LINEAR IDENTIFICATION OF ROTARY WHITE CEMENT KILN

Golamreza Noshirvani, Mansour Shirvani
ACECR Markazi Branch, Beheshti Street, Arak, Iran

Alireza Fatehi
Control Departmen , KNtoosi University, Tehran, Iran

Keywords: Rotary White Cement Kiln, Dynamic Modelling, Linear Identification, Box-Jenkins.

Abstract: Rotary cement kiln is the main part of a cement plant that clinker is produced in it. Continual and prolonged operation of rotary cement kiln is vital in cement factories. However, continual operation of the kiln is not possible and periodic repairs of the refractory lining would become necessary, due to non-linear phenomena existing in the kiln, such as sudden falls of coatings in the burning zone and probability of damages to the refractory materials during production. This is the basic reasoning behind the needs for a comprehensive model which is severely necessary for better control of this process. Such a model can be derived based on the mathematical analysis with consultation of expert operator experiences. In this paper linear model is identified for rotary kiln of Saveh white cement factory. The linear model is introduced using Box-Jenkins structure. The results of the obtained model were satisfactory compared to some other models and can be used for designing adaptive or robust controllers.

1 INTRODUCTION

During the years of clinker production, many changes and improvements have been occurred. Rotary kilns is not just for cement production, while it is used in different chemical industries such as lime burning, crude oil calcinations, solid garbage ash, titanium dioxide calcinations, aluminium oxide process and etc. In all cases, use of rotary kiln, due to its basic role about energy consumption, desired reaction performance and many other advantages is preferred. However, control of the kiln in optimal condition is of primary importance and is not possible unless having a good knowledge and a comprehensive model based on important phenomena occurring in the system. In this way, several research papers have been published among which the original modelling of Spang, based on material and energy balance of the kiln can be mentioned (Spang, 1972). In Spang's mechanistically model several assumptions have been used. Also, Frish assumed the kiln as cylindrical vessel with internal non adiabatic heating source, and focused on the monotonically state. He assumed the heat transfer based on radiated rather than displacement type (Frish and Jeschar, 1983). In figure 1, a schematic of the kiln with its cyclone pre-heater is shown.

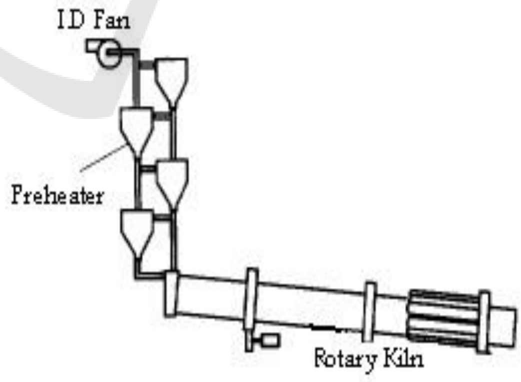

Figure 1: Rotary Cement kiln Process.

In this paper we will use a black box identification procedure for modelling the Saveh white cement kiln. It is a 65 m long, 4.7 m diameter kiln with 4 stage double string pre-heater and water immersion cooler. The main manipulated variables of the kiln are:

Noshirvani G., Shirvani M. and Fatehi A.
LINEAR IDENTIFICATION OF ROTARY WHITE CEMENT KILN.
DOI: 10.5220/0002191501900195
In *Proceedings of the 6th International Conference on Informatics in Control, Automation and Robotics (ICINCO 2009)*, page
ISBN: 978-989-674-001-6

- kiln speed
- Fuel Flow Rate
- ID. Fan speed
- Raw Material Flow Rate

Also the output variables according to the operator's experiences are as following:

- back end temperature
- Remained (unused) oxygen, O_2
- CO content of outlet gases from the kiln
- Kiln DC motor current
- Preheater temperature
- Cooler temperature

Based on these variables the rotary kiln is a 4-inputs 6-outputs plant as shown in figure 2.

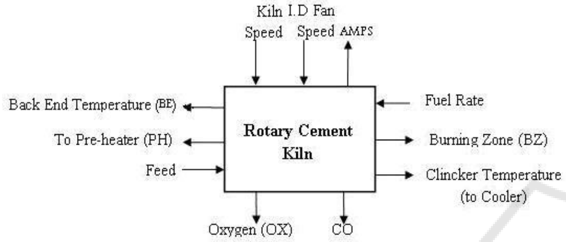

Figure 2: Block diagram of the kiln based on input-output.

