Fuzzy Rule Reduction and Tuning of Fuzzy Logic Controllers for a HVAC System*

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Summary. Heating, Ventilating and Air Conditioning (HVAC) Systems are equipments usually implemented for maintaining satisfactory comfort conditions in buildings. The design of Fuzzy Logic Controllers (FLCs) for HVAC Systems is usually based on the operator's experience. However, an initial rule set drawn from the expert's experience sometimes fail to obtain satisfactory results, since inefficient or redundant rules are usually found in the final Rule Base. Moreover, in our case, the system being controlled is too complex and an optimal controller behavior is required.

Rule selection methods directly obtain a subset of rules from a given fuzzy rule set, removing inefficient and redundant rules and, thereby, enhancing the controller interpretability, robustness, flexibility and control capability. On the other hand, different parameter optimization techniques could be applied to improve the system accuracy by inducing a better cooperation among the rules composing the final Rule Base.

In this chapter, we present a study of how several tuning approaches can be applied and combined with a rule selection method to obtain more compact and accurate FLCs concerning energy performance and indoor comfort requirements of a HVAC system. This study has been performed considering a physical modelization of a real test environment.

Keywords: HVAC systems; Fuzzy logic controller; tuning approaches ; rule selection methods; parameter optimization techniques.

1 Introduction

HVAC Systems are equipments usually implemented for maintaining satisfactory comfort conditions in buildings. 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

* Supported by the Spanish CICYT Project TIC-2002-04036-C05-01 (KEEL).

R. Alcalá et al.: *Fuzzy Rule Reduction and Tuning of Fuzzy Logic Controllers for a HVAC System*, StudFuzz **201**, 89–117 (2006)
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equipments. Therefore, the use of appropriate automatic control strategies, as FLCs [18, 38, 39], for HVAC systems control could result in important energy savings when compared to manual control, specially when they explicitly try to minimize the energy consumption [1, 5, 31, 43].

In current systems [5, 7, 22, 31, 37, 43, 44, 51, 52], several criteria are individually considered, thermal regulation, energy consumption or comfort improvement (the next section includes a deeper explanation of these works). However, different criteria must be considered jointly in order to reduce the energy consumption maintaining a desired comfort level. In our case, five criteria will be optimized and 17 variables are considered by the FLC. Furthermore, control systems in buildings are often designed using rules of thumb not always compatible with the controlled equipment requirements and energy performance. Therefore, the different involved criteria should be optimized for a good performance of the HVAC system.

A way to solve these problems is removing rules that degrade the system behavior [32, 33, 36] (*rule selection* methods). Other technique that improves the FLC performance is the tuning of parameters. Two different tuning approaches could be considered:

- *The classical tuning*: This approach consists of a tuning of the parameters that define the linguistic labels [24, 28, 34, 35, 40]. In this way, considering triangular-shaped membership functions three parameters are optimized.
- *The lateral tuning*: This technique was presented in [4], to reduce the size of the search space in complex problems, since the 3 parameters considered per label are reduced to only one symbolic translation parameter.

The smart combination of rule selection with tuning techniques can improve even more the system behavior [3, 23]. In this work, we present a study of how these tuning approaches can be applied and combined with a rule selection method to obtain more compact and accurate FLCs concerning energy performance and indoor comfort requirements of a HVAC system.

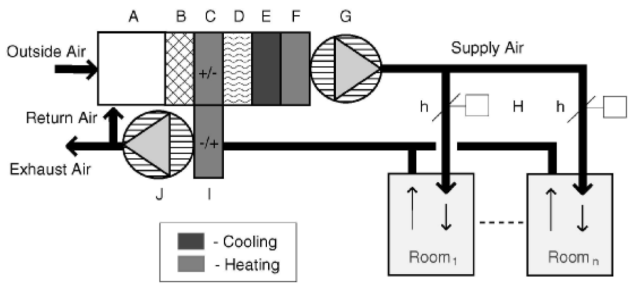
This contribution is arranged as follows. In the next section, the basics of the HVAC systems control problem are presented, studying how FLCs can be applied to it. In Section 3, the proposed real test site and the control objectives are introduced, establishing the concrete problem that will be solved. Section 4 introduces the rule selection, the classical and the lateral tuning. Section 5 describes the different evolutionary post-processing algorithms. Experimental results are shown in Section 6. Finally, Section 7 points out some conclusions.

2 Heating, Ventilating, and Air Conditioning Systems

A HVAC system is comprised by all the components of the appliance used to condition the indoor 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. Therefore, in a quiet and energy-efficient way at low life-cycle cost, a HVAC system should achieve two main tasks:

- To dilute and remove emission from people, equipment and activities and to supply clean air (Indoor Air Quality).
- To maintain a good thermal quality (Thermal Climate).

There are no statistical data collected on types and sizes of HVAC systems delivered to each type of building in different European countries. Therefore, to provide a HVAC system compatible with the ambiance is a task of the Building Energy Management System (BEMS) designer depending on its own experience. 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.



A - This module mixes the return and the outside air to provide supply air, and also closes outside air damper and opens return air damper when fan stops. **B** - It is a filter to reduce the outside air emissions to supply air. **C** - The preheater/heat recovery unit preheats the supply air and recovers energy from the exhaust air. **D** - A humidifier raising the relative humidity in winter. **E** - This is a cooler to reduce the supply air temperature and/or humidity. **F** - An after-heater unit to raise the supply air temperature after humidifier or to raise the supply air temperature after latent cooling (dehumidifier). **G** - The supply air fan. **H** - The dampers to demand controlled supply air flow to rooms. **I** - It is a heat recovery unit for energy recovery from exhaust air. **J** - The exhaust air fan.

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

2.1 The HVAC System Control Problem

Temperature and relative humidity are essential factors in meeting physiological requirements. When temperature is above or below the comfort range, the environment disrupts person's metabolic processes and disturbs his activities.

Therefore, a HVAC system is essential to a building in order to keep occupants comfortable. A well-designed operated, and maintained HVAC system is essential for a habitable and functional building environment. Outdated, inappropriate, or misapplied systems result in comfort complaints, indoor air quality issues, control problems, and exorbitant utility costs. Moreover, many

HVAC systems do not maintain an uniform temperature throughout the structure because those systems employ unsophisticated control algorithms. In a modern intelligent building, a sophisticated control system should provide excellent environmental control [5].

Within this framework (building automation), the objective of a global controller is to maintain the indoor environment within the desired (or stipulated) limits. In our case, to maintain environmental conditions within the comfort zone and to control the indoor air quality. Furthermore, other important objectives are usually required, e.g, energy savings (our main objective), system stability, etc. In any case, numerous factors have to be considered in order to achieve these objectives. It makes the system being controlled very complex and present a strong non linearity.

To obtain an optimal controller, control and controlled parameters [2] have to be chosen regarding the control strategy being implemented, the technical feasibility of the measurements as well as economic considerations. Fortunately, the BEMS designer is usually able to determine these parameters.

In the following subsections, the most usually used control and controlled parameters are presented. The specific parameters considered in the test site (building) presented in this work will be selected among them in Section 3, where this site is introduced.

Control or explicit parameters: Controller's variables

To identify the FLC's variables, various (control or explicit) parameters may be considered depending on the HVAC system, sensors and actuators. Usually, these parameters are selected among the following ones:

- *Predicted Mean Vote (PMV) index for thermal comfort*: Instead of only using air temperature as a thermal comfort index, we could consider the more global PMV index selected by international standard organization ISO 7730 (http://www.iso.org/iso/en/ISOOnline.frontpage), incorporating relative humidity and mean radiant temperature.
- *Difference between supply and room temperatures*: Possible disturbances can be related to the difference between supply and mean air temperature. When ventilation systems are used for air conditioning, such a criterion can be important.
- *CO_2 concentration*: Indoor air quality was found to be critical. As CO_2 concentration is a reliable index of the pollution emitted by occupants, it can be selected as indoor air quality index. It is therefore supposed that

[2] Control or explicit parameters are variables which may be used as inputs or outputs for a control strategy (controller's variables), whilst controlled or implicit parameters are variables which are affected by the action of a controlled device, and may be considered in order to evaluate the performance of such controller (problem's objectives).

both the building and the HVAC system have been properly designed and that occupants actually are the main source of pollution.

- *Outdoor temperature*: Outdoor temperature also needs to be accounted for, since during mid-season periods (or even mornings in summer periods) its cooling (or heating) potential through ventilation can be important and can reduce the necessity of applying mechanical cooling (or heating).
- *HVAC system actuators*: They directly depends on the concrete HVAC system, e.g., valve positions, operating modes, fan speeds, etc.

Controlled or implicit parameters: Problem's objectives

To identify global indices for assessment of the indoor building environment, various (controlled or implicit) parameters may be measured depending on the objectives of the control strategy. In these kinds of problems, these parameters could be selected among:

- Thermal comfort parameters: Indoor climate control is one of the most important goals of intelligent buildings. Among indoor climate characteristics, thermal comfort is of major importance. This might include both global and local comfort parameters.
- Indoor air quality parameters: Indoor air quality is also of major concern in modern buildings. It is controlled either at the design stage by reducing possible pollutants in the room and during operation thanks to the ventilation system. As our work is dedicated to HVAC systems, indoor air quality is also an important parameter to account for.
- Energy consumption: If appropriate indoor air quality and thermal comfort levels have to be guaranteed in offices, this has to be achieved at a minimum energy cost. Therefore, energy consumption parameters would need to be incorporated.
- HVAC system status: A stable operation of the controlled equipments is necessary in order to increase life cycle and thus reduce the maintenance cost. Information of the status of the equipments at the decision time step or on a longer period must thus be considered.
- Outdoor climate parameters: Indoor conditions are influenced by outdoor conditions (air temperature, solar radiation, wind). Moreover, in an air distribution HVAC system, the power required to raise or lower the supply temperature is a function of outdoor temperature and humidity. Some of these parameters would thus need to be selected.

2.2 Fuzzy Control of HVAC Systems

Nowadays, there is a lot of real-world applications of FLCs like intelligent suspension systems, mobile robot navigation, wind energy converter control, air conditioning controllers, video and photograph camera autofocus and imaging stabilizer, anti-sway control for cranes, and many industrial automation applications [30].

In these kinds of problems (HVAC system controller design), various criteria are considered independently, thermal regulation, maintaining a temperature setpoint or range, which only considers implicit energy savings [5, 22, 31, 44, 51, 52]. In [7], the more global PMV is used to control thermal comfort (incorporating relative humidity and mean radiant temperature), but again it does not explicitly optimize the energy consumption, the system stability or the indoor air quality (CO_2 concentration). In [37], an adaptive neuro-fuzzy inference system (ANFIS) is employed to optimization of the system energy consuption by the control in-building section of HVAC system (indoor air loop and chilled water loop). In [43], a FLC involving 7 variables (5 inputs and 2 outputs) is optimized by means of an evolutionary algorithm to decrement the energy consumption and to maintain a temperature setpoint, which also set aside some important criteria.

However, in this work, various different criteria must be considered in order to reduce the energy consumption maintaining a desired comfort level. Therefore, many variables have to be considered from the controlled system, which makes the problem very complex. In our case, five criteria will be optimized and 17 variables are considered by the FLC.

In current systems, the Knowledge Base (KB) is usually constructed based on the operator's experience. However, FLCs sometimes fail to obtain satisfactory results with the initial rule set drawn from the expert's experience [31]. Moreover, in our case the system being controlled is too complex and optimal FLCs are required. Therefore, this approach needs of a modification of the initial KB to obtain an optimal controller with an improved performance.

Many different possibilities to improve Linguistic Fuzzy Modeling have been considered in the specialized literature [8]. They can also be applied to the framework of fuzzy control (e.g., a tuning on the semantics of a FLC previously obtained from human experience could be performed by modification of the Data Base components [1, 2]). All of these approaches share the common idea of improving the way in which the linguistic fuzzy model/controller performs the interpolative reasoning by inducing a better cooperation between the rules in the KB.

There are two of these approaches presenting complementary characteristics, the parameter tuning and the rule selection. In this work, we combines the tuning methods (classical and lateral tuning) with rule selection, which present a positive synergy, reducing the search space, easing the system readability and even improving the system accuracy.

On the other hand, to evaluate the FLC performance a physical modelization of the controlled buildings and equipments is usually needed. These models have been developed by BEMS designers using building simulation tools, and they are able to account for all the parameters considered in the control process. Thus, we will have the chance to evaluate the FLCs designed in the simulated system with the desired environmental conditions. In the same way, these system models can be used by the experts to validate the initial KB before the automatic optimization process. Besides, it is of major importance to assess the fitness function in this process.

3 The GENESYS Test Cell

Within the framework of the JOULE-THERMIE programme under the GENESYS [3] project, a real test site (building) provided by a French private enterprise —whose name must remain anonymous— was available for experimentation. From now on, this site will be called the GENESYS test site.

Located in France, this test environment consists of seven single zone test cells. Around the walls of these cells, an artificial climate can be created at any time (winter conditions can be simulated in summer and *viceversa*). The cells considered are medium weight constructions. Figure 2 illustrates this environment and presents its main characteristics. Two adjacent twin cells were available for our experiments, the cells number four and five. Both test cells were equipped with all sensors required according to the selected control and controlled parameters. The HVAC system tested was a fan coil unit supplied by a reverse-cycle heat pump, and a variable fan speed mechanical extract for ventilation.

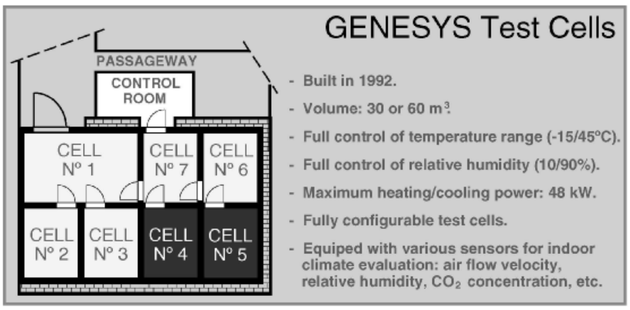


Fig. 2. Representation and main characteristics of the GENESYS test cells

The first task was to develop the thermal model of this test site. The main achievement was the development of a full monozone building model. This model was built from scratch within the Matlab-Simulink environment, being developed as a general purpose model which could be used for any other conditions, projects or applications in the future. However, in order to improve its performance, it was later customized to suit the GENESYS test site. The thermal simulation was based on finite-differences methods for the conduction

[3] 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).

model. The maximum value for the time-step of the simulation was calculated using the stability condition according to the discretization scheme. Simulation time step could be reduced to 60 seconds. Due to the relatively small thickness and large thermal conductivity of windows, the heat conduction model for the windows was considered constant. Convective heat exchanges were based on constant heat convection coefficients. Radiant temperature was calculated as a function of surface temperature, weighted by their relative area. The HVAC system model was based on manufacturers data and modules developed in the frame of *IEA (International Energy Agency) task 22* provided by the Royal Technical Institute of Stockholm.

Data were available and used for model calibration. The main problems in the calibration concerned the modelization of the HVAC equipment as well as solar radiation effects on internal heat gains. *The experimentation of this work has been performed considering the calibrated and validated GENESYS test cell simulation model.* Concretely, the GENESYS summer-season model.

3.1 Objectives and Fitness Function

As said, our main optimization objective was the energy performance but maintaining the required indoor comfort levels. Therefore, we should consider the development of a fitness function aiming at characterizing the performance of each tested controller towards thermal comfort, indoor air quality, energy consumption and system stability criteria. In this way, the global objective is to **minimize** the following five criteria:

O_1 Upper thermal comfort limit: $if\ PMV > 0.5, O_1 = O_1 + (PMV - 0.5)$.
O_2 Lower thermal comfort limit: $if\ PMV < -0.5, O_2 = O_2 + (-PMV - 0.5)$.
O_3 IAQ requirement: $if\ CO_2\ conc. > 800ppm, O_3 = O_3 + (CO_2 - 800)$.
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 change states for a change in the system operation, i.e., it counts the system operation changes (a change in the fan speed or valve position).

In our case, these criteria are combined into one overall objective function by means of a vector of weights. This technique (objective weighting) has much sensitivity and dependency toward weights. However, 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. Since trustworthy weights were obtained from experts, we followed this approach.

Hence, an important outcome was to assign appropriate weights to each criterion of the fitness function. The basic idea in this weight definition was to find financial equivalents for all of them. Such equivalences are difficult to define and there is a lack of confident data on this topic. Whereas energy consumption cost is easy to set, comfort criteria are more difficult. Recent studies have shown that a 18% improvement in people's satisfaction about indoor climate corresponds to a 3% productivity improvement for office workers. Based on typical salaries and due to the fact that PMV and CO_2 concentrations are related to people's satisfaction, such equivalences can be defined. The same strategy can be applied to the systems stability criterion, life-cycle of various systems being related to number of operations. Based on this, weights can be obtained for each specific building (test site). Thus, trusted weights for the GENESYS test cell objective weighting fitness function were obtained by the experts with the following values: $w_1^O = 0.0083022$, $w_2^O = 0.0083022$, $w_3^O = 0.00000456662$, $w_4^O = 0.0000017832$ and $w_5^O = 0.000761667$. Finally, the fitness function to be minimized was computed as:

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

3.2 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. The GENESYS summer-season FLC architecture, variables and initial Rule Base are presented in Figure 3 and Figure 4.

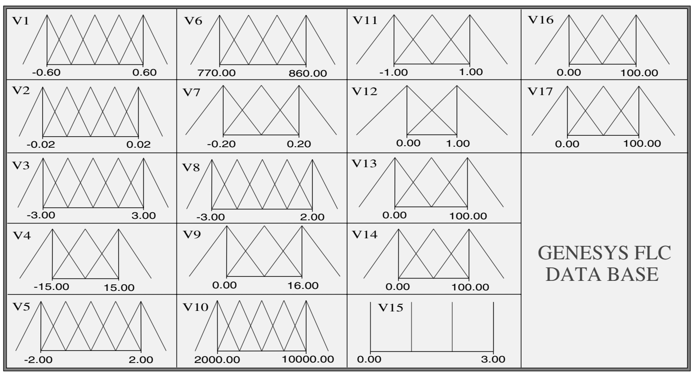


Fig. 3. Data Base of the GENESYS FLC

As Data Base, we considered symmetrical fuzzy partitions of triangular-shaped membership functions for each variable. These membership functions were labeled from $L1$ to Ll_i, with l_i being the number of membership functions of the i-th variable. Figure 3 depicts the Data Base. Both, the initial Rule Base and the Data Base, were provided by the BEMS designer.

Notice that, Figure 4 represents the decision tables of each module of the hierarchical FLC considered in terms of these labels. When the Rule Base considers more than two input variables (as in the case of modules M-2 in layer

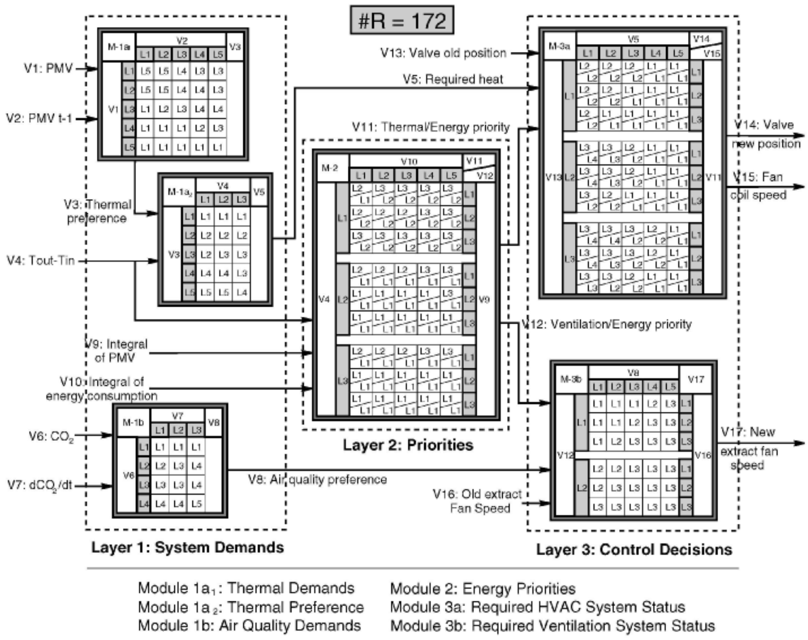


Fig. 4. Initial Rule Base and generic structure of the GENESYS FLC

2 and M-3a and M-3b in layer 3 where three input variables are involved), the three-dimensional table is decomposed into three two-dimensional decision tables (one for each possible label of the first variable) in order to clearly show its composition. Therefore, 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. Notice that, when there are two consequents, they are placed in the same cell (divided by a diagonal line).

4 Three Different Post-Processing Approaches

This section introduces the three different post-processing approaches considered in this work: rule selection, classical tuning and lateral tuning.

4.1 Rule Selection

In complex multidimensional problems with highly nonlinear input-output relations many redundant, inconsistent and conflicting rules are usually found in the obtained Rule Base (especially in the case when they are generated by only considering the expert's knowledge). On the other hand, in high-dimensional problems, the number of rules in the Rule Base grows exponentially as more inputs are added. A large rule set might contain many redundant, inconsistent and conflicting rules. These kinds of rules are detrimental to the FLC performance and interpretability.

Rule Selection methods directly aggregate multiple rules and/or select a subset of rules from a given fuzzy rule set in order to minimize the number of rules while at the same time maintaining (or even improving) the system performance [12, 13, 25, 47, 48, 49, 53]. Inconsistent and conflicting rules that degrade the performance are eliminated thus obtaining a fuzzy rule set with better cooperation. Using Genetic Algorithms (GAs) to search for an optimized subset of rules is motivated in the following situations:

- the integration of an expert rule set and a set of fuzzy rules extracted by means of automated learning methods [27],
- the selection of a cooperative set of rules from a candidate fuzzy rule set [14, 15, 16, 32, 33, 36],
- the selection of rules from a given KB together with the selection of the appropriate labels for the consequent variables [11],
- the selection of rules together with the tuning of membership functions by coding all of them (rules and parameters) in a chromosome [23], and
- the derivation of compact fuzzy models through complexity reduction combining fuzzy clustering, rule reduction by orthogonal techniques, similarity driving simplification and genetic optimization [45].

Two of them are of particular interest in our case, the second and the fourth. In this work, we propose the selection of a cooperative set of rules from a candidate fuzzy rule set together with the tuning of parameters coding all in a chromosome. This pursues the following aims:

- To improve the FLC accuracy selecting the set of rules best cooperating while a tuning of membership functions is performed.
- To obtain easily understandable FLCs by removing unnecessary rules.

4.2 Classical Tuning of Membership Functions

This approach, usually called data base tuning, involves refining the membership function shapes from a previous definition once the remaining FRBS components have been obtained [14, 24, 28, 34, 35, 40].

The classical way to refine the membership functions is to change their definition parameters. For example, if the following triangular-shape membership function is considered:

$$\mu(x) = \begin{cases} \frac{x-a}{b-a}, \text{ if } a \le x < b \\ \frac{c-x}{c-b}, \text{ if } b \le x \le c \\ 0, \quad \text{otherwise} \end{cases},$$

changing the basic parameters — a, b, and c — will vary the shape of the fuzzy set associated to the membership function, thus influencing the FRBS performance (See Figure 5). The same yields for other shapes of membership functions (trapezoidal, gaussian, sigmoid, etc.).

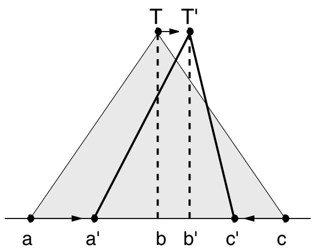


Fig. 5. Tuning by changing the basic membership function parameters

Tuning membership functions involves fitting the characterization of the membership functions associated to the primary linguistic terms considered in the system. Thus, the meaning of the linguistic terms is changed from a previous definition (an initial data base). In order to ensure a good interpretability through the membership functions optimization process [9, 41, 42], some researchers have proposed several properties. Considering one or more of these properties several constraints can be applied in the design process in order to obtain a BD maintaining the linguistic model comprehensibility to the higher possible level [6, 14, 10, 21].

An example of evolutionary tuning can be seen in Figure 6, where each membership function is encoded by means of three gene values representing its definition points.

4.3 The Lateral Tuning of Membership Functions

The lateral tuning is a new model of tuning considering the linguistic 2-tuples representation to laterally tune the support of a label, which maintains the interpretability associated to the FLC. A new model for rule representation based on the linguistic 2-tuples is introduced. This concept is presented in [29] and allow a lateral displacement of the labels named symbolic translation. The symbolic translation of a linguistic term is a number within the interval [-0.5, 0.5) that expresses the domain of a label when it is moving between its two lateral labels. Formally, we have the couple,

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

Figure 7 shows the lateral displacement of the label M. The new label "y_2" is located between B and M, being enough smaller than M but closer to M.

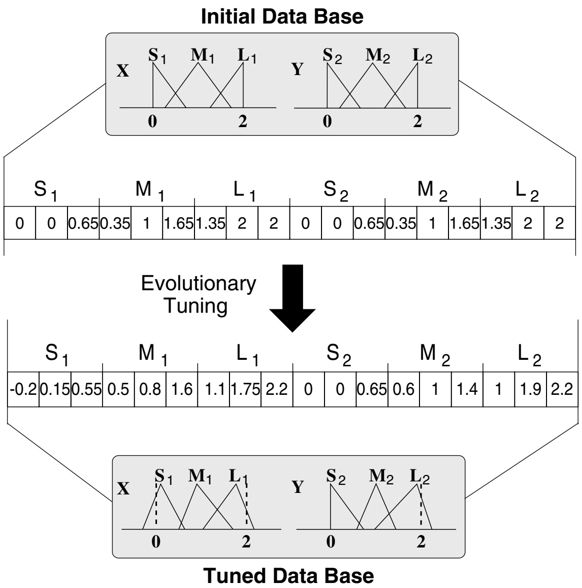


Fig. 6. Example of evolutionary tuning

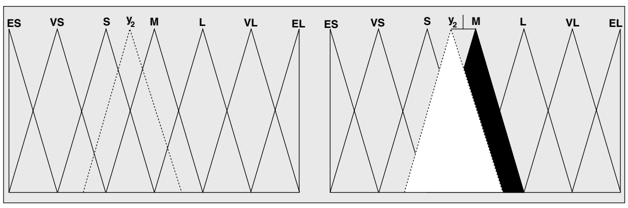


Fig. 7. Lateral Displacement of the Linguistic Label M

In [29], both the linguistic 2-tuples representation model and the needed elements for linguistic information comparison and aggregation are presented and applied to the Decision Making framework. In the context of Fuzzy Modeling and control, we are going to see its use in the linguistic rule representation. In the next we present this approach considering a simple control problem.

Let us consider a control problem with two input variables, one output variable and a Data Base defined from experts with the following labels:

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

Figure 8 shows the concept of classical rule and linguistic 2-tuples represented rule. Analized from the rule interpretability point of view, we could interpret the tuned rule as:

Classical Rule:
R1: If the **Error** is Zero and the **Error Variation** is Positive then the **Power** is High

Rules with 2-tuples Representation:
R1: If the **Error** is (Zero, 0.3) and the **Error Variation** is (Positive, -0.2) then the **Power** is (High, -0.1)

Fig. 8. Classical Rule and Rule with 2-Tuple Representation

If the **Error** is "higher than Zero" and
the **Error Variation** is "a little smaller than Positive"
then the **Power** is "a bit smaller than High".

This proposal decreases the tuning problem complexity, since the 3 parameters considered per label are reduced to only 1 symbolic translation parameter. As to how perform the lateral tuning there are two possibilities, the most interpretable one and the most accurate one:

- Global Tuning of the Semantics. In this case, the tuning is applied to the level of linguistic partition. In this way, the couple (X_i, label) takes the same tuning value in all the rules where it is considered. For example, X_i is (High, 0.3) will present the same value for those rules in which the couple "X_i is High" is initially considered.
  Considering this approach, the global interpretability of the final model is maintained. It is analogous to the classical tuning of the Data Base considering descriptive fuzzy rules [14], i.e., a global collection of fuzzy sets is considered by all the fuzzy rules. Therefore, this approach obtains more interpretable but less accurate linguistic models than the local approach.
- Local Tuning of the Rules. In this case, the tuning is applied to the level of rule. The couple (X_i, label) is tuned in a different way in each rule, based on the quality measures associated to the tuning method (usually the system error).

  Rule k: X_i is (High, 0.3) (more than high)
  Rule j: X_i is (High, -0.2) (a little lower than high)

  In this case, the global interpretability is lost to some degree and, the obtained model should be interpreted from a local point of view. This approach is analogous to the classical tuning of approximate fuzzy rules [14], i.e., each fuzzy rule has associated its own local fuzzy sets. However, in our case, the tuned labels are still related to the initial ones, preserving the global interpretability to some degree. Anyway, this approach presents more accuracy but less interpretability than the global approach.

5 Five Different Optimization Methods

Once the rule selection and two different tuning approaches have been presented, the genetic optimization algorithms developed for rule selection [32, 46], classical tuning [24, 28], lateral tuning [4] and, the combined action of rule selection with both tuning approaches (rule selection and classical tuning, rule selection and lateral tuning) are proposed in this section. However, only four of them will be presented, the second one, the third one and the last ones, since the algorithm for rule selection can be obtained as a part of this last, the C_S part.

In the following, the common parts of the said algorithms are introduced to later present its application (coding scheme and operators) to the classical and lateral tuning methods and to the combined action of rule selection with both tuning approaches.

5.1 Common Aspects of the Algorithms

It consists of a GA based on the well-known steady-state approach and considering an objective weighting-based fitness function. The steady-state approach [50] 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 our case it is very important since the model evaluation takes several minutes).

In order to make the method robust and more independent from the weight selection for the fitness function, the use of fuzzy goals for dynamically adapting the search direction in the space of solutions will be considered. The selection scheme is based on the Baker's stochastic universal sampling together with an elitist selection.

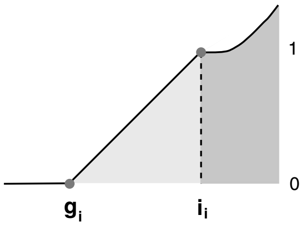
Evaluating the chromosome:

The fitness function (see Section 3.1) 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 penalize each objective whenever its value worse with respect to the initial solution. To do so, a function modifier parameter is considered, $\delta_i(x)$ (taking values over 1.0). 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). Therefore, the global fitness is evaluated as:

$$F' = \sum_{i=1}^{5} w_i^O \cdot \delta_i(O_i) \cdot O_i \ ,$$

Two situations can be presented according to the value of the goal g_i, and the value of the initial solution i_i. Depending on these values, two different δ functions will be applied:

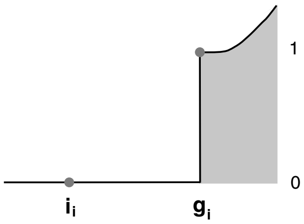
- When the value of g_i is lesser than the value of i_i, the objective is not considered if the goal is met and penalized if the initial results are worsened (see Figure 9).



