Robust Stabilization of Cement Milling Process Using Efficient Simulations

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Abstract: - A simulation of the dynamic behavior of an actual cement mill (CM) is described aiming to optimize an existing PID controller. The M-constrained Integral Gain Optimization (MIGO) method is implemented to compute the basic parameters set. As optimization criterion the Integral of Absolute Error (IAE) is considered. The optimized PID is put in operation and the performance is evaluated. The real process modeling and simulation offers also the possibility to investigate other control strategies.

Key-Words: - Dynamics, Cement, Mill, Grinding, Model, Uncertainty

1 Introduction
The robust feedback stabilization of cement grinding circuits is a delicate task. Nonlinearities, existence of external disturbances, uncertainties and model mismatches require the control engineers to tune or to design controllers able to alleviate the stated obstacles. For productivity and quality reasons, grinding mostly is performed in closed circuits: The ball cement mill (CM) is fed with raw materials. The milled product is fed via a recycle elevator to a dynamic separator. The high fineness stream of the separator constitutes the final circuit product, while the coarse material returns back to the CM to be ground again. In the current automatics one of the following has usually selected as process variable. (1) The power of the recycle elevator. (2) The return flow rate from the separator. (3) An electronic ear in the mill inlet. (4) The mill power or combination of the above.

As it has been noticed by Astrom et al. [1] in the industrial process control the PID type controllers constitute a percentage more that 95% of the installed ones but only a small portion of them operate properly as Ender [2] points out. J. Wang [3] developed a multivariable PID decoupling controller for grinding systems. However linear controllers based on a linear approximation of the process, are stable and effective only in a range around the nominal operating point. To overcome this constraint, several designs based on Model Predictive Control strategies have been developed with varying degrees of complexity [4-11] usually based on non linear models. The common between all these designs is the assumption of a model describing the process dynamics. Boulvin et al.[12], Tsamatsoulis [13] and Huusom et al [14] developed models based on the solution of the differential equations of the grinding circuit mass balances, describing in detail the grinding and separation process. In spite that the corresponding simulations predict accurately the closed circuit behavior, it is not easy to apply them for on line automatic control of a CM, because of their complexity. But they can be proved very strong tools for off-line tuning of existing controllers.

However design based on linearization maintains its popularity since the field of nonlinear control still does not offer systematized procedures [7]. For the model based control of a CM, not only the values of the dynamic model parameters are necessary, but also their uncertainty. Sometimes there is a lack of actual information about the parameters uncertainty that could lead the simulations used to tune the controller coefficients to not optimum results. On the other hand frequently the process engineers shall tune an existing controller, supplied with the CM operating system, usually of PID type, not having the opportunity to apply another control law. Tsamatsoulis built on simplified dynamical models of given CM, derived from long term and real time operating data [15] by expressing them with the respective transfer functions and estimating simultaneously the parameters uncertainty. Then the M-constrained integral gain optimization (MIGO) method was applied to tune the existing PID controllers. MIGO described in [1], proved to be a
very effective loop shaping methodology. For the same models and tuning method, Tsamatsoulis [16] developed an initial optimization algorithm, to find the optimum between the proportional, integral and differential parameters \((k_p, k_i, k_d)\), derived by the MIGO application. Aim of the present study is improve the simulator of the cement mill operation developed in [16], by incorporating additional process dynamics characteristics. The simulator is applied to CM6 of Halyps cement plant and four months actual operating data are considered. Using the simulator the optimum of the \((k_p, k_i, k_d)\) sets, found by implementing the MIGO method, is searched and then applied to the real CM circuit. The actual CM results are assessed by comparing with the previous CM operational data.

2 Process Model

The purpose of the existing CM automatic operation is to keep the power of the recycle elevator as much as possible constant around a set point by changing the mill feed flow rate. Therefore the power elevator constitutes the process variable, while the feed flow rate is the control variable. The cement mill feedback loop is presented in the simplest possible form in Figure 1. All the system main components appear: The grinding process \(G_p\), the filter added to attenuate the measurement noise \(G_f\), the weight feeders transfer function \(G_w\) and the controller \(G_c\). The additional characteristic added to the simulator in comparison with the one examined in [16], is the dynamic of the weight feeders, proven to play an important role in the CM regulation.

As disturbances, \(d\), can be considered changes in the cement composition, grindability, raw materials temperature. Another portion of the disturbance is represented by the gas flow rate; its heat and the mass flow of the separator return. Additionally, to avoid undesirable noise, a first order filter is added to the power signal. The transfer functions of the different components are provided from the equations (1) to (7).

Weight feeders:

\[
G_w = \frac{u_1}{u} = \frac{1}{1 + T_w \cdot s} \tag{1}
\]

Where \(T_w\) = the feeders first order time constant equal to 12 sec (0.2 min).

Cement mill circuit:

\[
G_p = \frac{x}{u_1} = \frac{k_v \cdot e^{-T_d \cdot s}}{s} \tag{2}
\]

\[
x = KW - KW_0 \tag{3}
\]

\[
u_1 = Q - Q_0 \tag{4}
\]

Where: \(k_v\) = the gain \((\text{h/tn})\), \(T_d\) = the delay time \((\text{min})\), \(KW\) = the current elevator power \((\%)\), \(Q\) = the mill inlet flow rate \((\text{tn/h})\), \(KW_0\) = the elevator power \((\%)\) and \(Q_0\) = the mill inlet flow rate in steady state conditions. The parameters average values and the corresponding uncertainties expressed as standard deviations are the following [15]:

\[
k_v = 3.2 \times 10^{-2} \pm 1.1 \times 10^{-2} \text{h/tn}, \quad T_d = 10.3 \pm 4 \text{ min}
\]

\[
Q_0 = 66.8 \pm 2.1 \text{ tn/h}, \quad KW_0 = 36.6 \pm 6.6 \%
\]

Filter:

\[
G_f = \frac{y}{x} = \frac{1}{1 + T_f \cdot s} \tag{5}
\]

Where: \(T_f\) = the first order filter time constant equal to 3 min.

Error:

\[
e = y_{sp} - y \tag{6}
\]

Where \(y_{sp}\) = the set point of the recycle elevator power.

Controller:

\[
u = k_p \cdot \frac{e}{s} + k_i \cdot \frac{e}{s} + k_d \cdot \frac{e}{s} \tag{7}
\]

Where: \(k_p, k_i, k_d\) = the proportional, integral and derivative parts of the PID controller respectively.

The equations (6) and (7) expressed in time difference form are given by (8), (9).

\[
e_n = y_{st} - y \tag{8}
\]

\[
u_{next} = u_{prev} + k_p \cdot (e_n - e_{n-1}) + \frac{\Delta t}{60} \cdot k_i \cdot e_n + k_d \cdot \frac{\Delta t}{\Delta t} \cdot (e_n + e_{n-2} - 2 \cdot e_{n-1}) \tag{9}
\]

Where \(\Delta t\) = the sampling period in seconds, \(u_{prev}\) and \(u_{next}\) the previous and next set points of the weight feeders. The current value of the sampling

Figure 1. Feedback control loop
period is 1 sec. The subscripts n, n-1, n-2 correspond to three successive sampling instances. The set point of the feeders is updated every Δt_feed in seconds that is a parameter for optimization. Subsequently Δt_feed = k ∙ Δt, where k ≥ 1.

3 Process and loop simulation
As performance criterion the sensitivity function is selected computed by (9). The maximum sensitivity, Ms, calculated by (10), is used as robustness measure.

\[
S = \frac{1}{1+G_c G_w G_p G_f} \quad (9)
\]

\[
M_s = \text{Max}(|S(i\omega)|) \quad (10)
\]

The performance of the implemented controllers is assessed in the following way:
- Based on existing software the operating CM data are accessed on line.
- As sampling period one minute is chosen. Therefore in 24 hours, up to 1440 points are loaded.
- For a given set point of the power, \( y_{sp} \), the automatic mode operation performance is evaluated via the Integral of Absolute Error – IAE – computed by (11).

\[
IAE = \frac{1}{10} \int_0^{10} \left| KW(t) - KW_{sp} \right| dt \quad (11)
\]

A constraint in the M_s is placed and the sets \((k_p, k_i, k_d)\) are determined, from \(k_d=0\) up to a maximum value of \(k_d\) satisfying the M_s constraint. As \(k_d\) increases, the same also occurs for \(k_p, k_i\). The function between the PID coefficients for M_s values ranging from 1.3 to 2.5 is shown in the Figures 2 and 3.

4 Results and Discussion
4.1 Initial Simulations
Initially for a given time constant of the feeders, T_w, the impact of the period of updating the feeder set point on the optimum PID and on the minimum IAE is studied. As T_w a value of 4 sec is considered. For all the range of M_s and k_d the simulation is applied for Δt_feed = 1 sec. The results are shown in Figure 4.

The simulation verifies the assumption, that for the same maximum sensitivity, the IAE is not the same for different k_d. For these settings an optimum \((M_s, k_d)\) area appears: 1.4≤ M_s ≤1.7 and 0 ≤ k_d ≤3.4

The time Δt_feed is a design parameter. For a given M_s=1.5 and T_w=4 sec the optimum time Δt_feed is searched for all the k_d range. The results are depicted in Figure 5.
As it is concluded from Figure 5, the selection of $\Delta t_{\text{Feed}}$ has a severe impact on the optimum IAE. For $\Delta t_{\text{Feed}}=T_w$, a minimum IAE is obtained, for a wider range of $k_d$.

### 4.2 Optimum PID for actual feeder time constant

As it referred in section 3, the average time constant of the CM6 feeders is 12 sec. This value is utilized to find the optimum controller and the optimum time $\Delta t_{\text{Feed}}$. Initially an $M_s=1.5$ is selected and $\Delta t_{\text{Feed}}$ is varied from 3 to 20 sec. The results are shown in Figure 6. The strong impact of $\Delta t_{\text{Feed}}$ on the IAE is obvious from this figure. A selection $\Delta t_{\text{Feed}}=T_w$ provides an optimum IAE.

From the optimum area the following set is selected and placed on the actual PID: $(k_p, k_i, k_d) = (1.089, 0.02, 4)$ corresponding to an $M_s=1.5$. The performance of the controller is evaluated calculating the daily IAE as described in section 3. The results are shown in Figure 8. The set of data “Trial and Error” corresponds to the initial tuning of the controller by trial and error, while the “MIGO Init” to a tuning using MIGO method but without optimization. The “MIGO Opt In” is based on an initial optimum tuning according to [16]. Finally the set “MIGO Opt Fin” corresponds to the values mentioned before and based on the optimal tuning described.
6 Conclusions
The dynamic behavior of an actual cement mill is simulated efficiently, taking into account all the main process components including the feeders time constant as well as the time interval the feeders’ set points are updated. It is proven that the values of these two last variables play a significant role to the regulating process. The simulation is utilized to optimize the operation of an existing PID controller. The basic parameters sets are derived using the M-constrained Integral Gain Optimization (MIGO) method for different maximum sensitivities. Then the optimum range of sets is determined via the simulation by minimizing the IAE. One set belonging to the optimum area is placed in operation, providing a significant improvement of the actual daily average IAE. Thanks to the process modeling and simulation other control strategies could also deeply investigated to a high energy consuming process as the grinding is.

References: