Robust Data Reconciliation to Determine Basic Oxygen Furnace Set-points

IFAC MMM 2009
Workshop on Automation in Mining, Mineral and Metal Industry

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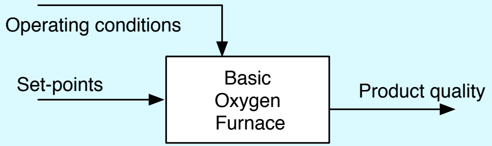
Plan

1. Batch process set-points determination

Industrial problem

- Determination of the control system set-points of batch processes in order to reach given product specifications thanks to a process model.
- Process models are inaccurate.
- Measurements are corrupted by different errors (noises, biases) or are lacking



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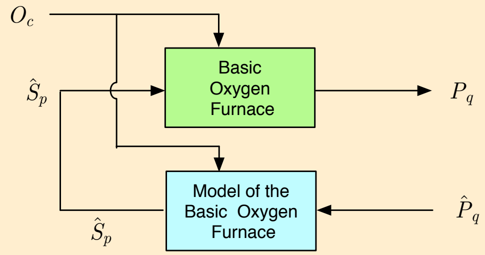

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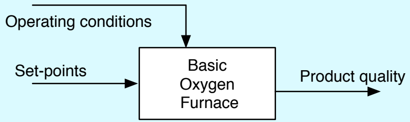

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Objectives and proposed method

- Necessity to have consistent measurements $\rightarrow$ use of data reconciliation method
- Ensure the monitoring of system component deterioration along the time (due to wear-out, clogging) $\rightarrow$ model parameter estimation

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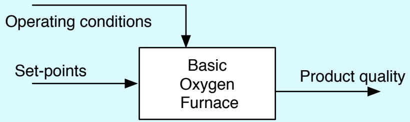

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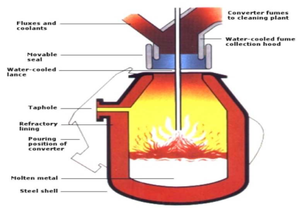
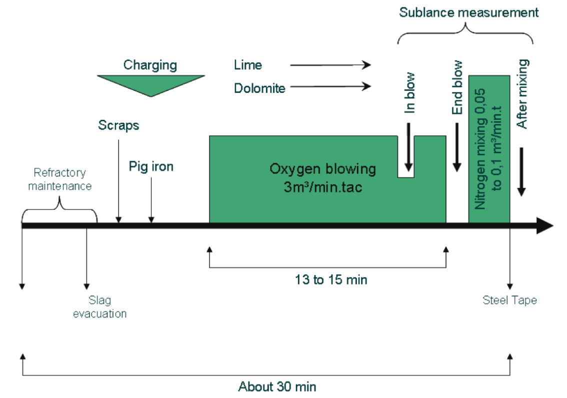
$\Rightarrow$ Use of method allowing simultaneously data reconciliation

1. Operation scheduling of a Basic Oxygen Furnace





1. Application target - the Basic Oxygen Furnace (BOF)

Main objectives of a BOF

- To refine the hot metal produced in a blast furnace into raw liquid steel
- To decarburize and remove phosphorus from the hot metal
- To optimize the steel temperature so that any further treatments prior to casting can be performed with minimal reheating or cooling of the steel

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Setup problem and means

- 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
- Static load computation based on a model formed by comprehensive heat and mass balances

"Classical" data reconciliation

- Model of the system : a set of measurements x_i and a set of constraints f

$$\begin{cases} x_i = x_i^* + \varepsilon_{x_i} \\ f(x_i^*, a) = 0 \end{cases} \quad , \quad i = 1, ..., N \ ,$$

  where x_i^* are the state variables and a the known model parameters.

