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Dynamic model of reheating furnace based on fuzzy system and genetic algorithm

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Abstract: A simple method is introduced to determine the structure of the fuzzy model. In this process, the membership function on each variable is increased separately in each iteration and performance is evaluated to decide whether to continue this operation. This procedure continues till the numbers of membership functions on all the variables are fixed. The method is used to a reheating furnace and parameters thereof are tuned by adaptive genetic algorithm. Simulations show the effectiveness of the constructed system.

Key words: fuzzy system; genetic algorithm; structure identification; reheating furnace model

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基于模糊系统和遗传算法的加热炉动态模型

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摘要: 介绍了一种由采样数据确定模糊模型结构的方法.方法中变量上的隶属函数个数不断增加并通过性能评价来确定是否保留这些操作,该过程重复直至变量上的隶属函数个数确定下来.该方法被用于加热炉的建模并由遗传算法来调节其中的参数.仿真结果证明了这种方法的有效性.

关键词: 模糊系统; 遗传算法; 结构辨识; 加热炉模型

1 Introduction

Fuzzy modeling has been successfully employed in various areas[1]. It is flexible, simple and its parameters have clear meaning[2~5]. However, it is difficult to determine its structure. In this paper, a method is introduced to determine its structure and adaptive genetic algorithm (GA)[6] is used to improve its performance. Instead of tuning parameters of the model at each iteration[7], the parameters are tuned at the end of algorithm because GA is time-consuming. On the other hand, if gradient or least square based algorithm is used, the results will depend on the choosing of initial value and it can often be trapped into local minimum.

2 Problem description

Reheating furnace is an important device in the steel industry. Its structure is shown in Fig. 1. Due to its highly nonlinearity and various disturbances, it is difficult to build the model by using conventional mathematical methods. The universal approximation theorem[8] provides a theoretical foundation for constructing dynamic model of reheating furnace using fuzzy system. In this paper, the input and output is decided in advance as follows:

$y(k+1)$ = the predictive temperature of a zone at time instant $k+1$, the output of the system.

$x_1(k)$ = heat absorbing ability of slabs in a zone at instant k.

$x_2(k)$ = the fuel flux of a zone at time instant k.

$x_3(k)$ = the temperature of a zone at instant $k-1$.

The system can be written as:

$$y(k+1) = \hat{f}[x_1(k), x_2(k), x_3(k)].$$

In this paper, the system and its parameter tuning str-

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ategy can be illustrated in Fig.2.

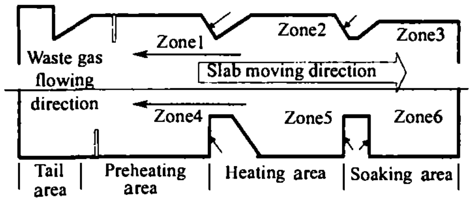

Fig. 1 The structure of the reheating furnace

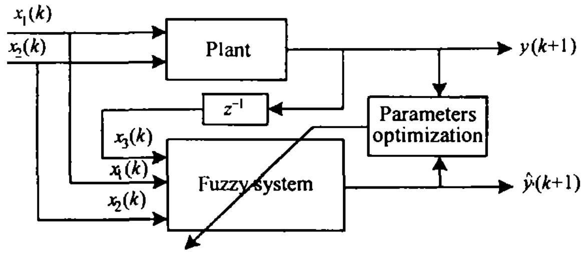

Fig. 2 Identifying parameters of the system using genetic algorithm

3 Determine the structure of the fuzzy model

The model will be constructed as follows.

Step 1 Define a small number of membership functions on each variable.

Without loss of generality, membership functions with triangular shape, which are uniformly spread, is defined to cover each variable. The number of membership functions is not fixed. For simplicity, these variables are denoted as unfixed variable.

Step 2 Construct the fuzzy system based on table lookup method[2], and evaluate its performance.

For the furnace system, in time instant k, the extracted fuzzy rules can be expressed as follows:

R^k: IF $x_1(k)$ is A_1^l and $x_2(k)$ is A_2^m and $x_3(k)$ is A_3^n,

THEN $y(k)$ is B^j,

where $x_1(k), x_2(k), x_3(k)$ are the input, $y(k)$ is the output. A_1^l, A_2^m, A_3^n are the fuzzy sets on the input variables x_1, x_2, x_3. B^j is the fuzzy sets on the output variable. Then, the model can be constructed and its performance can be evaluated.

$$\text{Aver(error)} = \frac{\sum_{i=1}^{N} |\hat{y}(i) - y(i)|}{N}, \quad (1)$$

where $\hat{y}$ and y are the output of the constructed system and the real system respectively.