$$\delta_i(x) = \begin{cases} 0, & \text{if } x \leq g_i \\ \dfrac{x - g_i}{i_i - g_i}, & \text{if } g_i < x < i_i \\ \dfrac{x - i_i}{x - x \cdot p_i} + 1, & \text{if } i_i \leq x \end{cases}.$$

Fig. 9. $\delta_i(x)$ when $g_i \leq i_i$

- When the value of i_i is lesser than the value of g_i, the initial results can be worsened while the goal is met and, it is penalized otherwise (see Figure 10).



$$\delta_i(x) = \begin{cases} 0, & \text{if } x < g_i \\ \dfrac{x - g_i}{x - x \cdot p_i} + 1, & \text{if } g_i \leq x \end{cases}.$$

Fig. 10. $\delta_i(x)$ when $g_i > i_i$

Restarting approach:

Finally, to get away from local optima, this algorithm uses a restart approach [19]. 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.

5.2 Evolutionary Algorithm for Classical Tuning

In this subsection, the coding scheme and genetic operators of the algorithm proposed for classical tuning are explained. To do so, the WMC-SSGA algorithm presented in [2] for classical tuning will be briefly described.

The coding scheme represents a solution by joining the representation of the m^i labels of each one of the n variables composing the Data Base:

$$C_i = (a^i_1, b^i_1, c^i_1, \ldots, a^i_{m^i}, b^i_{m^i}, c^i_{m^i}), \;\; i = 1, \ldots, n \;\; ,$$
$$C_T = C_1 C_2 \ldots C_n \;\; .$$

To make use of the existing knowledge, the Data Base previously obtained from experts is included in the population as an initial solution. The remaining individuals are randomly generated maintaining their genes within their respective variation intervals. These intervals are computed from the initial Data Base, having the same interval the group composed by the vertex of a label and the nearest points of the next and the previous labels. From these groups, the interval extremes are obtained computing the middle point between the nearest points of the corresponding consecutive groups [2]. Finally, these intervals are dynamically adapted from the best individual for each generation.

Since a real coding scheme is considered, the crossover and mutation operators have been selected according to this aspect: the Max-Min-Arithmetical crossover and Michale-wicz's non-uniform mutation (more complete information on these operators can be found in [2, 17]). Once the mutation operator is applied on the four offspring generated by the crossover operator, the two best are selected as the final descendents.

5.3 Evolutionary Algorithm for Lateral Tuning

This subsection presents the coding scheme and genetic operators of the lateral tuning algorithm.

Coding scheme and initial gene pool:

Taking into account that two different types of tuning have been proposed (global tuning of the semantics and local tuning of the rules), there are two different kinds of coding schemes. In both cases, a real coding is considered, i.e., the real parameters are the GA representation units (genes).

In the following both schemes are presented:

- Global tuning of the semantics: Joint of the parameters of the fuzzy partitions. 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),

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

See the C_T part of Figure 11 (in the next section) for an example of coding scheme considering this approach.

- Local tuning of the rules: Joint of the rule parameters. Let us consider that the FRBS has M rules: $(R1, R2, \ldots, RM)$, with n system variables. Then, the chromosome structure is,

$$C_T = (c_{11}, \ldots, c_{1n}, c_{21}, \ldots, c_{2n}, \ldots, c_{M1}, \ldots, c_{Mn}).$$

To make use of the available information, the initial FRBS obtained from automatic fuzzy rule learning methods or from expert's knowledge is included in the population as an initial solution. To do so, the initial pool is obtained with the first individual having all genes with value '0.0', and the remaining individuals generated at random.

Genetic operators:

The genetic operator considered is crossover. No mutation is considered in this case in order to improve the algorithm convergence. A description of the crossover operator is presented in the following.

The BLX-α crossover [20] and a hybrid between a BLX-α and an arithmetical crossover [26] are considered. In this way, if two parents, $C_T^v = (c_{T1}^v, \ldots, c_{Tk}^v, \ldots, c_{Tm}^v)$ and $C_T^w = (c_{T1}^w, \ldots, c_{Tk}^w, \ldots, c_{Tm}^w)$, are going to be crossed, two different crossovers are considered:

1. Using the BLX-α crossover [20] (with α being a constant parameter chosen by the GA designer), one descendent $C_T^h = (c_{T1}^h, \ldots, c_{Tk}^h, \ldots, c_{Tm}^h)$ 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 [26] in the wider interval considered by the BLX-α, $[I_{L_k}, I_{R_k}]$, results in the next descendent:

   $$C_T^h \text{ with } c_{Tk}^h = aI_{L_k} + (1-a)I_{R_k},$$

   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 an interest characteristic.

5.4 Evolutionary Algorithm for Rule Selection + Tuning

In this subsection, the coding scheme and genetic operators of the algorithms combining rule selection with both tuning approaches are presented.

Coding scheme and initial gene pool:

A double coding scheme ($C = C_S + C_T$) for both *rule selection* and *tuning* 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, 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.

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

- The C_T part represent the coding scheme previously explained for the classical or lateral tuning algorithm.

Finally, a chromosome C^p is coded in the following way:

$$C^p = C_S^p C_T^p$$

An example of the coding scheme considering the global lateral tuning with rule selection can be seen in Figure 11.

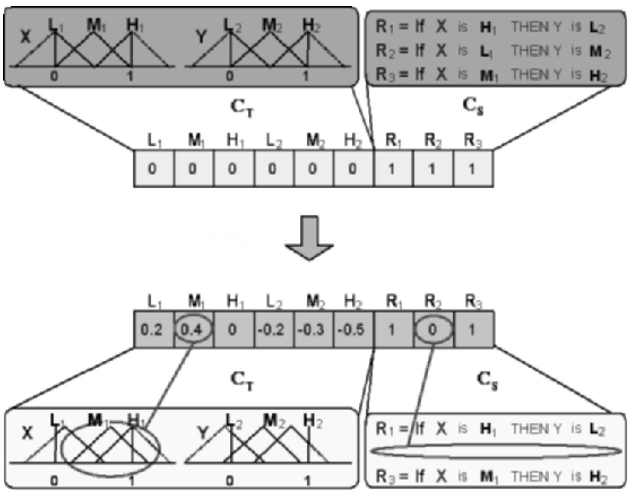


Fig. 11. Example of Coding Scheme Considering the Global Lateral Tuning and Rule Selection

To make use of the available information, the FLC previously obtained from expert knowledge is included in the population as an initial solution. To do so, the initial pool is obtained with an individual having all genes with value '1' in the C_S part and the initialization previously explained for the classical or lateral tuning algorithms in the C_T part. The remaining individuals are generated at random.

