Proceedings of BS2013:
13th Conference of International Building Performance Simulation Association, Chambéry, France, August 26-28

HVAC CONTROL AND COMFORT MANAGEMENT IN NON-RESIDENTIAL BUILDINGS

Antoine Garnier[1,2], Julien Eynard[2,3], Matthieu Caussanel[2,3], Stéphane Grieu[2,3]
[1]Pyrescom, Mas des Tilleuls, 66680 Canohès, France
[2]PROMES-CNRS, Rambla de la thermodynamique, Tecnosud, 66100 Perpignan, France
[3]University of Perpignan Via Domitia, 52 Avenue Paul Alduy, 66860 Perpignan, France
a.garnier@pyres.com; {julien.eynard; matthieu.caussanel; stephane.grieu}@promes.cnrs.fr

ABSTRACT

In France, non-residential buildings account for a significant part in energy consumption. Moreover, a large part of this consumption is due to Heating, Ventilation and Air-Conditioning (HVAC) systems, which are generally badly handled. So, the present work deals with an efficient approach allowing energy consumption to be minimized while ensuring thermal comfort. In this sense, a predictive control strategy is proposed for existing zoned HVAC systems considering the Predicted Mean Vote (PMV) index as a thermal comfort indicator. In order to test the developped strategy in simulation, a non-residential building located in Perpignan (south of France) has been modelled using the EnergyPlus™ software. The aim is to limit the times during which the HVAC sub-system is turned on and to ensure a satisfactory thermal comfort during working time. This approach, computationally tractable, allows thermal comfort requirements to be met without wasting energy.

INTRODUCTION

Almost half of the electricity consumption in non-residential buildings is due to Heating, Ventilation and Air-Conditioning (HVAC) systems (Pérez-Lombard et al., 2008). As a result, new approaches are needed to make (central or zoned) HVAC systems more efficient. In addition, thermal comfort requirements must be met but thermal comfort is subjective, hard to define and even harder to achieve in non-residential buildings.

As an interesting work, Endravadan (2006) has developed a method to achieve a good thermal comfort in buildings using a Local Heating System (LHS) for each occupant. This technique allows significant energy savings but is not well adapted in case of occupants moving frequently. Moreover, such a technique needs additional heating equipments to be installed, whereas our objective is to develop an efficient solution for existing HVAC systems. Moroşan et al. (2010) have proposed a predictive approach, what is a very interesting solution, but on-line optimization is needed. Otherwise, the Pyrescom Company, our industrial partner, has developed a monitoring system that carries out meteorological parameters and energy measurements to improve energy efficiency in non-residential buildings (Batnrj project, www.pyres.com). The collected data are sent to a remote server with a significant computational power. These data are used to find out possible ways to finalize an efficient HVAC control strategy. Several buildings are instrumented with the Pyrescom monitoring system, including a $1000\,\mathrm{m}^2$ non-residential building located in Perpignan (south of France). This reference (pilot) building has been modelled using the EnergyPlus™ software and allowed the proposed strategy about HVAC management to be tested and evaluated. As a first approach, only the manufacturing area is considered. In the other rooms of the building, the HVAC sub-systems are all turned off. Energy consumption, thermal comfort and computation time are considered as performance indicators. Thermal comfort is evaluated on the basis of the Predicted Mean Vote (PMV) index, which is a standardized indicator designed to estimate the thermal sensation of occupants (NF EN ISO 7730, 2006). This index allows temperature to be adjusted in a building according to the period of the year or work activities and behaviours. So, we propose in this paper a predictive strategy for managing zoned HVAC systems without on-line optimization. This strategy is computationally tractable and the developed algorithms will be implanted in an embedded system. In order to develop the predictive controller allowing the strategy to be implanted, a linear model that mainly links the PMV index with solar radiation, outdoor temperature and internal heat gain has been identified. With this model, the PMV index can be used as a set-point and thermal comfort can be maintained in a desired interval which can be adjusted by people working in the considerd non-residential building.

The paper is organized in the following way: first, the reference building modelled using the EnergyPlus™ software is described. The following section focuses on thermal comfort as well as on the way the PMV index can be controlled using the proposed strategy. Next, the PMV linear model and its identification process are described. Then, the predictive control strategy we propose and the results we obtained in simulation are presented. We compared these results with the results given by various standard (non-predictive) strategies. The paper ends with a conclusion and an outlook to future work.

REFERENCE 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

Table 1: Properties of the materials used in exterior walls

LAYER	THICKNESS (cm)	CONDUCTIVITY ($\mathrm{W \cdot m^{-1} \cdot K^{-1}}$)	DENSITY ($\mathrm{kg \cdot m^{-3}}$)	SPECIFIC HEAT ($\mathrm{J \cdot kg^{-1} \cdot K^{-1}}$)
Brick	10	0.89	1920	790
Heavy weight concrete	20	1.45	2000	1000
Insulation board	5	0.03	43	1210
Gypsum board	3	0.16	800	1090

simulations, as demonstrated by Henninger and Witte (2012). The considered building is a real two-storey building of $1000\,\mathrm{m}^2$, built in 2008 and located in Perpignan (south of France). It is facing south and agrees with the 2005 French Thermal Regulation (République Française, 2006). This non-residential building features three main areas of $340\,\mathrm{m}^2$ each (figure 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 area where about 6 persons work seated or in a standing position. The last room of the ground floor is a warehouse (blue area). This room is not heated.

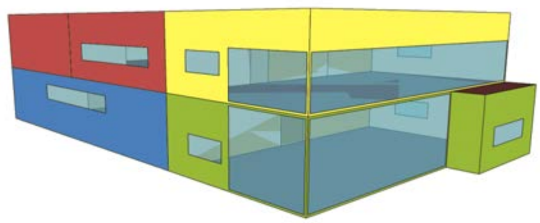

Figure 1: Topology of the reference building

For both the warehouse and the manufacturing area, ceiling is $3.90\,\mathrm{m}$. In the offices, there is a suspended ceiling at $2.70\,\mathrm{m}$. The materials used in the building are listed in table 1. Exterior walls consist of several layers of different materials. From the outside to the inside, there is a brick layer, heavy weight concrete, an insulation board, and finally a gypsum board. Interior walls are composed of two gypsum boards. The south face and a part of the west face of the building are composed of a large glazed area. These glasses were treated by filtering infrared beam to avoid overheating due to excessive solar radiation exposure in summer. The other glasses in the building consist in $3\,\mathrm{mm}$ double glazed bays. Heating is handled in the building by a zoned electrical HVAC system consisting in several sub-systems, one for each area. Only the temperature set-point (with a thermostat for heating and another one for cooling) can be adjusted. As previously mentioned in the paper, only the manufacturing area and the process of heating are considered to test the proposed approach about HVAC system management. This manufacturing area is composed of an open space of $230\,\mathrm{m}^2$ and three storage rooms of $110\,\mathrm{m}^2$. HVAC power is $10\,\mathrm{kW}$. Coefficient of Performance (CoP) is 3.8 while maximum air flow rate is $0.6\,\mathrm{m^3 \cdot s^{-1}}$, which represents $2.4\,\mathrm{vol \cdot h^{-1}}$.

Weather data (outdoor temperature, solar radiation, wind speed) are required to perform the simulation. So, we used real data from year 2011 provided by the Pyrescom monitoring system. Since atmospheric pressure measurements were missing, we used data from the Perpignan airport which is located $7\,\mathrm{km}$ away from the building. Measurements were carried out with a time step of 30 seconds while averaged values were saved every 15 minutes and stored in a database. As a consequence, the time step of the simulation is 15 minutes. A Mediterranean climate, relatively mild, can be found in Perpignan. Figure 2 shows how outdoor temperature evolves at 6 a.m., from January to December 2011 (the simulation period).

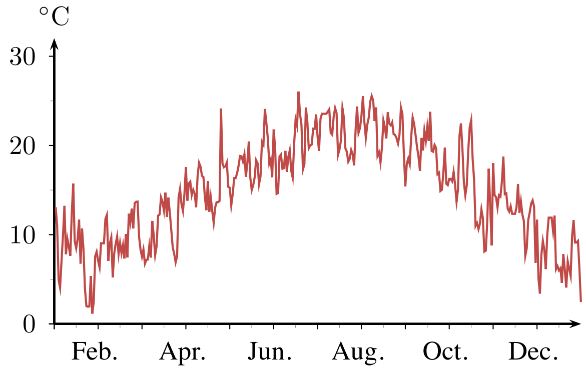

Figure 2: Outdoor temperature at 6 a.m., from January to December 2011

THERMAL COMFORT

Predicted Mean Vote

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 (NF EN ISO 7730 (2006) and ANSI/ASHRAE Standard 55 (2010)). The PMV index quantifies the thermal sensation felt by people in a room and is described by a scale ranging between -3 (cold) and +3 (hot) (Table 2).

Table 2: Thermal sensation scale

PMV VALUE	THERMAL SENSATION
+3	hot
+2	warm
+1	slightly warm
0	neutral
-1	slightly cool
-2	cool
-3	cold

The exchange of heat between the human body and its environment impacts on thermal comfort. Thermal comfort 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:

$$PMV = [0.303 exp^{-0.036M} + 0.028] \times L \quad (1)$$

with L the difference between the heat produced and the heat lost.

$$L = M - W - H_1 - H_2 - H_3 - H_4 - H_5 - H_6 \quad (2)$$

M is the metabolism, which is described below. W is the external work and is considered to be null. H_n are the heat fluxes (W·m^{-2}). H_1 is the heat loss by diffusion through the skin and H_2 is the heat loss by sweating. H_3 and H_4 are the losses by latent and dry respiration, respectively. Finally, H_5 is the heat loss by radiation and H_6 is the heat loss by convection. To calculate these heat losses, several parameters about environment and occupants are taken into account: indoor air temperature (T_{air}), radiant temperature (T_{wall}), relative humidity (HR), air speed (v_{air}), metabolic activity and clothing thermal insulation. It can be noticed that air speed is not calculated by the EnergyPlus^{TM} software. However, this missing information is not critical because air speed has no influence on the PMV value as long as it remains below 0.1 m·s^{-1}. This is mostly the case within the non-residential building we considered as reference building. Moreover, metabolic activity is supposed to be constant and only depends on the considered area. In offices, people work in a sitting position most of the time and, as a result, M is set to 70 W·m^{-2} (i.e. 1.2 met). Activity in the manufacturing area is more dynamic and value is set higher to 116 W·m^{-2} (i.e. 2 met).

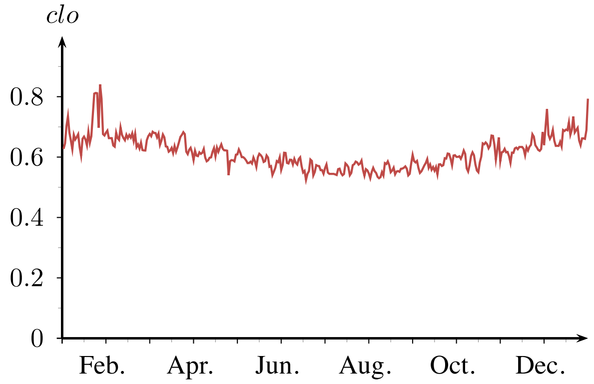

Figure 3: Evolution of clothing thermal insulation from January to December 2011

Besides, clothing thermal insulation is variable and people dress in a different way, according to outdoor temperature. Schiavon and Lee (2013) worked on predictive models to estimate clothing thermal insulation (noted *ICL*). Clothing insulation is defined, each day, according to outdoor temperature at 6 a.m. (t_6), as shown in table 3.

Table 3: Clothing thermal insulation

INTERVAL	***ICL* VALUE** (clo)
$t_6 < -5°C$	1
$-5°C \leq t_6 < 5°C$	$0.818 - 0.0364t_6$
$5°C \leq t_6 < 26°C$	$10^{-0.1635-0.0066t_6}$
$t_6 \geq 26°C$	0.46

According to theses equations, clothing thermal insulation varies from 0.58 clo, during winter time, to 0.46 clo, during summer time. Figure 3 depicts the way clothing thermal insulation evolved between January and December 2011. Usual clothes for summer are a pant with a short-sleeved shirt, while during winter, usual clothes are a trouser with a long-sleeved shirt. Looking at figure 2, the result seems to be realistic. We can highlight that the 2011 winter was mild, so the clothing thermal insulation was moderate. At the end of January, temperature has strongly decreased and the algorithm has automatically adjusted the clothing thermal insulation value.

Control of thermal comfort

The air temperature set-point T_{air}^{sp} is adjusted by the HVAC sub-system to maintain an adequate thermal comfort in the manufacturing area. A desired value for the PMV index (PMV_{sp}) has to be reached, that is why we need to estimate the necessary air temperature T_{air} from T_{wall}, HR, v_{air} and M. Because of the complexity as well as the nonlinearity of the PMV equation, one can not solve this equation in an analytical way to find the appropriate air temperature. Thus, numerical methods are used to solve equation 3. Next, T_{air}^{sp} is set according to the computed value of T_{air}.

$$PMV(T_{air}, \theta) = PMV_{sp} \quad (3)$$

with θ bringing together T_{wall}, HR, v_{air}, and M and PMV_{sp} the PMV set-point from which we computed the air temperature set-point T_{air}^{sp}.

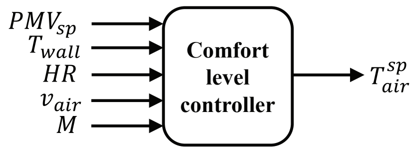

Figure 4: Control of thermal comfort

Different iterative methods have been tested with the aim of finding the fastest and the most efficient one. The standard algorithms we tested will not be detailed here. The stopping criterion is a tolerance of 0.05°C for T_{air}. First, we used the binary search algorithm. The number of iterations is related to the desired accuracy, given that convergence is linear. The initial values of the minimal and maximal thresholds were set to 15 and 30°C, respectively. At each iteration, the gap around the solution is reduced until it is lower than the desired accuracy. The second algorithm used is the Newton–Raphson method. The solution is computed, applying a correction term defined as the ratio between the function and its derivative. Since it is not possible to find the derivative analytically, it is approximated. The initial value was set to 20°C. The main advantage of the Newton-Raphson method lies in its quadratic convergence. The third algorithm we considered is the secant method. It is quite similar to the Newton–Raphson method, but uses a specific equation to approximate the derivative, based on the two previous values. The initial values were 20°C and 25°C.

