GENERIC MULTI-OBJECTIVE OPTIMIZATION METHOD OF INDOOR AND ENVELOPE SYSTEMS' CONTROL

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Growing concerns about energy consumption reduction and comfort improvement inside buildings make it necessary to optimize the control of any indoor and envelope thermal system. This study proposes a generic on-line method based on Genetic Algorithms for controllers' setting optimization, with regard to two objectives: energy consumption and indoor discomfort. Consumption and discomfort prediction is used for performance assessment of individuals. Even though prediction is carried out by using physical modelling in this article, the method is doomed to use Neural Networks prediction in the future, in order to save development and simulation time. The method was assessed by being compared to off-line optimization, and showed similar performance.

Keywords: Genetic Algorithms, on-line control optimization, energy consumption, Indoor discomfort

1. Introduction

In the last decade, there has been a growing demand for improving indoor comfort while reducing energy consumption. It is still necessary to make efforts in that sense today, as fossil resources' price is expected to increase again and concerns about the healthiness of indoor environments are still at high level. Meanwhile, demand for high indoor comfort standards makes it necessary to optimize the control of each of the buildings' equipments. Indoor comfort is a very important issue as human beings meanly spend 80% of their time inside buildings [1]. Moreover, poor comfort in employees' environment can reduce their productivity at work [2]. Therefore, research is facing a multi-objective problem.

Previous research has showed that energy consumption reduction with high level of comfort could be reached by improving the way thermal systems are controlled [3, 4], without necessarily changing those systems. This is an interesting result for ancient buildings' retrofitting. However, recent buildings are

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more and more complex systems, with high-performance equipments. Fine optimization of these equipments' control is therefore necessary.

Recent studies have already showed the efficiency of on-line approaches [5]. Predictive control is also a method for on-line control optimization of many thermal devices, using extremely basic physical modeling and enumerative optimization method at regular time step [6]. However, such a method requires model calibration before use.

Optimization can be carried out by many methods: enumerative methods, calculus-based methods and stochastic methods [7]. The first two categories need the objective functions to be explicitly known, continuous and differentiable. Genetic Algorithms (GAs) are stochastic methods. They are already used for buildings' energy systems design optimization [8], buildings or systems dimensioning optimization [9] and off-line control optimization [10]. On-line optimization of systems' control requires robust stochastic optimization method such as GAs, as no explicit objective function is known.

The aim of this study is to develop a generic on-line method, based on GAs, for basic and advanced controllers' setting optimization, avoiding physical modeling and calibration. The method should be autonomous from any human action, to avoid development and implementation tasks. It is intended to be applicable to all buildings' indoor and envelope equipments.

In this paper, the optimization method will first be described. Then, its implementation and assessment procedure on a heating device will be detailed. Finally, assessment results will be presented and discussed.

2. Methods

2.1 General description of the on-line optimization method

The on-line optimization method presented in this section is based on GAs. GAs are capable of doing multi-objective optimization of a given problem. The possible solutions for this optimization problem are called individuals, as a reference to Darwin's evolutionary theory: a population of N individuals adapts to its environment, one generation after the other, by selecting its best individuals and making them reproduce. Mutation of some of the individuals is also possible.

To do so, each individual has to be evaluated by being given a rating corresponding to each objective function. In this study, individuals represent settings of controllers, and the objective functions to be minimized are energy consumption and indoor discomfort.

The settings of three types of controllers were optimized: ON-OFF, Proportional–Integral–Derivative (PID) and fuzzy controllers. Optimization is done on-line at every beginning of periods of fixed duration to find optimal setting for the next period (see Fig. 1). 2- and 6-hour periods were tested in this survey. Only monozonal buildings were considered.

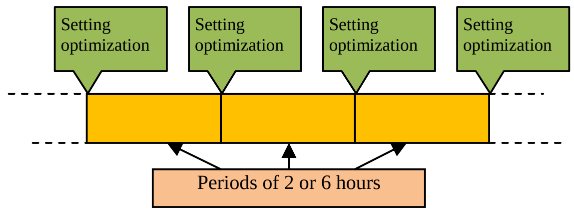

Fig. 1. Time sequencing in periods of constant duration

2.2 Description of the optimization algorithm: NSGA-II

NSGA (Non-Dominated Sorting in GAs) algorithm was developed by Srinivas and Deb [11] in 1994. It is a non-domination based GA for multi-objective optimization. It has been updated in 2002 [12] to improve its sorting algorithm and was named NSGA-II.

An initial population of N individuals is randomly chosen: each individual is made of P parameters randomly chosen within specific ranges, called the decision space. Individuals are sorted based on non-domination and crowding distance. An individual dominates another if the rating for all objectives, called objective functions, are not worse than the other and at least in one of its objective functions it is better than the other. Non-domination sorting assigns every individual a rank and all individuals having the same rank form a front. The front with rank equal to 1 is called the Pareto front and contains all non-dominated individuals (see Fig. 2). The front with rank 2 contains individuals dominated only by individuals from the Pareto front and so on. The crowding distance is the Euclidian distance calculated between individuals in a front in the two-dimensional hyper space associated to the objective functions. The higher the crowding distance, the higher the diversity of the population. Once the population is sorted, selection is carried out by using binary tournament selection. The winner of the tournament has either the lowest rank or the highest crowding distance, in case both individuals have the same rank. This way, diversity of the population is preserved.

Reproduction between selected individuals uses Simulated Binary Crossover [13] operator and polynomial mutation [12]. Offspring population is added to the parents' population and the resulting population is sorted using non-domination and crowding distance. The next generation is created by selecting the *N* best individuals in this population. The same process is repeated to generate the following generations.

NSGA-II algorithm used in this study was programmed by Seshadri [14] using Mathworks MATLAB software. A major change was made on the algorithm in this study: the choice of random individuals in the decision space is no more only restricted by ranges, but also by specific variation paces for each parameter. Each random parameter is rounded to the nearest multiple of the corresponding variation pace. New parameters obtained by crossover and mutation are also rounded the same way. This change was made to have better control on convergence speed by reducing the number of possible values without modifying the ranges.

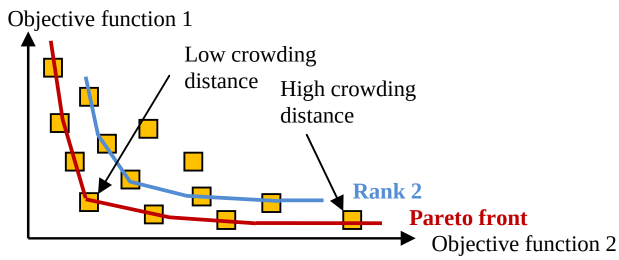

Fig. 2. Representation of individuals in the two-dimensional hyper space associated to the objective functions

Next section deals with the definition of the objective functions used in this survey.

2.3 Calculation of the objective functions

NSGA-II calls objective functions to evaluate hourly discomfort level and hourly energy consumption generated by each of the tested controllers' settings on the coming period of time. Objective functions were calculated by running simulations on the numerical model HYBCELL described in section 0. The building described in the same section was modeled. Hourly discomfort was calculated by summing the differences between indoor temperature and temperature setpoint at each time step, multiplied by the time step. Temperature setpoint was 20 °C in this study. Energy consumption was the demand of the heating device.

2.4 Setting of NSGA-II

NSGA-II has a lot of parameters to be fixed before it can be used. Table 1 shows a list of these parameters and the corresponding selected values in this study. Tested values are also reported in this table. Selected values were those which caused minimum computation time to reach convergence. Convergence was considered to be reached when the Pareto front was not modified from one generation to another. Some parameters were fixed at commonly used values.

Table 1

Selected parameters for NSGA-II

Parameter	Selected value	Tested values
Population size (individuals)	200	{100 ; 200}
Number of generations	20	[1 ; 200]
Crossover probability	0.9	0.9
Mutation probability	0.7	{0.3 ; 0.5 ; 0.6 ; 0.7 ; 0.8}
Distribution index for crossover	20	20
Distribution index for mutation	20	20

2.5 Choice of generic controllers

As seen previously, the aim of this survey is to optimize the setting of controllers without using heavy physical modeling and without requiring calibration on each specific building. Therefore, the chosen controllers must be applicable to a large range of buildings if not all types of buildings. Such controllers are called generic controllers:

- ON-OFF (0-100%) controllers are the most basic way of regulating systems. They can be implemented on every kind of systems to be maintained to a given setpoint;
- Proportional–Integral–Derivative (PID) controllers are applicable to any first order system. A building can be considered as a first-order system to a first approximation;
- Fuzzy controllers [15] were demonstrated as being advanced and precise controllers [16]. They are applicable to a large typology of buildings [17].

These three controllers where considered as generic controllers in this study and were used for setting optimization. The decision space for each of them was defined after doing a first optimization on a large decision space with small variation paces, and observing the composition of the final Pareto front. Ranges presented in Table 2 were chosen based on this front. Stability, which is not an objective function in this study, was taken into account by preventing ON-OFF dead band of being lower than 0.5 °C.

Table 2

Decision space for controllers’ setting optimization

Controller	Parameter	Unit	Range	Variation pace
ON-OFF	Dead band	°C	[0.5 ; 3]	0.1
PID	Kp	% / °C	[1 ; 10]	0.1
	Ti	min	[0.1 ; 20]	0.1
	Td	min	[0 ; 5]	0.1
Fuzzy	K	%	[0.1 ; 3]	0.1
	θ	min	[0.5 ; 200]	0.5

Fuzzy parameter K in Table 2 is the output gain of the controller. 1/θ is the input gain of the derivative input. Fig. 3 shows input membership functions (named Negative Medium (NM), Negative Small (NS), Zero (ZE), Positive Small (PS) and Positive Medium (PM)), output membership functions as well as fuzzy rules.

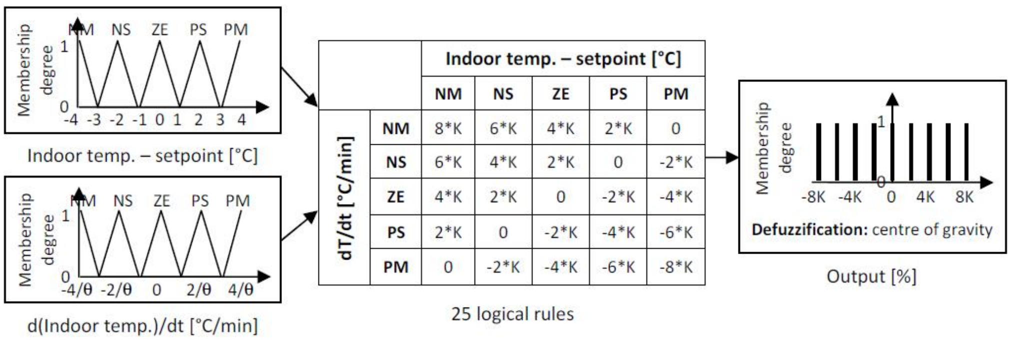

Fig. 3. Setting of the fuzzy controller with parameters K [%] and θ [min]

2.6 Numerical assessment of the on-line optimization method

2.6.1 Modeling

Simulations were carried out on the numerical model called HYBCELL, developed and validated by El Mankibi [18]. This model is based on two coupled models: a thermal model based on finite differences and a pressure air flow model [19]. It was developed under Mathworks MATLAB/SIMULINK environment. It was chosen because it has open source, it is fast and controllers such as ON-OFF, PID and fuzzy can be easily implemented on the modeled building. Coupling with MATLAB functions used for the optimization method is also very easy.

The modeled building is a 5.1-meter-long, 3.5-meter-wide and 2.9-meter-high room, which can represent a large office or a meeting room. It is located in the ENTPE laboratory. It is monitored by various sensors: temperature, relative humidity and CO_2 concentration. An electric heater, window motors and a ventilation device are controlled by a computer with specific software developed under the LABVIEW environment. Human occupancy is simulated by sensible heat supply devices and CO_2 generation. More details about this experimental room are given by El Mankibi [18, 20].

2.6.2 Assessment

The on-line optimization method was compared to off-line optimization. Off-line optimization uses the same optimization algorithm as on-line, except that it only optimizes the setting once, at the very beginning of the simulation, instead of optimizing it at each period's beginning. By doing so, the optimized setting is the same as if it was calculated by a specific numerical survey before the building's construction. Efficiency of the off-line optimized setting is used as a reference to assess the efficiency of the on-line method.

The comparison is done for a two-day simulation time (January, 1^{st} and 2^{nd}) in the climate of Lyon, France. This quite short simulation time is justified by very long calculation time.

3. Results

Results were obtained for 2- and 6-hour periods for the on-line method. For both methods, the selected individual in the final Pareto front was the closest one to the origin of the objective-functions' space. Thus, discomfort and energy consumption were considered with equivalent importance. Other individuals could have been selected if the objective functions were weighted differently.

Table 3 and 4 show the results obtained for discomfort and energy consumption during the 2-day simulation. The comparison between off-line and on-line methods gives information about the efficiency of the developed on-line method.

Table 3

Total discomfort and heating loads for a 2-day simulation with 2-hour periods

	Discomfort [°C.min]			Heating loads [kWh]		
	Off-line method	On-line method	Benefit	Off-line method	On-line method	Benefit
ON-OFF	2779.2	2772.8	0.2 %	67.75	68.17	-0.6 %
PID	110.4	111.6	-1.1 %	70.43	70.43	0.0 %
Fuzzy	1461.6	1263.8	13.5 %	69.50	69.55	-0.1 %

Table 4

Total discomfort and heating loads for a 2-day simulation with 6-hour periods

	Discomfort [°C.min]			Heating loads [kWh]		
	Off-line method	On-line method	Benefit	Off-line method	On-line method	Benefit
ON-OFF	2779.2	2982.6	-7.0 %	67.75	67.75	0.0 %
PID	110.4	111.4	-0.9 %	70.43	70.43	0.0 %
Fuzzy	1806.6	1401.8	22.4 %	69.39	70.35	-1.4 %

4. Discussion

First, it is to notice that PID controller gave much lower discomfort levels than both other controllers, with almost equivalent energy consumption. Discomfort for PID represents 4% of discomfort for ON-OFF controller and 9% of discomfort for fuzzy controller.

Then, the benefits given by Table 3 and 4 make it possible to conclude about the performance of the on-line method. It should be pointed that the performance of the on-line method was here compared to the performance of a fixed setting which has been off-line optimized. Therefore, the comparison referential was already very efficient. The difference between both methods was less than 2% for most configurations. However, three exceptions are to be noticed:

- On-line optimization on the fuzzy controller had good results for 2- and 6-hour periods, with respectively 13.5% and 22.4% benefit compared to off-line;
- On-line optimization on ON-OFF controller generated a 7% loss compared to off-line, for 6-hour periods.

5. Conclusion

The on-line optimization method presented in this article is an efficient method. Compared to off-line optimization, it gives similar and sometimes better results.

Future work should be done to get rid of the numerical model in the calculation of objective functions. It should be replaced by an Artificial Neural Network (ANN) to predict indoor discomfort and energy consumption. The ANN could be trained by using data collected from previous periods. Thus, the on-line method would probably calculate quicker the optimized setting, and no more expensive calibration task of the model would be necessary. The method would be autonomous from any human action, and would be able to adapt to each particular building by learning its behavior through the ANN.

Generalization to every kind of buildings' indoor and envelope equipments should follow.

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