Research Journal of Applied Sciences, Engineering and Technology 4(14): 2147-2152, 2012
ISSN: 2040-7467

Submitted: March 12, 2012 Accepted: April 03, 2012 Published: July 15, 2012

T-S Neural Network Model Identification of Ultra-Supercritical Units for Superheater Based on Improved FCM

[1, 2]Yunjuan Li and [2]Yanjun Fang
[1]Kunming University, Kunming 650214, China
[2]Department of Automation, Wuhan University, Wuhan 430072, China

Abstract: The study constructs the T-S neural network model for the superheater with multiple inputs and single output and presents an improved FCM algorithm aiming to solve the inputs' space division problem. The function parameters of the Gaussian membership are obtained to identify the model structure and the recursive least squares method is adopted to identify model parameters. Simulations results show that the improved method has good performance in model identification and the identified models have preferable accuracy and generalization ability.

Key words: Model identification, superheater, T-S neural network, ultra-supercritical units

INTRODUCTION

Main steam parameter of Ultra-Supercritical (USC) unit is high, it use once-through boiler technology and the media has strong rigidity. Water and vapor cycle speed in unit increases, which speeds up the process characteristics. So a higher and more stringent performance requirement is needed for the main steam temperature control (Ming-zhu *et al*., 2007). Currently model-based control technology is widely used in the main steam temperature control for thermal power plants (Mehdi and Alireza, 2009). Unlike conventional units, USC unit main steam temperature dynamics characteristics are more complex and the model structure will change a lot when the load changes. Therefore, it is important to design control system using identification of ultra-supercritical unit superheater model.

Conventional superheater model identification methods are least-squares method (Feng *et al*., 2006), the step response method (Ahmed *et al*., 2008), etc. The identified models are usually simplified in the fixed conditions and they are linear time-invariant models. But the main steam temperature has big delay, non-linear, time varying and other complex dynamics characteristics. So it is difficult to express them accurately. The fuzzy neural network combines fuzzy systems and neural network technology and it has a good function approximation capabilities and powerful self-learning function. So it is used to solve non-linear model identification problem. In this study, an improved Fuzzy c-Means clustering algorithm (FCM) is proposed to divide the input variable space and a superheater MISO model based on T-S neural network.

By determining the membership function and the use of recursive least squares method to achieve the model parameter identification, it has improved identification accuracy. It provides a model reference to the main steam temperature control system design because the identification model can more accurately reflect the actual dynamic characteristics of the superheater.

METHODOLOGY

Building superheater T-S neural network model: T-S neural network using neural network structure to achieve T-S fuzzy inference, it extracts the qualitative knowledge from the system input and output data and converts it into a neural network mapping process. So it can accurately describe dynamics of complex systems (Cai and Yin-Chao, 2006). T-S fuzzy model (Hong-jun *et al*., 2005) rule consequent is a linear function of input variables, which is based on local linear and a global non-linear can be achieved through the fuzzy inference. It is easy to spread to the MIMO fuzzy system to facilitate the adjustment of parameters. In addition, the local linear model is easy to combine with PID control and optimization. And the controller with optimization and adaptive capacity or the fuzzy modeling tool can be realized.

Model input variable determination: Taking 1000 mw unit of USC power plant as a study object, it uses once-through boiler with third stage superheater and second stage spray desuperheating devices (Liu, 2010) and the process is shown in Fig. 1.

In Fig. 1 and 2 is the total water supply quantity of the boiler; F4 is spraying water from the outlet of economizer; F3 is the feed water flow and it is used to adjust fuel-water ratio rapidly; T3 and T5 are inlet temperature and outlet temperature of the fist stage

Corresponding Author: Yunjuan Li, Kunming University, Kunming 650214, China

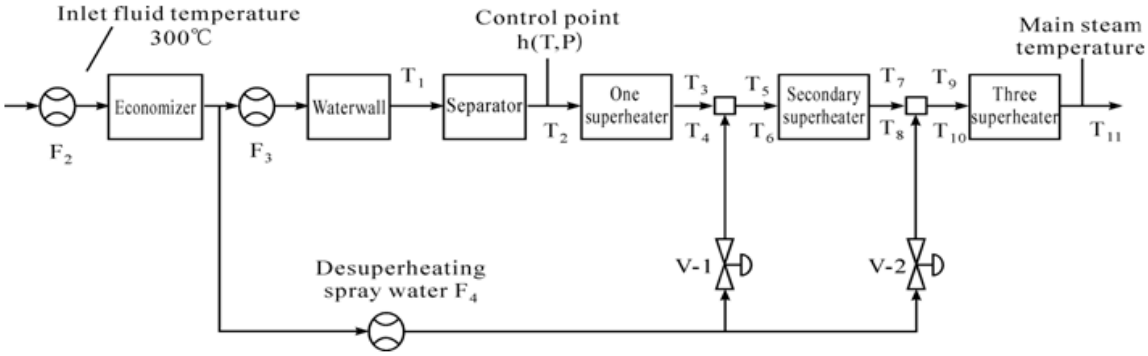


Fig. 1: Ultra-supercritical unit superheater flow chart

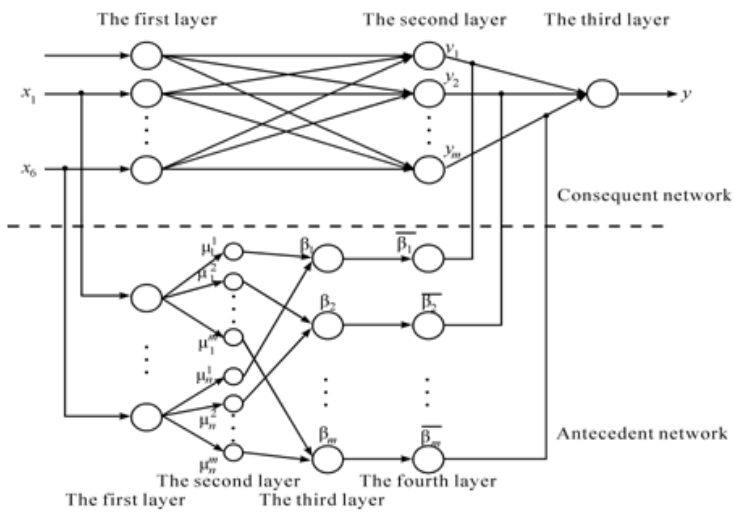


Fig. 2: T-S neural network model structure of superheater

desuperheater in the A side, T7, T9 are inlet temperature and outlet temperature of the second stage desuperheater in the A side,T11 is the main steam temperature of the boiler.

It can be directly seen from the USC superheater system artwork that there are some relationships between the impact factors of the main steam temperature. To achieve effective control of the main steam temperature, it is necessary to determine the main factors of the main steam temperature to construct a reasonable model of controlled object.

On the basis of the analysis of USC superheater dynamics and the actual operating data this study determines the main factors of the main steam temperature as the input variables of T-S neural network models. It uses trial and error method through extensive test and analysis to confirm six input variables, including the main steam temperature t(k-1), the amount of coal c(k), air flow a(k), a temperature reduction of water f(k), a temperature reduction of water f(k-4), unit load p(k).

Input variable space fuzzy division: Division of input variable space often uses Fuzzy Clustering Algorithm (FCM). The main idea of FCM (Zhu *et al*., 2009) is to determine the initial value in the cluster center and then gets the final cluster center by continuous iterative adjustment under the subordinate matrix and cluster centers to minimize the objective function value.

When determining the initial cluster centers, the commonly used method is randomly selecting m-vector as the initial cluster centers from the feature space in the data samples. But the selection method led to the global optimal clustering results into a low probability.

In view of the FCM algorithm insufficiency, it makes some improvement on the definite of the initial cluster number and the choice of the initial cluster center. Subtractive clustering (Pei-qiang *et al*., 2006) is an algorithm used to estimate the number of clusters and the cluster center location, which considers each data point as a possible cluster center and calculates the possibility according to the density of surrounding data points.

The data points near the selected point which is considered as cluster center are excluded because there is the highest data density around it. In this way, the next cluster center is selected. It keeps on cycling until all remaining data points as potential cluster centers below a certain threshold.

Subtractive Clustering has fast speed. When using this method to initialize the number of cluster categories and cluster centers, it can eliminate the initial value sensitive issues.

T-S neural network structure of superheater: Using the improved FCM algorithm to make cluster analysis of the input variable space about the model of the superheater, it can get a group of cluster centers to reflect the system prototype. And it uses the cluster centers to construct the first-order T-S fuzzy neural network model about the superheater. This non-linear model has 6 inputs and 1 output. Assuming that the results of cluster analysis get the m cluster centers, the model network structure is shown in Fig. 2.

T-S neural network of superheater consists of antecedent network and consequent network. The antecedent network is to match the antecedence of a fuzzy rule. The consequent network computes the consequence of a fuzzy rule.

- **Antecedent network:** The first layer is input layer and has six nodes. Every node of the layer is directly connected with every component xi of the input vector. It transmits the input value to next layer. The second layer is the membership function layer and its total nodes are 6*m. It calculates the membership functions whose type is Gaussian:

$$\mu_A^j(x_i) = \exp\left[-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}\right] \quad (1)$$

i = 1, 2, …, 6; j = 1, 2, …, m

The third layer is the rule layer, whose role is to match the antecedent of fuzzy rules to calculate the degree of application of each rule. $\beta_i = \prod_{j=1}^{n} \mu_j^i$ i=1, 2,…, m

The fourth layer is the normalized layer and the calculation is used to achieve normalization:

$$\bar{\beta}_j = \beta_j / \sum_{i=1}^{m} \beta_i \qquad j = 1, 2, \ldots, m$$

- **Consequent network:** The first layer is input layer, which is used to transmit the input variables to the second layer. Input layer nodes value x0 = 1, whose role is to provide the constant term of the consequence about the fuzzy rule. The second layer is rule layer and the number of nodes is m, its role is to calculate the consequence of every rule:

$$y_j = p_{j0} + p_{j1}x_1 + \ldots + p_{jn}x_n = \sum_{k=0}^{n} p_{jk}x_k,\ j = 1, 2, \ldots, m \quad (2)$$

The third layer is output layer:

$$y = \sum_{j=1}^{m} \bar{\beta}_j y_j \quad (3)$$

Obviously, y is the weighted sum of every regular consequence; the weighting system is suitable for each fuzzy rule after the normalization.

MODEL PARAMETER IDENTIFICATION

Antecedent parameter identification: It is most essential to determine Gaussian membership function parameters in formula 1. This study makes the fuzzy division to the input space by using improved FCM algorithm to obtain the cluster center:

$C_j = (c_{1j}, c_{2j}, c_{nj})$

And the center of Gaussian function is:

$c_{ij} = (c_{1j}, c_{2j}, c_{nj})$

The width parameter σ_{ij} of Gaussian membership function directly affects the curve shape of the membership function. Improved FCM algorithm outputs an m-vector cluster center and a fuzzy dividing matrix. According to the principle of maximum membership in fuzzy set, every sample point is classified; the Euclidean distance of every type of cluster center between sample points is calculated and averaged. Thus the averaged value is the radius of the cluster; also it is the width of the Gaussian membership function.

Consequent parameter identification: T-S neural network rule consequent is a linear function on input variables. Its parameter is the consequent parameter. Taking into account the recursive least squares calculation features such as simple and easy to be implemented by computer, this study uses it to identify the consequent parameter.

The basic idea of recursive least squares method is that it pluses the previous estimate based on time and the correction term to get the new parameter estimate. The objective function using recursive least squares method is set to:

$$J_N = \sum_{j=1}^{N} \left[f(X_i) - t_i \right]^2 \tag{4}$$

In this formula, n is the number of input sample points and it is the actual system output when xi is the input. T-S neural network model of superheater can be expressed as:

$$\begin{aligned} t(k)_i &= \theta_{i0} + \theta_{i1} t(k-1) + \theta_{i2} c(k) + \theta_{i3} a(k) \\ &+ \theta_{i4} f(k) + \theta_{i5} f(k-4) + \theta_{i6} p(k) \end{aligned} \tag{5}$$

θ_{ij} is the consequent parameter needed to be identified; j = 1, 2, …, 6; i = 1, 2, …, m; m is the number of the cluster centers.

Input is Xi = [t(k-1) c(k) a(k) f(k) f(k-4) p(k)] = [x1 x2 x3 x4 x5 x6]. Output nodes of the normalized layer are noted as:

$$\left[\bar{\beta}_1 \ \bar{\beta}_2 \ \ldots \ \ldots \ \bar{\beta}_m \right]$$

Each fuzzy rule output is noted as:

$$y_i = \theta_{i0} + \theta_{i1} x_1 + \theta_{i2} x_2 + \theta_{i3} x_3 + \theta_{i4} x_4 + \theta_{i5} x_5 + \theta_{i6} x_6$$

Total output of t-s neural network model for the Superheater is noted as:

$$\begin{aligned} y &= \sum_{i=1}^{m} \bar{\beta}_i y_i = \bar{\beta}_1 y_1 + \bar{\beta}_2 y_2 + \ldots + \bar{\beta}_m y_m \\ &= \bar{\beta}_1 \left(\theta_{10} + \theta_{11} x_1 + \theta_{12} x_2 + \theta_{13} x_3 + \theta_{14} x_4 + \theta_{15} x_5 + \theta_{16} x_6 \right) \\ &+ \bar{\beta}_2 \left(\theta_{20} + \theta_{21} x_1 + \theta_{22} x_2 + \theta_{23} x_3 + \theta_{24} x_4 + \theta_{25} x_5 + \theta_{26} x_6 \right) \\ &+ \ldots + \bar{\beta}_m \left(\theta_{m0} + \theta_{m1} x_1 + \theta_{m2} x_2 + \theta_{m3} x_3 + \theta_{m4} x_4 + \theta_{m5} x_5 + \theta_{m6} x_6 \right) \\ &= h^T \theta \end{aligned}$$

$$h = \left[\bar{\beta}_1 \ \ \bar{\beta}_1 x_1 \ \ \bar{\beta}_1 x_2 \ \ldots \ \bar{\beta}_1 x_6 \ldots \bar{\beta}_m \ \ \bar{\beta}_m x_1 \beta_m x_2 \ldots \bar{\beta}_m x_6 \right]^T$$

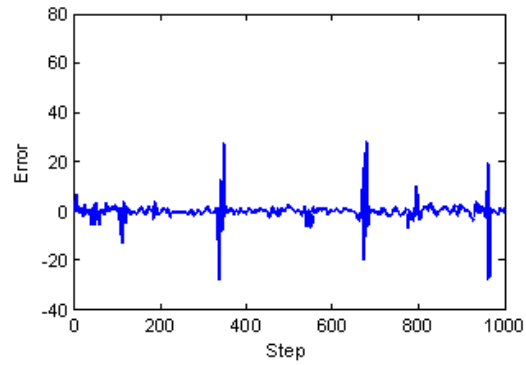
$$\theta = \begin{bmatrix} \theta_{10} & \theta_{11} & \theta_{12} & \theta_{13} & \theta_{14} & \theta_{15} & \theta_{16} \\ \cdots \theta_{m0} & \theta_{m1} & \theta_{m2} & \theta_{m3} & \theta_{m4} & \theta_{m5} & \theta_{m6} \end{bmatrix}^T$$

$$\bar{B}_i = B_i / \sum_{J=1}^{m} B_j$$

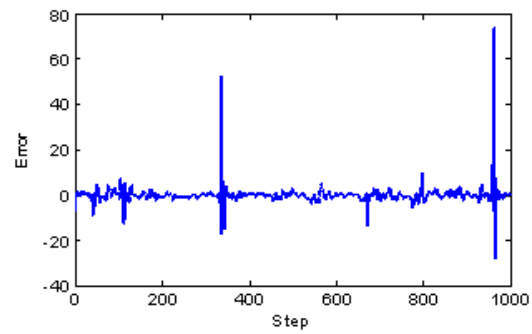
$$\beta_i = \prod_{j=1}^{n} \mu_j^i \ ; \ i = 1, 2, \ldots, m$$

