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A genetic rule weighting and selection process for fuzzy control of heating, ventilating and air conditioning systems ☆

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Abstract

In this paper, we propose the use of weighted linguistic fuzzy rules in combination with a rule selection process to develop accurate fuzzy logic controllers dedicated to the intelligent control of heating, ventilating and air conditioning systems concerning energy performance and indoor comfort requirements. To do so, a genetic optimization process considering an efficient approach to perform rule weight derivation and rule selection is developed. This allows the tuning of the system to be developed at the rule level. The proposed technique was tested considering a physical modelization of a real test site.

Keywords: HVAC systems; Fuzzy logic controllers; Weighted fuzzy rules; Rule selection; Genetic algorithms

1. Introduction

In EU countries, primary energy consumption in buildings represents about 40% of total energy consumption, and depending on the countries, 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 (Dexter et al., 1996). With this aim, BEMSs are generally applied only to the control of active systems, i.e., heating, ventilating, and air conditioning (HVAC) systems.

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 equipments. The use of knowledge-based systems can represent a more efficient approach to the HVAC System management, providing BEMSs with artificial intelligence. By means of artificial intelligence, the system is capable of assessing, diagnosing and suggesting the best operation mode. Within the framework of machine learning, some artificial intelligence techniques could be successfully applied to enhance the HVAC System capabilities (Alcalá et al., 2001; Arima et al., 1995; Calvino et al., 2004; Huang and Nelson , 1994; Jian and Wenjian, 2000; Pargfrieder and Jörgl, 2002; Rahmati et al., 2003; Yang et al., 2003) or to aid the HVAC System modeling (Angelov, 2002). In this way, the use of appropriate automatic control strategies, as fuzzy logic controllers (FLCs) (Driankov et al., 1993; Mamdani, 1974; Mamdani and Assilian, 1975), for HVAC systems control could result in important energy savings when compared to manual control, specially

Abbreviation: BEMS, building energy management system; HVAC, heating, ventilating, and air conditioning; FLC, fuzzy logic controller; KB, knowledge base; GA, genetic algorithm; PMV, predicted mean vote index for thermal comfort

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when they explicitly try to minimize the energy consumption (Alcalá et al., 2001; Arima et al., 1995; Huang and Nelson , 1994; Pargfrieder and Jörgl, 2002).

However, in current systems, various criteria are considered independently one from another and in most cases the used control strategy only search for a thermal regulation, maintaining a temperature setpoint or range, which only considers implicit energy savings (Arima et al., 1995; Glorennec, 1991; Huang and Nelson , 1994; Jian and Wenjian, 2000; Rahmati et al., 2003; Yang et al., 2003). In (Calvino et al., 2004), the more global predicted mean vote (PMV) index for thermal comfort (incorporating relative humidity and mean radiant temperature) is optimized, but again it does not explicitly optimize the energy consumption, the HVAC system stability or the indoor air quality (CO_2 concentration). In (Pargfrieder and Jörgl, 2002), 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. In our case, five criteria will be optimized and 17 variables are considered by the FLC.

On the other hand, considering fuzzy logic, control systems in buildings are often designed using rules of thumb not always compatible with the controlled equipment requirements, energy performance and users expectations and demand. Therefore, the different involved criteria should be optimized for a good performance of the HVAC System. Due to the nature of the problem, a rational operation and improved performance of FLCs is required. In our case, the main objective is the energy performance but maintaining the required indoor comfort levels. A way to improve the FLC performance without losing interpretability to a high degree is to extend its usual structure making it more flexible. Many different possibilities to extend the linguistic model structure have been considered in the specialized literature (Casillas et al., 2002). All of them share the common idea of improving the way in which the FLC performs the interpolative reasoning by inducing a better cooperation among the rules in the knowledge base (KB).

A possibility to extend the FLC structure is to consider weighted rules, where an importance degree is associated to each rule in the fuzzy reasoning process (Cho and Park, 2000; Ishibuchi and Takashima, 2001; Pal and Pal, 1999; Yu and Bien, 1994). The use of rule weights as a local tuning of linguistic rules, enhances the robustness, flexibility and system modeling capability (Pal and Pal, 1999). It is based on the ability of this technique to indicate the interaction level of each rule with the remaining ones. In this way, FLCs could be obtained from human experience to subsequently derive the corresponding rule weights using automatic techniques.

In this work, the use of weighted linguistic fuzzy rules in combination with a rule simplification (Chiu, 1994; Halgamuge and Glesner, 1994; Rovatti et al., 1993; Setnes et al., 1998; Setnes and Hellendoorn, 2000; Yen and Wang, 1999) are proposed to develop accurate FLCs dedicated to the control of HVAC systems with regard to the energy performance and indoor comfort requirements. To do so, an evolutionary optimization process (Holland, 1975; Michalewicz, 1996) considering an efficient approach to perform the derivation of rule weights together with rule selection has been developed and tested considering the calibrated and validated models of a real test building. The initial FLC to be optimized will be obtained from human experience.

This contribution is arranged in the following way. 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 in this work. In Sections 4 and 5, the use of rule weights and rule selection are presented in depth, considering them as two complementary ways to improve the FLC performance. Section 6 presents the evolutionary optimization process performing the rule selection together with the rule weight derivation. Experimental results are shown in Section 7. In Section 8, some concluding remarks are pointed out. Finally, the used abbreviations is presented.

2. Heating, ventilating, and air conditioning 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. Therefore, in a quiet and energy-efficient way at low life-cycle cost, an 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 both in summer and winter (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 an HVAC system compatible with the ambiance is a task of the BEMS designer depending on its own experience. In Fig. 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.

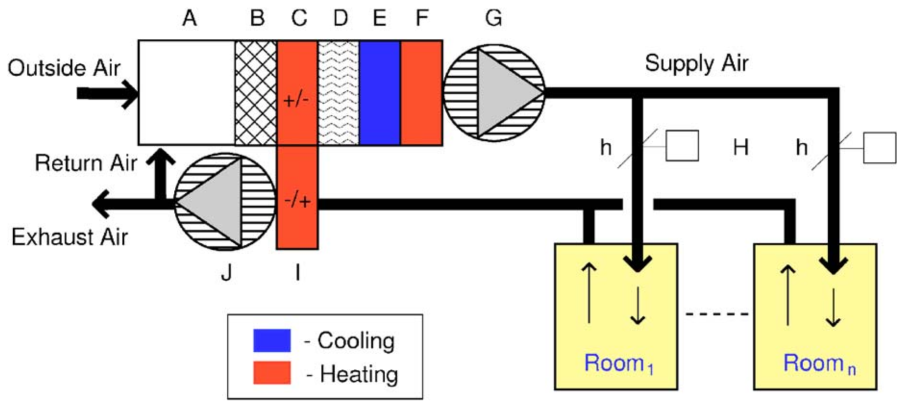


Fig. 1. Generic structure of an office building HVAC system. **A** - This module mixes the return and the outside air to provide supply air, and also closes outside air damper and opens return air damper when fan stops. **B** - It is a filter to reduce the outside air emissions to supply air. **C** - 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.

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, an 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 (Arima et al., 1995).

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[1] 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.

2.1.1. Control or explicit parameters: controller's variables

To identify the FLCs 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

[1]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).

that 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.

2.1.2. 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 (Hirota, 1998).

An FLC (Driankov et al., 1993; Mamdani, 1974; Mamdani and Assilian, 1975) is a kind of fuzzy rule-based system which is composed of a KB that comprises the information used by the expert operator in the form of linguistic control rules, a *Fuzzification Interface*, that transforms the crisp values of the input variables into fuzzy sets that will be used in the fuzzy inference process, an *Inference System* that uses the fuzzy values from the fuzzification interface and the information from the KB performing the reasoning process, and a *Defuzzification Interface*, which takes the fuzzy control action from the inference process and translates it into crisp values for the control variables. The KB is comprised of two components: the data base and the rule base. The data base contains the definitions of the linguistic labels, that is, the membership functions for the fuzzy sets. The rule base is a collection of fuzzy control rules, comprised by the linguistic labels, representing the expert knowledge of the controlled system. Fig. 2 shows the generic structure of an FLC.

In the specific case of HVAC systems, most works apply FLCs to solve simple problems such as thermal regulation, maintaining a temperature setpoint which does not explicitly consider the energy consumption optimization (Arima et al., 1995; Glorennec, 1991; Huang and Nelson , 1994; Jian and Wenjian, 2000; Rahmati et al., 2003; Yang et al., 2003). In (Calvino et al., 2004), the PMV is optimized, but again it does not explicitly optimize the energy consumption, the HVAC system stability or the indoor air quality (CO_2 concentration). In (Pargfrieder and Jörgl, 2002), a FLC involving 7 variables (5 inputs and 2 outputs) is optimized by 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

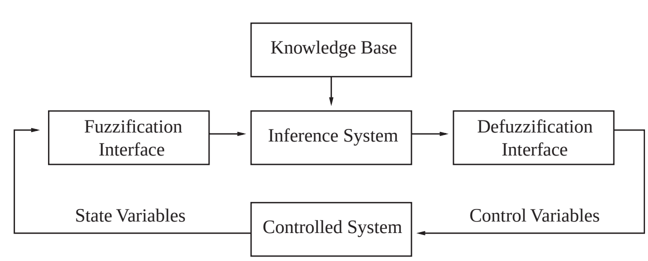


Fig. 2. Generic structure of a FLC.

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 these kinds of problems (HVAC system controller design), the 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 (Huang and Nelson , 1994). 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.

A possible way to improve the FLC performance without losing interpretability to a high degree is to extend its usual structure making it more flexible. Many different possibilities to improve linguistic fuzzy modeling have been considered in the specialized literature (Casillas et al., 2002). They can also be applied to the framework of fuzzy control (e.g., a tuning on the semantic of an FLC previously obtained from human experience could be performed by modification of the data base components (Alcalá et al., 2001, 2003)). 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 rule weight derivation and the rule selection. In this work, FLCs will be obtained from human experience to subsequently derive rule weights and select the rule subset presenting the best cooperation by the application of automatic techniques.

On the other hand, to evaluate the FLC performance, 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[2] 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. Fig. 3 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.

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 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 s. 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.

[2]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).

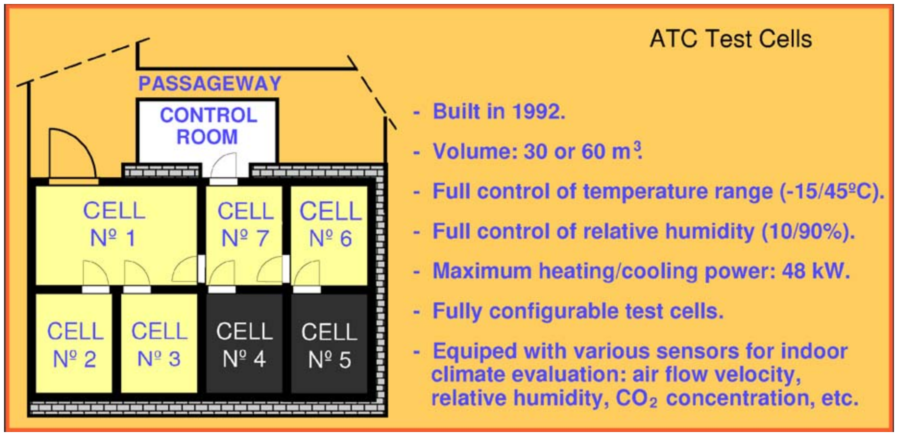


Fig. 3. Representation and main characteristics of the GENESYS test cells.

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 Fig. 4.

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 ith variable. Fig. 5 depicts the data base. Both, the initial rule base and the data base, were provided by the BEMS designer.

Notice that, Fig. 4 represents the decision tables of each module of the hierarchical FLC considered in terms of these labels. When the rule base considers more

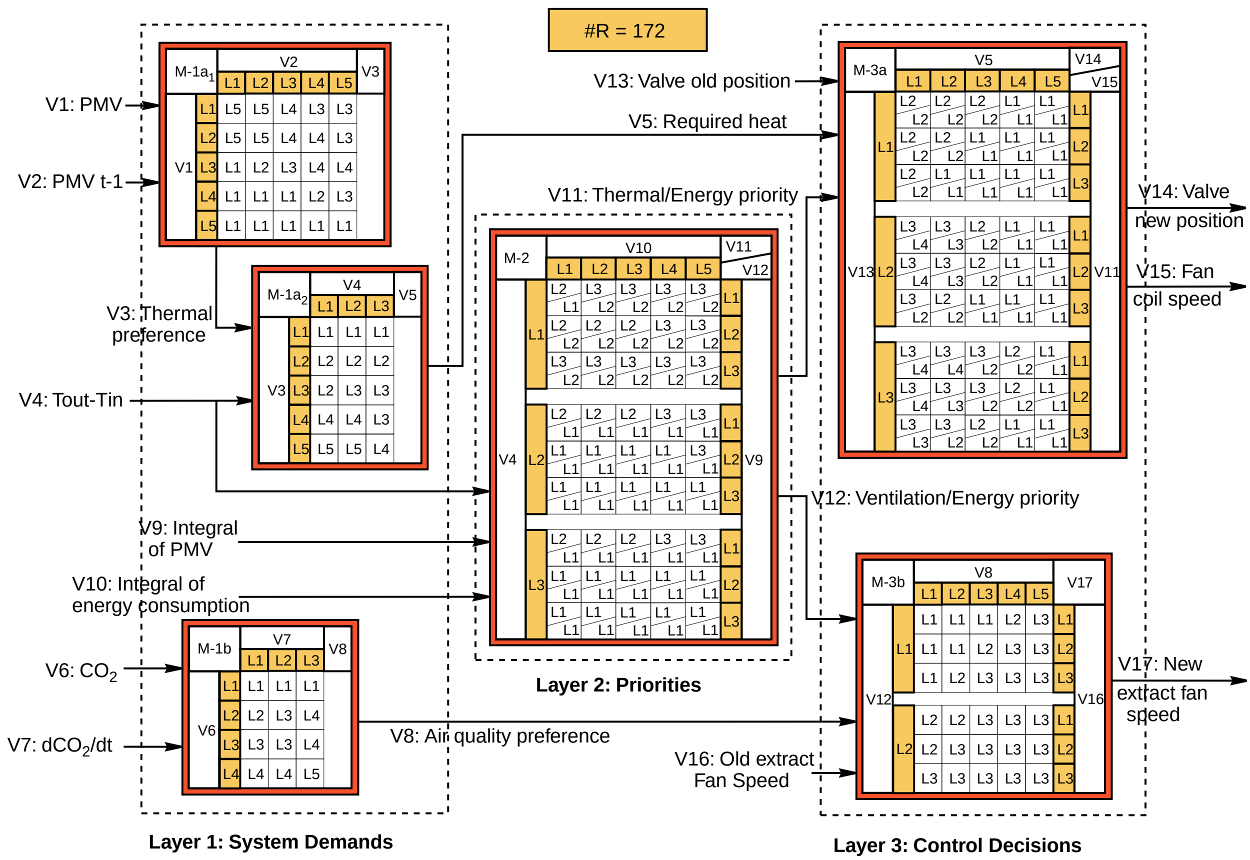


Fig. 4. Initial rule base and generic structure of the GENESYS summer-season FLC. Module $1a_1$: Thermal demands; Module $1a_2$: Thermal preference; Module 1b: Air quality demands; Module 2: Energy priorities; Module 3a: Required HVAC system status; Module 3b: Required ventilation system status.

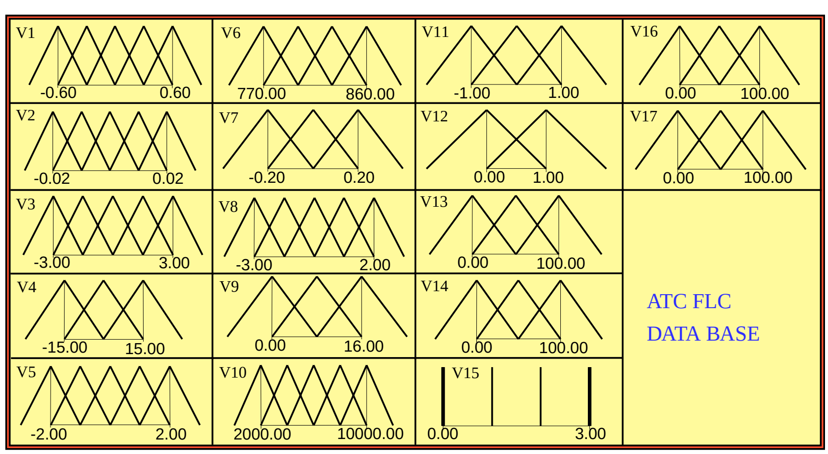


Fig. 5. Data base of the GENESYS summer-season fuzzy logic controller.

than two input variables (as in the case of modules M-2 in layer 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. Weighted linguistic rules

Using rule weights (Cho and Park, 2000; Ishibuchi and Takashima, 2001; Pal and Pal, 1999; Yu and Bien, 1994) has been usually considered to improve the way in which the rules interact, improving the accuracy of the learnt model. In this way, rule weights suppose an effective extension of the conventional fuzzy reasoning that allows the tuning of the system to be developed at the rule level (Cho and Park, 2000; Pal and Pal, 1999). It is clear that considering rule weights will improve the capability of the model to perform the *interpolative reasoning* and, thus, its performance. This is one of the most interesting features of fuzzy rule-based systems and plays a key role in their high performance, being a consequence of the cooperative action of the linguistic rules existing in the KB.

Weighted linguistic models/controllers are less interpretable than the classical ones but, in any case, these kinds of systems can be interpreted to a high degree, and also make use of human knowledge and a deductive process. When weights are applied to complete rules, the corresponding weight is used to modulate the firing strength of a rule in the process of computing the defuzzified control action. From human beings, it is very near to consider this weight as an importance degree associated to the rule, determining how this rule interacts with its neighbour ones. We will follow this approach, since the interpretability of the system is appropriately maintained. In addition, we will only consider weight values in [0,1] since it preserves the KB readability. In this way, the use of rule weights represents an ideal framework to extend the FLC structure when we search for a trade-off between accuracy and interpretability.

As we have said, rule weights will be applied to complete rules. In order to do so, we will follow the weighted rule structure and the Inference System proposed in (Pal and Pal, 1999):

IF X_1 **is** A_1 **and** ... **and** X_n **is** A_n **THEN** Y **is** B *with* $[w]$,

where X_i (Y) are the input (output) linguistic variables, A_i (B) are the linguistic labels used in the input (output) variables, w is the real-valued rule weight, and *with* is the operator modeling the weighting of a rule.

With this structure, the fuzzy reasoning must be extended. The classical approach is to infer with the FITA (first infer, then aggregate) scheme (Cordón et al., 1997) considering the matching degree of the fired rules. In this contribution, the *Mean Of Maxima weighted by the matching degree* will be considered as defuzzification strategy (Cordón et al., 1997):

$$y_0 = \frac{\sum_i h_i \cdot w_i \cdot P_i}{\sum_i h_i \cdot w_i},$$

with y_0 being the crisp control action obtained from the defuzzification process, h_i being the matching degree of the ith rule, w_i being the weight associated to it, and P_i being the characteristic value—*Mean Of Maxima*—of the output fuzzy set inferred from that rule, B_i'. On the other hand, we have selected the singleton fuzzification and the *minimum t-norm* playing the role of the implication and conjunctive operators.

A simple approximation for weighted rule learning would consist on considering an optimization technique—e.g., genetic algorithms (GAs) (Holland, 1975; Michalewicz, 1996)—to derive the associated weights of a previously obtained set of rules.

5. Implicit/explicit 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.

It is known that the use of rule weights as a local tuning of linguistic rules, enables the linguistic fuzzy models/controllers to cope with inefficient and/or redundant rules and thereby enhances the robustness, flexibility and control capability (Pal and Pal, 1999). Hence the ability of this technique to indicate the interaction level of each rule with the remaining ones is considered, improving the global cooperation. In this way, when we start from a previous set of rules, inefficient or redundant rules could be removed assigning a zero weight to each of them, i.e., an *implicit rule selection* could be performed.

However, weights close to zero are usually obtained form the derivation process, practically avoiding the effects of such rules but maintaining them in the KB. It is due to the large search space tackled by this process, and cannot be solved by removing these rules since in some cases they could be important rules with a low interaction level. Moreover, redundant, inconsistent and conflicting rules could be weighted as important rules if their neighbours are incorrectly weighted. Therefore, rule weighting processes could be improved considering any complementary technique that directly determines what rules should be removed.

This way, *explicit 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. Inconsistent and conflicting rules that degrade the performance are eliminated thus obtaining a fuzzy rule set with better cooperation.

Rule reduction methods have been formulated using neural networks, clustering techniques and orthogonal transformation methods, and algorithms based on similarity measures, among others (Chiu, 1994; Halgamuge and Glesner, 1994; Rovatti et al., 1993; Setnes et al., 1998; Setnes and Hellendoorn, 2000; Yam et al., 1999; Yen and Wang, 1999). In (Combs and Andrews, 1998), a different approach was proposed which attempts to reduce the growth of the rule base by transforming elemental fuzzy rules into DNF-form.

On the other hand, using 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 (Herrera et al., 1998).
- The selection of a cooperative set of rules from a candidate fuzzy rule set (Cordón and Herrera, 1997, 2000; Cordón et al., 1998; Ishibuchi et al., 1997, 1995; Krone et al., 2000).
- The selection of rules from a given KB together with the selection of the appropriate labels for the consequent variables (Chin and Qi, 1998).
- The selection of rules together with the tuning of membership functions by coding all of them (rules and parameters) in a chromosome (Gómez-Skarmeta and Jiménez, 1999).
- The derivation of compact fuzzy models through complexity reduction combining fuzzy clustering, rule reduction by orthogonal techniques, similarity driving simplification and genetic optimization (Roubos and Setnes, 2000).

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 learning of rule weights coding all of them (rules and weights) in a chromosome. This pursues the following aims:

- To improve the FLC accuracy selecting the set of rules best cooperating while a local tuning of rules is performed to improve the interaction among them.
- To obtain simpler, and thus easily understandable, FLCs by removing unnecessary rules.

6. Introducing weights and rule selection in the FLC

As we have said, considering rule weights and rule selection could result in important improvements of the system accuracy, maintaining the interpretability to an acceptable level. To do so, the two following tasks must be performed:

- Genetic selection of a subset of rules presenting good cooperation.
- Genetic derivation of the weights associated to these rules.

Focusing on our specific HVAC problem, taking into account the existence of trusted objective weighting coefficients—notice than these weighting coefficients are different to the rule weights considered to extend the FLC structure—and in order to benefit from them (see Section 3.1), we propose a simple steady-state GA with a double coding scheme and with a fitness function based on objective weighting. In this way, we will follow the same approach of the weighted multi-criterion steady-state GA proposed in (Alcalá et al. (2001 and 2003)) which in those cases was considered for membership function tuning. In the following subsections, steady-state GAs are briefly introduced to later present the proposed genetic weight derivation and rule selection algorithm.

6.1. Genetic algorithms: the steady-state approach

GAs are general-purpose global search algorithms that use principles inspired by natural population genetics to evolve solutions to problems. The basic principles of the GAs were first laid down rigorously by (Holland, 1975) and are well described in many texts such as (Michalewicz, 1996).

The basic idea is to maintain a population of knowledge structures that evolves over time through a process of competition and controlled variation. Each structure in the population represents a candidate solution to the specific problem and has an associated *fitness* to determine which structures are used to form new ones in the process of competition.

Hence, a subset of relatively good solutions are selected for reproduction to give offspring that replace the relatively bad solutions which die. Usually, offspring replace their parents for the next generation (generational approach). These new individuals are created by using genetic operators such as crossover and mutation. The crossover operator combines the information contained into the parents increasing the average quality of the population (exploitation), while the mutation operator randomly changes the new individuals helping the algorithm to avoid local optima (exploration).

On the other hand, the steady-state approach (Whitley and Kauth, 1998) consists of selecting two of the best individuals in the population and combining them to obtain two offspring. Then, 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.

6.2. Genetic weight derivation and rule selection algorithm

As we have said, it consists of a GA based on the well-known steady-state approach (Whitley and Kauth, 1998). Its fitness function considers an objective weighting. However, 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 (Baker, 1987) together with the elitist selection. Fig. 6 presents the flowchart of the proposed method, while its main components are introduced as follows.

6.2.1. Coding scheme and initial gene pool

A double coding scheme ($C = C_1 + C_2$) for both *rule selection* and *weight derivation* is used:

- For the C_1 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_1^p for the pth chromosome will be a binary vector representing the subset of rules finally obtained.
- For the C_2 part, the coding scheme generates real-coded strings of length m. The value of each gene indicates the weight used in the corresponding rule. They may take any value in the interval [0,1]. In this case, the corresponding part C_2^p for the pth chromosome will be a real-valued vector representing the weights associated to the fuzzy rules considered.

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

$$C_1^p = (c_{11}^p, \ldots, c_{1m}^p) \mid c_{1i}^p \in \{0, 1\},$$
$$C_2^p = (c_{21}^p, \ldots, c_{2m}^p) \mid c_{2i}^p \in [0, 1],$$
$$C^p = C_1^p C_2^p.$$

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 both parts, and the remaining individuals generated at random:

$$\forall k \in \{1, ..., m\},\; c_{1k}^1 = 1 \text{ and } c_{2k}^1 = 1.0.$$

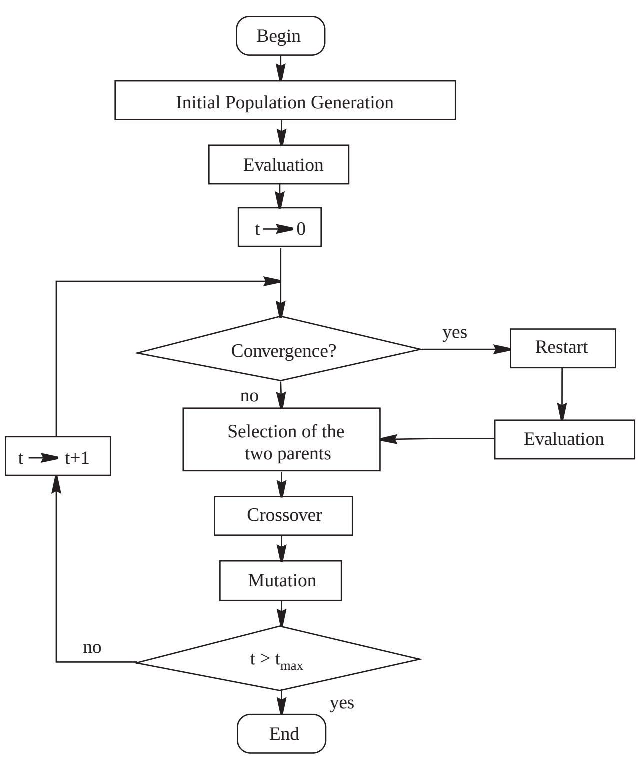


Fig. 6. Flowchart of the GA process.

6.2.2. Evaluating the chromosome

This fitness function is based on objective weighting. However, it has been modified in order to consider the use of fuzzy goals for dynamically adapting the search direction in the space of solutions, decreasing the improvement chance of those objectives which satisfy their goals in the first place. Thus, a function modifier parameter, $\delta_i(x)$ (taking values over 1.0), is used with two main motivations:

- To decrement the importance of each individual fitness value whenever it comes to its respective goal (taking values close to 0.0).
- To penalize each objective whenever its value worsens with respect to the initial solution.

To do so, a penalization rate has been included in $\delta_i(x)$, allowing the user to set up priorities in the objectives. This penalization rate, p_i, is a real number from 0.7 to practically 1 for each objective O_i, although the user specifies this penalization from 0 to 1 (less and more priority, respectively), which is more interpretable. Therefore, the global fitness is evaluated as:

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

with O_i being the considered criteria (objectives) and w_i^O being the corresponding weighting coefficients (see Section 3.1).

Two situations can be presented in the corresponding individual 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:

- The first case is when the value of g_i is lesser than the value of i_i, presenting the following behaviour (see Fig. 7).
  In this case, the objective is not considered if the goal is met and penalized if the initial results are worsened.
- The second case happens when the initial value, i_i, is lesser than the goal value, g_i (see Fig. 8).
  Now, the initial results can be worsened while the goal is met, and it is penalized otherwise.

Notice that the penalization function allows the search to slightly worsen a specific goal, improving other objectives to subsequently met that goal again, i.e., a dynamic adaptation of the search direction in the space of solutions is continuously performed.

6.2.3. Genetic operators

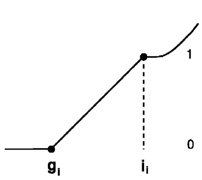
The crossover operator will depend on the chromosome part where it is applied: in the C_1 part, the standard two-point crossover is used, whilst in the C_2 part, the BLX-α crossover (Eshelman and Schaffer, 1993) and a hybrid between a BLX-α and an arithmetical crossover (Herrera et al., 1997) are considered.

The two-point crossover involves exchanging the fragments of the parents contained between two points selected at random (resulting two different descendents). On the other hand, if two parents, $C_2^v = (c_{21}^v, \ldots, c_{2k}^v, \ldots, c_{2m}^v)$ and $C_2^w = (c_{21}^w, \ldots, c_{2k}^w, \ldots, c_{2m}^w)$, are going to be crossed in C_2, two different crossovers are considered:

1. Using the BLX-α crossover (Eshelman and Schaffer, 1993) in the second parts (with α being a constant parameter chosen by the GA designer), one descendent $C_2^h = (c_{21}^h, \ldots, c_{2k}^h, \ldots, c_{2m}^h)$ is obtained, with c_{2k}^h being randomly generated within the interval $[I_{L_k}, I_{R_k}] = [c_{\min} - I \cdot \alpha, c_{\max} + I \cdot \alpha]$, $c_{\min} = \min(c_{2k}^v, c_{2k}^w)$, $c_{\max} = \max(c_{2k}^v, c_{2k}^w)$ and $I = c_{\max} - c_{\min}$.
2. The application of the arithmetical crossover (Herrera et al., 1997) in the wider interval considered by the BLX-α, $[I_{L_k}, I_{R_k}]$, results in the next descendent:

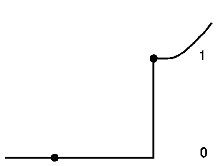
   C_2^h with $c_{2k}^h = aI_{L_k} + (1-a)I_{R_k}$,

   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 since rule weights are highly dependent on their neighbours.



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

Fig. 7. $\delta_i(x)$ when $g_i \leqslant i_i$.



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

Fig. 8. $\delta_i(x)$ when $g_i > i_i$.

Finally, four offspring are generated by combining the two ones from the C_1 part (two-point crossover) with the two ones from the C_2 part (our hybrid crossover).

As regards the mutation operator, it flips the gene value in the C_1 part and takes a value at random within the interval [0,1] for the corresponding gene in the C_2 part. In this way, once the mutation operator is applied over the four offspring obtained from the crossover operator, the resulting descendents are the two best of these four individuals.

6.2.4. Restart approach

Finally, to get away from local optima, this algorithm uses a restart approach (Eshelman, 1990). 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 variation intervals. It allows the algorithm to perform a better exploration of the search space and to avoid getting stuck at local optima.

7. Experiments and analysis of results

To evaluate the goodness of the proposed technique, 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 new weighted rules FLC on the said GENESYS summer model are presented. In order to see the advantages of the combined action of the rule weight derivation and the rule selection, three different studies have

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

Model	#R	Fitness		PMV		CO_2,	Energy		Stability	
		F	%	O_1	O_2	O_3	O_4	%	O_5	%
On–off	—	6.58	—	0.0	0	0	3 206 400	—	1136	—
FLC	172	6.32	4	0.0	0	0	2 901 686	9.50	1505	−32.48
Goals (g_i)	—	—	—	1.0	1	7	2 000 000	—	1000	—
Rates (p_i)	—	—	—	1	1	1	0.9	—	0.97	—

been performed:

1. *Only considering rule weights*. We will call this approach as weighted (W) rule learning, which will be performed by only considering the C_2 part of the proposed algorithm.
2. *Considering both together, rule weights and rule selection*. We will call this approach as weighted and simplified (WS) rule learning, being performed by the algorithm proposed in this work.
3. *Analysis of both approaches*. A comparison will be performed pointing out the good performance obtained when both, rule weights and rule selection, 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 the initial expert FLC and to the performance of a classic on-off controller. *The goals and improvements will be computed with respect to this classical controller as done in the GENESYS* (see footnote 1) *project*. The intention from experts was to try to have 10% energy saving (O_4) together with a global improvement of the system behaviour 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 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 $O_1 \ldots O_3$, 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, and 0.3 for the factor α in the crossover operator. The termination condition will be the development of a fixed number of iterations, which will depend on the approach (W or WS) followed, in order to perform a fair comparative study as we will see as follows. In order to evaluate the GA good convergence, three different runs have been performed considering three different seeds for the random number generator.

7.1. Results only considering rule weights

The models 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 the best individuals from the population at iteration 1000 considering the three runs performed. Moreover, the averaged results have been presented for each criterion. The time required for each model evaluation is 215 seconds approximately. Therefore, the estimated run time was, four days for 1000 iterations (computed as product of the number of evaluations per generation,[3] the evaluation time and the number of generations).

In this case, practically all the expert goals have been easily met by only considering weighted rule learning. However, excepting the third run (seed 3), the obtained results for the stability criterion were very poor and therefore unacceptable. It is obvious that in this case, the energy and the stability are the most complex objectives to be satisfied. Both criteria presents contradictory sakes. Therefore, when the algorithm tries to optimize one of them the other is indirectly affected. Moreover, the solutions present a non desirable diversity in the results making evident that the proposed technique does not correctly handle the large search space involved in this problem. Due to this reason, the algorithm does not correctly converge and gets stuck at local optima.

[3]Two evaluations only considering the C_2 part.

Table 2
Results obtained by only considering rule weights (W)

Model	#R	Fitness		PMV		CO_2,	Energy		Stability	
		F	%	O_1	O_2	O_3	O_4	%	O_5	%
On–off	–	6.58	–	0.0	0	0	3 206 400	–	1136	—
FLC	172	6.32	4	0.0	0	0	2 901 686	9.50	1505	−32.48
W-Seed 1	172	6.01	9	0.0	0	0	2 759 152	13.95	1426	−25.53
W-Seed 2	172	5.85	11	0.3	0	4	2 799 129	12.70	1129	0.62
W-Seed 3	172	5.78	12	0.0	0	0	2 790 748	12.96	1050	7.57
$\overline{W}$	172	5.88	11	0.1	0	1	2 783 010	13.21	1202	−5.81

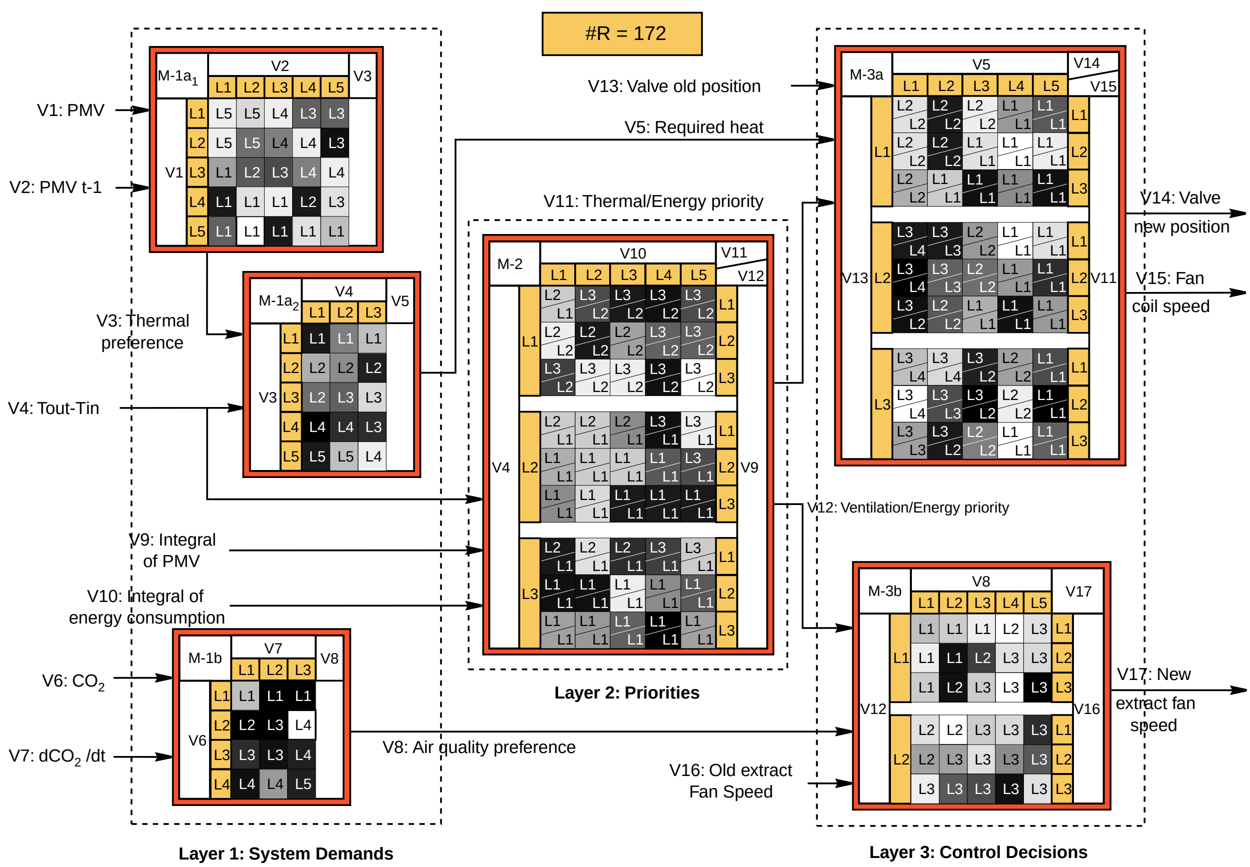


Fig. 9. Weighted rule base of the GENESYS summer-season FLC (Seed 3). Module $1a_1$: Thermal demands; Module $1a_2$: Thermal preference; Module 1b: Air qulaity demands; Module 2: Energy priorities; Module 3a: Required HVAC system status; Module 3b: Required ventilation system status.

In any case, important improvements were performed in energy, and even stability, respect to the initial FLC (see the averaged results), and approximately a 10% in their overall performance (fitness function) respect to the on-off controller. Moreover, comfort and air quality criteria were maintained within the requested levels, which is a difficult task since they pursue contradictory interests to the energy and stability.

The decision tables of the modules obtained in the third run are presented in Fig. 9. An explanation for these kinds of figures can be found in Section 3.2. In this case, the *absolute importance weight* for each fuzzy rule has been graphically shown by means of the grey colour scale, from black (weight 1.0) to white (weight 0.0). Hence, we can easily see the importance of a rule with *respect to their neighbours* which could help the system experts to identify important rules. Notice that, many rules present weights close to zero. However, in any case the obtained weight was exactly zero, thus maintaining all the rules in the KB.

7.2. Results considering rule weights and rule selection

The models presented in Table 3 correspond to the best individuals from the population at iteration 500 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). The averaged results have been also presented for each criterion. Now, both parts, rule weight derivation (C_2) and rule selection (C_1), are considered and four evaluations are required per iteration. In order to maintain the number of evaluations equal to the one considered in the previous subsection only 500 iterations will be considered. Therefore, the estimated run time was four days for 500 iterations (computed as product of the number of evaluations per generation, the evaluation time and the number of generations).

In view of the obtained results, we can point out that all the controllers derived by the proposed method 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. WS—weighted and simplified rule learning—presents improvement rates of about a 14% in energy and about a 16.5% in stability. Since the remaining criteria for comfort and air quality are within the requested leves, it improves the fitness function until improvement rates of about a 14% respect to the on-off controller. Moreover, the proposed algorithm presents a good convergence and seems to be independent of random factors.

Fig. 10 represents the decision tables of the model obtained from WS considering the second seed (see Section 3.2). Once again, the *absolute importance weight* for each fuzzy rule has been graphically shown by means of the grey colour scale. In this case, a large number of rules have been removed from the initial FLC, obtaining much simpler models (more or less 70 rules were eliminated in each run). This fact improves the system readability, and allows us to obtain simple and accurate FLCs. Notice that, no rules present weights close to zero.

7.3. Analyzing both approaches

In order to see how the consideration of the rule selection affects to the rule weight derivation, Table 4 presents a comparison between both approaches, W and WS. The averaged results and the typical deviation obtained from the three different runs performed in the previous subsections are shown in the table. The standard deviation gives information of how deviated are the samples, i.e., the higher the standard deviation, the more the dispersion of the samples. In our case, in order to say that the proposed technique is robust, similar results should be obtained when using the same parameters.

The proposed technique has yielded much better results than the classical on-off controller, showing the good results that the rule weight derivation together with a rule selection can achieve on these kinds of complex problems. Moreover, since the initial rules and membership functions remains fixed, the interpretability level of the weighted FLC so obtained is very near to the original one (by only considering the importance level for each rule).

It is notorious the fact that the simplified FLCs present much better results that the ones obtained by only weighting the rules. The simplified FLCs only maintain a 63% of the initial rules. Theoretically, the same models could be obtained by only considering rule weights. On the other hand, considering rule selection helps to the weight derivation reducing the search space and favor the ability of such technique to obtain good solutions. We can see that the proposed algorithm is robust to random factors not presenting significant deviations in the results, which does not occur by only considering rule weights. Hence, only adding weights to the rule set provided by experts is not sufficient. It is due to the strong dependency among the obtained rules and the weights associated to them, which makes very complex for the process to obtain the appropriate weights especially when inappropriate rules are present

Table 3
Results obtained considering rule weights and rule selection (WS)

Model	#R	Fitness		PMV		CO_2,	Energy		Stability	
		F	%	O_1	O_2	O_3	O_4	%	O_5	%
On–off	—	6.58	—	0.0	0	0	3 206 400	—	1136	—
FLC	172	6.32	4	0.0	0	0	2 901 686	9.50	1505	−32.48
WS-Seed 1	123	5.68	14	0.9	0	0	2 769 621	13.62	970	14.61
WS-Seed 2	102	5.59	15	0.7	0	0	2 731 798	14.80	942	17.08
WS-Seed 3	103	5.65	14	0.2	0	0	2 766 135	13.73	936	17.61
$\overline{WS}$	109	5.64	14	0.6	0	0	2 755 851	14.05	949	16.46

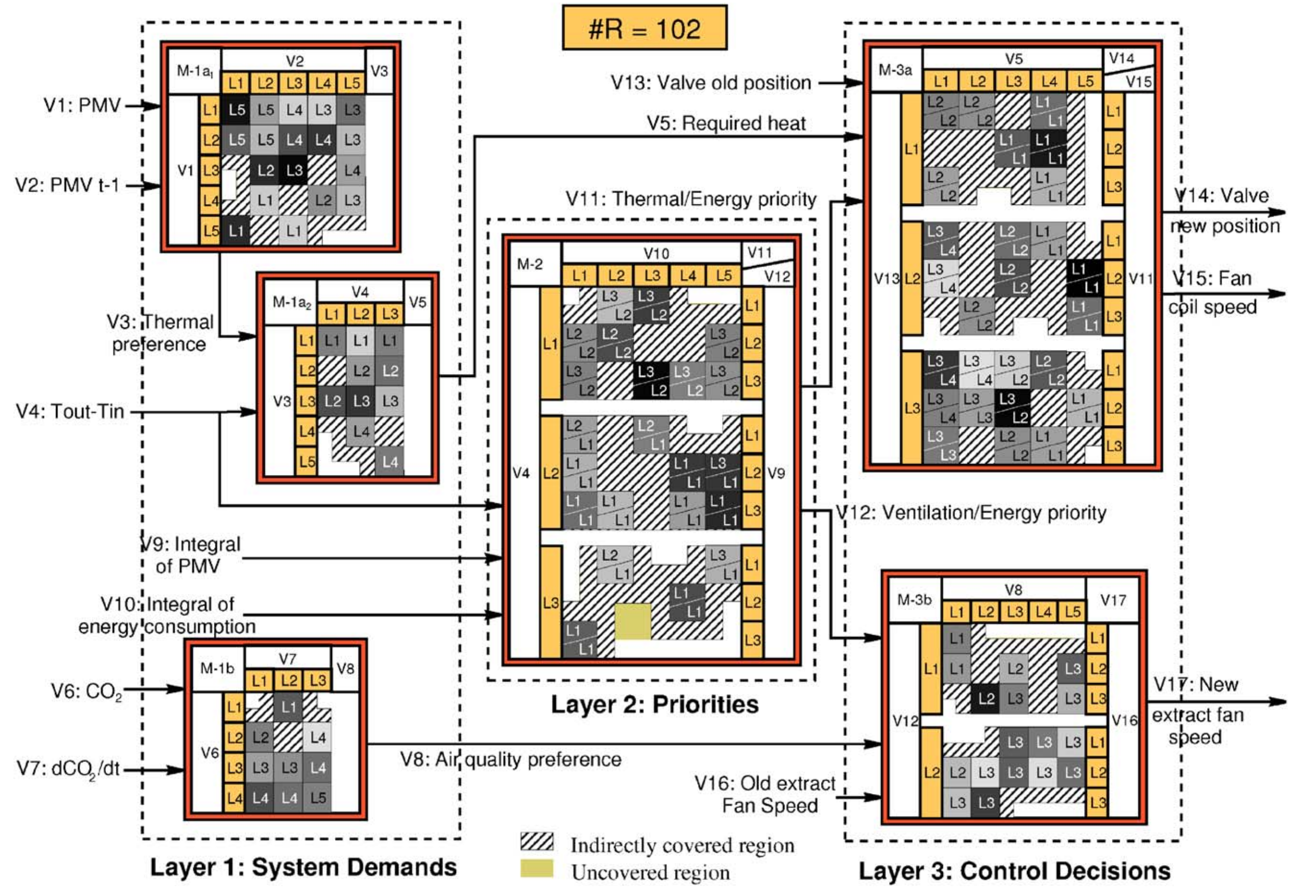


Fig. 10. Weighted rule base and final structure of the GENESYS summer-season FLC (seed 2). Module $1a_1$: Thermal demands; Module $1a_2$: Thermal preference; Module 1b: Air qulaity demands; Module 2: Energy priorities; Module 3a: Required HVAC system status; Module 3b: Required ventilation system status.

