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GENERATING FUZZY RULES FROM NUMERICAL DATA

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Abstract- In this paper a fuzzy rule based system from the numerical data pairs is presented for an air conditioning system by utilizing the Wang and Mendel [6] technique. Firstly, the input and output variables of the given numerical data is divided into fuzzy regions. Then fuzzy rules are generated from this data. Degree of each of the generated rule is calculated and the rule with highest degree among the conflicting rules is accepted. In this way a combined rule base system is developed from the generated rules. Then 'centroid defuzzification formulae' is used to determine the output. The core work of this paper is to generate fuzzy rules from the numerical data for an air conditioning system, collect these fuzzy rules and the linguistic fuzzy rules into a common fuzzy rule base, and, finally design a control system based on this combined fuzzy rule base.

Key words: Fuzzy Rule Based System (FRBS), Fuzzy rules, Rule Base (RB), fuzzy regions, Fuzzy Logic Controller.

I. INTRODUCTION

Mamdani and Assilian's work [1] introduced the first rule-based controller powered by a fuzzy inference mechanism. Such a system is commonly called Fuzzy Rule Based System (FRBS). The most important task to accomplish a FRBS is to find a set of fuzzy rules suitable for a specific problem called Rule-base (RB) of the system. Rule-base is the most important aspect of FRBS design, as both the accuracy and interpretability of the system is based upon it. Usually, we have two types of approaches to define the Rule-base of a fuzzy system. One approach is to obtain knowledge from experts and translate their knowledge directly into fuzzy rules can be termed as expert driven approach.This approach has the disadvantages that the process of knowledge acquisition and validation is difficult and time-consuming. It is very likely that an expert may not be able to express his or her knowledge explicitly and accurately. Another approach is to generate fuzzy rules through a learning process, in which knowledge can be automatically, extracted by the system fromnumerical data examples, termed as data driven approach. However, the trends mentioned above are not mutually exclusive, and hybrid approaches were also explored.For example in [2] a data driven approach to fine-tune an expert-driven system is presented.

FRBSs gained the attention of the community through their capacity to handle the imprecisions of real-world data and capture the essence of a given phenomenon in a way that is understandable and interpretable by humans. Moreover, as shown in [3], [4], FRBSs act as universal function approximators, meaning that they can be adjusted to approximate any continuous function up to arbitrary precision.

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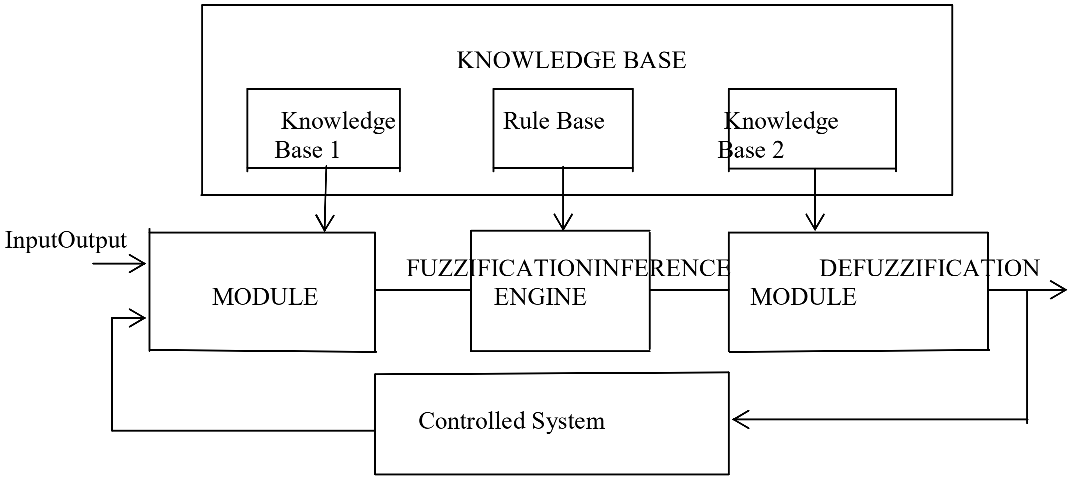
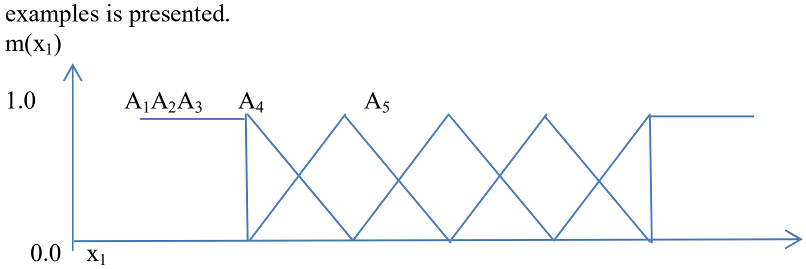


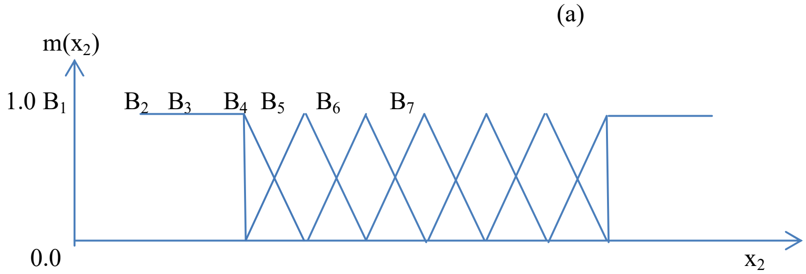
Figure-1: Fuzzy Rule Based System

The work of Sugeno [5] provided a fully-automated strategy to generate fuzzy rules from numerical data. However, the crisp outputs produced by Sugeno's rules, while improving accuracy, considerably affected the overall interpretability of the system. Another important milestone in data-driven RB learning was established by Wang and Mendel [6] who proposed a non-iterative method to generate complete linguistic rules from data. Over time, the efficiency of the Wang-Mendel (WM) approach was successfully proven in many real-world applications [7], [8], [9] and it is now considered an important benchmark for researchers. Since the proposed RB generation method detailed in Section II relies on the principles of the WM method we shall first present the key aspects of this method.

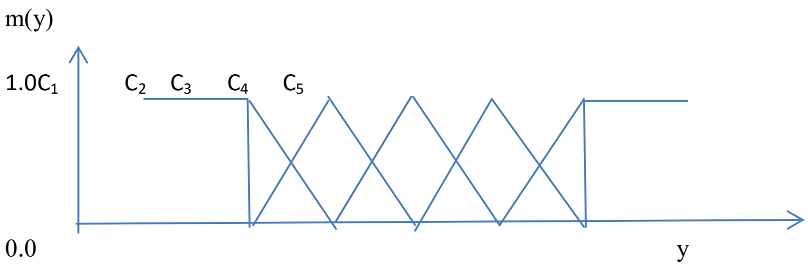
In [10] an inductive learning algorithm in fuzzy systems is presented. In [11] authors have presented a method for generating fuzzy rules from relational database systems for estimating null values. In [12] a method to automatically extract fuzzy if-then rules from a trained neural network is presented. In [13] an algorithm to induce fuzzy rules and membership functions from training examples is presented. In [14] a method for constructing a fuzzy controller from data is presented. In [15] a heuristic method for generating fuzzy rules from numerical data is presented. In [16] a method for constructing membership functions and fuzzy rules from training examples is presented. In [17] a genetic algorithm for generating fuzzy classification rules from training examples is presented.



(a)



(b)



(c)

Figure-2: Division of the input and output spaces into fuzzy regions and the corresponding membership functions. (a) $m(x_1)$ (b) $m(x_2)$ (c) $m(x_3)$.

Given the above, this paper is structured as follows. Section I proposes a literature survey on some of the most successful data-driven rule-base generation methods. Next, in Section II, a general method to generate fuzzy rule base developed by Wang and Mendel [6] is described in five steps. In section III an air-conditioning system design problem is undertaken. A fuzzy rule based system from the numerical data is developed for the air conditioning system by utilizing the Wang and Mendel [6] technique. Each data pair generates one rule; lot of rules which may be conflicting also will be generated. Only rules which describe the FRBS most appropriately are kept and removing the others while still preserving system accuracy. In this way, both numerical and linguistic information are codified into a common framework- The combined fuzzy rule base. Finally, in Section IV conclusions and remarks will be presented.

II. WANG AND MENDAL APPROACH:

Wang and Mendel [6] work developed a general method to generate fuzzy rules from numerical data. In the work they generated fuzzy rules from the numerical data pairs, collect these fuzzy rules and the linguistic rules into a common fuzzy rule base, and finally design a control system based on this combined fuzzy rulebase. They applied the method to a truck baker-upper control problem and a chaotic time-series prediction problem. They proposed a five step procedure for generating fuzzy rules from numerical data pairs in their work.

Step 1- Divide the input and output spaces into Fuzzy Regions:

First the range of the input and output variables are assessed from the numerical data. The variables most probably will lie in this interval. Then this range interval is divided into 2N+1 regions (N can be different for different variables, and the lengths of these regions can be equal or unequal), denoted by terms like small, big etc. and assign each region a fuzzy membership function. Triangular membership function has been used for every variable in the present work. However, other divisions of the domain regions and other shapes of membership functions are also possible.

Step 2- Generate fuzzy rules from given data pairs:

Suppose x_1, $x_{2,}$ y are the input and output variables. First, determine the degrees of these variables in different regions. For example x_1 in Fig. 2 (a) has degree 0.8 in A, degree 0.2 in A, and zero degree in all other regions. Second, assign the given value of x_1, x_2 and y to the region with maximum degree. For example, x_1 in Fig. 2 (a) is considered to be A, and x_2 in Fig. 2(b) is considered to be B. Finally obtain one rule from one pair of desired input-output data.

Step 3-Assign a Degree to Each Rule:

Since there are lots of data pairs, and each data pair generates one rule, it is highly probable that there will be some conflicting rules, i.e., rules that have the same IF part but different THEN part. One way to resolve this conflict is to assign a degree to each rule generated from data pairs, and accept only the rule from a conflict group that has maximum degree. In this way not only is the conflict problem resolved, but also the number of rules is greatly reduced. Following product strategy is used to assign a degree to each rule: For the rule: "IF x_1 is A and x_2 is B, THEN y is C, " the degree of this rule, denoted by D(rule), is defined as;

$$D(\text{rule}) = m_A(x_1)\, m_B(x_2)\, m_C(x_3) \quad (1)$$

The degree of a rule is defined as the product of the degrees of its components and the degree of the data pair that generates the rule.

Step 4- Create a Combined Fuzzy Rule Base:

The form of a fuzzy rule base is illustrated in fig.-3. Fill the boxes of the base with fuzzy rules according to the following strategy: a combined fuzzy rule base is assigned rules from either those generated from numerical data or linguistic rules (linguistic rule has a degree that is assigned by a human expert and reflects the expert's belief of the importance of the rule); if there is more than one rule in one box of the fuzzy rule base, use the rule that has maximum degree. In this way, both numerical and linguistic information are codified into a common

A_7					
A_6					
A_5					
A_4					
A_3					
A_2					
A_1					
	B_1	B_2	B_3	B_4	B_5

Figure 3. The form of a fuzzy rule base

framework-The combined fuzzy rule base. If a linguistic rule is an "And" rule, it fill only one box of the fuzzy rule base; but, if a linguistic rule is an "or" rule (i.e. , a rule for which the THEN part follows if any condition of the IF part is satisfied), it fills all the boxes in the rows or columns corresponding tothe regions of the IF part. For example, suppose we have the linguistic rule "IF x_1 is A or x_2 is B THEN y is C" for the fuzzy rule base of fig. 3; Then we fill the seven boxes in the column of A and the five boxes in the row of B with . The degrees of all the in these boxes equal the degree of this "or" rule.

Step 5- Determine a Mapping Based on the Combined Fuzzy Rule Base:

For the given inputs x_1, x_2 , combine the antecedents of the i^{th} fuzzy rule using product operation determine the degree, m_O , of the output control i.e.,

$$m_O = m_I(x_1)\, m_I(x_2), \quad (2)$$

where O denotes the output region of Rule i, and I denotes the input region of Rule i. Then, the following centroid defuzzification formula is used to determine the output

$$y = \frac{\sum_{i=1}^{K} m_O y'}{\sum_{i=1}^{K} m_O}$$

(3)

where y' denotes the centre value of the region O, and K is the number of fuzzy rules in the combined fuzzy base.

III. AIR CONDITIONING SYSTEM MODEL DESIGN:

Design a rule base for a fuzzy logic based air-conditioning system model shown in figure 4. The air conditioning system has two inputs and a single output as;

1. Temperature difference that is the difference between the actual room temperature and the desired room temperature.
2. Air flow rate as the second input.
3. The output variable is the electrical power consumed by the air-conditioning system in watts.

Air conditioning unit Specifications:Power source: 230 V, 50 Hz, 1-phase, Voltage Rating: 230 V(ac)
Current rating: 10.2 A, Power input: 2240 W, Cooling tones: 2.

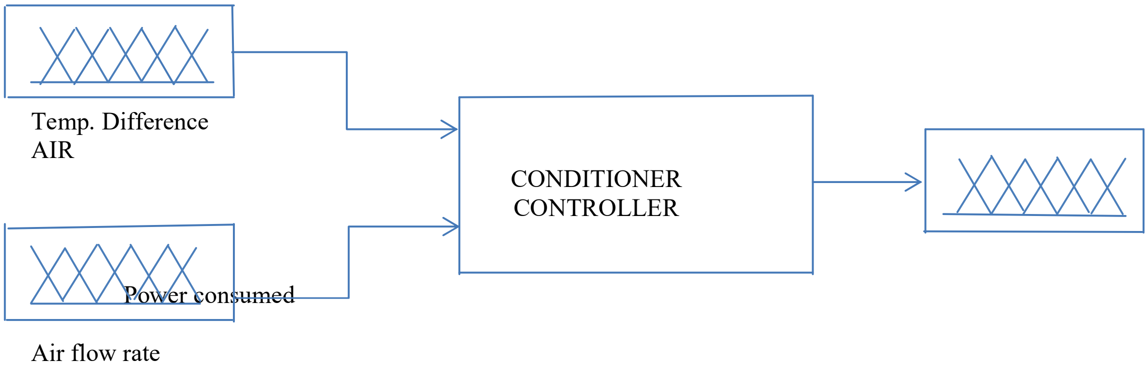


Figure 4. Fuzzy logic based air-conditioning system model

Table 1 shows the real time input-output observed data of the air-conditioning system model. As evident from the observed data the room temperature varies from 23°C to 47°C and the desired room temperature varies from 15°C to 24°C. The second input variable i.e. rate of flow of air has two levels only. The Wang and Mendel method is applied to design the fuzzy rule based model of the system.

The observed data is modified to three variables only that are temperature difference, airflow rate and power consumed. The data is arranged in ascending order for temperature difference is drawn in table-2. In order to obtain the required fuzzy rule base we follow the algorithm steps as;

(Step-1) It can be seen from the table that temperature difference varies from 2°C to 29°C and air flow rate is either 245 x 10^{-3} cu.m./sec. or 264 x 10^{-3} cu.m./sec. Power consumed varies from 1660 W to 2590 W. The input variable temperature difference is divided into three fuzzy regions namely low, medium and high. The second input variable air flow rate has only two states .So, the appropriate fuzzy states are named low and normal. The output variable i.e. Power consumed by the system is divided into five fuzzy regions. These are named as very low, low, normal, high & very high. The membership functions for the input & output variables are shown in figure 5.

Table-1 Observed data

S.No.	Existing room temp. (°C)	Desired room temp. (°C)	Temp. Difference (°C)	Air flow rate (m^3/sec) x10^{-3}	Power consumed (watts)
1	23.9	17.2	6.7	245	1660
2	23.9	19.4	4.5	245	1670
3	23.9	21.7	2.2	245	1690
4	29.4	17.2	12.2	245	1820
5	35	15	20	245	1950
6	40.6	21.7	18.9	245	2320
7	40.6	23.9	16.7	245	2360
8	46.1	17.2	28.9	245	2350
9	46.1	19.4	26.7	245	2580
10	23.9	17.2	6.7	264	1670
11	23.9	19.4	4.5	264	1690
12	29.4	21.7	7.7	264	1870
13	35	15	20	264	1970
14	35	19.4	15.6	264	2020
15	35	21.7	13.3	264	2050
16	35	23.9	11.1	264	2080
17	40.6	17.2	23.4	264	2260
18	46.1	17.2	28.9	264	2520
19	46.1	19.4	26.7	264	2550
20	46.1	21.7	24.4	264	2590

(Step 2) Consider as an example the data set at serial no. 5 of table -2, in which temperature difference is 16.7°C, air flow rate is 245 x 10^{-3} cu.m. /sec and power consumed is 2360 W. Temperature difference in fig. 5 (a) has degree 0.8 in fuzzy region Medium, degree 0.2 in High, and zero degree in the Low region. The first input variable temperature difference is assigned the region of maximum degree i.e. Medium region.The second input i.e. air flow rate has a degree 1 in Low region and degree 0 in Normal. So, it is assigned the Low region. The output variable i.e. power consumed has degree o.7 in fuzzy region High, degree 0.3 in V. High and zero degree in all other regions. So, the output variable is assigned the fuzzy region High.

Table-2

S.No.	Temp. Difference (°C)	Air flow rate (m^3/sec) x10^{-3}	Power consumed (watts)
1	2.2	245	1690
2	4.5	245	1670
3	6.7	245	1660
4	12.2	245	1820
5	16.7	245	2360
6	18.9	245	2320
7	20	245	1950
8	26.7	245	2580
9	28.9	245	2550
10	4.5	264	1690
11	6.7	264	1670
12	7.7	264	1870
13	11.1	264	2080
14	13.3	264	2050
15	15.6	264	2020
16	20	264	1970
17	23.4	264	2260
18	24.4	264	2590
19	26.7	264	2550
20	28.9	264	2520

The rule generated from the data pair is "IF temperature difference (ΔT) is Medium and air flow rate is Low, THEN power consumed is High.In the similar way fuzzy rules are generated for every data pair of the table-2.

(Step 3) Degree of this rule, denoted by D(rule), is given by ;

D(rule) = 0.8x1x0.7 = 0.56

(Step 4) All the rules generated by every data pairs are filled to form a combined rule base as shown in table-3.

Table 3 Combined rule base

<table>
<tr><td rowspan="3">Temperature Difference</td><td>High</td><td>Rule 8: V.High- 1.0
Rule 9: V.High- 1.0</td><td>Rule 17: High- 0.64
Rule 18:V. High- 0.9
Rule 19: V.High- 1.0
Rule 20: V.High- 1.0</td></tr>
<tr><td>Medium</td><td>Rule 4: Low- 0.42
Rule 5: High- 0.56
Rule 6: High- 0.9
Rule 7: Low- 0.35</td><td>Rule 13: Normal- 0.54
Rule 14: Normal- 0.64
Rule 15: Normal- 0.54
Rule 16: Low- 0.3</td></tr>
<tr><td>Low</td><td>Rule 1: V.Low-1.0
Rule 2: V.Low-1.0
Rule 3: V.Low-0.8</td><td>Rule 10: V.Low- 1.0
Rule 11: V.Low- 1.0
Rule 12: Low- 0.63</td></tr>
<tr><td colspan="2" rowspan="2"></td><td>Low</td><td>Normal</td></tr>
<tr><td colspan="2">Air Flow Rate</td></tr>
</table>

(Step 5) From the table 3 of combined rule base we choose one rule from every box that has maximum degree. The selected rules are listed below;

1. IF Temperature difference (ΔT) is Low and air flow rate is Low THEN power consumed is V.Low.

2. IF Temperature difference (ΔT) is Low and air flow rate is Normal THEN power consumed is V.Low.
3. IF Temperature difference (ΔT) is Medium and air flow rate is Low THEN power consumed is High.
4. IF Temperature difference (ΔT) is Medium and air flow rate is Normal THEN power consumed is Normal.
5. IF Temperature difference (ΔT) is High and air flow rate is Low THEN power consumed is V.High.
6. IF Temperature difference (ΔT) is High and air flow rate is Normal THEN power consumed is V.High.

There are three possible states for input variable temperature difference and two states for the airflow rate. Therefore, there can be at most 3x 2=6 combinations or antecedents of the rules as presented above.

IV. CONCLUDING REMARKS:

This work implemented a control strategy using a fuzzy methodology proposed by Wang and Mendel. The methodology confirmed that a fuzzy controller is relatively simple to construct and that a fuzzy model is in itself a plain structure. Involved mathematical insight was not required and the process relied more on intuition and experience.

This methodology gives three important advantages. First, both numerical and linguistic information was used under one common framework. As opposed to other "learning from examples" techniques, the rules generated by the fuzzy inference are easy to extract and they are already in an understandable, human readable format.

