WIPSO Algorithm for Line Flow based WLAV State Estimation Technique

M.Kalpanadevi*
R.Neela[1]**

Author correspondence:

M.Kalpanadevi, Assistant Professor, Dept. of Electrical Engg. Annamalai University, Annamalai Nagar, TamilNadu, India.

Abstract

This paper provides a new Line-Flow based Least Absolute Value (LFWLAV) technique for Line-Flow Power Systems, Bus Power Injections and Bus Voltage Magnitudes as indicated by the WIPSO-Measurement Matrix. State variables are calculated using a constant Jacobian matrix based on line flow generated from the network equations. The proposed set of state variables has been beneficial because it turns out that the jacobian matrix is constant which reduces the computational burden. Weighted Least Squares (WLS) technique has been implemented to solve the proposed line flow based state equations in the absence and also in the presence of bad measurements, and the results are validated against those obtained using conventional WLAV technique. Computer simulations tested the feasibility of the proposed solution over three test systems: (1) 14- bus IEEE test system, (2) 30-bus IEEE test system and 57-bus IEEE test system. Its convergence and calculation time were carefully calculated and compared to the options acquired using the standard WLAV process. The results show that the proposed LFWLAV method spends less execution time with identical convergence features than the standard method does.

Keywords: State Estimation; Weighted Least Absolute value method; Line flow based WLAV; LFWLAV-WIPSO; Power System.

1. Introduction

In monitoring and controlling the current power grid, State estimates plays a significant role. State calculation techniques are essentially data processing algorithms applied to power systems to get the best approximation of current operating system from the available collection of redundant measurements and network topology information. Fred C. Schweppe developed a state estimation problem in 1968. The mathematical model is explained in [1], as well as the general state estimation. There is an important mathematical model in [2], and a method to detect and identify. Relevant problems pertaining to the application dimension, speed of the device, storage and time variations of the power systems are also discussed in [3]. A technique to test measured electrical grid data to ensure that device variables are properly estimated. The use of the Taylor series as seen in [4], along with its least squared criterion. In [5], the fast-decoupled SE technique is explored on the basis of comparable current and rectangular co-ordinates. Furthermore, this is an inconvenience as it has led to similar sub gain matrices that needed to be modified and only then taken into account. This method, which is promising from a speed and applicability point of view, appears to produce a compromise estimate by maintaining the same weighting factors for both real and reactive components.

In order to solve SE problem, the alternative terminology of the state calculation problem Weight Least Absolute Values (WLAV) has been used. In [6], the leverage point WLAV

[1**] Professor, Dept. of Electrical Engg. Annamalai University, Annamalai Nagar, TamilNadu, India.

transformation based estimator is shown. Normal representations of the factor space of many regressions systematically disburse leverage points. This transformed method of measurement equation is then used to obtain a WLAV estimator for state of system. The paper [7] deals with the use of indoor point methods for 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 fast decoupled WLAV state estimator with a constant Jacobian matrix has been built on the basis of a few hypotheses [9] and the technique produced an estimate, even faster, that represented the impact of the assumptions made.

The line flow and bus load flow model described in [10] is shown in this paper to create a similar SE model that has been overcome using WLS technology using PSO and WIPSO algorithms. This method tends to prevent most of the matrix-related matrix manipulation problems found so far.

The presence of poor data has a significant impact on the accuracy of the estimate provided by the least squared estimator, and thus special techniques have been developed to identify and measure its effects. A linear recursive bad data recognition technique based on power system decomposition has been implemented in [11]. The neural network based filter was used for weak data detection and identification in [12] where, once fitted, the filter easily identifies the majority of measurement errors simultaneously by comparing the square difference of the raw measurements and their corresponding estimated values with certain thresholds.

Bad data prefiltering using wavelet transformation was introduced in [13] and this approach detects and filters bad data even before the system status is calculated by the state estimation algorithm. An Algorithm of Recognition based on the largest normalized residual considering the statistical correlation between measurements is given in [14]. As the proposed solution here uses a constant Jacobian, unlike the conventional WLS estimator, the effect of incorrect measurements on the calculation has been significantly reduced and thus does not require a special algorithm to sort out incorrect measurements. Soft computing algorithms have played a major role in solving optimization problems over the past few decades. Evolutionary programming algorithms are notable in terms of their ability to avoid local maxima and minima. Many of the evolutionary PSO algorithms have been commonly used from the point of view of guaranteed accuracy and programming flexibility. The PSO algorithm has been successfully implemented to solve the SE problem.

2. Problem Formulation

2.1 Conventional WLAV State Estimation

Due to its quadratic objective function, the WLS estimator isn't stable. Therefore an estimator with a non-quadratic goal function is used. This estimator offers a more reliable calculation by that minimizing the

$$\mathrm{J[diag(R_1)]zh(x)} \tag{1}$$

$$= \sum_{j=1}^{nz} \frac{|z_j - h_j(x)|}{\sigma_j^2} \tag{2}$$

Since the above-mentioned target minimizes the absolute value of the error weighted by the measurement accuracy of π j^(-2), generally referred to as the WLAV estimator.

Goal for Eq. (1) WLAV problem solving is reformulated using LP:

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

Subject to

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

$\gamma, \eta \geq 0$

The SE solution is achieved by solving the problem of the Eq-given LP. (3) It is possible to use x as an iterative until it is small enough. This approach is highly inefficient, requiring great machine memory and involving the time-consuming LP method, which is itself an iterative process and thus not real for real-time applications.

Moreover, this algorithm is robust and stable in the sense that, due to the impact of large weighting factors assignment and the prevention of factorization and multiplication of multiple matrices, it has the inherent characteristic of rejecting bad measurements by interpolating only *ns* between *nz* measurements and without conditioning. The aim of this paper is to increase the computational efficiency of the robust WLAV technique by means of linearization.

2.2 Proposed Method

Based on the real line flows, reactive line flows and Vm2 the real and reactive bus power can be entered as

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

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

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

$$[Z] = [f(x)] \tag{6}$$

Where

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

The WLAV objective function can be written as

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

The equation above does not include line capabilities and shunt susceptibility and is therefore insufficient to estimate the system state. Nonetheless, the problem can be overcome if constraint equations including branch voltage drop and phase angle drop are considered. These limitations may 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

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

Subject to

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

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

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

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 algorithm has converged. It should be noted that the A, H and G jacobian matrices are constant matrices that require calculation only at the beginning of the iterative process. However, RHS vectors f(x), g(x) h(x) have to be recomputed during the iterative process.

2.2.1 Introduction of WIPSO

The basis for the WIPSO method is the improved function of the weight parameter. In order to achieve a better global solution, the traditional PSO algorithm is enhanced by changing the inertia weight, cognitive and social factors. That is, the velocity of the individual WIPSO shall be determined by

$$V_i^{k+1} = W_{new}V_i^k + C_1 * r_1 * \left(P_{besti} - S_i^k\right) + C_2 * r_2 * (G_{besti} - S_i^k) \quad (11)$$

$$W_{new} = W_{min} + W * r_3 \quad (12)$$

$$W = W_{max} - \frac{W_{max} - W_{min}}{iter_{max}} * iter \quad (13)$$

$$C_1 = C_{1max} - \frac{C_{1max} - C_{1min}}{iter_{max}} * iter \quad (14)$$

$$C_2 = C_{2max} - \frac{C_{2max} - C_{2min}}{iter_{max}} * iter \quad (15)$$

$r_{1,}r_2$ and r_3: The random numbers selected between 0 and 1.
W_{max}, W_{min} : Initial and Final Weights
C_{1min}, C_{1max} : Initial and Final cognitive factor
C_{2min}, C_{2max} : Initial and Final social factor
$Iter_{max}$ = Maximum iteration number

2.2.1.1 WIPSO Algorithm

The WIPSO LF-based SE problem algorithm is defined as follows.
1. Select population size, generation number, Wmin, Wmax, C1min, C1max, C2min, C2max, pbest, gbest.
2. Initiate the velocity and position of all particles randomly, ensuring that they are within limits.
Here, individuals represent real and reactive power flows and the magnitude of bus voltage.
3. Set the generation counter to t=1.
4. Test fitness for every particle using equation (10) based on objective function.
5. Compare the fitness function of the particle to its Pbest i. If the current value is greater than Pbest I then Pbest I is equal to the current value. Identify the neighborhood particle with the greatest results so far and allocate it to Gbest.
6. Update the weight factor value using the equation (15).
7. Update the velocity by using the best individual and global particle.
8. Update the position using the updated velocities. Each particle is going to change its position.
9. If the stopping criteria are not met, set t = t+1 and go to step 4.Otherwise stop.

3. Simulation and Results

The proposed LFBSE problem was resolved using the WIPSO 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, total migration and migration rates for each island = 1, and mutation probability = 0.1, Maximum generation = 100. The measuring vector was given 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 actual and reactive power flows through the lines were taken as state variables. In order to achieve the necessary accuracy, all line flows, bus power injections and bus voltage magnitudes on evenly numbered busses have been included in the measurement package. 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 numbers of bad measurements were randomly inserted in each measurement range. The output of the proposed algorithm was validated by comparing the results of the proposed method against the results obtained using the standard WLS State Estimate and LFWLAV State Estimate. The algorithm has been tested at a flat start and a convergence tolerance of 0.0001. In order to verify the efficiency of the proposed technique, three performance indices are formed which are ΔVrms, Δprms and Δqrms.

$$\Delta V_{rms} = \sqrt{\frac{1}{nb}\sum_{i}^{nb}(V_i^t - V_i)^2} \qquad (16)$$

$$\Delta p_{rms} = \sqrt{\frac{1}{nl}\sum_{i}^{nl}(P_i^t - P_i)^2} \qquad (17)$$

$$\Delta q_{rms} = \sqrt{\frac{1}{nl}\sum_{i}^{nl}(q_i^t - q_i)^2} \qquad (18)$$

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

Table 1: Results for IEEE 14 Bus Systems

Measurements	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-WIPSO	0.0846	0.1088	0.1091	143
5	WLAV	0.1405	0.1286	0.1631	210
	LFWLAV	0.0882	0.1074	0.1094	136
	LFWLAV-WIPSO	0.0837	0.1029	0.1081	144
10	WLAV	0.1363	0.1277	0.1573	212
	LFWLAV	0.0635	0.1034	0.1083	137
	LFWLAV-WIPSO	0.0509	0.1027	0.108	144
15	WLAV	0.1349	0.1215	0.138	212
	LFWLAV	0.0246	0.1027	0.1078	137
	LFWLAV-WIPSO	0.0179	0.1022	0.1065	146

Table 2: Results for IEEE 30 Bus Systems					
Measurements	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-WIPSO	0.0646	0.2133	0.1313	197
5	WLAV	0.0833	0.3794	0.2109	469
	LFWLAV	0.0397	0.2159	0.1319	188
	LFWLAV-WIPSO	0.0309	0.2129	0.1304	198
10	WLAV	0.0609	0.3756	0.2099	469
	LFWLAV	0.0328	0.2138	0.1311	189
	LFWLAV-WIPSO	0.0298	0.2117	0.1296	198
15	WLAV	0.0454	0.3743	0.2081	469
	LFWLAV	0.0283	0.213	0.1305	189
	LFWLAV-WIPSO	0.022	0.2012	0.1289	199

Table 3: Results for IEEE 57 Bus Systems					
Measurements	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-WIPSO	0.0282	0.1152	0.1077	253
5	WLAV	0.0788	0.2553	0.1332	709
	LFWLAV	0.0283	0.1164	0.1083	234
	LFWLAV-WIPSO	0.0262	0.1145	0.1061	254
10	WLAV	0.0782	0.2527	0.132	709
	LFWLAV	0.0272	0.1158	0.1071	232
	LFWLAV-WIPSO	0.0252	0.1138	0.1048	254
15	WLAV	0.0774	0.2502	0.1313	710
	LFWLAV	0.0258	0.115	0.106	232
	LFWLAV-WIPSO	0.0246	0.1131	0.1038	254

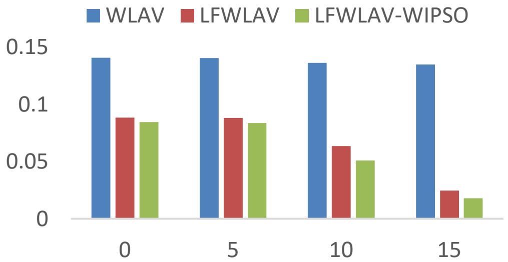

Fig.1 Measurement Vs ΔVrms(14 Bus)

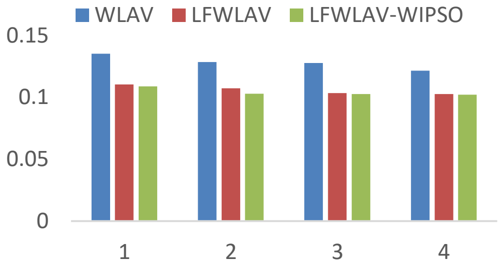

Fig.2 Measurement Vs ΔPrms(14 Bus)

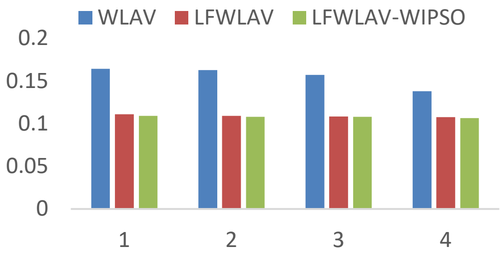

Fig.3 Measurement Vs ΔQrms(14 Bus)

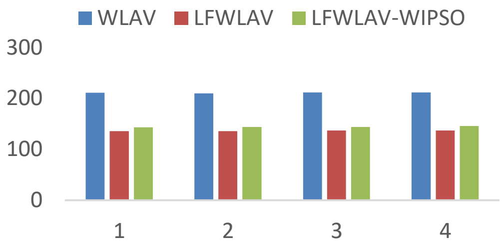

Fig.4 Measurement Vs NET(14 Bus)

