Development of a Method for Detecting Systematic Errors in Electric Power System Measurements

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Abstract – **The paper presents a method for detecting and eliminating systematic errors in measurements in the case of low information redundancy. The developed method represents the implementation of the following steps: testing of the null hypothesis about the equality between the mean values of measurements and their estimates (a coincidence of mathematical expectations of measurements and estimates testifies to the absence of an error in the considered measurement with statistical accuracy), calculation and analysis of the Euclidean distance between the vector of statistical criteria, which is obtained online and the reference vectors prepared in advance.**

***Index Terms*—measurements, systematic error, electric power system, information redundancy, state estimation.**

I. Introduction

The efficiency of problems, solved at electric power system control, including the problems of the analysis of operational reliability is determined by the extent to which the data on the current state of electric power system are valid and complete. These data are collected using the SCADA system (Supervisory Control and Data Acquisition) and PMUs (Phasor Measurement Units). In electric power system control, validity and completeness of data are provided by the state estimation procedure [1], which calculates steady state variables on the basis of a measurement snapshot (measurements obtained at one and the same time point). High quality of estimates is ensured, when gross errors in measurements are detected and eliminated in advance. The problem of detecting errors in measurements is solved provided the information is redundant. The information redundancy implies the presence of additional measurements in the measurement data that are not essential for the electric power system observability. These measurements help detect and eliminate distortions in the data, which occur in the course of data transfer, processing, or for some other reasons. In the case of low information redundancy, it is impossible to detect distortions of measurements (a gross error in the measurement) when processing one snapshot of measurements. This means that the problem of measurement verification is not solved, the measurements remain unchecked, and as a result, the data validity is not ensured. If a gross error has been in the measurement for a long time, it is called systematic error. Being aware of the fact that an error is systematic, we can eliminate its causes. For instance, it becomes reasonable to study the whole metrological path, by which the given measurement gets to the dispatching center, in order to find and replace the faulty component.

Systematic error in the measurement is detected through the analysis of a certain parameter chosen to be the controlled parameter. According to this parameter, the existing methods for measurement verification can be divided into three groups.

The first group of methods includes the methods intended for checking whether or not the balance ratios are met. The authors of [2] proposed an algorithm for detecting systematic errors in the measurements included in test equations. The discrepancy of the test equation is used as the analyzed parameter. Large discrepancy testifies to the presence of a systematic error in one of the measurements. In the case of low information redundancy, part of the measurements are not included in test equations, and therefore, remain unchecked.

The second group of methods is based on the calculation and check of innovations, i.e. the difference between the measurement value and the forecast [3], [4]. The disadvantage of this method is the wrong identification of erroneous measurements in the case of incorrect forecast, which is unacceptable under the conditions of low measurement redundancy.

The methods of the third group detect errors in the measurements on the basis of the residues of estimates, i.e. the difference between the measurements and estimates [5]. These methods do not meet the requirements imposed on real-time problems, since after the detection of erroneous measurement the state estimation problem should be solved again.

This research is aimed at developing a method for the detection of systematic errors in measurements under the conditions of low information redundancy on the basis of pseudo-dynamic state estimation, which is necessary to ensure the validity and completeness of data on the electric power system state.

By pseudo-dynamic state estimation we mean static state estimation performed in the electric power system control cycle, where the unmeasured state vector components are represented by their values calculated at the previous time point (in the previous cycle).

II. Initial Data for State Estimation

Online data processed using the state estimation methods are represented by the vector of measurements:

$$\bar{y} = (U_i, P_i, Q_i, P_{ij}, Q_{ij}, \delta_i), \qquad (1)$$

where U_i – magnitudes of nodal voltages; P_i, Q_i – injections of active and reactive powers at nodes; P_{ij}, Q_{ij} – power flows in transformers and lines, δ_i – voltage phases.

The model of the measurement has the following form:

$$\bar{y}_i = y_{true(i)} + \xi_{y(i)}, \qquad \xi_{y(i)} \in N(0, \sigma^2_{y(i)}), \qquad (2)$$

where $y_{true(i)}$ – true value; $\xi_{y(i)}$ – normally distributed noise (random error); $\sigma^2_{y(i)}$ – measurement error variance determined on the basis of the characteristics of the metrological path.

The model of the measurement with a gross or systematic error has the following form:

$$\bar{y}_{r(i)} = y_{true(i)} + \xi_{r(i)}, \quad \xi_{r(i)} \in N(\mu, \sigma^2_{y(i)}), \qquad (3)$$

where μ – mathematical expectation of error.

An error in the measurement lowers the quality of state estimation results. To maintain the quality, it is essential to reduce the influence of an erroneous measurement on the state estimation result. To this end, the variance value is increased proportionally to the value of mathematical expectation, and mathematical expectation is equated to zero. Considering the possibility of entering the symmetrical interval, standard deviation of a systematic error is calculated by formula

$$\sigma^{н}_y = 2 * (3\sigma_y + \mu)/3. \qquad (4)$$

As a result of these operations, model (3) gets reduced to form (2).

III. Method for Identifying Systematic Errors

The method for identifying systematic errors in measurements is based on the statement that if there is no error in the measurement, the values of mathematical expectations of measurement $M(\bar{y})$ and estimate $M(\hat{y})$ are equal.

The null hypothesis has the form

$$H_0 : M(\bar{y}_j) = M(\hat{y}_j). \qquad (5)$$

The statistical criterion is represented by value [6]

$$Z_y = \frac{\bar{y}_{av} - \hat{y}_{av}}{\sqrt{\sigma^2_{\bar{y}}/(k2-1) + \sigma^2_{\hat{y}}/(k2-1)}}, \qquad (6)$$

where $\bar{y}_{av}$, $\hat{y}_{av}$ – average values of measurements and estimates in *k2* snapshots, $\sigma^2_{\bar{y}}$, $\sigma^2_{\hat{y}}$ – variances of measurements and estimates.

To test the hypothesis, we determine the right-hand limit of the two-sided critical range from condition

$\Phi(z_{cr}) = (1-\alpha)/2$, where α – level of hypothesis significance.

At

$$Z_y < z_{cr},$$

the hypothesis is not rejected, and measurement $\bar{y}_j$ is considered valid. In real life, an error in one measurement often causes a rejection of hypotheses for several valid measurements, or vice versa, a null hypothesis with a specified significance level is not rejected for the erroneous measurement. Under these circumstances, it is suggested that the erroneous measurement be identified by calculating the criteria for all the studied measurements and analyzing the criteria vector rather than each criterion individually. By the analysis of the criteria vector we mean the comparison of the obtained vector with the reference vector.

Similarity or difference between the vectors is determined depending on the chosen metric distance between them. Each vector is described by the indices (values of the criteria) and can be represented by a point in the n-dimensional space. The similarity to other vectors is determined according to the following rule: the shorter the distance, the greater the similarity. This research uses the Euclidean distance as the measure of distance, i.e. the erroneous measurement is identified by calculating and analyzing the Euclidean distance between the criteria vectors. This approach requires that the snapshots with erroneous and valid measurements be formed beforehand. The criteria vectors for each snapshot are calculated offline. The first snapshot consists of valid measurements. A gross error is modeled in one of the measurements in each successive snapshot. Thus, an $(n*k)$, -dimensional matrix of criteria is created, where n – number of studied measurements; +1 - an increase in the number of columns due to the criteria vector of a snapshot without erroneous measurements $k = n*m+1$, $m > 0$. The Euclidean distance between the criteria vector of a real snapshot and the vectors of the matrix formed beforehand is calculated online. The shortest distance indicates the coincidence of the vectors, and the number of the matrix row indicates the number of the erroneous measurement.

IV. CASE STUDY

The performance of the proposed method is illustrated in a simulation experiment. The problem of detecting systematic errors in the measurements with low redundancy is solved using a 13-node scheme (Fig.1) for the reactive model. In this scheme 15 state variables are measured, 3 state variables are redundant.

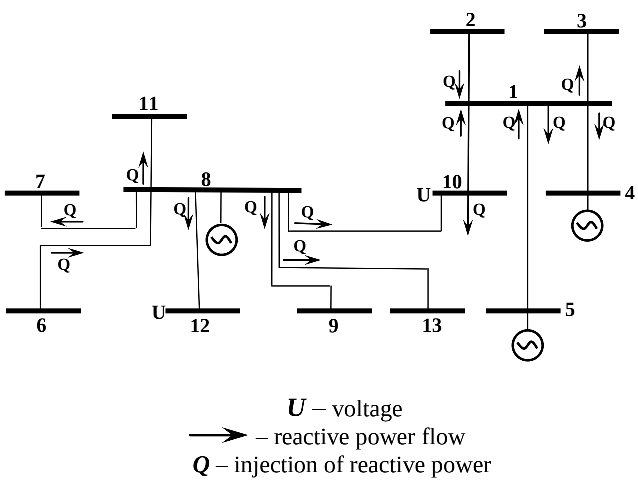

Figure.1. Test scheme

The algorithm for detecting erroneous measurement consists of two stages: offline and online.

