DETECTION OF GROSS ERROR BY MODIFIED RELAXATION STATE ESTIMATION IN POWER SYSTEM

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Abstract **– This paper proposes a modified relaxation-based method for gross error identification. Toward this end,a participation matrix is defined. It consists of the elements of the residue sensitivity matrix and the corresponding measurements. The sum of row elements of the participation matrix constitutes the residues. The column elements of the participation matrix are also a source of information of masking which sum is quantified as distortion. Large distortion and large residues are proposed to indicate the quality of measurements. The measurement corresponding to the poorest quality is then corrected using the modified form of relaxation. The above procedure is repeated sequentially until all residues are within a particular tolerance. The method gives a measurement set very near to true measurement set.**

Keywords: *state estimation, error filtering, relaxation methods*

1. INTRODUCTION

Power system state estimation is an important algorithm used in monitoring and control the power system. The presence of gross errors in measurements tends to bias the estimated state of the system. Hence, it is essentially to eliminate grossly erroneous measurements. Measurement residuals are conventionally used for this purpose. However, the measurement residuals suffer from the phenomenon of smearing, [1 … 4]. Different strategies could be employed for grouped search, as given by [5]...[9]. All of them have acknowledged the importance of measurement correction.

Slutsker, [10], has exploited the best of both the ordered and the grouped search techniques. The method comes up with the unique proposition of unmasking of the residuals with the help of measurement compensation. The selection of the initial suspected set is done using the unmasking property of measurement compensation. This unmasking property is due to the partial neutralization of the errors. The method estimates the error in the measurements in an optimal way, [8 … 9]), and identification of gross error is carried out using hypothesis testing. The advantages of ordered search for extraction of gross error over the optimal error estimation in brought out clearly in [11]. The role of the column elements of the residue sensitivity matrix in the formation of the residues is well illustrated by [12] . The importance of the sequential correction of measurements for better identification has been highlighted in [7], [10] and [13]. In [2] and [14] it was confirmed that the interaction of measurements takes place in its neighborhood only. Slusker, [15] discusses the requirement of localized search. A study of repeated application of measurement correction using a modified form of relaxation technique to the identified grossly erroneous measurements revealed that it is possible to correct the identified measurements toward their true values. In [16] it was applied the relaxation for the estimation of large power systems.

This paper makes an attempt to formulate a scheme for gross error identification using a modified form of relaxation. It tries to make the best use of the rich knowledge available in the above literature to formulate the scheme. Toward this end it s proposed a new approach of the error residue equation related through the residual sensitivity matrix "W ". In the proposed method the error vector is viewed as a set of objects. Each element of the residue sensitivity matrix W is considered as a filter. When the objects are seen through the filters, the images are obtained. The images are in form of a matrix called image matrix "IM". The sum of the row elements of the image matrix is called the residual image vector $\underline{RIM}$. The column elements represent the quantum of image transmission of an error into the residual image vector, [12]. The sum of the column elements of the image matrix is therefore defined as the image distortion vector $\underline{DIM}$. Image distortion is defined as the cause of masking.

Computation of $\underline{RIM}$ and $\underline{DIM}$ vectors cannot actually be carried out because $\underline{e}$ is an unknown vector. The residues and distortions are therefore defined using the elements of measurement vector as objects. The matrix consisting of the product of elements of W matrix and the corresponding measurement is defined as the participation matrix. The sum of the row elements of the participation matrix then gives the residue vector. The sum of the magnitude of the column elements of participation matrix is defined as the distortion vector.

The information contained in the residue vector and the distortion vector is used to obtain a set of suspected measurements. The residues and the distortions are further employed to describe the quality of a measurement. The measurement having a poor quality and belonging to the suspected set is presumed as a grossly erroneous measurement, and is a correction by injecting a fictious error into this measurement. This procedure is repeated by picking the poorest quality measurements, one at a time, to nullify its residue. The convergence implies that the applied corrections have pruned the errors contained in the measurements. Correcting one grossly erroneous measurement at a time, other residues are influenced. This is effective in uncovering the masking of the residues. The technique applied iteratively finally approaches the true value of the measurements. Individual gross error magnitudes are then precisely and readily and computed. The proposed method has been implanted on IEEE-30 bus system for $P-\delta$ formulation.

