STATE AND PARAMETER ESTIMATION IN CEMENT GRINDING CIRCUITS - PRACTICAL ASPECTS

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Abstract: Due to the lack of reliable and/or inexpensive hardware sensors in cement grinding, development of software sensors is particularly significant for control and monitoring purposes. In this study, a nonlinear distributed-parameter, full-horizon observer is designed, which allows the contents of the mill to be described in terms of hold-up and particle size distribution. When measurements are available at relatively high sampling rates and at, at least, two spatial locations along the mill, fast observer convergence is obtained. However, in practical situations where measurements can be collected at the mill outlet only and with a relatively low sampling rate, the observer convergence deteriorates and , as the sampling rate decreases, performance becomes similar to an asymptotic (simulation) observer. The robustness of the software sensor can be improved by on-line identification of some time-varying parameters, such as the material grindability. These several concepts are discussed and tested in simulation based on a realistic process model.

Keywords: distributed-parameter systems; nonlinear models; softsensing; observers; process control; industrial production systems.

1. INTRODUCTION

Control and monitoring of cement grinding circuits are notoriously delicate tasks. Together with the strong nonlinearity of the process, the general lack of (reliable) measurement sensors of relevant process variables are among the major difficulties to be faced. When available, measurement signals are usually corrupted by noise (e.g., the mechanical vibrations affecting the elevator power used as a mill flow rate measurement), and collected at relatively low sampling rates (e.g., sample analysis in laboratory facilities to determine particle size distribution, color, etc.). On the other hand, the cost of on-line analyzers is still prohibitive in most industrial applications (Hodouin and Del Villar, 1994).

Therefore, the development of software sensors for reconstructing the process state variables on line is particularly significant. These software sensors are based on a dynamic model of the process and some available measurement signals.

With regard to the process nonlinearity and stochastic nature of the measurement signals, a natural approach is given by full-horizon observers

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which estimate the most-likely initial conditions for the process model. The algorithm minimizes a maximum-likelihood criterion which measures the deviation between the model prediction and the real system outputs (Bogaerts and Hanus, 2001). In this particularly versatile approach, signals of different nature (e.g., mass flow rates, particle size distributions, etc.) can be incorporated in the criterion, measurement errors can be taken into account, initial conditions can be parameterized, and equality and/or inequality constraints can be easily included. In addition, periodic model updates can be computed as well, based on parameter estimation techniques. Finally, this optimization-based state estimation technique is consistent with a nonlinear model predictive control (NMPC) approach (Lepore *et al.*, 2003) in terms of concepts, model and software tools.

The contribution of this paper is therefore:

- to develop a distributed-parameter, full-horizon observer, based on a process model consisting of partial differential equations (Lepore *et al.*, 2002), which allows the particle size distribution inside the mill to be described. This feature has to be contrasted from results published in the mineral processing literature, where attention is mostly focused on global variables, such as sieve residue at the mill and/or classifier outlet or material mass content of the mill (Hodouin and Del Villar, 1994). The particle size distribution inside the mill is, however, of primary interest for the operator to evaluate the mill operation, and for model-based control, such as the nonlinear model predictive control schemes presented in (Lepore *et al.*, 2002; Lepore *et al.*, 2003);
- to analyze, through a simulation case study, the properties of the observer in terms of convergence and reliability. This study considers two situations: a) the ideal case, for which several sensors are available inside the mill and measurements are collected at high sampling rate, b) the nonideal (or real) case, for which measurements are available at low sampling rate at the mill outlet only;
- to discuss the potentiality of on-line parameter estimation to periodically update the process model.

The continuation of this article is divided into five sections. Section 2 describes the process and the model equations. The design of full-horizon observers in the context of cement grinding is discussed in Section 3. In Section 4, numerical results are presented, whereas Section 5 is devoted to future extensions, including on-line parameter updates. Finally, conclusions and perspectives can be found in Section 6.

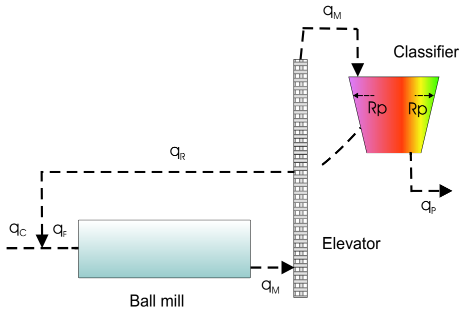

Fig. 1. Closed-loop grinding circuit

2. PROCESS DESCRIPTION AND MODELLING

2.1 Process description

A typical cement grinding circuit is represented in figure 1, which consists of a single-compartment ball mill in closed-loop with an air classifier. The raw material (usually clinker) flow q_C is fed to the rotating mill, in which balls perform the breakage of the material particles by fracture and/or attrition. At the other end, the output or mill flow q_M is lifted up by a bucket elevator onto the classifier which separates the material into two parts: the product flow q_P and the rejected flow q_R, which is recirculated to the mill inlet. The selectivity of the classifier and, in turn, the product fineness, can be modified by acting on special registers Reg. The sum of q_C and q_R is the total feed flow, denoted by q_F.

2.2 Process model

The size continuum is divided into three size intervals (noted *s.i.* in the following) numbered 1, 2 and 3 for the coarse, intermediate-size and fine particles, respectively. Mass balances lead to:

$$\frac{\partial X_i}{\partial t} = -u_i \frac{\partial X_i}{\partial x} + D_i \frac{\partial^2 X_i}{\partial x^2} + \sum_{j=1}^{2} k_{ij}\varphi_j \quad \text{; i=1,2,3}$$

$$(k_{ij}) = \begin{pmatrix} -1 & 0 \\ +k & -1 \\ 1-k & +1 \end{pmatrix} \tag{1}$$

where:

- X_i is the mass per unit of length of the particles in s.i. i;
- k is the yield fraction of the particles in size interval 2 appearing from the breakage of the particles in s.i. 1; φ_j is the breakage rate of the material in s.i. j;
- u_i and D_i are the convection velocity and the diffusion coefficient, respectively, of the particles in s.i. i;

The partial differential equations (1) are supplemented by initial (2) and boundary (3) conditions:

$$X_i(0,x) = H_0(x) w_{0;i}(x) \quad \forall \text{ x; i=1,2,3} \qquad (2)$$

$$0 = u_i X_i - D_i \frac{\partial X_i}{\partial x} - q_F w_{F;i} \quad \text{x=0; i=1,2,3}$$
$$0 = \frac{\partial X_i}{\partial x} \quad \text{x=L; i=1,2,3} \qquad (3)$$

where:

- $H_0(x)$ is the initial material content per unit of length (e.g., in tons per meter), $w_{0;i}(x)$ is the corresponding mass fraction in s.i. i;
- q_F is the total feed flow rate, $w_{F;i}$ is the corresponding mass fraction in s.i. i.

The breakage rates are formulated as follows:

$$\varphi_j = \alpha_j X_j e^{-\beta H} \qquad \text{; j=1,2} \qquad (4)$$

where α_j is the specific rate of breakage for s.i. j, H is the hold-up, i.e., $(X_1 + X_2 + X_3)$, β is an inhibition coefficient.

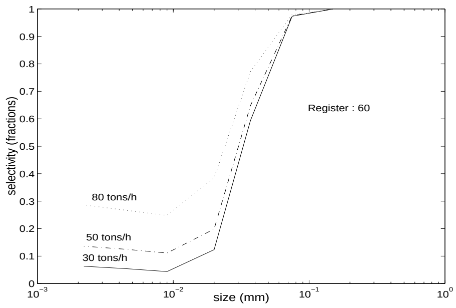

Fig. 2. Classifier selectivity (for a single register position and several mill flow rates)

The classifier has very fast dynamics compared to the mill and is therefore described by a nonlinear steady-state model. Selectivity is the fraction of material in each size interval which is recirculated (see the "fish-hook" curves in figure 2).

3. FULL-HORIZON OBSERVER

3.1 Basic principles

Consider the general nonlinear model:

$$\frac{dx}{dt} = f(x(t), u(t)), \qquad x(t_0) = x_0 \qquad (5)$$
$$y(t_k) = h(x(t_k)) + \epsilon(t_k) \qquad (6)$$

where $x(t)$, $u(t)$, $y(t)$ are the vectors of states, inputs and measurements, respectively, t_k are the sampling times and $\epsilon(t_k)$ is a white noise sequence with zero mean and variance $Q(t_k)$.

Following (Allgöwer *et al.*, 1999; Bogaerts and Hanus, 2001) and the references therein, the observer is defined as:

$$\hat{x}(t) = g(t, u(t), \hat{x}_{0;k}) \qquad \forall t \in [t_0 \ t_k[\qquad (7)$$

where $g(.)$ is the state trajectory of model (5) and $\hat{x}_{0;k}$ is the estimated initial-condition vector at time t_k.

$\hat{x}_{0;k}$ is obtained by minimizing the maximum-likelihood criterion $J_k(x_{0;k})$:

$$J_k(x_{0;k}) = \sum_{j \in HO_k} \epsilon(t_j)^T Q(t_j)^{-1} \epsilon(t_j) \qquad (8)$$
$$\epsilon(t_j) = y(t_j) - h(g(t_j; u(t_j); x_{0;k})) \qquad (9)$$

where HO_k is the observation horizon, of which $x_{0;k}$ is the initial condition, $y(t_j)$ are the measured values.

When all the measurements, from t_0 up to t_k, are used to estimate the initial condition, $HO_k = 0, 1, \ldots k$ and the observer is called a *full-horizon observer*.

3.2 Implementation

Spatial discretization of the PDE model (1-4) leads to a large number of variables to estimate (for instance, in a finite difference scheme, the number of state variables increases proportionnally with the number of spatial grid points). However, experimental and simulation results demonstrate that the spatial profiles of the hold-up and the weight fractions inside the mill can be reasonably approximated by simple, linear or quadratic functions. Hence, five parameters describe the state vector
$x_0 = H_0(x).[w_{1;0}(x) \ w_{2;0}(x) \ w_{3;0}(x)]^T$,
based on the following assumptions:

- hold-up: $H_0(x)$ is constant (requires one parameter);
- coarse particles: $w_{1;0}(x)$ is a concave quadratic law, the minimum value being reached at the outlet of the mill (requires two parameters);
- fine particles: $w_{3;0}(x)$ is a convex quadratic law, the maximum value being reached at the outlet of the mill (requires two parameters);
- intermediate-size particles: $w_{2;0}(x)$ requires no parameter since it is equal to $1 - w_{1;0}(x) - w_{3;0}(x)$.

On the other hand, several box and linear inequality constraints can be derived from the fact that:

- $H_0(x) \geq 0$, $\forall x$;
- $0 \leq w_{i;0}(x) \leq 1$, $\forall i, x$.

To keep the things clear, let us consider, say, that $w_{1;0}(x) = \theta_{w_1;1} x(x - 2L) + \theta_{w_1;2}$ is the quadratic law defined on $[0\ L]$ (L being the mill length). Convexity and $0 \leq w_{1;0}(0) \leq 1$ result in $\theta_{w_1;1} \geq 0$ and $0 \leq \theta_{w_1;2} \leq 1$, respectively (box contraints) whereas $0 \leq w_{1;0}(L) \leq 1$ results in $0 \leq -\theta_{w_1;1}L^2 + \theta_{w_1;2} \leq 1$ (linear inequality constraints). Similar arguments are applied on $H_0(x)$ and $w_{3;0}(x)$ leading to box and linear inequality constraints on the three other parameters.

In addition, in order to evaluate quantitatively and qualitatively the information available to determine the vector θ, the sensitivity functions, $S_{i;\theta_j}(t) = (\frac{\partial h_i}{\partial \theta_j})(t)$, are analyzed and, in order to estimate the confidence in the parameters, the covariance matrix is reasonably approximated by the inverse of the Fisher information matrix defined as follows:

$$F(\hat{\theta}) = \sum_{j \in HO_k} (\frac{\partial h}{\partial \theta})^T_{t_j} Q(t_j) (\frac{\partial h}{\partial \theta})_{t_j} \qquad (10)$$

The minimization of (8) is performed using the "Optimization toolbox 2.2", Matlab 6.5.0. The solution of the partial differential equations is achieved using (a) a "method of lines" Matlab procedure for spatial differentiation (b) standard solvers from Matlab 6.5.0 for the integration in time of the differential equations.

4. NUMERICAL RESULTS

A mathematical model, previously calibrated to mimic an industrial grinding circuit (Lepore *et al.*, 2002; Boulvin *et al.*, 2002), is used in this study as a reference system to test the performance of the observer. Figure 3, which represents the evolution of the relevant operating variables, illustrates a change in the operating point of the cement grinding circuit: from a steady state, the manipulated variables are moved at time 40 so as to produce more cement (see the increase in the product flow rate q_P) of lower quality (see the decrease in the weight fraction of the fine particles $w_{P;3}$) while maintaining the same grinding efficiency (in fact, one holds the mill flow rate and the weight fraction of the intermediate-size particles $w_{M;2}$ at constant values).
From time 0 on, several state estimations are performed. In all the observer designs considered in this study, the flow rate and the particle size distribution of the input material are supposed to be measured. In order to assess the quality of the state estimates, a global indicator,
$e_r(X) = \|\hat{X} - X\|/\|X\|$ is used, where $\hat{X}$ and X are the predicted and the actual state vector, respectively, and $\|.\|$ is the Euclidean norm.

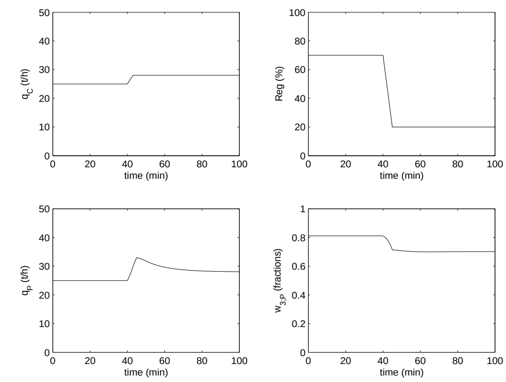

Fig. 3. Change in the cement production: decrease of the cement fineness

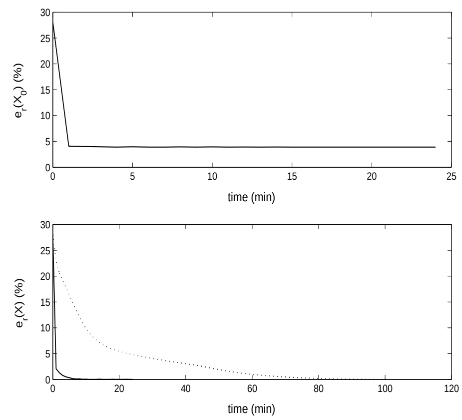

Fig. 4. Deviation between estimated and real values in the ideal case; upper: initial state vector; lower: state vector; (dotted: deviation when plain simulator is used)

4.1 Ideal case

In the following, we consider that the material hold-up and particle size distribution are available at two locations inside the mill (18% and 100% of the mill length), at sufficiently high sampling rate ($T_s = 1\ min$). The maximum error on the measurements is 0.005 t/m (overall mean value of the measurements is 0.25 t/m). Figure 4, which represents the temporal evolution of the deviation between the real and estimated states (at the initial time and at the current time), shows that the estimation error of the initial conditions quickly converges to a minimum, yet nonzero, value. This nonzero minimum results from the approximation of the real spatial profiles of the initial conditions by polynomials. Despite this residual error, the state estimates converge rapidly towards the system states, as depicted in figure 4. For comparison purposes, the convergence of a plain simulator (which can be viewed as an asymptotic observer) is also shown in figure 4. In addition, Table 1 confirms the high reliability of the procedure since the individual error on the initial condition estimates is very small (globally, a few percents).

θ_H	$\theta_{w_1;1}$	$\theta_{w_1;2}$	$\theta_{w_3;1}$	$\theta_{w_3;2}$
0.7473	0.2084	0.2264	−0.3425	0.1680
0.0006	0.0042	0.0031	0.0034	0.0024

Table 1. Confidence in the parameter estimates in the ideal case; row 1: parameter value; row 2: standard deviation

4.2 Nonideal (real) case

In the following, we consider only on-line measurements that can be achieved at reasonable costs in practice. Particularly, flow rates and particle size distributions obtained by a two-sieve technique (i.e., weight fractions of coarse, intermediate-size and fine particles) can be measured in real-life operation, provided that the sampling period is large enough. This way, at each time t_j in the horizon HO_k, the following measurements are available at the mill output: the flow rate q_M and the weight fractions $w_{M;i}$ $(i = 1 \ldots 3)$.

Figure 5 depicts the deviation between real and estimated states for three different sampling periods (20 min: solid; 10 min: dashed; 5 min: dash-dotted). The following conclusions can be drawn:

- $T_s = 20\,min$ appears to be a limiting period, for which the full-horizon observer and the asymptotic observer exhibit similar convergence speeds;
- the asymptotic values of the estimation error on the initial conditions are much larger than in the ideal case;
- however, despite this observation, it appears that a small correction of the initial conditions is responsible for a significant improvement in the estimation of the actual state.

However, very large uncertainties are associated with the parameters of the polynomial approximations of the initial condition profiles. From the evolution of the sensitivity functions $S_{M;i\theta}(t) = \frac{\partial X_{M;i}}{\partial \theta}(t)$ ($X_{M;i}$ being the material weight in size interval i at the mill output) (see figure 6), the following conclusions can be drawn:

- valuable information with respect to the initial hold-up is available until $t = 80\,min$;
- valuable information with respect to size interval 3 and size interval 1 are available until $t = 20\,min$ and $t = 10\,min$, respectively.

So, unless a sufficiently small sampling period is used (appropriately, $1 \sim 2\ min$), which is unfeasible in practice, the particle weight fractions cannot be determined with enough accuracy when using a single measurement at the mill output. On the other hand, since the hold-up can be reconstructed accurately in all cases, an additional sensor (such as an electronic ear) to measure the hold-up is probably useless (due to the low level of accuracy and reliability of these equipments).

5. EXTENSIONS

Whatever the solution adopted (full-horizon observer or asymptotic observer), an accurate model is a prerequisite to the design of a state estimator. However, it is by no means true that all the parameters are constant during normal operation. For instance, due to changing storage conditions, the grindability of the input material is subject to variations. In the following, we will focus on the estimation of the grindability factor, which is the variation of the fragmentation rates α_1 and α_2 from their reference values.
The estimate of the grindability factor $\hat{\theta}_k$ at time t_k is obtained by minimizing a maximum-likelihood criterion $J_k(\theta_k)$:

$$J_k(\theta_k) = \sum_{j \in HO_k} \epsilon(t_j)^T Q(t_j)^{-1} \epsilon(t_j) \qquad (11)$$

$$\epsilon(t_j) = y(t_j) - h(g(t_j; u(t_j); x_{0;k}; \theta_k)) \qquad (12)$$

As a test example, consider that the process is in steady state until time 30, at which a change in the process grindability factor of −20% occurs. This process variation is supposed to be detected, so that an identification procedure can start. Figure 7 represents 1) the real and estimated grindability factors, 2) the standard deviation of the estimates, for three horizon lengths, i.e., 1, 5 and 10 sampling periods (with $T_s = 10\,min$). The following conclusions can be drawn:

- the longer the horizon, the smaller is the deviation from the real value;
- whatever the horizon length, the results in terms of standard deviations of the estimates are very satisfactory.

