Modeling of Raw Materials Blending in Raw Meal Grinding Systems
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Abstract: - The objective of the present study is to build a reliable model of the dynamics between the chemical modules in the outlet of raw meal grinding systems and the proportion of the raw materials. The process model is constituted from three transfer functions, each one containing five independent parameters. The computations are performed using a full year industrial data by constructing a specific algorithm. The results indicate high parameters uncertainty due to the large number of disturbances during the raw mill operation. The model developed can feed with inputs advanced automatic control implementations, in order a robust controller to be achieved, able to attenuate the disturbances affecting the raw meal quality.

Key-Words: - Dynamics, Raw meal, Quality, Mill, Grinding, Model, Uncertainty

1 Introduction
One of the main factors primarily affecting the cement quality is the variability of the clinker activity [1] which depends on the conditions of the clinker formation, raw meal composition and fineness. A stable raw meal grinding process provides a low variance of the fineness.

Figure 1. Flow chart of raw meal production

Figure 1 depicts a typical flow chart of raw meal production. In the demonstrated closed circuit process, the feeding of the raw materials is performed via three weight feeders, feeding first a crusher. The crusher outlet goes to the recycle elevator and from there to a dynamic separator, the speed and gas flow of which controls the product fineness. The fine exit stream of the separator is the main part of the final product. The coarse separator return, is directed to the mill, where is ground and from there via the recycle elevator feeds the separator. The material in the mill and classifier are dried and dedusted by hot gas flow.

The variation of this parameter is related to the homogeneity of the raw materials in the raw mill (RM) inlet, the mixing efficiency of the homogenizing silo and the regulation effectiveness as well. Due to its complexity and significance, different automated systems are available for sampling of and analyzing the raw mix as well as for adjustment of the mill weight feeders according to the raw meal chemical modules in the RM outlet. The regulation is mainly obtained via PID and adaptive controllers. Several adaptive controllers of varying degrees of complexity have been developed [2, 3, 4, 5, 6]. Tsamatsoulis [7] tuned a
classical PID controller between chemical modules in the RM output and raw materials proportions in the mill feed, using as optimization criterion the minimum standard deviation of these modules in the kiln feed. He concluded that the application of stability criteria is necessary. He also proved that the variance of the kiln feed composition not only depends on the raw materials variations and the mixing capacity of the silos but also is strongly related with the effectiveness of the regulating action. The reason that so intensive efforts are devoted to the raw meal regulation is that advanced raw mill control delivers improved economic performance in cement production, as Gordon [8] points out.

The common field between all these attempts and designs is the assumption of a model describing the process dynamics. The aim of the present study is to develop a reliable model of the dynamics between the raw meal modules in the RM outlet and the proportions of the raw materials in the feeders for an existing closed circuit RM of the Halyps plant. Due to the uncertainty of the materials composition, it is necessary not only to describe the mixing process using a representative model, but to estimate the parameters uncertainty as well. The model coefficients and their uncertainty are computed exclusively from routine process data without the need of any experimentation as usually the model identification needs. Then, this process model can be utilized to build or to tune a large variety of controllers to regulate this challenging industrial process.

2 Process Model

2.1 Proportioning Moduli Definition

The proportioning moduli are used to indicate the quality of the raw materials and raw meal and the clinker activity too. For the main oxides, the following abbreviations are commonly used in the cement industry: C = CaO, S=SiO\(_2\), A=Al\(_2\)O\(_3\), F=Fe\(_2\)O\(_3\). The main moduli characterizing the raw meal and the corresponding clinker are as follows [1]:

\[
\text{Lime Saturation Factor} \quad LSF = \frac{100 \cdot C}{2.8 \cdot S + 1.18 \cdot A + 0.65 \cdot F} \tag{1}
\]

\[
\text{Silica Modulus} \quad SM = \frac{S}{A + F} \tag{2}
\]

\[
\text{Alumina Modulus} \quad AM = \frac{A}{F} \tag{3}
\]

The regulation of some or all of the indicators (1) to (3) contributes drastically to the achievement of a stable clinker quality.

2.2 Block Diagram

Limestone and clay are fed to the mill via two silos: the first silo contains limestone while the second one mixture of limestone and clay with volume ratio clay: limestone=2:1. This composite material is considered as the “clay” material of the process. The third silo contains either the corrective material of high iron oxide or high alumina content or both of them. The block diagram is illustrated in Figure 2, where the controller block also appears.
%Lim, %Add, %Clay = the percentages of the limestone, additive and clay in the three weight feeders. LSF\textsubscript{Mill}, SM\textsubscript{Mill} = the spot values of LSF and SM in the RM outlet, while LSF\textsubscript{S}, SM\textsubscript{S}, LSF\textsubscript{M}, SM\textsubscript{M} = the modules of the average sample and the measured one. Finally LSF\textsubscript{KF}, SM\textsubscript{KF} = the corresponding modules in the kiln feed. The LSF and SM set points are indicated by LSF\textsubscript{SP} and SM\textsubscript{SP} respectively, while e\textsubscript{LSF} and e\textsubscript{SM} stand for the error between set point and respective measured module.

