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Predictive Control of Multizone HVAC Systems in Non-residential Buildings

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Abstract: In France, buildings account for a large part of the energy consumption and carbon emissions. Both are mainly due to Heating, Ventilation and Air-Conditioning (HVAC) systems. So, the present work deals with the predictive control of multizone HVAC systems in non-residential buildings. We used the PMV (Predicted Mean Vote) index as a thermal comfort indicator and developed low-order ANN-based models to be used as controller's internal models. A genetic algorithm allowed the optimization problem to be solved. The proposed strategy allows the operation time of each HVAC sub-system to be optimized (and, as a result, electrical power consumption) and thermal comfort requirements to be met. In order to test this approach, a real non-residential building located in Perpignan (south of France) has been modelled using the EnergyPlus software. The results we obtained in simulation allows the pertinence of the predicitive strategy to be highlighted.

Keywords: Multizone HVAC system, non-residential buildings, predicted mean vote, predictive control, optimization problems, feedforward neural networks, genetic algorithms.

1. INTRODUCTION

Within non-residential buildings, almost half of the energy consumption is due to Heating, Ventilation and Air-Conditioning (HVAC) systems (Pérez-Lombard et al., 2008). Older, oversized or poorly maintained systems may be using more energy and costing more to operate than necessary. As a result, new approaches dealing with energy ressources management are needed to make HVAC systems more efficient. First, energy efficiency can be improved in central heating and cooling systems by introducing zoned operation. This allows a more granular application of heat and HVAC sub-systems can be controlled independently. Another key point is thermal comfort. Thermal comfort is mainly related to indoor conditions and impacted by both the effectiveness of the building envelope and the way the centralized or zoned HVAC system is used.

Many works focusing on both the control of HVAC systems and the management of thermal comfort have been conducted over the last few years. Bermejo et al. (2012) used artificial intelligence tools to develop interesting approaches. However, these approaches require to turn the HVAC systems on at a fixed time and, as a result, this can impact thermal comfort negatively if these systems are started too late, or energy consumption if triggering happens too soon. As it has been highlighted by many studies, predictive control can take advantage of the intermittent use of non-residential buildings and allows the behaviour of the considered system to be anticipated (Paris et al., 2010) In this sense, we proposed a new approach allowing energy consumption to be significantly reduced and the HVAC sub-systems of a non-residential building to be turned on and off at the right time (Garnier et al., 2013). Only heating has been considered. We used the PMV (Predicted Mean Vote) index as a thermal comfort indicator and focused on satisfying constraints. The algorithm we developed offers very good performance and does not require on-line optimization. As a result, it is computationnaly tractable and can be implemented in an embedded system whose resource is limited. Its main drawback lies in the simultaneous engaging and stop of all of the HVAC sub-systems. That is why the present paper focuses on improving this predicitive approach by optimizing for each room the operation time of its HVAC sub-system. Both heating and cooling operation modes are now considered. We decided for a Genetic Algorithm (GA) in order to solve the optimization problem (Holland, 1975) and used artificial neural networks to develop the controller's internal models. Such algorithms are commonly used in energy resources and thermal comfort management (Attia et al., 2013). Berthou et al. (2013) used a GA to manage thermal comfort into a unique room of a building, without considering interaction (i.e. heat transfer) with the other rooms. Thermal comfort has been defined on the basis of temperature thresholds. Liu et al. (2013) also used a GA to optimize the operation of HVAC systems by searching for optimal control settings. The controllable variables include supply air and chilled water temperatures.

The paper is organized as follows: section 2 is about the non-residential building we modelled using the EnergyPlus

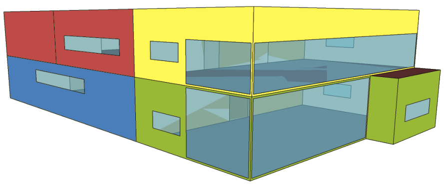

Fig. 1. Topology of the non-residential building.

software. Section 3 deals with the Predicted Mean Vote (PMV) we used as a thermal comfort indicator. Next, the predictive strategy as well as the low-order ANN-based models we developed and used as controller's internal models are described (section 4). Finally, the management results are analyzed and compared with the results given by standard strategies (section 5). The paper ends with a conclusion and an outlook to future work.

