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SIMULATION AND DEVELOPMENT OF INTERNAL MODEL CONTROL APPLICATIONS IN THE BAYER PROCESS

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Traditional PID feedback control system is limited in its use in the Bayer cycle due to the important and omnipresent time delays which can lead to stability problems and sluggish response. Advanced modern control techniques are available, but suffer in an industrial environment from a lack of simplicity and robustness. In this respect the Internal Model Control (IMC) method may be considered as an exception. After a brief review of the basic theoretical principles behind IMC, an IMC scheme is developed to work with single-input, single-output, discrete-time, nonlinear systems. Two applications of IMC in the Bayer process, both in simulations and on industrial plants, are then described : control of the caustic soda concentration of the aluminate liquor and control of the Al2O3/Na2O caust. ratio of the digested slurry. Finally, the results obtained make this technique quite attractive for the alumina industry.

INTRODUCTION

Automatic process control in hydrometallurgical processing and especialy in the Bayer process has greatly developed during the past few years. The main reasons are:

- the relative inexpensiveness of computers,
- the availibility of accurate and reliable on-line measuring instruments,
- the fact that the 1980s are a decade of modernization and upgrading rather than new-plant construction,
- a better understanding of the effects of important variables on process behaviour.

Indeed the process understanding has rapidly improved through complex unit modelling and steady-state /dynamic simulation of complete mineral processing plants.

But these developments have generally been made without the aid of most of the modern control techniques because of the performance requirements and the system characteristics encountered in the hydrometallurgical process industries.

Back to the Bayer cycle, systems are most often sluggish and strongly nonlinear with dynamics being usually well approximated by a first, second or third order lag combined with a dead time. The requirements on the closed loop transient responses are generally loose, the problem being essentially of the regulatory type (no offset). Finally the major important issue for control systems, at least in the alumina industry, is perhaps to be easily understandable and adjustable by operating personnel without university level training [1]. The ability of the Internal Model Control (IMC) scheme to deal effectively with these issues has made it quite attractive for industrial applications.

In this paper a brief review of IMC is proposed and two applications in the Bayer cycle are described to illustrate the transparency and the robustness of the IMC structure : control of the caustic soda concentration of the aluminate liquor and control of the Al2O3/Na2O caust. ratio of the digested slurry. The underlying theme of this paper is the practical approach to the design of control schemes via process modelling and dynamic simulations.

INTERNAL MODEL CONTROL

The IMC Structure

Consider the block diagram for the basic IMC structure shown in figure 1. The process is represented by its Laplace transfer matrix H(s) and $\tilde{H}(s)$ is the transfer matrix of the process model. The input signal to the controller G(s) results from the comparison between a setpoint vector $\underline{s}(s)$ and a feedback signal $\tilde{\underline{d}}(s)$ equal to the difference between the measured process output vector $\underline{y}(s)$ and the model output vector $\underline{Ym}(s)$. The disturbance vector is called $\underline{d}(s)$ and $\underline{u}(s)$ is the input signal to the process.

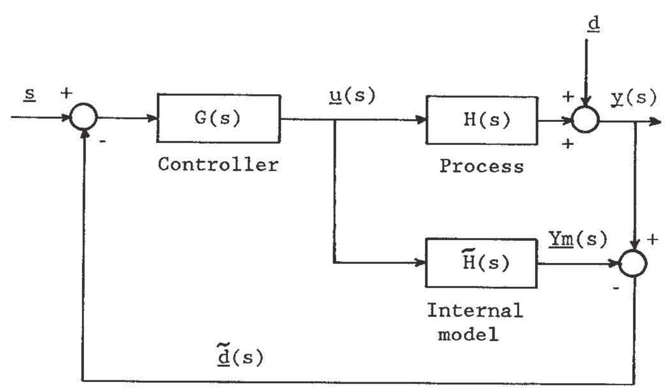

Figure 1. Basic IMC structure.

The following equations are obtained from the block diagram in figure 1.

$$\underline{\tilde{d}}(s) = [I+(H-\tilde{H})G]^{-1} [(H-\tilde{H})G\underline{s}+\underline{d}] \qquad (1)$$

$$\underline{u}(s) = G [I+(H-\tilde{H})G]^{-1} (\underline{s}-\underline{d}) \qquad (2)$$

$$\underline{y}(s) = H G [I+(H-\tilde{H})G]^{-1} \underline{s} + (I-HG)[I+(H-\tilde{H})G]^{-1} \underline{d} \qquad (3)$$

In these equations appears the difference $H-\tilde{H}$. This term, which corresponds to the modelling errors, is generally not equal to zero. Moreover it often varies with time. In the absence of setpoint changes, the equation (1) gives :

$$\underline{\tilde{d}} = [I+(H-\tilde{H})G]^{-1} \underline{d} \qquad (4)$$

This last expression shows that the feedback signal is directly affected by the modelling errors. So the larger the term $H-\hat{H}$, the greater the correcting effect. That augurs well of the IMC capability of maintaining a good level quality of regulatory control.

General Properties of IMC

The IMC structure combines most of the advantages of open loop and feedback control [2,3], namely:

i) Under the hypothesis of no modelling errors and in the absence of disturbances, the output signal becomes:

$$\underline{y} = H G \underline{s} \qquad (5)$$

In these conditions, IMC behaves identically as an open-loop scheme. This property is remarkable since it allows an easy controller design (for the desired transfer $\underline{y} = K \underline{s}$, $G = H^{-1} K$). Thus, when $\tilde{H}(s) \simeq H(s)$ the controller is defined as

$$G(s) = \tilde{H}^{-1}(s) K(s) \qquad (6)$$

ii) The condition of equality between the steady-state gain of the controller and the inverse of the model gain - $G(0) = \tilde{H}^{-1}(0)$ - yields zero offset with $K(0) = I$.

iii) Stability of both controller G and process H is sufficient for overall system stability when the process model is exact. This can be proved easily from equations (2) and (3).

Adjustements for single-input, single-output systems

Most of the processes we come across in the Bayer cycle are governed by only a few parameters, but these often are of nearly equal importance with respect to their effect. Predictive input-output relations that adequately describe the steady-state behaviour generally are nonlinear multi-input, single-output expressions. But it is common that only one input variable may be manipulated to operate such processes, knowing that other inputs, though continuously measured and of paramount importance, are to be considered as disturbances from a control standpoint.

To ignore measured disturbance information in a control system may be a limiting factor of performance. thus the idea is to modify conventional IMC structure so as to take benefit of the information contained in some of the disturbance measurements.

Output of our processes can be written rigorously

$$y(s) = \Gamma o\, Ho(s)\, u(s) + \sum_{i=1}^{n} \Gamma_i\, H_i\,(s)\, d_i(s) \qquad (7)$$

where $\Gamma_j H_j(s)$ is the j-th element of the transfer matrix relating output y to the action u or to the measured disturbance d_j, Γ_j is a static gain and H_j is a unit gain transfer function. Γ_j and H_j depend on operating conditions: u and $d_1,\ldots,d_n$.

The model given by the preceding equation is difficult to obtain. Therefore we replace it by an approximated form as follows:

$$y(s) = \phi\,[Ho(s)u(s),\ H_1(s)d_1(s)\ldots,\ H_n(s)d_n(s)] \qquad (8)$$

The approximation comes from the facts that, on one hand the unit gain transfer function H_i is supposed not to depend any more on the operating conditions, on the other hand ϕ is an algebric equation which represents a steady-state model of the process that can be solved for y in terms of u, $d_1,\ldots, d_n$, that is $y = \phi\ (u,\ d_1,\ldots,\ d_n)$.

A symbolic diagram of equation (8) is shown in figure 2.

