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Robust data reconciliation for the determination of the control system set-points of a basic oxygen furnace

Julien Francken ^{*,**} Didier Maquin ^{*} José Ragot ^{*}
Bertrand Bèle ^{**}

^{*} Centre de Recherche en Automatique de Nancy, UMR 7039 –
Nancy-Université, CNRS, 2, Avenue de la forêt de Haye, 54516
Vandœuvre-lès-Nancy Cedex, France (e-mail:
julien.francken@arcelormittal.com).

^{**} ArcelorMittal Research Maizières, Voie Romaine, 57280
Maizières-lès-Metz, France (e-mail: bertrand.bele@arcelormittal.com).

Abstract: In the steel industry, the determination of the control system set-points of batch processes is a common problem. It consists in adjusting the set-points in order to reach the given product specifications thanks to a process model. Small changes in operating conditions may impact final product quality. This is particularly true for the Basic Oxygen Furnace (BOF) where the information collected during a specific batch serves to adjust the set-points of the next batch. For being able to control that type of process, measurements must be made coherent and it may be convenient to use data reconciliation procedure. The proposed paper describes a method allowing simultaneous data reconciliation and model parameter estimation. Parameter estimation results can either be used to update the process model or to detect abnormal parameter variations due, e.g. to fouling, corrosion, degradation of parts of the process.

Keywords: Data reconciliation; Parameter estimation; Set-point control; Batch Process; Estimation techniques.

1. INTRODUCTION

1.1 Context

In the steel industry, the determination of the control system set-points of batch processes is a common problem. It consists in adjusting the set-points in order to reach the given product specifications thanks to a process model. Batch processes are characterized by prescribed processing of raw materials into refined products. The objective is to produce products of the desired quality. However, small changes in operating conditions may impact final product quality. Moreover, batch processes with the same trajectory generally exhibit some degree of batch-to-batch variation. This is particularly true for the Basic Oxygen Furnace (BOF) where the information collected during a specific batch serves to adjust the set-points of the next batch. Usually measurements collected from an industrial process contain random errors, systematic biases or gross errors due to the quality of the instrumentation chain and its environment. Based on first principles (mass and energy balances, chemical equilibrium relationships, etc), model-filtering approach, commonly called data reconciliation may be used to provide coherent data. However, the main hypothesis underlying these methods is that the model describing the system is perfectly known which is not the case in real world. The proposed paper describes a method allowing simultaneous robust data reconciliation and model parameter estimation.

1.2 The Basic Oxygen Furnace

Basic oxygen furnace is a method of primary steelmaking in which carbon-rich molten iron is made into refined steel. The vast majority of steel manufactured in the world is produced using the basic oxygen furnace. Modern furnaces will take a charge of iron of up to 350 tons and convert it into steel in less than 40 minutes.

By blowing oxygen through molten pig iron, the carbon content of the alloy is lowered and changes the material into low-carbon steel. The basic oxygen furnace actions are scheduled as follows: molten iron from a blast furnace is poured into a large refractory-lined container. Then the container is filled with the required ingredients which quantities are computed thanks to a setup charge balance model. As the required thermal energy is produced during the process, it is relevant to maintain a proper charge balance. A water-cooled lance is so lowered down into the vessel to blow pure oxygen onto the steel and iron, igniting the carbon dissolved in the steel and burning it to form carbon oxide, causing the temperature to rise to about 1700°C. This melts the scrap, lowers the carbon content of the molten iron and helps remove unwanted chemical elements. Other fluid components are added to form slag which absorbs impurities of the steelmaking process and emulsifies to make easier the refining process. At the end of the blowing cycle, the temperature is measured and samples are taken to give a chemical analysis.

For the BOF, the setup problem consists to determine the quantity of iron ore to add and the oxygen volume to blow to reaching the target of Carbon rate in steel and the temperature defined for each heat (batch) by the given product specification. This task is done by a static charge computation based on a model formed by comprehensive heat and mass balances. Notice that for each heat, the system state variables may have a different operating point.

