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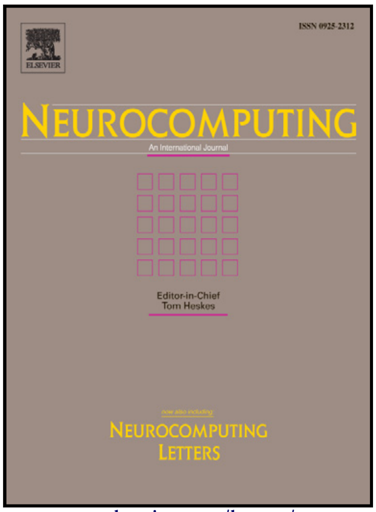

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A Robust LWS State Estimation Including Anomaly Detection and Identification in Power Systems

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Abstract

The electrical power system measurements are transmitted to the control center through a communication network. These measurements may contain bad data due to communication errors, systematic errors, incorrect wiring or infrequency of instrument calibration. As stated in the statistical literature, the estimators with high breakdown point are robust enough to overcome the effect of bad data. This paper discusses the application of one such estimator, Least Winsorized Square (LWS) by applying it to Tracking State Estimation (TSE). The proposed estimator detects, identifies the anomalies such as the existence of bad data and sudden change in load if present in the power system. Discrimination between the anomalies has been accomplished by a test of asymmetry (skewness measure). The proposed estimator has an inbuilt bad data rejection property with an ability to operate at any operating point without undergoing re-analysis phase of the TSE. The state estimation problem has been solved using JADE-adaptive differential evolution algorithm as an optimization problem. The effectiveness of the LWS technique has been tested on three different IEEE standard test systems. The results of the proposed method are compared with conventional weighted least square, particle swarm optimization, and gravitational search algorithm based state estimation techniques. Simulation results demonstrate the efficacy of the proposed algorithm as state estimates of the proposed method are highly precise even when the anomalies are present in the power system.

***Keywords**:* Anomalies; differential evolution; least winsorized square; power system; state estimation.

1. Introduction

1.1 Motivation and Aim

During the decade, electric sector has been witnessing a continuous change from the traditional monopoly-based system to a deregulated environment. In a deregulated environment, the pattern of power flow has become less predictable. Therefore, accurate monitoring of the power system has become essential for stable, economical, reliable, and secure operation [1]. To achieve such a task, true states (node voltages, power flows, etc.) of the power system are essential at any time. These states are estimated by a tool called state estimator

(SE). SE is an important component of the energy management system (EMS) which computes accurate and consistent states of the power system for a given set of redundant measurements. These measurements are remotely captured from the power system [2]. Power system state estimators (PSSE) have two basic approaches, viz. static and tracking. In a static approach, the estimator determines the static state estimates by considering a static model of the power system. The measured data in this approach are assumed to be time-invariant. Whereas, TSE tracks the changes in the power system by utilizing the recently available measurement data to obtain the state estimations in the subsequent time sampling [3]. Very often, the available measurements may be polluted by systematic errors and may be biased due to the infrequency of instrument calibration, instrument failures, measurement scaling, incorrect wiring, etc. Such measurements are termed as bad and constitute a bad data [4]. Another anomaly encountered in a real-time analysis of power system is the sudden change in states caused due to a sudden loss of load or generator, loss of transmission lines, etc. If these anomalies are not identified and detected correctly, then the outputs of the estimator are distorted, thereby producing inaccurate state estimates [5]. Such situations result in insecure, inefficient, and unreliable operation of the power system. In order to tackle such anomalies, an iterative process is usually performed to detect and eliminate the suspected measurements and re-estimating the states of the power system from the remaining data. However, in such a situation the computational time taken to estimate the state of the power system increases [2]. Consequently, there is a need to develop an efficient state estimator, which can accurately estimate the states of the power system even in the presence of anomalies. Therefore, the aim of the present paper is to propose a robust estimator having inbuilt bad data rejection properties and the ability to operate in any operating condition without having any re-analysis phase.

1.2 Literature review

The literature is quite rich in fundamental frequency power system state estimation [6-20]. The most outstanding papers relating to the SE problem can be found from the list of references in [6]. The most common estimator used in the technical literature is weighted least square (WLS) based SE technique. Tracking state estimation using WLS estimator has been developed in [5]. Newton method for static and tracking state estimation in power system using WLS approach is proposed in [7]. The performance of Newton method proposed in [7] has been validated on ill-conditioned systems which encounter problems in converging to the optimal solution. Although, WLS has a higher efficiency compared to other estimators, it has zero breakdown point, i.e. a single outlier can severely affect the estimation solution. Hence, WLS is said to be a non-robust estimator [8]. In order to overcome the disadvantage of WLS estimator, many alternative techniques which are less sensitive to outliers have been proposed by various researchers. The weighted least absolute value (WLAV) estimator using linear programming is discussed in [9]. It is found that WLAV estimator shows automatic bad data rejection properties without any separate re-analysis phase. Owing to this advantage, the authors in [3] have extended the static WLAV estimator by applying it to tracking state estimation. Later it has been found that WLAV estimator fails to provide an accurate solution when measurements are positional outliers also known as leverage points [10]. Another shortcoming of WLAV estimator is its high computational time for large power system problems [11]. This issue has been addressed by applying WLAV to the larger power system using an L_1 linear approximation algorithm in [11]. In [10], the transformed system of measurement equations is suggested to maintain the robustness of the WLAV estimator even in the presence of leverage points.

A least median square (LMS) estimator which minimizes υ^{th} order squared residual has been discussed in [4, 12]. The LMS estimator has the property of eliminating the highest number of outliers compared to other estimators. A least trimmed square (LTS) estimator presented in [13] minimizes the sum of the squared residuals of order υ and has a highest breakdown point similar to the LMS estimator. Meanwhile, other estimators based on non-quadratic functions have been reported in the literature [14-18]. Ref [14], suggested two non-quadratic estimators, namely quadratic-linear (QL) and quadratic-constant (QC) to identify and eliminate bad measurements. However, these estimators suffer from higher computational time compared to WLS based SE method. A transformation decoupled state estimator along with variable QC criteria has been employed in [15] to perform state estimation and bad data processing simultaneously. In [16], an iteratively reweighted least squares using Given-Rotations based on quadratic-tangent estimator criteria is presented. The performance of three different estimators, namely WLS, QC, and linear criterion has been tested for developing a fast tracking state estimator in [17]. The performance of the estimators is validated in the presence of small measurements and sudden state variation conditions. Recently, similar to LMS estimator, a state estimation procedure based on maximum agreement algorithm has been investigated in [18]. This approach maximizes the agreement between the measurements. A mixed integer programming based state estimator is proposed in [19]. The authors in [20] have extended the work suggested in [19] to simultaneously detect and reject gross measurement error, parameter error, and topology error.

However, these methods assume that the objective function is differentiable and continuous. Further, with the existence of non-linear devices in the network such as var compensators, distributed generators, and transformers with on load tap changers, the system equations and therefore, the objective function is non-linear, discontinuous, and not differentiable. Hence, these non-linear power system equations have to be approximated as a linear perturbation model which decreases the accuracy of the conventional state estimator. Furthermore, Gauss-Newton method used in conventional estimators may not converge if the problems are highly non-linear and if the initial guess is far away from the optimal value [21]. Hence, the use of evolutionary techniques (ET) to obtain a solution is evident. The main advantage of ETs compared to traditional methods are that these techniques are derivative free approaches and require only the objective function to direct the search process [22]. Moreover, from the above literature [4-20], it has been found that most of the robust estimators have been applied for static state estimation by concentrating either on increasing the robustness of the estimator against anomalies or improving the accuracy of the estimated states. Also, the performance of the estimators has not been tested in the presence of errors caused due to sudden load change conditions.