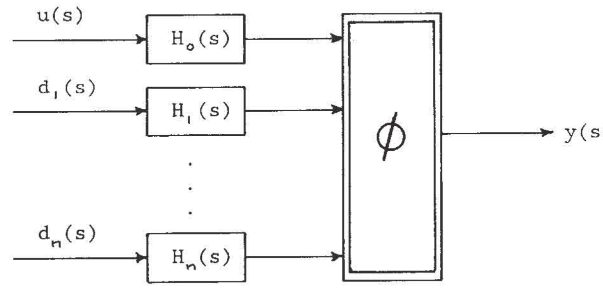

Figure 2. The internal model diagram

The zero offset property of IMC structure is achieved by forcing the steady state relation ϕ of our internal model to be solvable for u. The reverse function $u = \phi^{-1}(y,\ d_1,\ldots,\ d_n)$ becomes the static part of the controller.

Since our control problems are mostly of regulatory type, no attempt is made to compensate the proper dynamics of the real process. Under these conditions, the design of the IMC controller is reduced to the computation of the function ϕ^{-1}.

SOME WORDS ABOUT THE SIMULATION ENVIRONMENT

Much effort has been devoted to successfully developing and constructing appropriate phenomenological models of pieces of equipement or plant-units that are found in the Bayer cycle. Based on these models, static as well as dynamic simulations are run at least for the following purposes:

i) To build internal models.

ii) To verify performances of control systems and experiment with them prior to implementation.

iii) To determine the optimal values of the operating parameters (setpoints) which significantly affect the economy of a Bayer plant.

Process operation at a stationary state is simulated with a flowsheeting system which has already been described (4).

Dynamic system simulations are performed with a computer package DYNAM based on the principle of modularity, similar to what is encountered in flowsheeting. It is worth mentioning that any dynamic simulation has to be preceded by a static simulation in order to compute all initial conditions values.

A basic distinction is to be made between control and process unit modules; indeed the general computation procedure consists in alternatively executing these modules expressed in subroutine terms: the former determine actions to be applied upon process during a sampling period, the latter calculate the state variables that describe the process at sample time.

Most of the facilities currently offered by commercial packages are available at present in DYNAM: real-time curve plotting, snapshot, data storage, generation of samples from various statistical distributions, etc...

CONTROL OF THE ALUMINATE LIQUOR CONCENTRATION

Process Description

One of the major variables to be maintained at a predetermined value in a Bayer cycle is the caustic soda concentration of the aluminate liquor. The process governing this parameter is represented in figure 3:

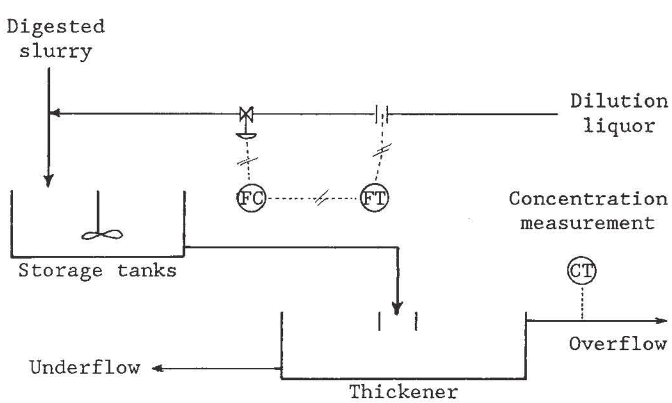

Figure 3. Schematic representation of dilution process.

The bauxite digested slurry is mixed with a dilution liquor before entering agitated storage tanks. The flowrate Qd of the dilution liquor controls the caustic soda concentration of the thickeners overflow. Suspension is then fed by gravity into thickeners.

Information about operating conditions is very limited. The flowrate of the dilution liquor and the caustic soda concentration of the thickeners overflow are the only continuously measured variables. In addition, the flowrate value of the liquor to be diluted can be valuably estimated from the flowrate of the suspension entering the digestion series of autoclaves.

