Tractable Predictive Control Strategies For Heating Systems In Buildings

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Julien Eynard[1], Romain Bourdais[2], Hervé Gueguen[2] and Didier Dumur[3]
[1]PROMES-CNRS Laboratory, University of Perpignan Via Domitia, Perpignan, France
[2]Hybrid System Control Team, IETR, Supélec, Rennes, France
[3]Automatic Control Department, E3S, Supélec, Gif-sur-Yvette, France
julien.eynard@promes.cnrs.fr, romain.bourdais@supelec.fr, herve.gueguen@supelec.fr, didier.dumur@supelec.fr.

ABSTRACT

Model Predictive control is an advanced control technique that has been used to optimize thermal comfort in buildings. Nowadays, the new buildings are characterized by an important inertia as well as low power heating systems. Since the thermal losses are very low, taking into account the intermittent occupancies in the control strategy is questionable. More precisely, in this paper, two model predictive controllers are developed to reduce energy consumption while preserving the thermal comfort. These strategies keep using the local controllers and they are adapted for being implemented in embedded systems. The simulation results show lower energy consumptions and higher comfort levels in comparison with non-predictive strategies.

INTRODUCTION

In order to reduce the impact of buildings in the global energy consumption, an important effort has been made on their insulation. New buildings are now characterized by their great inertia and are equipped with low-power heating systems. For many of them, in tertiary sector, the occupancy is intermittent. Some thermal discomfort can be felt, when the heating system takes in consideration this intermittency. Indeed, after a cold night or week-end without heating, the building needs time to be warmed. Heating systems are saturated and generate a peak of heat power and the temperature stays too cold during the morning. Other strategies with heating 24/7 can satisfy the thermal comfort but could lead to important overconsumption. In previous works, Model Predictive Control (MPC) techniques have been introduced to optimize the energy bill while maintaining the thermal comfort of the occupants Morosan et al. (2010a). But as new buildings are well insulated, the potential energetic gain of this advanced control technique can be limited.

So, a first question can be raised: are predictive control techniques still interesting to take into account intermittent occupancy to manage thermal comfort while minimizing the energy consumption? This is the problem addressed in this paper. Moreover, due to the internal heat gains, the good capacities of the windows to collect the solar radiation and the inertia of walls, the afternoon can lead to a peak of temperature, accentuating the thermal discomfort. A second question can be raised: can predictive control techniques be an efficient solution to avoid the temperature peaks induced by the solar radiations?

A report of the European Union (Union Europenne, 2006) has already highlighted that BEMSs (Building Energy Management System) are one of the best ways to improve significantly the energy efficiency of buildings. Looking at the literature on this domain a lot of approaches have been developed to improve the control of energetic systems in conventional buildings. Fraisse et al. (1999) inventories different model-based strategies to anticipate the effect of night cooling. Due to the relative long time constants of such systems, MPC controllers have been widely developed for the control of energetic system in buildings. More precisely, MPC has been used to control the PMV (Predictive Mean Vote) (Freire et al., 2008), a comfort criterion dedicated to thermal comfort in buildings, but also the heating floor (Chen, 2002), the HVAC (Heat Ventilation and Air Conditioning) system (Yuan and Perez, 2006; Huang et al., 2009; Hadjiski et al., 2006; Paris et al., 2010), and also to manage different energetic systems in a room (Lamoudi et al., 2011) or in distributive way in different rooms of a building Morosan et al. (2010a). MPC has also been coupled with artificial intelligence like adaptive neuro-fuzzy inference systems (Terziyska et al., 2006) to manage energy in buildings.

Some of these strategies are very efficient but it can be difficult to implement them in embedded systems. More precisely, it requires not only optimization algorithms that could be nonlinear but also a good technical expertise for the tuning phase of these advanced controllers. In this paper, the problem is tackled with a logical control strategy which relies on a predictive model of the building that takes in consideration exogenous perturbations forecast (outdoor temperature and solar radiations). For tertiary buildings, it is not possible to control directly the power of each heating system: the local regulators cannot be removed so they have to be taken into account in the prediction model. Under these considerations, the model predictive control optimizes the temperature set-point of the zone. Although the prediction model is a simple linear model, the resulting optimization is under constraints because of the local regulator (saturation of the PID for instance). In the first part the global approach to design a model-based predictive controller is described. Then, the second part present two computationally tractable MPC to address the problem. Finally, to illustrate these two approaches, a case study (a building) is proposed in the fourth section, and the different simulation results are compared in the fifth part. Conclusions and future work are given in a last section.

