Genetic Lateral and Amplitude Tuning with Rule Selection for Fuzzy Control of Heating, Ventilating and Air Conditioning Systems*

R. Alcalá[1], J. Alcalá-Fdez[1], F.J. Berlanga[2], M.J. Gacto[1], and F. Herrera[1]

[1] University of Granada, Dept. Computer Science and A.I., E-18071 Granada, Spain
{alcala, jalcala, herrera}@decsai.ugr.es, mjgacto@ugr.es
[2] University of Jaén, Dept. Computer Science, E-23071 Jaén, Spain
berlanga@ujaen.es

Abstract. In this work, we propose the use of a new post-processing method for the lateral and amplitude tuning of membership functions combined with a rule selection to develop accurate fuzzy logic controllers dedicated to the control of heating, ventilating and air conditioning systems concerning energy performance and indoor comfort requirements.

1 Introduction

Heating, Ventilating and Air Conditioning (HVAC) systems are equipments usually implemented to maintain satisfactory comfort conditions in buildings. The energy consumption as well as indoor comfort aspects of buildings are highly dependent on the design, performance and control of their HVAC systems. Therefore, the use of automatic control strategies, as Fuzzy Logic Controllers (FLCs), could result in important energy savings compared to manual control [1, 10].

FLCs in buildings are often designed using rules of thumb not always compatible with the controlled equipment requirements, energy performance and users expectations and demand. However, different criteria should be optimized for a good performance of the HVAC system and, due to the nature of the problem, a rational operation and improved performance of FLCs is required [10]. A way to improve the FLC performance is the tuning of Membership Functions (MFs).

Recently, a new linguistic rule representation was presented to perform a fine genetic Lateral and Amplitude tuning (LA-tuning) of MFs [3]. It is based on a new symbolic representation with three values (s, α, β), respectively representing a label, the lateral displacement and the amplitude variation of the support of this label. The tuning of both parameters involves a reduction of the search space that eases the derivation of optimal models respect to classical tuning. This work proposes to apply and to combine the LA-tuning with a rule selection [11, 12] to develop accurate FLCs dedicated to the control of HVAC systems.

This paper is arranged as follows. The next section presents the basics of the HVAC system control problem. Section 3 introduces the genetic LA-tuning and

* Supported by the Spanish Ministry of Science and Technology under Projects TIC-2002-04036-C05-01 and 04, and TIN-2005-08386-C05-01 and 03.

M. Ali and R. Dapoigny (Eds.): IEA/AIE 2006, LNAI 4031, pp. 452–461, 2006.

rule selection. Section 4 proposes the evolutionary algorithm for the LA-tuning with rule selection. Section 5 applies the proposed method to the HVAC control problem. And finally, Section 6 points out some concluding remarks.

2 The HVAC System Control Problem

An HVAC system is comprised by all the components of the appliance used to condition the interior air of a building. The HVAC system is needed to provide the occupants with a comfortable and productive working environment which satisfies their physiological needs. In Figure 1, a typical office building HVAC system is presented. This system consists of a set of components to be able to raise and lower the temperature and relative humidity of the supply air.

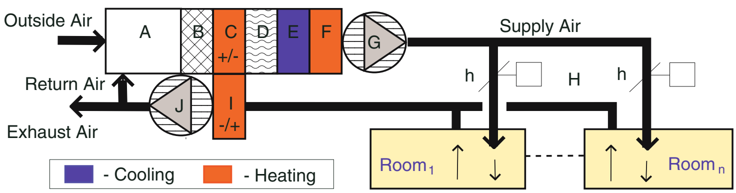

Fig. 1. Generic structure of an office building HVAC system

Some artificial intelligence techniques could be successfully applied to enhance the HVAC system capabilities [5, 10]. However, most works apply FLCs to individually solve simple problems such as thermal regulation (maintaining a temperature setpoint), energy savings or comfort improvements. On the other hand, the initial rule set is usually constructed based on the operator's control experience using rules of thumb, which sometimes fail to obtain satisfactory results [10]. Therefore, the different involved criteria should be optimized for a good performance of the HVAC System. Usually, *the main objective is to reduce the energy consumption while maintaining a desired comfort level*.

