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BBO Algorithm for Line Flow Based WLS State Estimation ✯

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Abstract

State estimation techniques are extensively used by all the utilities to make the best possible estimate of the present system state from the available set of redundant measurements. Conventional estimates most commonly emerge as generating bus voltage magnitudes and angles which should be converted later into line loadings to entire security analysis. BBO algorithm has been applied for line flow based state estimation technique which offers the output in terms of real and reactive power flows and bus voltage magnitudes. The proposed method when applied on standard test systems in the presence of various percentages of bad measurements has been found to give better outcome over those conventional WLS technique in terms of normalized error values and net computation time.

Keywords: State Estimation, Weighted Least Squares method, Line flow based WLS, BBO and Power System.

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Nomenclature

LFBSE	Line Flow Based State Estimation
SE	State Estimation
WLS	Weighted Least Squares
PM	Proposed Method
BBO	Biogeography Based Optimization

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LFWLS	Line flow based WLS
z	Measurement Vector
x^0	Initially assumed values of state vector
x_k	State vector at k^{th} iteration
x_{k+1}	State vector at $k+1^{th}$ iteration
Δx_k	State correction vector after k^{th} iteration
H	Jacobian Matrix
h(x)	Objective function
J(x)	Objective function
v	Vector of measurement residues
$[H^T WH]$	Gain matrix
P_i	Real bus power injection
Q_i	Reactive bus power injection
A_{ij},	ij^{th} element of bus incidence matrix
A_{ij}	ij^{th} element of modified bus incidence matrix
P_j	Real power flow in j^{th} line
l_j	Real power loss in j^{th} line
Q_j	Reactive power flow in j^{th} line
m_j	Reactive power loss in j^{th} line
H	Diagonal matrix formed by the sum of shunt and compensating susceptances at each bus
R	Diagonal matrix of line resistances
X	Diagonal matrix of line reactances
Λ	Diagonal matrix of order 1 with the values equal to the square of the tap settings
A_{1+} and A_{1-}	Positive and negative element of A_1
λ and μ	Lagrangian Multipliers
C	Loop incidence matrix
$\boldsymbol{\alpha}$	Phase angle of the phase shifter, taken as 1 otherwise
ΔV_{rms}, Δp_{rms}, Δq_{rms}	Root Mean Square values of the corresponding quantities
V_i^t, p_i^t, q_i^t	True values of the respective quantities on i^{th} bus
x_i^k	Position of individual i at iteration k
X_i^{k+1}	Position of individual i at iteration k + 1
v_i^k	Velocity of individual i at iteration k
w	weight parameter
C_1	Cognitive factor
C_2	Social factor
$P_{best\ i}^k$	best position of individual i until iteration k
$G_{best\ i}^k$	best position of group until iteration k
$rand_1\, rand_2$	random numbers between 0 and 1.
w_{min}, w_{max}	initial and final weights
C_{1min}, C_{1max}	initial ad final cognitive factors
C_{2min}, C_{2max}	initial and final social factors
$Iter_{max}$	maximum iteration number
Iter	current iteration number
$rand_3$	random numbers between 0 and 1

1. Introduction

State estimation assumes a critical part in the observing and control of present day power system. State estimation techniques are basically data processing algorithms which are applied on power systems to obtain the best estimate of current operating state from the available set of redundant measurements and network topology information. In 1968, Fred C. Schweppe introduced state estimation to the power system. The mathematical model and the general state estimation are explained in [1]. In [2] an approximate mathematical model and solution for detection and identification are discussed. Different usage issues connected with dimensionality, computer speed, storage and the time-varying nature of actual power systems is additionally discussed in [3]. Applying Taylor series and a least-squares criterion is outlined in [4]. A fast decoupled SE technique based on equivalent current injections and rectangular co-ordinates is discussed in [5]. This actually is a break through technique as it resulted in identical sub gain matrices that needed to be updated and factorized most effective once. This technique, promising from the point of view of speed and applicability tends to generate a compromising estimate, by maintaining same weighting factors for both real and reactive components.

