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Line Flow Based WLAV State Estimation Technique using BBO Algorithm

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Abstract - *This paper shows a new Line Flow-based Weighted Least Absolute Value (LFWLAV) technique for power systems which use line flows, bus power injections, and bus voltage magnitudes which are aided by a measuring vector and resolved using BBO. State variables are determined using a constant, line flow-based jacobian matrix constructed from the network equations. The proposed choice of state variables has been useful as the Jacobian matrix tends to be constant, which reduces the computational burden. Weighted Less Squares (WLS) methodology was used to solve the proposed line flow based state equations in the absence of these poor measurements and the findings are verified against those obtained using the traditional WLAV methodology. The efficacy of the proposed approach was tested by computer simulations using three test systems: (1) 14- bus IEEE test system, (2) 30-bus IEEE test system and 57-bus IEEE test system. It's time for convergence and measurement was carefully calculated and compared with the options acquired by the WLAV standard process. The results show that the proposed LFWLAV method spends less execution time with identical convergence features than the standard method does.*

Key Words: State Estimation, Weighted Least Absolute value method, Line flow based WLAV, LFWLAV-BBO and Power System.

1. INTRODUCTION

State estimation plays an important role in the monitoring and control of the existing power system. State estimation techniques are simply data handling algorithms that are applied to power systems to achieve the best estimate of current operating status from the available set of redundant measurements and network topology details. In 1968, Fred C. Schweppe developed a state calculation of the power system. The mathematical model as well as the general estimation of the state are clarified in [1]. In [2] there is an effective mathematical model and a solution for detection and recognition. Additionally, specific application issues related to dimension, computer speed, storage and the time-varying complexity of actual power systems are addressed in [3]. A procedure used to process the calculated data from electrical power grids in order to achieve the best possible estimate of the system variables. The use of the Taylor series and the least squared criterion is illustrated in [4]. A fast-decoupled SE technique based on equivalent current injections and rectangular coordinates is discussed in (5). In addition, this is a break through technique because it resulted in identical sub-gain matrices that needed to be modified and factored only once. This technique, which is promising from the point of view of speed and applicability, tends to produce a compromising estimate by retaining the same weighting factors for both actual and reactive components.

The alternative formulation of the state estimation problem, Weight Least Absolute Values (WLAV) has been used to solve the SE problem. The WLAV transformation-based estimator with leverage points is shown in [6]. Leverage points are uniformly disbursed by linear transformations in the factor space of multiple regressions. This transformed measurement equation method is then used to obtain a WLAV estimator for the method states. The paper [7] deals with the application of indoor point methods to the Weighted Least Absolute Value State Estimate Problem. The IRLAV [8] method is almost the same as WLAV, except the weights are periodically changed based on the residual measurements to match new conditions during iterations. A quick decoupled WLAV state estimator with a constant Jacobian matrix was built based on a few assumptions [9] and the technique, even faster, produced an estimate that represented the impact of the assumptions made.

The line flow and bus voltage load flow model described in (10) is shown in this paper to build a related SE model that's been overcome using WLS technology using PSO and WIPSO algorithms. This approach appears to avoid most of the matrix-related matrix manipulation problems listed so far.

The existence of bad data has a major impact on the quality of the estimate produced by the least squared estimator, and therefore special techniques have been required to recognize and quantify its effects. A linear recursive bad data recognition technique based on power system decomposition was introduced in (11). The neural network based filter was used for poor data detection and identification in(12) where, once equipped, the filter rapidly identifies the majority of measurement errors simultaneously by comparing the square difference of the raw measurements and their corresponding approximate values with certain thresholds.

Bad data prefiltering using wavelet transformation has been introduced in (13) and this method detects and filters bad data even before the device status is determined by the state estimation algorithm. An recognition algorithm based on the largest normalized residual considering the statistical association between measurements is provided in (14). As the proposed approach here uses a constant Jacobian, unlike the traditional WLS estimator, the effect of the wrong measurements on the calculation has been greatly minimized and thus does not require a special algorithm to sort out the wrong measurements. Soft computing algorithms have played a significant role in solving optimization problems in the past few decades. Evolutionary programming algorithms are interesting in terms of their ability to escape local maxima and minima. From the point of view of guaranteed consistency and programming versatility, many of the evolutionary PSO algorithms have been widely used. PSO algorithm has been successfully implemented to solve the SE problem despite apprehensions such as higher computational time, etc. (15). In this work, a WLAV-based line flow estimation problem has been developed and resolved in the absence of BBO technique.

