

Observer design
for state and clinker hardness estimation
in cement mill

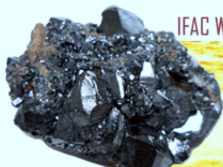
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- 1 Short presentation of our laboratory
- 2 Short presentation of diagnosis
- 3 System under investigation
- 4 What is a multi-model ?
- 5 State estimation
- 6 Conclusions

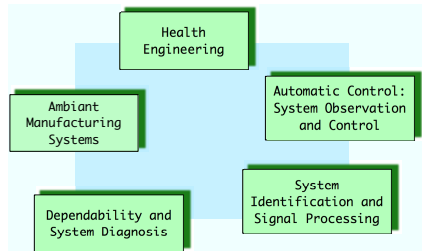
1. A short presentation about our lab



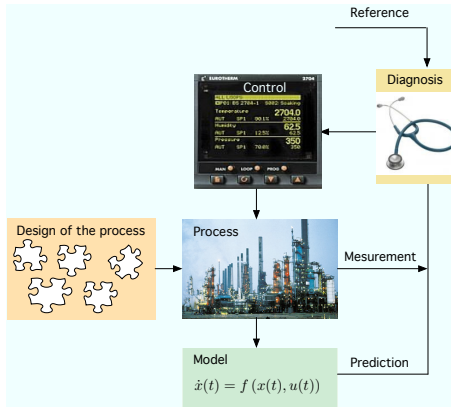
The « Centre de Recherche en Automatique de Nancy » (Automatic Control) is a Research Centre funded by the "Centre National de la Recherche Scientifique (CNRS)" and two universities in Nancy : UHP (Université Henri Poincaré) and INPL (Institut National Polytechnique de Lorraine).

The CRAN was set up in Nancy (France) in 1980. It totals 180 persons. The research activities concentrate on 5 principal themes :

- Systems Observation and Control
- System Identification and Signal Processing
- Dependability and System Diagnosis
- Health Engineering
- Ambient Manufacturing Systems.



2. A short presentation of process diagnosis



2. A short presentation of process diagnosis

For the elaboration of a global approach for the design and the operation (supervision, maintenance, reconfiguration) of complex automated industrial systems, **it is necessary** :

- ▶ to guarantee the system **safety**, i.e. to guarantee that the system will operate according to the given specifications
- ▶ to **forecast** alternate modes allowing the system to continue to operate even if some parts of it are out of order
- ▶ to **detect any fault**, i.e. to decide that the system does not operate normally, using the overall available information on the actual behavior (obtained through the measurements) and on the expected behavior (forecast by a system model)
- ▶ to **isolate the faults**, i.e. to decide which function (or, at least, which component) is faulty based on data redundancy
- ▶ to **identify the faults**, i.e. to estimate the magnitude of the fault and to estimate its time evolution
- ▶ to **compensate for the faults**, i.e. to implement a fault tolerant control (that leads eventually to a degraded system performance) or reconfigure either the control architecture or the process architecture itself.



3. System under investigation. Flowsheet

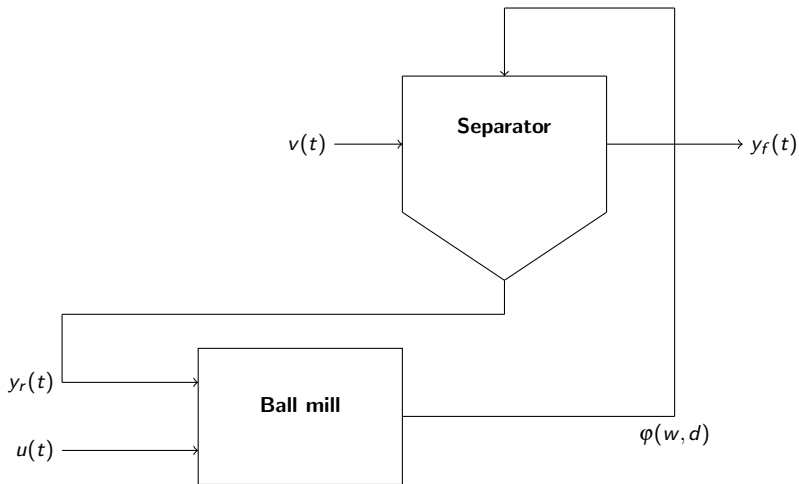


FIGURE: Cement mill process

3. System under investigation. Mathematical model

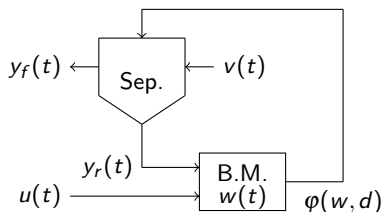


FIGURE: Cement mill process

Control	u v	feeding rate separator speed
State	y_r q_e $\varphi(w, d)$ $\alpha(v)$ y_f w	recycled flow ball mill input ball mill output separation function finished product flow load inside the mill
Perturbation	d	clinker hardness
Parameters	T_f T_r	time constant time constant

Separator

$$T_f \dot{y}_f(t) = -y_f(t) + (1 - \alpha(v))\varphi(w(t), d(t))$$

Ball – mill

$$T_r \dot{y}_r(t) = -y_r(t) + \alpha(v)\varphi(w(t), d(t))$$

Load

$$\dot{w}(t) = -\varphi(w(t), d(t)) + y_r(t) + u(t)$$

where

$$\varphi(w(t), d(t)) = p_1 w(t) \exp(-p_2 d(t) w(t))$$

$$\alpha(v(t)) = p_3 v^3(t) + p_4 v^4(t) + p_5 v^5(t)$$

3. System under investigation. Mathematical model

Then, the system is described by the following state equations

$$\begin{cases} \dot{x}(t) &= f(x(t), d(t)) + Bu(t) \\ y(t) &= Cx(t) \end{cases}$$

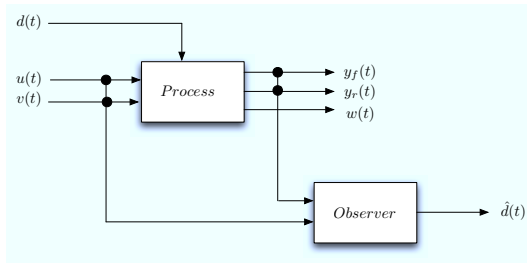
where

$$x(t) = \begin{bmatrix} y_f(t) \\ y_r(t) \\ w(t) \end{bmatrix} \quad B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \quad C = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$
$$f(x(t), d(t)) = \begin{bmatrix} \frac{1}{T_f} (-x_1(t) + (1 - \alpha(v))\varphi(x_3(t), d(t))) \\ \frac{1}{T_r} (-x_2(t) + \alpha(v)\varphi(x_3(t), d(t))) \\ x_2(t) - \varphi(x_3(t), d(t)) \end{bmatrix}$$

in which the hardness $d(t)$ is unknown.

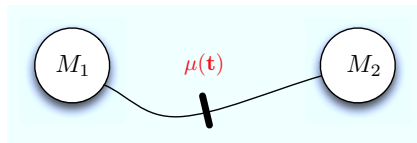
$$\begin{bmatrix} \dot{y}_f(t) \\ \dot{y}_r(t) \\ \dot{w}(t) \end{bmatrix} = \begin{bmatrix} -1/T_f & 0 & 0 \\ 0 & -1/T_r & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} y_f(t) \\ y_r(t) \\ w(t) \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} (1 - \alpha(v)) \\ \alpha(v)\varphi(x_3, d) \\ -\varphi(x_3, d) \end{bmatrix}$$

3. System under investigation. Objectives



- ▶ Estimate the hardness $d(t)$
- ▶ Difficulty : the system is non linear
- ▶ Proposed approach : multi-model representation of the system

4. What is a multi-model? Definition



$$\mathcal{S} \begin{cases} M_1 & : \quad \dot{y}(t) = a_1 \cdot y(t) + b_1 \cdot u(t), \quad \text{if } y(t) > 2.5 \\ M_2 & : \quad \dot{y}(t) = a_2 \cdot y(t) + b_2 \cdot u(t), \quad \text{if } y(t) < 2.5 \end{cases}$$

$$\mathcal{S} \begin{cases} \dot{y}(t) = a(t) \cdot y(t) + b(t) \cdot u(t) \\ a(t) = \mu(t) \cdot a_1 + (1 - \mu(t)) \cdot a_2 \\ b(t) = \mu(t) \cdot b_1 + (1 - \mu(t)) \cdot b_2 \\ \mu(t) = \frac{1}{2}(1 + \text{sign}(y(t) - 2.5)) \end{cases}$$

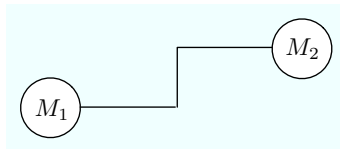
$$\mathcal{S} \begin{cases} \dot{y}(t) = \sum_{i=1}^2 \mu_i(t) (a_i \cdot y(t) + b_i \cdot u(t)) \\ \mu_1(t) = \frac{1}{2}(1 + \text{sign}(y(t) - 2.5)) \\ \mu_2(t) = 1 - \mu_1(t) \end{cases}$$

Summarizing, a multi-model, or a multiple-model, is a weighting sum of local models. These local models are chosen linear in respect to the state and control variable

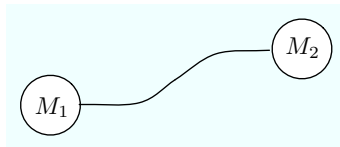
4. What is a multi-model? Definition

Two kinds of weighting functions

- Switching



- Smooth transition



4. How to transform a non-linear model into a multi-model ?

$$\dot{x}(t) = \begin{bmatrix} -\frac{1}{T_f} & 0 & \frac{z_1(t)}{T_f} \\ 0 & -\frac{1}{T_r} & 0 \\ 0 & 1 & -\frac{z_1(t)}{T_f} \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} -\frac{z_2(t)}{T_f} \\ \frac{z_2(t)}{T_r} \\ 0 \end{bmatrix} d(t)$$

where the variables $z_1(x(t), d(t))$ and $z_2(t)$, later selected as premise variables, are defined by

$$z_1(t) = p_1 \exp(-p_2 d(t) x_3(t))$$

$$z_2(t) = \alpha(v(t)) p_1 x_3(t) \frac{\exp(-p_2 d(t) x_3(t))}{d(t)}$$

$$\begin{aligned} z_1^{\min} &\leq z_1(t) \leq z_1^{\max} \\ z_2^{\min} &\leq z_2(t) \leq z_2^{\max} \end{aligned}$$

4. How to transform a non-linear model into a multi-model ?

Since they are bounded, the premise variables can be written as a weighting sum of their bounds. For the first one :

$$\begin{aligned} z_1(t) &= \mu_1^0(z_1(t))z_1^{\min} + \mu_1^1(z_1(t))z_1^{\max} \\ &= \sum_{i=0}^1 \mu_1^i(z_1(t))z_1^i \end{aligned}$$

where the functions μ_1^0 and μ_1^1 are defined by

$$\mu_1^0(z_1(t)) = \frac{z_1^1 - z_1(t)}{z_1^1 - z_1^0}, \quad \mu_1^1(z_1(t)) = \frac{z_1(t) - z_1^0}{z_1^1 - z_1^0}$$

and satisfy the following property :

$$0 \leq \mu_1^0(z_i(t)) \leq 1$$

$$0 \leq \mu_1^1(z_i(t)) \leq 1$$

$$\mu_1^0(z_i(t)) + \mu_1^1(z_i(t)) = 1$$

4. How to transform a non-linear model into a multi-model ?

$$\dot{x}(t) = \begin{bmatrix} -\frac{1}{T_f} & 0 & \frac{z_1(t)}{T_f} \\ 0 & -\frac{1}{T_r} & 0 \\ 0 & 1 & -\frac{z_1(t)}{T_f} \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} -\frac{z_2(t)}{T_f} \\ \frac{z_2(t)}{T_r} \\ 0 \end{bmatrix} d(t) \quad z_1(t) = \sum_{i=0}^1 \mu_1^i(z_1(t))$$

$$\dot{x}(t) = \begin{bmatrix} -\frac{1}{T_f} & 0 & \frac{\sum_{i=0}^1 \mu_1^i(z_1(t)) z_1^i}{T_f} \\ 0 & -\frac{1}{T_r} & 0 \\ 0 & 1 & -\frac{\sum_{i=0}^1 \mu_1^i(z_1(t)) z_1^i}{T_f} \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} -\frac{z_2(t)}{T_f} \\ \frac{z_2(t)}{T_r} \\ 0 \end{bmatrix} d(t)$$

$$\dot{x}(t) = \sum_{i=0}^1 \mu_1^i(z_1(t)) \left(\begin{bmatrix} -\frac{1}{T_f} & 0 & \frac{z_1^i}{T_f} \\ 0 & -\frac{1}{T_r} & 0 \\ 0 & 1 & -\frac{z_1^i}{T_f} \end{bmatrix} x(t) + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u(t) + \begin{bmatrix} -\frac{z_2(t)}{T_f} \\ \frac{z_2(t)}{T_r} \\ 0 \end{bmatrix} d(t) \right)$$

The same transformation is made for the variable $z_2(t)$.

4. How to transform a non-linear model into a multi-model ?

$$\dot{x}(t) = \sum_{i=1}^4 \mu_i(z(t)) (A_i x(t) + B u(t) + E_i d(t)) \quad 0 \leq \mu_i \leq 1, \quad \sum \mu_i = 1$$

$$A_1 = \begin{bmatrix} -\frac{1}{T_f} & 0 & -\frac{z_1^1}{T_f} \\ 0 & -\frac{1}{T_r} & 0 \\ 0 & 1 & -z_1^1 \end{bmatrix}, \quad A_3 = \begin{bmatrix} -\frac{1}{T_f} & 0 & -\frac{z_1^0}{T_f} \\ 0 & -\frac{1}{T_r} & 0 \\ 0 & 1 & -z_1^0 \end{bmatrix},$$

$$E_1 = \begin{bmatrix} -\frac{z_2^1}{T_f} \\ \frac{z_2^1}{T_r} \\ 0 \end{bmatrix}, \quad E_2 = \begin{bmatrix} -\frac{z_2^0}{T_f} \\ \frac{z_2^0}{T_r} \\ 0 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}, \quad A_2 = A_1, \quad A_4 = A_3, \quad E_3 = E_1, \quad E_4 = E_2$$

Advantage of this formulation :

- a systematic representation into a weighting sum of simple local models
- the possibility use results established for linear systems (stability, observer, control)

5. State estimation : joint state and perturbation reconstruction

▷ Model of the observer

$$\begin{cases} \dot{\hat{x}}(t) &= \sum_{i=1}^4 \mu_i(\hat{z}(t))(A_i x(t) + Bu(t) + E_i \hat{d}(t) + L_i(y(t) - \hat{y}(t))) \\ \dot{\hat{d}}(t) &= \sum_{i=1}^4 \mu_i(\hat{z}(t))K_i(y(t) - \hat{y}(t)) \\ \hat{y}(t) &= C\hat{x}(t) \end{cases}$$

$$\begin{cases} x_a(t) &= [x^T(t) \ d^T(t)]^T \\ e_a(t) &= x_a(t) - \hat{x}_a(t) \\ \dot{e}_a(t) &= \sum_{i=1}^4 \mu_i(\hat{z}(t))(\mathcal{A}_i - \mathcal{M}_i \mathcal{C})e_a(t) + \Delta(t) \end{cases}$$

where

$$\mathcal{A}_i = \begin{pmatrix} A_i & E_i \\ 0 & 0 \end{pmatrix}, \quad \mathcal{M}_i = \begin{pmatrix} L_i \\ K_i \end{pmatrix}, \quad \mathcal{C} = (C \ 0),$$

$$\Delta(t) = \sum_{i=1}^4 (\mu_i(z(t)) - \mu_i(\hat{z}(t)))\mathcal{A}_i x_a(t)$$

▷ Design of the observer : adjust E_i , L_i and K_i such that e_a is bounded.

5. Numerical results

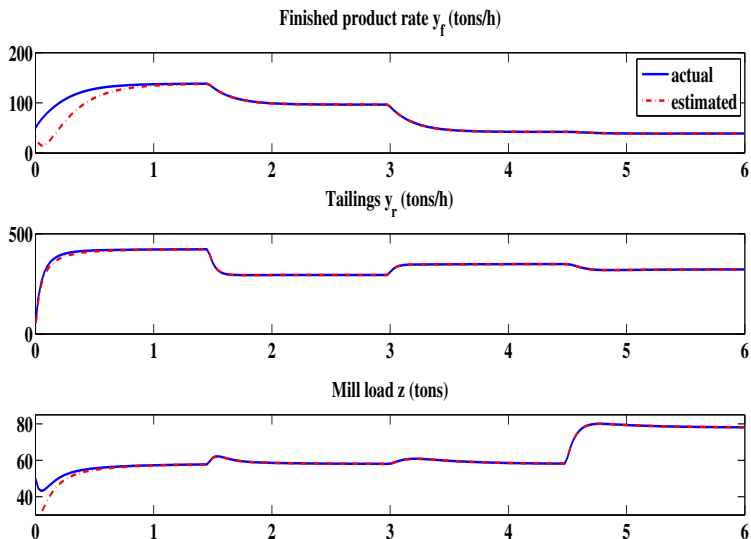


FIGURE: System states and their estimates

6. Numerical results

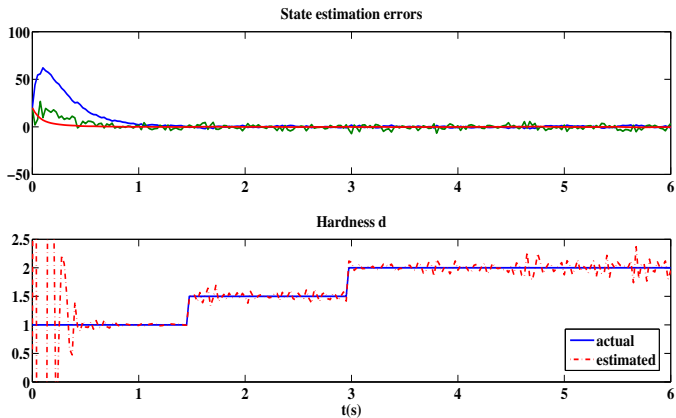


FIGURE: State estimation errors (top) and clinker hardness and its estimate with noised measurements

7. Extension : particle size distribution reconstruction

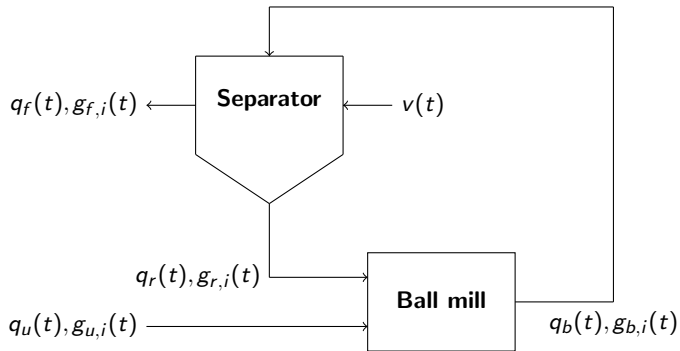


FIGURE: Cement mill process

7. Extension : particle size distribution reconstruction

Process equation

$$\left\{ \begin{array}{lcl} T_f \dot{q}_f(t) & = & -q_f(t) + (1 - \alpha(v)).q_b(t) \\ T_r \dot{q}_r(t) & = & -q_r(t) + \alpha(v).q_b(t) \\ \dot{w}(t) & = & -\varphi(t) + q_r(t) + u(t) \\ q_b(t) & = & p_1.w(t). \exp(-p_2.d.w(t)) \\ \frac{d(g_{b,i}(t))}{dt} & = & \frac{1}{w(t)} (q_u(t)(g_{u,i}(t) - g_{b,i}(t)) + q_r(t)(g_{r,i}(t) - g_{b,i}(t))) \\ & & -s_i g_{b,i}(t) + \sum_{j=i}^N g_{b,j}(t)s_j b_{ij}, \quad i = 1, \dots, N \end{array} \right.$$

Control loop equation

$$\left\{ \begin{array}{lcl} u(t) & = & -q_r(t) + k_1(w^*(t) - w(t)) \\ v(t) & = & k_2(q_f(t) - q_f^*(t)) \end{array} \right.$$

- ▷ The goal of this paper is to design an observer for mill load and clinker hardness estimation in cement mill process with only the knowledge of the feeding u , the tailings y_r and the finished product rate y_f .
- ▷ Work is underway to extend the proposed state reconstruction when one takes into account, in addition to flow rates, the whole particle size distributions of the product throughout the separation-grinding loop.

Ladies and Gentleman, thank you very much for your attention !

