PID Parameterization of Cement Kiln Precalciner Based on Simplified Modeling

Dimitris C. Tsamatsoulis and Georgi Zlatev

***Abstract*—** This study aims in tuning a PID controller of cement kiln precalciner between the feed rate of the primary fuel and the temperature at precalciner exit. A simplified dynamic modeling has been used, including perfect mixers connected in series. The optimum number of tanks and the dynamical parameters has been computed using industrial data. The PID gains are determined by loop shaping technique using the maximum sensitivity as robustness criterion. The uncertainty of their values is computed based on the uncertainty of the dynamic parameters. Due to simplicity of the model, the tuning results could be used at least as initial PID values in real process.

***Keywords* —** Cement, modeling, clinker, kiln, precalciner, dynamics, PID, control

I. Introduction

USAGE OF ALTERNATIVE FUELS is rapidly increasing in cement industry aiming to be more friendly to environment by replacing traditional solid fuels. Alternative fuels are fed mainly on kiln precalciner (PCK) and are characterized by high variance in calorific value. The stable operation of the precalciner has great importance in the process and quality. The operation control is mainly achieved by: (a) proportioning the fuels in main burner and precalciner burners, (b) regulating the precalciner primary fuel flow rate using quality or process variables. As quality parameters the hot meal calcination degree and clinker free lime are utilized. Suitable process parameters for the fuel feed rate setting are the temperature at the exit of precalciner or at the gas outlet of bottom cyclone. Smooth operation of PCK is one of the critical issues in a cement plant therefore the automatic operation is highly preferred. This is implemented by closing the loop between the primary fuel feeder and the chosen temperature, leading in a challenging problem of modeling and control. Due to the complexity of the processes involved, one can find a limited number of attempts in the literature in modeling and in utilization of the model in controller development.

Koumboulis and Kouvakas [1]-[2] in two consecutive publications presented artificial neural network (ANN) models, purposing in controlling and improving clinker calcination. ANNs applied for modeling the dynamics between temperature of the outlet gases from the precalciner – T_G - and several variables and several variables, such as the mass flow of raw meal and solid fuels, the temperature and mass flow of the tertiary air, the temperature of the raw meal. Using digital implementation of the transfer function, they proceeded to the development of a PI controller to regulate the feed rate of solid fuel, using TG as process variable. Witsel et al. [3] developed a dynamic model for simulating the behavior of cement kiln and using the frequency approach, they designed a multi-loop control scheme, based on two PI controllers. Stadler et al. [4] applied model predictive control for the stabilization of a kiln precalciner of a cement plant. The results of this approach indicated a significantly improved performance and more beneficial operating points were obtained. Wang et al. [5] developed a first principles dynamic model of the pre-calcining process. The model is based on the principle of mass and energy balances and consists of a set of ordinary differential equations. A stationary solution for the model was found and dynamic simulations of step changes in the input variables were also presented. Yang et al. [6] developed two kinds of ANN models; back propagation (BPNN) and Radial Basis Functions (RBFNN) neural networks which they applied in cement calcination process. RBFNN based model reached very high fitting results, but the BPNN based model had good generalization ability. Their conclusion is that BPNN based model could be used as simulation model of the calcination process for exploring new control algorithms. X. Lin et al. [7] used Adaptive Dynamic Programming (ADP) to implement a multi-parameter control of kiln precalciner. The results of their simulation show that, after the fluctuations in the early control period, the controlled parameters tend to be stabilized guaranteeing the quality of clinker calcination. Yang et al. [8] developed a multi-variable optimal control of calcination process based on dual heuristic programming (DHP). Typical DHP structure consists of three modules: Critic Network, Action Network, and Model Network.

The objective of the current study is to parameterize a PID controller between the temperature in precalciner outlet and the feed rate of the primary fuel that is pet coke in the case examined. The tuning is based on the results of a simplified dynamical model between the same parameters presented by Tsamatsoulis [9]. An efficient loop shaping technique developed by Astrom, Hagglund and Panagopoulos [10] – [12] is implemented. The obtained sets of PID parameters

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satisfying a robustness constraint along with the dynamic results and their uncertainty constitute the entries of extensive simulators to define the optimum area of PID coefficients as concerns performance. A similar approach has been presented by Tsamatsoulis [13] – [15] in optimizing PID of different processes: regulation of the cement raw meal quality modules [13]; cement mill operation [14]; kiln cooler operation [15].

