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Identification, Prediction and Detection of the Process Fault in a Cement Rotary Kiln by Locally Linear Neuro-Fuzzy Technique

Masoud Sadeghian and Alireza Fatehi

***Abstract*—**In this paper, we use nonlinear system identification method to predict and detect process fault of a cement rotary kiln. After selecting proper inputs and output, an input-output model is identified for the plant. To identify the various operation points in the kiln, Locally Linear Neuro-Fuzzy (LLNF) model is used. This model is trained by LOLIMOT algorithm which is an incremental tree-structure algorithm. Then, by using this method, we obtained 3 distinct models for the normal and faulty situations in the kiln. One of the models is for normal condition of the kiln with 15 minutes prediction horizon. The other two models are for the two faulty situations in the kiln with 7 minutes prediction horizon are presented. At the end, we detect these faults in validation data. The data collected from White Saveh Cement Company is used for in this study.

***Keywords*—**Cement Rotary Kiln, Fault Detection, Delay Estimation Method, Locally Linear Neuro Fuzzy Model, LOLIMOT.

I. INTRODUCTION

THE reliability, security and accessibility of industrial plants play a key role during their operative use. It is significant specifically nowadays, when industrial plant and control algorithms are becoming more and more intricate, and economics pressure to decrease the expenses, the downtime of plants and to cut down the time necessary to processing a product. In simple technology systems, human examination was enough but the enhance complication of industrial systems and the high level of process quality, reliability and security requirements compel the automation of diagnostics in order to make it possible to determine the reason, place, and time of the fault exactly [1-3]. Early detection of faults can be accomplished by model-based fault detection system. The method is based on residual generation by a comparison of the estimates of the measured signals with the model outputs. The approach is the subject of concentrated research in the area of diagnostics due to many pivotal properties:

1) It can detect small scale faults.
2) The solution is relatively reasonable because complex equipment is not essential.
3) The installation of the fault diagnosis system usually does not need any interposing in the existing system; the installed sensors to control the process can usually be used for data acquisition for fault detection system.

Instantaneous fault detection needs correct models of processes. Real processes are usually dynamic, nonlinear and stochastic. Analytical approaches of identification are scarcely appropriate for them. One of the powerful approaches suggests using artificial intelligence methods like neural networks, fuzzy systems, neuro-fuzzy (N-F) systems and expert systems [4-6]. This paper focuses on N-F systems [7-9].

Qualitative and quantitative knowledge may be used to attune the model in this case [10-12]. Two types of fuzzy systems are typically used for the modeling purpose: the Mamdani fuzzy system and the Takagi–Sugeno fuzzy system. Commonly, Takagi–Sugeno structures are frequently used if the knowledge can be extracted from raw data, and Mamdani systems would rather when the knowledge is given by human experts in the form of semantic expressions.

In this paper we use nonlinear system identification method in order to predict and detect common abnormal conditions in the most important 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 [9]. To learn its weights LOLIMOT algorithm is used [13].two kind of abnormality are detected; ringing and coating.

The paper is organized as follows: In the next section, a brief description on rotary kiln is given. Also some abnormal conditions that may happen frequently in it are mentioned. Then the reasons about input-output selection to detect faulty situation are discussed. In section 3, we compute the input channel delays on the model are estimated base on Lipschitz Method [14]. Afterward in section 4, with NNLF model and LOLIMOT learning algorithm, three models for normal and faulty situation of the kiln are designed. 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.

II. CEMENT ROTARY KILN

Cement is a substance which is made of grinded gypsum and cement clinker which itself is produced from a burned

Masoud Sadeghian is with the Mechatronics Department, School of Science and Engineering, Sharif University of Technology International campus, Kish Island, Iran, (phone:+98-913-113-4382; e-mail: m_sadeghian@kish.sharif.edu).
Alireza Fatehi is with Advanced Process Automation & Control (APAC), Mechatronics department, School of Electrical engineering of K.N. Toosi University of Technology, Tehran, Iran (e-mail: fatehi@kntu.ac.ir).

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.