Table 4: Evaluation of the tested algorithms

METHOD	NUMBER OF ITERATIONS	COMPUTATION TIME (ms)
Binary search	9	4.6
Newton-Raphson	2-3	5
Secant	4-5	2.4

Table 4 summarizes the performance results we obtained using these three methods. Although the Newton-Raphson method needs three time less iterations to reach the solution than the binary search algorithm, computation time is similar. Slowness is due to the PMV index being calculated three times per iteration instead of only one time with the binary search algorithm. With the secant method, convergence is slightly slower but the PMV index is computed only once per iteration. As a consequence, computation time is reduced by half and the secant method has been chosen among the three methods we tested.

IDENTIFICATION OF A LINEAR MODEL

PMV model of reduced order

In order to maintain the PMV index in the desired interval using a predictive control approach, a model of the system to be controlled is required. So, a real-time model that links the PMV index and (i) outdoor temperature (T_{out}), (ii) solar radiation (SR) and (iii) internal heat gain (IG) has been identified. Internal heat gain deals with the heat generated by people in a room (metabolism) and devices (mainly lighting and electrical devices). The heating system is indirectly taken into account via the air temperature set-point (T_{air}^{sp}). Figure 5 depicts the input/output model we proposed.

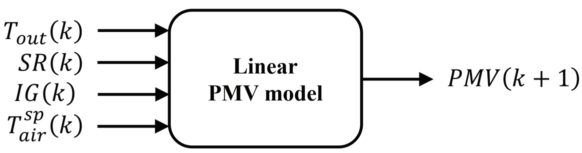

Figure 5: PMV linear model

State-space model

As previously mentioned, the proposed management solution has to be computationally tractable. Indeed, it will be implanted in an embedded system that will control the different areas of a building (let us remember that we focus here on the manufacturing area). So, a model with reduced order is needed to carry out simulation on such a platform. However, identification will be realized using a remote server, which has more powerful computing capabilities. The chosen model is a state-space model which is equivalent to a linear transfer function. We considered a n-order space model, i.e. a discrete MISO (Multiple Input/Single Output) system defined as follows:

$$\begin{cases} x_{k+1} = Ax_k + Bu_k \\ y_k = Cx_k \end{cases} \tag{4}$$

where $A \in \mathbb{R}^{n\times n}$, $B \in \mathbb{R}^{n\times r}$ and $C \in \mathbb{R}^{1\times n}$. n is the system order and r the number of inputs. $u_k \in \mathbb{R}^{r\times 1}$ is the command vector at instant k while $x_k \in \mathbb{R}^{n\times 1}$ is the state vector. $y_k \in \mathbb{R}$ is the system output.

Identification

To find the optimal parameters of the model (matrix A, B and C), an identification phase is necessary. So, a dataset has been generated using the EnergyPlus™ model of the considered non-residential building. Let us note that in a real building, identification will be carried out directly from measurements provided by the Pyrescom monitoring system, without using the thermal model of the building. Using generated (or measured) data, identification is achieved using Matlab® and the N4SID (Numerical algorithm for Subspace State Space System IDentification) algorithm, based on the work of Overschee and Moor (1994). In the present work, we used eight weeks of data to identify the model parameters.

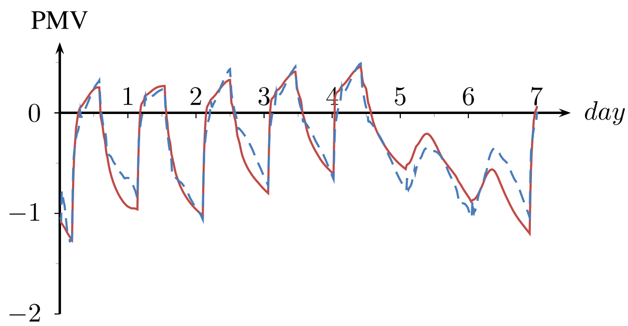

Figure 6: PMV index estimation. The red solid line is the PMV index given by EnergyPlus and the blue dashed line is the fitted PMV index (linear model)

We obtained the best fitting results with a 4-order model. Models of a higher order of complexity led to over-estimated parameters, oscillations and a decreasing accuracy. In opposition, models of a lower order of complexity led to under-estimated parameters and a low accuracy. The identification process was performed in 21 seconds, so it can be handled by a remote server. Figure 6 shows PMV values given by EnergyPlus™ and the developed linear model. The temperature set-point is set to 22°C during occupancy. The FIT is 73.8%, the Mean Relative Error (MRE) is 6.6% and the Mean Absolute Error (MAE) is 0.11. Table 5 shows the time constant of each pole and zero of the identified linear model.

Table 5: Poles and zeros of the identified linear model (: two conjugated roots)*

ROOTS	**TIME CONSTANT** (seconds)	**TIME CONSTANT** (hh:mm:ss)
Poles	830 *	0:13:51
	29221 *	8:07:02
Zeros (T_{out})	786	0:13:06
	2543596 *	706:33:16
Zeros (S_R)	7767	02:09:28
	37055 *	10:17:35
Zeros (T_{sp})	1485	0:24:45
	1801	0:30:01
	21125	5:52:05
Zeros (I_G)	704	0:11:45
	700152 *	194:29:13

State observer

In order to perform a simulation with the state-space model (a forecasting of the PMV index over the prediction horizon), the model has to be initialized correctly. That is why we used a state observer to keep the model as close as possible to the state of the real system. By using a state observer, one can avoid divergence due to perturbations or non-modelled dynamics. So, the observer allows estimating the state vector $\hat{x}_k$ from measured inputs (u_k) and outputs (y_k) (equation 5):

$$\begin{cases} \hat{x}_{k+1} &= A\hat{x}_k + Bu_k + K(y_k - \hat{y}_k) \\ \hat{y}_k &= C\hat{x}_k \end{cases} \quad (5)$$

with $\hat{y_k}$ the output rebuilt by the observer and $K \in \mathbb{R}^{n\times 1}$ its gain matrix. The gain matrix K is computed to obtain a new system with poles 10 times faster than those of the identified linear model.

PREDICTIVE CONTROL STRATEGY

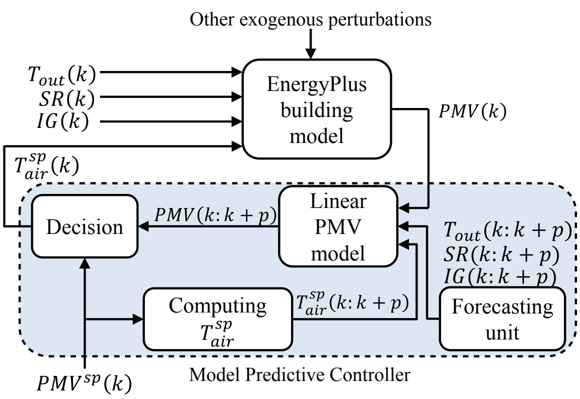

Figure 7: The proposed predictive control strategy

The proposed predictive strategy is summarized by figure 7. EnergyPlus™ is used to simulate the behaviour of the real non-residential building we considered as reference building. The controlled output is the PMV index. The proposed Model Predictive Controller (MPC) uses the identified linear model to perform some predictions and to optimize the way the heating system will operate (when it will be turned on and off), taking into account the constraints about thermal comfort during occupancy. The controller computes the HVAC air temperature set-point (the manipulated input). The state observer is used to initialize correctly the state vector of the internal model before each prediction. Based on previous day values, the forecasting unit estimates the considered exogenous disturbances (T_{out}, SR and IG). As previously mentioned in the paper, thermodynamic simulations are carried out using EnergyPlus™ with MPC set-point values computed by Matlab®. These two softwares are interfaced using the MLE+ toolbox (Nghiem, 2010). In real buildings equipped with HVAC systems, EnergyPlus™ simulations are no more needed. As a first approach, only the manufacturing area is considered. In the other rooms, the HAVC sub-systems are turned off. To assess performance, energy consumption and thermal comfort during occupancy periods are considered. The main objective is to satisfy thermal comfort requirements when people work in the manufacturing area and to avoid enegy waste during the rest of the time. The thermal comfort interval is defined on the basis of a PMV value ranging between -0.5 and 0.5. The temperature set-point is so computed with a PMV index equal to zero. In real buildings, these parameters will be adjusted in real time, according to the thermal sensation of the workers. With the proposed strategy, one can optimize the way the HVAC sub-system switches from one operation mode to another. Figure 8 depicts the predictive algorithm used. As mentioned above, the sampling time is 15 minutes. First, the air temperature set-point is computed to set the PMV set-point ($PMV_{sp} = 0$). Moreover, the state of the state-space model is defined by the observer. Depending on occupancy, two cases are possible:

(i) When the manufacturing area is occupied ($Z(k) = 1$), we want to turn off the HVAC sub-system as soon as possible while ensuring that thermal comfort will meet requirements until all the people leave the room, taking into account its thermal inertia. The HVAC sub-system is considered to be turned off ($HVAC(k : k + p/k) = 0$) along the forecasting horizon while outdoor temperature, solar radiation and internal gain (exogenous disturbances) are estimated on the basis of previous day values. The PMV index is forecasted using the proposed linear model. As long as the manufacturing area is occupied, the predictive algorithm checks if thermal comfort requirements are satisfied $(PMV(k : k + i/k) > -0.5) \wedge (PMV(k : k + i/k) > 0.5)$. If the constraints are not met, it means that the HVAC sub-system must not be turned off now and, as a result, the air-temperature set-point is set to the value initially computed. When the manufacturing area is no more occupied ($Z(k+i/k) = 0$), thermal comfort is necessarily satisfied and the HVAC sub-system is turned off ($HVAC(k) = 0$).

