Applied Intelligence 18, 155–177, 2003

Fuzzy Control of HVAC Systems Optimized by Genetic Algorithms

RAFAEL ALCALÁ
Department of Computer Science, University of Jaén, 23071 Jaén, Spain
alcala@ujaen.es

JOSE M. BENÍTEZ, JORGE CASILLAS, OSCAR CORDÓN AND RAÚL PÉREZ
Department of Computer Science and Artificial Intelligence, University of Granada, 18071 Granada, Spain
jmbs@decsai.ugr.es
casillas@decsai.ugr.es
ocordon@decsai.ugr.es
fgr@decsai.ugr.es

Abstract. This paper presents the use of genetic algorithms to develop smartly tuned fuzzy logic controllers dedicated to the control of heating, ventilating and air conditioning systems concerning energy performance and indoor comfort requirements. 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 restrictions, a genetic tuning strategy considering an efficient multicriteria approach has been proposed. Several fuzzy logic controllers have been produced and tested in laboratory experiments in order to check the adequacy of such control and tuning technique. To do so, accurate models of the controlled buildings (two real test sites) have been provided by experts. Finally, simulations and real experiments were compared determining the effectiveness of the proposed strategy.

Keywords: HVAC systems, fuzzy logic controllers, genetic tuning, multiple criteria

1. Introduction

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.

On the other hand, a study performed in the frame of the ALTENER[1] project has shown that the use of automatic control for passive systems (e.g., shading or free cooling) and its integration into a BEMS could result in important energy savings when compared to manual control [1]. Therefore, the role of automatic control is thus of major importance. However, 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.

Moreover, 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 at an industrial level.

The use of rule-based controllers, specially Fuzzy Logic Controllers (FLCs) [2–4], would enable the implementation of multicriteria control strategies incorporating expert knowledge. However, a rational operation and improved performance of FLCs is required for implementing complex control techniques. The use of smart setting and tuning techniques for these controllers could improve the energy savings and the indoor comfort by fitting previously obtained Knowledge Bases (KBs) provided by experts [5]. Genetic Algorithms (GAs) [6, 7] present the ideal framework to tune these FLCs [8] when multiple criteria are considered.

In this paper, the use of GAs to develop smartly tuned FLCs to control HVAC systems concerning energy performance and indoor comfort requirements is presented. To evaluate the goodness of the proposed technique, several FLCs incorporating the said innovations 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 technique, accurate models of the controlled buildings (two real test sites) were provided by experts in order to assess the fitness function.

This paper is set up in the following way. In the next section, the basics of HVAC systems and FLCs are presented, explaining how these kinds of controllers can be applied to HVAC systems. In Section 3, the HVAC systems tuning restrictions are introduced, proposing a particular genetic tuning technique to solve this problem. Section 4 shows the experiments performed in the two test sites. First, several experiments are set up, showing the oddities from each system to be controlled. Later, simulated and experimental results are analyzed. In Section 5, some concluding remarks are pointed out, showing how this methodology could be applied to other systems and progressively implemented at industrial level. Finally, a table with the used acronyms is presented in Appendix A.

2. HVAC Systems and their Control with FLCs

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.

In the specific case of HVAC systems, most works apply FLCs to solve simple problems such as thermal regulation, maintaining a temperature setpoint [9–11]. However, in this work various different criteria must be considered in order to reduce the energy consumption maintaining a desired comfort level. Therefore, many variables have to be considered from the controlled system, which makes it very complex.

In the following we will see how we can solve this complex problem by the application of FLCs.

2.1. Heating, Ventilating, and Air Conditioning Systems

An HVAC system is comprised by all the components of the appliance used to condition the interior air of a building. The HVAC system is needed to provide the occupants with a comfortable and productive working environment which satisfies their physiological needs.

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 a 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 [9].

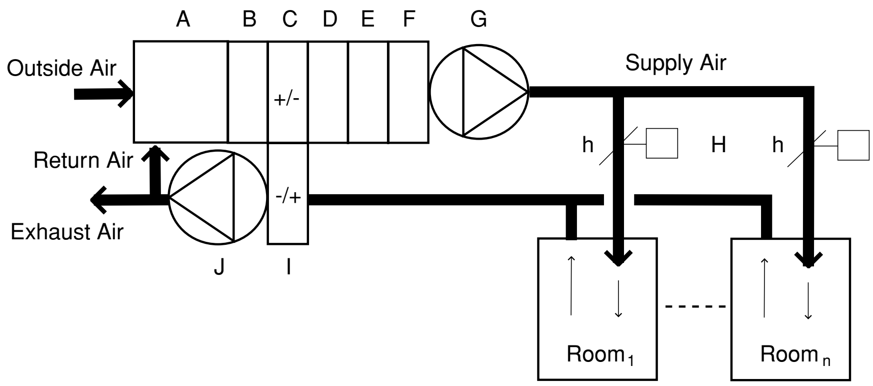

Figure 1. Generic structure of an office building HVAC system.

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:

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

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.

2.2. *Fuzzy Logic Controllers*

FLCs [2–4] are suitable for engineering because their inputs and outputs are real-valued variables, mapped with a non-linear function. These kinds of systems achieve an alternative for those applications where classical control strategies do not achieve good results. In many cases, these systems have two characteristics: the need for human operator experience, and a strong non linearity, where it is not possible to obtain a mathematical model.

Expert Control is a field of Artificial Intelligence that has become a research topic in the domain of system control, with the purpose of avoiding the aforementioned drawbacks with respect to classical control strategies. Fuzzy Logic Control is one of the topics within Expert Control. Moreover, FLCs, as initiated by Mamdani and Assilian [3, 4], are now considered as one of the most important applications of Fuzzy Set Theory proposed by Zadeh [12] in 1965. This theory is based on the notion of fuzzy set as a generalization of the ordinary set characterized by a membership function μ that takes values in the interval [0, 1] representing degrees of membership to the set. FLCs typically define a non-linear mapping from the system's state space to the control space. Thus, it is possible to consider the output of an FLC as a non-linear control surface reflecting the process of the operator's prior knowledge.

An FLC 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

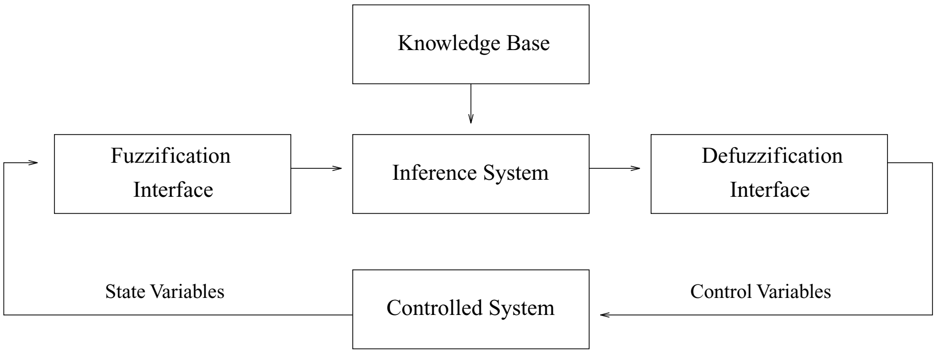

Figure 2. Generic structure of a fuzzy logic controller.

Fuzzification Interface and the information from the KB to perform 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. Figure 2 shows the generic structure of an FLC.

The **KB** encodes the expert knowledge by means of a set of fuzzy control rules. A fuzzy control rule is a conditional statement in which the antecedent is a condition in its application domain, the consequent is a control action to be applied in the controlled system and both, antecedent and consequent, are associated with fuzzy concepts, that is, linguistic terms. The KB is comprised by two components: the Data Base (DB) and the Rule Base (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.

According to the form of the consequents of the fuzzy control rules, we can usually distinguish two main different types of FLCs in the specialized literature, Mamdani FLCs [4] and Takagi-Sugeno-Kang FLCs [13, 14]:

- Mamdani-type rules are composed of input and output linguistic variables taking values on a linguistic term set with a real-world meaning:

  $$R_i\text{: } \textit{If } X_1 \textit{ is } A_{i1} \textit{ and } \ldots \textit{ and } X_n \textit{ is } A_{in} \textit{ then } Y \textit{ is } B_i,$$

- Takagi-Sugeno-Kang-type rules are based on the division of the input space into several fuzzy subspaces in which each rule defines a linear input-output relationship by means of the real-valued coefficients p_{ij}:

  $$R_i\text{: } \textit{If } X_1 \textit{ is } A_{i1} \textit{ and } \ldots \textit{ and } X_n \textit{ is } A_{in} \textit{ then } Y = p_{i1} \cdot X_1 + \cdots + p_{in} \cdot X_n + p_{i0},$$

where X_i and Y are the input and output linguistic variables and the A_{ij} and B_i are linguistic labels with fuzzy sets associated specifying their meaning.

Without lack of generality, in the following we consider an RB constituted by m Mamdani-type fuzzy control rules R_i, $i = 1, \ldots, m$.

The **Fuzzification Interface** establishes a mapping between each crisp value of the input variable and a fuzzy set defined in the universe of the corresponding variable. Being x_0 a crisp value defined in the input universe U, A' a fuzzy set defined in the same universe and F a fuzzifier operator, it works as follows:

$$A' = F(x_0).$$

There are two main types of fuzzification, the first one being the most usual:

a *Singleton Fuzzification*: A' is built like a singleton fuzzy set with support x_0:

$$A'(x) = \begin{cases} 1, & \text{if } x = x_0 \\ 0, & \text{otherwise.} \end{cases}$$

b *Non-Singleton or Approximate Fuzzification*: In this case, when $x = x_0$, $A'(x_0) = 1$, and the membership of the rest of the values for U decreases while moving away from x_0.

The **Inference System** is based on the application of the Generalized Modus Ponens, an extension of the classical Modus Ponens, proposed by Zadeh in the way:

$$\frac{\begin{array}{l} \textit{If } X \textit{ is } A \textit{ then } Y \textit{ is } B \\ X \textit{ is } A' \end{array}}{\qquad\qquad Y \textit{ is } B'}$$

The fuzzy conditional statement *If X is A then Y is B* (with X, Y being linguistic variables and A, B fuzzy sets) represents a fuzzy relation between A and B defined in $U \times V$, with U and V being the universes of the variables X and Y, respectively. The fuzzy relation is expressed by a fuzzy set R whose membership function $\mu_R(x, y)$ is given by:

$$\forall x \in \mathbf{U}, y \in \mathbf{V}\text{: } \mu_R(x, y) = I(\mu_A(x), \mu_B(y)),$$

with $\mu_A(x)$ and $\mu_B(y)$ being the membership functions of the fuzzy sets A and B, respectively and I being a fuzzy implication operator (rule connective) modeling the fuzzy relation. The consequent B', obtained from the Generalized Modus Ponens, is deduced by projection on V by means of the Compositional Rule of Inference, given by the following expression in which T' is a connective:

$$\mu_{B'}(y) = Sup_{x \in U}\{T'(\mu_{A'}(x), I(\mu_A(x), \mu_B(y)))\}.$$

When Singleton Fuzzification is considered, the fuzzy set A' is a singleton. Thus, the Compositional Rule of Inference is reduced to the following expression:

$$\mu_{B'}(y) = I(\mu_A(x_0), \mu_B(y)).$$

As said, the calculation of $\mu_A(x_0)$ consists of the application of a conjunctive operator T on $\mu_{A_i}(x_i)$:

$$\mu_A(x_0) = T\big(\mu_{A_1}(x_1), \mu_{A_2}(x_2), \ldots, \mu_{A_n}(x_n)\big).$$

The Inference System produces the same amount of output fuzzy sets as the number of rules collected in the KB. These groups of fuzzy sets are aggregated by the *also* connective, which is modeled by an operator G. However, they must be transformed into crisp values for the control variables. This is the goal of the **Defuzzification Interface**. To describe its operation mode, we denote by B_i' the fuzzy set obtained as output when performing inference on rule R_i, and by y_0 the global output of the FLC for an input x_0.

There are two types of defuzzification methods [15–17] according to the way in which the individual fuzzy sets B_i' are aggregated through the *also* connective, G:

- *Mode A: Aggregation First, Defuzzification After*. The Defuzzification Interface performs the aggregation of the individual fuzzy sets inferred, B_i', to obtain the final output fuzzy set B':

$$\mu_{B'}(y) = G\big\{\mu_{B_1'}(y), \mu_{B_2'}(y), \ldots, \mu_{B_n'}(y)\big\}.$$

  Usually, the aggregation operator modeling G is the minimum or the maximum. After that, the fuzzy set B' is defuzzified using any strategy D, like the Mean of Maxima, or the Center of Gravity mostly:

$$\mu_0 = D(\mu_{B'}(y)).$$

- *Mode B: Defuzzification First, Aggregation After*. It avoids the computation of the final fuzzy set B' by considering the contribution of each rule output individually, obtaining the final control action by taking a calculation (an average, a weighted sum or a selection of one of them) of a concrete crisp characteristic value associated to each of them.

More complete information on FLCs can be found in [2, 18, 19].

2.3. Applying Fuzzy Logic Controllers to Heating, Ventilating, and Air Conditioning Systems

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. 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 has defined the system to be controlled (building and HVAC specification), the construction of the corresponding 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.

In the following, several of these design tasks are analyzed more deeply.

2.3.1. The Composition of the FLC KB. As said, the KB encodes the expert knowledge of the controlled system. Therefore, it depends on the concrete application making the accuracy of the designed FLC directly depend on its composition. There are four modes of derivation of fuzzy control rules, that are not mutually exclusive [19]. 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 [20].
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 [11]. This is because of:

- the gathering and structuring of expertise is not easy,
- the setting up of the KB 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 of a modification of 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. Other possibility is to perform the rule learning together with the derivation of the DB components [21].

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 FLC 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 the control process. 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.

2.3.2. Control and Controlled Parameter Selection. 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*: Indoor Air Quality was found to be critical. As CO_2 concentration is a reliable index of the pollution emitted by occupants, it can be selected as Indoor Air Quality index. It is therefore supposed that 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 of applying 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 (controlled or implicit) parameters may be measured depending on the objectives of the control strategy. In these kinds of problems, these parameters could be selected among:

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

The selection of these parameters is a task concerned to the BEMS designer as well. In our case, several controller architectures involving different variables (control or explicit parameters) have been developed depending on the concrete testing site (building) considered (see Fig. 8 in Section 8 for a concrete FLC architecture and its respective parameters).

2.3.3. FLC 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 [16, 22], 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 [23, 24], which allows us to divide the control tasks among different modules, is proposed for our FLC. Using the expert knowledge of the system to partition the controller permits an adequate control with much fewer rules. Moreover, with this approach, the subsequent control tuning becomes easier since the modification of one parameter influences a smaller number of rules.

In addition, it is recommended that three controllers (rather than a single one) be developed for each testing site (in our case, by only changing the corresponding KB and maintaining the FLC architecture). The reason for this lies in the important climate variations all over the year and the 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 propose 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 propose 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 [25], we will use triangular membership functions, which are simpler. Their formula is:

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

Among all the associative functions, t-norms are the more suitable to be used to define the connective *and* [16]. Two basic t-norms have been usually considered: minimum ($\mathrm{Min}(x, y) = \min(x, y)$) 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 [16], 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 Mode B defuzzification (see Section 2.2) because the defuzzification method working in this mode is more robust, quick and easier to compute than those used in Mode A [16]. As characteristic value and control crisp value, we propose the Mean of Maxima weighted by the rule antecedent matching, h_i, since according to the results reported in [16], it renders the best accuracy among the 17 different defuzzification methods tested.

3. Genetic Tuning of FLCs for HVAC Systems

The tuning of FLCs for HVAC systems presents two specific restrictions that make it very particular and complex. The following subsections address these problems proposing an efficient genetic tuning technique to develop smartly tuned FLCs dedicated to the control of HVAC systems.

3.1. HVAC Systems Tuning Restrictions

Tuning problems 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 reducing the solution search space. 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 objectives (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.

Although there are many genetic tuning techniques [26–28], neither of them in their original proposed forms can be satisfactorily used because they do not properly address these restrictions. On the one hand, neither of them is initially prepared to tackle with multiobjective optimization (of course, they could be adapted to do so). On the other hand, the choices considered for the GA components in these proposals (generational replacement, coding scheme, etc.) would make the optimization process extremely slow if applied directly to a problem like ours where the simulation performed to evaluate each chromosome could take approximately 200 seconds. Therefore, in order to solve these two problems, efficient tuning approaches considering both restrictions should be developed.

GAs can represent any type of fuzzy rules, present flexibility to work with different FLC architectures and have a good capability to include expert knowledge [8]. 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 [29].

From this point of view, the **first restriction** will be solved by using multicriteria genetic optimization techniques that will 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 those multicriteria approaches based and not based on aggregation of the objectives.

All classical multicriteria aggregation-based methods scalarize the objective vector reducing it to a scalar optimization problem. Probably, the simplest of all these classical techniques is the objective weighting method. In this case, multiple objective 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 reduces the search space providing the adequate direction into the solution space and its use is highly recommended. Therefore, the main question to be considered in this approach is: have we trusted weights to estimate the importance of each objective?

In our case, trustworthy weights were provided by the BEMS designer. Therefore, the fitness function will be based on objective weighting. 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.

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 when trustworthy weights are used.
- A steady-state GA [30], that involves selecting two of the best individuals in the population and combining them to obtain two offspring. This approach improves the convergence and simultaneously decreases the number of evaluations.
- 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.

Both, the multicriteria and the efficient tuning approaches will be considered in the proposed tuning method.

3.2. Genetic Tuning Proposal

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 [31] and with a fitness function based on objective weighting, the so called *Weighted Multi-Criteria Steady-State Genetic Algorithm* (WMC-SSGA).

In the following subsections, GAs and multicriteria genetic plain aggregation approaches are briefly introduced to subsequently present the proposed WMC-SSGA.

3.2.1. Genetic Algorithms: The Steady-State Approach. GAs are general-purpose global search algorithms that use principles inspired by natural population genetics to evolve solutions to problems. The basic principles of the GAs were first laid down rigorously by Holland [32] and are well described in many texts such as [7].

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

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

On the other hand, the steady-state approach [30] consists of selecting two of the best individuals in the population and combining them to obtain two offspring. Then, these two new individuals are included in the population replacing the two worst individuals if the former are better adapted than the latter. An advantage of this technique is that good solutions are used as soon as they are available. Therefore, the convergence is accelerated while the number of evaluations needed is decreased.

3.2.2. 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 into three groups [29]: plain aggregating approaches, population-based non-pareto approaches, and pareto-based approaches.

The method of objective weighting belongs to the former approach. Within this approach, as conventional GAs require scalar fitness information to work on, a scalarization 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.

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, when trustworthy weights are available this problem disappears.

3.2.3. Weighted Multi-Criteria Steady-State Genetic Algorithm. WMC-SSGA consists of a GA based on the well-known steady-state approach [30]. Its main characteristic is the fact that good solutions are used as soon as they are available, thus accelerating the convergence and decreasing the number of evaluations needed. Figure 3 presents the flowchart of the proposed method, while its main components are introduced as follows.

3.2.3.1. Coding Scheme. WMC-SSGA uses a real coding scheme [31]. A solution is directly encoded into a chromosome by joining the representation of the l_i labels of each one of the m variables composing the DB. For example:

$$C_i = \left(a_1^i, b_1^i, c_1^i, \ldots, a_{l_i}^i, b_{l_i}^i, c_{l_i}^i\right), \quad i = 1, \ldots, m,$$
$$C = C_1 C_2 \ldots C_m.$$

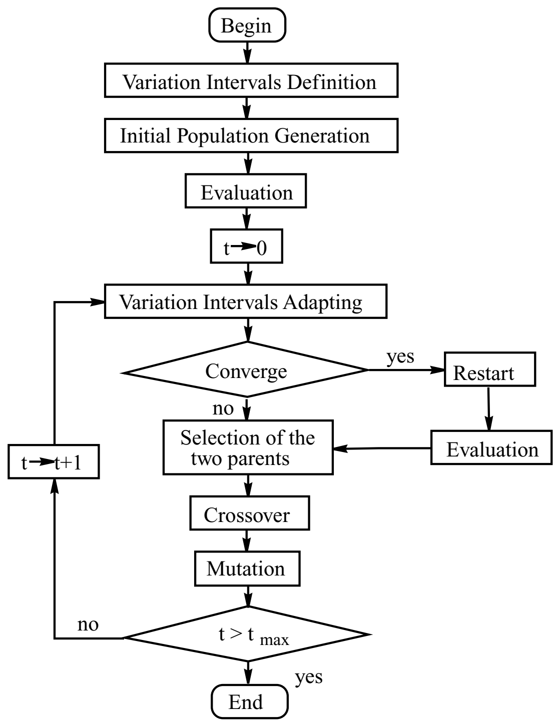

Figure 3. Flowchart of the GA process.

3.2.3.2. 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. Thus, 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 as

$$
\begin{aligned}
\{l^1_a, l^2_a\} &= \{\max(c^i_{j-3}, b^i_{j-2}, a^i_{j-1}), \min(c^i_{j-2}, b^i_{j-1}, a^i_j)\}\\
\{r^1_a, r^2_a\} &= \{\max(c^i_{j-2}, b^i_{j-1}, a^i_j), \min(c^i_{j-1}, b^i_j, a^i_{j+1})\}\\
[L_{a^i_j}, R_{a^i_j}] &= \left[l^2_a - \frac{l^2_a - l^1_a}{2}, r^1_a + \frac{r^2_a - r^1_a}{2}\right],\\
\{l^1_b, l^2_b\} &= \{\max(c^i_{j-2}, b^i_{j-1}, a^i_j), \min(c^i_{j-1}, b^i_j, a^i_{j+1})\}\\
\{r^1_b, r^2_b\} &= \{\max(c^i_{j-1}, b^i_j, a^i_{j+1}), \min(c^i_j, b^i_{j+1}, a^i_{j+2})\}\\
[L_{b^i_j}, R_{b^i_j}] &= \left[l^2_b - \frac{l^2_b - l^1_b}{2}, r^1_b + \frac{r^2_b - r^1_b}{2}\right],\\
\{l^1_c, l^2_c\} &= \{\max(c^i_{j-1}, b^i_j, a^i_{j+1}), \min(c^i_j, b^i_{j+1}, a^i_{j+2})\}\\
\{r^1_c, r^2_c\} &= \{\max(c^i_j, b^i_{j+1}, a^i_{j+2}), \min(c^i_{j+1}, b^i_{j+2}, a^i_{j+3})\}\\
[L_{c^i_j}, R_{c^i_j}] &= \left[l^2_c - \frac{l^2_c - l^1_c}{2}, r^1_c + \frac{r^2_c - r^1_c}{2}\right],
\end{aligned}
$$

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.

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 Fig. 4). 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

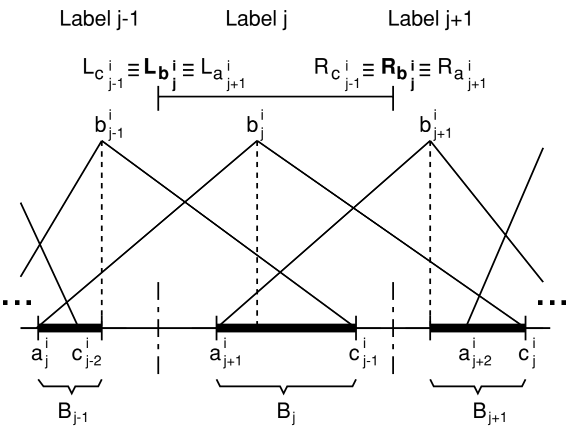

Figure 4. Variation interval of b^i_j, c^i_{j-1} and a^i_{j+1}.

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).

Figure 4 graphically depicts the variation intervals for those points contained in B_j 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.

Finally, these intervals are dynamically adapted from the best individual for each generation, avoiding the restrictions of fixing them from the beginning of the GA run. Once these intervals have been calculated, the genes out of range are randomly generated within them.

3.2.3.3. Evaluating the Chromosome. The fitness function was finally selected with the following typical components:

- O_1 Upper thermal comfort limit: *if PMV* > 0.5, $O_1 = O_1 + (PMV - 0.5)$.
- O_2 Lower thermal comfort limit: *if PMV* < -0.5, $O_2 = O_2 + (-PMV - 0.5)$.
- O_3 Indoor Air Quality requirement: *if* CO_2 *conc.* $>$ 800 ppm, $O_3 = O_3 + (CO_2 - 800)$.
- O_4 Energy consumption: $O_4 = O_4 +$ Power at time t.
- O_5 System stability: $O_5 = O_5 +$ System change from time t to $(t - 1)$, where system change states for a change in the system operation, i.e., it counts the system operation changes (a change in the fan speed or valve position).

This fitness function is based on objective weighting. However, it has been modified in order to consider the use of fuzzy goals for dynamically adapting the search direction in the space of solutions, decreasing the improvement 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:

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

with w_i being the weighting coefficients to be set for each specific problem.

Two cases can happen 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. 5):

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

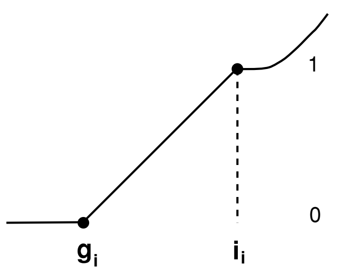

Figure 5. $\delta_i(x)$ when $g_i \le i_i$.

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. 6):

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

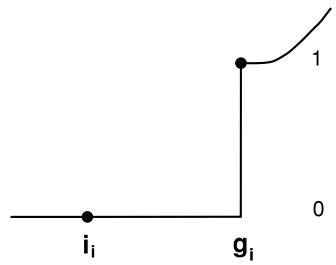

Figure 6. $\delta_i(x)$ when $g_i > i_i$.

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.

3.2.3.4. Genetic Operators. 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 [33] and Michalewicz's non-uniform mutation [7].

Let $C^v = (c_1, \ldots, c_k, \ldots, c_H)$ and $C^w = (c'_1, \ldots, c'_k, \ldots, c'_H)$ be the two parents selected for crossover. Using the max-min-arithmetical **crossover**, the resulting descendents are the two best of the next four offspring:

$$\begin{aligned} C^{1\prime} &= aC^w + (1-a)C^v \\ C^{2\prime} &= aC^v + (1-a)C^w \\ C^{3\prime} &\text{ with } c_{3k} = \min\{c_k, c'_k\} \\ C^{4\prime} &\text{ with } c_{4k} = \max\{c_k, c'_k\}, \end{aligned}$$

with a being a constant parameter chosen by the GA designer, 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 $c'_k = c_k - \Delta(t, c_k - L_{c_k})$, otherwise. 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.

On the other hand, the **selection** is based on the Baker's stochastic universal sampling [34] together with the elitist selection.

3.2.3.5. Restart. Finally, to get away from local optima, this algorithm uses a restart approach [35]. Thus, when the population of solutions converges to very similar results, the entire population but the best individual is randomly generated within the variation intervals. This allows the algorithm to perform a better exploration in the search space and to avoid getting stuck at local optima.

4. Experiments and Results Obtained

To evaluate the goodness of the proposed technique, several experiments have been carried out within the framework of the JOULE-THERMIE programme under the GENESYS[2] project. Two real test sites were available for the experiments. The first one is provided by both Centre National de la Recherche Scientifique (CNRS) and the Ecole Nationale des Travaux Publics de l'Etat (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 cells—from Anonymous Test Cell—. In both cases, the main objective was the energy performance but maintaining the required indoor comfort levels.

To run the proposed tuning technique, accurate models of these controlled buildings were provided by experts for each season. These models assess the tuning algorithm for fitness computation (see Section 2.3.1 and Section 3). The results obtained were very satisfactory, specially for the ATC summer-season model. However, due to the large number of results, we will work only with a cross-section of the models, the CNRS ENTPE mid-season and summer-season models, and the ATC summer-season model.

In this section, the experiments performed with the said models are presented. After the experiments are set up—showing the oddities from each system to be controlled—, simulated and experimental results will be analyzed. Results will be compared to the performance of the initial expert FLC and to a classical control technique, an On-Off controller.

4.1. Experimental Set-Up

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 aspects of these sites are the following:

- 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 2000 m^3/h (test cells volume is 80 m^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. 7 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)

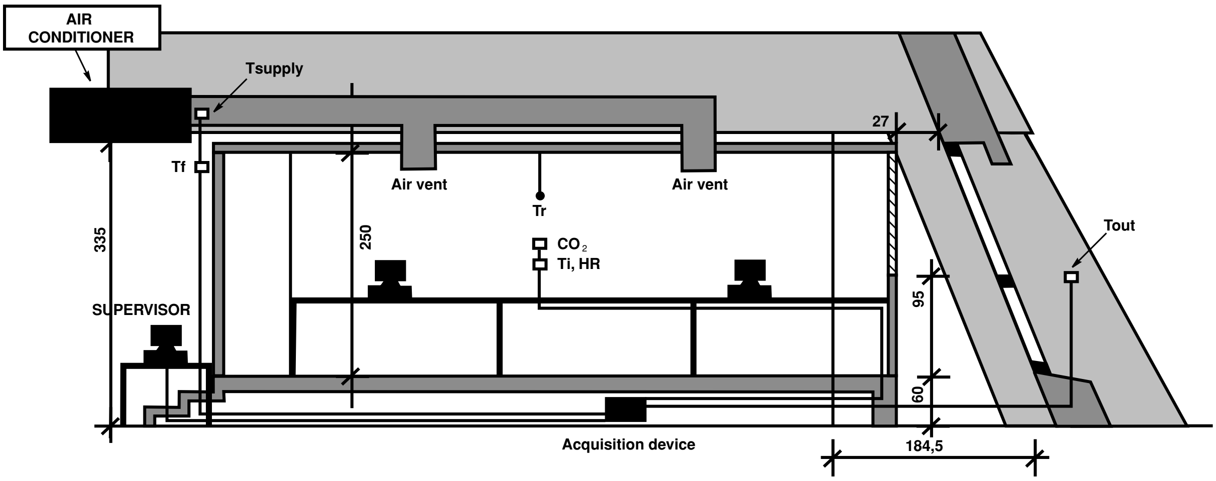

Figure 7. Representation of the CNRS ENTPE test cells.

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.

Fitness function and fuzzy inference algorithms (see Section 2.3.3) 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, Indoor Air Quality discomfort and energy consumption for a 30 minutes to 1 hour period prior to the control decision. The ATC FLC architecture is presented in Fig. 8.

Another important outcome was the development of the fitness function aiming to characterize the performance of each tested controller towards thermal comfort, Indoor Air Quality, energy consumption and system stability criteria. This was presented in Section 3.2.3. However, in order to compare the different solutions obtained, the fuzzy goals will not be considered to compute the fitness value of the results presented in tables.

This fitness function was comprised of five criteria. The main problem was then to assign appropriate weights to each criterion. 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 office (or test cell in our case). Thus, trusted weights for both test cells were obtained. For CNRS ENTPE model the chosen values

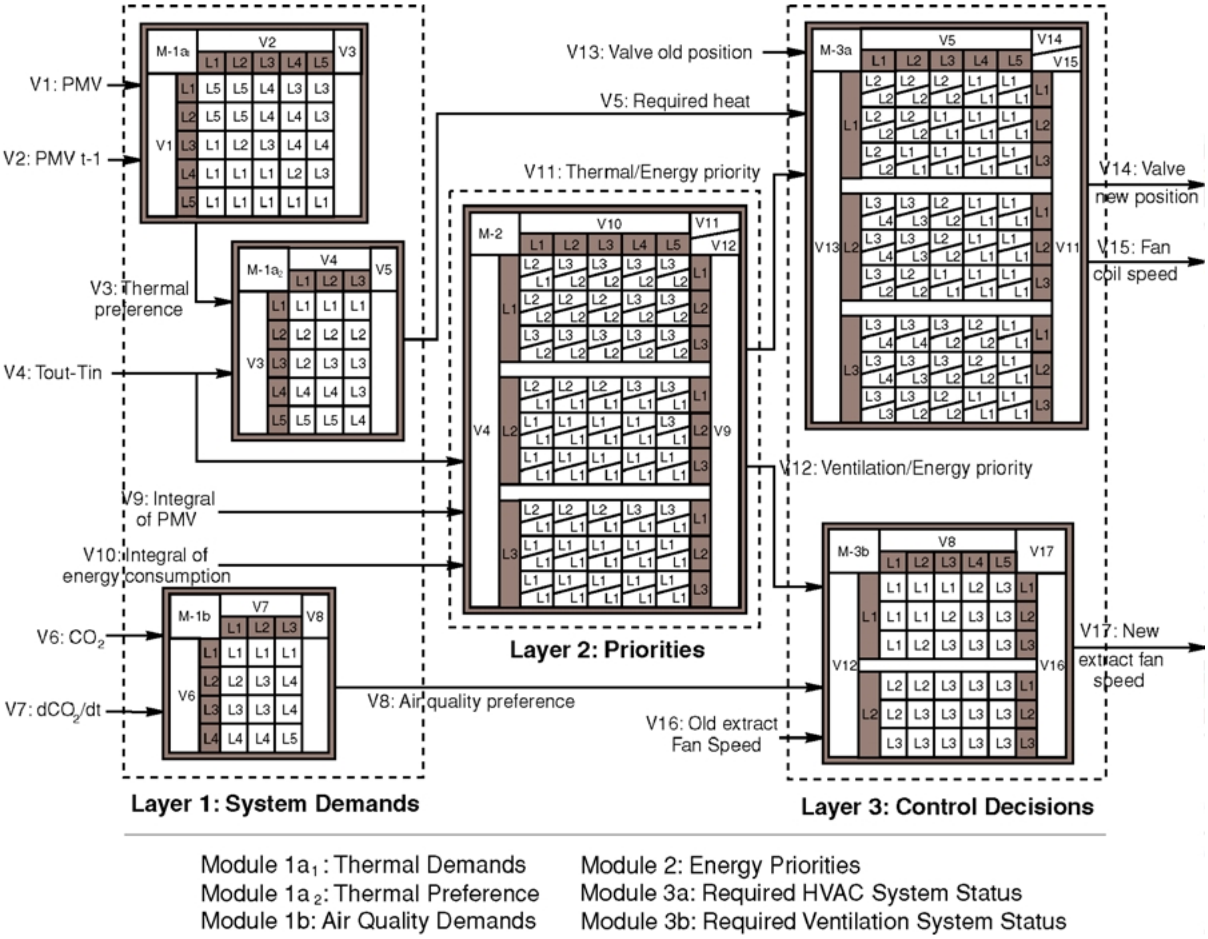

Figure 8. Initial rule base and generic structure of the ATC summer-season fuzzy logic controller.

were: $w_1 = 0.0083022$, $w_2 = 0.0083022$, $w_3 = 0.00000456662$, $w_4 = 0.0000017832$ and $w_5 = 0.000761667$. For ATC model: $w_1 = 0.0041511$, $w_2 = 0.0041511$, $w_3 = 0.00000228333$, $w_4 = 0.0000017832$ and $w_5 = 0.000761667$.

Finally, initial KBs were obtained from BEMS designers for each model and season. Figures 8 and 9 show the initial RB and DB of the ATC FLC for summer-season. 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. Notice that in Fig. 8 we represent the decision tables of each module of the hierarchical FLC considered in terms of these labels. When the RB considers more than two variables (as in the case of modules M-2 in layer 2 and M-3a and M-3b in layer 3 where three input variables are involved), the three-dimensional table is decomposed into three two-dimensional decision tables (one for each possible label of the first variable) in order to clearly show its composition. Therefore, each cell of the table represents a fuzzy subspace and contains its associated output consequent(s), i.e., the corresponding label(s). The output variables are denoted in the top left square for each module. Notice that, when there are two consequents they are placed in the same cell (divided by a diagonal line).

4.2. Experiments Developed on Simulated Systems

Three different models were implemented, the CNRS ENTPE mid-season and summer-season models, and the ATC summer-season model. The FLCs obtained

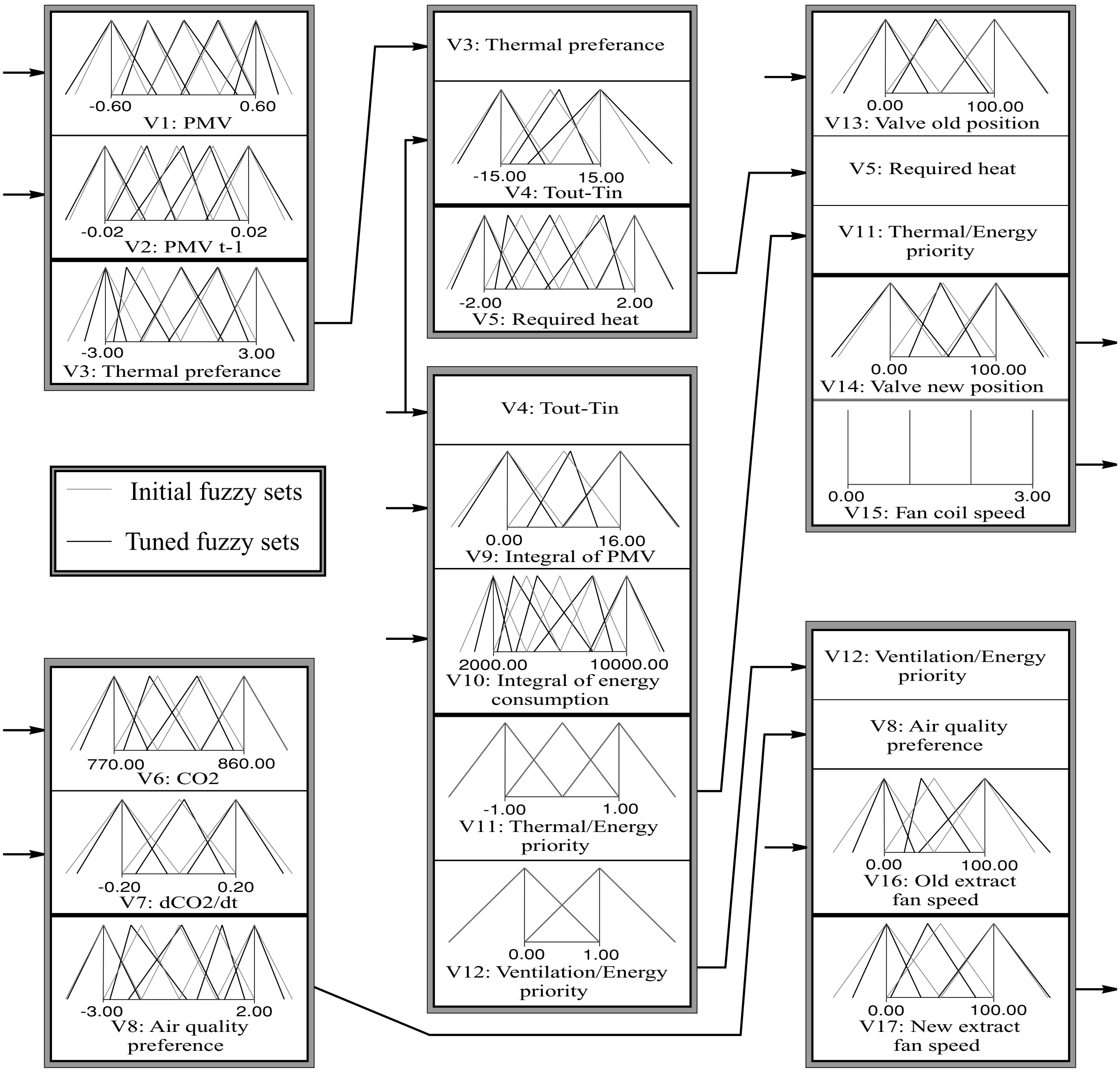

Figure 9. Initial and tuned DB of the ATC fuzzy logic controller.

from the proposed technique will be compared among them, to the original FLC without tuning and to a classical On-Off controller for all of these models (the goals and improvements will be computed with respect to this classical controller).

The tuning strategy was assessed with simulations of 10 days with the correspondent climatic conditions. The results obtained by the tuning method for each model are presented in the following and they are picked up from the last population obtained from each strategy.

4.2.1. CNRS ENTPE Mid-Season Model. In this case, WMC-SSGA was run two times, first from the initial DB and then from the best DB obtained in the previous run. Each run had 500 iterations.

Since the time required for each model evaluation was approximately 200 seconds, the estimated run time was four days for 500 iterations (computed as the product of the number of evaluations per generation, the evaluation time and the number of generations).

Our goal from experts was to achieve up to 15% energy saving with a system stability at least equal to

Table 1. Results obtained with the CNRS ENTPE Mid-Season model.

ENTPE model	Fitness		PMV > 0.5		PMV < −0.5		CO_2		Energy		Stability	
	Val.	%	Val.	%	Val.	%	Val.	%	Val.	%	Val.	%
On-Off	43.49	–	0	–	95.7	–	0	–	22780	–	2730	–
Init. FLC	40.82	6.14	0	–	100.1	−4.7	0	–	21857	4.05	1340	50.9
Goals	–	–	–	–	105.0	−10.0	–	–	19363	15.00	2730	0.0
WMC-1	38.52	11.43	0	–	100.3	−4.9	0	–	20044	12.01	2557	6.3
WMC-2	38.53	11.41	0	–	100.3	−4.9	0	–	20065	11.92	2527	7.4
WMC-3	38.24	12.07	0	–	103.7	−8.4	0	–	19700	13.52	2960	−8.4
WMC-4	38.09	12.42	0	–	104.0	−8.7	0	–	19484	14.47	3270	−19.8

the On-Off controller stability (2730) and PMV inferior criteria no more than 10% higher than for On-Off (PMVinf < 105) —see Table 1—. However, the values imposed to the method were the following: 0, 108, 0, 19363 and 2800, respectively for fitness, PMV superior, PMV inferior, CO_2, energy and stability. The penalization rates considered were 0.0, 0.0, 0.0, 0.5 and 0.7, respectively.

From Table 1, 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%, and completely meets the remaining ones. On the other hand, the third solution 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.

4.2.2. CNRS ENTPE Summer-Season Model. In this case, WMC-SSGA was run three times from the best DB obtained in the previous run. Each run had 500 iterations.

The time required for each model evaluation was approximately 220 seconds. Therefore, the computation time was similar to that of the mid-season model.

Our goal was to reduce PMV superior to 0 and to maintain HVAC stability as close as possible to the On-Off controller (1160), with energy not greater than 10000 (see Table 2). In this way, the values imposed to WMC-SSGA were the following ones: 0, 13.7, 0, 9000 and 1477, with penalization rates of 1, 1, 1, 0.9 and 0.99, respectively.

In view of the results shown in Table 2, 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, due to 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 100% from the initial FLC results, and all the remaining goals have been practically met; hence it is a very good result for this tuning method.

Table 2. Results obtained with the CNRS ENTPE Summer-Season model.

ENTPE model	Fitness		PMV > 0.5		PMV < −0.5		CO_2		Energy		Stability	
	Val.	%	Val.	%	Val.	%	Val.	%	Val.	%	Val.	%
On-Off	21.60	–	0.00	–	13.84	–	0	–	11557	–	1160	–
Init. FLC	18.40	14.81	4.50	−450	13.70	1.01	0	–	9148	20.85	2579	−122.3
Goals	–	–	0	100	–	–	–	–	10000	–	1160	0.0
WMC-1	18.71	13.37	2.35	−234	13.55	2.04	0	–	9799	15.21	1451	−25.1
WMC-2	18.76	13.13	0.05	−4.7	13.77	0.49	0	–	9823	14.99	1486	−28.1
WMC-3	18.76	13.13	0.03	−2.5	13.77	0.49	0	–	9827	14.96	1476	−27.2
WMC-4	18.73	13.26	0.03	−2.5	13.77	0.49	0	–	9811	15.09	1476	−27.2

It is noticeable that energy savings were about 15% for all the solutions, this being 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.

4.2.3. ATC Summer-Season Model. The tuned DBs presented in Table 3 for the Summer ATC model correspond to three individuals from the population at generation 500 with WMC-SSGA.

The time required for each model evaluation is approximately 215 seconds. Therefore, once again the algorithm was in the known times.

The goals determined by the experts were to try to have 15% energy saving and global fitness reduced by 10% compared to On-Off control. Comfort parameters could be slightly increased if necessary (no more than 1 point for objectives 1 and 2). In this way, the goal values imposed to WMC-SSGA were the following ones: 1, 1, 7, 2000000 and 1000, with penalization rates of 1, 1, 1, 0.9, and 0.97, respectively. Notice that these goals imposed to the algorithm are higher than the ones initially required since the initial goals were easily met.

In this case, the goals have been easily met by WMC-SSGA. Moreover, the solutions present a desirable diversity that allowed us to select different and interesting FLCs.

From the results in Table 3, experts selected the third DB from WMC-SSGA as the most promising one. In this case, the solutions obtained present improvement rates of about 20% in energy and fitness.

Figure 9 represents the initial and the final DBs for the ATC FLC taking as final DB the third solution from WMC-SSGA in Table 3. It shows that small variations in the membership function parameters cause large improvements in the FLC performance.

4.2.4. Method Analysis. The proposed technique has 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.

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 10 illustrates the evolution chart of the fitness (original expression without considering goals) and performance values obtained by the WMC-SSGA method when tuning the ATC summer model. The chart has been generated obtaining the values of the best individual (according to the fitness with 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, a negative value for a worsened result, and a positive value for an improved result.

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

Table 3. Results obtained with the ATC Summer-Season model.

ENTPE	Fitness		PMV > 0.5		PMV < −0.5		CO_2		Energy		Stability	
model	Val.	%	Val.	%	Val.	%	Val.	%	Val.	%	Val.	%
On-Off	6.58	–	0.0	–	0	–	0	–	3206400	–	1136	–
Init. FLC	6.32	3.99	0.0	–	0	–	0	–	2901686	9.50	1505	−32.48
Goals	–	10.00	1.0	–	1	–	–	–	–	15.00	–	–
WMC-1	5.44	17.33	0.0	–	0	–	0	–	2575949	19.66	1115	1.85
WMC-2	5.43	17.45	0.0	–	0	–	0	–	2587326	19.31	1077	5.19
WMC-3	5.43	17.49	0.0	–	0	–	0	–	2596875	19.01	1051	7.48

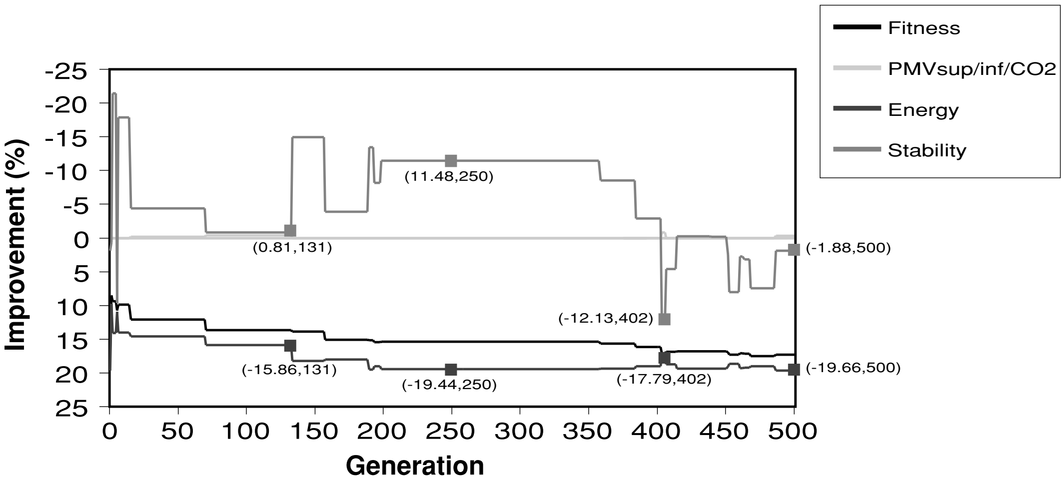

Figure 10. Evolution of the WMC-SSGA in the ATC summer season model.

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 convergence degree of the WMC-SSGA 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. This means that good solutions are quickly obtained and the process could be stopped in this state if severe time constraints are imposed.

4.3. *Experiments on the CNRS ENTPE and ATC Real Test-Cells*

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 4), 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

Table 4. ATC Summer-Season model: Simulation results vs. test results (two days period only).

	Fitness	PMV > 0.5	PMV < -0.5	CO_2	Energy	Stability
Simulation						
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						
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

Table 5. CNRS ENTPE Summer-Season 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

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 the 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.

For CNRS ENTPE (Table 5), 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.

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.

5. Concluding Remarks

In this paper, a GA has been considered to develop smartly tuned FLCs dedicated to the control of HVAC systems concerning energy performance and indoor comfort requirements. To evaluate the goodness of the proposed technique, 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 technique, accurate models of the controlled buildings (two real test cells) were provided by experts.

The proposed technique has 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 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 the proposed technique to solve this problem.

The proposed tuning algorithm has an interesting advantage for industrial application: the consideration of fuzzy goals to perform the multicriteria optimization. These fuzzy goals significantly improve the tuning performance and make 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 these 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.

Appendix A. Acronyms

Acronym	Meaning
BEMS	Building Energy Management System
HVAC	Heating, Ventilating, and Air Conditioning
FLC	Fuzzy Logic Controller
KB	Knowledge Base
GA	Genetic Algorithm
DB	Data Base
RB	Rule Base
PMV	Predicted Mean Vote index for thermal comfort
WMC-SSGA	Weighted Multi-Criterion Steady-State Genetic Algorithm
CNRS	Centre National de la Recherche Scientifique
ENTPE	Ecole Nationale des Travaux Publics de l'Etat
ATC	The Anonymous Test Cell from a French private enterprise

Acknowledgments

This research has been supported by the European Commission under the Genesys Project JOE-CT98-0090.

This work has been carried out within the framework of the JOULE-THERMIE programme under the GENESYS[2] Project sponsored by the European Commission, Directorate-General XII for Energy.

We would like to thank the GENESYS[2] project partners for their careful implementation of the presented models and for their valuable assistance.

Notes

1. ALTENER Project: Promoting the use of renewable energy sources, European Commission, Directorate-General XVII for Energy.
2. GENESYS Project: Fuzzy controllers and smart tuning techniques for energy efficiency and overall performance of HVAC systems in buildings, European Commission, Directorate-General XII for Energy (contract JOE-CT98-0090).

References

1. M. Bruant, G. Guarracino, P. Michel, A. Voeltzel, and M. Santamouris, "Impact of a global control of bioclimatic buildings in terms of energy consumption and building's performance," in *Proc. of the 4th European Conference on Solar Architecture and Urban Planning*, Berlin, pp. 537–540, 1996.
2. D. Driankov, H. Hellendoorn, and M. Reinfrank, *An Introduction to Fuzzy Control*, Springer-Verlag, 1993.
3. E.H. Mamdani, "Applications of fuzzy algorithms for control a simple dynamic plant," in *Proc. of the IEEE*, vol. 121, no. 12, pp. 1585–1588, 1974.
4. E.H. Mamdani and S.Assilian, "An experiment in linguistic synthesis with a fuzzy logic controller," *International Journal of Man-Machine Studies*, vol. 7, pp. 1–13, 1975.
5. R. Alcalá, J. Casillas, J.L. Castro, A. González, and F. Herrera, "A multicriteria genetic tuning for fuzzy logic controllers," *Mathware and Soft Computing*, vol. 8, no. 2, pp. 179–201, 2001.
6. D.E. Goldberg, *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley, 1989.
7. Z. Michalewicz, *Genetic Algorithms + Data Structures = Evolution Programs*, Springer-Verlag, 1996.
8. O. Cordón, F. Herrera, F. Hoffmann, and L. Magdalena, *Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Bases*, World Scientific: Singapore, 2001.
9. M. Arima, E.H. Hara, and J.D. Katzberg, "A fuzzy logic and rough sets controller for HVAC systems," in *Proc. of the IEEE WESCANEX'95*, vol. 1, NY, 1995, pp. 133–138.
10. P.Y. Glorennec, "Application of fuzzy control for building energy management," in *Building Simulation: International Building Performance Simulation Association 1*, Sophia Antipolis: France, 1991, pp. 197–201.
11. S. Huang, and R.M. Nelson, "Rule development and adjustment strategies of a fuzzy logic controller for an HVAC system—Parts I and II (analysis and experiment)," *ASHRAE Transactions*, vol. 100, no. 1, pp. 841–850, 851–856, 1994.
12. L.A. Zadeh, "Fuzzy sets," *Information and Control*, vol. 8, pp. 338–353, 1965.
13. M. Sugeno and G.T. Kang, "Structure identification of fuzzy model," *Fuzzy Sets and Systems*, vol. 28, pp. 15–33, 1988.
14. T. Takagi and M. Sugeno, "Fuzzy identification of systems and its application to modeling and control," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 15, no. 1, pp. 116–132, 1985.
15. A. Bardossy and L. Duckstein, *Fuzzy Rule-Based Modeling with Application to Geophysical, Biological and Engineering Systems*, CRC Press, 1995.
16. O. Cordón, F. Herrera, and A. Peregrín, "Applicability of the fuzzy operators in the design of fuzzy logic controllers," *Fuzzy Sets and Systems*, vol. 86, pp. 15–41, 1997.
17. L.X. Wang, *Adaptive Fuzzy Systems and Control. Design and Stability Analysis*, Prentice-Hall, 1994.
18. P.P. Bonissone, "Fuzzy logic controllers: An introduction reality," in *Computational Intelligence: Imitating Life*, edited by J.M. Zurada, R.J. Marks II, and C.J. Robinson, IEEE Press, 1994, pp. 316–327.
19. C.C. Lee, "Fuzzy logic in control systems: Fuzzy logic controller—Parts I and II," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 20, pp. 404–418, 419–435, 1990.
20. R. Palm, D. Driankov, and H. Hellendoorn, *Model Based Fuzzy Control*, Springer-Verlag, 1997.
21. L.A. Sánchez and J.A. Corrales, "Niching scheme for steady state GA-P and its application to fuzzy rule based classifiers induction," *Mathware and Soft Computing*, vol. 7, nos. 2/3, pp. 337–350, 2000.
22. J. Kiszka, M. Kochanska, and D. Sliwinska, "The influence of some fuzzy implication operators on the accuracy of a fuzzy

model—Parts I and II," *Fuzzy Sets and Systems*, vol. 15, pp. 111–128, 223–240, 1985.
23. A.E. Gegov and P.M. Frank, "Hierarchical fuzzy control of multivariable systems," *Fuzzy Sets and Systems*, vol. 72, pp. 299–310, 1995.
24. R.R. Yager, "On the construction of hierarchical fuzzy systems model," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 22, pp. 1414–1427, 1992.
25. M. Delgado, M.A. Vila, and W. Voxman, "On a canonical representation of fuzzy numbers," *Fuzzy Sets and Systems*, vol. 93, no. 1, pp. 125–135, 1998.
26. O. Cordón and F. Herrera, "A three-stage evolutionary process for learning descriptive and approximative fuzzy logic controller knowledge bases from examples," *International Journal of Approximate Reasoning*, vol. 17, no. 4, pp. 369–407, 1997.
27. F. Herrera, M. Lozano, and J.L. Verdegay, "Tuning fuzzy controllers by genetic algorithms," *International Journal of Approximate Reasoning*, vol. 12, pp. 299–315, 1995.
28. C. Karr, "Genetic algorithms for fuzzy controllers," *AI Expert*, pp. 26–33, 1991.
29. C.M. Fonseca and P.J. Fleming, "An overview of evolutionary algorithms in multiobjective optimization," *Evolutionary Computation*, vol. 3, pp. 1–16, 1995.
30. D. Whitley and J. Kauth, "GENITOR: A different genetic algorithm," in *Proc. of the Rocky Mountain Conference on Artificial Intelligence*, Denver, 1988, pp. 118–130,.
31. F. Herrera, M. Lozano, and J.L. Verdegay, "Tackling real-coded genetic algorithms: Operators and tools for the behaviour analysis," *Artificial Intelligence Review*, vol. 12, pp. 265–319, 1998.
32. J.H. Holland, *Adaptation in Natural and Artificial Systems*, The University of Michigan Press: Ann Arbor, 1975 (The MIT Press, London, 1992).
33. F. Herrera, M. Lozano, and J.L. Verdegay, "Fuzzy connectives based crossover operators to model genetic algorithms population diversity," *Fuzzy Sets and Systems*, vol. 92, no. 1, pp. 21–30, 1997.
34. J.E. Baker, "Reducing bias and inefficiency in the selection algorithm," in *Proc. of the 2nd International Conference on Genetic Algorithms*, edited by J.J. Grefenstette, Lawrence Erlbaum: Hillsdale, NJ, 1987, pp. 14–21.
35. L.J. Eshelman, *The CHC Adaptive Search Algorithm: How to Have Safe Search when Engaging in Nontraditional Genetic Recombination*, Morgan Kauffman: San Mateo, CA, 1990.

Rafael Alcalá received the M.Sc. degree in Computer Science in 1998 from the University of Granada, Spain.

He is an Assistant Professor with the Department of Computer Science, University of Jaén, Spain. His research interests relate to fuzzy modeling.

José M. Benítez received the M.S. Degree in 1994 and the Ph.D. Degree in 1998, both in Computer Science and from the University of Granada, Spain.

Currently, he is a Tenured Professor at the Department of Computer Science and Artificial Intelligence (DECSAI) of the University of Granada. He is a member of the Research Group in Intelligent Systems. Along with Dr. Castro and Dr. Mantas, he is a co-ordinator of the EUSFLAT Working Group on Neuro-Fuzzy Systems. His research interests include neural networks, fuzzy rule-based systems, neuro-fuzzy systems, cluster computing and e-commerce.

He is a member of IEEE, IEEE Computer Society, ACM and EUSFLAT.

Jorge Casillas was born in Granada, Spain, in 1975. He received the M.Sc. degree in Computer Engineering in 1998 and the Ph.D. in Computer Science in 2001, both from the University of Granada, Spain.

He is an Assistant Professor with the Department of Computer Science and Artificial Intelligence, University of Granada. His research interests include fuzzy modeling, and learning/tuning fuzzy systems for modeling, control, and classification with different metaheuristics.

Oscar Cordón received the M.Sc. degree in Computer Science in 1994 and the Ph.D. in Computer Science in 1997, both from the University of Granada, Spain.

He is an Associate Professor with the Department of Computer Science and Artificial Intelligence at the University of Granada. He has published about 30 papers in international journals and he is co-author of the book "Genetic Fuzzy Systems: Evolutionary Tuning and Learning of Fuzzy Knowledge Bases" (World Scientific, 2001). As edited activities, he has co-organized several special sessions in international conferences and co-edited some special issues in international journals on "Genetic Fuzzy Systems" and "Information Retrieval." His current main research interests are in the fields of: fuzzy rule-based systems, fuzzy and linguistic modeling, fuzzy classification, genetic fuzzy systems, evolutionary algorithms, ant colony optimization, and information retrieval.

Raúl Pérez was born in 1969. He received the M.S. (Computer Science) and Ph.D. degrees from the University of Granada, Spain, in 1992 and 1997, respectively.

He is currently an Associate Professor in the Department of Computer Science and Artificial Intelligence, University of Granada, Spain. His doctoral dissertation was in learning fuzzy rules using genetic algorithms. His research interests include fuzzy logic, learning systems, search algorithms, control and related applications.

Dr. Pérez is a member of the Intelligence Systems Group.