Electrical Power and Energy Systems 98 (2018) 463–473

Contents lists available at ScienceDirect

Electrical Power and Energy Systems

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

Three-phase state estimation in the medium-voltage network with aggregated smart meter data

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ARTICLE INFO

Keywords:
Smart meter
State estimation
Distribution system
Measurement uncertainty
Data aggregation

ABSTRACT

In distribution networks, the lack of measurement data is usually thought to be an inevitable bottleneck of conventional grid operation and planning. Recently, the availability of smart meters in the distribution network has provided an opportunity to improve the network observability. In medium-voltage (MV) distribution networks, there is an increasing demand to use aggregated smart meter data for the state estimation, instead of adopting pseudo-measurements with a low level of accuracy. However, the performance of an estimator requires good knowledge of the available measurements, in terms of both expected values and associated uncertainties. Therefore, this paper intends to firstly pave a new way of utilizing smart meter data gathered from the low-voltage (LV) feeders in a concrete and reliable manner. For the purpose of state estimation in MV distribution networks, smart meter data is to be processed through three steps: phase identification, data aggregation and uncertainty evaluation. The feasibility of the proposed method is verified on the IEEE European LV Test Feeder with a set of real-world smart meter data. Afterwards, the influence of the aggregated smart meter data on the three-phase state estimation are investigated on the modified IEEE 13-node test system and IEEE 34-node test system. Simulation results show that the effect of aggregated smart meter data on the accuracy of state estimators is dependent on both the accuracy level of the aggregated data and the measurement configuration in the network. Furthermore, the use of aggregated smart meter data is shown to be able to provide improved state estimation.

1. Introduction

With the large penetration of distributed energy resources and storage devices to distribution networks, the power flow pattern is becoming more complicated. Hence, distribution system state estimation (DSSE), which is able to provide the recent state information to the control center, plays an important role in the grid planning and operation. The concept of state estimation in power systems as proposed by Fred Schweppe in 1970 [1], is devoted to inferring the most likely estimate for each system state based on the network model and available real-time measurements from the system. If system states are known, the other quantities of the power grid can be derived.

Prior to the state estimation, an observability analysis of the network, which determines if the state estimation function can be performed with the available measurements, should be carried out [2]. A power system is fully observable if a unique solution of the state estimation function can be obtained, and vice versa. In general, an increase in the number of measurement data improves the numerical observability of a power system. However, there are insufficient measurement data for state estimation in most of the distribution networks for economic and technical reasons. Conventionally, only measurements at the substation and critical loads are available to grid operators of the distribution network. Such situation of lacking measurement data hinders development of DSSE though various advanced algorithms have been intensively proposed in the last decades [3,4].

In order to execute the state estimation function on the numerically unobservable parts of a power system, pseudo-measurements are adopted to augment the available measurements. Pseudo-measurements, which are much less accurate than the real-time measurements, are typically obtained from historical data, generation dispatch or short-term load forecasting [5]. Although pseudo-measurements make the system artificially observable, they offer a relatively poor knowledge of the measurand, thus they have high variances in the DSSE. It was found that the accuracy of measurements notably affects

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https://doi.org/10.1016/j.ijepes.2017.12.033
Received 8 February 2017; Received in revised form 23 October 2017; Accepted 25 December 2017
0142-0615/ © 2017 Published by Elsevier Ltd.

performances of the DSSE in [6]. Moreover, conventional state estimators that use a weighted least square (WLS) method might fail to function due to a large amount of gross errors in the pseudo-measurements.

