Multicriteria Genetic Tuning for the Optimization and Control of HVAC Systems

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Abstract. This work presents the use of genetic algorithms for the optimization and control of Heating, Ventilating and Air Conditioning (HVAC) systems developing smartly tuned fuzzy logic controllers for energy efficiency and overall performance of these systems.

An optimum operation of the HVAC systems is a necessary condition for minimizing energy consumptions and optimizing indoor comfort in buildings. This problem has some specific restrictions that make it very particular and complex because of the large time requirements existing due to the need of considering multiple criteria (which enlarges the solution search space) and to the long computation time models require to assess the accuracy of each individual.

To solve these problems, three efficient genetic tuning strategies, considering different multicriteria approaches, have been presented and tested in two real test sites (buildings) obtaining satisfactory results.

1 Introduction

Heating, Ventilating, and Air Conditioning (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.

Therefore, the use of appropriate automatic control strategies, as Fuzzy Logic Controllers (FLCs) [13], for HVAC systems decision support could result in important energy savings when compared to manual control [1]. In this way, some works apply FLCs to solve simple problems such as thermal regulation, maintaining a temperature setpoint [3,19,28].

However, in current systems, various criteria are considered and optimized independently one from another: variable air flows are used for indoor air quality control, controlled air temperature is used for thermal comfort management, and temperature set points are modified for energy consumption control. No global strategy for a coupled and integrated management of all these criteria has been yet efficiently implemented. Moreover, control systems in buildings are often designed and tuned using rules of thumb not always

compatible with the controlled equipment requirements, energy performance and users expectations and demand.

Therefore, an optimum operation of these systems is a necessary condition for minimizing energy consumptions and optimizing indoor comfort. To do so, this contribution aims to develop optimum fuzzy controllers dedicated to the control of HVAC systems with regard to the energy performance and indoor comfort requirements, with the following main innovations:

- The use of FLCs: it will enable the implementation of multicriteria control strategies incorporating expert knowledge.
- The development of smart setting and tuning techniques for these controllers: it will enable a rational operation and improved performance of the fuzzy logic controllers –by fitting the Data Base (DB) parameters of previously obtained Knowledge Bases (KBs) provided by experts– and is a necessary condition for implementing complex control techniques.

Genetic algorithm (GAs) [21] have been recognized to be possibly well-suited to multicriteria optimization [6,11,16,41,45]. However, since the controller accuracy is assessed by means of simulations which usually take a long time, neither of them can be used satisfactorily because they do not properly address this restriction. Therefore, in order to solve these problems, efficient multicriteria genetic tuning approaches considering them should be developed [2]. To do so, three efficient genetic tuning strategies considering different multicriteria approaches have been developed and tested in two real test sites (buildings). Accurate models of the controlled buildings have been provided by experts.

This chapter is organized as follows. In Sect. 2 the HVAC systems are presented, showing the importance of these kinds of systems in the building sector. Section 3 explains how the FLCs can be applied to HVAC systems. In Sect. 4, the HVAC systems tuning restrictions are introduced, proposing some specific solutions to them. Section 5 presents three efficient genetic tuning techniques considering different multicriteria approaches. Section 6 shows the experiments performed in the two test sites. To sum up, in Sect. 7, some concluding remarks are pointed out, showing how this methodology could be applied to other systems and progressively implemented at industrial level.

2 Heating, Ventilating, and Air Conditioning Systems

In EU countries, primary energy consumption in buildings represents about 40% of total energy consumption and it has grown from 1974 over 13% overall. This energy consumption is highly dependent on weather conditions. Moreover, 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. 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. Therefore, the use of appropriate automatic control strategies, as FLCs, for HVAC systems control could result in important energy savings when compared to manual control.

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. 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 [3].

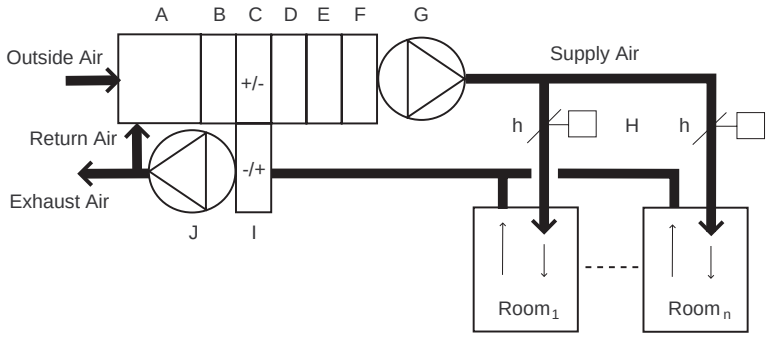


Fig. 1. Generic structure of an office building HVAC system

In Fig. 1, a typical office building HVAC system is presented. This HVAC system would comprise the following components to be able to raise and lower the temperature and relative humidity of the Supply Air (SA):

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

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 the following section we will see how FLCs can be applied to the control of HVAC Systems.

3 Fuzzy Control of HVAC Systems

Nowadays, there are 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.

An FLC [13,33,34] 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 the *Defuzzification Interface*, which takes the fuzzy action from the inference process and translates it into crisp values for the control variables. The KB is comprised of two components: the DB and the RB. The DB contains the definitions of the linguistic labels, that is, the membership functions for the fuzzy sets. The RB is a collection of fuzzy control rules, comprised by the linguistic labels, representing the expert knowledge of the controlled system.

In the specific case of HVAC Systems, some works apply FLCs to solve simple problems such as thermal regulation, maintaining a temperature setpoint [3,19,28]. However, in this work various different criteria must be considered in order to reduce the energy consumption maintaining a desired comfort

level. In building automation, the objective of a global controller would be 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 (IAQ). Furthermore, other important objectives could be required, e.g, energy savings, 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. In these cases, FLCs are very robust tools which would enable the implementation of multiple criteria control strategies incorporating expert knowledge.

As it is known, the design of an FLC is focused on the following parameters and characteristics:

- *Control and controlled parameter selection.* Controlled parameters are variables which are affected by the action of a controlled device receiving signals from a controller, whilst control parameters are variables which may be used as inputs or outputs for a control strategy.
- *The composition of the FLC KB*, that is, the set of fuzzy control rules forming the RB, and the set of linguistic terms in the fuzzy partitions of the input and output spaces forming the DB.
- *FLC architecture and operators*, i.e., the rule type and architecture of the FLC, the membership function type, the conjunctive operator *and*, the implication function, the defuzzification mode, the characteristic value and the control crisp value.

In this way, after the BEMS designer defines the system to be controlled (building and HVAC specification), the construction of the correspondent FLC can be performed. This task can be subdivided in the following subtasks:

1. Knowledge extraction method selection.
2. Identification of the controlled and the control parameters.
3. Identification of global indices for assessment of the indoor building environment.
4. Description of number and architecture of fuzzy controllers.
5. KB derivation method selection.
6. Selection of the inference system operators.
7. KB derivation.

3.1 Knowledge Base Derivation

As said, the KB encodes the expert known knowledge of the controlled system. Therefore, it depends on the concrete application making the accuracy of the designed FLC directly depends on its composition. There are four modes of derivation of fuzzy control rules, that are not mutually exclusive [32]. These modes are the following:

a *Expert experience and control engineering knowledge*: It is the most widely used, being effective when the human operator is able to linguistically express the control rules he uses to control the system. Since they present an adequate form to represent expert knowledge, these rules are usually of Mamdani type.
b *Modeling of the operator's control actions*: The control action is formed making a model of the operator actions without interviewing him.
c *Based on the fuzzy model of a process*: It is based on developing a fuzzy model of the system and constructing the fuzzy rules of the KB from it. This approach is similar to that traditionally used in Control Theory. Hence, structure and parameter identification are needed [36].
d *Based on learning and self-organization*: This method is based on the ability for creating and modifying the fuzzy control rules in order to improve the controller performance by means of automatic methods.

In these kinds of problems (HVAC System controller design), the KB is usually constructed by using the first method, i.e., 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 [28]. This is because of:

- the gathering and structuring of expertise is not easy,
- the setting up of the knowledge base is an extensive task, and
- although a lot of knowledge is generic, the structure of the system to which it will apply varies substantially.

Moreover, in our case the system being controlled is too complex and optimal controllers are required. Therefore, this approach needs to modify the initial KB to obtain an optimal controller. To do so, a tuning on the semantic of an FLC previously obtained from human experience could be performed by modification of the DB components.

In this work, FLCs will be obtained from human experience to subsequently be tuned by the application of automatic tuning techniques. Thus, the learning method is a combination of the first and fourth derivation modes.

On the other hand, to evaluate the FLCs performance, physical modelization of the controlled buildings and equipments is needed. These models will be developed by BEMS designers using building simulation tools, and they will have to be able to account for all the parameters considered in control. The models will be validated using experimental data corresponding to the real sites being simulated. Many data corresponding to various operation conditions and heat or cooling load will be prepared and compared with simulations.

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 tuning process. On the other hand, it is of major importance to assess the fitness function in tuning.

3.2 Control and Controlled Parameters

Control and controlled parameters 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.

However, our intention is to develop both controllers and tuning strategies. This requires the use of explicit parameters (directly used as fuzzy controller's inputs or outputs) as well as implicit parameters used in the fitness function developed in order to evaluate the performance of each controller.

To identify the FLC's variables various parameters (control or explicit parameters) may be considered depending on the HVAC system, sensors and actuators. We propose the following parameters:

- *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 ISO 7730 (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*: IAQ was found to be critical. As CO_2 concentration is a reliable index of the pollution emitted by occupants, it can be selected as IAQ index. It is therefore supposed that the building and HVAC system have been properly designed and that occupants actually are the main source of pollution.
- *Outdoor temperature* also needed 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 to apply mechanical cooling (or heating).
- *HVAC system actuators*: It directly depends on the concrete HVAC system, e.g., valve positions, operating modes, fan speeds, etc.

To identify global indices for assessment of the indoor building environment, various parameters (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 goal of intelligent buildings. Among indoor climate characteristics, thermal comfort is of major importance. This might include both global and local comfort parameters.
- IAQ parameters: IAQ 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, IAQ is also an important parameter to account for.

- Energy consumption: If appropriate IAQ 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.

The selection of these parameters is a task concerned to the BEMS designer as well.

3.3 Architecture and Operators

Architecture and inference operators are factors that have a significant influence on the FLC behavior. The influence of several of these factors is analyzed in [8,30], taking as a basis several control applications.

As we have already seen, there are different alternatives to select these factors. In this section, we will propose one of them attending to their advantages and weaknesses in some aspects of the KB derivation process. We will strive to apply operators as simple as possible without loss in the system accuracy. If so, these operators will be easier to implement and faster to compute.

A distributed hierarchical architecture [18,44], which allows to divide the control tasks, is proposed for our FLC. Using the expert knowledge of the system to partition the controller allows adequate control with much fewer rules. Moreover, with this approach the control tuning becomes easier since the modification of one parameter influences a smaller number of rules.

In adition, it is recommended that three controllers (rather than a single one) be developed for each testing site. The reason for this lies in important climate variations all over the year and variable expectations from occupants according to season. Therefore, one controller per season will be developed considering fall and spring as the same kind of season. These controllers could be switched according to dates or by mixing the three controllers including a new meta-level in the hierarchical FLC.

On the other hand, the remaining factors to be considered are the following: rule type, type of membership functions, conjunctive operator, implication function, defuzzification mode, characteristic value and control crisp value. The selection of all of them is presented below.

We use the Mamdani-type rules because they provide a natural framework to include expert knowledge in the form of linguistic rules which is of major importance in our problem. In the same way, we use the triangular membership functions instead of the trapezoidal or the gaussian ones —being the former two linear functions and the latter a non-linear function—. Since we expect a KB derivation from experts, linear functions are more intuitive and easier to manage. Moreover, as all of them achieve similar results [12], we will use triangular membership functions, which are simpler. Their formula is:

$$\mu_{A_i}(x) = \begin{cases} \dfrac{x-a}{b-a}, \text{ if } a \leq x < b \\ \dfrac{c-x}{c-b}, \text{ if } b \leq x \leq c \\ 0, \qquad \text{otherwise} \end{cases} .$$

Among all the associative functions, t-norms are the more suitable to be used to define the connective *and* [8]. Two basic t-norms have been considered: minimum ($Min(x,y) = min(x,y)$) and product ($\Pi(x,y) = x \cdot y$). Minimum operator achieves co-operative rules while product operator achieves competitive rules. Since we have recommended triangular membership functions and a good co-operation among rules is interesting in this case, the minimum operator is proposed. On the other hand, from the results reported in [8], we recommend the use of the minimum t-norm (Mamdani implication) also as implication operator (rule connective) because it yielded the best behavior among the 41 implication operators tested.

We use the FITA (First Infer, Then Aggregate) scheme considering the rule antecedent matching, h_i, because the defuzzification method working in this mode is more robust and easier to compute than those using the FATI (First Aggregate, Then Infer) scheme [8]. As characteristic value and control crisp value, we propose the Weighted Mean Of Maxima (WEMOM), since according to the results reported in [8], it renders the best accuracy among the 17 different defuzzification methods tested.

4 Multicriteria Genetic Tuning of FLCs for HVAC Systems

Tuning approaches are usually based on the availability of a predefined RB and a preliminary set of membership functions associated to the fuzzy partitions, DB. Their main aim is to find a better set of parameters by only changing the DB components, thus making optimum the FLC behavior. In this way, FLCs could be obtained from human experience or learning methods to subsequently be tuned by the application of automatic tuning techniques. We have followed the same approach but, in our case, the problem has two specific restrictions which make it very particular and complex:

- The evaluation is based on multiple criteria (energy consumption, occupants thermal comfort, indoor air quality, peak load electrical demand, ...). This fact adds complexity to the search because we must obtain the best trade-off among the different criteria.
- The controller accuracy is assessed by means of simulations which usually take a long time. This causes the run time of the algorithms to be extremely long.

In this case, numerous factors have to be considered in order to address these restrictions. It makes the system being controlled very complex and presents a strong non linearity. Therefore, an efficient operation of the automatic tuning techniques is a necessary condition in order to achieve good results.

GAs are general-purpose global search techniques 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 [27] and are well described in many texts such as [21,35]. 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.

GAs present flexibility to work with different FLC architectures and have a good capability to include expert knowledge [9]. Furthermore, the ability to handle complex problems, involving features such as discontinuities, multimodality, disjoint feasible spaces and noisy function evaluations, reinforces the potential effectiveness of GAs in multicriteria search and optimization. For these reasons, GAs have been recognized to be possibly well-suited to multicriteria optimization [6,11,16,41,45].

Although there are many genetic tuning approaches [5,7,22,24,29], neither of them can be used satisfactorily because they do not properly address the said restrictions. Therefore, in order to solve these two problems, efficient genetic tuning approaches considering both restrictions should be developed.

4.1 Tuning Restrictions

As we have indicated, the two important restrictions we want to solve are the need of considering multiple criteria (which enlarges the solution search space) and the long computation time models require to assess the accuracy of each individual.

The **first restriction** will be solved by using multicriteria optimization techniques that allow us to work with fitness functions comprised by competitive objectives. In these cases, we could obtain not only an optimal solution, but a possible solution set. Depending on the number of solutions obtained, we can distinguish between two multicriteria approaches:

- Multicriteria aggregation-based methods: All classical methods scalarize the objective vector reducing it to a scalar optimization problem. Probably, the simplest of all these classical techniques is the method of objective weighting. In this case, multiple criteria functions are combined into one overall objective function by means of a vector of weights. This technique has much sensitivity and dependency toward weights. However, when trustworthy weights are available, this approach reduce the search space providing the adequate direction into the solution space and its use is highly recommended. Therefore, the main question to consider this approach is: Have we trusted weights to estimate the importance of each objective?
- Multicriteria non aggregation-based methods or multiobjective methods: In a typical multicriteria optimization problem, there is a set of solutions that are superior to the rest in the search space when all the objectives are considered. These solutions are known as non-dominated solutions (pareto set), whilst the remaining solutions are known as dominated solutions. None of the solutions in the non-dominated set is absolutely better than the other ones.
  Mathematically, the concept of *Pareto-optimality* or *non-dominance* is defined as follows. Let us consider, without loss of generality, a multicriteria function $f(x) = (f_1(x), f_2(x), \ldots, f_n(x))$ to be minimized with m parameters, $x = (x_1, x_2, \ldots, x_m) \in X$, and n objectives. A decision vector $a \in X$ dominates $b \in X$ (noted as $a \succ b$) if, and only if:

$$\forall i \in \{1, 2, \ldots, n\},\ f_i(a) \leq f_i(b) \quad \wedge$$

$$\exists j \in \{1, 2, \ldots, n\} \ \mid \ f_j(a) < f_j(b) \ .$$

  Any vector that is not dominated by any other is said to be pareto-optimal or non-dominated.

In order to solve the **second restriction**, the use of efficient tuning methods is necessary. There are some approaches that increase the convergence speed of GAs:

- An objective weighting technique would reduce the search space providing the adequate direction into the pareto when trustworthy weights are used.
- A steady-state GA [42], that consists of selecting two of the best individuals in the population and combining them to obtain new offspring. This approach improves the convergence and simultaneously decreases the number of evaluations.
- In order to reduce the GAs search space, an integer coding could be used. This one uses discrete parameter domains forcing to take values from a finite value set [20] (see Fig. 2). The cardinality of this set must be rich enough in order to allow the tuning process to achieve accurate results, but small enough so that small changes provoke significant variations.

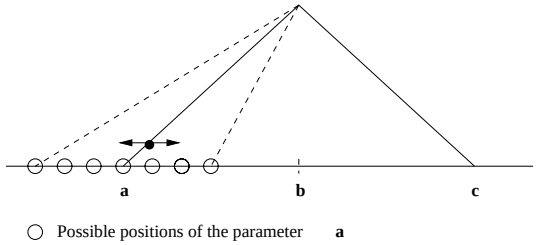


Fig. 2. Integer coding to tune fuzzy sets

- Reducing the population size, the number of evaluations is significantly decreased. However, this size must be large enough in order to maintain the diversity in the genetic population.

Several efficient tuning methods with different characteristics will be proposed based on the combination of multicriteria techniques with these different approaches. In order to do so, the different multicriteria genetic approaches will be introduced in the following subsection.

4.2 Multicriteria Genetic Optimization

Generally, multicriteria GAs only differ from the rest of GAs in the fitness function and/or in the selection operator. The evolutionary approaches in multicriteria optimization can be classified in three groups [16]: plain aggregating approaches, population-based non-pareto approaches, and pareto-based approaches.

Plain Aggregating Approaches

As conventional GAs require scalar fitness information to work on, a scalarisation of the objective vectors is always necessary. In most problems, where no global criterion directly emerges from the problem formulation, objectives are often artificially combined, or aggregated, into a scalar function according to some understanding of the problem, and then the GA is applied. Practically, all the classical aggregation approaches can be used with GAs. Some approach of this kind has been reported in the literature: weighted sum [39], distance functions [43], etc.

Optimizing a combination of the objectives has the advantage of producing a single compromise solution, requiring no further interaction with the decision-maker. The problem is that, if the optimal solution can not be accepted, new runs of the optimizer may be required until a suitable solution is found. However, in the case of objective weighting, when trustworthy weights are available this problem disappears.

Population-Based Non-Pareto Approaches

This approach allows to exploit the special characteristic of GAs. The use of an population of individuals offers the possibility to treat non-commensurable objectives separately and to search for multiple non-dominated solutions concurrently in a single GA run.

Now, a non-dominated set of individuals is obtained instead of obtaining only one of them. In order to do this, the selection operator is changed. Generally, the best individuals according to each objective are selected (in many occasions, an order according to its importance is followed) and then these partial results are combined to obtain the new population.

Different proposals based on this idea can be found in [17,23,31,37].

Pareto-Based Approaches

The population-based non-pareto approaches attempt to promote the generation of multiple non-dominated solutions. However, none makes direct use of the actual definition of Pareto-optimality. As the best solution cannot be selected among the non-dominated solutions set, the approaches should assign equal probability of reproduction to all of them. In GAs based on the concept of pareto-optimality, to calculate the reproduction probability of each individual, the solutions are compared by means of the dominance relation ($\succ$). Some approaches of these kinds can be found in [15,38].

Although the Pareto-based ranking correctly assigns all the non-dominated individuals the same fitness, it does not guarantee that the Pareto set be uniformly sampled. When it is presented with multiple equivalent optima, finite populations tend to converge to only one of them, due to stochastic errors in the selection process. This phenomenon is known as *genetic drift* [10].

Since preservation of diversity is crucial in the field of multiobjective optimisation, several multiobjective GAs have incorporated the *niche* and *specie* concepts for the purpose of favouring such behaviour [15,38].

5 Three Different Multicriteria Genetic Tuning Strategies

Thinking on these three different multicriteria approaches, we must consider an important aspect in the selection of the best techniques and methods to accomplish the tuning process: Have we trusted weights to estimate the importance of each objective? Depending on whether we can obtain them or not, the recommended strategy will be different. Nevertheless, we will be able to use several tuning processes with and without weights if we want to compare the results or if we are not sure of the weight reliability. In this way, combining the multicriteria and the said efficient tuning approaches, three strategies have been developed (Table 1 shows a summary of the three developed methods):

- Taking into account the existence of trusted weights and in order to benefit from them, we propose a simple steady-state GA with the classical real coding [26] and with a fitness function based on objective weighting that considers them. It will be called, Weighted Multi-Criterion Steady-State Genetic Algorithm (WMC-SSGA) [1,2]. Furthermore, the use of fuzzy goals for dynamically adapting the search direction in the space of solutions will be considered. It will make the method robust and more independent from the weight selection for the fitness function.
- If we do not have trustworthy weights, we must search for advanced multiobjective techniques with adequate characteristics to obtain the desired convergence, e.g., the use of the integer coding. In this way, two different multiobjective approaches based in the two well-known algorithms presented in [15] and [38] are proposed. On the one hand, the so called Multi-Objective Steady-State Genetic Algorithm (MO-SSGA) [2] presents likely premature convergence getting a quick search speed at the expense of decreasing the diversity. This algorithm is complemented with the use of a steady-state approach. On the other hand, the so called Non-Dominated Sorting Genetic Algorithm (NDS-GA) obtains a good distribution over the non-dominated individuals set at the expense of the search speed by using a generation-based GA. Therefore, while the first one is quicker obtaining good solutions, the second one is theoretically more robust and sure.

Table 1. Summary on Tuning Strategies

Method	When	Multicriteria approach	Features
One	TW exist	Aggregation	SSGA + RC
Two	TW not exist	Pareto-based	SSGA + IC
Three	TW not exist & robust results are required	Pareto-based	GA + IC + FSh

TW Trusted Weights. RC/IC Real/Integer Coding. FSh Fitness Sharing.

There is an important aspect that the proposed methods address in the same way, the definition of the variation intervals for each gene. In the following subsection, this common characteristic is introduced. After this, the three proposed methods will be widely explained.

5.1 Dynamic Variation Intervals

In order to be meaningful, each chromosome (a complete DB) must maintain their genes (the DB definition points) within their respective variation intervals. These intervals are usually computed and fixed from the initial solution

—DB provided by experts—. However, in our case, these intervals are dynamically adapted from the best individual for each GA iteration, avoiding the restrictions of fixing them from the beginning of the GA run [2]. Thus, once these intervals have been calculated, the genes out of range are randomly generated within them.

Let (a^i_j, b^i_j, c^i_j) be the definition points of the j-th membership function label of the i-th variable. In a strong fuzzy partition (those in which the membership degree within the variable domain is kept to 1.0) the vertex of each label (b^i_j) coincides with the nearest extreme points of its neighbor labels, $c^i_{j-1} = b^i_j = a^i_{j+1}$. In this case, only the vertex of the labels has to be considered and the same variation interval can be defined for coincident points. Thus, the variation intervals are usually defined by the middle points between the correspondent vertex and the vertex of the previous and the next label.

In our case, a more flexible approach is considered and the vertex of the labels does not have to coincide with the nearest extreme points of its neighbor labels (see Figure 3). However, considering these three points as a simple set for each label $B_j = \{c^i_{j-1}, b^i_j, a^i_{j+1}\}$ and taking into account that they have the same variation interval, the same approach can be followed. In this way, the middle point between two sets can be computed considering the maximum point of the first set and the minimum point of the second set. Therefore, to calculate the left extreme of the variation interval for a concrete definition point $x \in B_j$, we should consider the maximum point of B_{j-1} (l^1_x) and the minimum point of the corresponding set B_j (l^2_x). And for the corresponding right extreme, we should consider the maximum point of B_j (r^1_x) and the minimum point of B_{j+1} (r^2_x).

Finally, taking into account that $a^i_j \in B_{j-1}$, $b^i_j \in B_j$ and $c^i_j \in B_{j+1}$, the variation intervals of each definition point of the j-th label membership function of the i-th variable, (a^i_j, b^i_j, c^i_j), are calculated from the initial or best individual as,

$$\{l^1_{a^i_j}, l^2_{a^i_j}\} = \{\max(c^i_{j-3}, b^i_{j-2}, a^i_{j-1}), \min(c^i_{j-2}, b^i_{j-1}, a^i_j)\}$$
$$\{r^1_{a^i_j}, r^2_{a^i_j}\} = \{\max(c^i_{j-2}, b^i_{j-1}, a^i_j), \min(c^i_{j-1}, b^i_j, a^i_{j+1})\}$$
$$[L_{a^i_j}, R_{a^i_j}] = [l^2_{a^i_j} - \frac{l^2_{a^i_j} - l^1_{a^i_j}}{2}, r^1_{a^i_j} + \frac{r^2_{a^i_j} - r^1_{a^i_j}}{2}] \ ,$$

$$\{l^1_{b^i_j}, l^2_{b^i_j}\} = \{\max(c^i_{j-2}, b^i_{j-1}, a^i_j), \min(c^i_{j-1}, b^i_j, a^i_{j+1})\}$$
$$\{r^1_{b^i_j}, r^2_{b^i_j}\} = \{\max(c^i_{j-1}, b^i_j, a^i_{j+1}), \min(c^i_j, b^i_{j+1}, a^i_{j+2})\}$$
$$[L_{b^i_j}, R_{b^i_j}] = [l^2_{b^i_j} - \frac{l^2_{b^i_j} - l^1_{b^i_j}}{2}, r^1_{b^i_j} + \frac{r^2_{b^i_j} - r^1_{b^i_j}}{2}] \ ,$$

$$\{l^1_{c^i_j}, l^2_{c^i_j}\} = \{\max(c^i_{j-1}, b^i_j, a^i_{j+1}), \min(c^i_j, b^i_{j+1}, a^i_{j+2})\}$$
$$\{r^1_{c^i_j}, r^2_{c^i_j}\} = \{\max(c^i_j, b^i_{j+1}, a^i_{j+2}), \min(c^i_{j+1}, b^i_{j+2}, a^i_{j+3})\}$$
$$[L_{c^i_j}, R_{c^i_j}] = [l^2_{c^i_j} - \frac{l^2_{c^i_j} - l^1_{c^i_j}}{2}, r^1_{c^i_j} + \frac{r^2_{c^i_j} - r^1_{c^i_j}}{2}] \ ,$$

Notice that the associated variation intervals of the corresponding extreme values, a^i_j and c^i_j, are calculated exactly as the intervals for b^i_{j-1} and b^i_{j+1}, respectively.

Figure 3 graphically depicts the variation intervals for the i-th variable following the proposed approach. We have considered that the vertex of the labels at the edges of the variables' domain must coincide with the extreme points. These labels will be symmetrical with respect to their vertexes.

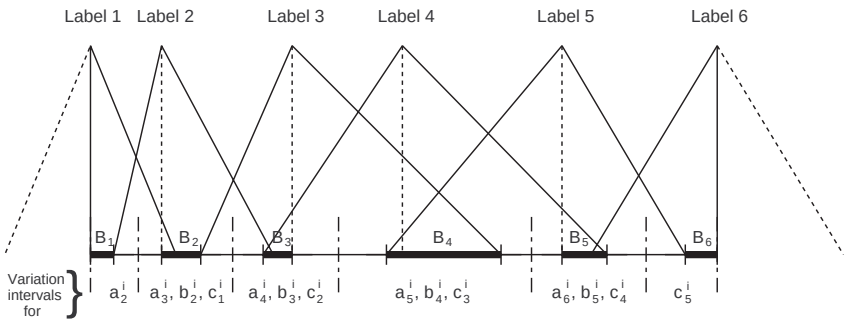


Fig. 3. Variation intervals of the i-th variable

5.2 Weighted Multi-Criterion Steady-State Genetic Algorithm

WMC-SSGA [1,2] consists of a GA based on the well-known steady-state approach [42]. Its fitness function is based on 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.

Coding scheme: WMC-SSGA uses a real coding scheme [26]. A solution is directly encoded in a chromosome by joining the definition points (a^i_j, b^i_j, c^i_j) of the l_i labels of each one of the m variables composing the DB. For example:

$$C_i = (a^i_1, b^i_1, c^i_1, \ldots, a^i_{l_i}, b^i_{l_i}, c^i_{l_i}), \ \ i = 1, \ldots, m \ ,$$
$$C = C_1 C_2 \ldots C_m \ .$$

Initial gene pool: To make use of the existing knowledge, the DB previously obtained from expert knowledge is included in the population as an initial solution. The remaining individuals are randomly generated maintaining their genes within their respective variation intervals. These intervals are computed from the initial solution (see Sect. 5.1).

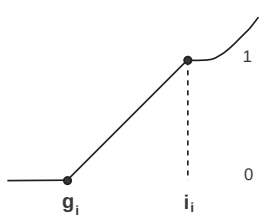
Evaluating the chromosome: The fitness function is based on objective weighting. However, it has been modified in order to consider the use of fuzzy goals for dynamically adapting the search direction in the space of solutions, decreasing the improvement possibility of those objectives which approach their goals in the first place. Thus, a function modifier parameter, $\delta_i(x)$, is used to penalize each objective (taking values over 1.0) whenever its value gets worse with respect to the initial solution or to decrement the importance of each individual fitness value whenever it comes to its respective goal (taking values close to 0.0). Moreover, 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, for each objective is a real number from 0.7 to practically 1, 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:

$$F = \sum_{i=1}^{n} w_i \cdot \delta_i(C_i) \cdot C_i \quad ,$$

with C_i being the considered criteria (objectives) for each specific problem and w_i being the corresponding weighting coefficients.

Two cases 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 behavior (see Fig. 4).

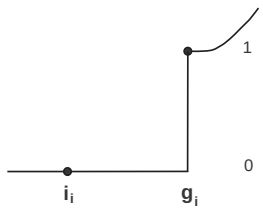


$$\delta_i(x) = \begin{cases} 0, & \text{if } x \leq g_i \\ \dfrac{x - g_i}{i_i - g_i}, & \text{if } g_i < x < i_i \\ \dfrac{x - i_i}{x - x \cdot p_i} + 1, & \text{if } i_i \leq x \end{cases} \quad .$$

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

In this case, the objective is not considered if the goal is met and penalized if the initial results are worsen.

- The second case happens when the initial value, i_i, is lesser than the goal value, g_i (see Fig. 5).



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

Fig. 5. $\delta_i(x)$ when $g_i > i_i$

Now, the initial results can be worsen while the goal is met, and it is penalized otherwise.

Notice that the penalization function allows the search to slightly worsen the goal, improving other objectives to subsequently met the goal again.

Genetic operators: The **selection** is based on the Baker's stochastic universal sampling [4] (by only selecting two individuals). WMC-SSGA also follows the interval adapting scheme explained in Sect. 5.1.

Since WMC-SSGA uses the real coding scheme, the crossover and mutation operators have been selected according to this aspect: the Max-Min-Arithmetical crossover [25] and Michalewicz's non-uniform mutation [35].

Using the max-min-arithmetical **crossover**, if $C_v^t = (c_1, \ldots, c_k, \ldots, c_H)$ and $C_w^t = (c'_1, \ldots, c'_k, \ldots, c'_H)$ are going to be crossed, the next four offspring are obtained:

$$\begin{aligned} C_1^{t+1} &= aC_w^t + (1-a)C_v^t \\ C_2^{t+1} &= aC_v^t + (1-a)C_w^t \\ C_3^{t+1} &\text{ with } c_{3k}^{t+1} = \min\{c_k, c'_k\} \\ C_4^{t+1} &\text{ with } c_{4k}^{t+1} = \max\{c_k, c'_k\} \ , \end{aligned}$$

with a being a constant parameter chosen by experts, and H being the number of genes.

In the case of the Michalewicz's non-uniform **mutation**, a gene c_k, with a variation interval $[L_{c_k}, R_{c_k}]$, can be mutated as $c'_k = c_k + \Delta(t, R_{c_k} - c_k)$ with probability 0.5, or as $c'_k = c_k - \Delta(t, c_k - L_{c_k})$, in other case. With t being the current generation, function $\delta(t, y)$ returns a value in the range $[0, y]$ such that the probability of $\delta(t, y)$ being close to 0 increases as the number of generations increases. This function is formulated as $\delta(t, y) = y(1 - r^{(1-\frac{t}{T})^b})$, with r being a random number in $[0, 1]$, T the total number of generations, and b being selected by the user to determine the dependency with t.

Thus, 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.

Restart approach: Finally, to get away from local optima, this algorithm uses a restart approach [14]. Thus, when the population of solutions converges to very similar results (practically the same fitness value in 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 in the search space and to avoid getting stuck at local optima.

5.3 Multi-Objective Steady-State Genetic Algorithm

MO-SSGA [2] consist on an integer coded steady-state GA for multiobjective optimization. This algorithm presents likely premature convergence getting a quick search speed at the expense of decreasing the diversity. Its fitness function is based on the multiobjective approach presented in [15]. However a new scheme to accommodate goal attainment have been proposed.

Coding scheme: Once again, a solution is encoded in a chromosome by joining the representation (definition points) of the l_i labels of each one of the m variables composing the DB. However, in this case, an integer coding scheme is used to represent the possible solutions. This one uses discrete parameter domains for each one of the m variables, forcing to take values from a finite value set. The cardinality of these domains, G_i, is determined by the global granularity parameter G —chosen by experts— and directly depends on the corresponding number of labels l_i:

$$G_i = G * l_i + 1, \;\; i = 1, \ldots, m.$$

Let L^i and R^i be the left and right extremes of the i-th variable domain. The corresponding possible values for this variable are uniformly distributed from L^i to R^i. Therefore, the distance between a point and the next one will be,

$$d_i = \frac{R^i - L^i}{G_i - 1}.$$

In this way, a mapping between an integer ordered set (from 0 to $G_i - 1$) and the set B_i of the corresponding real discrete values could be established as follows:

$$D : \{0, 1, \ldots, G_i - 1\} \longrightarrow B_i,$$
$$D(x^i) = L^i + x^i * d_i, \; \forall \; x^i \in \{0, 1, \ldots, G_i - 1\}.$$

The integer coding scheme consists on coding the possible solutions by using these integer ordered sets to represent the corresponding real discrete values —which can be easily obtained by using $D(x)$—. This representation eases the application of the genetic operators.

Initial gene pool: The initial pool is comprised of one individual containing the DB previously obtained from expert knowledge and the remaining ones generated at random maintaining their genes within their respective variation intervals. The intervals in which will switch around each gene are established from the initial solution as explained in Sect. 5.1. However, since this method is based on integer coding, once the variation intervals are computed as in the real coding, the upper and lower limits defining these intervals and the initial solution values must be encoded by rounding to the closer corresponding integer in the coding scheme as follows:

$$C : [L^i, R^i] \longrightarrow \{0, 1, \ldots, G_i - 1\},$$
$$C(x^i) = round\left(\frac{x^i - L^i}{\frac{R^i - L^i}{G_i - 1}}\right), \ \forall\ x^i \in [L^i, R^i].$$

After this, the initial gene pool can be generated within these variation intervals following the integer coding.

Evaluating the chromosome: A rank-based fitness assignment method for Multiple Objective GA (MOGA) was developed by Fonseca and Fleming in [15]. With this purpose, a rank is assigned to each individual of the population. These individuals are sorted to be selected according to rank. MO-SSGA is based on this approach. Thus, the position in the individuals' ranking can be given by:

If *non-dominated* **then** $rank(x_i) = 1$
Else $rank(x_i) = 1 + (dominants\ of\ x_i)$

The traditional assignment of fitness according to rank may be extended as follows:

1. Sort population according to rank.
2. Assign fitness to individuals interpolating from the best (rank 1) to the worst (rank $n^* \leq N$) in the usual way, according to some function, usually linear but not necessarily.
3. Average the fitness of individuals with the same rank, so that all of them will be sampled at the same rate. Note that this procedure keeps the global population fitness constant while maintaining appropriate selective pressure, as defined by the function used.

A scheme to accommodate goal attainment was proposed in [15]. It consists on modifying the ranking scheme for selection. In this way, the ranking in MO-SSGA was extended to accommodate goal information by altering the way in which individuals are compared with one another. However, considering the original approach interesting individuals were lost. Therefore, a new scheme has been implemented replacing the *concept of dominance* by the *concept of preferable*. Following this new scheme, individuals that meet

more goals are more important than individuals that meet less even if they do not dominate to these latter ones. Thus, $y_a = (y_{a,1}, \ldots, y_{a,q})$ is preferable to $y_b = (y_{b,1}, \ldots, y_{b,q})$:

- If y_a meets more number of goals than y_b, or,
- If y_a meets exactly the same goals than y_b, $k+1, \ldots, q$, and y_a dominates to y_b in $k+1, \ldots, q$ objectives.

Genetic operators: The chromosome **selection** is based in the Baker's stochastic universal sampling [4]. However, in this case only two individuals are selected. These two individuals replace the to worst in the population.

The genetic operators are a two points crossover and a mix mutation. Using the two points **crossover**, two points are randomly generated and the genes between these points are exchanged to obtain two offsprings. After this, the mix **mutation** is applied over these two offspring. It consists on randomly using one of the following mutation operators:

- A random mutation, by randomly selecting an integer value within the variation interval of the corresponding gene.
- The Thrift mutation [40], by changing the gene one level either up or down.

In the same way that WMC-SSGA, this method follows the same interval adapting scheme explained in Sect. 5.1. However, since the integer coding is considered, the best solution in each iteration must be decoded —by using $D(x)$— to compute the variation intervals as in the real coding scheme. After this, the upper and lower limits defining these intervals must be encoded by using $C(x)$.

5.4 Non-Dominated Sorting Genetic Algorithm

This method is based on the non-dominated sorting of the population and the niche method in the parameters values of each individual presented in [38]. In this case, the method consists on an integer coded generation-based GA, obtaining a good distribution over the non-dominated individuals set at the expense of the search speed. Therefore, this method is theoretically more robust and sure, but much more slower.

The same coding scheme, initialization and genetic operators in MO-SSGA have been considered in NDS-GA. Therefore, the integer coding, the two points crossover and the mix mutation have been implemented. Furthermore, this method follows the interval adapting scheme explained in Sect. 5.1 in the same way that MO-SSGA.

The main differences with MO-SSGA are the generational approach and the multiobjective approach considered. In this case, a percentage of the population is selected for reproduction, and once the new population is generated the mutation operator is applied with a predetermined probability. The population ranking in NDS-GA is computed as follows.

Evaluating the chromosome: The population is progressively grouped in fronts and for all the individuals in a front is given an equal ranking value that must be lesser than the value assigned to the previous front. Thus, the non-dominated individuals present in the population are picked out to constitute the first non-dominated front and assigned a large dummy fitness value. To maintain diversity in the population, these classified individuals are then shared with their dummy fitness values. Afterwards, these non-dominated individuals are temporary ignored and the rest of the population is processed in the same way to find the second front. The new assigned dummy fitness value must be kept smaller than the minimum shared dummy fitness value of the previous front. This process is continued until the entire population is classified into several fronts.

When each individual has its sharing dummy fitness value assigned, the algorithm continues using a stochastic remainder proportionate selection. In this case, the Baker selection [4] is used. This would result in quick convergence of the population toward non-dominated regions, but sharing helps to distribute it over these regions. The used sharing function is calculated in the following way:

$$Sh(d_{ij}) = \begin{cases} 1 - \left(\dfrac{d_{ij}}{\sigma_{share}}\right)^2, & \text{si } d_{ij} < \sigma_{share} \\ 0, & \text{otherwise} \end{cases},$$

where d_{ij} is the phenotypic distance between two individuals i and j in the current front, and σ_{share} is the maximum phenotypic distance allowed between any two individuals to become members of a niche (some guidelines to set σ_{share} appear in [10]). A parameter niche count is calculated adding the above sharing function values for all individuals in the current front. Finally, the shared fitness value of each individual is calculated dividing its dummy fitness value by its niche count.

The same scheme presented in MO-SSGA to accommodate goal attainment is considered, replacing the *concept of dominance* by the *concept of preferable*.

6 Experimental Results and Analysis

In order to evaluate the goodness of the proposed tuning techniques, several experiments have been carried out within the framework of the JOULE-THERMIE programme under the GENESYS [1] project. Two real test sites (buildings) were available for the experiments. The first one is provided by both Centre National de la Recherche Scientifique and the Ecole Nationale des

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

Travaux Publics de l'Etat (CNRS ENTPE) from France, whilst the second belongs to a French private enterprise whose name must remain anonymous. From now on, the latter will be called ATC test site —from Anonymous Test Cell—.

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

C_1 Upper thermal comfort limit: $if\ PMV > 0.5, C_1 = C_1 + (PMV - 0.5)$.
C_2 Lower thermal comfort limit: $if\ PMV < -0.5, C_2 = C_2 + (-PMV - 0.5)$.
C_3 IAQ requirement: $if\ CO_2\ conc. > 800ppm, C_3 = C_3 + (CO_2 - 800)$.
C_4 Energy consumption: $C_4 = C_4 +$ Power at time t.
C_5 System stability: $C_5 = C_5 +$ System change from time t to $(t-1)$.

To assess the proposed tuning techniques for fitness computation, accurate models of these controlled buildings (as well as the corresponding initial FLCs) were provided by experts for each season, considering fall and spring as the same kind of season. These models require long computation times, which makes more complex the tuning process. The results obtained were very satisfactory, specially for the ATC Summer model. However, due to the large number of results, we will work only with a cross-section of the models, the CNRS ENTPE Spring and Fall model, the CNRS ENTPE Summer model, and the ATC Summer model. In this section, the experiments performed with the said models are presented.

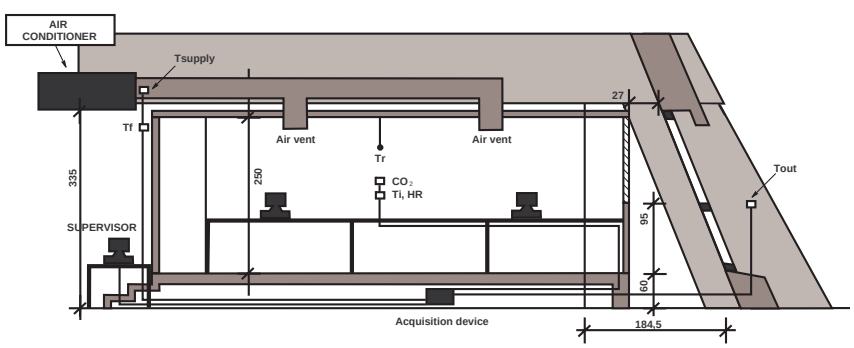


Fig. 6. Representation of the CNRS ENTPE test cells

6.1 The CNRS ENTPE and ATC Test Sites

The first task was to develop the thermal models of the two test sites that would be used in the complete learning process. These test sites have different characteristics, specially regarding the composition of their HVAC system. The main characteristics of these sites are the followings:

- CNRS ENTPE test site: Two single zone twin cells with low thermal mass located in a large hall whose climatic conditions can be controlled. The climatic control of the large hall temperature make it possible to create artificial climate with at least $8°C$ amplitude per day (e.g. from 23 to $31°C$ in summer conditions). The HVAC system is based on an air supply ventilation system with a maximum air flow rate of $2000m^3/h$ (test cells volume is $80m^3$), with direct expansion cooling and an electric coil controlled through a triac. Three fan speeds make it possible to slightly control supplied air flow rates (Fig. 6 illustrates these test cells).
- ATC test site: Also located in France, this test environment consists of two adjacent twin cells. Around these test cells walls, an artificial climate can be created at any time (winter conditions can be simulated in summer and vice-versa). These test cells are medium weight constructions. The HVAC system tested is a fan coil unit supplied by a reverse-cycle heat pump, and a variable fan speed mechanical extract for ventilation.

These test cells were equipped with all sensors required according to the selected control and controlled parameter.

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 each testing facility (different test sites and seasons). This customization (such as including HVAC systems models) might be slightly changed in the future in order to account for further experiments and calibration.

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 seconds for these test cells. Due to the relatively small thickness and large thermal conductive of windows, the heat conduction model for the windows was considered constant. Convective heat exchanges were based on constant heat convection coefficients. Radiant temperature is calculated as a function of surface temperature, weighted by their relative area. The HVAC system models were based on manufacturers data and modules developed in the frame of *IEA task 22* provided by the Royal Technical Institute of Stockholm.

The fitness function and fuzzy inference algorithm were also added within these models. Data were available and used for models calibration. The main

problems in the calibration concerned the modelization of the HVAC equipments as well as solar radiation effects on internal heat gains.

For each of the two testing sites, a different hierarchical FLC architecture was selected, regardless of the season considered in each case. They are very slightly different in their structure but all of them include at least PMV, CO_2 concentration, previous HVAC system status and outdoor temperature. In addition, the architecture developed for the ATC FLC included measures of thermal discomfort, IAQ discomfort and energy consumption for a 30 minutes to 1 hour period prior to the control decision. Both, the control parameters finally selected (see Sect. 3.2) and the FLC architecture for the ATC Summer FLC are presented in Fig. 7 as example. Each module in the figure represents a simple fuzzy controller and as we mentioned in Sect. 3.3, the *minimum t-norm* playing the role of the implication and conjunctive operators, and the WEMOM deffuzification strategy were used.

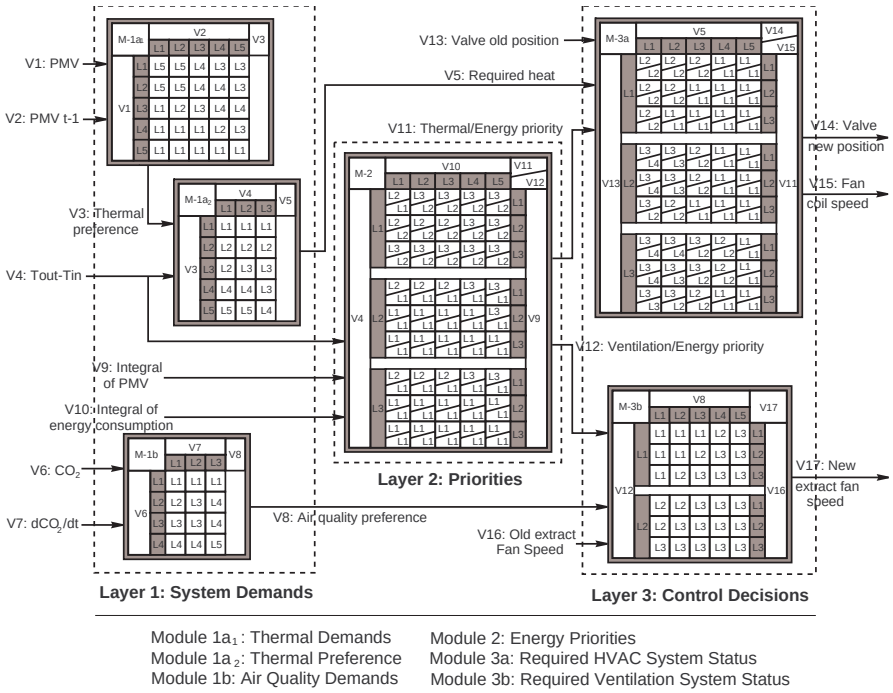


Fig. 7. Initial rule base and generic structure of the ATC Summer FLC

Initial KBs were obtained from BEMS designers for each model and season. For instance, Figs. 7 and 8 show the initial RB and DB of the ATC Summer FLC. This initial RB is fixed for all the tuning process. As initial DB, we considered symmetrical fuzzy partitions of triangular-shaped membership functions for each one of the m variables. These membership functions

were labeled from $L1$ to Ll_i, with l_i being the number of membership functions of the i-th variable. The decision table (initial RB) for each simple FLC (module) for the ATC Summer FLC is represented in Figure 7 in terms of this labels. Therefore, each cell of the table represents a fuzzy subspace and contains its associated output consequent(s), i.e., the correspondent label(s).

Thinking on the WMC-SSGA method, another 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 an 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 both test cells were obtained:

- For CNRS ENTPE test site the chosen values were: $w_1 = 0.0083022$, $w_2 = 0.0083022$, $w_3 = 0.00000456662$, $w_4 = 0.0000017832$ and $w_5 = 0.000761667$.
- And for the ATC test site: $w_1 = 0.0041511$, $w_2 = 0.0041511$, $w_3 = 0.00000228333$, $w_4 = 0.0000017832$ and $w_5 = 0.000761667$.

6.2 Experiments Developed on Simulated Systems

Three different models were implemented, the CNRS ENTPE Spring and Fall model, the CNRS ENTPE Summer model, and the ATC Summer model. The FLCs obtained from the proposed techniques will be compared to the performance of the initial expert FLC and to the performance of a classic On-Off controller for all of these models (the goals and improvements will be computed with respect to this classical controller).

The tuning strategies were assessed with simulations of 10 days with the corresponding climatic conditions. The results obtained by the tuning methods for each model are presented in the following subsections.

CNRS ENTPE Spring and Fall Model

The results obtained by the proposed methods with the CNRS ENTPE Spring and Fall model are shown in Table 2 together with the goal values (g_i) imposed to them, where % stands for the improvement rate with respect to the On-Off controller for each criterion. In this case, WMC-SSGA was run two times, first from the initial DB and after from the best DB obtained

in the previous run. Each run had 500 iterations. MO-SSGA was run 500 iterations, but restarting the method from a previously tuned DB did not substantially improve the results by which it made no sense more runs with this technique. Something similar occurred with NDS-GA, which was run for 150 iterations.

Since the time required for each model evaluation was approximately 200 seconds, the estimated run times were, four days for 500 iterations in WMC-SSGA, two days for 500 iterations in MO-SSGA and eight days for 150 iterations in NDS-GA (computed as product of the number of evaluations per generation, the evaluation time and the number of generations).

The intention from experts was to achieve up to 15% energy saving (C_4) with system stability (C_5) at least equal to On-Off stability (2730) and PMVlow criteria (C_1) no more than 10% higher than for On-Off (PMVlow $<$ 105). Following the experts intention, the values imposed to the methods were the following ones (see Table 2): $g_1 = 0$, $g_2 = 108$, $g_3 = 0$, $g_4 = 19363$ and $g_5 = 2800$, with penalization rates of $p_1 = 0.0$, $p_2 = 0.0$, $p_3 = 0.0$, $p_4 = 0.5$, and $p_5 = 0.7$ for WMC-SSGA, and granularity $G = 40$ for MO-SSGA and NDS-GA.

Table 2. Results obtained with the CNRS ENTPE Spring and Fall model

ATC	PMV>0.5		PMV<-0.5		CO_2		Energy		Stability	
MODEL	C_1	%	C_2	%	C_3	%	C_4	%	C_5	%
ON-OFF	0	–	95.7	–	0	–	22780	–	2730	–
INIT.	0	–	100.1	-4.7	0	–	21857	4.05	1340	50.9
GOALS (g_i)	0	–	108.0	–	0	–	19363	–	2800	–
WMC-1	0	–	100.3	-4.9	0	–	20044	12.01	2557	6.3
WMC-2	0	–	100.3	-4.9	0	–	20065	11.92	2527	7.4
WMC-3	0	–	103.7	-8.4	0	–	19700	13.52	2960	-8.4
WMC-4	0	–	104.0	-8.7	0	–	19484	14.47	3270	-19.8
MO-1	0	–	100.3	-4.8	0	–	20488	10.06	2730	0.0
MO-2	0	–	100.3	-4.8	0	–	20489	10.06	2770	-1.5
NDS-1	0	–	101.8	-6.4	0	–	20587	9.63	2790	-2.2
NDS-2	0	–	101.9	-6.5	0	–	20594	9.60	2620	4.0

From Table 2, and taking into account the requested goals, experts considered as the best solution the first obtained by WMC-SSGA, that practically meets the energy goal with a 12% of improvement compared to On-Off, and

completely meets the remaining ones. On the other hand, the third solution from WMC-SSGA with only an 8% of loss in stability gets notorious improvements in energy. It shows that even in the case of considering an objective-weighting fitness function, diverse individuals could be obtained. Moreover, all these individuals increase the global fitness in more than 10% showing that all of them are very acceptable solutions.

The results obtained from MO-SSGA and NDS-GA are exceeded in every respect by the results from WMC-SSGA. However, they present more or less 10% of improvement in energy and fitness having a good behavior. Moreover, solutions from MO-SSGA requires much less computation time.

CNRS ENTPE Summer Model

As in the Spring and Fall model, the computation time was also spent in its largest share by WMC-SSGA because from the very first it presented a better behavior than the rest ones. In this case, WMC-SSGA was run three times from the best DB obtained in the previous run. Each run had 500 iterations. Once more time MO-SSGA was only run 500 iterations and NDS-GA was run only 150 generations. The time required for each model evaluation was 220 seconds approximately. Therefore, the computation times were similar to the mid-season model ones.

The intention from experts was to reduce PMVupp criteria (C_1) to 0 and to maintain HVAC stability (C_5) as close as possible to the On-Off controller (1160), with energy (C_4) not larger than 10000. Following the experts intention, the goal values imposed to WMC-SSGA, MO-SSGA and NDS-GA were the following ones (see Table 3):

- WMC-SSGA: $g_1 = 0$, $g_2 = 13.7$, $g_3 = 0$, $g_4 = 9000$ and $g_5 = 1477$, with penalization rates of $p_1 = 1$, $p_2 = 1$, $p_3 = 1$, $p_4 = 0.9$, and $p_5 = 0.99$, respectively.
- MO-SSGA and NDS-GA: $g_1 = 0$, $g_2 = 13.7$, $g_3 = 0$, $g_4 = 9823$ and $g_5 = 1200$, with granularity $G = 40$.

In view of the results shown in Table 3, all the goals but the stability were practically met. In this case, the solution presenting the best stability value (-25.1%) is the first from WMC-SSGA, by which it was considered the best one by the experts. However, this solution does not meet the PMV goal, thus making the fourth solution a good alternative. In any case, values in stability were improved in a 100% from the initial FLC results, and all the remaining goals have been practically met, what is a very good result for this tuning method.

The results obtained from MO-SSGA and NDS-GA present very high stability values respect the On-Off controller results. In this case, to guide the search thorough the pareto space is more difficult than for WMC-SSGA and the results are not exactly what were expected. However, stability was

Table 3. Results obtained with the CNRS ENTPE Summer model

ATC	PMV>0.5		PMV<-0.5		CO_2		Energy		Stability	
MODEL	C_1	%	C_2	%	C_3	%	C_4	%	C_5	%
ON-OFF	0.00	–	13.84	–	0	–	11557	–	1160	–
INIT.	4.50	-450	13.70	1.01	0	–	9148	20.85	2579	-122.3
WMC (g_i)	0.00	–	13.70	–	0	–	9000	–	1477	–
MO/NDS (g_i)	0.00	–	13.70	–	0	–	9823	–	1200	–
WMC-1	2.35	-234	13.55	2.04	0	–	9799	15.21	1451	-25.1
WMC-2	0.05	-4.7	13.77	0.49	0	–	9823	14.99	1486	-28.1
WMC-3	0.03	-2.5	13.77	0.49	0	–	9827	14.96	1476	-27.2
WMC-4	0.03	-2.5	13.77	0.49	0	–	9811	15.09	1476	-27.2
MO-1	0.00	0.0	13.04	5.72	0	–	9636	16.62	1766	-52.2
MO-2	0.00	0.0	13.06	5.64	0	–	9624	16.73	1783	-53.7
NDS-1	0.00	0.0	13.54	2.17	0	–	9795	15.25	1635	-41.0
NDS-2	0.00	0.0	13.54	2.17	0	–	9800	15.20	1635	-41.0

improved in about a 50% from the initial FLC results for both methods, and the computation time for MO-SSGA is much lesser than the required for WMC-SSGA.

It is noticeable that energy savings were about 15% for all the solutions, being this the main objective in the project. Moreover, the improvement of the fitness function was about 13% which show a good general behavior of the obtained FLCs.

ATC Summer Model

The tuned DBs presented in Table 4 for the Summer ATC model correspond to three individuals from the population at iteration 500 with WMC-SSGA. As in the previous models, the remaining results were obtained at iteration 500 with MO-SSGA and generation 150 with NDS-GA. The time required for each model evaluation is 215 seconds approximately. Therefore, once again the algorithms were in the known times.

The intention from experts was to try to have 15% energy saving (C_4) together with a global improvement of the system behavior compared to On-Off control. Comfort parameters could be slightly increased if necessary (no more than 1.0 for criteria C_1 and C_2). Following the experts intention, the goal values imposed to WMC-SSGA, MO-SSGA and NDS-GA were the following ones:

- WMC-SSGA: $g_1 = 1$, $g_2 = 1$, $g_3 = 7$, $g_4 = 2000000$ and $g_5 = 1000$, with penalization rates of $p_1 = 1$, $p_2 = 1$, $p_3 = 1$, $p_4 = 0.9$, and $p_5 = 0.97$, respectively.
- MO-SSGA and NDS-GA: $g_1 = 1$, $g_2 = 1$, $g_3 = 8$, $g_4 = 2700000$ and $g_5 = 1100$, with granularity $G = 40$.

Notice that these goals imposed to the algorithms are higher than the ones initially required since the initial goals were easily met.

Table 4. Results obtained with the ATC Summer model

ATC	PMV>0.5		PMV<-0.5		CO_2		Energy		Stability	
MODEL	C_1	%	C_2	%	C_3	%	C_4	%	C_5	%
ON-OFF	0.0	–	0	–	0	–	3206400	–	1136	–
INIT.	0.0	–	0	–	0	–	2901686	9.50	1505	-32.48
WMC (g_i)	1.0	–	1	–	7	–	2000000	–	1000	–
MO/NDS (g_i)	1.0	–	1	–	8	–	2700000	–	1100	–
WMC-1	0.0	–	0	–	0	–	2575949	19.66	1115	1.85
WMC-2	0.0	–	0	–	0	–	2587326	19.31	1077	5.19
WMC-3	0.0	–	0	–	0	–	2596875	19.01	1051	7.48
MO-1	0.1	-10	0	–	0	–	2697449	15.87	1543	-35.83
MO-2	0.5	-51	0	–	0	–	2836160	11.55	1053	7.31
NDS-1	0.3	-32	0	–	0	–	2703631	15.68	1095	3.61
NDS-2	0.3	-28	0	–	0	–	2693120	16.01	1156	-1.76

In this case, the expert goal has been easily met by WMC-SSGA. Moreover, the solutions present a desirable diversity that allow us to select different and interesting FLCs.

From the results in Table 4, experts selected the third DB from WMC-SSGA as the most promising one. In this case, the solutions obtained from this method present improvement ratios of about 20% in energy and 5% in stability. Again, the results obtained with MO-SSGA and NDS-GA were clearly worse than the ones obtained with WMC-SSGA. However, in the case of MO-SSGA acceptable solutions could be quickly obtained.

Figure 8 represents the initial and the final DBs for the ATC FLC taking as final DB the third solution from WMC-SSGA in Table 4. It shows that small variations in the membership function parameters provoke large improvements in the FLC behavior.

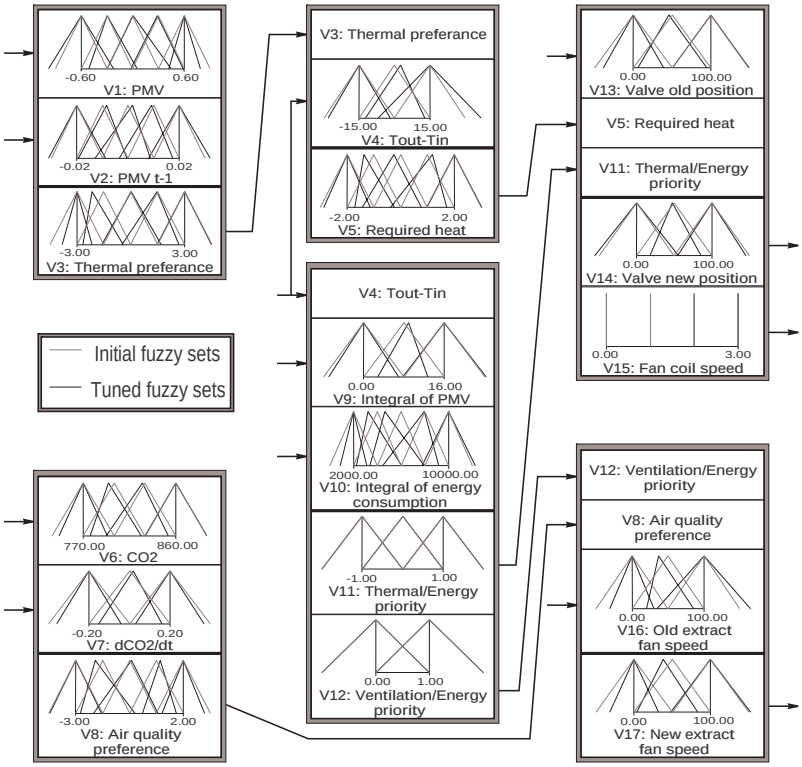


Fig. 8. Initial and tuned DB of the ATC summer FLC

6.3 Methods Analysis

A similar behavior for each method can be observed in all the different models, presenting WMC-SSGA the best results over the remaining methods and practically meeting all the requested goals. On the other hand, we also have seen as MO-SSGA generates acceptable solutions with less computation time than WMC-SSGA. In any case, the computation time for WMC-SSGA is reasonable.

About MO-SSGA and NDS-GA they present similar results but NDS-GA is far slower than MO-SSGA, by which MO-SSGA would be preferable and it could be a very interesting technique in order to quickly obtain acceptable solutions.

All the proposed techniques have yielded much better results than the classical On-Off controller, showing the good behavior FLCs can achieve on these kinds of complex multicriteria problems.

From this experimental study, we could say that WMC-SSGA is the best strategy for this problem. However, we must think that it is possible thanks to properly guide the search by using trusted weights, while MO-SSGA and

NDS-GA perform a robust search. Therefore, in the case in which trusted weights can not be provided probably MO-SSGA would be the best strategy.

The good results obtained by WMC-SSGA can be attributed to the use of a method of objective weighting that can directly guide to the best solution, to the use of fuzzy goals for dynamically adapting the search direction in the space of solutions, and to the restart approach getting away from local optima. In the following, a convergence analysis on WMC-SSGA will be made in order to see the way in which these factors affect to the fitness function.

Figure 9 illustrates the evolution chart of the fitness (expression without considering fuzzy goals) and performance values (C_i) obtained by the WMC-SSGA method when tuning the ATC summer FLC (PMVupp, PMVlow, and CO_2 improvements have been depicted with the same shade since they presents a very similar behavior with values near of 0%). The chart has been generated obtaining the values of the best individual (according to the fitness with fuzzy goals) in each generation. The improvement attained by the tuning process with respect to the On-Off controller solution is represented in vertical axis, where 0% stands for no improvement, negative value for a worsened result, and positive value for an improved result.

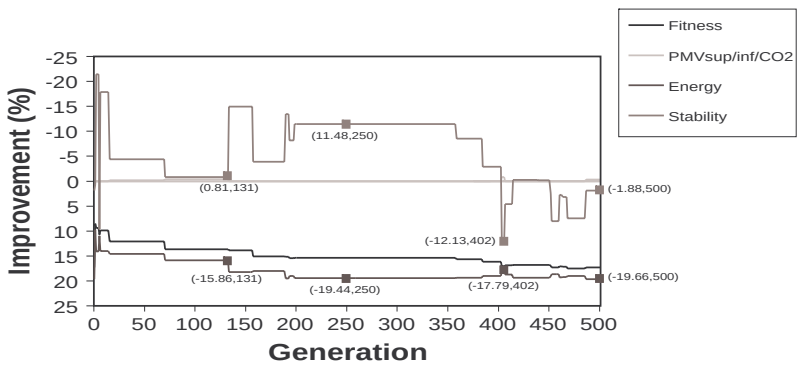


Fig. 9. Evolution of the WMC-SSGA in the ATC Summer model

Analyzing the chart, we can observe how, after some initial generations where the algorithm is being stabilized, the energy consumption is gradually decreased until the generation 131 where almost 16% of improvement is achieved. Stability and hence fitness are also improved during this period. After that, a significant improvement of the energy causes a worse stability to be obtained and the algorithm lies in a local optimum where an improvement of 19.4% for energy is obtained at the expense of stability, 11.5% worse than that of the On-Off controller. This is kept until the generation 402 where making the energy slightly worse involves finding a good stability result 12.1% better than the On-Off controller. This fact is derived from the restart action performed some generations before and it allows the algorithm to get

away from the local optimum. From this generation to the end of the run, the energy is gradually improved with an acceptable stability that entails decreasing the fitness function value.

The obtained chart leads us to notice the restart influence and the convergence degree of this algorithm, and analyze the tuning process from the efficiency (time-consuming) point of view. From this angle, it is interesting to verify that a good solution where the energy consumption is improved in a 15.9% with the rest of performance values similar to the On-Off controller is obtained in less than 100 generations.

6.4 Experiments Developed on the Real Test Sites

Results are presented only for both CNRS ENTPE and ATC summer-season experiments. From now on, *experiments* is referred to the tests in the real sites. These experiments were performed using an FLC with the best DB selected by experts for each model.

At ATC (see Table 5), experimental results show that energy savings are interesting (12.5%). However, the stability criterion is far more important than initially expected. This could also be observed when new simulations have been performed with the same climatic conditions. The reason for this is partly due to the CO_2 concentration model. In the model, mixing is supposed perfect, which is not the case in the real test cells. Despite sensor being located close to extract fan, CO_2 concentration proved to be measured at much higher values than expected. Fan operation has therefore been more important and so did stability.

Table 5. ATC Summer model: Simulation results vs test results (two days period only)

SIMULATION	**Fitness**	**PMV>0.5**	**PMV<-0.5**	**CO_2**	**Energy**	**Stability**
On-Off	0.7189	0	0	10.13	344190	138
fuzzy	0.7135	0	0	0	304270	224.35
Difference (%)	**0.75**	**0**	**0**	**0**	**11.60**	**-62.57**
EXPERIMENT	**Fitness**	**PMV>0.5**	**PMV<-0.5**	**CO_2**	**Energy**	**Stability**
On-Off	0.7409	0	0	1015.5	350813	142
fuzzy	0.6881	0	0	1016.5	304031	188.62
Difference (%)	**7.12**	**0**	**0**	**-0.10**	**13.34**	**-32.83**

For CNRS ENTPE (Table 6), excellent results have been obtained with up to 30% energy savings. Experimental conditions created outdoor conditions

from $21°C$ at night up to $31°C$ during the day. Outdoor air cooling potential in the morning is therefore quite important for these experiments, which explains these excellent results. On the other hand, stability proved to be very bad. A possible reason for this is a rounding problem within the controller. Actuator is operated with a small number of positions (4 for fan speed and 3 for mode) and rounding is required between fuzzy output and actuator signal, thus creating unstabilities.

Table 6. CNRS ENTPE Summer model: Test results (four days period only)

EXPERIMENT	**Fitness**	**PMV>0.5**	**PMV<-0.5**	**CO_2**	**Energy**	**Stability**
On-Off	8.07	0	0.21	4925	8493541	1280
fuzzy	6.97	0	0.11	4822	5951575	4330
Difference (%)	**13.63**	**0**	**47.62**	**2.09**	**29.93**	**-238.28**

Summarizing, it has been proved that energy consumption is greatly reduced during experimentation in real tests cells. Moreover, comparisons between simulations and experiments are in good agreement for the BEMSs designers. Therefore, the proposed technique has been demonstrated to be effective to solve this problem.

7 Concluding Remarks

In this contribution, the use of GAs to develop smartly tuned FLCs dedicated to the control of HVAC systems concerning energy performance and indoor comfort requirements is presented. Three efficient genetic tuning strategies considering different multicriteria approaches have been presented. Several FLCs have been produced and tested in laboratory experiments in order to check the adequacy of such control and tuning techniques. To run the proposed tuning techniques, accurate models of the controlled buildings (two real test cells) were provided by experts.

From this experimental study, we could say that probably the objective weighting method WMC-SSGA is the best option when trusted weights are available while in the case in which trusted weights can not be provided probably a most robust technique as MO-SSGA would be the best option. Moreover, the proposed techniques have yielded much better results than the classical On-Off controller showing the good behavior that FLCs can achieve on these kinds of complex multicriteria problems.

Regarding the experimentation in the real test cells, comparisons between simulations and experiments are in good agreement for the BEMSs designers,

presenting significant energy savings in both cases. It shows the effectiveness of this automatic control technique to solve this problem.

The proposed tuning algorithms have an interesting advantage for industrial application: the consideration of goals to perform the multicriteria optimization. These goals significantly improve the tuning performance and it makes easier the expert's knowledge interpretation since the specification of goals, i.e., when each objective has been properly improved, seems to be easy to give. Furthermore, the use of fuzzy goals together with the penalization factor internally changes the initial proposed weights during the evolution of the WMC-SSGA algorithm, dynamically adapting the search direction in the space of solutions. It makes this method robust and more independent from the weight selection for the fitness function.

The results of this work should be ready for implementation in real buildings for the specific studied systems. An extended test of our prototypes will however be necessary before product marketing. Moreover, appropriate interfaces will have to be developed. First industrial applications of our results could therefore start approximately in two years.

This methodology could then be applied to other systems and progressively implemented at industrial level. However, the marketing potential should be particularly studied as well as the way by which they could be efficiently extended to other equipments and buildings.

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