Identification of Fuzzy Relation Model Using HFC-Based Parallel Genetic Algorithms and Information Data Granulation

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Abstract. The paper concerns the hybrid optimization of fuzzy inference systems that is based on Hierarchical Fair Competition-based Parallel Genetic Algorithms (HFCGA) and information data granulation. The granulation is realized with the aid of the Hard C-means clustering and HFCGA is a kind of multi-populations of Parallel Genetic Algorithms (PGA), and it is used for structure optimization and parameter identification of fuzzy model. It concerns the fuzzy model-related parameters such as the number of input variables, a collection of specific subset of input variables, the number of membership functions, and the apexes of the membership function. In the hybrid optimization process, two general optimization mechanisms are explored. The structural optimization is realized via HFCGA and HCM method whereas in case of the parametric optimization we proceed with a standard least square method as well as HFCGA method as well. A comparative analysis demonstrates that the proposed algorithm is superior to the conventional methods.

Keywords: fuzzy relation model, information granulation, genetic algorithms, hierarchical fair competition (HFC), HCM, multi-population.

1 Introduction

Fuzzy modeling has been a focal point of the technology of fuzzy sets from its very inception. Fuzzy modeling has been studied to deal with complex, ill-defined, and uncertain systems in many other avenues. In the early 1980s, linguistic modeling [1] and fuzzy relation equation-based approach [2] were proposed as primordial identification methods for fuzzy models. The general class of Sugeno-Takagi models [3] gave rise to more sophisticated rule-based systems where the rules come with conclusions forming local regression models. While appealing with respect to the basic topology (a modular fuzzy model composed of a series of rules) [4], these models still await formal solutions as far as the structure optimization of the model is concerned, say a construction of the underlying fuzzy sets—information granules being viewed as basic building blocks of any fuzzy model.

Some enhancements to the model have been proposed by Oh and Pedrycz [5,6]. As one of the enhanced fuzzy model, information granulation based fuzzy relation fuzzy

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model was introduced. Over there, binary-coded genetic algorithm was used to optimize structure and premise parameters of fuzzy model, yet the problem of finding “good” initial parameters of the fuzzy sets in the rules remains open.

This study concentrates on optimization of information granulation-oriented fuzzy model. Also, we propose to use hierarchical fair competition-based parallel genetic algorithm (HFCGA) for optimization of fuzzy model. GAs is well known as an optimization algorithm which can be searched global solution. It has been shown to be very successful in many applications and in very different domains. However it may get trapped in a sub-optimal region of the search space thus becoming unable to find better quality solutions, especially for very large search space. The parallel genetic algorithm (PGA) is developed with the aid of global search and retard premature convergence. In particular, as one of the PGA model, HFCGA has an effect on a problem having very large search space [9].

In the sequel, the design methodology emerges as two phases of structural optimization (based on Hard C-Means (HCM) clustering and HFCGA) and parametric identification (based on least square method (LSM), as well as HCM clustering and HFCGA). Information granulation with the aid of HCM clustering helps determine the initial parameters of fuzzy model such as the initial apexes of the membership functions and the initial values of polynomial function being used in the premise and consequence part of the fuzzy rules. And the initial parameters are adjusted effectively with the aid of the HFCGA and the LSM.

2 Information Granulation (IG)

Usually, information granules [7] are viewed as related collections of objects (data point, in particular) drawn together by the criteria of proximity, similarity, or functionality. Granulation of information is an inherent and omnipresent activity of human beings carried out with intent of gaining a better insight into a problem under consideration and arriving at its efficient solution. In particular, granulation of information is aimed at transforming the problem at hand into several smaller and therefore manageable tasks. In this way, we partition this problem into a series of well-defined subproblems (modules) of a far lower computational complexity than the original one. The form of information granulation (IG) themselves becomes an important design feature of the fuzzy model, which are geared toward capturing relationships between information granules.

It is worth emphasizing that the HCM clustering has been used extensively not only to organize and categorize data, but it becomes useful in data compression and model identification [8]. For the sake of completeness of the entire discussion, let us briefly recall the essence of the HCM algorithm.

We obtain the matrix representation for hard c-partition, defined as follows.

$$M_C = \left\{ \mathrm{U} \mid u_{gi} \in \{0,1\},\ \sum_{g=1}^{c} u_{gi} = 1,\ 0 < \sum_{i=1}^{m} u_{gi} < m \right\} \tag{1}$$

[Step 1]. Fix the number of clusters $c (2 \le c < m)$ and initialize the partition matrix $\mathbf{U}^{(0)} \in M_C$

[Step 2]. Calculate the center vectors $\mathbf{v}_g$ of each cluster:

$$\mathrm{v}_g^{(r)} = \{v_{g1},\ v_{g2}, \cdots,\ v_{gk}, \cdots,\ v_{gl}\} \tag{2}$$

$$v_{gk}^{(r)} = \sum_{i=1}^{m} u_{gi}^{(r)} \cdot x_{ik} \Bigg/ \sum_{i=1}^{m} u_{gi}^{(r)} \tag{3}$$

Where, $[u_{gi}]= \mathbf{U}^{(r)}$, $g = 1, 2, \ldots, c$, $k=1, 2, \ldots, l$.

[Step 3]. Update the partition matrix $\mathbf{U}^{(r)}$; these modifications are based on the standard Euclidean distance function between the data points and the prototypes,

$$d_{gi} = d(\mathrm{x}_i - \mathrm{v}_g) = \left\| \mathrm{x}_i - \mathrm{v}_g \right\| = \left[\sum_{k=1}^{l} (x_{ik} - v_{gk})^2 \right]^{1/2} \tag{4}$$

$$u_{gi}^{(r+1)} = \begin{cases} 1 & d_{gi}^{(r)} = \min\{d_{ki}^{(r)}\} \ \text{ for all } \ k \in c \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

[Step 4]. Check a termination criterion. If

$$\| \mathbf{U}^{(r+1)} - \mathbf{U}^{(r)} \| \le \varepsilon \ \ \text{(tolerance level)} \tag{6}$$

Stop ; otherwise set $r = r + 1$ and return to **[Step 2]**

3 Design of Fuzzy Model with the Aid of IG

The identification procedure for fuzzy models is usually split into the identification activities dealing with the premise and consequence parts of the rules. The identification completed at the premise level consists of two main steps. First, we select the input variables $x_1, x_2, \ldots, x_k$ of the rules. Second, we form fuzzy partitions of the spaces over which these individual variables are defined. The identification of the consequence part of the rules embraces two phases, namely 1) a selection of the consequence variables of the fuzzy rules, and 2) determination of the parameters of the consequence (conclusion part). And the least square error (LSE) method used at the parametric optimization of the consequence parts of the successive rules.

In this study, we use the isolated input space of each input variable and carry out the modeling using characteristics of input-output data set. Therefore, it is important to understand the nature of data. The HCM clustering addresses this issue. Subsequently, we design the fuzzy model by considering the centers of clusters. In this manner the clustering help us determining the initial parameters of fuzzy model such as the initial apexes of the membership functions and the order of polynomial function being used in the premise and consequence part of the fuzzy rules.

3.1 Premise Identification

In the premise part of the rules, we confine ourselves to a triangular type of membership functions whose parameters are subject to some optimization. The HCM clustering helps us organize the data into cluster so in this way we capture the characteristics of the experimental data. In the regions where some clusters of data have been identified, we end up with some fuzzy sets that help reflect the specificity of the data set

The identification of the premise part is completed in the following manner. Given is a set of data $\mathbf{U}=\{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_l ; \mathbf{y}\}$, where $\mathbf{x}_k=[x_{1k}, \ldots, x_{mk}]^T$, $\mathbf{y}=[y_1, \ldots, y_m]^T$, l is the number of variables and , m is the number of data.

[Step 1]. Arrange a set of data $\mathbf{U}$ into data set $\mathbf{X}_k$ composed of respective input data and output data.

$$\mathbf{X}_k=[\mathbf{x}_k ; \mathbf{y}] \quad (7)$$

$\mathbf{X}_k$ is data set of k-th input data and output data, where, $\mathbf{x}_k=[x_{1k}, \ldots, x_{mk}]^T$, $\mathbf{y}=[y_1, \ldots, y_m]^T$, and k=1, 2, …, l.

[Step 2]. Complete the HCM clustering to determine the centers (prototypes) $\mathbf{v}_{kg}$ with data set $\mathbf{X}_k$.

[Step 2-1]. Classify data set $\mathbf{X}_k$ into c-clusters, which in essence leads to the granulation of information.

We can find the data pairs included in each cluster based on the partition matrix u_{gi} by (5) and use these to identify the structure in conclusion part.

[Step 2-2]. Calculate the center vectors $\mathbf{v}_{kg}$ of each cluster.

$$\mathrm{v}_{kg}=\{v_{k1},\ v_{k2}, \ldots, v_{kc}\} \quad (8)$$

Where, k=1, 2, …, l, g = 1, 2, …, c.

[Step 3]. Partition the corresponding isolated input space using the prototypes of the clusters $\mathbf{v}_{kg}$. Associate each clusters with some meaning (semantics), say Small, Big, etc.

[Step 4]. Set the initial apexes of the membership functions using the prototypes $\mathbf{v}_{kg}$.

3.2 Consequence Identification

We identify the structure considering the initial values of polynomial functions based upon the information granulation realized for the consequence and antecedents parts.

[Step 1]. Find a set of data included in the fuzzy space of the j-th rule.

[Step 1-1]. Find the input data included in each cluster (information granule) from the partition matrix u_{gi} of each input variable by (5).

[Step 1-2]. Find the input data pairs included in the fuzzy space of the j-th rule

[Step 1-3]. Determine the corresponding output data from above input data pairs.

[Step 2]. Compute the prototypes $\mathbf{V}_j$ of the data set by taking the arithmetic mean of each rule.

$$\mathrm{V}_j=\{V_{1j}, V_{2j}, \ldots, V_{kj}; M_j\} \quad (9)$$

Where, k=1, 2, …, l. j=1, 2, …, n. V_{kj} and M_j are prototypes of input and output data, respectively.

[Step 3]. Set the initial values of polynomial functions with the center vectors $\mathbf{V}_j$.

The identification of the conclusion parts of the rules deals with a selection of their structure that is followed by the determination of the respective parameters of the local functions occurring there.

In Case of Type 2: Linear Inference (linear conclusion)

The conclusion is expressed in the form of a linear relationship between inputs and output variable. This gives rise to the rules in the form

$$R^j : If\ x_1\ is\ A_{1c}\ and \cdots and\ x_k\ is\ A_{kc}\ then\ y_j - M_j = f_j(x_1, \cdots, x_k) \tag{10}$$

The calculations of the numeric output of the model, based on the activation (matching) levels of the rules there, rely on the expression

$$y^* = \frac{\sum_{j=1}^{n} w_{ji} y_i}{\sum_{j=1}^{n} w_{ji}} = \frac{\sum_{j=1}^{n} w_{ji}(f_j(x_1, \cdots, x_k) + M_j)}{\sum_{j=1}^{n} w_{ji}} = \sum_{j=1}^{n} \hat{w}_{ji}(a_{j0} + a_{j1}(x_1 - V_{j1}) + \cdots + a_{jk}(x_k - V_{jk}) + M_j) \tag{11}$$

Here, as the normalized value of w_{ji}, we use an abbreviated notation to describe an activation level of rule R^j to be in the form

$$\hat{w}_{ji} = \frac{w_{ji}}{\sum_{j=1}^{n} w_{ji}} \tag{12}$$

where R^j is the j-th fuzzy rule, x_k represents the input variables, A_{kc} is a membership function of fuzzy sets, a_{j0} is a constant, M_j is a center value of output data, n is the number of fuzzy rules, y^* is the inferred output value, w_{ji} is the premise fitness matching R^j (activation level).

Once the input variables of the premise and parameters have been already specified, the optimal consequence parameters that minimize the assumed performance index can be determined. In what follows, we define the performance index as the mean squared error (MSE).

$$\mathrm{PI} = \frac{1}{m} \sum_{i=1}^{m} (y_i - y_i^*)^2 \tag{13}$$

where y^* is the output of the fuzzy model, m is the total number of data, and i is the data number. The minimal value produced by the least-squares method is governed by the following expression:

$$\hat{\mathbf{a}} = (\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{Y} \tag{14}$$

where

$\mathbf{x}_i^T = [\ \hat{w}_{1i} \cdots \hat{w}_{ni}\ \ (x_{1i} - V_{11})\hat{w}_{1i} \cdots (x_{1i} - V_{1n})\hat{w}_{ni} \cdots (x_{ki} - V_{k1})\hat{w}_{1i} \cdots (x_{ki} - V_{kn})\hat{w}_{ni}\ ]$,

$\hat{\mathbf{a}} = [a_{10} \cdots a_{n0}\ a_{11} \cdots a_{n1} \cdots a_{1k} \cdots a_{nk}]^T$,

$$\mathbf{Y} = \left[y_1 - \left(\sum_{j=1}^{n} M_j w_{j1} \right) \quad y_2 - \left(\sum_{j=1}^{n} M_j w_{j2} \right) \quad \cdots \quad y_m - \left(\sum_{j=1}^{n} M_j w_{jm} \right) \right]^T$$

$\mathbf{X} = [\mathbf{x}_1 \quad \mathbf{x}_2 \quad \cdots \quad \mathbf{x}_i \quad \cdots \quad \mathbf{x}_m]^T$.

4 Optimization by Means of HFCGA

The premature convergence of genetic algorithms is a problem to be overcome. The convergence is desirable, but must be controlled in order that the population does not get trapped in local optima. Even in dynamic-sized populations, the high-fitness individuals supplant the low-fitness or are favorites to be selected, dominating the evolutionary process. Fuzzy model has many parameters to be optimized, and it has very large search space. So HFCGA may find out a solution better than GAs.ï

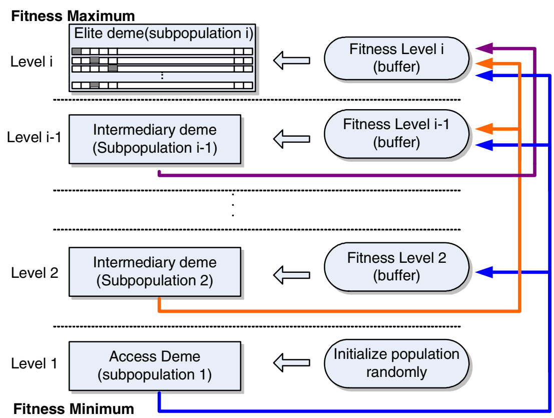


Fig. 1. HFC based migration topology

In HFCGA, multiple demes (subpopulation) are organized in a hierarchy, in which each deme can only accommodate individuals within a specified range of fitness. The universe of fitness values must have a deme correspondence. Each deme has an admission threshold that determines the profile of the fitness in each deme. Individuals are moved from low-fitness to higher-fitness subpopulations if and only if they exceed the fitness-based admission threshold of the receiving subpopulations. Thus, one can note that HFCGA adopts a unidirectional migration operator, where individuals can move to superior levels, but not to inferior ones. The figure 1 illustrates the migration topology of HFCGA. The arrows indicate the moving direction possibilities. The access deme (primary level) can send individuals to all other demes and the elite deme only can receive individuals from the others. One can note that, with respect to topology, HFCGA is a specific case of island model, where only some moves are allowed.

Fig. 2 depict flowchart of implemented HFCGA, it is real-coded type, we can choice the number of demes, size of demes, and operators(selection, crossover, mutation algorithms) for each deme. Where, each deme can evolve with different operators. In this study, we use five demes (subpopulation), Size of demes is 100, 80, 80, 80, and 60 respectively, where elite deme is given as the least size. And we use same operators as such linear ranking based selection, modified simple crossover, and dynamic mutation algorithm for each deme.

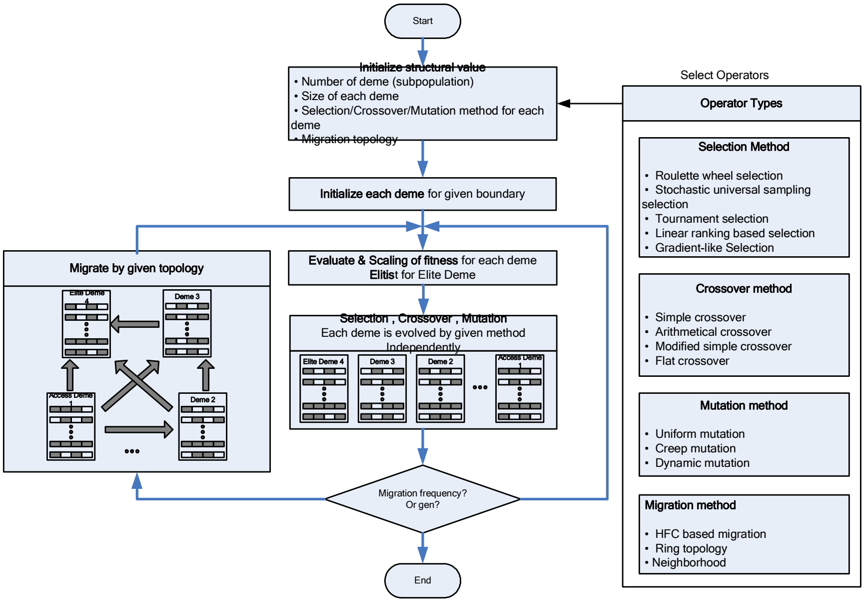


Fig. 2. Flowchart for HFCGA

Identification procedure of fuzzy model consists of two phase, structural identification and parametric identification. HFCGA is used in each phase. At first, in structural identification, we find the number of input variables, input variables being selected and the number of membership functions standing in the premise and the type of polynomial in conclusion. And then, in parametric identification, we adjust apexes of the membership functions of premise part of fuzzy rules. Figure 3 shows an arrangement of chromosomes to be used in HFCGA.

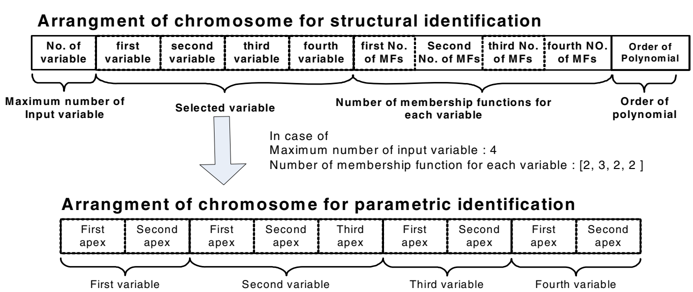


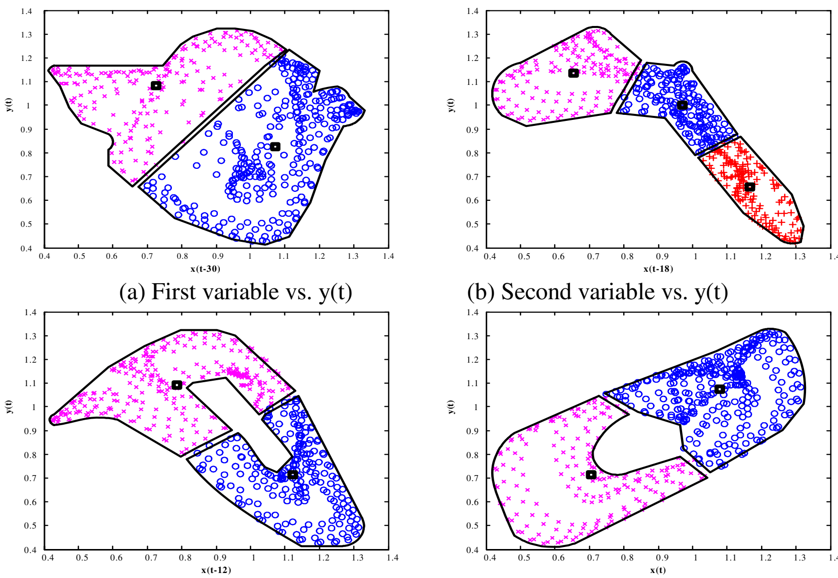
Fig. 3. Arrangement of chromosomes for identification of structure and parameter identification

5 Experimental Studies

In this section we consider comprehensive numeric studies illustrating the design of the fuzzy model. We demonstrate how IG-based FIS can be utilized to predict future values of a chaotic time series. The performance of the proposed model is also contrasted with some other models existing in the literature. The time series is generated by the chaotic Mackey–Glass differential delay equation [10] of the form:

$$\dot{x}(t) = \frac{0.2x(t-\tau)}{1+x^{10}(t-\tau)} - 0.1x(t) \tag{15}$$

The prediction of future values of this series arises is a benchmark problem that has been used and reported by a number of researchers. From the Mackey–Glass time series $x(t)$, we extracted 1000 input–output data pairs for the type from the following the type of vector format such as: [$x(t$-30), $x(t$-24), $x(t$-18), $x(t$-12), $x(t$-6), $x(t)$; $x(t$ +6)] where t = 118–1117. The first 500 pairs were used as the training data set while the remaining 500 pairs were the testing data set for assessing the predictive performance. We consider the RMSE being regarded here as a performance index. We carried out the structure and parameters identification on a basis of the experimental data using HFCGA and real-coded GA (single population) to design IG-based fuzzy model.



(a) First variable vs. y(t) (b) Second variable vs. y(t)

(c) Third variable vs. y(t) (d) Fourth variable vs. y(t)

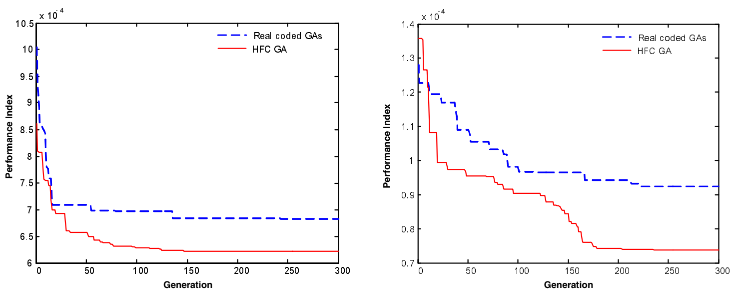
Fig. 4. Groups and central values through HCM for each input variable

Figure 4 depicts groups and central values through HCM for each input variable. Where, the number of input variables and number of groups (membership function) to be divided are obtained from structural optimization procedure. Clustering results are used for information granulation.

Table 1 summarizes the performance index for real-coded GA and HFCGA. It shows that the performance of the HFCGA based fuzzy model is better than real-coded GA based one for premise identification. However, for structure identification, same structure is selected. To compare real-coded GA with HFCGA, show the performance index for the Type 2 (linear inference). Figure 5 show variation of the performance index for real-coded GA and HFCGA in premise identification phase.

Table 1. Performance index of IG-based fuzzy model by means of HFCGA

Evolutionary algorithm	Structure Identification					Parameter Iden.	
	Input variables	No. of MFs	Type	PI	E_PI	PI	E_PI
HFCGA	x(t-30)	2	Type 3 (Quadratic)	0.00008	0.00021	0.00006	0.00007
	x(t-18)	3					
	x(t-12)	2	Type 2 (Linear)	0.00140	0.00136	0.00070	0.00062
	x(t)	2					



(a) Type 2 (b) Type 3

Fig. 5. Convergence process of performance index for real-coded GA and HFCGA

The identification error (performance index) of the proposed model is also compared with the performance of some other models; refer to Table 2. Here the non-dimensional error index (NDEI) is defined as the root mean square errors divided by the standard deviation of the target series.

Table 2. Comparison of identification error with previous models

Model	No. of rules	PI_t	PI	E_PI	NDEI
Wang's model [10]	7	0.004			
	23	0.013			
	31	0.010			
Cascaded-correlation NN [11]					0.06
Backpropagation MLP [11]					0.02
6th-order polynomial [11]					0.04
ANFIS [12]	16		0.0016	0.0015	0.007
FNN model [13]			0.014	0.009	
Our model	24		0.00006	0.00007	0.00032

6 Conclusions

In this paper, we have developed a comprehensive hybrid identification framework for information granulation-oriented fuzzy model using hierarchical fair competition–based parallel genetic algorithm. The underlying idea deals with an optimization of information granules by exploiting techniques of clustering and genetic algorithms. We used the isolated input space for each input variable and defined the fuzzy space by information granule. Information granulation with the aid of HCM clustering help determine the initial parameters of fuzzy model such as the initial apexes of the membership functions and the initial values of polynomial function being used in the premise and consequence part of the fuzzy rules. The initial parameters are fine-tuned (adjusted) effectively with the aid of HFCGA and the least square method. The experimental studies showed that the model is compact (realized through a small number of rules), and its performance is better than some other previous models. The proposed model is effective for nonlinear complex systems, so we can construct a well-organized model.

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