Optimization of the Rules Base of Genetic Fuzzy Systems[1]

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Abstract

Hybrid genetic fuzzy systems are considered as an artificial intelligence subfield. The rule base work and the database that form the fuzzy system knowledge base are described. The results of testing the algorithm for optimizing the fuzzy genetic system rule base are presented.
It is shown that the hybridization of fuzzy control systems and genetic algorithms is promising, providing the adjustment of the parameters of genetic parameters, which are used to adjust the parameters of fuzzy systems based on artificial intelligence. Hybrid genetically fuzzy systems are considered as objects of the system of intelligent control of complex technological processes and industries. The functioning of the rule base and the database, which are part of the knowledge base of fuzzy control systems, is described. The results of test control and management of the optimization process of the base of support for the adoption of rules by a genetic fuzzy control system are presented.

Keywords:

artificial intelligence, hybrid systems, rule base, genetic fuzzy system, membership function, linguistic variables.

1. Introduction

Hybrid systems are designed and implemented in such a way that certain computational paradigm advantages of artificial intelligence are used to compensate for their other shortcomings. Fuzzy systems and genetic algorithms hybridization is implemented in two directions (Figure 1):

- the fuzzy system adjusts its genetic algorithm and selects parameters of the genetic operators types;
- genetic algorithms are used to adjust the fuzzy system parameters [1,2].

The main ideas of the fuzzy sets theory were proposed by Lotfi Zadeh in 1965. From his rigorous theoretical developments, various directions in the fuzzy sets and fuzzy logic develop: continuation principle, fuzzy graphs, fuzzy relations, fuzzy differentiation and integration, theory of possibilities, fuzzy logic, approximate reasoning, fuzzy databases, intelligent knowledge analysis, fuzzy linear programming, fuzzy dynamic programming, etc. [3-7].

In the classical mathematical theory of sets, the concept of "set" is a collection of objects or elements (numbers, names, colors, etc.) of a given object, which belongs (or does not belong) to set$A \subseteq U$, where U – is a universe. In the first case, the statement "x belongs to the set A^n" - true, and in the second - false. The classical set can be specified: through the listed elements analytically or through the characteristic function $x_A(x)$ as follows:

$$x_A(x) = \begin{cases} 1| & x \in A \\ 0| & x \notin A \end{cases}. \quad (1)$$

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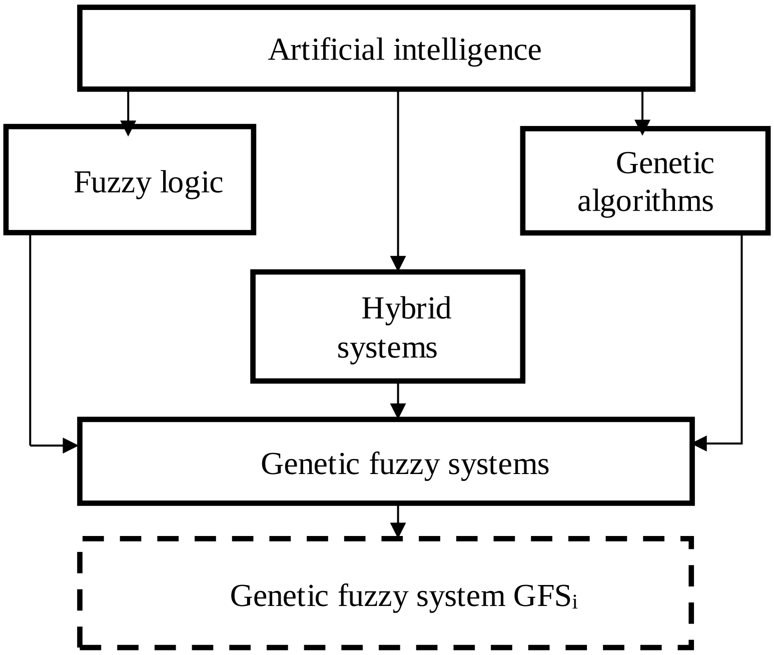

Figure 1: Genetic fuzzy systems as an artificial intelligence subfield.

When disclosing the concept of "fuzzy set" in the classical set, the idea is used that objects can belong to this set with varying degrees of belonging, which is measured by real numbers in the interval [0,1]. So, for example, if U – is an universe, and A $\subseteq U$, - its fixed subset, then the set of the ordered two

$\varphi A = \{< x; \mu_A(x) > 1 \ x \in U\}$ (2)

is called fuzzy set U, if functionμ_{A}(x)for any x $\in U$ exactly matches one real number belonging to the interval [0; 1] (Figure 2). Expression μ_{A}(x)is called the degree of membership [3].

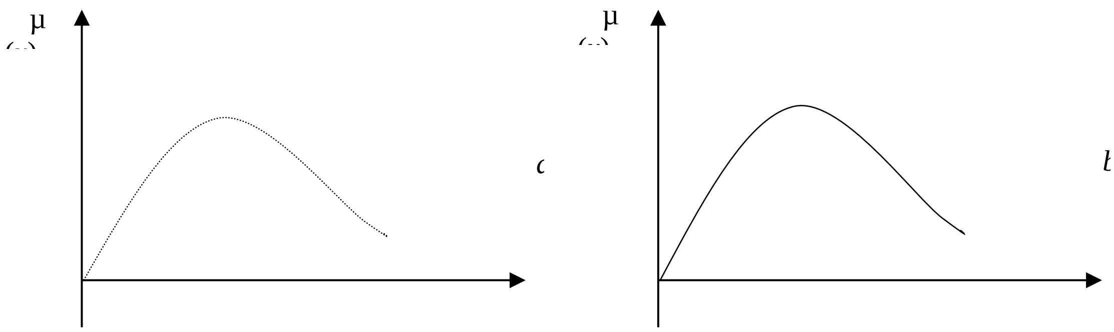

Figure 2: Discrete (a) and continuous (b) membership functions μ_{A}(x).

Fuzzy logic [1-4] uses linguistic variables, fuzzy logic of judgments, linguistic modifiers and inference rules. Linguistic variables are specified as a tuple - five <x,T(x), U, G,M>, where x– is a variable name; T(x) – is a term set; U – is an universe, G – is a synthetics rule and M – is a semantic rule.

Linguistic modifiers are:

not T, where $\mu_{not}^{T}(x) = 1 - \mu_T(x)$;

T1 andT2, where$\mu_{T_1} and T_2(x) = min\{\mu_{T_1}(x)\mu_{T_2}(x)\}$;

T1 or T2, where $\mu_{T_1} and\ T_2(a) = min\{\mu_{T_1}(x)\mu_{T_2}(x)\}$; (3)

very T, where$\mu_{very}T(x)[\mu_T(x)]^2$;

nearly T, where$\mu_{nearly}T(x)[\mu_T(x)]^2$.

Fuzzy inference system (FIS) – computing system using the fuzzy sets theory of rules of the form IF-THEN and fuzzy logic [4-7].

The basic structure of a fuzzy inference system contains three conceptual components:

- a rule base that includes all fuzzy decision rules;
- database (dictionary) containing all membership functions;
- an inference machine that performs decision-making procedures based on rules and fact data generated by a knowledge base (Figure 3) [8-10]

