The Third AFSS(1998), 701－706

FUZZY IDENTIFICATION BY MEANS OF AUTO-TUNING ALGORITHM AND WEIGHTING FACTOR

Chun Seong PARK[a], Sung Kwun OH[a], Tae Chon AHN[a], and Witold PEDRYCZ[b],

a. Department of Control and Instrumentation Engineering, Wonkwang University
344-2 Shinyong-Dong, Iksan, Chon-Buk, 570-749 Korea
Tel:+82-653-850-6342 Fax:+82-653-52-2196 E-mail:ohsk@wonnms.wonkwang.ac.kr

b. Department of Electrical and Computer Engineering, University of Manitoba,
Winnipeg, Manitoba, R3T 2N2, Canada
Tel:+11-204-474-8380 Fax:+11-204-261-4639 E-mail:pedrycz@ee.umanitoba.ca

Abstract

A design method of rule-based fuzzy modeling is presented for the model identification of complex and nonlinear systems. The proposed rule-based fuzzy modeling implements system structure and parameter identification in the efficient form of "IF..., THEN..." statements, using the theories of optimization and linguistic fuzzy implication rules. The improved complex method, which is a powerful auto-tuning algorithm, is used for tuning of parameters of the premise membership functions in consideration of the overall structure of fuzzy rules. The optimized objective function, including the weighting factors, is auto-tuned for better performance of fuzzy model using training data and testing data. According to the adjustment of each weighting factor of training and testing data, we can construct the optimal fuzzy model from the objective function. The least square method is utilized for the identification of optimum consequence parameters. Gas furance and a sewage treatment process are used to evaluate the performance of the proposed rule-based fuzzy modeling.

Keywords : Identification of fuzzy model, auto-tuning, weighting factor, optimal fuzzy model

1 Introduction

In the early 1980, linguistic approch[1,2] and fuzzy relationship equation-based approch[3,4] were proposed as identification methods of fuzzy models. In the linguistic approch, Tong identified gas furnace process by means of logical examination of data[7]. B. Li et al. obtained good results through the modification of Tong's method[6] and also proposed the modified algorithm of adaptive model based on decision table. But the algorithm has some problems due to the computer capacity and computation time which is important, when it was applied to the high-order multivariable systems[5]. Pedrycz analyzed the identification of fuzzy system from the viewpoint of linguistic implication rule modeling, using the referential-fuzzy-set concept[2]. T. Li et al. presented a self-learning algorithm for the simple SISO fuzzy model[5]. In the fuzzy relationship equation-based approch, Pedrycz identified fuzzy systems, using the referential fuzzy set and Zadeh's conditional possibility distribution, that is, the new composition rule which were made by the fuzzy relationship equations[3]. Xu constructed and identified the fuzzy relationship model using the referential fuzzy set theory and the self-learning algorithm[5,6]. The direct inference utilized by two methods did not perform better than the linear inference. Sugeno identified the structure of systems through the standard least square methods[10], but the structure of premises of the rules was determined more heuristically through the experience and iterative fuzzy partitioning of the input space. Sugeno also applied his method to the fuzzy identification of gas furnace process, using fuzzy C-means clustering[11,12], but the method did not produce the identification of good performance: this could be alleviated to the use of direct linear inference[8].

In this paper, two types of fuzzy inferences are considered, that is, simplified (Type 1) and linear (Type 2) reasoning models. According to the proposed auto-tuning algorithm-the improved complex method, the parameters of such membership function can be easily adjusted. Furthermore we introduce an aggregate objective function that deals with traning data and testing data, and elaborate on its optimization to produce a meaningful balance between approximation and generalization abilities of the model. The proposed ruled-based fuzzy modeling is carried out for time series data for gas furnace process[9] and activated sludge process in sewage treatment system[13].

2 System modeling by means of fuzzy inference

The identification algorithm of fuzzy model is divided into the identification activities of premise and consequence parts of the rules. The identification at the premise level 1) selects the input variables $x_1, x_2, \cdots, x_n$ of the rules, and 2) determines the fuzzy partitions (*Small, Large,* etc.) of fuzzy spaces. This means the determination of the number of the optimal fuzzy space partitions, that is, fuzzy subspaces that determinate the number of fuzzy implication rules. The premise identification has to determine the membership values of fuzzy variables. The consequence identification embraces the following phases 1) selection of the consequence variables of the fuzzy implication rules, 2) determination of the consequence parameters.

