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Power System Static State Estimation and Bad Data Processing

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ABSTRACT: State Estimation is very important for online power system security. The state variables of Power System are voltage magnitude and phase angles at all network buses. This paper presents a methodology to solve the states using WLS method and Bad Data processing. In this paper data is taken from load flow results using NR method and the concept of WLS is adopted for solving states of the system. The SE detects the presence of Bad Data. In this work, Bad Data Detection has been done by using Chi-Square Test and Identification using LNR method. The proposed methodologies are tested on IEEE14 Bus test system using Matlab-programming.

KEYWORDS: State Estimator (SE), Weighted Least Square Method (WLS), Supervisory Control and Data Acquisition System (SCADA), Chi-Square Test, Largest Normalised Residual Method (LNRM).

I.INTRODUCTION

Fred C. Schweppe introduced the concept of static state estimation into terrestrial power systems [1]. In static SE power system is treated as Quasi-static system i.e. variations of state with respect to time is negligible. The static SE has to be run for every five minutes in order to estimate the states, whereas the future states of system cannot be determined unlikedynamic stateestimation. SCADA receives information from all the sensors, meters and remote terminal units (R.T.U). The information received by SCADA may be corrupted due to the failure of sensors, gross error in the meters and improper connection of transducer etc. If the analysis was carried out based on corrupted data it may result in false tripping of power system element or grid failure [2]. In order to identify and estimate the redundant meter reading the state estimation technique was incorporated in building blocks of energy control center.

II. STATE ESTIMATION USING WLS

A non-linear state estimator model can be formulated as measurement model

$$Z=h(x)+e \tag{1}$$

Where,

$Z=[P_{inj}, P_{flow}, Q_{inj}, Q_{flow}, V_{mag}, I_{mag}]$

$x=[V_1, V_2\ldots V_n, \Theta_1, \Theta_2\ldots \Theta n]$ is the state vector

h(x) is the vector having non-linear function mapping measurements and state variables.

'e' is the vector of measurement errors.

'n' is the total number of buses with the first bus being the slack bus.

A. *Measurement Function h(x)*

The dimensions of themeasurement function is m x n where m is the number of measurements and n is the number of states.

$$P_i=V_i\sum V_j\,(Gij\cos\theta_{ij}+Bij\sin\theta_{ij}) \tag{2}$$

$$Q_i=V_i\sum V_j\,(Gij\sin\theta_{ij}-Bij\cos\theta_{ij}) \tag{3}$$

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$$P_{ij}=V_i^2(g_{si}+G_{ij})-V_iV_j(G_{ij}\cos\theta_{ij}+Bij\sin\theta_{ij}) \quad (4)$$

$$Q_{ij}=-V_i^2(b_{si}+B_{ij})-V_iV_j(G_{ij}\sin\theta_{ij}-B_{ij}\cos\theta_{ij}) \quad (5)$$

B.Gain Matrix

$G=H^TR^{-1}H$ (6)

Gain matrix is sparse, symmetric and positive definite, provided system is observable. It is obtained by product of Hat matrix and weighting matrix.R^{-1} is weighting matrix, whose diagonal elements are often chosen as measurement error variance i.e.

$$= \begin{bmatrix} \sigma1^2 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma m^2 \end{bmatrix} (7)$$

$H(x) = \partial h(x)/\partial x$ (8)

Weighted least square technique is an iterative method. The objective function involves minimization of weighted square of error.

$$J(x)=\sum_{i=1}^{m}\frac{(Z_i\text{-}hi(x))^2}{\boldsymbol{\sigma}^2} \quad (9)$$

$$G(x^k) = H^T(x^k)R^{-1}H(x^k) \quad (10)$$

$$\Delta x^{k+1} = [G(x^k)]^{-1}H^T(x^k)\,W\,[z\text{-}h(x^k)] \quad (11)$$

After estimating the state variables, $Z^{true}$is estimated and measurement error is calculated.

$Zest = h\, x_{est}$ (12)

$e= Z_{est} – Z_{meas}$ (13)

C. Steps for State Estimation Using WLS

State estimates for IEEE 14 bus system (14 bus voltage and 13 bus angles) can be determined through following procedure.

1. Load flows: Determine the true values of the measurements like voltage magnitude, power injections & power flows from the load flow analysis usingNewton-Raphson method, which is a measurement data for state estimation (Z).
2. Adding of errors to Measurements: A random error is introduced into the above measurements.

$Z_i=A_{i*}(1+RND*\boldsymbol{\sigma}_i)$ (14)

Where,

Ai=actual value from load flows

$\boldsymbol{\sigma}_i$=standard deviation of measurement

3. Check observability: For the system to be completely observable, %redundancy should be greater than one.

% Redundancy= No Of Measurements/No Of States (15)

4. Set iteration count to zero, initialize the state vector as flat start i.e. voltage is 1 pu and the angle is zero degrees.
5. Calculate the Gain matrix from the equation (10) and solve for Δx^k using the equation11.
6. Stop iteration if $(\Delta x^{k+1} - \Delta x^k)$ <tolerance i.e. convergence is achieved.
7. Else update $x^{k+1}=x^k+\Delta x^k$ and go to step5.

The performance of state estimation algorithm for different % redundancy depends on Error indices. For good performance of state estimation algorithm error indices should be minimum.

Error Index [1] =LI_norm/no: of measurement(16)

Error Index [2] =Infinity norm (17)

Where,

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Infinity norm = maximum ($|z_{meas}$ - $z_{est}|$)(18)
LI_norm=$\sum |z_{meas}$ - $z_{est}|$ (19)

III. BAD DATA PROCESSING

The measurement errors are classified into two types.

1. Random errors: $-3\boldsymbol{\sigma} \leq \text{error} \leq 3\boldsymbol{\sigma}$
2. Gross errors:$error \geq 3\boldsymbol{\sigma}$

Random error a commonly occurring error in the meters and they follow statistical distributions. Large extraneous errors are known as Gross errors. Consider that Bad data has been occurred due to the presence of Gross error in themeters. BD processing includes Detection and Identification. In this paper, Bad DataDetection has beendone using Chi-Square Test and Identification using identification by elimination, i.e. Largest Normalised Residual Method [4].

A *Bad data detection.*

It refers to whether the measurement set actually containsbad data or not. The Statisticalproperties of measurement facilitate the detection of bad data presence in measurement set. Chi-square test is one of the statistical method to detect the presence of bad data. The Chi-square distribution with k degree of freedom can be represented as.

$$Y=\sum_{i=1}^{k}(X_i)^2 \qquad (20)$$

Where,X_i is a random variable following Normal distribution. The equation (9) and equation (20) are duals. The objective function of WLS method follows a chi-square distribution. When bad data is present in measurement set the objective function of WLS exceeds the critical value obtained from Chi-square distribution Table at a particular degree of freedom and confidence limit. The Flowchart for bad data detection is shown below in Fig1.

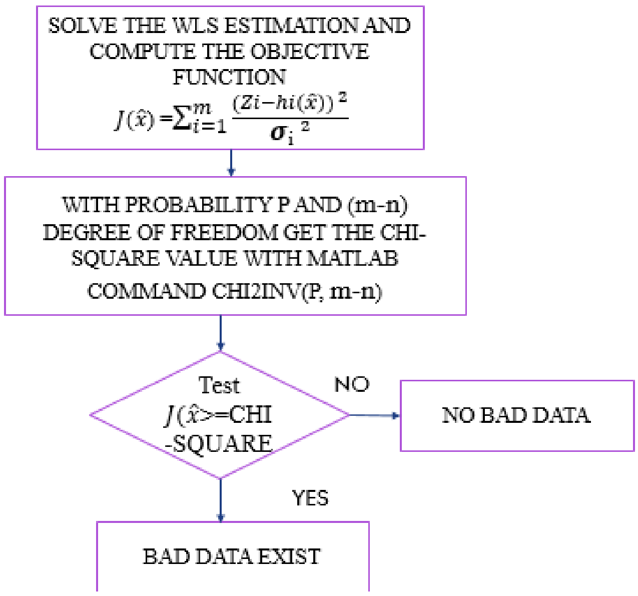

Fig1.Flowchart for Bad Data Detection.

In Fig1, the probability p is generally taken as 95% confidence limits, it indicatesthat there is achance of 5% existence of Bad data. If p is taken as 99% the Bad data identification will be difficult. (m-n) indicate thedegree of freedom (m is

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a number of measurement, n is anumber of states).The critical value is obtained from the Chi-square distribution table or by using MATLAB Command CHI2INV (p, m-n).