- Hypothesis

$$\mathcal{H}_1 : \varepsilon_{x_i} \sim \mathcal{N}(0, V)$$

$$or$$

$$\mathcal{H}_2 : \varepsilon_{x_i} \in [-\delta \quad +\delta]$$

- Data reconciliation: estimate the state variables of the system. For example, with $\mathcal{H}_1$:

$$\hat{x}_i = \arg\min_{x_i^*} \Phi = \|x_i - x_i^*\|^2_{V^{-1}}$$

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Interests

- Provide coherent data (more likelihood data than raw measurements)
- Allow to detect and isolate sensor faults
- Estimate unmeasured state variables

2. Theoretical formulation: data reconciliation with uncertain model

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Constraint: the model is assumed to be perfectly known

2. Historical point of view

• Importance of covariance in mass balancing of particle size distribution data	C. Bazin, D. Hodouin	1999
• Design and upgrade of process plant instrumentation	J. Romagnoli	2000
• Data reconciliation and gross error detection	S. Narasimhan, C. Jordache	2000
• Fault detection and diagnosis in industrial systems	L.H. Chiang, E.L. Russell, R.D. Braatz	2001
• Redescending estimators for data reconciliation and parameter estimation	N. Arora, L.T. Biegler	2001
• Robust data reconciliation based on a generalized objective function	D. Wang, J.A. Romagnoli	2002
• Data reconciliation in gas pipeline systems	M.J. Bagajewicz, E. Cabrera	2003
• Data reconciliation: a robust approach using contaminated distribution. Application in mineral processing for multicomponent products	M. Alhaj-Dibo, D. Maquin, J. Ragot	2004
• Mass balance equilibration: a bilinear case with a robust approach using contaminated distribution	J. Ragot, M. Chadli, D. Maquin	2005
• Using sub-models for dynamic data reconciliation.	L. Lachance, A. Desbiens, D. Hodouin	2006
• In-Line monitoring of bulk polypropylene reactors based on data reconciliation procedures	D. Martinuez Prata, E.L. Lima, J.C. Pinto	2008
• Adaptation and testing of data reconciliation software for CAPE-OPEN compliance	E. Radermecker, M.N. Dumont, G. Heyen	2009

Proposed approach – Simultaneous data reconciliation and parameter estimation

- The considered system is modeled using a set of measurements x_i, a set of constraints f and an *a priori* knowledge of the parameter values.

$$\begin{cases} x_i = x_i^* + \varepsilon_{x_i} \\ f(x_i^*, a^*) = 0 \end{cases} , \quad i = 1, \dots, N$$

- Uncertainties on the knowledge of the parameters are expressed with a "pseudo-measurement" equation:

$$a = a^* + \varepsilon_a \ , \quad \varepsilon_a \sim \mathcal{N}(0, W)$$

- Simultaneous estimation problem (maximum likelihood approach)

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

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$$(\hat{x}_i, \hat{a}) = \arg \min_{(x_i, a)} \mathcal{V} = \prod_{i=1}^{N} p_{xi} p_a$$

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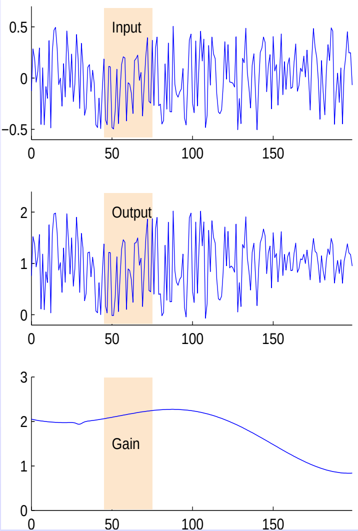
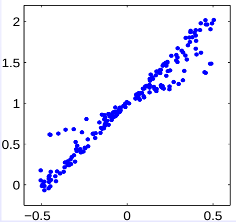
Some difficulties and extensions

- Unmeasured variables
- Dynamic model
- Convergence proof

2. An academic example: basic formulation of data reconciliation

- Data





- Model

$$y^* - ax^* = 0$$

- Measurement

$$x_i = x_i^* + \varepsilon_{x_i}$$
$$y_i = y_i^* + \varepsilon_{y_i}$$

- Lagrange function

$$\mathcal{L} = \sum_{i=k}^{k+N} \left(\frac{x_i - x_i^*}{\sigma_{x,i}}\right)^2 + \left(\frac{y_i - y_i^*}{\sigma_{y,i}}\right)^2 + \lambda_i(y_i^* - ax_i^*)$$