1.3 Main objectives and proposed method

Data reconciliation and parameter estimation are fundamental components to real time optimization of industrial processes. Great efforts have been made to develop models for various processes. However, as mentioned by Rolandi et al. (2006), physical and chemical process phenomena are complex and difficult to model conceptually and mathematically. Indeed, thermodynamic and transport properties and reaction rates are difficult to characterize experimentally and are subject to parametric uncertainties. Moreover, even when measurements are sufficiently numerous, raw process-instrumentation data are also corrupted by different errors. Indeed, data sets taken at a certain operation point are not model-consistent. Online optimization provides a mean to run a process near its optimum operating condition by providing real-time computed optimal set-points to the control system (Faber et al., 2007). However, the implemented algorithms need to be fed by coherent data. The more classical way to deal with that problem consists to reconcile process data based on the minimization of measurement errors subject to satisfying the model constraints and next estimate the model parameters from these reconciled values. An alternative to this two-step approach consists to develop simultaneous strategies for data reconciliation and parameter estimation (Rod et al., 1980; Tjoa et al., 1991; Joe et al., 2004). The proposed paper is dedicated to the presentation of such method.

On a mathematical point of view, data reconciliation is generally based on the assumption that the measurement errors have Gaussian probability density function (pdf) with zero mean. As some model parameters are uncertain, they are also modeled as random Gaussian variables. Simultaneous state variable and parameter estimates are obtained using a maximum likelihood estimation approach applied on a sliding time window of observation data. To make less sensitive the parameter estimation to measurement uncertainties, the parameters are considered as constant value on a given time window. Parameter estimation results can either be used to update process model or to detect abnormal variation due, e.g. to fouling, corrosion, degradation of parts of the process.

2. SIMULTANEOUS DATA RECONCILIATION AND PARAMETER ESTIMATION

The proposed paper describes a method allowing simultaneous data reconciliation and model parameter estimation in order to provide model-consistent data. In real process, model parameters are subjected to smooth evolution/degradation, that's why simultaneous state variable and parameter estimates will be extracted from a sliding

time window of observation data. For each observation data window, parameters are assumed to be constant whereas state variables evolve around different operating points. This computation artifice will make less sensitive the parameter estimates to measurement uncertainties. The method of simultaneous data reconciliation and parameter estimation on a given window of length N is firstly presented and the corresponding algorithm is outlined. Next, the practical implementation using a sliding window is described

2.1 The process model

Consider the system described by:

- a set of nonlinear equations in relation to a vector of state variables x_i^* and a parameter vector with true value a^* .

$$F(x_i^*, a^*) = 0, \quad i \in [1, N] \quad (1)$$

$$x_i^* \in \mathbb{R}^v, \quad a^* \in \mathbb{R}^p, \quad F : \mathbb{R}^{v+p} \rightarrow \mathbb{R}^n$$

- observation equations

$$x_i = x_i^* + \varepsilon_{xi}, \quad i \in [1, N] \quad (2)$$

- a priori knowledge of the parameters

$$a = a^* + \varepsilon_a \quad (3)$$

The batch process dynamics are managed as a sequence of static constraints F , without any time correlation between the different state variable x_i . The x_i measurements of the true values x_i^* are available for the N observations. For the parameter a^* , the a priori knowledge is formulated as a kind of ‘‘observation equation’’. The parameter is defined on the basis of a nominal value and a ‘‘pseudo-noise’’. This form allows to express in the same manner, the state variable and parameters probability density functions, given as follows:

$$p_{xi} = \frac{1}{(2\pi)^{v/2} |V|^{1/2}} \exp\left(-\frac{1}{2}(x_i^* - x_i)^T V^{-1}(x_i^* - x_i)\right) \quad (4)$$

$$p_a = \frac{1}{(2\pi)^{p/2} |W|^{1/2}} \exp\left(-\frac{1}{2}(a^* - a)^T W^{-1}(a^* - a)\right) \quad (5)$$

with V and W the variance matrices of the state variables and parameters respectively, $|\cdot|$ is used for the determinant of the matrix. The measurement and parameter error distributions are assumed independent random variables.

