Simplified Modeling of Cement Kiln Precalciner

Dimitris C. Tsamatsoulis

Abstract— This study aims in developing of a simplified dynamic model of cement kiln precalciner between the feed rate of the primary fuel and the temperature at precalciner exit. The model includes perfect mixers connected in series. The optimum number of tanks and the dynamic parameters has been computed using production data. A successful attempt has been also performed to model the errors between the actual process values and the calculated ones by the dynamic model by autoregressive equations. The distributions of gain and time constant were also determined, providing information about the model uncertainty. The described simplified model could be used for parameterization of a PID controller for regulating the process. Due to its simplicity, the tuning results could be used at least as initial values of the controller.

Keywords — Cement, modeling, clinker, kiln, precalciner, dynamics

I. Introduction

MODERN PRECALCINER systems are steadily and increasingly used in cement industry aiming to increase the kiln capacity, to use a wide range of primary and alternatives fuels, to improve the clinker quality, to reduce the thermal load of the kiln and to prolong the lifetime of brick lining. A simplified flow sheet showing the basic components of a rotary kiln system (RK) equipped with a four stage preheater, precalciner and grate cooler is demonstrated in Figure 1.

Raw meal is initially fed to the suspension preheater where it is heated from the hot gases coming from the kiln and precalciner. From cyclone 3 is fed to the precalciner (PCK) where is calcined. The decomposed material is introduced to the kiln through cyclone 4 where the calcination is completed and clinkerization follows. Afterwards clinker falls onto the grates of the cooler through the hood of kiln and then it is unloaded into storage. The air volumes needed for the combustion come from the primary and secondary air for the kiln burner as well as from primary and tertiary air for precalciner burners. In precalciner usually more than one fuel are fed: A finely ground primary fuel, e.g. pet coke and a wide range of alternative ones.

The achieved calcination degree of the raw mix at precalciner exit has a strong impact on the clinker quality and on thermal consumption. Therefore stable operation of precalciner is of high importance. The operation control is mainly achieved by: (a) proportioning the fuels in main burner and precalciner burners, (b) regulating the fuel flow rate of the precalciner using quality or process variables. As quality parameters the hot meal calcination degree and clinker free lime are utilized. Process parameters convenient to regulate fuel rate are the temperature in precalciner outlet or in gas outlet of bottom cyclone.

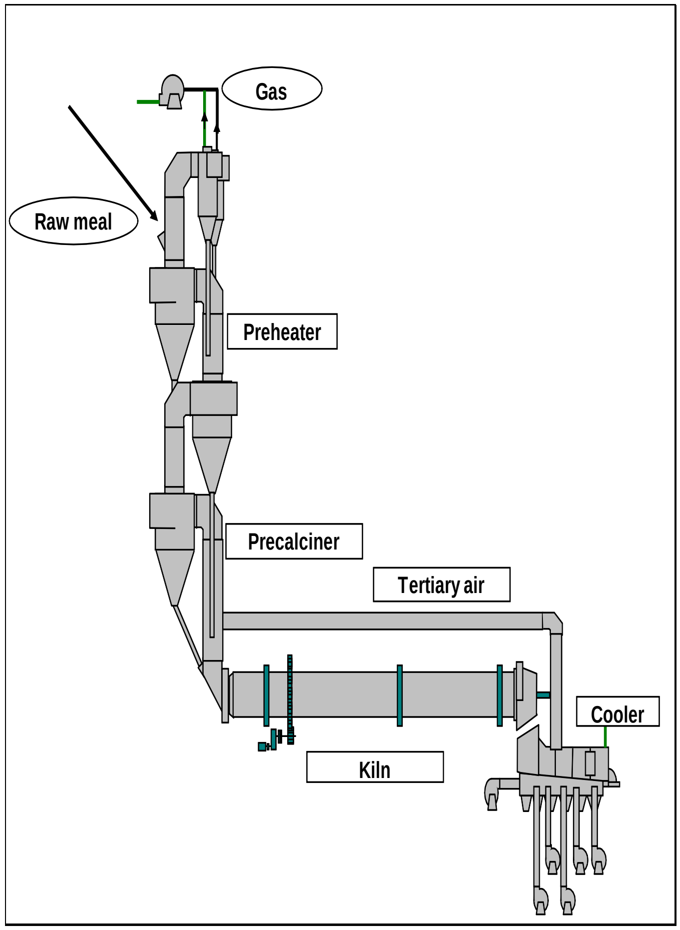

Fig. 1 Typical rotary kiln installation

The stable 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 solid fuel feeder and the temperature in PCK output or in gas outlet of

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bottom cyclone leading in a challenging modeling and control problem. Due to the complexity of the processes involved, one can find a limited number of attempts in literature to model the operation and use the modeling in controller development.

