CHEMICAL ENGINEERING TRANSACTIONS
VOL. 35, 2013
A publication of AIDIC
The Italian Association of Chemical Engineering
www.aidic.it/cet
Guest Editors: Petar Varbanov, Jiří Klemeš, Panos Seferlis, Athanasios I. Papadopoulos, Spyros Voutetakis

ISBN 978-88-95608-26-6; **ISSN** 1974-9791
DOI: 10.3303/CET1335202

A Data Reconciliation Based Approach to Accuracy Enhancement of Operational Data in Power Plants

Xiaolong Jiang, Pei Liu*, Zheng Li

State Key Laboratory of Power Systems, Department of Thermal Engineering, Tsinghua University, Beijing 100084, China
liu_pei@tsinghua.edu.cn

Accuracy of operational data of a power plant is essential for power plant performance monitoring and fault diagnosis. However, due to inevitable occurrence of systematic and measurement errors in the course of obtaining operational data, these errors can only be reduced to a certain level but never be eliminated. In this work, we propose a data reconciliation based approach to reduce the errors of operational data thus enhance the accuracy of the data. The reconciled data can then be used in performance monitoring and fault diagnosis systems to improve their performances. The proposed method is based on more efficient use of redundant data and a first-principle mathematical model of a power plant. Then an optimization process is performed where the weighted least square form of aggregated differences between measured data and their estimated values are minimized. To illustrate the capability of the proposed method, we provide a case study of data reconciliation for feedwater heater heat balance analysis in a 660 MW coal-fired power plant in China. Results show that uncertainty of four key parameters, namely feed water mass flow rate, condensate mass flow rate, deaerator pressure and outlet temperature, can be reduced by 24 %, 30 %, 5 % and 65 %, whilst the uncertainty of other parameters are also reduced to various extent. Moreover, the results also indicate that the proposed approach is effective over a wide range of measured data quality, where quality of some data could be much worse than others and the estimated measurement uncertainties of operational data may not be accurate.

1. Introduction

To pursue higher process reliability and efficiency, performance monitoring methods for fault diagnosis and operation optimization were widely used. Da Silva et al., (2009) proposed a quantitative model-based fault detection and diagnosis algorithm which can classify the discrepancies between the actual system behavior, represented by a phenomenological model and that of the input-output Laguerre function based system model to help the operator to take confident decisions in case of operation disturbances. Curilem et al., (2011) designed a data-driven Neural Networks and Support Vector Machine model for on-line estimation of the filling level of a semiautogenous mill to help operators for optimizing its energy consumption. When applying these methods for real operating processes, the accuracy of measured operational data is of great importance. Data reconciliation is a technique to improve the accuracy of measured data by reducing effect of random errors occurred during data measurement. The major difference between data reconciliation and other data filtering techniques is that data reconciliation explicitly uses process redundancy model and obtains estimates which satisfy the process constraints (Narasimhan and Jordache, 2000).
Data reconciliation was firstly introduced in 1961 by Kuehn and Davidson (1961) and is an already important technique used in chemical and petrochemical industries. For power industry, data reconciliation has been used in boiler heat balance analysis to improve the accuracy of feed water flow rate, heat value and flow rate of coal to a boiler (Liu et al. 2003). Fuchs (2003) used data reconciliation in steam turbine heat balance analysis, with performance test data where the accuracy of data is much higher than measured operational data. Harter et al., (2005) embedded data reconciliation algorithm into an existing heat balance program of a coal-fired power plant, which greatly reduced effort of process modeling.

Please cite this article as: Jiang X., Liu P., Li Z., 2013, A data reconciliation based approach to accuracy enhancement of operational data in power plants, Chemical Engineering Transactions, 35, 1213-1218 DOI:10.3303/CET1335202

Valdetaro and Schirru (2011) developed a method to perform simultaneously: the tuning of the Hampel's three part redescending estimator constants, the robust data reconciliation and gross error detection for a nuclear power plant. Martini et al. (2013) applied the data reconciliation and gross error detection technique to a micro-turbine-based test rig.
In this work, we present a simulation study to illustrate the capability of data reconciliation for operational data accuracy improvement in feedwater heater system heat balance analysis in a 660 MW coal-fired power plant in China. We also illustrate application of data reconciliation in cases where redundant measured data have different accuracies or estimated uncertainties of measured data deviate greatly from their true values.

2. Principle of data reconciliation

Redundancy exists in a process measurement when the number of measured values is larger than the number of unknown parameters. Due to inevitable errors, the redundant measured data will not fulfil the constraint equations, but result in conflicts. By means of correction calculation, it is possible for data reconciliation to proceed from contradictory measured values **y** to non-contradictory estimates **x** for the true values of the measured variables. The most likely estimates **x** are obtained by maximizing the likelihood function of the multivariate normal distribution (Narasimhan and Jordache, 2000):

$$\underset{\mathbf{x}}{Max} \quad \frac{1}{(2\pi)^{n/2}|\mathbf{\Sigma}|^{n/2}} \exp\left\{-0.5(\mathbf{y}-\mathbf{x})^T \mathbf{\Sigma}(\mathbf{y}-\mathbf{x})\right\} \tag{1}$$

The covariance matrix of the measured data is represented by **Σ**. The diagonal element of **Σ**, σ^2_i, is the variance in measured variable i, and the off-diagonal element σ^2_{ij} is the covariance of the errors in variables i and j. **|Σ|** is the determinant of **Σ.**
It is assumed that the matrix **Σ** is diagonal, if the measured data are independent from each other. As a result, Eq(1) can be simplified as:

$$\underset{x}{Min} \quad \xi_0 = \sum_{i=1}^{n}(y_i - x_i)/\sigma_i^2 \tag{2}$$

The estimates are required to satisfy the constraints, which would have to be fulfilled by the true values of the measured variables, as shown in Eq(3):

$$f(\mathbf{x},\mathbf{v}) = 0 \tag{3}$$

The unmeasured variables are represented by **v**. The constraints equations may include simple laws of physics, like the principles of the conservation of mass or energy or simple relationships from chemistry, e.g. the laws of stoichiometry.
In general, data reconciliation problem can be formed as:

$$\begin{aligned} &\underset{x}{Min} \quad \xi_0 = \sum_{i=1}^{n}(y_i - x_i)^2/\sigma_i^2 \\ &s.t. \quad\quad f(\mathbf{x},\mathbf{v}) = 0 \end{aligned} \tag{4}$$

3. Case study problem

3.1 System description

In this work, we use the high pressure feed-water heater and deaerator system in a 660 MW coal-fired power plant to illustrate the effect of data reconciliation, as shown in Figure 1.
The system includes three high pressure feedwater heaters, a feedwater pump and a deaerator. In the deaerator, gases dissolved in the condensate are removed by a mixing process with the drain water from high pressure feedwater heater and extracted steam from turbine stage. Feedwater pump is located downstream of the deaerator and pressurize the feedwater to specified pressure. Feedwater is then preheated by extracted steam in the high pressure feedwater heater. After heating the feedwater, extracted steam becomes subcooled drain water and is sent to the next feedwater heater and finally enters the deaerator.

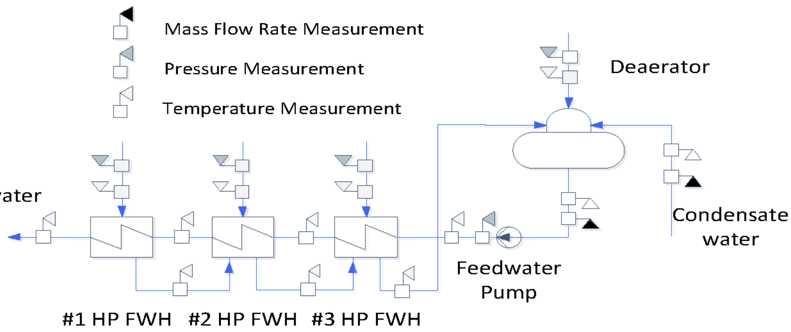

Figure 1: High pressure feedwater heater and deaerator system of a 660 MW coal-fired power plant

The system includes three kinds of measurement points, namely mass flow rate, pressure and temperature, as shown in Figure 1. Mass flow rate is measured for the condensate and feedwater. Pressure is measured for extracted steam (at the inlet of the feedwater heater steam side) and feedwater. Temperature is measured for the extracted steam, deaerator outlet, feedwater pump outlet, feedwater heater outlet and drainage. In this work, mass flow leakage and pressure drops at the feedwater heater the water and steam side are neglected.

