APPROACH TO DYNAMIC DATA RECONCILIATION BASED ON EXTENDED WARM-START TECHNIQUE

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Abstract

Dynamic data reconciliation can supply consistent data for dynamic optimization, fault diagnosis and process control. These applications require that dynamic data reconciliation should complete computation in a short time, but existing methods of dynamic data reconciliation cannot meet the requirement. In this paper the warm-start technique is extended and an approach to dynamic data reconciliation based on this technique is proposed. The aim of this approach is to decrease the scale of the discretized model. Based on the extended warm-start technique, the past measurements, which have been reconciled once in the previous moving window, will not be reconciled again at the current moment but they are still included in the current moving window as fixed values taken from previous calculation results directly. Thus, in the current moving window only the measurements at the current time need to be reconciled. As a result, the scale of reconciliation model will be reduced greatly. The reconciled results of Tennessee Eastman Challenge Problem show that the method not only can obtain good results, but also has much less computation time than others. So it could meet the speed requirement of dynamic optimization, fault diagnosis and process control.

Keywords

Dynamic data reconciliation, warm-start technique, collocation method

1. Introduction

Dynamic optimization, dynamic fault diagnosis and process control require consistent data supplied by dynamic data reconciliation (DDR). Among existing methods of dynamic data reconciliation, the constrained non-linear programming method is more robust than extended Kalman filtering (Jang, 1986), but the non-linear programming method requires much longer computation time than extended Kalman filtering (Karjala, 1996) because of the large scale of the discretized model. The computation inefficiency presents the bottleneck of the application of non-linear programming method.

Although there are some methods of dynamic data reconciliation proposed to accelerate the reconciliation (Kong, 2000; Liebman, 1992; Binder, 1998), their speed could not meet the requirements of dynamic optimization, fault diagnosis and process control. These methods all adopted a moving time window approach in order to capture the process dynamics contained in the measurements. In this case, if the length of moving window is too small, there may not be enough dynamic information available for estimation. If it is too large, the formulated nonlinear programming (NLP) problem will be very large (Liebman, 1992). Because in current moving window, only measurements at current time need to be reconciled, the warm start technique (Liebman, 1992; Binder, 1998) is extended and used to decrease the scale of the discretized model. In the proposed method, the past measurements, which have been reconciled within previous moving window, will not be reconciled again at current moment, and the reconciled results of past measurements are fixed and taken from previous calculation results directly. Thus, only variables at current time are included in the discretized dynamic data reconciliation model. By using this technique, the scale of the model is reduced greatly. As a result, the computation time of reconciliation will be shortened. This method was used on the Tennessee Eastman Challenge Problem (TE) (Ricker, 1995a; 1995b). The reconciliation results of TE problem show that the method can obtain good results and its calculation speed can also meet the requirements of dynamic optimization, fault diagnosis and process control. In section 2, the method will be illustrated in detail. Tennessee Eastman Challenge Problem will be used to test the method in section 3.

2. Approach based on extended warm-start technique

2.1. Characteristic of dynamic data reconciliation and disadvantages of existing methods

The main purpose of dynamic data reconciliation is to supply consistent reconciled results for online fault diagnosis, dynamic optimization, process control, etc. These applications often require that reconciled results of current measurements should be obtained before next sampling time.

There are differential equations in the model of dynamic data reconciliation, so the existing dynamic data reconciliation approaches (Kong, 2000; Liebman, 1992; Binder, 1998) based on non-linear programming method all adopted moving window techniques (Liebman, 1992). This window must be long enough to capture relevant process dynamics but brief enough to keep the computation load for the NLP problem tractable. In order to reconcile the current measurements, the past measurements are included within the moving window and are reconciled again (Karjala, 1996). Namely, there are overlaps in the calculation horizons, which is very time consuming. The computation time required for the NLP solution method for dynamic data reconciliation can be significant, and is much longer than Kalman filtering (Karjala, 1996). It is obvious that the basic reason of calculation inefficacy is that the scale of the discretized model is too large. To effectively accelerate the dynamic data reconciliation, here we propose an approach to DDR based on the extended warm-start technique (EWST).

2.2. Extended warm-start technique (EWST)

Warm-start technique is a kind of method to accelerate the optimization. It utilizes the former calculation results to speed up the current computation. At present, the methods of dynamic data reconciliation (Liebman, 1992; Binder, 1998) usually adopted non-linear programming method based on moving window technique. These methods all used warm-start technique in which the reconciled results of former moving window are taken only as the initial values of variables in current moving window. In this case, the scale of reconciliation model is unaltered.

Actual physical processes are all causal system, namely, the state variables at the current time are determined by their historical states and are not affected by future states. It is reasonable not to reconcile the previously reconciled measurements again in the current moving window. Here the extended warm-start technique is proposed that the previously reconciled results are taken as fixed values rather than initial ones of variables. Because of the overlaps of the moving windows, in this extended warm-start technique, the reconciled values of previous measurements in the current moving window are taken from the calculation results of last moving window directly. The calculated reconciled values at the current time should not have great bias, which can be seen from the reconciled results of the following example.

2.3. Approach to dynamic data reconciliation based on EWST

The general model of the dynamic data reconciliation is:

$$\begin{aligned} &\min g(y) \\ &st. \quad \frac{dy}{dt} = h(y,u) \\ &\qquad f(y,u) = 0 \\ &\qquad c(y,u) \le 0 \end{aligned} \tag{1}$$

Where all variables are all functions of time, y represents the reconciled variables that need to be calculated, u represents unmeasured variables. $g(y)$ is the objective function, and in dynamic data reconciliation, it is usually a least square function. $h(y,u)$ is the right item of differential equation. $f(y,u)$, $c(y,u)$ are equality constraint and inequality constraint respectively.

In existing methods (Kong, 2000), in order to solve the model, it needs to convert the differential equations to algebraic ones. After discretization by using collocation method, the above model became:

$$\min g(Y_r)$$

$$st. \quad (M \cdot Y_r)_i = h(y_i, u_i) \tag{2}$$

$$\begin{aligned} f(y_i,u_i) = 0 \\ c(y_i,u_i) \le 0 \end{aligned} \tag{3}$$

Where M is a constant coefficient matrix, $Y_r = [y_1, \cdots, y_K]^T$, K is the amount of sampling.

In the existing method that adopted collocation method on finite elements (Kong, 2000), the expression of y for each finite element is:

$$\mathrm{y}(t) = \sum_{i=0}^{N} a_i(t) \cdot y(t_i) \tag{4}$$

Where, t_i is sampling time, $y(t_i)$ is the reconciled value that needs to be calculated at the time of t_i, N is the number of collocation points, $a_i(t)$ is a known function of time, in the following approach, it is lagrange base function. After the model of dynamic data reconciliation is discretized using collocation method, its scale is very large. On the other hand, if the current time is

t_N, the measurements between $t_0 \sim t_{N-1}$ have already been reconciled, but they are reconciled repeatedly at t_N.

So based on the extended warm-start technique, the function expression of the last finite element in the current moving window can be represented as follows:

$$\mathrm{y}(t) = \sum_{i=0}^{N-1} a_i(t) \cdot \hat{y}(t_i) + a_N(t) \cdot y(t_N) \qquad (5)$$

Where, $\hat{y}(t_i)$ is the known reconciled result at the time of t_i which is taken from the calculation results of previous moving window, $y(t_N)$ is the unknown reconciled value that need be calculated at the time of t_N, $a_i(t)$ is a known function of time. Namely, the known reconciled results of past time and unknown reconciled values at current time are used together to approximate the estimated functions. According to the collocation method, we substitute the expression (5) for differential equations and the residual of the constraints at the current time is set to zero. In this way, there are only equations associated with the variables at the current time in the model, so the scale of the model is reduced greatly. If the length of the moving window is m, the scale of the model using the proposed method is about $1/m$ of the previous one. The reduction of model scale will accelerate the calculation obviously.

The main difference between existing method and the proposed oneis the difference of component element s of Y_r. In existing method, all elements of Y_r are required to be calculated, so in equation 2, $i = 2, \cdots, N$ and for equation 3, $i = 1, \cdots, N$, but in proposed method, all elements of Y_r except for the last one are the reconciled results obtained from previous moving window and fixed in the current horizon, so in equations 2 and 3, $i = N$. Only variables associated with current time are unknown in the model.

Because the proposed approach needs to utilize the previous reconciled results, it is necessary to reconcile measurements within a moving window using existing method at the beginning and continue the reconciliation using the proposed method. The algorithm is illustrated in detail as follows:

1. At the beginning, the length of moving window is N (N=7) and the measurements within the moving window are reconciled.
2. For the next sampling time, the function is approximated by equation 5 which is substituted for the differential constraints to obtain a set of algebraic equations. The dynamic reconciliation problem is solved by using an improved SQP method (Kong, 2001).
3. Repeat step 2.

3. Tennessee Eastman Challenge Problem

Downs and Vogel have proposed an "industrial challenge problem" for researchers in process control and related fields (Downs, 1993). The problem is based on a Tennessee Eastman Company process, as shown in Figure 1. It is used as a classic example for testing different kinds of algorithms. (Downs, 1993; Ricker, 1995a, 1995b)

The Tennessee Eastman industrial process mainly includes four units that include a reactor. The process streams have no more than eight components, which are A, B, C, D, E, F, G, and H. The components of G and H are products.

The detailed process model is shown in Ricker and Lee's paper (Ricker, 1995a). The model has 76 algebraic equations, 26 differential equations and 112 variables including 68 measured ones. These variables are all functions of time. The measurements include flowrate of streams (No.1-No.10), temperature and pressure of reactor and separator, concentrations of streams (No.5-No.11). Measurements are simulated using the simplified model (Ricker, 1995a) and a random amount of error is added to each measurement. The sampling time is 27 minutes long. The interval of sampling is 1 minute.

