# Improving Fuzzy Rule-Based Decision Models by Means of a Genetic 2-Tuples Based Tuning and the Rule Selection*

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.** The use of knowledge-based systems can represent an efficient approach for system management, providing automatic control strategies with Artificial Intelligence capabilities. By means of Artificial Intelligence, the system is capable of assessing, diagnosing and suggesting the best operation mode. One important Artificial Intelligence tool for automatic control is the use of fuzzy logic controllers, which are fuzzy rule-based systems comprising the expert knowledge in form of linguistic rules. These rules are usually constructed by an expert in the field of interest who can link the facts with conclusions. However, this way to work sometimes fails to obtain an optimal behavior. To solve this problem, within the framework of Machine Learning, some artificial intelligence techniques could be applied to enhance the controller behavior.

In this work, a post-processing method is used to obtain more compact and accurate fuzzy logic controllers. This method combines a new technique to perform an evolutionary lateral tuning of the linguistic variables with a simple technique for rule selection (that removes unnecessary rules). To do so, the tuning technique considers a new rule representation scheme by using the linguistic 2-tuples representation model which allows the lateral variation of the involved linguistic labels.

## 1 Introduction

The use of knowledge-based systems can represent an efficient approach for system management, providing automatic control strategies with Artificial Intelligence capabilities. By means of Artificial Intelligence, the system is capable of assessing, diagnosing and suggesting the best operation mode. One important Artificial Intelligence tool for automatic control is the use of Fuzzy Logic Controllers (FLCs). FLCs are Fuzzy Rule-Based Systems (FRBSs) comprising the expert knowledge in form of linguistic rules. These rules are usually constructed by an expert in the field of interest who can link the facts or evidence with conclusions. When a real-world situation is presented to the computer, it can

* Supported by the Spanish Ministry of Science and Technology under Project TIC-2002-04036-C05-01.

V. Torra et al. (Eds.): MDAI 2006, LNAI 3885, pp. 317–328, 2006.

use these rules to draw conclusions based on different situations in the way an expert would. However, this way to work sometimes fails to obtain an optimal behavior. To solve this problem, within the framework of Machine Learning, some Artificial Intelligence techniques could be successfully applied to enhance the controller behavior.

Recently, to improve the behavior of FRBSs, a new linguistic rule representation model was proposed to perform a genetic lateral tuning of Membership Functions (MFs) [2]. This new approach was based on the linguistic 2-tuples representation [10], that allows the symbolic translation of a label by considering an unique parameter per label. It involves a reduction of the search space that eases the derivation of optimal models respect to the classical tuning.

On the other hand, rule selection methods directly select a subset of rules from a given fuzzy rule set in order to minimize the number of rules, maintaining the system performance [9, 12, 13, 14]. The combination of the lateral tuning with rule selection methods can present a positive synergy, reducing the tuning search space, easing the system readability and even improving the system accuracy.

In this work, we present a study of how this new tuning approach can be combined with a rule selection method to improve fuzzy rule-based decision models obtained from the experts's experience. To do that, we propose an evolutionary method combining these two approaches to obtain more compact and accurate FLCs. Additionally, we analyze the positive synergy between both techniques, showing its behavior by solving a real-world problem for the control of a Heating, Ventilating and Air Conditioning (HVAC) system.

This paper is arranged as follows. The next section presents the lateral tuning and rule selection techniques. Section 3 describes the evolutionary algorithm for the global lateral tuning and rule selection. Section 4 presents the HVAC system control problem. Section 5 shows an experimental study of the method behavior applied to the HVAC problem. Finally, Section 6 points out some conclusions.

## 2 Lateral Tuning and Rule Selection

This section introduces the global lateral tuning of MFs and presents the basics and characteristics of the rule selection technique.

### 2.1 Lateral Tuning of Membership Functions

In [2], a new model of tuning of FRBSs was proposed considering the linguistic 2-tuples representation scheme introduced in [10], which allows the lateral displacement of the support of a label and maintains the interpretability associated to the obtained linguistic FRBSs. This proposal also introduces a new model for rule representation based on the concept of symbolic translation [10].

The symbolic translation of a linguistic term is a number within the interval [-0.5, 0.5), expressing this interval the domain of a label when it is moving between its two adjacent lateral labels (see Figure 1.a). Let us consider a set of labels $S$

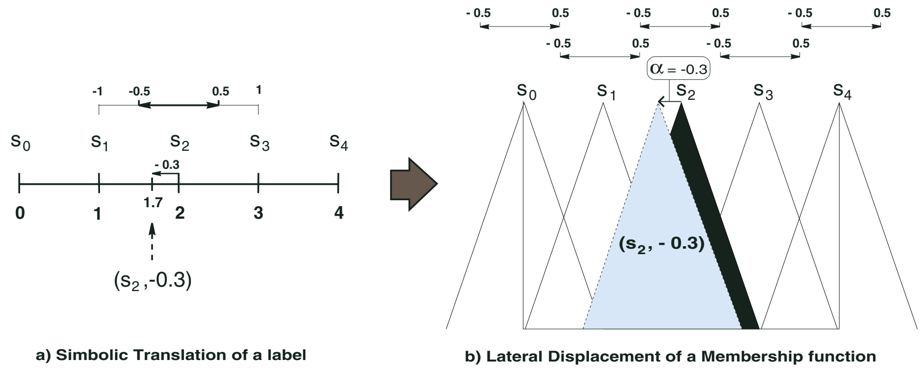


**Fig. 1.** Symbolic Translation of a Linguistic Label and Lateral Displacement of the involved MF

representing a fuzzy partition. Formally, to represent the symbolic translation of a label in $S$ we have the 2-tuple,

$$(s_i, \alpha_i), \ \ s_i \in S, \ \ \alpha_i \in [-0.5, 0.5).$$

Actually, the symbolic translation of a label involves the lateral displacement of its associated MF. As an example, Figure 1 shows the symbolic translation of a label represented by the pair $(s_2, -0.3)$ together with the lateral displacement of the corresponding MF.

In the context of the FRBSs, we are going to see its use in the linguistic rule representation. Let us consider a control problem with two input variables, one output variable and a Data Base (DB) defined from experts determining the MFs for the following labels:

$$Error, \ \triangledown Error \rightarrow \{N, Z, P\}, \ Power \rightarrow \{L, M, H\} \ .$$

Based on this DB definition, an example of classical rule and linguistic 2-tuples represented rule is:

*Classical Rule*,

If **error** is Zero and $\triangledown$**Error** is Positive then **Power** is High.

*Rule with 2-Tuples Representation*,

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

In [2], two different rule representation approaches were proposed, a global approach and a local approach. In our particular case, the learning is applied to the level of linguistic partitions (global approach). In this way, the pair ($X_i$, label) takes the same $\alpha$ value in all the rules where it is considered, i.e., a global collection of 2-tuples is considered by all the fuzzy rules. For example, $X_i$ is (High, 0.3) will present the same value for those rules in which the pair "$X_i$ is High" was initially considered. Since the 3 parameters usually considered per label are reduced to only 1 symbolic translation parameter, this proposal decreases the learning problem complexity easing indeed the derivation of optimal models. Other important issue is that, from the parameters $\alpha$ applied to each label, we could obtain the equivalent triangular MFs, by which a FRBS based on linguistic 2-tuples could be represented as a classical Mamdani FRBS.

### 2.2 The Rule Selection Technique

Rule set reduction techniques try to minimize the number of rules of a given FRBS 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 [9, 12, 13]. In [14], 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 FRBSs to subsequently select the most relevant ones.

These kinds of techniques for rule selection could be easily combined with other post-processing techniques to obtain more compact and accurate FRBSs. In this way, some works have considered the selection of rules together with the tuning of MFs by coding all of them (rules and parameters) in the same chromosome [5, 7]. In this work, we propose the combination of the rule selection with the lateral tuning of MFs.

## 3 Algorithm for the Lateral Tuning and Rule Selection

To perform the lateral tuning together with the rule selection we consider a Genetic Algorithm (GA) based on the well-known steady-state approach. The steady-state approach [15] 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: coding scheme and initial gene pool, chromosome evaluation, the genetic operators and a restarting approach to avoid premature convergence.

### 3.1 Coding Scheme and Initial Gene Pool

To combine the rule selection with the global lateral tuning, a double coding scheme for both *rule selection* ($C_S$) and *lateral 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 FRBS, obtained from expert knowledge). Depending on whether a rule is selected or not, the alleles '1' or '0' will be respectively assigned to the corresponding gene. Thus, the corresponding part $C_S^p$ for the $p$-th chromosome will be a binary vector representing the subset of rules finally obtained,

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

- 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 $\alpha$ parameters of each fuzzy partition. Let us consider the following number of labels per variable: $(m^1, m^2, \ldots, m^n)$, with $n$ being the number of system variables. Then, a chromosome has the following form (where each gene is associated to the tuning value of the corresponding label),

$$C_T = (c_{11}, \ldots, c_{1m^1}, c_{21}, \ldots, c_{2m^2}, \ldots, c_{n1}, \ldots, c_{nm^n}).$$

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 FRBS previously 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' in the $C_T$ part. The remaining individuals are generated at random.

