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A Study on Optimal Fuzzy Identification by means of Hybrid Identification Algorithm

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Abstract

In order to optimize fuzzy model, we use the optimal algorithm with a hybrid type in the identification of premise parameters and standard least square method in the identification of consequence parameters of a fuzzy model. The hybrid optimal identification algorithm is carried out using a genetic algorithm and improved complex method. Also, the performance index with weighting factor is proposed to achieve a balance between the results of performance for the training and testing data. Several numerical examples are used to evaluate the performance of the proposed model.

1. Introduction

Many investigators have studied that natural phenomena is understood and used. Fuzzy theory was initiated by Lotfi A. Zaded in 1965 with his seminal paper "Fuzzy Sets". Fuzzy theory was applied to nonlinear complex systems, and so it took results better than mathematical models.

In the early 1980, linguistic approach[1,2] and fuzzy relationship equation-based approach[3,4] were proposed as identification methods of fuzzy models. In the linguistic approach, 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[5] 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 multi-variable systems[8]. Pedrycz analyzed the identification of fuzzy system fron 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[8]. In the fuzzy relationship equation-based approach, 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[5,8]. 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[6], 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, but the method did not produce the identification of good performance; this could be alleviated to the use of direct linear inference.

The proposed rule-based fuzzy modeling implements system structure and parameter identification using the fuzzy inference methods and the optimization theories for unknown systems. In here, two types of fuzzy inferences are considered, that is, simplified (Type 1) and linear (Type 2) reasoning models. In each fuzzy inference, we consider triangular membership functions.

The optimal identification algorithm is a hybrid type which is joined a genetic algorithm and improved complex method, because a genetic algorithm has marginal efficiency for solutions of a system. In order to optimize fuzzy model, we use the optimal algorithm with a hybrid type in the identification of premise parameters and standard least square method in the identification of consequence parameters of a fuzzy model. Furthermore we introduce an objective function that deals with training 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], activated sludge process in sewage treatment system[12] and traffic route choice[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.

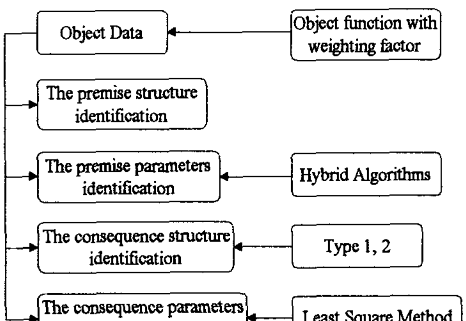


Figure 1. Overall scheme of fuzzy modeling.

In this paper, in order to the optimization of a fuzzy modeling, we use the optimal algorithm of a hybrid type in the identification of the premise parameters of fuzzy model. The parameters of the consequence part of the rules are determined using the standard least square method(Gaussian elimination with maximal pivoting algorithm). Overall scheme of fuzzy modeling is shown in Figure 1.

3 An algorithm of fuzzy identification

3.1 Premise identification

We determined the premise structure of a fuzzy model to compare the performance index using hybrid algorithm with other fuzzy models. The premise of fuzzy rules use triangular membership function and two-input. A triangular membership function has two parameters(a,b) which are identified automatically by the hybrid algorithm.(Figure 2)

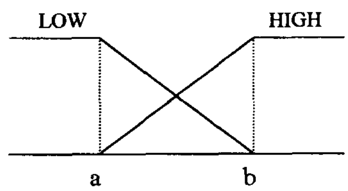


Figure 2. Fuzzy variable with two parameters

3.2 Consequence identification

The identification of the conclusion parts of 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)

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

$$R^j \; IF \; x_1 \; is \; A_{j1} \text{ and } \cdots \text{ and } x_k \; is \; A_{jk} \; Then \; a_{j0} \qquad (1)$$

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

$$y^* = \frac{\sum_{j=1}^{n} w_{ji}\, y_j}{\sum_{j=1}^{n} w_{ji}} = \frac{\sum_{j=1}^{n} w_{ji}\, a_{j0}}{\sum_{j=1}^{n} w_{ji}} = \sum_{j=1}^{n} \widehat{w_{ji}}\, a_{j0} \qquad (2)$$

If the input variables of the premise and parameters are given in consequence parameter identification, the optimal consequence parameters which minimize the assumed performance index can be determined. In what follows, we define the performance index as a sum of squared errors.

$$PI = \frac{1}{m} \sum_{i=1}^{m} (y_i - y_i^*)^2 \qquad (3)$$

The consequence parameters a_{j0} can be determined by the standard least-square method. The minimal value produced by the least-square method is determined as follows.

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

Type 2 (First-order linear Equation)

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

$$R^j \ IF \ x_1 \ is \ A_{j1} \text{ and } \cdots \text{ and } x_k \ is \ A_{jk} \quad Then \ y = f_j(x_1, \cdots, x_k) \tag{5}$$

Where f_j is a linear function of the input variables

$$f_j = a_{j0} + a_{j1}x_1 + \cdots + a_{jk}x_k \tag{6}$$

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

$$y^* = \frac{\sum_{j=1}^{n} w_{ji}\, y_j}{\sum_{j=1}^{n} w_{ji}} = \frac{\sum_{j=1}^{n} w_{ji}\, f_j(x_{1i}, \cdots x_{ki})}{\sum_{j=1}^{n} w_{ji}} = \sum_{j=1}^{n} \widehat{w_{ji}}\,(a_{j0} + a_{j1}x_{1i} + \cdots + a_{jk}x_{ki}) \tag{7}$$

The consequence parameters are produced by the standard least-square method.

4. Optimization using hybrid algorithm

4.1 Hybrid algorithm

Genetic algorithm(GA) exhibits superior capability among optimal techniques of a model. It eliminates local value of many minimal points and searches global minimum while performance index of model is searched minimal value. But, genetic algorithm is difficult of access to global minimum because it has a marginal efficiency for solutions of a system.

Complex method which is based on a geometrical concept depends on initial value. Hence the determination of initial values is very important.

In this paper, we proposes hybrid optimal algorithm that is combined by genetic and complex algorithm. The determination of initial values of complex algorithm and the marginal efficiency of genetic algorithm are solved as the initial values of complex algorithm are determined by genetic algorithm.

4.2 Genetic algorithms

A genetic algorithm is a stochastic search technique based on the principles of biological evolution, natural selection, and genetic recombination, simulating "survival of the fittest" in a population of potential solutions or individuals. GA are capable of globally exploring a solution space, pursuing potentially fruitful paths while also examining random points to reduce the likelihood of setting for a local optimum(Goldberg, 1989).

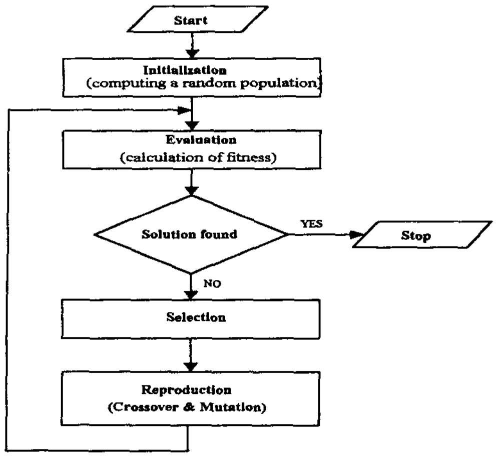


Figure 3. The Basic genetic algorithm

A genetic algorithm begins with a population of strings generated either randomly or from some set of known specimens, and cycles through three step - evaluation, selection, and reproduction. The process of the genetic algorithm is shown in Figure 3.

