NONLINEAR MODEL PREDICTIVE CONTROL OF CEMENT GRINDING CIRCUITS

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Abstract: Based on a reduced-order model of a cement grinding circuit, a nonlinear model predictive control strategy is developed. The first step of this NMPC study is the definition of control objectives which consider product fineness, product flow rate and/or grinding efficiency. At this stage, one of the main concerns is to relate these objectives to easily measurable particle weight fractions. Second, NMPC is implemented so as to take the various constraints on the manipulated variables and operating conditions of the mill into account. Third, robustness with respect to model uncertainties is analyzed, and the most critical parameters are highlighted. Finally, an NMPC scheme, combining a stable inner loop for controlling the mill flow rate and a DMC-like compensation of the model mismatch, is proposed.

Keywords: nonlinear systems; modeling; predictive control;
grinding (comminution); cement industry

1. INTRODUCTION

Control of cement grinding circuits is a delicate task. According to (Hulbert, 1989) and (Hodouin and Del Villar, 1994), the difficulties associated with control arise from two major causes:

- process complexity and nonlinearity: grinding depends on the material content of the mill, separation is affected by the material flow rate and the process has recycle;
- lack of measurements: some variables cannot be measured on-line, others are heavily corrupted by noise.

In recent years, some studies have witnessed the relevance of model predictive control for cement grinding processes. In (Martín Sánchez and Rodellar, 1996), a single mill is considered (no downstream classification) and maximization of the product flow rate is achieved while stabilizing the degree of material filling. In (Magni *et al.*, 1999), a nonlinear model of a grinding circuit has been developed and the delicate problem of stability has been treated. These studies essentially consider global variables, e.g., flow rates, total material content of the mill,. . . .

In contrast with these studies, the authors have focused on the transport of the material in the mill and, mostly, on the particle size distribution, which is highly related to the final properties of cement, such as the compressive strength. From this latter philosophy, they have developed:

(1) a distributed-parameter population model, which has been identified on an industrial closed-loop grinding process (C.B.R., Belgium) (see (Boulvin, 2000) and (Boulvin *et al.*, 2002));

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(2) a simplified distributed-parameter model, based on a reduced number of size intervals (Lepore *et al.*, 2002).

The contribution of the present study is:

- to formulate new control objectives in agreement with the coarser size discretization used in the reduced-order model (2), i.e., a) a well-determined fineness of the product, b) either a maximization of the product flow rate or an optimization of the grinding efficiency;
- to design a multivariable, constrained NMPC scheme achieving these objectives, which considers the input flow rate and the classifier selectivity as manipulated variables. Constraints apply a) on magnitudes and slew rates of the inputs (saturation effects), b) on the mill flow rate variable (preventing temperature increase and/or wear as well as mill overfilling);
- to treat the following aspects of model inaccuracy: to investigate NMPC robustness to model uncertainties, to perform a thorough parameter sensitivity analysis and to study two types of model mismatch compensation: (a) a typical DMC-like scheme, which considers the mismatch as a constant disturbance over the prediction horizon, (b) the DMC-like scheme with prior stabilization of the mill flow rate by a proportional control loop.

In the sequel, the document is divided into five sections. Section 2 contains the description of the process and the equations of the reduced-order model. New control objectives are formulated in Section 3. In Section 4, the NMPC strategy is presented, then robustness analysis is considered in Section 5. Some conclusions and perspectives are finally presented in Section 6.

2. PROCESS DESCRIPTION AND MODELING

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 Rp. The sum of q_C and q_R is the total feed flow, denoted by q_F.

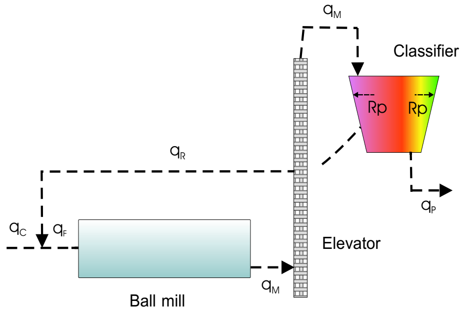

Fig. 1. Closed-loop grinding circuit

2.2 Modeling

Consider the size continuum as divided into three size intervals numbered 1, 2 and 3 for the coarse, intermediate 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 size interval i;
- k is the yield fraction of the particles in size interval 2 appearing from the breakage of the particles in size interval 1; φ_j is the breakage rate of the material in size interval j;
- u_i is the convection velocity and D_i is the diffusion coefficient of the particles in size interval i;

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

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

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

$$0 = \frac{\partial X_i}{\partial x} \quad \text{x=L; i=1,2,3} \tag{3}$$

where:

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

The breakage rates are formulated as follows:

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

where:

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

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

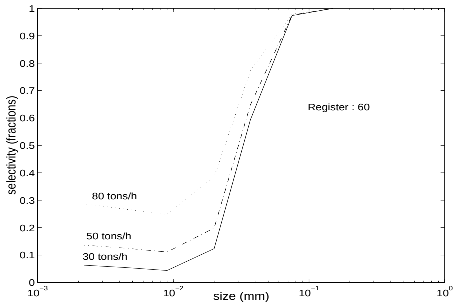

Fig. 2. Classifier selectivity (for a single register position and several mill flow rates)

3. CONTROL OBJECTIVES

The compressive strength specified by the client is the main goal of the cement manufacturer. Among the many characteristics of cement, the chemical composition, which is essentially set during the kiln operation, and the particle size distribution are the variables influencing at most the compressive strength. So, given the chemical composition (as it is considered for the grinding circuit), the compressive strength is dependent a priori on the total particle size distribution, which represents a very complex, hardly interpretable objective.
However, from recent industrial results (experimental data collected at C.B.R., Belgium), it appears that a strong relationship exists between the compressive strength and the weight fraction of the fine particles in the product, denoted by $w_{P;3}$. In figure 3 ($w_{M;2}$ is the weight fraction of the intermediate particles at the mill outlet), the arc $\overline{AB}$ represents all operating points corresponding to some constant $w_{P;3}$ that are compatible with operational restrictions on the mill flow rate, which prevent on the one hand dramatic temperature increase and/or wear of the equipment (e.g., at least 50 t/h), on the other hand mill overfilling (e.g., at most 140 t/h).

The second objective, usually more related to the economical strategy of the company itself, will set a well-determined operating point on the characteristic $\overline{AB}$. One common strategy is the maximization of the product flow rate. Provided that the process characteristic $\overline{AB}$ is available, this objective can be uniquely identified by the corresponding value $w_{M;2}^{Pmax}$ (see point 1). This strategy requires the process to be run at the stability limit. In fact, the arcs $\overline{A1}$ and $\overline{1B}$ correspond to stable and unstable operating points, respectively.
Another strategy could be to optimize the grinding efficiency or, in other words, to avoid overgrinding. From our description based on three size intervals, it is suggested to achieve this goal by avoiding at maximum coarse particles (obviously!) and also fine particles (overgrinding) at the mill outlet. So, increasing $w_{M;2}$ up to a reasonable limit, could be the criterion (e.g., point 2). It is noted that this strategy requires the process to be run completely in the unstable region.

Several advantages arise from using $w_{P;3}$ and $w_{M;2}$ as controlled variables:

- the measurements are simple (two sieve measurements only for each variable) and can be achieved automatically at moderate cost; measurement error is small since one can expect high values for $w_{P;3}$ ($0.7 \sim 0.8$) and $w_{M;2}$ ($0.5 \sim 0.7$); the measurement of $w_{M;2}$ is more reliable than, say, the elevator power which is very affected by mechanical vibrations (low-frequency noise);
- the use of $w_{M;2}$ for the achievement of operating point 1 converts an ill-conditioned optimization problem (well-determined product fineness and maximization of the product flow rate) into a well-conditioned minimization of an output error.

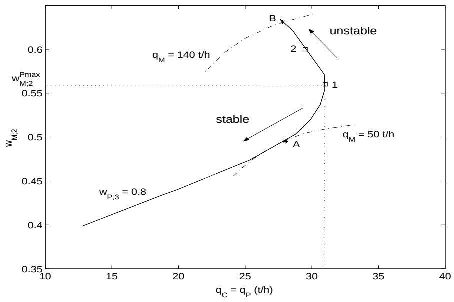

Fig. 3. Steady-state relationship for constant $w_{P;3}$

4. NMPC STRATEGY

NMPC consists in determining a set of manipulated-variable moves over a control horizon of N_u sampling periods that minimizes an objective function J over a prediction horizon of N_h sampling periods. The manipulated variables are the feed flow rate q_C and the register position Rp and the controlled variable y is the vector $[w_{P;3}\ w_{M;2}]^T$. At time instant k, the function J and the reference trajectory $y_{r;i}$ are defined as follows:

$$J(k) = \sum_{i=1}^{N_h} (y_{r;i} - \hat{y}_{k;i})^T Q (y_{r;i} - \hat{y}_{k;i}) \qquad (5)$$

$$y_{r;i} = y^* + (y_k - y^*)e^{-\frac{iT_s}{T_r}} \tag{6}$$

where:

- $\hat{y}_{k;i}$ is the predicted value at time $(k + i)T_s$;
- $y_{r;i}$ is the reference value at time $(k + i)T_s$;
- Q is the weighting matrix
- T_s is the sampling period;
- T_r is the time constant of the reference trajectory;
- y^* is the two-component set point $[w^*_{P;3}\ w^*_{M;2}]^T$
- y_k is the two-component measured value

In addition, the following constraints apply:

- box constraints on the manipulated variables: $0 \leq q_C \leq q_C^{max}$ (saturation of the feeding mechanism), $0 \leq Rp \leq Rp^{max}$ (minimum and maximum displacement of the registers)
- linear constraints on the manipulated variables (limits to the slew rates): $\mid q_C(i+1) - q_C(i) \mid \leq \Delta q_C^{max}$, $\mid Rp(i+1) - Rp(i) \mid \leq \Delta Rp^{max}$
- nonlinear constraints: limits to the mill flow rate value at the end of the prediction horizon preventing high cement temperatures ($q_M((k + H_p)T_s) \geq q_M^{min}$), mill overfilling ($q_M((k + H_p)T_s) \leq q_M^{max}$)

Table 1 contains the values of the most important parameters mentioned above.

T_s	10 min	q_C^{max}	50 t/h	q_M^{min}	50 t/h
T_r	10 min	Rp^{max}	100	q_M^{max}	140 t/h
H_u	1	Δq_C^{max}	10 t/h	Q	$I_{(2,2)}$
H_p	5	ΔRp^{max}	50		

Table 1. Parameter values of the NMPC

The minimization of the objective function (5) is performed using the "Optimization toolbox 2.0" from Matlab 6.0. 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 6.0 for the integration in time of the differential equations.

5. ROBUSTNESS ANALYSIS AND MODEL MISMATCH COMPENSATION

In the sequel, we will (1) study the effect of grinding efficiency on steady-state characteristics , and, in turn, on the performance of the NMPC (2) evaluate systematically the impact of individual changes in the parameters (sensitivity analysis) (3) discuss two correction schemes, i.e., a simple DMC-like scheme and a DMC-like scheme with prior stabilization of the mill flow rate by an internal proportional loop.
For illustration purposes, we consider a step change in the set point y^* from the steady-state value $[0.71\ 0.46]^T$ (stable region) to $[0.80\ 0.56]^T$ (stability limit).

5.1 Effect of grinding efficiency on steady-state characteristics

Occurrences of model mismatch are obtained by modifying the process specific rates of breakage $\alpha_i^{mod} = \alpha_i^{proc} \cdot C$ $(i = 1, 2)$; cases (a) $(C = 0.9)$ and (b) $(C = 1.1)$ correspond to lower and higher efficiency, respectively. The static characteristics for the process and the two model occurrences are represented in figure 4, circles indicate the two corresponding operating points targeted by the optimization algorithm.

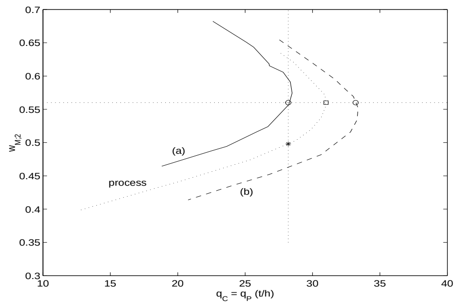

Fig. 4. Steady-state relationship for $w_{P;3} = w^*_{P;3}$; (a): $C = 0.9$; (b): $C = 1.1$

From the temporal evolution of the most relevant variables (see figure 5), it can be deduced that:

- in case (a), the high gain existing between Rp and $w_{P;3}$ allows the desired steady-state value $w_{P;3} = 0.8$ to be reached for the process. On the other hand, the input flow rates computed by the algorithm drive the process to the operating point represented by a star in figure 4 ($w_{M;2} = 0.498$); so, NMPC leads to the desired product fineness but to lower production flow rate than expected, the difference increasing with the model mismatch;
- in case (b), the manipulated-variable values computed by the optimization algorithm (particularly a too high input flow rate) lead inevitably to process overfilling. As a result, the two weight fractions, $w_{P;3}$ and $w_{M;2}$, tend to zero.

5.2 NMPC sensitivity to individual parameter inaccuracies

In the sequel, each parameter is modified by -10% and $+10\%$ from the estimated value and figure 6 represents the resulting effect on the steady-state characteristics. It is mostly noted that:

- variations in α_2 affect substantially the behaviour of the model whereas those in α_1 do not (in fact, the lower values of α_2 determine the dominant time constants of the model);

- the parameters k and β are as relevant as α_2;
- changes in the velocity u and, particularly, the diffusion D have little influence on the steady-state characteristics.