MODEL-BASED PREDICTIVE CONTROL

Structure of the system

Many factors are linked to the evolution of the temperature in buildings: the heating power, the internal gains of the occupants, and also the outdoor temperature and the solar radiations. In many buildings, the outdoor temperature is measured and the number of occupants can be well estimated. These factors can be integrated in the prediction model. Even if some sensors can measure the solar radiations, many buildings are not equipped with such sensors. The influence of the solar radiation will not be considered in the prediction model, but will be considered as unknown disturbance.
The thermal behavior of the building can be described by a discrete state equation, as follows:

$$\begin{cases} \mathbf{x_b}(k+1) = & \mathbf{A_b}\mathbf{x_b}(k) + \mathbf{B_b}\begin{bmatrix} U_{HS}(k) \\ T_{out}(k) \\ N_{oc}(k) \end{bmatrix} \\ T_{op}(k) = & \mathbf{C_b}\mathbf{x_b}(k) \end{cases} \tag{1}$$

In this equation, T_{op} is the operative temperature which can be seen as a good approximation of the temperature felt by the occupants. It can be approximated by the mean between the wall temperature and the air temperature. U_{HS} is the heating power, T_{out} is the outdoor temperature and N_{oc} is the number of occupants in the building.
For most tertiary buildings, it is not possible to manage directly the power of each heating system, because of the local controllers that cannot be removed. So they have to be taken into account in the prediction model. Consequently, the control variable of the MPC controller is not the power allocated to the heating system but its temperature set-point. In most cases, the local controller is a PI which can also be described by a discrete state equation, as follows:

$$\begin{cases} \mathbf{x_c}(k+1) = & \mathbf{A_c}\mathbf{x_c}(k) + \mathbf{B_c}\varepsilon(k) \\ U_{HS}(k) = & \mathbf{C_c}\mathbf{x_c}(k) + \mathbf{D_c}\varepsilon(k) \end{cases} \tag{2}$$

In this equation, ε is the input of the PI controller. In practice, this is the difference between the temperature set-point $\mathbf{T_{sp}}$ and the measured temperature $\mathbf{T_{op}}$. The presence of a proportional gain implies a direct term $\mathbf{D_c}$ between its input and its output.
From all these considerations, the structure of the thermal behavior is detailed in figure 1.

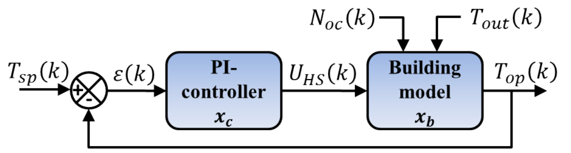

Figure 1: Layout of the system

Towards a prediction model

For a given prediction horizon N_h, $\mathbf{U_{HS}}(k:k+N_h-1)$ denotes the vector of all the control inputs over the prediction horizon. $\mathbf{T_{op}}(k+1:k+N_h)$ is the predicted output constructed from the state $\mathbf{x_c}(k)$ and according to the input vector $\mathbf{U_{HS}}(k:k+N_h-1)$ a prediction of the internal gain $\mathbf{N_{oc}}(k:k+N_h-1)$ and the outdoor temperature $\mathbf{T_{out}}(k:k+N_h-1)$. $\mathbf{T_{op}}(k+1:k+N_h)$ can be defined recursively by:

$$\begin{aligned} & T_{op}(k+j) = \mathbf{C_b}\mathbf{x_b}(k+j) \\ & = \mathbf{C_b}\Big(\mathbf{A_b}^{(j)}\mathbf{x_b}(k) \\ & + \sum_{i=1}^{j}\mathbf{A_b}^{(j-i)}\mathbf{B_b}\begin{bmatrix} U_{HS}(k+i-1) \\ T_{out}(k+i-1) \\ N_{oc}(k+i-1) \end{bmatrix}\Big) \end{aligned} \tag{3}$$

This equation can been aggregated in the following equation:

$$\begin{aligned} & \mathbf{T_{op}}(k+1:k+N_h) = \mathbf{M_b}\mathbf{x_b}(k) \\ & + \mathbf{N_b}\begin{bmatrix} \mathbf{U_{HS}}(k:k+N_h-1) \\ \mathbf{T_{out}}(k:k+N_h-1) \\ \mathbf{N_{oc}}(k:k+N_h-1) \end{bmatrix} \end{aligned} \tag{4}$$

With a similar approach, the predictive equation of the PI controller can be expressed as follows:

$$\mathbf{U_{HS}}(k:k+N_h-1) = \mathbf{M_c}\mathbf{x_c}(k) + \mathbf{N_c}\varepsilon(k:k+N_h-1) \tag{5}$$

