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State Estimation in Distribution Systems

L. GARCIA-GARCIA*, D. APOSTOLOPOULOU
Commonwealth Edison Company
United States

SUMMARY

The electric grid is currently undergoing a significant renovation process towards the so-called smart grid, featuring larger hosting capacity, widespread penetration of renewable energy sources, better quality of service, and higher reliability. One of the major aspects of this modernization is the widespread deployment of dispersed measurement, monitoring, and actuation devices. State estimation (SE) in the distribution systems was not very developed due to the lack of measurements. However, the deployment of smart devices has enabled measurements at the distribution level. Especially, with the increased penetration of distributed generation into the system, more distribution automation will be required. Specific characteristics of distribution systems, such as their radial nature, make the deployment of SE techniques cumbersome.

In this paper, we have developed a SE method for distribution systems which is based on both actual and pseudo-measurements. The introduction of pseudo-measurements, such as the load forecast of the system, is necessary to make the system observable. The application of the SE algorithm is illustrated through the IEEE 34-bus test system. We test the robustness of the SE algorithm to erroneous measurements by running sensitivity studies where the input measurements are modified, and discover the limitations of the SE algorithm.

KEYWORDS

Distribution Systems, State Estimation, Pseudo-measurements, Observability, Sensitivity Studies

*lgarciag@hawk.iit.edu

1. INTRODUCTION

In order to monitor and maintain operational reliability, power system operators perform several static security analyses. The results of online N-1 contingency analysis help operators determine whether or not the system will meet operational reliability requirements in case of outage of a generator or a line, and further whether or not corrective actions, such as generation re-dispatch in a constrained system, are required. These studies are based on creating a map of the grid based on measurements and accurate state estimation (SE) techniques. SE in the transmission system is well-established, however due to the lack of measurements in distribution systems, SE in the distribution level is not very developed [1], [2]. The electric grid is currently undergoing radical changes towards the so-called smart grid, featuring widespread penetration of renewable energy sources, improved quality of service, and higher reliability. Small and utility-scale renewable resources have begun to complement large coal, gas, and oil-fired power plants. As a result, energy will begin to flow not just from utility to consumer, but from consumer to consumer, and from consumer to utility, making the SE in the distribution level necessary. Another major aspect of the grid modernization is the widespread deployment of dispersed measurement, monitoring, and actuation devices. The introduction of smart devices in the distribution level, such as advanced metering infrastructure, increases the number of available measurements, hence making the SE process implementable in the distribution systems [3].

There are some specific characteristics that define the distribution systems and differentiate them from transmission systems. Thus, the application of the same estimation algorithm could fail its purpose. For instance, distribution systems are commonly radial, the system phases are unbalanced, the line flows are uni- or bi-directional based on the availability of distributed generation, and loads are stochastic [4], [5]. One of the main challenges, however, is the system observability. Depending on the measurements that are available (quantity and location) the introduction of pseudo-measurements, such as load forecasts, is necessary to be able to apply SE algorithms [6]. There are some relevant works in the literature that have also looked at SE algorithms in the distribution systems. In [7], a distribution SE is used to extend the network observability and provide satisfactory voltage estimates with a minimum of actual measurements. In [8], the authors use current magnitude measurements, and the state of each bus is obtained by balancing remote measured currents and distribution transformer load currents.

In this paper, we have developed a SE method for distribution systems and applied it to the IEEE 34-bus test system. Since the number of available real-time measurements is still very limited, we used pseudo-measurements, based on forecasted or historical data, to represent un-measured loads. We wish to test the applicability of the SE algorithm to distribution systems and investigate its robustness with respect to bad quality input data. To this end, we include some sensitivity studies, where we modify the input variables and calculate the relative error in each case. The tests show that the SE algorithm behaves well even when the input data are of bad quality. The remainder of the paper is organized as follows. In Section 2, we set the basis for the SE algorithm, which is developed in Section 3. In Section 4, we illustrate the SE algorithm and test its robustness to erroneous measurements through the IEEE 34-bus test system, and in Section 5 we make some concluding remarks.

2. PRELIMINAIRIES ON STATE ESTIMATION

SE is a mathematical procedure that takes as input a set of measurements of the system and gives as output the estimated state variables, establishing the relation between both of them. There are different approaches to find the solution, but the standard procedure to approximate solution of over-determined systems, which we follow in this paper, is the weighted least square (WLS). This implies that the state variables' estimations are required to minimize the weighed squares of the residuals of the measurements. In the WLS algorithm the measurement errors are assumed to have a Gaussian distribution with the mean and the variance of the distribution as the parameters.