These variables are so important and selected with fundament of expert operators, such as with these input, the kiln can be controlled. The burning zone temperature is not only one of the most important kiln control variables but also the most difficult one to monitor (Peray, 1986). Despite the fact that burning zone condition in modern kilns are shown as temperature profile that used for manual controllers.

2 CONDITION OF DATA GATHERING

There are three important factors in modelling based on the identification techniques:

- Useful and valid data
- A perfect and useful model
- Strong method to adjust the model

Input and outputs must be selected such that input change affects output variables. Also the recognition of process behavior will be much simpler if input-output data is reach, i.e. it consists different operating points and frequency contents. However, system identification based on input output data does not introduce a physical model with exact structure but it does a model that fits the data. Therefore, selection of a proper model is important. Also, the obtained data should have the process information to be used for identification.

An important point concerning data gathering is that to be careful that the disturbances and unexpected events such as creation of coating and coating fall in the kiln and do not change the system behaviour. The white cement rotary kiln identification is passive process, meaning that we can only observe the plant variables under a given circumstance and it is technically impossible to introduce extra excitation on these systems. The data from these systems may not be informative enough. This can make the identification of the system difficult (Zhu, 2001). Therefore it is not possible to expect from the presented model to have the same behaviour with the real system in an abnormal condition unless these conditions are occurred a few times during data gathering.

For this reason, data gathered during a period of 18 hours for several times. Finally, the best conditioned data were obtained for the rotary kiln in 2008-05-07. Figure 3 shows the input variables. The output variables are shown in figure 4.

3 DATA PRETREATMENT

After collecting perfect data from rotary kiln, the data will not be used directly for identification process. One of its reasons is high frequency noises and spikes on the main signals. Sometimes immeasurable disturbances occur and take the system out of its linear range. Changing Operation point causes entering nonlinear effects in output data. To solve the problem of high frequency noises and some of these problems, it is tried to use some pre-processing methods mentioned in identification references to reach a perfect model of process (Ljung, 1999; Nelles, 2001) . For considering rest of them, we tried to choose the model structure and focus on its flexibilities.

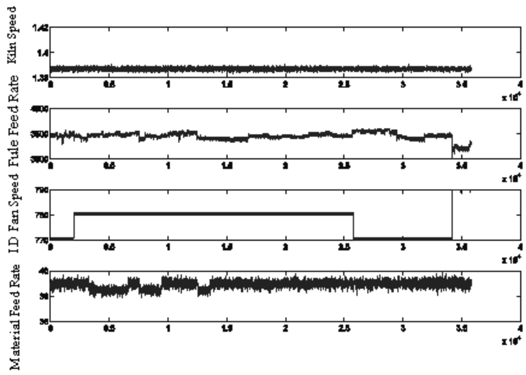

Figure 3: Input data representation for white cement kiln identification.

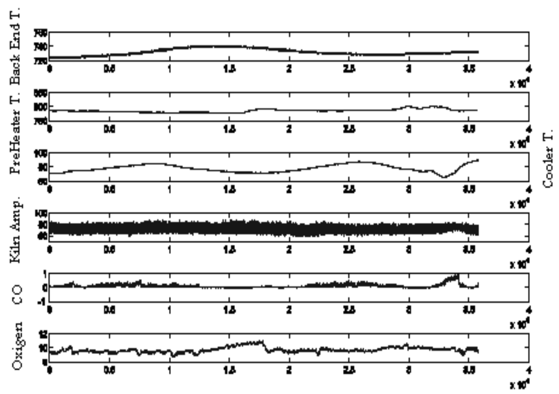

Figure 4: Output data representation for white cement kiln identification.

3.1 Peak Shaving

At the first stage, it is necessary to pay attention on data to recognize the system dynamics based on the available input and output data. It is important to smooth the spikes and shave the peaks. Spikes are because of sensors operation or data acquisition card that causes a numerical fault in data representation (Astrom, 1984), whereas the high energy of spikes interfere the model parameters estimation and its validation. Applying a third order digital Butterworth filter on the data gathered from the kiln.

The filtered output for kiln back temperature is shown in figure 5. Correlation analysis is used to obtain the weight and important dynamics between input and output data (Noshirvani, 2005). The similarity of two signals will be measured in correlation analysis. In this analysis, the correlation order of two signals is measurable. These contexts can be written as the following formulas:

$$\Phi_{u,y}(\tau) = E\{u(t)\cdot y(t-\tau)\} = \lim_{N\to\infty}\frac{1}{N}\sum_{k=1}^{N}u(k)\cdot y(k-\tau) \qquad (1)$$

where $\Phi_{u,y}(\tau)$ is the cross correlation of u and y and

$$\Phi_{u,u}(\tau) = E\{u(t)\cdot u(t-\tau)\} = \lim_{N\to\infty}\frac{1}{N}\sum_{k=1}^{N}u(k)\cdot u(k-\tau) \qquad (2)$$

where $\Phi_{u,u}(\tau)$ is the autocorrelation of u.

