Applied Mathematical Sciences, Vol. 1, 2007, no. 42, 2091 - 2099

Neuro-Fuzzy Modeling of Superheating System of a Steam Power Plant

Morteza Mohammadzaheri†, Ali Mirsepahi†,

Orang Asef-afshar‡ and Hamidreza Koohi‡

†The University of Adelaide
‡Islamic Azad University (Sabzevar and Amol Branches)

Abstract

In this paper the superheating system of a 325MW steam power generating plant is modeled by usage of recurrent neuro-fuzzy networks and subtractive clustering. The experimental data are obtained from a complete set of field experiments under various operating conditions. Neuro-fuzzy models are constructed for each subsystem of the superheating unit. The nine fuzzy models are then constructed in a combination of series and parallel units in accordance with real power plant subsystems. Comparing the response of nonlinear neuro-fuzzy model of a subsystem with the response of its linear model obtained based on LSE method; shows that the nonlinear neuro-fuzzy model is more accurate than linear model in the sense that its response is closer to the response of the actual system. Since LSE is optimum modeling method for linear systems, it can be concluded that some of power plant subsystems are of nonlinear processes.

Keywords: Fuzzy logic, Modeling, Neuro-fuzzy, Steam power plant

Introduction

Model-based control schemes require the existence of a suitable process model. Proper models are, furthermore, needed to test new controllers. It is mathematically proved that the least square error (LSE) method is the optimum modeling method for linear systems [1,2]. For nonlinear plants, in addition to physics based modeling, there are some I/O data based methods, as well. I/O data based methods offer different models, such as perceptron neural networks and fuzzy models [3]. Neural networks are usually considered as black boxes, but systems can be expressed in fuzzy rules with using fuzzy modeling. Fuzzy rules are formed mainly by linguistic variables. There are some methods for fuzzy modeling such as fuzzy genetics and neuro-fuzzy networks [4, 5]. Neuro-fuzzy networks are one of the most favorable structures for fuzzy modeling. In this paper superheating system of a 325MW unit of a steam power plant, including seven subsystems is modeled, using recurrent neuro-fuzzy networks; as a connected set of series and parallel fuzzy models.

Modeling Strategy

In this paper one of the most common structures of neuro-fuzzy network identified as adaptive neuro-fuzzy inference systems (ANFIS) [1,6,7,8] is considered. Figure1 shows a scheme of a linear sugeno type FIS (fuzzy inference system) [1, 6, 7]. In this structure, *antecedent* of rules contains fuzzy sets (as membership functions) and *consequent* is a first order polynomial (a crisp function). The structure shown in Figure1 can be transformed to the neuro–fuzzy network shown in Figure2.

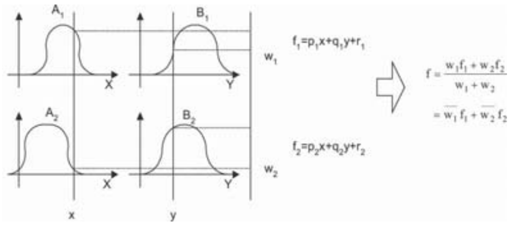

Figure1: A Sugeno-type FIS

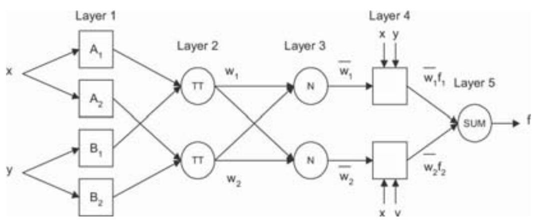

Figure2: a Sugeno-type neuro-fuzzy network

In this method, a fuzzy inference system is designed based on system specifications. This initial model is transformed to a neuro-fuzzy network and then trained by experimental recorded data of the system. The training procedure involves both gradient error back propagation (to adjust membership function coefficients) and LSE (to adjust linear output parameters).

In fuzzy inference systems, fuzzy rules number is equal to number of membership functions powered by number of inputs. Sometimes, to cover all input space, so many rules are needed. Training such FIS's is too time consuming or practically impossible. In order to reduce fuzzy rules number with minimum accuracy loss, a method namely *subtractive clustering* is applied [1, 7]. In this method, rules with most probable antecedents in recorded data of actual system are selected. The model derived from subtractive clustering is used as initial model for training.

All mentioned modeling methods can be applied to model both static and dynamic systems. If the output of the model at a moment is applied as its input at the next moment; the model is a *dynamic (recurrent) model*. In other words, in recurrent models, output of the model at the existing moment, is influenced by the output of the model, at previous moments. For example, in this research, current outlet temperature of a de-superheater model is dependent on its outlet temperature in earlier times. The nonlinear dynamic model can be described by the discrete time equation:

$$y(k)=f(u(k-1), \ldots, u(k-nu), y(k-1), \ldots, y(k-ny)) \quad (1)$$

Dynamic systems can only be modeled satisfactorily by recurrent (dynamic) neural or neuro-fuzzy networks (i.e. Fig2) not by static (memory-less) networks.

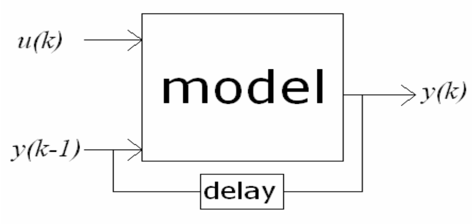

Figure3: A scheme of a typical recurrent model, *u* and *y* are input and output

Superheating system modeling

The structure of a superheating system in a steam power generating plant is shown in Fig 4. The steam flow inters to the superheater and after passing through the heat exchangers it inters to the high pressure turbine. For normal operation of the plant and when the capacity of the power plant is over 30% of its nominal value, the desired output temperature of superheater is 540 Celsius degree ($^{\circ}c$) .This temperature is adjusted at the de-superheater by spraying water through spraying valves.

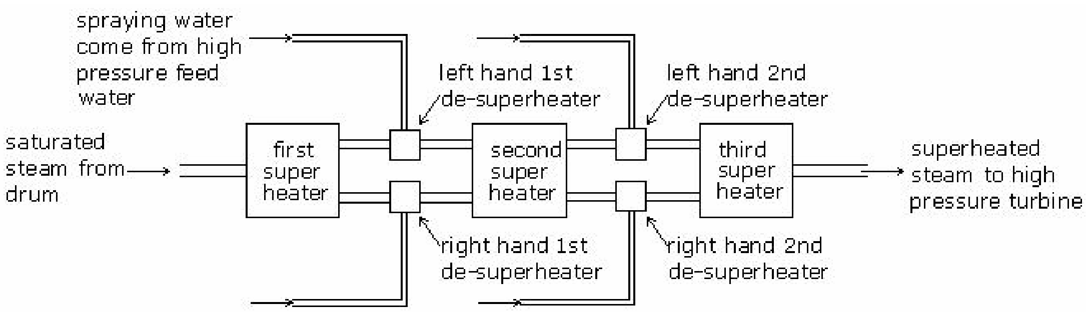

Fig4: Super heating system of the power plant

In this paper 1st order (linear) Sugeno type fuzzy inference systems are used [1, 6, 7]. *T-norm* is algebraic product and membership functions are Gaussian, expressed:

$$\textit{Membership grade} = \mathbf{exp}\Big[-\frac{1}{2}\Big(\frac{x-c}{\sigma}\Big)^2\Big] \quad (2)$$

x is the input and c and σ are membership function variables[1].

The modeling is performed using a complete set of data, including 4000 data sets of "Shazand" power plant, the sampling time equals to 1 second. Additionally, 1400 sets of data are used as checking data. Recording date is 26th Aug 2004. In order to model the superheating system, for each subsystem a neuro-fuzzy inference system is constructed by subtractive clustering and trained by hybrid learning method of ANFIS. Superheating system consists of three superheaters and four de-superheaters. Since the first and second superheaters are MIMO systems, they are modeled as two parallel MISO systems. In total, nine FIS's are constructed and trained for seven superheating subsystems. Models have 8~11 inputs and one output. Then, all these components are put together as parallel or series elements, whereas in final run, many of inputs of subsystems model are outputs of preceding subsystems.

In order to use recorded data for modeling, the following points are considered;

1. Delays are included in modeling. For instance, it takes 20 seconds to steam passes through a superheater. Therefore, when the temperature of inlet steam is applied in modeling that superheater, 20 seconds delay should be considered.
2. In order to improve the speed of convergence of parameters and coefficients in neuro-fuzzy model, their sensitivity to the variation of inputs signals should be increased. To do so elements of each column of training data are substituted with same elements subtracted from the mean value of elements in that column. It causes that the quantity $\left|\frac{error}{data\ magnitude}\right|$ increases, where, *error* in the numerator is the difference between outputs of the model and the actual system.
3. Noting that the algorithm for adjusting the neuro-fuzzy model depends on the magnitude of inputs data ; therefore, all inputs are normalized .
4. In neuro-fuzzy modeling, minimizing of the checking error is the criterion of successful modeling and over training is avoided.

In order to clarify the modeling process, a subsystem of superheating system, the second left-hand de-superheater is selected. Modeling process for this subsystem is comprehensively offered.

Second left-hand de-superheater modeling

Figure 5 shows the inputs and output signals of the second left-hand de-superheater, where the three inputs are; the steam temperature before spraying water T_b (inlet temperature), the water mass rate V and the steam mass rate f. The output is the steam temperature after spraying water T_a.

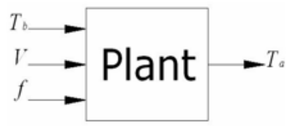

Fig5: Inputs and output of de-superheater: (a) plant,

The steam mass rate (f) is summation of two other signals. The first is half of total mass flow of water entering the drum (after drum the steam flow is divided into two branches, Fig3) and the second signal is the first step spraying water mass rate which is added to main steam flow. The de-superheater system is influenced by both of these signals with delay (Fig 7).
Figure 6 illustrates the input-output signals of the neuro-fuzzy model for the de-superheater in the discrete domain. In this Figure, the values of T_b, V and f at present time, their values at two steps before (for T_b and V) and one step before (for T_b, V and f) and also the values of T_a at the past two time increments are all input signals. The output of the neuro-fuzzy model is the output temperature of the de-superheater $T_a(k)$.

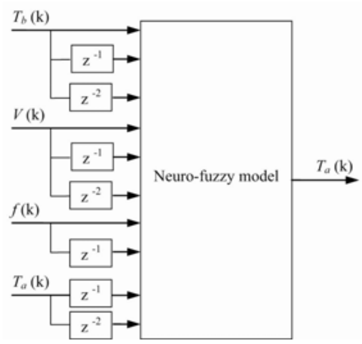

Fig6: Inputs and output of de-superheater neuro-fuzzy model

The relation between the ten inputs and one output of Fig6 for each fuzzy rule is given by the following equation:

$$\begin{aligned} T_a(k) &= \alpha_1 T_b(k) + \alpha_2 T_b(k-1) + \alpha_3 T_b(k-2) + \alpha_4 V(k) + \alpha_5 V(k-1) + \\ &\alpha_6 V(k-2) + \alpha_7 f(k) + \alpha_8 f(k-1) + \alpha_9 T_a(k-1) + \alpha_{10} T_a(k-2) + \alpha_{11} \end{aligned} \tag{3}$$

Parameters $\alpha_i, i = 1,...,11$ and coefficients of Gaussian membership functions for all associated fuzzy rules are adjusted in neuro-fuzzy model. Note that Eq.(3) is written for each fuzzy rule, while for simplicity the subscript of the associated fuzzy rule is omitted in this equation. If the left hand side of Eq.(3) for the *jth* fuzzy rule is shown by $T_{aj}(k)$, then the output of neuro-fuzzy model is:

$$T_a(k)=\frac{\sum_j \eta_j T_{aj}(k)}{\sum_j \eta_j} \tag{4}$$

Where η_j is the firing strength of the *jth* rule.

For neuro-fuzzy modeling, all quantities T_a, T_b, V and f are measured and put in column vectors.

Figure 7 shows the schematic diagram of this de-superheater neuro-fuzzy model. Noting that the number of inputs in this model is 10, if only 3 linguistic variables (ie, positive medium or positive large) are assigned for each input, the number of rules would result in 3^{10} rules. An alternative approach is subtractive clustering [1, 7], with using this method, the number of rules reduces to only 22 rules. Note that for each rule in addition to parameters $\alpha_i, i=1,...,11$, coefficients σ and c in all membership functions of 10 inputs must be adjusted. Thus for all rules a total sum of 682 parameters and coefficients are adjusted.

Using the same measured data, a linear model of this de-superheater is also derived based on the least square error (LSE) method in the form of a third order transfer functions ;

$$T_a(z)=\left(\frac{0.029z^{-2}-0.176z^{-1}+0.154}{-0.01z^{-3}+0.02z^{-2}-1.01z^{-1}+1}\right)T_b(z)+ \left(\frac{0.059z^{-2}-0.084z^{-1}+0.004}{-0.01z^{-3}+0.02z^{-2}-1.01z^{-1}+1}\right)V(z)+\left(\frac{-0.005z^{-2}+0.003z^{-1}+0.002}{-0.01z^{-3}+0.02z^{-2}-1.01z^{-1}+1}\right)f(z) \tag{5}$$

In this equation, the variables $T_a(z)$, $T_b(z)$, $V(z)$ and $f(z)$ are the Z transform of steam temperature after and before spraying, water mass rate and steam mass rate, respectively.

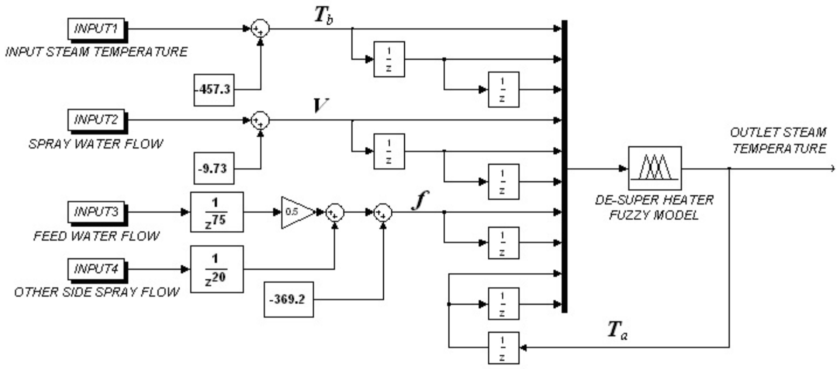

Fig7: Input and output signals of neuro-fuzzy model

Simulation Results

In this section, we first investigate the simulation results of implementing the neuro-fuzzy approach for modeling the second left-hand de-superheater of power generating plant, and then study the results of implementing this modeling method for whole superheating system.

Figure 8 illustrates the response of the second left-hand de-superheater, obtained from recorded data of the actual plant. It also shows the responses obtained from simulation results for both LSE and neuro-fuzzy models. Figure 9 shows similar responses of the actual plant and the models under special operating conditions. Both Fig's 8 and 9 indicate that the neuro-fuzzy model is more accurate than the LSE model, in the sense that, its response is closer to the response of the actual plant. Noting that the LSE method is optimum for modeling linear systems, the simulation results confirm that the de-superheater is a nonlinear subsystem of a power plant.

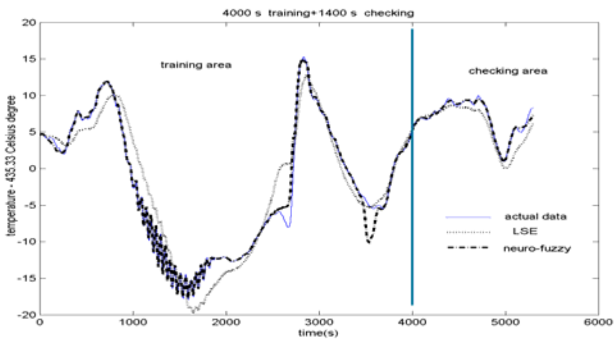

Figure 8: neuro-fuzzy and LSE modeling result, both for training and checking area

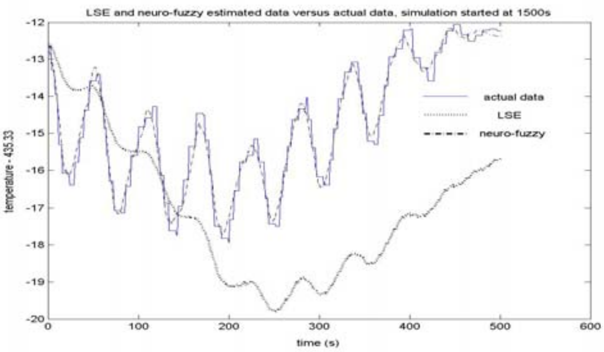

Figure9: neuro-fuzzy and LSE modeling result, under special operating condition

Figure10 shows the simulation result of whole model, formed by 9 series and parallel fuzzy models, for both for training and checking areas.

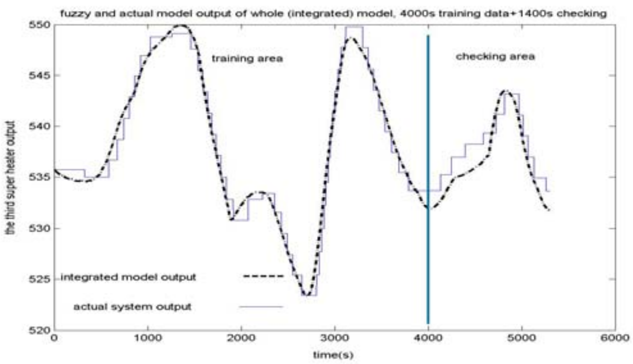

Figure10: neuro-fuzzy modeling result, for integrated model (including nine sub-models)

Conclusion

In this paper, neuro-fuzzy modeling is performed for a power plant superheating system, including three superhetaers and four de-superheaters. Then all these models put together as a total model. In modeling, some significant notes are considered, such as time delays. After all considerations and using subtractive clustering, to reduce the number of fuzzy rules, a relatively good accuracy is achieved for this set of complex models. Many of inputs of total model elements are outputs of other elements or their own outputs at earlier times. Also, it is indicated that some of power plant subsystems are of a nonlinear nature, with comparison between LSE modeling result and neuro-fuzzy modeling.

Acknowledgement

Authors wish to thank the staff of Shazand power plant for their cooperation in this research.

References

[1] J. R. Jang, C. Sun, E. Mizutani. "Neuro-Fuzzy and Soft Computing". Prentice-Hall Inc.1997
[2] L. Ljung " System Identification - Theory for the User", Prentice Hall, Upper Saddle River, N.J. 2nd edition, 1999.
[3] J.Vieira, F. Morgado Dias, A. Mota "Artificial Neural Networks and Neuro-fuzzy Systems for Modeling and Controlling Real Systems: A Comparative Study", Engineering Applications of Artificial Intelligence 17 (2004) 265–273
[4] H. ghezelayagh, K. Y.Lee, "Training Neuro-Fuzzy Boiler Identifier with Genetic Algorithm and Error-Back Propagation" Power Engineering Society Summer Meeting, 1999. IEEE , Volume: 2 , 18-22 July 1999 ,pp978 - 982 .
[5] A. Afzalian, D.A. Linkens, "Training Of Neurofuzzy Power Systems Stabilizers Using Genetic Algorithm", 22nd conference of Electrical Power and Energy Systems(2003), pp93-102
[6] J. Jantzen,. "Neurofuzzy Modeling", Technical University of Denmark, Department of Automation, Bldg 326, DK-2800 Lyngby, Denmark, Tech. report no 98-H-874 (nfmod), 30 Oct. 1998
[7] J.R. Jang, "Fuzzy Logic Toolbox User's Guide",2nd Version. MathWorks Inc.2000
[8] J.R. Jang, "ANFIS: Adaptive-network-based Fuzzy Inference Systems" .IEEE Transactions on Systems, Man, and Cybernetics 23 (3), 1993,pp665-685.
[9]K. J. Astrom, T. Hagglund, PID Controllers: Theory, Design, and Tuning, ISA, Research Triangle Park, NC, 1995.

Received: January 18, 2007