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II. Process Model and PID Controller Design

A. Transfer Function and Autoregressive Model

The simplified model is composed by a series of equal well stirred tanks and is analytically described in [15]. The governing equations are briefly repeated. For a number of tanks equal to N_0 the transfer function G_p is given in Laplace form by (1). The time constant of each tank is T_0 (min) and the gain is k_v. The input x and output y are percentages of the maximum range and given by (2)-(3). These variables are the control and process variables.

$$G_p = \frac{y}{x} = \frac{k_v}{\left(1 + s \cdot T_0\right)^{N_0}} \tag{1}$$

$$y = \frac{T}{T_{Max}} \cdot 100 - y_0 \tag{2}$$

$$x = \frac{Q}{Q_{Max}} \cdot 100 - x_0 \tag{3}$$

Where T (°C) is the temperature in precalciner outlet, T_{Max} is the maximum T and y_0 (%) is the steady state precalciner output. Respectively Q (t/h) is the fuel feed rate, Q_{Max} the maximum Q and x_0 (%) is the steady state of fuel input, deriving an output y_0. The set of the model parameters consists of the number of tanks N_0, the gain k_v, the time constant T_0, the flow rate x_0 and temperature y_0 corresponding to the steady state, under the specified operating conditions, such as: (a) the flow rate, temperature and chemical composition of the raw meal entering precalciner; (b) the flow rate and calorific value of the alternative fuels; (c) the gas flow and temperature of tertiary air. The short and long term variance of these conditions generates the parameters uncertainty. In the current state of modeling, these disturbances have not been modeled. This is a further challenging issue for improving the reliability of the model. The parameters are estimated using the convolution theorem between the input signal x and the process variable y, expressed by (4).

$$y = \int_0^t u_1(\tau) \cdot g(t - \tau)\, d\tau \tag{4}$$

Where $g(t)$ is the impulse system response. Exclusively operating data are used by sampling with appropriate software. The sampling period is 1 min. By using a non-linear regression technique, the optimum dynamic parameters are computed by minimizing the residual error provided by (5):

$$s_{res}^2 = \sum_{I=1}^{N} \frac{\left(y_{calc}(I) - y_{\exp}(I)\right)^2}{N - k_0} \tag{5}$$

Where s_{res} represents the residual error, y_{calc} is calculated from the model and y_{exp} is the actual one according to (2). The number of experimental points is N and k_0 is the number of the independent model parameters. At time I the error between y_{calc} and y_{exp}, $Err(I)$, is given by (6). This error accumulates load disturbances and signal noise and it is modeled with the autoregressive equation (7).

$$Err(I) = y_{\exp}(I) - y_{calc}(I) \tag{6}$$

$$Err(I) = A_0 + A_1 \cdot Err(I-1) + A_2 \cdot Err(I-2) + s_{Err} \tag{7}$$

Where A_0, A_1, A_2 are the coefficients of the autoregressive model. To investigate whether this model's error is adequate, its regression coefficient is checked and its standard error compared with the residual error of the dynamic model.

To identify the model parameters, software was developed to load and to process industrial data of kiln operation, extracted from the Devnya Cement plant database. The total period of data used was 20 continuous days, a period adequate to estimate and assess the process dynamics. Then the software checks for pet coke feeder stoppages and finds continuous operating data sets of 120 minutes duration. Afterwards the software determines the optimum dynamic parameters for each data set and the corresponding regression coefficient, R. A minimum coefficient, R_{Min}=0.7, is selected and the software creates the cumulative distribution of samples as function of R, $C(z; R<R_0)$, where $z \in [0, 1]$ and $0 < R_0 \leq 1$. The number of consecutive tanks N_0 is an independent parameter and its optimal value is the one presenting the lowest fraction of samples with $R<R_{Min}$, computed from the cumulative distribution $C(z; R<R_0)$.

Table I. Dynamical Parameters

N_0	Aver. k_v		Median k_v	Std. Dev. k_v	%CV k_v
5	0.214		0.210	0.049	22.9
6	0.203		0.197	0.045	22.2
N_0	Aver. T_0		Median T_0	Std. Dev. T_0	%CV T_0
5	2.2		2.1	0.6	26.2
6	1.9		1.7	0.4	24.8
N_0	A1	A2	Aver. s_{Err} of $C(z;R \geq R_{Min})$		s_{Err}/s_{Res}
5	1.54	-0.62	0.057		0.212
6	1.54	-0.62	0.057		0.212

The computation provide optimal N_0 = 5 or 6. The average and median values of gain and time constant as well as standard deviations and coefficients of variation are depicted in Table I for the optimal number of tanks. The coefficients of autoregressive equations are also presented in the same table for N_0 = 5,6.

B. *Controller Design*

The loop shaping design approach is to maximize integral gain subject to a constraint on the maximum sensitivity defined by (8). For the specific feedback control loop, formula (9) relates the sensitivity with the controller and process transfer functions, G_c and G_p respectively:

$$M_s = Max(|S(i\omega)|) \tag{8}$$

$$S = \frac{1}{1+G_c G_p} \tag{9}$$

The controller transfer function G_c is provided by (10). The variables k_p, k_i, k_d constitute the proportional, integral and differential gains of the controller correspondingly. The error e between set point y_{sp} and process value y is provided by (11).

$$G_c = \frac{x}{e} = k_p + \frac{k_i}{s} + k_d s \tag{10}$$

$$e = y_{sp} - y \tag{11}$$

The algorithm to calculate the PID gains as function of M_s is described analytically in [12] and applied successfully in [13]-[15].

III. PID TUNING AND PARAMETERS UNCERTAINTY

For M_s belonging to the interval [1.3, 2.5] and with a stepwise increase of 0.1, the triples (k_p, k_i k_d) are computed using the median dynamic parameters shown in Table I, for N_0=5 and 6. In this way, for each pair (M_s, k_d), a set of PID parameters is determined. The proportional and integral gains as function of M_s and k_d are depicted in Fig.1 for N_0=5. The corresponding functions for N_0=6 are demonstrated in Fig. 2. The general trend is as follows: An increase of k_d causes an increase of k_i and k_p; increasing M_s, both k_p and k_i are increasing. The comparison of Figs 1 and 2 shows that for higher number of perfect mixers N_0, both k_p and k_i are lower for the same M_s and k_d.

To investigate deeper the function between k_p, k_i and N_0, proportional and integral gain are plotted as function of (M_s, N_0) for M_s ϵ [1.3, 2.5] and N_0 ϵ [3, 7] independently if N_0 provides optimal dynamic parameters. The results are demonstrated in Fig. 3 from where it is concluded clearly that increasing N_0 causes a drop to k_p and k_i. Therefore for given k_p and k_i values there are functions f_1, f_2 so that $f_1(M_s, N_0)=k_p$ and $f_2(M_s, N_0)=k_i$. However because the slopes of these functions are different as shown in Fig. 3, from different pairs (M_s, N_0) different k_p and k_i are obtained and each (k_p, k_i k_d) is unique.

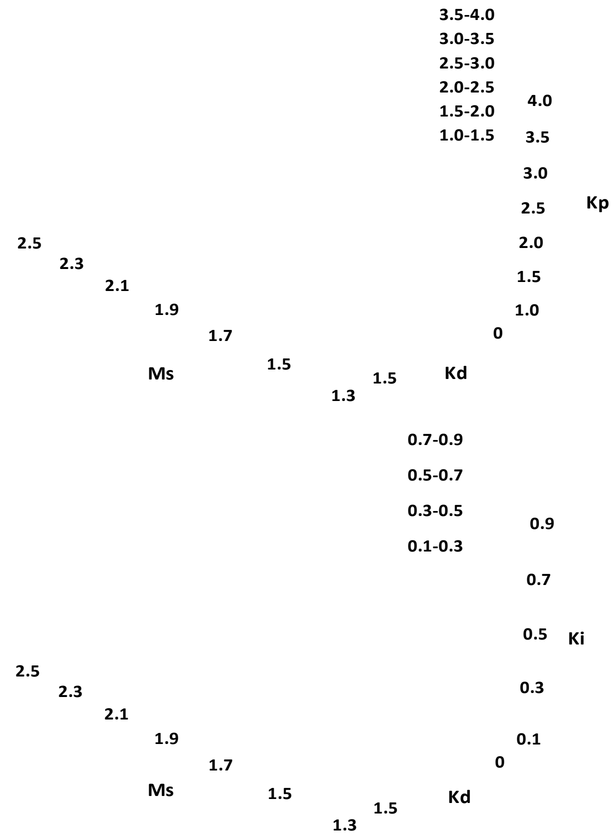

Fig. 1 k_p and k_i as function of M_s, k_d for N_0=5.