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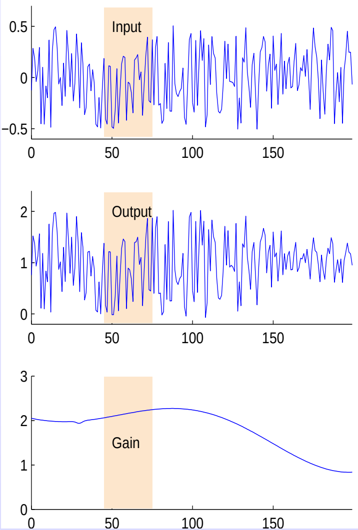

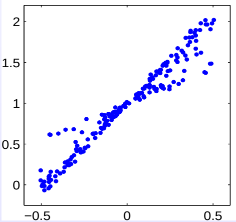

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Optimality equation

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$$\begin{cases} V_x^{-1}(\hat{x} - x) - \lambda a = 0 \\ V_y^{-1}(\hat{y} - y) + \lambda = 0 \\ \hat{y} - a\hat{x} = 0 \\ \lambda^T \hat{x} = 0 \end{cases}$$

Numerical solution may be obtained

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Numerical solution may be obtained

Implementation

Perform estimation on a time window of length N :

$$W_1 = [1 \quad N]$$

Then, perform estimation on a time window of length N

$$W_2 = [2 \quad N+1]$$

. . .

2. An academic example: proposed formulation of data reconciliation

Optimality equation

$$\mathcal{L} = \sum_{i=k}^{k+N} \left(\frac{x_i - x_i^*}{\sigma_{x,i}}\right)^2 + \left(\frac{y_i - y_i^*}{\sigma_{y,i}}\right)^2 + \lambda_i (y_i^* - a x_i^*)$$

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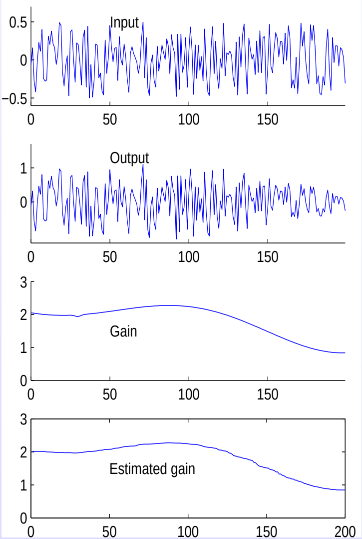
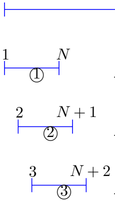


Practical implementation



$$X_1, \ldots X_N \quad , a^{(0)} \longrightarrow \hat{X}_1, \ldots \hat{X}_N \quad , \hat{a}^{(1)}$$

$$X_2, \ldots X_{N+1}, a^{(1)} \longrightarrow \hat{X}_2, \ldots \hat{X}_{N+1}, \hat{a}^{(2)}$$

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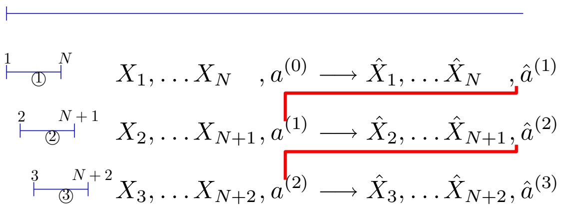

2. Theoretical formulation: data reconciliation with uncertain model

Practical implementation

1 – N ①
$$X_1, \dots X_N \;, a^{(0)} \longrightarrow \hat{X}_1, \dots \hat{X}_N \;, \hat{a}^{(1)}$$

2 – N + 1 ②
$$X_2, \dots X_{N+1}, a^{(1)} \longrightarrow \hat{X}_2, \dots \hat{X}_{N+1}, \hat{a}^{(2)}$$

3 – N + 2 ③
$$X_3, \dots X_{N+2}, a^{(2)} \longrightarrow \hat{X}_3, \dots \hat{X}_{N+2}, \hat{a}^{(3)}$$