The measurement vector z and state variables vector x are related by $z = h(x) + e$, where e represents the vector of measurement errors and $h(x)$ is the measurement function. The residual error,

$r = z - h(x)$, needs to be minimized to find the solution, so the following optimization problem is solved

$$\min_x J(x) = [z - h(x)]^T W [z - h(x)] \ , \ (1)$$

where W represents the penalty factor of the measurements. The optimal x must satisfy $\frac{\partial J(x)}{\partial x} = 0$, which gives

$$H^T(x) W [z - h(x)] = 0 \ , \ (2)$$

where $H(x) = \frac{\partial h(x)}{\partial x}$ is the Jacobian matrix with respect to the state variables. The solution to the above nonlinear equation can be obtained by the following iterative approach

$$x_{k+1} = x_k + \Delta x_k \ , \ \ (3)$$

where the increment Δx_k is given by

$$[G(x_k)]\Delta x_k = H^T(x_k) W [z - h(x_k)] \ , \ \ (4)$$

and $G(x) = H^T(x) W H(x)$, as described in [9]-[11].

3. STATE ESTIMATION APPLICATION TO DISTRIBUTION SYSTEMS

We use the algorithm developed in Section 2 and apply it to a three phase distribution system with N nodes. SE provides the most likely values of state variables, which include the bus voltage magnitudes and angles. An advantage of using SE is to identify gross errors in actual measurements. The approach used in this paper assumes that the available information is: (i) the actual measurements subject to errors, such as active and reactive power flows and injections, branch current magnitudes, bus voltage magnitudes, status of switching devices, position of transformer taps; and (ii) pseudo-measurements subject to errors, such as forecasted load injections.

In order to formulate mathematically the problem, we denote the vector of forecasted real (reactive) injections by P^f (Q^f); the vector of line current measurements by I_l; the vector of voltage magnitudes by V_m; and the vector of voltage angles by θ_m. The measurement vectors of the real (reactive) bus injections at generator nodes are denoted by P (Q), and the vector of real (reactive) bus withdrawals at load nodes are denoted by $P_L (Q_L)$. We define the measurement vector $z = \left[{P^f}^T, {Q^f}^T, {I_l}^T, {V_m}^T, P^T, Q^T, {P_L}^T, {Q_L}^T\right]^T$, and the state variable vector $x = \left[{V_m}^T, \theta^T\right]^T = [V_{1,a}, V_{1,b}, V_{1,c}, \dots, V_{N,a}, V_{N,b}, V_{N,c}, \theta_{1,a}, \theta_{1,b}, \theta_{1,c}, \dots, \theta_{N,a}, \theta_{N,b}, \theta_{N,c}]^T$. The Jacobian matrix can be formulated as

$$H(x) = \begin{bmatrix} \frac{\partial P^T}{\partial V} & \frac{\partial Q^T}{\partial V} & \frac{\partial {I_l}^T}{\partial V} & \frac{\partial {V_m}^T}{\partial V} & \frac{\partial P^T}{\partial V} & \frac{\partial Q^T}{\partial V} & \frac{\partial {P_L}^T}{\partial V} & \frac{\partial {Q_L}^T}{\partial V} \\ \frac{\partial P^T}{\partial \theta} & \frac{\partial Q^T}{\partial \theta} & \frac{\partial {I_l}^T}{\partial \theta} & \frac{\partial {V_m}^T}{\partial \theta} & \frac{\partial P^T}{\partial \theta} & \frac{\partial Q^T}{\partial \theta} & \frac{\partial {P_L}^T}{\partial \theta} & \frac{\partial {Q_L}^T}{\partial \theta} \end{bmatrix}^T . \ (5)$$

We divide the z vector into two categories to represent that the value of the forecasted load is less than the value of actual measurements. To this end, we define the penalty factor of the measurements by

$$W_{ii} = \begin{cases} 1, & \text{for the forecasted load} \\ 10, & \text{for the actual measurements} \end{cases} . \ (6)$$

The state estimation algorithm follows (3)-(4), and its detailed procedure is described below.

State Estimation Algorithm

Step 1: Initialize the state variables x_0 and set the iteration index k to zero. There are two methods to determine the initial state variables. The first one is called flat start, where the voltage magnitudes are set to 1.05 pu and the voltage angles to zero. The second method is to use a feasible power solution if available as the initial state, which reduces the number of iterations since we start closer to the SE solution.

Step 2: Calculate $G(x_k), H(x_k),$ and $h(x_k)$;
Step 3: Calculate Δx_k;
Step 4: Obtain a new state vector;
Step 5: If $|\Delta x_k| \leq \varepsilon$, then stop; otherwise $k = k + 1$, go to Step 2, where ε is some tolerance level.

4. NUMERICAL EXAMPLES

We present several case studies to demonstrate the capabilities of the proposed SE algorithm and test its robustness. We use the IEEE 34-bus system to gain insights into the proposed approach. We applied the algorithm, described in Section 3, by using the flat start method for the initial values with tolerance $\varepsilon = 10^{-4}$, to the IEEE 34-bus system, which is depicted in Fig. 1. The system includes a radial feeder, mostly 3-phase except from some single-phase laterals [12].