4.3 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 $g_j(x) \leq 0$, $j=1,2,\cdots,m$

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

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

The parameters to be optimized include the elements of the fuzzy model. They include each parameter(a and b) of the triangular membership function. They are defined as $X_k = (x_1^k, x_2^k, \cdots, x_n^k\ ;\ k=1,2,\cdots n, n+1, \cdots, m)$ and form the points in an "n" dimensional space. In general, the value of "m" is selected as being equal 2n (where n is the number of the initial vertices). The initial values of α, γ and β is specified using the Reflection, Expansion and Contraction of simplex concept as follows:

i) Reflection : $X_r = X_o + \alpha(X_o - X_h)$

ii) Expansion : $X_e = X_o + \gamma(X_r - X_o)$

iii) Contraction : $X_c = X_o + \beta(X_h - X_o)$

The method is assumed to have converged whenever the standard deviation of the function at the vertices of the current simplex is smaller than some prescribed small quantity ε as follows:

$$Q=\left(\sum_{i=1}^{n+1}\frac{[f(X_i)-f(X_0)]^2}{n+1}\right)^{1/2} \le \varepsilon \tag{8}$$

4.4 The objective function with weighting factor

We elaborate on the performance index. The objective function for the training data and testing data is assumed as follow and is utilized as a cost function of the fuzzy model.

$$f=\theta\times PI+(1-\theta)\times E\_PI \tag{9}$$

Where, θ is 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 are modified(optimized).

The performance index used in the ensuing numerical experiment will be as an Euclidean and Hamming distances, that is,

$$PI=\frac{1}{N}\sum_{i=1}^{N}(y_i-\hat{y}_i)^2 \tag{10}$$

$$PI=\frac{1}{N}\sum_{i=1}^{N}|\,y_i-\hat{y}_i\,| \tag{11}$$

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.

5 Experimental studies

5.1 Gas furnace process

In this section, the proposed rule-based fuzzy modeling is applied to the time series data of gas furnace utilized by Box and Jenkins[9]. The flow rate of methane 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.

$$U(t)=0.60-0.048\times U_m(t) \tag{17}$$

Table 1, 2 are performance index that it identifies parameters of fuzzy input space using genetic and hybrid algorithm. Also, these include the performance index of each model by selected θ.

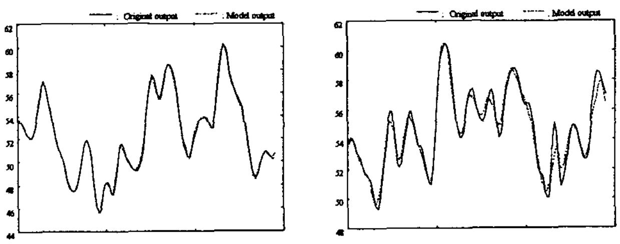
Table 1. The Performance index of type 1

gx1	gx2	Weight (θ)	GA PI	GA E_PI	GA+Complex PI	GA+Complex E_PI
u(t-3)	y(t-1)	0.0	0.117397	0.306032	0.115408	0.305943
		0.25	0.056886	0.316511	0.056886	0.316446
		0.4	0.025553	0.328181	0.025620	0.328044
		0.5	0.023456	0.344973	0.024575	0.329052
		0.6	0.023995	0.329839	0.024217	0.329494
		0.75	0.022856	0.335137	0.023413	0.331272
		1.0	0.022855	0.335407	0.022855	0.335427

Table 2. The Performance index of type 2

gx1	gx2	Weight (θ)	GA PI	GA E_PI	GA+Complex PI	GA+Complex E_PI
u(t-3)	y(t-1)	0.0	0.031077	0.278938	0.018977	0.262199
		0.25	0.029384	0.283629	0.018849	0.263069
		0.4	0.019560	0.278573	0.018752	0.263105
		0.5	0.018809	0.264046	0.018510	0.265127
		0.6	0.018944	0.279414	0.018533	0.264212
		0.75	0.018859	0.279530	0.018533	0.264212
		1.0	0.018360	0.350625	0.017770	0.289803

In here, we select $\theta=1.0$ of type 2 for fuzzy model. For selected model, the output of fuzzy model is shown in Figure 4.