Interests of simultaneous data reconciliation and parameter estimation

- Provide coherent data (state variables + model parameter)
- Allow the monitoring of model parameter (drifts, component deterioration)
- Feed model adaptation algorithms for the next batch

Mass and heat balances

$$(-0.99 + x_3^*)x_2^* + (0.95 - x_6^*)x_5^* + a_1^* = 0$$
$$0.001x_1^* - (0.007 + 3x_3^*)x_2^* - (0.024 + a_2^* x_6^*)x_5^* + 1.19 = 0$$
$$(-4\text{e-}3x_3^* x_4^* + a_3^* x_3^* - 2\text{e-}6x_4^* + 3\text{e-}3)x_2^*$$
$$-(1\text{e-}4x_6^* x_7^* + 0.12x_6^* + 2\text{e-}6x_7^* + 2\text{e-}3)x_5^* - 0.256 = 0$$

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Data

Table: Measurement ranges and accuracies

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

Table: "A priori" parameter knowledge

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

Generation of 200 sets of measurements, length of the sliding window $N = 10$

3. Application to a simplified BOF process

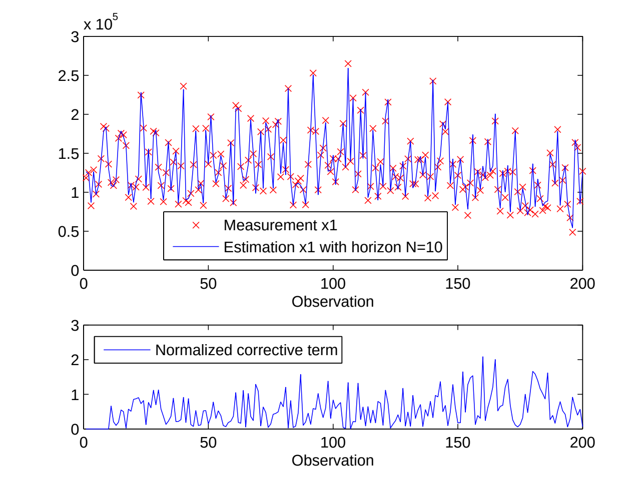

Figure: x_1 state estimation and measurement

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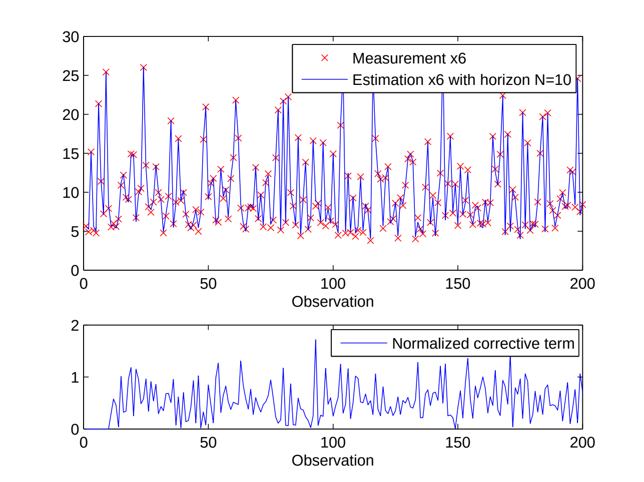