In our case, five criteria should be optimized improving an initial FLC obtained from human experience (involving 17 variables) by using the LA-tuning and rule selection. To do so, we consider the calibrated and validated models of a real test building. Both, the initial FLC and the simulation model were developed within the framework of the JOULE-THERMIE programme under the GENESYS [1] project (see [1, 4] for more information on this problem).

2.1 Objectives and Fitness Function

Our main optimization objective is the energy performance but maintaining the required indoor comfort levels, specifically to *minimize* the following five criteria:

[1] GENESYS Project: Fuzzy controllers and smart tuning techniques for energy efficiency and overall performance of HVAC systems in buildings, European Commission, Directorate-General XII for Energy (contract JOE-CT98-0090).

O_1 Upper thermal comfort limit[2]: $if\ PMV > 0.5,\ O_1 = O_1 + (PMV - 0.5)$.
O_2 Lower thermal comfort limit: $if\ PMV < -0.5,\ O_2 = O_2 + (-PMV - 0.5)$.
O_3 Indoor air quality: $if\ CO_2\ conc. > 800ppm,\ O_3 = O_3 + (CO_2 - 800)$.
O_4 Energy consumption: $O_4 = O_4 +$ Power at time t.
O_5 System stability: $O_5 = O_5 +$ System change from time t to $(t-1)$, where system changes states for a change in the system operation.

These criteria are combined into one overall objective function by means of a vector of weights. When trustworthy weights are available, this approach reduces the size of the search space providing the adequate direction into the solution space and its use is highly recommended. In our case, trusted weights were obtained by the experts for the objective weighting fitness function: $w_1^O =$ 0.0083022, $w_2^O = 0.0083022$, $w_3^O = 0.00000456662$, $w_4^O = 0.0000017832$ and w_5^O = 0.000761667. Finally, the fitness function to be minimized was computed as:

$$F = \sum_{i=1}^{5} w_i^O \cdot O_i \ .$$

2.2 FLC Variables and Architecture

The DB is composed of symmetrical fuzzy partitions with triangular MFs labeled from $L1$ to Ll_i (with l_i being the number of labels of the i-th variable). Figure 3 depicts the initial DB together with the tuned DB to optimize the paper size.

A hierarchical FLC architecture considering the PMV, CO_2 concentration, previous HVAC system status and outdoor temperature was proposed for the GENESYS site. The architecture, variables and initial Rule Base (RB) can be seen in Figure 4 together with the final selected rules again for the paper size. Figure 4 represents the decision tables of each module of the hierarchical FLC in terms of these labels. Each cell of the table represents a fuzzy subspace and contains its associated output consequent(s), i.e., the corresponding label(s). The output variables are denoted in the top left square for each module. Both, the initial RB and DB, were provided by experts.

3 LA-Tuning and Rule Selection

This section presents the two techniques that are combined to improve the FLC behavior in the HVAC control problem, the LA-tuning and the rule selection.

3.1 The LA-Tuning of Membership Functions

In [2], a new model of tuning of MFs was proposed considering the linguistic 2-tuples representation scheme introduced in [9], that allows the symbolic translation of a label by considering an only parameter per label. The LA-tuning [3]

[2] PMV is the more global Predicted Mean Vote thermal comfort index 7730 selected by the international standard organization ISO, incorporating relative humidity and mean radiant temperature (http://www.iso.org/iso/en/ISOOnline.frontpage).

is an extension of the lateral tuning to also perform a tuning of the support amplitude of the MFs. To adjust the displacements and amplitudes of the MF supports we propose a new rule representation considering two parameters, α and β, relatively representing the lateral displacement and the amplitude variation of a label. In this way, each label can be represented by a 3-tuple (s, α, β), where α is a number within the interval [-0.5, 0.5) that expresses the domain of a MF when it is moving between its two lateral MFs (as in the 2-tuples representation), and β is also a number within the interval [-0.5, 0.5) that allows an increase or decrease in the support amplitude of a MF by 50% of its original size. Let us consider a set of labels S representing a fuzzy partition. Formally, we have the triplet,

$$(s_i, \alpha_i, \beta_i), \;\; s_i \in S, \; \{\alpha_i, \beta_i\} \in [-0.5, 0.5)$$

As an example, Figure 2 shows the 3-tuple represented label $(s_2, -0.3, -0.25)$ together with the lateral displacement and amplitude variation of the corresponding MF. Let c_{s_2} and a_{s_2} be the right and the left extreme of the s_i support, and Sup_{s_2} be its size. The support of the new label $s'_2 = (s_2, -0.3, -0.25)$, can be computed in the following way:

$$Sup_{s'_2} = Sup_{s_2} + \beta * Sup_{s_2} \quad \text{, with } Sup_{s_2} = c_{s_2} - a_{s_2}$$

In our case, the learning is applied to the level of linguistic partitions. In this way, the pair (X_j, label) takes the same tuning values in all the rules where it is considered. For example, X_j is (High, 0.3, 0.1) will present the same values for those rules in which the pair "X_j is High" was initially considered. Notice that, since symmetrical triangular MFs and a FITA (*First Infer, Then Aggregate*) fuzzy inference will be considered, a tuning of the amplitude of the consequents has no sense, by which the β parameter will be only applied on the antecedents.

In the context of the FLCs, we are going to see its use in the linguistic rule representation. Let us consider a control problem with two input variables, one

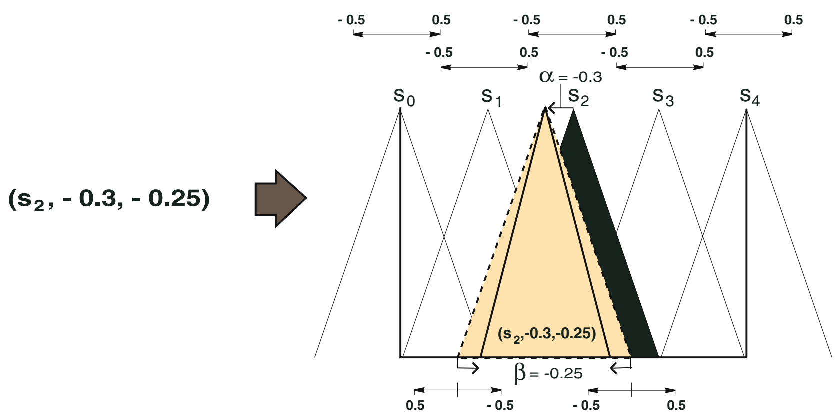

Fig. 2. LA-Variation of the MF Associated to s_2

output variable and a DB defined from experts determining the MFs for the following labels: $Error$ and $\bigtriangledown Error \rightarrow \{N, Z, P\}$, and $Power \rightarrow \{L, M, H\}$. Based on this DB definition, an example of a 3-tuples represented rule is:

If *Error* is (Zero,-0.3,0.1) and $\bigtriangledown$*Error* is (Positive,0.2,-0.4) then *Power* is (High,-0.1).

3.2 Rule Selection

Rule set reduction techniques try to minimize the number of rules of a given fuzzy rule-based system while maintain (or even improve) the system performance. To do that, erroneous and conflicting rules that degrade the performance are eliminated, obtaining a more cooperative fuzzy rule set and therefore involving a potential improvement of the system accuracy. Furthermore, in many cases the accuracy is not the only requirement of the model but also the interpretability becomes an important aspect. Reducing the model complexity is a way to improve the system readability, i.e., a compact system with few rules requires a minor effort to be interpreted.

Fuzzy rule set reduction is generally applied as a post-processing stage, once an initial fuzzy rule set has been derived. One of the most known fuzzy rule set reduction techniques is the rule selection. This approach involves obtaining an optimal subset of fuzzy rules from a previous fuzzy rule set by selecting some of them. We may find several methods for rule selection, with different search algorithms that look for the most successful combination of fuzzy rules [11, 12]. In [13], an interesting heuristic rule selection procedure is proposed where, by means of statistical measures, a relevance factor is computed for each fuzzy rule composing the fuzzy system to subsequently select the most relevant ones.

These kinds of techniques could be easily combined with other post-processing techniques to obtain more compact and accurate fuzzy models. In this way, some works have considered the rule selection together with the tuning of MFs by coding all of them (rules and parameters) in the same chromosome [7]. In this work, we combine the rule selection with the LA-tuning of MFs.

4 Algorithm for LA-Tuning and Rule Selection

To perform the LA-tuning together with the rule selection we consider a Genetic Algorithm (GA) based on the well-known steady-state approach. The steady-state approach [14] consists of selecting two of the best individuals in the population and combining them to obtain two offspring. These two new individuals are included in the population replacing the two worst individuals if the former are better adapted than the latter. An advantage of this technique is that good solutions are used as soon as they are available. Therefore, the convergence is accelerated while the number of evaluations needed is decreased.

In the following, the components needed to design this process are explained. They are: chromosome evaluation, coding scheme and initial gene pool, the genetic operators and a restarting approach to avoid premature convergence.

4.1 Evaluating the Chromosome

The fitness function (see Section 2.1) has been modified in order to consider the use of fuzzy goals that decrement the importance of each individual fitness value whenever it comes to its respective goal or that penalize each objective whenever its value is worse with respect to the initial solution. To do so, a function modifier parameter is considered, $\delta_i(x)$. A penalization rate, p_i, has been included in $\delta_i(x)$, allowing the user to set up priorities in the objectives (0 less priority and 1 more priority). With g_i being the goal value, i_i being the initial solution value and $q_i = max(g_i, i_i)$, the global fitness is evaluated as:

$$F' = \sum_{i=1}^{5} w_i^O \cdot \delta_i(O_i) \cdot O_i \ \ , \ \ with \quad \delta_i(x) = \begin{cases} 0, & \text{if } x \leq g_i \\ \dfrac{x - g_i}{i_i - g_i}, & \text{if } g_i < x < i_i \\ \dfrac{x - q_i}{x - x \cdot p_i} + 1, & \text{if } x \geq q_i \end{cases} .$$

4.2 Coding Scheme and Initial Gene Pool

To combine the rule selection with the LA-tuning, a double coding scheme for both *rule selection* (C_S) and *LA-tuning* (C_T) is used:

- For the C_S part, the coding scheme generates binary-coded strings of length m (with m being the number of fuzzy rules in the existing FLC). Thus, the corresponding part C_S^p for the p-th chromosome will be a binary vector that determines when a rule is selected or not (values '1' and '0' respectively),

$$C_S^p = (c_{S1}^p, \ldots, c_{Sm}^p) \mid c_{Si}^p \in \{0, 1\} \ .$$

- For the C_T part, a real coding is considered, i.e., the real parameters are the GA representation units (genes). This part is the joint of the parameters of the fuzzy partitions, lateral (C^L) and amplitude (C^A) tuning. Let us consider the following number of labels per variable: $(m^1, \ldots, m^n)$, with n being the number of system variables ($n-1$ input variables and 1 output variable). Then, a chromosome has the following form,

$$\begin{aligned} C_T = (C^L + C^A) = (&c_{11}^L, \ldots, c_{1m^1}^L, \ldots, c_{n1}^L, \ldots, c_{nm^n}^L) \ + \\ &(c_{11}^A, \ldots, c_{1m^1}^A, \ldots, c_{(n-1)1}^A, \ldots, c_{(n-1)m^n}^A). \end{aligned}$$

Finally, a chromosome C^p is coded in the following way: $C^p = C_S^p C_T^p$.

To make use of the available information, the initial FLC obtained from expert knowledge is included in the population as an initial solution. To do so, the initial pool is obtained with first individual having all genes with value '1' in the C_S part and having all genes with value '0.0' (no displacement or amplitude variation) in the C_T part. The remaining individuals are generated at random.

4.3 Genetic Operators

The crossover operator will depend on the chromosome part where it is applied:

- For the C_T part, the BLX-α crossover [6] and a hybrid between a BLX-α and an arithmetical crossover [8] are considered. In this way, if two parents, $C_T^v = (c_{T1}^v, \ldots, c_{Tk}^v, \ldots, c_{Tg}^v)$ and $C_T^w = (c_{T1}^w, \ldots, c_{Tk}^w, \ldots, c_{Tg}^w)$, are going to be crossed, two different crossovers are considered,
  1. Using the BLX-α crossover [6] (with $\alpha = 0.3$), one descendent $C_T^h = (c_{T1}^h, \ldots, c_{Tk}^h, \ldots, c_{Tg}^h)$ is obtained, with c_{Tk}^h being randomly generated within the interval $[I_{L_k}, I_{R_k}] = [c_{min} - I \cdot \alpha, c_{max} + I \cdot \alpha]$, $c_{min} = min(c_{Tk}^v, c_{Tk}^w)$, $c_{max} = max(c_{Tk}^v, c_{Tk}^w)$ and $I = c_{max} - c_{min}$.
  2. The application of the arithmetical crossover [8] in the wider interval considered by the BLX-α, $[I_{L_k}, I_{R_k}]$, results in the next descendent:
  $$C_T^h \text{ with } c_{Tk}^h = aI_{L_k} + (1-a)I_{R_k},$$
  and with $a \in [0,1]$ randomly generated each time this operator is applied.
- In the C_S part, the standard two-point crossover is used.

Finally, four offspring are generated by combining the two ones from the C_S part with the two ones from the C_T part. The mutation operator flips the gene value in the C_S part but, to improve the convergence no mutation is considered in the C_T part. Once the mutation is applied on the four generated offspring, the resulting descendents are the two best of these four individuals.

4.4 Restart Approach

Finally, to get away from local optima, this algorithm uses a restart approach. Whenever the population converges to similar results (practically the same fitness value), the entire population but the best individual is randomly generated within the corresponding variation intervals. It allows the algorithm to perform a better exploration of the search space and to avoid getting stuck at local optima.

5 Experiments

To evaluate the goodness of the approach proposed (LA-tuning with rule selection), the HVAC problem is considered to be solved. The FLCs obtained from the proposed approach will be compared to the performance of a classic On-Off controller and to the performance of the initial FLC (provided by experts). *The goals and improvements will be computed with respect to this classical controller as done in the GENESYS* [3] *project.* The intention from experts was to try to have 10% energy saving (O_4) together with a global improvement of the system behavior compared to On-Off control. Comfort parameters could be slightly increased if necessary (no more than 1.0 for criteria O_1 and O_2). The methods considered in this study are shown in Table 1.

The values of the parameters used are: 31 individuals, 0.2 as mutation probability per chromosome (except for GL and GLA without mutation) and 0.35

Table 1. Methods Considered for Comparison

Method, Ref.	**Year**	**Description**
S, [4]	2005	Rule Selection (C_S part of GLA-S)
CL, [1]	2003	Classical Tuning
GL, [2]*	2004	Global Lateral-tuning (C^L part of GLA-S)
CL-S, –	–	Classical Tuning (CL) + Rule Selection (S)
GL-S, –	–	Global Lateral-tuning (GL) + Rule Selection(S)
GLA, –	–	Global LA-tuning (C_T part of GLA-S)
GLA-S, –	–	Global LA-Tuning + Rule Selection

* The global lateral tuning proposed in [2] adapted to this problem.

Table 2. Comparison among the different methods

MODEL	#R	PMV O_1	O_2	CO_2 O_3	Energy O_4	%	Stability O_5	%
ON-OFF	–	0.0	0	0	3206400	–	1136	–
Initial FLC	172	0.0	0	0	2901686	9.50	1505	-32.48
$\overline{S}$	160	0.1	0	0	2886422	9.98	1312	-15.52
$\overline{C}$	172	0.0	0	0	2586717	19.33	1081	4.84
$\overline{C-S}$	109	0.1	0	0	2536849	20.88	1057	6.98
$\overline{GL}$	172	0.9	0	0	2325093	27.49	1072	5.66
$\overline{GL-S}$	113	0.7	0	0	2287993	28.64	800	29.58
$\overline{GLA}$	172	0.9	0	0	2245812	**29.96**	797	29.84
$\overline{GLA-S}$	**104**	0.8	0	0	2253996	29.70	634	**44.19**

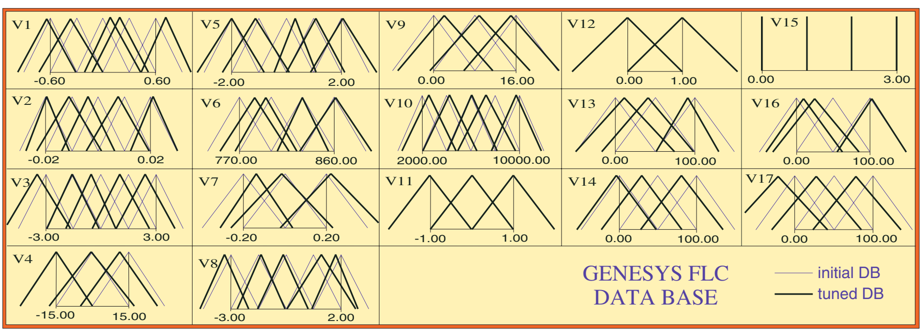

Fig. 3. Initial and Tuned DB of a Model Obtained with GLA-S (seed 1)

as factor a in the max-min-arithmetical crossover in the case of CL. The termination condition is to reach 2000 evaluations. To see the GA convergence, three runs have been performed with different seeds for the random number generator.

The results presented in Table 2 correspond to averaged results obtained from the three different runs, where % stands for the improvement rate with respect to the On-Off controller and #R for the number of rules. No improvement

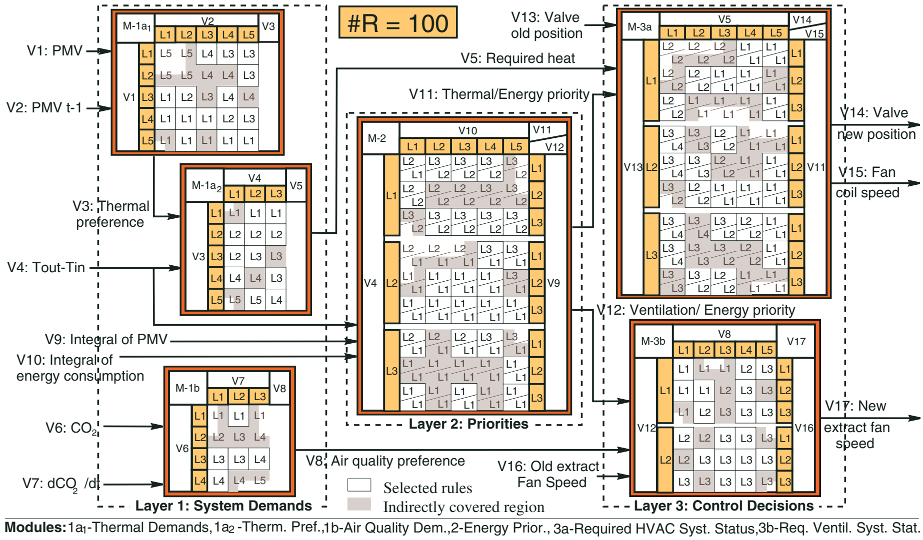

Fig. 4. RB and final structure of a Model Obtained with GLA-S (seed 1)

percentages have been considered in the table for $O_1 \ldots O_3$, since these objectives always met the experts requirements (goals). A good trade-off between energy and stability was achieved by GLA-S. GLA-S presents improvement rates of about a 29.7% in energy and about a 44.2% in stability, with the remaining criteria for comfort and air quality within the requested levels. Moreover, the proposed algorithm presented a good convergence and seems to be robust.

