Identify and simulation a furnace of steam boiler based on a new fuzzy modeling approach

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Abstract
In this paper, one system identification method based on T-S fuzzy modeling approach is presented for modeling a furnace of steam boiler . In this method, NFCRM is applied to build the fuzzy structure and then identify the premise parameters; a new criterion is proposed to auto determine the number of rules in fuzzy modeling; after the fuzzy rules have been decided, orthogonal least square is exploited to identify the consequent parameters. Comparison between the responses of the proposed models with the responses of the plants and mathematical model validates the accuracy and performance of the modeling approach.

Keywords:furnace model, fuzzy model, system identification.

1. Introduction

One of the most important processes influencing boiler thermal efficiency is the efficiency of heat exchange in its furnace. Therefore, a lot of models analyzing and predicting heat exchange processes in boiler furnaces have been developed. These models are based on rudimentary principles of physics with different degrees of simplification. Huang et al. [1] presented a fire-tube boiler model that examines thermal flue gases and boiling water, and heat exchange efficiency. The modeling includes heat exchange between the external surface of the boiler and the environment. Applying this kind of model, we can simulate boiler efficiency at different heat loads. Also, Guru Z [2] described a mathematical model of heat exchange in the furnace by taking into account its soot deposit. Furthermore, a computer simulation model was presented by Claus and Stephan [3] to determine the steam boiler heat parameters by using the indirect method for testing its efficiency.

The key problem in system identification is to find a suitable model structure within which a good model is to be found. Fitting a modelwithin a given structure (parameter estimation) is in most cases a lesser problem. A basic rule in estimation is not to estimate what you already know. In other words, one should utilize prior knowledge and physical insight about the system when selecting the model structure[4].The identification and modeling of dynamic systems through the use of experimental data is a problem of considerable importance to the nuclear industry. Such procedures are useful in that: (1) they can be used to quantify the characteristics of intricate systems that cannot be analyzed in detail due to their complexity, unknown internal system structure, or sheer number of components that would have to be represented in an adequate model, and (2) the procedures could be a convenient method for diagnosing the condition of a wide class of systems, thereby making the technique useful for defect identification and damage assessment. System identification techniques can be classified on the basis of a priori knowledge of the system structure which is required for their implementation[5]. Mathematical modeling including identification and simulation have become key techniques, central to all disciplines of science and engineering[6].In the case of black-box linear type models, the development time is smaller, but the amount of parameters increases considerably, and the result is a model quality highly dependent on the system operating conditions inherited from the identification experiment.

Fuzzy modeling is a powerful technique for the modeling of complicated nonlinear systems. Among rule based fuzzy-modeling approach, Takagi–Sugeno (T–S) fuzzy model has attracted great deal of attention for its wonderful features [7]. For a dynamic system, the output is a function of past inputs or past outputs or both: identification of this system is not as direct as identification of a static system. To deal with temporal problems of dynamic systems, the commonly used model is a black box model or a fuzzy model [8].The problem with this approach is that the exact order of the dynamic system is usually unknown. To solve this problem, recurrent networks for processing dynamic systems can be used. Interest in these networks has been steadily growing in recent years [9]. However, recurrent networks deal with optimal fuzzy membership functions and defuzzification schemes for applications by using learning algorithms to adjust the parameters of fuzzy membership functions and defuzzification functions. Further more, the number of fuzzy rules is an important factor that affects the modeling performance, while too many redundant rules result in a complex fuzzy model, and too few rules may be insufficient to achieve the modeling objective. Sincefuzzy-clustering algorithms are widely used in fuzzy modeling;cluster validity criteria are helpful to decide the suitable number of rulers.

Fig. 1.TheSteam generator of oil refining company of Kermanshah

This article is organized as follows: The Systemdescribed In Section 2.Mathematical model is presented In Section 3.T–S fuzzy model offered In Section 4. The Fitting performances are shown in Section 5.The conclusion is given in Section 6.

2. System description

In this section, an overall view of the steam generator presented. In this paper, the furnace of the steam boiler Installed in the Kermanshahoil refining company,Iran,was investigated and assumed for identification and modeling approach. The steam generator installed in the oil refining company of Kermanshah, Iran, is Standard Fasel-Lent Jes BV with steam rate 30 ton/h (shown in Fig. 1).The model for the furnace in the form of one SISO system which has one input (fuel gas flow rate) and one output(steam temperature).Therecorded experimental data are for 24 h with 5 s sampling time. These data include the transient and steady state conditions. Four files were used for modeling the system, tow for acquiring the furnace input signal and tow for acquiring the furnace output signal. Each signal had 300 data samples. These data is selected through a set of 3760 points of the furnace data.

