A Study on the State Estimation of HMI platform for Substation Automation System

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Abstract - The validity of measured data is a critical factor for the power system automation. Measured values may have errors that are caused by communication errors and malfunctioning measuring devices. The accuracy and reliability of measured values at the substation is a significant condition for robust and fault tolerant automata. Though errors should be reduced by the state estimation, the global reliability of state estimation will decrease when there exist some bad data. In this paper, the least square state estimation and bad sensor detection algorithm based on the chi-square theory are proposed and applied to the Korean 154kV distribution substations.

Key-Words: state estimation, least square algorithm, bad data detection, chi-square, substation, simulator

1 Introduction

The power system is a major industry in the nation, and power system equipment is gradually growing on a large scale and becoming complicated due to continuously increased demand. Several types of observation and control equipment have been developed for the enhancement of safety and reliability of power systems. Acquisition of data with high accuracy is very important for the installation of automatic system but true data contain measurement residual and error that is created for data processing. By the appropriate estimation, application studies about state estimation for improving the accuracy and reliability of data have originated from many disciplines [1].

In 1970s, Fred Schweppe introduced a concept of state estimation in power systems, and then it was developed continuously. In the EMS, state estimation performed a basic function for operating other programs such as safety analysis, OPF, online PF, AGC, ELD and etc. This state estimation is playing a crucial role in EMS.

Measurement data in the power system involves the measurement device own fault and various problems of transfer process. Necessity of study on the state estimation to increase the accuracy and reliability of measurement value according to minimizing the error is raised its head. Performance of the state estimation has an influence upon accuracy of the measurement data. In the target power system, the error of measurement value is bigger than a permissible value. This type of error depreciates the whole value of state estimation [2].

In this context, processes for detection of fault measurement device and inaccuracy data are also required. Studies on the state estimation started from transmission system in 1990s. It has been read the paper on distribution system such as power flow state estimation [3] on distribution system and state estimation [4,5] on unbalanced three-phase distribution system. Also, it was proposed detection [6] of bad data on transmission system, read the paper on algorithms for state estimation and detection in Korean 154kV distribution substation recently.

The results of state estimation entirely depend on the accuracy of measurement data. Errors of measurement data are more than a permissible value, and this type of error will hamper the reliability of all values of state estimation so that the detection of inaccuracy data and disabled measurement are needed.

In this paper, a study on the state estimation to increase the reliability toward the true measurement value, to change the deviation of error due to the accuracy of each measurement device and to provide the weighted value to reliability of each measurement devices is performed. Also a study on the detection of disabled measurement device to applied Chi-Square theory is performed on Korean 154kV distribution substation.

2 State Estimation for Substation

2.1 State Estimation

State estimation can be formulated based on a relationship between the measurement data and the data error as seen in (1).

$$z^{means} = z^{true} + v$$

z^{means} : *The value of a measurement*

z^{true} : *The true value of the quantity being measured*

v : *The random measurement error*

(1)

Here, if the measurement error is unbiased, the PDF (Probability Density Function) of error is usually chosen as a Gaussian distribution with zero mean, where the PDF of *v* is given in (2).

$$PDF(v) = \frac{1}{\sigma\sqrt{2\pi}}\exp(-v^2/2\sigma^2) \qquad (2)$$

Where
σ : Standard deviation

Thus the PDF of z^{meas} is expressed as follows.

$$PDF(z^{meas}) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left[\frac{-(z^{meas} - z^{true})^2}{2\sigma^2}\right] \qquad (3)$$

z^{true} is expressed as measurement function x as shown in (4). Measurement function x at PDF of z^{meas} that has maximum value can be estimated true measurement variable. It is summarized in (5).

$$PDF(z^{meas}) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left[\frac{-(z^{meas} - f(x))^2}{2\sigma^2}\right] \qquad (4)$$

$$\max_{x} \frac{1}{\sigma\sqrt{2\pi}}\exp\left[\frac{-(z^{meas} - f(x))^2}{2\sigma^2}\right] \qquad (5)$$

As the PDF of z^{meas} has a maximum value, we can easily find the measurement function x in the same way that the measurement function x at PDF of z^{meas} has a maximum value, taking a natural logarithm. It can be presented in (6) for fast computation. Also, (7) can be presented by a quadratic term coefficient of (6) since (6) has a negative value.

$$\max_{x}\left[-\ln(\sigma\sqrt{2\pi}) - \frac{1}{2}\frac{(z^{meas} - f(x))^2}{\sigma^2}\right] \qquad (6)$$

$$\min_{x}\left[\frac{(z^{meas} - f(x))^2}{\sigma^2}\right] \qquad (7)$$

When the error of measurement device is negligible and the PDF of error is usually chosen as a Gaussian distribution with zero mean, a method of maximum likelihood estimation is quite similar to that of weighted least square. That is, the state estimation respecting a large number of measurement devices are presented in (8).

$$\min_{x} J(x) = \sum_{i=1}^{N_m}\frac{(z_i^{meas} - f_i(x))^2}{\sigma_i^2} \qquad (8)$$

Where

f_i : Function to calculate the value measured by the i^{th} measurement

σ_i^2 : Variance for the i^{th} measurement

$J(x)$: Measurement residual

N_m : Number of independent measurements

z_i^{meas} : i^{th} measured quantity

If f_i is a linear equation, then the following equation is produced.

$$f(x) = \begin{bmatrix} f_1(x) \\ f_2(x) \\ \vdots \\ f_{N_m}(x) \end{bmatrix} = [\mathrm{H}]\,X \qquad (9)$$

$$z^{meas} = \begin{bmatrix} z_1^{meas} \\ z_2^{meas} \\ \vdots \\ z_{N_m}^{meas} \end{bmatrix} \qquad (10)$$

$$[R] = \begin{bmatrix} \sigma_1^2 & & & & & \\ & \sigma_2^2 & & & & \\ & & \cdot & & & \\ & & & \cdot & & \\ & & & & \cdot & \\ & & & & & \sigma_{N_m}^2 \end{bmatrix} \tag{11}$$

Setting up (8) using (9) through (11) is equivalent to (12).

$$\min_{X} J(X) = \left[z^{meas} - [\mathrm{H}]\ X\right]^T \left[R^{-1}\right]\left[z^{meas} - [\mathrm{H}]\ X\right] \tag{12}$$

In (12), the optimal condition for minimization a measuring apparatus error is equivalent to the solution of (13), enabling X to be X^{est} (namely, estimation value).

$$\nabla J(X) = -2[\mathrm{H}]^T [R^{-1}] z^{meas} + 2[\mathrm{H}]^T [R^{-1}][\mathrm{H}]\ X = 0 \tag{13}$$

2.2 Modeling of Substation System

In this paper, we executed the state estimation and bad data detection by a status function with current measurement. For example, the target substation is displayed in Fig. 1.

The assumption for performing the state estimation is as follows.

- In a target substation, the minuteness loss does not occur to a line.
- There is no current through a neutral line.
- Measurement of supplying current from upper transmission line to a target substation result in a positive value and measurement of supplying current to outer has a negative value.

The current transformer (CT) in a target substation is located as shown in Fig. 1. Measurement value of CT may have errors and the relationship between measurement value of a measuring apparatus and real status associated with error $v_1 \sim v_{24}$ is represented by (14).

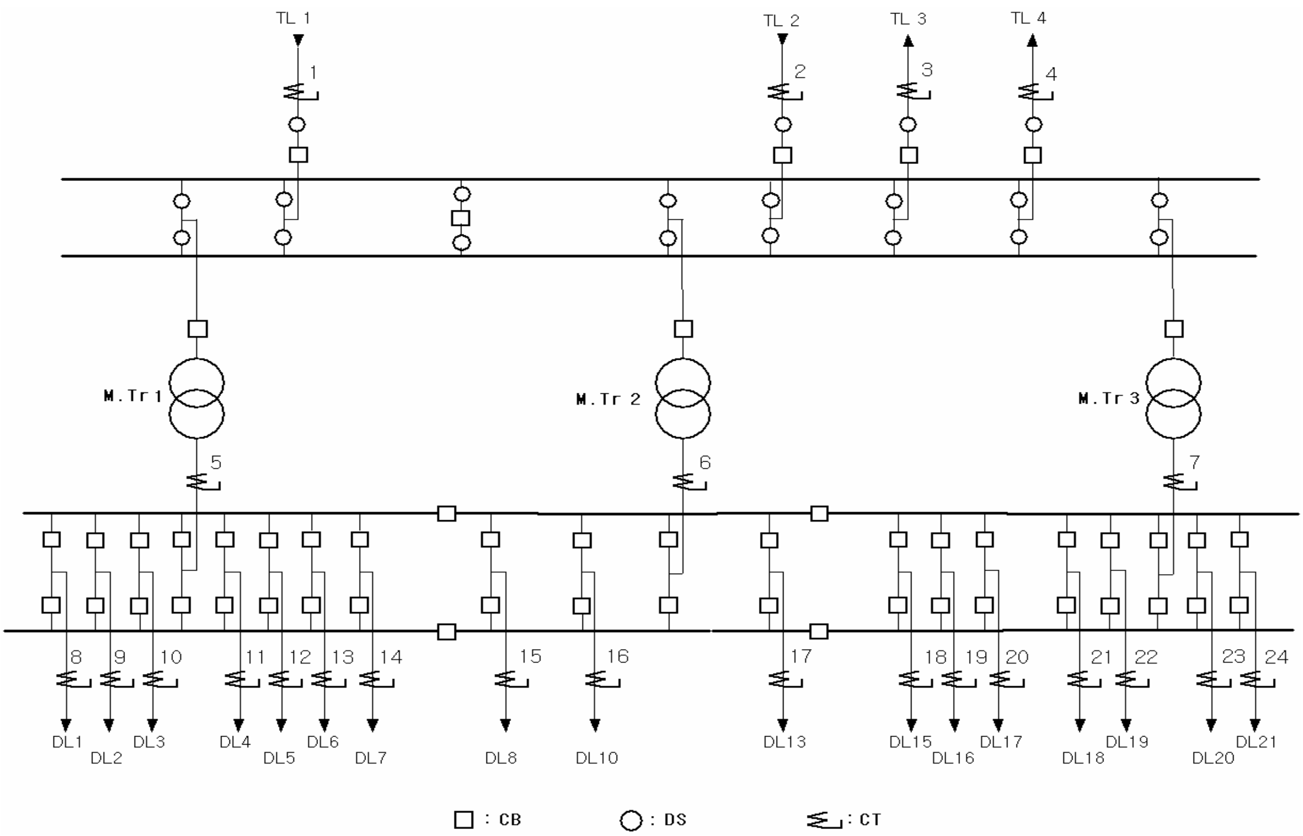

Fig. 1 Schematic of substation

$$\begin{bmatrix} z_1^{meas} \\ z_2^{meas} \\ \vdots \\ z_{24}^{meas} \end{bmatrix} = \begin{bmatrix} z_1^{true} \\ z_2^{true} \\ \vdots \\ z_{24}^{true} \end{bmatrix} + \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_{24} \end{bmatrix} \tag{14}$$

$$z_1^{true} + z_2^{true} + z_3^{true} + z_4^{true} - 0.148 \times (z_5^{true} + z_6^{true} + z_7^{true}) = 0 \tag{15}$$

$$z_5^{true} - (z_8^{true} + z_9^{true} + z_{11}^{true} + z_{13}^{true} + z_{14}^{true} + z_{15}^{true} + z_{16}^{true}) = 0 \tag{16}$$

$$z_6^{true} - (z_{10}^{true} + z_{12}^{true} + z_{17}^{true}) = 0 \tag{17}$$

$$z_7^{true} - (z_{18}^{true} + z_{19}^{true} + z_{20}^{true} + z_{21}^{true} + z_{22}^{true} + z_{23}^{true} + z_{24}^{true}) = 0 \tag{18}$$

