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Identification of Cement Rotary Kiln in Noisy Condition using Takagi-Sugeno Neuro-fuzzy System

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Abstract
Cement rotary kiln is the main part of the cement production process, which has always attracted many researchers' attentions. However, this complex non-linear system has not been modeled efficiently, which can make an appropriate performance especially in the noisy condition. In this work, the Takagi-Sugeno neuro-fuzzy system (TSNFS) is used for identification of the cement rotary kiln, and the gradient descent (GD) algorithm is applied for tuning the parameters of antecedent and the consequent parts of fuzzy rules. In addition, the optimal inputs of the system are selected by genetic algorithm (GA) to achieve less complexity in the fuzzy system. The data related to the Saveh White Cement factory is used in the simulations. The Results obtained demonstrate that the proposed identifier has a better performance in comparison with the neural and fuzzy models presented earlier for the same data. Furthermore, in this work, TSNFS is evaluated in noisy condition, which had not been worked out before in related research works. The simulations show that this model has a proper performance in different noisy conditions.

Keywords: *Cement Rotary Kiln, Takagi-Sugeno Fuzzy System, Feature Selection, Noisy Condition.*

1. Introduction

It is an important issue to reach the model of real systems in almost all sciences for analyzing the system behavior. Especially in engineering fields, a system model is employed, e.g. in the optimization, control, diagnosis, and fault detection cases [1]. On the other hand, the intelligent techniques like neural [2] and fuzzy systems have been employed successfully in many applications such as system identification among several existing methods. For example, using the fuzzy sets theory [3] in industrial control problems [4-6] and combination of fuzzy control with neural networks [7, 8] have had proper results, particularly for complex systems. Cement rotary kiln is such a complex cylindrical device that is the main part of cement industry equipment, consuming fuel to get pre-heated to a high temperature, which is necessary to produce clinker. It rotates around its axis, and the raw meal dust sticks adhesively to its walls, and thus it becomes burned and baked. A schematic representation of a cement production unit is shown in Figure 1 [9]. Many effective parts of the cement production process such as baking the mixture of input materials occurs in the kiln [10], and thus the kilns' operation affects the whole plant, and it is necessary to obtain an efficient model for it. However, the rotary kiln is a non-linear and time-variant system, which is very complex. We can see a few effective works on the kilns' modeling during 1970-2003 [11-19], for example, in [15], a model based on computational fluid dynamics (CFD) has been presented. Some other new ideas have been developed for rotary kiln in the recent years, like the research work that has compared the Box-Jenkins method with the linear usual techniques such as ARMAX and O.E. [20]. However, along this procedure, applying the artificial intelligence and expert systems are paid attention widely, and are used for rotary kiln's modeling and controls. In one of the models presented, neural networks such as multi-layer perceptron (MLP) have been used [21, 22]. Another research work contains a predictor and simulator model for the rotary kiln by the locally

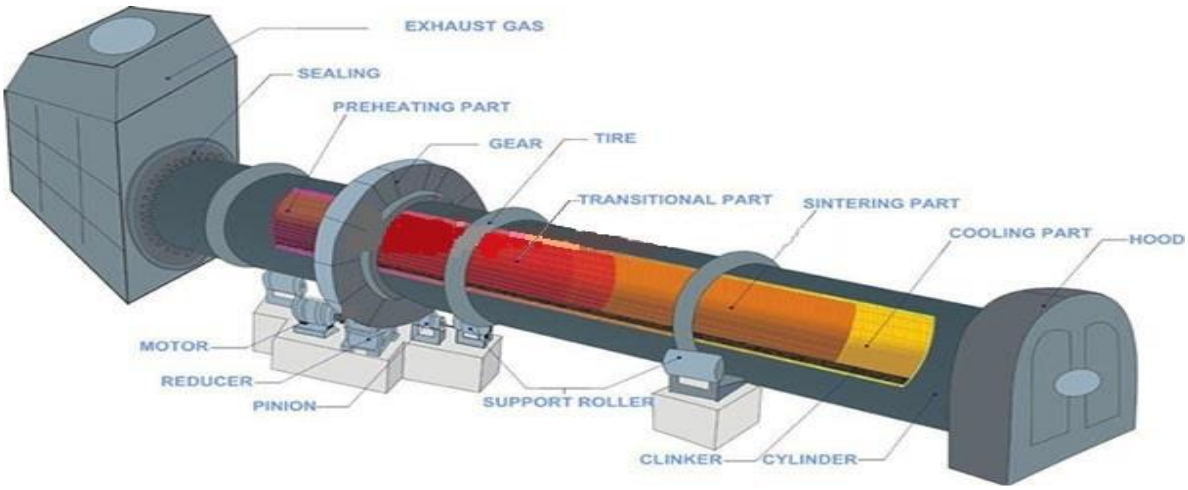

Figure 1. Schematic representation of cement production and rotary kiln operation [23].

linear neuro-fuzzy method [24]. In addition, an adaptive neuro-fuzzy inference system (ANFIS) has been proposed, which uses special selected inputs to identify each output [25]. The last one is a hierarchical wavelet fuzzy inference system (HWFIS) [9], which applies eight input variables for each output, and compares the mean square error (MSE) of HWFIS with nine other models.