Table 4
Comparison between W and WS (considering and not rule selection)

Model	#R	Fitness		PMV		CO_2,	Energy		Stability	
		F	%	O_1	O_2	O_3	O_4	%	O_5	%
On-off	—	6.58	—	0.0	0	0	3 206 400	—	1136	—
FLC	172	6.32	4	0.0	0	0	2 901 686	9.50	1505	−32.48
Considering rule weights (W)										
$\overline{W}$	172	5.88	11	0.1	0	1	2 783 010	13.21	1202	−5.81
σ_w	0	0.09	—	0.1	0	2	17159	—	159	—
Considering rule weights and rule selection(WS)										
$\overline{WS}$	109	5.64	14	0.6	0	0	2 755 851	14.05	949	16.46
σ_{ws}	13	0.04	—	0.3	0	0	17121	—	29	—

in the KB. Therefore, we need to combine the learning of rule weights with a rule selection process to achieve an optimal behaviour.

Fig. 11 depicts the six different models analyzed in this work. These graphics can be studied as a mask on the decision table presented in Fig. 4. In this way, we could know the label associated to each input subspace since this information is not modified with respect to the original rule base.

Due to the kind of fuzzy partition considered (see Fig. 5), there are many input subspaces which, in spite of having no rule associated, are indirectly covered by their neighbour rules, e.g., the input subspace labeled as $L_1 - L_1$ in module 1b.

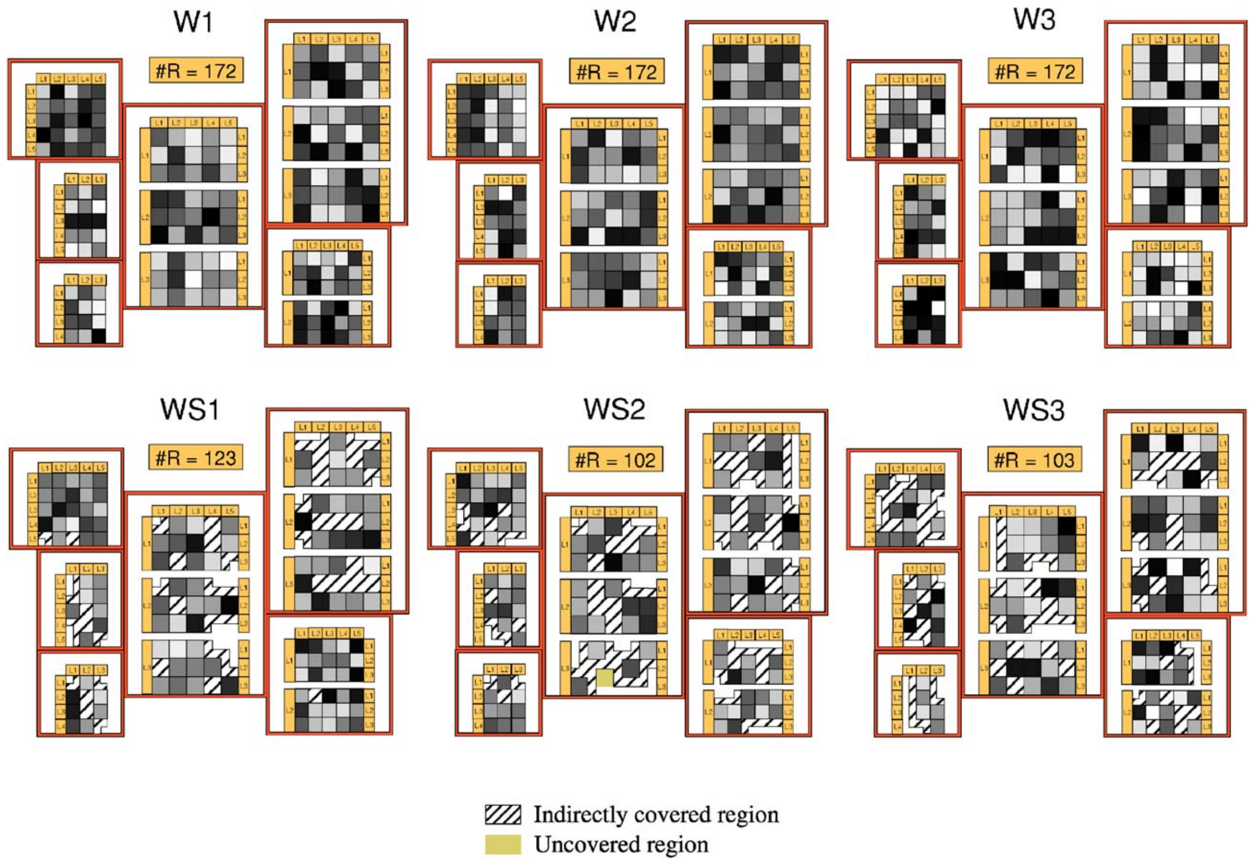


Fig. 11. Comparing the models obtained. **W1, W2, W3** - Weighted rule learning considering seeds 1, 2 and 3, respectively. **WS1, WS2, WS3** - Weighted and simplified rule learning considering seeds 1, 2 and 3, respectively.

Studying Fig. 11, we can observe that much simpler models have been obtained considering rule selection. Several rules were always removed from the rule base. In the case of only considering rule weights, some of them were always weighted with values close to zero as $L_1 - L_1$ in module 1b. However, some others of the rules always removed also presented great rule weights with any of the considered seeds. It is the case of $L_5 - L_1$ in module 1a$_2$.

8. Concluding remarks

In this work, we propose the use of weighted linguistic fuzzy rules 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, a GA considering an efficient approach to perform rule weight derivation and rule selection has been developed.

The proposed technique has yielded much better results than the classical on-off controller showing its good behaviour on these kinds of complex problems. It is due to the following reasons:

- The ability of rule weights to indicate the interaction level of each rule with the remainder, improving the global performance of the weighted FLC.
- The complementary characteristics that the use of weights and the rule selection approach present. The ability of rule selection to reduce the search space by only selecting the rules presenting a good cooperation is combined with an improvement of the rule cooperation capability by determining the interaction levels among the selected rules by the use of weights.

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