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MODELING AND PREDICTIVE CONTROL OF CEMENT GRINDING CIRCUITS

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Abstract: The purpose of this paper is to show that a distributed-parameter model of a continuous ball mill can be developed by discretizing the particle size continuum into a few size intervals only. Despite this coarse discretization of the particle size distribution, the ball mill model provides a good representation of the real process, which can be combined with a classifier model to build a complete simulator of a closed-loop grinding circuit. This simplified process representation is compared with a detailed first-principle model previously developed and validated by the authors. The main advantage of the simplified model is that it can be easily incorporated in an on-line control scheme. For illustrative purposes, a NMPC scheme is implemented to regulate the product fineness when variations in the grindability of the raw material occur as a measurable disturbance. The control objective, based on a size interval content, is compatible with traditional fineness measurements. *Copyright © 2002 IFAC*

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1. INTRODUCTION

Clinker and raw material grinding is a fundamental step in cement manufacturing. This highly energy-consuming operation is usually performed in closed-loop grinding circuits, including a ball mill and an air classifier.

Modeling of industrial grinding circuits is a delicate task due to the lack of reliable measurements of some key variables, such as material hold-up and particle size distribution inside the mill, which are function of space and time (Austin, *et al.*, 1984).

In previous studies (Boulvin, *et al.*, 1999; Boulvin, 2000), the authors have developed and validated a first-principle model of a closed-loop grinding circuit of the cement manufacturer CBR (Belgium). This first-principle model, which consists of sets of partial differential equations (PDEs) and algebraic equations (AEs), can be used as a tool to investigate process dynamics, to study the effect of changes in material properties, and to test control schemes.

Even though this approach has proved quite successful, the resulting model is too complex in nature to allow model-based control to be readily implemented. As a next step, it is therefore required to develop simplified models and, in (Lepore, *et al.*, 2001), a reduced-order model is proposed for a laboratory-scale fed-batch process.

The objective of the present study is twofold:

- to extend the results presented in (Lepore, *et al.*, 2001) to a full-scale closed-loop grinding circuit. This objective involves the development of a low-order distributed-parameter model for a continuous ball mill, which would allow the description of the particle size distribution along the mill axis, the estimation of the unknown model parameters, and the validation of this model with respect to the previously developed, more complex, first-principle model.
- to design a nonlinear predictive control (NMPC) based on the low-order distributed-parameter model.

Recently, several black-box approaches to the control of cement grinding circuits have been published; see (Van Breusegem, *et al.*, 1996; Magni, *et al.*, 1999). The main advantage of our modeling approach is that it enables the description of the particle size distribution inside the grinding circuit, whereas black-box approaches often refer to some global variables only (such as the material flow rates or the total mass content of the mill).

The present paper is organised as follows. Section 2 describes the closed-loop grinding process and presents the classical modeling approach developed in (Boulvin, 2000). In Section 3, a new model structure and parametrization are proposed. In Section 4, a simulation study shows how the unknown model parameters can be estimated by minimising a maximum-likelihood criterion and demonstrates the good agreement with the more complex, first-principle model. Section 5 is devoted to NMPC. Finally, Section 6 presents some concluding remarks.

2. PROCESS DESCRIPTION

The cement grinding circuit represented in figure 1 consists of a single-compartment ball mill in closed-loop with an air classifier. The raw material flow q_C is fed to the rotating mill, where steel balls perform the breakage of the material particles by fracture and/or attrition. At the other end, the mill flow q_M is lifted up by a bucket elevator to the classifier which separates the material into two parts: the product flow q_P and the retail 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 registers Rp. The sum of q_C and q_R is the total feed flow, denoted by q_F.