### 3.2 Evaluating the Chromosome

The fitness function depends on the problem being solved (see Section 4.1).

### 3.3 Genetic Operators

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

- For the $C_T$ part, the BLX-$\alpha$ crossover [6] and a hybrid between a BLX-$\alpha$ 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-$\alpha$ crossover [6] (with $\alpha$ being a constant parameter chosen by the GA designer), 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-$\alpha$, $[I_{L_k}, I_{R_k}]$, results in the next descendent:
$$C_T^h \text{ with } c_{Tk}^h = aI_{L_k} + (1-a)I_{R_k},$$
with $a \in [0,1]$ being a random parameter generated each time this crossover operator is applied. In this way, this operator performs the same gradual adaptation in each gene, which is a good characteristic.

– 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 and no mutation is considered in $C_T$ part, in order to improve the algorithm convergence. In this way, once the mutation operator is applied over the four offspring obtained from the crossover, the resulting descendents are the two best of these four individuals.

### 3.4 Restarting Approach

Finally, to get away from local optima, this algorithm uses a restart approach. Thus, when the population of solutions converges to very similar results (practically the same fitness value in all the population), 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.

## 4 The HVAC System Control Problem

In EU countries, primary energy consumption in buildings represents about 40% of total energy consumption and more than a half of this energy is used for indoor climate conditions. On a technological point of view, it is estimated that the consideration of specific technologies like Building Energy Management Systems (BEMSs) can save up to 20% of the energy consumption of the building sector, i.e., 8% of the overall Community consumption. With this aim, BEMSs are generally applied only to the control of active systems, i.e., HVAC systems.

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 2, 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.

The energy consumption as well as indoor comfort aspects of ventilated and air conditioned buildings are highly dependent on the design, performance and control of their HVAC systems and equipments. Therefore, the use of appropriate automatic control strategies, as FLCs, for HVAC systems control could result in important energy savings when compared to manual control [1, 11].

Some artificial intelligence techniques could be successfully applied to enhance the HVAC system capabilities [4, 11]. However, most works apply FLCs

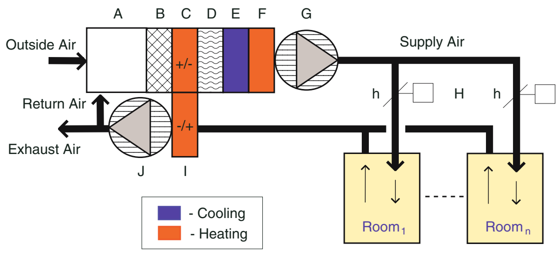


**Fig. 2.** Generic structure of an office building HVAC system

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 [11]. 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 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 the application of the proposed technique for the lateral tuning of the MFs 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. From now on, this test building will be called the GENESYS test site.

In the following subsections the five different objectives and the final fitness function to be optimized will be presented together with the initial FLC architecture and variables (see [1] for more information on this problem).

### 4.1 Objectives and Fitness Function

*Our main optimization objective is the energy performance but maintaining the required indoor comfort levels*. In this way, the global objective is to *minimize* the following five criteria:

- $\mathbf{O_1}$ Upper thermal comfort limit: $if\ PMV > 0.5,\ O_1 = O_1 + (PMV - 0.5)$, where 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[2].
- $\mathbf{O_2}$ Lower thermal comfort limit: $if\ PMV < -0.5,\ O_2 = O_2 + (-PMV - 0.5)$.
- $\mathbf{O_3}$ Indoor air quality requirement: $if\ CO_2\ conc. > 800ppm,\ O_3 = O_3 + (CO_2 - 800)$.

[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).

[2] http://www.iso.org/iso/en/ISOOnline.frontpage

**$O_4$** 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 change states for a change in the system operation, e.g., a change in the fan speed or valve position.

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:

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

## 4.2 FLC Variables and Architecture

A hierarchical FLC architecture considering the PMV, $CO_2$ concentration, previous HVAC system status and outdoor temperature was proposed by the BEMS designer for this site. This architecture, variables and initial Rule Base (RB) are presented in Figure 3.

The DB is composed of symmetrical fuzzy partitions with triangular-shaped MFs labeled from $L1$ to $Ll_i$ (with $l_i$ being the number of labels of the $i$-th

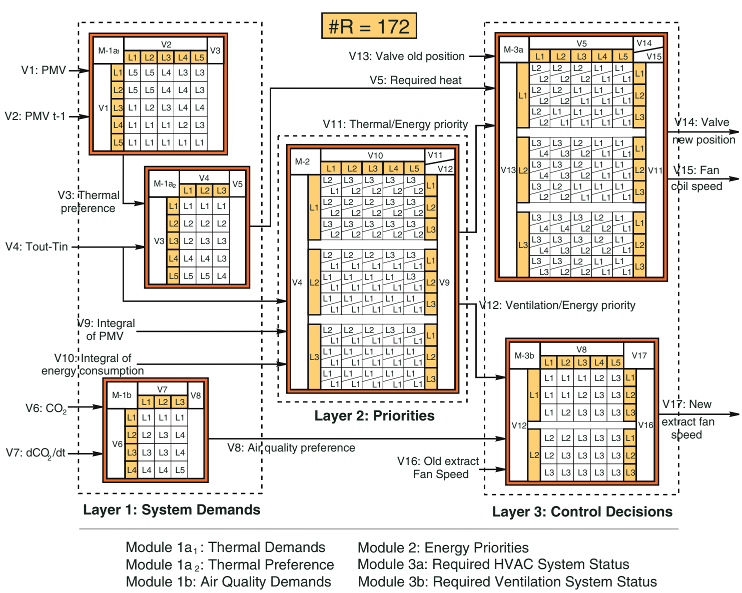


**Fig. 3.** Initial RB and generic structure of the GENESYS FLC

variable). The initial DB is depicted in Figure 4 together with the tuned DB. Figure 3 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 the DB, were provided by the BEMS designer.

## 5 Experiments

To evaluate the goodness of the approach proposed (global lateral 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.

**Table 1.** Methods Considered for Comparison

| Method, Ref. | Year | Description |
|---|---|---|
| **S**, [3] | 2005 | Rule Selection ($C_S$ part of GL-S) |
| **CL**, [1] | 2003 | Classical Tuning |
| **GL**, [2]* | 2004 | Global Lateral-Tuning ($C_T$ part of GL-S) |
| **CL-S**, – | – | Classical Tuning (CL) + Rule Selection (S) |
| **GL-S**, – | – | The proposed method |

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

The values of the parameters used in all of these experiments are presented as follows: 31 individuals, 0.2 as mutation probability per chromosome (except for the lateral tuning which has no mutation), 0.3 for the factor $\alpha$ in the hybrid crossover operator and 0.35 as factor $a$ in the max-min-arithmetical crossover in the case of CL. The termination condition will be the development of 2000 evaluations, in order to perform a fair comparative study. In order to evaluate the GA good convergence, three different runs have been performed considering three different seeds for the random number generator.

The results presented in Table 2, where % stands for the improvement rate with respect to the On-Off controller for each criterion and #R for the number of fuzzy rules, correspond to averaged results obtained from the three different runs. The results obtained with the On-Off and the initial FLC controller are also included in this table. No improvement percentages have been considered in the table for $O_1 \ldots O_3$, since these objectives always met the experts requirements and the On-Off controller presents zero values for these objectives.

**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 | – |
| 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 |
| $\overline{GL}$ | 172 | 0.9 | 0 | 0 | 2325093 | 27.49 | 1072 | 5.66 |
| $\overline{C-S}$ | 109 | 0.1 | 0 | 0 | 2536849 | 20.88 | 1057 | 6.98 |
| $\overline{GL-S}$ | 113 | 0.7 | 0 | 0 | 2287993 | **28.64** | 800 | **29.58** |

A good trade-off between energy and stability was achieved for all the models obtained from GL-S, maintaining the remaining criteria within the optimal values. GL-S presents improvement rates of about a 28.6% in energy and about a 29.6% in stability, with the remaining criteria for comfort and air quality within the requested levels. Moreover, the proposed algorithm presents a good convergence and seems to be independent of random factors.

