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Gross error isolability for operational data in power plants

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ABSTRACT

Power plant on-line measured operational data inevitably contain random and gross errors. Data reconciliation is a data preprocessing technique, which makes use of redundant measured data to reduce the effect of random errors, and identify gross errors together with a statistical test method. When applying the data reconciliation based gross error identification method in real-life process, it is sometimes difficult to isolate a small magnitude gross error in one measurement from another due to the influence of system constraint nature and random errors. As a result, the magnitude of a gross error should satisfy a quantitative criterion to make sure of its sufficient isolation from other measurements. In this work, we propose a mathematical method to evaluate the minimum isolable magnitude for a gross error in one measurement to be isolated from another with a required probability for data reconciliation based gross error identification. We also illustrate an application of the proposed method to the feed water regenerative heating system in a 1000 MW ultra-supercritical coal-fired power generation unit. Validation of the proposed method through simulation studies is also provided, together with the influence of system constraint nature and random error standard deviations on the gross error minimum isolable magnitudes.

1. Introduction

Power plant on-line measured operational data inevitably contain random and gross errors, which are propagated into the uncertainty of power plant performance monitoring and diagnosis results [1–3]. To pursue higher efficiency and reliability of performance monitoring and diagnosis, data preprocessing techniques are usually applied to reduce the effect of random errors and identify gross errors.

Data reconciliation is a data preprocessing technique, which makes use of redundant measured data to reduce the effect of random errors in the data [4]. Data reconciliation can also be used for gross error identification together with a statistical test method [5,6]. Data reconciliation and gross error identification methods have been widely used in chemical and petrochemical industries [7–9]. Recently, these techniques are also of increasing interests in power industry and have been applied to nuclear power plants [6,10–12], gas turbine and combined cycle power generation units [13–16] and coal-fired power generation units [17–22].

Usually, data reconciliation based gross error identification can be carried out in two steps. The first step is gross error detection, aiming to detect whether there is a gross error in the measurements. And the second step is to identify the measurement which contains a gross error. When applying the data reconciliation based gross error detection and identification methods in real-life processes, it is important to answer the questions of whether it is possible to detect and identify a gross error in measurements and what quantitative criterion should the magnitude of a gross error satisfy to make sure of its sufficient isolation from other measurements.

For gross error detection, it is theoretically possible to detect gross errors in redundant measurements, whose values can be estimated by other measurement when its own measurement is removed [4]. Sometimes, due to the nature of the system constraints and the influence of random errors, a gross error is practically detectable only when it efficiently contributes to the constraint residuals. And the magnitude of a gross error should exceed a threshold value to make sure of its sufficient detection [23].

For gross error identification, previous researches have figured out various qualitative gross error identification conditions. Iordache et al. [24] pointed out that if the column vectors of constraint equation matrix corresponding to two measurements are linearly independent, gross errors contained in these two measurements can be distinguished. Narasimhan and Mah [25] indicated that in the generalized likelihood ratio method, gross errors with different

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gross error signature vectors can be distinguished. Bagajewicz and Jiang [26] proposed the concept of equivalent sets of gross errors and indicate that if two gross errors do not belong to an equivalent set, they can be isolated. Kong et al. [27] proves that for dynamic data reconciliation if the column vectors of the constraint equation Jacobian matrix are linearly independent, the system is identifiable for gross errors. These qualitative conditions are necessary for a gross error in measurements to satisfy to make sure of its identification.

However, in some circumstances we may find that although the qualitative condition for gross error identification is satisfied, the probability to isolate a small magnitude gross error in one measurement from another is rather small due to the influence of system constraint nature and random errors. In this case, the magnitude of a gross error in one measurement should further satisfy a quantitative criterion to make sure of its sufficient isolation from other measurements. In the sensor fault diagnosis area, researches have been carried out to evaluate the gross error quantitative isolation criterions when using principal component analysis methods [28], structured residuals approaches [29] and residual direction methods [30]. However, research on the quantitative gross error isolation criterion for data reconciliation based gross error identification is still rather limited.

In this work, we propose a mathematical method to evaluate minimum isolable magnitude for a gross error in one measurement to be isolated from another with a required probability, under the background of applying data reconciliation and the global test for gross error identification in a serial elimination strategy. In this study, we focus on evaluating the minimum isolable magnitude of a single gross error and leave the multiple gross error situations for future research. The structure of this paper is organized as follows. Firstly, we introduce the basics for the data reconciliation based gross error identification method. Then, we derive a method for evaluating the gross error minimum isolable magnitudes and applied this method to the feed water regenerative heating system in a 1000 MW ultra-supercritical coal-fired power generation unit. Finally, we validate the evaluated gross error minimum isolable magnitudes through simulation studies and study the influence of constraint equation nature and random error standard deviations on the gross error minimum isolable magnitudes.

2. Data reconciliation and gross error identification

2.1. Data reconciliation method

A nonlinear steady-state data reconciliation problem is generally formulated as a least square minimization problem as follows [4]:

$$\min \quad \gamma = (\mathbf{x}-\hat{\mathbf{x}})^T \sum^{-1} (\mathbf{x}-\hat{\mathbf{x}}) = \sum_{i=1}^{n} \frac{(x_i-\hat{x}_i)^2}{\sigma_i^2} \qquad (1)$$
$$s.t. \quad \mathbf{f}(\hat{\mathbf{x}},\mathbf{y}) = \mathbf{0}$$

where γ represents the objective function; $\mathbf{x}_{n\times 1}$ and $\hat{\mathbf{x}}_{n\times 1}$ represent the vector of measured and reconciled values for measured parameters; $\sum_{n\times n}$ represents the covariance matrix of the measured data; σ_i represents the random error standard deviation for the ith measurement; $\mathbf{f}_{m\times 1}$ represents the steady state system constraint equations; $\mathbf{y}_{p\times 1}$ represents the vector of calculated values for the unmeasured parameters; m, n and p represent the number of constraint equations, measured parameters and unmeasured parameters, respectively.

When there is redundant measured data in a system, the number p of unmeasured parameter is smaller than the number m of constraint equations and a data reconciliation problem can be formulated. We can then solve a data reconciliation problem with the successive linearization method described in Appendix A and obtain the reconciled values $\hat{\mathbf{x}}_{n\times 1}$ of measured parameters, calculated values $\mathbf{y}_{p\times 1}$ of the unmeasured parameters and linearized constraint equations as follows:

$$\mathbf{M}\hat{x} - \mathbf{D} = \mathbf{0} \qquad (2)$$

where $\mathbf{M}_{(m-p)\times n}$ and $\mathbf{D}_{(m-p)\times 1}$ represent the coefficient matrix and constant vector for the linearized constraint equations, respectively.

In Eq. (2), the constraint equations only include measured parameters and can be used to generate residual vector and test statistic for gross error detection and identification.

2.2. Gross error detection and identification

The global test method detects a gross error in measurements with the test statistics γ_R given by Ref. [4]:

$$\gamma_R = \mathbf{r}^T\mathbf{K}^{-1}\mathbf{r} = (\mathbf{Mx}-\mathbf{D})^T\left(\mathbf{M}\sum\mathbf{M}^T\right)^{-1}(\mathbf{Mx}-\mathbf{D}) \qquad (3)$$

where $\mathbf{r}_{(m-p)\times 1}$ represents the residual vector for the linearized constraint equations.

In Eq. (3), the residual vector $\mathbf{r}$ is obtained when substituting the reconciled values in the constraint equations with the measured values and the number of rows for the residual vector is $m-p$. It can be proven that when there is no gross error in the measured data, the test statistics γ_R follows a chi-square distribution with a degree of freedom of $\nu = m-p$ [4]. The test criterion for gross error detection is then chosen as$\chi^2_{1-\alpha,m-p}$, which is the critical value of chi-square distribution at the chosen α level of significance. If the test statistic γ_R is equal to or larger than the test criterion$\chi^2_{1-\alpha,m-p}$, a gross error is detected in the measurements. Usually, the level of significance α is chosen as 5% and when there is no gross error in the measured data, the probability for the test statistic to be larger than the test criterion is equal to or smaller than 5%.

Once a gross error is detected, the standard serial elimination strategy can be used for gross error identifications, in which each of the suspected measured parameters for containing a gross error is eliminated one by one and treated as an unmeasured parameter to formulate a data reconciliation problem of a reduced size [4]. As the elimination of a measured parameter increases the number of unmeasured parameter by one, the test criterion for gross error identification in the serial elimination strategy is chosen as$\chi^2_{1-\alpha,m-p-1}$. A gross error is identified in the measurement whose elimination leads to a test statistics $\gamma_{R,j}$ smaller than the test criterion$\chi^2_{1-\alpha,m-p-1}$.

Assuming there is a gross error in the ith measurement, if the test statistic $\gamma_{R,i,j}$ obtained for eliminating the jth measurement is larger than the test criterion$\chi^2_{1-\alpha,m-p-1}$, the jth measurement is not identified as containing a gross error. In this case, the gross error in the ith measurement is isolated from the jth measurement. As a result, to make sure of sufficient isolation of the gross error in the ith measurement from the jth measurement, the probability for the test statistic $\gamma_{R,i,j}$ to exceed the test criterion $\chi^2_{1-\alpha,m-p-1}$ should be large enough.

3. Gross error minimum isolable magnitude

In this section, we derive the method for evaluating gross error minimum isolable magnitudes through a theoretical analysis of the