Offline

Database of criteria is formed. The database structure is as follows

$$\begin{bmatrix} \bar{y}_1 & \bar{y}_2 & \bar{y}_3 \ldots & \bar{y}_n \\ \bar{y}_1 + b_1 & \bar{y}_2 & \bar{y}_3 \ldots & \bar{y}_n \\ \bar{y}_1 + b_2 & \bar{y}_2 & \bar{y}_3 \ldots & \bar{y}_n \\ \bar{y}_1 + b_3 & \bar{y}_2 & \bar{y}_3 \ldots & \bar{y}_n \\ \ldots\ldots & & & \\ \bar{y}_1 & \bar{y}_2 + b_1 & \bar{y}_3 \ldots & \bar{y}_n \\ \ldots\ldots & & & \\ \bar{y}_1 & \bar{y}_2 & \bar{y}_3 \ldots & \bar{y}_n + b_j \end{bmatrix} \begin{matrix} (1) \\ (2) \\ (3) \\ (4) \\ (..) \\ (x) \\ (..) \\ (k) \end{matrix}$$

$$\left(\begin{array}{l} (1) - \textit{vector of valid measurements} \\ (2) - \textit{vector with the error } (\mathrm{b}_1) \textit{ in the first measurement} \\ (3) - \textit{vector with the error } (\mathrm{b}_2) \textit{ in the first measurement} \\ (4) - \textit{vector with the error } (\mathrm{b}_3) \textit{ in the first measurement} \\ (..) - \ldots\ldots \\ (x) - \textit{vector with the error } (\mathrm{b}_1) \textit{ in the second measurement} \\ (..) - \ldots\ldots \\ (\mathrm{k}) - \textit{vector with the error } (\mathrm{b}_j) \textit{ in the } k-s \textit{ measurement} \end{array} \right)$$

Table 1 shows part of the database. Table 1 shows the values of the statistical criterion (6) to fifteen measurements in the presence of an error in one of the three provided horizontally measurements.

TABLE 1. PART OF THE DATABASE

Number	Measurement	Erroneous measurement		
		U_{12}	U_{10}	Q_{8-12}
1	U_{12}	4.5691	-2.8642	1.1345
2	U_{10}	-3.7091	6.0776	-1.3405
3	Q_1	0.0641	0.1930	0.1523
4	Q_{1-2}	-0.0558	-0.1826	-0.1628
5	Q_{1-3}	-0.0664	-0.1970	-0.1534
6	Q_{1-4}	-0.0581	-0.2180	-0.1647
7	Q_{1-5}	-1.5439	-5.8780	0.0143
8	Q_{1-10}	1.2621	4.8260	-0.3547
9	Q_{6-8}	0.0000	-0.0000	0.0000
10	Q_{7-8}	0.0004	-0.0006	0.0001
11	Q_{8-9}	-0.0000	0.0000	0.0000
12	Q_{8-10}	-7.8346	5.7598	-2.2465
13	Q_{8-11}	-0.0000	-0.0000	-0.0000
14	Q_{8-12}	2.8106	-2.0399	0.8339
15	Q_{8-13}	-0.0000	0.0000	0.0000

Online

Fig. 2 shows an algorithm for detecting errors in the measurements.

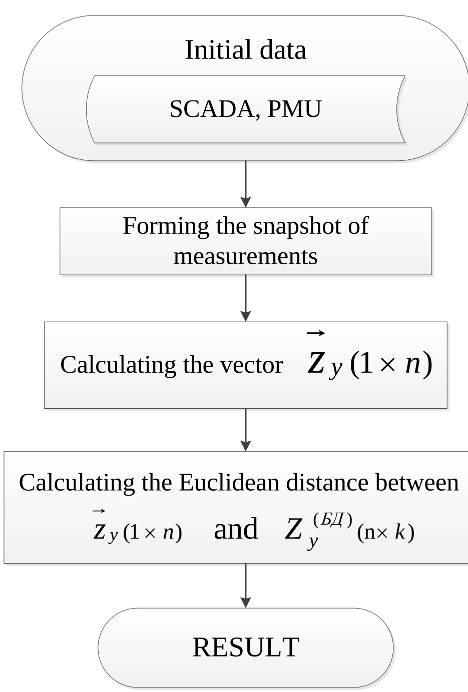

Figure 2. The algorithm for determining the erroneous measurement

The results of applying the method for detecting different errors in two measurements are presented in Table 2. The significance of the hypothesis is $\alpha = 0.05$, *k2=30*, $z_{cr} = 2.04$.

TABLE 2. THE RESULTS OF APPLYING THE ERROR DETECTION METHOD

Measurements	Q_{8-12}		U_{10}	
$\pm 3\sigma$	$\pm$ 18		$\pm$ 1,5	
$\pm \mu$	24	34	1.9	2.9
Suspect measurements	1,2,12	1,2,12	1,2,7,8,12	1,2,7,8,12,14
Solution in (%)	90	100	70	100
σ^2	784	1156	3.24	5.76

where: 1 $-U_{12}$, 2 $-U_{10}$, 7$-Q_{1-5}$, 8$-Q_{1-10}$, 12 $-Q_{8-10}$, 14$-Q_{8-12}$.

The first row shows an erroneous measurement, in the second and third rows there are the values of random and systematic errors, respectively, and the fourth row presents the measurements, for which the null hypothesis is rejected. The fifth row presents the result of error detection (the probability of correct solutions in percentage terms). The sixth row gives the value of variance, at which an erroneous measurement does not affect the state estimation result. The Table 1 shows that if a systematic error exceeds the random error by less than 20%, the solution cannot be obtained with one hundred percent certainty. A more accurate result can be obtained using the Kohonen artificial neural network. The fourth row shows that erroneous measurement Q_{8-12} is not a suspect measurement, although it is identified as erroneous. Fig. 3 shows the estimate (1), measurement (2), and the reference (3) of erroneous measurement Q_{8-12}.

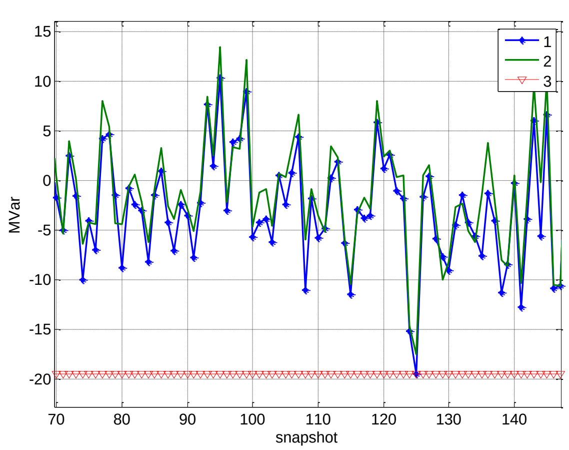

Figure.3. Q_{8-12} – erroneous measurement

Fig. 4 shows that the graphs of measurements and estimates after the snapshot 150 are similar to reference. This means that an erroneous measurement is identified correctly, and an error suppression process is performed correctly.

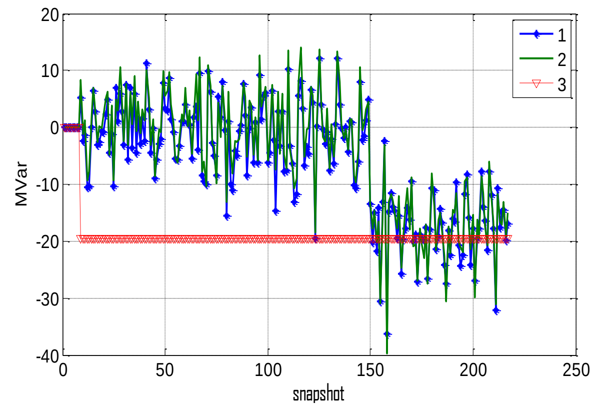

Figure 4. Q_{8-12} before and after adjustment. 1–-estimates, 2–measurement, 3 – reference

V. CONCLUSION

The paper presents a method for detecting and eliminating systematic errors in the measurements under the conditions of low information redundancy. The developed method detects even an erroneous measurement, for which the null hypothesis is not rejected at a specified level of significance.

The performance of the method is tested in a simulation experiment. The experiment shows that for the considered scheme, the proposed method is capable of detecting an error with a 100% probability provided the value of a systematic error exceeds the value of a random error by more than 20%. It is shown that the influence of an erroneous measurement on the state estimation result decreases with an increase in the measurement variance.

REFERENCES

[1] A.M. Glazunova, I.N. Kolosok, E.S. Korkina, "Monitoring of EPS operation by the state estimation methods," *in Proc. 2011 Innovative Smart Grid Technologies (ISGT Europe-2011)*, #49.

[2] I.N. Kolosok, E.S. Korkina, "Detection of systematic error in instrument transformers by state estimation methods using PMU data," *in Proceedings of the Conference and Exhibition Relay Protection and Automation for Electric Power Systems*. 2014. pp. 526-530 (in Russian).

[3] A.M. Glazunova, I.N. Kolosok, E.S. Korkina, "Improvement in reliability of PMU measurements for calculation and analysis of current EPS operating conditions," *in Proc. 2011 Methodological issues of studying the reliability of large energy systems. Issue 61. Problems of studying and providing reliability of liberalized energy systems*, pp. 149–156 (in Russian).

[4] M.B. Do Coutto Filho, J.C Stacchini de Souza, R.S., "Freund. Forecasting-aided state estimation – Part 2: Implementation" *in IEEE Trans. Power Syst., vol. 24, No. 4, pp. 1667-1677, Nov. 2009*.

[5] N.G. Bretas, J.B.A. London Jr., L.F.C. Alberto, R.A.S. Benedito, "Geometrical approaches for gross errors analysis in power systems state estimation," *in Proc. 2009 Power Tech Conference, Bucharest*.

[6] Herald Cramer, *Mathematical methods of statistics.* Moscow: Publishing House MIR, 1975, p.207.