Hence, this paper discusses the application of robust LWS estimator using JADE-adaptive differential evolution technique to the non-linear power system. The robustness of this technique is evaluated while applying it to TSE problem in the presence of bad data and sudden load change conditions.

1.3 Contribution of the paper

The contribution of the paper is threefold: i) To present a least winsorized square estimator by applying it to track the time varying static state of the power system in the presence of anomalies without reinitiating the state estimator. ii) To improve the accuracy and robustness of the state estimator against anomalies. iii) Comparative study of the performance of the proposed estimator with statistical thoroughness.

1.4 Organization of the paper

The paper is organized as follows. Section 2 presents the state estimation problem formulation. Section 3 briefly explains the JADE algorithm. Solution methodology of the proposed method is outlined in Section 4. Simulation study to analyze the LWS technique is provided in Section 5. Results and discussion are presented in Section 6. Finally, conclusions are drawn in Section 7.

2. Problem Formulation

The main task of state estimation is to obtain the best estimates of the state variables, viz. the voltage phasors at all buses based on the available set of measurements [23]. A general mathematical model of the power system state estimation which relates measurement vector (z) to state variable vector (x) is given as:

$$z = h(x) + e \qquad (1)$$

where, z is a measurement vector of order $(m \times 1)$

x is a $(n \times 1)$ state vector $(n = 2N < m)$

$h(x)$ is a $(m \times 1)$ non-linear vector relating measurements to states

n represents number of state variables

m indicates the number of measurements

e symbolizes a measurement error vector of order $(m \times 1)$ and

N denotes the total number of buses.

The measurement error vector (e) in (1) can be either Gaussian or non-Gaussian random variables. This measurement error vector represents different errors, viz. i) Instrument errors such as incorrect wiring, systematic errors, and infrequency of instrument calibration. ii) Operational uncertainties caused due to time skew (communication errors) and unexpected system changes. iii) Mathematical model uncertainties caused because of inaccuracy in network parameters and modelling errors [24]. Measurements are obtained from the meters, placed optimally in the network such that the whole power system is observable. To ensure observability, the number of measurements (m) should be greater than the number of state variables (n). The resulting Jacobian matrix (a sensitivity matrix with respect to the state variables) for an observable power system has rank n, i.e. equal to the number of state variables. In the present paper, to cope with the disadvantages of WLS based SE technique; the least winsorized square estimator proposed in [25] has been adopted.

Let r_i^2 represents the i^{th} ordered weighted squared residual. The weighted residuals are squared and arranged in ascending order, i.e. $r_1^2 \le r_2^2 \le .. \le r_\upsilon^2 \le .. \le r_m^2$. Subsequently, the weighted residuals are winsorized at rank υ. This is done by replacing $(\upsilon+1)^{th}$ residual with υ^{th} residual. State estimation equation (1) is then solved by using least winsorized square by minimizing the objective function given in (2).

$$\min \sum_{i=1}^{\upsilon} (r^2)_{i:m} + (m-\upsilon)(r^2)_{\upsilon:m} \tag{2}$$

where, $\upsilon = \left[\frac{m}{2}\right] + \left[\frac{n+1}{2}\right]$

$r_{i:m}^2$ represents the i^{th} ordered squared residual arranged from smallest to largest.

3. JADE-Adaptive differential evolution algorithm

Classical differential evolution (DE) algorithm, proposed by Price and Stone [26] is a simple yet powerful evolutionary algorithm for solving many global optimization problems in real world applications. However, the performance of DE depends on mainly two components. The first component is its donor and trial vector generation strategy, and the second is its control parameter settings such as mutation factor (F), crossover probability (CR), and population size (N_P) [26-29]. As a result, the quality of the solution obtained and the efficiency of the search greatly depends on these parameters [27, 28]. Tuning the control parameters is a very time-consuming and tedious task [29]. To deal with the disadvantage of classical DE, JADE-adaptive differential evolution with an optional external archive is proposed by Zhang and Sanderson [29] along with a new mutation operator "DE/current-to-pbest". Similar to all other evolutionary algorithms (EAs), JADE begins with randomly generating individuals which satisfy the constraints of population P of size N_p with D decision parameters [26-29]. The population size remains constant throughout the optimization process that evolves over G generations to reach an optimal solution and a parent vector from the current generation is termed as target vector.

$$P^G = \begin{pmatrix} x_{11} & \cdots & x_{1D} \\ \vdots & \ddots & \vdots \\ x_{N_p 1} & \cdots & x_{N_p D} \end{pmatrix} \quad (3)$$

This population is randomly generated that is uniformly distributed in the feasible solution space. After initialization, JADE is carried out with three simple cycles of stages, namely the differential vector based mutation, crossover, and selection [26-29].

3.1 Difference Vector Mutation

For every generation G, another population called donor vector $v_{i,G}$ is obtained from target vector (current population) by performing difference vector mutation. Some of the widely used mutation operators in the literature [26-29] are:

1) " DE/rand/1"

$$v_{i,G} = x_{r1,G} + F.(x_{r2,G} - x_{r3,G}). \quad (4)$$

2) " DE/best/1"

$$v_{i,G} = x_{best,G} + F.(x_{r1,G} - x_{r2,G}). \quad (5)$$

3) "DE/rand/2"

$$v_{i,G} = x_{r1,G} + F.(x_{r2,G} - x_{r3,G}) + F.(x_{r4,G} - x_{r5,G}). \quad (6)$$

4) "DE/best/2"

$$v_{i,G} = x_{best,G} + F.(x_{r1,G} - x_{r2,G}) + F.(x_{r3G} - x_{r4,G}). \quad (7)$$

5) "DE/current-to-best/1"

$$v_{i,G} = x_{i,G} + F.(x_{best,G} - x_{i,G}) + F.(x_{r1G} - x_{r2,G}). \quad (8)$$

where, $r1, r2, r3, r4, r5$ are randomly chosen different chromosomes from target vector in the range $[1, \mathrm{N_P}]$, $x_{best,G}$ is the best vector in the current generation G and F is a mutation factor [26-29].

However, in the present JADE algorithm a new generation strategy "DE/current-to-pbest/1" with optional archive has been introduced. For this, a mutation vector without archive is generated and is given as:

$$v_{i,G} = x_{i,G} + F_i \cdot (x^p_{best,G} - x_{i,G}) + F_i \cdot (x_{r1,G} - x_{r2,G}) \quad (9)$$

where, $x^p_{best,G}$ is randomly chosen from one of the top $100p\%$ individuals in the current population with $p \in (0,1]$ and control parameter F_i is updated in an adaptive manner.

However, to provide the information about progress direction and to improve the diversity of the population, an archive that utilizes the historical data is created, viz. the archive A consists of recently explored inferior solutions [29]. The mutation vector strategy with archive is generated in the following manner:

$$v_{i,G} = x_{i,G} + F_i \cdot (x^p_{best,G} - x_{i,G}) + F_i \cdot (x_{r1,G} - \tilde{x}_{r2,G}) \quad (10)$$

where, $\tilde{x}_{r2,G}$ is randomly chosen from the union, $\mathrm{P} \cup \mathrm{A}$, of the current population and the archive.

