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Improving topology error identification through considering parameter and measurement errors

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ABSTRACT

In this paper, a new approach for simultaneous identification of incorrect branch status and erroneous parameters is proposed. This approach consists of a three-stage algorithm based on the properties of parameter estimation models. It only requires the results of a conventional state estimator to identify the errors. Different statistical analysis and comprehensive numerical experiments are carried out to illustrate the effectiveness of the proposed algorithm.

1. Introduction

1.1. Background and motivation

The correct performance of energy management system (EMS) applications highly depends on the accuracy of the state estimation (SE) function. The SE function uses the redundant analog measurements gathered by the SCADA system as well as the network topology obtained from status measurements of the SCADA system. Bad measurements, and incorrect network topology and parameters are factors that influence the correctness of the SE results. Error in metering devices and noise in communication equipment may lead to bad measurements and incorrect status of some circuit breakers (CBs). Additionally, inaccurate manufacturing data and out-of-date data bases are common reasons of network parameters' errors. Network topology and parameters' errors may have significant impact on the convergence and accuracy of the SE. Furthermore, they may exacerbate bad data interaction issues, complicating bad data identification.

1.2. Aim

In this paper, a new approach for detecting and identifying network topology errors is presented. The proposed topology error identification approach has the ability of identifying the incorrect branch status in the presence of bad data and inexact network parameters. It uses the normalized Lagrange multipliers of the constraints added for modeling CBs and parameter errors to identify the incorrect status of branches through estimating the parameters of suspicious branches pertaining to topology or parameters' errors. The parameter error identification comes into the problem as a subsidiary procedure to improve the performance of topology error identification.

Errors in network parameters are either permanent or dynamic. The permanent errors remain in the network database until they are eventually spotted and corrected. In the long-run, it should be expected that most permanent network parameters are properly identified. On the other hand, dynamic errors pertain to parameters that change continuously. For instance, tap positions of transformers have dynamic nature and can affect the parameter errors of transformer branches. Phase shifting transformers have similar impact on the parameter errors. Thus, parameter errors in addition to topology errors should be checked regularly.

1.3. Literature review

The methods implemented to detect and identify topology errors are generally based on a classical SE or a generalized SE. In the classical SE, the conventional bus-branch model, generated from the topology processor, is used to identify the incorrect status of branches. For example, in [1] the topology errors are identified by normalized residual tests. In [2], the state vector is augmented by introducing a binary variable per branch. Then, every binary variable is estimated to determine the connected/disconnected status of the associated branch.

The generalized SE, unlike the classical SE, incorporates an explicit model of each CB into the SE formulation [3]. Modeling CBs as zero impedance branches has been presented in [4,5]. In [3], the concepts of pocketing and zooming have been presented for topology error detection where the state estimation and bad data detection are conducted on the network pockets and then an incorrect status is identified when

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there is a gross error in the CB's measurements. To decrease the number of CBs modeled and the associated computation burden, reduced substation models and implicitly constrained substation models are presented in [6,7], respectively. The research works [8,9] focus on the observability of the generalized SE. This work is continued in [10] to consider observability issues. Topology error identification methods based on the normalized Lagrange multipliers of the SE constraints pertaining to CBs [11], Huber M-estimator [12], hypothesis testing identification, known as $J(\hat{x})$-test [13], and a geometric test based on geometric interpretation of Lagrange multiplier vector [14] have also been presented in the literature. Some other research works aim at estimating and identifying unknown CBs' status [15,16]. However, number of telemetered power flow measurements pertaining to CBs inside substations is highly limited in most dispatch centers where SE is regularly run, since monitoring these measurements significantly increases the cost of telemetry and SCADA systems. Monitoring analog measurements associated with CBs inside substations greatly increases the number of AIs (analog inputs), which in turn increases the cost of MR (marshaling rack) panels and HVI (high voltage interface) panels of interface system as well as the cost of remote terminal units (RTUs). Additionally, monitoring these analog measurements increases the point size of SCADA systems, while the cost of a SCADA system is directly proportional to its point size. For instance, the power flow measurements of only 7 CBs in 7 different substations among 463 substations with more than 5000 CBs in the Iran's power system are recorded in the dispatch centers, i.e., less than 0.14%. Therefore, practically, there is usually not enough measurement redundancy for the status of CBs inside substations to be fully observed. Even if it is assumed that the required measurement redundancy for the status of CBs inside substations is available in a power system, considering CBs inside substations significantly increases the number of states and constraints of SE, which increases its computation burden. For instance, the number of state variables required by different models considering CBs inside substations including full model [11], reduced model [6], and implicit model [7] are 272, 120, and 38, respectively, for a simple IEEE 14-bus test system, while its conventional bus-branch (standard SE) model has only 27 state variables [7]. However, a specific SE reformulation is proposed here such that no additional state and no additional constraint are required. In other words, the proposed method computes the normalized Lagrange multipliers of the constraints associated with CBs only based on the results of a standard SE.

Topology error identification methods reported in the literature, e.g., [6,7,11], assume that branch parameters are correct. Similarly, parameter estimation approaches reported in the literature, e.g., [18–20], assume that the network topology is correct. No method of these two categories can correctly work when both topology error and parameter error are present, while such a case can routinely occur in practical power systems. In this paper, a new method for identifying incorrect status and erroneous parameters of branches, when both of them are simultaneously present, is proposed.

1.4. Contributions

The main contributions of this paper are:

(1) To propose an efficient method with low computation burden for identifying network topology errors that take into account potential parameter errors.
(2) To use the proposed method to detect and identify network topology and parameters' errors as well as bad measurements even when all of them are simultaneously present.

1.5. Paper organization

In Section 2, models of CBs and parameter errors are presented. Based on these models, the proposed topology error identification approach is introduced in Section 3. The numerical results obtained from the proposed approach are presented in Section 4 and compared with the results of other method. Section 5 provides conclusions.

2. Models of CB and parameter error in SE

In this section, the standard SE is first presented. Then, branch CBs and parameters' errors are modeled within the standard SE.

2.1. Standard SE formulation

The standard SE based on the weighted least squares (WLS) method is a nonlinear optimization problem with equality constraints:

$$\min_{x_{SE}} J(x_{SE}) = [z-h(x_{SE})]^T\cdot R^{-1}\cdot[z-h(x_{SE})] \quad (1)$$

s.t.

$$c(x_{SE}) = 0:\ \lambda \quad (2)$$

where x_{SE} is the state vector including voltage angles and magnitudes of all system buses, vector z contains the available measurements, $h(x_{SE})$ is a vector of nonlinear equations that relate the states x_{SE} to the measurements z. Each measurement in the SCADA system includes an error e_i modeled as a random Gaussian noise with zero mean and variance σ_i^2. In (1), R is the covariance matrix of these errors. Also, (2) represents the equality constraints pertaining to zero injection buses and λ is the Lagrange multiplier vector for these equality constraints.

2.2. Lagrange multipliers

Based on the block matrix Eq. (A2), derived in the Appendix, we can write:

$$\begin{bmatrix} 2\cdot H^T\cdot R^{-1}\cdot H & C^T \\ C & 0 \end{bmatrix}\cdot\begin{bmatrix} \Delta x_{SE} \\ \lambda \end{bmatrix} = \begin{bmatrix} 2\cdot H^T\cdot R^{-1}\cdot e \\ 0 \end{bmatrix} \quad (3)$$

where C and H are defined in the Appendix and e is the measurement error vector.

Using the block matrix inversion formula [17] and defining $G = H^T\cdot R^{-1}\cdot H$, we obtain:

$$\begin{bmatrix} \Delta x_{SE} \\ \lambda \end{bmatrix} = \begin{bmatrix} F_1 & F_2^T \\ F_2 & F_3 \end{bmatrix}\cdot\begin{bmatrix} 2\cdot H^T\cdot R^{-1}\cdot e \\ 0 \end{bmatrix} \quad (4)$$

where (F_1 and F_3 are not required here):

$$F_2 = (C\cdot G^{-1}\cdot C^T)^{-1}\cdot C\cdot G^{-1} \quad (5)$$

According to (5), λ can be obtained as follows:

$$\lambda = F_2\cdot 2\cdot H^T\cdot R^{-1}\cdot e = [(C\cdot G^{-1}\cdot C^T)^{-1}\cdot C\cdot G^{-1}\cdot 2\cdot H^T\cdot R^{-1}]\cdot e = S_\lambda\cdot e \quad (6)$$

where S_λ is the sensitivity matrix for Lagrange multipliers of zero injection constraints.

2.3. Modeling of branch status with two CBs

The active and reactive power flows through each CB as well as the voltage magnitude and angle of its virtual end bus are added to the state variables to model the CB status. As an example, the two end buses of branch ij in Fig. 1, i.e., buses i and j, are actual buses of the system, while buses k and l are virtual buses added for modeling the two CBs of

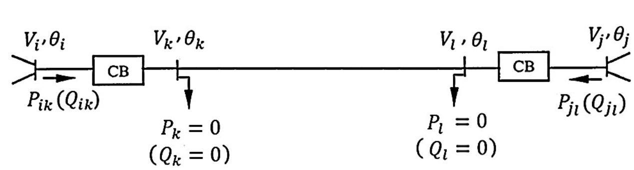

Fig. 1. A network branch with two equivalent CBs and its associated variables.