3. Mathematical model

A Dynamic model of boiler is describedby [10]. The dynamic model consists of Furnace model, the following assumptions is made in deriving the dynamic model for the furnace:

a) The fuel fiber and shell consumption is assumed to be constant.

b) The constant values are Calorific value, moisture content of the mixture of palm fiber and shell.

c) The air–fuel ratio is assumed to be constant.

d) Combustion gases temperature in furnace is proportional to the fuel rate.

e) In each tube bank the heat transfer rate is determined by the tube wall temperature, the average gas temperature is a function of the temperature of incoming gases and the amount of the heat loss of that particular bank.

f) Inertia of the hot gases is neglected and the velocity changes take place instantaneously.

g) Delay due to the heat capacitance of the hot gases is neglected; that is, temperature changes take place instantaneously in combustion gases.

h) Turbulent heat transfer is assumed throughout the process.

$$V_F \frac{d\rho_F}{dt} + V_A \frac{d\rho_A}{dt} = (w_F + w_A) - w_g \qquad (1)$$

COM:

$V_A \frac{d\rho_A}{dt} = 0$, therefore $(w_F + w_A) = w_g$ where

Air-fuelratio= $\frac{w_A}{w_F}, w_A = \frac{W_A}{W_F} w_F, w_g = w_F + \frac{w_A}{w_F} w_F$

$$w_g = \left(1 + \frac{w_A}{w_F}\right) \qquad (2)$$

COE:

$$V_g \frac{d\rho_g h_g}{dt} = (w_F h_F + w_A h_A) - w_g h_g - Q_g \qquad (3)$$

Where

$$V_g \frac{d\rho_g\, h_g}{dt} = 0, w_g = \left(1 + \frac{w_A}{w_F}\right) w_F, h_g = h_F + h_A$$

Therefore

$$Q_g = w_g h_g, Q_g = w_g C_g T_g, Q_g = w_g . LHV \qquad (4)$$

$$T_g = \frac{Q_g}{C_g (1 + w_A / w_F) w_F} \qquad (5)$$

4. Fuzzy modeling

4.1. T–S fuzzy model

The well-known T–S fuzzy model proposed by Takagi and Sugeno [11],that to describe complicated nonlinear system. For the identification of multiple input–multiple output (MIMO) systems, we take multiple input–single output (MISO) systems into consideration instead, while MIMO system can be divided into MISO systems. It is assumed that a MISO system P(x, y) is the system that needs identification, while x is the system input with$x \epsilon R^M$, and y is the system output with y e R the T–S fuzzy model of this system can be described by the following IF–THEN fuzzy rules [7]:

Rule i: IF x_1 is A_1^i and … and x_m is A_M^i THEN

$$y_{i=\, \theta_i^0 + \theta_i^1 x_i + \cdots + \theta_i^M x_{M,}} \qquad (6)$$

Where$i = 1, 2, \ldots, c, c$ is the number of fuzzy rule, $\boldsymbol{x}$ is the system input, $\boldsymbol{x} = [x1, x2, \ldots, x_M], M$Is dimension of input vector, yi is the ith output, and θ_i^M is the consequent parameter of the ith output. Note that the affine linear functions in the consequent part are hyperplanes (m-dimensional linear subspaces) in R^{M+1}.

The final output of T–S fuzzy model can be expressed by a weighted mean defuzzification as follows:

$$\widehat{y} = \frac{\sum_{i=1}^{c} w_i\, y_i}{\sum_{i=1}^{c} w_i} \qquad (7)$$

Where the weight wi represents the overall truth value of the premise of the jTh implication for the input which can be calculated as:

$$w_i = \prod_{j=1}^{M} \mu(A_i^j), \qquad (8)$$

Where$\mu(A_i^j)$is the grade of membership function and is described by a Gaussian function as:

$$\mu(A_i^j) = \exp\left(-\frac{(x_j - v_{ij})^2}{\sigma_{ij}}\right), \qquad (9)$$

$i = 1, \ldots, c\ , j = 1\ , \ldots, M\ ,$

3. The proposed T–S fuzzy-modeling approach

In this section, we will discuss a new T–S fuzzy-modeling approach in more detail, which is illustrated by Fig. 2. As shown in this figure,the approach is consisting of mainly two phases, namely, premise parameters identification and consequent parameters. In the first phase, NFCRMA is used to partition the input–output fuzzy space and extract fuzzy rules with the help of a criterion, which determines the right number of rules as the number varying. After fuzzy rules have been extracted in the first steps, the consequent parameter of the fuzzy model will be identified using orthogonal least square (OLS) method.