Since a combination of fuzzy systems with neural networks leads to an impressive ability in modeling complex plants, in this work, a Takagi-Sugeno neuro-fuzzy system (TSNFS) is used. The data that is applied in the simulations is related to the Saveh White Cement (SWC) factory. After a primary preparation of data, an input selection is done with the genetic algorithm (GA) to prevent increasing computations and achieve a simple model. Then we start training TSNFS. Now, the identifier should be tested. Since the existence of noise is an undeniable fact in industrial systems, and the recent works have not focused on this important subject, a noisy condition is applied besides the normal case in the testing process of TSNFS.

This paper is organized as what follows. In the following section, the structure and learning algorithm of TSNFS are presented. Data preprocessing is given in Section 3. In Section 4, the simulations and results are presented. Finally, the conclusions are given in Section 5.

2. Takagi-sugeno neuro-fuzzy system

2.1. Structure

The main job in a fuzzy inference system is organized in its fuzzy rules. These rules in a Takagi–Sugeno fuzzy inference system are presented generally in the following form:

$$R^i: \ If \quad x_1 \quad is \quad A_1^i \quad , \ \ldots \ , \quad x_n \quad is \quad A_n^i \qquad Then \quad f^i = F^i(X, \Gamma^i) \tag{1}$$

where $x_1, \ldots, x_n$ are the input variables, A_j^i ($i = 1, \ldots, M$, $j = 1, \ldots, n$) is the fuzzy set belonging to the jth input in ith fuzzy rule, f^i is the function of the consequent part of the ith fuzzy rule, and F^i is a function of X and Γ^i, which are defined as follow:

$$X = \left[x_1 \quad x_2 \quad \ldots \quad x_n \right] \tag{2}$$

$$\left[\Gamma^1 \quad \Gamma 2 \quad \ldots \quad \Gamma^M \right] = \begin{pmatrix} a_0^1 & \ldots & a_0^M \\ \vdots & \ddots & \vdots \\ a_n^1 & \cdots & a_n^M \end{pmatrix}_{(n+1)\times M} \triangleq \Gamma \tag{3}$$

where, a_0^i and a_{j}^i ($i = 1, \ldots, M$, $j = 1, \ldots, n$) are assigned by real values, and since we use a first order Takagi–Sugeno fuzzy inference system, f^i is given by:

$$f^i = a_0^i + \sum_{j=1}^{n} a_j^i x_j \tag{4}$$

If $\mu_j^i(x_j)$ is the membership function (MF) of the jth input in the ith fuzzy rule, the firing strength of this rule is calculated as:

$$w^i = \mu_{A_1}^i(x_1) \quad * \quad \ldots \quad * \quad \mu_{A_n}^i(x_n) \tag{5}$$

Here, $*$ is the t-norm product operator. Thus the normalized firing strength of the ith rule is given as:

$$W^i = \frac{w^i}{\sum_{i=1}^{M} w^i} \tag{6}$$

Finally, the output of the Takagi–Sugeno fuzzy inference system is obtained by:

$$\hat{y} = \sum_{i=1}^{M} f^i W^i \quad (7)$$

where, f^i and W^i are determined using (4) and (6), respectively.

The structure of the multi input-single output (MISO) TSNFS with *n* inputs and *K* MFs for each input is given in Figure 2. In the first layer, the input signals are distributed. In the second layer, for each input signal, the membership degree belonging to its corresponding fuzzy set (μ_j^i) is calculated. Realizing the inference engine happens in the third layer by determining the firing strength of each rule. In the fourth layer, the amount of function in the consequent part is set. The product of fourth layers' output and firing strength for each rule is applied in the fifth layer, and finally, in the sixth layer, defuzzification is done.

