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Optimal meter placement algorithm for state estimation in power distribution networks

Antonio A.M. Raposo, Anselmo B. Rodrigues, Maria da Guia da Silva *

Electrical Engineering Department, UFMA, São Luís, MA 65080-805, Brazil

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ABSTRACT

This paper proposes an algorithm to allocate meters in distribution networks to increase the accuracy of the state estimation. This algorithm considers three new issues in the meter placement problem: correlated measurements, multiple load levels and accuracy evaluation of state estimation without using Monte Carlo Simulation (MCS), that is, based on analytical approach. The objective function used in the meters placement problem is associated with the maximization of the accuracy of the state estimator. This objective function is optimized considering constraints for the maximum number of meters that can be installed and for the accuracy of the state estimator. The optimization problem is solved with the binary particle swarm algorithm. The tests results indicated that the meter placement obtained with the proposed algorithm is very accurate for all levels of the load curve. For example, it has been shown that the accuracy of state estimation is four times better when the correlation in power measurements is included in the model. In addition, the computational cost of estimating the accuracy of the state estimate based on the proposed analytical approach is about 47 times lower than that associated with MCS.

1. Introduction

In a near future based on smart grid paradigm, the state estimation will be the eye of the Distribution Management System (DMS) because it will provide the system vision (angle and magnitude of the nodal voltages) to the DMS (the brain) to make decisions regarding to: var/volt control to host renewable energy resources, demand side management, outage restoration based on self-healing, etc. Nevertheless, the most current DMS have some limitations regarding to application of state estimation in real time operation, for example: limited number of measurements devices installed in the network and the real time demand in the load points are unknown. Due to this, the loads are modeled as pseudo-measurement. The pseudo-measurements have high standard deviations and there are a large number of pseudo-measurements in distribution networks. Consequently, the accuracy and reliability of the estimated state is reduced. In other words, the system vision provided by the state estimation is fuzzy. It is necessary to allocate meters in the network. In other words, glasses must be put in DMS eyes to provide a more reliable and accurate vision of the system state. Usually, the meter placement in transmission systems is carried out in order to ensure the observability of the electrical network. The application of this paradigm in distribution networks is economically infeasible because there is a large number of meters required to ensure the network observability. This problem is due to the feeder routing follows the paths of the streets. Consequently, the system is highly branched and has large dimension. Thus, the meter placement in distribution networks is oriented to minimize accuracy indices for the state estimation, for example: standard deviation related to estimated nodal voltages and probabilities of violating limits for the relative errors between the estimated and true values of the nodal voltages.

Liu et al. [1] propose a method of allocating meters in distribution networks with DG, with lack of information on the DG output power. The method incorporates Phasorial Measurement Units (PMU) and smart meters devices in the state estimation of the distribution network. Furthermore, due to different types of consumers the loads were modeled using the method of Gaussian mixture. The objective function considered in this paper is the minimization of the standard deviation related with relative errors between the estimated and true values of the nodal voltages.

Muscas et al. [2,3] propose a method for the optimal allocation of multi-channel meters considering the stochastic behavior of the demand as well as uncertainties in measurement devices. The quality metrics used to assess the accuracy of a meter allocation is the weighted sum of the standard deviations of state variables.

* Corresponding author.
E-mail addresses: antonioamraposo@gmail.com (A.A.M. Raposo), anselmo.ufma@gmail.com (A.B. Rodrigues), mariaguiasilva@gmail.com (M.d.G. da Silva).

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Singh et al. [4] propose a meter placement algorithm that minimizes the probability that the relative error between the true and estimated values of the state variables is less than or equal to a specified value. In a later work, Singh et al. [5] applied ordinal optimization in order to obtain optimal places to install meters from a subset of candidate places. The advantage of the algorithm proposed in [5] is that the improvement in the relative errors between estimated and true values of the nodal voltages was achieved with a smaller number of meters than that obtained in [4].

The indices used in [1–5] to assess the accuracy of the state estimator are subject to uncertainties associated with measurement errors. The most appropriate approaches to take these uncertainties into account are probabilistic ones. The preferred probabilistic approach to analyze the accuracy of the state estimator, in the meter placement problem, has been the Monte Carlo Simulation (MCS) [1–5]. The MCS is simple and powerful technique for performing uncertainty propagation analysis and evaluating probabilistic indices. This advantage is due to the fact that the MCS generates a sample of system indices, from the probability distributions representing the uncertainties, and evaluates statistics for the indices of interest using this sample. The main drawback of MCS is its high computational cost due to the need to evaluate the index of interest for each element of the sample. In the state estimation problem, this evaluation is associated with the solution of an unconstrained nonlinear optimization problem through the Gauss-Newton Method (GNM). Additionally, the use of the MCS introduces a new type of uncertainty in the meter placement problem: the sample variability. That is, the estimated statistics for a given index are changed when different samples are generated by the MCS. In reliability studies this problem is overcome by using samples of sufficient size to estimate indices with acceptable precision. In the meter placement problem the samples are small (less than 100 elements) to reduce the computational burden to achieve an optimal solution. Consequently, the optimal meters placement based on MCS may result in an oversized or undersized meters allocation with regard to the accuracy of the state estimator.

Other important issue associated with state estimation, that has been ignored in the references [1–5], is the correlation between active and reactive power measurements. The assumptions that power measurements are uncorrelated simplify the formulation and solution of the state estimation problem. However, it is not consistent with practical aspects of measuring electrical quantities. For example, active and reactive power measurements associated with circuit flows and nodal injections are performed by a single meter that estimates these quantities from the same set of current and potential transformers. The errors in the measurement of the active power tend to be strongly correlated with those of the reactive power. A problem in the power meter affects both the active power measurement and the reactive power measurement. In recent years there have been many publications on state estimation with correlated measurements. Reference [6] is one of the first papers to include correlated measurements in the State Estimation of Distribution Networks (SEDN). The state estimator proposed in this reference is based on backward/forward sweep (to explore the radial topology) and considers non-normally distributed loads and load diversity (correlation). Caro et al. [7] demonstrate that state estimators with correlation modeling on measurements have more accuracy than those with uncorrelated measures. A methodology based on Gaussian Mixture Model is proposed in [8] to include correlation in the uncertainties related to load and wind generation in the SEDN. An optimization algorithm is applied aiming to reduce the number of components in the Gaussian Mixture Model. Ref. [9] assessed the impact of the input data correlation for a SEDN based on the branch currents. The correlation was modeled in both conventional and synchronized measurements. The results obtained in [9] recently showed that the correlation modeling increases the accuracy of the SEDN. Finally, Ref. [10] presents an algorithm for multiple bad data detection considering correlated measurements. The authors showed that the performance of the bad data detection algorithm is improved with the modeling of dependencies among the measurements.

Other important issue in the meter placement for state estimation are the load fluctuations. The load fluctuations in a study period are due to seasonal variations in the customer demand. However, the load fluctuations [1–5] have not been considered in the existing methodologies [1–5] for meter allocation. In other words, the meter placement is usually solved for a single load level. This problem is due to the high computational cost of evaluating the accuracy of state estimation through MCS. Consequently, the computational cost for the accuracy evaluation for a load curve will not be feasible. It is important to emphasize that a meter placement must be robust to allow the state estimator to provide accurate results for all levels in a load curve.

From the bibliographic review performed above, it can be concluded that the proposed methodologies for meter placement can be improved by including the following issues: load curve, correlated measurements and substitution of MCS by analytical techniques in the precision evaluation to reduce the computational cost. In this way, the main contribution of this paper is to propose a methodology to solve the problem of meter placement that surpasses the three deficiencies of the existing methodologies identified above, that is to say: high computational cost of the accuracy evaluation, uncorrelated measurements and modeling of multiple load levels. These three issues are embedded in an optimization problem solved through the Binary Particle Swarm Optimization (BPSO) algorithm. The objective function of this problem is related to minimizing the probability of the relative errors between the true and estimated values of the state variables being less than or equal to a specified value. This objective function is optimized considering constraints for the maximum number of meters that can be installed, that is, this constraint is a proxy for the capital budget constraint. The tests results showed that the meter placement obtained by the proposed algorithm is very accurate for all the load curve levels. Additionally, it was demonstrated that the inclusion of correlation in power measurements has significant impact in the meter placement.

2. State estimation with correlated measurements

Generally, the Weighted Least Squares (WLS) estimator is used in the state estimation of power systems. The WLS estimator provides consistent results when the measurement errors have a normal distribution. A summarized description of the WLS estimator applied to the state estimation problem is presented in following.

The nonlinear model associated with the measurement vector z is given by:

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

x is the state vector of the electrical network; $e_z = N(0, R_z)$ is the vector of measurement error with zero mean and covariance matrix $R_z = diag\{\sigma_{z1}^2, \sigma_{z2}^2, \ldots, \sigma_{zm}^2\}$; σ_{zi}^2 is the variance of the ith measurement; m is the number of measurements; $h(x)$ is a vector of nonlinear equations that associates the measurements with the state variables; z is the measurement vector.

The estimator based on the WLS minimizes the objective function defined in (2) to estimate the system state variables.

$$J(x) = [z - h(x)]^T R_z^{-1} [z - h(x)] \tag{2}$$

A number of numerical methods can be applied to find an estimate of the vector x, for example the Gauss–Newton Method