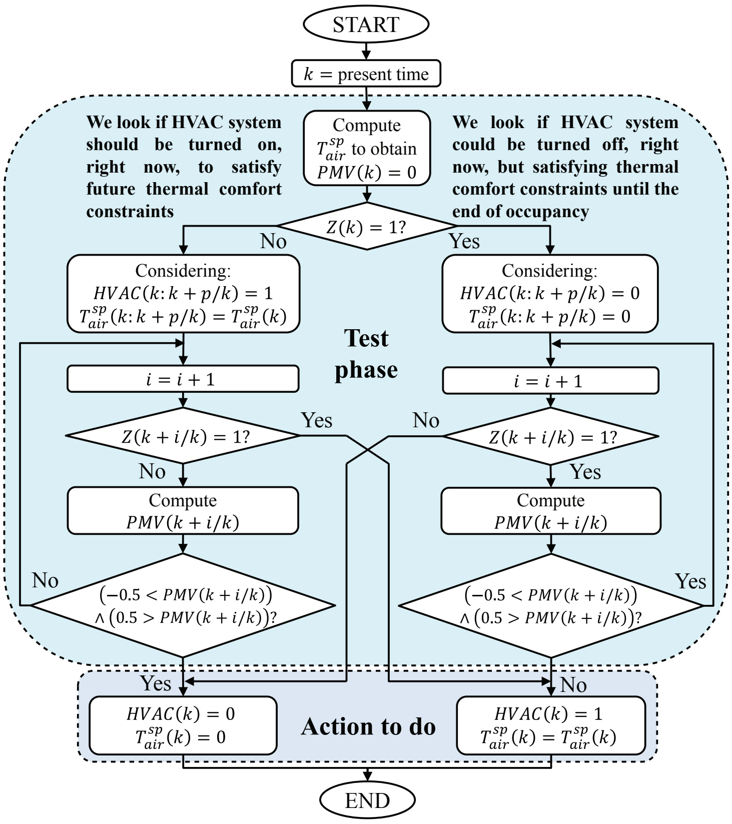

Figure 8: Predictive control algorithm

(ii) When the manufacturing area is empty ($Z(k) = 0$), the algorithm searches for the last moment to turn on the HVAC sub-system. The optimal instant to switch on the system is defined as the instant allowing thermal comfort requirements to be met at the time the first worker arrives in the manufacturing area. If thermal comfort is ensured at least two sample times before the first worker arrives, decision is delayed and the sub-system is switch off for now ($HVAC(k) = 0$). If thermal comfort is not ensured at least one sample time before the first worker arrives, the sub-system is switched on ($HVAC(k) = 1$) and the air temperature set-point initially computed is used.

RESULTS

This section of the paper focuses on the results we obtained with the predictive strategy we proposed to manage zoned HVAC systems in non-residential buildings. To evaluate performance dealing with thermal comfort, we considered the percentage in time for which the PMV value is between -0.5 and 0.5, the manufacturing area being occupied. This percentage is directly related to constraints satisfaction. The average value of the PMV index is already computed to evaluate the thermal sensation of people in the manufacturing area. Moreover, energy consumption is calculated. With these criteria, one can compare the proposed predictive strategy with non-predictive ones. Finally, the time needed to compute the air temperature set-point is recorded and allows computation requirements to be evaluated. The results are grouped in table 6.

Non-predictive strategies

In the real building, for now, the zoned HVAC system is always turned on and the air temperature set-point remains the same ($T_{air}^{sp} = 22°\mathrm{C}$) during daytime, nighttime and week-end periods. This is the reference scenario (S1). With this scenario, thermal comfort is good (the average PMV index is very close to zero) and constraints are always met. Figure 9 (a) depicts the way the PMV index (top) and power consumption (bottom) evolves. S2 allows the same strategy to be applied but using a PMV set-point, instead of an air-temperature set-point. So, T_{air}^{sp} is adjusted at each time step, what requires $2.4\,\mathrm{ms}$ to be calculated. Again, the average PMV index is very close to zero and the percentage in time for which the PMV value is between -0.5 and 0.5 (the comfort criterion) is 100%. As an other option, we used a scheduler to turn off the HVAC sub-system during the night and week-ends and to turn it on in the morning, two hours before people arrive in the manufacturing area. Two hours is a standard amount of time for heating the building. On this basis, we defined two more scenarios: S3 (air temperature set-point) and S4 (PMV set-point). The results we obtained highlight a significant decrease in energy consumption: -49% ($-204\,\mathrm{Wh/day{\cdot}m^2}$) with S3 and -42.5% ($-177\,\mathrm{Wh/day{\cdot}m^2}$) with S3, taking as a reference the results we obtained with S1. However, comfort is not quite as good (-2%). As it can be no-