Figure: x_6 state estimation and measurement

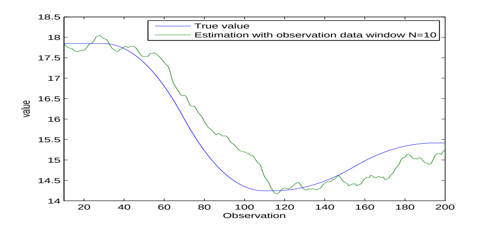

Figure: a_1 parameter estimation

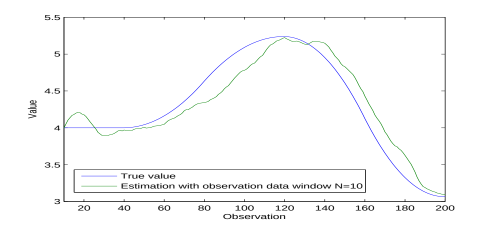

Figure: a_2 parameter estimation

3. Impact of the observation data window length

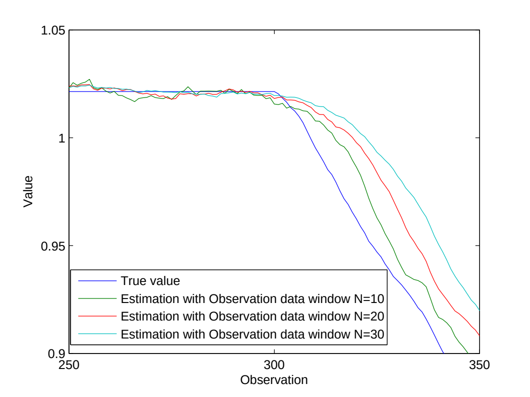

Figure: Impact of the observation data window length on parameter estimation

Compromise between : estimation delay $\leftrightsquigarrow$ measurement noise filtering

4. Data reconciliation may be dangerous !!!

Problem : reconciliate raw data is sensitive to outliers
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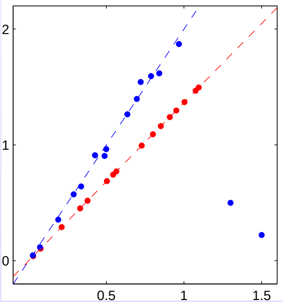

Figure: Outliers influence

Blue color : raw data and theoretical model
Red color : estimated variables and obtained model

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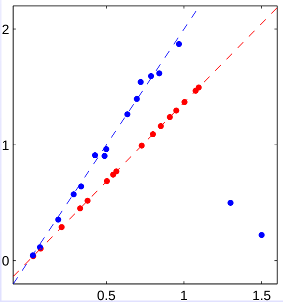

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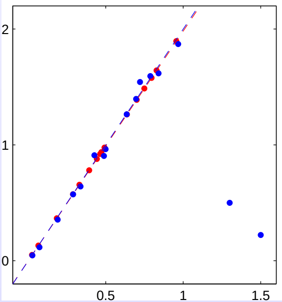

Figure: Removing outliers influence

Blue color : raw data and theoretical model
Red color : estimated variables and obtained model

4. Gross error rejection

Gross error

- Due to instrument malfunction, miscalibration or drift, leakage/poor sampling
- Precautions: to avoid biased measurement adjustments or estimates

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Method

Let us define the coefficient ratio r_j. Each component $(r_j)_k$ is defined by:

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

If one or several components $(r_j)_k > T$, let us denote $(r_j)_m = \max_k (r_j)_k$
The variance of $(x_j)_m$ is increased to simulate the lack of that measurement for the next sliding windows.

4. Gross error rejection

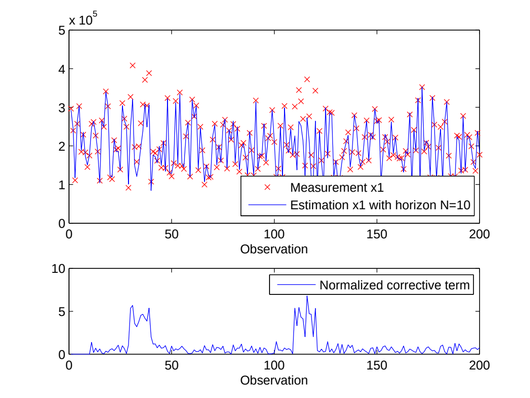

Figure: x_1 state estimation in the presence of a gross error

Conclusion

- Development of a general method for simultaneous data reconciliation and parameter estimation for non-linear models.
- Use of a sliding observation window $\rightarrow$ to reduce the model parameter estimate sensitivities to measurement errors
- Provide coherent data (state variables + model parameter)
- Robustness to measurement gross errors occurence

Conclusion and future prospects

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- Application to a complete BOF model with real data to observe the impact of control set-points adjustement on the next heat
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Thanks for your attention