In general, bad data is the term connected to measurements that go astray from the true quality by no less than a few times the difference related with that measurement. A typical erroneous measurement may invert the sign and/or drastically change the magnitude. To minimize the effect of bad data, several new methods for recognizing bad data have been created. Once bad data is recognized, it is both erased from the measurement set or replaced with the aid of the expected values. This modified measurement set is then utilized by the WLS estimator to get the state estimate as explained in [6]. There had been numerous attempts to enhance one-step algorithms that at the same time reject bad information and estimate the state of a power system. Bad data suppression (BDS) estimator which is based on a non-quadratic cost function which reduces to the least-squares estimator in the absence of bad data knowledge has been proposed in [7]. In [8] the identification of multiple bad data is re-characterized as a combinatorial issue which is taken care of by a-branch-and-bound procedure. A bad data removal and identification method based on methods corresponding to measurement compensation and linear residual calculation is provided in [9]. A bad data removal and identification method for LP state estimator in which bad measurements were identified and eliminated making use of hypothesis testing identification proposal is presented in [10].

A fuzzy logic based weighted least squares state estimation is proposed in [11] where the problem of minimizing the residuals is formulated as a multiobjective optimization problem. In recent times, non-deterministic approaches such as artificial neural network (ANN), Tabu search and genetic algorithm have been proposed [12]-[14]. Fuzzy based state estimators established on pattern realization concepts which might run faster than usual state estimators had been proposed in [15, 16]. However, the standard WLS based state estimators are still essentially the most desired due to their track-back ability during disasters. In this work a line flow based WLS state estimation problem has been formulated and it has been solved through BBO technique in the absence as well as the presence of bad measurements for various standard IEEE test systems.

2. Conventional WLS State Estimation

The state estimation techniques, the goal of finding out a set of state vectors that minimize the measurement residuals. Basically the crisis is a minimization problem and as the quantities involved are nonlinear, it is a problem of minimizing a nonlinear objective function which is suitably achieved using a least squares technique. The measurements are expressed as a function of the state vector of the system as

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

Here, the measurement errors which usually show normal distribution around a zero mean are assumed to be impartial of every other. Each one of the measurement is assigned a suitable weightage reflecting the accuracy and the reliability of that specified measurement whose values are determined based upon a few reasons such as the condition of the measuring equipment, noise of the telemetry channel etc.

The objective of WLS state estimator is to generate a suitable set of state variables in terms of bus voltage magnitudes and angles to minimize the weighted sum of the squares of the measurement errors ,to attain this the objective function is formulated as

$$\boldsymbol{J}(\boldsymbol{x}) = [\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})]^{\boldsymbol{T}}\, \boldsymbol{W}[\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})] \tag{2}$$

where W is the weightage matrix, which is a diagonal matrix formed by measurement covariances when the measurements are independent of each other. The above equation is solved iteratively for estimating the state vector that minimizes J. At the end of every $\boldsymbol{k^{th}}$ iteration, the state vector is updated using the correction vector as

$$\boldsymbol{x_{k+1}} = \boldsymbol{x_k} + \Delta\boldsymbol{x} \tag{3}$$

in which $\Delta\boldsymbol{x}$ obtained by solving the equation

$$\Delta\boldsymbol{x_k} = [\boldsymbol{H^T W H}]^{-\boldsymbol{1}} \boldsymbol{H^T W}[\boldsymbol{z} - \boldsymbol{h}(\boldsymbol{x})] \tag{4}$$

where $\boldsymbol{H}$ stands for the Jacobian and $[\boldsymbol{H^T W H}]$ represents the gain matrix.