Correlation analysis assumes a linear system and does not require a specific model structure; also it could be used to assess the effective dynamics.

Figure 6 shows the correlation between input fuel rate and the kiln speed to burning zone temperature.

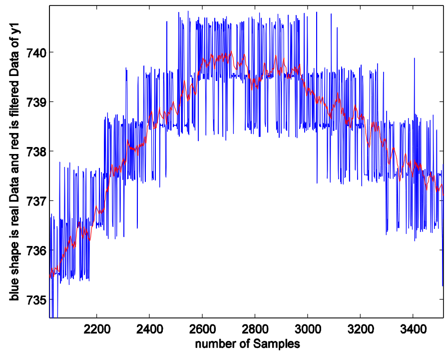

Figure 5: Real data and Filtered data representation.

The basic assumption in the discussion is that the identification model will be used in control. Therefore the main dynamics used for this output in identification have been shown, and then the plant is broken into 6 MISO models.

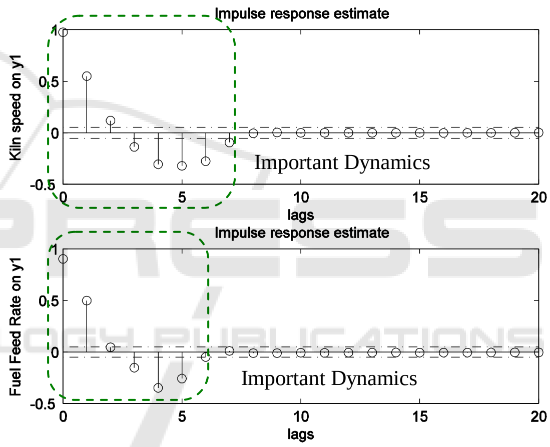

Figure 6: Correlation between first and second inputs with the first output.

4 LINEAR IDENTIFICATION

Different linear models were studied for system identification. The best obtained linear model for the kiln was Box-Jenkins (BJ) model which its result is explained here. BJ model is defined as:

$$y(k) = \frac{B(q)}{F(q)}u(k) + \frac{C(q)}{D(q)}\upsilon(k) \qquad (3)$$

This structure has been introduced by Box-Jenkins in 1970. The predictor for this model is illustrated in (5).

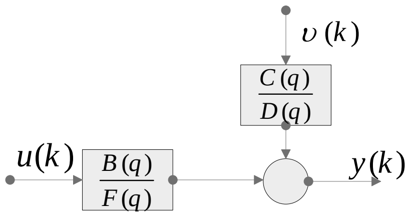

Figure 7: Box-Jenkins Structure.

$$\begin{aligned} F(q) &= 1 + f_1 q^{-1} + \cdots + f_n q^{-n} \\ B(q) &= b_1 q^{-1} + \cdots + b_n q^{-n} \\ C(q) &= 1 + c_1 q^{-1} + \cdots + c_n q^{-n} \\ D(q) &= 1 + d_1 q^{-1} + \cdots + d_n q^{-n} \end{aligned} \tag{4}$$

$$\hat{y}(k|k-1) = \frac{D(q)B(q)}{C(q)F(q)}u(k) + \left[1 - \frac{D(q)}{C(q)}\right]y(k) \tag{5}$$

where $\hat{y}(k)$ is the output of the model. The notation $|k-1$ is used because the optimal prediction of Box-Jenkins model utilizes previous process outputs in order to extract the information contained in the correlated disturbance, *n(k)* affects on output variable, that is defined in (6) and the prediction of error of this model can be obtained with (7).

$$e(k) = \frac{D(q)}{C(q)}y(k) - \frac{B(q)D(q)}{F(q)C(q)}u(k) \tag{6}$$

Box-Jenkins model is estimated by nonlinear optimization, where first an auto regressive estimation to determine the initial parameter values for b_i and f_i. The gradients of models function can be computed as follows.

$$\begin{aligned} F(q)C(q)\hat{y}(k|k-1) &= B(q)D(q)u(k) + \\ F(q)\ \ C(q) - D(q)\ \ y(k) & \end{aligned} \tag{7}$$

Differentiation of (7) with respect to b_i yields

$$F(q)C(q)\frac{\partial \hat{y}(k|k-1)}{\partial b_i} = D(q)u(k-i) \tag{8}$$

This leads to

$$\frac{\partial \hat{y}(k|k-1)}{\partial b_i} = \frac{D(q)}{F(q)C(q)}u(k-i) \tag{9}$$

Also these computations have done for c_i, d_i and f_i. The parameters of this model will be trained based on minimizing of the following cost function:

$$V_{BJ} = \frac{1}{N}\sum_{t=1}^{N}\left[\frac{D(q)}{C(q)}\left\{y(t) - \frac{B(q)}{F(q)}u(t)\right\}\right]^2 \tag{10}$$

The main advantage of Box-Jenkins is giving a better estimation for the closed-loop models, but its implementation is a challenging task (Eykoff, 1974).