2. NON-RESIDENTIAL BUILDING

In order to evaluate the proposed strategy, a reference building has been modelled using the EnergyPlus software, which is able to perform accurate building simulations. The considered building is a real two-storey building of 1000 m^2, built in 2008 and located in Perpignan (south of France). It is facing south and agrees with the French Thermal Regulation of year 2005. This non-residential building is divided into 3 main areas of 340 m^2 each (Fig. 1), with different uses. About a dozen employees work in offices at the ground and first floors (green and yellow areas). The red area in the first floor is a manufacturing room where about 6 persons work seated or in a standing position. The last room of the ground floor is a warehouse (blue area) that is not heated. For both the warehouse and the manufacturing area, ceiling is 3.90 m. In the offices, a suspended ceiling stands at 2.70 m. The materials used in the building are listed in table 1: l is the thickness (cm), λ is the conductivity (W·m^{-1}·K^{-1}), ρ is the density (kg·m^{-3}) and, finally, C is the specific heat (J·kg^{-1}·K^{-1}). The exterior walls consist of several layers. From the outside to the inside are juxtaposed a brick layer, heavy weight concrete, an insulation board, and finally a gypsum board. The interior walls are composed of two gypsum boards, for a total thermal resistivity of 2.2 m^2·K·W^{-1}. The south face and a part of the west face of the building are made from glass. Glass has been treated to filter infrared radiation and avoid overheating in summer. The other glasses consist in 3 mm double glazed bays.

Table 1. Properties of the materials used in the exterior walls.

Layer	l	λ	ρ	C
Brick	10	0.89	1920	790
Heavy weight concrete	20	1.45	2000	1000
Insulation board	5	0.03	43	1210
Gypsum board	2	0.16	800	1090

The present study focuses on the three following (occupied and equipped with sensors) rooms: the offices on both floors (R1 and R2) and the manufacturing area (R3), that is composed of an open space of 230 m^2 and three storage rooms of 110 m^2 (not heated). Heating is handled in the building by a zoned electrical HVAC system consisting in several sub-systems, one for each area, where only the temperature set-point can be adjusted. Each sub-system is managed by a local controller. The characteristics of the different HVAC sub-systems for each area are listed by table 2. All units have a coefficient of performance (CoP) equal to 3.8. As previously stated, the management approach is based on a model predictive controller that will supervise the HVAC sub-systems (Fig. 2).

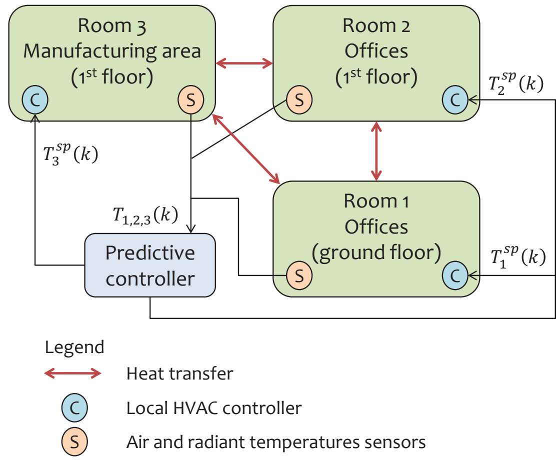

Fig. 2. The three considered rooms (R1, R2 and R3) equipped with sensors and HVAC sub-systems.

Table 2. Characteristics of the three considered rooms.

Characteristic	R1	R2	R3
Surface (m^2)	165	155	230
Volume (m^3)	450	420	900
Heating power (kW)	5	5	10
Number of occupants	8	5	6
Metabolic activity (W·m^{-2})	70	70	116
Lighting power (kW)	1	1	1.4

3. THERMAL COMFORT

The Predicted Mean Vote (PMV) index is used as a thermal comfort indicator. This indicator was developed by Fanger (1973), before to be standardized by international organizations. The PMV index quantifies the thermal sensation felt by people in a room. This sensation is described by a scale ranging from -3 (cold) to +3 (hot). The exchange of heat between the human body and its environment strongly governs thermal comfort. It is highly subjective and can be considered as perfect when the sum of exchanges is zero. Equation 1 depicts the way one can compute the PMV index, for the room j, $\forall j \in [\![1;3]\!]$:

$$PMV_j = [0.303exp^{-0.036M_j} + 0.028] \times L_j \quad (1)$$

with L_j the difference between the heat produced and the heat lost:

$$L_j = M_j - W_j - H_{j,1} - H_{j,2} - H_{j,3} - H_{j,4} - H_{j,5} - H_{j,6} \quad (2)$$

M_j is the metabolism (described below). W_j is the external work. $H_{j,1}, ..., H_{j,6}$ are the heat loss coefficients (W·m^{-2}). $H_{j,1}$ is the heat loss by diffusion through the skin and $H_{j,2}$ is the heat loss by sweating. $H_{j,3}$ and $H_{j,4}$ are the losses by latent and dry respiration, respectively. Finally,

$H_{j,5}$ is the heat loss by radiance and $H_{j,6}$ is the heat loss by convection. To calculate these heat loss coefficients, several parameters about environment and occupants are taken into account: indoor air temperature (T_j^a), radiative temperature (T_j^r), relative humidity (HR_j), air speed (v_j^a), metabolic activity, as well as clothing thermal insulation (ICL_j). Let us note that air speed is not calculated by the EnergyPlus software. However, this missing information is not critical at all because air speed has no influence on the PMV index as long as it remains below $0.1\,\mathrm{m{\cdot}s^{-1}}$. This is mostly the case within the non residential building we considered. Moreover, metabolic activity is supposed to be constant and only depends on the considered area. In offices (R1 and R2), people work in a sitting position most of the time and, as a result, M_j is set to $70\,\mathrm{W{\cdot}m^{-2}}$ (i.e. 1.2 met). Activity in the manufacturing area (R3) is more dynamic and M_j is set higher to $116\,\mathrm{W{\cdot}m^{-2}}$ (i.e. 2 met). Moreover, depending on climatic conditions, people dress differently. So, clothing thermal insulation in the room j (ICL_j) varies over time and is defined from the outdoor temperature observed at 6 a.m. (Schiavon and Lee, 2013).

4. MULTIZONE PREDICTIVE CONTROL

As previously stated, each room has its own HVAC subsystem, handled by a local controller (Fig. 2). Simulation is carried out using the EnergyPlus building model we developed and the predictive control strategy is implemented thanks to Matlab®. The MLE + interface enables both tools to communicate in real time (Nghiem, 2010).

4.1 Low-order ANN-based models

We used a total of six feedforward (multi-layer) artificial neural networks with only one hidden layer in order to model at time step $k+1$ ($\forall j,l,m \in [\![1;3]\!]$ such as $j \neq l \neq m$) the air (T_j^a) and radiative (T_j^r) temperatures as well as the electrical power consumed by the HVAC sub-systems (P_j) for both operation modes (heating and cooling) and the three considered rooms in the non-residential building (the offices on both floors and the manufacturing area). Estimation is carried out from several inputs: outdoor temperature (T_{out}), solar radiation (SR), room occupancy (O_j), T_j^a, T_j^r, T_j^{sp} and, finally, the HVAC temperature set-points in the two adjacent rooms (T_l^{sp} and T_m^{sp}) of room j at time step k (Fig. 3). These ANN-based models (used as controller's internal models) perform a one-step-ahead forecast and their outputs are reinjected as inputs, along the horizon. We identified their parameters through a training phase, thanks to the Levenberg-Marquardt Algorithm (LMA) (Hagan and Menhaj, 1994) as well as data generated by the EnergyPlus model. The LMA is accurate, very fast and uses matrix decomposition. We optimized the topology of the feedforward artificial neural networks and considered from 18 to 24 hidden neurons. Validation has been carried out using a 2-month database and we obtained correlation coefficients higher than 0.9 and mean relative errors lower than 5%, whatever the operation mode. Using equation 1 (section 3), $PMV_j(k+1)$, $\forall j \in [\![1;3]\!]$, is computed among others from $T_j^a(k+1)$ and $T_j^r(k+1)$. Let us note that M_j do not change over the simulation period (i.e. from June 1 to September 30 then from November 1 to March 31, 2011) while HR_j is supposed to be constant over the forecast horizon and equal to the value measured at the beginning of the optimization process. Indeed, changes in relative humidity are low and such a parameter has a limited impact on the PMV index. ICL_j is considered as constant from 6 a.m. (day d) to 6 a.m. (day $d+1$). v_j^a and W_j are considered to be null.

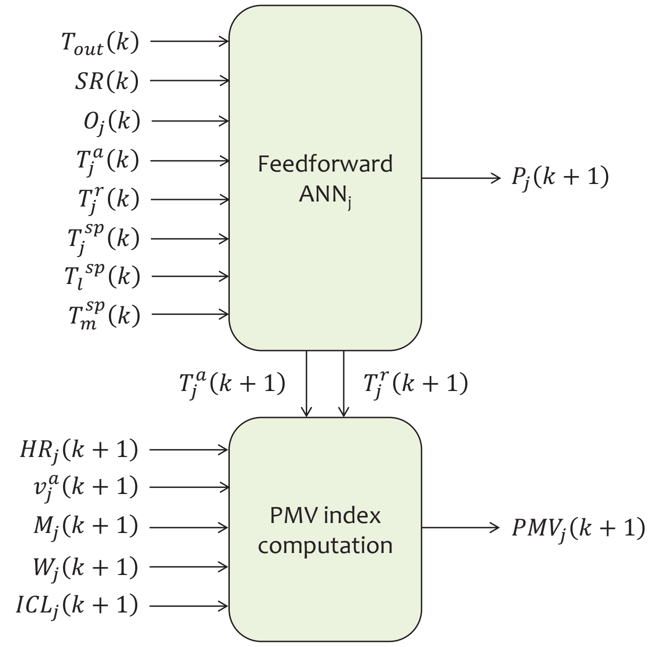

Fig. 3. ANN-based model for the room j, $\forall j,l,m \in [\![1;3]\!]$ such as $j \neq l \neq m$ (heating and cooling modes).

4.2 Control strategy

Fig. 4 depicts the predictive control strategy we developed first to search for the right time t_j to turn the HVAC subsystem on then off in the room j, $\forall j \in [\![1;3]\!]$, with the aim of minimizing the total consumption of electrical power (equation 3). The strategy deals also with the temperature set-point $\tilde{T}_j^{sp}$ (its value is fixed over the forecast horizon) allowing thermal comfort constraints to be met during periods of occupancy (i.e. leading to $PMV_j^{sp} = 0$). $\bar{t}$ is about the optimal switching times (integer values) for the three HVAC sub-systems we consider (equation 4). In addition, outdoor temperature (T_{out}) and solar radiation (SR) have been forecasted over an horizon (N) set to 8 hours, using previous day values corrected by current values. Room occupancy (O_j) is regular and, as a result, known in advance. Finally, T_j^{sp} is chosen by the decision block (Fig. 4), according to t_j and $\tilde{T}_j^{sp}$:

$$J(\bar{t}) = \min_{\bar{t} \in \mathbb{N}} \left(\sum_{k=1}^{N} \sum_{j=1}^{3} \left(P_j(t_j, k) \right) \right) \tag{3}$$

$$\begin{cases} \bar{t} = [t_j,\, t_l,\, t_m], \forall j,l,m \in [\![1;3]\!] \text{ s.a. } j \neq l \neq m \\ \bar{t}_0 < \bar{t} < \bar{t}_N, \text{ with } N \text{ the forecast horizon} \\ PMV_j^{min} < PMV_j(k) < PMV_j^{max}, \forall O_j(k) \neq 0 \end{cases} \tag{4}$$

PMV_j^{min} and PMV_j^{max} are thermal comfort thresholds defined for the room j, $\forall j \in [\![1;3]\!]$. These thresholds can be adapted to users' preference. For the simulations we decided for $PMV_j^{min} = -0.5$ and $PMV_j^{max} = 0.5$.

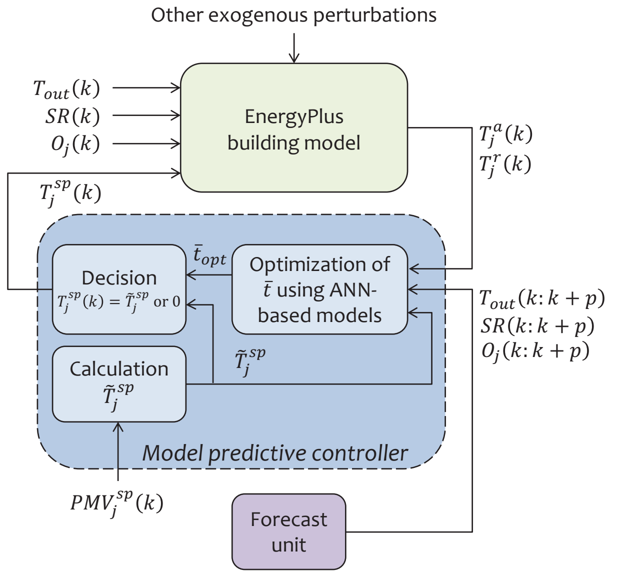

Fig. 4. Block diagram of the predictive control strategy.

4.3 Genetic algorithm for problem resolution

In order to solve the problem we formulated, we decided for a numerical optimizer able to deal with integer values and known to be efficient in the search for the optimal solution, by testing a reasonable number of possible solutions. As a result, we used the Genetic Algorithm from the Matlab® Global Optimization Toolbox (Palonen et al., 2013). At each step of the process, the best individuals are selected from the current population (the initial population is generated randomly) and serve as parents in order to produce the children for the next generation. Each individual is a vector $\bar{t} = [t_j, t_l, t_m], \forall j, l, m \in [\![1;3]\!]$ such as $j \neq l \neq m$. Selection is based on performance (typically, the genetic algorithm is more likely to select parents with better fitness values), that is why the thermal behaviour of the three considered rooms (R1, R2 and R3) in the non-residential building is simulated for each individual in the current population. Over successive generations, this population evolves toward an optimal solution $\bar{t}_{opt}$ allowing electrical power consumption in the room j of the building to be minimized (P_j, $\forall j \in [\![1;3]\!]$) and thermal constraints to be met (equation 4). As a key point, we performed crossover (recombinations of individuals) and mutation (random alterations of individuals) operations during the optimization process. We decided for a crossover fraction equal to 0.8 and a rate at which the average amount of mutation decreases equal to 1. The process ends if the maximum number of generations is reached or the solution found is not improved for 10 successive generations. The parametric analysis we performed also allowed the impact on performance of both the population size and the number of successive generations to be highlighted. Taking a look at Figure 5, one can observe that the higher both the number of individuals in the population and the number of generations, the higher the percentage of optimal solutions related to the minimization of P_j, $\forall j \in [\![1;3]\!]$, while meeting thermal constraints. Figure 6 shows how a given solution is related to overconsumption of electrical power (reference is the optimal solution). One can clearly observe that with a too low number of individuals, the search for an acceptable solution is not successful. In opposition, starting from 10 individuals and with a sufficient number of successive generations, a solution in the neighbourhood of the optimal one can be found. So, we decided for 15 individuals and 40 successive generations. In this case, overconsumption of electrical power is insignificant and the number of tested solutions is reduced.

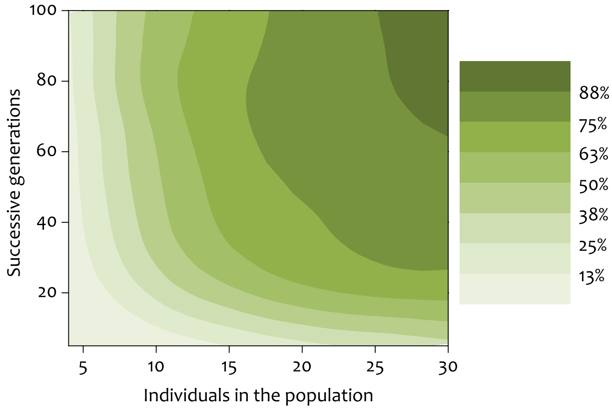

Fig. 5. Optimal responses percentage.

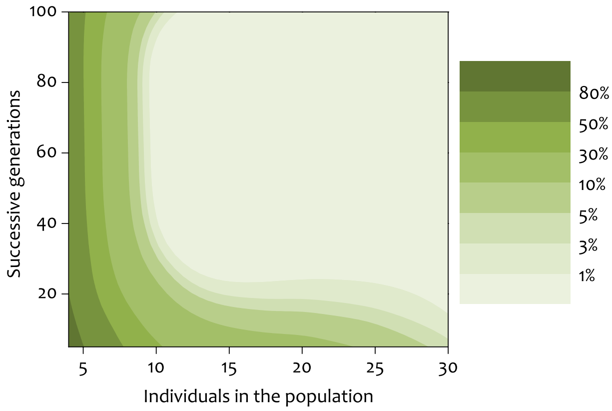

Fig. 6. Overconsumption of electrical power.

5. RESULTS

5.1 Non-predictive strategies

We considered two non-predictive strategies in order to highlight the benefits of the predictive approach we propose for multizone HVAC systems in non-residential buildings. The first strategy (S1) is basic: all the sub-systems operate all the time. The second strategy (S2) is a scheduler used to stop the sub-systems during periods of non-occupancy and to turn them on in the morning, two hours before people arrive at the building (i.e. at 6 a.m.). The sub-systems are turned off when people leave (i.e. at 6 p.m.). S2 is the strategy currently used in the real non-residential building located in Perpignan (south of France) we modelled. For both strategies, heating and cooling set-points are set to 22°C (only during occupancy periods for S2) and the PMV is near zero, whatever the room. Let us remember that the predictive strategy we propose allows the right time to turn the HVAC sub-systems on then off to be found in each of the considered rooms of the building while meeting with thermal comfort requirements (S3). As a result, energy consumption can be significantly reduced.

Table 3. Performance of the different strategies, $\forall j \in [\![1;3]\!]$. The simulation period is from November 1 to March 31, 2011 (heating mode).

	Occupancy period	Non-occup. period	Consumption (Wh/day·m^2)	Discomfort criterion
S1	$T_j^{sp} = 22°C$	$T_j^{sp} = 22°C$	209.5	19.4%
S2	$T_j^{sp} = 22°C$	Off	80.9	14.4%
S3	$PMV_j^{sp} = 0$	Off	69.0	6.4%

Table 4. Performance of the different strategies, $\forall j \in [\![1;3]\!]$. The simulation period is from June 1 to September 30, 2011 (cooling mode).

	Occupancy period	Non-occup. period	Consumption (Wh/day·m^2)	Discomfort criterion
S1	$T_j^{sp} = 22°C$	$T_j^{sp} = 22°C$	198.5	0.1%
S2	$T_j^{sp} = 22°C$	Off	122.6	0.2%
S3	$PMV_j^{sp} = 0$	Off	116.2	0.1%

Table 5. On/off switching times using strategy S3. The simulation period is from January 6 to January 12, 2011 (heating mode).

	Day	Jan. 6	Jan. 7	Jan. 8-9
R1	Starting time	6:15 a.m.	7:15 a.m.	n.a.
	Stopping time	2:00 p.m.	2:30 p.m.	n.a.
	Time saved (h)	4:15	4:45	n.a.
R2	Starting time	5:15 a.m.	6:15 a.m.	n.a.
	Stopping time	5:00 p.m.	2:00 p.m.	n.a.
	Time saved (h)	0:15	4:15	n.a.
R3	Starting time	6:15 a.m.	7:00 a.m.	n.a.
	Stopping time	2:00 p.m.	2:00 p.m.	n.a.
	Time saved (h)	4:15	5:00	n.a.
	Day	Jan. 10	Jan. 11	Jan. 12
R1	Starting time	6:30 a.m.	6:15 a.m.	7:00 a.m.
	Stopping time	2:15 p.m.	2:00 p.m.	1:45 p.m.
	Time saved (h)	4:15	4:15	5:15
R2	Starting time	5:00 a.m.	5:45 a.m.	6:15 a.m.
	Stopping time	6:00 p.m.	2:00 p.m.	1:00 p.m.
	Time saved (h)	-1:00	3:45	5:15
R3	Starting time	6:30 a.m.	6:15 a.m.	7:00
	Stopping time	2:15 p.m.	2:00 p.m.	2:00 p.m.
	Time saved (h)	4:15	4:15	5:00

5.2 Analysis of the results

In order to evaluate performance regarding thermal comfort, we considered the percentage of time for which the PMV value is out of the desired interval during occupancy periods $[-0.5; +0.5]$. Moreover, an average value (per day and square meter) is used for energy consumption. Tables 3 and 4 summarize the results we obtained for two simulation periods, from November 1 to March 31 (heating mode) and from June 1 to September 30, 2011 (cooling mode). Taking a look at these results, one can clearly observe that the predictive strategy (S3) allows energy consumption to be significantly reduced, whatever the operation mode and the period of the year, in comparison to what can be observed with the non-predictive strategies (S1 and S2). In addition, thermal comfort is better (heating mode) or similar (cooling mode) with S3 than when using S1 or S2. Considering the results we obtained using S2 as reference results, energy consumption and thermal discomfort are reduced from 80.9 to 69 Wh/day·m^2 (-15%) and from 14.4% to 6.4% (-56%), respectively (heating mode). In cooling mode, energy consumption and thermal discomfort are reduced from 122.6 to 116.2 Wh/day·m^2 (-5%) and from 0.2% to 0.1% (-50%), respectively. Table 5 gives the optimal on/off switching times computed by the predicitive controller (S3) in heating mode. The simulation period is from January 6 to January 12, 2011. One can highlight that the operation time of the HVAC subsystems is most of the time significantly reduced, whatever the room (comparison is between S2 and S3). The daily time saved can reach up to 5 hours. Fig. 7(a), 7(b) and 7(c) describe the way energy consumption and thermal comfort evolve from January 6 to January 12, 2011, whatever the strategy. With S1, overheating may happen during the afternoon and alters thermal comfort (heating mode). Using the scheduler (S2), overheating is delayed or even avoided, whatever the mode. As a result, thermal comfort is improved during cold periods. In cooling mode, thermal comfort is slightly worse (0.2 % vs. 0.1%) because of HVAC sub-systems being turned on later in the morning than with S1 when outdoor temperature is high. In addition, turning the HVAC systems off during non-occupancy periods allows energy consumption to be significantly reduced. With S3, heating is stopped sooner and overheating is completely avoided (heating mode). During hot periods, the benefits of using S3 are less important. Indeed, in cooling mode, the HVAC sub-systems can not be turned off as soon as during cold periods.

6. CONCLUSION

The present work deals with the predictive control of multizone Heating, Ventilation and Air-Conditioning (HVAC) systems in non-residential buildings. Such systems account for a large part of the energy consumption. Heating and cooling modes have been considered. In order to test the proposed approach, a real non-residential building located in Perpignan (south of France) has been modelled using the EnergyPlus software. We used the PMV (Predicted Mean Vote) index as a thermal comfort indicator and developed low-order ANN-based models to be used as controller's internal models. The optimization problem has been solved using a genetic algorithm. The proposed strategy allows the operation time of each HVAC subsystem to be optimized (i.e. the right time to turn the HVAC sub-systems on and off to be found) and thermal comfort requirements to be met. In comparison to what is observed when using a standard (non-predicitive) strategy, energy consumption is significantly reduced and thermal comfort is improved, whatever the operation mode and the period of the year. Future work will focus on implementing and validating the predictive strategy in the real building. Finally, natural ventilation will be considered in cooling mode with the aim of reducing energy consumption.

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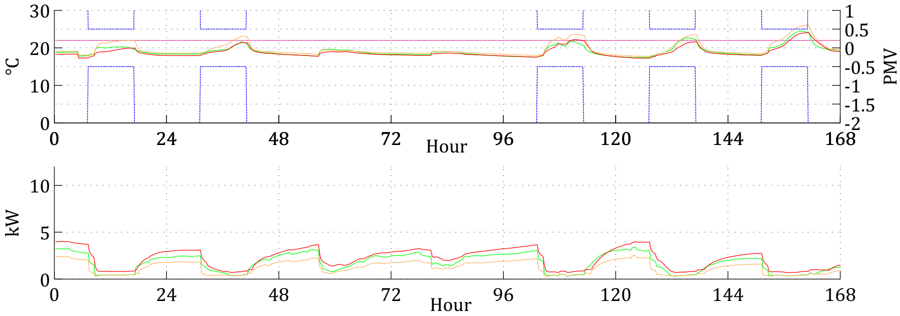
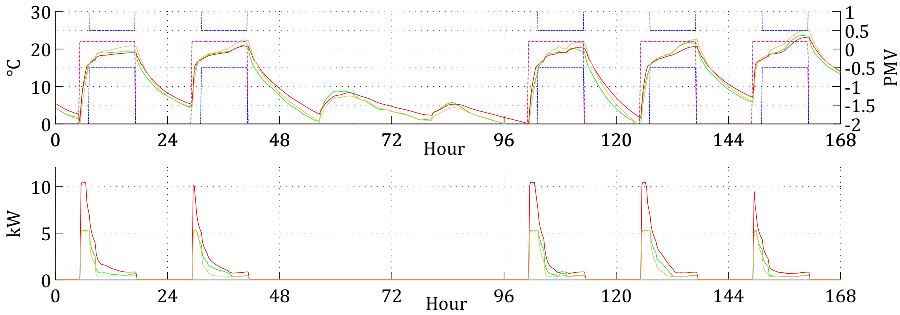
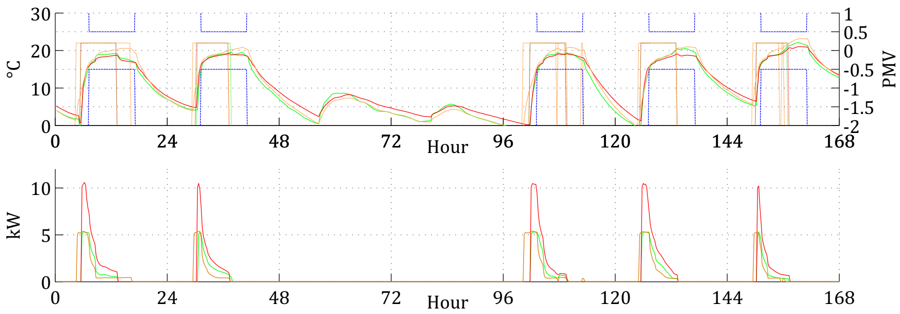


(a) S1. Energy consumption: 224.2 Wh/day·m^2. Discomfort criterion: 1.8%.



(b) S2. Energy consumption: 86.7 Wh/day·m^2. Discomfort criterion: 1.0%.



(c) S3. Energy consumption: 76.2 Wh/day·m^2. Discomfort criterion: 0.7%.

Fig. 7. Results from Jan. 6 to Jan. 12, 2011. Top: T_j^{sp} (magenta), PMV_j (green for ground floor offices, orange for first floor offices, red for manufacturing area), PMV_j^{min} and PMV_j^{max} (blue). Bottom: P_j (same colors as for PMV_j).

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