2.2. Learning algorithm strategy

As it is obvious in (4) to (7), there are some parameters in the fuzzy rules that should be tuned. In this work, we use the reliable gradient descent (GD) algorithm to determine the final amount of these parameters. Mean Square Error (MSE) is used as the cost function, defined by:

$$J = \frac{1}{N}\sum_{p=1}^{N} E_p \quad (8)$$

where, *N* is the total number of data samples, and E_p is given as:

$$E_p = \frac{1}{2}(y_p - \hat{y}_p)^2 \quad (9)$$

where, y_p and $\hat{y}_p$ are the target and output of fizzy identifier, respectively. For simplicity, we use *E* instead of E_p in the following equations.

Antecedent part of each rule consists of two parameters that belong to MFs including standard deviation (STD) and mean should be learned since we have chosen Gaussian MF for the antecedent part, as follows:

$$\mu_m^j(x_j) = e^{-\frac{(x_j - c_m^j)^2}{(\sigma_m^j)^2}} \quad (10)$$

where, $\mu_m^j(x_j)$ is the *m*th MF of the *j*th input; σ_m^j and c_m^j are its STD and mean, respectively. Also $m = 1, \ldots, K$ and $j = 1, \ldots, n$. According to the GD algorithm, by applying the momentum term [26] to improve the convergence speed, σ_m^j is updated by:

$$\sigma_m^j(k+1) = \sigma_m^j(k) - \eta_\sigma(k)\left(\frac{\partial J}{\partial \sigma_m^j}\right)_k + \gamma_\sigma(\sigma_m^j(k) - \sigma_m^j(k-1)) \quad (11)$$

where, $\eta_\sigma(k)$ is the adaptive learning rate updating by the Bold Driver method [27, 28], γ_σ is the momentum term, and *k* indicates the learning step. Also $\frac{\partial J}{\partial \sigma_m^j}$ in (11) is obtained according to (8) by:

$$\frac{\partial J}{\partial \sigma_m^j} = \frac{1}{N}\sum_{p=1}^{N}\left(\frac{\partial E}{\partial \sigma_m^j}\right)_p \quad (12)$$

where, the derivatives are computed by applying chain rule, so we have:

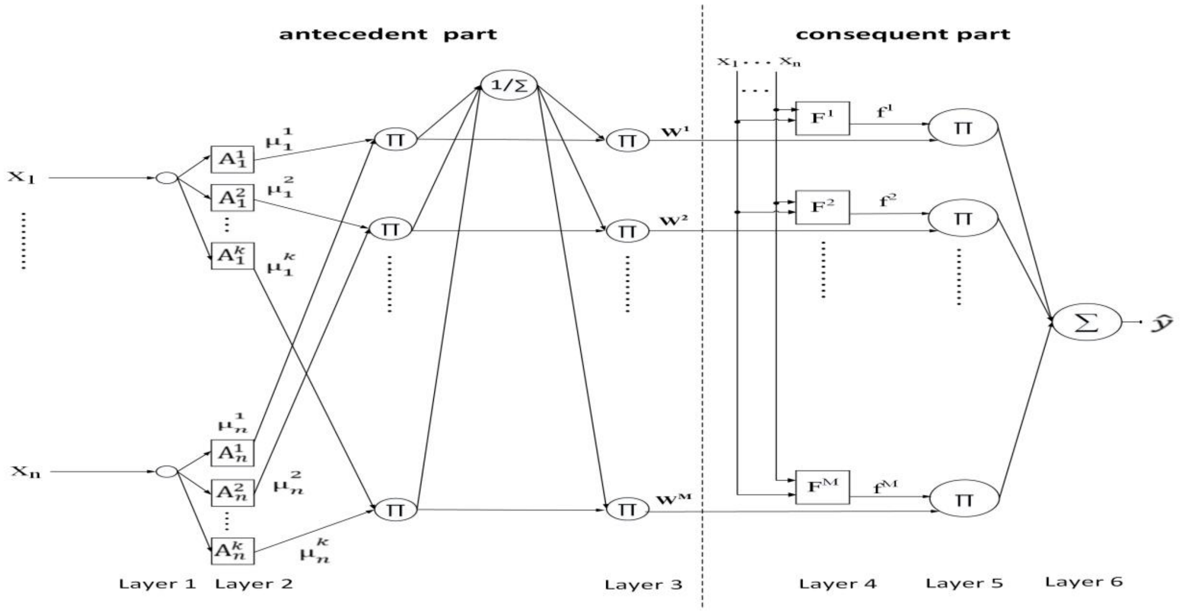

Figure 2. Structure of TSNFS.