Second, the design of the fuzzy controller architecture is flexible because membership functions can be defined in a large variety of shapes. In addition, and in order to obtain results that are closer to the desired control output, the modeller can adjust the number of fuzzy regions for each system variable with little effort. Although there is no method explaining what shape or how many fuzzy regions each system variable should have, FRBS can perform with stability since both input and output ranges are known through their degree of membership in the interval [0, 1].

Third, a FRBS can be developed with the use of a straightforward one-pass build-up procedure. The FRBS did not require an iterative process for the initial definition of the control rules. This one-pass procedure also eliminated conflicting or redundant rules. Calibration of the FRBS relies more on intuition and experience and the definition of fuzzy membership functions is a trial and error task. Because of these two characteristics, the initial design and validation of a FRBS could become a tedious and time consuming activity.

REFERENCES

[1] E. H. Mamdani and S. Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *International Journal of Man-Machine Studies*, vol. 7, no. 1, pp. 1–13, 1975.

[2] R. Alcalá, J. Casillas, O. Cordón, A. González, and F. Herrera, "A genetic rule weighting and selection process for fuzzy control of heating, ventilating and air conditioning systems," *Engineering Applications of Artificial Intelligence*, vol. 18,no. 3, pp. 279–296, 2005.

[3] L.-X. Wang, "Fuzzy systems are universal approximators,"*IEEE International Conference on Fuzzy Systems*,1992, pp. 1163–1170.

[4] B. Kosko, "Fuzzy systems as universal approximators," *IEEE Transactions on Computers*, vol. 43, no. 11, pp. 1329–1333, 1994

[5] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control," *IEEE Transactions on Systems, Man and Cybernetics*, vol. 1, no. 1, pp. 116–132, 1985.

[6] L.-X. Wang and J. M. Mendel, "Generating fuzzy rules by learning from examples," Systems, Man and Cybernetics, IEEE Transactions on, vol. 22, no. 6, pp. 1414–1427, 1992.

[7] X. Zeng and L. Koehl, "Representation of the subjective evaluation of the fabric hand using fuzzy techniques," *International Journal of Intelligent Systems*, vol. 18, no. 3, pp. 355–366, 2003.

[8] P.-C. Chang, C.-H. Liu, and R. K. Lai, "A fuzzy case-based reasoning model for sales forecasting in print circuit board industries," Expert Systems with Applications, vol. 34, no. 3, pp. 2049–2058, 2008.

[9] M. Blagojevi´c, M. Šelmi´c, D. Macura, and D. Šarac, "Determining the number of postal units in the network–fuzzy approach, serbia case study," *Expert Systems with Applications*, vol. 40, no. 10, pp. 4090–4095, 2013.

[10] J. L. Castro, and J. M. Zurita,"An inductive learning algorithm in fuzzy systems"*Fuzzy Sets and Systems*vol. 89, no. 2, pp. 193- 203, 1997.

[11] S. M. Chen and M. S. Yeh, "Generating fuzzy rules from relational database systems for estimating null values", Cybernetics and Systems, An International Journal, vol. 29, no. 6, pp. 363- 376, 1998.

[12] Y. Hayashi and A. Imura, "Fuzzy neural expert system with automated extraction of fuzzy if-then rules from a trained neural network",*Proceedings of the 1990 First International Symposium on Uncertainty Modeling and Analysis*, University of Maryland, College Park, MD, 1990.

[13] T. P. Hong and C. Y. Lee,"Induction of fuzzy rules and membership functions from training examples",*Fuzzy Sets and Systems*, vol. 84, no. 1, pp. 33- 47, 1996.

[14] F. Klawonn and R. Kruse"Constructing a fuzzy controller from data",*Fuzzy Sets and Systems* vol. 85, no. 2, pp. 177-193, 1997.

[15] K. Nozaki, H. Ishibuchi, and H. Tanaka, "A simple but powerful heuristic method for generatingfuzzy rules from numerical data",*Fuzzy Sets and Systems*, vol. 86, no. 3, pp. 251-270, 1997.

[16] T. P. Wu, and S. M. Chen, "A new method for constructing membership functions and fuzzy rules from training examples",*IEEE Transactions on Systems, Man, and Cybernetics-Part B*,vol. 29, no. 1, pp. 25-40, 1999.

[17] Y. Yuan and H. Zhuang,"A genetic algorithm for generating fuzzy classification rules",*Fuzzy Sets and Systems*,vol. 84, no. 1, pp. 1-19, 1996.