RST-Based System Design of Hybrid Intelligent Control*

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Abstract - *This paper proposes a RST-based fuzzy rules extraction program, which uses information entropy and closeness degree (defined in this paper) as heuristic information for attribute selection to enhance search speed of minimal attributes set, and takes full use of apriori knowledge and experiences. Based on this program, design method of reduced dimension multilayer fuzzy rules is constructed, in which every layer's fuzzy inference rules dimension is no more than three, in favor of understanding and correcting rules. The rough-fuzzy controller is combined with conventional PID forming hybrid intelligent controller with better control quality.*

Keywords: Rough set theory (RST), general approximation sets, closeness degree, rule extraction, fuzzy modeling.

1 Introduction

With technology development, the controlled process or object becomes more complex, but the control requirements are stricter and more elaborate. FLC, an important field of intelligent control (IC), can be applied to nonlinear, time-varying control system with large delay with high robustness. But FLC design is still short of systematism and has many problems to be solved, including selection of control rules, discourse universes, fuzzy membership functions and scaling factors. Controller dimension increases for high-order and multi-input problems, especially, fuzzy rules' number enhances exponentially when the numbers of input variables and their linguistic terms rise. Fuzzy rules are mostly acquired by experts' experience and knowledge. However, man's logic thinking is usually not more than 3 dimension. So determination of fuzzy rules turns into a bottleneck problem.

Rough set theory (RST), a new soft computing method, researches representation, learning and inducing methods of incomplete data, inexact knowledge. In the view of granular knowledge, RST employs the set boundary to represent the undetermined information. It can be used to reduce data and obtain minimal representation with essential information and without any apriori knowledge. This paper uses rough set algorithm to extract fuzzy rules and keep every layer's fuzzy inference rules dimension is no more than three.

2 General Approximation Sets and Closeness Degree

In rough set theory, upper and lower approximation sets of finite set X are

$$R_*(X) = \cup\{Y_i \in U \mid IND(R) : Y_i \subseteq X\} \qquad (1)$$

$$R^*(X) = \cup\{Y_i \in U \mid IND(R) : Y_i \cap X \neq \Phi\} \qquad (2)$$

But this kind of classification must be fully correct or certain. However, most of the working data and information contain noise and measure errors and so forth uncertain factors. Thus, partially incorrect classification should be taken into account. This paper proposes the concepts of general upper and lower approximation sets and their closeness degree that defines the level of misclassification.

Set X and Y are two non-empty subsets of a finite universe U. The inclusion degree of the set X with respect to set Y is defined as follows[1].

$$\text{inc(X,Y)}=\begin{cases} |X \cap Y|/|Y| & |X|>0 \\ 1 & |X|=0 \end{cases} \qquad (3)$$

where $|\cdot|$ denotes set cardinality. That is, inc(X,Y)*100% of X elements are in common with Y. Of course, it is just significative according to the specified majority requirement if and only if 0.5 $\le$ inc(X,Y) $\le$ 1. If inc(X,Y)=1, the classification is absolutely correct. Given the correct classification rate ζ , we have denotation $X \subseteq_\zeta Y$ if and only if inc(X,Y) $\ge \zeta$.

* **Financed by Chinese Nation Nature Science Foundation (60374029)**

Definition 1: Let the equivalent relation family R={X_1, X_2, ⋯, X_n} of finite universe *U*. The general upper and lower approximation sets of set X are defined as follows.

$$R_{=}(X)=\bigcup\{X_i \subseteq U/R : X_i \subseteq_{\zeta} X\} \quad (4)$$

$$R^{=}(X)=\bigcup\{X_i \subseteq U/R : \mathrm{inc}(X_i,X) > 1-\zeta\} \quad (5)$$

Consequently, the general boundary region of set X is given by

$$BN_{=}(X)=R^{=}(X)-R_{=}(X) =\bigcup\{X_i \subseteq U/R : 1-\zeta < \mathrm{inc}(X_i,X) < \zeta\} \quad (6)$$