The measurement values are 24. The number of a state variable is 20 according to $z_1^{true} + \cdots + z_4^{true} = 0.1477 \times (z_8^{true} + \cdots + z_{24}^{true})$. As it is possible to adopt the weighted least square, the measurement value into a state estimation algorithm is the solution related to (13) of a measurement function from (14) through (18). The measurement value of CT is solely dependent on the state of ON/OFF of Circuit Breaker (CB) or Distributed Switch (DS) in the substation. This is fairly linked with the expression of variable. If the state of ON/OFF is changed, it is accordingly reformulated with (14) to (18).

3 Detection of Bad Data

Chi-Square Test has been carried out for improving the reliability of state estimation values through the

3.1 Chi-Square Test

Given that error of measurement value is random, $J(x)$ is also random.

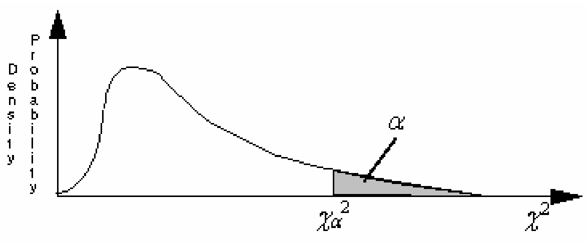

Fig. 2 Chi-Square Distribution Chart

Supposing that all of errors are reproduced by a standard density function, $J(x)$ has a probability density function called a Chi-Square distribution.

$$probability\ (J(x) > x_\alpha^2 \mid J(x)\ is\ a\ Chi-squared) = \alpha$$
$$with\ K\ degrees\ of\ freedom$$

$K(=N_m - N_s)$: Degree of freedom of the Chi-Squared Distribution

N_m : Number of measurements

N_s : Number of states

α : Significance level, typically 0.005 to 1

x_α^2 : Threshold value. Value of x^2 based on degree of freedom and significance level of detection in the target group

In case that $J(x)$ of data for detection is due to Chi-Square distribution, probability which value of $J(x)$ is bigger than x_α^2 is expressed as α. The area of a shaded part is α In Fig 2. As mentioned above, in case that $J(x)$ is the Chi-Square distribution, the detection can be performed by a method of statistic detection.

H_0 : The bad data is nonexistence.

H_1 : The bad data is existence.

Where

H_0 : Null hypothesis

H_1 : Alternative hypothesis

When $x^2(K)$ of a target system is larger than a threshold value, H_0 is changed to H_1.

3.2 Bad Data Detection

By the result of the Chi-Square test, $x^2(K)$ in a target system is more than a threshold value. Once bad data exist in the measurement, the process to certificate these bad data using the standardization error is covered.

$$y_i^{norm} = \frac{z_i^{meas} - f_i^{est}}{\sigma_{yi}} \tag{19}$$

y_i^{norm} : Standardized error

f_i^{est} : Result value of state estimation
σ_{yi} : Standard deviation

We use nine datum for getting the answer of σ_{yi}. Twenty-four measurement values is expressed as Z_i at each samples and the estimation value expressed as F_i. Twenty-four σ_{yi} are derived as (20).

$$\sigma_{yi} = \sqrt{\frac{\sum_{i=1}^{9}(Z_i - F_i)^2}{8}} \qquad (20)$$

When $|y_i^{norm}| > 3$, the measurement value is regarded as bad data. If value of J(x) of target data which is $|y_i^{norm}| > 3$ is more than the evaluation value, then bad data is assumed to be included in the measurement value, where a measurement value taking the largest y_i^{norm} is defined by bad data.