Koumboulis and Kouvakas [1]-[2] in two consecutive publications presented artificial neural network (ANN) structures aiming at controlling and improving clinker precalcination. They applied ANN to model the dynamics between temperature of gases in precalciner outlet – T_G - and several variables like mass flows of raw meal and solid fuel, temperature and mass flow of tertiary air, temperature of raw meal. Using digital implementation of the derived transfer function, they proceeded to the development of a PI feedback law to regulate the feed rate of solid fuel by using T_G as process variable. Witsel et al. [3] developed a dynamic model to simulate 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. 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 precalcination process. The model is based on 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. Fidaros and al. [6] developed also a model based on mass and energy balances to describe the flow and the transport phenomena in the precalciner. Their numerical model is based on the solution of the Navier–Stokes equations for the gas flow and on Lagrangean dynamics for the discrete particles. Yang et al. [7] developed two kinds of ANN models; back propagation (BPNN) and Radial Basis Functions (RBFNN) neural networks and they applied to 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 model could be used as simulation model of the calcination process for exploring new control algorithms.

The objective of the current study is to generate a simplified model between the temperature in precalciner outlet and the feed rate of the primary fuel that is pet coke in the case examined. Industrial data from the data base of Devnya plant have been used for this purpose. Tanks of equal volume connected in series have been considered. The residual errors depending on the tanks number have been estimated. An attempt is also made to model the errors between the actual process values and the computed ones by the dynamical model.

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II. Process Model

A. Transfer Function and Autoregressive Model

The simplified model is described by a series of equal well-stirred tanks with transfer function G_p 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 can be regarded as the control and process variables.

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

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

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

Where T (°C) is the temperature in precalciner outlet, T_{Max} is the maximum T and y_0 (%) is the steady state of precalciner output. Respectively Q (t/h) is the fuel feed rate, Q_{Max} is 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 system's steady state, under the specific operating conditions, such as: (a) flow rate, temperature and chemical composition of raw meal introduced in precalciner; (b) flow rate and calorific value of the alternative fuels; (c) gas flow and temperature of tertiary air. The short-term and long-term variance of these conditions generates the parameters' uncertainty.

The model 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 Newton-Raphson 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 is modeled with the autoregressive equation (7).

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

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

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.

B. *Identification of the Model Parameters*

The technique implemented to identify the model parameters as well as their uncertainty is very similar to the one described by Tsamatsoulis [8] during the development of an auto-tuner to evaluate the optimal PID to regulate the grinding in a cement mill. Software was developed to load and to process operating data of the kiln, extracted directly from the plant database. In each extraction two days of data are loaded, with a sampling period of one minute. The total period of data used was 20 continuous days, a period adequate to estimate and assess the dynamics of the process. Then the software checks for fuel 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 data sets presenting $R<R_{Min}$ are neglected in subsequent processing. In parallel the software creates the cumulative distribution of the samples population 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 needing optimization. As optimal N_0 is considered the one presenting the lowest fraction of samples with $R<R_{Min}$, computed from the cumulative distribution $C(z; R<R_0)$.

For the population of results with $R \geq R_{Min}$ the mean value and standard deviation of each dynamic parameter are computed. A minimum number of deviations, N_s, are employed as concerns k_v and T_0 populations. Sets not satisfying the constraints $|k_v - k_{v,Aver}| \leq N_s{\cdot}s_{kv}$ *or* $|T_0 - T_{0,Aver}| \leq N_s{\cdot}s_{T0}$ are considered as outlying and not taken into account in further processing. A value of N_s equal to 2 is taken in this investigation. The described double screening of the dynamic parameters can be thought of as a procedure to enhance the validity of the results and to reduce the impact of the load disturbances. The processing continues with the calculation of the mean and median values, as well as of the standard deviation, which is a measure of the parameters' uncertainty.

