = [I_r, I_x] \tag{2}$$

where I_r and I_x are the vectors of real and imaginary parts of the branch currents.

BSE estimates the state variables (i.e. branch currents) by minimizing the following objective function:

$$j(x) = \sum_{i=1}^{m} w_i (z_i - h_i(x))^2 = [z - h(x)]^T W [z - h(x)] \tag{3}$$

where W is a weighting diagonal matrix with w_i elements.

Minimizing this objective function leads to the best possible values of state variables using all available measuring resources. In order to minimize $j(x)$, the first-order optimality conditions have to be satisfied:

$$g(x) = \frac{\partial j(x)}{\partial x} = -H^T(x) W [z - h(x)] = 0 \tag{4}$$

where $H(x) = \left[\frac{\partial h(x)}{\partial x}\right]$.

Expanding the nonlinear function $g(x)$ into its Taylor series and ignoring the higher order terms leads to an iterative solution scheme known as Gauss–Newton method:

$$x^{k+1} = x^k - \left[G(x^k)\right]^{-1} g(x^k) \tag{5}$$

where:

$G(x) = \frac{\partial g(x)}{\partial x} = H^T(x) W H(x)$ is the gain matrix [24].

Starting from an initial guess, the state estimation algorithm iteratively updates the state variables until the objective function is minimized. The details of BSE are described in [22,23].

The algorithm

The proposed fault location algorithm is developed based on the concept of the branch-current-based state estimation method. As shown in the flowchart of Fig. 1, the input data is first checked for identification and elimination of bad data from the measurement set. Then, the faulted zone is determined as a group of neighboring nodes suspected of being the fault location. The main fault location process begins in the next step where all the suspected nodes are ranked by applying the fault at each of them and calculating a predefined index. The node with the largest value of index is identified as one end of the affected line. During this process, the fault is modeled as a special load temporarily connected to each analyzed node, one at a time, and its current is estimated using an iterative state estimation algorithm. Finally, the list of ranked