2.1.Proposed Method

The proposed method tries to resolve the SE problem by applying WLS technique on a line flow based model [6] which is constructed using power balance equations, line voltage equations and loop phase angle equations.
The general power balance equations for the system are written as

$$P(T) = e^{\frac{-\Delta F}{T_t}} \tag{5}$$

$$\mathrm{A.p} - \mathrm{P_{GL}} - \mathrm{A'.l} = 0 \tag{6}$$

$$\mathrm{A.q} - \mathrm{Q_{GL}} - \mathrm{A'.m} - \mathrm{H.V^2} = 0 \tag{7}$$

where A and $\mathrm{A'}$ are defined as bus incidence and modified bus incidence matrices in which all +1's in A are set to zeros, l and m represent the real and reactive power losses in the transmission lines, H is an (n-1) diagonal matrix formed by the sum of charging and compensating susceptances at each bus bar, $\mathrm{P_{GL}}$ and $\mathrm{Q_{GL}}$ are the real and reactive bus power injections, p and q are the real and reactive power flows measured at the receiving end of the transmission line. When the reactive mismatch equations are deleted at generator buses then the above equation can be rewritten as

$$\mathrm{A_1.q} - \mathrm{Q_{GL}}\,\mathrm{l} - \mathrm{A_{1\,.}m} - \mathrm{H_1.V^2} = 0 \tag{8}$$

in which $\mathrm{H'}$ is a diagonal matrix with only the elements corresponding to load buses present in it.

The line voltage equations are written based on a network branch model developed without taking into account the shunt elements including the line capacitances as,

$$2\mathrm{Rp} + 2\mathrm{Xq} - (\wedge \mathrm{A_{1+}^T} + \mathrm{A_{1-}^T})\mathrm{V^2} = -\mathrm{k} + \wedge \mathrm{A_C^T V_{PV}^2} \tag{9}$$

where k is the vector of apparent line losses, $\mathrm{A_C}$ is the bus bar incidence matrix corresponding to only the PV buses, $\mathrm{V_{PV}^2}$ is the vector of the square of the generator bus voltages, $\wedge$ is the diagonal matrix of order 1 with the values equal to the square of the tap settings, $\mathrm{A_{1+}}$ and $\mathrm{A_{1-}}$ are the positive and negative element parts of $\mathrm{A_1}$, R and X are the diagonal resistance and reactance matrices.

The loop phase angle equations are written based on the fact that the algebraic sum of phase angle drops around independent loops are zeros.

$$\mathrm{CXp} - \mathrm{CRq} = 0 \quad (10)$$

The real and reactive bus powers as a function of real line flows, reactive line flows, real line loss, reactive line loss and V_m^2 can be written as

$$P_i = \sum_{j=1}^{nl} A_{ij} \ \ p_j - \sum_{j=1}^{nl} A_{ij}^{'} \ \ l_j \quad (11)$$
$$Q_{i=} \sum_{j=1}^{nl} A_{ij} \ \ q_j - \sum_{j=1}^{nl} A_{ij} \ \ m_j \ + \ H_{ii} \ V_i^2 \quad (12)$$

Treating p, q and V_m as state variable$[x]$, the measurement set $[Z]$ can be represented as

$$[Z] = [f(x)] \quad (13)$$

where $[Z] = [P, Q, p, q, V^2]^T$. The WLS objective function is written as

$$Min\ \varphi = [f(x) - Z]^T [w][f(x) - Z] \quad (14)$$

As the above equation does not include line capacitances and shunt susceptances, it is inadequate to estimate the system state. However the problem is made solvable by considering the constraint equations involving branch voltage drop and phase angle variations. These equations are written as

$$h(x) = 2Rp + 2Xq - (\Lambda A_{1+}^T + A_{1-}^T)V^2 = 0 \quad (15)$$
$$g(x) = CXp - CRq - C\alpha = 0 \quad (16)$$

The constrained optimization problem involving equations (14), (15) and (16) is converted into an unconstrained problem through Lagrangian multipliers $\lambda\ and\ \mu$ as

$$Min\ \varphi = [f(x) - Z]^T [W][f(x) - Z] - \lambda h(x) - \mu g(x) \quad (17)$$