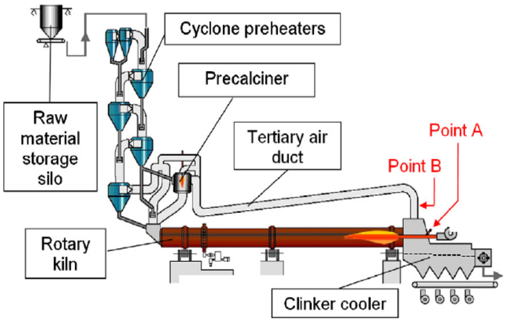

Fig. 1 A cement rotary kiln plant

The kiln works nonstop and an impending 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. Sudden kiln stop could damage various points of the kiln based on a high heat degree fluctuation. 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.

In this paper, in order to continue the previous attempts for fault detection in kiln [15], for the first time, the procedure of identification, prediction and detection of two common, meanwhile damaging fault in the process that is, ringing and coating, are introduced. In this procedure, during the identification process and analyzing the kiln data, we found that these two faults show a special behavior in cement rotary kiln output, upon occurrence. We use system identification approaches for the sake of abnormal condition detection. The output that is going to be identified is the temperature of the first point at the beginning of the kiln, which is called back-end temperature. It is in the calcining zone of the kiln and has a significant role on the quality of the clinker. The inputs are material feed rate, fuel feed rate, kiln speed, I.D. fan speed and secondary air pressure. The reason of using these inputs and output is the more affection confirmed by; negotiation with experts and process engineers of the factory often in kiln operation. In their point of view, the back end temperature 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.

We have been collecting and analyzing the data of a fourteen-week period of operation of the kiln data. According to the collected data in two cases the kiln stops. One condition is when there are some mechanical and electrical defects in the system; the other is when the operators change some of the inputs in accordance with operational policies. It means 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.

By studying the operators note and discussion with process engineers, we separate faulty data from normal data of the kiln data. Here, with each set of data we make an effort to eliminate constant, repetitive and faulty operational points. The reason why we eliminated the constant and repetitive points is that in this situation the variables are affected more by the small noise and disturbance and in practice the generated dynamics by these data are not the main dynamics of the process. On the other hand, if the volume of the used data for making a model is high in one operating point, this point gets more weight; as consequence increases error in other operating points for making a model. After removing invalid data and pre processing on them[16].That are divided to three parts: 50% of that is used as the training set, 20% as the test set and the rest of it as the validation data set.

III. Inputs Channels Delay Estimation

Before identifying the 5 inputs and 1 output model of the kiln, we should 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 increases some computational volume. Therefore determining the input channel delays shrinks the search space to a high extent and makes the rest of the identification phase easier and more accurate. The approach that we use is based on Lipschitz method which was presented by Makarmi et.al [14, 17]. The results are shown in table 1.

TABLE I Delays from Inputs to Output

Inputs	Delays (min)
Martial Feed Rate	18
Fuel Feed Rate	4
Kiln Speed	36
I.D Fan Speed	0
2ndary Air Pressure	0

IV. Identification and Prediction in Rotary Kiln

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 normal and faulty condition of kiln and the LOLIMOT1 algorithm to find the best structure and parameters of the network. In the following LLNF networks and the LOLIMOT algorithm is reviewed briefly. Then the result of applying them on kiln data is presented.

A. *Locally Linear Neuro-Fuzzy Network*

The most important reasons why LLNF network is selected follow:

1) High accuracy
2) Robustness
3) Computational efficiency and
4) Smooth switch for multiple models.

In the following LLNF networks and the LOLIMOT algorithm is reviewed briefly. Then the result of applying them on kiln data is represented.

The network structure of LLNF is depicted in Fig. 7. Each neuron realizes a Local Linear Model (LLM) and an associated validity function that determines the region of validity of the LLM. The network output is calculated as a weighted sum of the outputs of the local linear models, where the validity function is interpreted as the operating point dependent weighting factors. The validity functions are typically chosen as normalized Gaussians.

The local linear modeling approach is based on a divided-and-conquer strategy. A complex rotary kiln model divided into a number of smaller and thus simpler sub-problems, which are solved independently by identifying simple linear models [18-19]. The most important factor for the success of this model by a locally linear model method is the division strategy for the original complex problem. This will be done by an algorithm named LOLIMOT (Locally Linear Model Tree). LOLIMOT is an incremental tree construction algorithm that partitions the input space by axis-orthogonal splits [13]. In each iteration, a new rule or local linear model is added to the model and the validity functions that correspond to the actual partitioning of the input space are computed, and the corresponding rule consequence are optimized by a local weighted least squares technique.

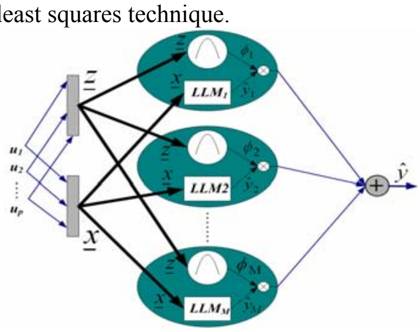

Fig. 2 Network structure of a Local Linear Neuro-Fuzzy model

In case of locally linear identification, the most imperative concern is the number of neurons. It is desirable that the number of neurons be as small as possible. The LOLIMOT algorithm is started from one neuron and gradually continues to arrive the neuron that shows an acceptable error based on sum of squared error curve so that the suitable number of neuron is distinct during the identification. Below are the brief five basic steps to identify the cement rotary kiln model [18-19]:

1) Start with one initial model of cement rotary kiln,
2) Find worst Locally Linear Model that has maximum local loss function.
3) Check all hyper-rectangles to split (through).
   (3a) Construction of the multi-dimensional Fuzzy membership Functions for both hyper rectangles.
   (3b) Construction of all validity functions.
   (3c) Local estimation of the rule consequent parameters for both newly generated LLMs.
   (3d) Calculation of the loss functions for the current overall model.
4) Find best division (the best of the alternatives checked in Step 3, and increment the number of LLMs: M → M+1).
5) Test for convergence.

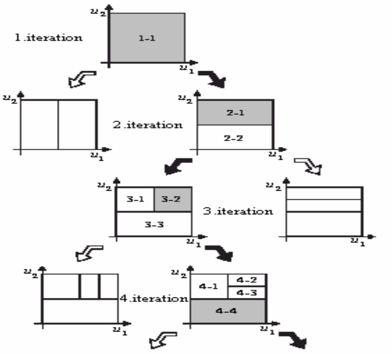

Fig. 3 Operation of the LOLIMOT algorithm in the first five Iterations for a two dimensional input space [13].

B. *Identification and Prediction of Normal and Faulty Status*

We used LLNF network with LOLIMOT learning algorithm to identify the kiln. The first problem we faced is to determine a common sample time. Each input has its particular duration of on effect the output. For instance, materials feed to the kiln, have a delay of about 18 minutes. Besides the variation of temperature inside the kiln, that is a consequence of changing fuel flow start to effect after 4 minutes. Kiln speed variation may effect after 30 minutes on back end temperature. Also, the time constant from the inputs to the output are not the same. For the fast affecting inputs smaller sampling rate is more appropriation. For the slow affecting inputs bigger sampling rate is more appropriation. By using different sampling time, we avoid increasing the space of the inputs of the model without addition of any information to it; while, using various sampling times, make problem in analyzing and modeling process. To solve this problem, we use a basic constant sampling time of 30 seconds, where the used input samples with slower affection is a coefficient rate of the basic constant sampling time [15]. Therefore, we resample each input with a different rate. Table 2 shows sampling time for each of them. For instant, the 2 samples of the kiln speed equals 600 seconds that equals 20 samples of the back end temperature.

TABLE II ACTUAL SAMPLING RATE FOR DIFFERENT VARIABLES

Variables	Sampling Time (sec)
Material Feed Rate	150
Fuel Feed Rate	90
Kiln Speed	300
I.D fan Speed	60
2ndary Air Pressure	60
Back End Temperature	60

The last problem was to find the number of dynamics of the output and the inputs. With regards to the pre-knowledge about the kiln properties, the range of inputs dynamism is obtained then through trial and error during identification, the best number of inputs and output dynamics are obtained. The best numbers of dynamics used for identification are presented in table 3.