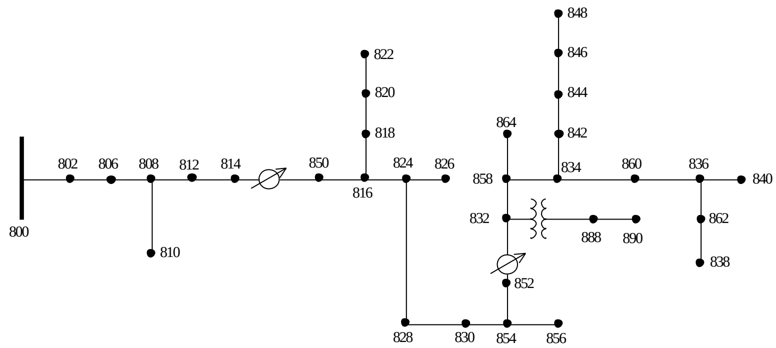
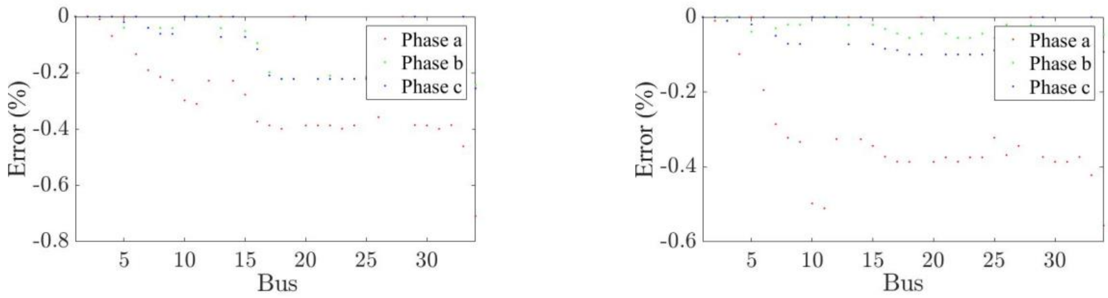


Fig. 1. IEEE 34-bus test system

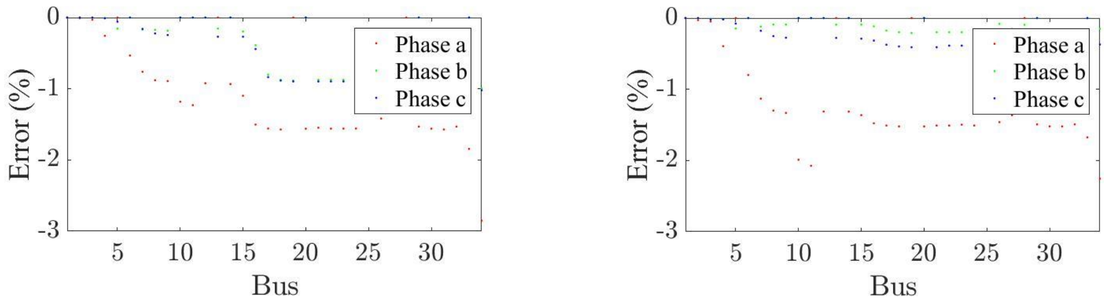
In order to test the behavior of the algorithm in different measurement types, we construct two main scenarios. The measurements included in Scenario 1 are (i) forecasted load of all load nodes with 10% of perturbation, (ii) power injection measurement at the substation, (iii) power flow measurements of lines 802-806, 824-828, 834-860, 836-862, and (iv) line current measurements of lines 800-802, 816-824, 860-836. Considering these data as input, the algorithm converged in 69 iterations. Due to space limitations, we do not reproduce the results. However, the residual error is $r = z - h(x) = 2.7494$. This is a satisfactory number, since the absolute value of the maximum difference between the estimated and the actual voltage magnitude was 0.09 pu. The measurements included in Scenario 2 are (i) forecasted load with 10% of perturbation, (ii) power injection measurement at substation, (iii) power flow measurements of lines 802-806, 834-860, and (iv) line current measurements of line 816-824. In this scenario, the algorithm converged in 67 iterations. The value of the residual in this case is $r = 2.5293$.

