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A multi-objective evolutionary algorithm for an effective tuning of fuzzy logic controllers in heating, ventilating and air conditioning systems

María José Gacto · Rafael Alcalá · Francisco Herrera

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Abstract This paper focuses on the use of multi-objective evolutionary algorithms to develop smartly tuned fuzzy logic controllers dedicated to the control of heating, ventilating and air conditioning systems, energy performance, stability and indoor comfort requirements. This problem presents some specific restrictions that make it very particular and complex because of the large time requirements needed to consider multiple criteria (which enlarge the solution search space) and the long computation time models required in each evaluation.

In this work, a specific multi-objective evolutionary algorithm is proposed to obtain more compact fuzzy logic controllers as a way of finding the best combination of rules, thus improving the system performance to better solve the HVAC system control problem. This method combines lateral tuning of the linguistic variables with rule selection. To this end, two objectives have been considered, maximizing the performance of the system and minimizing the number of rules obtained. This algorithm is based on the well-known SPEA2 but uses different mechanisms for guiding the search towards the desired Pareto zone. Moreover, the method implements some advanced concepts such as incest prevention, that help to improve the exploration/exploitation trade-off and consequently its convergence ability.

The proposed method is compared to the most representative mono-objective steady-state genetic algorithms previously applied to the HVAC system control problem, and to generational and steady-state versions of the most interesting multi-objective evolutionary algorithms (never applied to this problem) showing that the solutions obtained by this new approach dominate those obtained by these methods. The results obtained confirm the effectiveness of our approach compared with the rest of the analyzed methods, obtaining more accurate fuzzy logic controllers with simpler models.

Keywords Heating, ventilating, and air conditioning systems · HVAC systems · Fuzzy logic controllers · Genetic tuning · Linguistic 2-tuples representation · Rule selection · Multi-objective evolutionary algorithms

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M.J. Gacto (✉)
Dept. Computer Sciences, University of Jaén, Jaén, Spain
e-mail: mjgacto@ugr.es

R. Alcalá · F. Herrera
Dept. Computer Science and Artificial Intelligence,
University of Granada, Granada, Spain

R. Alcalá
e-mail: alcala@decsai.ugr.es

F. Herrera
e-mail: herrera@decsai.ugr.es

1 Introduction

In EU countries, primary energy consumption in buildings represents about 40% of total energy consumption, and depending on the countries, more than half of this energy is used for indoor climate conditions. From 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% in the energy consumption of the building sector. 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 consist of complex equipment usually implemented for maintaining satisfactory comfort levels in buildings. The energy consumption as well as indoor comfort aspects of buildings are highly dependent on the design, performance and control of their HVAC systems and equipment. Therefore, the use of appropriate automatic control strategies, such as Fuzzy Logic Controllers (FLCs) [1–4], for the control of HVAC systems could result in important energy savings when compared to manual control, particularly when we explicitly try to minimize the energy consumption [5–10].

Typically, FLCs have been applied to HVAC systems where several criteria are individually considered [5–7, 11–16], thermal regulation, energy consumption or comfort improvement (separately). However, these and other criteria must be considered jointly [8–10] in order to obtain the best global performance in terms of energy consumption, desired comfort level, air quality, system stability, etc. In our case, the problem consists of optimizing five criteria together. To this end, we make use of an initial FLC obtained by experts involving 17 variables and a fuzzy hierarchical structure. A good way to improve the global performance of such a system is to consider Genetic Algorithms (GAs) [17, 18] in order to refine the initial FLC. In any case, the problem becomes very complex since several criteria are taken into account, many variables are involved (large search space) and the fitness function (also defined by experts in order to consider the five criteria together) is based on a simulation requiring a lot of computing time for each evaluation (a small number of evaluations can be performed).

This HVAC system control problem has previously been presented and addressed using GAs in [8–10]. Firstly, this problem was considered in [8] by applying a parametric tuning of Membership Functions (MFs). Secondly, a rule selection combined with the learning of rule weights was considered in [9]. And finally, two advanced tuning techniques have been used and combined with a rule selection in [10] (rule selection plus lateral [19] or lateral and amplitude tuning [20]). All these optimization techniques are based on the use of steady-state GAs. The use of steady-state GAs allows a faster convergence, which is necessary for our problem, involving a large search space and where the number of available evaluations is small.

A very interesting conclusion from these previous works is that the combination with rule selection techniques significantly improves the global performance of the HVAC system. In the case of FLCs obtained from experts [10], this combination of tuning techniques and rule selection presents a highly positive synergy. For this reason, the use of Multi-Objective Evolutionary Algorithms (MOEAs) [21, 22] to evolve a set of solutions with a different number of rules (representing different promising rule combinations and therefore different precision levels) while tuning is concurrently performed, becomes a good way of finding the best performing FLC.

MOEAs have been widely used in the literature to obtain a set of non-dominated solutions with different complexities and performance degrees [23–33] by selecting or learning the set of fuzzy rules that best represent the system. Specifically, MOEAs [31, 32] have shown promising results in the combination of the rule selection with classic tuning techniques, improving the system accuracy by finding the appropriate fuzzy system complexity. General use and specific MOEAs for the tuning of MFs together with a rule selection [31, 32], have been successfully used in data-driven problems. However, they could not solve the HVAC control optimization problem, since they are based on a generational scheme and usually need many evaluations to obtain good results.

In this contribution, we propose an effective and efficient MOEA that incorporates specific mechanisms in order to better tackle the HVAC control optimization problem by using the following two objectives:

– Maximizing the performance of the system (by using the same aggregation function proposed in the previous works).
– Minimizing the number of rules (in order make finding better rule combinations easier).

The proposed MOEA performs a lateral tuning of MFs [19], which presented better results with respect to the classic tuning in [10], together with a rule selection and it is called Exploration-Exploitation based SPEA2 (LS-SPEA$2_{E/E}$). This algorithm is based on *SPEA*2 [34] and incorporates specific mechanisms for maintaining the population diversity and for expending few evaluations in the optimization process. This favors the quick convergence towards good solutions necessary to solve the HVAC problem.

To show the good performance of the proposed method it is compared with the single objective-based algorithms from the previous contribution [8–10] and with several MOEAs adapted to apply a lateral tuning of MFs together with a rule selection. In the experiments, we include the previous mono-objective steady-state GAs that perform a tuning of the MFs (classic, lateral or lateral with amplitude tuning) and/or rule selection [8, 10], together with the method for rule selection and rule weighting in [9]. In addition, the proposed method is compared with several basic MOEAs of general use, such as SPEA2 [34], NSGA-II [35] and two versions of NSGA-II [36] (for centering the search on the areas with the best trade-off between both objectives), and with SPEA2_{ACC} [31, 32] (an accuracy-oriented adaptation of SPEA2 devoted to performing a tuning of MFs together with a rule selection). Moreover, we include in the experiments the steady-state versions of NSGA-II [37], SPEA2 [37] and LS-SPEA$2_{E/E}$ (steady-state version of the proposed algorithm) in order to show that the proposed approach presents the best convergence ability for this complex problem.

In order to do this, this contribution is arranged as follows. The next section presents the basics of the HVAC system control problem that will be solved in this paper. Section 3 introduces the lateral tuning of MFs, the rule selection technique and analyzes the use of MOEAs for obtaining fuzzy systems. In Sect. 4, we present the LS-SPEA2$_{E/E}$ algorithm describing its main characteristics and the genetic operators considered. Section 5 shows the experimental study, the results obtained and an analysis of the FLCs and Pareto fronts obtained. Finally, Sect. 6 makes some conclusions.

2 Heating, ventilating, and air conditioning systems

An HVAC system is comprised of all the components of the appliance used to condition the interior air of a building. The HVAC system is needed to provide the occupants with a comfortable and productive working environment which satisfies their physiological needs. In a modern intelligent building, a sophisticated control system should provide excellent environmental control [5].

In this work, the problem that we will address is the control of a particular HVAC system described in [8–10]. It is implemented to maintain satisfactory comfort conditions and to decrease the energy consumption in large buildings. For our experiments a real test site is available. It has been provided within the framework of the GENESYS[1] project. The test site consists of seven single zone test cells and an artificial climate can be created at any time. Figure 1 illustrates this test site. In Fig. 2, a typical office building HVAC system is presented. This system consists of a set of components able to raise and lower the temperature and relative humidity of the supply air:

1. This module mixes the return air and the outside air to provide supply air, and also closes the outside air damper and opens the return air damper when the fan stops.
2. It is a filter to reduce the outside air emissions to supply air.
3. The preheater/heat recovery unit preheats the supply air and recovers energy from the exhaust air.
4. A humidifier raises the relative humidity in winter.
5. There is a cooler to reduce the supply air temperature and/or humidity.
6. An after-heater unit to raise the supply air temperature after the humidifier or to raise the supply air temperature after latent cooling (dehumidifier).
7. The supply air fan.
8. The dampers to demand controlled supply air flow to rooms.
9. A heat recovery unit for energy recovery from exhaust air.
10. The exhaust air fan.

To evaluate the performance of the controller a physical model of the controlled buildings is usually necessary. In this way, we can evaluate the controller by using a simulation tool with the desired environmental conditions.

2.1 Performance criteria

In this problem, we try to optimize the FLC in order to improve the energy performance and to maintain the required indoor comfort levels. In this way, as described in [8–10], our first objective is to minimize the following five measures:

M_1 Upper thermal comfort limit:
$if\ PMV > 0.5,\ M_1 = M_1 + (PMV - 0.5)$, *PMV*, *Predicted Mean Vote* is the index for thermal comfort ISO 7730,[2] incorporating relative humidity and mean radiant temperature.

M_2 Lower thermal comfort limit:
$if\ PMV < -0.5,\ M_2 = M_2 + (-PMV - 0.5)$.

M_3 Air Quality requirement:
$if\ CO_2\ conc. > 800$ ppm, $M_3 = M_3 + (CO_2 - 800)$.

M_4 Energy consumption: $M_4 = M_4 +$ Power at time t.

M_5 System stability: $M_5 = M_5 +$ System change from time t to $(t-1)$, where system change stands for a change in the system operation, i.e., it counts the system operation changes (a change in the fan speed or valve position).

The comfort and air quality measures should be maintained within some requested levels, which is a difficult task since they follow contradictory interests to those of energy and stability. In order to obtain a good controller these measures should have values within the stipulated limits, that is, no more than 1.0 for M_1, M_2, and 7 for M_3.

Each experiment has to consider these five measures. It makes the system being controlled very complex and presents a strong non linearity due to the fact that there are many measures to consider, and they can not be used as individual objectives by standard or even specific MOEAs. It is known that the current state-of-the-art MOEAs present important difficulties to effectively handle more than three objectives, which particularly affects in this problem that needs finding a good solution expending only a small number evaluations. Therefore, all these measures have to be combined in only one objective. In this event, they are combined into a fitness function by means of a vector of weights:

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

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

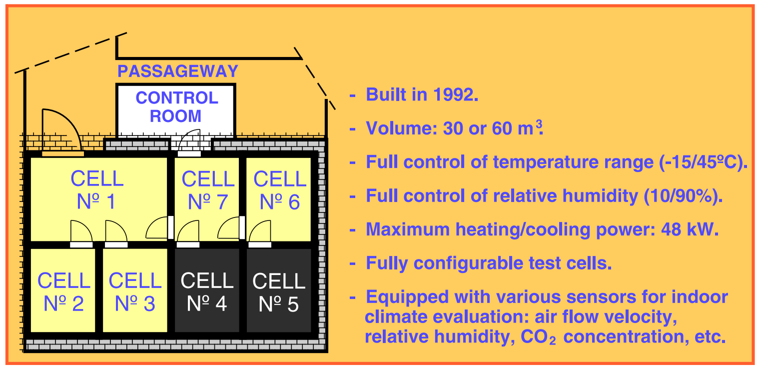


Fig. 1 Representation and main characteristics of the test cells

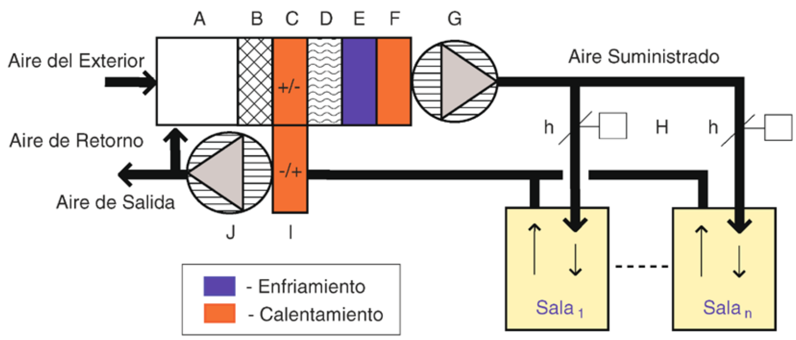


Fig. 2 Generic Structure of an Office Building HVAC System

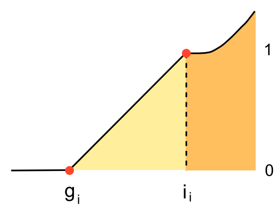
$w_1 = 0.0083022$, $w_2 = 0.0083022$, $w_3 = 0.00000456662$, $w_4 = 0.0000017832$ and $w_5 = 0.000761667$. Finally, the fitness function that has to be minimized was computed as:

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

However, the fitness function was modified [8–10] in order to consider the use of fuzzy goals that decrease the importance of each measure whenever it reaches its goal or penalize (increases their importance) each measure whenever its value gets worse in respect to the initial solution. To do so, a function $\delta_i(x)$ that modifies the value of adaptation for each individual measure is included (taking values over 1.0). A penalization rate, p_i, has been included, allowing the user to set up priorities in the measures (with 0 representing less priority and 1 more priority). Therefore, the fitness function is obtained as:

$$F' = \sum_{i=1}^{5} w_i \cdot \delta_i(M_i) \cdot M_i.$$

Taking into account that for each measure M_i, g_i and p_i are respectively the value of the goal and the penalization rate determined by the expert, i_i is the value of the initial solution and $\delta_i(x)$ is the penalization function used to modify its adaptation value in the fitness function calculation, two different situations have to be reflected in the $\delta_i(x)$ function computation according to the possible values of the goal, g_i, and the value of the initial solution, i_i. Depending on these values, two different δ functions have been defined in Figs. 3 and 4:

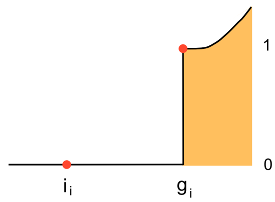


$$\delta_i(x) = \begin{cases} 0, & \text{if } x \le g_i \\ \dfrac{x - g_i}{i_i - g_i}, & \text{if } g_i < x < i_i \\ \dfrac{x - i_i}{x - x \cdot p_i} + 1, & \text{if } i_i \le x \end{cases}.$$

Fig. 3 $\delta_i(x)$ when $g_i \le i_i$

– When the value of g_i is less than the value of i_i, the measure is not considered if the goal is met and penalized if the initial results get worse (see Fig. 3).
– When the value of i_i is less than the value of g_i, this initial result may get worse while the goal is met and, it is penalized if so (see Fig. 4).

This F' fitness function was shown to be very effective to obtain good results in the previous works applied to this problem [8–10]. Therefore, F' represents the first objective of our MOEAs and its value is obtained by the test simulation model.



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

Fig. 4 $\delta_i(x)$ when $g_i > i_i$

2.2 Variables and architecture of the controller

The system has a hierarchical architecture considering the PMV, CO_2 concentration, previous HVAC system status and outdoor temperature. This architecture, variables and initial Rule Base (RB) are presented in Fig. 5. The initial Data Base (DB), that is depicted in Fig. 6, is composed of symmetrical fuzzy partitions with triangular-shaped MFs. For the sake of simplicity, from now we will use labels from $L1$ to Ll_i (with l_i being the number of labels of the ith variable) to refer to the corresponding linguistic terms (see Fig. 6). Therefore, Lj's are used as abbreviations in order to easily represent the linguistic terms defined in the DB in the shortest possible way for each variable. In this way, Fig. 5 represents the decision tables of each module of the hierarchical controller in terms of these labels. Each cell of the table represents a fuzzy subspace and contains its associated output consequent(s), i.e., the corresponding label(s). The output variables are denoted in the top left square for each module in the figure.

Due to the small number of evaluations of the system model and in order to obtain an efficient fuzzy inference system, we consider the Mean of Maxima weighted by the rule antecedent matching as defuzzification operator [2].

3 Preliminaries

This section introduces the global lateral tuning of MFs and presents the basics of the rule selection techniques. Moreover, a brief analysis of the state-of-the-art in the use of multi-objective genetic fuzzy systems (GFSs) [24, 38, 39] is also included at the end of the section.

3.1 Lateral tuning of membership functions

In [19], a model of the tuning of Fuzzy Rule-Based Systems (FRBSs) was proposed considering the linguistic 2-tuples representation scheme introduced in [40], which allows the lateral displacement of the support of a label and maintains the interpretability associated with the obtained linguistic FRBSs. This proposal also introduces a new model for rule representation based on the concept of symbolic translation [40].

The symbolic translation of a linguistic term is a number within the interval $[-0.5, 0.5)$, this interval expresses the domain of a label when it is moving between its two adjacent lateral labels (see Fig. 7.a). Let us consider a set of labels S representing a fuzzy partition. Formally, to represent the symbolic translation of a label in S we have the 2-tuple,

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

The symbolic translation of a label involves the lateral displacement of its associated MF. As an example, Fig. 7 shows the symbolic translation of a label represented by the pair $(s_2, -0.3)$ together with the lateral displacement of the corresponding MF.

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

$Error$, $\triangledown Error \to \{Negative, Zero, Positive\}$,
$Power \to \{Low, Medium, High\}$.

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

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

Rule with 2-Tuples Representation,
If **error** is (Zero, 0.3) and $\triangledown$**Error** is (Positive, -0.2)
then **Power** is (High, -0.1).

In [9], two different rule representation approaches were proposed, a global approach and a local approach. In our particular case, the learning is applied to the level of linguistic partitions (global approach). In this way, the pair (X_i, label) takes the same α value in all the rules where it is considered, i.e., a global collection of 2-tuples is considered by all the fuzzy rules. For example, X_i is (High, 0.3) will present the same value for those rules in which the pair "X_i is High" was initially considered.

We can highlight that, since the three parameters usually considered per label are reduced to only 1 symbolic translation parameter, this proposal decreases the learning problem complexity, easing the derivation of optimal models in very complex search spaces. Another important issue is that, from the parameters α applied to each label, we can obtain the equivalent triangular MFs, from which an FRBS based on linguistic 2-tuples could be represented as a classical Mamdani FRBS.

3.2 The rule selection technique

Rule set reduction techniques try to minimize the number of rules while maintaining (or even improving) the system per-

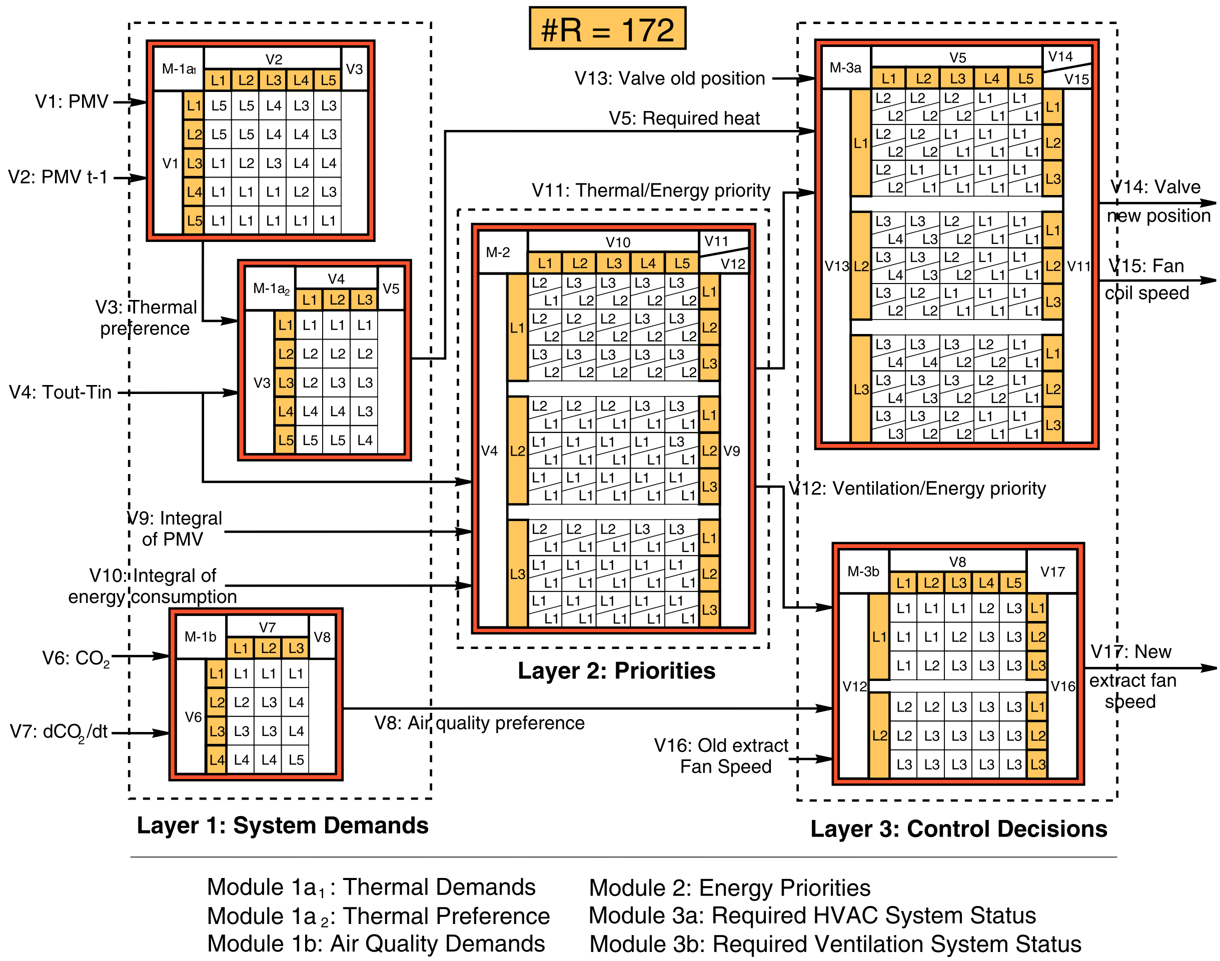


Fig. 5 Initial Rule Base and generic structure of the test module

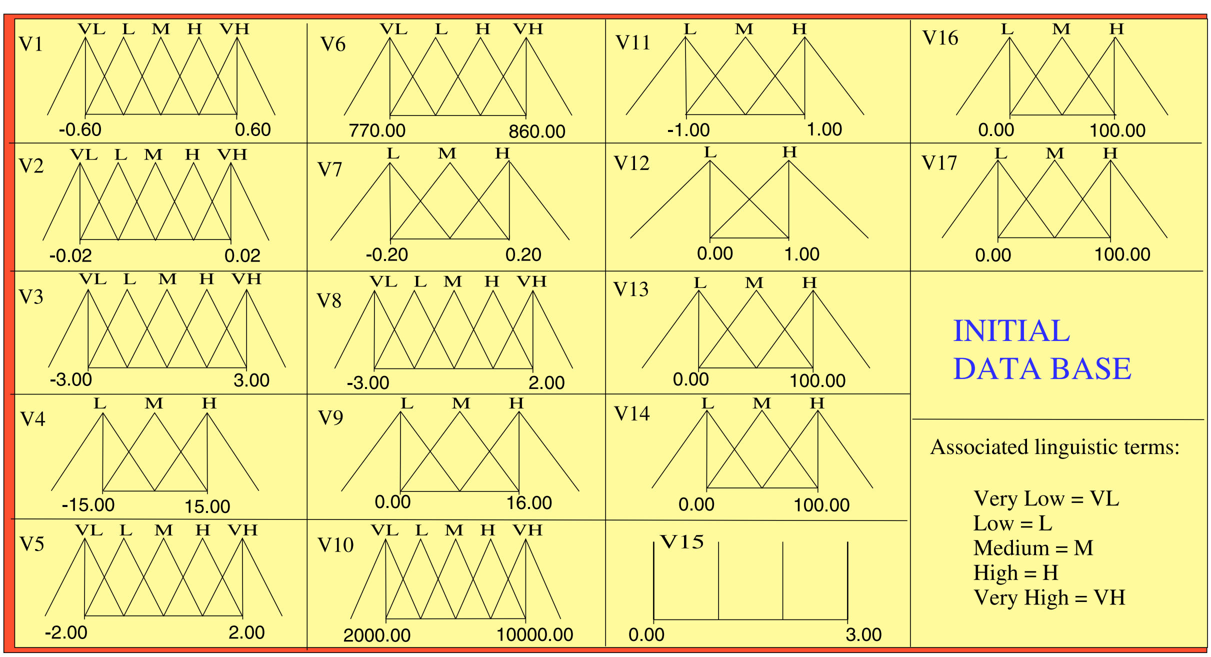


Fig. 6 Initial data base

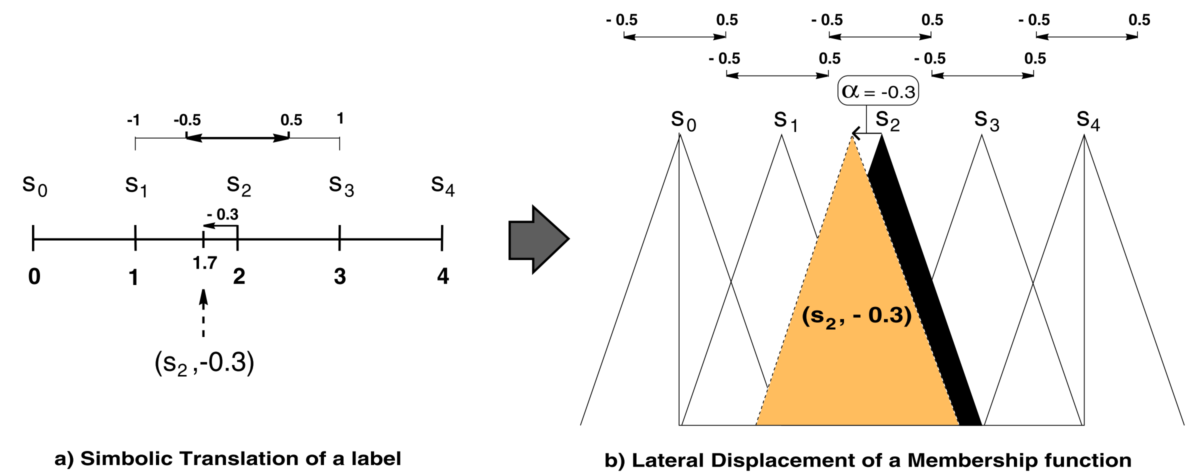


Fig. 7 Symbolic translation of a linguistic label and lateral displacement of the involved MF

formance. To do that, erroneous and conflicting rules that degrade the performance are eliminated, obtaining a more cooperative fuzzy rule set and therefore involving a potential improvement in the system accuracy. Furthermore, in many cases the accuracy is not the only requirement of the model but also its interpretability becomes an important aspect. Reducing the model complexity is a way of improving the system's readability, i.e., a compact system with few rules requires less effort to be interpreted.

Fuzzy rule set reduction is generally applied as a post-processing stage, once an initial fuzzy rule set has been derived. One of the most well known fuzzy rule set reduction techniques is rule selection [41]. This approach involves obtaining an optimal subset of fuzzy rules from a previous fuzzy rule set by selecting some of them. We may find several methods for rule selection, with different search algorithms that look for the most successful combination of fuzzy rules [1, 25, 41, 42]. In [43], an interesting heuristic rule selection procedure is proposed where, by means of statistical measures, a relevance factor is computed for each fuzzy rule composing the FRBSs to subsequently select the most relevant ones.

These kinds of techniques for rule selection could be easily combined with other post-processing techniques to obtain more compact and accurate systems. In this way, some works have considered the selection of rules together with the tuning of MFs by coding all of them (rules and parameters) in the same chromosome [19, 20, 44–46].

3.3 Multi-objective genetic fuzzy systems to control the complexity of the models

MOEAs generate a family of equally valid solutions, where each solution tends to satisfy a criterion to a higher extent than another. For this reason, MOEAs have also been applied to improve the difficult trade-off between the complexity and accuracy of FRBSs, where each solution in the Pareto front represents a different trade-off between both kinds of measures.

In the literature, we can find some papers of several researchers on this topic. Earlier works [25] considered rule selection of an initial set of classification rules and two different criteria, classification accuracy and number of rules. Rule length (sometimes considered in combination with the number of rules) has also been included to minimize the length of the rules by rule selection [26, 28] or rule learning [26, 29]. In [47], Cordon et al. use a classical MOEA for jointly performing feature selection and fuzzy set granularity learning with only two objectives.

It should be highlighted that all the mentioned methods have been applied to classification problems for rule selection or rule learning, without learning or tuning the MFs. In this sense, two similar MOEAs (based on NSGA-II) were proposed to postprocess an initial FRBS in classification problems [48, 49]. Both algorithms perform a tuning of the MFs while evolving the premises of the initial RB.

There are also a few works in the framework of fuzzy modeling for regression problems (closer to control). In [50], the authors show how a basic MOEA can be applied to a three-objective optimization problem to obtain Mamdani FRBSs. In [23], an adaptation of the efficient $(2+2)$PAES [51] has been applied to the identification of Mamdani FRBSs for regression problems by considering two minimization objectives (the system error and the number of variables involved in the antecedent of the obtained rules). Again, these approaches do not consider learning or tuning of the MF parameters.

Finally, the most interesting MOEAs, taking into account the HVAC system optimization problem, are those in [31, 32]. In these works [31, 32], the authors analyzed some of the most recognized MOEAs of general use and proposed a specific MOEA for solving regression problems. They demonstrated that the combination of a tuning technique with a rule selection method within a multiobjective framework presents a positive synergy (even better than when using mono-objective approaches). It would be interesting to use this combination in a real application like the HVAC system, because it helps the large amount of rule combinations to be handled better, thus improving the system performance even more. However, as mentioned in Sect. 1, these algorithms usually need a considerable amount of evaluations, which are not available in our particular problem. Because of this, in this work, we propose a specific more effective and efficient MOEA that performs the rule selection together with the lateral tuning of MFs [19] in order to solve the HVAC problem. We will also apply the algorithms in [31, 32] for the purpose of comparison.

4 Proposed multi-objective evolutionary algorithm

In this section, we present a specific MOEA, called Exploration-Exploitation SPEA2 (LS-SPEA2$_{E/E}$) for lateral tuning and rule selection in order to better address the HVAC problem. It is based on *SPEA*2 [34] and incorporates a set of characteristics that allow us to manage complex problems with a large number of variables and a reduced number of available evaluations. These characteristics are:

– A mechanism for guiding the search towards the desired Pareto region [31].
– A mechanism for incest prevention, in order to maintain population diversity.
– An advanced restarting mechanism, in order to avoid getting stuck at local optima.
– An intelligent crossover operator, that helps to improve the success probability, avoiding useless evaluations.

Thanks to the incest prevention mechanism, this algorithm expends few evaluations, because in the first generations few interesting cross-overs are performed. This favors a quick convergence towards good solutions provoking a good trade-off between exploration and exploitation, which is appropriate to solve this problem.

In the following sections, we show some important aspects of the algorithm, and then the main steps and specific characteristics are described.

4.1 Objectives

Every chromosome is associated with a two-dimensional objective vector, each element of which expresses the fulfillment degree of the following two objectives:

1. Maximization performance: F' (see Sect. 2.1).
2. Minimization number of rules.

4.2 Coding scheme and initial population

A double coding scheme for both *rule selection* (C_S) and *tuning* (C_T) is used:

$$C = C_S C_T.$$

In the C_S part, the coding scheme consists of binary-coded strings with m being the number of initial rules,

$$C_S = (c_{S1}, \ldots, c_{Sm}).$$

Depending on whether a rule is selected or not, values '1' or '0' are respectively assigned to the corresponding gene.

In the C_T part a real coding is used where we consider the following number of labels per variable $(m_1, m_2, \ldots, m_n)$, with n being the number of variables,

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

The initial pool is obtained with the first individual having all genes with value '1', and the remaining individuals generated at random in the C_S part. In the C_T part, the initial DB is included as an initial solution and the remaining individuals are randomly generated maintaining their genes in $[-0.5, 0.5)$ (their respective variation intervals).

See Fig. 8 for a graphical example of a coding scheme considering this approach.

4.3 Crossover and mutation

In this subsection, we propose an intelligent crossover and a mutation operator for the combined action of the lateral tuning [19] with the rule selection based on our experience with these techniques. This is able to adequately profit from the parents when rule selection and tuning are applied together. The steps to obtain each offspring are as follows:

– BLX-0.5 [52] crossover is applied to obtain the C_T part of the offspring.
– Once the C_T part offspring has been obtained, the binary part C_S is obtained based on the C_T parts (MF displacement parameters) of the corresponding parents and offspring. For each gene in the C_S part which represents a concrete rule:

   1. The displacement parameters of the MFs involved in such rules are extracted from the corresponding C_T parts for each individual involved in the crossover (offspring and parents 1 and 2). These displacements represent the specific differences between these three individuals for such rules.
   2. Euclidean distances are computed between the extracted offspring parameters and each parent parameters pairly, i.e., distance with parent 1 and distance

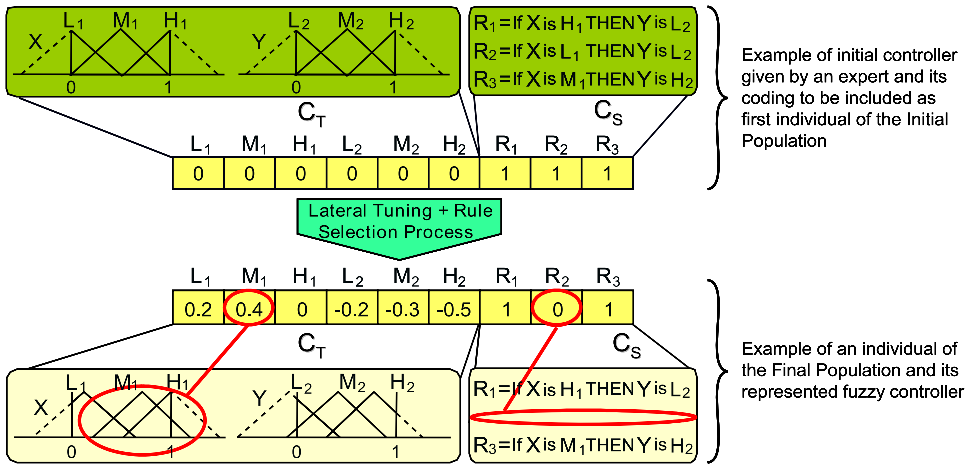


Fig. 8 Example of coding scheme considering lateral tuning and rule selection

with parent 2. The differences between each pair of displacements do not need to be normalized since all of them are in the interval $[-0.5, 0.5)$.

3. The parent with the closest distance to the offspring is the one that determines whether this rule is selected or not for the offspring by directly copying its value in C_S for the corresponding gene.

This process is repeated until all the C_S values are assigned to the offspring. Four offspring are obtained repeating this process four times (after considering mutation, only the two most accurate are taken as descendants).