III. Results and Analysis

The results for the gain, time constant and variables of steady state are demonstrated in Table I, as function of the number of tanks. For each dynamic parameter, the coefficient of variation %CV=100×Std. Dev. / Average is also computed. The parameters of the error model or the optimum number of tanks are presented in the same Table. Only the values of A_1, A_2 are shown because A_0 is almost zero in all cases. To investigate the adequacy of the autoregressive error model, the average values of s_{Err} and s_{Res} are compared and shown in Table I. Since the ratio of the two errors is ~0.21, it can be concluded that the superposition of the error model to the dynamical model contributes to a noticeable decrease of the estimation error.

Table I. Dynamical Parameters

N_0	$C(z;R<R_{Min})$	Aver. s_{Res} of $C(z;R\geq R_{Min})$	Aver. R of $C(z;R\geq R_{Min})$
1	0.794	0.306	0.766
2	0.643	0.279	0.800
3	0.593	0.270	0.805
4	0.551	0.268	0.806
5	0.536	0.268	0.810
6	0.529	0.268	0.810
7	0.551	0.264	0.810
8	0.562	0.259	0.802

N_0	Aver. k_v	Median k_v	Std. Dev. k_v	%CV k_v
1	0.765	0.799	0.301	39.4
2	0.324	0.302	0.117	36.1
3	0.251	0.241	0.072	28.8
4	0.226	0.219	0.055	24.6
5	0.214	0.210	0.049	22.9
6	0.203	0.197	0.045	22.2
7	0.202	0.200	0.045	22.1
8	0.197	0.193	0.046	23.2
N_0	Aver. T_0	Median T_0	Std. Dev. T_0	%CV T_0
1	35.2	40.0	9.8	27.8
2	7.2	7.1	2.3	32.2
3	4.0	3.7	1.2	30.0
4	2.8	2.7	0.8	27.3
5	2.2	2.1	0.6	26.2
6	1.9	1.7	0.4	24.8
7	1.6	1.5	0.4	27.9
8	1.5	1.3	0.6	42.6
	Aver. x_0	Median x_0	Std. Dev. x_0	%CV x_0
1	65.2	62.7	23.6	36.2
2	58.4	57.9	45.5	77.9
3	59.2	51.4	46.7	78.9
4	62.5	52.3	42.1	67.3
5	61.7	50.3	35.4	57.3
6	54.4	50.3	28.3	52.0
7	56.0	50.3	26.1	46.5
8	57.9	51.1	25.1	43.3
N_0	Aver. y_0	Median y_0	Std. Dev. y_0	%CV y_0
1	44.3	43.4	8.0	18.0
2	42.1	42.0	14.3	34.1
3	42.6	42.3	12.5	29.4
4	43.5	42.6	10.2	23.5
5	43.7	41.9	8.2	18.8
6	42.2	42.0	5.9	13.9
7	42.2	42.0	5.3	12.6
8	42.8	42.1	5.0	11.8

N_0	A1	A2	Aver. s_{Err} of $C(z;R\geq R_{Min})$	Aver. R of $C(z;R\geq R_{Min})$	s_{Err}/s_{Res}
5	1.54	-0.62	0.057	0.97	0.212
6	1.54	-0.62	0.057	0.97	0.212

The cumulative population with $R < R_{Min}$, the average values of k_v, T_0 and the coefficient of variation of k_v, T_0 are shown in Fig. 2. From Table I and Fig. 2 the subsequent conclusions are derived.

- The optimum number of connected in series perfect mixers is N_0=5 and N_0=6 as for these values $C(z;R<R_{Min})$ becomes minimal.

