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Identification and Abnormal Condition Detection of a Cement Rotary Kiln

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Abstract: In this paper, we use system identification methods for abnormal condition detection of a cement rotary kiln. After selecting proper inputs and output, an input-output model is identified for the plant. A novel approach is used in order to estimate the delays of the input channel of the kiln. By means of that, the identification task gets easier and the results are more accurate. To identify the kiln, Locally Linear Neuro-Fuzzy (LLNF) model is used. This model is trained by LOLIMOT algorithm which is an incremental tree-structure algorithm. Finally, a model for the healthy mode of the kiln is obtained through which it is possible to detect abnormal conditions in the process. We distinguished two common abnormal conditions in kiln and another one which was not characteristically known for cement experts as well.

1. INTRODUCTION

During the operation of a plant, some process variables are measured to monitor the behavior of the plant, either to control them or for safety reasons. In automation system of a plant, these variables are compared by their proposed normal values and if their values are beyond some thresholds, control or safety commands are given or warning alarms are produced. But, generally there are many abnormal conditions where the sensory and automation system of the plant cannot recognize them. In these cases, an expert operator who knows how the plant should operate in normal condition can detect its abnormality. Due to the importance of these abnormal conditions, automatic abnormal condition monitoring is necessary for a full automatic control system.

For this reason, modern condition monitoring approaches are introduced. With these approaches, it is possible to diagnose and/or prognosticate a faulty situation beforehand in the operation of a plant in order to prevent damages to instruments or a collapse in the process.

In this paper we use system identification methods in order to detect common abnormal conditions in the most vital part of a cement factory, i.e. cement rotary kiln. To identify the kiln, we use LLNF model, also referred to as Takagi-Sugeno fuzzy models (Takagi *et al*, 1985). We used LOLIMOT algorithm (Nelles, 2001) to learn the weights.

In the next section, a brief description on rotary kiln is given. Also some abnormal conditions that may happen in it are mentioned. Then the reasons above input-output selection are discussed. In section 3, using a novel approach which was first presented by the authors (Makaremi, 2007, Makaremi *et al*, 2008), the input channel delays on the model are estimated. Afterward in section 4, with NNLF model and LOLIMOT learning algorithm, a model for the kiln is obtained. Section 5 is devoted to the discussion on detecting three abnormal conditions that were observed in test and validation data. Conclusion comes at the end.

2. CEMENTROTARY KILN

Cement is a substance which is made of grinded gypsum and cement clinker which itself is produced from a burned mixture of limestone and clay in certain percentages. Cement is used to bind other materials together.

Since cement factory is much expanded and it is consisted of different instruments and various processes in each part, modern condition monitoring methods are seemed suitable to be used in order to prevent abnormal conditions which end in a loss.

Cement rotary kiln is the most vital part of a cement factory whose outcome is cement clinker. A rotary kiln is a cylinder with a length of around 70 meters and a diameter of around 5 meters in a factory with a capacity of producing about 2000 tons of clinker in a day. The kiln is rotated by a powerful electrical motor. The temperature in the hottest point in the kiln is up to 1400ºC.

The kiln works nonstop and an impeding fault may cause inferior product at the end of the line or a halt in a large part of the factory with irreparable damages to equipments. Hence, it is essential to use some methods in order to prevent such faults.

Many of the abnormal conditions in the plant are detected and reported by the plant automation and safety system such as high temperature of cyclones, lack of pressure in hydraulic systems and so on. There are, however, other abnormal conditions which are not detected by conventional automation systems. In these cases, none of the measured variables are beyond their limitations, but the overall behavior of the plant is abnormal. An expert operator can recognize these conditions by comparing the current behavior of the plant by what was expected from the normal condition behavior. What we are concerned about in this paper is these types of faults or abnormality which cause poor product or are the origin of a halt in the process. For instance, some of the common abnormalities in the kiln are

- Coating disintegration
- Ringing
- Super heated or super chilled

We use system identification approaches for the sake of abnormal condition detection. The output that is going to be identified is the consumed power by the motor which spins the kiln. The inputs are kiln speed, raw material feed rate, fuel feed rate, secondary air pressure, and I.D. fan speed. The reason of this selection is a negotiation with experts and process engineers of the factory. In their point of view, power of the electrical motor illustrates the internal condition of the kiln and by means of the selected inputs it is possible to recognize whether the process is going well or something undesirable is taking place.

Saveh white cement company[1] is where we develop the method for. This factory produces about 500 tons white cement every day. We used past data of the plant. The data were collected during normal operation of the plant without any interference to optimize it for condition monitoring. Therefore, as an abnormal condition happens, operators detect it and make proper reaction to overcome the condition. It means that the period which an abnormal condition stays is short and we have to detect it in this short period.

They are for 7 days of normal operation of the plant. In some periods of time, operator changes some of the inputs abruptly due to some operation policies. These intervals are deleted from the data set. The remained data set has 300,000 data points which 50% of that is used as the training set, 20% as the test set and the rest of it as the validation data set.

3. INPUT CHANNELS DELAY ESTIMATION

Before identifying the 5 input – 1 output model of the kiln, we are going to estimate its input channels delays. The reason that we estimate the inputs delays with a free-model approach is that determining them during the identification, makes this task burdensome and computational effort increases exponentially. Therefore determining the input channel delays shrinks the search space to a high extent and makes the rest of the work easier and more accurate.

The approach that we use is based on Lipschitz numbers (He *et al*, 1993). In the following, this method is briefly described and then the consequence of applying it on this problem is represented.

3.1- Delay Estimation Based on Lipschitz Numbers

This approach is based on Lipschitz theorem which states that every continuous mapping has bounded gradient which can be estimated by the maximum of the gradients at the known points. Therefore this idea can be used if it is assumed that the relation between input and output is a smooth map which is obligatory in any black-box nonlinear system identification. The algorithm which was proposed for the first time by (Makaremi, 2007, Makaremi *et al*, 2008) has two steps.

In the first step the Lipschitz method is performed on the output and a set of different delays of input, $\{x_1, x_2, \dots, x_D\}$, where x_k is the $k-$th delay of the input. The Lipschitz quotient and Lipschitz number are calculated as (1) and (2) respectively:

$$L_{ij}^{n} = \frac{|y(i)-y(j)|}{\sqrt{(x_1(i)-x_1(j))^2+\cdots(x_n(i)-x_n(j))^2}} \tag{1}$$

$$L^{n} = \left(\prod_{k=1}^{p}\sqrt{n}L^{n}(k)\right)^{\frac{1}{p}} \tag{2}$$

where $L^n(k)$ is the $k-$th largest quotient among all L_{ij}^n. The amount of p is about 1 or 2 percent of the amount of data used for the calculations. By including more delays of the input, the Lipschitz number decreases gradually and when all of its relevant dynamics are included, this number does not decrease greatly afterward (Fig.1 (a)). Where the curve lies (the D_0-th delay), all relevant dynamics are included.

In the next step, the Lipschitz quotients and numbers should be calculated for a D_0-member set of delayed input, $\{x_1, x_2, \dots, x_{D_0}\}$, in a reverse way. For this purpose, the quotient of the $d-$th delay is calculated in the form of (3) and its Lipschitz number is obtained by (4):

$$LB_{ij}^{d} = \frac{|y(i)-y(j)|}{\sqrt{(x_d(i)-x_d(j))^2+\cdots(x_{D_0}(i)-x_{D_0}(j))^2}} \tag{3}$$

$$LB^{d} = \left(\prod_{k=1}^{p}\sqrt{(D_0-d+1)}\,LB^{d}(k)\right)^{\frac{1}{p}} \tag{4}$$

Fig.1 (b) shows Lipschitz numbers of the dynamics which are calculated in this part. The place where the first sudden increase in the values occurs is known as the first delay.

3.2- Estimating the Input Channel Delays of the Kiln Model

In this part, we apply the delay estimation method on the input-output data of the kiln. In the following the result of five inputs paired with the output is presented in Table 1. Fig.2 also shows the diagrams of Lipschitz numbers of raw material feed rate. Because of lack of space, the other diagrams are not brought in this paper. The results in Table 1

[1] Saveh Cement Company Homepage, http://www.savehcement.ir

are very close to what the experts stated. For instance, once a command is given to change the material feed rate, it takes about ten minutes to enter to the kiln and affect the consumed power by the motor. As it is stated in Table 1, and depicted in Fig.2, the input delay computed by this method is 13 minutes. As another example, when the kiln speed changes, its consumed power changes immediately, i.e. there is no delay between them. Again due to Table 1, the computed input delay is zero.

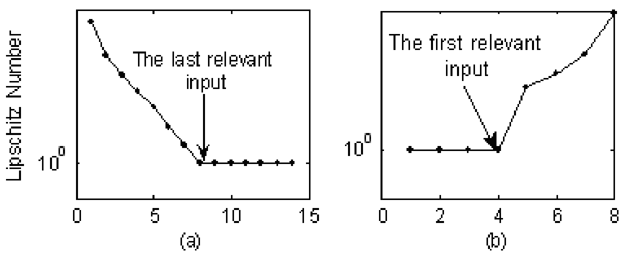

Fig 1: (a) Performing the first part of the algorithm which is the Lipschitz method, the number of relevant dynamics of the input is revealed. (b) The second part of the algorithm discloses the early delay of the input. The first abrupt raise in the value of Lipschitz number is where the first relevant dynamic of the input is eliminated.

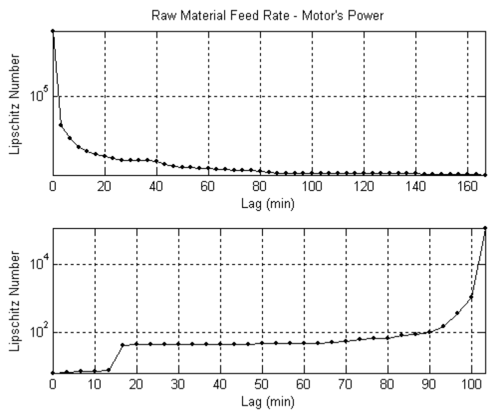

Fig 2: Diagrams of Lipschitz numbers of raw material feed rate.

Table 1: Estimated delays with delay estimation method.

Input	Delay (min)
Material Feed Rate	13
I.D. Fan speed	10
Fuel Feed Rate	27
2ndary Air Pressure	31
Kiln Speed	0

4. KILN IDENTIFICATION

In the preceding section, we estimated the input channel delays of the kiln. Knowing these parameters, the search space for the identification shrinks and it's easier to do the rest of the job, i.e. determining the suitable number of dynamics on each input and the output, and approximating the best function which represents the behavior of the kiln as well.

We use Locally Linear Neuro-Fuzzy (LLNF) network to identify the healthy condition of kiln and the LOLIMOT[2] algorithm to find the best structure and parameters of the network.

LLNF is one of the well-known structures in nonlinear system identification .Each cell in this structure contains a linear model which its validity is based on a membership function. The output of the network is the weighted outputs of locally linear models. In other word, with use of validation functions, the network can interpolate the intervals between locally linear models.

There are several learning algorithm for this network. LOLIMOT is one of the algorithms that can very effectively find the suitable structure of the model and estimate the parameters. LOLIMOT is an incremental tree-structure algorithm that partitions the input space respect to its orthogonal axis. In each iteration, a new rule, which represents a locally linear model, is added to the model. This algorithm uses a hierarchical method for producing the structure and eschews the nonlinear optimization algorithms. The consequent rules are optimized by weighted least square technique.

By means of NNLF network and LOLIMOT as its learning algorithm we identify the kiln behavior. Here is a problem we contributed during the identification. As it seems, each input has its particular effect duration on the output. For instance, materials fed to the kiln, are there for about 30 minutes. Besides the variation of temperature inside the kiln, which is a consequence of changing fuel flow rate and secondary air pressure, lasts for about 20 minutes. And kiln speed variation effects may not last more than two or three minutes on the consumed power of the motor.

Table 2: For different variables, discrepant sampling rate is used.

Input	Sampling Time (Sec)
Material Feed Rate	135
I.D. Fan speed	135
Fuel Feed Rate	225
2ndary Air Pressure	225
Kiln Speed	45
Motor Power	45

Considering this fact, one should take all the dynamics during the period that each input affects the output. But the other point is that these inputs are changed once in couple of minutes. Thus it is a wise decision to resample them with a larger rate to eschew enlarging the input space of the model without adding any proper information about them. Therefore, we resampled each input with a different rate. Table 2 shows sampling time for each of them.

[2] LOcally LInear MOdel Tree

The last problem was to find the number of dynamics of the output and the inputs. We determined them with pre-knowledge about the kiln properties and trial and error during identification. The best number of dynamics that was used for identification is as presented in table 3. Recall that 6 sample of the material feed rate equals 810 seconds, but 3 samples of the kiln speed equals 135 seconds using sampling times in Table 2.

Table 3: The best number of dynamics obtained for the output and the inputs.

Input	No. of Dynamics
Material Feed Rate	6
I.D. Fan speed	6
Fuel Feed Rate	4
2ndary Air Pressure	4
Kiln Speed	3
Motor Power	2

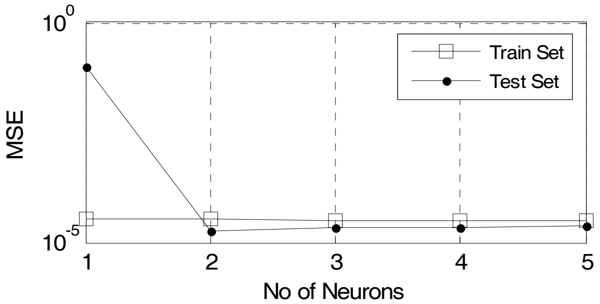

Fig 3: Error on train and test data respect to different number of neurons.

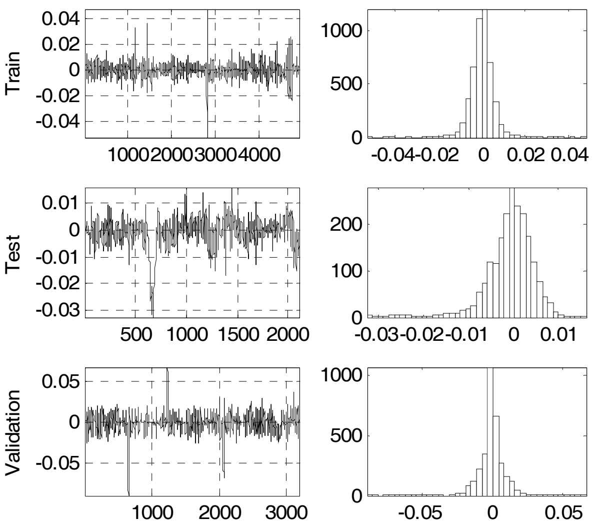

Fig 4: Errors on normalized data and their histograms.

Whereas our goal is abnormal condition detection, the prediction horizon in the identification is seven minutes to increase the prediction horizon in order to predict kiln conditions some minutes in advance.

Fig. 3 shows the error on train and test sets respect to the number of the neurons in the model. It shows that a LLNF with two neurons can model the plant adequately. Also Fig. 4 illustrates errors on normalized data and their histogram.

5. FAULT DETECTION IN CEMENT ROTARY KILN

In the previous section, a model for the kiln has been developed. In this part, some abnormal conditions that are in test and validation data are extracted and discussed. The concept that we use to detect an abnormality is that it has a more lasting effect on the output rather that those of noise or disturbance (Chiang *et al*, 2001). In the following, three abnormal situations observed in test and validation data are discussed. These conditions are distinguished with their large error and a long period lasting. It should be noticed that the backend temperature is also displayed. This variable can give an approximate estimation of the temperature in the kiln.

5.1- Super Heated

This situation comes to exist when the materials are burned sooner than the projected time. As a result, they will be sticky and while the kiln is rotating, they fall down in a higher angle. This causes in higher power consumption by the motor. This condition is detected in the test data. The real output and the model output are shown in Fig. 5. As it is obvious, the model approximates the output less than its real amount. Fig. 6 shows the inputs in the same interval. Operator has the quality of the material which is reported by the laboratory. Accordingly, he inferred that the material had changed that they were burned sooner than the expected time for material with normal quality. Therefore, he increased the material feed rate by about 0.5 ton/hr. He also decreases the fuel feed rate since the required heating energy for this kind of material is lower. Also the operator increased the kiln speed to exit the material from the kiln faster so the kiln bears not too much load. The backend temperature is also increased in a short period but with varying the speed of ID fan, it was again decreased.

5.2- Super Chilled

This is the opposite side of super heated condition. In this situation, because of the kiln condition or the material ingredients, they are not melted in time and they remain solid for a long time. Not being melted causes not being sticky enough to stick to the kiln's sidewall. Therefore the motor consumes less power than the normal situation.

Fig. 7 shows a similar situation in validation data where the output is less than what our model predicts. In this situation, according to Fig. 8, all of the inputs except the fuel feed rate which was increased, were constant. From this state, it can be inferred that because of the super chilled condition in the kiln, the operator decided to increase the fuel feed rate in order to increase the internal temperature and accordingly help the materials to be melted.

5.3- Unrecognized Condition

Fig. 9 shows a discrepancy between the model and real outputs again in validation data. This abnormality took place in a situation that most of the inputs were fixed except material and fuel feed rates (The amount of variation of the secondary pressure is not so much to be effective). In this interval, the material feed rate was suddenly decreased to a high extent and by increasing the fuel feed rate, the operator was going to increase the kiln temperature. But disregard to that, the power consumption is still growing up. It is corroborant of an abnormal condition. This fault was not distinguished by cement experts, but its abnormality is approved. This shows that this model is capable of illuminating undefined faults as well as those who are known by the experts.

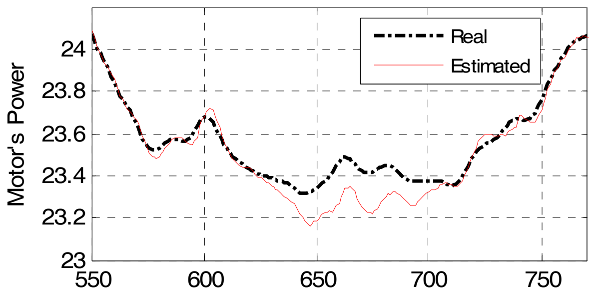

Fig 5: Super Heated. The model output is not as the same as the real output and this discrepancy lasts about 40 minutes.

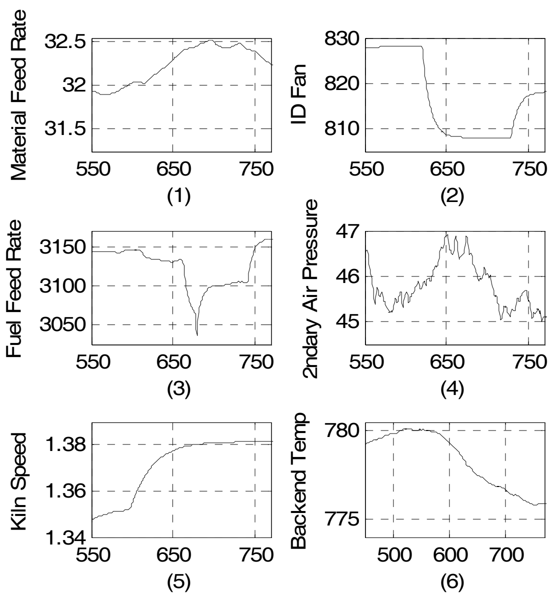

Fig 6: Inputs and backend temperature in the interval that the super heated fault occurred.

6. CONCLUSION

In this paper, system identification method was used to detect the abnormal conditions of the cement rotary kiln in Saveh Cement Company. Consumed power by the motor which spins the kiln was used as the process monitor of the condition. The special character of this variable is that it can illustrate various abnormal conditions inside the kiln. Then, the effective inputs were selected. To ease the identification of the kiln, we used a novel approach for estimating the input channel delays. This method is based on Lipschitz numbers. Then, with LLNF models and LOLIMOT learning algorithm, a model was developed for the healthy condition of the kiln. By means of that model, we could discriminate three abnormal conditions in test and validation data.

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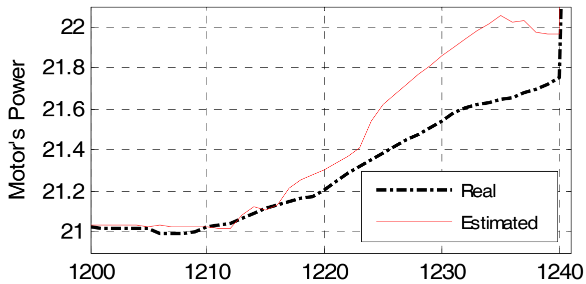

Fig 7: Super chilled. The model output is not as the same as the real output and this discrepancy lasts about 10 minutes.

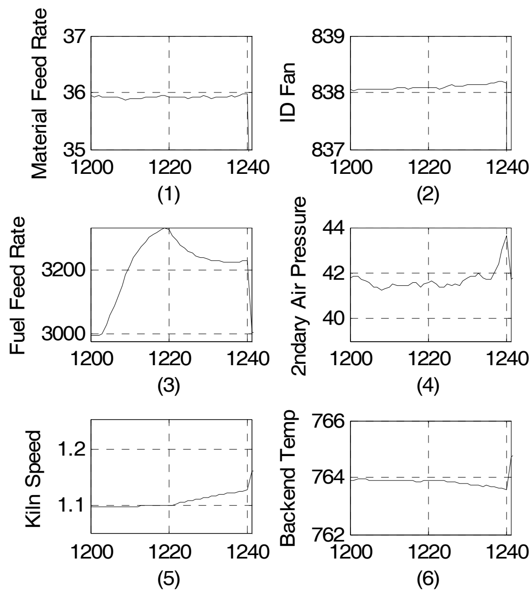

Fig 8: Inputs and backend temperature in the interval that the super chilled fault occurred.

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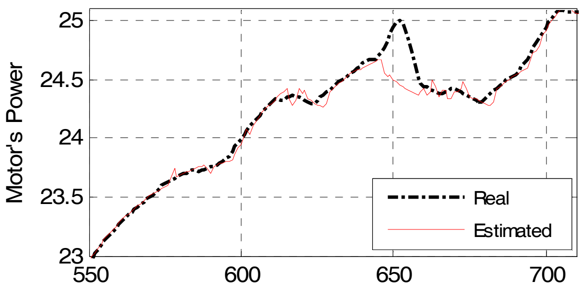

Fig 9: An unrecognized fault. The model output is not as the same as the real output and this discrepancy lasts about 20 minutes.

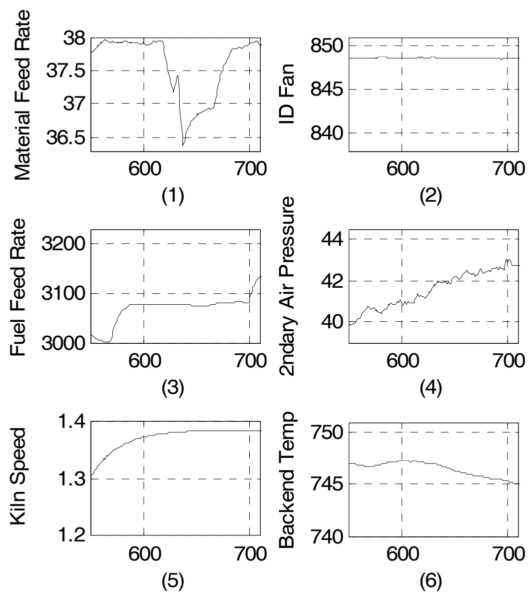

Fig 10: Inputs and backend temperature in the interval that the unknown fault occurred.