2. PROBLEM FORMULATION

2.1 Conventional WLAV State Estimation

The WLS estimator is not stable due to its quadratic objective function. An estimator involving a non-quadratic objective function is therefore used. This estimator gives a more accurate estimation, obtained by minimizing the

$$J[diag(R_1)]zh(x) \quad (1)$$

$$= \sum_{j=1}^{nz} \left|z_j - h_j(x)\right| / \sigma_j^2 \quad (2)$$

Since the above target minimizes the absolute value of the error weighted by the accuracy of the measurement σ_j^{-2}, commonly referred to as the WLAV estimator.

The goal for Eq. (1) is reformulated to solve the WLAV problem using LP:

$$\text{Minimise } J=[diag(R^{-1})]^T[\gamma+\eta] \quad (3)$$

Subject to

$$H\,\Delta x+\gamma-\eta=\Delta z$$

$$\gamma, \eta \geq 0$$

A SE solution is obtained by solving the Eq-given LP problem (3) iteratively for x until Δx is small enough. This approach is highly inefficient, requiring large computer memory and involving the time-consuming LP procedure, which is itself an iterative process and thus not appropriate for real-time applications.

However, this algorithm is robust and stable in the sense that due to the effect of large assignment of weighting factors and avoidance of factorisation and multiplication of multiple matrices, it has the inherent characteristic of rejecting bad measurements by interpolating only *ns* among the *nz* measurements and free of ill-conditioning. This paper aims to increase the computational efficiency of the robust WLAV technique by means of linearization.

2.2 Proposed Method

The real and reactive bus power, depending on the real line flows, reactive line flows and Vm^2 can be entered as

$$P_i = \sum_{j=1}^{nl} A_{ij} P_j - \sum_{j=1}^{nl} A'_{ij} l_j \quad (4)$$

$$Q_i = \sum_{j=1}^{nl} A_{ij} Q_j - \sum_{j=1}^{nl} A'_{ij} m_j \quad (5)$$

If P,Q and Vm^2 as state variable[x], the measurement set [Z] can be represented as

$$[Z] = [f(x)] \quad (6)$$

Where

$$[Z] = [P, Q, p, q, V^2]^T$$

The WLAV objective function can be written as

$$Min\ \varphi = \sum_{i=1}^{nm} wi[Z_i - f_i(x)] \quad (7)$$

The above equation does not include line capacitances and shunt susceptances and hence it is inadequate to estimate the system state. However the problem can be made solvable if constraint equations including branch voltage drop and phase angle drop are considered. These constraints can be represented as

$$h(x) = 2Rp + 2Xq - (\Lambda A_{1+}^{T} + A_{1-}^{T})V^2 = 0 \tag{8}$$

$$g(x) = CXp - CRq - C\alpha = 0 \tag{9}$$

The constrained optimization problem of equations 7, 8 and 9 can be formulated as a linear programming problem as

$$Min\ \varphi = \sum_{i=1}^{nm} wi\ [Si' - Si''] \tag{10}$$

Subject to

$$A.\Delta x + S' - S'' = Z - f(x^0)$$

$$H.\Delta x = -h(x^0)$$

$$G.\Delta x = -g(x^0)$$

Where

A, H and G are the jacobian matrices formed by partially differenting f(x), h(x) and g(x) with respect to x.

Δx is the state correction vector

S' and S'' are the slack variable vectors.

The above LP problem can be solved iteratively for x, until the convergence of the algorithm. It should be noted that the jacobian matrices A, H and G are constant matrices which require calculation only at the start of the iterative process. However RHS vectors f(x), g(x) h(x) must be recomputed during iterative process.

2.2.1 Introduction of BBO

Biography is a analysis of the distribution of animals by nature. The population migrates from one island to outstanding islands with a strong geological situation. Any island is legally referred to as a habitat. Geographical regions are well suited to specific animals that could be applied to as the Strong Habitat Suitability Index (HSI). Every habitat has specific characteristics that are known as Suitability Index Variables (SIV) habitability characteristics. The habitat SIV represents rainfall, land discipline and temperature. The ecosystem remains poor in HSI, the species living in that ecosystem appears to be extinct. These ecosystems occur when animals are emigrated. Likewise, immigration also happens when the ecosystem of HSI is immoderate. Mathematical Biogeography Units clarify how animals move and move within ecosystems. The BBO algorithm is built based on biogeographic mathematics. This only operates on two processes called migration and mutation. BBO is similar to other population-based optimization procedures. The island or habitat and HSI are similar to the single population and the fitness value of the Genetic Algorithm (GA) respectively. Identical to these algorithms, BBO shares knowledge between habitats. At the end of each generation, GA solutions die. Yet BBO solution will live forever. The same party solution is clustered in PSO and not in GA and BBO.

2.2.1.1. BBO Algorithm

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

1. Read the data on the device.

2. Initiate BBO parameters such as probability modification index, mutation rate, minimum and maximum migration and immigration rates, and elite parameters.

3. Start the generation now.

4. Evaluate the objective function of each habitat using equation (10).

5. If G < maximum generation and best fit ≠ 1, go to Step 13 otherwise.

6. Filter the habitat based on the HSI. Maintain the best HIS habitat (Elite HSI) and corresponding habitat (Elite habitat) for the next generation.

7. For each habitat, map the migration rate λ and the mortality rate to μ.

8. Using λ and μ to change each non-elite habitat in a probabilistic way.

9. Carrying out the mutation.

10. Evaluate and sort the fitness of a new habitat.

11. Replace the worst habitats with those of the Elite.

12. Place t=t+1 and move on to step 5.

13. Place the best Habitat.

3. SIMULATION AND RESULTS

The proposed LFBSE problem has been resolved using the BBO technique by selecting habitat sizes of 20 habitat alteration probabilities = 1, Immigration probability limits per gene = {0, 1}, step size for numerical integration of probabilities = 1, overall migration and migration rates for each island = 1, and mutation probability = 0.1, Maximum generation = 100. The measuring vector has been provided by adding a small percentage of noise to the values obtained from the load flow in Newton Raphson. Bus voltage magnitudes at the load busses and the real and reactive power flows through the lines were taken as state variables. In order to achieve the required consistency, all line flows, bus power injections and bus voltage magnitudes on evenly numbered busses were included in the measurement set. In order to test the efficiency of the algorithm in the presence of bad measurements as well as the absence of bad measurements, 5, 10 and 15 number of bad measurements were randomly inserted in each measurement range. The performance of the proposed algorithm has been validated by evaluating the results of the proposed method against the results obtained using standard WLS State Estimate and LFWLAV State Estimation. The algorithms have been tested with a flat start and a convergence tolerance of 0.0001. Three performance indices are established in order to validate the output of the proposed technique. Those are ΔVrms, Δprms, Δqrms.

$$\Delta V_{rms} = \sqrt{\frac{1}{nb}\sum_{i}^{nb}(V_i^t - V_i)^2} \quad (11)$$

$$\Delta p_{rms} = \sqrt{\frac{1}{nl}\sum_{i}^{nl}(P_i^t - P_i)^2} \quad (12)$$

$$\Delta q_{rms} = \sqrt{\frac{1}{nl}\sum_{i}^{nl}(q_i^t - q_i)^2} \quad (13)$$

Tables 1, 2 and 3 compare the effectiveness of the proposed technique with the WLAV, LFWLAV and LFWLAV-BBO estimation algorithms for the performance indices specified in 1, 2 and 3 and the NET. The improvement of the algorithm can also be seen in bar graphs in Fig 1 to 12.

Table 1: Results for IEEE 14 Bus Systems

Measure ments	Method	ΔVrms	ΔPrms	ΔQrms	NET in ms
0	WLAV	0.1406	0.1351	0.1643	211
	LFWLAV	0.0883	0.1103	0.111	136
	LFWLAV-BBO	0.0789	0.1081	0.1086	148
5	WLAV	0.1405	0.1286	0.1631	210
	LFWLAV	0.0882	0.1074	0.1094	136
	LFWLAV-BBO	0.0764	0.1027	0.1074	149
10	WLAV	0.1363	0.1277	0.1573	212
	LFWLAV	0.0635	0.1034	0.1083	137
	LFWLAV-BBO	0.0513	0.1019	0.1071	149
15	WLAV	0.1349	0.1215	0.138	212
	LFWLAV	0.0246	0.1027	0.1078	137
	LFWLAV-BBO	0.0176	0.1011	0.1053	149

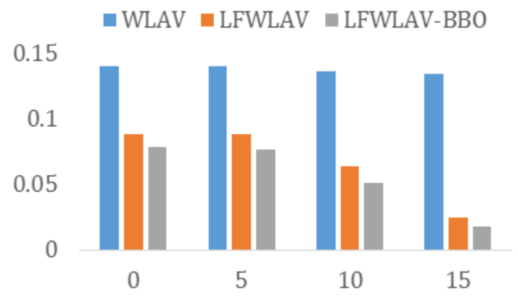

Fig.1 Measurement Vs ΔVrms(14 Bus)

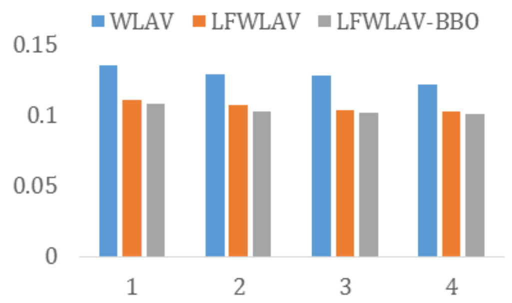

Fig.2 Measurement Vs ΔPrms(14 Bus)

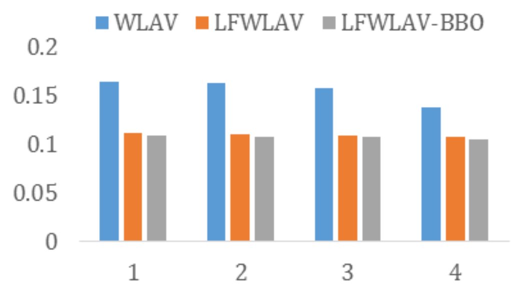

Fig.3 Measurement Vs ΔQrms(14 Bus)

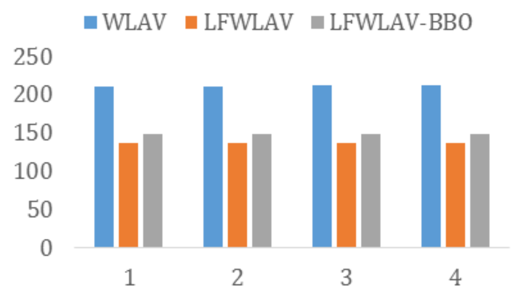

Fig.4 Measurement Vs NET(14 Bus)

Table 2: Results for IEEE 30 Bus Systems

Measure ments	Method	ΔVrms	ΔPrms	ΔQrms	NET in ms
0	WLAV	0.1742	0.3824	0.2117	468
	LFWLAV	0.0755	0.2173	0.1325	189
	LFWLAV-BBO	0.0639	0.2127	0.1304	202
5	WLAV	0.0833	0.3794	0.2109	469
	LFWLAV	0.0397	0.2159	0.1319	188
	LFWLAV-BBO	0.0303	0.2121	0.1295	201
10	WLAV	0.0609	0.3756	0.2099	469
	LFWLAV	0.0328	0.2138	0.1311	189
	LFWLAV-BBO	0.0286	0.2112	0.1287	202
15	WLAV	0.0454	0.3743	0.2081	469
	LFWLAV	0.0283	0.213	0.1305	189
	LFWLAV-BBO	0.0216	0.2003	0.1283	202

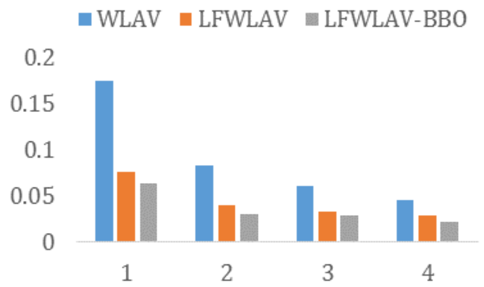

Fig.5 Measurement Vs ΔVrms(30 Bus)

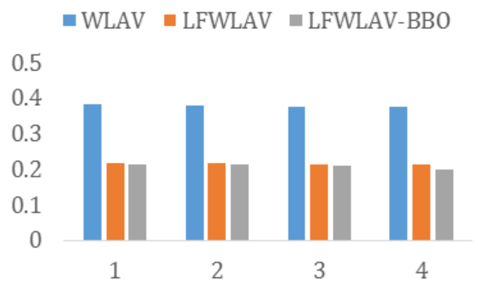

Fig.6 Measurement Vs ΔPrms(30 Bus)

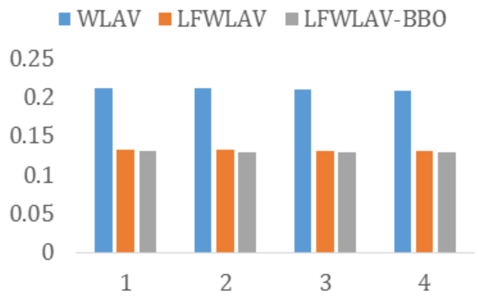

Fig.7 Measurement Vs ΔQrms(30 Bus)

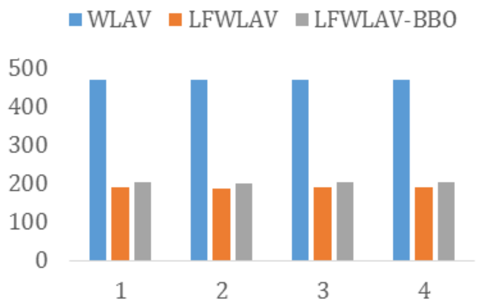

Fig.8 Measurement Vs NET(30 Bus)

Table 3: Results for IEEE 57 Bus Systems

Measure ments	Method	ΔVrms	ΔPrms	ΔQrms	NET in ms
0	WLAV	0.0791	0.2579	0.1346	711
	LFWLAV	0.0288	0.1173	0.1091	233
	LFWLAV-BBO	0.0276	0.1148	0.107	257
5	WLAV	0.0788	0.2553	0.1332	709
	LFWLAV	0.0283	0.1164	0.1083	234
	LFWLAV-BBO	0.0254	0.1139	0.1053	257
10	WLAV	0.0782	0.2527	0.132	709
	LFWLAV	0.0272	0.1158	0.1071	232
	LFWLAV-BBO	0.0246	0.1133	0.1041	258
15	WLAV	0.0774	0.2502	0.1313	710
	LFWLAV	0.0258	0.115	0.106	232
	LFWLAV-BBO	0.024	0.1124	0.103	259

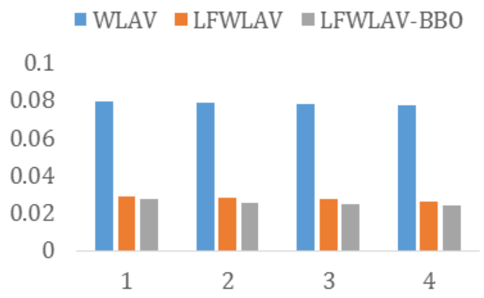

Fig.9 Measurement Vs ΔVrms(57 Bus)

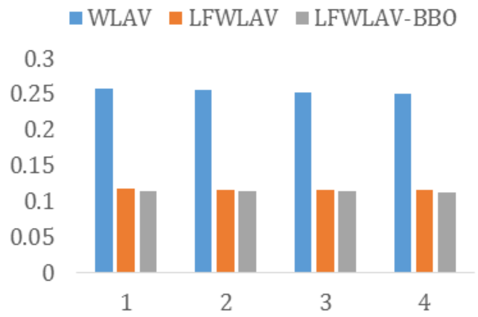

Fig.10 Measurement Vs ΔPrms(57 Bus)

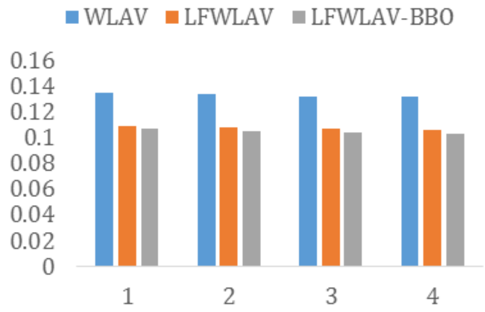

Fig.11 Measurement Vs ΔQrms(57 Bus)

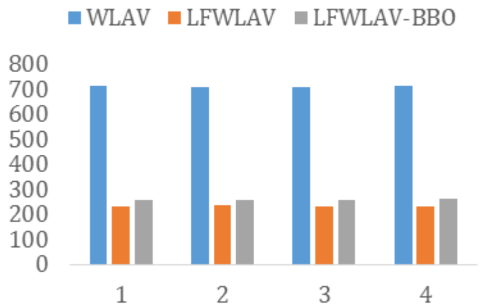

Fig.12 Measurement Vs NET(57 Bus)

4. CONCLUSION

This paper proposed a novel line flow-based state estimation technique which results in the formation of a constant jacobian and it was solved using WLAV method. BBO technique has been applied to solve the LFBWLAV problem both in the presence and in the absence of poor measurements. The findings suggest that the normalized value of the error between the real values and the expected values of the state variables is substantially lower for the proposed approach when resolved using BBO than for traditional WLAV and LFBWLAV techniques. There is also a small increase in computation time due to the heuristic search aspect of the BBO algorithm as the predicted system state is closer to the actual system state in the proposed process; the BBO method is very suitable for security studies of power systems.

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