We have validated that the proposed algorithm behaves well when the measurements used are close to the actual values. Now, we test the robustness of the proposed algorithm as well as its sensitivity to bad quality data. To this end, we perform sensitivity analysis to both scenarios, by perturbing the measurements. More specifically, we increase the line power flow measurements by 2.5%. We run the SE algorithm and depict in Fig. 2 the voltage magnitudes for Scenarios 1 and 2. We calculate the relative error for the voltage magnitudes at each bus, i.e., Error $= \frac{V_{estimate} - V_{actual}}{V_{actual}} \times 100\%$. We notice that in Fig. 2 the errors are relatively small compared to the 2.5% increase in the measurements. Thus, we may argue that the SE algorithm is robust. Now, we increase the line power flow measurements by 10%, and depict the results in Fig. 3. We notice that such an error is not acceptable since its magnitude is comparable to potential voltage sags. Next, we increase all the line power flow measurements as well as the current measurements by 2.5%. In Fig. 4, we depict the results, which are satisfactory as in Fig. 2. However, when we increase all the line power flow measurements as well as the current measurements by 10%, as we may see in Fig. 5, the results are not acceptable. From the presented case studies, we may see that in this system the voltage magnitude errors when we increase the measurements by 2.5% are small, however they reach 4% when the measurements are modified by 10%. As expected, the error increases as we provide worse quality data to the SE algorithm as input.



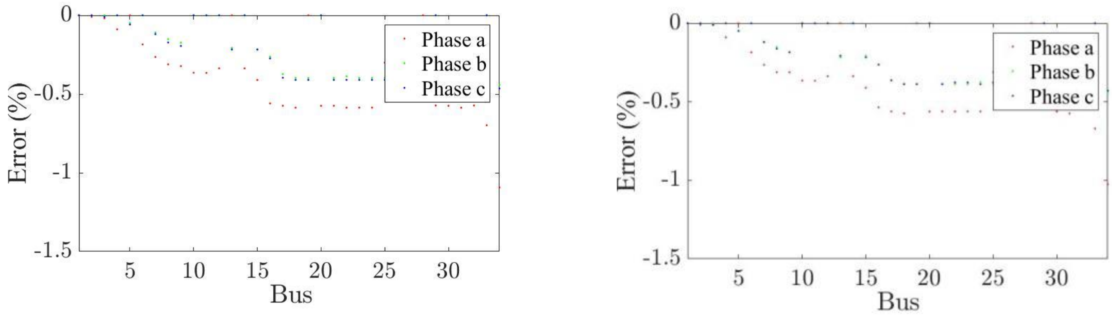
(a) Voltage magnitude error for Scenario 1 (b) Voltage magnitude error for Scenario 2

Fig. 2. Increase the power flow measurements by 2.5%



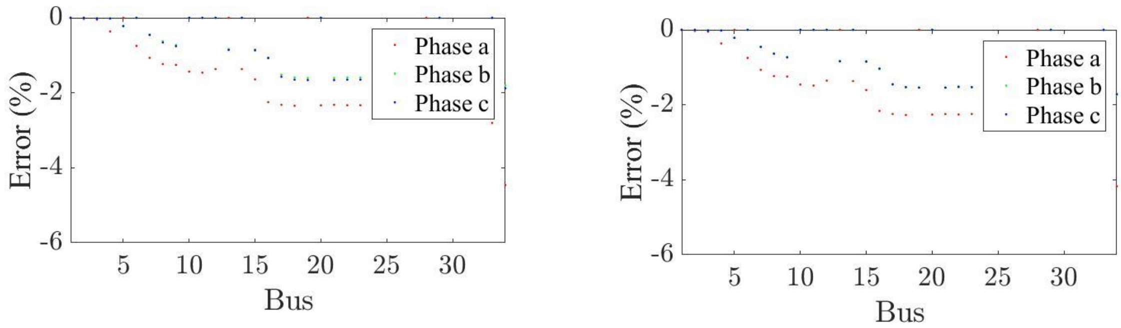
(a) Voltage magnitude error for Scenario 1 (b) Voltage magnitude error for Scenario 2

Fig. 3. Increase the power flow measurements by 10%



(a) Voltage magnitude error for Scenario 1 (b) Voltage magnitude error for Scenario 2

Fig. 4. Increase the power flow and line current measurements by 2.5%



(a) Voltage magnitude error for Scenario 1 (b) Voltage magnitude error for Scenario 2

Fig. 5. Increase the power flow and line current measurements by 10%

5. CONCLUSIONS

In this paper we presented a SE algorithm that may be used for the monitoring of distribution systems. The SE algorithm receives actual and pseudo-measurements as inputs and provides the voltage magnitude and angle at each bus. The procedure is based on the minimization of the residual errors. We investigated the behavior of the algorithm under various input scenarios. We established that the algorithm works even when either the actual or the pseudo-measurements contain some errors. However, we found that there were limitations in the percentage of error that the algorithm may withstand.

Through numerical results, we tested the robustness of the algorithm by modifying the input vector. We run several studies that showed that a perturbation of up to 10% in the input measurements provides reasonable results. Due to space limitations, we chose some representative case studies to validate the robustness of the SE algorithm.

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