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Data Processing of Thermal Power Plants Based on Dynamic Data Reconciliation

Sisi Guo, Pei Liu*, Zheng Li

State Key Lab of Power Systems, Department of Thermal Engineering, Tsinghua University, Beijing, China 100084

liu_pei@tsinghua.edu.cn

Performance monitoring of power plants at dynamic states is more significant for efficient operation due to wide-range and frequent operation changes in China. Data reconciliation is widely used in industry for improving the quality of measured data for better effect of modelling and performance monitoring. Most previous studies in power plants focus on steady state data reconciliation methods, while dynamic data reconciliation is necessary in real power plants since dynamic effects cannot be negligible. Due to the system complexity and defect of measurement instruments, research on dynamic data reconciliation in power plants is insufficient. In this work, we investigate the dynamic characteristics of the system considering equipment accumulation, and study the dynamic data reconciliation approach using simulation models for key equipment in thermal power plants. Case studies are constructed to analyse the effect of different sampling rates of data, initial values of data, and parameters in the algorithm on the results of dynamic data reconciliation separately. Results indicate that it is better to choose high sampling rates for measured data in a dynamic data reconciliation problem for better accuracy of reconciled results, and an optimized time window length can be selected for a fixed problem according to the required accuracy as well as computation complexity.

1. Introduction

Performance monitoring is widely used in power plants for better economy, and its effect strongly depends on the accuracy of measured data (Usón et al., 2010). Due to sensor degradation and consideration of operational costs, measurement errors inevitably exist (Guo et al., 2016). Therefore, data processing techniques are widely used for improving the quality of measured data in power plants. Data reconciliation is one promising technique to reduce the effect of measurement errors and improve the accuracy of measured data, which is widely applied in industry including chemical reactors (Farsang et al., 2015), mineral and metal processing (Vasebi et al., 2014), air separation process (Zhang et al., 2014), heat exchanger network (Yong et al., 2016), and others.

Data reconciliation can be categorized into steady state and dynamic data reconciliation (Narasimhan and Jordache, 1999). Steady state data reconciliation is used for steady state processes based on spatial redundancy if the power plants are operated under steady state conditions. For dynamic processes, dynamic data reconciliation (DDR) is applied based on temporal redundancy if the measurements of process variables change continually in time at a high sampling rate (Narasimhan and Jordache, 1999).

In the study of DDR, Kalman Filter has been effectively used in linear dynamic systems to smooth measurement data and give better estimates of parameters (Vasebi et al., 2015). For nonlinear systems, Extended Kalman Filters have been developed based on linearizing the nonlinear equations and applying the Kalman filter to the linearized system (Vachhani et al., 2006). Furthermore, nonlinear dynamic data reconciliation (NDDR) with a formulation as a weighted least-squares objective function is widely used for dynamic systems, which is more general than filtering models and applicable for inequality constraints (Zhang et al., 2015). Since the objective function formulated in the NDDR problem simultaneously estimates the variables from initial time to current time at each sampling instant, the computational cost of the NDDR problem is relatively high, especially when the complexity of the problem increases. Consequently, the NDDR problem is often solved iteratively on a moving time window for simplification.

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In recent years, most facilities in power plants in China stay in low-load operation for hours since the total electricity consumption increment has dropped (Gu et al., 2016). Consequently, thermal power plants are operated under frequently variable load conditions, and dynamic effects cannot be negligible in real power plants. Compared with steady state data reconciliation, dynamic data reconciliation performs better in estimation of parameters in transient states. Therefore, dynamic data reconciliation is quite important to performance monitoring of real power plants.

However, previous studies of dynamic data reconciliation in literature mostly focus on chemical processes, and research on dynamic data reconciliation of power plants is quite limited. This is partly because that it is difficult to obtain the accurate measured data of operational parameters at a high sampling rate in real power plants due to the system complexity and defect of measurement instruments. Furthermore, analysis on the dynamic characteristics of real power plant systems is also insufficient in previous studies, but is quite necessary to realize dynamic data reconciliation. Accordingly, novelties of this work mainly lie in three aspects. Firstly, simulation tools are employed to simulate the behaviours of measured data and compensate for the defects. Besides, dynamic characteristics of a steam turbine power plant in dynamic data reconciliation are discussed. Furthermore, the effect of different factors including sampling rates, input data, and parameters in the algorithm on the results of dynamic data reconciliation of power plants is investigated.