3.2 Binomial Crossover

After performing difference vector mutation, binomial crossover is executed to improve the diversity of the population. Binomial crossover is performed by generating a random number between 0 and 1 on each of the decision variables D to obtain another population called trial vector $u_{i,G}$. If the generated random number is greater than the crossover rate (CR) then the decision variable is inherited from the target vector $x_{i,G}$ else decision variable is inherited from the donor vector $v_{i,G}$, defined as follows:

$$u_{j,i,G} = \begin{cases} v_{j,i,G}, & \text{if } rand(0,1) \le CR \text{ or } j = q \\ x_{j,i,G}, & \text{otherwise} \end{cases} \quad (11)$$

where, $rand(0,1)$ is a uniform random number on the interval [0, 1], $i = 1,..,N_P$, $j = 1,...,D$ and q is a randomly chosen index $\{1,\ldots,N_p\}$ which guarantees that the trial vector gets at least one parameter from the mutant vector; CR is an algorithm control parameter which assists the algorithm to escape from local optima [26-29].

3.3 Selection

Finally, the selection process is performed based on the fitness function value of the individual to determine whether the trial vector or the target vector survives to the next generation. The selection operation is given according to (12).

$$x_{i,G+1} = \begin{cases} u_{i,G}, & \text{if } f(u_{i,G}) < f(x_{i,G}) \\ x_{i,G}, & \text{otherwise} \end{cases} \tag{12}$$

Hence, the population either gets better or remains the same in fitness status, but never deteriorates as the process is repeated. This, allows the individuals to improve their fitness as they explore the solution space in the search of optimal values [26-29].

In the present algorithm, a normal distribution and a Cauchy distribution are utilized to generate *CR* and *F* for each target vector, respectively. At each generation G, the crossover rate CR_i of each individual x_i is independently generated which is shown in (13).

$$CR_i = randn_i(\mu_{CR}, 0.1) \tag{13}$$

where, $randn_i$ is a normal distribution with mean μ_{CR} and standard deviation 0.1.

It is then truncated to [0, 1]. Let S_{CR} denotes the set of all successful crossover probabilities CR_i's at generation G [29]. The mean μ_{CR} is initialized to be 0.5 and then updated at the end of each generation as:

$$\mu_{CR} = (1-c).\mu_{CR} + c.\ mean_A(S_{CR}) \tag{14}$$

where, c is a positive constant between 0 and 1, and $mean_A(.)$ is the usual arithmetic mean.

Similarly, at each generation G, the mutation factor F_i of each individual x_i is independently generated which is given in (15)

$$F_i = randc_i(\mu_F, 0.1) \tag{15}$$

where, $randc_i$ is a Cauchy distribution with mean μ_F and standard deviation 0.1.

Here F_i is truncated to 1 if $F_i \geq 1$ or regenerated if $F_i \leq 0$. Let S_F denotes the set of all successful mutation factors in the generation G [29]. The location parameter μ_F of the Cauchy distribution is initialized to be 0.5 and then updated at the end of each generation as:

$$\mu_F = (1-c).\mu_F + c.\ mean_L(S_F) \tag{16}$$

where, $mean_L(.)$ is the Lehmer mean which is given as:

$$mean_L(S_F) = \frac{\sum_{F \in S_F} F^2}{\sum_{F \in S_F} F} \tag{17}$$

4. Solution methodology

Complete procedure of the proposed technique is presented in the flowchart shown in Fig. 1. Step by step procedure of the algorithm is explained below.

[Figure 1 Here]

Algorithm:

Step 1: In this step, the maximum number of generations, population size in each generation, adaptive control parameters c and p are initialized, and a measurement error of $\pm 5\%$ has been considered. The control parameters of the algorithm are provided in Table 1.

Step 2: Now, Newton Raphson (NR) load flow analysis is performed for each time sample on the test systems under study to obtain the measured data. Subsequently, in order to make the simulated measurements be the same as the practical field measurements a measurement error of $\pm 5\%$ is added according to the method described in [23]. In the technical literature [1, 2, 6, 7, 22] measurement errors have been traditionally modelled as Gaussian distribution random variables. This is reasonable assumption because Gaussian distribution provides a good approximation for most of the distributions that arise in a practical power system. Moreover, the central limit theorem states that under random sampling, as the number of degrees-of-freedom $(m-n)$ increases, the limiting distribution becomes more symmetric and is close to Gaussian. Hence, in the present work, the measurements are assumed to have a Gaussian error distribution with zero mean and standard deviation σ. Further, the proposed method works well even when the measurements have non-Gaussian distribution. This is due to the proposed LWS estimator pays more attention to the central portion of a distribution by transforming the $(\upsilon+1)^{th}$ residual with υ^{th} residual. This helps to pull the mean towards the middle of the distribution. Hence, the proposed method maintains optimal performance not only under the assumed Gaussian model but also for non-Gaussian model.

Step 3: JADE starts with randomly generated population of size N_P that follows a uniform distribution $x_j^{low} \le x_{j,i,0} \le x_j^{up}$, for $j = 1, 2, ..., D$, where, D is the dimension size of the problem. Here, number of state variables represents the dimension size of the problem. In the present work, node voltages are considered as state variables which are expressed in terms of magnitude and phase angle. Thus, for a N bus power system the total number of state variables will be $2N$, i.e. the voltages and the corresponding phase angles at all the buses. However, by considering the slack bus as reference, the total number of state variables which are to be estimated will now be $2N-1$. Therefore, each individual chromosome in a given population can be represented as:

$$x_i = \{U_{i1},\ U_{i2},...,\ U_{iN},\ \delta_{i2},...,\ \delta_{iN}\},\ i = 1,\ 2,\ 3,\ldots,\ N_P \tag{18}$$

where, $U_{i1},\ U_{i2},...,\ U_{iN}$ are the voltage magnitudes of i^{th} chromosome and $\delta_{i2},...,\delta_{iN}$ are the voltage phasors of i^{th} chromosome.

Thus, the dimension size of the population is $N_P \times D$.

In order to obtain the boundary conditions provided in (19), load flow analysis is performed initially by varying the load randomly between $\pm 35\%$ at each load bus from its base case of the test systems under study. Thus obtained maximum and minimum values of voltage magnitudes and voltage angles are selected as boundary conditions. It has been observed from the simulation study that the choice of limits does not affect the solution and these limits can easily be relaxed for higher load variations.

$$\begin{gathered} 0.75 \text{ p.u.} \le U \le 1.25 \text{ p.u.} \\ -80^o \le \delta \le 80^o \end{gathered} \tag{19}$$

where, p.u. represents per unit.

Step 4: Set time sample $k = 1$.

Step 5: In this step, field measurements set is determined for time sample k. After obtaining the field measurements, test of innovation process is performed to identify the presence of anomaly. If the presence of anomaly is detected, then skewness of measure test is performed to discriminate the anomalies, namely either a sudden load change or a bad data.

Step 6: SE having a statistical criterion estimates the true states of the system by minimizing the objective function shown in (2). The SE problem formulated in (2) is a combinatorial in nature and requires Monte-Carlo like method to carry out a limited number of state estimation computations to determine one of the z essential sets which is free from bad data. In this paper, a method similar to the proposed method in [18] has been performed to obtain an essential set of measurements. Then these measurements are used to determine the fitness value of each chromosome of the current generation.

Step 7: After the initial six steps, for each chromosome crossover rate (CR) is initialized according to a normal distribution of mean $\mu_{CR} = 0.5$ and standard deviation 0.1. Similarly, scaling constant (F) for each chromosome in the population is initialized according to the Cauchy distribution with location parameter $\mu_F = 0.5$ and scale parameter 0.1.

Step 8: In this step, calculation of the fitness function of the current population is carried out in three simple cycles of stages, viz. differential vector based mutation, crossover, and selection. Another population called donor vector is obtained through difference vector mutation.

Step 9: After difference vector mutation, the donor population undergoes a binomial crossover operation to enhance the diversity of the population.

Step 10: In this step, the selection process is performed to select best fitted chromosomes amongst the target population and corresponding trial population in the current iteration. This helps to obtain the target population for the next iteration.