2.2 State and parameter estimation method

The problem issue concerns the estimation of the true value of the state variables and the model parameters based on the knowledge of the measurements (2) on the given horizon $[1, N]$, the a priori knowledge (3) of the parameter and the process model (1). The estimation can be performed by the maximum likelihood principle. Taking into account that measurement errors are independent, the likelihood function \mathcal{V} is the product of the probability density functions:

$$\mathcal{V} = \prod_{i=1}^N p_{xi} p_a \quad (6)$$

Estimations \hat{x}_i , \hat{a} of the true values maximize the likelihood function \mathcal{V} in relation to x_i^* and a^* with respect to the constraint (1) satisfaction.

Let Φ be the Lagrange function relative to the log-likelihood function and the constraint that have to be satisfied:

$$\Phi = \ln \mathcal{V} + \sum_{i=1}^N \lambda_i^T F(x_i^*, a^*) \quad (7)$$

where $\lambda_i \in \mathbb{R}^n$ are the Lagrange parameters.

Generally, this nonlinear optimisation problem must be solved using an iterative algorithm solution. In this case, instead of a global system linearization arised from Lagrange regularity conditions, it is advisable to previously linearize the constraint equations.

For all the observations $i \in [1, N]$, at the iteration j , we assume that a solution pair $\{\hat{x}_{i,j}, \hat{a}_j\}$ is available. From this solution pair, estimates can be improved based on a first order Taylor series expansion in the neighborhood of this solution pair. Assuming the convergence of the estimation process, the successive solution pairs constitute a convergent series toward the problem solution.

At the iteration $j + 1$, for a solution pair $\{\hat{x}_{i,j+1}, \hat{a}_{j+1}\}$, in the neighborhood of $\{\hat{x}_{i,j}, \hat{a}_j\}$, the constraint first order Taylor series is:

$$F(\hat{x}_{i,j+1}, \hat{a}_{j+1}) = F(\hat{x}_{i,j}, \hat{a}_j) + G_x(\hat{x}_{i,j}, \hat{a}_j)(\hat{x}_{i,j+1} - \hat{x}_{i,j}) + G_a(\hat{x}_{i,j}, \hat{a}_j)(\hat{a}_{j+1} - \hat{a}_j) \quad (8)$$

with the constraint Jacobians as follows:

$$G_x(\hat{x}_{i,j}, \hat{a}_j) = \left. \frac{\partial F(x_i^*, a^*)}{\partial x_i^{*T}} \right|_{x_i^* = \hat{x}_{i,j}, a^* = \hat{a}_j} \quad (9a)$$

$$G_a(\hat{x}_{i,j}, \hat{a}_j) = \left. \frac{\partial F(x_i^*, a^*)}{\partial a^{*T}} \right|_{x_i^* = \hat{x}_{i,j}, a^* = \hat{a}_j} \quad (9b)$$

For more readability, these last expressions will be denoted F_i , G_{ix} , G_{ia} omitting the dependency with regard to the quantities at iteration index j . At iteration $j + 1$, estimation problem reduces to the search of the Φ_{j+1} Lagrange function extremum in relation to $x_{i,j+1}^*$, a_{j+1}^* , and λ_i :

$$\begin{aligned} \Phi_{j+1} = & \Phi_0 - \frac{1}{2}(a_{j+1}^* - a)^T W^{-1}(a_{j+1}^* - a) \\ & - \frac{1}{2} \sum_{i=1}^N (x_{i,j+1}^* - x_i)^T V^{-1}(x_{i,j+1}^* - x_i) \\ & + \sum_{i=1}^N \lambda_i^T (F_i + G_{ix}(x_{i,j+1}^* - \hat{x}_{i,j}) + G_{ia}(a_{j+1}^* - \hat{a}_j)) \end{aligned} \quad (10)$$

where Φ_0 is the constant component of Lagrange function.