(a) Training output (b) Testing output

Figure 4. Model output of type 2 ($\theta=1.0$)

Table 3. Comparisón of identification error with previous fuzzy models($\theta=0.5$)

Model name			PI	E_PI	Total No of rules
Tong's model[7]			0.469		19
Pedrycz's model[2]			0.776		20
Xu's model[8]			0.328		25
Oh's model [13]	Simplified	Triangular	0.149		6
			0.024	0.328	4
	Linear	Triangular	0.134		4
			0.022	0.326	4
Our model	Simplified	Triangular	0.024575	0.329052	4
	Linear	Triangular	0.018510	0.265127	4

5.2 Sewage treatment process

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. Table 4 are performance index of the identified fuzzy input space using genetic and hybrid algorithm. Table 5 includes the weighting factor for input WSR, DOSP.

Table 4. The performance index
(1:MLSS, 2:WSR, 3:RRSP, 4:DOSP, $\theta=0.5$)

Type	gx1	gx2	Complex[13]		GA		GA+Complex	
			PI	E PI	PI	E PI	PI	E PI
1	1	2	13.726	16.206	12.847437	14.155079	12.403503	12.200090
	1	3	13.03	13.25	12.873838	13.531213	12.809488	13.565745
	1	4	16.287	10.601	14.609385	17.124805	14.343359	16.300016
	2	3	19.143	16.901	15.221871	13.473765	14.195404	12.696920
	2	4	15.285	10.136	15.659515	14.344687	12.395741	11.752867
	3	4	17.347	14.811	17.854191	15.889150	17.347515	14.811461
2	1	2	6.396	54.233	7.087610	32.970261	7.157825	24.658316
	1	3	2.735	88.818	13.319167	65.584373	5.800677	49.121113
	1	4	5.023	83.892	7.556438	26.155487	7.774071	25.265299
	2	3	8.049	111.119	8.657568	26.561729	8.465644	20.982182
	2	4	7.878	46.393	6.871958	28.599873	6.333284	26.715973
	3	4	4.253	32.884	4.135979	66.810814	8.484018	21.284546

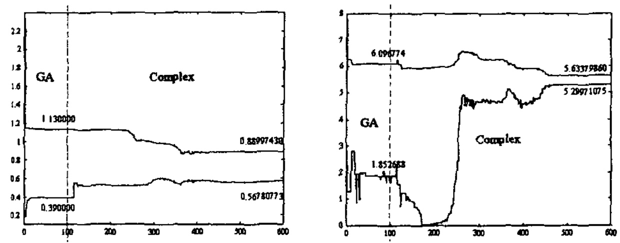
Table 5. The performance index of type 1

gx1	gx2	Weight	GA		GA+Complex	
			PI	E PI	PI	E PI
2	4	0.0	15.986461	14.182557	13.136251	11.003107
		0.25	15.982741	14.182261	13.137272	11.056588
		0.4	15.673412	14.334855	12.828024	11.746323
		0.5	15.659515	14.344687	12.395741	11.752867
		0.6	15.645371	14.362533	12.994895	11.902082
		0.75	14.126393	17.383896	12.726414	16.390539
		1.0	14.062714	17.719112	11.411669	15.692510

Table 6. Comparison of identification error with previous fuzzy models(MLSS, WSR, $\theta=0.5$)

Model name			PI	E_PI	Total No. of rules
Oh's model [13]	Simplified	Triangular	13.726	16.206	4
			14.107	16.563	6
			12.802	15.915	8
	Linear	Triangular	6.396	54.233	4
			1.461	80618.742	6
			0.0018	923.324	8
Our model	Simplified	Triangular	12.403503	12.200090	4
			11.361042	10.731465	6
			12.358129	16.447329	8
	Linear	Triangular	7.157825	24.658316	4
			0.000054	132.480255	6
			0.001837	638.857422	8

We selected WSR(2), DOSP(4), and $\theta=0.5$ of type 1 for fuzzy model. The search process of parameters and the identified parameters of type 1 are shown in Figure 5, 6.