Since last few years, the introduction of Advanced Metering Infrastructure (AMI) in the distribution system provides an opportunity to use smart metering data for the DSSE, instead of pseudo-measurements [7]. The "smart meter" term refers to an electronic measurement device in general, which is able to measure natural gas, water, heat or electricity. Comparing with the electro-mechanical meters, smart meters offer a range of benefits for both end-users and different utility stakeholders. In this paper, the smart meter of electricity is of concern. Unlike conventional electricity meters that can only measure the total amount of electricity over a billing period, the smart meter is able to record and store the electrical consumption at given intervals, e.g. every 15, 30 or 60 min. In addition to electrical consumption data, the smart meter is also able to provide power factor, voltage, current, and power quality information. Owing to its appealing functionality, the smart meter has been used for operation and planning in distribution networks, such as evaluating line losses, identifying energy thefts, improving load forecast and optimizing voltage profiles [8,9].

Smart meter devices are typically installed at end-users on the low-voltage (LV) feeders. Hence, smart meter data with given accuracy level is ready to be adopted by the DSSE in LV distribution networks, akin to measurements from conventional meters [10]. Regarding the medium-voltage (MV) distribution network, a set of smart meter data needs to be processed before being employed as an MV nodal input for the state estimation algorithm. In recent years, there is a growing interest in using smart meter data for DSSE in the MV distribution system [11–16]. However, a detailed analysis on the performance and accuracy of the aggregated smart meter data has not been addressed in the literature yet. For instance, the accuracy of smart meter measurements was roughly assumed as 2% or 10% in [12], and 10% in [13].

Besides the lack of available measurement data, distribution networks have some other specific features that are not present in transmission networks, e.g. radial construction, high ratios of resistance to reactance and phase imbalances. For an unbalanced power system, using a model based on the positive sequence model only is no longer representative and reliable. Hence, the DSSE needs a three-phase model, instead of a single-sequence model adopted in the transmission network state estimation [17]. In order to offer a nodal input to the three-phase DSSE in MV distribution systems by means of aggregating smart meter data, uncertainty analysis of the aggregated data is of great importance.

In our previous paper [18], a new way of processing smart meter data on a single LV feeder under the net feed-in tariff scheme was introduced, in which the mean value of the aggregated data and its associated uncertainty due to several identified error sources can be calculated. In this paper, the approach proposed in [18] has been further extended to deal with multiple LV feeders under both net feed-in tariff and gross feed-in tariff schemes. Moreover, the influence of the processed smart meter data on the DSSE in MV distribution networks has been investigated. The IEEE test system is modified to simulate different scenarios of available measurements, and to investigate the effect of the uncertainties associated with the nodal powers on the accuracy of the DSSE. The structure of the remainder of this paper is as follows: state estimation with the aggregated smart meter data is introduced in Section 2; the proposed methodology is described in Section 3; simulation results are discussed in Section 4, whereas conclusions are summarized in Section 5.

2. Problem formulation

State estimation was introduced into power systems as a data processing algorithm to infer optimal states of an electric power system, by means of the network model and a set of meter readings.

2.1. Weighted least square estimate

In a power system, the mathematical model of state estimation can be build up based on the relations between a given set of measurements and the state variables, i.e.,

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

in which $\mathbf{z} = \{z_1, z_2, \ldots, z_m\}$ is the vector of measurement variables; $\mathbf{x}$ is the vector of state variables to be estimated; $h(\mathbf{x})$ formulates the relation between $\mathbf{x}$ and $\mathbf{z}$; $\mathbf{e}$ is the vector of measurement errors which is assumed as a normally distributed random vector with zero means and known variances $var(\mathbf{e}) = \{\sigma_1{}^2, \sigma_2{}^2, \ldots, \sigma_m{}^2\}$.

In Eq. (1), $\mathbf{z}$ is a Normal random variable with the expected value $h(\mathbf{x})$ and covariance $\mathbf{R} = diag\{\sigma_1{}^2, \sigma_2{}^2, \ldots, \sigma_m{}^2\}$. The probability density function of $\mathbf{z}$ is given by,

$$f(\mathbf{z}) = \frac{1}{\sqrt{(2\pi)^m det(\mathbf{R})}} \exp\{-\frac{1}{2}[\mathbf{z}-h(\mathbf{x})]^T\mathbf{R}^{-1}[\mathbf{z}-h(\mathbf{x})]\} \tag{2}$$