In this paper, in order to identify the premise structure and parameters of fuzzy linguistic rules, two essential input variables of process influenced are considered and the improved complex method which is a powerful auto-tuning algorithm is used. Furthermore, we restrict ourselves to some types of membership function such as Gaussian-like and triangular ones. The parameters of the membership functions are tuned with the help of the autotuning method. The parameters of the consequence part of the rules are determined using the standard least square method (Gaussian elimination with maximal pivoting algorithm). We also discuss a modified performance index(objective function) that aims at achieving a balance between approximation and prediction capabilities of the fuzzy model.

3 An algorithm of fuzzy identification

In this section we elaborate on algorithmic details of the identification method discussing the optimization problem to the antecedent (condition part) of the rules as well as an enhancements of their conclusions.

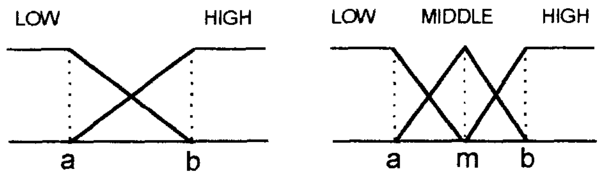
3.1 Premise identification

In the premise part of the rules we confine ourselves to Gaussian-like and triangular type function. The Gaussian type of the membership function assumes the form

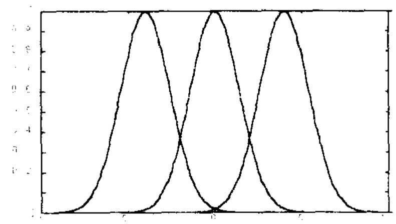
$$f(x) = e^{\frac{-s(x-a)^2}{b^2}}$$

Furthermore we consider Gaussian membership functions involving fixed slope, and assume several levels of their parametric flexibility

In the case of the same slope and different slope, these mean the same and different slope in each input variable, and the slope parameter of each case is auto-tuned according to the proposed optimization.



(a) 2 & 3 fuzzy variables with 2 & 3 modifiable parameters



(b) 3 fuzzy variables with 3 modifiable parameters(s, a, and b)

Fig. 1 Parameters of triangular & Gaussian type membership function

3.2 Consequence identification

The identification of the conclusion parts of the the rules deals with a selection of their structure (type 1 and type 2) and a determination of the respective parameters of the functions therein.

Type 1 (Constant: Consequence part)

The consequence part of the simplified inference mechanism where the rules have constant conclusion part is given as follows.

$$R^i: \text{ If } x_1 \text{ is } A_{i1}, \cdots, \text{ and } x_k \text{ is } A_{ik}, \text{ then } y = a_i \quad (1)$$

The calculations of the numeric output of the model are carried out in the well-known form,

$$y^* = \frac{\sum_{i=1}^{n} \mu_i a_i}{\sum_{i=1}^{n} \mu_i} = \sum_{i=1}^{n} \hat{\mu}_i a_i$$

where R^i is the i-th fuzzy rule, x_j is input variables. A_{ij} is a membership function of fuzzy sets, a_i is a constant, n is the number of the fuzzy rules, y^* is the infered value, μ_i is the premise fitness matching of R^i (activation level) and $\hat{\mu}_i$ is the normalized premise fitness of R^i. In what follows, we define the performance index as a sum of squared errors.

$$PI = \frac{1}{m} \sum_{i=1}^{m} (y(k) - y^*(k))^2 \tag{2}$$

where y^* is the output of the fuzzy model, k denotes the number of the input variables, and m stands for the total number of data. Furthermore $x_{1i}, x_{2i}, \cdots, x_{ki}, y_i (i=1,2,\cdots,m)$ are pairs of input-output data set. The consequence parameters a_i can be determined by the standard least-square method. In the fuzzy model of Type 1, the parameters can be estimated by solving the optimization problem.

Type 2 (First-order linear Equation)

The consequence is expressed in the form of a linear relationship. The use of the linear (or complex) inference method gives rise to the expression

$$R^i: \text{ If } x_1 \text{ is } A_{i1}, \cdots, \text{ and } x_k \text{ is } A_{ik}, \text{ then } y = f_i(x_1, \cdots, x_k) \tag{3}$$

Where f_i is a linear function of the input variables

$f_i(x_1, \cdots, x_k) = a_{i0} + a_{i1}x_1 + \cdots + a_{ik}x_k$

The numeric output y^* is determined in the same way as in the previous approach

$$y^* = \frac{\sum_{i=1}^{n} \mu_i f_i(x_1, \cdots, x_k)}{\sum_{i=1}^{n} \mu_i} = \sum_{i=1}^{n} \hat{\mu}_i f_i(x_1, \cdots, x_k)$$

Again R^i is the i-th fuzzy rule, x_j is an input variable, A_{ij} is membership functions of fuzzy sets, a_{ij} is consequence parameters, n is the number of the fuzzy rules, y^* is the inferred value, μ_i is the truth value of R^i in the premises and $\hat{\mu}_i$ is the normalized truth value of μ_i.

The consequence parameters are produced by the standard least-square method, that is

$$\hat{a} = (X^T X)^{-1} X^T Y \tag{4}$$

3.3 The objective function with weighting factor

We elaborate on the performance index. The objective function for the training data and testing data assumes the form

f (PARA1＊PI + PARA2＊E_PI)/2

and is utilized as a cost function of the fuzzy model. Where, PARA1 and PARA2 are two weighting factors for PI and E_PI, respectively. PI and E_PI denote the values of the performance index for the training data and testing data, respectively. For the purpose of minimization of this objective function, all parameters of the premise membership functions such as Gaussian-like and triangular function are modified(optimized). The performance index used in the ensuing numerical experiment will be as an Euclidean distance, that is,

$$PI = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{5}$$

The variables of a cost function to be optimized come as the parameters of the membership functions, fuzzy rules, and weighting factors of the performance index. Based upon a selection of sound fuzzy reasoning type, specification of the membership function type, and weighting factors we can design an optimal fuzzy model.

3.4 Autotuning by improved complex method

Usually, by combining these optimization tasks we end up with a problem that is highly nonlinear and may not fit well to the domain of gradient-based techniques. To alleviate the problem, we propose to use an autotuning algorithm that is an adaptation of the improved complex method.

We realize the algorithm by augmenting the simplex concept to the complex method [2] - constrained optimization technique. In fact, the algorithm known as the improved complex method, is the constrained complex method of the form:

Minimize f(x)

Subject to $g_j(x) \le 0, \quad j=1,2,\cdots,m$

$X_i^{(l)} \le X_i \le X_i^{(u)} \quad i=1,2,\cdots,n$

where the superscripts l and u denote the lower and upper bound of the corresponding variable.

4 Experimental studies

Once the identification methodology has been established, one can proceed with intensive experimental studies. In this section, we report on the experiments using some well-known data sets used in fuzzy modeling. These include gas furnace data and sewage treatment process.

4.1 Gas furnace process

In this section, the proposed rule-based fuzzy modeling is applied to the time series data of gas furnace utilised by Box and Jenkins[9]. We try to model the gas furnace using 296 pairs of input-output data. The flow rate of metane gas, $U_m(t)$ used in laboratory changes from -2.5 to 2.5, the control $U(t)$ used in real process, ranges from 0.5 to 0.7 following the expression.

$$U(t) = 0.60 - 0.048\,U_m(t) \tag{6}$$

U denotes the flow rate of methane as input, the output stands for the carbon dioxide density i.e., the outlet gas. The structure and parameter identification of premise are performed using the improved complex method. The improved complex method extracts the optimal fuzzy rules and upgrades the performance by auto-tuning parameters of premise membership function. The reflection, expansion and contraction coefficients which are the initial parameters of the improved complex method are set as α =1, γ =2 and β =0.5, respectively. The consequence parts of two kinds of types are used. Table 1 shows the performance index of the optimal rules obtained using the improved complex method for each fuzzy model consisted of the consequence types of simplified and linear inference, and the premise types of Gaussian type function with fixed slope, same slope and different slope versions.

