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# Data reconciliation and gross error detection for operational data in power plants

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ABSTRACT

The quality of on-line measured operational data is usually not satisfactory for the performance monitoring of coal-fired power plants, due to the low accuracy of measuring instrument. Data reconciliation is a data preprocessing technique which can improve the accuracy of measured data through process modeling and optimization, and can also be used for gross error detection together with a statistical test method. In this work, we provide a mathematical framework for gross error detection in power plants via data reconciliation. We also provide case studies to implement the proposed framework in the feed water regenerative heating system of a real-life 1000 MW ultra-supercritical coal-fired power generation unit. Data reconciliation simulation results show that the relative root mean squared errors of the primary flow measurements, namely the outlet flow rate of the #1 feed water heater, the outlet flow rate of the feed water pump, and the inlet flow rate of condensate water in the deaerator are reduced by 72%, 40%, 22%. Simulation results also show that data reconciliation is effective for accuracy improvement when estimated error standard deviations are different from the actual ones and when random errors follow generalized normal distributions. We then provide a case study where gross error detection is performed together with a global test and a serial elimination strategy, and a gross error in the measurement of outlet flow rate of the feed water pump is successfully detected and validated by the on-site inspection and maintenance records of the power plant.



## 1. Introduction

To pursue higher process reliability and efficiency, methods for efficiency analysis [1], condition monitoring [2] and operation optimization [3] are widely used in power plants. The actual effects of these methods in real-life power plants rely on the accuracy of measured operational data, because measurement errors are propagated into the uncertainty of the analysis results. Jiang and Cao [4] pointed out that the accuracy of on-line measured operational data, especially those for the primary flow rate and power rate, has significant influence on the steam turbine heat rate monitoring results. Verda and Borchiellini [5] found that for power plant thermo-economic diagnosis, parameters of efficiencies and unit exergy consumptions are significantly affected by the measurement errors, thus are not suitable for the diagnosis based on measured data. As a result, data accuracy is of great importance for power plant on-line performance monitoring.

The accuracy of on-line measured operational data is usually not satisfactory due to the low accuracy of measuring instrument. This problem is particular serious for the steam turbine system in a coal-fired power generation unit, where the primary flow rate for heat balance analysis is usually measured with a low accuracy flow meter and can introduce great uncertainty to the heat balance analysis and following performance monitoring results [6].

On the other hand, redundancy usually exists in the measurement of power plant operational data, *i.e.*, more data are available than those required by heat balance analysis. For instance, usually only one of the feed water and condensate water flow rates is needed as primary flow measurement for heat balance analysis [6], but both of them are measured in a coal-fired power plant. In this case, one measurement is called the redundant measurement of the other.

In a process with redundant measurements, the data reconciliation method can be used to improve the accuracy of measured data by reducing the effect of random errors. Data reconciliation is a data preprocessing technique, which explicitly makes use of redundant measured data and adjusts the redundant data according to their estimated standard deviations to obtain estimates that

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satisfy system constraints [7]. Data reconciliation was firstly introduced in 1961 by Kuehn and Davidson [8], and it has become an important technique in process industries, with wide applications in the polypropylene reactor [9], the sulfur recovery unit [10], the gas separation plant [11], the oil sands process [12], mineral and metallurgical plants [13], absorption refrigeration systems [14], and so on.

In the power industry, most previous studies are for nuclear power plants, where requirements on data accuracy and operation safety are much higher than those on other types of power plants. Langenstein and Jansky [15] enabled the thermal reactor power in a nuclear power plant to be determined with an uncertainty of less than $\pm 0.5\%$ through data reconciliation. Langenstein [16] pointed out that data reconciliation in nuclear power plants could hold the true thermal reactor power in a very narrow range, thus avoiding producing losses. Sunde and Berg [17] carried out data reconciliation to a turbine cycle supplied with steam from a boiling water reactor and used an overall assessment index to express the quality of reconciled results. Valdetaro and Schirru [18] developed a method to perform simultaneously model parameter tuning, data reconciliation and gross error detection in thermal reactor power calculation.

Recently, data reconciliation has also been applied to gas turbine and combined cycle power generation units. Chen and Andersen [19] pointed out that data reconciliation will eliminate the common contradictions among the balance equations and make it more confident to optimize the daily operation of a gas turbine. Gülen and Smith [20] found that with data reconciliation method the gas turbine power output and inlet airflow can be determined with an uncertainty of $\pm 0.5\%$ and $\pm 1.15\%$ in a single-shaft combined cycle system. Martini et al. [21] applied the data reconciliation method to a micro-turbine based test rig and showed the ability of data reconciliation for accuracy improvement and gross error detection.

Researches on the application of data reconciliation in coal-fired power plants are as follows. Liu et al. [22] applied data reconciliation method for boiler heat balance analysis to reconcile the feed water mass flow rate, heat value and flow rate of coal to improve the data accuracy. Fuchs [23] applied the data reconciliation method to increase the accuracy of the calculated value of steam turbine exhausting steam enthalpy and steam cycle heat rate based on thermal acceptance test data. Zhou et al. [24] developed a simultaneous data reconciliation and gross error detection method and applied it to a boiler spray water system. Harter et al. [25] embedded data reconciliation method into a commercial heat balance software and reduced the effort for data reconciliation problem formulation.

For data reconciliation, it is generally assumed that measured data only contain random errors which follow normal distributions with zero means and known standard deviations. However, this general assumption may be violated in the following situations. Firstly, there may be gross errors in the measured operational data in a real-life power plant. For instance, in a coal-fired power plant, pressure and temperature measuring instrument are usually calibrated and maintained on a regular basis, but the flow meters, which are usually orifices or nozzles, are only calibrated once before installation [6]. During the operation process, flow meter malfunctions could happen due to the wear and corrosion effect and introduce gross errors to the flow measurements.

Secondly, the standard deviations of estimated random error for data reconciliation may be different from the actual ones. The standard deviations of estimated random errors, which are used in data reconciliation for data adjustment, are usually evaluated by statistical analysis of a series of sample observations or by scientific judgment based on the available information including manufacturer's specifications and instrument calibration records [26]. Since this kind of evaluation is usually based on a finite number of samples or limited information, the estimated error standard deviations are usually different from the actual ones.

Thirdly, the random errors may follow other distributions than normal distributions. Although random errors are generally assumed to follow normal distributions in data reconciliation, there are many other common error distribution types, including the uniform distribution, triangular distribution, trapezoid distribution, Laplace distribution, and so on [27]. These distributions have very different shapes and can be expressed in a more general form of a generalized normal distribution with different shape parameters [28].

Existence of gross errors can limit the effectiveness of data reconciliation and reduce the reliability of the reconciled data. Thus, measurements with gross errors should be detected, identified and eliminated before data reconciliation. Usually, data reconciliation and gross error detection can be carried out iteratively. Statistical test methods, including the global test and the measurement test [29], the constraint test [30], the generalized likelihood ratio test [31] can be used for gross error detection. If a gross error is detected in the measured data, a standard serial elimination method can be further executed to identify the measurement with gross error [7]. Moreover, there are also methods which can solve the problem of data reconciliation and gross error detection and identification simultaneously. Tjoa and Bigler [32] formulated the data reconciliation problem based on a combined error distribution function, which takes into account contributions from random and gross errors, and could give unbiased reconciled values in the presence of gross errors and detect a gross error simultaneously. Prata et al. [9] developed a method which allows for robust implementation of nonlinear dynamic data reconciliation with simultaneous gross error detection and model parameter estimation and indicated that the proposed method can be implemented in real industrial environments. A detailed review of the theory and practice of simultaneous data reconciliation and gross error detection can also be seen in Ref. [33]. Although there are already many existing gross error detection and identification methods, research on application and validation of these methods in a real-life coal-fired power plant is still rather limited.

In this work, we apply the data reconciliation and gross error detection method to a feed water regenerative heating system in a real-life 1000 MW ultra-supercritical coal-fired power generation unit. Firstly, we evaluate the effect of data reconciliation for accuracy improvement in an ideal simulation based case study. Secondly, the data reconciliation effect is evaluated in cases where the standard deviations of estimated error are different from the actual ones and random errors follow generalized normal distributions with different shape parameters. Finally, we apply the global test and serial elimination strategy together with data reconciliation to detect and identify gross errors. Gross error detection results are then validated by checking the power plant on-site inspection and maintenance records.

## 2. System description

### 2.1. System configuration and redundancy

It is shown in Fig. 1 an illustration of the feed water regenerative heating system in a real-life 1000 MW ultra-supercritical coal-fired power generation unit. Key equipment in Fig. 1 includes, the #1, #2 and #3 high pressure feed water heater (HPFW1, HPFW2 and HPFW3), a FWP (feed water pump) and a DA (deaerator).

In the deaerator, air dissolved in the condensate water is removed by a mixing process with extracted steam from the steam