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Power system static state estimation using a least winsorized square robust estimator

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ABSTRACT

State estimation is the heart of the energy management system, primarily used for control and monitoring of electrical power systems. Commonly used conventional weighted least square estimator is not reliable, particularly in the presence of bad data. Subsequently, bad data processing techniques have been developed to detect, identify, and eliminate the bad data present in the measurement set. In the present paper, a robust least winsorized square (LWS) estimator is proposed for the power system static state estimation. One of the main advantages of this estimator is that it has an inbuilt outlier rejection property and is less sensitive to bad data (outliers) measurements. The power system state estimation problem has been solved as an optimisation problem using the jDE-self adaptive differential evolution algorithm. The proposed approach has been implemented and tested on standard IEEE test systems. The effectiveness of the LWS estimator has been demonstrated under different operating conditions, namely, normal operating condition, bad data condition, different operating points, different measurement condition, under the ill-conditioned system, and the presence of false data injection. The performance of the proposed approach has been compared with the conventional and the evolutionary based state estimation techniques. Based on the various performance indices, the results thus obtained show that the proposed technique has better accuracy, robustness, and reliability compared to the results obtained using conventional and evolutionary based state estimation techniques.

1. Introduction

During the last decade, the electric power system network has expanded drastically all over the world. With the integration of distributed generators to the power system and deregulation of power system network, the power flow pattern has been less predictable. Consequently, control centres have to monitor and control the power system network efficiently so as to operate the power system in a secure and reliable manner. Therefore, to accomplish such a task, energy management system (EMS) is equipped with a tool called state estimator (SE). SE is a mathematical procedure that utilises the redundant set of measurements collected across the network to compute the best state estimates (voltage phasors) of the power system [1–5].

From the technical literature [1–9], it is found that weighted least square (WLS) technique is used most commonly to estimate the states of the power system. This is due to its simplicity, stability, and efficiency. Further, WLS estimator exhibits an efficient filtering property and computes accurate state estimates provided an error-free measurement set is available. However, the measurements that are telemetered measurements to the control centre over a communication network usually consist of bad data owing to systematic, communication, and random errors. It is reported in the literature that the conventional WLS estimator computes accurate state estimates under normal condition, however, providing highly distorted state estimates even in the presence of a single outlier (single bad data measurement) [1–9]. Due to this reason WLS estimator is known as a non-robust estimator. Thus, WLS estimator has to be equipped with bad data processing technique to detect, identify, and eliminate the outliers (bad data measurements) if present in the measurement set [1]. The most common approach adopted for the sequential elimination of suspected measurements is based on the statistical tests, namely the chi-square test and the largest normalised residual test [2]. This requires the residual covariance matrix to rank the normalised residuals [3]. Even if there exists a single bad measurement, the power system state estimation (PSSE) is performed by removing the same from the measurement set to obtain accurate state estimates [4]. With this, the computational time required to estimate the states of the power system increases. The computational time taken to obtain the state estimates further increases

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proportionally with an increase in the number of bad data measurements [1]. Moreover, with the removal of bad measurements from the measurement set the measurement redundancy is decreased. Thereby, reducing the accuracy of the estimated states compared to normal operating condition.

In addition to the computational aspects elevated above, bad data processing techniques based on normalised residuals are likely to be affected when gross measurements are leverage points known as positional outliers [3]. In order to overcome these drawbacks, an alternative approach which is based on iterative reweighted least squares (RWLS) technique has been formulated in [3,5,6]. During the iterative process, this RWLS approach increases the robustness of the algorithm against bad data by dynamically readjusting the measurement weights based on their respective variances. Due to this reason, the RWLS approach does not require any additional bad data processing techniques. In spite of its simplicity, this method may lead to biased solution, particularly in the presence of conforming type multiple interacting bad data [1].

The search for alternative techniques which are less sensitive to the bad data measurements has led to the development of non-quadratic estimators [7–9] and the weighted least absolute value estimator (WLAV) [10–12]. However, non-quadratic state estimators suffer from high computational cost compared to WLS estimator and are prone to convergence problems [2]. On the other hand, WLAV estimator suffers from the high computational burden and is highly vulnerable against leverage measurements [13].