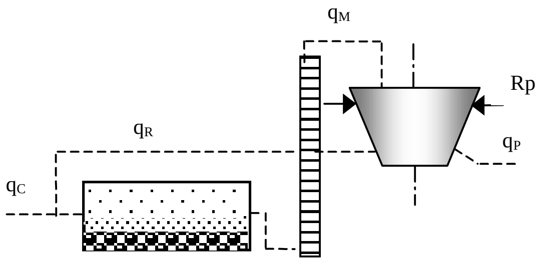

Fig. 1. Closed-loop grinding circuit

Based on the pioneering works of Mika (1971) and Austin (1984), the first-principle model developed in (Boulvin, *et al.*, 1999; Boulvin, 2000) considers the size continuum as divided in N size intervals (numbered from 1 to N towards the lowest sizes, typically N is between 15 and 30) and consists of a set of partial differential equations describing the mass balances for each size interval:

$$\frac{d(Hw_i)}{dt} = -u_i \frac{\partial Hw_i}{\partial x} + D_i \frac{\partial^2 Hw_i}{\partial x^2} - s_i Hw_i + \sum_{j=1}^{i-1} b_{ij} s_j Hw_j \quad (1)$$

where H(x,t) is the material content per unit of length (hold-up) and $w_i(x,t)$ is the weight fraction of material in size interval i. The last two terms are concerned with the fragmentation phenomena: the parameter s_i is the specific rate of breakage for size interval i and the parameters b_{ij} describe the primary breakage distribution from size interval j. The transport phenomena are expressed by the first two terms: u_i and D_i are the convection velocity and the diffusion coefficient for size interval i, respectively.

These PDEs are supplemented with appropriate initial and boundary conditions:

$$Hw_i = H_0(x) w_{0;i}(x) \qquad t = 0 ; 0 \le x \le L \qquad (2)$$

where $H_0(x)$ is the initial hold-up and $w_{0;i}(x)$ the initial weight fraction of material in size interval i, L is the length of the mill;

$$u_i Hw_i - D_i \frac{\partial (Hw_i)}{\partial x} = q_F w_{F;i} \qquad t > 0 ; x = 0 \qquad (3a)$$

$$u_i Hw_i - D_i \frac{\partial (Hw_i)}{\partial x} = \varepsilon_i Hw_i \qquad t > 0 ; x = L \qquad (3b)$$

where $q_F(t)$ and $w_{F;i}$ are the flow rate and the weight fraction in size interval i of the total feed, respectively. ε_i is the classifying effect of the grate discharge and is normally equal to 1.
The effect of the hold-up, which diminishes the efficiency of the grinding process, introduces a strong nonlinearity in the model through the specific rates of breakage s_i.

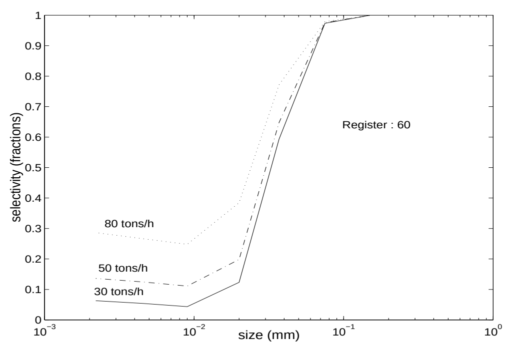

Fig. 2. Separation curves of the classifier

The separation curves of the classifier (see figure 2) can be described by models introduced in (Zhang, 1992). Experimental correlations allow the effect of several variables on the separation curve to be modeled, e.g. the register position or the input flow rate to the classifier (Boulvin, 2000).

In the sequel, the full model is used as an appropriate representation of the closed-loop grinding circuit. It serves as a reference and provides the simulation data used for parameter estimation in Section 4. It also allows the NMPC scheme developed in Section 5 to be tested in realistic scenarii.

3. NEW MODEL FORMULATION

The idea underlying the development of a low-order model is that it is possible to describe the dynamic behavior of the ball mill by monitoring the evolution of the particle distribution between a few size intervals, say three size intervals. This is in contrast with the commonly accepted idea that a large number of size intervals (typically in a geometric progression $1/\sqrt{2}$, see (Austin, 1984)) is necessary to discretize the size continuum and to derive adequate models.
Here two intermediate size limits define three size intervals within the size continuum, numbered 1, 2 and 3 for coarse, medium and fine particles, respectively. To represent the fragmentation phenomena, we consider that the coarse particles break at rate α_1, yielding a mass fraction k of medium particles and a mass fraction (1-k) of fine particles. The medium particles break entirely into fine particles at rate α_2. On the other hand, the transport of particles in each size interval is expressed by means of the convection and diffusion terms considered in previous studies (Boulvin, 2000; Mika, 1971).

The previous considerations lead to the following system of partial differential equations:

$$\frac{dX_i}{dt} = -u_i\frac{\partial X_i}{\partial x} + D_i\frac{\partial^2 X_i}{\partial x^2} + \sum_{j=1}^{2} k_{ij}\varphi_j \qquad ;i = 1,2,3 \quad (4a)$$

$$\left[k_{ij}\right] = \begin{bmatrix} -1 & 0 \\ +k & -1 \\ 1-k & +1 \end{bmatrix} \quad (4b)$$

where:

- X_i is the mass per unit of length in size interval i;
- k is the yield coefficient and φ_i is the breakage rate for material in size interval i;
- u_i is the convection velocity and D_i is the diffusion coefficient for size interval i.

These equations are supplemented by initial and boundary conditions:

$$X_i(0,x) = H_0(x)w_{0;i}(x) \qquad \forall x; i = 1..3 \quad (5)$$

where $H_0(x)$ is the initial hold-up and $w_{0;i}(x)$ is the initial mass fraction for size interval i;

$$0 = u_i X_i - D_i\frac{\partial X_i}{\partial x} - q_{F;i} \qquad x = 0; i = 1..3 \quad (6a)$$

$$0 = \frac{\partial X_i}{\partial x} \qquad x = L; i = 1..3 \quad (6b)$$

where $q_{F;i}(t)$ is the total feed flow rate for size interval i.

By analogy with the description of reaction kinetics in biochemical systems (Bogaerts and Hanus, 2000), the breakage rates φ_i are assumed to be first-order laws modified by exponential factors representing various inhibition effects. In cement grinding, the ventilation of the mill is generally sufficient to avoid the slowing-down effect caused by the accumulation of very fine particles in the mill, so that only the inhibition effect of the material hold-up is taken into account. Hence, the breakage rates can be formulated as follows:

$$\varphi_i = \alpha_i X_i e^{-\beta H} \qquad i = 1,2 \quad (7)$$

where:

- α_i is the specific rate of breakage for size interval i;
- β is the coefficient for the hold-up effect;
- H is the hold-up, that is (X_1+ X_2+ X_3).

This way, the breakage mechanism can be interpreted as a “chemical reaction” with an associated “kinetics”.

On the other hand, the complex separation mechanism (“fish-hook” curve of the classifier) is represented by Zhang’s equations and the correlations mentioned in Section 2 (Zhang, 1992; Boulvin, 2000). These equations are based on the assumption that the size continuum is subdivided in a relatively large number of size intervals (N~15-30).

It is therefore necessary to ensure the compatibility of the two model components (the ball mill and the air classifier) despite the fact that they are based on different numbers of size intervals. Numerous simulation and experimental considerations have led us to the assumption that the material at the mill outlet can be described with reasonable approximation by the following Rosin-Rammler law (Austin, 1984):

$$R(z) = e^{-(\frac{z}{z_0})^n} \quad (8)$$

where R(z) is the weight fraction oversize, the parameters z_0 and n represent the location and the dispersion of the distribution, respectively. Since these two unknown parameters can be uniquely determined with two weight fractions, the mill output distribution - as reproduced by the low-order mill model - can be used to reconstruct a complete size distribution compatible with the classifier model.
The resulting model of the closed-loop grinding circuit, which is given by relations (4-8) is much simpler and the purpose of the next section is to demonstrate the agreement of this simplified model with the complex, first-principle model detailed in Section 2, based on a set of particular experiments.