The transfer function of the raw meal mixing in the RM is analyzed in more detail in Figure 3. The functions between the modules and the respecting percentages of the raw materials are indicated by $G_{\text{LSF,Lim}}$, $G_{\text{SM,Clay}}$, $G_{\text{SM,Add}}$. This configuration includes some simplifications and assumptions which are proved as valid in connection with the current raw materials analysis:

- There is not impact of the limestone to SM as the S, A, F content of limestone is in general very low compared with the other raw materials.
- Moreover there is no effect of the additive on the LSF as its percentage is very low, less than 3%.
- The materials humidity is neglected, to simplify the calculations.
- As to the clay, the function %Clay=100-%Lim-%Add is taken into account.

### 2.3 Process Transfer Functions

For the existing RM circuit, the objective of the analysis is to model the transfer function between the raw meal modules in the RM outlet and the proportions of the raw materials in the feeders. Consequently only for the functions $G_{\text{Mill}}$, $G_{s}$, $G_{M}$ analytical equations in the Laplace domain are needed. The $G_{M}$ represents a pure delay, therefore is given by equation (4):

$$G_{M} = e^{-t_{M}} \quad (4)$$

The delay $t_{M}$ is composed by the time intervals of sample transferring, preparation, analysis and computation of the new settings of the three feeders and finally transfers of those ones to the weight scales. For the given circuit the average $t_{M} = 25$ min = 0.42 h. By the application of the mean value theorem and the respective Laplace transform, the function $G_{s}$ is calculated by the formula (5):

$$G_{s} = \frac{1}{T_{s}} (1 - e^{-T_{s} s}) \quad (5)$$

The sampling period $T_{s}$ is equal to 1 h. Based on the step response results of [7], performed in the same RM a second order with time delay (SOTD) model is chosen for each of the functions $G_{\text{LSF,Lim}}$, $G_{\text{SM,Clay}}$, $G_{\text{SM,Add}}$ described by the equation (6):

$$G_{x} = \frac{k_{g,x}}{1 + T_{0,x} s} \cdot e^{-t_{d} s} \quad (6)$$

Where $x = \text{LSF,Lim, SM,Clay or SM,Add}$. The constant $k_{g}$, $T_{0}$, $t_{d}$ symbolize the gain, the time constant and the time delay respectively. The value of these nine variables shall be estimated. As measured inputs and outputs of the process are considered the %Lim and %Add as well as LSF\textsubscript{M} and SM\textsubscript{M}. The functions (4)-(6) in the time domain are expressed by the following equations:

$$LSF_{M}(t) = LSF_{S} (t - t_{M}) \quad (7)$$
$$SM_{M}(t) = SM_{S} (t - t_{M})$$

$$LSF_{S}(t) = \frac{1}{T_{s}} \int_{t-T_{s}}^{t} LSF_{\text{Mill}} \, dt \quad (8)$$
$$SM_{s} = \frac{1}{T_{s}} \int_{t-T_{s}}^{t} SM_{\text{Mill}} \, dt$$

$$\frac{y - y_{0}}{u - u_{0}} = k_{g,x} \cdot \left(1 - e^{-\frac{t-t_{d}}{T_{0,x}}} \cdot \frac{t-t_{d}}{T_{0,x}} - e^{-t_{d} \cdot \frac{t-t_{d}}{T_{0,x}}} \right) \quad (9)$$

Where $y = LSF_{\text{Mill}}$ or $SM_{\text{Mill}}$, $u = %\text{Lim, Clay or Add}$ and x as defined in the equation (6). The $u_{0}$ and $y_{0}$ parameters stand for the steady state values of the input and output variables. The process variable, $y$, is derived from the input signal, $u$, by applying the convolution between the input and the system pulse function, $g$, expressed by (10).

$$y(t) - y_{0} = \int_{0}^{t} (u(\tau) - u_{0}) \cdot g(t - \tau) \, d\tau \quad (10)$$

### 2.4 Parameters Estimation Procedure

Each of the three transfer function $G_{s}$, defined by the formulae (6) in frequency domain or (9) in time domain contains five unknown parameters: The gain $k_{g}$, the time constant $T_{0}$, the delay time $t_{d}$ and the steady state process input and output $u_{0}$ and $y_{0}$ respectively. The determination of these 15 in total coefficients is obtained via the following procedure:
One full year hourly data of feeders’ percentages and proportioning moduli are accessed from the plant data base.

For each pair of input and output and using convenient software, continuous series of data are found. Because for each one of the three functions, five parameters need determination, the minimum acceptable number of continuous in time data is set to ≥14.

For each mentioned pair, the average number of data of the uninterrupted sets is 18 and the total number of sets is more than 200. Therefore the sample population is high enough, to derive precise computation of both the average parameter values and their uncertainty.

For each data set and using non linear regression techniques, the five parameters providing the minimum standard error between the actual and calculated values are estimated. For the optimum group of parameters the regression coefficient, R, is also computed.