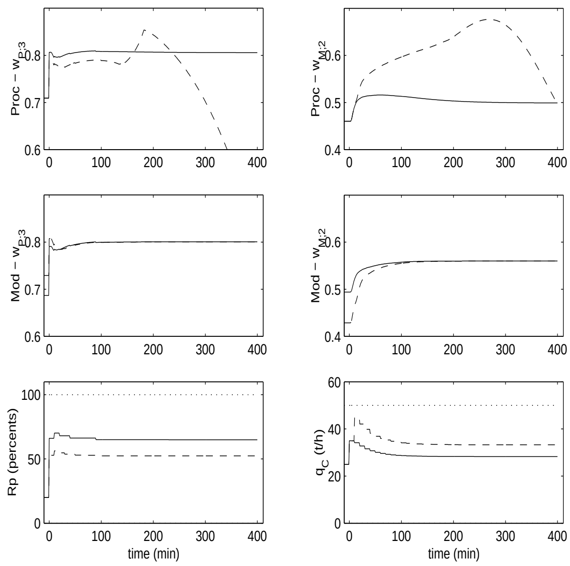

Fig. 5. NMPC performance with model mismatch (solid) : $C = 0.9$; (dashed) : $C = 1.1$; (dotted): maximum value constraints

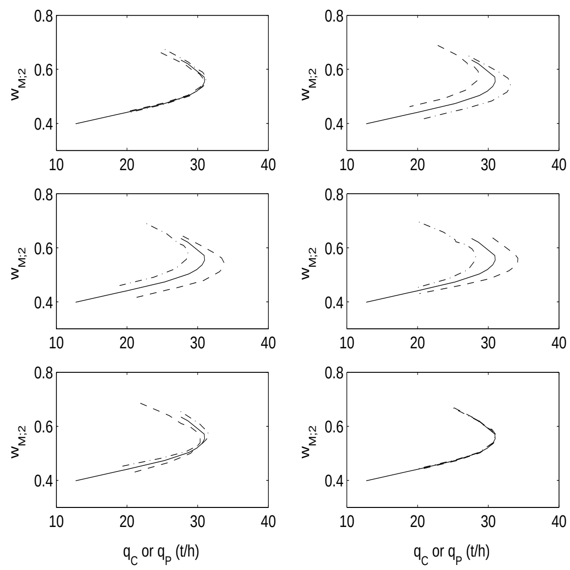

Fig. 6. Parameter sensitivity analysis : α_1 and α_2 (top figures), k and β (intermediate figures), u and D (bottom figures); (dashed) -10%, (dash-dotted) $+10\%$ on the parameter estimate, respectively

5.3 Model mismatch compensation

5.3.1. DMC-like scheme In this scheme, the mismatch at time t_k between the process and the model is viewed as an external, constant disturbance on the state vector all over the prediction horizon. The disturbance d_k is first estimated by $d_k = x_{proc;k} - x_{mod;k}$, then the reference trajectory is adjusted by the corresponding constant value over the prediction horizon. Figures 7 and 8 show the following results when this correction is applied in cases (a) and (b) of model mismatch:

- case (a): the modified reference trajectories (dotted lines) require the model to be run in the unstable region where constraints on the mill flow rate variable (140 t/h) become active (see the evolution of the model prediction in figure 8). This constraint is responsible for the limitation on the input flow rate q_C. The closed-loop process is stable but the steady-state values (particularly $w_{M;2}$) are not satisfactory;
- case (b): the modification of the reference trajectory brings the targeted set point into the stable region, so that the closed-loop process is stable and no steady-state error appears.

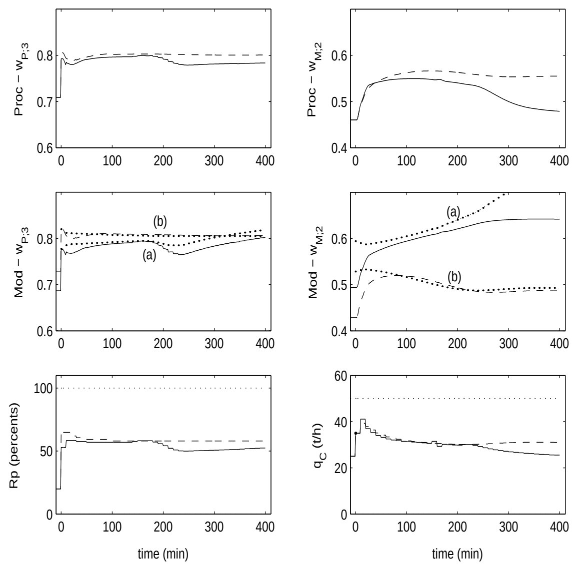

Fig. 7. DMC-like compensation results; (solid): $C = 0.9$, (dashed): $C = 1.1$

In conclusion, the DMC-like correction, which considers the model inaccuracy as a disturbance, guarantees feasibility and stability but does not guarantee satisfactory performance, particularly with respect to the steady-state error of $w_{M;2}$.

5.3.2. DMC-like scheme with prior stabilization Two embedded schemes are used: (a) an inner proportional loop controls the mill flow rate by acting on the input flow rate and ensures stable operation (b) the outer scheme is the NMPC itself which uses the mill flow rate set point q_M^* of the inner loop instead of the input flow rate q_C as the second manipulated-variable component. The

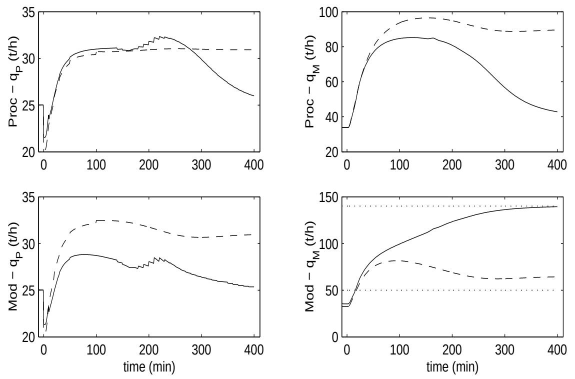

Fig. 8. DMC-like compensation results; (solid): $C = 0.9$, (dashed): $C = 1.1$

capabilities of the NMPC are entirely devoted to the performance achievement. Box constraints apply on q_M^* (0 and 200 t/h) and supplementary nonlinear constraints apply on the absolute value of q_C, which is now an intermediate variable.

Figure 9 shows the results obtained when the correction is applied to cases (a) and (b). Both cases demonstrate stability, satisfactory time responses and negligible steady-state error.

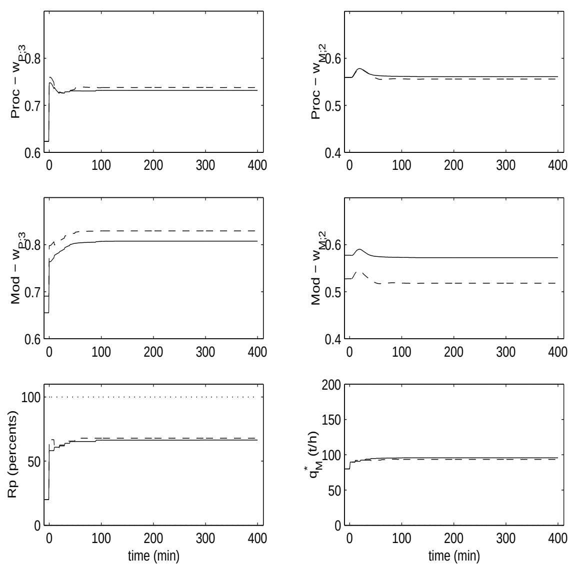

Fig. 9. DMC-like with prior stabilization; (solid): $C = 0.9$, (dashed): $C = 1.1$

6. CONCLUSION

Based on a reduced-order model of a cement grinding plant, a nonlinear model predictive control strategy is developed and analyzed. As a first step, new control objectives are defined, which are based on two weight fractions only: (a) the fraction of fine particles in the product, which is related to the compressive strength (b) the fraction of intermediate-size particles at the mill output, which is related to product maximization or optimum grinding efficiency. One major advantage is that two-sieve measurements of these variables could be achieved at low cost.

NMPC achieves these objectives by using the registers' position and the input flow rate as manipulated variables.

Robustness analysis leads to the following observations:

- model mismatch may lead to closed-loop instability (for example when the model has higher grinding efficiency); otherwise, steady-state errors affect the mill output but not the product fineness;
- not all the individual parameters have the same impact; experiments should be designed to accurately estimate grinding efficiency and, particularly, the appearance and the disappearance mechanisms of the intermediate-size particles and the inhibition effect of the material content;
- a DMC-like scheme cannot guarantee satisfactory performance; however, when a prior stabilization of the mill flow rate is achieved (here with a simple proportional loop using the input flow rate as a manipulated variable), very satisfactory results are obtained with DMC-like scheme in terms of stability and steady-state error.

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