(a) WSR (b) DOSP

Figure 5. The search process of parameters of type 1 by hybrid algorithm ($\theta=0.5$)

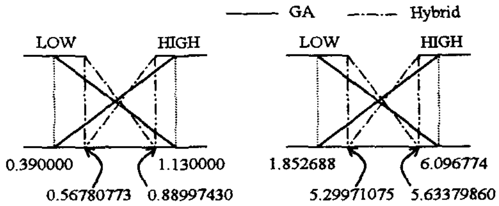


Figure 6. Identified parameters of type 1 ($\theta=0.5$)

5.3 Traffic route choice process

We consider simple problem related to traffic route choice which is based on two routes mentioned above. The model was considered as conventional example for traffic route choice model. Then, we assume that the object for traffic routes is driver and our interest is focused on how to express traffic behavior at the individual level. The performance index is defined as shown in eq. 11.

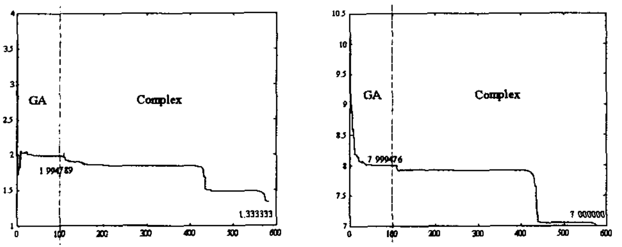
Table 7. The performance index of type 1

gx1	gx2	Weight	GA		GA+Complex	
			PI	E PI	PI	E PI
T1	T2	0.0	2.084053	7.985284	2.349190	7.847324
		0.25	2.012299	7.989752	1.866863	7.928181
		0.4	1.993030	7.996797	1.847566	7.919746
		0.5	1.994789	7.999476	1.333333	7.000000
		0.6	1.993053	7.997437	1.771442	7.386550
		0.75	1.498040	9.327701	1.468349	9.314816
		1.0	1.432097	9.562164	1.428842	9.548505

Table 8. The performance index of type 2

gx1	gx2	Weight	GA		GA+Complex	
			PI	E PI	PI	E PI
T1	T2	0.0	1.970911	8.256198	0.908430	8.195915
		0.25	1.865623	8.173512	0.904552	8.181231
		0.4	1.771913	8.423475	0.907860	8.206291
		0.5	1.515679	8.748238	0.906429	8.186235
		0.6	1.521940	8.461909	0.906238	8.186863
		0.75	0.259952	9.792402	0.000183	9.018824
		1.0	0.316230	10.122863	0.000308	11.386923

In here, we select $\theta=0.5$ of type 1 for fuzzy model. Optimal search process of fuzzy model by hybrid algorithm is shown in Figure 7.



(a) training data (b) for testing data

Figure 7. Optimal search process of type 1 by hybrid algorithm ($\theta=0.5$)

The performance index of each model is compared with other fuzzy modeling methods and the results are summarized in Table 9.

Table 9. Comparison of identification error with previous models ($\theta=0.5$)

Model name			PI	E_PI	Total No. of rules
Oh's model [13]	Simplified	Triangular	1.768	8.709	4
			1.631	8.551	6
			1.605	7.855	8
	Linear	Triangular	2.016	8.209	4
			0.787	7.604	6
			0.00605	8.787	8
Our model	Simplified	Triangular	1.333333	7.000000	4
			1.333901	7.000069	6
			1.333333	7.000001	8
	Linear	Triangular	0.906429	8.186235	4
			0.002317	7.147333	6
			0.000022	7.741185	8

6. Conclusions

In this paper, the efficient identification technique is presented which automatically extract the optimal fuzzy rules, using the hybrid algorithm and the weighting factors of object function. The hybrid algorithm is used for auto-tuning of parameters of the premise membership functions in consideration of the overall structure of fuzzy rules. Two types of fuzzy reasoning method (simplified(type 1), linear(type 2)) are used and we consider triangular membership function. we are carried out design to optimal fuzzy model which is a robust and efficient model in the complex and nonlinear process system. Also, we constructed the fuzzy model through a harmony balance between approximation and generalization by using the objective function with weighting factor.

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