Considering the closed-loop structure of the system (figure 1), the combination of the two predictive models (4) and (5) leads to define the prediction of the heating system power consumption $\mathbf{U_{HS}}(k:k+N_h-1)$ as well as the prediction of the operative temperature $\mathbf{T_{op}}(k+1:k+N_h)$, from the states $\mathbf{x_b}(k)$ and $\mathbf{x_c}(k)$ and according to a planning of the temperature set-point $\mathbf{T_{SP}}(k:k+N_h-1)$, the predictions of the internal gain $\mathbf{N_{oc}}(k:k+N_h-1)$ and the outdoor temperature $\mathbf{T_{out}}(k:k+N_h-1)$.

$$\begin{aligned} & \mathbf{T_{op}}(k+1:k+N_h) = \tilde{\mathbf{M}}_\mathbf{b}\mathbf{x_b}(k) + \tilde{\mathbf{M}}_\mathbf{bc}\mathbf{x_c}(k) \\ & + \tilde{\mathbf{N}}_\mathbf{b}\begin{bmatrix} \mathbf{T_{SP}}(k:k+N_h-1) \\ \mathbf{T_{out}}(k:k+N_h-1) \\ \mathbf{N_{oc}}(k:k+N_h-1) \end{bmatrix} \end{aligned} \tag{6}$$

And for the heating power consumption, the prediction is:

$$\begin{aligned} & \mathbf{U_{HS}}(k:k+N_h-1) = \tilde{\mathbf{M}}_\mathbf{c}\mathbf{x_c}(k) + \tilde{\mathbf{M}}_\mathbf{cb}\mathbf{x_b}(k) \\ & + \tilde{\mathbf{N}}_\mathbf{c}\begin{bmatrix} \mathbf{T_{SP}}(k:k+N_h-1) \\ \mathbf{T_{out}}(k:k+N_h-1) \\ \mathbf{N_{oc}}(k:k+N_h-1) \end{bmatrix} \end{aligned} \tag{7}$$

The expression of the different matrices $\tilde{\mathbf{M}}_{\mathbf{c}}, \tilde{\mathbf{M}}_{\mathbf{b}}, \ldots$ can be directly deduced from the equations (4) and (5), with $\varepsilon(k : k + N_h - 1) = \mathbf{T_{SP}}(k : k + N_h - 1) - \mathbf{T_{op}}(k : k + N_h - 1)$.

Optimization problem

The optimization problem can be formulated from the equations (6) and (7). It consists in maximizing the thermal comfort during the occupation times, while minimizing the energy bill. These two objectives are antagonist and then a compromise has to be defined. As achieved in previous work Morosan et al. (2010a), the first idea is to formalize this compromise by representing the comfort problem as constraints on the operative temperature, which has to be maintained under a given band, called band of comfort, but only during the occupancy periods. As the number of occupants N_{oc} is supposed to be known over the prediction horizon, the occupancy periods are also supposed to be known.
The optimization variables are the temperature setpoint vector $\mathbf{T_{SP}}(k : k + N_h - 1)$ and the objective function is linked to the heating power consumption over the prediction horizon $\mathbf{U_{HS}}(k : k + N_h - 1)$. These considerations leads to the following optimization problem:

Problem 1 *Initial optimization problem.*
At a time k, given $\mathbf{x_b}(k)$, $\mathbf{x_c}(k)$, $\mathbf{T_{out}}(k : k+N_h-1)$ and $\mathbf{N_{oc}}(k : k + N_h)$, the optimization problem is:

$$\min_{\mathbf{T_{SP}}(k:k+N_h-1)} \sum_{j=0}^{N_h-1} U_{HS}(k+j), \tag{8}$$

s.t. $\forall j = 1..N_h \backslash N_{oc}(k + j) \neq 0$

$$T_{op,min} \leq T_{op}(k+j) \leq T_{op,max} \tag{9}$$

It is interesting to notice that the resulting problem is a linear optimization problem which could be easily solved by an efficient solver (Cplex for instance). Anyway, two points should be developed:

- The equation (9) is linked to the comfort, but, under certain conditions, there could exist no inputs such that these constraints are fulfilled: if the initial temperature is too low and there is not enough power to increase the temperature enough over a given time. In practice, to ensure that the optimizer will always give a solution, these constraints are softened by the introduction of slack variables. This technique will not be detailed in this paper. The reader may refer to Morosan et al. (2010a) or Camacho and Bordons (2004) for more details.
- The second point is linked to the limited power of the heating systems. The local PI controllers that are integrated in buildings are saturated. If we take in consideration these saturations, the problem becomes nonlinear and solving it can be much more difficult. The idea considered here is to add more constraints on U_{HS} so that U_{HS} remains between 0 and U_{HS}^{max}. Contrary to the thermal comfort constraints, there always exists an input T_{op} such that the constraints are fulfilled. This can be formalized as follows, $\forall j \in 0..N_h - 1$:

$$0 \leq U_{HS}(k+j) \leq U_{HS}^{max} \tag{10}$$

Control Structure

The optimization problem being defined, it can be interesting to present the global structure. It is detailed in figure 2. At each time step k, the MPC controller receives the required predictions: the outdoor temperature, the occupancy profile. The state of the system is a parameter of the optimization problem. It could be given to the MPC controller by a state observer.