Step 3 Increase the number of membership functions on an unfixed variable, then repeat Step 2 to decide whether to continue this increase operation or not.

If the performance improves, then this increase operation is kept and the number of membership functions on this variable can be increased in the following iteration. If the performance of the system does not improve or the improvement is below a threshold, then this increase is interrupted and this variable is marked as fixed variable. The number of membership functions on this variable will not be increased in the following iteration.

Setp 4 Repeat Step 3 until all the variables are marked as fixed variables. Then the structure of the model is determined.

The flow chart of the algorithm is illustrated in Fig.3.

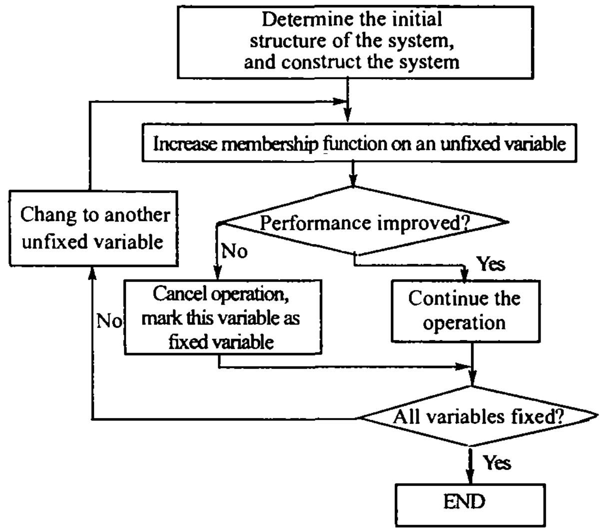

Fig. 3 The flow chart of the proposed algorithm

4 Identify parameters through genetic algorithm

In this paper, the bases of membership functions are left free, which are adjusted automatically according to their centers. So the number of adjustable parameters is $m_1 + m_2 + m_3 + n$. Our objective is to minimize the error between the constructed model output and real system output. To reach this goal, the data set is divided into study set, which is used to construct the system, and the test set, which is used to evaluate the performance. The relationship between the parameters and errors on the two sets is illustrated in Fig.4, where we achieved the optimal parameter which is expected.

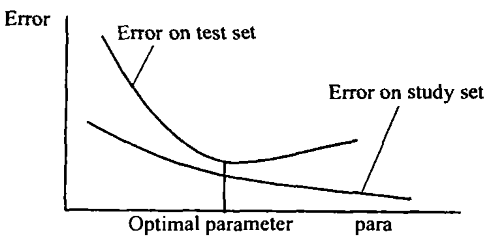

Fig. 4 The relationship between parameters and errors on study set and test set

In this system, the error on the test set should be as small as possible, so a larger weighting factor is assigned to error on this set while a smaller weighting factor to error on the study set. The objective function is:

$$f(x) = \min\left[\alpha_1 \cdot \frac{\sum_{k=1}^{N_1} |\hat{y}(k) - y(k)|}{N_1} + (1-\alpha_1) \cdot \frac{\sum_{j=1}^{N_2} |\hat{y}(j) - y(j)|}{N_2}\right], \tag{2}$$

where N_1 and N_2 are numbers of data in study and test sets. $\alpha_1 \in [0,1]$ and $(1-\alpha_1)$ are weighting factors of error on study and test sets.