Table 6: Results for the strategies performance from January to February 2011. (C) is Continuous strategy, (S) is Scheduler operating mode and (P) is Predictive strategy

	OCCUPANCY SET-POINT	VACANCY SET-POINT	CONSUMPTION (Wh/day·m^2)	COMFORT CRITERION	AVERAGE PMV	COMPUTATION TIME (ms)
S1 (C)	$T_{air}^{sp} = 22°C$	$T_{air}^{sp} = 22°C$	416	99.8%	0.05	0
S2 (C)	$PMV = 0$	$PMV = 0$	412	100%	0.01	2.4
S3 (S)	$T_{air}^{sp} = 22°C$	OFF	212	97.7%	-0.20	0
S4 (S)	$PMV = 0$	OFF	239	98.0%	-0.03	2.4
S5 (P)	$PMV = 0$	OFF	231	99.3%	-0.05	3 to 5

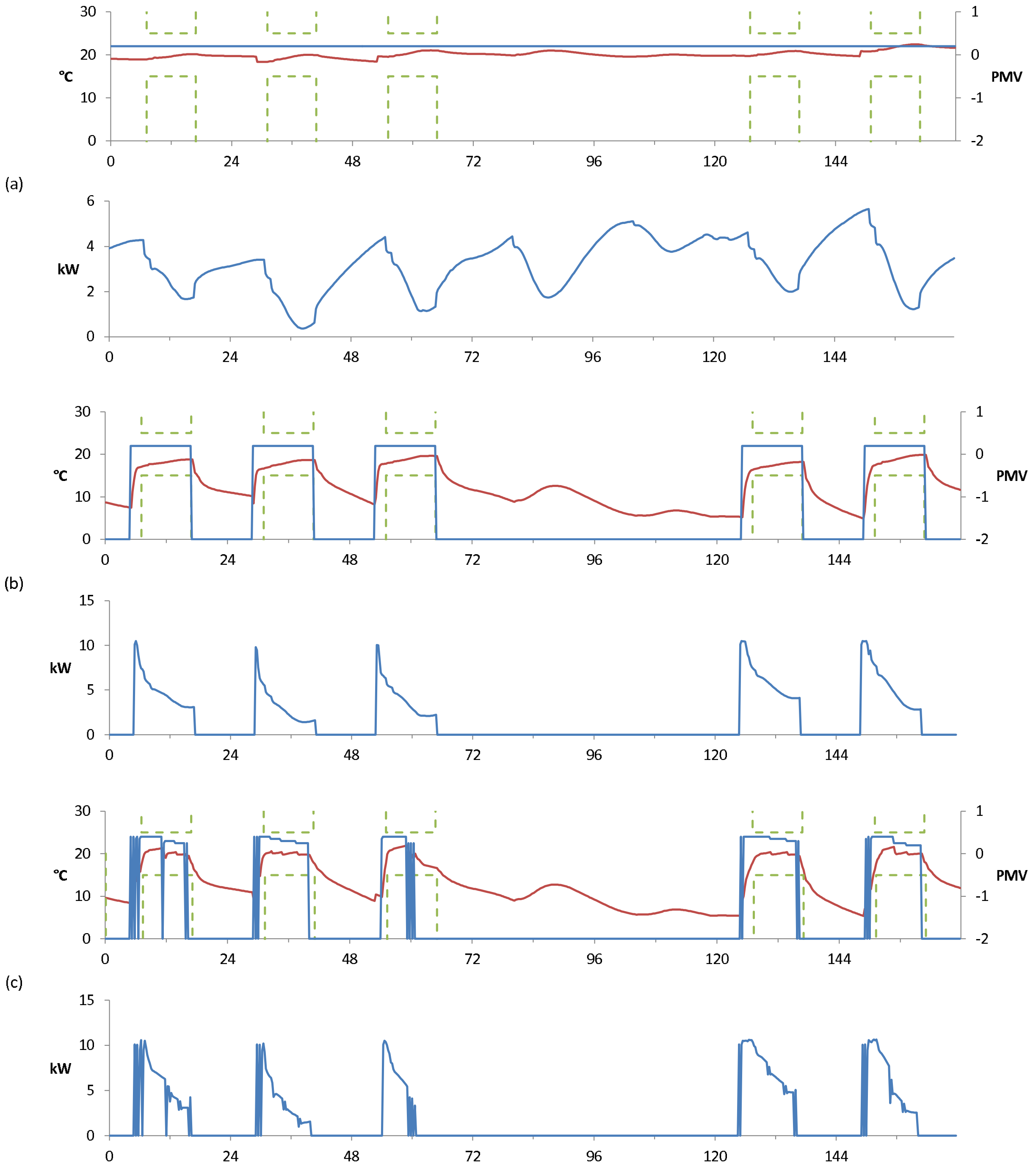

Figure 9: (a) Scenario S1, (b) Scenario S3, (c) Scenario S5. Simulation is from January 26 to February 1st, 2011. Top: Indoor temperature set-point (blue line), PMV index (red line) and thermal comfort constraints (green dashed line). Bottom: Power consumption (blue line)

ticed in figure 9 (b), S3 suffers from a lack of flexibility. Some days, thermal comfort is reached too early, what leads to energy waste. Sometimes it is reached too late. In this case, thermal comfort is not ensured.