Step 11: Using normal distribution the crossover rate CR is updated with mean μ_{CR} and standard deviation 0.1.

Step 12: Using Cauchy distribution the mutation factor F is updated with mean μ_F and standard deviation 0.1.

Step 13: Steps 8 to 12 are then repeated until the number of generations reaches the maximum number of generations.

Step 14: Update the time sample k as $k = k+1$.

Step 15: Steps 5 to 14 are repeated until the number of time samples reaches the maximum number.

Step 16: Stop.

4.1 Parameter Selection

SE is performed using different control parameter settings. After detailed study of 100 trials of the proposed algorithm, best control parameters corresponding to the minimum fitness value have been considered. The control parameters which are selected in this work are tabulated in Table 1. Control parameters c, p, N_P, and G are selected based upon the empirical study. For each test system under consideration, simulation study has been performed using different parameter combinations such as adaptive control parameter $c \in \{0.01,\ 0.05,\ 0.1,\ 0.2,\ 0.5,\ 1\}$, adaptive control parameter $p \in \{0.01,\ 0.05,\ 0.1,\ 0.2,\ 0.5\}$, five different population sizes $N_P \in \{50,\ 75,\ 100,\ 125,\ 150\}$, and maximum number of generations $G \in \{250,\ 500, 750\}$. After performing the simulation study, minimum fitness value has been found when the maximum number of generations is 250, population size of 100, adaptive control parameter $c =$ 0.1, and adaptive control parameter $p = 0.05$. Therefore, these parameters are taken in this paper.

[Table 1 Here]

5. Simulation Study

The objective of the simulation study is to analyze the LWS based JADE technique by applying it to TSE. Further, validation of the performance of the estimator has been carried out under normal operation, bad data, and sudden load change conditions.

5.1 Test systems

Simulation tests have been performed on three test systems, viz. IEEE 14-bus, IEEE 30-bus, and IEEE 57-bus systems [30].

5.2 Measurement generation

States of the power system are estimated by utilizing the information obtained from the PMUs and conventional meters, placed optimally across the network. In this paper, an over-determined system with a measurement redundancy $(m/n \approx 2)$ has been considered. A system is said to be over-determined if the number of measurements are greater than the number of state variables. In the present work, 46 measurements, 102 measurements, and 192 measurements have been used for IEEE 14-bus, IEEE-30 bus, and IEEE 57 bus systems respectively. The simulation study is performed by linearly varying the load at each bus from 70% to 130% with a trend of $2\%,$ plus a random fluctuation of 2% of the trend component. Constant power factor has been assumed so that reactive power follows the active power [31]. In the absence of practical field data, Newton Raphson load flow analysis is performed for each time sample on the test systems under study to obtain the simulated data (true values). In order to make the simulated measurements resemble the field measurements, $\pm 5\%$ randomly generated measurement error has been added. The final measurement vector thus obtained acts as an input to the proposed state estimator and the operation of the test systems is given below:

a) Normal operation: For normal operating condition, the loads are varied linearly. Measurements in this operation are assumed to be noisy. Moreover, it is assumed that these measurements are free from bad data.

b) Measurement set with bad data: The proposed method has been simulated for a scenario where bad measurements are present in the measurement set. To obtain this measurement set, five different conditions are considered on all the test systems under consideration. These conditions are as follows:

i) introducing one bad data measurement selected randomly with reverse polarity at 5^{th} time sample.

ii) introducing two bad data measurements selected randomly with reverse polarity at 10^{th} time sample.

iii) introducing two bad data measurements selected randomly with reverse polarity at 15^{th} time sample.

iv) introducing three bad data measurements selected randomly with reverse polarity at 20^{th} time sample.

v) introducing four bad data measurements selected randomly with reverse polarity at 25^{th} time sample.

It is assumed that the bad measurement disappears after the particular time sample.

c) Sudden load change operation: The performance of the proposed method has also been investigated under sudden load change conditions. Measurement set for this condition has been determined under the following scenarios:

For test case 1, i.e. IEEE 14-bus system, the following sudden load change conditions are observed:

i) 50% load reduction at 6^{th} time sample on bus 3

ii) Sudden loss of load at 10^{th} time sample on bus 9

iii) 50% load increase at 15^{th} time sample on bus 3

iv) 20% load increase at 20^{th} time sample on all the load buses

v) Sudden loss of load at 23^{rd} time sample on bus 14

vi) 20% load decrease at 31^{st} time sample on all the load buses

For test case 2, i.e. IEEE 30-bus system, different sudden load change situations are simulated. These are:

i) 50% load reduction at 6^{th} time sample on bus 30

ii) Sudden loss of load at 10^{th} time sample on bus 19

iii) 50% load increase at 15^{th} time sample on bus 30

iv) 20% load increase at 20^{th} time sample on all the load buses

v) Sudden loss of load at 23^{rd} time sample on bus 8

vi) 20% load decrease at 31^{st} time sample on all the load buses

and finally for the third test case, i.e. IEEE 57-bus system, the following sudden load change conditions are assumed to occur:

i) 50% load reduction at 6^{th} time sample on bus 50

ii) Sudden loss of load at 10^{th} time sample on bus 51

iii) 50% load increase at 15^{th} time sample on bus 50

iv) 20% load increase at 20^{th} time sample on all the load buses

v) Sudden loss of load at 23^{rd} time sample on bus 18

vi) 20% load decrease at 31^{st} time sample on all the load buses

d) Discrimination of bad data and sudden load change: In the power system, sudden change in states may occur due to sudden loss of loads or unscheduled generator outage and switching operation of the power system elements. Therefore, in order to discriminate between bad data and sudden load changes, a method proposed in [32] has been adopted in the present work. To accomplish such a task, two tests have been performed. In the initial step, the test of innovation process is performed to detect the presence of any anomaly in the measurement set. This is defined as follows:

$$|\lambda_i(k)| = |\vartheta_i(k)| / \sigma_{N,i}(k) \le \lambda_{\max} \tag{20}$$

where, $\vartheta(k)$ is the innovation vector at time instant k .

σ_N is the standard deviation of innovation vector $\vartheta(k)$.

In order to discriminate the anomaly due to bad data and sudden change in load, skewness of measure test is then performed [31]. It is pointed out here that only in case of bad data in the measurement set; the innovation vector $\vartheta(k)$ becomes asymmetrically distributed and its asymmetry index (skewness measure) is given by the following equation:

$$|\gamma(k)| = M_3(k) / \sigma^3(k) \tag{21}$$

where, M_3 is the third moment.

σ is the standard deviation of the distribution at t_k .

From (21), occurrence of bad data is determined. If $|\gamma(k)|$ is greater than a pre-defined threshold value say $(a_{\max})$, then measurements have gross errors else sudden load change is detected.

5.3 Performance evaluation

The following important performance index and statistical parameters are used to assess the performance of the proposed method and its comparison is carried out with WLS, particle swarm optimization (PSO), and gravitational search algorithm (GSA) based SE techniques [33].

5.3.1 Performance index

Filter effect $J(k)$ is calculated to assess the overall estimation performance and is given in (22)

$$J(k) = \frac{\sum_{i=1}^{m} |\hat{z}_i(k) - z_i^t(k)|}{\sum_{i=1}^{m} |z_i(k) - z_i^t(k)|} \tag{22}$$

where, $\hat{z}_i$, z_i^t, and z_i are the final estimated, true, and measured measurement values.

In case of good filtering the above performance index $J(k)$ should be less than one.

5.3.2 Statistical parameters

The following different statistical parameters as specified in [33] are used:

The maximum of mean square error (MMSE): MMSE of the state estimates is computed according to (23)

$$MMSE = \max\left[\frac{1}{NS}\sum_{k=1}^{NS}(\hat{x}_i(k) - x_i^{true}(k))^2\right] \tag{23}$$

where, NS represents the number of time samples.