TABLE III THE BEST NUMBER OF DYNAMICS FOR THE INPUTS AND OUTPUT

Variables	Number of Dynamics		
	Normal Condition	Coating Fault	Ringing Fault
Material Feed Rate	5	5	2
Fuel Feed Rate	3	3	3
Kiln Speed	2	2	3
I.D Fan Speed	11	4	2
2ndary Air Pressure	3	2	4
Back End Temperature	10	11	4

Whereas our goal is abnormal condition detection, the prediction horizon in the identification is seven minutes for abnormal conditions and fifteen minutes for normal condition to increase the prediction horizon in order to predict kiln conditions some minutes in advance. Fig. 4 shows the error on train and test sets respect to the number of the neurons in the normal model. It shows that a LLNF with two neurons can model the plant adequately in the normal situation.

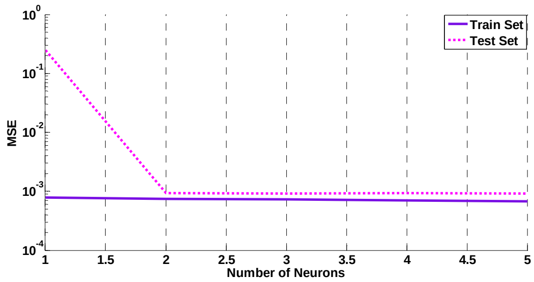

Fig. 4 Error on train and test data respect to different number of neurons

Figure 5 to 7 show the response of the normal model output and the real output from five to fifteen minutes prediction horizon and figure 8 to 10 show the response of the coating fault model output and the real output from three to seven minutes prediction horizon for test data. Also, figure 11 to 13 show the response of the ringing fault model output and the real output from three to seven minutes prediction horizon for test data.

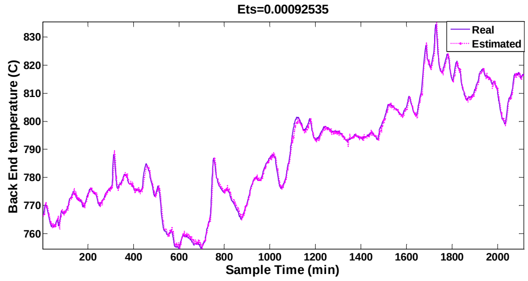

Fig. 5 Normal model with 5 min prediction horizon

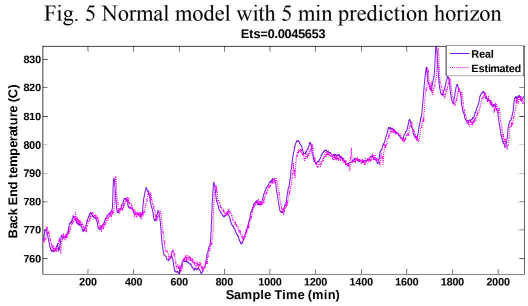

Fig. 6 Normal model with 10 min prediction horizon

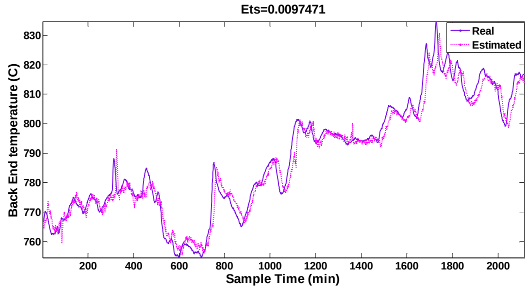

Fig. 7 Normal model with 15 min prediction horizon

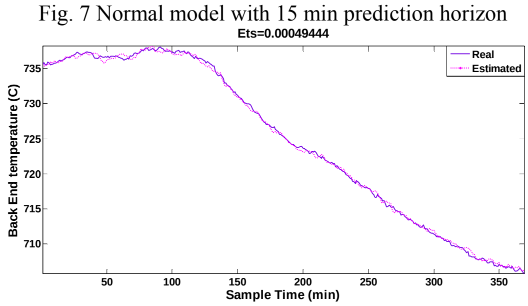

Fig. 8 Coating model with 3 min prediction horizon

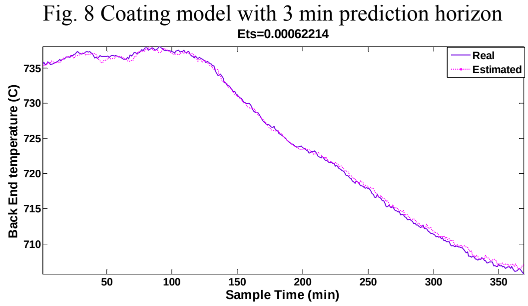

Fig. 9 Coating model with 5 min prediction horizon

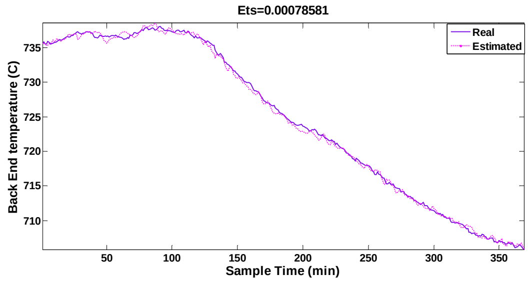

Fig. 10 Coating model with 7 min prediction horizon

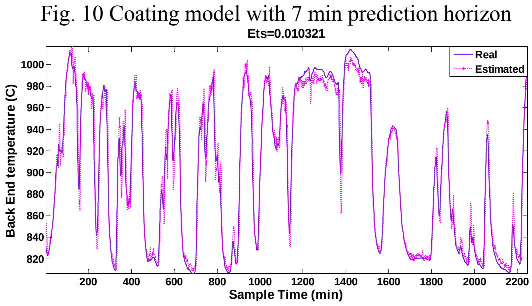

Fig. 11 Ringing model with 3 min prediction horizon

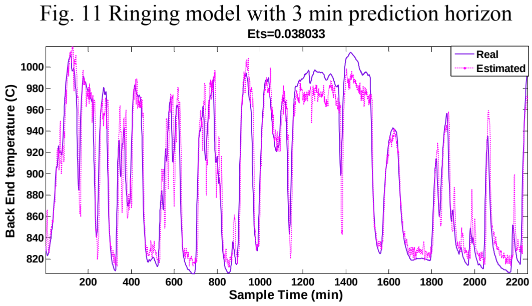

Fig. 12 Ringing model with 5 min prediction horizon

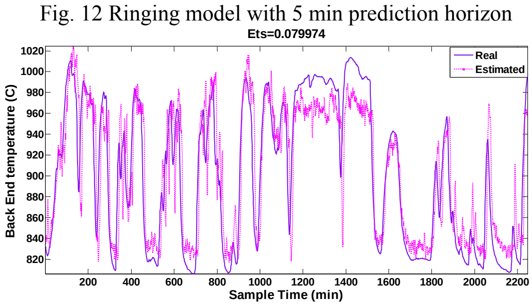

Fig. 13 Ringing model with 7 min prediction horizon

For different operation among these models we calculated root mean square error (RMSE) for test data which are shown in table 4.

TABLE IV ROOT MEAN SQUARE ERROR (RMSE)

Prediction Horizon (min)	Normal Condition	Coating Fault	Ringing Fault
1	0.00004	0.00018	0.00018
3	0.00027	0.00049	0.01032
5	0.00092	0.00062	0.03803
7	0.00256	0.00078	0.07997
10	0.00456	-	-
15	0.00974	-	-

One of the most important things that we realized after the identification and analysis of the faulty models is the behavior of faulty condition when they occur. We understood that when ringing fault is going to occur the back end temperature begins to fluctuate rapidly. The reason why it shows this behavior is that, the feed material which go through the kiln are rich with alkalescency characteristic in comparison with normal materials. They begin to stick to the kiln wall that ends in formation the ring. In this condition, the ring prevents the flow of hot air to the back end zone; consequently, the back end temperature is decreased. When the kiln rotates sometimes the ring is collapsed from top of the kiln. This occurrence causes a temperature increase, in the back end zone. This event will be taking place from time to time; as a result, the back end temperature shows a fluctuation behavior. The other fault is called coating fault which is more harmful for the kiln and clinker producing. The most important fact about coating fault is that it may cause the back end temperature decreases with a linear negative slope. The reason why it shows this behavior is that the kiln wall surface is completely covered by coating layers in the back end zone. The coating prevents the flow of hot air to the back end zone; after passing some the coating becomes thicker and thicker and if not detected by the operator on time, they will be forced to stop the kiln. Naturally, the operation will resume after the kiln is cleaned.