The fitness function transforms the measure of performance into an allocation of reproductive opportunities:

$$\text{fitness} = \begin{cases} C - f(x), & \text{if } f(x) < C, \\ 0, & \text{if } f(x) \geqslant C, \end{cases} \tag{3}$$

where C is a predefined large enough number. Then, the reproduction probabilities of each individual is:

$$p_{ir} = F_i / \sum_{i=1}^{M} F_i, \tag{4}$$

where M is the size of population and F_i is the fitness of i-th individual. In adaptive genetic algorithm, the probabilities of crossover p_c and mutation p_m are varied according to the fitness values of the solutions[7]:

$$\begin{cases} p_c = k_1 \cdot (f_{max} - f')/(f_{max} - \bar{f}), & f' \geqslant \bar{f}, \\ p_c = k_3, & f' < \bar{f}, \\ p_m = k_2 \cdot (f_{max} - f)/(f_{max} - \bar{f}), & f \geqslant \bar{f}, \\ p_m = k_4, & f < \bar{f}, \end{cases} \tag{5}$$

where f_{max} and $\bar{f}$ are the maximum and average fitness of the population in current generation, f' is the larger fitness of the solutions to be crossed, f is the fitness of the solution to be mutated, and $k_1 = k_3 = 1.0, k_2 = k_4 = 0.5$. Then for a paired solution $(x^i; x^j)$, $x^i = (x_1^{i1}, x_i^{i2}, \cdots, x_1^{im_1}, x_2^{i1}, \cdots, y^{in})$ and $x^j = (x_1^{j1}, x_1^{j2}, \cdots, x_1^{jm_1}, x_2^{j1}, \cdots, y^{jn})$, a new solutions can be gotten:

$$\begin{cases} x^{i\prime} = \alpha \cdot x^i + (1-\alpha) \cdot x^j, \\ x^{j\prime} = \alpha \cdot x^j + (1-\alpha) \cdot x^i, \end{cases} \tag{6}$$

where $\alpha \in [0,1]$ is a random number.

For the point in a solution that mutates, a random value in the corresponding range is chosen to replace it.

After this process, the next generation of population is formed.

5 Simulation results

In this section, several simulations are presented. The parameters of genetic algorithm are set as follows: initial number of membership functions on each variable is 4, the population of each generation is 50 and the maximal generation is 200. The weighting factor of the error on study set and test set in objective function are 0.4 and 0.6. The space of possible parameters is determined by the limitation of variables which is determined by reheating furnace in discussion. Since temperature is a slow process, the sample rate of all data is 1 minute. To all figures, outputs of model, real system and their error are shown respectively. The vertical axis is temperature and its unit is centigrade, the horizontal axis is time and its unit is minute.

First, 600 pairs of 950 data pairs are denoted as study set and the last 350 pairs as test set. The result is shown in Fig. 5.

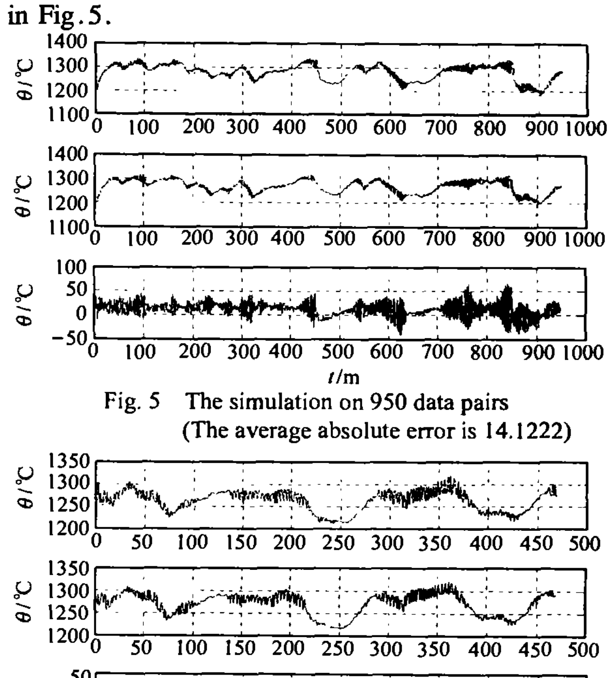

Fig. 5 The simulation on 950 data pairs (The average absolute error is 14.1222)

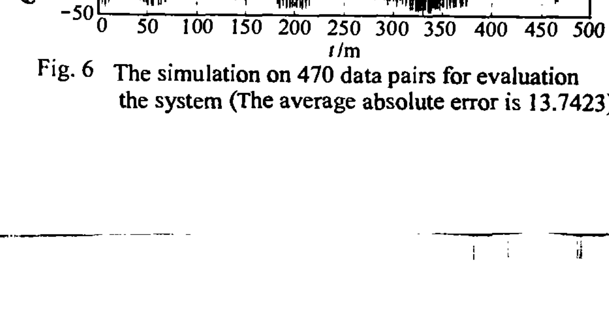

Fig. 6 The simulation on 470 data pairs for evaluation the system (The average absolute error is 13.7423)

From Figs. 5 and 6, it is clear that the proposed scheme has good performance on both data for study and test.