3.2 Data reconciliation in heat balance analysis

Heat balance analysis is the process of applying mass and energy balance equations to model power plant systems with the objective of determining detailed thermodynamic properties of the system. It is a primary step for further performance monitoring or fault diagnosis.

For the heat balance of the proposed system with conventional methods provided in the standard published by ASME (2006), only one parameter of the feed water and condensate mass flow rate can be taken as the heat balance analysis input, although both of them are measured. They are a pair of redundant measured data. Another case of redundancy in this system is for the deaerator pressure and outlet temperature. As the deaerator outlet temperature is saturated, its state can be determined by just one state parameter. If both the pressure and temperature are measured, they are also redundant because they can be related by the steam property equations.

For conventional heat balance method, when redundancy exists, decisions must be made to choose which measured parameters are to be used as inputs for heat balance analysis. As a result, some redundant measurement information is wasted.

On the other hand, using data reconciliation approach for heat balance analysis can use the measurement redundancy to improve the accuracy of the operational data. A new set of reconciled data which has higher accuracy and satisfy all the mass and energy balances and physical property equations can be used to represent the system operation status.

In this simulation study, operational data was generated as follows:

$$y_i = x_{true,i} + \varepsilon_i \tag{5}$$

where y_i represents the measured value of an operational datum, $x_{true,i}$ represents its actual value, and ε_i represents random error. The actual value, $x_{true,i}$, is taken from the heat balance diagram for design load and the random error ε_i, is a random number which follows a normal distribution with zero mean and specified standard deviation σ_i.

Accuracy of a measured datum is expressed in terms of the confidence level of its uncertainty. For instance, a measured datum $y_i \pm U_i$ (p=95 %) means the confidence level of its measurement uncertainty is 95 %, and U_i can be expressed in terms of σ_i as follows:

$$U_i = 1.96\sigma_i \tag{6}$$

In this work, we use the relative uncertainty $U_i/x_{true,i}$ to represent the accuracy of measured and reconciled data, which makes the accuracy of data with different ranges comparable.

Three cases are designed to show the effect of data reconciliation to improve accuracy of measured data with different magnitude of uncertainty, i.e., measured with metres of different accuracy. Relative measurement uncertainty is assumed to be the same for a certain type of measurement, i.e., mass flow rate, pressure, and temperature, and their values in the three cases are presented in Table 1.

Table 1: Relative measurement uncertainty

Measurement point	Base case	Case A	Case B
Mass flow rate	1 %	2 %	3 %
Pressure	0.8 %	1.6 %	2.4 %
Temperature	0.5 %	1 %	1.5 %

4. Results discussion

In the simulation study, calculations were repeated many times for each case. In each calculation, a group of simulated measurement data was first generated and then reconciled. After repeating the calculations for many times, the relative uncertainty for data was calculated as Eq(7).

$$RU_i = 1.96\sqrt{\sum_{j=1}^{n}\left(y_{i,j}-\overline{y_i}\right)^2/(n-1)}/\overline{y_i} \tag{7}$$

where $y_{i,j}$ represent the value of measured or reconciled data for the i_{th} variable at the j_{th} calculation and $\overline{y_i}$ represents the average of the i_{th} variable in all the numerical experiments.

4.1 Accuracy improvement of data reconciliation for the Base Case

For the Base Case operational data, the simulation calculation was repeated for 100 times. Relative uncertainty of the measured and reconciled data for the proposed system is shown in Figure 2.

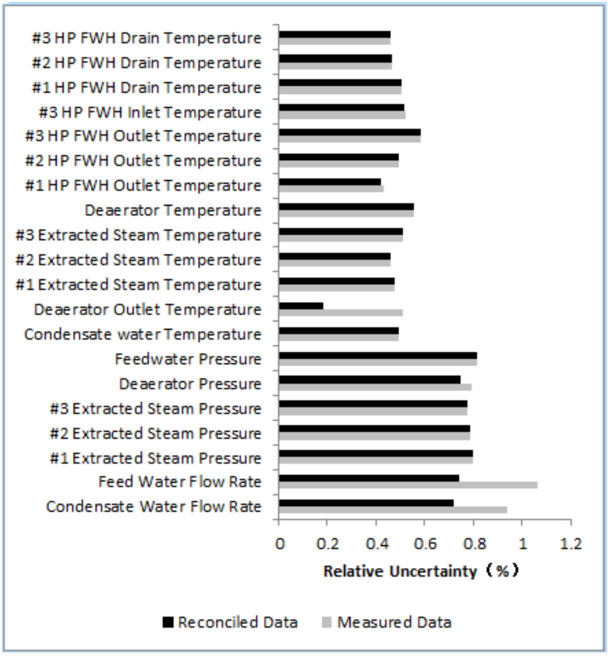

Figure 2: Relative uncertainties of measured and reconciled data for base case operational data

Results show that the relative uncertainty of four key parameters, namely feed water mass flow rate, condensate mass flow rate, deaerator pressure and outlet temperature, can be reduced by 24 %, 30 %, 5 % and 65 % for the Base Case. It is whilst the relative uncertainty of other parameters are also reduced to various extent. For Case A and Case B, similar results were obtained and were not discussed here.

4.2 Data reconciliation effect for redundant data with different accuracies

In the Base Case, measured data of the same kind was assumed to have the same accuracy, which may not be true for the actual situation in a power plant. For example, the measurement for the condensate mass flow rate usually has better accuracy compared with those for the feedwater mass flow rate. For traditional heat balance calculation using operational data in China, it is recommended to use the condensate mass flow rate as input for heat balance analysis.

For the data reconciliation approach, redundant data with different accuracies are all used. To investigate the effect of data reconciliation at this situation a case study was carried. From Case C-1 to Case C-5, the relative uncertainty of measured feedwater mass flow rate was set to be 1 %, 2.5 %, 5 %, 7.5 % and 10 %, while the relative uncertainty of other measured data was the same as in the Base Case.
As the results in Figure 3 shows, in this case study reconciled data always have smaller relative uncertainties than measured data for both the condensate and feedwater mass flow rate. Even in Case C-5, when the feedwater mass flow rate measured relative uncertainty was 10.09 %, the reconciled relative uncertainty was 1.06 %. At the same time, the relative uncertainty of condensate mass flow rate, whose accuracy was improved efficiently in the Base Case, was changed from 1.10 % to 1.06 % after data reconciliation. The results show that data reconciliation can always reduce the data uncertainty, even when redundant data are of different accuracies.

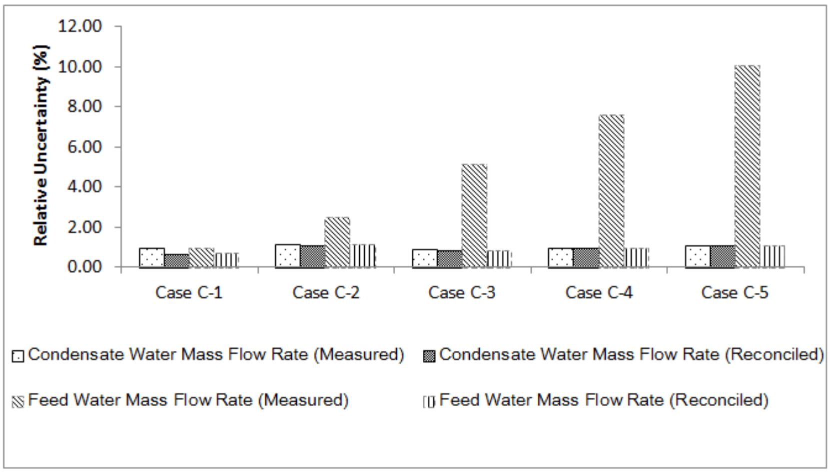

Figure 3: Relative uncertainties of measured and reconciled data from Case C-1 to Case C-5

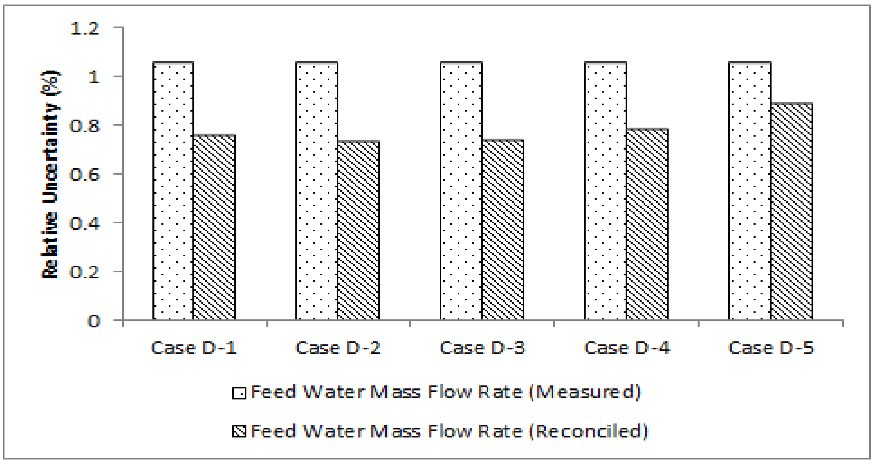

Figure 4: Relative uncertainties of measured and reconciled data from Case D-1 to Case D-5

4.3 Data reconciliation effect with poorly estimated measurement uncertainty

To carry out data reconciliation for real on-line operational data, another potential obstacle is how to estimating the measured data uncertainty accurately. The estimated measurement uncertainties are used in the data reconciliation process as an evaluation of the measured data accuracy and have direct impacts on the reconciliation results. As the process data cannot be measured repeatedly, the measured data uncertainties can only be estimated by their instrument grades. These estimations may not be accurate since the situations in power plants are rather complicated. We carried out a case study to investigate the impact of poorly estimated measurement uncertainty on data reconciliation. From Case D-1 to Case D-5, the relative uncertainties of measured feedwater mass flow rate was set to be 1 % as in Base Case, while the estimated relative uncertainties of the feedwater mass flow rate were set to be 0.5 %, 0.75 %, 1 %, 1.25 % and 1.5 % . Case D-1 and D-2 means the measurement uncertainty of the feedwater mass flow rate was underestimated, while Case D-4 and D-5 means an overestimation of the measurement uncertainty.

Results in Figure 4 shows that poorly estimated measured data uncertainties will have impact on the data reconciliation effects. As in Case D-5 the relative uncertainty of the reconciled feedwater mass flow rate was 0.89 % although in Case D-3 it can be reduced to be 0.74 %. However, in Case D-5, the relative uncertainty of the reconciled feedwater mass flow rate is still smaller than the measured one of 1.06 %, which still shows an obvious accuracy improvement effect. In this Case study, the reconciled data always have a smaller relative uncertainty compared with the measured data.

5. Conclusions

In this work, we propose a data reconciliation approach to improve the operational data accuracy for coal-fired power plants. To illustrate the capability of the proposed method, we provide a simulation study of data reconciliation for the heat balance analysis of the feedwater heater system in a 660 MW coal-fired power plant in China. A MATLAB program is used to solve the proposed data reconciliation problem. It is found that in the Base Case the relative uncertainties of four key parameters, namely feed water mass flow rate, condensate mass flow rate, deaerator pressure and outlet temperature, can be reduced by 24 %, 30 %, 5 % and 65 %, whilst the relative uncertainties of other parameters are also reduced to various extent. The simulation results also indicate that the proposed approach is effective over a wide range of measured data quality, where quality of some data could be much worse than others and the estimated measurement uncertainties of operational data may not be accurate.

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