$$\frac{\partial E}{\partial \sigma_m^j} = -(y-\hat{y})\frac{(x_j - c_m^j)^2}{(\sigma_m^j)^3}\frac{1}{\sum_{i=1}^{M} w^i} \times \sum_{q\in Q_\sigma} w^q (f^q - \hat{y}) \tag{13}$$

where, Q_σ is the set consisting of all rule indices containing σ_m^j (e.g. in a system with n = 5 and K = 2, there are 32 rules; σ_1^1 exists in the rules 1 to 16, thus Q_σ = {1, 2, …, 16}) and f^q and w^q are given by (4) and (5), respectively. Also updating c_m^j is possible by:

$$c_m^j(k+1) = c_m^j(k) - \eta_c(k)\left(\frac{\partial J}{\partial c_m^j}\right)_k + \gamma_c(c_m^j(k) - c_m^j(k-1)) \tag{14}$$

where, $\eta_c(k)$ is the adaptive learning rate, γ_c is the momentum term, and $\frac{\partial J}{\partial c_m^j}$ is calculated by:

$$\frac{\partial J}{\partial c_m^j} = \frac{1}{N}\sum_{p=1}^{N}\left(\frac{\partial E}{\partial c_m^j}\right)_p \tag{15}$$

where, $\frac{\partial E}{\partial c_m^j}$, by applying chain rule, is given by:

$$\frac{\partial E}{\partial c_m^j} = -(y-\hat{y})\frac{x_j - c_m^j}{(\sigma_m^j)^2}\frac{1}{\sum_{i=1}^{M} w^i} \times \sum_{q\in Q_c} w^q (f^q - \hat{y}) \tag{16}$$

Here, Q_c is the set consisting of all rule indices containing c_m^j. Also in the consequent part of the rules, Γ should be updated by:

$$\Gamma(k+1) = \Gamma(k) - \eta(k)\left(\frac{\partial J}{\partial \Gamma}\right)_k + \gamma(\Gamma(k) - \Gamma(k-1)) \tag{17}$$

$\frac{\partial J}{\partial \Gamma}$ in (17) is given according to (8), as follows:

$$\frac{\partial J}{\partial \Gamma} = \frac{1}{N}\sum_{p=1}^{N}\left(\frac{\partial E}{\partial \Gamma}\right)_p \tag{18}$$

in which by applying chain rule, we have:

$$\frac{\partial E}{\partial \Gamma} = -(y-\hat{y})\begin{pmatrix} 1 \\ X^T \end{pmatrix} W \tag{19}$$

where, W is given as:

$$W = \begin{bmatrix} W^1 & W^2 & \text{K} & W^M \end{bmatrix} \tag{20}$$

3. Data Preprocessing

Another issue that should be noted to get the proper results in an identification process is to use the real dataset. The data we use in the simulations is collected from the SWC factory, which includes high frequency noise, offset, and maybe sudden variations, so it is necessary to prepare a valid data for applying to the model. We will explain how the data is preprocessed in the rest of this section.

3.1. Input-output variables

In our modeling, the data corresponding to 12 weeks is considered, which consists of nine inputs and outputs, given in Table 1.

Table 1. Input and output variables in cement rotary kiln.

Variable Name	Abbreviation	Symbol	Type
Material feed rate	MAT	x_1	Input
Fuel feed rate	FU	x_2	Input
Kiln speed	KS	x_3	Input
I.D. fan speed	FA	x_4	Input
Secondary air pressure	AP	x_5	Input
Kiln ampere	KA	y_1	Output
CO content	CO	y_2	Output
Back-end temperature	BE	y_3	Output
Pre-heater temperature	PRE	y_4	Output

3.2. Sampling

Since continuous signals are not usable in computing tools such as computers, a conversion to discrete type with a proper sampling frequency is required. Here, we determine T_s, the sampling time, as follows:

$$T_s = \frac{\tau_{\min}}{3} \tag{21}$$

The smallest time constant of the system has been calculated to be three minutes [30], thus T_s will be 60 s by (21).

3.3. Detecting outlier data

The samples may have different behaviors beyond expectations, called the outlier data. It is possible to obtain a compact clustering for data by getting rid of or replacing them. There are several methods available to determine the outlier data. Here, we use T^2 statistics [31] for this goal. Suppose that X is a matrix containing N samples with dimension P, as follows:

$$X = \begin{bmatrix} x_1^T \\ x_2^T \\ \vdots \\ x_N^T \end{bmatrix}_{N\times P} \tag{22}$$

First, a clustering is applied to this dataset by the k-means algorithm to reach k clusters name $C_1,\ldots,C_k$ with centers $c_1,\ldots,c_k$, respectively. Then T^2 statistics for samples of each cluster is calculated by:

$$T_j^2 = (x_j - c_i)^T S_i^{-1} (x_j - c_i) \tag{23}$$

where, $x_j \in C_i$, $i = 1,...,k$, $j = 1,...,n_i$ and n_i is the number of samples in the ith cluster. Also S_i in (23) is obtained by:

$$S_i = \frac{1}{n_i - 1}\sum_{j=1}^{n_i}(x_j - c_i)(x_j - c_i)^T \tag{24}$$

Finally, each sample will be checked by:

$$T_j^2 \le \alpha^2 \tag{25}$$

where, α determines the number of outlier data (smaller α results in more outliers). The samples satisfying the condition in (25) are denoted as normal, otherwise outlier. Then the outliers are replaced with the mean value of the previous and next samples.

3.4. Filtering

There may be some sudden changes and peaks in data that have a large amount of energy in a high frequency range. Since they degrade the performance of model, it is necessary to smooth them by passing the data through a proper filter [8]. In order to reach this goal, a first-order Butterworth low-pass filter with a 10^{-4} Hz band width is used here.

3.5. Applying input-output delay

The pure delay of a system is always a very effective parameter in the identification process. For the rotary kiln of the SWC factory, as it has been shown in Table 2, we use the delay results mentioned in [32] by means of the Lipschitz method.

Table 2. Input–output delays (minute).

Variable Name	KA	CO	BE	PRE
MAT	10	15	30	18
FU	25	5	10	4
KS	0	5	40	36
FA	10	0	5	0
AP	30	4	5	0

3.6. Input selection using GA

Since increasing the number of inputs results in more complexity in fuzzy systems, the best subset of inputs are selected in this work by applying GA to prevent increasing computations and achieving the best results. For this purpose, first, we gathered the more effective inputs for identifying each output (concluding the effective dynamics of kilns' inputs and the corresponding output) by analyzing the research works that have been done later [21, 25, 32], and then we used GA to select the best ones. In order to reach the minimum error and less inputs (both together) the cost is defined as:

$$z = W_1 f_1 + W_2 f_2 \tag{26}$$

where, f_1, f_2, are MSE and the number of inputs with weights W_1 and W_2, respectively. Figure 3 demonstrates the block diagram for rotary kiln identification with input selection by means of GA, and all the parameters required in GA are gathered in Table 3**Error! Reference source not found.**.

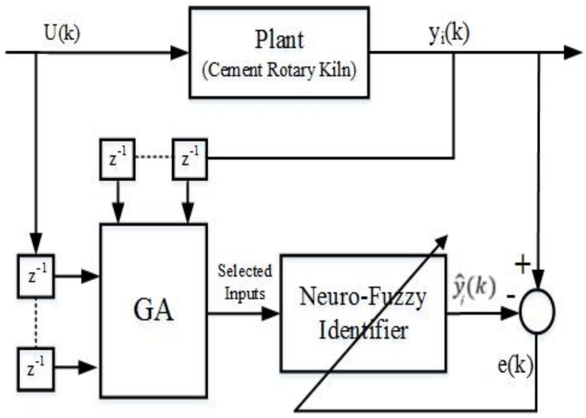

Figure 3. Identification block diagram with input selection by GA.

Table 3. Parameters used in GA.

Parameter	value
Population size	100
Maximum generation	20
Crossover rate	0.5
Mutation rate	0.2
W_1	10^4
W_2	1

In Figure 3, U(k) is defined as:

$$U(k) = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \end{bmatrix}^T \quad (27)$$

The results of applying GA shows that two dynamics of each output, i.e. $y_i(k-1), y_i(k-2)$, i = 1, …, 4 are the most proper inputs for it.

3.7. Normalizing data

We normalize the data in the [0,1] interval because the inputs and outputs have different ranges that lead to error in data quantization, and consequently, the plant is not identified well [24].

4. Simulation and results

In this section, the preprocessed data is applied to the TSNFS. The kiln that is a multi-input multi-output (MIMO) system is supposed as four MISO systems. Each of these dynamic MISO models are used as the schematic representation given in Figure 4. Structure learning of model to determine the number of inputs is done by GA (mentioned in the previous section). Also two MFs as the optimal number of MFs for each input have been achieved by trial-and-error. Thus there are four fuzzy rules with 20 learning parameters for TSNFS that are tuned by the GD method. Also the prepared data is divided into three parts consisting of 50% for train, 20% for validation, and 30% for test. In Figure 4, n(k) is the noise added to the model to evaluate it in a noisy situation. MSE for the test data when there is no noise, given in Table 4 and Figure 5, illustrates the output of the model and the actual output for KA.

Then we add a zero mean Gaussian noise and evaluate the model in different cases depending on the noise STD, whose results are presented in Table 5 to Table 8 for outputs, where σ_{Train} and σ_{Test} denote the STD of noise in the train and test data, respectively.

In these simulations, we consider two cases. In case I, σ_{Train} is fixed and σ_{Test} takes different values. In case II, σ_{Test} is fixed and different values are assigned to σ_{Train}.

According to the results of case I, we conclude in the same σ_{Train} if the amount of σ_{Test} increases, the MSE value will grow up. In Table 5, the results for KA show that when σ_{Train} is 0.7, the MSE values are 1.0162, 1.3944, 2.2934 in σ_{Test}= 0.7, σ_{Test} = 1, σ_{Test}= 1.5, respectively. Figure 6 shows

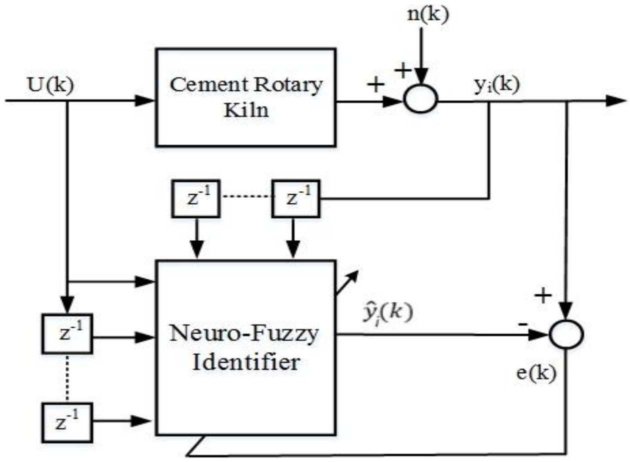

Figure 4. Schematic for dynamic nonlinear fuzzy identification of cement rotary kiln

the plot of the actual and identified output for KA in case σ_{Train}= 0.7.

Moreover, Case II denotes an interesting result. In fact, by growing up σ_{Train} for a fixed σ_{Test}, the model has less error. As in Table 5, the results for KA show that when σ_{Test}= 0.7, the MSE values are 1.0162, 0.7136, 0.3981 in σ_{Train}= 0.7, σ_{Train} = 1, σ_{Train} = 1.5, respectively. The actual and identified outputs for KA in case σ_{Test}= 0.7 are shown in Figure 7. (It is necessary to notice that an "error condition" has been specified in training algorithm to reach comparable results. Thus these MSE values can be very lower by changing the "error condition" in a trial-and-error process.)

5. Conclusion and future work

5.1. Conclusion

Table 5. MSE of model for KA test data in noisy condition.

Case I. Fixed σ_{Train} and variable σ_{Test}

Table 4. MSE of model for test data in normal condition

Output	MSE
KA	0.035972
CO	$9.4434*10^{-6}$
BE	0.18595
PRE	0.3236

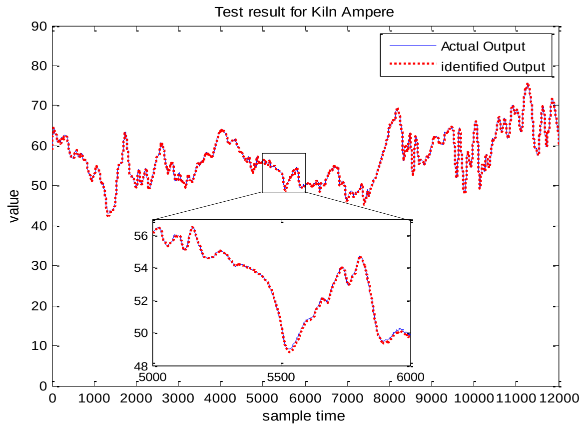

Figure 5. Plot of actual and identified outputs for KA in normal condition.

σ_{Train}	σ_{Test}		
	1.5	**3.5**	**5**
1.5	7.0332	14.4	23.695

Case II. Fixed σ_{Test} and variable σ_{Train}

σ_{Test}	σ_{Train}		
	0.7	**1**	**1.5**
0.7	1.0162	0.7136	0.3981

CO test data in noisy condition.

Case II. Fixed σ_{Test} and variable σ_{Train}

σ_{Test}	σ_{Train}		
	0.01	**0.02**	**0.03**
0.01	$2.8343*10^{-4}$	$2.2819*10^{-4}$	$0.6705*10^{-4}$

BE test data in noisy condition.

Case II. Fixed σ_{Test} and variable σ_{Train}

σ_{Test}	σ_{Train}		
	2	**3**	**4**
2	7.047	4.7546	3.1961

PRE test data in noisy condition.