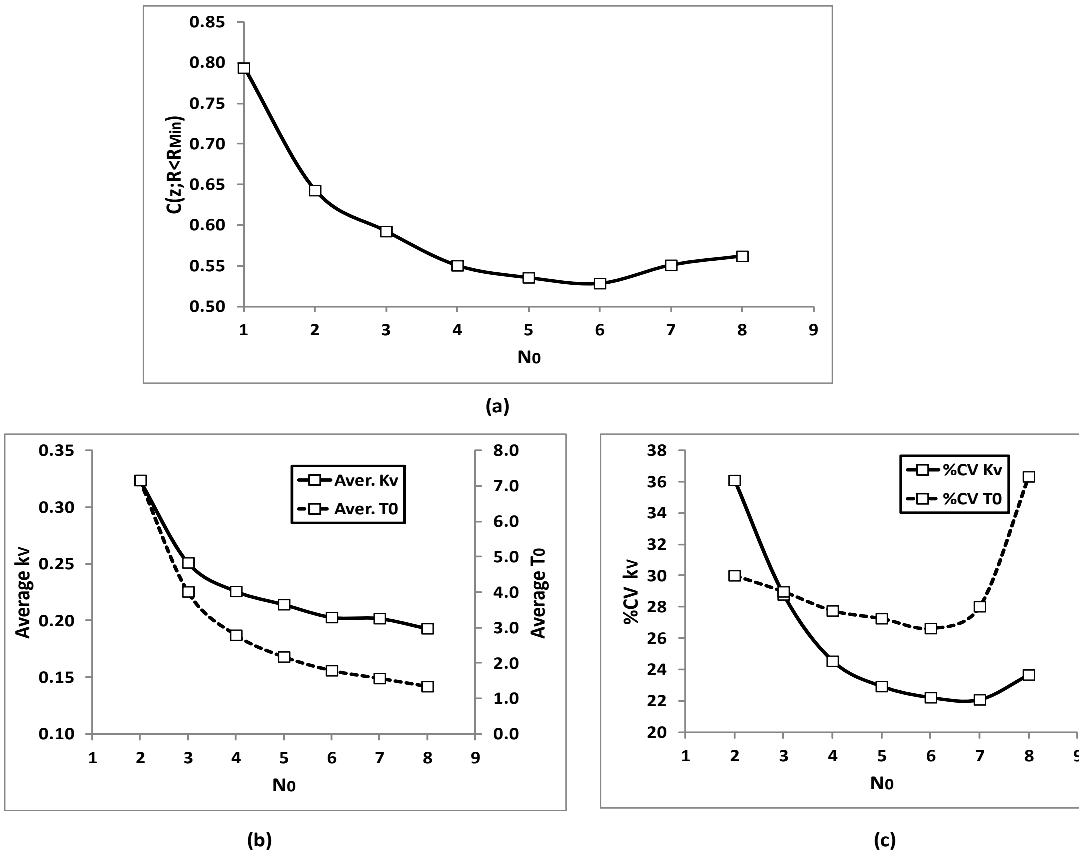

Fig. 2 Dynamic parameters: (a) $C(z;R<R_{Min})$; (b) average k_v and T_0; (c) $\%CV$ of k_v and T_0 as function of N_0.

- With increasing N_0, the average values of both k_v and T_0 decrease.
- For N_0=5, 6 the coefficients of variation of k_v and T_0 are minimal.
- From the %CV values it is concluded that the uncertainty of the dynamic parameters is high.

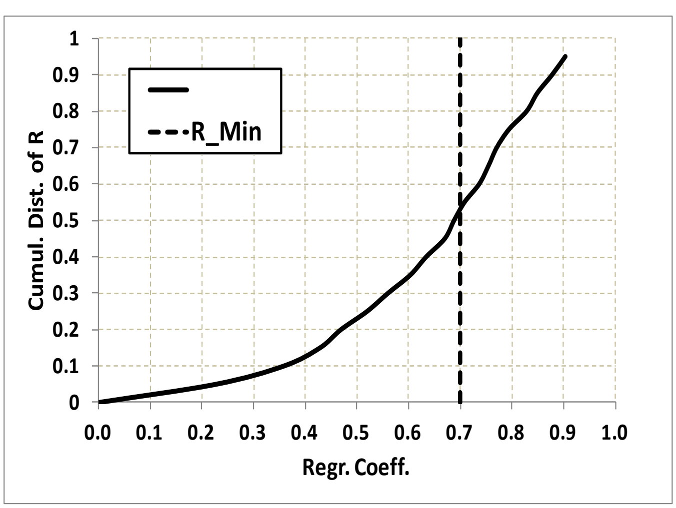

Fig. 3 Cumulative distribution of R for N_0=6.