In this work, the dynamic data reconciliation approach for key equipment in thermal power plants is carried out. The methodology of dynamic data reconciliation is firstly presented. After that, case studies of a general equipment model using simulation data are carried out to investigate the effects of dynamic data reconciliation.

2. Methodology

A dynamic data reconciliation problem is generally formulated as follows (Narasimhan and Jordache, 1999):

$$\underset{x}{Min}\, \phi = \sum_{j=t_0}^{t_N} \left[(y_j - x_j)^T \Sigma_j^{-1} (y_j - x_j) \right] \tag{1}$$

Subject to:

$$f(\dot{x}, x, u) = 0 \tag{2}$$

$$h(x, u) = 0 \tag{3}$$

where *y* and *x* represent vectors of measured values and reconciled values respectively, ∑ is the variance-covariance matrix, $\dot{x}$ is the derivative of *x* with respect to time, *u* is the vector of calculated values of unmeasured variables, *f* and *h* represent vectors of differential, and equality algebraic equations, the subscript *j* represents time instant, *t=jT* when the variables are measured from t_0 to t_N , and *T* is the sampling period.

As mentioned before, the computational cost of the NDDR problem is high when the complexity of the problem increases. Therefore, a moving time window method is usually applied to NDDR for simplification, where the data reconciliation problem is solved within a fixed time window *H*. At each time *t*, only a window of measurements from time (*t-H*) to time *t* are used to estimate all variables within the time window *H* (Narasimhan and Jordache, 1999), as shown in Eq(4).

$$\underset{x}{Min}\, \phi' = \sum_{j=t-H}^{t} \left[(y_j - x_j)^T \Sigma_j^{-1} (y_j - x_j) \right] \tag{4}$$

The solution strategy is based on the Optimization Toolbox in MATLAB to solve this constrained optimization problem. Reconciled values of variables can be obtained after the iterative algorithm converges at a defined termination tolerance.

3. Case study

Dynamic characteristics of steam turbine power plants are firstly discussed. Due to continuously changing inputs, the accumulation within a process unit also changes, which donates to a dynamic state of a process. Equipment accumulation generally includes mass accumulation, energy accumulation, and so on. The general mass conservation law can be expressed in the following form in Eq(5) (Narasimhan and Jordache, 1999):

Input – output – accumulation = 0 (5)

In the thermal system of steam turbine power plants, mass accumulation happens in containers with water levels, such as feed water heaters, condensers, the boiler drum and the deaerator. Because of the level change of the boiler drum, values of mass flow rate from the feed water heaters to the boiler is different from values of mass flow rate of main steam generated in the boiler. Similarly, mass flow rates of the exhaust steam from the last stage of steam turbines are different with mass flow rates of condensate water owing to the mass accumulation in the condenser. Even for a feed water heater in the regenerative system of the power plant, its inlet mass flow rates are different from its outlet mass flow rates due to the water level change in the heater tank.

No matter the shape and function of the equipment in the power plant, they can be simulated as a general physical model with different inlets and outlets. A general simulated container with changeable water level is taken as case studies to investigate the dynamic characteristics in a DDR problem. For simplification, a simple container with one inlet and one outlet is studied. Accumulation occurs in the container, and the change of water level of the container reflects the mass accumulation. The mass balance of the container in DDR should be formulated as follows:

$$m_{in} - m_{out} - \rho \frac{dV}{dt} = 0 \tag{6}$$

$$\frac{dV}{dt} = \frac{d(A * h)}{dt} \tag{7}$$

Where m_{in} and m_{out} represent the inlet and outlet mass flow rates, A is the cross area of the container, ρ is the density of water, t is time, h is the level of the container.

The mass balance of the container is a differential equation with an accumulation term, and a difference equation can be applied for simplification in the NDDR problem if the sampling instant is very short.

Since most distributions in limited ranges in real applications can be transformed to a series of a combination of sine functions by Fourier Transform, and the water level in a container under normal operations in power plants should have upper and lower bounds. Therefore, it can be assumed that the level measurements follow a simple sine function to simulate one type of level change in an ideal situation. In the sine function, the mean value is 0.1 m, the amplitude is 0.01 m and the period is 4 s. A random number generator in MATLAB is used to generate the values of outlet mass flow rates, which are random values between 98 kg/s to 100 kg/s. According to the mass balance of the container, the values of inlet mass flow rates can be calculated based on the values of outlet mass flow rates and mass accumulation in the container.

To illustrate the effect of different sampling rates of measured data on the results of DDR, we construct three scenarios with different sampling rates of measurements, namely Case A, Case B, and Case C. The sampling periods of these cases are $T_0 = 0.1$ s, $T_0 = 0.3$ s and $T_0 = 1$ s separately.

Furthermore, we also construct a case study with a larger fluctuation of the container level to analyse the effect of initial values of data on the DDR results, which is donated as Case D. Case C and Case D share the same model parameters including the sampling period, except that the amplitude of the sine function of the container level in Case D is 10 times of that in Case C.

4. Results and discussion

Based on 100 groups of simulated datasets and the methodology in former sections, the DDR problems in the case studies can be formulated and solved. Results and discussions are presented as follows.

4.1 Analysis of sampling rates of data

After data reconciliation, reconciled values of measurements with different time window lengths in Case A, B and C are obtained. Results of the container level are shown Figure 1, Figure 2, and Figure 3.