Parallel to these developments, another class of robust estimators known as high breakdown point estimators have been investigated by the researchers [13–18]. The breakdown point of an estimator is defined as the largest amount of contamination (number of bad data measurements) that an estimator can handle to provide an accurate solution. These estimators are not only less sensitive to the bad data measurements, but also capable of providing an accurate solution even if half the redundant measurements are positional outliers. This is the maximum extent of outliers that a robust estimator can handle [13]. In [13], a least median square (LMS) estimator has been employed. This LMS estimator has the capability to eliminate a large number of outliers as compared to other estimators. Similar to the LMS estimator, the authors in [14] have suggested another high breakdown estimator known as the least trimmed square (LTS) estimator. This LTS estimator minimises the sum of the smallest ordered squared residuals of order ν. In [15], a state estimator based on mixed-integer non-linear programming is developed to simultaneously eliminate the gross measurement errors, topology errors, and parameter errors. A robust state estimator based on heuristic estimation principle such as the maximum agreement between the available measurements and those in the sample is investigated in [2]. In [16], quadratic tangent function has been formulated to solve non-linear PSSE problem by utilising the dynamic leapfrog technique. The authors in [17] have modelled the maximum exponential square approach to overcome the shortcomings of the conventional WLS estimator. A robust estimator known as maximum constraints satisfaction has been presented in [18] based on the model of uncertainty in the measurements. In [19], power system tracking state estimation problem based on robust least winsorized square (LWS) estimator has been formulated using the JADE-adaptive differential evolution technique. Some of the alternative estimation methodologies proposed in the field of PSSE can be found in [20].

However, the common limitation of the classical optimisation technique is that as the dimension size of the problem increases the search space to obtain the optimal solution increases exponentially [21]. Further, the traditional Newton (Gauss–Newton) technique used in the SE problem depends on the choice of the initial guess to converge to an optimal solution. Furthermore, these approaches are not effective to handle the highly non-linear, non-differentiable, and discrete variable problems [22]. On the other hand, meta-heuristic techniques are considered as a powerful optimisation tool in solving non-linear, discontinuous, non-differentiable, and complicated search space problems [23]. As a result, evolutionary techniques have become very popular and have been used for many real-world applications over the last two decades [21,23–35]. This is due to the fact that unlike conventional optimisation techniques, evolutionary techniques are derivative-free approaches, have superior abilities to avoid local optima, have the flexibility to apply for different types of optimisation problems, and require only the objective function to guide the search process [36].

Among the prevalent evolutionary algorithms (EAs), the differential evolution (DE) algorithm due to its better performance, simplicity in implementation, powerful search capability, and few control parameters has been applied in various areas of research [24–32]. However, adjusting the algorithmic control parameters of EAs to a specific type of problem is an inefficient and laborious task. Therefore, in the present paper, jDE-self adaptive differential evolution algorithm [37] has been considered for solving the power system static state estimation (PSSSE) problem as an optimisation problem. This approach enhances the robustness of the algorithm by dynamically adjusting the parameters to the characteristic of the different fitness landscape. Hence, this paper is dedicated to the application of one robust estimator (high breakdown estimator) to the non-linear PSSSE problem using jDE-self adaptive differential evolution algorithm. Thus, the main advantages of the proposed LWS-jDE method are:

i) The proposed LWS-jDE estimator does not require any separate bad data processor owing to inbuilt bad data rejection property. Hence, re-analysis phase is not a prerequisite to eliminate the bad data measurements.
ii) Due to the absence of re-analysis phase during bad data condition, computational time required to estimate the states of the power system is similar to the normal operating condition.
iii) Measurement redundancy and accuracy of the estimated states are not decreased during bad data condition.
iv) The proposed approach estimates the states of the power system in non-linear form.

Consequently, the main contributions of the work is threefold: i) To introduce least winsorized square estimator by applying it to the power system static state estimation problem, ii) To improve the accuracy, robustness, and reliability of the state estimates under different scenarios, and iii) To compare the efficacy of the estimator with statistical rigour.

The rest of this paper is organised as follows. State estimation formulation is described in Section 2. Section 3 briefly introduces the jDE-self adaptive differential evolution algorithm. Implementation of the proposed methodology is outlined in Section 4. Numerical study of the LWS-jDE approach is explained in Section 5. Results and discussion are presented in Section 6. Finally, the conclusions of the present work are summarised in Section 7.

2. State estimation formulation

The main objective of the SE is to estimate the present operating state of the power system, viz. the voltage phasors (state variables) at all the buses using the over-determined set of non-linear equations [38]. These unknown state variables are represented as $x=[V^T \theta^T]^T$. The mathematical model for SE that relates measurements to the state variables is expressed by the following equation:

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