In general Box-Jenkins (BJ) model has several advantages over the output error method. Firstly, it will supply both a process model and a disturbance model. As shown in table1, this model will be consistent also in passive identification; this implies that this method will give a more accurate process model than an output error method for a given process under passive data condition. However, the BJ model has a more complex structure, which implies that numerical optimization will be more complicated.

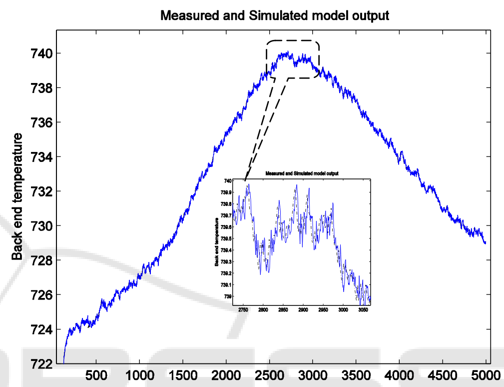

Figure 8: Actual and simulated signal of kiln back-end temperature.

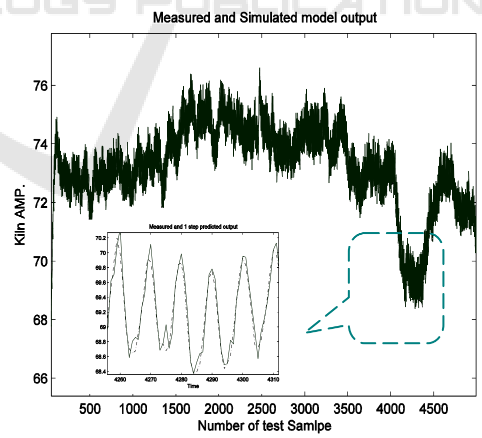

Figure 9: Actual and simulated signal of Kiln motor current.

Carbon monoxide analysis, because it samples dirty kiln gases and takes the sample at a location where high temperature prevail, has a tendency to multifunction frequently unless almost daily preventive maintenance is carried out on this unit. The location, where the sample probe is installed, is also key point to consider as false air in leakage could distort the true contents of CO in the exit gases (Shirvani et.al, 2004).

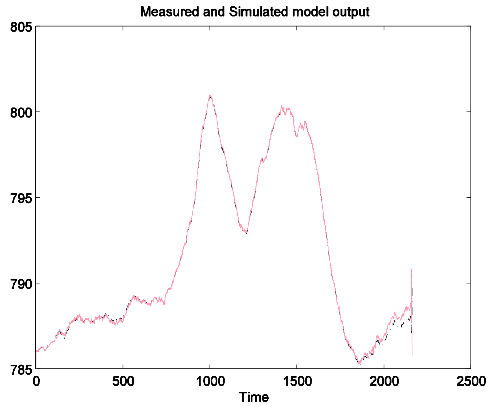

Figure 10: Actual and simulated signal of Pre-heater temperature.

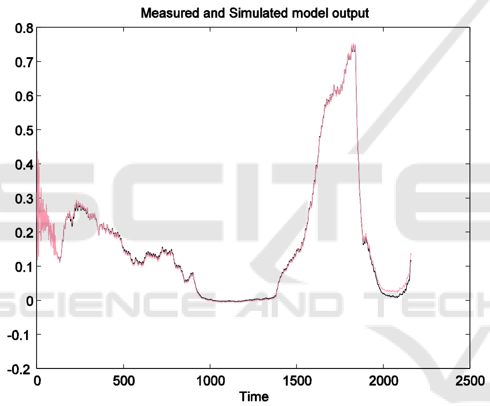

Figure 11: Actual and simulated signal of Carbon monoxide.