From the two-dimensional plot of the data set shown in Fig.2, in the case of the training data, the data sets (u(t-3),y(t-1),y(t)) and (u(t-4),y(t-1),y(t)) exhibit uniform and less sparse distribution than any other data set. Therefore we can anticipate that the fuzzy model structure for the fuzzy partition of data sets (u(t-3),y(t-1),y(t)) and (u(t-4),y(t-1),y(t)) could perform a little better than in the remaining sceneries.

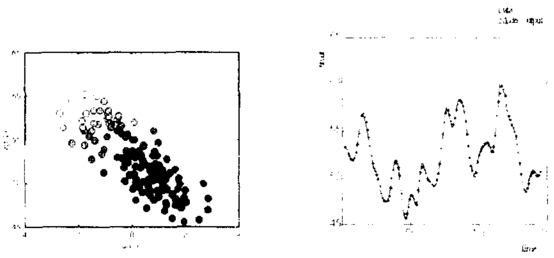
Table 1. Optimal performance index for each fuzzy model by means of the adjustment of weighting factors

(a) Simplified fuzzy reasoning method with Gaussian type membership function

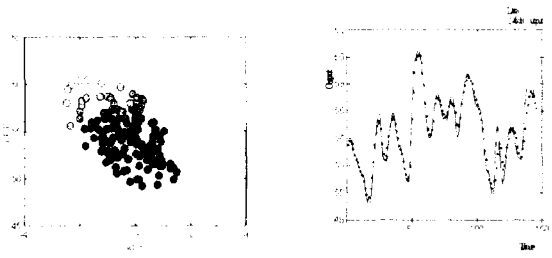
Model No.	Model Name & No. of Data	Weighting Factor (PARA1, PARA2)	Consequence Structure	Premise Structure	Input Variable & No. of Input MxN	FIXED SLOPE		SAME SLOPE		DIFFERENT SLOPE	
						PI	E_PI	PI	E_PI	PI	E_PI
1	GAS(145+145)	1,0	Simplified	Gaussian	u(t-3),y(t-1),2x2	0.022	[illegible]	[illegible]	0.335	0.022	[illegible]
2	GAS(145+145)	[illegible]	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	GAS(145+145)	1,2	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
4	GAS(145+145)	1,5	Simplified	Gaussian	[illegible]	0.048	[illegible]	0.049	[illegible]	0.049	[illegible]
5	GAS(145+145)	[illegible]	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	0.055	[illegible]	0.059	[illegible]
6	GAS(145+145)	1,30	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	0.055	0.365	[illegible]	[illegible]
7	GAS(145+145)	1,50	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
8	GAS(145+145)	[illegible]	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	GAS(145+145)	[illegible]	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
10	GAS(145+145)	10,1	Simplified	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
11	GAS(145+145)	30,1	Simplified	Gaussian	[illegible]	0.023	[illegible]	0.022	[illegible]	[illegible]	[illegible]
12	GAS(145+145)	50,1	Simplified	Gaussian	[illegible]	[illegible]	0.330	0.022	[illegible]	[illegible]	[illegible]

(b) Linear fuzzy reasoning method with Gaussian type membership function

Model No.	Model Name & No. of Data	Weighting Factor (PARA1, PARA2)	Consequence Structure	Premise Structure	Input Variable & No. of Input MxN	FIXED SLOPE		SAME SLOPE		DIFFERENT SLOPE	
						PI	E_PI	PI	E_PI	PI	E_PI
1	GAS(145+145)	[illegible]	Linear	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2	GAS(145+145)	1,1	Linear	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	GAS(145+145)	1,3	Linear	Gaussian	u(t-3),y(t-1),2x2	0.0195	0.274	0.0199	[illegible]	[illegible]	[illegible]
4	GAS(145+145)	1,5	Linear	Gaussian	[illegible]	0.022	[illegible]	0.0196	[illegible]	0.020	[illegible]
5	GAS(145+145)	[illegible]	Linear	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	0.271	0.0199	[illegible]
6	GAS(145+145)	1,30	Linear	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
7	GAS(145+145)	1,50	Linear	Gaussian	[illegible]	[illegible]	[illegible]	[illegible]	0.270	[illegible]	[illegible]
8	GAS(145+145)	[illegible]	Linear	Gaussian	[illegible]	0.020	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
9	GAS(145+145)	5,1	Linear	Gaussian	[illegible]	[illegible]	0.274	0.0191	[illegible]	0.019	[illegible]
10	GAS(145+145)	10,1	Linear	Gaussian	u(t-3),y(t-1),2x2	[illegible]	0.275	0.0189	[illegible]	[illegible]	[illegible]
11	GAS(145+145)	30,1	Linear	Gaussian	[illegible]	[illegible]	[illegible]	0.0186	[illegible]	[illegible]	[illegible]
12	GAS(145+145)	50,1	Linear	Gaussian	[illegible]	0.0189	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]