$\hat{x}_i(k)$ and $x_i^{true}(k)$ are the estimated and the true measurements of the state vector at k^{th} time sample.

The maximum standard deviation error (MSDE): MSDE of the state estimates is determined as:

$$MSDE = \max\left[\frac{1}{(NS-1)}\sum_{k=1}^{NS}(\hat{x}_i(k) - x_i^{true}(k))^2\right]^{0.5} \tag{24}$$

The maximum of sum squared error (MSSE): MSSE of the state estimates is calculated according to (25)

$$MSSE = \max\left[\sum_{k=1}^{NS}(\hat{x}_i(k) - x_i^{true}(k))^2\right] \tag{25}$$

The average of absolute error (AAE): AAE of state estimates is determined as:

$$AAE = \frac{1}{NS}\sum_{k=1}^{NS}\frac{1}{(2\times N-1)}\sum_{i=1}^{(2\times N-1)}\left|(\hat{x}_i(k) - x_i^{true}(k))\right| \tag{26}$$

6. Results and discussion

As discussed in Section 5, the proposed method is applied on three IEEE test systems to study the performance of the estimator under three different scenarios, namely normal operation, bad data, and sudden load change conditions. Simulated results thus obtained are presented and discussed in this section.

6.1 Normal operation condition

Fig. 2 outlines the performance of the LWS technique based on statistical parameters. Comparison of the LWS with WLS, PSO, and GSA for the normal operating condition is also given in Fig. 2. As can be seen from the figure, the LWS estimator demonstrates the best performance for all the test systems as statistical parameters have least values indicating that the state estimates are nearly equal to the true states. GSA based SE technique provides reduced statistical parameters compared to WLS technique; however, this is larger than proposed LWS technique. Based on the statistical parameter values given in Fig. 2, it can be seen that PSO based SE technique provides poor results compared to other SE techniques. It can also be observed from Fig. 2, the statistical parameter values of WLS, PSO, and GSA increase with an increase in the system size. While the statistical parameter values of the LWS based SE technique are intact. This proves that the LWS technique provides better estimates compared to the WLS, PSO, and GSA based SE techniques.

[Figure 2 Here]

6.2 Bad data condition

In this case, LWS estimator is assessed in the presence of bad data. The bad measurements are introduced in the measurement set as explained in Section 5.2 (b). These bad data measurements may be caused due to incorrect wiring, time skew, systematic errors, infrequency of instrument calibration, etc.

Fig. 3 provides the comparison of the performance index $J(k)$ of the proposed LWS estimator under normal and bad data conditions for the various test cases under study. It can be observed from Fig. 3 that the difference in the variation of performance index $J(k)$ is not drastic for all the test systems, as if there are no bad measurements. This is because of the proposed method provides an effective way of dealing with such type of problems by transferring the bad data measurements toward the most fitted values. This helps to pull the mean towards the middle of the distribution. As a result, the effect of bad data measurements on remaining good measurements is decreased, thus increasing the accuracy of the state estimates. Furthermore, measurement redundancy is also kept intact since the bad data measurements are not eliminated. Therefore, it is confirmed from Fig. 3 that the estimated results are not affected even in the presence of bad measurements. This shows the robustness, i.e. rejection properties of the proposed method against bad data. Hence, the proposed method does not require any re-analysis phase for bad data rejection.

However, in case of WLS, PSO, and GSA based SE techniques that are optimal under normal operating condition generally have a large distorting influence even in the presence of single bad data, i.e. the remaining good measurements tend to compensate for the effect of one bad data measurement. This significantly degrades the accuracy of the estimated states. Hence, re-analysis phase is necessary for WLS, PSO, and GSA based SE techniques to identify and remove these bad data measurements. Moreover, the removal of bad data measurement is associated with a decrease in measurement redundancy.

Fig. 4 describes the comparison of statistical parameter values of the LWS estimator without bad data processor and WLS, PSO, and GSA based SE techniques with the inclusion of the bad data processor. From Fig. 4, it can be observed that LWS estimator provides better estimated states compared to other SE based techniques even in the presence of bad measurements. Similar to the normal condition, LWS estimator has small statistical parameter values. These values have been retained for all the test systems under consideration. However, the statistical parameter values of WLS, PSO, and GSA based SE techniques increase with an increase in the system size. This is an indication that LWS estimator is more reliable and robust compared to the other SE techniques.

[Figure 3 Here]

[Figure 4 Here]

6.3 Sudden load changes

In this case, sudden change in load condition is considered to evaluate the performance of the LWS based SE technique. For this, the system is operated at different operating points to accommodate sudden load changes as explained in Section 5.2 (c). Fig. 5 illustrates the comparison of performance index $J(k)$ of the LWS estimator under normal operation and sudden load change conditions. It can be observed from Fig.5 that even in the presence of sudden load changes; the difference in performance index $J(k)$ is not high and behaves as if there is no sudden state variation in the system operating conditions. This is due to the reason that LWS based JADE algorithm is a population based SE technique embedded with different state scenarios (candidate solutions) and hence takes care of the sudden load change condition smoothly. Further, to improve the computational time, LWS estimator utilizes the latest available estimated system states for the subsequent time sample. That is, the estimated system states obtained in the present sample are added to the population of the subsequent time sample as single chromosome. Remaining $N_P - 1$ chromosomes are then reinitialized. This process makes the LWS based SE technique robust even for sudden load change conditions. Summary of the statistical parameters of the LWS based SE method is presented in Table 2. From the table, it can be observed that similar to normal operation, the statistical parameter values are small even for sudden state variation conditions. Hence it can be concluded that the proposed LWS estimator provides better estimates even in the presence of sudden load changes. This demonstrates the superiority of the proposed LWS technique.

[Figure 5 Here]

[Table 2 Here]

6.4 Anomaly detection and identification

In this subsection, detection and identification of bad data measurements have been performed by two tests, viz. the test of innovation process and the test of skewness of measure. Both are explained in Section 5.2 (d). After obtaining a new set of measurements, anomaly detection is performed using normalized innovation vector $\lambda(k)$. After multiple offline simulations of 100 trials, the threshold value $\lambda_{\max}$ of 1.5 p.u. has been set to identify the presence of anomaly. When anomalies are present in the measurement set, then $\lambda_i(k)$ of corresponding measurement value will be larger than $\lambda_{\max}$. Further, to discriminate the anomalies caused either by bad data or sudden load change, skewness of measure test is performed. For this the threshold value $a_{\max} = 4$ has been established for all the test systems after multiple simulations of 100 trials. It means that, if 'asymmetry index' $|\gamma_k|$ is greater than $a_{\max}$ then the identified anomalies using normalized innovation vector are bad data. Otherwise, errors in the vectors are due to sudden load change.

For the sake of illustration, IEEE 14-bus system has been considered. Fig. 6 shows the normalized innovation vector corresponding to 5^{th} time sample. As can be seen from Fig. 6, the normalized innovation value of active power measurement P_{25} of bus 2 to bus 5 exceeds the predefined threshold value $\lambda_{\max} = 1.5$ p.u. This indicates the presence of anomaly. It can be found from Fig. 8 (a), during 5^{th} time sample the asymmetry index $|\gamma_k|$ exceeds the threshold value $a_{\max} = 4$ which confirms the anomaly is due to the presence of bad data in the measurement set.