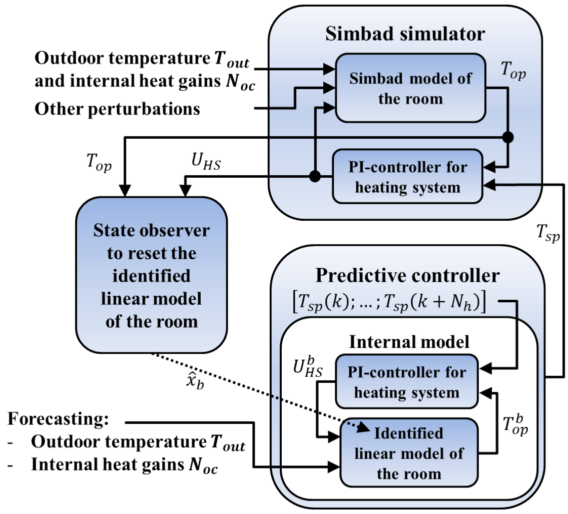

Figure 2: General scheme of the MPC supervisor

TWO MODEL PREDICTIVE STRATEGIES

Strategy 1: on-line linear optimization problem

The first strategy is straightforward from the optimization problem 1, with the additional power constraint (10). This problem is a constrained linear problem that could be easily solved by an optimization toolbox. Two parameters have to be fixed. The time step, and the size of the prediction horizon. First, $Te = 1$ min is an admissible value for the sampling period. The length of the prediction horizon should be long enough to take into account the inertia of the building, but can not be too long, to ensure that the problem remains tractable. As the number of optimization variables is not huge, this point is not a real problem, then, the horizon must be chosen so that the next occupancy period can be seen (about 50 hours from Friday evening to Monday morning for a tertiary building). As it was proposed in Morosan et al. (2010b), this length has been chosen time-variable to improve the behavior of the controller, minimizing the number of optimization parameters. Regarding the time constant of the system, the optimal control sequences are not computed

and applied at each step time, but only for each 30 min, reducing the number of optimization phases.
The results of this technique are presented in the next section with comparisons with other control strategies. Its main drawback is the consequence of the on-line optimization that requires to embed an optimization solver. This is why another strategy is proposed in the following based on logical decisions.

Strategy 2: logical decision based on the prediction model

This strategy is based on two simple questions that the controller will try to answer at each time step.

- During the inoccupancy periods, the question is: should the heating be turned on now or can it wait for another step time, so that the temperature will be in the comfort band when people arrive at work?
- During the occupation periods, the question is: can the heating system be turn off so that the temperature stays in the comfort band as long as there are people in the office?

The answers are given by using the closed-loop prediction model (6).

Case 1:

For the first question, the prediction horizon is chosen in such a way that the end of the prediction horizon $(k + N_h)$ coincides with the beginning of the occupancy period. For a desired temperature T_{SP}, the input vector $\mathbf{T_{SP}}(k : k+N_h)$ used for the simulation is

$$\mathbf{T_{SP}}(k : k+N_h) = [0,\ T_{SP},\ T_{SP}, \dots\ T_{SP}]^{\mathrm{T}} \quad (11)$$

Then, if $T_{op}(k + N_h) \geq T_{op,min}(k + N_h)$ then apply $T_{SP}(k) = 0$. If not, it is time to start heating, by applying $T_{SP}(k) = T_{SP}$.

Case 2:

For the second question, as the temperature set-point is the control input, turning off the heating system is equivalent to consider $T_{SP} = 0$. In this case, the end of the prediction horizon coincides with the end of the next occupancy period. The input vector $\mathbf{T_{SP}}(k : k+N_h)$ used for the simulation is

$$\mathbf{T_{SP}}(k : k+N_h) = [0,\ 0,\ 0,\ 0,\ \dots\ 0]^{\mathrm{T}} \quad (12)$$

Then, if $\forall i = 1..N_h,\ T_{op}(k+i) \geq T_{op,min}(k+i)$ then apply $T_{SP}(k) = 0$. If not, it is not the time to turn off the heating system and then the control applies $T_{SP}(k) = T_{SP}$, which is the desired temperature.
The advantage of this strategy is that it does not require any optimization toolbox. The next session presents the various results obtained by simulations, using the Simbad toolbox to simulate the tertiary building.

CASE STUDY

Geometric and thermal parameters

For this study, we used a room of an office building. All the parameters described in the model have been chosen according to a real building.

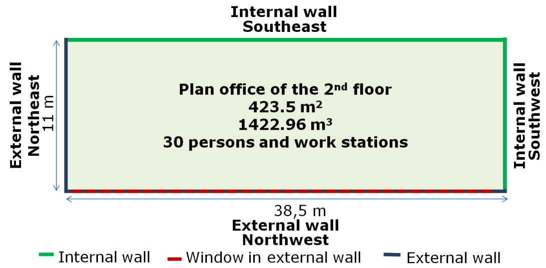

Figure 3: Configuration of the room

The room has a rectangular shape with a volume of $1422.96\,\mathrm{m}^3$ (length = $38.5\,\mathrm{m}$, width = $11\,\mathrm{m}$, height = $3.36\,\mathrm{m}$) and a surface area of $423.5\,\mathrm{m}^2$. This room is located at the second floor of the building which has four floors. So, the ceiling and the floor of the room are not external but internal walls. The room has two vertical external walls, on the Northeast and on the Northwest. Only the Northwest wall has windows. The Southeast and the Southwest walls are internal walls with other rooms of the building. The Northwest and the Southeast walls have a surface area of $129.26\,\mathrm{m}^2$ and the Northeast and the Southwest walls have a surface area of $36.96\,\mathrm{m}^2$. Each one of the 28 windows of the Northwest wall has a surface area of $1.8\,\mathrm{m}^2$, so the total glass surface of this wall is $50.4\,\mathrm{m}^2$. The model of the room has been developed using the Simbad toolbox of the CSTB (SIM). The most important parameters are presented in Table 2 for the walls and in Table 1 for the windows.

Table 1: Window characteristics

PARAMETER	VALUE
Thermal diffusivity ($\mathrm{W{\cdot}m^{-2}{\cdot}K^{-1}}$)	1.8
Solar absorption	0.095
g factor	0.42
Light transmission	0.71
Emissivity of exterior side	0.095
Emissivity of interior side	0.095

Internal heat gains

This room can accommodate 30 persons and their work stations. Each employee produces a heat power of about 100 W (the office work is a relative low activity) and the office electric materials produce about 180 W for each work station. This total heat power (8460 W for the whole room) is divided in two equal parts, a radiative and a convective heat power.

Table 2: *Characteristics of the walls*

WALL	LAYER	THICKNESS m	DENSITY $kg \cdot m^{-3}$	CAPACITY $J \cdot kg^{-1} \cdot K^{-1}$	CONDUCTIVITY $W \cdot m^{-1} \cdot K^{-1}$
External	Reinforced concrete	0.2	2150	1008	1.650
	Rockwool “Rockfaçade®”	0.12	39	1030	0.036
	Unventilated air gap	0.02	1	1000	0.130
	Ventilated air gap	0.022	1	1000	0.192
	Terra cotta “Terreal Zéphir®”	0.014	2286	1008	0.98
Internal	Drywall “BA13”	0.0125	825	1008	0.25
	Unventilated air gap	0.025	1	1000	0.155
	Drywall “BA13”	0.0125	825	1008	0.25
Floor	Concrete	0.31	2350	880	2.3

Some characteristics of the lamps are given in table 3. Indeed, the lighting of the room is composed of 72 low-energy lamps (40 W each). The type and the number of lamps allow ensuring a minimal illumination of 500 lux with a low-energy consumption, whatever the natural lighting. The total heat power (25 % of the electric consumption) produced by the lamps is estimated to 720 W.

Table 3: *Artificial lighting parameters*

NAME	UNIT	VALUE
Total lighting power	W	40
Illuminance efficiency	lm/W	88
Luminaire mean efficiency	–	0.8
Luminaire maintenance factor	–	1.11
Lighting heat gain	–	0.25

HVAC systems

The ventilation system is a mechanical ventilation with a heat recovery system, whose efficiency is $\varepsilon = 84\%$. The air flow in the room was evaluated at $0.3454\,kg \cdot s^{-1}$ during working time and $0.034\,54\,kg \cdot s^{-1}$ when there is nobody present in the building. The heat power (U_{HS}) can be adjusted linearly between 0 and its maximal value: $U_{HS}^{max} = 12\,588\,W$. The heating system is not very powerful, only about $8.8\,W \cdot m^{-3}$, but it is very typical from low-energy buildings. The main part of this heating power is radiant (70 % of whole power), and so, convective for the rest, i.e. 30 % of the whole power. The heating system has a response time of 30 minutes.

SIMULATION RESULTS

Identification of an internal model

According to the Simbad model of the room, a black-box reduced-order model has been identified. As previously mentioned, it is a discrete and linear state space model based on equation 1. It estimates the operative temperature according to three inputs: (i) the outdoor temperature, (ii) the internal heat gains and (iii) the heat power supplied. The identification of this four-order model ($\dim(\mathbf{x_b}) = 4$) has been achieved using the subspace method for the identification of state-space models described by Ljung (1999).