The the constructed model is used on other 470 data pairs and the result is shown in Fig.6.

Another example is that first 350 pairs out of 470 pairs are denoted as study set, the last 120 pairs as test set. The result is shown in Fig.7.

Then the constructed model is used on 950 pairs and the result is shown in Fig.8 and proves satisfactory.

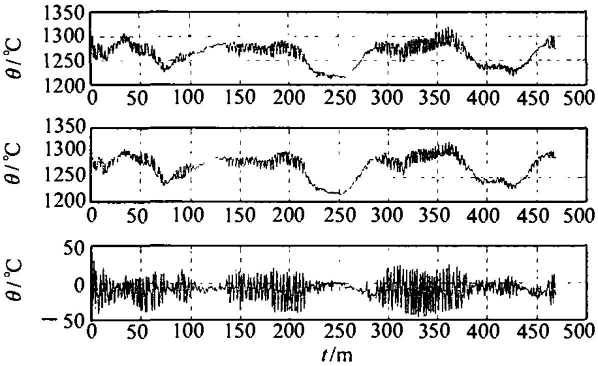

Fig. 7 The simulation on 470 data pairs (The average absolute error is 14.3629)

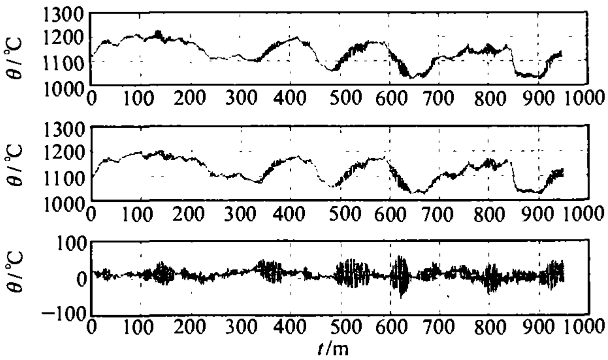

Fig. 8 The simulation on 950 data pairs for evaluating the system (The average absolute error is 15.1020)

6 Conclusions

In this paper, a new method is introduced to determine the structure of fuzzy model. The method starts from a small number of membership functions on each variable, which then increase their numbers respectively. Meanwhile, the performance of the system is evaluated. The procedure is repeated until the structure of the system is determined. Then, adaptive genetic algorithm is employed to get the parameters of the model. Simulation results show that the proposed scheme works quite well.

References:

[1] WANG Li-xin. *Adaptive Fuzzy Systems and Control: Design and Stability Analysis* [M]. Englewood Cliffs, NJ: Prentice Hall, 1994.

[2] WANG Li-xin, MENDEL J M. Generating fuzzy rules by learning from examples [J]. *IEEE Trans on Systems, Man, and Cybernetics*, 1992, 22(6): 1414 - 1427.

[3] NIE J. Constructing fuzzy model by self-organizing counter propagation network [J]. *IEEE Trans on Systems, Man, and Cybernetics*, 1995, 25(6): 963 - 970.

[4] ABE S, LAN M S. A classifier using fuzzy rules extracted directly form numerical data [A]. *Proc IEEE Conf on Fuzzy System* [C]. San Francisco: [S.n.], 1993: 1991 - 1998.

[5] WANG Li-xin. Fuzzy systems are universal approximators [A]. *Proc IEEE Int Conf on Fuzzy Systems* [C]. San Diego: [s.n.], 1992: 1163 - 1170.

[6] GEN M, CHENG Runwei. *Genetic Algorithm and Engineering Design* [M]. New York: Wiley, 1997.

[7] CAO S G, REES N W, FENG G. Analysis and design for a class of complex control system Part I: Fuzzy modelling and identification [J]. *Automatica*, 1997, 33(6): 1017 - 1028.

[8] SRINIVAS M, PATNAIK L M. Adaptive probabilities of crossover and mutation in GA [J]. *IEEE Trans on Systems, Man, and Cybernetics*, 1994, 24(4): 656 - 667.

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