Internal Models

As previously stated, dynamic and steady-state internal models are treated separately. A mass balance over dilution leads to the approximated expression:

$$Co = Ce\ Qe/(Qe+Qd) + Cd\ Qd/(Qe+Qd) \qquad (9)$$

where C is the caustic soda concentration in kg/m3, Q is the flowrate in m3/h and e, d and o are subscripts refering respectively to the liquor to be diluted, the dilution liquor and the thickeners overflow.

Concentrations Ce and Cd, which are not measured, are kept to their mean value. This leads to the internal static model in the form :

$$Co = a\ Qe/(Qe+Qd) + b\ Qd/(Qe+Qd) \qquad (10)$$

The steady-state gain of the controller, obtained by rearrangement of the preceding equation, is given by:

$$Qd = Qe\ (a - Co)+(Co - b) \qquad (11)$$

The dynamic model of the process expresses the dependence of the caustic soda concentration of thickener overflow on the conditions of feed to dilution. Using the Strejc-Quentin's method to identify the step response obtained by computer simulation, the transfer function of the system is found to be

$$H(s) = \exp(-\tau' s)/(1 + \tau s)^n \qquad (12)$$

with $n = 3$, $\tau' = 5000$ seconds and $\tau = 8000$ seconds.

In practice discrete state equations (D.S.E.) are implemented in the control algorithm. This leads to the following block structure:

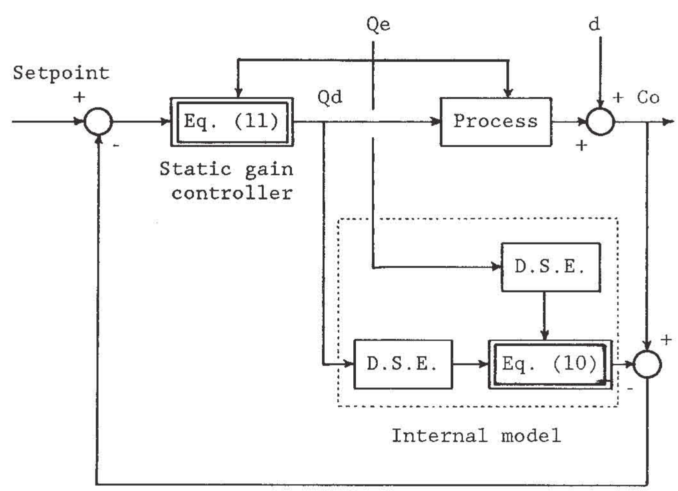

Figure 4. Block diagram for controling the caustic soda concentration of the aluminate liquor.

Results

Simulations have been carried out to demonstrate good performance of our control system faced with regulatory problems. Such a situation, frequently met in reality, is the occurence of step disturbance in feed flowrate. Responses to a 12% step decrease in the flowrate of liquor to be diluted (Qe) are shown in figure 5.

Ratio of feed concentrations is equal to 3 in that case. A maximum transient deviation of 0.5% around the setpoint value, with zero offset at steady-state, is the proof of a satisfactory control.

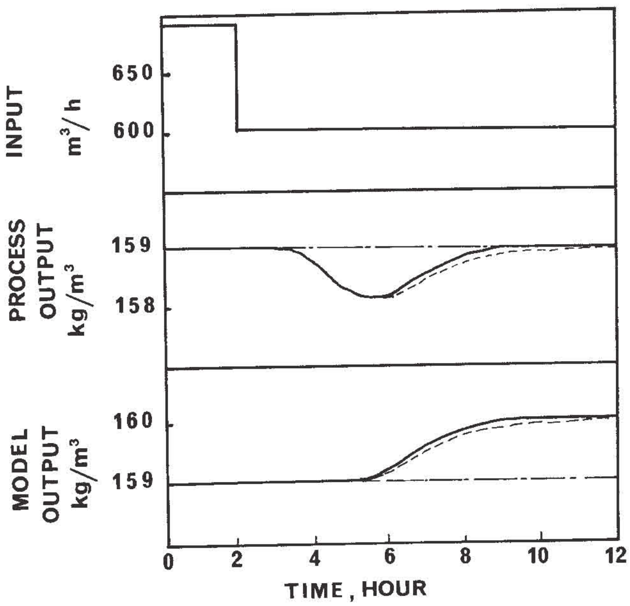

Figure 5. Responses to a step feed flowrate disturbance. (correct model = solid line, disadapted model = dashed line).

To change the time constant of the dynamic model from 8000 to 10000 seconds induces a disadaptation which has little effect as reported on figure 5. Furthermore constants a and b in our static model equation (10) have been calculated in order to fit exactly the process at time zero. Consequently any change in the operating conditions causes a steady-state model disadaptation. The offset observed on the model output is the result of this disadaptation. Though the disturbance compensation is not perfect, measure stays in good agreement with setpoint which confirms robustness of the controller.

Figure 6 shows the comparison of process operational results under similar operating conditions between open loop control and IMC which brings marked improvement in control performance.

CONTROL OF THE DIGESTED SLURRY

Process description

One of the first steps in the production of alumina consists of leaching bauxite in a series of continuously stirred reactors with a poor alumina-bearing caustic soda liquor to dissolve alumina. Boehmitic bauxite is mixed with leaching liquor before grinding and storage tanks so as to have a fixed proportion of liquor with respect to solid. An important point is maintaining the liquor obtained from bauxite digestion at a specified weight ratio level of alumina over caustic soda, called RP. This RP depends on the leaching liquor quality, the bauxite quality, residence times and thermic conditions in the reactors and on the ratio of solid over liquor present in the feed to the digestion unit. Since those parameters often vary, the desired RP is achieved by adjusting the leaching liquor flow at the entrance of the first reactor. A scheme of this process is given in figure 7.

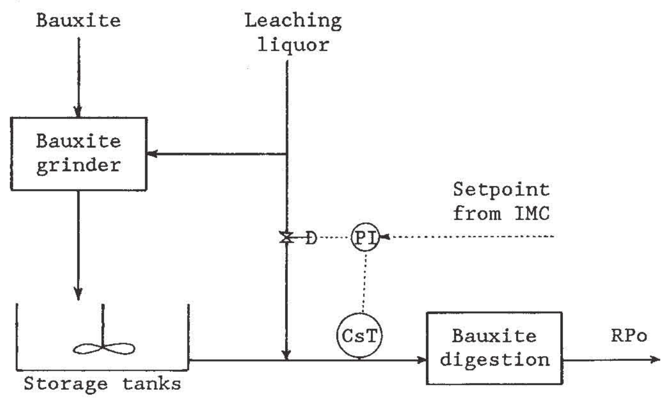

Figure 7. Schematic representation of bauxite treatment.

The following parameters are continuously measured on plants :

- RPo, RP of the output liquor of digestion unit,
- d1 and d2 respectively RP and Na2O caustic concentration of the liquor of the feed to reactors,

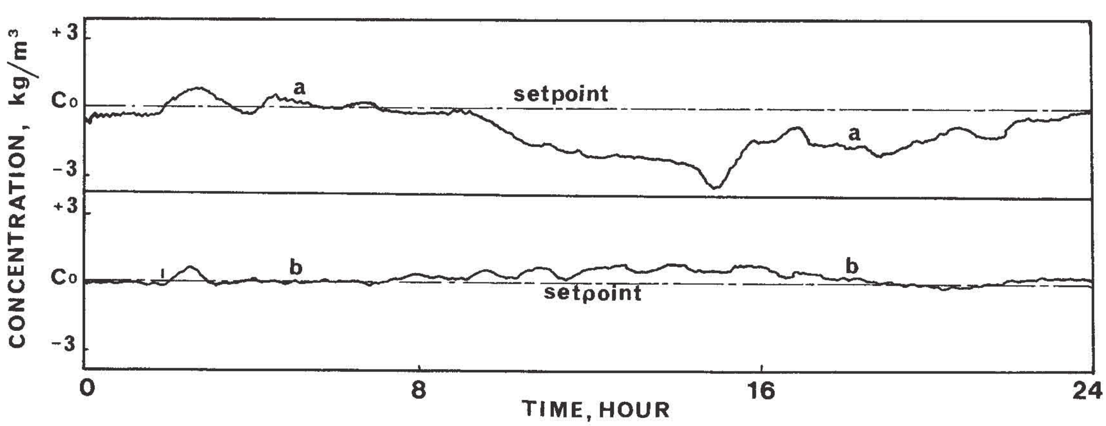

Figure 6. On-site recorder traces for concentration measurement. a/ before IMC implementation, b/ after.

- d3, temperature of the slurry leaving the last reactor,
- d4, feed flowrate to the digestion unit.
- Cs, solid concentration of the incoming feed.

The bauxite quality characterized by the alumina concentration d5 of the solid, though having an important effect upon the output RPo, is not measured continuously on site. A point of great interest is to evaluate to what extent control performances are affected by keeping the control system under study continuously informed or not of the alumina content of bauxite. Therefore this parameter d5 is considered as a measured disturbance in all what follows.

Internal Model

Since the controlled variable is RPo and the solid concentration Cs is the action (input to the process), the steady-state model of the process is expressed as below

$$RPo = \emptyset\,(Cs, d1, d2, d3, d4, d5) \qquad (13)$$

This empirical relationship reduces to a second degree polynomial fitted to the data that result from a set of experiments using factorial design. Actually data are steady-state process simulation outputs.

The inverse function $\emptyset^{-1}$ which is to become part of the controller for the zero offset condition to be satisfied, is drawn from rearrangement of the expression above as:

$$Cs = \emptyset^{-1}(RPo, d1, d2, d3, d4, d5) \qquad (14)$$

The dynamic part of the model consists of the set of unit gain transfer function between process output RPo and measured process inputs Cs, d1 to d5. These functions are established through identification of the diverse simulated step responses. Dynamic effect of the temperature d3 in the last reactor on RPo is neglected (zero order model) while the effect of feed flowrate d4 is correctly represented by a first-order model (H1). Assuming ideal stirred tank reactors, other unit gain transfer functions are identical; they are found to be adequately approximated by a third order model with delay (H3). Time constants of 30 minutes and a delay of 45 minutes are typical values for this kind of process. The resulting block diagram is shown in figure 8.

Results

Numerous situations were simulated for this application, only the most frequent of them are presented in this paper; for example, figure 9 shows responses to a .01 setpoint decrease in RP. Internal model output (curve 4) and process model output RPo (curve 3) are changing over time in a similar way which indicates that time constants and delay for the dynamic model are properly estimated; the difference between both signals, even when steady-state is reached, demonstrates that the static model which is used is not perfect. In spite of this model error, the control system immediately enforces the solid concentration of the slurry entering digestion reactors to fall down to a value close to its new steady-state value so that the measured RP nearly comes straight down to the setpoint (curve 2).

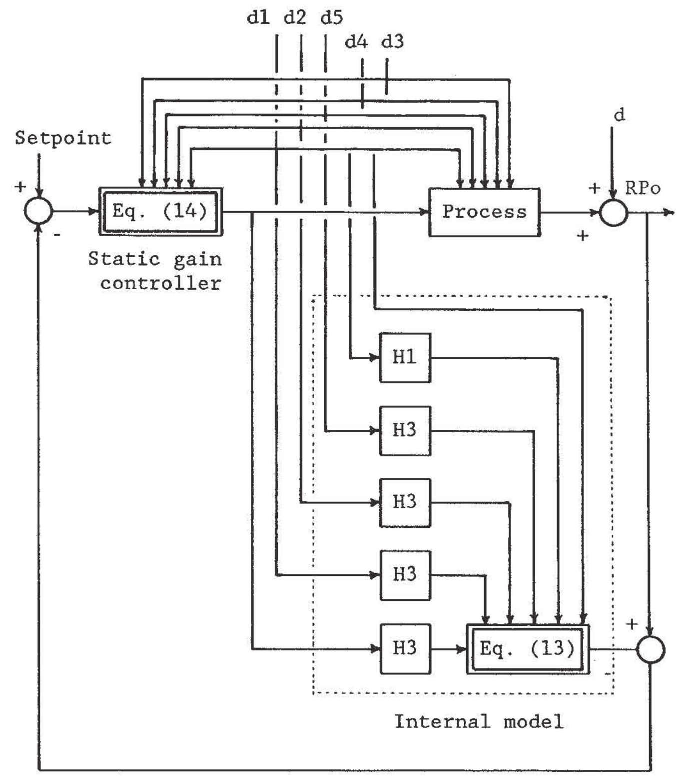

Figure 8. Block diagram for controling the RP of the digested liquor.

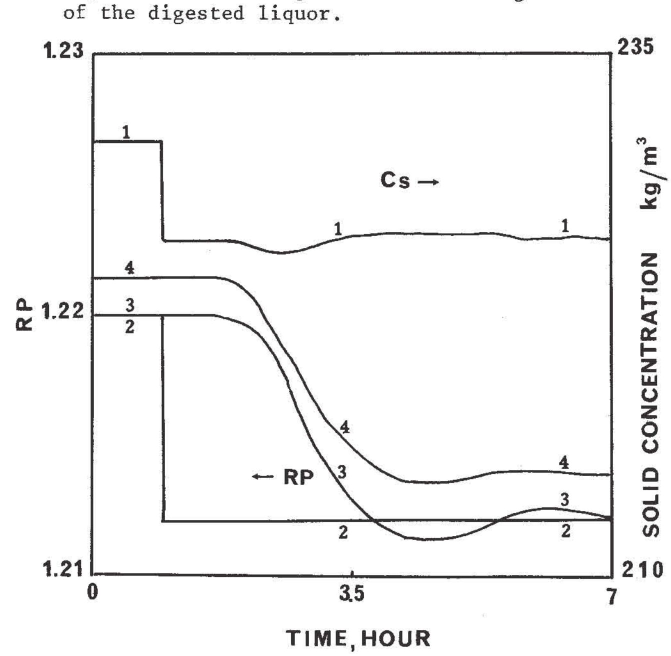

Figure 9. Responses to a setpoint change in RP. (1 = solid concentration Cs, 2 = RP setpoint, 3 = measured RP, 4 = internal model output)

Bauxite composition often varies depending on its origin. This is particularly true for French bauxites. Therefore solid composition fluctuations were stochastically generated for simulation purposes. Based on the assumptions that a normal distribution describes the bauxite alumina content and that time between successive changes in ore composition is constant, solid alumina concentration may vary with time as illustrated on figure 10.

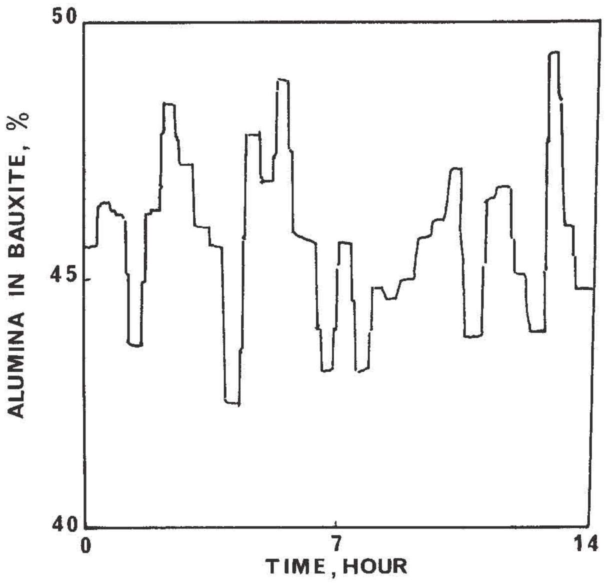

Figure 10. Alumina percentage variations in bauxite.

To study the behaviour of the overall system subject to these variations of bauxite alumina content, several simulations were conducted. Two of them are reported herein. Results shown in figure 11.a correspond to the case when alumina percentage in solid is measured continuously to inform the control system of the disturbance. One can see that control is nearly perfect since the output RPo is kept within .001 of setpoint. Figure 11.b shows the system response to the same probabilistic ore composition fluctuations. But those variations are no longer measured. Consequently, the internal static model takes into account a fixed bauxite composition, namely the expected mean composition. Under these conditions, control performances remain acceptable since the process output RPo stays within less than .005 of RP setpoint. Moreover this last result constitutes an element of answer to the question: is it worth or not to invest in an on-line bauxite analyzer ?

CONCLUSIONS

IMC qualities claimed in litterature, namely simplicity and robustness have proved to be real through experiences of both reported applications. Large Bayer process deadtimes do not limit the use of IMC though altering global control performances.

Splitting the internal process model into a purely dynamic model and a static expression enables the general IMC structure to account for measured disturbances. Thus the problem of internal model identification is made easier to solve on the one hand, while on the other hand controller design becomes straight forward when the dynamics of the closed loop system is kept equal to the process dynamics. The use of such a static relationship allows to minimize internal model disadaptation when operating conditions change in a large extent.

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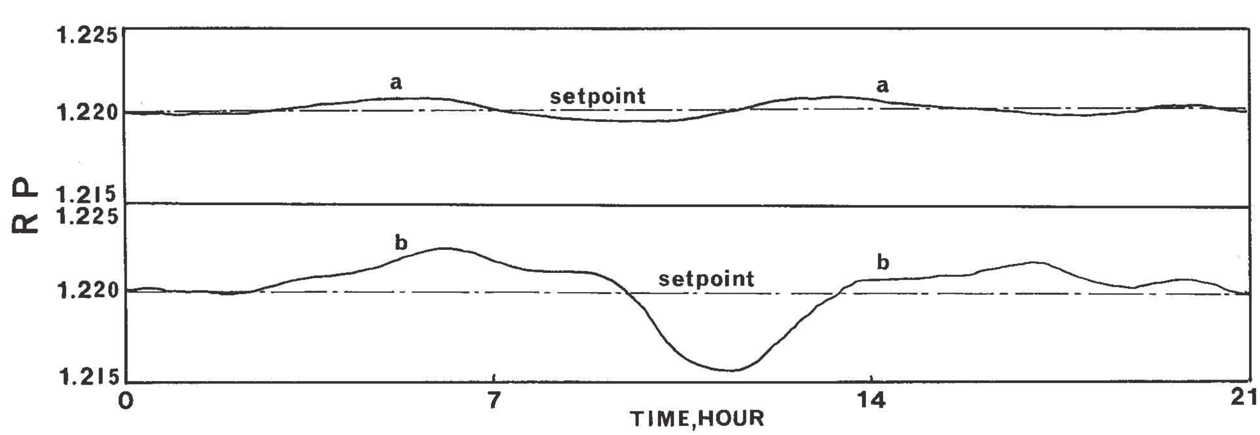

Figure 11. Response to probabilistic bauxite alumina content fluctuations.
a. with continuous ore analysis, b. without ore analysis.