2. ERRORS AS OBJECTS AND W MATRIX AS A SET OF FILTERS

Let $\underline{e} = [e_1, e_2, ..., e_i, ..., e_m]^T$ (1)

be the error vector of dimension "m", where m is the number of measurements in a given system. Consider the individual elements of $\underline{e}$ as objects. Let the i-th error e_i be represented by a circle with radius $|e_i|$ and the zero error represented by a point. Figure 1 shows this pictorial representation. A similar representation will hold for images too.

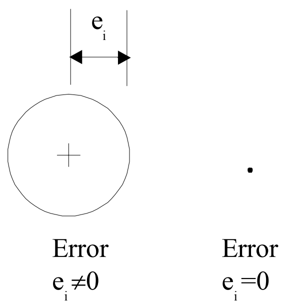

Figure 1: Representation of error

Let W_{ij} be called a filter. The object e_i, when seen through the W_{ij} filter produces an image called subimage IM_{ij}. The subimage IM_{ij} is represented by a circle with radius $|IM_{ij}|$. Individual elements of the image matrix are given by:

$$IM_{ij} = W_{ij} \cdot e_j \text{, i=1,2, ..., m; j=1, 2, ..., m} \quad (2)$$

The i-th column of the W matrix is a column filter corresponding to the error e_i. Each error input gives a column of subimages, depending on the property of its column filter. The image matrix consists of subimages due to errors present in $\underline{e}$. The sum of this subimages taken row wise is called residual image RIM, at i-th location. This is numerically the residue r_i. Also, e_i distorts all images except i-th, through the i-th column of W. Sum of the magnitudes of the i-th column is therefore termed as the image distortion DIM_i due to the i-the error e_i (Figure 2).

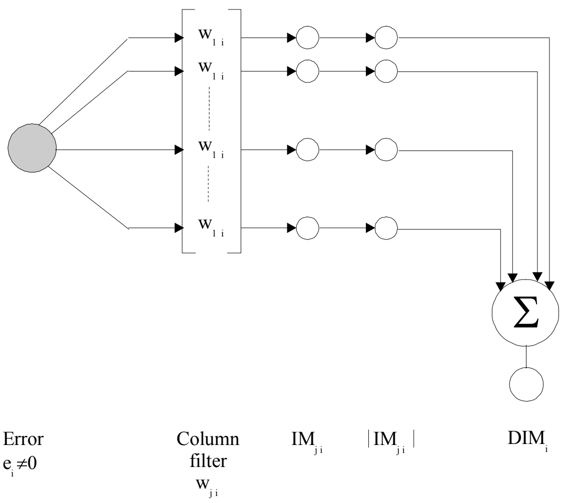

Figure 2: Image distortion

In Figure 2, some of the images are shown shaded to indicate that the image can be an inverted image. Therefore, the magnitudes of the images are computed to calculate the distortion.
Mathematical forms of $\underline{RIM}$ and $\underline{DIM}$ are given as:

$$\underline{R\,\mathrm{Im}} = IM \cdot \underline{U} \quad (3)$$

where $\underline{U}$ is a m vector with all elements equal to one and:

$$\underline{DIM} = \{DIM_i\}_{i=1}^{i=m} \quad (4)$$

where $DIM_i = \sum_{j=1}^{m} |IM_{ji}|$

3. PARTICIPATION MATRIX

Consider the equation:

$$\underline{z} = \underline{z}_t + \underline{e} \quad (5)$$

where $\underline{z}$ is the given measurement vector, $\underline{z}_t$ is the true measurement vector and $\underline{e}$ is the error vector, all of order m. $\underline{z}_t$ and $\underline{e}$ are unknown. Also, as explained in [1] and [2], for the linear state estimation:

$$\underline{r} = W \cdot \underline{z} = W\left(\underline{z}_t + \underline{e}\right) = W \cdot \underline{e} \quad (6)$$

where the W matrix is given by:

$$W = I - H\left[H^T R^{-1} H\right]^{-1} H^T R^{-1} \quad (7)$$

H is the Jacobian matrix and R is the covariance matrix with i-th measurement having a variance of σ_i^2. Now define a participation matrix P such that:

$$P_{ij} = W_{ij} \cdot z_j \text{, i=1, 2, ...,m; j=1, 2, ...,m} \quad (8)$$

The residue vector $\underline{r}$ and the distortion vector $\underline{d}$ in terms of the participation matrix is given by:

$$\underline{r} = P \cdot \underline{U} \quad (9)$$

$$\underline{d} = \{d_i\}_{i=1}^{i=m} \quad (10)$$

where:

$$d_i = \sum_{j=1}^{m} \left|P_{ji}\right| \quad (11)$$

This definition is helpful in two ways:

(a) The distortion $\underline{d}$ can be numerically computed from $\underline{z}$ unlike $\underline{DIM}$ of equation (4).

(b) The parallelism between $\underline{DIM}$ and $\underline{d}$ is maintained.

It is observed that a large d_i is an indication of a large magnitude of measurement and a large masking effect, in case it is grossly erroneous. The information available in $\underline{r}$ and $\underline{d}$ is now used judiciously to identify the location of gross errors. A set theoretic formulation is described bellow.

4. SET THEORETIC FORMULATION

Let

$$S = \{z_i\}_{i=1}^{i=m} \quad (12)$$

be the given measurement set and let:

$$S_{r_n} = \{r_i\}_{i=1}^{i=m} \quad (13)$$

denote the set of normalized residues:

$$r_{ni} = \frac{r_i}{\sqrt{W_{ii}} \cdot \sigma_i} \text{, i=1, 2, ...,m} \quad (14)$$

Let r_{nk} be the largest residue in S_{r_n}. Then r_{nk} indicates the presence of bad data in a particular k-th measurement z_k, or in the neighborhood associated with z_k. The neighborhood S_{dl} (set of measurements) of z_k is defined on the basis of P matrix as follows:

$$\text{If } P_{kj} > \lambda_p \text{, then } z_j \in S_{dl} \quad (15)$$

where λ_p is a chosen "participation threshold". S_{dl} thus specifies the measurements that create large distortions in r_{nk}. It can be seen that measurements in S_{dl} belong to the same local area.

Define a group of measurements with large residues:

$$S_{rl} = \{z_i : r_{ni} > \lambda_r\} \quad (16)$$

where λ_r is a chosen "residue threshold". Let:

$$S_{nl} = \{z_k\} \quad (17)$$

Define:

$$S_s = \left(S_{rl} \cap S_{dl}\right) \cup S_{nl} \quad (18)$$

The set S_s comprises the set of suspected grossly erroneous measurements in the neighborhood of the largest residue. As stated in the introduction, one measurement from S_s is to be chosen for correction. A quality factor:

$$q_i = \left(\left|r_{ni}\right|\right)^{\alpha_1} \cdot \left(d_i\right)^{\beta_1} \quad (19)$$

is introduced for this purpose. A large q_i means poor quality. Factors α_1 and β_1 denote the importance assigned to residue at the distortion, respectively. A subset S_q of S_s is defined as:

$$S_q = \{z_i : q_i > \lambda_q\} \quad (20)$$

where λ_p is a chosen "quality threshold". Threshold λ_p is chosen such that it selects only one measurement z_q.

5. MEASUREMENT CORRECTION

The measurement z_q, which is defined as grossly erroneous, is now corrected as follows. The q-th residue r_q is given by:

$$r_q = W_{qq} \cdot z_q + \sum_{\substack{j=1 \\ j \neq q}}^{m} W_{qj} \cdot z_j \quad (21)$$

Let $SC_q = W_{qq} \cdot z_q$ and $MC_q = \sum_{\substack{j=1 \\ j \neq q}}^{m} W_{qj} \cdot z_j$ (22)

SC_q denotes the contribution of z_q to the residue r_q and MC_q denotes the contribution f other than the q-th measurement to r_q. Let

$$z_q^{new} = \frac{-MC_q}{W_{qq}} \tag{23}$$

so that $r_q^{new} = 0$. With z_q^{new}, we have:

$$r_i^{new} = \sum_{j=1}^{m} W_{ij} \cdot z_j \Big|_{z_q = z_q^{new}} \text{, i=1, 2, ...,m} \tag{24}$$

and

$$P_{jq}^{new} = W_{jq} \cdot z_q^{new} \text{, j=1, 2, ...,m} \tag{25}$$

Replacing z_q by z_q^{new} thus amounts to injecting a fictious error (correction) in z_q which forces r_q to zero. This replacement modifies residue vector $\underline{r}$ as above. The procedure can now be repeated with the new residue vector $\underline{r}^{new}$, obtained from equation (24) to give new sets S_{rl}^{new} and S_{dl}^{new}.

The intersection of these new sets yields a new suspected set S_s^{new} and so on. Poorest quality measurement from S_s^{new} is taken up for correction in each iteration. This process is applied until the suspected set becomes a null set. The final measurement vector is then claimed to be true measurement vector within a tolerance.

6. ALGORITHM

(a) Obtain the W matrix, $\underline{r}$ and $\underline{r}_n$ using equations (7), (6) and (14), respectively.
(b) Obtain P matrix using equation (8).
(c) Sort $\underline{r}_n$ and select the largest residue $r_{nk}^{\max}$.
(d) Obtain participation P_{kj}, j=1,2,...,m. Choose a participation threshold λ_p and obtain a distortion set S_{dl} using equation (15).
(e) Calculate distortions d_i for $z_i \in S_{dl}$ using equation (11).
(f) Choose a residue threshold λ_r and obtain S_{rl} using equation (16).
(g) Obtain S_s from equation (18).
(h) With appropriate values of α_1 and β_1 in equation (19), obtain the quality of measurements $q_i, i \in S_s$.
(i) Correct the measurement corresponding to the largest q_i using equation (23), thereby obtaining z_q^{new}.
(j) Obtain $\underline{r}^{new}$ and $\underline{r}_n^{new}$ using equations (24) and (14).
(k) Go to step (c) and continue iterations until S_{rl} becomes an empty set.
(l) The new measurement vector is claimed to be the true measurement vector.

7. NUMERICAL RESULTS

The tests were made in the IEEE-14 bus system (presented in detail in [17]). For the purpose of setting up experiments with different measurements and errors, it must be notes that masking occurs in case of interacting bad data, [18]. Masking is the process where two or more interacting grossly erroneous measurements add (subtract) each other's errors, resulting in large (small) residuals at the location of bad data [19]. The subtracted masked measurements are a challenge for identification, as they defy the statistical threshold. The standard deviation for computing the magnitude of gross error is taken as 0.02 times the magnitude of measurement. The following cases are discussed below:

1) Additively masked data.
2) Short line with subtarctively masked data.
3) Small measurements containing gross errors.
4) A combination of small and large measurements containing gross errors.

For the purpose of operational ease, the following threshold were selected in all cases: alpha =1, beta=0.5. Participation threshold=20% of the largest participation in largest normalized residue; however the residue threshold was varied between 0.03 to 0.06 of the largest distortion measurement.

7.1. Additively Masked Data (Case 1)

In this example the gross errors were injected in lineflow 1-2 and injection 1. The true values of measurements and the error magnitude are given in Table 1.1. Table 1.2 gives the grossly erroneous measurements of their residuals and quality factors in each iteration. It can be observed that the injection measurement 1 gets corrected to a value of 2.68 which is closer to the true value of 2.32 than the given 1.32. Similarly, the lineflow measurement gets corrected to 1.79 from 2.59. Thus the corrected measurement is closer to true value. But it is observed that the quality of the measurements becomes good with a low quality factor. Also, their normalized residuals have become small. Therefore the iterations are stopped at this step.

Sr. No.	Measurement			Error in magnitude
	Type	True	Given	
1	I_1	2.32	1.3243	0.9975
2	F_{1-2}	1.56	2.5955	-0.9645

Table 1.1: Measurement and error

Notations:

I_x Injection at bus x

F_{x-y} Line flow on line x-y

It Iteration number

M Measurement

NR Normalized residuals

QF Quality facotr

It	Injection at bus 1			Line flow 1-2		
	M	NR	QF	M	NR	QF
0	1.32	1.28	0.72	2.59	1.32	0.64
1	3.34	0.0	0	2.59	0.37	0.27
2	3.34	0.27	0.18	2.15	0	0
3	2.91	0	0	2.15	0.2	0.11
4	2.91	0.144	0.09	1.92	0	0
5	2.68	0.0	0	1.92	0.10	0.06
6	2.68	0	0	1.79	0	0

Table 1.2: Measurement, normalized residual and quality factor in each iteration

7.2. Subtractively Masked Data (Case 2)

In this example the gross errors were injected in lineflow 1-2 and injection 1. It is also to be noted that this is a case of gross error in shortline 1-2 associated measurement and the error magnitude are given in Table 2.1. Table 2.2 gives the grossly erroneous measurements, their residuals, the quality factors in each iteration. It should be noted that the normalized residual of injection 1 is very small and hence does not get included into the suspected set of measurements. Therefore, the only way out for subtractively measurements is repeated unmasking. It can be observed that the injection measurement 1 gets corrected to a value of 2.137, which is closer to the value of 2.32 than the given value of 1.377. Similarly, the lineflow measurements get corrected to 1.92 from 0.56. Thus the corrected measurement is closer to true value. The iterations are stopped because the residues are smaller than the residue threshold.

Sr. No.	Measurement			Error in magnitude
	Type	True	Given	
1	Injection 1	2.32	1.3778	0.9432
2	Line flow 1-2	1.56	0.5603	0.9997

Table 2.1: Measurement and error

It	Injection at bus 1			Line flow 1-2		
	M	NR	QF	M	NR	QF
0	1.38	0.04	0	2.59	-	0.16
1	1.38	0.031	0.16	2.59	0.58	0.0
2	1.86	0	0	2.15	0	0.11
3	1.86	0.176	0.09	2.15	0.2	0
4	2.14	0	0	1.92	0	0

Table 2.2: Measurement, normalized residual and quality factor in each iteration

7.3. Small Measurements Containing Gross Errors (Case 3)

In this example the gross errors were injected in lineflow 12-13 and injection 12. The true value of measurements, the given values of measurements and the error magnitudes are given in Table 3.1. Table 3.2 gives the grossly erroneous measurements, their residuals and quality factors in each iteration. It should be noted that the measurements have small magnitudes, unlike those in case 1 and case 2. It can be observed that the injection measurement 12 gets corrected to a value of 0.0313, which is closer to the true value of -0.061 than the given value of -0.1648. Similarly, the lineflow measurement gets corrected to 0.0417 from 0.0162. Thus the corrected measurement is closer to the true value. Because the normalized residuals are below threshold, the iterations are stopped. This example, therefore, shows that this method can also be applied to small measurements containing errors.

Sr. No	Measurement			Error in magnitude
	Type	True	Given	
1	I_{12}	-0.06	-0.16	0.104
2	F_{12-13}	0.02	0.165	-0.148

Table 3.1: Measurement and error

It	Injection at bus 1			Line flow 1-2		
	M	NR	QF	M	NR	QF
0	-0.16	0.13	0.02	0.16	0.02	0.05
1	0.03	0	0	0.16	0.11	0.01

Table 3.2: Measurement, normalized residual and quality factor in each iteration

7.4. Gross Errors in Small and Large Measurements (Case 4)

In this example the gross errors were injected in five measurements. Table 4 gives the measurement type, given value of measurement, corrected value of measurement, true value of measurement, normalized residual and quality factor in each iteration. The measurement set contains both large and small errors. It should be observed that the method successfully identifies and corrects all the measurements to their true value.

It	Measurement				NR	QF
	Type	Given	Corrected	True		
1	I_1	3.34	2.22	2.32	0.7	0.47
2	F_{6-13}	0.78	0.2	0.18	0.5	0.13
3	F_{2-5}	0.042	0.37	0.41	0.4	0.08
4	I_{14}	-0.32	-0.15	-0.15	0.1	0.02
5	I_1	2.22	2.32	3.32	0.1	0.04
6	F_{6-13}	0.13	0.08	0.08	.05	0.006

Table 4: Measurement, normalized residual and quality factor in each iteration

7.5. Gross Errors in Small and Large Measurements (Case 5)

In this example the gross errors were injected in seven line flow measurements. Table 5 gives the measurement type, given value of measurement, corrected value of measurement, true value of measurement, normalized residual and quality factor in each iteration. The method successfully identifies and corrects the measurements to their true values.

It	Measurement				NR	QF
	Type	Given	Corrected	True		
1	F_{1-2}	-1.07	-1.56	-1.58	0.44	0.218
2	F_{2-3}	0.37	0.69	0.733	0.29	0.095
3	F_{2-4}	0.56	0.5	0.559	0.23	0.066
4	F_{2-5}	0.41	0.38	0.413	0.22	0.056
5	F_{6-13}	0.32	0.17	0.178	0.13	0.026
6	F_{6-12}	0.21	0.06	0.078	0.14	0.016
7	F_{6-11}	0.21	0.055	0.074	0.11	0.018

Table 5: Measurement, normalized residual and quality factor in each iteration

7.5. Discussion of Results

The examples show that the proposed method is quite attractive in the sense that it identifies and correct measurements at the same time. The choice of $\alpha_1 = 1$ and $\beta_1 = 1$ in example 1 points to the fact that the residues in this example have been assigned dominant weightage, whereas the distortions are given much less importance.

By assigning the participation threshold to be 10% of the largest element in row, corresponding to r_n, in the participation matrix, the search for gross error has been localized, as can be observed from the set of measurements with large distortion quality factor. Those measurements with large residuals, which do not contribute to distortion in the largest residual, naturally get eliminated in the procedure. Thus, the proposed method has the inherent property of the localized search. By considering column elements in the form of distortions, the method is capable of identifying and correcting the grossly erroneous measurements.

It is a common observation that the residues of all measurements in the vicinity of the largest residue also possess large residues. Therefore, the fact that masking exists is readily indicated by a low residue in the vicinity of the measurement with the largest residue. This has been the main consideration in the selection of values for α_1 and β_1; however, further research is needed to establish criterion for deciding the values of α_1 and β_1.

8. CONCLUSIONS

In this paper, conventional relaxation procedure is modified and applied to the measurement residue equation to quantitatively determine the actual errors contained in the measurements. The gross error residue equation is looked upon as a set of objects and images related through the filters, namely, the elements of the residual sensitivity matrix, W. A pictorial presentation helps understand the mechanism of distortion. A participation matrix is formed. Distortion vector is then defined to determine the measurement quality. Noting that residues shall all be zero with a set a perfectly true measurements, the proposed method sequentially corrects the measurements by injecting a fictious error in order to nullify the residues to zero. Quality of measurement is employed to determine this sequence. In essence, a modification is incorporated in relaxation technique, concerning the sequence of measurement correction.

The procedure employs a set theoretical approach for segregating the grossly erroneous measurements. The choice of α_1 and β_1 and other threshold need further investigation. Concepts of under-correction and over-correction can also be examined, depending on whether the residue is forced, not to zero, but to a value greater or less than zero. This has a strong relevance to additive and subtractive masking that may be present in the system. Even employing the normal correction, as here, the procedure has been successful in unmasking the interacting grossly erroneous measurements. The method ultimately corrects the grossly erroneous measurements to their true values within a tolerance.

References

[1] F.C. Schweppe, J.Wildes, "Power System Static State Estimation", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-89, No.1, Jan. 1970, pp.120-135.

[2] E.Handschin, F.C.Schweppe, J.Kohlas, A.Fiechter, "Bad Data Analysis for Power System State Estimation", IEEE Trans. on Power Apparatus and Systems, Vol. PAS-94, No.2, March/April 1975, pp.329-337.

[3] H.M.Merrill, F.Cschweppe, "Bad Data Suppression in Power System State Estimation", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-90, 1971, pp.2718-2725.

[4] A.Garcia, A.Monticelli, P.Abreu, "Fast Decoupled State Estimation and Bad Data Processing", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-98, No.5, 1979, pp.1645-1652.

[5] N.D.Xiang, W.Shi-Ying, Y.ER-Keng, "A New Approach for Detection and Identification of Multiple Bad Data in Power System State Estimation", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-101, No.2, 1982, pp.454-462.

[6] F.Zhuang, R.Balasubrahmanian, "Bad Data Processing in Power System State Estimation by Direct Data Deletion and Hypothesis Tests", IEEE Trans. on Power Systems, Vol.PWRS-2, No.2, May 1987, pp.321-330.

[7] B.M.Zhang, S.Y.Wang, N.D.Xiang, "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, Aug.1992, pp.1378-1385

[8] L. Mili, Th.Van Cutsem, M.Ribbens Pavella, "Hypothesis Testing and Identification. A New Approach for Bad Data Analysis in Power System State Estimation", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-103, No.11, Nov.1984, pp.3239-3252.

[9] L. Mili, Th.Van Cutsem, "Implementation of Hypothesis Testing and Identification in Power System State Estimation", IEEE Trans. on Power Systems, Vol.PWRS-3, 1988, pp.887-893.

[10] I.W.Slutsker, "Bad Data Identification in Power System State Estimation Based on Measurement Compensation and Linear Residual Calculation"", IEEE Trans. on Power Systems, Vol.4, No.1, Feb.1989, pp. 53-60.

[11] A.Monticelli, F.F.Wu, "Multiple Bad Data Identification Methods in Power System Estimation: A Comparative Study", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-104, No.11, 1985, pp.3046

[12] V.H.Quintana, A.Simoes Costa, M.Mier, "Bad Data Detection and Identification Techniques Using Estimation Orthogonal Methods", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-101, No.9, 1982, pp.3356-3364.

[13] N.Vempati, R.R.Shoults, "Sequential bad Data Analysis in State Estimation Using Orthogonal Transformations", IEEE Trans. on Power Systems, Vol.6, No.1, 1991, pp.157-166.

[14] G.N.Korres, G.C. Contaxis, "A Reduced Model for Bad Data Processing in State Estimation", IEEE Trans. on Power Systems, Vol.6, No.2, 1991, pp.550-557.

[15] I.W.Slutsher, "Discussion: 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, 1992, p.1385.

[16] K.Seidu, H.Muhai, "Parallel Multiarea State Estimation", IEEE Trans. on Power Systems, Vol.PAS-104, No.5, 1985, pp.1026-1034.

[17] M.A.Pai, "Computer methods in Power System Analysis", Tata McGraw Hill Publishing, 1978.

[18] L. Mili, Th.Van Cutsem, "Bad Data Identification Methods in Power System State Estimation: A Comparative Study", IEEE Trans. on Power Apparatus and Systems, Vol.PAS-104, No.11, 1985, pp.3037-3049.

[19] A.Monticelli, F.F.Fu, M.Yen, "Multiple Bad data Identification for State Estimation Using Combinatorial Optimization", IEEE Trans. on Power Delivery, Vol.PWRD-1, No.3, 1986, pp.361-366.