This Lagrange function presents an extremum for $x_{i,j+1}^*$ and $a_{j+1}^* = \hat{a}_{j+1}$ if:

$$\frac{\partial \Phi_{j+1}}{\partial x_{i,j+1}^*} = 0, \quad \frac{\partial \Phi_{j+1}}{\partial a_{j+1}^*} = 0 \quad \frac{\partial \Phi_{j+1}}{\partial \lambda_i} = 0 \quad (11)$$

Equation (11) can be transformed into the following system:

$$-V^{-1}(\hat{x}_{i,j+1} - x_i) + G_{ix}^T \lambda_i = 0 \quad (12)$$

$$-W^{-1}(\hat{a}_{j+1} - a) + \sum_{i=1}^N G_{ia}^T \lambda_i = 0 \quad (13)$$

$$F_i + G_{ix}(\hat{x}_{i,j+1} - \hat{x}_{i,j}) + G_{ia}(\hat{a}_{j+1} - \hat{a}_j) = 0 \quad (14)$$

From (12), (13) and (14), one can deduce:

$$\hat{x}_{i,j+1} = x_i + V G_{ix}^T \lambda_i \quad (15)$$

$$\hat{a}_{j+1} = a + W \sum_{i=1}^N G_{ia}^T \lambda_i \quad (16)$$

$$G_{ix} \hat{x}_{i,j+1} = G_{ix} \hat{x}_{i,j} - F_i - G_{ia}(\hat{a}_{j+1} - \hat{a}_j) \quad (17)$$

The Lagrange parameters can be deduced from (15) and (17):

$$\lambda_i = (G_{ix} V G_{ix}^T)^{-1} (G_{ix}(\hat{x}_{i,j} - x_i) - F_i - G_{ia}(\hat{a}_{j+1} - \hat{a}_j)) \quad (18)$$

Substituting (18) in (16) gives:

$$\hat{a}_{j+1} = a + W \sum_{i=1}^N S_i (G_{ix}(\hat{x}_{i,j} - x_i) - F_i - G_{ia}(\hat{a}_{j+1} - \hat{a}_j)) \quad (19)$$

with S_i defined by:

$$S_i = G_{ia}^T (G_{ix} V G_{ix}^T)^{-1} \quad (20)$$

Let us define R as follows:

$$R = I + W \sum_{i=1}^N S_i G_{ia} \quad (21)$$

Assuming that the matrix R is regular,

$$\hat{a}_{j+1} = R^{-1} W \sum_{i=1}^N S_i (G_{ix}(\hat{x}_{i,j} - x_i) - F_i + G_{ia} \hat{a}_j) + R^{-1} a \quad (22)$$

Finally the expression of the state estimation is obtained from (15) and (18):

$$\hat{x}_{i,j+1} = x_i + V G_{ix}^T (G_{ix} V G_{ix}^T)^{-1} (G_{ix}(\hat{x}_{i,j} - x_i) - F_i - G_{ia}(\hat{a}_{j+1} - \hat{a}_j)) \quad (23)$$

The estimations \hat{x}_i and \hat{a} reliant to x_i and a are obtained using successive iterations provided algorithm convergence (the analysis of this latter can be based on the norms of the Jacobian matrices G_{ix} and G_{ia}).

2.3 Algorithm

For an observation data window of length N , an algorithm based on the method developed in the previous section could be formulated in the following way:

- *Initialization*
 $j = 0, \forall i \in [1; N], \hat{x}_{i,j} = x_i$ and $\hat{a}_j = a$
- *Repeat*
Compute F_i, G_{ix} and G_{ia} using (8), (9a) and (9b).
Compute \hat{a}_{j+1} using (22)
Compute $\hat{x}_{i,j+1}$ using (23)
 $j = j + 1$
until norms of G_{ix} and G_{ia} are below a given threshold.
- *Update the parameter and variable estimates*
 $\hat{a} = \hat{a}_{j+1}$
 $\hat{x}_i = \hat{x}_{i,j+1}, \forall i \in [1; N]$

This algorithm gives coherent parameter and state estimates for a given observation data window of length N . Let us now examine the practical implementation of this algorithm.