Predictive strategy

With the proposed predictive strategy (scenario S5), the above-mentioned problem is solved. Indeed, as it can be seen in figure 9, anticipation is related to the considered day. During cold days or after week-ends, anticipation time is longer than in case of warm days. Thermal comfort requirements are just met when the first worker arrives at the building in the morning. As a result, energy waste is low and thermal comfort is very good. The HVAC sub-system is switched off at the end of the day, some hours before occupancy ends. This allows energy savings without impacting (negatively) thermal comfort. During warmer weeks, the predictive strategy has other advantages. Anticipation time is shorter than when using the scheduler and the HVAC sub-system is often turned off at the end of the morning, what allows big energy savings during the afternoon. Thermal comfort requirements are met until the last worker leaves the building. Energy consumption is reduced of about 44.5% ($-185\,\mathrm{Wh/day{\cdot}m^2}$) and 43.9% ($-181\,\mathrm{Wh/day{\cdot}m^2}$), in comparison to the results we obtained with strategies S1 and S2, respectively. Thermal comfort is quite identical. In addition, energy consumption is similar than when using the scheduler but thermal comfort is always better. Finally, this predictive strategy has a low-computational cost. Only 3 to 5 ms more are needed than with S1 or S3. As a result, the algorithm can be implanted in an embedded system.

CONCLUSION

This paper focuses on a predictive strategy used to manage energy consumption as well as thermal comfort in non-residential buildings. In order to test the proposed strategy in simulation, we modelled a building located in Perpignan (south of France). As a first approach, only the manufacturing area has been considered. We used the Predicted Mean Vote (PMV) index as a thermal comfort indicator. The strategy is computationally tractable and the developped algorithms can be implanted in an embedded system, what is the main objective of the Batnrj project (supported by the Pyrescom company). As a key point, it clearly appears, when comparing the results we obtained in simulation with the proposed predictive approach and the results given by different standard (non-predictive) strategies, that predictive control offers a significant gain in energy consumption reduction and thermal comfort satisfaction. The predictive strategy allows the HVAC sub-system to be turned on and off at the right time. As a result, the system is turned on a few hours before the next occupation period to satisfy thermal comfort requirements (when people come to the building) and is turned off before people leave the building to reduce energy consumption. Future work will focus on applying the proposed predictive strategy to all the occupied rooms of the building. Then, this strategy will be tested in real buildings. Finally, a predictive controller with on-line optimization carried out by a dedicated remote server will be developed.

ACKNOWLEDGMENT

The authors want to thanks the Pyrescom company for its financial support. Jean-Michel Cabanat and Cédric Calmon are acknowledged for their technical help.

REFERENCES

ANSI/ASHRAE Standard 55 2010. Thermal environmental conditions for human occupancy.

Endravadan, M. 2006. *Régulation des systèmes de chauffage et de climatisation basée sur la sensation thermique humaine. Impact sur la consommation d'énergie dans les bâtiments*. PhD thesis, University of Toulouse 3.

Fanger, P. O. 1973. Assessment of man's thermal comfort in practice. *British Journal of Industrial Medicine*, 30(4):313–324.

Henninger, R. H. and Witte, M. J. 2012. Energyplus testing with global energy balance test. Technical report, U.S. Department of Energy, Energy Efficiency and Renewable Energy, Office of Building Technologies.

Moroşan, P.-D., Bourdais, R., Dumur, D., and Buisson, J. 2010. Building temperature regulation using a distributed model predictive control. *Energy and Buildings*, 42(9):1445 – 1452.

NF EN ISO 7730 2006. Détermination analytique et interprétation du confort thermique par le calcul des indices PMV et PPD et par des critères de confort thermique local.

Nghiem, T. X. 2010. MLE+: a Matlab-EnergyPlus co-simulation interface. www.seas.upenn.edu/ nghiem/mleplus.html.

Overschee, P. V. and Moor, B. D. 1994. N4SID subspace algorithms for the identification of combined deterministic-stochastic systems. *Automatica*, 30(1):75 – 93.

Pérez-Lombard, L., Ortiz, J., and Pout, C. 2008. A review on buildings energy consumption information. *Energy and Buildings*, 40(3):394 – 398.

République Française 2006. Arrêté du 24 mai 2006 relatif aux caractéristiques thermiques des bâtiments nouveaux et des parties nouvelles de bâtiments.

Schiavon, S. and Lee, K. H. 2013. Dynamic predictive clothing insulation models based on outdoor air and indoor operative temperatures. *Building and Environment*, 59(0):250 – 260.