B *Bad Data Identification*:
The Bad data identification is followed by Bad data detection. In this paper largest normalized residual method is used to identify Bad Measurement. Identification refers which measurement in the measurement set actually contain Bad Data.

Ω=S*R; (residual covariance matrix) (21)
S= (I-K); (residual sensitivity matrix) (22)
K=H (inv (G))*H'*inv(R); (Hat matrix) (23)

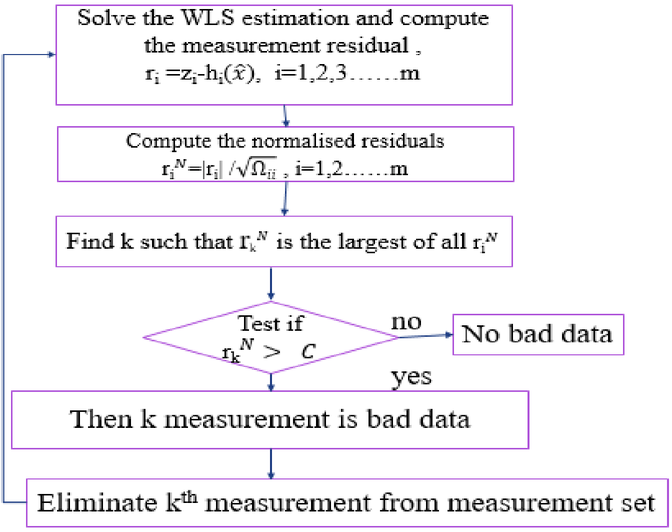

Fig 2. Flow chart for Bad Data Identification

The value of C is taken as 3.0. After eliminating K^{th} measurement chi-squared test is carried out again to improve the state estimation accuracy.

IV. RESULTS &DISCUSSION

A. *State estimation using WLS*
In this paper work an IEEE14 bus system considered as the test system and data was referred from [7]. The number of states is 27 for given test system. The number of samples taken shouldbe greater than 27 for observability. The samples are amix of voltage magnitude, power injection and power flows. The results presented and discussed by writing a program in M-file. State estimation using WLS was performedfordifferent % redundancy and error indices tabulated in Table1.

Table1. Error index for different % redundancy

%Redundancy	LI-norm	Infinity-norm	Error index[1]	Error index[2]
110(30 samples)	0.0054	0.0034	1.8e-4	0.0034
150(41 samples)	0.0065	0.0034	1.6e-4	0.0034
180(50 samples)	0.0142	0.0556	2.8e-4	0.0556

From the Table1 of error index it is identified that the error index [1] is minimum for 150% redundancy which indicate state estimation results are more accurate at 150% redundancy.

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Table 2 SE results using WLS for 150% redundancy

S.N0	VOLTAGE	ANGLE
1	1.0749	0
2	1.0601	-4.8185
3	1.0254	-12.308
4	1.0286	-9.875
5	1.032	-8.4466
6	1.0843	-13.975
7	1.061	-12.763
8	1.0945	-12.765
9	1.0459	-14.287
10	1.0453	-14.507
11	1.0611	-14.356
12	1.0678	-14.803
13	1.0611	-14.845
14	1.0347	-15.525

B *Measurement set containing Single Bad Data*

Among 41 samples in order to detect a single bad data the measurement shouldn't be critical nor critical pair. 9^{th} and 14^{th}measurements in the sample are identified as bad data.If Single Bad Data is present at measurement 3 i.e. bus-3 power injection has been recorded as -0.8426 pu insteadof -0.9426 pu. SE is followed by bad data detection. The residual value obtained at the end of first iteration tabulated in Table 3.

Table3. Simulation results obtained from Chi-square test at end of 1^{st}iter

Residual value	Critical value	RV > CV
34.246	23.68	BD present in sample

The BD identification is followed by BD detection. The normalized residual plot is shown in Fig4.

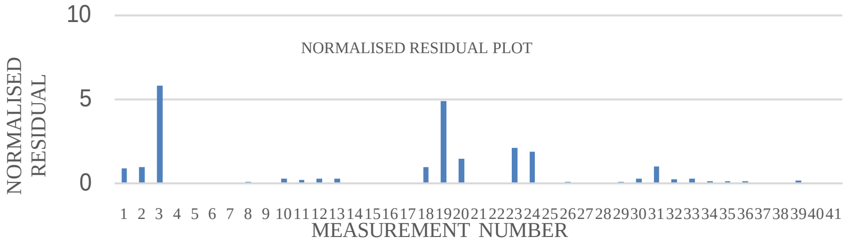

Fig4.Normalised Residual plot for BD at Measurement 3

The largest normalised residual obtained at measurement number 3 indicates presence of bad data at measurement 3.Eliminate measurement 3 from measurement set followed by SE. The residual value obtained at end of second iteration tabulated in Table 4.

Table4. Simulation results obtained from Chi-square test at end of 2^{nd} iter

Residual value	Critical value	RV < CV
0.2970	22.36	BD absent in sample

Comparison between Actual, Estimated values at measurement 3 shown in Fig5 for different scenario.

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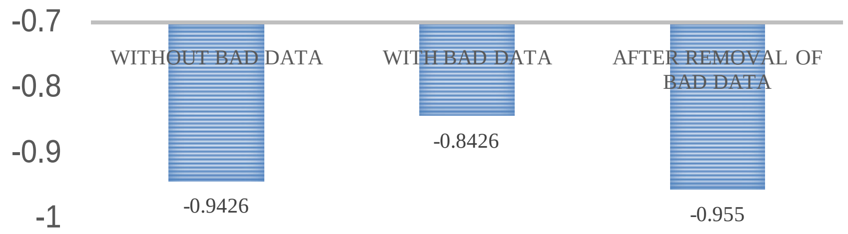

Fig5.Comparison between Actual, Estimated values at measurement 3.

C. *Measurement set containing Multiple Bad Data*

In this paper a case study on multiple BD is carried out for measurement whose residuals are weakly correlated.If Multiple BD is present at measurement 4 i.e. P_i (7) has been recorded as 0.2 pu instead of Zero, measurement 8 i.e. P_i (12) has been recorded as -0.3604 Pu instead of -0.0604 pu. SE is followed by bad data detection. The residual value obtained at the end of first iteration tabulated in Table 5.

Table5. Simulation results obtained from Chi-square test at end of 1st iter.

Residual Value	Critical value	RV > CV
362.6320	23.68	BD present in sample

The BD identification is followed by detection. The normalized residual plot is shown in Fig6.

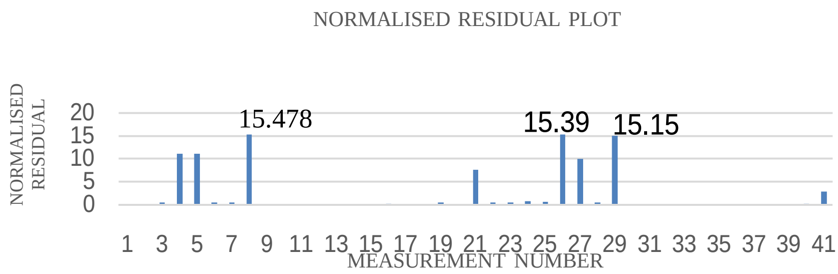

Fig6. Normalized Residual Plot for Multiple BD at Measurement 4 & 8

The largest normalised residual obtained at measurement number 8. Which indicate BD present at measurement 8.Eliminate measurement 8 from measurement set followed by SE. The critical and residual value obtained at end of second iteration tabulated in Table 6.

Table6. Simulation results obtained from Chi-square test at end of 2nd iter

Residual value	Critical value	RV > CV
124.9758	22.36	BD present in sample

The BD identification is followed by BD detection. The normalized residual plot is shown in Fig5.

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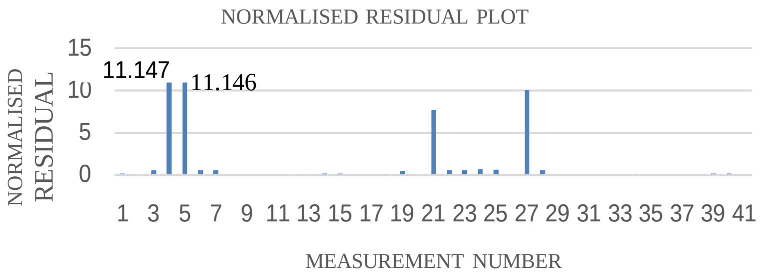

Fig6. Normalized Residual Plot after eliminating BD at Measurement 8.

The largest normalised residual obtained at measurement number 4. Which indicate BD present at measurement 4.Eliminate measurement 4 from measurement set followed by SE. The critical and residual value obtained at end of third iteration tabulated in Table 7.

Table7. Simulation results obtained from Chi-square test at end of 3rd iter

Residual value	Critical value	RV <CV
0.7086	21.026	BD absent in sample

Comparison between Actual, Estimated values at measurement 4&8 shown in Fig7. For different scenario.

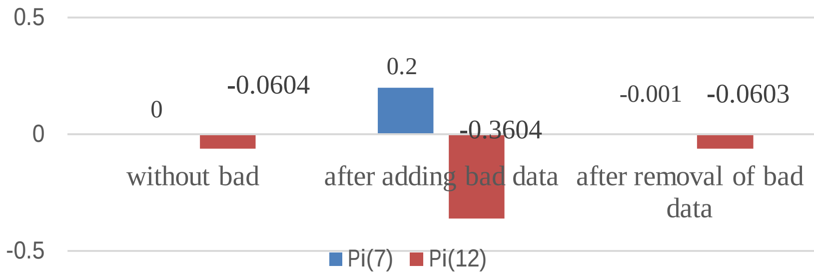

Fig7. Comparison between Actual, Estimated values at measurement 4&8.

V.CONCLUSION

Weighted least square method is commonly usedmethod because of its ease of implementation. In this paper, state estimation is carried out for different % redundancy followed by bad data processing for the test system. Single bad data and multiple bad data are injected into measurement and they are detected, identified successfully. Besides bad data processing, the true values of bad data measurements are estimated.

VI. FUTURE WORK

State estimation performance can be improved by placing PMU's in the test system. The change in network parameter can also be cause for the occurrence of bad data. The above work can be extended to network parameter estimation.

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APPENDIX

TYPE: 1.Voltage Magnitude, 2. Active Power Injection, 3. Reactive Power Injection, 4.Active Power Flow, 5. Reactive Power Flow

Table8. Measurement Data

S.NO	TYPE	VALUE	FROM BUS	TO BUS	Rii
1	1	1.0785	1	0	9.00E-04
2	2	0.1812	2	0	1.00E-04
3	2	-0.9426	3	0	1.00E-04
4	2	0	7	0	1.00E-04
5	2	0	8	0	1.00E-04
6	2	-0.0903	10	0	1.00E-04
7	2	-0.0349	11	0	1.00E-04
8	2	-0.0604	12	0	1.00E-04
9	2	-0.1489	14	0	1.00E-04
10	3	0.3456	2	0	1.00E-04
11	3	0.0857	3	0	1.00E-04
12	3	0	7	0	1.00E-04
13	3	0.2082	8	0	1.00E-04
14	3	-0.0573	10	0	1.00E-04
15	3	-0.0177	11	0	1.00E-04
16	3	-0.016	12	0	1.00E-04
17	3	-0.0492	14	0	6.40E-05
18	4	-1.5722	1	2	6.40E-05
19	4	0.7386	2	3	6.40E-05
20	4	0.5594	2	4	6.40E-05
21	4	0.2709	4	7	6.40E-05
22	4	0.1541	4	9	6.40E-05
23	4	0.4124	2	5	6.40E-05
24	4	-0.5956	4	5	6.40E-05
25	4	0.4627	5	6	6.40E-05
26	4	0.186	6	13	6.40E-05
27	4	0.2698	7	9	6.40E-05
28	4	0.0818	6	11	6.40E-05
29	4	0.0188	12	13	6.40E-05
30	5	-0.1753	1	2	6.40E-05
31	5	0.0593	2	3	6.40E-05
32	5	0.0291	2	4	6.40E-05
33	5	-0.1565	4	7	6.40E-05
34	5	-0.025	4	9	6.40E-05
35	5	0.0472	2	5	6.40E-05
36	5	0.1145	4	5	6.40E-05
37	5	-0.2073	5	6	6.40E-05
38	5	0.1001	6	13	6.40E-05
39	5	0.1482	7	9	6.40E-05
40	5	0.0885	6	11	6.40E-05
41	5	0.0142	12	13	6.40E-05