V. FAULT DETECTION IN THE CEMENT ROTARY KILN

In the previous section, three distinct models for the kiln have been developed and introduced. One of the models is a normal model and the others are related to ringing and coating fault. In this part, we want to detect and extract abnormal conditions that exist in validation data. The procedure that we use in detecting an abnormality is that it has a more lasting effect on the output rather than those of noise or disturbance. This procedure is able to track the output as well. In other words, we give three validation data where each set relates to one of the kiln condition, then we give each validity data to the three models that have been developed to check whether the models could track the real output in correct manner; for example, when the normal validation data is given to the three models, the normal model must have the minimum error in comparison with the real output of the other fault models. If the ringing validation data is given to the three models the ringing model must have the minimum error compared to the normal and coating models. These conditions are distinguished with their major error and a long lasting period. Figure 14 to 16 show the evaluation of the three models with normal validity data. As you see the faulty models could not identify and recognize the validity data. Figure 17 to 19 show the evaluation of the three models with ringing validity data. Figure 20 to 22 show the evaluation of the three models with coating validity data.

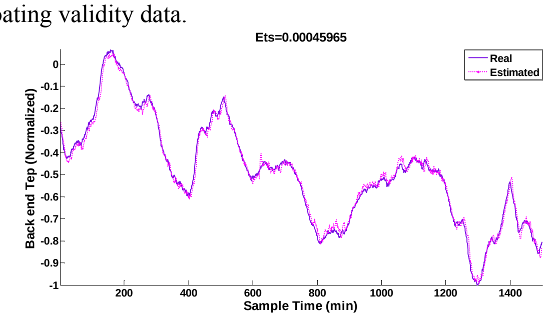

Fig. 14 Test of the normal model with the normal validity data

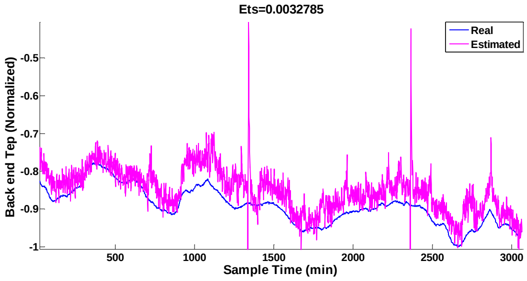

Fig. 15 Test of the ringing model with the normal validity data

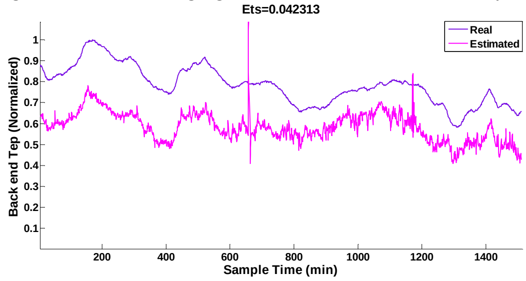

Fig. 16 Test of the coating model with the normal validity data

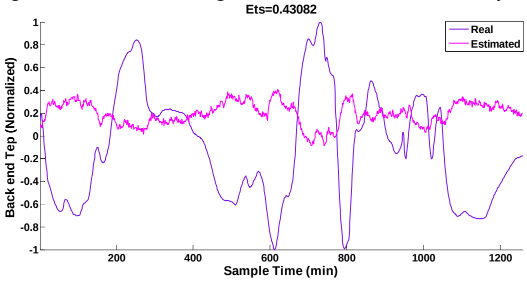

Fig. 17 Test of the normal model with the ringing validity data

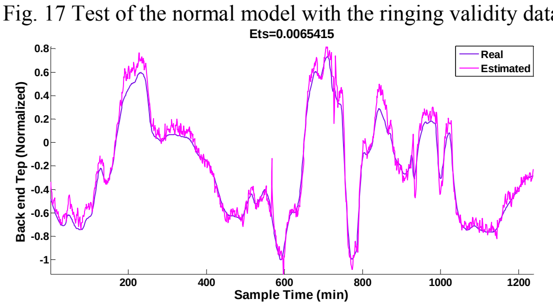

Fig. 18 Test of the ringing model with the ringing validity data

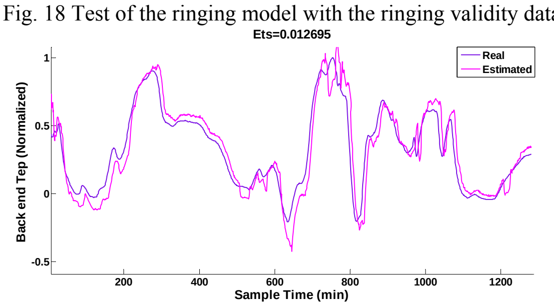