Linearising the above equation around a known operating point x^0 , and then differentiating it and equating it to zero will result in a matrix equation of the following form

$$\cdot\begin{bmatrix} 2F^T WF & -H^T & \_G^T \\ H & 0 & 0 \\ G & 0 & 0 \end{bmatrix} \begin{bmatrix} \Delta x \\ \lambda \\ \mu \end{bmatrix} = \begin{bmatrix} -2F^T W(f(x^0) - Z) \\ -h(x^0) \\ -g(x^0) \end{bmatrix} \quad (18)$$

where $F, H\ and\ G$ represent the jacobian matrices. These matrices are constant ones and the right hand side vector is divided into two groups, one consisting of the bus power injections and generator bus voltages which are constants and the other consisting of the loss term and charging and compensating powers which are nonlinear. So the right hand side vector is partially linearised. The algorithm for solving the objective function given in (18) is explained in the following section.

3. Introduction of BBO

Biogeography Optimization, an efficient optimization method was introduced by Dan Simon. BBO algorithm tries to solve the optimization problem by means of simulation of immigration and emigration behaviour of the species in and out of a habitat. Species travel in and out of the habitats relying upon various factors such as availability of food, temperature existing in that habitat, already existing species count in that area, variety of vegetation, and species in that region etc. and the procedure strikes a balance when the rate of immigration is equivalent to the rate of migration. However these behaviours are probabilistic in nature. BBO algorithm exploits the search of the individuals to find them a suitable habitat to search into the promising regions of the search space. A habitat is formed via a set of integers that form a feasible solution for the problem and an ecosystem consist of a number of such habitats.

A set of habitats are generated randomly, fulfilling the constraints and their HSI is evaluated. As a way to hold elitism, remarkable good solutions are retained while amendment operation is carried out over the rest of the members, HIS recalculated for the modified ones thereafter mutation operation is implemented over the extremely good and bad solutions leaving apart the solutions in the middle range. Stopping criteria is much like some other widespread population based algorithm where the algorithm terminates after a pre defined number of trials or after the elapsing of the stipulated time or where there is no major change in the solution after a number of successive trials.

3.1. BBO Algorithm

The BBO algorithm for LF based SE problem is described as follows.

1. Read the system data.
2. Initialize the BBO parameters like the size of suitability index variable n, maximum numbers of iterations, limits of each variable in the habitat are initialized. Start the generation.
3. The habitats are randomly initialized. For each habitat, evaluate the objective function using equation (17).
4. The immigration rate λ_1 and emigration rate μ_1 are determined for each of the habitats.
5. Elite habitats are identified and they are exempted from modification procedure.
6. A habitat *Hi* is selected for modification proportional to its immigration rate λ_{1i} and the source for this modification will be from the habitat *Hj* proportional to its emigration rate $\mu_{1j.}$ This represents the migration phenomena of the species wherein the new habitats are formed through migration.
7. The probability of mutation P_i calculated from λ_1 and μ_1 is used to decide the habitat *Hi* for mutation and its jth SIV is replaced by a randomly generated SIV.
8. Already existing set of elite solutions along with those resulting from the migration and mutation operations result in a new ecosystem over which the Steps 4–6 are applied until any one of the stopping criteria is reached.
9. The same procedure is repeated for different measurements.

4. Simulation Results

The proposed LFBSE problem has been solved using BBO technique by selecting a habitat size of 20 habitat modification probability =1, Immigration probability bounds per gene = {0, 1}, step size for numerical integration of probabilities =1, maximum immigration and migration rates of each island = 1 and mutation probability =0.1, Maximum Generation =100.