The state estimation and bad data detection is naturally illustrated in Fig. 3.

- The current measurement is obtained from the CT that is one of the measurement devices in a target substation
- The state estimation is achieved based on the acquired measurement value.

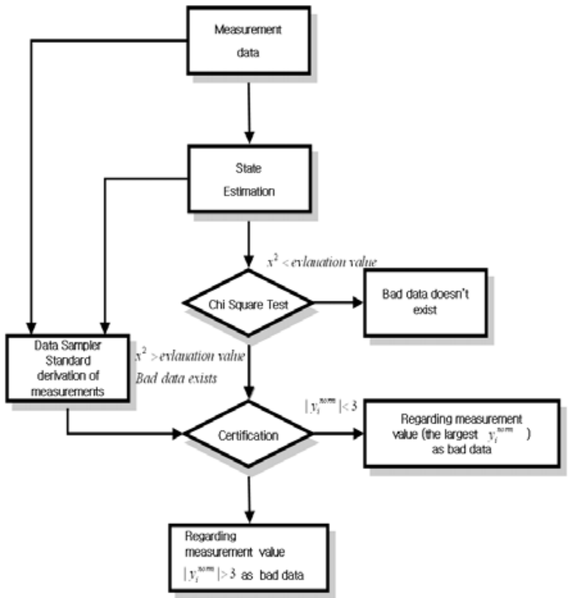

Fig. 3 Flow chart of the proposed algorithm

- The existence of bad data is determined probabilistically by applying the results of state estimation to Chi-Square test.
- When the result of Chi-Square test is relatively less than a threshold value by significance value of certification and degrees of freedom calculated from a substation, it is judged that there are no bad data.
- On the contrary, when the result of Chi-Square test is more than degrees of freedom, it is assumed that there are bad data in itself.
- If there are bad data, then get the y_i^{norm} at every measurement device. The value of measurement device including y_i^{norm} larger than 3(here, 3 is the absolute value) is considered as bad data.
- Although the absolute value of y_i^{norm} is less than 3, the existence of bad data was verified already through the Chi-Square test. Therefore the value of measurement device including the biggest y_i^{norm} is thought of as the bad data.

4 Simulator

The developed measurement detection simulator is far more user-friendly as shown in Fig. 4.

The simulator consists of a module to transfer the substation measurement data and a module to display the result of detection of bad data by state estimation and Chi-square test.

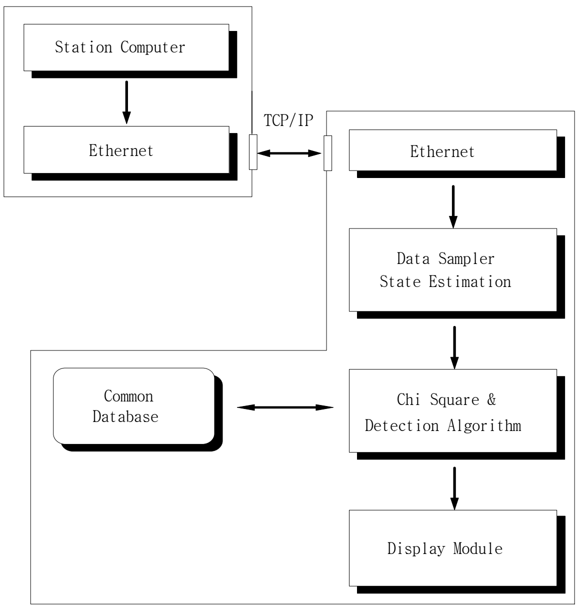

Fig. 4 Structure of the simulator

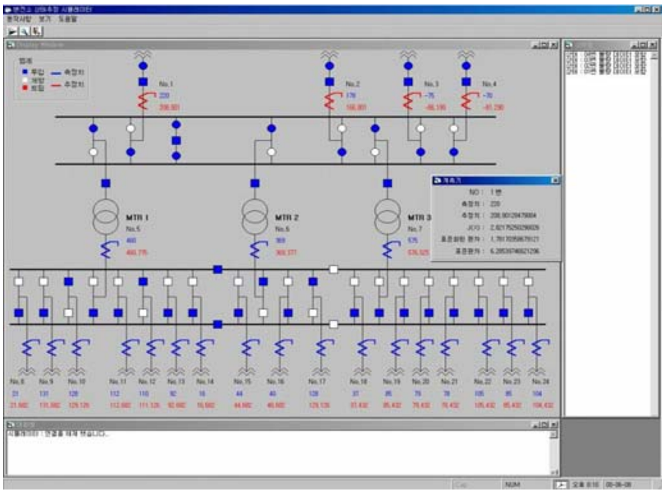

Fig. 5 Bad Data Detection Result

The detection simulator records automatically the detection result of bad data, measurement value, and estimation value based on the data of measurement transfer module in which the state estimation is realized in real time.

5 Case Study

The data used in this case study are the true measurement value of CT in a target substation. We used the 9^{th} continuous measurement values to get the standard deviation of measurement device. Fixing the significance level as 0.005, a threshold value is 9.488 since the degree of freedom in a target system is 4. In Fig. 5, the standardized error from CT No. 1 to CT No. 4 is 1.7818. The measurement value taking the largest standardized error is regarded as a bad data when J(x) of target data is 11.66 and more than threshold values. After performing the state estimation and chi-square test based on the transferred data, if bad data exist, then detection module performs the bad data detection. When detection of bad data is complete, then it displays the measurement value of measurement device, estimation value, and the result of detection. Fig. 5 shows the final result of bad data detection from the disorder of measurement by pop-up messages located in the right side.

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6 Conclusion

The measurement value obtained from the substation includes the error of measurement because of measurement device own fault, some problems of transfer process, and etc. This error leads to the malfunction of several systems. This paper has addressed the state estimation with different weights according to accuracy of measurement device and the bad data detection algorithm called Chi-square theory with domestic distribution substation of double-bus and double-breaker structure for the next generation automatic substation system. The simulator of GUI type with this algorithm was easily implemented by displaying the measurement device on the monitor.

With both the state estimation by a weighted least square method and detection algorithm by Chi-square test, the simulator developed in this paper will be utilized effectively in the substation automation and the fault measurement device detection in near future.

References

[1] William J. Ackerman, "Substation Automation and the EMS," IEEE Transmission and Distribution Conference, Vol. 1, pp. 274-279, 1999.

[2] J. F. Dopazo, O. A. Klitin, A. M. Sasson, "State Estimation for Power Systems: Detection and Identification of Gross Measurement Errors" Proceedings 8th PICA Conference, Minneapolis, June 1973.

[3] A. P. Sakis, Fan Zhang, "Multiphase Power Flow and State Estimation for Power Distribution Systems" IEEE Trans. on PWRS, Vol. 11, No. 2, pp. 939-946, May 1996

[4] Ke Li, "State Estimation for Power Distribution System and Measurement Impact", IEEE Trans. on PWRS, Vol. 11, No. 2, pp. 911-916, May 1996.

[5] C. N. Lu, J. H. Teng, et al.,"Distribution System State Estimation", IEEE Trans. on PWRS, Vol. 10, No. 1, pp. 229-240, February 1995.

[6] R. L. Lugtu, D. F. Hackett, K. C. Liu, D. D. Might, "Power System State Estimation: Detection Of Topological Errors", IEEE Trans. on PAS, Vol. PAS-99, No. 6, November/December 1980.

[7] W. H. Edwin Liu, Swee-Lian Lim, "Parameter Error Identification and Estimation in Power System State Estimation" IEEE Trans. on PWRS, Vol. 10, No. 1, February 1995.