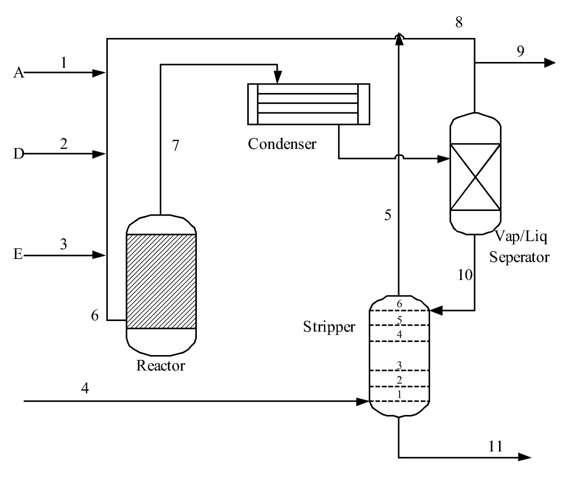

Figure 1 Flowsheet of TE Problem

The extended warm-start technique was used to reconcile the measurements of the TE process. The reconciled results are shown in following table.

The calculation results show that the proposed method can obtain good reconciled results and the reduction of model scale does not make results deteriorated (Table 1). The reason is that the reduction of model scale is carried out on the reuse of former reconciled results and not on the simplification of the process physical model.

Table 1 is the comparison of the proposed method with the one without using the warm-start technique (Kong, 2001) for the same TE problem. In the table, the number of constraints and variables refer to the number of corresponding item for the discretized model. The calculation expression of error mean is equation 6. From the table, it can be concluded that the scale of model is reduced and the speed of calculation is accelerated greatly. It should be noted that the total time of the proposed method includes the time used for calculating the first moving window by using existing method, which is 115.636 seconds. It is obvious that the time which the following calculation requires is only 16.894 seconds, so the proposed method has great superiority in speed, and the accuracy of reconciliation by using the proposed method has no apparent change relative to existing method.

$$\text{error mean} = \frac{\sum \text{ABS}\left(\frac{\text{reconciled - measurement}}{\text{variance}}\right)}{\text{count of measurements}} \quad (6)$$

Table 1 Comparison of reconciled results

Method	Number of constraints	Number of variables	Error mean	Total time (s)
Method without EWST	688	784	0.0954646	2415.563
Method with EWST	102	112	0.1323271	132.530

4. Conclusions

According to the characteristic of dynamic data reconciliation, the warm-start technique is extended and a new approach is proposed based on this technique. Through reusing the previous reconciled results, the scale of reconciliation model is reduced greatly, so the time used to solve the reconciliation model is shortened. On the other hand, the accuracy of the reconciled results only has little deterioration compared with that obtained by using existing method. The approach could meet the speed requirement of dynamic optimization, dynamic fault diagnosis, process control etc.

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References

Binder, T., L. Blank, W. Dahmen, and W. Marquardt. (1998). Towards Multiscale Dynamic Data Reconciliation. *Nonlinear Model Based Process Control*. NATO-ASI Series Kluwer. Dordrecht, 623-665.

Downs, J. J., and E. F. Vogel. (1993). A Plant-Wide Industrial Process Control Problem. *Computers chem. Engng.* **17** 245-255.

Jang, S. S. (1986). Comparison of Two Approaches to On-line Parameters and State Estimation of Nonlinear Systems. *Ind. Eng.Chem. Proc. Des. & Dev.*, **25**, 809-814.

Karjala, T. W., and D. M. Himmelblau (1996). Dynamic Rectification of Data via Recurrent Neural Nets and the Extended Kalman Filter. *AIChE J.*, **42**, 2225-2239.

Kong, M. F., B. Z. Chen, and B. Li. (2000). An Integral approach to dynamic data rectification. *Computers chem. Engng.* **24**, 749-753.

Kong, M. F., J. Wang, B. Z. Chen, X. R. He. (2001). An Improved SQP Approach to Dynamic Data Reconciliation for Non-linear Process, in: 6th IFAC SYMPOSIUM on Dynamic and Control of Process Systems (Eds. Stephanopoulos G, J. H. Lee & E. S. Yoon), 573-578.

Liebman, M. J., T. F. Edgar, and L. S. Lasdon. (1992). Efficient Data Reconciliation and Estimation for Dynamic Processes Using Nonlinear Programming Techniques. *Computers chem. Engng.* **16**, 963-986.

McBrayer, K. F., T. A. Soderstrom, T. F. Edgar, *et al.*(1998). The Application of Nonlinear Dynamic Data Reconciliation to Plant Data. *Computers Chem. Engng.* **22**, 1907-1911.

Ricker, N. L. (1995a). Optimal Steady-state Operation of the Tennessee Eastman Challenge Process. *Computers chem. Engng.*, **19**, 949-959.

Ricker, N. L. and J. H. Lee. (1995b). Nonlinear Modeling and State Estimation for the Tennessee Eastman Challenge Process. *Computers chem. Engng.* **19**, 983-1005.