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Application of an adaptive neural fuzzy inference system to thermal comfort and group technology problems

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Abstract

The Adaptive Neural Fuzzy Inference System (ANFIS) is used to design two vague systems, namely thermal comfort and group technologies in production and operations management. Results show that both systems can be modeled successfully by the combined use of a fuzzy approach and neural network learning.

Keywords: Adaptive neural fuzzy inference system (ANFIS); Thermal comfort; Group technology

1. Introduction

Since Jang [1] proposed the Adaptive Neural Fuzzy Inference System (ANFIS), its applications are numerous in various fields including engineering, management, health, biology and even social sciences. Specifically, literature has several articles on the application of ANFIS to decision making, medicine, quality control, pattern recognition and inventory control.

Kelly et al. [2] designed a neural fuzzy controller that allows for the combination of the qualitative knowledge in fuzzy rules and the learning capabilities of neural networks. This method offered two unique features, namely the ability to eliminate human decision making and enhance the learning capability. The results of this paper show that the neural fuzzy controller, developed using ANFIS as part of the control system, successfully learns to control a second order plant autonomously after a short training time, gives better control than the conventional PID, and corresponds with the change made to the original control plant.

Sun et al. [3] introduced the adaptive-network-based fuzzy inference system (ANBFIS), using the ANFIS architecture and the Kalman filtering algorithm. He used the ANBFIS to identify the structure and parameters of a fuzzy rule base. The learning results show that a desired input/output pair mapping can be achieved. He recommended that the ANBFIS be used in fields such as data compression, pattern recognition, and decision analysis, where human expertise is not available or episodic.

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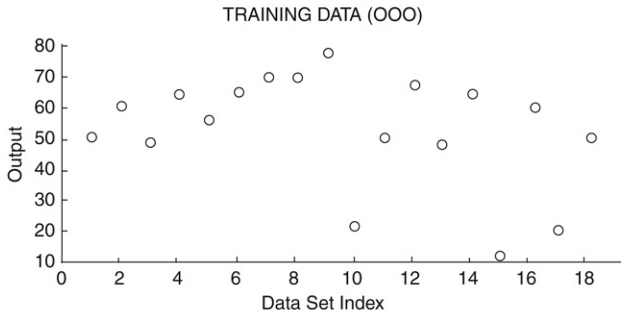

Fig. 1. The training data output plots—Thermal comfort.

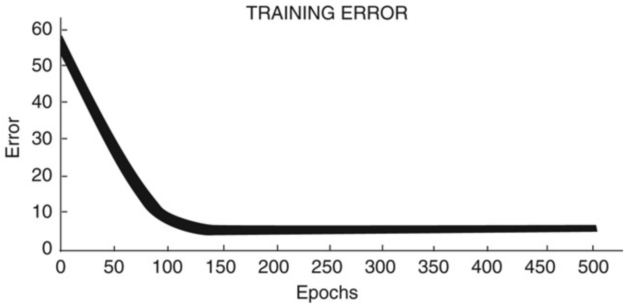

Fig. 2. The error measure plot for a zero-order Sugeno system with four membership functions (back-propagation learning)—Thermal comfort.

Lin and Lee [4] proposed a similar method, called the reinforcement neural-network-based fuzzy logic control system (RNN-FLCS) by integrating two neural-network-based fuzzy logic controllers (NN-FLC's), each of which is a connectionist model with a feed-forward multi-layer network developed for the realization of a fuzzy controller. During the network learning process, both structure learning and parameter learning are performed simultaneously in the two NN-FLC's using the fuzzy similarity measure. Computer simulations of the cart-pole-balancing problem satisfactorily verified the validity and performance of the algorithm for RNN-FLCS.

Jang et al. [5] pointed out the following major areas for ANFIS applications: automatic control, pattern recognition, robotics, nonlinear regression, nonlinear system identification and adaptive signal processing. In our paper, ANFIS is applied to the design of two vague systems, namely thermal comfort and group technology in production and operations management.

2. Application of ANFIS to thermal comfort

ASHRAE defines thermal comfort for a person, as that condition of the mind which expresses satisfaction with the thermal environment. Fanger [6] pointed out if a group of people is subjected to the same room climate, it will not be possible, due to biological variance, to satisfy everyone at the same time; one must then aim at creating an optimal thermal comfort for the group, i.e., a condition in which the highest possible percentage of the group is in thermal comfort.

The following sample papers discuss thermal comfort in different applications. Corlett and Clark [7] emphasized that thermal comfort plays a very important role in creating a suitable work environment. Kon [8] described a comfort sensor that revolutionizes indoor comfort control and a building automation (BA) system.

The reasons for applying ANFIS to thermal comfort problems are as follows:

1. The judgment of thermal comfort, which is subjective and imprecise, varies from one individual to another.
2. The mood of an individual affects the judgment of thermal comfort.
3. There are other important variables, which influence the condition of thermal comfort, namely activity level (heat production in the body), thermal resistance of the clothing, air temperature, mean radiant temperature, relative air velocity and ambient water vapor pressure [6].

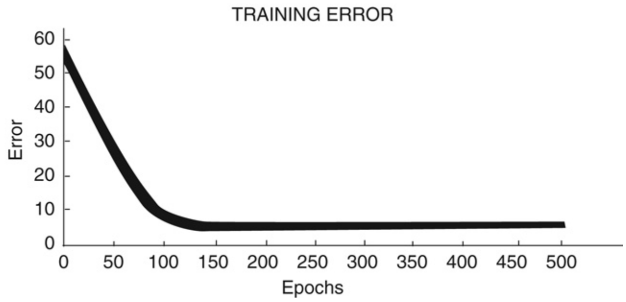

Fig. 3. The error measure plot for a zero-order Sugeno system with six membership functions (back-propagation learning)—Thermal comfort.

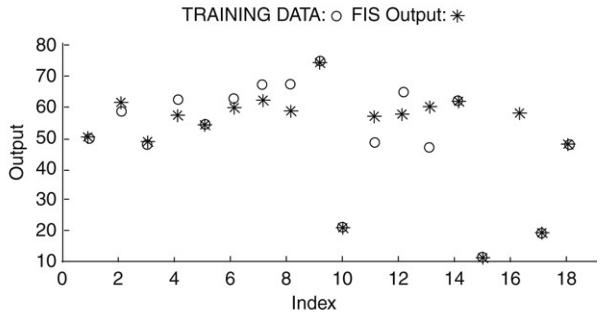

Fig. 4. The training data and FIS output plots for a first-order Sugeno system with four membership functions (back-propagation learning)—Thermal comfort.

2.1. Thermal comfort measure

Chen [9] and Cheng [10] employed the same sets of data to evaluate thermal comfort using fuzzy theory. Rohles and Milliken [11] designed a scaling procedure to quantify thermal comfort as follows:

$$\mathrm{TC}(\%) = \left\{\sum(\text{Rating} * \text{Loading}) - 3.17\right\} * 5.2576. \tag{1}$$

The thermal comfort vote of each person is calculated by using Eq. (1). In order to have the same room conditions aggregated into a fuzzy measure, the average vote can be regarded as the mode, and the maximal deviation from the average vote as the spread. The actual data and calculations employed by Chen [9] are summarized in Table 1.

It is considered a fuzzy control problem to determine the relationship between the room conditions (X) and the thermal comfort (Y). The Sugeno fuzzy system is adapted as the fuzzy inference system. An ANFIS with linguistic variables is formulated to simulate the control system, in which x_1 and x_2 represent the conditions of temperature and humidity respectively. The output of this ANFIS is the comfort vote. The linguistic values can be defined by the Gaussian function given below:

$$\mu_{o_i}, h_i(x_i) = \mathrm{e}^{\left[-\left(\frac{x_i - v_i, h_i}{\sigma_i, h_i}\right)\right]}. \tag{2}$$

The learning algorithms for the premise and consequence parameters are discussed in the following sections.

2.2. Learning of premise parameters

The overall error function of the network is expressed as follows:

$$e = \frac{1}{N}\sum_{i=1}^{N} e_i^2 = \frac{1}{N}\sum_{i=1}^{N}(Y_i - \hat{Y})^2. \tag{3}$$

Table 1
Room conditions and thermal comfort votes

Independent variables		Thermal comfort (TC) votes (%)			Dependent variables
Average temperature	Average humidity	Highest	Lowest	Mean	Fuzzy measure of TC (mode, spread)
75.5	31.5	64.0	40.0	50.1	(50.1, 13.9)
74.5	37.3	83.0	17.0	59.9	(59.9, 42.9)
74.0	34.5	83.0	20.0	48.1	(48.1, 34.9)
76.0	33.5	100.0	33.0	63.7	(63.7, 36.3)
77.0	28.9	86.0	30.0	55.2	(55.2, 30.8)
78.5	33.7	92.0	33.0	64.0	(64.0, 31.0)
76.0	36.1	93.0	50.0	68.8	(68.8, 24.2)
75.0	35.4	96.0	51.0	68.8	(68.8, 27.2)
77.5	40.7	100.0	54.0	76.4	(76.4, 23.6)
79.0	24.4	39.0	0.0	21.0	(21.0, 21.0)
78.0	31.7	63.0	40.0	49.1	(49.1, 13.9)
79.0	30.7	83.0	53.0	65.8	(65.8, 17.2)
76.0	34.9	86.0	0.0	46.9	(46.9, 46.9)
73.0	39.7	89.0	33.0	62.8	(62.8, 29.8)
85.5	26.7	20.0	0.0	10.6	(10.6, 10.6)
81.0	26.9	96.0	33.0	58.6	(58.6, 37.4)
83.5	26.2	34.0	0.0	19.1	(19.1, 19.1)
82.5	23.4	69.0	17.0	48.4	(48.4, 31.4)

The above error has been simplified by Jang and Sun [12]:

$$\frac{\partial^+ E}{\partial \beta} = \sum_{p=1}^{p} \frac{\partial^+ E_p}{\partial \beta}. \tag{4}$$

The learning rate of networks, η, is given by

$$\eta = \frac{K}{\sqrt{\sum_{\beta} \left(\frac{\partial E}{\partial \beta}\right)^2}}. \tag{5}$$

2.3. Learning of consequence parameters

Cheng [10] used the fuzzy regression method to solve for the consequence parameters. In the Sugeno fuzzy model, the overall network output is expressed in a linear combination of the consequence parameters, as the values of the premise parameters are fixed. The overall output is rewritten as follows:

$$\hat{Y} = \bar{w}^1(k_o^1 + k_1^1 x_1^1 + \cdots + k_q^1 x_q) + \bar{w}^2(k_0^2 + k_1^2 x_1 + \cdots + k_q^2 x_q) + \cdots + \bar{w}^m(k_0^m + k_1^m x_1 + \cdots + k_q^m x_q). \tag{6}$$

By expanding, Eq. (6) is rewritten as

$$\hat{Y} = k_o^1 \bar{w}^1 + k_1^1(\bar{w} x_1) + \cdots + k_q^1(\bar{w}^1 x_q) + \cdots + k_q^m(\bar{w}^m x_q). \tag{7}$$

The learning process is performed by the MATLAB Fuzzy Logic Toolbox, a product of the Math Works Inc. In this process, we choose the number of membership functions as 4 and 6 with the first order Sugeno fuzzy inference system.

3. Application of anfis to group technology

Group Technology (GT) is a planning philosophy, which takes advantage of parts similarity to reduce the manufacturing cost. Su [13] proposed a multi-criteria fuzzy approach in deciding part families.

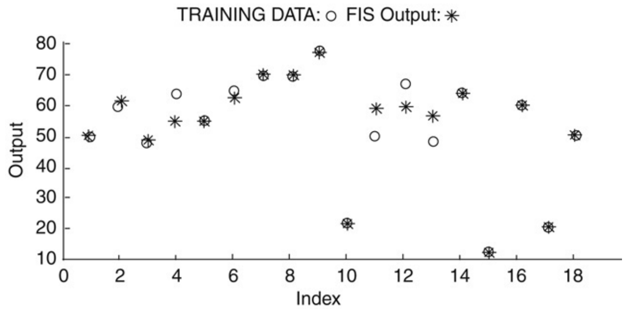

Fig. 5. The training data and FIS output plots for a first-order Sugeno system with six membership functions (back-propagation learning)—Thermal comfort.

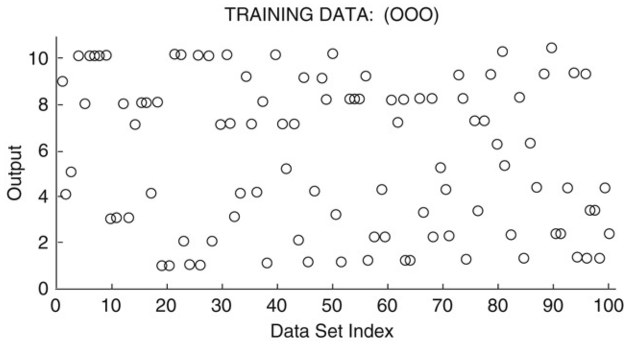

Fig. 6. The training data output plots—Group technology.

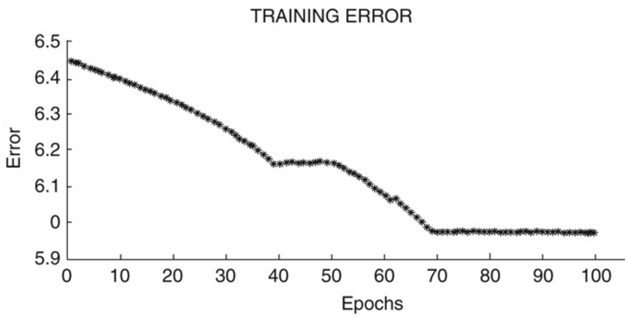

Fig. 7. The error measure plot for a zero-order Sugeno system with four membership functions (back-propagation learning)—Group technology.

Carpenter et al. [14] introduced the fuzzy adaptive resonance theory (ART) to cluster analog and binary input data rapidly. On the structure point of view, fuzzy ART is an unsupervised learning and pattern recognition network. Burke and Kamal [15] proposed a framework to handle the part family/machine group problem by using the fuzzy adaptive resonance (ART) network. To measure the performance of the fuzzy ART, three criteria, namely the number of machine cells (part families), the number of inter-cell movements for parts (number of critical or shared machines), and the maximum cell (family) size were used.

Kamal and Burke [16] also proposed another fuzzy application, called fuzzy art with add clustering technique (FACT), in the cell formation problem. FACT can be applied to cluster machines and parts under a multiple objective environment. In fact, there were three major components, namely (i) the "Add" method, to overcome the shortcomings of the fuzzy ART neural network; (ii) the method of extracting the embedded information in the weight vectors of the neural networks for clustering parts and machines at the same time; and (iii) the technique of clustering new parts and machines without reclustering all parts or machines.

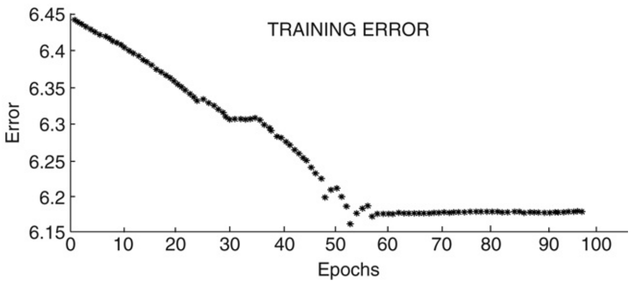

Fig. 8. The error measure plot for a zero-order Sugeno system with six membership functions (back-propagation learning)—Group technology.

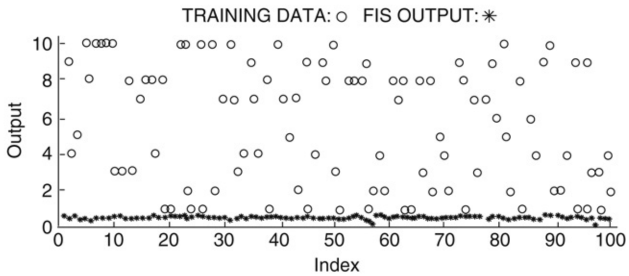

Fig. 9. The training data and FIS output plots for a first-order Sugeno system with four membership functions (back-propagation learning)—Group technology.

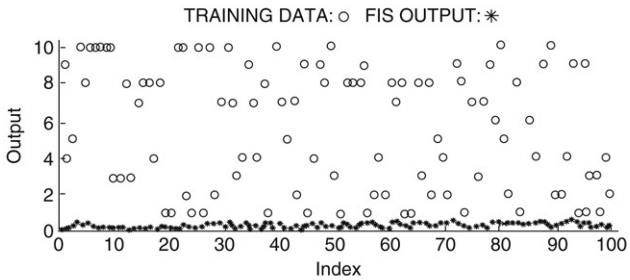

Fig. 10. The training data and FIS output plots for a first-order Sugeno system with six membership functions (back-propagation learning)—Group technology.

3.1. Learning of premise parameters

Nomura et al. [17] formulated a descent method of fuzzy logic control to solve network control problems, using data similar to the crisp input-output data. The gradient descent method using a modified back-propagation learning algorithm is simpler and more rationalized than other optimization methods. This method provided a simple way of explicitly stating the fuzzy set learned by the network, assuming symmetric triangular fuzzy numbers.

The overall error is simplified [12] by Eq. (4). The learning rate of networks, η, is given by Eq. (5).

3.2. Learning of consequence parameters

Pai [18] applied the adaptive fuzzy system with back-propagation training algorithm to multi-layer feed-forward networks in which processing elements are continuous differentiable activation functions. In this supervised learning method, the learning chain rule is used to calculate the gradient vectors in the direction opposite to the flow of the output of each node.

The overall output is given by Eqs. (6) and (7).

Table 2
Using back-propagation in thermal comfort

Network inputs	Network outputs	Number of membership functions	Membership function type	Number of epochs	Results
1. Average temperature 2. Average humidity	Thermal comfort votes	4	Linear (first order Sugeno system)	500	The diagrams of error measure are shown in Figs. 2 and 3. The plots of training data and FIS output are shown in Figs. 4 and 5
1. Average temperature 2. Average humidity	Thermal comfort votes	6	Linear (first order Sugeno system)	500	

Table 3
Part attributes—uniformly distributed random numbers

Part no.	Primary shape	Tolerance	Group no.
1	0.319193091	0.720755638	9
2	0.413983581	0.766472365	4
3	0.625843074	0.969176305	5
4	0.872188482	0.423047578	10
5	0.875759148	0.130680258	8
6	0.972594378	0.533738212	10
7	0.852961821	0.044953764	10
8	0.718436232	0.955229347	10
9	0.045228431	0.577806940	10
10	0.466444899	0.094851527	3
–	–	–	–
–	–	–	–
–	–	–	–
91	0.865871151	0.689046907	4
92	0.269447920	0.712057863	9
93	0.702932829	0.476485488	1
94	0.320841090	0.182256539	9
95	0.658772546	0.069093905	1
96	0.729544969	0.891628773	3
97	0.784752953	0.988128300	3
98	0.753624073	0.467024751	1
99	0.132358776	0.843867306	4
100	0.573076571	0.416791284	2

4. Results and discussion

For the thermal comfort problem, the training process is displayed in Table 2. The training data output plots are shown in Fig. 1. The error measure plots are shown in Figs. 2 and 3. The fuzzy inference system (FIS) test plots are shown in Figs. 4 and 5. The error measure plots show that the network error drops rapidly after about 110 iterations, and maintains the same value. The tendency of these two diagrams shows that the network finally reaches a local optimal value.

For the group technology problem, the sample primary shape and tolerance data, shown in Table 3 are uniformly distributed random numbers generated by the Microsoft Excel computing software. The training process is displayed in Table 4. The training data output plots are shown in Fig. 6. The error measure plots are shown in Figs. 7 and 8. The fuzzy inference system (FIS) test plots are shown in Figs. 9 and 10. The error measure plots show that the network error drops rapidly after about 70 iterations, and maintains the same value. The tendency of these two diagrams shows that the network finally reaches a local optimal value.

Table 4
Using back-propagation in group technology

Network inputs	Network outputs	Number of membership functions	Membership function type	Number of epochs	Results
1. Primary shape 2. Tolerance	Group number	4	Linear (first order Sugeno system)	100	The diagrams of error measure are shown in Figs. 7 and 8. The plots of training data and FIS output are shown in Figs. 9 and 10
1. Primary shape 2. Tolerance	Group number	6	Linear (first order Sugeno system)	100	

For both the thermal comfort and the group technology problems, the results show that fuzzy inference system outputs can avoid extreme points on the training data sets and keep the network outputs in a more stable condition than the training data sets.

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