Then, this linear model has been coupled with the model of the PI-controller in order to define the closed-loop model of the room. So, the internal model of MPC takes into account three inputs: (i) the set-point operative temperature given to the PI-controller, (ii) the internal heat gains and (iii) the outdoor temperature. The two outputs are (i) the operative temperature, (ii) the thermal power of the heating system.

The closed-loop model has been validated over a range of seven weeks and the two scenarios: V1 (heating control always switched on) and V2 (heating control works only during occupancy periods). The statistic criterion for comparing operative temperature given by the Simbad reference model T_{op}^{Simbad} and the reduced-order model T_{op}^{LM} is the FIT defined in equation 13. Results are grouped in Table 4 and show very good correlation for the two outputs $\mathbf{T_{op}}$ and $\mathbf{U_{HS}}$.

$$FIT = 100 \times \left(1 - \frac{\left\| T_{op}^{LM} - T_{op}^{Simbad} \right\|_2}{\left\| T_{op}^{Simbad} - \left\langle T_{op}^{Simbad} \right\rangle \right\|_2} \right) \tag{13}$$

Table 4: *Validation of the closed-loop model*

CRITERION	UNIT	V1	V2
FIT of T_{op}	%	95.59	96.68
FIT of U_{HS}	%	80.13	95.78
Total energy difference	%	−0.62	0.26

Scenarios

Simulations have been carried out considering one week (Wednesday 00:00 AM to Thursday 12:00 PM) during winter. Figure 4 shows the most significant exogenous inputs that have been used for the simulations: the outdoor temperature, the occupancy of the room (number of persons) and the solar radiation.

The occupancy of the building is defined according to working time. So, people works only five days a week (Monday to Friday) and only during the day from 8:00 to 19:00. During the other periods, there is nobody in the room. It is assumed that the 30 persons arrive gradually from 8:00 to 9:00 and leave progressively from 18:00 to 19:00. Moreover, 25 persons leave the room during lunch time (from 12:00 to 13:00).

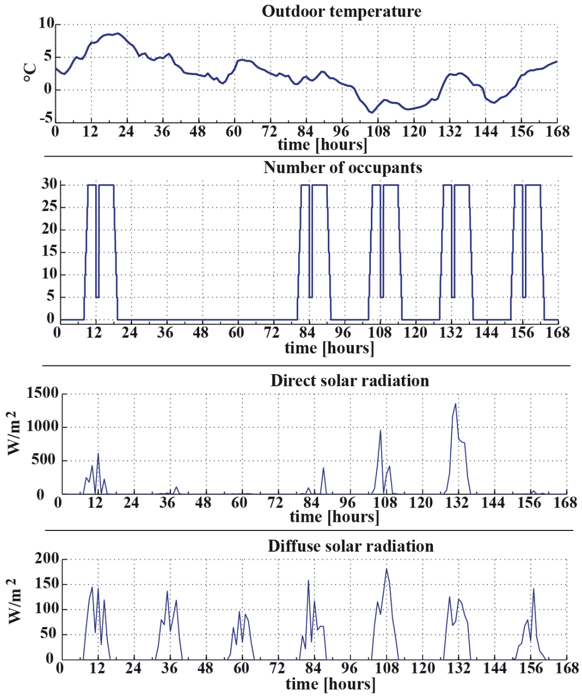

Figure 4: Main exogenous inputs of the model

Thermal comfort post evaluation

One of the most famous models to estimate the thermal comfort is based on the work of Fanger (1970). He introduced two indicators for the thermal comfort, the PMV "Predictive Mean Vote" and the PPD "Predicted Percentage Dissatisfied". These criteria are a good representation of the thermal comfort. But they can be difficult to compute, because they are based on many parameters. In Dufton et al. (1932), the authors showed that the thermal comfort depends mainly on the operative temperature, on which thermal comfort indicators have been defined in this paper.

We have chosen TS_1, TS_2 and TS_3 to represent the percentage of time spent, during the occupancy, in three temperature domains, defined as follows:

- D_1: the optimal comfort domain (a 1°C width temperature band, centered around the set-point).
- D_2: the low discomfort domain.
- D_3: the high discomfort domain, when the occupants feel an important thermal discomfort.

The numerical definition of these domains is given in Table 5. It is important to notice that these indicators are a posteriori computed for each simulation. They are used to compare the performances of the various controllers.