It has been tested on standard IEEE 14, 30 and 57 bus test systems. The measurement vector has been generated by adding a small percentage of noise to the values obtained from the Newton Raphson load flow. Bus voltage magnitudes at the load buses and real and reactive power flows through the lines were taken as state variables. All the line flows, bus power injections and bus voltage magnitudes at the even numbered buses were considered in the measurement set to achieve necessary redundancy. To study the performance of the algorithm in the presence as well as absence bad measurements, in each of the measurement set, 5, 10 and 15 number of bad measurements were introduced randomly. The performance of the algorithm has been validated by comparing the results of the proposed method against the results obtained using standard WLS state estimation and LFWLS State Estimation

The algorithms were tested with a flat start and a convergence tolerance of 0.0001. Three performance indices are defined to validate the performance of the proposed technique. They are $\Delta V_{rms},\ \Delta p_{rms},\ \Delta q_{rms}$.

$$\Delta Vrms = \sqrt{\frac{1}{nb}\sum_{i}^{nb}(V_i^t - V_i)^2} \qquad (19)$$

$$\Delta p_{rms} = \sqrt{\frac{1}{nl}\sum_{i}^{nl}(P_i^t - P_i)^2} \tag{20}$$

$$\Delta q_{rms} = \sqrt{\frac{1}{nl}\sum_{i}^{nl}(q_i^t - q_i)^2} \tag{21}$$

Tables 1, 2 and 3 compare the performance of the proposed method with WLS and LFWLS estimation algorithm in terms of the performance indices defined in 19, 20 and 21 and NET. The performance of the algorithm is also illustrated through bar charts in Fig 1 to 12.

Table 1: Results for IEEE 14 Bus Systems

Measurements	Method	NET in ms	ΔVrms	ΔPrms	ΔQrms
0	WLS	197	0.148	0.1351	0.1643
	LFWLS	123	0.093	0.110	0.111
	LFWLS-PSO	129	0.0918	0.1097	0.1097
	LFWLS-WIPSO	129	0.0891	0.1088	0.1091
	LFWLS-BBO	133	0.083	0.1081	0.1086
5	WLS	198	0.1479	0.1286	0.1631
	LFWLS	123	0.0928	0.1074	0.1094
	LFWLS-PSO	130	0.0913	0.1045	0.1085
	LFWLS-WIPSO	129	0.0871	0.1029	0.1081
	LFWLS-BBO	134	0.0804	0.1027	0.1074
10	WLS	198	0.1435	0.1277	0.1573
	LFWLS	124	0.0669	0.1034	0.1083
	LFWLS-PSO	130	0.0616	0.1033	0.1079
	LFWLS-WIPSO	129	0.0536	0.1027	0.108
	LFWLS-BBO	134	0.0541	0.1019	0.1071
15	WLS	198	0.1421	0.1215	0.138
	LFWLS	123	0.0259	0.1027	0.1078
	LFWLS-PSO	131	0.0245	0.1026	0.107
	LFWLS-WIPSO	129	0.0189	0.1022	0.1065
	LFWLS-BBO	133	0.0186	0.1011	0.1053

Fig.1: Measurement Vs ΔVrms (14 Bus)

Fig.2: Measurement Vs ΔPrms (14 Bus)

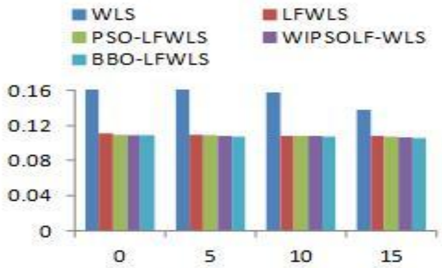

Fig.3: Measurement Vs ΔQrms (14 Bus)

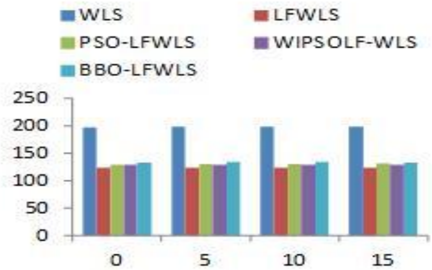

Fig.4: Measurement Vs NET (14 Bus)