- Because the simplified method followed in this study does not include modeling of several disturbances, e.g. alternative fuels flow rate and heat content, rate and temperature of tertiary air, in the optimum case only 47% of the experimental sets presents R > 0.7. To notice that the disturbances are partially modeled by the autoregressive model, but the dynamics of each one is not included. The cumulative distribution of R for N_0=6 is shown in Fig. 3.

The differential distributions for gain k_v and time constant T_0, for N_0=6 are demonstrated in Fig. 4 and 5 respectively.

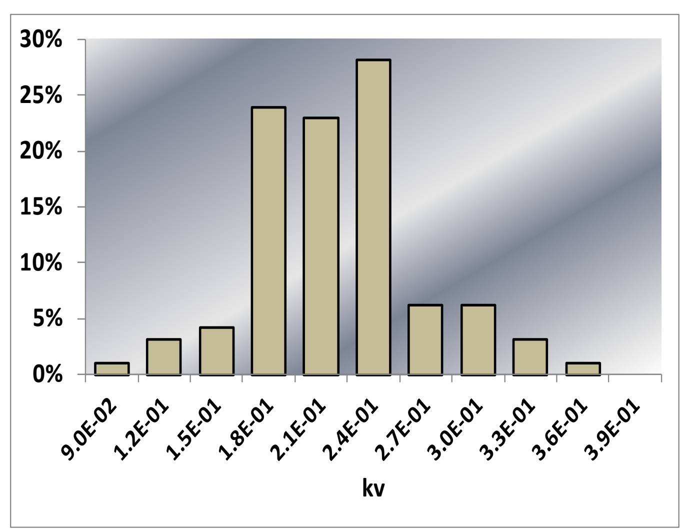

Fig. 4 Differential distribution of the gain k_v.

The shape of these distributions leads to the result that both variables follow a normal distribution. This conclusion can be useful in process simulation.

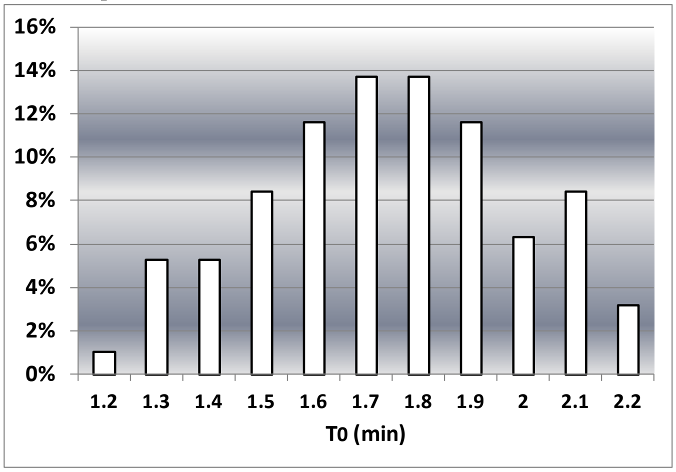

Fig. 5 Differential distribution of time constant T_0.

IV. Conclusions

The stable operation of kiln precalciner is one of the critical issues in a cement plant and the automatic control is highly preferred. Due to the complexity of the processes involved, an analytic modeling is extremely difficult as well as the use of such models for control purposes. In this study a simplified dynamic model between the temperature in the outlet of precalciner and feed rate of the primary fuel is presented. The evaluation of the dynamic parameters is based on industrial data. Tanks of equal volume connected in series have been considered. The residual errors depending on the tanks number have been estimated. The errors between the actual process values and the calculated ones from the dynamic model have been correlated by an autoregressive model. For each dataset the dynamic parameters are determined, the corresponding regression coefficient R, as well as the distribution of R for all the population of datasets. The optimum number of tanks, deriving the minimum error is five and six. The distributions of gain and of time constant were also determined. The described simplified model could be used for parameterization of a PID controller for regulating the process. Due to its simplicity, the tuning results could be used as initial PID values, needing a more detailed and accurate modeling.

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