4. PARAMETER ESTIMATION

The parameter vector θ to be estimated is composed of the parameters k, α_1, α_2, β, u and D (here the transport does not depend on the particle size). The three size intervals are defined by the two intermediate size limits 0.150 and 0.016 mm. The mass content per unit of length in each size interval is measured at discrete times t_i and at regularly distributed points x_j along the mill axis, yielding the measurement vector Y_{ij}. These measurements correspond to the so-called “crash-test” procedure used in the cement industry, in which the ball mill is halted at regular intervals in order to take cement samples at several locations in the mill. The errors on the measurement Y_{ij} are supposed to be normally distributed white noises with zero mean and variance matrix $Q = \sigma^2 I$ (the errors on each component are uncorrelated, so independent because of the normality assumption, of equal variance σ^2 and I is the 3-by-3 identity matrix). The parameter vector θ is estimated using the maximum-likelihood criterion, i.e., the minimization of the cost function $J_{ML}(\theta)$:

$$J_{ML}(\theta) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_x}(Y_{ij} - X_{ij})Q^{-1}(Y_{ij} - X_{ij})^T \qquad (9)$$

The following quantity R:

$$R = \sqrt{\frac{\sum_{i=1}^{N_t}\sum_{j=1}^{N_x}(Y_{ij} - X_{ij})^T(Y_{ij} - X_{ij})}{N_t.N_x}} \qquad (10)$$

compared to the mean value on all the measurements Y_{ij} provides a better estimation of the agreement between measured and predicted values than the cost function.
The lower bound on the parameter covariance matrix $E\left[(\hat{\theta}-\theta)(\hat{\theta}-\theta)^T\right]$, given by the inverse of the Fisher information matrix, can be estimated in the following way (Walter and Pronzato, 1997):

$$F(\hat{\theta}) = \sum_{i=1}^{N_t}\sum_{j=1}^{N_x}\left\{\left(\frac{\partial X}{\partial \theta}\right)_{t=t_i;x=x_j} Q^{-1}\left(\frac{\partial X}{\partial \theta^T}\right)_{t=t_i;x=x_j}\right\} \qquad (11)$$

The minimization of (9) is performed using the "Optimization Toolbox 2.0" from MATLAB 5.3. The solution of the partial differential equations is achieved using (a) a "method of lines" Matlab procedure for spatial differentiation (Stengle, *et al.*, 2000) (b) standard solvers from MATLAB 5.3. for the integration in time of the differential equations.

Experiment 1, used for parameter estimation and direct validation, is designed as follows:

- the grinding circuit is initially in steady state with 23 tons/h of raw material flow rate and register position of 75;
- a step from 75 to 20 is performed on the register position;
- after 40 minutes, a step is performed on the raw material flow rate from 23 to 29 tons/h.

Table 1 Parameter vector: estimates (row 1) and standard deviations (row 2)

k	α_1	α_2	u	D	β
0.875	0.894	0.115	1.012	2.414	0.784
0.005	0.008	0.002	0.001	0.021	0.013

Figure 3 shows the spatiotemporal evolution of the variables X_i and the hold-up in the mill during 80 minutes. It can be noticed that:

- relevant information about the transport phenomena is available thanks to the evolution of the variables along the mill
- the nonlinear effects should be emphasized by the drastic hold-up changes following the steps in t = 0 and t = 40 min.

The estimated values of the parameters are reported in table 1 and figure 4 displays how the predicted values fit the experimental data in a very satisfactory way. This good agreement is also confirmed by the value of R equal to 0.0027 tons/m (compared to the mean value of the Y_{ij} equal to 0.201 tons/m).

Experiment 2, consisting in the initial loading of the mill followed by a supplementary increase of the recirculation, is used for cross-validation (see figure 5). The experiment is designed in order to exhibit a nonlinear behavior in a very drastic way. The experimental and simulation results are compared in figure 6. The numerical value of R equal to 0.0117 tons/m (compared to the mean value of the Y_{ij} equal to 0.237 tons/m) demonstrates how satisfactorily the low-order model reproduces (or predicts) the outputs of the real system (i.e., our reference simulator described in Section 2).

The standard deviations of the parameter estimates, computed with a constant standard deviation of the measurement errors σ = 0.002 tons/m, are very satisfactory (see table 1).

The correlation coefficients, which are reported in table 2, exhibit globally low values, so that confidence intervals can be reliably obtained from the individual standard deviations. However, it must be observed that there exist:

- a strong correlation between the yield coefficient k and the specific breakage rate α_2;
- a strong correlation between each specific breakage α_i and the hold-up coefficient β.