Table 2: Results for IEEE 30 Bus Systems

Measurements	Method	NET in ms	ΔVrms	ΔPrms	ΔQrms
0	WLS	450	0.0984	0.3824	0.2117
	LFWLS	167	0.0795	0.2173	0.1325
	LFWLS-PSO	176	0.0694	0.2165	0.1318
	LFWLS-WIPSO	179	0.068	0.2133	0.1313
	LFWLS-BBO	183	0.0673	0.2127	0.1304
5	WLS	452	0.0877	0.3794	0.2109
	LFWLS	166	0.0418	0.2159	0.1319
	LFWLS-PSO	177	0.0331	0.2157	0.1314
	LFWLS-WIPSO	179	0.0326	0.2129	0.1304
	LFWLS-BBO	187	0.0319	0.2121	0.1295
10	WLS	150	0.0641	0.3756	0.2099
	LFWLS	166	0.0345	0.2138	0.1311
	LFWLS-PSO	176	0.0329	0.213	0.1307
	LFWLS-WIPSO	180	0.0314	0.2117	0.1296
	LFWLS-BBO	186	0.0301	0.2112	0.1287
15	WLS	450	0.0478	0.3743	0.2081
	LFWLS	166	0.0298	0.213	0.1305
	LFWLS-PSO	176	0.0257	0.2024	0.1299
	LFWLS-WIPSO	180	0.0232	0.2012	0.1289
	LFWLS-BBO	186	0.0227	0.2003	0.1283

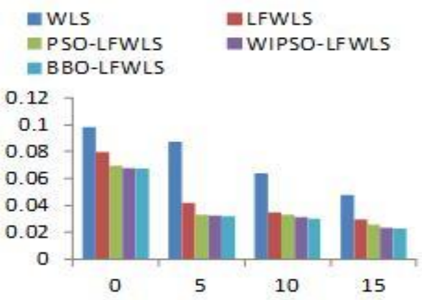

Fig.5: Measurement Vs ΔVrms (30 Bus)

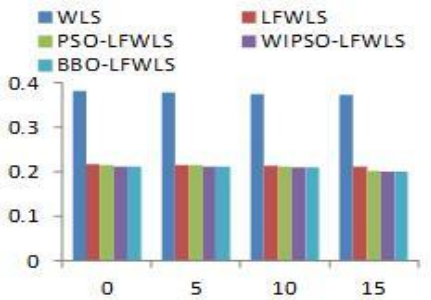

Fig.6: Measurement Vs ΔPrms (30 Bus)

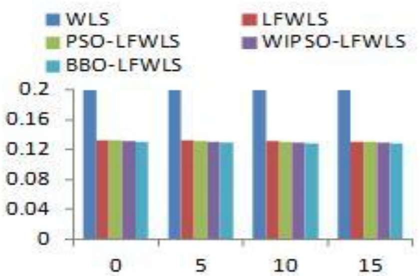

Fig.7: Measurement Vs ΔQrms (30 Bus)

Fig.8: Measurement Vs NET (30 Bus)

Table 3: Results for IEEE 57 Bus Systems

Measurements	Method	NET in ms	ΔVrms	ΔPrms	ΔQrms
0	WLS	579	0.0833	0.2579	0.1346
	LFWLS	207	0.0304	0.1173	0.1091
	LFWLS-PSO	218	0.0303	0.1161	0.1083
	LFWLS-WIPSO	223	0.0297	0.1152	0.1077
	LFWLS-BBO	224	0.0291	0.1148	0.107
5	WLS	583	0.0829	0.2553	0.1332
	LFWLS	207	0.0298	0.1164	0.1083
	LFWLS-PSO	218	0.0284	0.1152	0.1305
	LFWLS-WIPSO	224	0.0276	0.1145	0.1061
	LFWLS-BBO	225	0.0267	0.1139	0.1053
10	WLS	580	0.0823	0.2527	0.132
	LFWLS	208	0.0286	0.1158	0.1071
	LFWLS-PSO	219	0.0272	0.1147	0.1293
	LFWLS-WIPSO	222	0.0265	0.1138	0.1048
	LFWLS-BBO	225	0.0259	0.1133	0.1041
15	WLS	581	0.0815	0.2502	0.1313
	LFWLS	208	0.0272	0.115	0.106
	LFWLS-PSO	220	0.0264	0.114	0.1288
	LFWLS-WIPSO	223	0.0259	0.1131	0.1038
	LFWLS-BBO	226	0.0253	0.1124	0.103

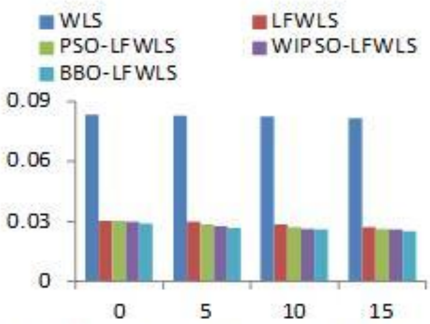

Fig.9: Measurement Vs ΔVrms (57 Bus)

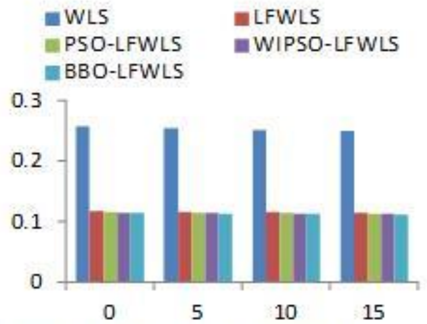

Fig.10: Measurement Vs ΔPrms (57 Bus)

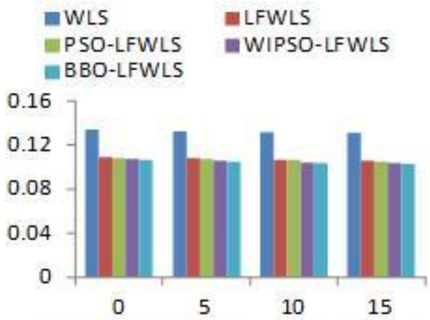

Fig.11: Measurement Vs ΔQrms (57 Bus)

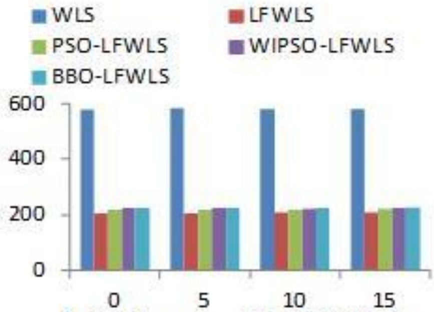

Fig.12: Measurement Vs NET (57 Bus)

5. Conclusion

A new state estimation technique which results in the formation of constant jacobian matrix has been presented in this paper and it has been solved through BBO technique for various percentages of bad measurements. The results indicate that the normalized value of the error between the actual values and estimated values of the state variables is significantly lesser in the case of proposed method when solved using BBO than that of the conventional WLS technique. Further it can be observed that the presence of bad measurements significantly affects the accuracy of estimation in the conventional WLS technique whereas it is not so with the proposed LFBSE technique. In conventional WLS estimated state variables deviate widely from their true values and this deviation increases with the increase in the number of bad measurements. But in the proposed method this deviation is appreciably less due to the fact that the jacobian turns out to be a constant matrix. BBO has only marginally increased the computation time and this increased computational time could be compromised against by the reduction of the normalized error values. Hence it can be concluded that the proposed BBO based LFWLS generates more accurate estimates than the conventional WLS method and it takes lesser computation time and shows lesser sensitivity towards the presence of bad measurements which makes suitable for real time studies.

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