Case II. Fixed σ_{Test} and variable σ_{Train}

σ_{Test}	σ_{Train}		
	1.5	**3.5**	**5**
1.5	7.0332	6.7525	1.9196

In this paper, a Takagi-Sugeno neuro-fuzzy system (TSNFS) was proposed for identification of Saveh White Cement rotary kiln in the normal and noisy conditions. The basis of TSNFS is a set of fuzzy rules consisting of fuzzy sets in the antecedent part and a linear function in the consequent part that enables the system to give a better model for non-linear dynamic plants and handle noisy information effectively. Also the GD algorithm was applied for updating parameters, and the data preprocessing was done completely. Especially, input selection that is derived based on GA, plays a key role in the models' simplicity and proper results.

The efficiency of the model was shown through simulations. A comparison between these results and other newly proposed models such as [8, 23] showed smaller MSE values for TSNFS in this paper, despite the smaller number of rules and learning parameters. Also this model was evaluated in noisy condition (that has not been noted in the recent studies), and had rather successful results. For larger amounts of noise on test data, the error increases so the error is tracking the noise and the model knows the noise well. Besides, we concluded the model works better (it had less error) when its parameters were tuned in a stronger noisy condition, and this is possible because of the fuzzy systems' properties.

5.2. Future work

In our future work, we will consider the changes such as using the recurrent structure in the proposed model. Also applying the type-2 neuro-fuzzy system for identification of cement rotary kiln in noisy condition, will be another future work.

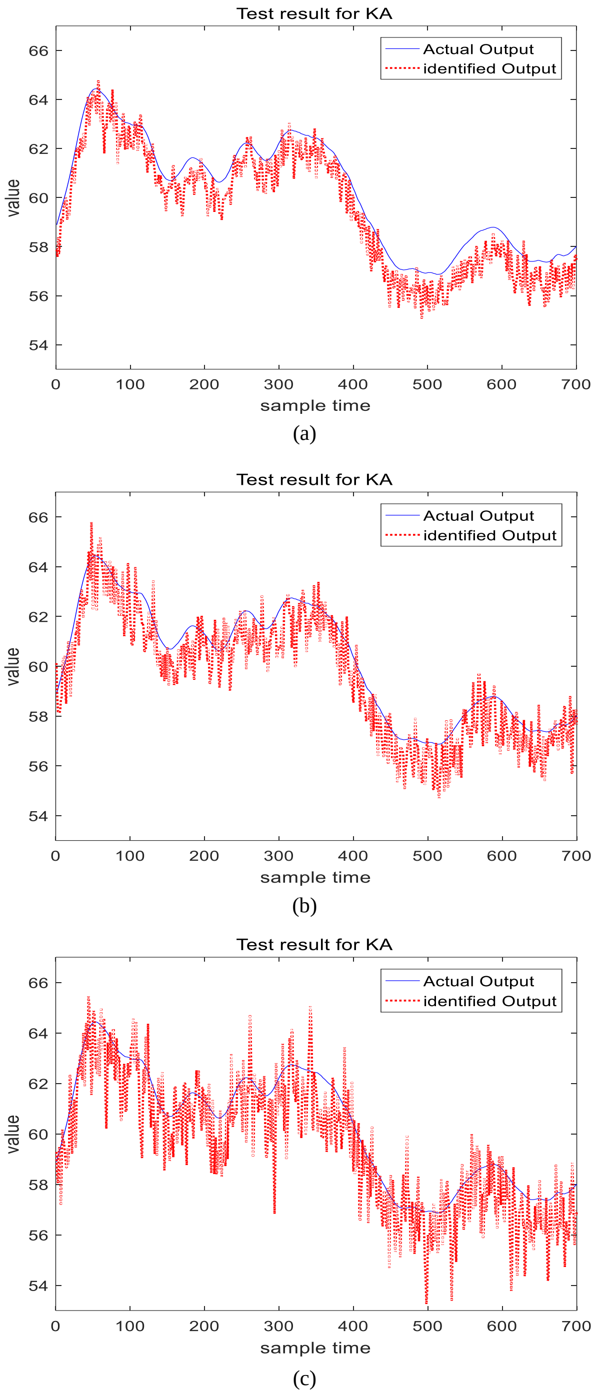

Figure 6. Plot of the actual and identified output for KA in case σ_{Train}=0.7 and (a) σ_{Test} =0.7 (b) σ_{Test}=1 (c) σ_{Test}=1.5