3. PRACTICAL IMPLEMENTATION

3.1 Estimation on a sliding window

In order to be able to monitor the time evolution of the model parameters, the proposed algorithm is implemented using a sliding window. Let us consider a first observation window of length N . Let us denote $a^{(N)}$ the *a priori* nominal value of the parameter vector (given by the user) for this observation window. From the knowledge of x_1, \dots, x_N and $a^{(N)}$, the proposed algorithm provides the estimates $\hat{x}_1, \dots, \hat{x}_N$ and $\hat{a}^{(N)}$. The observation window is then slid from one observation. Based on the knowledge of the measurements x_2, \dots, x_{N+1} and the previously estimated value of parameter vector $\hat{a}^{(N)}$ which serves as the nominal value for this new observation data window, the algorithm is used to provide the estimates $\hat{x}_2, \dots, \hat{x}_{N+1}$ and $\hat{a}^{(N+1)}$. However, in a real-time context, only the last state variable estimate \hat{x}_{N+1} is exploited. This process, which is depicted on figure 1 is re-iterated based on the availability of new sets of measurements along the time.

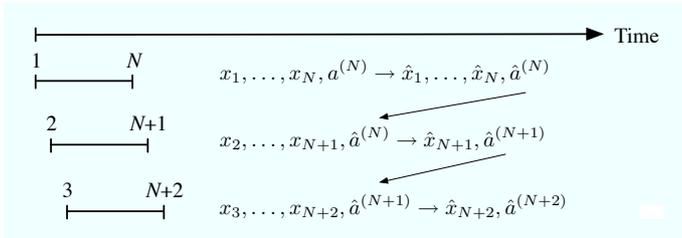


Fig. 1. Principle of estimation on a sliding window

As previously said, the determination of the control system set-points of batch processes in the steel industry is difficult to solve. Indeed, small changes in the operating conditions may impact final product quality and some degree of batch-to-batch variation exists. Therefore, model adaptation algorithm are frequently implemented for that kind of processes. Clearly, the performances of the existing model adaptation algorithm will be enhanced when fed by the coherent estimated values provided by the proposed method.

3.2 Variable scaling

In many industrial process, instrumentation chains provide access to a wide variety of different scaled process data measurements. Applications for on-line data reconciliation and optimization methods must be efficient and numerically robust. To avoid numerical difficulties and make this type of application robust, a suitable scaling method is required before any efficient estimation methods.

Indeed, the performance in term of time and convergence of algorithms based on estimation methods depends crucially on how the problem is formulated. As mentioned by Lid (2007), a proper scaling ensures an important issue to this problem. Note that the scaling is a preliminary step and can be performed off-line. Thus, the computational complexity of the scaling itself is not important. Rather, the objective of the scaling is to minimize the computation time in improving the convergence speed and precision

of the algorithms required by estimation or optimization methods.

An unconstrained optimization problem is said to be poorly scaled if a change in x_i (resp. a) in one direction produces a much larger change in $F = F(x_i, a)$ than in another direction (Nocedal et al., 1999). The measure of poor scaling is not so clear in constrained optimization, but a poorly scaled model is likely to generate larger rounding errors which may degrade the performance of the algorithm (Lid, 2007).

The scaled process model for the proposed method of data reconciliation and parameter estimation is written as:

$$\tilde{F}(\tilde{x}_i, \tilde{a}) = 0 \quad (24)$$

with the scaled variable $\tilde{x}_i = S_{vx}^{-1}x_i$ and the scaled parameter $\tilde{a} = S_{va}^{-1}a$. The scaled model can be written as $\tilde{F}(\tilde{x}, \tilde{a}) = S_n F(S_{vx}\tilde{x}_i, S_{va}\tilde{a})$ where S_{vx} , S_{va} and S_n are fixed diagonal scaling matrices.

The equation scaling factors are the reciprocal of an integer power of 10 of the value of a given term or group of terms, normally related to the scale factors of the relevant variable and parameter:

$$S_{vx}(j, j) = 10^{-k_j}, \quad k_j = \text{int}(\log_{10} |(\bar{x})_j|), \quad j = 1, \dots, v \quad (25)$$

where \bar{x} is a mean value of a set of measurement vectors x_i , $()_j$, the j th component of a vector, and:

$$S_{va}(j, j) = 10^{-k_j}, \quad k_j = \text{int}(\log_{10} |(a)_j|), \quad j = 1, \dots, p \quad (26)$$

For the S_n scaling factor, we have chosen to use an integer power of 2, because residual values are already close to each other.

$$S_n(j, j) = 2^{-k_j}, \quad k_j = \text{int}(\log_2 |(f(\bar{x}, a))_j|), \quad j = 1, \dots, n \quad (27)$$

This scaling method have notable impact on Jacobian matrices:

$$\tilde{G}_{ix} = S_n G_{ix} S_{vx}, \quad \tilde{G}_{ia} = S_n G_{ia} S_{va} \quad (28)$$

and variance-covariance matrices:

$$\tilde{V} = S_{vx}^{-1} V S_{vx}^{-1}, \quad \tilde{W} = S_{va}^{-1} W S_{va}^{-1} \quad (29)$$

3.3 Gross error rejection

The proposed method is well adapted for filtering random measurement errors. However, measurements are frequently subject to systematic errors also named “gross errors”. These errors may be due to instrument malfunction, miscalibration or drift, leakage or even poor sampling. If some measurements have gross errors, precautions have to be taken to avoid biased measurement adjustments or estimates. Generally, gross errors are detected and identified using statistical tests (Romagnoli et al., 1981) or by the use of robust objective functions (Tjoa et al., 1991; Alhaj-Dibo et al., 2008).

For the concerned application, we have just implemented an empirical approach consisting to modify dynamically the variance of the measurement suspected to contain a gross error. Indeed, the influence of each measurement in the optimization criteria is weighted by its variance. It is then possible to adjust this variance in order to minimize the influence of abnormal data. Let us consider a given observation data window which comprises the N measurement vectors x_{j-N+1}, \dots, x_j . First, a correction

ratio vector r_j is calculated. Each component $(r_j)_k$ is defined by:

$$(r_j)_k = \frac{(|x_j - \hat{x}_j|)_k}{\sqrt{V(k, k)}}, \quad k = 1, \dots, v \quad (30)$$

The components $(r_j)_k$ are then compared to a given threshold T . When one or several components exceed the threshold, let us denote by m the index corresponding to the greater correction:

$$(r_j)_m = \max_k (r_j)_k, \quad k = 1, \dots, v \quad (31)$$

In that case, the variance of the corresponding measurement $(x_j)_m$ is set to a bigger value (let say ten times its original value) in order to simulate the lack of that measurement for the next sliding windows.

4. APPLICATION TO A SIMPLIFIED BOF PROCESS

The proposed simultaneous state and parameter estimation method has been applied to a simplified nonlinear process model of a basic oxygen furnace (BOF).

4.1 The process model

Due to the random nature of chemical reaction in the non homogeneous slag or to the wear-out refractory-lined container or other many causes, the process cannot accurately be described with equilibrium balances. Therefore some of the model parameters need to be estimated simultaneously with state variables.

The model is a set of mass and heat balances. Let the nonlinear equation system be a simplified model of basic oxygen furnace described as next:

$$\begin{aligned} (c_1 + x_3^*)x_2^* + (c_2 - x_6^*)x_5^* + a_1^* &= 0 \\ c_3x_1^* + (c_4 + c_5x_3^*)x_2^* + (c_6 - a_2^*x_6^*)x_5^* + c_7 &= 0 \\ (c_8x_3^*x_4^* + a_3^*x_3^* + c_9x_4^* + c_{10})x_2^* & \\ + (c_{11}x_6^*x_7^* + c_{12}x_6^* + c_{13}x_7^* + c_{14})x_5^* + c_{15} &= 0 \end{aligned}$$

The first equation represents the iron mass balance where x_2 , x_5 are material quantities, x_3 and x_6 are iron mass percentage and a_1 is a parameter corresponding to the iron loss (projection due to the oxygen blowing and to the deformation of the converter) which evolves along the time. In the same manner, the second equation describes an oxygen volume balance and the third a heat balance.

The variable measurement ranges and the measurement accuracies (assumed constant) are given in the table 1.

Variable	x_1	x_2	x_3	x_4
Min value	63593	3.76	4.7	4000
Max value	96750	4.79	5.74	5232
Standard deviation	3339	0.19	0.24	202
Variable	x_5	x_6	x_7	
Min value	3.71	7.27	1.04	
Max value	4.68	12.96	2,02	
Standard deviation	0.19	0.48	0.052	

Table 1. Measurement ranges and accuracies

For that example, it is desired to monitor the values of the three parameters a_1^* , a_2^* and a_3^* , the other parameters c_i being assumed constant (see table 3). A priori knowledge on a_1 , a_2 and a_3 parameters are gathered in table 2.

Parameter	a_1	a_2	a_3
Nominal value	17.85	0.4	16
Standard deviation	0.893	0.02	0.8

Table 2. ‘‘A priori’’ parameter knowledge

Constant	c_1	c_2	c_3	c_4	c_5
Value	-0.99	0.95	0.001	-0.007	-3
Constant	c_6	c_7	c_8	c_9	c_{10}
Value	-0.024	1.19	-0.004	$-2 * 10^{-6}$	0.003
Constant	c_{11}	c_{12}	c_{13}	c_{14}	c_{15}
Value	-10^{-4}	-0.12	$-2 * 10^{-6}$	-0.002	-0.256

Table 3. Parameter constant values

4.2 Results

To validate the proposed method, a data base composed of measurement data and true values of evolving parameters has been created for 200 measurement sets. The simultaneous state and parameter estimation algorithm described above was performed based on the measurement data, the knowledge of the model, and the parameter nominal values given in table 2. Because data come from simulated data base, we can easily observe the performance of the parameter estimation by matching parameter estimates with the true values. For the two parameters a_1 and a_2 , results are given in figure 2 and 3 when the observation data window length is fixed to $N = 10$, parameter estimates are near to the true value.

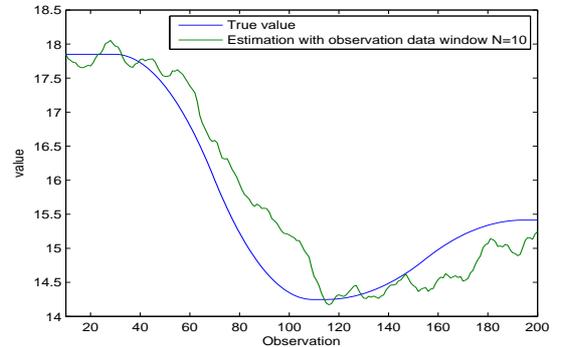


Fig. 2. a_1 parameter estimation

The filtering capacity of the proposed estimator is pointed out. The more the window length is bigger, the more the parameter estimation filters the noise measurement, but, in the same time, the more the estimation is delayed. Figures 4 and 5 show the measurements of the two state variables x_1 and x_6 and their estimations. As the measurements are unbiased, the estimations are closed to the measurements.

Figure 6 shows the measurements and the state estimation of the variable x_1 as well as the normalized corrective term in the presence of a gross error. Between instants 30 and 40, and between 110 and 120 the magnitude of the measurement has been multiplied by 1.3 (this situation can correspond to an error on the sensor gain). The proposed algorithm together with the gross error rejection explained in section 3.3 allow a good estimation of the

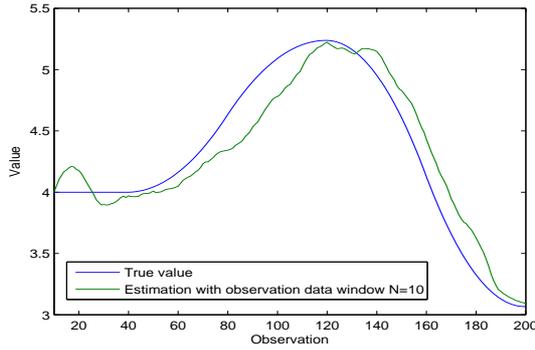


Fig. 3. a_2 parameter estimation

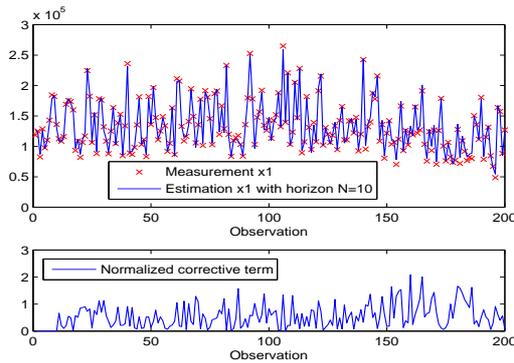


Fig. 4. x_1 state estimation and measurement

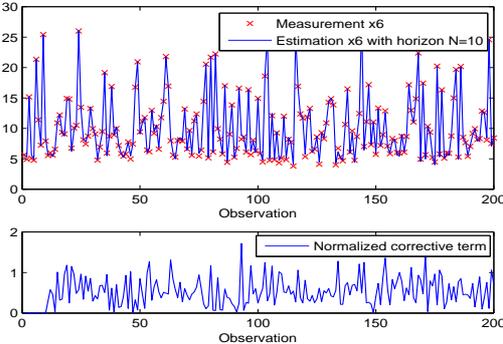


Fig. 5. x_2 state estimation and measurement

state variable x_2 . As this rejection is correct, the estimates of the different parameters a_i are little affected by the presence of this bias.

5. CONCLUSION

In this paper, a general methodology for simultaneous robust data reconciliation and parameter estimation for nonlinear model has been proposed. Data reconciliation based on balances was performed to obtain model-consistent measurement data and simultaneously parameter estimates. The use of a sliding window on which parameters are considered as constant values allows the desensitization of their estimations with regard measurement uncertainties. It is interesting to note that the knowledge of parameter distribution errors is not a limiting factor, indeed it would be easy to modify the algorithm in order

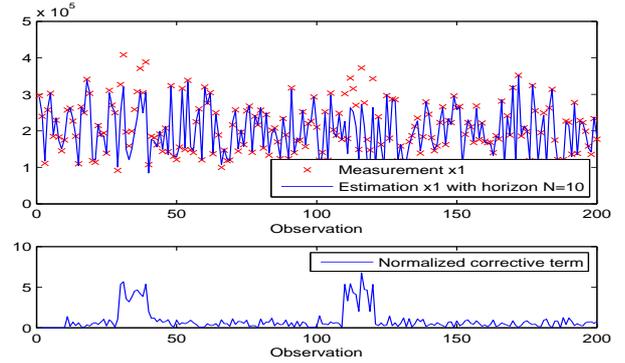


Fig. 6. x_1 state estimation in the presence of a gross error to run without any parameter knowledge. The robustness property with regard gross measurement errors has been introduced. Another approach using a so-called contaminated distribution in the maximum likelihood estimation (Arora et al., 2001; Alhaj-Dibo et al., 2008) is being developed. Finally the proposed method must be evaluated on real process model with real data in terms of process model adjustment along the successive heat to observe the impact of the set-points adjustment on the successive batch processes.

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