Tuning Fuzzy Logic Controllers for Energy Efficiency Consumption in Buildings

R. Alcalá
DECSAI, University of Granada
18071 – Granada, Spain
e-mail: alcala@decsai.ugr.es

J. Casillas
DECSAI, University of Granada
18071 – Granada, Spain
e-mail: casillas@decsai.ugr.es

A. González
DECSAI, University of Granada
18071 – Granada, Spain
e-mail: A.Gonzalez@decsai.ugr.es

Abstract

In EU countries, primary energy consumption in buildings represents about 40% of total energy consumption and more than a half of this energy is used for indoor climate conditions. The use of appropriate automatic control strategies for passive systems control could result in energy savings when compared to manual control. Fuzzy Logic Controllers (FLCs) have been successfully applied to a wide range of real-world problems from different areas. However, due to the complexity of the problem, the development of smart tuning techniques for these controllers will enable a rational operation and improved performance of FLCs and it is a necessary condition to solve it.

The problem has some specific restrictions that get it to be very particular and complex because of there are large time restrictions due to the long computation of the model and to the necessity of a multiobjective fitness function, that enlarges the solution search space. In order to solve the first restriction, a two-stage tuning methodology is proposed, in which the first stage is a rough global tuning (using a Genetic Algorithm) and the second one is a refined local tuning (using a Simulated Annealing). The second restriction is solved by multiobjective techniques that allow to work with fitness functions with competitive objectives. This combination of tuning with different search space granularity and multiobjective approaches is a novel way of facing up to these kinds of problems.

This work is being carried out within the framework of the GENESYS European Project.

Keywords: fuzzy logic controllers, tuning techniques, multiobjective optimisation, energy efficiency, buildings, BEMS, HVAC systems

1 Introduction

In EU countries, primary energy consumption in buildings represents about 40% of total energy consumption and grew from 1974 to 1992 by 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 20% of the energy consumption of the building sector, i.e., 8% of the overall Community consumption. HVAC systems (Heating, Ventilating, and Air Conditioning) [4] 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 is highly dependent on the design, performance and control of their HVAC systems and equipments.

A study performed in the frame of an ALTENER project [1] by CNRS (Centre National de la Recherche Scientifique) from France, and University of Athens from Greece, has shown that the use of appropriate automatic control strategies for passive systems control (e.g., shading or free cooling) could result in energy savings ranging from 15% to up to 85% according to climate and users behaviour when compared to manual control [2]. The role of automatic controls is thus of major importance. Control systems in buildings are however 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 minimising energy consumptions and optimising indoor comfort.

Moreover, in current systems, various criteria are considered and optimised 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 industrial level.

A European project is being developed in this subject, the GENESYS Project (http://genesys.entpe.fr). Its main objective is to develop optimum Fuzzy Logic Controllers (FLCs) [5] dedicated to the control of HVAC systems concerning energy performance and indoor comfort requirements. The University of Granada plays an important role in this project developing the setting and tuning strategies of the FLC. These automatic tuning strategies improve the energy savings fitting previously obtained Knowledge Bases (provided by experts).

The problem has two specific restrictions that get it to be very particular and complex:

- The controller accuracy is assessed by means of a simulation that approximately takes three hours. This provokes extremely slow algorithms.
- 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.

Although there are many tuning techniques, neither of them can be used satisfactorily because they do not work properly with these restrictions. In this paper, a tuning approach that considers them is presented. In order to solve the first restriction, a two-stage tuning methodology is proposed. In the first stage, by means of a Genetic Algorithm (GA) [10], a rough global tuning will be made. This allows us to obtain acceptable solutions quickly. As soon as these solutions are obtained, a more refined second stage, by means of a Simulated Annealing (SA) [12], is applied to obtain more quality solutions polishing the results. The second restriction is solved by multiobjective techniques that allow us to work with fitness functions with competitive objectives. In these cases, there are not an optimal solution, but a possible solution set. The multiobjective techniques will be used in both stages of the tuning methodology.

In order to do so, the paper is organised as follows. In Section 2 the two-stage tuning methodology will be presented. Section 3 will show the proposed multiobjective approach. Finally, in Section 4 some concluding remarks will be pointed out.

2 Two-stage Tuning Methodology

The performance of an FLC depends on its Rule Base and on the membership functions associated to the fuzzy partitions, i.e., the Data Base. Hence, it is very important to adjust these parameters to the process to be modelled. Tuning methods [3, 7, 8] fit the membership function shapes of the fuzzy rules obtaining high-performance membership functions, usually minimising an error function defined by means of the system behaviour or the evaluation of a training example set.

In complex problems or with assessments taking a long time, the traditional tuning methods do not work correctly since either the search space is huge and the algorithm does not converge, or the invested time to obtain a reasonable solution cannot be tolerated. With the aim to palliate these problems, we are going to propose a two-stage tuning methodology that will allow us to obtain good solutions in a reasonable time.

The proposed tuning methodology is composed of two stages that have different granularity degree in the tuning process:

- *First Stage: Rough Global Tuning.* The objective of this stage is to accomplish a superficial tuning without pay attention to an excessive accuracy. It allows to reduce the search space and to obtain acceptable solutions quickly.
- *Second Stage: Refined Local Tuning.* From the previous contribution, this second stage polishes the solutions by means of small local modifications accomplished by quicker techniques.

The first stage will work like a partial solution generator. Although the second stage begins to work with the partial solutions, the first one goes on generating more partial solutions. These stages can be considered respectively as exploration and exploitation ones. In the following two subsections the general characteristics of these stages are presented.

2.1 First Stage: Rough Global Tuning

The aim of this stage is to obtain partial solutions quickly. Its function is to provide these solutions to the second stage, i.e., acting as a “nursery”. GAs are very suitable for this mission because they are ideal to use populations and generate diversity. We will use a GA with some peculiarities. As we have indicated, the two important restrictions we want to solve are the complexity of the problem and the long duration of the evaluation.

The first aspect is solved reducing the GAs search space. In order to do that, an integer coding will be used. This one uses discrete parameter domains forcing to take only one value set (see Figure 1). The cardinality of this set must be rich enough in order to allow diversity, and it must be small enough so that small changes provoke significant variations. Acting so, although the tuning is rough, good partial solutions are obtained quickly.

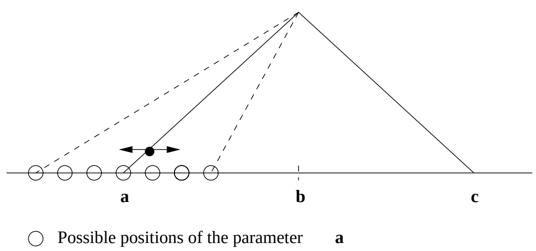

Figure 1: Integer coding in the first stage of the tuning methodology.

In order to solve the second aspect, the long duration of the evaluation, the GA's evaluations number can be reduced using some or both of the following two proposals. On the one hand, a steady-state GA [14] could be used. A steady-state GA consists of selecting two of the best individuals in the population and combining them to obtain two offspring. They are included in the population standing in the worst two individuals. An advantage of this technique is that good solutions are used as soon as they are available. Therefore, the convergence is accelerated and the evaluations number is decreased. On the other hand, reducing the population size, the evaluations number is significantly dropped. This size must be large enough in order to allow diversity.

Several GAs can be used at the same time with the purpose of obtaining individuals with different characteristics (e.g., maintaining the diversity in one, and provoking a quick convergence in another).

2.2 Second Stage: Refined Local Tuning

The second stage is used like a local search in a small zone around each tuned parameter, i.e., the search space is now reduced to a promising optimal region. Now, the generation of diversity is not important but the depth of the search. In order to do that, the SA is very suitable (the (1+1) - Evolution Strategies [10] can be also used due to its similarity with SA). Furthermore, these algorithms accomplish fewer evaluations than GAs and it is favourable to confront the long computation time restriction.

In this stage, the main feature is the use of a real coding to allow small variations of the parameters (see Figure 2).

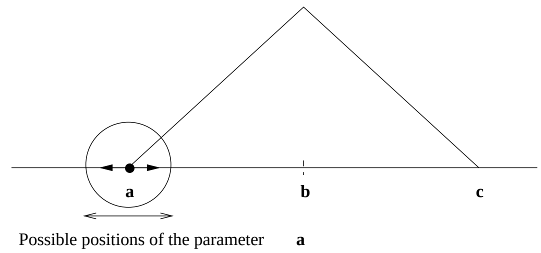

Figure 2: Real coding in the second stage of the tuning methodology.

3 Multiobjective Approach

The multiobjective techniques allow us to work with fitness functions with competitive objectives, where improving one of them can implies to make worse another one. There are many kinds of multiobjective optimisation algorithms. Some of them are the classic techniques with aggregation functions, multiobjective SA, multiobjective Evolutionary Algorithms (MOEAs), etc.

MOEAs are a recent algorithmic tool which solves multiple objective problems [13]. Their popularity can be attributed to several desirable characteristics. They have the ability to search partially ordered spaces for several alternative trade-offs. Probably most important, however, is the capability to track several solutions simultaneously via its population.

For the first stage of the methodology, we have selected two MOEAs taking advantage of their appropriate characteristics in this problem. The first one to increase the search speed at the expense of decreasing the diversity, and the second one to get the contrary results:

- *The Multiple Objective Genetic Algorithm* (MOGA). MOGA [6] is a rank-based fitness assignment method for multiple objective GA that incorporates fitness sharing on the objective value domain. This method has been modified to be quicker in the search by means of the use of a steady-state approach and taking away the fitness sharing.

- *The Non-dominated Sorting Genetic Algorithm* (NSGA). NSGA [11] is based in a non-dominated sorting of the population that is grouped in fronts with the same rank progressively, and in a niche method to avoid excessive domain of some individuals. In this case, the method is not modified keeping the sharing approach to maintain the diversity in the population.

For the second stage of the methodology a multiple objective SA method has been implemented, the Lee and Wang's algorithm [9]. The main difference with other SA algorithms is that the probability function is changed considering the global effect provoked by the whole objectives set. Hence, when to go to the next state involve that some objectives are made worse, the global benefit is analysed, advancing with greater or smaller probability.

4 Concluding Remarks

Combining techniques and strategies previously developed, a new approach has been established to facing up to problems where the controller accuracy evaluation takes a long computation time and it is based on multiple objectives.

In order to solve the first restriction, a new two-stage tuning methodology has been expounded. The objective of the first stage is to accomplish a superficial tuning without pay attention to an excessive accuracy. It reduces the search space and obtains acceptable solutions quickly. From the previous contribution, the second stage polishes the solutions by means of small local modifications accomplished by quicker techniques.

To solve the multiobjective problem we have selected two MOEAs for the first stage of the above mentioned methodology and one SA multiobjective algorithm for the second stage. These MOEAs have different approaches, the first one improves the convergence speed and the second one maintains the diversity.

To finish up, we should say that the results obtained seem to be good, and we are currently doing a more exhaustive experimentation.

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