(a) In the case of traininging data



(b) In the case of testing data

Fig. 2 Data points induced by I/O data set (u(t-3),y(t-1),y(t)) and the comparison of original data and output data for fuzzy model No. 2 (Table 1-a)

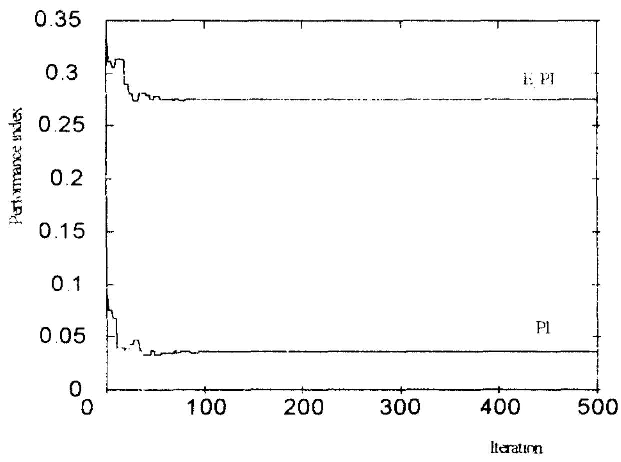


Fig. 3 Convergence procedure to optimal value of PI & E_PI for fuzzy model No. 2 (Table 1-a)

Table 2. Performance index in the each fuzzy reasoning method by means of the change of no. of fuzzy variables

(a) Simplified fuzzy reasoning method with input variables u(t-3) and y

		(b) No. of Fuzzy variables									
		2		3		4		5		6	
		PI	E_PI	PI	E_PI	PI	E_PI	PI	E_PI	PI	E_PI
(a) No. of Fuzzy variable	Gaussian (fixed slope)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.215	0.048	[illegible]	0.034	0.272
	Gaussian (same slope)	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	0.261	[illegible]	0.277
	Gaussian (different slope)	[illegible]	[illegible]	[illegible]	[illegible]	0.092	[illegible]	[illegible]	0.259	[illegible]	0.262
	Triangular	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

(b) Linear fuzzy reasoning method with input variables u(t-3) and y

		(b) No. of Fuzzy variables							
		[illegible]		[illegible]		4		6	
		PI	E_PI	PI	E_PI	PI	E_PI	PI	E_PI
(a) No. of Fuzzy variable	Gaussian (fixed slope)	[illegible]	0.278	0.019	0.270	0.075	0.289	0.029	0.279
	Gaussian (same slope)	0.026	0.271	0.027	0.274	0.183	0.341	0.020	0.293
	Gaussian (different slope)	0.020	0.271	0.018	0.286	0.021	0.282	0.020	0.294
	Triangular	0.022	[illegible]	[illegible]	0.284	0.026	[illegible]	[illegible]	[illegible]

4.2 Sewage treatment process

Sewage treatment generally uses the activated sludge process which consisted of sand basin, primary sedimentation basin, aeration tank and final sedimentation basin. Suspended solid included in sewage is sedimented by gravity in sand and primary sedimentation basins. Air is consecutively absorbed in sewage in the aeration tank for several hours. Microbe lump (that is called floc or activated sludge) springing naturally, mainly remove the organic matters in aeration tank. Activated sludge biochemically oxygenates, proliferates and resolve the organic matters into hydrogen and carbon dioxide by metabolism. In final sedimentation basin, floc is sedimented, recycled and again used to remove the organic matters and then purified water is transported to teritery sedimentation basin.

The activated sludge process is the process that involves an aeration tank and final sedimentation. We measure the biological oxygen demand(bod) and the concentration of suspended solid(ss) in influent sewage at primary sedimentation basin, and effluent bod(ebod) and ss(ess) in effluent sewage at final sedimentation basin. Because ebod and ess are changed, dependent on bod and ss, dissoved oxygen set-point(dosp) and recycle sludge ratio set-point(rrsp) are set so that ess and ebod should be kept up less than the prescribed small quantity. Ebod and ess depend on mixed liquid suspended solid(mlss), waste sluge ratio(wsr), rrsp and dosp. Bod has a correlation with ss.

In this paper, a sewage treatment system plant in Seoul, KOREA, is chosen as a model. The rule-based fuzzy modeling by two kinds of fuzzy inference is carried out using the 52 pairs of input-output data obtained from the activated sludge process. From four input variables, we choose two input variables that minimize the evaluation criterion and fuzzy rule number, and extract more than two fuzzy partitions(*Big and Small*) from each input-output pair of data. The identified parameters of premise and consequence of the optimal fuzzy rules are obtained using the improved complex method.

Table 3 shows the performance index of the optimal rules obtained using the improved complex method for each fuzzy model consisted of the consequence types of simplified and linear inference, and the premise type of triangular type function.

Table 3. Performance index in the each fuzzy reasoning method by means of the adjustment of weighting factor

(a) Simplified fuzzy reasoning method with triangular type membership function

Model No.	Model Name & No. of Data	Weighting Factor(PARA, PARA2)	Consequence Structure	Premise Structure (Gauss, Tria)	Input Variable & No. of Input (MxN)	No. Rul	PI	E_PI
1	WAT(26+26)	1,0	Simplified	Triangular	gx1=1,gx2=2,2x2	4	7.937	17.571
2	WAT(26+26)	1,1	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.726	16.306
3	WAT(26+26)	1,3	Simplified	Triangular	gx1=1,gx2=2,2x2	4	13.757	16.180
4	WAT(26+26)	1,5	Simplified	Triangular	gx1=1,gx2=2,2x2	4	13.786	16.173
5	WAT(26+26)	1,10	Simplified	Triangular	gx1=1,gx2=2,2x2	4	13.851	16.164
6	WAT(26+26)	[illegible]	Simplified	Triangular	gx1=1,gx2=2,2x2	4	[illegible]	16.169
7	WAT(26+26)	1,50	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.904	16.160
8	WAT(26+26)	[illegible]	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.654	16.322
9	WAT(26+26)	5,1	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.633	16.406
10	WAT(26+26)	10,1	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.633	16.406
11	WAT(26+26)	[illegible]	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.633	16.41[illegible]
12	WAT(26+26)	50,1	Simplified	Triangular	gx1=1,gx2=2,2x2	4	12.633	16.411
13	WAT(26+26)	[illegible]	Simplified	Triangular	gx1=1,gx2=2,[illegible]	6	[illegible]	16.562
14	WAT(26+26)	1,1	Simplified	Triangular	gx1=1,gx2=2,4x2	9	12.802	15.915
15	WAT(26+26)	1,1	Simplified	Triangular	gx1=1,gx2=2,3x3	9	12.189	15.115
16	WAT(26+26)	1,1	Simplified	Triangular	gx1=1,gx2=2,5x[illegible]	16	11.02[illegible]	[illegible]

(b) Linear fuzzy reasoning method with triangular type membership function

Mode No.	Model Name & No. of Data	Weighting Factor (PARA, PARA2)	Consequence Structure	Premise Structure (Gauss,Tri, &...)	Input Variable & No. of Input (MxN)	N I	PI	E_PI
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	[illegible]	[illegible]
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.396	54.233
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	[illegible]	[illegible]
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.397	53.198
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.396	53.198
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	[illegible]	[illegible]
[illegible]	WAT 36+36	1.50	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.397	53.198
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.396	[illegible]
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	[illegible]	[illegible]
10	WAT 36+36	10.1	Linear	Triangular	gx1=1,gx2=2,2x2	4	[illegible]	54.349
11	WAT 36+36	[illegible]	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.406	50.705
12	WAT 36+36	50.1	Linear	Triangular	gx1=1,gx2=2,2x2	4	6.534	41.561
[illegible]	WAT 36+36	[illegible]	Linear	Triangular	[illegible]	6	[illegible]	[illegible]
14	WAT 36+36	1.1	Linear	Triangular	gx1=1,gx2=2,4x2	5	0.0015	902.324
15	WAT 36+36	[illegible]	Linear	Triangular	[illegible]	9	[illegible]	[illegible]
16	WAT 36+36	[illegible]	Linear	Triangular	[illegible]	10	0.000084	[illegible]

5 Conclusions

In this paper, the efficient identification technique is presented which automatically extract the optimal fuzzy rules, using a auto-tuning algorithm and the weighting factors of object function. The improved complex method, which is a powerful auto-tuning, is used for auto-tuning of parameters of the premise membership functions in consideration of the overall structure of fuzzy rules. By means of the adjustment of weighting factors of objective function for both traning and testing data, and the auto-tuning of the parameters of each membership function, we can get better performance of fuzzy model. According to the increase of no. of membership function of each input variable of process system, generally the PI(Performance Index) for fuzzy model using training data is improved, but the PI for fuzzy model using testing data gets worse. And the PI for fuzzy model by means of linear inference method using the testing data gets much worse than that of simplified inference method. Generally, in the case of same-slope, we can get better performance. The PI for testing data in the case of the simplified method is better than that produced in the case of the linear method. Furthermore in this case of the simplified method, the difference between PI(performance index for training data) and E_PI(performance index for testing data) is much smaller. Moreover the performance of the fuzzy model with the simplified inference method using testing data is better than that exploiting the linear type of the inference method.

Acknowledgement

This paper was supported in part by fund for Post-doctoral program(1996) of Korea Science and Engineering Foundation, the Republic of Korea.

References

[1] R.M. Tong, "Synthesis of fuzzy models for industrial processes", *Int. J. Gen. Syst.*, Vol. 4, 143-162, 1978.

[2] W. Pedrycz, "An identification algorithm in fuzzy relational system", *Fuzzy Sets Syst.*, Vol. 13, 153-167, 1984.

[3] W. Pedrycz, "Numerical and application aspects of fuzzy relational equations", *Fuzzy Sets Syst.*, Vol. 11, 1-18, 1983.

[4] E. Czogola and W. Pedrycz, "On identification in fuzzy systems and its applications in control problems", *Fuzzy Sets Syst.*, Vol. 6, 73-83, 1981.

[5] C.W. Xu and Y. Zailu, "Fuzzy model identification self-learning for dynamic system", *IEEE Trans. on Syst. Man, Cybern.*, Vol. SMC-17, No. 4, 683-689, 1987.

[6] C.W. Xu, "Fuzzy system identification", *IEE Proceeding* Vol. 126, No. 4, 146-150, 1989.

[7] R.M. Tong, "The evaluation of fuzzy models derived from experimental data", *Fuzzy Sets Syst.*, Vol. 13, 1-12, 1980.

[8] M. Sugeno and T. Yasukawa, "Lingustic modeling based on numerical data", *IFSA'91 Brussels, Computer, Management & System Science*, 264-267, 1991.

[9] G.E.P. Box et al., *"Time Series Analysis, Forcasting and Control"*, Holden Day, SanFrancisco, CA.

[10] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its applications to modeling and control", *IEEE Trans. Syst. Cybern.*, Vol.SMC-15, No. 1, 116-132, 1985.

[11] M.A. Ismail, *"Soft Clustering Algorithm and Validity of Solutions"*, Fuzzy Computing Theory, Hardware and Applications, edited by M.M. Gupta, North Holland, 445-471, 1988.

[12] L.X. Xuanli and B. Gerado, "Validity measure for fuzzy cluster", *IEEE Trans. Pattern Anal. Machine Intell.*, Vol. PAMI-13, No. 8, 841-847, Aug. 1991.

[13] S.K. Oh and K.B. Woo, "Fuzzy Identification by means of Fuzzy Inference Method and its Application to Waste Water Treatment System", *Journal of the Korean Institute of Telematics and electronics(KITE)*, 43-52, June, 1994.

[14] S.K. Oh and W. Pedrycz, "Identification of Fuzzy Systems by means of an Auto-tuning Algorithm and Its Application to Nonlinear System", *Fuzzy Sets Syst.(submitted)*.