More efficient meant full than the former FCRM-clustering algorithm. The selection of initial values of hyper-panes needs to be discussed in a further step. The initial value is crucial for algorithm with gradient method. In order to get suitable initial values, we try to partition the input–output space coarsely. This step is concerned with the application of a suitable unsupervised learning process in order to dismember the input space into a number of subspaces (clusters). To do this, the fuzzy c-means (FCM) algorithm is employed. And then, the clusters obtained in the previous step are considered to form a hyper-plane, which is be gotten by using least square (LS) method. The parameters of obtained c initial hyper-planes will be used in the fuzzy-clustering algorithm NFCRMA as initial values [7].

4.2. Identification of premise parameters

We use the proposed NFCRMA to separate the input–output space and obtain the premise part of each fuzzy rule the membership functions of the fuzzy sets in the premise part of each fuzzy rule as described by Eq. (9). As mentioned in Kim [12], in view of this equation, the fuzzy set centers vij $(1 \leq i \leq c, 1 \leq j \leq M)$, and the respective standard deviations σ_{ij}can be easily obtained by using μ_{ik}, the membership of (xk, yk) belonging to ith clustering representing hyper-plane as follows of rules blindly. However, it is not easy to find out the most suitable number of rules. In fuzzy-clustering algorithm-based T–S fuzzy-modeling method, researchers tried to get the optimum rules number through a certain cluster validity criterion when the fuzzy-clustering algorithm used to partition the fuzzy space. Cluster validity criterion fitting to the FCRM-clustering algorithm in T–S fuzzy modeling, while the rules numbers are decided by the partition of the input fuzzy space. It is maybe a reasonable way to decide the number of rules because a suitable cluster validity criterion can help us getting the optimal fuzzy partition as cluster number varying, thus deciding the number of rules [7].

In this paper, we design a new criterion to help deciding the number of rules in fuzzy modeling,

$$v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ik}.x_{kj}}{\sum_{k=1}^{n} \mu_{ik}} i = 1, \dots, c, j = 1, \dots, M, \quad (10)$$

$$\sigma_{ij} = \sqrt{\frac{2\sum_{k=1}^{n} \mu_{ik} \cdot (x_{kj} - v_{ij})^2}{\sum_{k=1}^{n} \mu_{ik}}} \quad (11)$$

$i = 1, \dots, c, j = 1, \dots, M,$

This takes into consideration two important aspects: accuracy and concision. Assume n Input–output data pairs (x, y) being partitioned into clusters $C1, C2, \dots, Cc$ by NFCMA. Then, the criterion is described as

$$L(c) = \alpha \frac{D(c)}{D(max)} + (1 - \alpha) \frac{c}{c_{max}} \quad (12)$$

Where$c$the number of rules is, $Cmax$ is the set maximum number of rules, $\alpha(0 < 1)$ is a coefficient$Dmax = max\{D(c)\}$, and $D(c)$ is defined as

$$D(c) = \frac{1}{c} \sum_{i=1}^{c} \left\{ \frac{1}{N} \sum_{(x_k y_k) \in c_i} (y_k - [x_k^1]\theta_i) \right\} \quad (13)$$

WhereNi represent the number of samples in it h cluster.

From Eq. (12), it is manifested that $L(c)$ consists of two normalized terms, while the first part indicates accuracy of fuzzy model or the linearity of the fuzzy model, the second part indicates simply of the fuzzy model. It is reasonable that the increase in number of rules will improve accuracy, but deteriorate concision of structure of the model, and reduce the generalization ability of the model. So the first term and the second term in Eq. (12) are incompatible, and we use a coefficient α to control the balance between accuracy and concision. In experiments, it is found that $\alpha = 0.4$ can produce wonderful results.

