Line Flow Based WLAV State Estimation Technique for Power Systems with Bad Measurements

M. Kalpanadevi*

Assistant Professor, Dept. of Electrical Engg., Annamalai University, Annamalai Nagar-608002, Tamilnadu, India. sharikka09@yahoo.com

Dr. R. Neela

Professor, Dept. of Electrical Engg., Annamalai University, Annamalai Nagar-608002, Tamilnadu, India. neelaaueee@gmail.com

Abstract

State estimation techniques are data processing algorithms that have been developed with an objective of obtaining the current operating state of power systems from the available set of redundant measurements. These algorithms are required to satisfy the requirements such as lower memory consumption, higher speed of operation and robustness. Robustness is a quality that precisely indicates whether the algorithm is sensitive to the presence of bad measurements or not. As the most widely used WLS based state estimation technique shows a larger sensitivity towards the presence of bad measurements WLAV based state estimation techniques had been developed. Though they were robust, they were highly time consuming and their memory requirement was also large and this made them practically unsuitable for real time applications. In this paper a line flow based state estimation problem has been formulated and it has been solved applying WLAV technique. In contrary to the generally adopted line flow based techniques, where the problem linearization is done through several assumptions, here no assumptions were made but a constant Jacobian Matrix has been arrived at by the manipulation of network equations. This drastically reduces the memory requirement and remarkably improves the speed of execution. The proposed technique has been tried IEEE 14, 30 and 57bus systems and to analyze the performance in the presence of bad measurements, testing has been done with 5, 10 and 15 bad measurements in the measurement set of each of the above systems.

Keywords: State Estimation, Weighted Least Absolute Value, Line flow based WLAV, Bad Measurements and Electric Power System.

Nomeclature

Nomeciature		
LFBSE	_	Line Flow Based State Estimation
SE	_	State Estimation
WLS	_	Weighted Least Squares
PM	_	Proposed Method
Z_{\circ}	_	Measurement Vector
$\overset{O}{x}$	_	Initially assumed values of state vector
$\mathcal{X}_{\mathbf{k}}$	_	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^{κ}	-	Jacobian Matrix
h(x)	_	Measurement 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_{m}^{m} element of bus incidence matrix
A_{ij}	=	<i>ii</i> element of modified bus incidence matrix
P_{j}	=	Real power flow in $i^{\prime\prime\prime}$ line
l_j	=	Real power loss in i'' line
Q_{j}	=	Reactive power flow in j'' line
$m_{\dot{l}}$	=	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
	– Do	square of the tap settings
4 1		sitive and negative element of A_1
λ and μ	=	Lagrangian Multipliers
C	-	Loop incidence matrix
α	-	Phase angle of the phase shifter, taken as 1 otherwise
ΔV_{rms} , Δp_{rms} , Δq_{rm}	ıs –	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>i</i> th bus

Introduction

State estimation techniques were developed with an objective of arriving at a system state which reflects the current operating state of the power system. The results of state estimation procedure are used to carry out security related real time studies such

as contingency analysis and security enhancement and hence these algorithms are required to be fast, occupy lesser memory space, should generate an estimate that actually represents the current operating state of the system. SE techniques invariably try to minimize some form of an objective function which actually is conceived by considering the differences between the values of measurement functions and the corresponding actual measurements. WLS technique had been widely used for solving SE problem and it tries to reduce the squared deviations of measurement errors wherein the results get drastically affected by the presence of bad measurements in the measurement set.(1) WLAV technique was later developed and this method simultaneously detected and rejected the bad measurements and accurately estimated the system state. As this technique had been an interpolation technique, it generated an estimate satisfying the good measurements (2). But this technique suffered drawbacks such as consumption of lot of memory space and utilization of a large computation time. To overcome these FDSE techniques were developed in which the problem had been decoupled into two separate ones and the Jacobian matrix had been made constant through certain assumptions (FDSE). But this had resulted in approximation errors due to decoupling. A fast super decoupled state estimator is suggested in which both, the vectors of measurement function and state variables are operated by a rotational operator resulting in a formulation that demands alternate iterations of active and reactive equations thereby avoiding the approximation errors due to decoupling.(4).

A bad data removal and identification method based on techniques such as measurement compensation and linear residual calculation is presented in (5). A bad data identification method for LP state estimator in which bad measurements were identified and eliminated using hypothesis testing identification concept is presented in (6).A sequential identification technique for bad data based on orthogonal transformation is presented in (7) where a suspect list of bad data is built based on their normalized residuals and then it is pruned to reveal the bad data (8).

A neural network based filter in which network had been trained using the correct values of measurements is presented in (9) and this trained network filters out the bad measurements. Most forms of the gross measurement errors were identified by this filter. The concept of power system decomposition had been used to identify the multiple interacting bad data [10]. Identification of conforming analog measurement errors had been carried out using Tabu search technique (11).

