Electric Power Systems Research 136 (2016) 69–78

Contents lists available at ScienceDirect

Electric Power Systems Research

journal homepage: www.elsevier.com/locate/epsr

Distribution systems state estimation using sparsified voltage profile

M. Majidi, M. Etezadi-Amoli*, H. Livani, M.S. Fadali

Department of Electrical and Biomedical Engineering, University of Nevada, Reno, NV 89557-0260, USA

ARTICLE INFO

Article history:
Received 4 December 2015
Received in revised form 30 January 2016
Accepted 6 February 2016

Keywords:
State estimation
Distribution networks
Micro-phasor measurement units (μPMUs)
ℓ_1-Norm minimization
Compressive sensing (CS)
Bad data processing

ABSTRACT

This paper exploits an electrical characteristic of distribution networks to cast the state estimation problem into a sparse vector recovery problem. In distribution networks, voltage differences between two buses of each line segment are much smaller than the infeed bus voltage. Therefore, the voltage profile signal can be sparsified with a difference transformation and recovered from only a few micro-phasor measurement units (μPMUs) using compressive sensing (CS) and ℓ_1 regularization. The effectiveness of the proposed algorithm is verified through the simulation results of a standard unbalanced distribution network, the IEEE 123-bus system, under different operation conditions. The method accurately estimates system states even with multiple bad current measurements. It also detects, identifies, and corrects bad voltage measurements. In addition, a problem of binary integer linear programming is solved to obtain and optimally place the minimum number of μPMUs necessary to provide a unique solution for the proposed state estimation formulation.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

1.1. Literature review

The proliferation of distribution energy resources (DER) e.g. electric vehicles, distributed generators (DGs), and demand response necessitates visibility and situational awareness in smart distribution networks. Unlike legacy radial networks with one-way power flow, smart distribution networks with multiple sources contain notable variability and uncertainties that must be continuously observed and actively managed [1]. Active management (AM) is provided in distribution networks if a distribution management system (DMS) with various functionalities, such as state estimation (SE), fault detection, isolation, and restoration (FDIR), and volt/var control, are enabled for system operation. The performance of several DMS applications relies on the quality of the state estimates provided by the distribution system state estimation (DSSE) application. DSSE is a subject of several contributions in the literature since early nineties. In [2], DSSE is formulated by Kirchhoff's laws and load data is estimated from statistical models. Baran and Kelley [3] introduce the weighted least-squares (WLS)-based DSSE algorithm whose performance relies heavily on load allocation accuracy. In [4], they proposed an unbalanced three-phase SE approach using branch current measurements. Lu et al. [5] developed a two-step current-based DSSE in which distribution transformer loadings are forecasted first and nonlinear load flow formulations are subsequently solved by Newton's method. In [6,7], the current-based DSSE is examined by decoupling the gain matrix in the state estimation process. In [8], load allocation challenges are discussed by implementing a state estimator in a real distribution network.

Unlike transmission networks, supervisory control and data acquisition (SCADA) measurements are not widely available in distribution networks. This results in low measurement redundancy and is the major obstacle for improving the quality of state estimation in distribution networks. Most DSSE algorithms complement the limited set of available real-time measurements with pseudo-measurements, usually obtained from load forecast studies. Li [9] statistically modeled the loads based on their time-varying characteristic and weather conditions. Ghosh et al. [10] used a non-normal distribution of load variations to develop a probabilistic load model. Recently, artificial intelligence (AI) methods e.g. artificial neural networks (ANNs), nonlinear autoregressive techniques, and fuzzy logic were used to forecast the load data in DSSE algorithms [11–13]. However, high uncertainties in power injection patterns and lack of synchronization between the predicted loads and real-time measurements limit the practical usefulness of the load allocation methods for DSSE.

More recently, intelligent meter data have been also used to improve the measurement redundancy and, consequently, improve the performance of state estimators [14]. However, smart meters (SMs) have a number of problems affecting the performance of

* Corresponding author. Tel.: +1 775 784 6090; fax: +1 775 784 6627.
E-mail address: etezadi@unr.edu (M. Etezadi-Amoli).

http://dx.doi.org/10.1016/j.epsr.2016.02.017
0378-7796/© 2016 Elsevier B.V. All rights reserved.

DSSE methods. SMs generally record the sampling time of their measurements with some error. These measurements cannot be simultaneously transmitted due to bandwidth limitations [14]. In addition, different SMs send their measured data to the monitoring center with different time delays [15]. Therefore, SMs often provide unsynchronized measurements in such a way that sampling times of some measurements may vary significantly under some operating conditions. The error due to lack of synchronization is compensated for by adding an error term to the measurement device error in the WLS-based DSSE methods [14]. However, this approach makes the SM measurements less reliable and consequently affects DSSE performance. In addition, the high cost of deploying SMs and their corresponding infrastructures for a huge number of nodes prevent distribution companies from making their networks fully observable. In [16], the Hamilton cycle theory is used to estimate the states in the distribution networks. It is assumed that the magnitudes and angles of voltages and currents are synchronously measured by smart meters in some buses of the distribution networks.

1.2. Contribution

A more efficient and more accurate DSSE method using a few low-cost and ultra-high-resolution micro-phasor measurement units (μPMUs) is proposed here. μPMU is a new technology developed and certified at the University of California in collaboration with the Power Standards Lab (PSL) and Lawrence Berkeley National Lab (LBNL), funded by the U.S Department of Energy. The device has been installed and tested in two nodes of a real distribution network and will be installed in hundreds of buses at partner utilities [17].