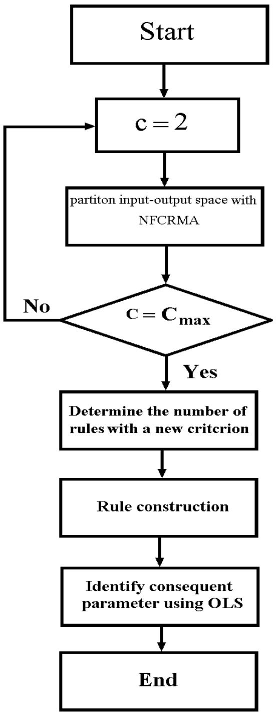

Fig. 2.An illustration for the proposed fuzzy-modeling approach

3.3. Identification of consequent parameters

$$y = p\theta + e \qquad (14)$$

Where

$$\theta = [\theta_1^0, \dots, \theta_1^d, \dots, \theta_c^0, \dots, \theta_c^M],$$

$$y = [y_1, y_2, \dots, e_2, \dots, e_n]^T$$

is the error vector with $\boldsymbol{e}_k = y_k - \hat{y}_k (1 \le p = [p_1, p_2, \dots, p_r](r = c(1+m))$ is the coefficient I

$$[p^i(x_1), p^i(x_2), \dots, p^i(x_n)](1 \le i \le r)$$

From description in section 2, it is easy to find that

$$p^i(x_k) = [1, \lambda_{1k}x_{k1}, \dots, \lambda_{1k}x_{kM}, \dots, 1, \lambda_{ck}x_{k1}, \dots, \lambda_{ck}x_{kM}],$$

Where$xkj(1 \le k \le n, 1 \le j \le d)$ reperesent the jth element of kth input, for$\boldsymbol{xk}$,

Once the premise fuzzy set parameters have been identified, the consequent parameters can be obtained from the following matrix equation, $\lambda_{ik}(1 \le i \le c, 1 \le k \le n)$ Reperesent the combination of weights of rules, which is expressed as:

$$\lambda_{ik} = \frac{w_i}{\sum_{k=1}^{n} w_i} \qquad (15)$$

$$\lambda_{ik} = \frac{w_i}{\sum_{k=1}^{n} w_i} \qquad (16)$$

5. Fitting performance

The data are divided in two groups follow as estimate data and validate data. Then, the various nonlinear estimators of input and output system have been chosen for estimate the system in represent the nonlinearity behavior. The developed programming using MATLAB software will check accuracy of the drum of the boiler. Figs. 3 and 4 show the actual outputs, the predicted outputs by the mathematical model and the fuzzy modeling approach, respectively.

6. Conclusions

The nonlinear system identification using novel fuzzy-clustering-based modeling is the new method to modeling the furnace. The modeling can imitate behavior of system by black-box approach. Simulation experiments demonstrated that the proposed modeling method is able to build fuzzy model for complicated nonlinear system with compact fuzzy rules and high accuracy. The model as the representation of the system can be analyzed in aspect of control system, stability. The applications of modeling are widely use for example model predictive control, power plant system impact analysis, etc.

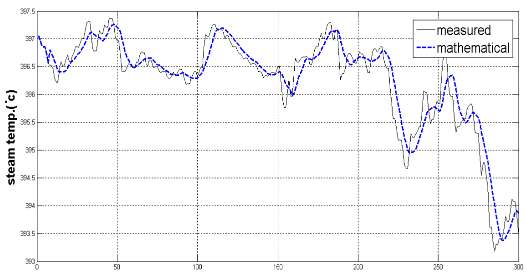

Fig. 3.The visual comparison of the actual output and response of mathematical model

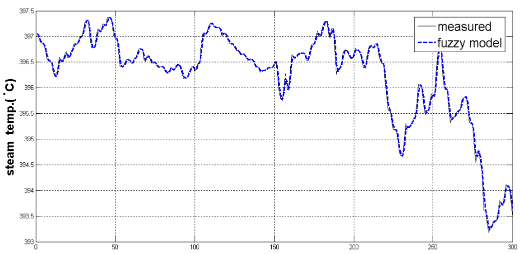

Fig.4.The visual Comparison between actual output and response of fuzzy model.

Acknowledgments

The authors are grateful for financial support of this work from the Kermanshah oil refiningompany . We also appreciate Mrs Shabnam Mohammadi Azam,Dr Homan Sajdian, Dr Mehrdad Javadi for their kind assistance.

Nomenclature

COM:	Conservation of Mass
COE:	Conservation of Energy
Cg	heat capacitance of flue gas (J/kg°C)
hF, hg, hAenthalpy of fuel, flue gas and air (J/kg)	
Qgsteady-state heat release (J/s Btu/s)	
Tgflue gas temperatures (°C)	
VF,Vg,VAvolume of fuel, flue gas and air (m3)	
wA/wFair/fuel ratio	
wF, wg,wAmass flows of fuel,fluegas and air(kg/s)	
z	time shift operator
ρ_F, ρ_g, ρ_Aflue, flue gas and air densities(kg/m3)	

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