2. Knowledge base

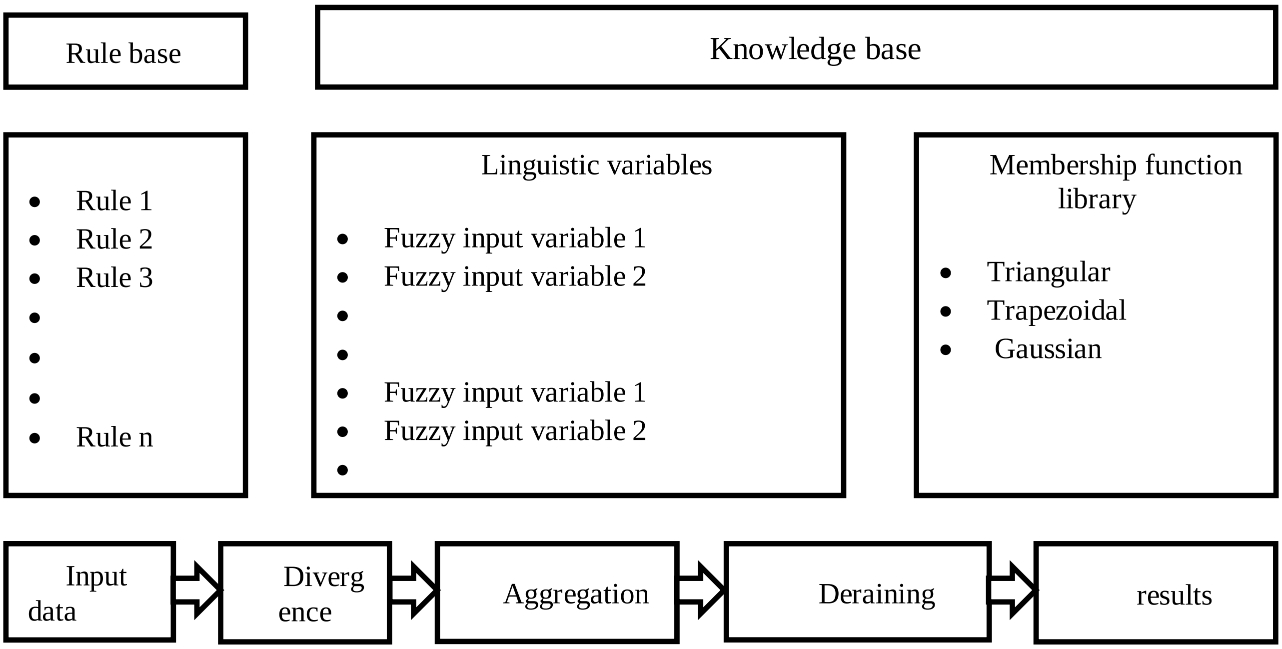

Figure 3: Rule-based fuzzy system.

Genetic algorithm [11,12] is an adaptive algorithm defined by the following operators and parameters:

$$GA < PP, \phi, F, S, \Omega, \Psi, \varsigma > \quad (4)$$

where PP – is a population object, ϕ with chromosome elements $c^j = \left(c_1^j, c_2^j, \dots, c_i^j\right) \in PP, j = 1, 2, \dots, \phi$ which are l - dimensional binary vectors; F- are functions of l variables and with the range of functional properties Rt, called fitness functions (objective function):

$$F: c^j \longrightarrow R^+, \quad j = 1, 2, \dots, \phi; \quad (5)$$

where S –is a selection operator, after the application of which Uparents Pk are selected from the PP population:

$$\delta: PP \longrightarrow \{P^1, P^2, \dots, P^u\}; \quad (6)$$

Ω - set of genetic operators

$$\Omega = \{\Omega_{cross}; \Omega_{mut;} \dots\}. \quad (7)$$

Ψ – operator cash out υ the number of current population chromosomes, where the next (i+1) population, it turns out, according to the formula

$$PP(i+1) = PP(i) - \psi\big(PP(i)\big) + \{q^1, q^2, \dots, q^v\}; \quad (8)$$

ξ – is an algorithm termination criterion.

Operators δ and Ω are always probabilistic, and Ψ can be both probabilistic and deterministic.