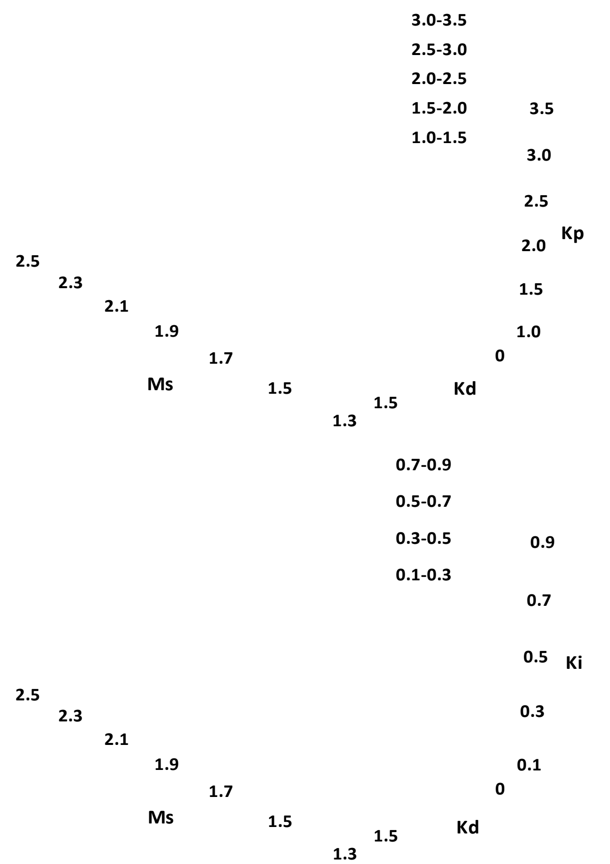

Fig. 2 k_p and k_i as function of M_s, k_d for N_0=6.

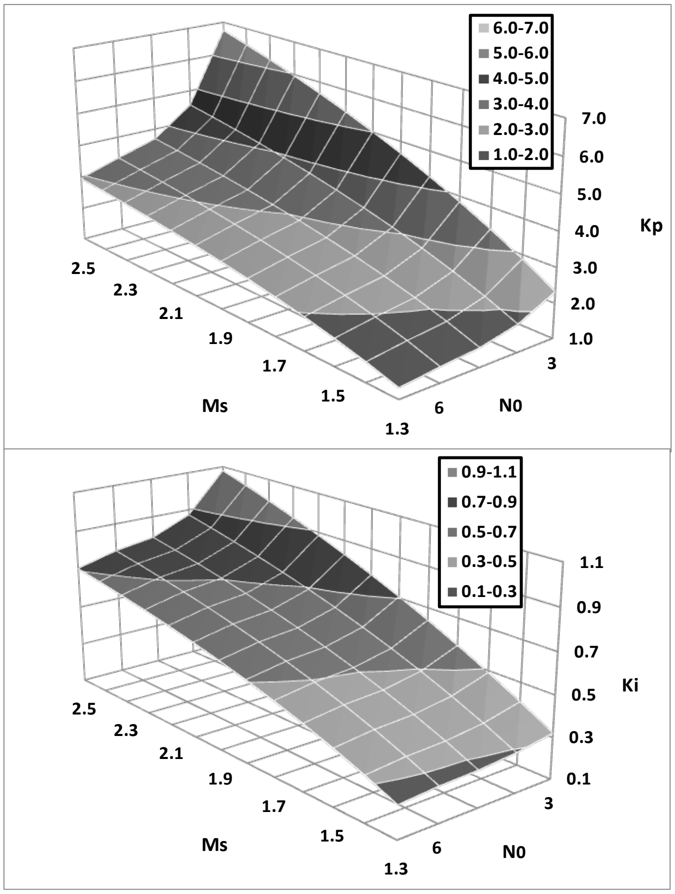

Fig. 3 k_p and k_i as function of M_s, N_0 for k_d =1.

For the given control system the open loop transfer function G_{ol} is defined by the product $G_c \cdot G_p$. The variable $1/M_s$ can be interpreted as the shortest distance between G_{ol} Nyquist curve and the critical point (-1,0) as shown in the Figure 4.

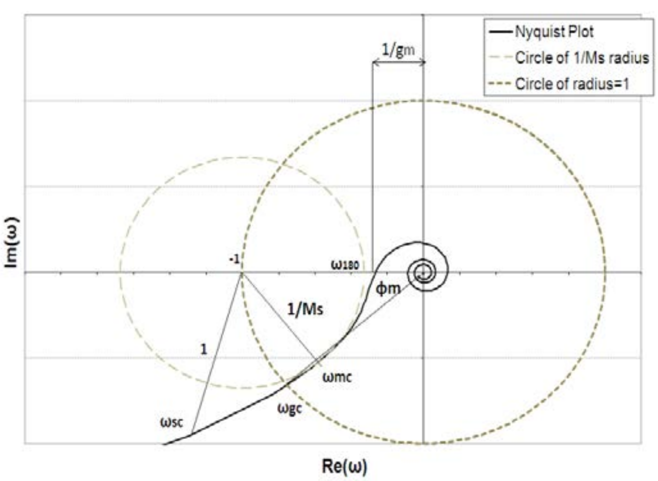

Fig. 4 Open loop transfer function and system properties.

In the same figure additional properties, characterizing the system stability, are depicted also:

- gain margin, g_m, the reverse of the distance of the point G_{ol} curve cuts the real axis from the (0, 0) point.
- phase margin, φ_m, the angle created, between the point G_{ol} cuts a circle with centre the centre of the two axes and of radius1and the real axis
- gain crossover frequency, ω_{gc}, the frequency corresponding to the G_{ol} point, deriving the phase margin
- sensitivity crossover frequency, ω_{sc}, the frequency corresponding to the G_{ol} point having a distance equal to 1 from the point (-1, 0)
- maximum sensitivity crossover frequency, ω_{mc}, the frequency corresponding to the G_{ol} point where this curve is tangent to a circle with centre (-1, 0) and radius $1/M_s$. As M_s is increasing, gain margin and phase margin are decreasing and the controller becomes less robust.

The Nyquist plots of G_{ol} for N_0=5, M_s=2, k_d=0, 2, 4 are shown in Fig. 5. From this Figure the application of the selected loop shaping technique becomes clearer.

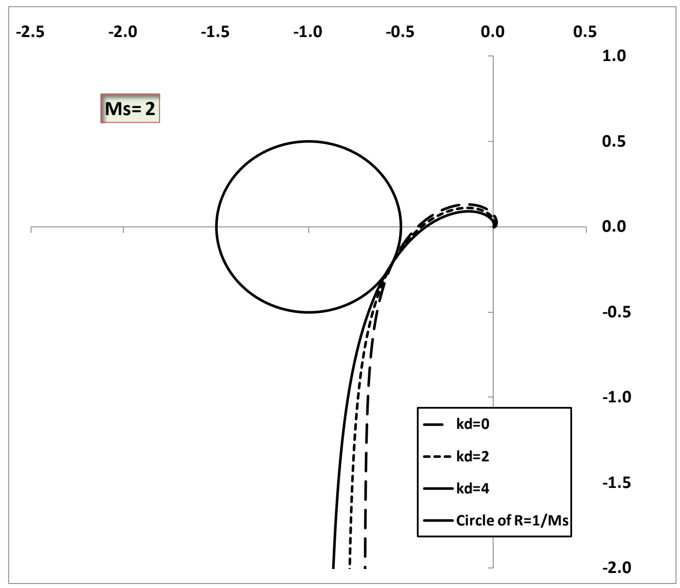

Fig. 5 Nyquist plot of G_{ol} for N_0=5, M_s=2, k_d=0, 2, 4 .

The dynamic parameters' uncertainty expressed by the respective variance in Table I has a noticeable effect on the open loop features. For M_s=2 and k_d=1 the open loop properties are computed for each data set and the cumulative distributions are created. Such distributions for gain margin, phase margin and maximum sensitivity, are shown in Fig. 6. From the Figure of maximum sensitivity it is observed that, although the median value is 2, a large dispersion exists influencing the regulation in the actual process. The same happens for gain and phase margins. One can select a robust M_s between 1.5 and 2 and then for a predefined gain margin to compute k_d. Then from M_s and k_d the other two PID gains are obtained. This design method has very good probability of success but it is not enough. The high uncertainty of the dynamic parameters could decrease the controller robustness. The big advantage of the design under consideration is that it is based on actual process data, thus the uncertainties are sufficiently known.