At this stage, one should investigate other issues, such as estimating additional model parameters (e.g., transport velocity), selection of the horizon length (e.g., grindability could be considered as an

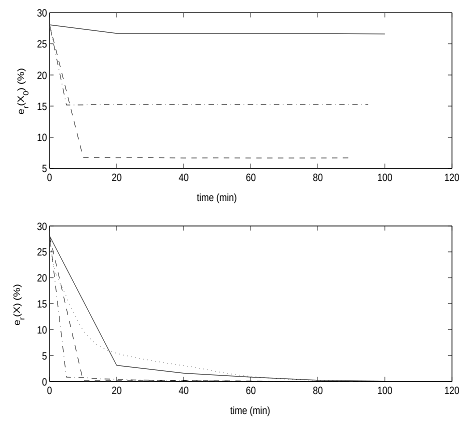

Fig. 5. Deviation between estimated and real values in the nonideal (real) case; upper: initial state vector; lower: state vector; (dotted: deviation when plain simulator is used);

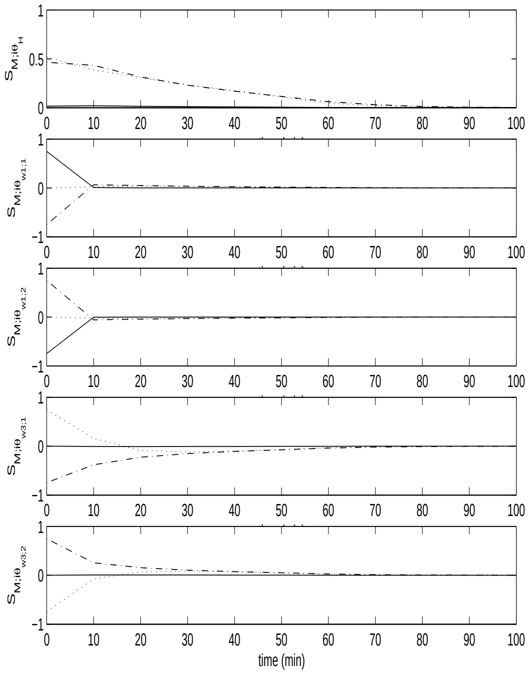

Fig. 6. Sensitivity functions at the mill output w.r.t. the parameters in the nonideal case; $i = 1$: solid, $i = 2$: dash-dotted, $i = 3$: dotted

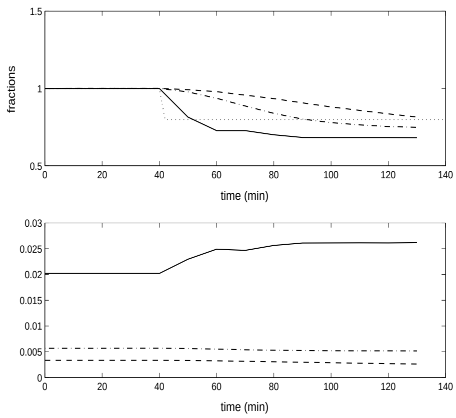

Fig. 7. Grindability factor - upper: real (dotted) and estimated values, lower: standard deviation; for three horizon lengths (in periods of $10\,min$) (1: solid; 5: dash-dotted; 10: dashed)

additional model state, estimated together with the initial conditions), stability issues, etc.

6. CONCLUSION

A distributed-parameter, full-horizon observer is implemented in order to predict the material contents of the mill (i.e., hold-up and particle size distribution). The observer is based on the computation of the most-likely initial conditions, expressed via a small number of parameters.

With a reference model calibrated to mimic an industrial plant, the observer has been evaluated in two different situations. In the ideal situation, for which several sensors are available along the mill and measurements are collected at high sampling rates, the algorithm exhibits good performance, especially when compared to the asymptotic observer, and reliability (or confidence) with respect to the estimates. On the other hand, in practical situations, for which only a few low-cost measurements (low sampling rate) are available at the mill output only, an important degradation of the performance is noticed, which is confirmed by the analysis of the sensitivity functions. This observation tends to designate the asymptotic observer as the only feasible solution in this real situation. Interestingly, hold-up is estimated accurately in all cases, which tends to demonstrate that additional equipements, such as electronic ear, could be of little use, considering the low accuracy and reliability of these hardware sensors.

Finally, in order to ensure robust estimation, on-line parametric adaptation of the observer is tested. Preliminary results are obtained for the estimation of the material grindability using a receding-horizon parameter estimation procedure. Future studies should focus on the estimation of more than one parameter (for example, grindability and transport velocity), considering the correlations between parameter estimates and stability issues. Work should also be devoted to the automatic detection of such parameter variations.

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