Parameter vector θCan be calculated using recursive least squares method:

$$\begin{aligned} \theta_{k+1} &= \theta_k + K_k \left[y_k - h_k^T \theta_k \right] \\ K_{k+1} &= P_k h_{k+1} \left[1 + h_{k+1}^T P_k h_{k+1} \right]^{-1} \\ P_{k+1} &= \left[I - K_{k+1} h_{k+1}^T \right] P_k \end{aligned} \tag{6}$$



(a)



(b)

Fig. 3: Model identification error curve based on traditional FCM

Model identification simulation: Simulation data uses historical operating data of USC power plant 1000 mw unit, based on the identified model input and output variables, it selects the data length of 1220 samples, the sampling time interval of 15s. And the 1220 data constitute a set of input and output data sets of simulation studies, which the first set of 1000 data are used for the training data, the second set of 220 data is used for testing.

Using conventional FCM clustering algorithm to identify T-S neural network structure of superheater, it gets a reasonable result that the number of cluster centers m equals to 8 through Continuous experiment. Figure 3 shows the two error curves of the model identification simulation. In Fig. 3a the mean square value of error is 8.6167, while in Fig. 3b the mean square value of error 12.5628, the two simulation results are quite different.

The reason is that in simulation process the traditional FCM algorithm randomly selects the initial cluster centers. So the simulation error results are uncertain and the model identification process has a poor robustness.

When using the improved FCM clustering algorithm to identify model, it use subtractive FCM clustering function to determine the number of cluster centers and

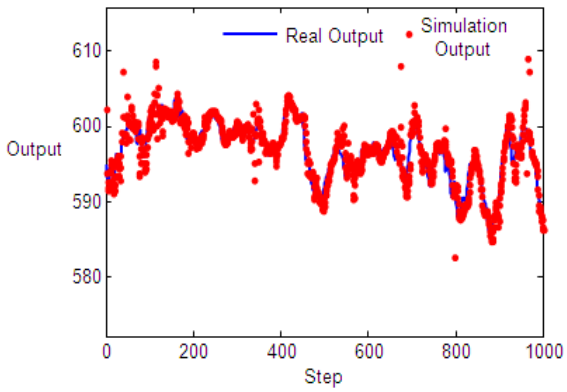


Fig. 4: Model identification output curve based on improved FCM

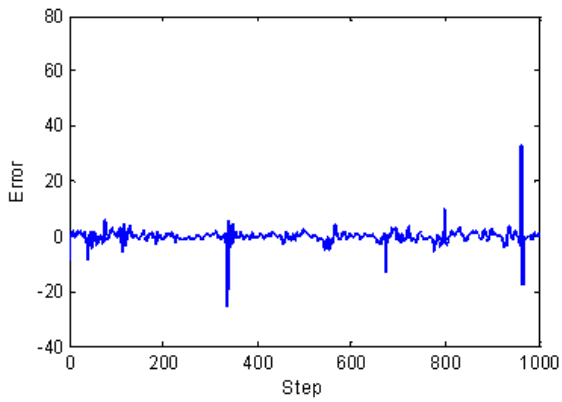


Fig. 5: Model identification error curve based on improved FCM

the initial cluster centers, the input space of the cluster center C is as follows:

$$C = \begin{bmatrix} C_1 \\ C_2 \\ C_3 \\ C_4 \\ C_5 \\ C_6 \\ C_7 \end{bmatrix} = \begin{bmatrix} 596.7696 & 320.6361 & 2849.0603 & 16.3394 & 13.7208 & 787.8036 \\ 593.7895 & 270.4995 & 2430.246 & 13.1373 & 12.767 & 655.7769 \\ 598.4428 & 289.9291 & 2573.0517 & 19.4763 & 18.9707 & 690.7431 \\ 596.7048 & 347.6351 & 3097.9721 & 45.4305 & 56.2788 & 826.4547 \\ 599.9294 & 344.5208 & 2972.5634 & 9.3021 & 10.501 & 800.0656 \\ 595.0324 & 224.407 & 2120.7479 & 2.7861 & 2.9226 & 563.2724 \\ 595.9547 & 396.4741 & 3330.2333 & 23.0603 & 28.7367 & 878.8857 \end{bmatrix}$$

Input variable space is divided into seven sub-spaces, so the number of fuzzy rules is 7. It is confirmed that the numbers of nodes of the layers in antecedent structure are respectively 6, 42, 7 and 7. Subspace clustering radiuses are 59.9927, 64.9624, 52.3026, 83.6978, 39.5120, 52.2049 and 61.1553. They are the width of the Gaussian-type membership function and the membership values can be calculated according to Eq. (1).

Figure 4 and 5 are main steam temperature curve and the corresponding output error curve based on improved FCM, in which the mean square of error is 4.9602. The absolute error between simulation output and actual output of is greatly reduced. Model identification results have been greatly improved.

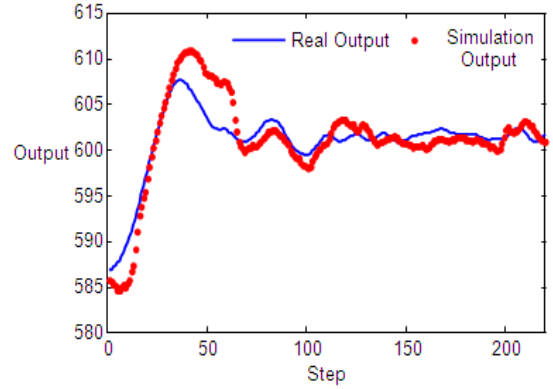


Fig. 6: Main steam temperature output curve in test

Figure 6 shows the simulation output curves of the main steam temperature, the simulation output a is very close to actual output, the mean square value of error is 4.3241, it indicates that the T-S neural network model identification OF superheater has good generalization ability and it can reflect the dynamic characteristics of the main steam temperature more accurately.

CONCLUSION

This study has analyzed the USC unit superheater process. It has determined the model input variables. Improved FCM algorithm has been proposed. It has completed fuzzy division of the input variable space, built the T-S neural network model of superheater MISO; by determining the membership function parameters and using recursive least squares method, it has achieved the model parameter identification. By simulating the field operating data from an USC power plant, research results show that T-S neural network identification model of superheater based on improved FCM algorithm has a faster speed, the identified model has better generalization ability; it can reflect the dynamic characteristics of the main steam temperature more accurately.

REFERENCES

Ahmed, S., B. Huang and S.L. Shah, 2008. Identification from step responses with transient initial conditions. J. Process Contr., 18(1): 121-130.

Cai, W.J. and Z. Yin-Chao, 2006. A system identification for t-s model based on neural network. Contr. Automat., 22(2): 176-178.

Feng, D., C. Tongwen and Q. Li, 2006. Bias compensation based recursive least-squares identification algorithm for MISO systems. IEEE T. Syst-II, 53(5): 349-353.

Hong-jun, L.I.U., W. Na and H. Pu, 2005. Dentification method of T-S fuzzy system and its application in superheated steam. J. North China Electric Power Univ., 32(5): 47-51.

Liu, W., 2010. Ultra-Supercritical Unit Control Method and Application. China Electric Power Press, Beijing, pp: 175.

Mehdi, A.N. and Y. Alireza, 2009. Neural network-based imc-pid controller design for main steam temperature of a power plant. Proceeding of the 6th International Symposium on Neural Networks: Advances in Neural Networks-Part-II, pp: 1059-1068.

Ming-zhu, X., L.I.U. He-Ping and L.I. Xiao-li, 2007. Stable Adaptive Predictive Functional Control of Main Steam Temperature. Proceedings of the CSEE, 27(11): 88-92.

Pei-Qiang, L., L. Xin-Ran and C. Hui-Hua, 2006. Neural network load modeling based on subtractive clustering. Trans. China Electro Technical Soc., 21(9): 2-6.

Zhu, L., W. Shi-tong and D. Zhao-hong, 2009. Research on generalized fuzzy c-means clustering algorithm with improved fuzzy partitions. J. Comput. Res. Dev., 46(5): 814-822 .