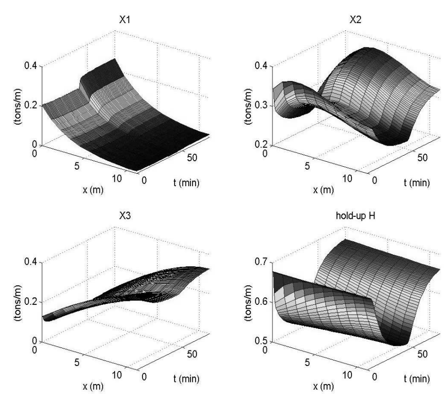

Fig. 3. Experiment 1: space and time evolution of the variables X_i and of the hold-up H

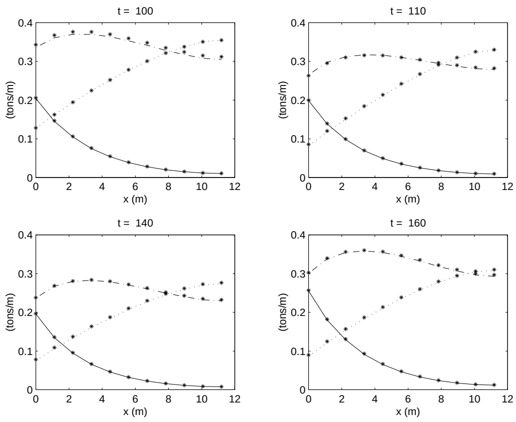

Fig. 4. Experiment 1: direct validation (solid: X_1, dashed: X_2, dotted: X_3, *: experimental values)

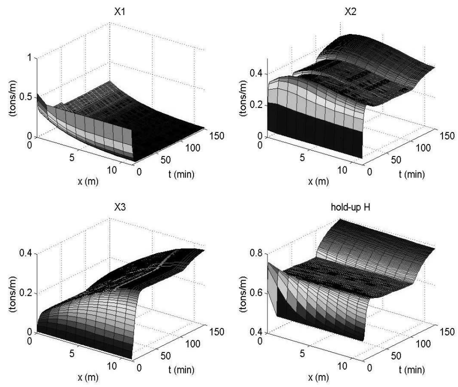

Fig. 5. Experiment 2: space and time evolution of the variables X_i and of the hold-up H

Table 2 Correlation coefficients

	k	α_1	α_2	u	D
α_1	+0.35	--	--	--	--
α_2	+0.83	+0.73	--	--	--
u	+0.12	-0.01	+0.13	--	--
D	+0.61	-0.02	+0.40	+0.49	--
β	+0.51	+0.89	+0.90	+0.13	+0.14

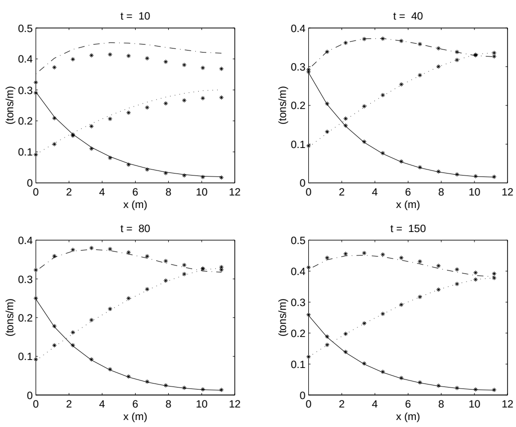

Fig. 6. Experiment 2: cross-validation (solid: X_1, dashed: X_2, dotted: X_3, *: experimental values)

These abnormal correlation values could be diminished by designing appropriate experiments in which:

- appearance of medium-size particles (breakage of coarse particles) and disappearance of these particles (due to breakage) are not simultaneous;
- hold-up could be maintained constant despite the fact that the recirculation is very sensitive to the changes in the particle distribution.

Such experiments are almost impossible to achieve in practice and an in-depth analysis should probably include a mix of experiments, e.g., crash-tests, tracers,… combined with appropriate experiment design. Such aspects, which are beyond the scope of this study, are already tackled by the authors.
The purpose of the next section is to show how the simplified model can be used in a model-based control scheme, such as nonlinear predictive control.