Fig. 19 Test of the coating model with the ringing validity data

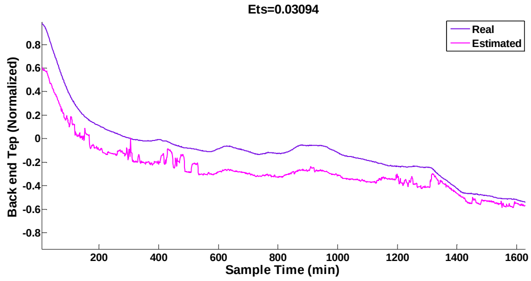

Fig. 20 Test of the normal model with the coating validity data

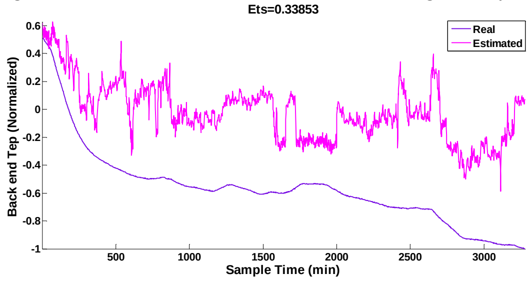

Fig. 21 Test of the ringing model with the coating validity data

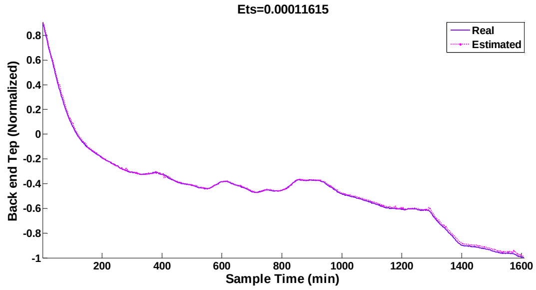

Fig. 22 Test of the coating model with the coating validity data

For comparing the three models and their response to the various validity data we calculated root mean square error (RMSE) for each of them. They are shown in table 5.As it is shown in this table for each situation of the kiln behavior; the respected model has lower RMSE. Therefore, comparing RMSE of the models errors determines the condition of the kiln.

TABLE V ROOT MEAN SQUARE ERROR FOR DIFFERENT MODEL IN VARIOUS MODES

	Validity Data		
Model	Normal	Ring	Coating
Normal	0.000459	0.430821	0.030940
Ring	0.003278	0.006542	0.338630
Coating	0.042313	0.012692	0.000116

VI. CONCLUSION

In this paper, nonlinear system identification method was used for identification, prediction and detection of the fault process in the cement rotary kiln in White Saveh Cement factory. Back end temperature was used as the process monitor of the various conditions. The special character of this variable is that it can show the normal and abnormal conditions inside the kiln. At first, for this purpose, the effective inputs were selected. Then, to ease the identification of the kiln, we calculated input channel delays estimation is based on Lipschitz numbers. Next, the effective dynamic for each input corresponding to the output method. After that, with LLNF models and LOLIMOT learning algorithm, three nonlinear models were developed for the healthy and faulty condition of the kiln. All models could predict their respected situation with proper prediction horizon. Finally, by means of these models, we could distinguish fault and normal conditions in validation data. The result of the fault detection algorithm performance indicates that we can predict the fault occurrence seven minutes in advance.