This paper proposes an original application of compressive sensing (CS) to DSSE that drastically differs from the usual WLS-based state estimation. It is inspired by the underlying hypothesis that voltage differences between any two buses of every line segment are small and negligible compared with the infeed point voltage in distribution networks. Therefore, the voltage profile is transformed to a sparse domain using a difference transformation and is recovered from far fewer measurements than those required for WLS and other conventional techniques. The use of CS for distribution network fault location and power system state estimation has been presented in [18–21]. This paper extends the application of CS to distribution system state estimation and enhances DMS capabilities. In addition, a problem of binary integer linear programming is solved to obtain and optimally place the minimum number of μPMUs necessary to provide a unique solution for the proposed state estimation formulation.

The rest of the paper is organized as follows. Section 2 presents the state estimation equations solved by CS and ℓ_1 regularization based techniques and proposes a bad data detection, identification, and correction procedure. Section 3 demonstrates the simulation results of the proposed DSSE algorithm in different operation scenarios. The effects of the noisy measurements, bad data, DGs, and the meshed operation mode on the performance of the proposed method are examined. Section 4 compares the proposed method with other methods and discusses the advantages of our approach. Our conclusion is presented in Section 5.

2. State estimation formulation

μPMUs measure current flows through incident branches to buses and bus voltages synchronously [22]. The measured phasors are expressed in terms of the system states by

$$Z_0 = H_0 x_0 + \nu_0 \tag{1}$$

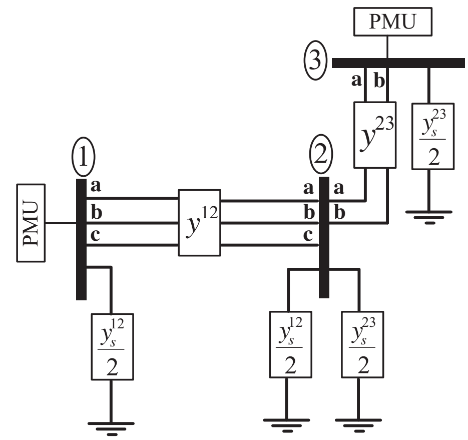

Fig. 1. 3-Bus distribution network.

where $Z_0 \in R^{m_0}$, $m_0 = p + q$, is the measurement vector including p three-phase voltage and q three-phase current measurements, $x_0 \in R^{n_0}$ is the three-phase state vector, $\nu_0 \in R^{m_0}$ is the measurement error vector. $H_0 \in R^{m_0 \times n_0}$ is the constant measurement Jacobian matrix

$$H_0 = \begin{bmatrix} II \\ yA + y_s \end{bmatrix} \tag{2}$$

where $II \in R^{p \times n_0}$ is the three-phase representation of the voltage measurement-bus incident matrix, $y \in R^{q \times q}$ is the three-phase series admittance matrix, $A \in R^{q \times n_0}$ is the three-phase representation of current measurement-bus incident matrix, and $y_s \in R^{q \times n_0}$ is the three-phase shunt admittance matrix. For example, the equivalent PI circuit of a 3-bus distribution system is shown in Fig. 1. Note that lines 2–3 have only two phases.where:

$$y^{12} = \begin{bmatrix} y_{aa}^{12} & y_{ab}^{12} & y_{ac}^{12} \\ y_{ba}^{12} & y_{bb}^{12} & y_{bc}^{12} \\ y_{ca}^{12} & y_{cb}^{12} & y_{cc}^{12} \end{bmatrix}, \quad y^{23} = \begin{bmatrix} y_{aa}^{23} & y_{ab}^{23} \\ y_{ba}^{23} & y_{bb}^{23} \end{bmatrix},$$

$$y_s^{12} = \begin{bmatrix} y_{s,aa}^{12} & y_{s,ab}^{12} & y_{s,ac}^{12} \\ y_{s,ba}^{12} & y_{s,bb}^{12} & y_{s,bc}^{12} \\ y_{s,ca}^{12} & y_{s,cb}^{12} & y_{s,cc}^{12} \end{bmatrix}, \quad y_s^{23} = \begin{bmatrix} y_{s,aa}^{23} & y_{s,ab}^{23} \\ y_{s,ba}^{23} & y_{s,bb}^{23} \end{bmatrix}$$

If two μPMUs are installed at buses 1 and 3, we have

$$Z_0 = \begin{bmatrix} V_a^1 & V_b^1 & V_c^1 & V_a^3 & V_b^3 & I_a^{12} & I_b^{12} & I_c^{12} & I_a^{32} & I_b^{32} \end{bmatrix}^T$$

$$x_0 = \begin{bmatrix} V_a^1 & V_b^1 & V_c^1 & V_a^2 & V_b^2 & V_c^2 & V_a^3 & V_b^3 \end{bmatrix}^T$$

$$II = \begin{bmatrix} I_3 & O_{3\times3} & O_{3\times2} \\ O_{2\times3} & O_{2\times3} & I_2 \end{bmatrix}$$

$$A = \begin{bmatrix} I_3 & -I_3 & O_{3\times2} \\ O_{2\times3} & -I_2 \vdots O_{2\times1} & I_2 \end{bmatrix}$$

$$y = \begin{bmatrix} y^{12} & O_{3\times2} \\ O_{2\times3} & y^{23} \end{bmatrix}, y_s = \begin{bmatrix} y_s^{12} & O_{3\times3} & O_{3\times2} \\ O_{2\times3} & O_{2\times3} & y_s^{23} \end{bmatrix}$$

Download English Version:

https://daneshyari.com/en/article/703073

Download Persian Version:

https://daneshyari.com/article/703073

Daneshyari.com