In the presence of random measurements $\mathbf{z}$, it is reasonable to obtain an estimation of $\mathbf{x}$ by maximizing the probability density function as shown in (2). Considering the property of the exponential function in (2), the state vector $\mathbf{x}$ can be estimated by:

$$\begin{aligned}\max_{\mathbf{x}} f(\mathbf{z}) &= \max_{\mathbf{x}} \frac{1}{\sqrt{(2\pi)^m det(\mathbf{R})}} \exp\left\{-\frac{1}{2}[\mathbf{z}-h(\mathbf{x})]^T\mathbf{R}^{-1}[\mathbf{z}-h(\mathbf{x})]\right\} \\ &= \min_{\mathbf{x}} [\mathbf{z}-h(\mathbf{x})]^T\mathbf{R}^{-1}[\mathbf{z}-h(\mathbf{x})]\end{aligned} \tag{3}$$

in which $\mathbf{R}$ is determined by measurement uncertainties; is thus introduced to trust those measurements with relatively lower variances whereas de-emphasizing the ones with greater variances. In this context, the state estimation in (3) is called the weighted least square (WLS) estimate [1], since the squared error to be minimized is weighted by the measurement accuracy. According to the optimality condition, the solution of (3) $\hat{\mathbf{x}}$ satisfies the following equation:

$$\mathbf{H}^T(\hat{\mathbf{x}})\mathbf{R}^{-1}[\mathbf{z}-h(\hat{\mathbf{x}})] = 0, \text{ with } \mathbf{H}^T(\mathbf{x}) = \frac{\partial h(\mathbf{x})}{\partial \mathbf{x}} \tag{4}$$

where $\mathbf{H}(\mathbf{x})$ is the Jacobian matrix of the measurement function $h(\mathbf{x})$. The solution of nonlinear equation (4) can be obtained by an iteration process as follows:

$$\begin{aligned}\Delta\mathbf{x}^{k+1} &= \mathbf{x}^{k+1} - \mathbf{x}^k = [G(\mathbf{x}^k)]^{-1}\mathbf{H}^T(\mathbf{x}^k)\mathbf{R}^{-1}[\mathbf{z}-h(\mathbf{x}^k)], G(\mathbf{x}^k) \\ &= \mathbf{H}^T(\mathbf{x}^k)\mathbf{R}^{-1}\mathbf{H}(\mathbf{x}^k).\end{aligned} \tag{5}$$

in which k stands for the iteration step; $\Delta\mathbf{x}^{k+1}$ is the correction term; $\mathbf{x}^{k+1}$ is the new estimate of state variables; $\mathbf{x}^k$ is the recent value of state variables; and $G(\mathbf{x}^k)$ is the so-called gain matrix. The optimal estimation is obtained by iterations till the value of $\Delta\mathbf{x}^{k+1}$ is within a predefined tolerant range; otherwise a new iteration process will start from $\mathbf{x}^{k+1}$ again. The flowchart that shows the general steps of the WLS process is depicted inFig. 1.

2.2. Available measurements in the MV distribution network

In an MV distribution network with n MV buses, the voltage magnitude and angle at the HV/MV substation are always metered. The MV bus of the HV/MV substation thus could be treated as the slack bus, which will serve as an angular reference for all other buses in the system, and whose voltage magnitude is assumed to be 1 p.u.

Then the state estimator is going to obtain voltage magnitudes and angles at the other $n-1$ buses. Given a set of measurements, the network is observable if a unique solution of the system state can be determined. Consider the WLS estimate in (5), a unique solution can be obtained if $\mathbf{H}^T(\mathbf{x}^k)\mathbf{R}^{-1}\mathbf{H}(\mathbf{x}^k)$ is nonsingular, that is, the Jacobian matrix $\mathbf{H}$ has full column rank. In order to guarantee the observability of the whole network, some other types of measurements (such as the branch power in critical lines), virtual measurements or pseudo-measurements

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