Now, consider a sudden change in load condition for the same test system. Fig. 7 depicts the normalized innovation vector for the sudden loss of load at bus 14 during 23^{rd} time sample. It can be observed from Fig. 7, the normalized innovation values $(\lambda_i(k))$ corresponding to the measurements $(P_{9,14}$ and $P_{13,14})$ near to bus 14 exceeds the threshold value $\lambda_{\max} = 1.5$ p.u. this indicates the presence of anomalies. To confirm the anomaly is due to sudden load change condition, skewness of measure test is performed. As seen from Fig. 8 (b), during 23^{rd} time sample the asymmetry index $|\gamma_k|$ is well below the threshold value $a_{\max}$ confirming that the anomaly is due to sudden state variation and not because of bad data [34].

[Figure 6 Here]

[Figure 7 Here]

[Figure 8 Here]

Further, the computational time taken by the proposed SE method is computed and is tabulated in Table 3. Table 3 consists of three columns indicating the test system under consideration, the total computational time, and the time taken for the first appearance of the solution with acceptable accuracy respectively. It is observed from the table that the major challenge of the proposed LWS technique is the computational burden which increases with an increase in the system size. This is due to an increase in the search space for finding the optimal solution. Although, the proposed method provides more precise estimates and highly robust against outliers compared to WLS technique, it cannot compete with WLS based SE technique in terms of computational efficiency. This is due to the reason that LWS based JADE technique works on population, i.e. set of solutions while, WLS works with a single solution [18]. However, this drawback can be overcome by decomposing the large system into a multi-area system which significantly decreases the computational burden. This shall be the future work of the authors. Moreover, the computational burden can be decreased by effective programming and with an increase of computer speeds as being witnessed every year. Under these conditions, the evolutionary approach shall be very fast very soon [35, 36]. Hence, in the present day scenario the proposed method is an effective and efficient tool for off-line studies.

[Table 3 Here]

7. Conclusions

In this paper, a new robust LWS based JADE-adaptive differential evolution is presented. LWS estimator has been implemented for tracking of the time varying static state of the power system. The proposed method has been validated on different IEEE test systems. The performance of the LWS estimator has been demonstrated by considering various simulation conditions, including pre-estimation detection and identification methods. The results obtained reveal that the proposed method can operate under any operating conditions without the need of reinitiating the tracking state estimator. The computational performance of LWS estimator has been compared with WLS, PSO, and GSA based SE techniques. On the basis of various performance indices used in the work, the results thus obtained substantiate that the proposed method provides precise state estimates. Also, the estimator is highly insensitive against anomalies compared to other PSSE techniques. Finally, it is confirmed from the results that the proposed technique shows reliable and robust performance in cases such as normal noisy operation, single and multiple bad data (outliers), and sudden load change conditions.

References

[1] G. N. Korres, N. M. Manousakis, A state estimator including conventional and synchronized phasor measurements, Computers Electrical Engineering 38 (2) (2012) 294-305.

[2] E. Caro, R. Mínguez, A. J. Conejo, Robust WLS estimator using reweighting techniques for electric energy systems, International Journal of Electric Power Systems Research 104 (2013) 9-17.

[3] W. W. Kotiuga, Development of a least absolute value power system tracking state estimator, IEEE Transactions on Power Apparatus and Systems PAS-104 (5) (1985) 1160-1166.

[4] L. Mili, M. G. Cheniae, N. S. Vichare, P. J. Rousseeuw, Algorithms for least median of squares state estimation of power systems, in: Procedings of IEEE Int. Conf. on Circuits and Systems of the 35th Midwest Symposium, August 1992, pp. 1276-1283.

[5] R. D. Masiello, F. C. Schweppe, A tracking static state estimator, in: Proceeding of IEEE int conf on Summer Power Meeting and EHV, 1970, pp. 1025-1033.

[6] A. Abur, A. G. Exposito, Power system state estimation theory and implementation, first ed., Marcel Dekkar Inc, New York, 2004.

[7] S. C. Tripathy, D. S. Chauhan, G. D. Prasad, Static and tracking state estimation in power system using newton's method, Electric Machines & Power Systems 18 (2) (1990) 97-111.

[8] E. Caro, A. J. Conejo, State estimation via mathematical programming a comparison of different estimation algorithms, IET Generation, Transmission and Distribution 6 (6) (2012) 545-553.

[9] M. R. Irving, R. C. Owen, M. J. H. Sterling, Power-system state estimation using linear programming, Proceedings of the Institution of Electrical Engineers 125 (9) (1978) 879-885.

[10] M. K. Celik, A. A Abur, Robust WLAV state estimator using transformations, IEEE Transactions on Power Systems 7 (1) (1992) 106-113.

[11] A. Abur, M. K. Celik, A fast algorithm for the weighted least absolute value state estimation, IEEE Transactions on Power Systems 6 (1) (1991) 1-8.

[12] L. Mili, V. Phaniraj, P. J. Rousseeuw, Least median of squares estimation in power systems, IEEE Transactions on Power Systems 6 (2) (1991) 511-523.

[13] L. Mili, M. G. Cheniae, P. J. Rousseeuw, Robust state estimation of electric power systems, IEEE Transactions on Circuits and Systems I Fundamental Theory and Applications 41 (5) (1994) 349-358.

[14] R. Baldick, K. A. Clements, Z. Pinjo-Dzigal, P. W. Davis, Implementing non-quadratic objective functions for state estimation and bad data rejection, IEEE Transactions on Power Systems 12 (1) (1997) 376-382.

[15] F. Zhuang, R. Balasubramanian, Bad data suppression in power system state estimation with a variable quadratic-constant criterion, IEEE Transactions on Power Apparatus and Systems PAS-104 (4) (1985) 857-863.

[16] R. C. Pires, A. S. Costa, L. Mili, Iteratively reweighted least-squares state estimation through Givens Rotations, IEEE Transactions on Power Systems 14 (4) (1999)1499-1507.

[17] D. M. Falcao, P. A. Cooke, A. Brameller, Power system tracking state estimation and bad data processing, IEEE Transactions on Power Apparatus and Systems PAS-101 (2) (1982) 325-333.

[18] S. Gastoni, G. Granelli, M. Montagna, Robust state-estimation procedure based on the maximum agreement between measurements, IEEE Transactions on Power Systems 19 (4) (2004) 2038-2043.

[19] M. R. Irving, Robust state estimation using mixed integer programming, IEEE Transactions on Power Systems 23 (3) (2008) 1519-1520.

[20] M. R. Irving, Robust algorithm for generalized state estimation, IEEE Transactions on Power Systems 24 (4) (2009) 1886-1887.

[21] Y. Del Valle, G. K. Venayagamoorthy, S. Mohagheghi, J. C. Hernandez, and R. G. Harley, Particle swarm optimization: basic concepts, variants and applications in power systems, IEEE Transactions on Evolutionary Computation 12 (2) (2008) 171-195.

[22] D. H. Tungadio, B. P. Numbi, M. W. Siti, A. A. Jimoh, Particle swarm optimization for power system state estimation, Neurocomputing (2014), http://dx.doi.org/10.1016/j.neucom.2012.10.049i.

[23] G. N. Korres, N. M. Manousakis, State estimation and bad data processing for systems including PMU and SCADA measurements, International Journal of Electric Power Systems Research 81 (2011) 1514-1524.

[24] A. K. Al-Othman, M. R. Irving, Uncertainty modelling in power system state estimation. IEE Proceedings Generation, Transmission and Distribution 152 (2) (2005) 233-239.

[25] P. J. Rousseeuw, A. M. Leroy, Robust regression and outlier detection, first ed., John Wiley Sons, New York, 2005.

[26] R. Storn, K. Price, Minimizing the real functions of the icec'96 contest by differential evolution, in: Proceedings of IEEE Int. Conf. on Evolutionary Computation, 1996, pp. 842–844.

[27] S. Das, P.N. Suganthan, Differential Evolution A Survey of the State-of-the-Art, IEEE Transactions on Evolutionary Computation 15 (1) (2011) 4-31.

[28] J. Brest, S. Greiner, B. B. Skovic, M.Mernik, V. Zumer, Self-adapting control parameters in differential evolution: a comparative study on numerical benchmark problems, IEEE Transactions on Evolutionary Computation 10 (6) (2006) 646-657.

[29] J. Zhang, A.C. Sanderson, JADE: Adaptive differential evolution with optional external archive, IEEE Transactions on Evolutionary Computation 13 (5) (2009) 945-958.

[30] R. Christie, Power System Test Archive, Aug. 1999. [Online]. Available: http://www.ee.washington.edu/research/pstca.

[31] J. K. Mandal, A. K. Sinha, , L. Roy, Incorporating nonlinearities of measurement function in power system dynamic state estimation, IEE Proceedings Generation, Transmission and Distribution 142 (3) (1995) 289-296.

[32] K. Nishiya, J. Hasegawa, T. Koike, Dynamic state estimation including anomaly detection and identification for power systems, IEE Proceedings Generation, Transmission and Distribution 129 (5) (1982) 192-198.

[33] S. Mallick, S. P. Ghoshal, P. Acharjee, S. S. Thakur, Optimal static state estimation using improved particle swarm optimization and gravitational search algorithm, International Journal of Electrical Power Energy Systems 52 (2013) 254-265.

[34] G. Valverde, V. Terzija, Unscented Kalman filter for power system dynamic state estimation, IET Generation, Transmission and Distribution 5 (1) (2011) 29-37.

[35] C. Rakpenthai, S. Premrudeepreechacharn, S. Uatrongjit, N. R. Watson, An interior point method for WLAV state estimation of power system with UPFCs, International Journal of Electrical Power and Energy Systems 32 (2012) 671-677.

[36] C. Madtharad, S. Premrudeepreechacharn, N. R. Watson, Power system state estimation using singular value decomposition, International Journal of Electric Power Systems Research 67 (2003) 99-107.

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Figure Captions

Fig. 1. Flowchart of the proposed LWS based JADE-Adaptive differential evolution estimation technique

Fig. 2. Statistical parameter values under normal operation condition

Fig. 3. Performance index $J(k)$ in the presence of bad data

Fig. 4. Statistical parameter values under bad data condition

Fig. 5. Performance index $J(k)$ in the presence of sudden load change conditions

Fig. 6. Normalized innovation vector for bad data condition during 5th time sample

Fig. 7. Normalized innovation vector for sudden load change condition during 23rd time sample

Fig. 8. Skewness computation

Table Captions

Table 1 Control parameter settings.

Table 2 Statistical parameters under sudden load change conditions.

Table 3 Computational time (sec) taken by proposed technique.

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Table 1
Control parameter settings.

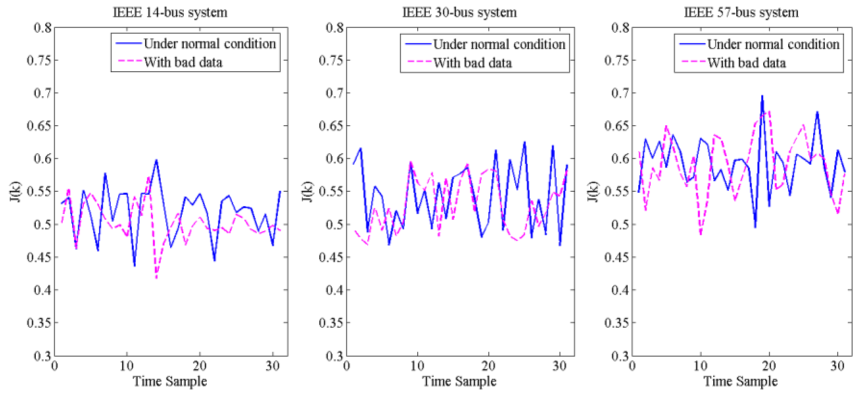
Algorithm	Control Parameters
JADE	Population Size = 100 No of Iterations = 250 Adaptive Control Parameter c = 0.1 Adaptive Control Parameter p = 0.05

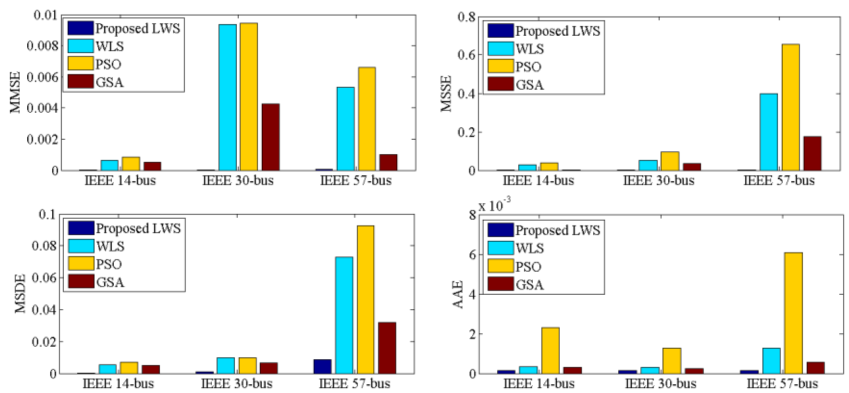
Table 2
Statistical parameters under sudden load change conditions.

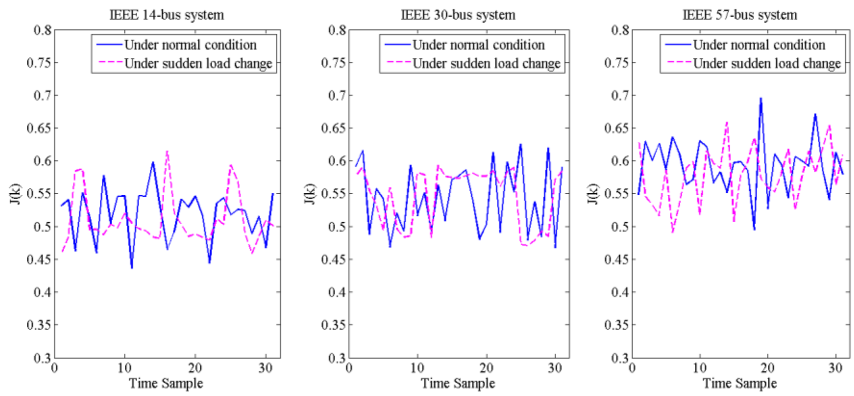
Test System	MMSE	MSDE	MSSE	AAE
IEEE 14-bus	1.04×10^{-7}	3.3×10^{-4}	3.23×10^{-6}	1.44×10^{-4}
IEEE 30-bus	9.05×10^{-5}	0.009671	0.002806	4.86×10^{-4}
IEEE 57-bus	9.41×10^{-6}	0.003118	2.92×10^{-4}	1.27×10^{-4}

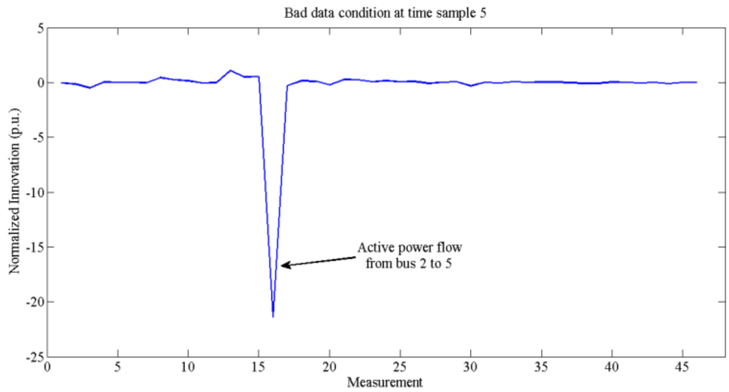
Table 3
Computational time (sec) taken by proposed technique.