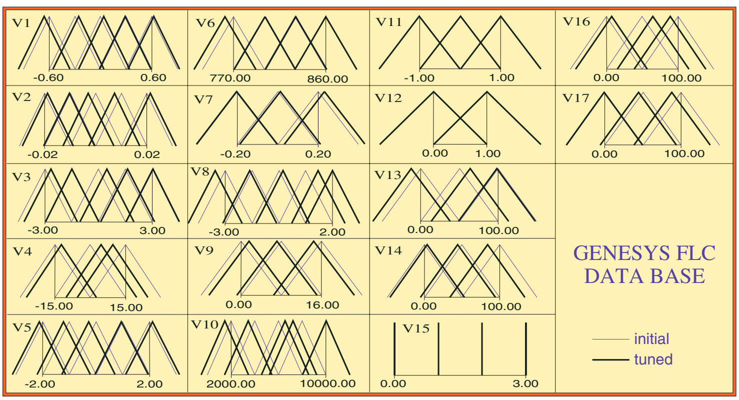


**Fig. 4.** Initial and Tuned DB of a Model Obtained with GL-S (Seed 1)

Figure 4 represents the initial and the final DB of the FLC obtained by GL-S with seed 1. It shows that small variations in the MFs cause large improvements in the FLC performance. Figure 5 represents the decision tables of the FLC obtained from GL-S1 (see Section 4.2). In this case, a large number of rules have been removed from the initial FLC, obtaining much simpler models (more or less 59 rules were eliminated). This fact improves the system readability, and allows us to obtain simple and accurate FLCs.

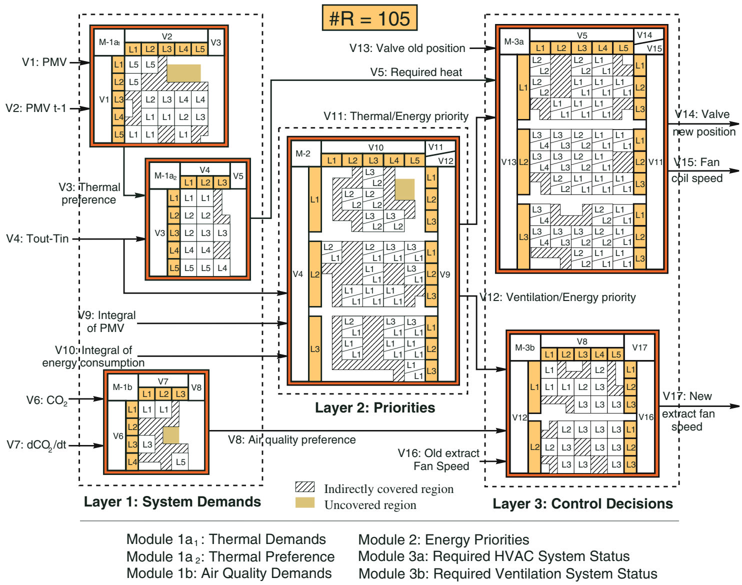


**Fig. 5.** RB and final structure of a FLC Obtained with GL-S (seed 1)

## 6 Concluding Remarks

In this work, we propose the use of a global lateral tuning together with the rule selection to obtain FRBSs to aid the BEMS expert in the control of HVAC Systems. The techniques based on lateral 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 lateral tuning involves in complex problems. It allows to these techniques to obtain more optimal FLCs.
– The complementary characteristics that the use of the tuning approaches and the rule selection approach present. The ability of the rule selection to reduce the number of rules by only selecting the rules 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 and 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., 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
4. 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
5. Casillas J., Cordón O., del Jesus M.J., Herrera F.: Genetic tuning of fuzzy rule deep structures preserving interpretability and its interaction with fuzzy rule set reduction. IEEE T. Fuzzy Syst. **13:1** (2005) 13–29
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., Lozano M., Verdegay J.L.: A learning process for fuzzy control rules using genetic algorithms. Fuzzy Sets Syst. **100** (1998) 143–158
10. Herrera F., Martńez L.: A 2-tuple fuzzy linguistic representation model for computing with words. IEEE T. Fuzzy Syst. **8:6** (2000) 746–752
11. 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.
12. 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
13. 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
14. Krone A., Taeger H.: Data-based fuzzy rule test for fuzzy modelling. Fuzzy Sets Syst. **123:3** (2001) 343–358
15. Whitley D., Kauth J.: GENITOR: A different genetic algorithm. Proc. of the Rocky Mountain Conf. on Artificial Intelligence (1988) 118–130