A minimum acceptable \( R_{\text{min}} \) is defined. The results are screened and only the sets having \( R \geq R_{\text{min}} \) are characterized as adequate for further processing. The usual causes of a low regression coefficient are random disturbances inserted in the process or changes in the dynamics during the time interval under examination.

For the population of the results presenting \( R \geq R_{\text{min}} \), the average value and the standard deviation of each model parameter is determined. The standard deviation is a good measure of the parameters uncertainty.

4 Results and Discussion

4.1 Model Adequacy

There are various sources of disturbances and uncertainties affecting the ability to model the process dynamics. As main causes of such variances can be characterized the following:

(i) The limestone and clay unstable composition. The average LSF of 140 limestone samples taken during a full year is 840 with a standard deviation of 670. The respective average LSF of 480 samples of clay is 17 with a standard deviation of 5. This large uncertainty not only has an impact on the gain value, but also on the process time constant and delay.

(ii) The variance of the raw materials moisture. For the same samples referred in (i), the limestone humidity is 3.4±1.2, while the clay one is 10.2±1.7.

(iii) Disturbances of the RM dynamics caused by various conditions of grinding. For example variations of the gas flow and temperature, of the RM productivity, of the circulating load, of the raw mix composition etc.

(iv) Some uncertainty of the time needed for sample preparation and analysis.

(v) Some noise introduced in the measurement during the sample preparation and analysis procedure.

Due to all these unpredicted disturbances and the resulting uncertainties, to investigate the model adequacy, the cumulative distribution of the regression coefficients are determined for each one of the three dynamics. In spite that the %clay to SM and %additive to SM transfer functions are considered as independent to simplify the computations, in reality are strongly interrelated: The change of the clay percentage results in a disturbance of the second dynamics - from %additive to SM – and vice versa. The three cumulative distributions are depicted in Figure 4.

![Figure 4. Cumulative distributions of the regression coefficients.](image)

If as minimum acceptable level for good regression a value of \( R_{\text{min}} \) equal to 0.6 is chosen, then only 50-55% of the experimental sets present an \( R \geq R_{\text{min}} \). Subsequently the effect of the different disturbances on the model identification becomes clear. On the other hand the model describes adequately the blending process during the grinding of the raw mix in the closed RM circuit, for at least the half of the data sets. For further calculations \( R_{\text{min}}=0.6 \) is selected.
4.2 Evaluation of the Model Parameters and their Uncertainty

Based on the analysis presented in section 4.1 the average value and its standard deviation, $s$, for each parameter are determined. The results are shown in Table 1. The coefficients of variation, $\%CV = s/\text{Aver} \times 100$, are also indicated.

Table 1. Model parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Average</th>
<th>$s$</th>
<th>$s/\text{Aver.}\times 100$</th>
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<tbody>
<tr>
<td>$G_{\text{LSF,Lim}}$</td>
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<td>$k_g$</td>
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<td>0.85</td>
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<td>$T_0$</td>
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<td>$\text{Lim}_0$</td>
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<td>9.1</td>
<td>17.5</td>
</tr>
<tr>
<td>$G_{\text{SM,Clay}}$</td>
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<td></td>
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<td>19.1</td>
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<tr>
<td>$G_{\text{SM,Add}}$</td>
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<td>0.71</td>
<td>48.7</td>
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</table>

These values are computed from the data sets with $R \geq 0.6$ resulting in an average regression coefficient of 0.736. A typical comparison of actual and calculated LSF values is depicted in Figure 5.

Figure 5. Calculated vs. actual LSF values

As mentioned earlier, the standard deviation is a good measure of the parameter uncertainty. Due to the sufficient number of data sets, extracted from actual operating data, the estimation of the parameters average and uncertainty are reliable. The distribution of the gain between LSF and $\%\text{Limestone}$ is demonstrated in Figure 6.

Figure 6. Cumulative distribution of $k_g$ $\text{LSF,Lim}$.

For the three models under investigation the gain uncertainty is ranging from 34% to 40%, while the corresponding range of the time constant and delay time is from 40% to 50% and 25% to 60% respectively. It is verified that the enlarged disturbances cause a substantial uncertainty to the determination of the model parameters. Subsequently it becomes evident that advanced automatic control techniques are necessary to reject the mentioned disturbances.

6 Conclusions

The dynamics of raw materials mixing in raw meal grinding systems is modeled effectively, by considering the transfer functions between the raw meal chemical moduli and the material proportions to the feeders. The sampling procedure and the delay time for sample preparation and analysis are taken into account. The process model is constituted from three transfer functions including five independent parameters each one. To compute these parameters with the maximum possible reliability a full year industrial data are collected and a specific algorithm is implemented. The results prove that the parameters uncertainty is elevated enough due to the large number of unpredicted disturbances during the raw meal production. Consequently advanced control theory and techniques are needed to attenuate the impact of these disturbances on the raw meal quality. The model developed can feed these tools with the results presented in order a robust controller to be achieved. The same technique to model the raw meal blending can also be applied to raw mills of the same or similar technology.
References: