Uncertainty analysis of power system state estimates and reference bus selection

Eduardo Caro*

Technical University of Madrid, Madrid, Spain

ARTICLE INFO

Article history:
Received 5 October 2015
Received in revised form 28 February 2016
Accepted 16 March 2016

Keywords:
Power system state estimation
Estimation uncertainty
Reference bus selection

ABSTRACT

The state estimation (SE) in an electric power system is subject to uncertainty, due to random measurement errors, inaccurate line parameters, etc. Specifically, the location of the reference bus may influence over the accuracy of some estimated states. This paper analyzes this effect and proposes an algorithm to select the reference bus, pursuing maximum overall accuracy. Two realistic case studies are analyzed and conclusions duly drawn.

© 2016 Elsevier B.V. All rights reserved.

1. Introduction

1.1. Motivation

A secure and efficient operation of any electric power system can only be achieved if the Control Center has access to accurate information of the status of the system at any time. This information is provided by the state estimator. The main purpose of the state estimator is to compute the most-likely state of the power system, given a redundant set of measurements. Additionally, the state estimation procedure allows the detection and identification of bad measurements, the detection of topology errors, and the detection of inaccurate values for the model parameters.

Due to random measurement errors, any resulting estimate is subject to an estimation error, i.e., the estimate usually does not exactly coincide with the unknown true value. Since the measurements can be modeled by statistical distribution functions, the estimates can also be modeled by distribution functions. Considering that these distributions are Gaussian, each estimate can be characterized by its mean and variance. This variance measures the dispersion of the range within which it can be assured that the unknown true state lies.

The location of the reference bus may have a significant impact over the quality of the estimated voltage angle states. In fact, a large amount of works in the SE technical literature employ the voltage magnitude/angle states to evaluate the estimation accuracy obtained. As a consequence, a change of the reference bus may affect those results obtained. For this reason, in this paper a variance analysis of the state estimates is performed and a method to allocate the reference bus is proposed, pursuing a higher overall estimation accuracy. It should be noted that the selection of the reference bus does not affect neither the estimated active/reactive power flows nor the estimated voltage magnitudes.

1.2. Literature review

In power systems, the concept of state uncertainty was first used by Schweppe [1], and later applied to other areas, such as hydro systems [2]. Reference [3] develops an uncertainty analysis for power system state estimation, proposing a method to compute the confidence interval of the estimates based on a linear optimization problem. Work [4] improves and generalizes the method in [3], developing an algorithm to compute the confidence bounds of the estimates considering uncertainty in both measurements and parameters, leading to a sequential quadratic optimization problem. Recently, the method proposed in [3] has been improved in [5], and solved using constrained nonlinear optimization and Monte Carlo simulation. A similar uncertainty analysis has been also applied to power flow studies in [6], using an affine arithmetic-based methodology.

On the other hand, a significant number of works check the estimation accuracy of their methods employing metrics based on the voltage magnitude/angle state estimates. These works address different aspects concerning the SE, such as meter placement algorithms [7,8], SE in distribution networks [9–11], inclusion of PMUs
in the measurement set [12–16], implementation of heuristics or 
artificial neural network techniques [10,17], and multiarea 
and robust estimation methods [18–21], among others. In the 
forementioned works, the numeric results obtained may vary if the 
reference bus is relocated in other bus of the corresponding system 
studied.

To the best of author’s knowledge, no prior work has analyzed 
the effect of the reference bus selection over the accuracy of 
the estimated states.

The location of the slack bus in the framework of power flow 
analysis has been deeply studied by the technical literature. Some 
works develop the distributed slack bus concept, developing algo-
rithms based on participation factors [22–25]: such as a highly 
decoupled load flow method [22], the computation of system incre-
mental costs [24], or the computation of reference, congestion 
and loss prices [25]. Other works provide a slack bus location 
method in order to reduce the power imbalance [26] or even a tech-
nique to remove the slack bus maintaining an equal incremental 
cost [27].

1.3. Contribution

The contribution of this paper is twofold. First, using numerical 
simulations, it is shown that the uncertainty of the voltage angle 
estimates significantly varies depending on the selection of the ref-
ere bus. Second, three methods are developed to optimally 
select the reference bus with the aim of minimizing the average 
variance of the estimated states. The robustness of the proposed 
algorithm is also analyzed.

1.4. Paper structure

The rest of this paper is organized as follows. Section 2 briefly 
describes the state estimation technique, and numerically shows 
that the variance of the voltage angle estimates depends on the 
selection of the reference bus. In Section 3, three algorithms are 
developed to optimally select the reference bus, based on exten-
sive search and local search methods. In Section 4, a robustness 
study is performed, examining the robustness of the solutions of 
the proposed algorithms. In Section 5, the developed algorithms 
are tested using the IEEE 118-bus and the 300-bus systems, and 
their performances are compared. Finally, conclusions are presented in 
Section 6.

2. State estimation

Almost any state estimator can be formulated as an optimization 
problem using the Weighted Least Squares approach [28]:

\[ \min_x \| z - h(x) \|^2 R_z^{-1} \| z - h(x) \| \] (1)

where \( x \) is the \((n \times 1)\) state vector, \( z \) is the \((m \times 1)\) measurement 
vector, and \( R_z \) is the covariance matrix of measurements. Vectors 
\( x \) and \( z \) are related by the equation \( z = h(x^{true}) + \varepsilon \), where \( h(\cdot) \) is 
a multifunctional vector, \( x^{true} \) is the unknown true system state, and 
\( \varepsilon \) is the unknown measurement error vector.

In this work, it is assumed that each measurement error is an 
independent unbiased Gaussian-distributed random 
variable, and cross correlations between measurement errors are 
disregarded, i.e., \( R_z \) is considered a diagonal matrix. Thus, \( R_z = \text{diag}(\sigma_1^2, \sigma_2^2, \ldots, \sigma_m^2) \), where \( \sigma_i^2 \) is the variance of the \( i \)-th mea-
surement. The proposed procedure is general, and it can be 
straightforwardly expanded to consider non-Gaussian and/or cor-
related input measurements.

![Fig. 1. IEEE 14-bus system.](image)

The optimal solution \( \hat{x} \) of problem (1) can obtained as the limit 
of a sequence of states \( \hat{x}_n \), by means of a Newton-based recursive 
algorithm, one step of which is:

\[ \hat{x}_{n+1} = \hat{x}_n - (H^T R_z^{-1} H(\hat{x}_n))^{-1} H^T R_z^{-1} [z - h(\hat{x}_n)] \] (2)

where \( v \) corresponds to the iteration number.

The optimal solution is \( \hat{x} = [\hat{V}_1 \ldots \hat{V}_n \hat{\theta}_1 \ldots \hat{\theta}_i]^T \), \( \hat{V}_i \) and \( \hat{\theta}_i \) are the 
estimated values of voltage magnitude and angle at the \( i \)-th bus, 
respectively; and matrix \( H(\cdot) \) is the Jacobian of \( h(\cdot) \). The optimal 
solution does not include the reference angle as an element of 
the optimization variable vector.

To deal with non-Gaussian input variables, the method described in [29] 
can be applied: Rosenblatt and Nataf transformations are employed to compute an alternative weighting matrix, to be 
identified in Eq. (1). The iterative algorithm to obtain the optimal esti-
ated state (Eq. (2)) and the proposed method described in Section 
3 are valid.

If input variables are correlated, those cross-correlations are 
modeled by using a block-diagonal weighting matrix in (1), as 
described in work [30]. These non-diagonal elements in \( R_z \) (corre-
sponding to second-order cross-moments) can be computed using either the point estimate method [31] or the unscented 
transformation [32]. Again, the Newton-Raphson algorithm in (2) and 
the developed methodology described in Section 3 are valid.

2.1. Estimation accuracy and estimation variance

The accuracy of an estimate \( \hat{x} \) can be expressed as the “distance” 
between \( \hat{x} \) and \( x^{true} \). The higher the distance, the less accurate 
the estimation is. As it is customary, we assume that the estimate is 
close enough to the true state:

\[ E[\hat{x}] \approx x^{true} \] (3)

However, it is important to consider also the variability of 
the estimate. The variability of an estimate denotes the dispersion 
of the range of the estimation value, and it can be quantified by means 
of the estimation variance. The higher the estimation variance, 
the higher the dispersion of the range of the estimate.

For example, let us consider two estimates: \( \hat{x}_1 \) and \( \hat{x}_2 \). Let us 
assume that the variances of these estimates are \( \sigma_1^2 \) and \( \sigma_2^2 \), 
respectively, and that \( \sigma_2^2 < \sigma_1^2 \). Then, although \( E[\hat{x}_1] \approx x^{true} \) and 
\( E[\hat{x}_2] \approx x^{true} \), it is very likely that \( |\hat{x}_1 - x^{true}| < |\hat{x}_2 - x^{true}| \). Note that 
\( |\hat{x}_2 - x^{true}| \) is higher than \( |\hat{x}_1 - x^{true}| \) because the dispersion of \( \hat{x}_2 \) is 
higher than that of \( \hat{x}_1 \). Thus, the state variable \( x_2 \) is estimated with 
more uncertainty than the state variable \( x_1 \), i.e., the estimation of 
variable \( x_2 \) is less accurate.

For illustrative purposes, the IEEE 14-bus system [33] is consid-
ered (see Fig. 1). For a given measurement location configuration, 
one thousand measurement scenarios are generated using ran-
dom Gaussian-distributed errors added to the known true state 
\( x^{true} \) computed from a power flow solution. For each measurement
دریافت فوری متن کامل مقاله

امکان دانلود نسخه تمام متن مقالات انگلیسی
امکان دانلود نسخه ترجمه شده مقالات
پذیرش سفارش ترجمه تخصصی
امکان جستجو در آرشیو جامعی از صدها موضوع و هزاران مقاله
امکان دانلود رایگان ۲ صفحه اول هر مقاله
امکان پرداخت اینترنتی با کلیه کارت های عضو شتاب
دانلود فوری مقاله پس از پرداخت آنلاین
پشتیبانی کامل خرید با بهره مندی از سیستم هوشمند رهگیری سفارشات