By applying this operator, an exploration is performed of the C_T part, and C_S is directly obtained based on the previous knowledge that each parent has about the use or not of a specific configuration of MFs for each rule. This avoids the possibility of recovering a bad rule that was discarded for a concrete configuration of MFs, while allowing the recovery of a good rule that is still considered for this concrete configuration, increasing the probability of success in the selection or elimination of a rule for each concrete configuration of MFs.

Since a better exploration is performed for the C_S part, the mutation operator does not need to add rules. In this way, once an offspring is generated the mutation operator changes a gene value at random in the C_T part and directly sets to zero a gene selected at random in the C_S part (one gene is modified in each part) with probability P_m.

Applying these operators two problems are solved. Firstly, crossing individuals with very different rule configurations is more productive. And secondly, this way of working favors rule extraction since mutation is only engaged to remove unnecessary rules.

4.4 Main characteristics and steps of LS-SPEA2$_{E/E}$

In this section, we describe the main differences of the LS-SPEA2$_{E/E}$ algorithm with respect to the well-known *SPEA*2 [34], and its main steps are presented. We have chosen as the base of our method the SPEA2 algorithm since, in [31], approaches based on SPEA2 were shown to be more effective than the methods based on *NSGA-II* [35] for the problem of tuning and rule selection of FRBSs.

In order to focus the search on the desired Pareto zone, high performance with the least possible number of rules, we propose several mechanisms that give more selective pressure to those solutions that have a high performance and that favor a better exploration for the C_T part. Next, we describe and motivate these mechanisms, and then present the algorithm scheme.

– A restarting operator is applied by only maintaining the individual with the best performance as a part of the new population (external population must be empty) and obtaining the remaining individuals with the same rule configuration and with the tuning parameters generated at random within the corresponding variation intervals. In this way, we concentrate the search only on the desired Pareto zone (similar rule configurations in a zone with high performance) and get away from local optima or specific configurations in the C_T part.
– This algorithm includes an incest prevention mechanism in order to avoid premature convergence in the C_T part (real coding), that is the main cause of performance improvements and represents a more complicated search space than the C_S part (binary coding). Only those parents whose hamming distance divided by 4 is higher than a threshold are crossed. Since we consider a real coding scheme (only C_T parts are considered), we have to transform each gene considering a Gray Code with a fixed number of bits per gene (*BGene*) determined by the system expert. In this way, the threshold value is initialized as:

$$L = (\#C_T * BGene)/4,$$

where $\#C_T$ is the number of genes in the C_T part of the chromosome. At each generation of the algorithm, the threshold value is decremented by one allowing closer solutions to cross.

– Restarting should be applied when we detect that all the possible crossovers are allowed. However, in order to avoid premature convergence we apply the first restart if 50 percent of crossovers are detected at any generation (the required ratio can be defined as $\%_{Required} = 0.5$). This value is updated each time restarting is performed as:

  $\%_{Required} = (1 + \%_{Required})/2.$

  Moreover, the solution with the best performance should be improved before each restart. To preserve a well formed Pareto front at the end, the restart is not applied in the last evaluations. The number of evaluations without restarting can be estimated as the number of evaluations needed to apply the first restart multiplied by 4. Additionally, the restart is disabled if it was never applied before reaching the middle of the total number of evaluations. See Steps 5 and 7 in the LS-SPEA2$_{E/E}$ Algorithm Scheme of Fig. 9.
– At each stage of the algorithm (between restarting points), the number of solutions in the external population ($\overline{P}_{t+1}$) considered to form the mating pool is progressively reduced, by focusing only on those with the best performance. To do that, the solutions are sorted from the best to the worst (considering performance as criterion) and the number of solutions considered for selection is reduced progressively from 100% at the beginning to 50% at the end of each stage by taking into account the value of L.

The main steps of LS-SPEA2$_{E/E}$ are finally presented in Fig. 9 (see SPEA2 in [34]).

Input:

N (population size), $\overline{N}$ (external population size), E (maximum number of evaluations), $BGene$ (bit per gene for gray code).

Output:

A (set of non-dominated solutions).

Terminology:

$\#C_T$ (number of genes in the real part C_T),
L (threshold for incest prevention),
$InitL = (\#C_T * BGene)/4$ (initial threshold),
$R\%$ (descendant % required to perform restart),
Rst (internal variable to activate restart),
$Nded$ (evaluations needed to form a Pareto),
Evs (current number of evaluations),
$Perf^+$ (performance improvement is detected in the solution with the best performance from the latest restart).

Algorithm:

1. Generate P_0 (initial population) and create $\overline{P}_0 = \emptyset$ (empty external population).
2. Evaluate individuals in P_0 and set:
   – $L = InitL$; $R\% = 0.5$; $Rst = false$;
   – $Evs = N$; $Nded = 0$; $t = 0$;
3. Calculate fitness values of individuals in P_t and $\overline{P}_t$. Copy all non-dominated individuals in $P_t \cup \overline{P}_t$ to $\overline{P}_{t+1}$. If $|\overline{P}_{t+1}| > \overline{N}$ apply standard SPEA2 truncation operator (which guarantees the preservation of boundary solutions, see [34]). If $|\overline{P}_{t+1}| < \overline{N}$ fill with dominated in $P_t \cup \overline{P}_t$.
4. If $Evs \geq E$, return A and stop.
5. If (Rst) and ($Evs < E - Nded$) and ($Perf^+$):
   – $L = InitL$; $R\% = (R\% + 1)/2.0$; $Rst = false$;
   – If $Nded$ is 0, $Nded = Evs * 4$; $Evs += N - 1$.
   – Copy the individual with the best performance to P_t. Empty $\overline{P}_t$ ($\overline{P}_t = \emptyset$). Fill remaining $N - 1$ individuals in P_t with C_T at random and C_S equal to the individual with the best performance.
   – Evaluate $N - 1$ new individuals in P_t and go to Step 3.
6. Generate the next population:
   – Set $P = (L/(InitL * 2.0) + 0.5)$. Perform binary tournament selection with replacement on the $\lfloor \overline{N} * P \rfloor$ solutions with the best performance of $\overline{P}_{t+1}$ in order to fill the mating pool.
   – Apply crossover (BLX) and mutation for each two parents in the mating pool if the hamming distance between their C_T part Gray codings divided by 4 is over L.
   – Set P_{t+1} to the resulting population with the obtained G descendant. Set $evs += G * 2$.
7. Variables updating:
   • If $G \geq N * R\%$, $Rst = true$; If $L > 0$, $L = L - 1$;
   • If $Nded$ is 0 and $evs \geq E/2$, $Nded = E$.
8. Go to Step 3 with $t = t + 1$.

Fig. 9 LS-SPEA2$_{E/E}$ algorithm scheme

5 Experiments

To evaluate the usefulness of the LS-SPEA2$_{E/E}$ method, the HVAC problem presented in Sect. 2 is considered in order to be solved. This section is organized as follows:

– Section 5.1 presents the experimental set-up.
– Section 5.2 shows the results obtained by the different methods.
– Section 5.3 analyzes the obtained FLCs and includes an example of the DB and RB obtained by the proposed method.
– Section 5.4 shows an analysis of the obtained Pareto Fronts. Moreover, examples of the Pareto front are presented in order to graphically show the results of the different methods.

5.1 Experimental setup

The methods considered for the experiments are briefly described in Table 1. All the mono-objective GAs consider the fitness function F' presented as the sole objective (previous approaches solving the HVAC problem [8–10]). The MOEAs perform the rule selection together with lateral tuning of MFs considering two objectives: the function F' and the number of rules. In these experiments, MOEAs of general use are utilized, as SPEA2 [34], NSGA-II [35] and two modifications of NSGA-II [36] (LS-NSGA-II$_A$ and LS-NSGA-II$_U$) for finding knees. Moreover, we also consider in the experiments an adaptation of *SPEA*2 to focus the search on the desired Pareto zone (LS-SPEA2$_{ACC}$ [31]) and the proposed method LS-SPEA2$_{E/E}$. All these MOEAs were adapted to perform a classic tuning plus rule selection for FRBSs and applied to problems based on the existence of example data (data driven-based problems) in [32]. Therefore, they represent good alternatives for comparison.

Besides, the steady-state versions of LS-NSGA-II, LS-SPEA2 and LS-SPEA2$_{E/E}$ are also included in the experiments. Considering the modifications proposed in [37], the main changes to apply a steady-state scheme to these MOEAs are:

– NSGA-II steady-state method is easily implemented by using an offspring population of size 1.
– The steady-state versions of the SPEA2-based methods (LS-SPEA2$_{SS}$, LS-SPEA2$_{E/E,SS}$) use a population of size 1. The initial population must have the same size as the archive, since in the first generation the archive is filled by all the members belonging to the population.
– In all the steady-state methods, the crossover operator obtains two offspring, and only the one with the best performance is taken as a descendant.

The number of evaluations can not be very high, due to the complexity of the fitness function calculation which is obtained by means of a simulated system. In this case, we can perform the tests at a reasonable time carrying out 2000 evaluations. The time required for each simulation is one minute approximately (most of the simulations take less than one minute, but some specific simulations require 10 minutes, particularly those evaluating a bad FLC). Therefore, the run times are approximately 1.5 days. In order to obtain average results, three different runs have been performed for all the algorithms considering three different seeds for the random number generator, as was done in [8–10].

Table 1 Methods considered for comparison

Method	Ref.	Description
Mono-objective steady-state genetic algorithms (the previous approaches solving the HVAC problem)		
S	[9]	Rule Selection
T	[8]	Tuning of Parameters (named C in [10])
TS	[10]	Tuning & Selection (named C-S in [10])
W	[9]	Rule Weights
WS	[9]	Rule Weights and Rule Selection
L	[10]	Lateral Tuning of Parameters (named GL in [10])
LS	[10]	Lateral Tuning & Selection (named GL-S in [10])
LA	[10]	Lateral and Amplitude Tuning of Parameters (named GLA in [10])
LAS	[10]	Lateral and Amplitude Tuning & Selection (named GLA-S in [10])
Multi-objective steady-state evolutionary algorithms		
LS-NSGA-II$_{SS}$	–	Lateral Tuning & Selection by the steady-state NSGA-II [37]
LS-SPEA2$_{SS}$	–	Lateral Tuning & Selection by the steady-state SPEA2 [37]
LS-SPEA2$_{E/E,SS}$	–	Lateral Tuning & Selection by the steady-state SPEA2$_{E/E}$ (Exploration/Exploitation)
Multi-objective evolutionary algorithms		
LS-NSGA-II	[31, 32]*	Lateral Tuning & Selection by NSGA-II [35]
LS-NSGA-II$_A$	[32]*	Lateral Tuning & Selection by NSGA-II with angle-measure [36]
LS-NSGA-II$_U$	[32]*	Lateral Tuning & Selection by NSGA-II with utility-measure [36]
LS-SPEA2	[31, 32]*	Lateral Tuning & Selection by SPEA2 [34]
LS-SPEA2$_{ACC}$	[31, 32]*	Lateral Tuning & Selection by SPEA2$_{ACC}$ (Accuracy-Oriented)
LS-SPEA2$_{E/E}$	–	Lateral Tuning & Selection by SPEA2$_{E/E}$ (Exploration/Exploitation)

*Based on these algorithms (adaptation from classic to lateral tuning since it performs better in the HVAC problem)

The performance of the controller obtained from said approaches will also be compared to the performance of a classic On-Off controller (improvement percentages are computed with respect to it) and to the performance of the initial controller. Comfort measures could be slightly increased if necessary (no more than 1.0 for M_1, M_2, and 7 for M_3).

The values of the parameters used in the mono-objective GAs are the same ones used in [8–10] (also with 2000 evaluations). The values of the input parameters considered by MOEAs are: 2000 evaluations, population size of 100, external population size of 31 (in the case of SPEA2 based algorithms), 0.5 for the factor α in the BLX crossover operator, 0.2 as mutation probability, and 30 bits per gene for the Gray codification (used by LS-SPEA2$_{E/E}$ and LS-SPEA2$_{E/E.SS}$ methods).

The steady-state versions of the MOEAs use a population size of 1 in the case of approaches based on SPEA2, and consider an auxiliary population size of 1 in the case of NSGA-II.

5.2 Results

The results obtained by the different methods are presented in Table 2, where % stands for the improvement rate with respect to the On-Off controller, #R for the number of fuzzy rules, F for the performance function defined by experts and F' for the fitness function. The results with the On-Off and the initial controller are also included in this table. The values presented in Table 2 correspond to averaged results obtained from the three different runs considering the methods described in the Table 1. In the case of MOEAs, the averaged values are calculated considering the solution with the best performance (F') from each Pareto front obtained. Therefore, #R is the average number of finally selected rules for these solutions.

Of course, all the analyzed methods but S present important improvements, better results in energy and stability, than the On-Off controller and the initial controller. Further, only the proposed MOEA improves the results of the best

Table 2 Comparison among the different methods

			PMV			CO_2	Energy		Stability	
Method	#R	F'	F	M_1	M_2	M_3	M_4	%	M_5	%
Initial controllers										
ON-OFF	–	6.58	6.58	0.0	0	0	3206400	–	1136	–
Initial controller	172	5.69	6.32	0.0	0	0	2901686	9.5	1505	−32.5
Mono-objective steady-state genetic algorithms										
S	160	5.91	6.15	0.1	0	0	2886422	10.0	1312	−15.5
T	172	4.55	5.71	0.0	0	0	2586717	19.3	1081	4.8
TS	109	4.36	5.66	0.1	0	0	2536849	20.9	1057	7.0
W	172	5.37	5.88	0.1	0	1	2783010	13.2	1202	5.8
WS	109	4.95	5.64	0.6	0	0	2755851	14.1	949	16.5
L	172	3.75	4.97	0.9	0	0	2325093	27.5	1072	5.7
LS	113	3.35	4.69	0.7	0	0	2287993	28.6	800	29.6
LA	172	3.23	4.61	0.9	0	0	2245812	30.0	797	29.8
LAS	104	3.14	4.50	0.8	0	0	2253996	29.7	634	44.2
Multi-objective steady-state evolutionary algorithms										
LS-NSGA-II$_{SS}$	82.7	3.757	4.913	0.9	0	0	2358414	26.4	923	18.7
LS-SPEA2$_{SS}$	80	3.323	4.643	1.0	0	1	2298715	28.3	709	37.5
LS-SPEA2$_{E/E,SS}$	84.3	3.195	4.558	0.9	0	0.3	2248528	29.9	715	37.1
Multi-objective evolutionary algorithms										
LS-NSGA-II	82.7	3.830	4.909	0.5	0	1.3	2480182	22.6	636	44.0
LS-NSGA-II$_A$	**69.3**	3.964	5.003	0.7	0	0	2502374	21.9	706	37.8
LS-NSGA-II$_U$	71.3	4.304	5.264	0.6	0	0	2562149	20.1	909	19.9
LS-SPEA2	82	3.587	4.830	0.8	0	0	2373620	26.0	780	31.3
LS-SPEA2$_{ACC}$	96.3	3.383	4.708	1.0	0	0	2264251	29.4	874	23.0
LS-SPEA2$_{E/E}$	70.7	**3.064**	**4.412**	0.9	0	0	2231310	**30.4**	564	**50.3**

models obtained by the previous approaches [8–10] (mono-objective methods).

Analysing the results showed in Table 2 more deeply, we can highlight the following facts:

– First, the presented method presents improvement rates of about 30.4% in energy and about 50.3% in stability, obtaining a good balance between energy-stability. Also in the F' objective, it obtains 53.4% improvement. Moreover, a large number of rules have been removed from the initial RB (more or less 100 rules), improving the global performance of the system. LS-SPEA2$_{E/E}$ algorithm finds the best trade-off between accuracy and simplicity (obtaining controllers with the best performance)
– Even though theoretically LS-NSGA-II$_A$ and LS-NSGA-II$_U$, based on finding knees, should obtain the most promising Pareto zones, these methods obtain solutions with a small number of rules but bad average values in performance (for both energy and stability measures). This is due to the fact that knees represent good points along the evolution, but do not necessarily indicate the best direction for finding the optimum Pareto front.
– Mono-objective steady-state GAs obtain solutions with more rules than those obtained by the studied MOEAs. It shows that some unnecessary or inadequate rules cannot be removed by the single-objective approaches. Moreover, the proposed method obtains better results than the mono-objective GAs taking into account the solution with the best performance. LS-SPEA2$_{E/E}$ has other solutions in the Pareto front obtained (see the analysis of the Pareto fronts presented in Sect. 5.4) which allows the experts to select other solutions from the Pareto front.
– The steady-state MOEAs (LS-SPEA2$_{SS}$ and LS-NSGA-II$_{SS}$) obtain better results than their generational versions except in the case of the proposed algorithm.

In general, the LS-SPEA2$_{E/E}$ method has a good trade-off between simplicity and performance and it is well suited to solving this problem, that has a low number of available evaluations since the convergence of the method is accelerated while the number of evaluations needed is decreased.

5.3 Analysis of the obtained FLCs

Figure 10 represents the initial and the final DB of the FLC with the best performance obtained by LS-SPEA2$_{E/E}$ in the Pareto front obtained from a single trial (seed 3). It shows that small variations in the MFs cause large improvements in the controller performance. Figure 11 represents the decision tables of the same controller obtained from LS-SPEA2$_{E/E}$ considering the third seed (for an explanation of these kinds of figures, see Sect. 2.2). In this case, a large number of rules have been removed from the initial controller, obtaining a much simpler model (more or less 100 rules were eliminated). This fact improves the system readability, and allows us to obtain simple controllers with better performance. Additionally, Fig. 11 includes information about the obtained solution such as number of rules, fitness function and values obtained in each of the measures.

In Fig. 11, we only show the rules that are maintained after the rule selection. This figure shows that some regions

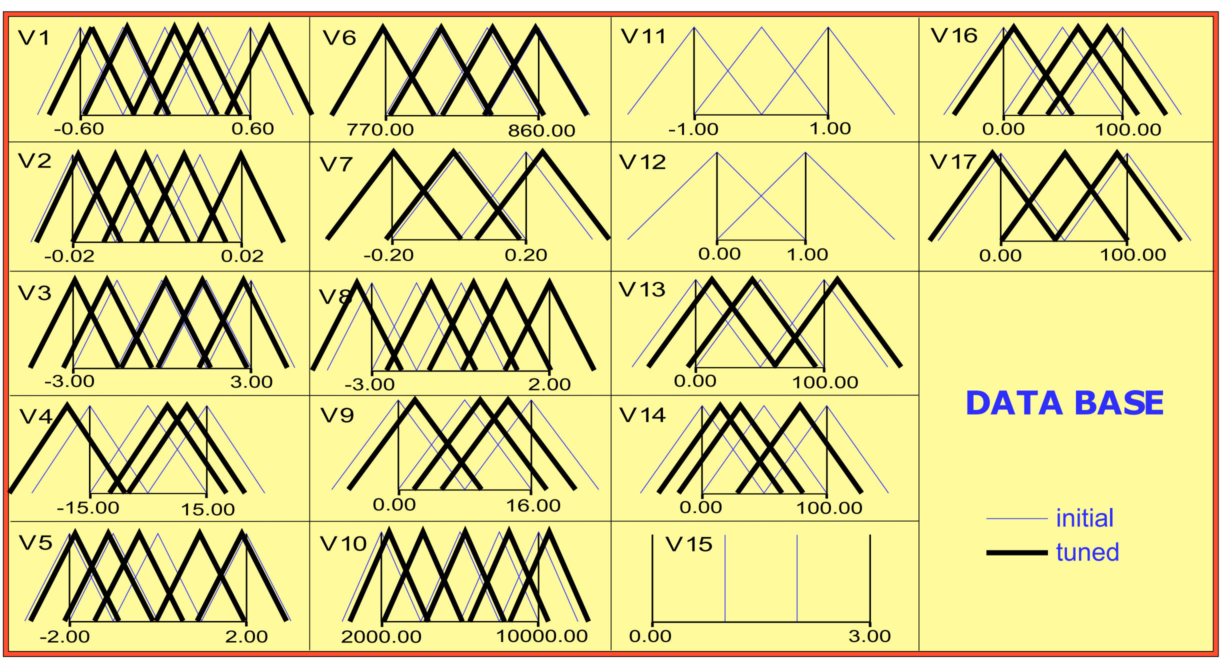


Fig. 10 Initial and tuned DB of a model obtained with LS-SPEA2$_{E/E}$ (model with the best performance from seed 3)

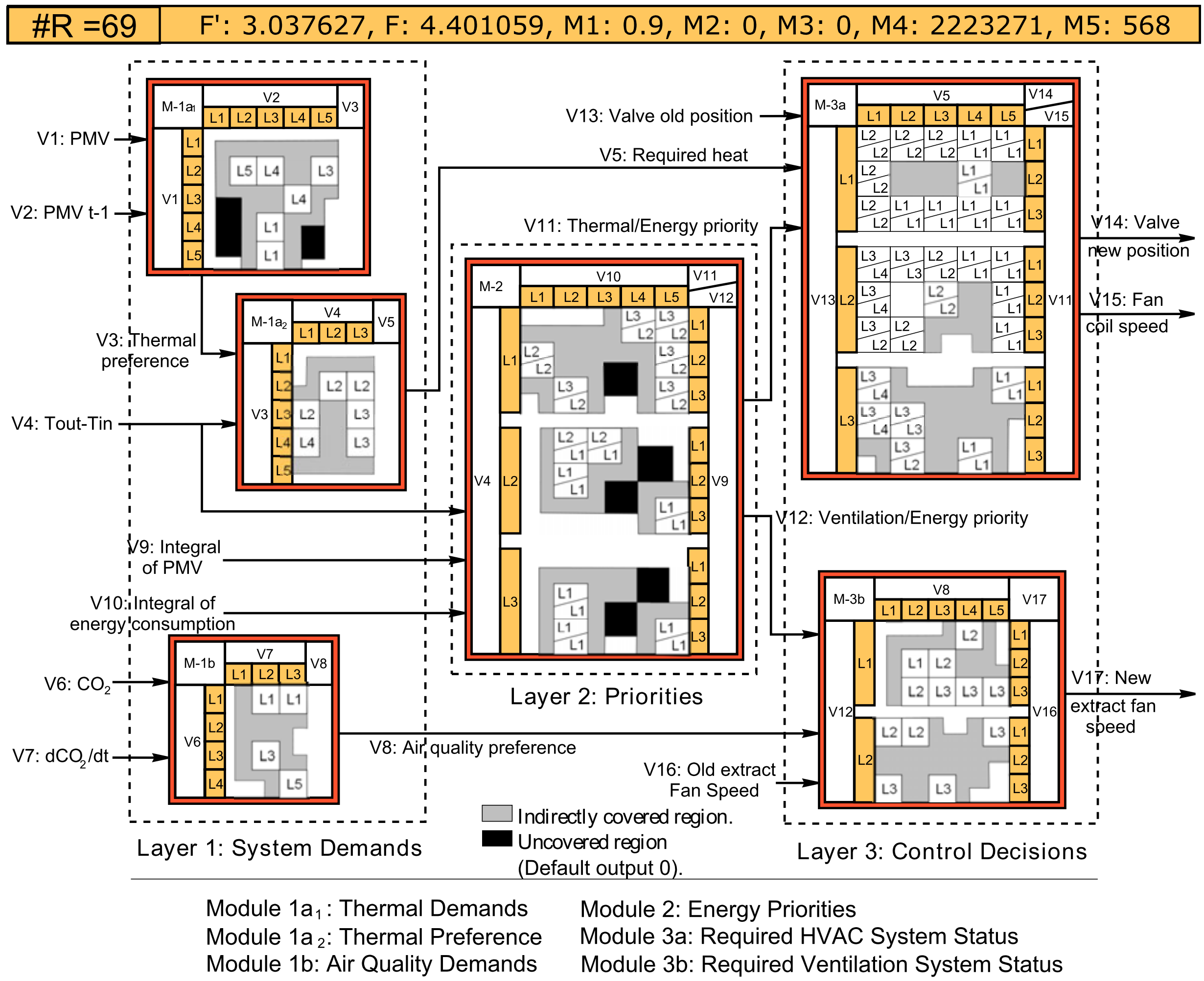


Fig. 11 RB and final structure of a model obtained with LS-SPEA2$_{E/E}$ (model with the best performance from seed 3)

of the space are indirectly covered (in gray) by nearby rules. Moreover, there are some small uncovered regions (in black) that correspond with infrequent inputs/situations. The default output in these cases is zero (the typical default output in control). For module M-1a$_1$ the default output (zero) can be interpreted for Variable 3 as the label L3 and in module M-2 as the label L2 for Variable 11 and as the label L1 for Variable 12.

These Figs. 10 and 11 present a representative example of the FLC obtained in the most precise solution of the Pareto front in seed 3. Similar solutions are obtained in the remaining seeds.

5.4 Analysis of the Pareto fronts

This section analyzes the performance of LS-SPEA2$_{E/E}$ algorithm in the remaining solutions that it obtained in the Pareto fronts. To do that, we plot the average Pareto fronts composed of the average values of three representative solutions in each of the three Pareto fronts. The first average solution is the one shown in Table 2, i.e., the average of the most accurate solutions obtained in each of the three Pareto fronts. The second solution is obtained in the same way but considering the median solution in each of the three Pareto fronts. The last average solution is obtained in the same way but considering the solution with the least number of rules in each of the three Pareto fronts.

These three points are a glimpse of the Pareto fronts obtained. The final user could select the most appropriate solution from the final Pareto front, by looking for any other concrete trade-off between the number of rules and fitness function, depending on its own preferences.

Figure 12 shows the average Pareto fronts (the three representative points) obtained with the methods presenting the best performances, MOEAs LS-SPEA2, LS-SPEA2$_{SS}$, LS-NSGA-II, LS-NSGA-II$_{SS}$, LS-SPEA2$_{E/E}$ and LS-SPEA2$_{E/E,SS}$, and mono-objective GAs LS and LAS. This figure includes symbols that, by means of their relative size, can represent additional information on the energy and sta-

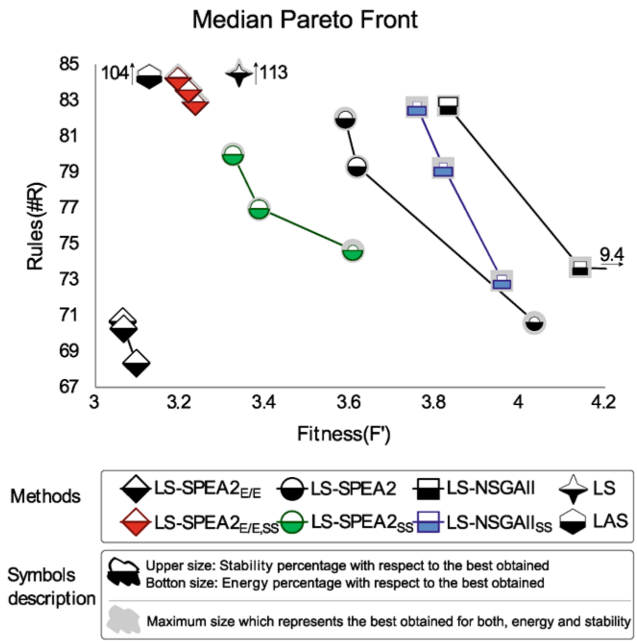


Fig. 12 Average Pareto front of the methods with the best performance

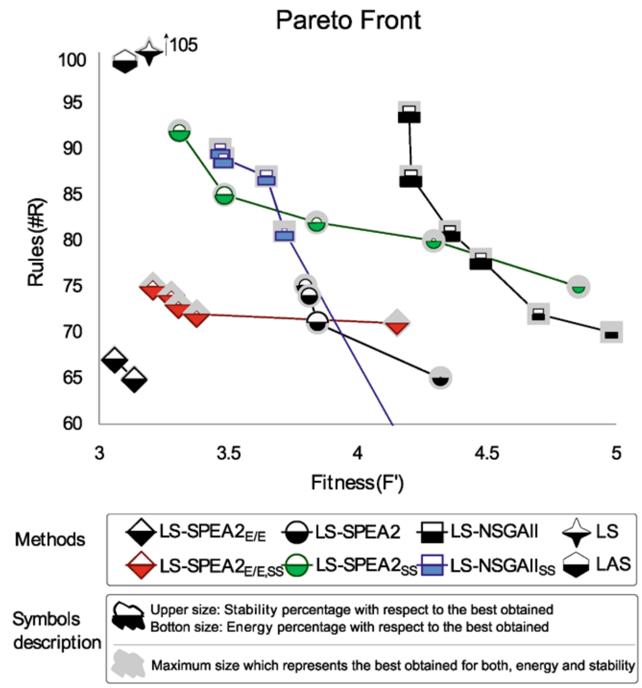


Fig. 13 Example Pareto fronts from a single run (seed 1)

bility values at each point of the Pareto front. The upper white part size represents the percentage in stability (M_5) with respect to the best obtained from all the analyzed algorithms and the bottom dark part size represents the percentage with respect to the best obtained in energy (M_4). When the symbol is bigger it indicates better values in these measures, i.e., greater energy savings and greater improvement in stability. In gray color behind the symbols the maximum size can be seen, which represents the best for each measure (30.41 in energy and 50.76 in stability).

From the results depicted in Fig. 13, most of the solutions obtained with LS-SPEA2$_{E/E}$ dominate in average those obtained by the remaining methods. Moreover, the solutions in all the analyzed methods present an important decrement in both measures (particularly in the stability) from the point with the best performance to the point with a smaller number of rules in their respective Pareto fronts. This does not happen with LS-SPEA2$_{E/E}$, which achieves very high values in energy and stability measures at all the points of the Pareto front. The Pareto fronts obtained by the steady-state MOEAs in general outperform the generational versions, except in the case of the LS-SPEA2$_{E/E}$ algorithm.

In order to show an example of the approximated Pareto fronts provided by each MOEA, in Fig. 13 we also present the Pareto fronts obtained from a single trial in the same seed (seed 1). Symbols in this figure should be interpreted as was explained for Fig. 12. Again, the solutions obtained with the remaining methods are dominated by solutions obtained from LS-SPEA2$_{E/E}$, except for a couple of solutions that have very bad performance.

LS-SPEA2$_{E/E}$ obtains better values in the measures of energy and stability with a good trade-off between complexity-accuracy even though the Pareto fronts are not too large. By contrast the NSGA-II-based methods obtain wider Pareto fronts, but they present quite bad results in the fitness objective, with bad values in energy and stability measures.

The results obtained by the proposed method helps to improve the exploration/exploitation trade-off in the search process obtaining not too large fronts but dominating the larger fronts of the remaining MOEAs.

6 Conclusions

In this work, we propose a method to obtain high performance FLCs to solve the control problem of the HVAC system. To this end, we present an advanced MOEA that performs a lateral tuning of MFs together with a rule selection. This problem has two objectives: minimizing the number of rules and maximizing the system performance. In any event, this algorithm looks for the FLCs with the best combination of rules, by rule minimization, and therefore presents the best performance.

The presented technique has yielded much better results than the previous approaches, mono-objective GAs, [8–10] and than recognized MOEAs to perform tuning plus rule selection [31, 32], showing a good performance in these kinds of complex problems. The obtained controller has the best trade-off between energy and stability of the HVAC system.

The solutions obtained by the proposed MOEA dominate in general the ones obtained by the mono-objective GAs and by the rest of the MOEAs (steady-state and generational versions).

The main advantage of this technique is to obtain good solutions quickly by promoting a faster convergence. This is the key point in a problem where the numbers of possible evaluations is small, since each evaluation requires a low computing time and it is only possible to carry out 2000 evaluations.

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María José Gacto received the M.Sc. degree in Computer Science in 1999 and the Ph.D. degree in Computer Science in 2010, both from the University of Granada, Spain. She is currently an Assistant Professor in the Department of Computer Science at the University of Jaén, where she is a Member of the Intelligent Systems and Data Mining Research Group.
She has over 25 international publications. She has worked on several research projects supported by the Spanish government and the European Union. Her research interests include, multi-objective genetic algorithms and genetic fuzzy systems, particularly the learning/tuning of fuzzy systems for modeling and control with a good trade-off between accuracy and interpretability.

Rafael Alcalá received the M.Sc. degree in Computer Science in 1998 and the Ph.D. degree in Computer Science in 2003, both from the University of Granada, Spain. From 1998 to 2003, he was with Department of Computer Science, University of Jaén. He is currently an Associate Professor in the Department of Computer Science and Artificial Intelligence at the University of Granada, where he is a Member of the Soft Computing and Intelligent Information Systems Research Group.
He has published over 70 papers in international journals, book chapters and conferences. As edited activities, he has co-edited the IEEE Transactions on Fuzzy Systems Special Issue on "*Genetic Fuzzy Systems: What's next*", the Evolutionary Intelligence Special Issue on "*Genetic Fuzzy Systems: New Advances*" and the Soft Computing Special Issue on "*Evolutionary Fuzzy Systems*". He has worked on several research projects supported by the Spanish government and the European Union. He currently serves as member of the editorial/reviewer board of the journals: International Journal of Computational Intelligence Research, Journal of Advanced Research in Fuzzy and Uncertain Systems, Journal of Universal Computer Science and Applied Intelligence. He is a member of the Fuzzy Systems Technical Committee (FSTC) at the IEEE Computational Intelligence Society (CIS), and president of the "Genetic Fuzzy Systems" Task Force from January 2009. He is a Program Co-Chair of GEFS 2010, General Co-Chair of GEFS 2011 and Area Co-Chair of FUZZ-IEEE 2011.
His current research interests include multi-objective genetic algorithms and genetic fuzzy systems, particularly the learning/tuning of fuzzy systems for modeling and control with a good trade-off between accuracy and interpretability, as well as fuzzy association rules.

Francisco Herrera received the M.Sc. degree in Mathematics in 1988 and the Ph.D. degree in Mathematics in 1991, both from the University of Granada, Spain.

He is currently a Professor in the Department of Computer Science and Artificial Intelligence at the University of Granada. He has published more than 180 papers in international journals. He is coauthor of the book "*Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Bases*" (World Scientific, 2001).

As edited activities, he has co-edited five international books and co-edited twenty one special issues in international journals on different Soft Computing topics. He currently acts as Editor in Chief of the international journal Progress in Artificial Intelligence (Springer) and serves as area editor of the Journal Soft Computing (area of evolutionary and bioinspired algorithms). He acts as associated editor of the journals: IEEE Transactions on Fuzzy Systems, Information Sciences, Advances in Fuzzy Systems, and International Journal of Applied Metaheuristics Computing; and he serves as member of several journal editorial boards, among others: Fuzzy Sets and Systems, Applied Intelligence, Knowledge and Information Systems, Information Fusion, Evolutionary Intelligence, International Journal of Hybrid Intelligent Systems, Memetic Computation, Swarm and Evolutionary Computation.

He received the following honors and awards: ECCAI Fellow 2009, 2010 Spanish National Award on Computer Science ARITMEL to the "Spanish Engineer on Computer Science", International Cajastur "Mamdani" Prize for Soft Computing (Fourth Edition, 2010).

His current research interests include computing with words and decision making, bibliometrics, data mining, data preparation, instance selection, fuzzy rule based systems, genetic fuzzy systems, knowledge extraction based on evolutionary algorithms, memetic and genetic algorithms.