General set $R_{=}(X)$ of lower approximation set $R_*(X)$ includes not only $R_*(X)$, but also the collection of all those elements which can be classified into X with the correct classification rate greater than ζ and smaller than 1. Those elements belong to $R^*(X)$ and don't belong to $R_*(X)$. Similarly, general set $R^{=}(X)$ of upper approximation set $R^*(X)$ is the collection of all those elements of *U* with the classification error not greater than ζ. IF and only if ζ =1, the general approximation sets are totally equal to the standard approximation sets, i.e., $R_{=}(X) = R_*(X)$ and $R^{=}(X) = R^*(X)$. IF the misclassification is the biggest, that is, ζ =0.5, then $R_{=}(X)=R^{=}(X)$ and $BN_{=}(X) =\Phi$. The relation of these sets is $R_*(X) \subseteq R_{=}(X) \subseteq R^{=}(X) \subseteq R^*(X)$. This paper defines ζ as the closeness degree of general approximation sets with respect to upper and lower approximation sets.

Definition 2: The lower closeness degree ζ_- of a general lower approximation set $R_{=}(X)$ with respect to $R_*(X)$ is defined as follows.

$$\zeta_- = \min(\mathrm{inc}(X_i,X) | X_i \subseteq R_{=}(X)) \quad (7)$$

Definition 3: The upper closeness degree ζ^- of a general upper approximation set $R^{=}(X)$ with respect to $R^*(X)$ is defined as follows.

$$\zeta^- = \max((1-\mathrm{inc}(X_i,X)) | X_i \subseteq R^{=}(X)) \quad (8)$$

Definition 4: The closeness degree of general approximation sets is defined as follows.

$$\zeta = \min(\zeta^-, \zeta_-) \quad (9)$$

Given general approximation sets, the closeness degree can estimate the relative classification ability of attributes with respect to the whole knowledge representation system, and provide some heuristic information of attribute importance for attribute reduction algorithm.

3 RST-Based Data Extraction Rapid Algorithm

Traditional modeling method is oriented to *object* and ignorant of the *man's* effect in the optimal process. But it is important and necessary to consider the man's effect in the system optimal process involved the action of man. The data reduction algorithm introduced by this paper reflects this problem and take full advantage of the rough set methodology and man's apriori knowledge during the process of data reduction and knowledge extraction. Fig.1 shows the logic structure of the data reduction algorithm based on RST for fuzzy rule extraction.

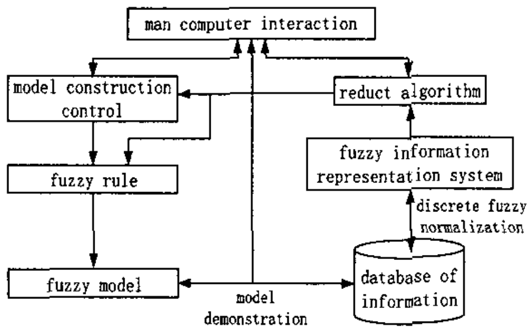


Figure 1. logic structure of data reduction

The algorithm procedures show as follows.

Step 1: The condition attributes (input variables) and decision attributes (output variables) are properly selected by the measured data of inputs and outputs, then the decision table is made out. When we want to get the plant control strategy, every sample time t is an object of decision table.

Step 2: The redundant rows are deleted to get relative-reduction decision table. The consistent degree is computed. IF it isn't satisfied, turn back to step 1; otherwise, continue.

Step 3: The measured data is normalized by discrete fuzzy normalization algorithm[2], and the knowledge representation system of fuzzy information is established.

According to the real problem, the data is discretized at first. Then the actual basic universe is transformed to fuzzy inference universe by scaling factors. The discrete fuzzy normalization makes every attribute value be fuzzy concept described by fuzzy membership function. After that, knowledge representation system of fuzzy information is achieved, in which the columns denote fuzzy attributes and rows objects. Every row, its meaning same to that of the original knowledge representation system, describes a piece of information of that object defined by two vectors *vt* and *vm*.

$$vt=(t_1, t_2, \cdots, t_n)$$
$$vm=(m_1, m_2, \cdots, m_n) \quad (10)$$

Where *vt* shows fuzzy linguistic terms corresponding to every attribute and *vm* indicates membership degree of fuzzy linguistic terms.

Step 4: The core attributes $CORE_D$ of decision D for decision table is calculated.

Core attributes $CORE_D$ is calculated by improved C-D indiscernible matrix[3,4], that is,

$$CORE=\{a\in A: |b_{ij}|=1\}\ i,j=1,2,\ldots,n;\ i\neq j \quad (11)$$

Step 5: The core attributes $CORE_D$, adding some important attributes in light of apriori knowledge, are employed as the starting-point of calculation. The most important attribute is chosen at a time by heuristic information until the selected attributes set satisfied the request, which is $RED_D(C)$ generally.

Different condition attributes have different contribution of dependence between condition and decision attributes. Every time add the attribute, whose contribution is the greatest, to the reduction until quasi-optimal attribute set is acquired.

Information increment $\Delta I_D(r,R)$ of decision D shows the classification ability of attributes, defined as:

$$\Delta I_D(r,R)=I(r\cup R/D)-I(R/D) \quad (12)$$

where $I(\cdot/D)$ indicates information entropy with respect to decision D[5]. But there is prematurity sometimes if only employing it as heuristic information.

The closeness degree ζ of general approximation sets with respect to standard approximation sets also describes the relative classification ability of attributes. So this algorithm applies these two functions as heuristic function of attribute selection.

$$HF(r,R,D)=\alpha\ \Delta I_D(r,R)+(1-\alpha)\Delta\zeta_D(r,R) \quad (13)$$

in which *HF*(r,R,D) represents the classification ability increment after addition of attributer r to attribute set R. Obviously, the more greater *HF*(r,R,D) is, the more important attribute r is and the more classification ability r increases for R. α is weighting factor and $\alpha\in[0, 1]$. The weighting degree of information increment and closeness degree can be adjusted by factor α. The terminal function of evaluation is defined as follows.

$$TF(R,D)=\alpha\ I_D(R)+(1-\alpha)\zeta_D(R) \quad (14)$$

Step 6: The decision table of fuzzy information is reduced and the redundant rows are deleted.

Same fuzzy rules with different belief degrees can summarize as a fuzzy rule whose belief degree is maximum or average value.

Step 7: The quasi-optimal fuzzy rules with formal IF-THEN are attained.

Fuzzy condition attributes and decision attributes of fuzzy decision table are premise and consequent components respectively. Fuzzy rules are in the form of IF-THEN rules.

4 Reduced-Dimension FLC Design

The fuzzy rule determination is a key for design of fuzzy logic controller. The design essences of reduced-dimension FLC are input-space dimension decrease by input variables combination, simulating man's thinking way and using multi-level control strategy nesting to simplify the controller design. So the rationality depends on right states combination. RST has the ability of data mining, selecting optimal attributes (states) based on requirements, extracting rules and discovering knowledge from digital data. This paper employs the above extraction algorithm to select optimal input variables (states) and establish reduced dimension fuzzy rules.

Set controlled process is MIMO, in which, input and output dimensions are R and M respectively. It can be divided into M MISO systems by RST data reduction algorithm. Knowledge representation system is established by sample database, choosing properly N condition attributes, such as given instruction, error, error change, etc, adopting controller's output, namely, process control quality as decision attribute. After sample data discretization and normalization, fuzzy information representation system (FIRS) is established and redundant rows are deleted. Then reduction attributes set are computed. Suppose reduction attributes set is consisted of condition attributes set $C=[C_1, C_2, \cdots, C_n]$ (where n denotes attributes number) and decision attribute D. These condition and decision attributes are corresponding to premise and consequent components of fuzzy rules respectively. Reduction of condition attributes equals dimension decrease of FLC, thus the input number of FLC is reduced from N to n.

The most important attributes set C_{p1}= [C_1, C_2, $\cdots$, C_{p1}] is calculated in fuzzy decision table, where $1 \le p_1 \le n$. Attribute important degrees are evaluated by heuristic function (*HF*) of attribute selection.

By these p_1 condition attributes and decision attribute D, FIRS is parted to two fuzzy decision tables, consistent table S_{11} and inconsistent table S_{12}. The rules carried by table S_{11} are as follows:

Rule i : If C_1 is A_{1i}, $\cdots$, and C_{p1} is A_{p1i}, Then D is B_i

Confidence degrees of fuzzy rules are defined by fuzzy membership degrees. In inconsistent table S_{12}, these p_1 condition attributes divide objects into x_1 classes. Then x_1 rules are as follows.

Rule j : If C_1 is A_{1j}, $\cdots$, and C_{p1} is A_{p1j}, Then Y_1 is E_{1j}

In which, Y_1 is taken as temporary pre-decision and E_{1j} (j=1, 2, ..., p_1) is attribute value. The rules based on tables S_{11} and S_{12} are corresponding to fuzzy inference function as first level inference.

Pre-decision Y_1 is used to denote attributes [C_1, C_2, $\cdots$, C_{p1}] in inconsistent table S_{12}. For the new represented table S_{12}, second selection of most important attributes C_{p2}= [C_{p1+1}, C_{p1+2}, $\cdots$, C_{p1+p2}] is done according to the same data reduction algorithm, in which $1 \le p_1 + p_2 \le n$. The attributes set [Y_1, C_{p1+1}, C_{p1+2}, $\cdots$, C_{p1+p2}] distinguishes decision table as consistent table S_{21} and inconsistent table S_{22}. Same to above procedure, fuzzy rules are acquired.

By analogy, all reduction attributes [C_1, C_2, $\cdots$, C_n] are calculated. All reduced-dimension multilayer rough-fuzzy rules based on RST are shown in table 1.

In last level, inconsistent rules are permitted, that is, the same conditions can get different decisions. But their action degrees are differentiated by confidence degrees. In fact, the existence of inconsistent rules accords to practical conflict phenomena, which shows the objectivity and conclusion soundness of RST-based reduced algorithm.

The reduced-dimension multilevel rough-fuzzy controller not only decreases total dimension of FLC, but also discovers multilevel fuzzy inference function using RST to evaluate important degrees of controller's input variables. In every level, fuzzy function has small dimension. According to man's thinking character that dimension is not more than 3, p_1, ..., p_r are set as 2 or 1. That makes all rules easy to be understood, suitable to thinking characters, favor of comparison with experts' knowledge and checking rules correctness.

5 Simulation Research

In thermal power plant, the electric generating unit, as the controlled plant of the load control system, is a multi-variable coupling object, which is composed of boiler and turbine-generator whose dynamic characters are totally different. During load control process for unit, energy balance of supply and demand must be properly kept, considering load response performances and operation parameters stability.

In light of control task, FLC input variables select N_0, p_0, p_T, N_E, traditional PID controller's inputs and their changes, in which N_0, p_0, N_E and p_T represent load instruction, main steam pressure setting value, steam turbine's real power and main steam pressure respectively. FLC output variables adopt the opening degree of turbine's main throttle and the fuel volume of boiler in

Table 1. All reduced-dimension multilayer fuzzy rules based on RST

First level:	Rule i :	If C_1 is A_{1i}, $\cdots$, and C_{p1} is A_{P1i}, Then D is B_i
	$\cdots$	$\cdots$
	Rule j :	If C_1 is A_{1j}, $\cdots$, and C_{p1} is A_{P1j}, Then Y_1 is E_{1j}
	$\cdots$	$\cdots$
Second level:	Rule i :	If Y_1 is E_{1j}, and C_{p1-1} is A_{2i}, $\cdots$, and C_{p1-p2} is A_{p2i}, Then D is B_i
	$\cdots$	$\cdots$
	Rule j :	If Y_1 is E_{1j}, and C_{p1-1} is A_{2j}, $\cdots$, and C_{p1-p2} is A_{p2j}, Then Y_2 is E_{2j}
	$\cdots$	$\cdots$
r-th level:	Rule i :	If Y_{r-1} is E_{r-1j}, and C_{pr-1-1} is A_{ri}, $\cdots$, and C_n is A_{pri}, Then D is B_i
	$\cdots$	$\cdots$
	Rule j :	If Y_{r-1} is E_{r-1j}, and C_{pr-1} is A_{rj}, $\cdots$, and C_n is A_{prj}, Then D is B_j
	$\cdots$	$\cdots$
$\cdots$	$\cdots$	$\cdots$

denotation of μ_T and μ_B. FLC is corresponding to nonlinear PD controller with good dynamic characteristics. But it's difficult for FLC to avoid errors in small ranges. In this paper, hybrid intelligent controller, combining reduced-dimension multilayer rough-fuzzy controller with PID control, takes full use of their advantages and is applied to load control system. In big error range, this new type of FLC adjusts coarsely, and PID controller gives fine control in small error range. This kind of hybrid intelligent controller has good real-time properties, rapid response and high ability to eliminate stable errors. To avoid switch disturbance, soft switch is a nice choice. An error function $f(e)$ is introduced as follows

$$f(e)=\begin{bmatrix} K_f(e) \\ K_p(e) \end{bmatrix}=\begin{bmatrix} \dfrac{|e|}{r}\times 100\% \\ \dfrac{r-|e|}{r}\times 100\% \end{bmatrix} \tag{15}$$

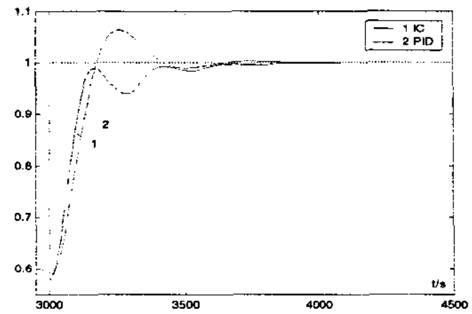
Weighted factors for outputs of FLC and PID are adjusted automatically, that is,

$$u = K_f(e)\,u_f + K_p(e)\,u_p$$
$$[K_f(e)\ K_p(e)]^{\mathrm{T}} = f(e) \tag{16}$$

Based on above design method, a certain mathematic model of electric generating unit is studied for simulation experiments[6]. The transform function is:

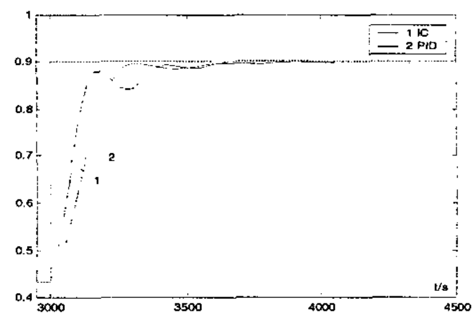
$$\begin{bmatrix} p_T \\ N_E \end{bmatrix}=\begin{bmatrix} \dfrac{2.194}{(1+80s)^2} & -2.194(0.064+\dfrac{0.093}{1+124s}) \\ \dfrac{1}{(1+80s)^2} & \dfrac{68.81s}{(1+12s)(1+82s)} \end{bmatrix}\begin{bmatrix} \mu_B \\ \mu_T \end{bmatrix} \tag{17}$$

In which, p_T and N_E are actual values of main steam pressure and steam turbine power respectively; μ_B and μ_T are the fuel volume for boiler and throttle opening degree of steam turbine. Fig.2 and fig.3 present tracking characteristic curves, where curve 1 shows simulation results of hybrid intelligent control consisted by reduced-dimension multilayer rough-fuzzy controller and PI controller; curve 2 is conventional PID control that employs the mode of boiler following turbine for unit load control. Accordingly, hybrid control has high rise speed, small overshoot. Fig.4 and fig.5 illuminate comparative curves for robust characteristics after plant's parameters variation. Thereby, hybrid intelligent control has better dynamic characteristics and strong robustness.



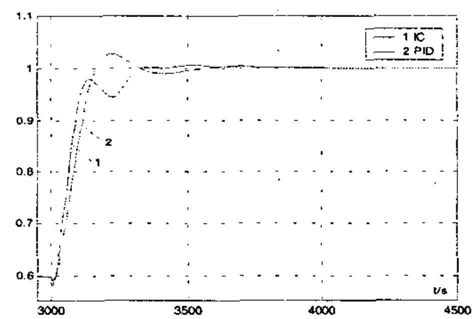
Time (s)

Fig. 2 p_T response curves under load instruction from 43.3% to 90%.



Time (s)

Fig. 3 N_E response curves under load instruction from 43.3% to 90%.



Time (s)

Fig. 4 p_T response curves under load instruction from 43.3% to 90% after parameters variation

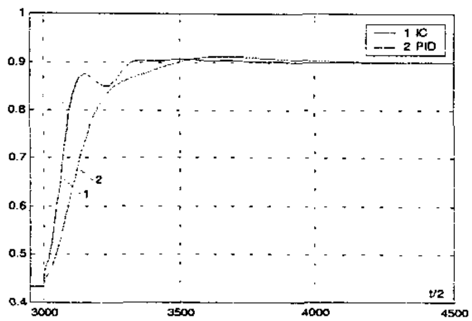


Fig. 5 N_E response curves under load instruction from 43.3% to 90% after parameters variation

6 Conclusions

A new data reduction algorithm is designed to extract fuzzy rules from original database of information, which considers the man's effect in the system optimal process involved the action of man and takes full advantage of the rough set methodology and man's apriori knowledge during the process of data reduction and knowledge extraction. To accelerate selective velocity of optimal attributes set, heuristic informatin uses increments of information entropy and closeness degree proposed in this paper. Then, a new fuzzy modeling method is introduced which extracts knowledge from field data and establishes fuzzy rules of reduced-dimension multiplayer fuzzy controller. The essential use of reduced-dimension control is dimension number decrease by input variables' integration to simplify controller design. And the established rules are advantageous for understanding, checking rules and artificial correction to keep every level's fuzzy inference rules in three-dimension sizes. The rough-fuzzy controller is combined with conventional PID, building up hybrid intelligent controller. The simulation of thermal power unit control system shows that hybrid controller has high control quality with high speed, small overshoot and strong robustness.

References

[1] Wojciech Ziarko. "Variable precision rough set model ". *Journal of computer and system sciences*, 1993, 46, pp. 39-59.

[2] Mohamed Quafafou. "α-RST: a generalization of rough set theory". *Information Sciences*. 2000. 124, pp. 301-316.

[3] Skowron, A., C. Rauszer. "The discernibility matrices and functions". In intelligent decision support, *Handbook of application and advances of the rough set theory*. Ed. R. Slowinski, pp. 331-362, 1992. Boston: Kluwer Academic Publishers.

[4] Fang Wang, Keming Xie, "Rough sets-based reduction algorithm for fuzzy rules extraction". *Journal of Taiyuan University of Technology*, 2004, (5).

[5] Li Deyu, Liang Jiye, Miao Duoqian. "A Criterion Guaranteeing the Information Entropy Nonincreasing Under a Homomorphismic Communication Between Two Pawlak Information Systems" *Journal of engineering mathmatics*. 2000, vol17, pp. 122-124.

[6] Yongsheng Fang, Zhigao Xu, Laijiu Chen. "Study of adaptive fuzzy control of boiler superheated steam temperature based on dynamic mechanism analysis". Proceedings of the CSEE, Vol.17. No.1. 1997, pp. 23-28.