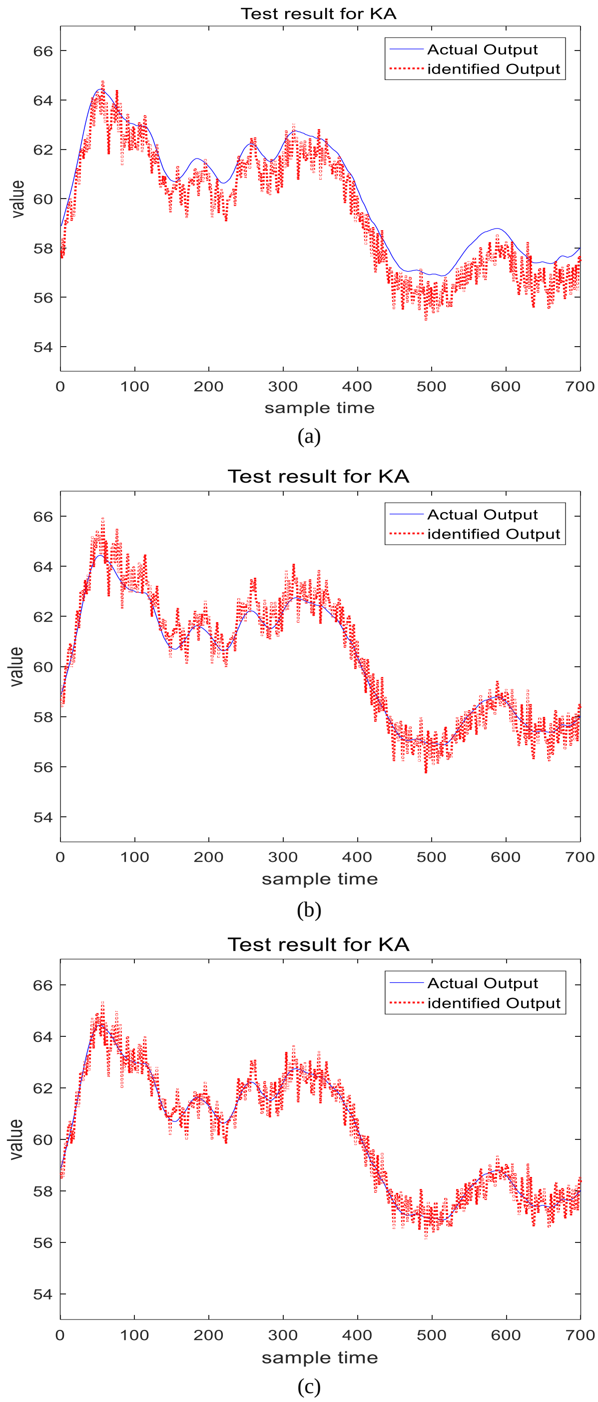

Figure 7. Plot of actual and identified output for KA in case σ_{Test} = 0.7 and (a) σ_{Train} = 0.7 (b) σ_{Train} = 1 (c) σ_{Train}=1.5

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نشریه هوش مصنوعی و داده کاوی

شناسایی کوره دوار سیمان در شرایط نویزی با استفاده از سیستم عصبی-فازی تاکاگی سوگنو

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چکیده:

کوره دوار سیمان به‌عنوان اصلی‌ترین بخش فرایند تولید سیمان همواره مورد توجه پژوهشگران زیادی قرار داشته است. اما تاکنون مدلی که بخصوص در شرایط نویزی دارای عملکرد مناسبی باشد، برای این سیستم غیرخطی پیچیده ارائه نشده است. در این پژوهش، از سیستم عصبی-فازی تاکاگی-سوگنو (TSNFS) برای شناسایی کوره دوار سیمان، استفاده و الگوریتم گرادیان نزولی (GD) برای تنظیم پارامترهای بخش‌های مقدم و تالی قواعد فازی به کار برده شده است. همچنین، ورودی‌های مناسب برای این سیستم با کمک الگوریتم ژنتیک (GA) انتخاب گردیده تا سیستم فازی دارای کمترین پیچیدگی باشد. در شبیه‌سازی‌ها، داده‌های مربوط به کارخانه سیمان سفید ساوه مورد استفاده قرار گرفته است. نتایج حاصل نشان می‌دهد شناساگر پیشنهادی در مقایسه با مدل‌های عصبی و فازی ارائه شده در پژوهش‌های پیشین، دارای عملکرد بهتری است. بعلاوه، در این پژوهش، مدل TSNFS در شرایط نویزی نیز مورد ارزیابی قرار گرفته است که این مسئله در پژوهش‌های اخیر به چشم نمی‌خورد. شبیه‌سازی‌ها حاکی از آن است که این مدل در شرایط نویزی مختلف، عملکرد مطلوبی دارد.

کلمات کلیدی: کوره دوار سیمان، سیستم فازی تاکاگی-سوگنو، انتخاب ویژگی، شرایط نویزی.