Figure 3 depicts the initial and final DB of a FLC obtained by GLA-S (seed 1). It shows that not so strong variations in the MFs can involve important improvements. Figure 4 represents the corresponding decision tables (GLA-S, seed 1). In this case, a large number of rules have been removed from the initial FLC, obtaining much simpler models (72 rules were removed). This fact improves the system readability, and allows us to obtain simple and accurate FLCs.

6 Concluding Remarks

In this work, we propose the use and combination of the LA-tuning with the rule selection to obtain accurate FLCs dedicated to the control of HVAC systems. Techniques based on the LA-tuning, specially that including rule selection, have yielded much better results than the remaining approaches, showing their good behavior on these kinds of complex problems. It is due to the following reasons:

– The search space reduction that the LA-tuning involves in complex problems. It allows to these techniques to obtain more optimal FLCs.
– The complementary characteristics that the tuning approaches and the rule selection present. The ability of the rule selection to reduce the number of rules by only selecting those presenting a good cooperation is combined with the tuning accuracy improvement, obtaining accurate and compact FLCs.

As further work, we propose the use of multiobjective GAs in order to obtain even simpler FLCs maintaining a similar accuracy.

References

1. Alcalá R., Benítez J.M., Casillas J., Cordón O., Pérez R.: Fuzzy control of HVAC systems optimized by genetic algorithms. Applied Intelligence **18** (2003) 155–177
2. Alcalá R., Herrera F.: Genetic tuning on fuzzy systems based on the linguistic 2-tuples representation. Proc. of the IEEE Int. Conf. on Fuzzy Syst. **1** (2004) 233–238
3. Alcalá R., Alcalá-Fdez J., Gacto M.J., Herrera F.: Genetic lateral and amplitude tuning of membership functions for fuzzy systems. Proc. of the 2nd Int. Conf. on Machine Intelligence (ACIDCA-ICMI'2005) 589–595
4. Alcalá R., Casillas J., Cordón O., González A., Herrera F.: A genetic rule weighting and selection process for fuzzy control of HVAC systems. Engineering Applications of Artificial Intelligence **18:3** (2005) 279–296
5. Calvino F., Gennusa M.L., Rizzo G., Scaccianoce G.: The control of indoor thermal comfort conditions: introducing a fuzzy adaptive controller. Energy and Buildings **36** (2004) 97–102
6. Eshelman L.J., Schaffer J.D.: Real-coded genetic algorithms and interval-schemata. Foundations of Genetic Algorithms **2** (1993) 187–202.
7. Gómez-Skarmeta A.F., Jiménez F.: Fuzzy modeling with hybrid systems. Fuzzy Sets Syst. **104** (1999) 199–208
8. Herrera F., Lozano M., Verdegay J.L.: Fuzzy connectives based crossover operators to model genetic algorithms population diversity. Fuzzy Sets Syst. **92:1** (1997) 21–30
9. Herrera F., Martńez L.: A 2-tuple fuzzy linguistic representation model for computing with words. IEEE T. Fuzzy Syst. **8:6** (2000) 746–752
10. Huang S., Nelson R.M.: Rule development and adjustment strategies of a fuzzy logic controller for an HVAC system - Parts I and II (analysis and experiment). ASHRAE Trans. **100:1** (1994) 841–850, 851–856.
11. Ishibuchi H., Murata T., Türksen I.B.: Single-objective and two objective genetic algorithms for selecting linguistic rules for pattern classification problems. Fuzzy Sets Syst. **89:2** (1997) 135–150
12. Krone A., Krause H., Slawinski T.: A new rule reduction method for finding interpretable and small rule bases in high dimensional search spaces. Proc. of the IEEE Int. Conf. on Fuzzy Syst. **2** (2000) 693–699
13. Krone A., Taeger H.: Data-based fuzzy rule test for fuzzy modelling. Fuzzy Sets Syst. **123:3** (2001) 343–358
14. Whitley D., Kauth J.: GENITOR: A different genetic algorithm. Proc. of the Rocky Mountain Conf. on Artificial Intelligence (1988) 118–130