Genetic operators:

The crossover operator will depend on the chromosome part where it is applied: in the C_S part, the standard two-point crossover is used, whilst in the C_T part for the classical tuning is applied the Max-Min-Arithmetical operator and for the lateral tuning is applied a hybrid between a BLX-α and an arithmetical crossover. The two-point crossover involves exchanging the fragments of the parents contained between two points selected at random (resulting two different descendents). Finally, eight/four offspring are generated by combining the two ones from the C_S part with the four/two ones from the C_T part (classical/lateral tuning).

As regards the mutation operator, it flips the gene value in the C_S part. In the C_T part, for classical tuning the Michale-wicz's non-uniform mutation is used and for lateral tuning no mutation is applied. In this way, once the mutation operator is applied over the offspring obtained from the crossover operator, the resulting descendents are the two best individuals.

6 Experiments and Analysis of Results

To evaluate the goodness of the studied techniques, several experiments have been carried out considering the GENESYS test site. The main characteristics, the control objectives and the initial FLC for this site have been presented in Section 3. In this section, the experiments performed with the said algorithms are presented. In order to see the advantages of the combined action of the rule selection and the tuning techniques, three different studies have been performed:

1. *Considering the said post-processing approaches separately.* In this case, we consider the different proposed techniques individually:
   - Rule Selection.
   - Classical Tuning.
   - Lateral Tuning (both approaches, global and local).
2. *Combining the rule selection with the tuning approaches.* In this case, we consider the rule selection and the different tuning approaches jointly:
   - Rule Selection and Classical Tuning.
   - Rule Selection and Lateral Tuning (both approaches, global and local).
3. *Analysis of the different algorithms.* A comparison will be performed pointing out the good performance obtained when both, rule selection and tuning, are combined.

To assess the proposed techniques for fitness computation, accurate models of this controlled building (as well as the corresponding initial FLC) were provided by experts. The proposed optimization strategy was assessed with simulations of 10 days with the corresponding climatic conditions.

The FLCs obtained from the proposed technique will be compared to the performance of a classic On-Off controller and to the performance of the initial FLC. *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).

Table 1. Initial results and fitness function (F') parameters

		Fitness		PMV		CO_2	Energy		Stability	
MODEL	#R	F	%	O_1	O_2	O_3	O_4	%	O_5	%
ON-OFF	–	6.58	–	0.0	0	0	3206400	–	1136	–
FLC	172	6.32	4	0.0	0	0	2901686	9.50	1505	-32.48
Goals (g_i)	–	–	–	1.0	1	7	2000000	–	1000	–
Rates (p_i)	–	–	–	1	1	1	0.9	–	0.97	–

Table 1 presents the results obtained with the On-Off and the initial FLC controllers together with the parameters considered to compute the fitness function in the GA (F'), fuzzy goals and penalization rates (the objective weights can be seen in Section 3.1). Notice that, the goals imposed to the algorithm are higher than the ones initially required by the experts since we are trying to obtain even better results. No improvement percentages have been considered in the table for $O_1 \dots O_3$, since these objectives always met the experts requirements and the On-Off controller presents zero values for these objectives.

Finally, 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 α in the hybrid crossover operator and 0.35 as factor a in the max-min-arithmetical crossover. 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.

6.1 Results Separately Considering the Said Post-Processing Approaches

The methods considered in this study are shown in Table 2. The models presented in Table 3, 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 the best individuals from the last population considering the three runs performed. The time required for each model evaluation is 215 seconds approximately. Therefore, the run times are approximately four days (evaluations × evaluation time).

Table 2. Methods Considered for Comparison

Method	Description
S	Rule Selection
C	Classical Tuning
GL	Global Lateral Tuning
LL	Local Lateral Tuning

Table 3. Results obtained with rule selection and tuning approaches

		PMV		CO_2	Energy		Stability	
MODEL	#R	O_1	O_2	O_3	O_4	%	O_5	%
ON-OFF	–	0.0	0	0	3206400	–	1136	–
FLC	172	0.0	0	0	2901686	9.50	1505	-32.48
Rule Selection								
S1	147	0.2	0	0	2867692	10.56	991	12.76
S2	162	0.0	0	0	2889889	9.87	1441	-26.85
S3	172	0.0	0	0	2901686	9.50	1505	-32.48
Classical Tuning								
C1	172	0.0	0	0	2575949	19.66	1115	1.85
C2	172	0.0	0	0	2587326	19.31	1077	5.19
C3	172	0.0	0	0	2596875	19.01	1051	7.48
Global Lateral Tuning								
GL1	172	0.7	0	0	2378784	25.81	1069	5.90
GL2	172	1.0	0	0	2327806	27.40	1066	6.16
GL3	172	0.9	0	0	2268689	29.25	1080	4.93
Local Lateral Tuning								
LL1	172	0.9	0	0	2386033	25.59	896	21.13
LL2	172	0.8	0	0	2343409	26.92	943	16.99
LL3	172	0.3	0	0	2377596	25.85	938	17.43

From the obtained results, the tuning approaches present better results in energy and stability than the rule selection, On-Off controller and the initial

FLC controller. However, the rule selection technique minimizes the number of rules presenting significant improvements respect to the On-Off controller.

Regarding the tuning approaches, the lateral tuning presents a good trade-off between energy and stability, since this approach reduces the size of the search space of this complex problem. The lateral tuning techniques are robust and perform a better exploration of the search space, avoiding getting stuck at local optima. Note that, the local lateral tuning obtains more accurate results than the global approach, since this technique presents more freedom degrees and locally tunes each parameter. The local tuning presents improvement rates of about a 26% in energy and about a 18% in stability.

6.2 Results Combining the Rule Selection with the Tuning Approaches

The methods considered in this study are shown in Table 4. The models presented in Table 5 correspond to the best individuals from the last population considering the three proposed seeds (once again % stands for the improvement rate with respect to the On-Off controller and #R for the number of fuzzy rules). Again, the run times are approximately four days.