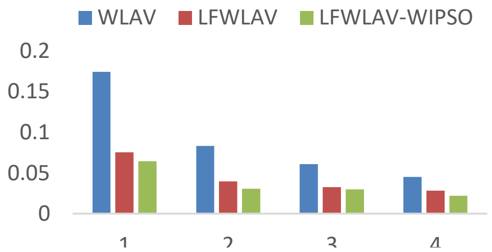

Fig.5 Measurement Vs ΔVrms(30 Bus)

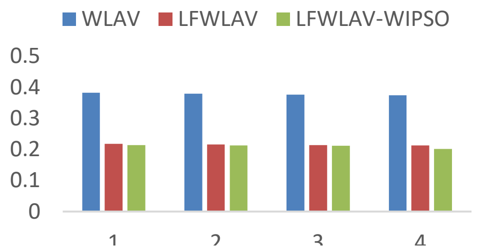

Fig.6 Measurement Vs ΔPrms(30 Bus)

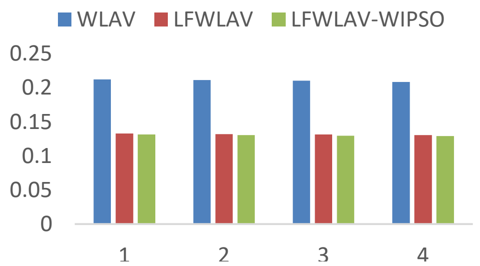

Fig.7 Measurement Vs ΔQrms(30 Bus)

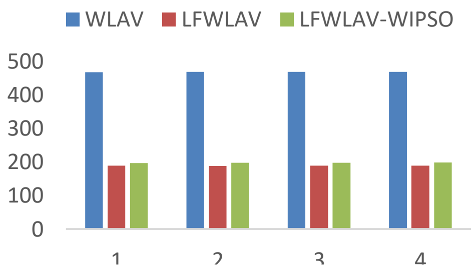

Fig.8 Measurement Vs NET(30 Bus)

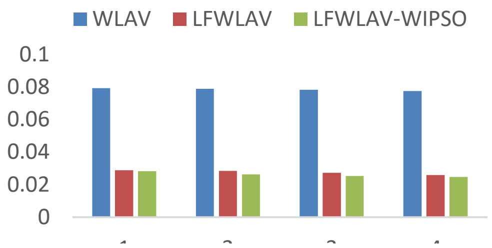

Fig.9 Measurement Vs ΔVrms(57 Bus)

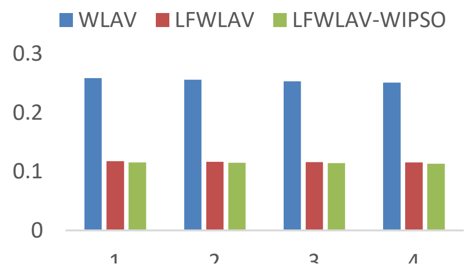

Fig.10 Measurement Vs ΔPrms(57 Bus)

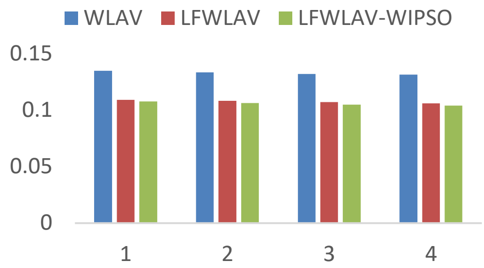

Fig.11 Measurement Vs ΔQrms(57 Bus)

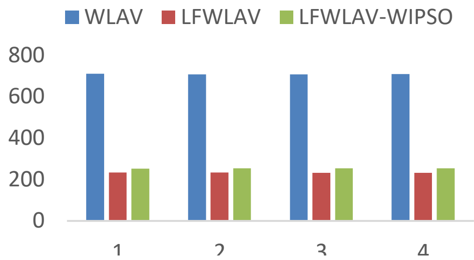

Fig.12 Measurement Vs NET(57 Bus)

4. Conclusion

This paper proposed a novel line flow-based state estimation technique that results in the creation of a constant jacobian and has been resolved using the WLAV method. WIPSO technique has been used to solve the LFBWLAV problem both in the presence and in the absence of incorrect measurements. The findings suggest that the normalized value of the error between the actual values and the expected values of the state variables is significantly lower for the proposed approach when resolved using WIPSO than for traditional WLAV and LFBWLAV techniques. There is also a slight increase in computation time due to the heuristic search feature of the WIPSO algorithm as the expected system state is closer to the actual system state in the proposed process; the WIPSO method is very useful for safety studies of power systems.

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