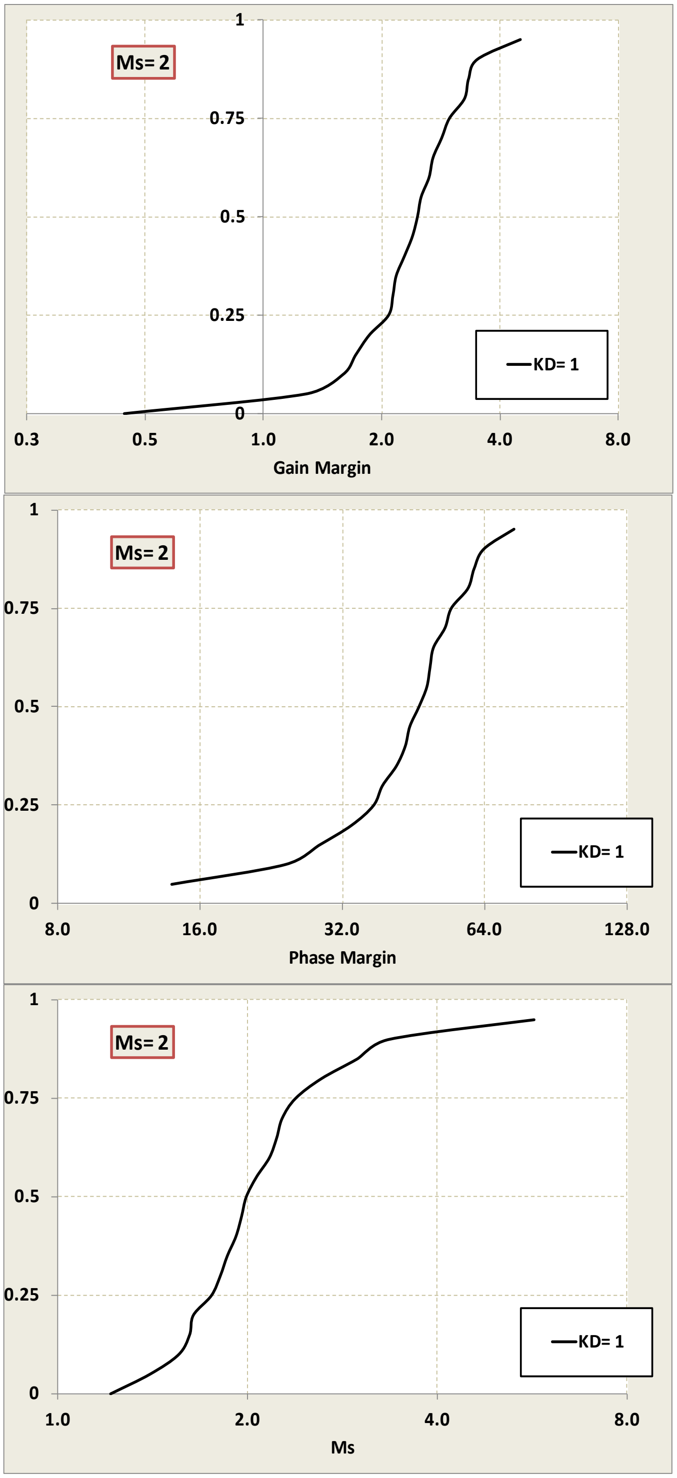

Fig. 6 Cumulative distributions of M_s, g_m, φ_m

A simulator taking into account these uncertainties is able to determine the optimum region of the PID gains, which provide the minimum variance of the process variable.

IV. Conclusions

The stable operation of kiln precalciner is one of the critical issues in a cement plant and the automatic operation is highly preferred. Due to the complexity of the processes involved, an analytical modeling is extremely difficult as well as to utilize such model for control purposes. In this study a simplified dynamic model between the temperature in precalciner outlet and feed rate of the primary fuel is presented using a series of equal connected tanks. The model with the optimum number of tanks providing the minimal residual errors is used to tune a PID controller between process and control variables. The uncertainty of the dynamic parameters is provided as well. The M - Constrained Integral Gain Optimization loop shaping technique has been applied based on the robustness constraint of maximum sensitivity, M_s. In this way, families of PID gains are calculated using M_s as design parameter. In parallel, several loop properties, like gain margin, phase margin, crossover frequencies, have been computed. The uncertainty of their values is computed based on the uncertainty of the dynamic parameters. Due to its simplicity, the tuning results could be used at least as initial PID values in real process A more precise parameterization needs a more detailed and accurate modeling.

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