Table 4. Methods Considered for Comparison

Method	Description
C-S	Classical Tuning and Rule Selection
GL-S	Global Lateral Tuning and Rule Selection
LL-S	Local Lateral Tuning and Rule Selection

In view of the obtained results, we can point out that all the controllers derived by the studied methods achieve significant improvements over both, the On-Off controller and the initial FLC controller. In this case, all the goals required by experts were met, amply exceeding the expected results.

A good trade-off between energy and stability was achieved for all the obtained models, 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.

Figure 12 represents the initial and the final data base of the FLC obtained by GL-S1 in Table 5. It shows that small variations in the membership functions cause large improvements in the FLC performance. Figure 13 represents the decision tables of the FLC obtained from GL-S1 (see Section 3.2). 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 in each

Table 5. Results obtained combining rule selection with the tuning approaches

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
Selection with Classical Tuning								
C-S1	94	0.0	0	0	2540065	20.78	1294	-13.91
C-S2	109	0.1	0	0	2492462	22.27	989	12.94
C-S3	100	0.1	0	0	2578019	19.60	887	21.92
Selection with Global Lateral Tuning								
GL-S1	105	1.0	0	0	2218598	30.81	710	37.50
GL-S2	115	0.4	0	0	2358405	26.45	818	27.99
GL-S3	118	0.8	0	0	2286976	28.68	872	23.24
Selection with Local Lateral Tuning								
LL-S1	133	0.5	0	0	2311986	27.90	788	30.63
LL-S2	104	0.6	0	0	2388470	25.51	595	47.62
LL-S3	93	0.5	0	0	2277807	28.96	1028	9.51

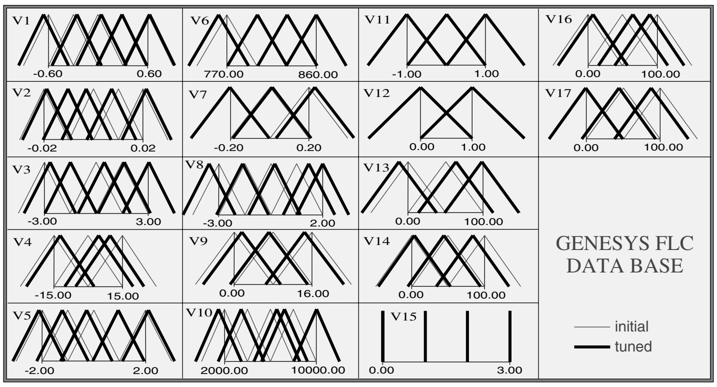


Fig. 12. Initial and Tuned Data Base of a Model Obtained with GL-S (Seed 1)

run). This fact improves the system readability, and allows us to obtain simple and accurate FLCs.

6.3 Analyzing Both Approaches

In order to see how the consideration of the rule selection affects to the tuning approaches, Table 6 presents a comparison. The averaged results obtained from the three different runs performed in the previous subsections are shown in the table.

The methods combining the rule selection with the tuning approaches has yielded much better results than the different post-processing approaches

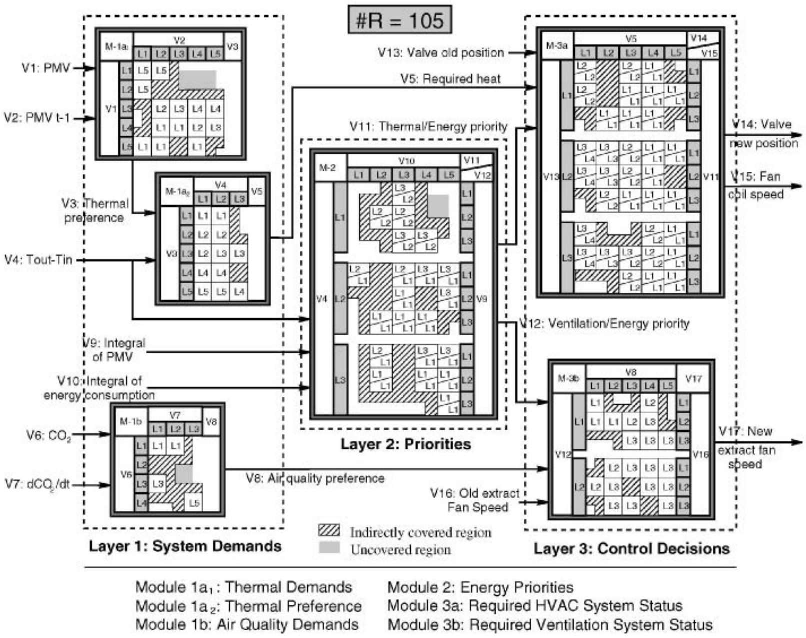


Fig. 13. Rule Base and final structure of a Model Obtained with GL-S (seed 1)

Table 6. Comparison among the different methods

		PMV		CO_2	Energy		Stability	
MODEL	#R	O_1	O_2	O_3	O_4	%	O_5	%
ON-OFF	–	0.0	0	0	3206400	–	1136	–
FLC	172	0.0	0	0	2901686	9.50	1505	-32.48
				Averaged Results				
$\overline{S}$	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
$\overline{LL}$	172	0.7	0	0	2369013	26.12	926	18.52
$\overline{C-S}$	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**
$\overline{LL-S}$	110	0.5	0	0	2326088	27.46	804	29.26

separately, specially in the case of the global lateral tuning together with the rule selection. Moreover, in the case of GL-S, the interpretability level obtained is very near to the original one, since the initial rules and membership function shapes remain fixed. It is notorious the fact that, in general, the simplified FLCs only maintain a 64% of the initial rules. Furthermore, considering rule selection helps to reduce the search space and favors the ability of the tuning techniques to obtain good solutions.

On the other hand, the methods based on the lateral tuning present better results than the ones based on the classical tuning. The lateral tuning is a particular case of the classical tuning, however, the search space reduction helps to these kinds of techniques to obtain more optimal results.

7 Concluding Remarks

In this work, we propose the use of tuning approaches together with a rule selection to develop accurate FLCs dedicated to the control of HVAC systems concerning energy performance and indoor comfort requirements. To do so, different GAs considering an efficient approach for tuning and rule selection have been developed.

The studied techniques, specially those based on lateral tuning, have yielded much better results than the classical On-Off controller 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.

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