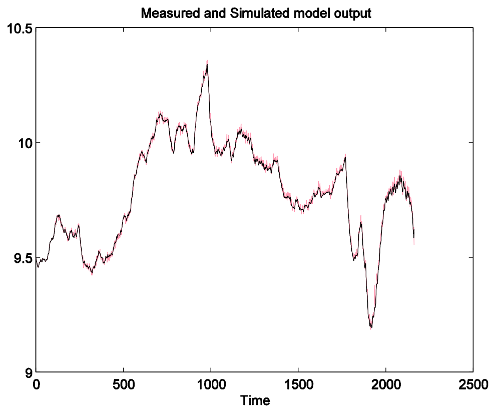

Figure 12: Actual and simulated signal of Oxygen.

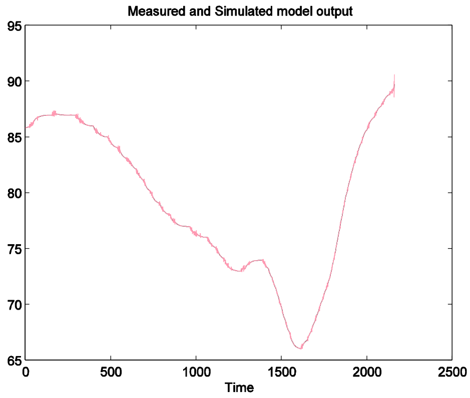

Figure 13: Actual and simulated signal of Cooler temperature.

Equation11 is known as the mean square error of model. It is an estimation of the standard deviation of the model error with respect to data.

$$E = \frac{1}{N}\sum_{K=1}^{N}\left|y(k) - \hat{y}(k)\right|^2 \qquad (11)$$

The models are compared with test data that obtained also in 2008-08-15 for # hours from control system of Saveh white cement plant. The fitness of the model with the plant can be computed as (Eykoff, 1974). Then the best criterion is (12).

$$fitness = \left(1 - \frac{\left|y - \hat{y}\right|}{\left|y - \bar{y}\right|}\right) \times 100 \qquad (12)$$

where $\bar{y}(k)$ is the mean of $y(k)$.

By comparing different dynamic models like output error (OE) and ARMAX in equation (12) can be concluded that BJ modelling has a better response (Noshirvani, 2005). This result is because passive modelling of kiln system is severely non-linear. Therefore, as it is shown in Table1, the most enriched linear model has relatively better performance.

Table 1: comparing different linear Models of plant.

Variable	B.J.	ARMAX	O.E.
Back end temperature	85%	64%	37%
Current motor Kiln	84%	70%	29%
Preheater Temperature	91%	75%	40%
Carbon mono oxide	88%	68%	39%
Oxygen	89%	68%	30%
Cooler temperature	87%	61%	35%

5 CONCLUSIONS

In this paper, some linear approaches for system identification and model parameter estimation have been applied to an industrial scale white cement kiln.

Since the white cement rotary kiln identification is passive and the process input data were inadequate and the signal to noise rate was very high, it is a complex process which needs some comprehensive identification procedure. Different kind of linear models are examined in which BJ dynamic model presents the best result compare to other linear models.

Linear structure can be used for identifying the rotary cement kilns, but in this procedure, the coating fall and its creation in the kiln, will be ignored. Thus, the train and test data have been gathered with this assumption.

Weakness of linear modelling based on O.E is that it is proper for slow damping process, but in this plant slow dynamics related to the system and fast dynamics related to noise are not completely segregated and obtained error is mostly related to enforced noise in output signals.

REFERENCES

Spang, H.A., 1972. Dynamic Model of a Cement kiln, Vol. 8, pp. 309 – 323,

Frish, V., Jeschar, R., 1983. Possibilities for Optimizing the Burning Process in Rotary Kiln, Vol. 10/83, pp.549-560,

Peray, K.E., 1986. The Rotary Cement Kiln, 2nd edition

Zhu, Y.C., 2001. Multivariable System Identification for process control, PERGAMON

Ljung, L., System Identification: Theory for the user. 1999 *Prentice- Hall*, 2nd edition

Nelles, O., 2001. Nonlinear system identification, Springer

Astrom, K. J. and Wittenmark, B., 1984. Computer Controlled Systems: Theory and Design, Prentice-Hall, Englewood Cliffs

Noshirvani, R., Identification of White Cement Rotary Cement Kiln, M.Sc Thesis, K.N.Toosi University Control Engineering Department of K.Ntoosi, 2005

Eykoff, P., 1974. System Identification: Parameter and state Estimation, John Wiley & Sons, New York

Shirvani, M., Dustary, M., Shahbaz, M. Eksiri, Z. Heuristic, 2004. Process Model Simplification inFrequency Response Domain, International of Engineering, Vol. 17/B, pp.31-52