5. PREDICTIVE CONTROL

Nowadays, in most industries, the material fed to the grinding circuit can be stored in several sites (not completely closed buildings, outdoor stockpiles) and hence subject to different atmospheric conditions. This storage policy leads to some variations in the material physical characteristics, e.g., its grindability. If the operators wish to control the fineness of the product, a typical control strategy could be (a) to obtain a prior measurement of the grindability change, e.g., by laboratory-scale grinding tests (b) to implement a control of the fineness taking into account the foreseeable evolution of that disturbance. A nonlinear model predictive control (NMPC), using the simplified model presented in section 3, appears to be well suited to achieve this strategy. Since the Blaine of the product (specific surface commonly adopted as a measurement of the fineness in industrial practice) cannot be computed with a few size intervals only, the percentage of material in a specific size interval constitutes an alternative fineness objective.

NMPC, in accordance with the classical formulation, consists in determining a set of manipulated-variable moves over a control horizon of N_u sampling periods which minimizes an objective function J over a prediction horizon of N_h sampling periods. The register position (Rp) and the weight fraction of the fine particles in the product are selected as the manipulated and the controlled variables, respectively. The objective function is expressed as an output-error least-square criterion measuring the deviation of the predicted values from the set point. This criterion is subject to bound constraints on the register position, i.e. $0 \le Rp \le 100$.

The effect of modeling errors is treated as an additive, unmeasured disturbance in a way similar to DMC. The process state vector is supposed available at each sample time (in practice, a state observer should be designed). The disturbance is estimated by $d_k = x_{measured;k} - x_{model;k}$ (t_k being the sample time).

The NMPC program is implemented using the "Optimization Toolbox 2.0" and standard solvers from MATLAB 5.3.

The manipulated variable is constituted of one move over the entire horizon (N_u=1). The selected values of the sampling period T_s and the horizon are respectively 10 min and 50 min (N_h=5), that is, about 0.5 and 2 times the time constant of the circuit.

Consider the following process set point:

- feed flow rate = 25 tons/h, Rp = 37
- weight fraction of the fine particles in the product = 0.774, spec. surface = 5050 cm^2/g

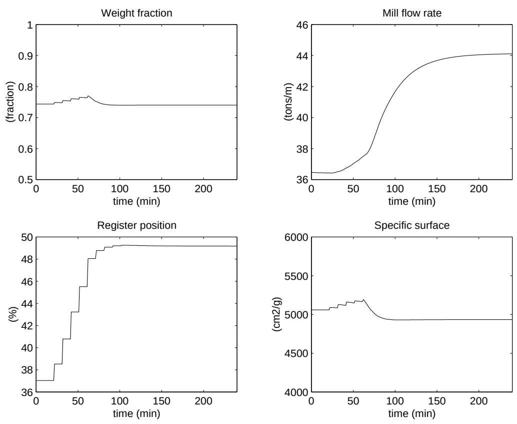

Fig. 7. Predictive control results

A decrease of 15 % in the grindability of the raw material occurs after 60 min.

Figure 7 shows the temporal evolution of the weight fraction, the mill flow rate and the register position. NMPC induces no instability and the steady state is reached within reasonable time limits (80 minutes). On the other hand, the evolution of the Blaine specific surface shows that a control of the particle content in the fine-size interval could be sufficient to guarantee the fineness of the product. This latter observation allows further investigations to be achieved in order to more thoroughly evaluate the potentials of this control policy.

6. CONCLUSION

In this study, a low-order model for a ball mill, which describes mass balances between a reduced number of size intervals, is introduced. Combined with Zhang's relations for the classifier, it provides a simplified representation of a cement closed-loop grinding circuit. The parameters of the ball mill are estimated using "crash-test" simulation data from a previously developed, complex model. The validation procedures as well as the standard deviations on the estimates demonstrate the reliability of the identified model. The correlations between the parameters also suggest an in-depth analysis of experiment design using new techniques (e.g., tracers). To illustrate the potentials of the new model formulation, a nonlinear model predictive control (NMPC) scheme is designed to control the cement fineness when measurable grindability changes occur in the feed material. The fineness control objective - defined by means of a single size interval - is compatible with traditional fineness objectives defined in terms of Blaine specific surface to be fulfilled. Further research is needed to define relationships between size distribution (in one or two intervals) and the cement properties.

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