Any genetic algorithm consists of sequentially constructed populations [7]

$$PP(0), PP(1), \dots, PP(i), PP(i+1), \dots \quad (9)$$

Since the initial population PP(0) is chosen randomly, the transition from the population PP (i) to the population PP(i+1) is carried out through the genetic operators δ, Ω and Ψ. This transition is called generation and is analogous to iteration in numerical methods.

The genetic algorithm can also be described as a procedure for solving an optimization problem of the form [13-15]

$max\{F(c)|c \in \{0,1\}^i\}$ (10)

or

$min\{F(c)|c \in \{0,1\}^i\}$ (11)

where F – ia an objective function and c – is an individual who is a possible solution (10) or (2)

Genetic fuzzy system GFS_n to customize the knowledge base

The goal that is achieved when programming and implementing a hybrid fuzzy genetic system (Genetic Fuzzy Software System for Asset Management) GFS_n is to use a genetic algorithm to adjust the knowledge base parameters of an already created fuzzy system (Figure 4).

In the system under consideration, the knowledge base consists of both the membership base functions of term sets of input and output fuzzy variables, and the rules base. Applications for which the hybrid system is designed to adjust the membership functions parameters by searching for optimal values without changing their form and rule base are described in the work [16].

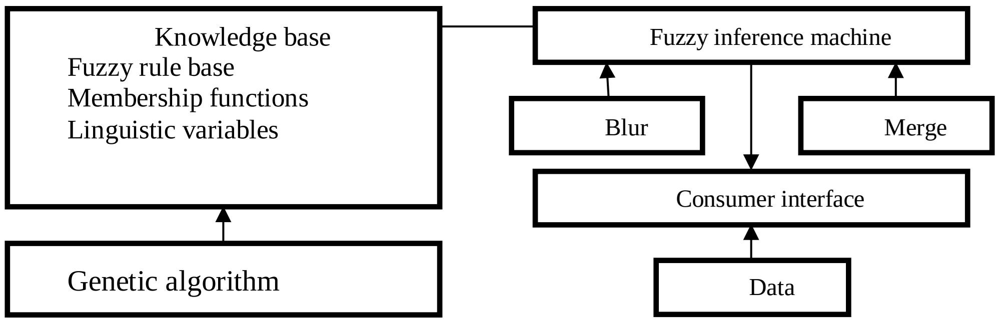

Figure 4: Genetic fuzzy knowledge base tuning system.

3. Optimizing the rule base

In this work, the genetic algorithm can be used both to optimize the rule base and the membership parameters function of input and output variables.

Any rule in a fuzzy system has the form

IF

$\{K_{m_1}\ is\ x_{m_1}j_{m_1}\}\ AND\ \{K_{m_2}\ is\ x_{m_2}j_{m_2}\}\ AND\ ...\ AND\ \{K_{m_u}\ is\ x_{m_u}j_{m_u}\}$

THEN

(12)$\{Q_{m_1}isY_{m_1}j_{m_1}\}AND\{Q_{m_2}isY_{m_2}j_{m_2}\}AND\ ...\ AND\{Q_{m_u}isY_{m_u}j_{m_u}\}$,

m1=1,2,…,M,

where м– number of rules.

After the choice and execution of the mth rule, the considered system uses the min operator to calculate the value Θm according to the formula

$$\theta_m = \min\{\ \mu_{m_1 j_{m_1}}(x^*), \mu_{m_2 j_{m_2}}(x_2^*), \ldots, \mu_{mkj_{me}}(x_k^*)\} \quad (13)$$

Every rule has weight ωm for m= 1,2,…,M and after multiplying the obtained value by Θm with the corresponding weight, a weighted value is obtained:

$\theta_m^\circ = \theta_m \cdot \omega_m$ (14)

After fulfilling all the rules of the rule base for each term set Y_{sp} of output variables, the corresponding membership degrees are obtained

$\mu_{sp}^m = \theta_m^\circ$ (15)

Aggregation is obtained after recalculation

$P_{sp} = max\{\mu_{sp}^1, \mu_{sp}^2, \ldots, \mu_{sp}^m\}$ (16)

for any Ysp,s=1,2,3,…,s и p=1,2,3,…,Ps.

The last defuzzification procedure Ysp is to obtain the input variable Q.

In the system under consideration, 24 rules are implemented with the corresponding 24 rules ωm for m=1,2,…,24. For example, rule n with ωm=0,8 weight is as follows:

Rule n: If the return is very high and the Risk is neutral and q is large, then Q is good.

The weight choice was made both using an expert opinion and in the pre-set initial values system shown in Table 1.

The genetic algorithm searches for c individuals values, at which the objective function minimum is achieved:

$$F = (Q_1 - Q_2)^2 + (Q_1 - Q_3)^2 + (Q_2 - Q_3)^2 \qquad (17)$$

where Q1, Q2, Q3 – the value of the output variables Q, calculated at regular intervals.

Individuals from a population of 24-dimensional vectors

$$c = (\omega_1, \omega_2, \omega_3, \dots \omega_{23}, \omega_{24}). \qquad (18)$$

4. The discussion of the results.

The tests series was carried out in which variable values of parameters ngen (number of generations), nPop – is a population size, Pc– is a probability of crossing). Pm is a (probability of mutation) genetic algorithm [9,10]. Table 1 shows the results of four tests.

Table 1.

Testing results of a genetic fuzzy system for optimizing weight rules

Gen	Pop	c	m	ω1	ω2	ω3	ω4	ω5	ω6	ω7
Initial value				1	1	1	1	0,8	0,8	0,8
0	0	0,75	0,2	0,976654	0,820508	0,766591	0,868349	0,717322	0,656674	0,130368
0	0	0,5	0,05	0,745752	0,907513	0,672978	0,872377	0,359415	0,772108	0,174125
00		0,2	0,2	0,817967	0,713620	0,802406	0,746703	0,554740	0,537281	0,324936
00		0,05	0,5	0,961473	0,827503	0,854606	0,886166	0,737303	0,460031	0,244658

ω8	ω9	ω10	ω11	ω12	ω13	ω14	ω15	ω16
0,8	0,8	0,8	0,7	0,7	0,7	0,7	1,0	1,0
0,315154	0,114078	0,872515	0,963561	0,820828	0,769732	0,86348	0,773251	0,750632
0,766436	0,064852	0,843793	0,842725	0,901302	0,377857	0,87272	0,9754118	0,410403
0,538790	0,284316	0,708947	0,896706	0,716036	0,8006659	0,76704	0,854374	0,278267
0,817248	0,564073	0,990088	0,673013	0,947549	0,846327	0,86167	0,833842	0,360323

ω17	ω18	ω19	ω20	ω21	ω22	ω23	ω24	nF mi
1	1	0,8	0,8	0,8	0,8	0,8	0,8	
0,826624	0,605526	0,114072	0,272518	0,650360	0,711492	0,862963	0,889126	0,0063489
0,553412	0,981641	0,064855	0,143789	0,774119	0,864329	0,692651	0,905124	0,00063489
0,692999	0,829301	0,284819	0,208943	0,924936	0,838792	0,906175	0,794910	0,00003211
0,828457	0,939215	0,561076	0,190088	0,844658	0,717243	0,905238	0,767541	0,00000069

The obtained results show that with the given architecture of the fuzzy system, there is no optimal weight with the value 1. In other words, no rule is absolutely essential. A significant part of the weights ωm for m=1,2,...,24 have values after optimization close to the initial ones. However, there are also rules for which the resulting weights have a different order [1, 16].

5. Conclusion

GFSi is a rule-based genetic fuzzy system implemented by GPS in the Matlab environment. The main goal when creating a system is to find the optimal value of the fuzzy systems parameters. The genetic algorithm and the fuzzy system hybridization is successful, because regardless of the optimal weight of several rules of different order with initial values, the objective function values are quite close.

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