Though all these methods were attractive, most of them involve a separate bad data identification procedure which consumes a definite computation time. Conventional WLAV loses its charm from the point of view of computational time and memory requirement though it rejects inherency the bad measurements. In this paper an attempt has been made to increase the computational efficiency of conventional WLAV by linearising the problem, which results in a constant jacobian. The problem has been decoupled without making any assumptions which results in partially constant right hand side matrices. The proposed method treats bus voltage magnitudes and real and reactive line flows at both ends as state variables and this LFWLAV has been tested on IEEE 14, 30 and 57 bus systems in the presence of varying number of bad measurements.

WLAV State Estimation

SE techniques developed using least squares minimization algorithm were not robust as they try to minimize the squared deviations of the actual measurements from the corresponding values obtained using the measurement functions. If a few wrong measurements had been assigned a higher weightages or the good measurements with previously assigned higher weightages become bad due to some reason, then that will tend to introduce deviations in the estimated system state. Therefore a nonquadratic objective function had been introduced and the SE problem has been formulated as a minimization problem which is solved through LP technique. The method is generally represented as WLAV estimator as it tries to minimize the absolute value of the error weighted by the measurement accuracy σ_j^{-2} .

$$J = \left[diag(R^{-1}) \right]^T \left| z - h(x) \right| \tag{1}$$

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

The above problem is reformulated as an LP problem as shown below through the introduction of the slack variables.

Minimise
$$J = \begin{bmatrix} diag(R^{-1}) \end{bmatrix}^T [\gamma + \eta]$$

Subject to (3)
 $H \Delta x + \gamma - \eta = \Delta z$
 $\gamma, \eta \ge 0$

Equation (3) is solved iteratively through LP technique to obtain the solution vector x until Δx becomes small enough so that the procedure can be terminated. But the method proves to be inefficient as it demands a lot of memory space and involves the solution through the time consuming LP which by itself is iterative, thereby making the procedure doubly iterative. Apart from these two shortcomings WLAV state estimator has several attractive features such as its inherent capability to reject bad measurements by trying to interpolate only ns among the nz redundant measurements, avoidance of round off errors introduced due to the factorization and multiplication of matrices, free from the effects of assignment of wide range of weightages. In order to exploit the above mentioned favorable qualities and overcome the short comings, the problem of SE is linearised first and then solved using WLAV technique.

Proposed Method

The real and reactive bus powers as a function of real line flows, reactive line flows and $V_m^{\ \ 2}$ can be written as

$$P_{i} = \sum_{j=1}^{nl} A_{ij} \ p_{j} - \sum_{j=1}^{nl} A'_{ij} \ l_{j}$$
 (4)

$$Q_{i=} \sum_{j=1}^{nl} A_{ij} \ q_j - \sum_{j=1}^{nl} A_{ij} \ m_j$$
 (5)

Treating P,Q and V_m^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

$$Min \varphi = \sum_{i=1}^{nm} wi \left[Zi - fi(x) \right]$$
 (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

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

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

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

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

Subject to

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

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

$$G.\,\Delta x=\,-\mathrm{g}(\mathrm{x}^0)$$

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 in the presence as well as absence of bad measurements till the algorithm converges. Bad measurements are generated by adding a random noise with Gaussian distribution to the measurement

vector. It is to be noted that the jacobian matrices A, H and G are constant matrices that require to be computed only once at the beginning of the iterative process.

However RHS vectors f(x), g(x), h(x) must be recomputed during iterative process.

Algorithm of the Proposed Method

- 1. Read the line data and load data.
- 2. Run the base case load flow and form the measurement vector.
- 3. Form the bus incidence matrix A.
- 4. Build the matrices for real and reactive power balance.
- 5. Form the matrix for loop phase angles.
- 6. From the above matrices form the necessary H, C, R and X matrices.
- 7. Reformulate WLAV based SE problem as an LP problem by adding slack variables and add constraints to satisfy KCL and KVL.
- 8. Solve the SE problem by applying LP technique.
- 9. Check for convergence.
- 10. If converged, the procedure is stopped, otherwise state vector is updated and steps 8 & 9 are repeated till convergence is attained.
- 11. Repeat steps 3 to 10 by introducing varying number of bad measurements in the measurement vector.

Simulation and Results

The proposed LFWLAV technique has been tested on standard IEEE 14, 30 and 57 bus test systems with and without bad measurements. The measurement vector has been generated by adding randomly generated low variance noise to the output of NR load flow. Measurement vector consists of bus power injections, real and reactive power flows at both ends of the transmission lines and bus voltage magnitudes. Sufficient redundancy has been created by considering the above mentioned measurements in all the even numbered buses. In order to highlight the bad data rejection capability of WLAV based technique, in each of the measurement set 0,5,10 and 15 number of bad measurements were introduced at random locations. The results obtained by running the conventional WLAV technique in the presence as well as absence of the bad measurements have been used for bench mark comparison.

In order to validate the performance, three performance indices namely $\Delta V_{rms}\Delta P_{rms}\Delta Q_{rms}$ were proposed and the algorithm's performance has been analyzed in terms of these indices and the net execution time NET, assuming a flat start and convergence tolerance of 0.0001.

$$\Delta Vrms = \sqrt{\frac{1}{nb}} \sum_{i}^{nb} (V_i^t - V_i)^2$$
 (10)

$$\Delta p_{\rm rms} = \sqrt{\frac{1}{nl}} \sum_{i}^{nl} (P_i^t - P_i)^2$$
 (11)

$$\Delta q_{\rm rms} = \sqrt{\frac{1}{n!}} \sum_{i}^{nl} (q_i^t - q_i)^2$$
 (12)

Values of the three performance indicators and the NET obtained by conventional WLAV and the proposed LFWLAV technique are shown in Tables 1, 2 and 3 for the purpose of comparison. Graphical representation of the results has also been presented in Figures 1 to 12.

	Table 1: Results for IEEE 14 Bus Systems								
Measur-	WLAV-	LFWLAV-	WLAV-	LFWLAV-	WLAV-	LFWLAV-	WLAV-	LFWLAV-	
ements	$\Delta Vrms$	ΔVrms	ΔPrms	ΔPrms	$\Delta Qrms$	ΔQrms	NET(ms)	NET(ms)	
0	0.1406	0.0883	0.1283	0.1048	0.1561	0.1055	211	136	
5	0.1405	0.0882	0.1222	0.102	0.1549	0.1039	210	136	
10	0.1363	0.0635	0.1213	0.098	0.1494	0.1029	212	137	
15	0.1349	0.0246	0.1154	0.0976	0.1311	0.1024	212	137	

Table 2: Results for IEEE 30 Bus Systems								
Measur-	WLAV-	LFWLAV-	WLAV-	LFWLAV-	WLAV-	LFWLAV-	WLAV-	LFWLAV-
ements	$\Delta Vrms$	ΔVrms	ΔPrms	ΔPrms	$\Delta Qrms$	ΔQrms	NET(ms)	NET(ms)
0	0.1742	0.0755	0.3633	0.2064	0.2011	0.1259	468	189
5	0.0833	0.0397	0.3604	0.2051	0.2003	0.1253	469	188
10	0.0609	0.0328	0.3568	0.2031	0.1994	0.1246	469	189
15	0.0454	0.0283	0.3556	0.2024	0.1977	0.1239	469	189

Table 3: Results for IEEE 57 BUS SYSTEM								
Measur-	WLAV	LFWLAV	WLAV	LFWLAV	WLAV	LFWLAV	WLAV	LFWLAV
ements	$\Delta Vrms$	$\Delta Vrms$	ΔPrms	ΔPrms	$\Delta Qrms$	ΔQrms	NET	NET
0	0.0791	0.0288	0.245	0.1114	0.1279	0.1036	711	233
5	0.0788	0.0283	0.2425	0.1106	0.1265	0.1029	709	234
10	0.0782	0.0272	0.2401	0.11	0.1254	0.1017	709	232
15	0.0774	0.0258	0.2377	0.1093	0.1247	0.1007	710	232

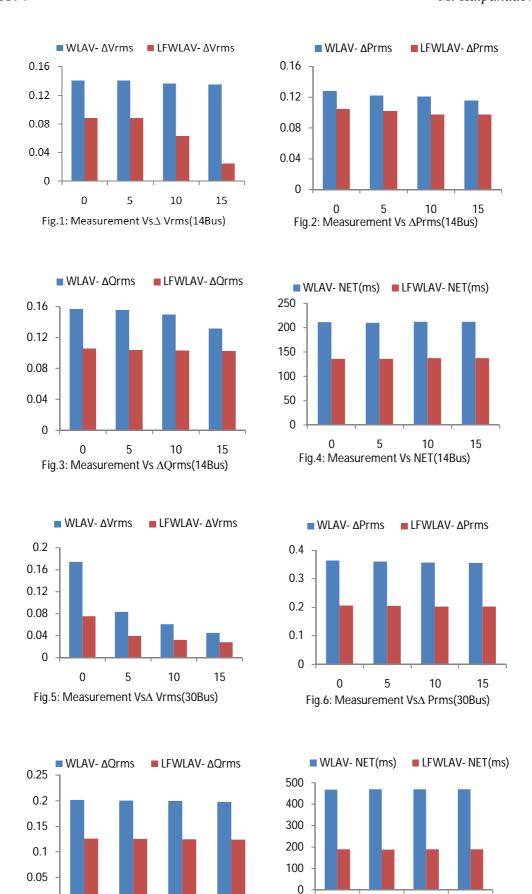
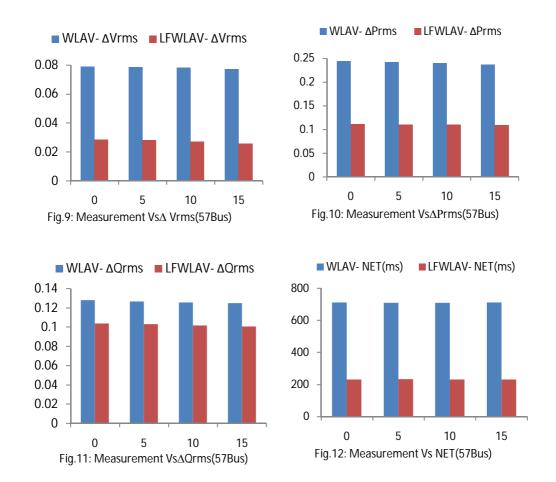


Fig.8: Measurement Vs NET(30Bus)

Fig.7: Measurement Vs ΔQrms(30Bus)



Conclusion

A new line flow based state estimation technique has been proposed and the solution has been obtained by the application of WLAV technique. This proposed LFWLAV method features a constant Jacobian which needs to be computed only once at the beginning and a partially constant right hand side vector. This was achieved through problem linearization and no assumptions had been made in order to make the Jacobian a constant one. This fact adds to the accuracy of the estimate and reduction in computation time. As WLAV has inherent capability to reject the bad measurements, the proposed technique results in a state vector which satisfies the n_s number of good measurements out of the n_m number of available measurements. This method of problem formulation generates an estimate which is in terms of bus voltage magnitudes and line flows and these are the quantities that are required to identify whether the system is secure or not. Hence it can be concluded that the proposed method results the most accurate estimate of the system state, which are presented in terms of the quantities of real interest and this estimate is obtained in a reasonably shorter duration and it is immune to the presence of bad measurements which makes it a suitable tool for online applications.

References

[1] Schweppe. F. C. and Wildes. J., 1970, "Power System Static State estimation, Part I: Exact Model", IEEE Tras. Power Appar.Syst., Vol. PAS-89, pp. 120-125.

- [2] Willy W.Kotiuga and M.vidyasagar, 1982, "Bad Data Rejection Properties of Weighted Least Absolute Value Techniques Applied to Static State Estimation", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-101, No.4, pp. 844-853.
- [3] Horisberger, H. P., Richard, J. C., and Rossier, C., 1976, "A fast decoupled static state-estimator for electric power systems," IEEE Trans. Power Appar. Syst., Vol. PAS-95, No. 1, pp. 208–215...
- [4] Roy. L. and Mohammed. T.A., 1997, "Fast decoupled state estimator for power systems", IEEE Tras. Power Appar. Syst., Vol. 12, No. 4, pp. 1597-1603.
- [5] Ilya W.Slutsker, 1989, "Bad Data Identification in Power System State Estimation Based on Measurement Compensation and Linear Residual Calcultion", IEEE Trans. on Power Systems, Vol.4, No.1, pp. 53-60.
- [6] Ali Abur, 1990, "A Bad Data Identification Method for Linear Programming State Estimation", IEEE Trans. on Power Systems, Vol.5, No.3, pp.894-900.
- [7] N.Vempati and R.R.Shoults, 1991, "Sequential Bad Data Analysis in State Estimation Using Orthogonal Transformations", IEEE Trans. on Power Systems, Vol.6, No.1, pp. 157-166.
- [8] B.M.Zhang, S.Y.Wang and N.D.Xiang, 1992, "A Linear Recursive Bad Data Identification Method with Real-Time Application to Power System State Estimation", IEEE Trans. on Power Systems, Vol.7, No.3, pp. 1378-1385.
- [9] H.Salehfar, R.Zhao, 1995, "A Neural Network Preestimation Filter for Bad Data Detection and Identification in Power System State Estimation", Electric Power System Research, No.34, pp.127-134.
- [10] M.G.Cheniae, L.Mili and P.J. Rousseeuw, 1996, "Identification of Multiple Interacting Bad Data via Power System Decomposition", IEEE Trans. on Power Systems, Vol.11, No.3, pp.1555-1563.
- [11] Eduardo N. Asada, Ariovaldo V. Garcia and R. Romero, 2005, "Identifying Multiple Interacting Bad Data in Power System State Estimation", Power Engineering Society General Meeting, IEEE, pp.571-577.