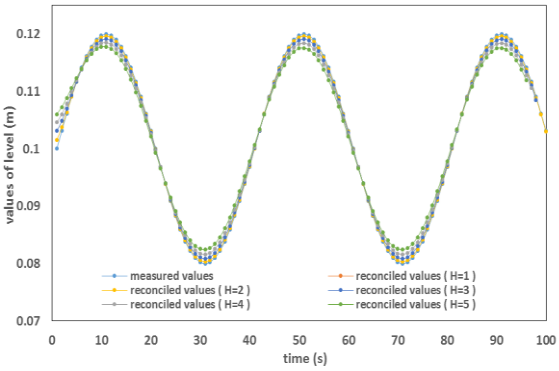

Figure 1: Measured values and reconciled values of the container level in Case A

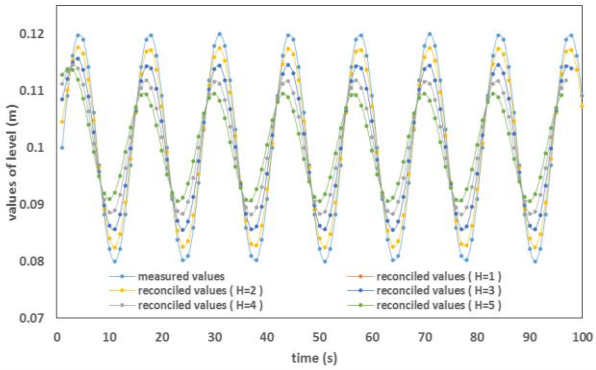

Figure 2: Measured values and reconciled values of the container level in Case B

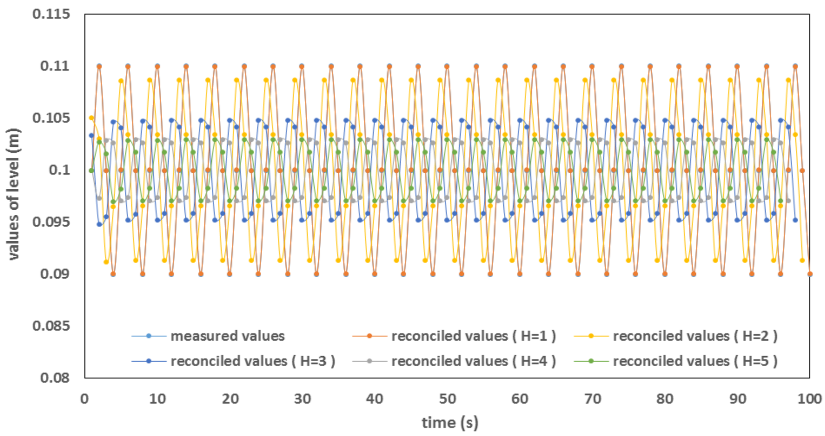

Figure 3: Measured values and reconciled values of the container level in Case C

In comparison of Figure 1, Figure 2, and Figure 3, it can be seen that different reconciled results are obtained after DDR with different sampling rates of data. At a high sampling rate, the difference term is closer to the differential term in the differential equation, so that the error of using difference term simplification can be negligible. In Case A, the data are measured at a higher sampling rate, so the reconciled values are quite closer to the measured values, indicating the system error introduced by difference term can be ignored. While at a low sampling rate, for instance in Case C, the error of using differential term simplification can be no longer negligible. The reconciled values are always smaller than the measured values due to the average function of difference terms in comparison with differential terms. Therefore, it is better to choose high sampling rates for measurements in a DDR problem for better accuracy of reconciled results. Considering the DCS sampling frequency and transmission time of the system, the highest sampling rates for measurements is always limited in real power plants.

4.2 Analysis of time window length

As can be seen from Eq(4), the time window length *H* is an important parameter in the DDR algorithm, which affects the accuracy of reconciled results and computation complexity of the DDR problem. The amplitudes of the measured values and reconciled values of the container level in Case C with different time window lengths are listed in Table 1.

Table 1: Amplitudes of the measured values and reconciled values of the container level in Case C (Unit: m)

Parameter	Measured values	Reconciled values (H=1)	Reconciled values (H=2)	Reconciled values (H=3)	Reconciled values (H=4)	Reconciled values (H=5)
Level	0.00711	0.00707	0.00660	0.00450	0.00277	0.00240
Parameter	Reconciled values (H=6)	Reconciled values (H=7)	Reconciled values (H=8)	Reconciled values (H=9)	Reconciled values (H=10)	Reconciled values (H=11)
Level	0.00242	0.00207	0.00161	0.00146	0.00147	0.00134

From Figure 3 and Table 1, we can see that the amplitudes of reconciled values after DDR are smaller that of measured values, no matter the length of time windows. Besides, with the increase of time window length *H*, the amplitudes of reconciled values after DDR decreases gradually. For example, the amplitudes of reconciled values after DDR with a window length of 4 is reduced by 61.04 % compared with measured values. This represents that the error of using differential term simplification are accumulated with the increase of time window lengths, because more differential equations are involved in computation in DDR with a larger time window length. The system errors have a strong effect on the final reconciled results, even compensating the benefit of larger time redundancy in the DDR problem brought by larger time window lengths. At first, the standard deviation of reconciled values decreases fast with the increase of *H* until it tends to be flat and gentle. With the increase of time window lengths, the number of equations in the DDR problem increase twofold and leads to higher computation complexity and cost. Therefore, an optimized window length should be selected for a fixed DDR problem according to the required DDR accuracy as well as computation time.

4.3 Analysis of water level ranges

Reconciled results with different time window lengths in Case D are also obtained after data reconciliation, and the values of the container level are shown in Figure 4.

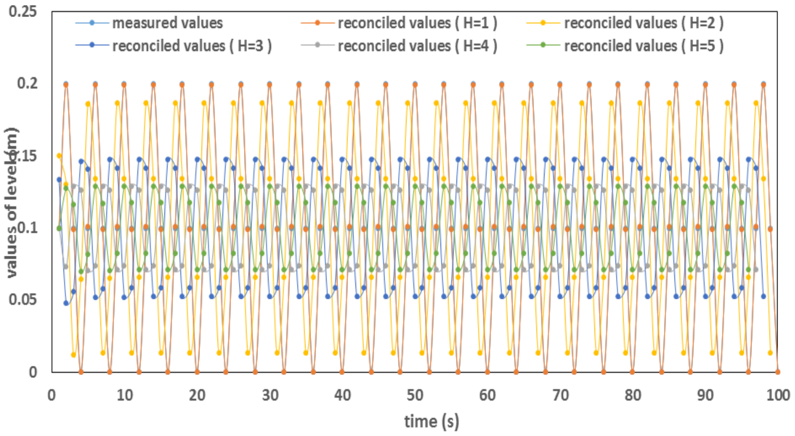

Figure 4: Measured values and reconciled values of the container level in Case D

The amplitudes of the measured values and reconciled values of the container level in Case D are also calculated in Table 2.

Table 2: Amplitudes of the measured values and reconciled values of the container level in Case D (Unit: m)

Parameter	Measured values	Reconciled values (H=1)	Reconciled values (H=2)	Reconciled values (H=3)	Reconciled values (H=4)	Reconciled values (H=5)
Level	0.07107	0.07072	0.06598	0.04501	0.02768	0.02401
Parameter	Reconciled values (H=6)	Reconciled values (H=7)	Reconciled values (H=8)	Reconciled values (H=9)	Reconciled values (H=10)	Reconciled values (H=11)
Level	0.02416	0.02071	0.01607	0.01464	0.01473	0.01340

We can see that all amplitudes of reconciled values with any time window length are reduced compared with that of measured values. The amplitudes of reconciled values after DDR decreases gradually with the increase of time window length *H*. The amplitudes of reconciled values decrease very fast at first, then the rate of reduction is slowing down with a large *H*. As explained before, the system errors of using difference term simplification are accumulated with the increase of time window length. Furthermore, the amplitudes of measured values and reconciled values of the container level in Case D are nearly ten times of that in Case C. In this circumstance, different water level ranges as initial values have minor influence on the accuracy of the DDR method. Besides, the measured values and reconciled values of the inlet mass flow rates of the container in Case C and Case D are also obtained and shown in Figure 5 and Figure 6.

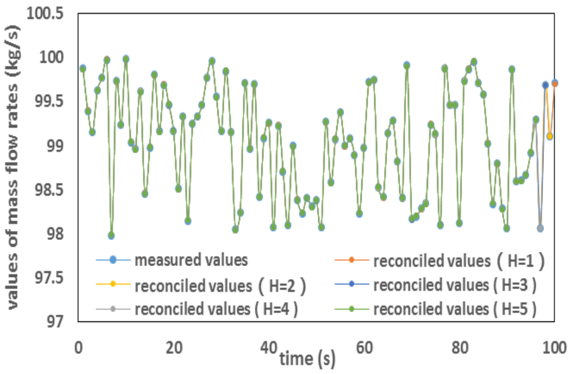

Figure 5: Measured values and reconciled values of the inlet mass flow rates in Case C

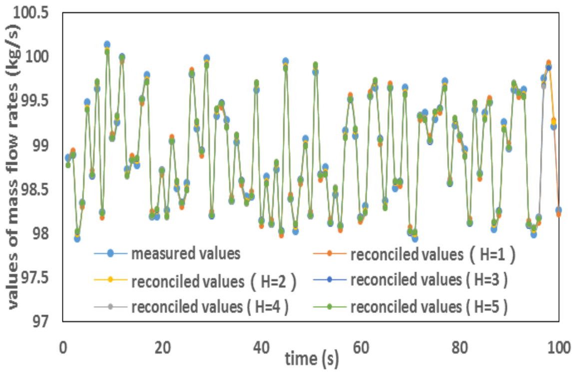

Figure 6: Measured values and reconciled values of the inlet mass flow rates in Case D

It can be seen from Figure 5 that the reconciled values of the inlet mass flow rates of the container in Case C show minor change to the measured values, which is different from that in Case D. The amplitude of the sine function of the container level in Case D is 10 times of that in Case C, so that larger fluctuations of the container level happen in Case D. Since the mass accumulation takes a larger share in the total mass flow in the container in Case D than that in Case C, larger adjustments of reconciled values of the inlet and outlet mass flow rates in Case D are obtained. Consequently, even different water level ranges as initial values have minor influence on the accuracy of the DDR method itself, they do have effects on the values of reconciled results of measured parameters in the system.

5. Conclusions

In this work, we study the dynamic data reconciliation approach using the moving time window method for key equipment in steam turbine power plants, and carry out case studies with simulation data to investigate the effect of different sampling rates of data, initial values of input data, and time window lengths on the results of DDR. Results show that the system errors introduced by differential term simplification can be ignored at high sampling rates of data, so it is better to choose high sampling rates for measured data for better accuracy of reconciled results. Besides, different water level ranges as initial values have minor influence on the accuracy of the DDR method itself, they do have effects on the values of reconciled results of measured parameters in the system. Furthermore, the system errors of using differential term simplification are accumulated with the increase of time window length, compensating the benefit of larger time redundancy in the DDR problem brought by larger time window lengths. Therefore, an optimized window length should be selected for a fixed DDR problem according to the required DDR accuracy as well as computation complexity. The study in this work is beneficial to understand the dynamic characteristics of the power plant system, and helps to expand the application of dynamic data reconciliation to real steam turbine power plants. If the requirements of high sampling rates and accuracy of real measured data are satisfied, dynamic data reconciliation of real power plants is possible, and better estimation of parameters and enhanced effect of performance monitoring can be obtained. Further research will be carried out to operational measured data of a real power plant in tfuture.

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References

Farsang B., Balogh I., Nemeth S., Szekvoelgyi Z., Abonyi J., 2015, PCA Based Data Reconciliation in Soft Sensor Development - Application for Melt Flow Index Estimation, Chemical Engineering Transactions, 43, 1555-1560.

Gu Y., Xu J., Chen D., Wang Z., Li Q., 2016, Overall review of peak shaving for coal-fired power units in China. Renewable and Sustainable Energy Reviews, 54, 723-731.

Guo S., Liu P., Li Z., 2016, Inequality constrained nonlinear data reconciliation of a steam turbine power plant for enhanced parameter estimation, Energy, 103, 215-230.

Narasimhan S., Jordache C., 1999, Data reconciliation and gross error detection: An intelligent use of process data, Gulf Professional Publishing, Houston, US, ISBN: 0-88415-255-3.

Usón S., Valero A., Correas L., 2010, Energy efficiency assessment and improvement in energy intensive systems through thermoeconomic diagnosis of the operation, Applied Energy, 87, 1989-1995.

Vachhani P., Narasimhan S., Rengaswamy R., 2006, Robust and reliable estimation via Unscented Recursive Nonlinear Dynamic Data Reconciliation, Journal of Process Control, 16, 1075-1086.

Vasebi A., Poulin É., Hodouin D., 2014, Selecting proper uncertainty model for steady-state data reconciliation – Application to mineral and metal processing industries, Minerals Engineering, 65, 130-144.

Vasebi A., Poulin É., Hodouin D., 2015, Determining a dynamic model for flotation circuits using plant data to implement a Kalman filter for data reconciliation, Minerals Engineering, 83, 192-200.

Yong J.Y., Nemet A., Varbanov P.S., Kravanja Z., Klemeš J.J., 2016, Data Reconciliation for Total Site Integration, Chemical Engineering Transactions, 52, 1045-1050.

Zhang Z., Chen J., 2015, Correntropy based data reconciliation and gross error detection and identification for nonlinear dynamic processes, Computers & Chemical Engineering, 75, 120-134.

Zhang Z., Chuang Y.Y., Chen J., 2014, Methodology of data reconciliation and parameter estimation for process systems with multi-operating conditions, Chemometrics and Intelligent Laboratory Systems, 137,110-119.