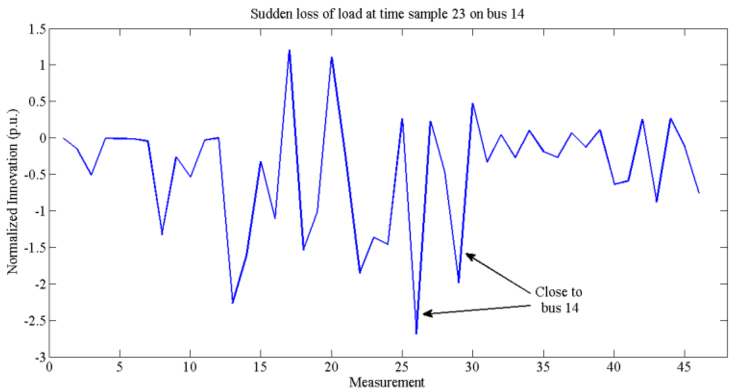
Test Bus System	T_{total}	T_{first}
IEEE 14-bus system	2.5386	0.8223
IEEE 30-bus System	3.9597	1.0256
IEEE 57-bus System	5.5224	1.7349

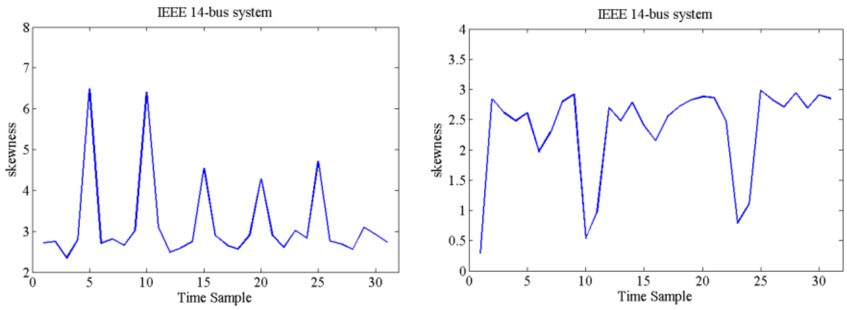




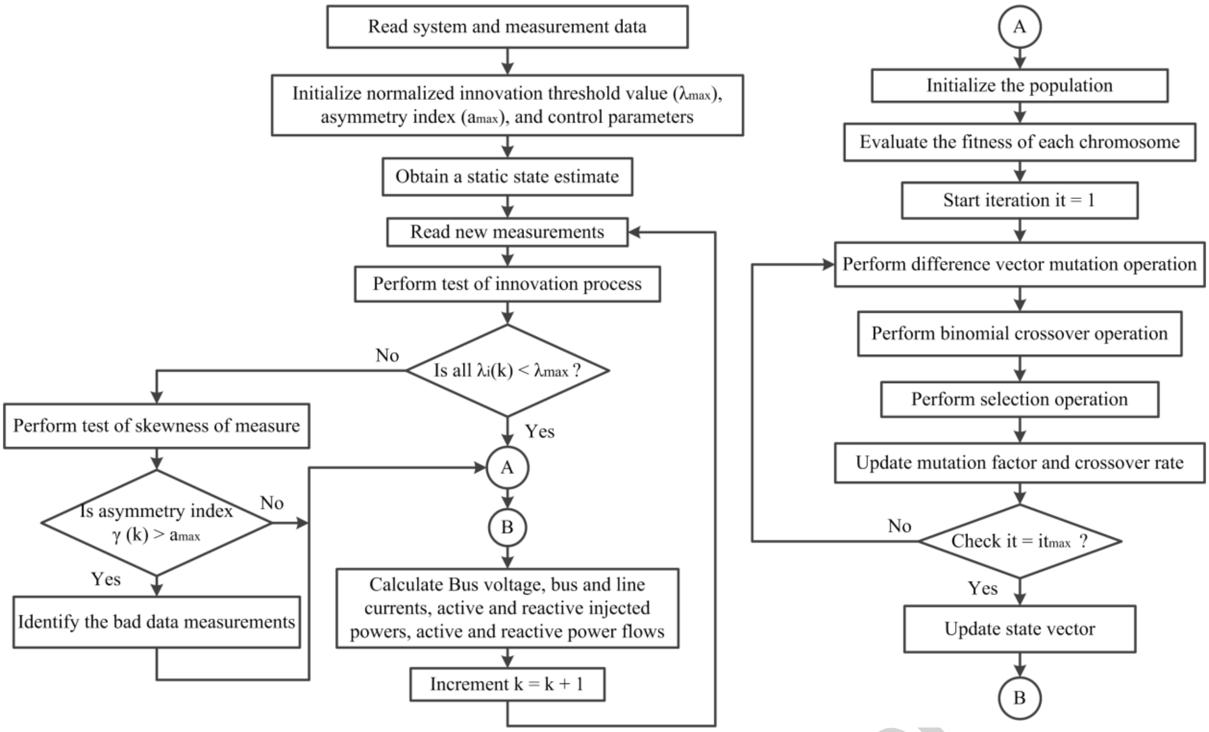


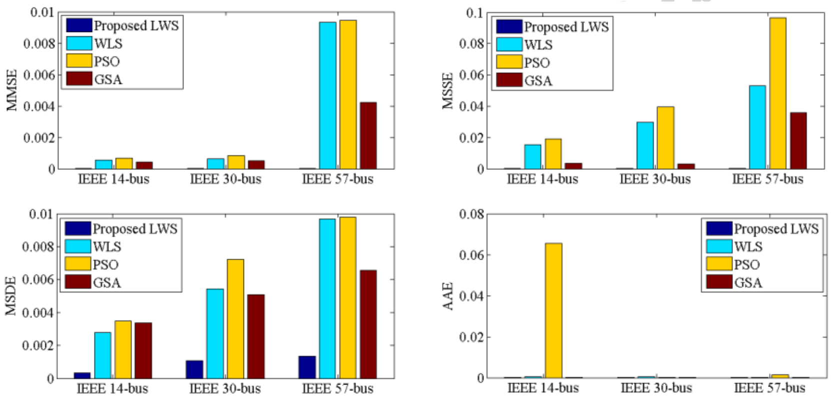

Bad data condition at time sample 5
Normalized Innovation (p.u.)
Measurement
Active power flow
from bus 2 to 5


Sudden loss of load at time sample 23 on bus 14
Normalized Innovation (p.u.)
Measurement
Close to
bus 14


IEEE 14-bus system
skewness
Time Sample
IEEE 14-bus system
skewness
Time Sample

(a) (b)


Read system and measurement data
Initialize normalized innovation threshold value (λmax), asymmetry index (amax), and control parameters
Obtain a static state estimate
Read new measurements
Perform test of innovation process
Is all λi(k) < λmax ?
No
Yes
Perform test of skewness of measure
Is asymmetry index γ (k) > amax
No
Yes
Identify the bad data measurements
A
B
Calculate Bus voltage, bus and line currents, active and reactive injected powers, active and reactive power flows
Increment k = k + 1
A
Initialize the population
Evaluate the fitness of each chromosome
Start iteration it = 1
Perform difference vector mutation operation
Perform binomial crossover operation
Perform selection operation
Update mutation factor and crossover rate
Check it = itmax ?
No
Yes
Update state vector
B


MMSE
MSSE
MSDE
AAE
Proposed LWS
WLS
PSO
GSA
IEEE 14-bus
IEEE 30-bus
IEEE 57-bus