Table 5: Thermal comfort domains

NAME	CONDITIONS
D_1	$\{T_{sp} + 0.5 > T_{op} > T_{sp} - 0.5\}$
D_2	$\{T_{sp} + 1.5 > T_{op} > T_{sp} + 0.5\}$ $\cup \{T_{sp} - 0.5 > T_{op} > T_{sp} - 1.5\}$
D_3	$\{T_{op} > T_{sp} + 1.5\}$ $\cup \{T_{op} < T_{sp} - 1.5\}$

Non-predictive strategies

In the first scenario, denoted PI-S1, the intermittent occupancy is not considered: the temperature set-point is set to its nominal value 24 hours a day, 7 days a week. In this scenario, the indoor temperature never falls under the optimal comfort zone. However, it induces an important energy consumption ($797\,\mathrm{kWh}$).

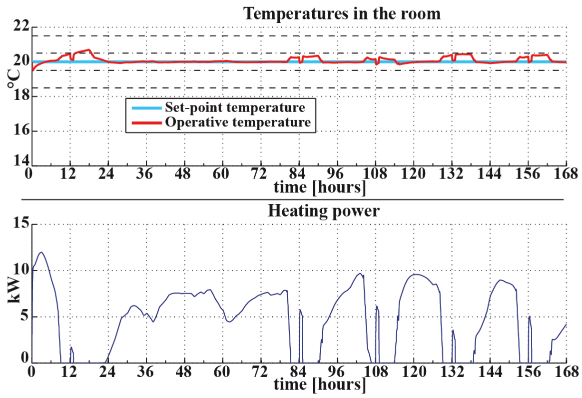

Figure 5: Temperatures and power for PI-S1

In order to reduce the energy consumption of the first strategy, the solution is to switch off the control during a part of the night or during the week-end. However, if the controller is on only during the occupancy periods, it is clear that the thermal comfort will be very degraded, because of the thermal inertia of the building. Indeed, after the night or the week-end the operative temperature is low, and several hours are necessary to reach the optimal comfort domain. This is the reason why in practice, the solution is to switch on the controllers some hours before the beginning of the working time. In this case, the difficulty is to choose the correct anticipation time. It has to be long enough to ensure a quite good thermal comfort but not too long to avoid the overconsumption of energy. The scenario PI-S2 is an example of this strategy with a 6 hours anticipation time depicted in figure 6.

The main drawback of this strategy is the consequence of the non-flexible anticipation time. Some days, this anticipation time is too short (in particular the morning after the week-end) whereas some days it is too long if the night is not too cold for instance. Looking at the results in Table 6, the energy consumption is reduced by 12.2% ($-97\,\mathrm{kWh}$) during the week compared with the PI-S1 strategy. However, this energy saving goes with a sharp drop of the thermal comfort. Indeed, the time lasted in the optimal comfort domain falls by 22.8% ($-20.8\,\mathrm{points}$). The results of these two simple strategies show that intermittent heating can save energy but can reduce the thermal comfort when it is used without a prediction model.

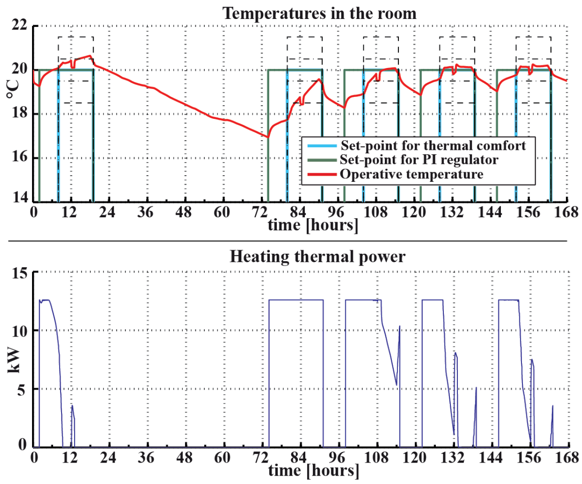

Figure 6: Temperatures and power for PI-S2

Predictive strategies

The simulation results for the predictive strategies are presented in figure 7 for the first one with on-line optimization, and in figure 8 for the second one (logical decision).

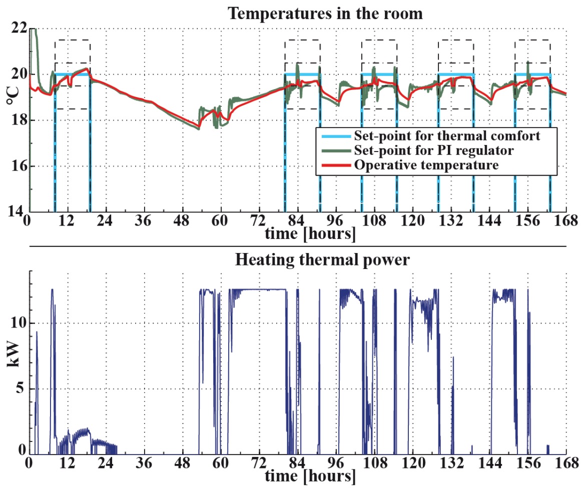

Figure 7: Temperatures and power for MPC-S1

Looking at these graphs, the major problem induced by the week-end and the nights, i.e. the drop of the indoor temperature (if no heating) or the excessive energy consumption (if heating during all the week-end) does not occur anymore: it is taken in consideration explicitly by the MPC. Indeed, the prediction model takes into account a forecast of the internal gains and the outdoor temperature. The heating starts each day with a different anticipation time, mainly according to the outdoor temperature and the duration of the inoccupancy (it starts earlier after the week-end than just after one night). Besides, it can be noticed that energy is saved during the afternoon because the heating system is switched off some hours before the evening without compromising the thermal comfort due to the high inertia of the building and the internal heat gains.

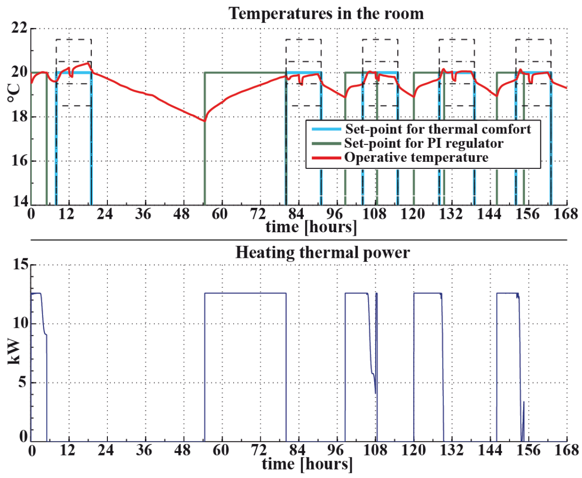

Figure 8: Temperatures and power for MPC-S2

To evaluate the gain in terms of energy given by the predictive strategies, the Δ_{PI-S1} criterion is defined to evaluate the rate of energy saved in comparison with the basic PI-control strategy (PI-S1).
The numerical results of the two basic scenarios with only PI-controllers and the numerical results of the two predictive controllers are grouped in Table 6.

Table 6: Results for the different control strategies

CRITERIA		PI		MPC	
Name	Unit	S1	S2	S1	S2
TS_1	%	91.1	70.33	95.2	99.3
TS_2	%	8.9	23.7	4.8	0.7
TS_3	%	0.0	5.97	0.0	0.0
$Energy$	kWh	797	700	670	700
Δ_{PI-S1}	%	0.00	-12.2	-15.9	-12.2

The two predictive controllers have a lower energy consumption that the PI-S1 and a very good level of thermal comfort. More interesting, they have the same level of energy consumption than the PI-S2 but with a much better thermal comfort. These strategies combine the advantages of the two non-predictive strategies without being impacted by their weaknesses! Indeed, the MPC-S1 has consumed $670\,\mathrm{kWh}$, i.e. 16% less than the PI-S1 and the saving of energy reaches about 12% with the MPC-S2 ($700\,\mathrm{kWh}$). If we look at the thermal comfort, it is clear that the two predictive controllers give very interesting results because the indoor operative temperature is maintained in the optimal comfort zone, respectively 99% of the time with the MPC-S2 strategy (very close to a perfect thermal comfort level), and 95% of the time with the MPC-S1, anyway, 4.5% better than the PI-S1.
The results are quite the same for the two algorithms but the main advantage of the second one lies on its simplicity. Indeed, no optimization algorithm is needed for implementation in an embedded system.

CONCLUSION

In this paper, simple but intelligent predictive strategies have been proposed to manage the thermal comfort in low-energy tertiary buildings under intermit-

tent occupancy. A special effort has been made to take in consideration industrial aspects. The strategies preserve the local controllers and they use computationally tractable algorithms for being implemented in embedded systems. The first relies on a linear optimization problem. The second one does not need online optimization but only a single simulation of the prediction model of the room at each step time. The effectiveness of these two strategies is very close but considerably better than non-predictive strategies. The integration of occupancy in the thermal control seems to be interesting in terms of energy savings. However, the behavior of the controller induced by this integration is very close to an on/off controller. It could be also interesting to consider the wear of the heating systems under such a strategy.
Future works will focus on different points like the estimation of operative temperature without any radiant measurement, the use of PMV instead of operative temperature to refine the comfort criterion, the generalization of these algorithms in the case of a multi-zone building, the control of multiple systems (blinding systems...) or the use of variable energy cost to optimize the use of decentralized energy production. Finally, the algorithms will be tested in real buildings in order to validate them experimentally.

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