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REFERENCES

[1] Isermann, R., Fault Diagnosis Systems. An Introduction from Fault Detection to Fault Tolerance. Springer, Berlin , 2005.
[2] Korbicz, J., Kos´cielny, J.M., Kowalczuk, Z., Cholewa, W. (Eds.) ,Fault Diagnosis. Models, Artificial Intelligence, Applications. Springer, Verlag, Berlin , 2004.
[3] Patton, R.J., Chen, J., Robust Model-Based Fault Diagnosis for Dynamic Systems. Kluwer Academic Publishers, London, 1999.
[4] Patton, R.J., Korbicz, J. (Eds.), Advances in computational intelligence for fault diagnosis systems. International Journal of Applied Mathematics and Computer Science (special issue) 9(3), 1999.
[5] Isermann, R., On fuzzy logic applications for automatic control, supervision, and fault diagnosis. IEEE Transactions on Systems, Man and Cybernetics Part A 28 (2), 221–235, 1998.
[6] Ayoubi, M., Isermann, R., Neuro-fuzzy systems for diagnosis. Fuzzy Sets and System 89 (3), 289–307, 1997.
[7] Rutkowska, D., Neuro-Fuzzy Architectures and Hybrid Learning Springer, New York, Heidelberg, 2002.
[8] Babusˇka, R., Fuzzy Modeling for Control. Kluwer Academic Publishers, London , 1998.
[9] Takagi, T., Sugeno, M., Fuzzy identification of systems and its application to modelling and control. IEEE Transaction on Systems, Man and Cybernetics 15 (1), 116–132, 1985.
[10] Czaban´ ski, R., Neuro-fuzzy modeling based on a deterministic annealing approach. International Journal of Applied Mathematics 11, and Computer Science 15 (4), 561–576, 2005.
[11] Rutkowski, L., New Soft Computing Techniques for System Modelling, Pattern Classification and Image Processing. Springer, Berlin, 2004.
[12] Rutkowska, D., Zadeh, L. (Eds.), Neuro-fuzzy and soft computing. (special issue) International Journal of Applied Mathematics and Computer Science 10(4), 2000.
[13] O. Nelles, *Nonlinear system identification*. Berlin: Springer Verlag 2001.
[14] Iman Makaremi, Alireza Fatehi, Babak Nadjar Araabi, "Lipschitz in Numbers: A Medium for Delay Estimation," 17th IFAC world congress, Seoul, Korea, July 6-11 2008.
[15] Makaremi, I., Fatehi, A., Nadjar-Araabi, B., "Abnormal Condition Detection in a Cement Rotary kiln with System Identification Methods", Accepted to be published in Journal of Process Control, 2009.
[16] Y.Zhu, *Multivariable system identification for process control*. Elsevier science Ltd, 2001.
[17] I. Makaremi, “Intelligent Condition Monitoring of a Cement Rotary on Kiln”, M.Sc. Thesis,KN Toosi Univ. of Tech, Feb 2007.
[18] O. Nelles, “Local linear model tree for on-line identification of time variant nonlinear dynamic systems,” *Proc. of International Conference on Artificial Neural Network*, pp. 115-120, Bochum,Germany, 1996.
[19] O. Nelles and R. Isermann, “Basis function networks for interpolation of local linear models,” *Proc. of IEEE Conference on Decision and Control*, pp. 470-475, Kobe, Japan, 1996.

Masoud Sadeghian received the B.S degree in Electrical Engineering from Islamic Azad University of Najafabad in 2006 and the M.Sc. degree in Mechatronics Engineering at Sharif University of Technology International Campus, in 2009. His main interests are identification and modeling, fault diagnosis and prognosis, intelligent control and robotics.

Alireza Fatehi received the M.Sc. degree from the University of Tehran, Iran, in 1995, and the Ph.D. degree from University of Tohoku, Japan, in 2001.He is an Assistant professor of K.N. Toosi University of Technology, Tehran, Iran, as well as director of Advanced Process Automation Control (APAC) and head of Mechatronics Engineering department of K.N. Toosi University of Technology. His research interests include intelligent control, multiple control, process control, and systems identification.