Model predictive control of a thermally activated building system to improve energy management of an experimental building: Part II - Potential of predictive strategy

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A B S T R A C T

Thermally Activated Building Systems (TABS) are difficult to control due to the time lag between the control sending and the response of the indoor temperature. Energy management of systems having such a high inertia can be improved by optimizing the restart time thanks to both occupancy and weather anticipation. Predictive control is suitable for systems with numerous constrained inputs and outputs whose objective function varies over time such as buildings with intermittent occupancy. This work proposes to use a Model Predictive Control (MPC) for one TABS in particular: a floor heating system (FHS) of an experimental building. Conventional control techniques and a state of the art on the predictive control of FHS are presented. A complete control loop (sensor, actuator, controller) was implemented on an experimental room. The predictive controller that integrate the model selected in Part I is compared with two conventional control strategies. The energy saving potential of the predictive controller is confirmed by both local experimentation and simulation on three climates. The energy saving is close to 40% over the whole heating season with an improved or equivalent comfort situation compared to the other two reference strategies. The absolute gain is constant over the heating period but the most significant relative gains are obtained in the mid-season.

1. Introduction

The importance of control in the building energy performance is often underestimated. The on/off, PI or PID regulators are suitable to follow a constant setpoint but the use of intermittent scenarios is more appropriate to decrease energy expenditure. Conventional regulators may not be always suitable for transient state control of systems having some inertia such as buildings. The principle of closed-loop control is based on the feedback of the controlled value. When the control of a high inertia system (time delay) is desired, conventional control techniques based on a fast system response are no longer sufficient. TABS are used in a « passive » way for basic heating in buildings with intermittent heating. Intermittence is often managed by an additional heating system whose use could be limited by a finer control of the TABS. In this work, attention is focused on the predictive control of a FHS, which is the most widespread TABS. Over the last decade, FHS have become popular thanks to low-temperature boilers suited to the operating temperatures of this system. A FHS can be used:

- alone to ensure a comfort temperature during the day with an idle at night, this scenario mainly concerns the individual dwellings,
- with an auxiliary system to permanently ensure a basic temperature while the auxiliary heating system ensures the comfort temperature during the day.

A FHS is an efficient system but delicate to control. The heating power of a FHS is generally modulated depending on outdoor conditions by using a « heating curve » giving the correspondence between the water supply temperature T_{ws} and the outside temperature T_e (Fig. 1). The principle is to compensate the heat losses through envelope which depends on the inside/outside temperature difference. Thus, the water supply temperature of the floor varies constantly. Losses evolve almost linearly with the temperature difference and the heating curve is a straight line. The slope depends on the characteristics of the envelope, the desired comfort temperature and the size of the floor. This regulation is therefore based on a continuous measurement of the outside temperature. A typical FHS installation includes the following elements:

- an outdoor temperature sensor located north and protected from direct sunlight,

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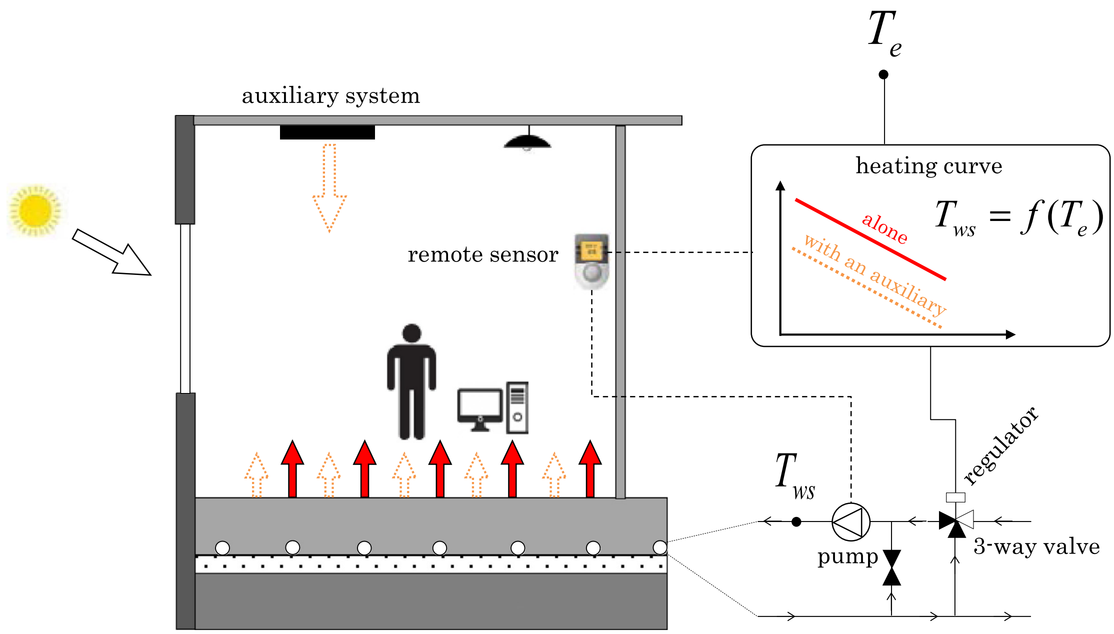

Fig. 1. Classical FHS regulation.

Nomenclature

Variables, parameters, abbreviations

AHU	Air Handling Unit
BEMS	Building Energy Management System
C	thermal capacitance (J.K^{-1})
C_p	specific heat capacity (J.kg^{-1}.K^{-1})
Dh	Degree-hour (°C.h)
UDD	Unified Degree-day (°C.day)
E	energy consumption (kWh)
FCU	Fan Coil Unit
FHS	Floor Heating System
I	interval
IG	free internal gains (kWh)
J	cost function
L	heat losses
m	control horizon
$\dot{m}$	mass flow (kg.s^{-1})
MPC	Model Predictive Control
p	prediction horizon
PID	Proportional-Integral-Derivative
P	power (W)
r	setpoint
R	thermal resistance (m².K.W^{-1})
T	temperature (°C)
TABS	Thermally Activated Building Systems
w	weight

Subscripts

c	controllable
$comf$	comfort
e	exterior
eco	economic
i	interior
nc	uncontrollable
tot	total
wr	water return
ws	water supply

Vectors and matrices

A	state matrix
B	input matrix
C	output matrix
D	feed through matrix
X	state vector
U	vector of inputs
Y	output vector

- a three-way valve adjusting the water supply temperature by mixing the water coming from the boiler and the water return temperature,
- a pump for water circulation in the pipes,
- an indoor temperature sensor, also known as « remote sensor », which is often required to prevent overheating due to occupants or solar gains.
- a regulator acting on the position of the three-way valve to adjust the water supply temperature according to the measurement of the outside temperature. The regulator can shut down the pump or modify the heating curve if the setpoint is reached thanks to a remote sensor.

The major part of FHS are used in the residential sector. A study by the National Union of Manufacturers of Components and Integrated Heating Systems (COCHEBAT) reveals that 40% of new homes in France are equipped with a FHS [1]. These systems are effective when the settings are appropriate. Nevertheless, the control is based on real-time measurements and is not able to anticipate the future disturbances. The potential of such a system can therefore be further improved by adding intelligence using a Model Predictive Control (MPC) technique.

First, a state of the art introduces the various research studies carried out on the predictive control of TABS. The following section presents the method to show the potential of a predictive strategy on the experimental room. The used equipment, measured values and control logic are presented. Finally, the experiment and the simulation results of the comparison between two reference strategies and the predictive control are presented in order to conclude on the relevance of such control.

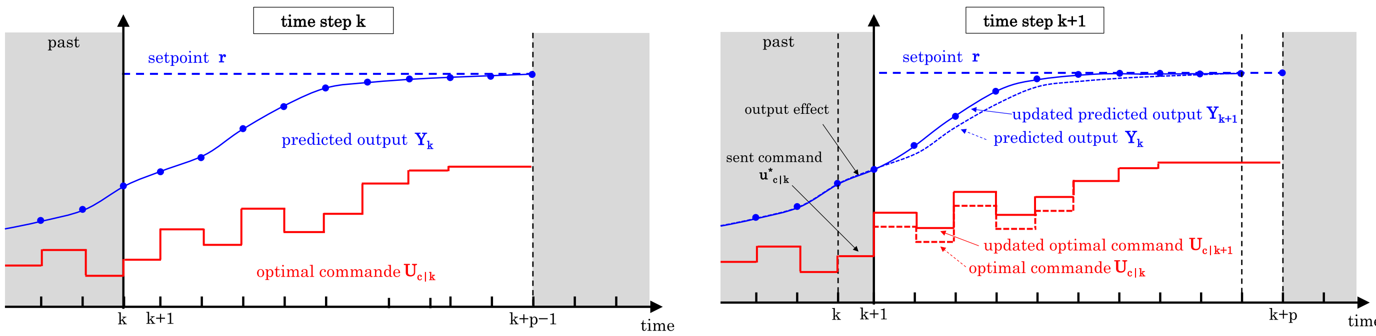

Fig. 2. MPC and receding horizon principle with $m = p$.

2. Principle and state of the art on predictive control technics for FHS

MPC is a control technique based on the optimization of a constrained problem. Controllable inputs and outputs are predicted by a model in order to fulfill an objective described by a function. The model is at the core of the MPC logic. It predicts the behavior of the system to be controlled and chooses an optimal trajectory. Feedback is provided by repeating this procedure at each time step. This controller comprises:

- a prediction model: describes the thermal behavior of the building subjected to controllable and uncontrollable inputs,
- a setpoint: the desired interior temperature,
- constraints: the available maximum power, rate of descent/climb,
- disturbances: forecasts of uncontrollable inputs (weather, occupation),
- a cost function: constraint on the indoor temperature (comfort criterion) and on energy consumption (economic criterion).

First, we must choose a model and define a cost function. These choices are not independent since the model depends on the objective. As specified by Kouvaritakis and Cannon [2], an MPC control is based on prediction, optimization and receding horizon principle. The output sequence of the model Y_k is predicted by the simulation at each time step k with a state model (Eq. (1)). The vector U_k contains the m controllable inputs to be optimized $U_{c|k}$ and the n uncontrollable predicted inputs $U_{nc|k}$ (Eq. (2)) for a prediction horizon corresponding to p times the sampling period (Eq. (3)). The feedback is ensured by optimizing the controllable inputs that minimize the cost function at time step k over the prediction horizon (Eqs. (4) and (5)). The term $J_{y|k}$ allows the n_y number of model outputs y to follow their respective setpoint r, which are assumed to be known. The term $J_{u|k}$ ensures that the n_c number of control variables u remain within their range constrained by the user. Similarly, the term $J_{\Delta u|k}$ constrains the variation of the control variables between two time steps (Eq. (6)). Weights w^y, w^u, $w^{\Delta u}$ are assigned respectively to outputs, commands and command variations. The scalars s^y, s^u, $s^{\Delta u}$ allow to respect the homogeneity. The cost function depends on $U_{c|k}$ and the optimal control sequence denoted $U^*_{c|k}$ is determined by minimizing J_k (Eq. (7)). The command u_c sent to the actuators corresponds to the first element $u^*_{c|k}$ of the optimal control $U^*_{c|k}$ (Eq. (8)). The minimization of the cost function is repeated at the next time step with the same prediction horizon that moves according to the principle of receding horizon (Fig. 2).

$$\begin{cases} X_{k+1} = AX_k + BU_k \\ Y_k = CX_k + DU_k \end{cases} \tag{1}$$

$$BU_k = B_c U_{c|k} + B_{nc} U_{nc|k} \tag{2}$$

$$U_k = \begin{bmatrix} u_{1,c|k} & & u_{m,c|k} & u_{1,nc|k} & & u_{n,nc|k} \\ u_{1,c|k+1} & & u_{m,c|k+1} & u_{1,nc|k+1} & & u_{n,nc|k+1} \\ \vdots & \cdots & \vdots & \vdots & \cdots & \vdots \\ u_{1,c|k+p-1} & & u_{m,c|k+p-1} & u_{1,nc|k+p-1} & & u_{n,nc|k+p-1} \end{bmatrix} \tag{3}$$

$$J_k = J_{y|k} + J_{u|k} + J_{\Delta u|k} \tag{4}$$

$$\begin{cases} J_{y|k} = \sum_{j=1}^{n_y} \sum_{i=1}^{p} \frac{w^y_{i,j}}{s^y_{i,j}} \cdot (r_{j|k+i} - y_{j|k+i})^2 \\ J_{u|k} = \sum_{j=1}^{n_u} \sum_{i=0}^{p-1} \frac{w^u_{i,j}}{s^u_{i,j}} \cdot (u_{j|k+i} - u_{j,target|k+i})^2 \\ J_{\Delta u|k} = \sum_{j=1}^{n_u} \sum_{i=0}^{p-1} \frac{w^{\Delta u}_{i,j}}{s^{\Delta u}_{i,j}} \cdot (u_{j|k+i} - u_{j|k+i-1})^2 \end{cases} \tag{5}$$

$$\begin{cases} \underline{U} \le U_k \le \overline{U} \\ \underline{\Delta U} \le \Delta U_k \le \overline{\Delta U} \\ \underline{Y} \le Y_k \le \overline{Y} \end{cases} \tag{6}$$

$$U^*_{c|k} = \arg\min J_k \tag{7}$$

$$u_c = u^*_{c|k} \tag{8}$$

The choice of the sampling time step T_{sample} depends on the desired application. A low sampling period allows a better rejection of unknown disturbances. However, its value also depends on the dynamics of the model since the smaller the sampling period is, the greater is the computational effort. It is therefore necessary to make a compromise between the desired performance and the computing power. With a small sampling period it is more difficult to extend the m control horizon as the processor needs to optimize m^*T_{sample} operations. The control horizon corresponds to the number of sampling periods on which the control is optimized at each time step. When m is small, the calculation time is reduced and the control becomes more stable. The choice of the control horizon is of great importance and depends on the supposed dynamic response of the system. For prediction horizon, a small p value can make the control unstable and lose the predictive aspect.

Only a few papers deal with the particular case of a predictive control of a FHS (Table 1). Chen [3] has shown the utility of the MPC for an electric FHS and specifies that conventional control technics cannot compensate the phase shift effect for intermittent heating. The works of Cho and Zaheer-Uddin [4] study the control of the FHS (simulation and experimental) in two test chambers with 28 sensors per room. A forecasting model is used to estimate the future outdoor temperature. The building behavior is described by a polynomial function of the outside temperature. The

Table 1
Papers dealing with MPC involving FHS control.

Autors	Year	Model	Cost function	Simulation/Experiment	Compared strategies	MPC gain	Ref
Chen	2002	Transfer functions	comfort economic	S/E	on/off PI	more stable control	[3]
Cho and Zaheer-Uddin	2003	Polynomial	comfort economic	S/E	schedule + PID	10–20%	[4]
Privara et al.	2010	State-space	comfort economic	S	on/off + PID + heating curve	17–29%	[5]
Verhelst et al.	2011	ODE	comfort economic	S	heating curve + PID	5%	[6]
Karlsson and Hagentoft	2011	2R2C	comfort	S	moving average	relevance for intermittently occupied building	[7]
Candanedo and Athienitis	2012	Transfer functions	comfort economic	S	PID	relevance of connecting thermal solar panels to FHS	[8]
Sourbron et al.	2013	4R2C	comfort economic	S	schedule + PID	7%	[9]
Berthou	2013	6R2C	comfort economic power	S	schedule	5%	[10]
Li et al.	2015	8R4C	comfort economic	S	PID	17%	[11]
Wang et al.	2017	State-space	comfort economic	S	PI	8% smoother temperature transition	[12]

MPC strategy is compared to a setpoint scenario over a three-day winter sequence and shows energy savings of 20% and lower temperature variations. In the works of Privara et al. [5], a radiant ceiling is used but the principle is the same as a FHS. The MPC with a 24 h horizon is compared with three management strategies: an on / off regulator, a weather-compensated control and a PID where the water supply temperature depends on deviation from the setpoint. Energy savings of 29% and better comfort are achieved with the MPC. In the case of Verhelst et al. [6] the FHS is connected to a heat pump. A heating curve is well adapted and effective to ensure comfort, but it does not allow exploiting the thermal capacity of the slab to reduce costs. For this reason the MPC is necessary. The authors point out that reactive systems are often electric heaters which explains why many publications deal with reducing the peak load demand on the network (hourly pricing system). The prediction horizon is also 24 h with a time step of 30 min (48 sequences to optimize). The MPC's use results in a saving of 5% of the energy expended by the compressor. In Karlsson and Hagentoft publication [7], the optimal plan is based on the power injected to the floor, this optimum power is then transformed into a corresponding water supply temperature. The measurement of the water return temperature allows compensating forecasting errors. In the works of Candanedo and Athienitis [8] and Li et al. [11], the FHS is connected to a solar thermal panel. A simplified building model is obtained from a detailed model. The studied room has a large glazed area and is well insulated. The comparison between the MPC and a PID control is performed using Matlab/Simulink. The results are conclusive for the tested building. The paper of Sourbron et al. [9] deals with the influence of uncertainties on the quality of predictive control in the case of a FHS coupled with additional fan coil units. The quality of the control decreases with the uncertainties: measurement error, prediction error and model error. The impact of these errors is evaluated on three criteria: energy consumed by the FHS, by fan coil units and comfort. The authors highlight the potential of coupling slow and fast systems but warn about important parameters. Thus the initial temperature of the floor is paramount. Berthou [10] compares three strategies of optimization:

- restart time optimization: the energy price is constant and the optimization is done on the value of the idle temperature setpoint, this strategy allows up to 20% of energy saving,
- price optimization: the price of energy varies and heating control is anticipated to store heat when the energy is cheap. The economic gain is about 8%,
- power optimization: the power peak is limited by optimization and reduced by 50%.

In the works of Wang et al. [12], a MPC strategy is used to keep the room within a range of temperature through the control of a FHS connected to an air/water heat pump. The energy consumption is reduced by 8% compared to a PI control. The bibliography confirms that predictive control is the most interesting technique compared to conventional ones for temperate climates and buildings/systems with important inertia.

3. Potential of a predictive control strategy applied to an experimental building

To confirm the conclusion of the state of the art section, the MPC strategy is compared with two conventional management strategies on the experimental room involving three systems (see Part I): a FHS, three fan coil units (FCU) and a dual flow air handling unit (AHU).

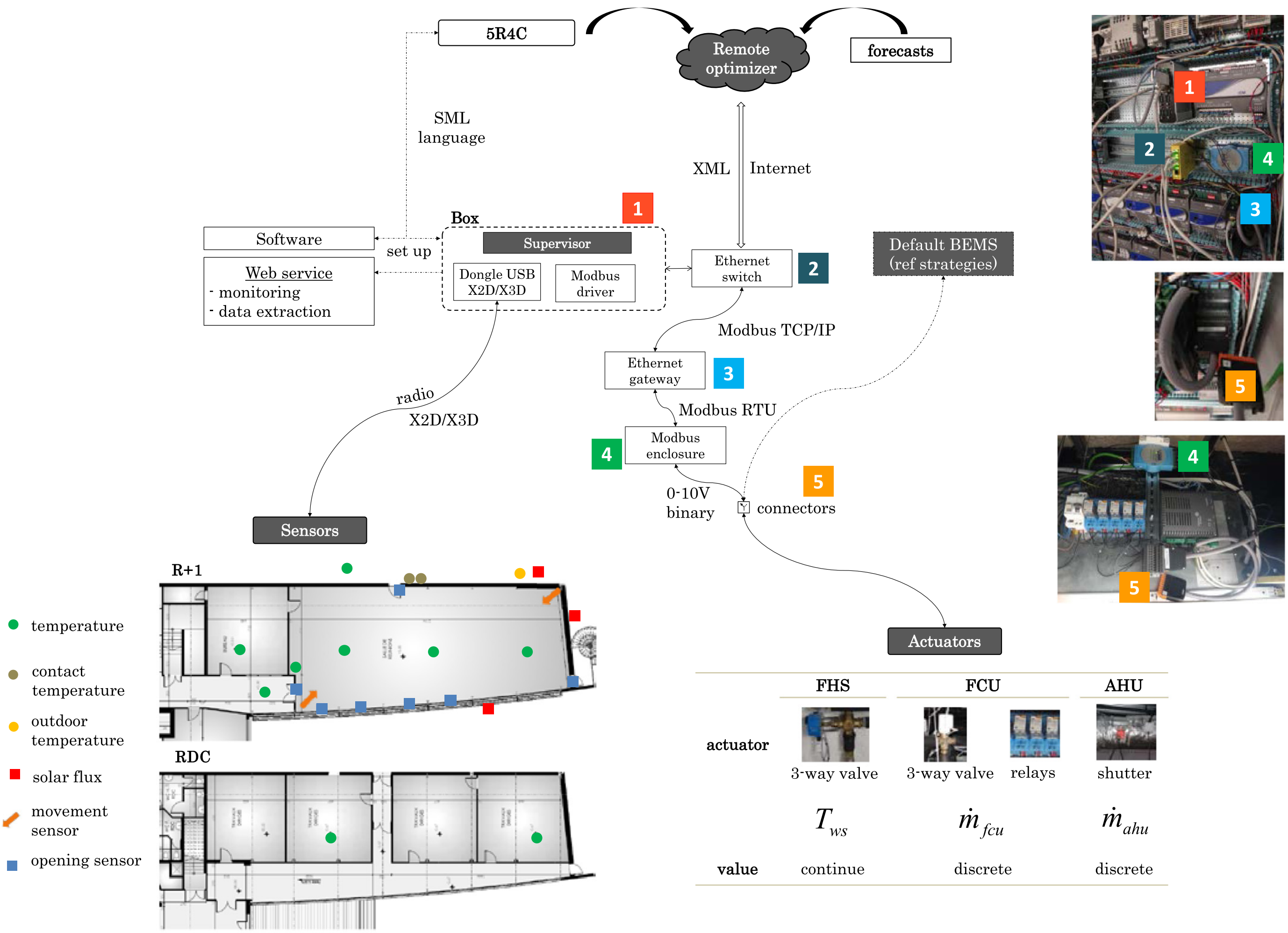

Fig. 3. Complete control loop architecture.

3.1. Experimental setup

A complete control structure was developed for the implementation of predictive control. Additional instrumentation was added and a box with an optimizer was set up with a partner company. Fig. 3 shows the general architecture of the installation:

- a set of **sensors** is installed in parallel with the existing ones, which allows to know the state of the building (temperature), the external conditions (temperature, solar radiation) and occupants' behavior (presence, windows/doors openings). Some sensors are used directly for the control while others are only used for information purposes to explain unexpected phenomena (opening sensors, temperature sensors in adjacent rooms). Three temperature sensors allow to have an idea of the heterogeneities in the volume of the room. The outdoor temperature sensor is placed on the roof above the workshop and protected from solar radiation. The three solar flux sensors are placed on a mat and oriented in the south, west and east directions respectively. They can measure the global solar hemispheric flux. The supply and return water temperatures of the FHS are measured by two contact temperature sensors placed between the copper pipe and the insulating sheath. Two movement sensors located in the opposite corners are used to detect the occupants for FCU and AHU control,
- **actuators** already installed for the default building energy management system (BEMS) act on the systems. The water supply temperature of the FHS is regulated by the opening of a three-way valve. FCU are also supplied with hot water through the opening of a three-way valve but the temperature is imposed and the blowing temperature is approximately 35 °C. The power control is done with the blowing speed which can vary between three positions thanks to electrical relays. For the AHU, the flow is imposed by the standard [13]. It is set at 1080 $m^3\ h^{-1}$ (18 $m^3\ h^{-1}$.occupant^{-1}). This flow is mechanically controlled by a shutter,
- a **box** centralizes the information of the sensors and sends the commands to the actuators. It ensures the reactive layer (FCU/AHU) but also the predictive layer (FHS) by application of the optimal control sequence received from the remote optimizer. The box is placed in the adjacent office and receives the data of the sensors thanks to radio waves. This data is then retrievable through a web service,
- a **remote optimizer** or scheduler receives sensor informations through the box, processes this data and calculates the optimal control sequence (water supply temperature of FHS). The sequence is sent to the box and then to the actuator (PID setpoint of the three-way valve),
- a **USB dongle** receives data from the sensors through proprietary X2D or X3D protocol,
- **Modbus enclosures** permit communication between the box and the actuators controlled in 0–10 V or binary,

- an **Ethernet switch** allows data sending to actuators through an Ethernet gateway and the Modbus TCP/IP protocol. It also allows communication between the box and the remote optimizer,
- **connectors** allow the actuators to receive either commands from the default BEMS or from the predictive controller. This makes it possible to compare the strategies and to quickly restore the building to normal operation by a simple connection.

The optimizer uses the 5R4C model identified in Part I. As specified by Bénard et al. [14,15], control techniques based on programming and software intelligence face many obstacles (manufacturers and users) due to the evolution of know-how compared to current methods. The control structure on the experimental room is the simplest way to introduce optimal control without fundamentally changing the installation. Indeed, the control is carried out by a conventional PID regulator whose setpoint results from an optimization realized by a remote computer.

3.2. Compared strategies

The reference strategies consist in two ways to ensure comfort. One is done by the FCU while the FHS guarantees a constant base temperature with a heating curve. For the other one, the FHS partly ensures comfort during occupancy periods. Thus three management strategies are studied for the FHS:

- reference 1 (ref 1): the heating curve is adjusted to ensure an indoor base temperature of 16 °C. The FHS is programmed to run continuously. The power delivered by the FHS depends only on the outside temperature without considering the occupied periods. The anticipative effect is null,
- reference 2 strategy (ref 2): the FHS is activated during occupancy periods with a fixed restart time defined by the user (scenario). During the week it is switched on all day from 6:00 am to 6:00 pm with a restart time two hours before occupied periods (8 am). On Monday, the FHS is launched three hours before occupied periods (5 am) to consider the week-end thermal discharge. When it is on, the water supply temperature is calculated with the heating curve to ensure an indoor temperature of about 20 °C. Here, the anticipative effect is based on the experience of the manager. However, it is fixed and does not depend on external conditions.
- predictive controller (MPC): FHS control is carried out by a MPC based on occupancy and outdoor conditions anticipation. Thus, anticipative effect is variable and optimized.

These strategies differ only in the way the FHS is piloted (Table 2). FCU and AHU are controlled similarly in all three cases. They operate during the week from 8:00 am to 12:00 pm and from 1:30 pm to 6:00 pm with a setpoint temperature of 20 °C. The control is performed by acting on the fan speed of FCU depending on setpoint deviation (Eq. (9)). When presence is detected on at least one of the two sensors, they switch on. The AHU works every day of the week from 8:00 am to 6:00 pm and is also subject to presence detection (Eq. (10)). A 15 min time-out in presence detection avoids short cycles. For the predictive strategy, the time step for measured data is ten minutes and the prediction horizon is 24 h. The role of the scheduler is to determine the optimum water supply temperature T_{ws} of the FHS. T_{ws} is a continuous variable constrained between 20 °C and 35 °C (Eq. (11)). The optimal control sequence is determined with a constraint on comfort and cost:

- comfort: the indoor temperature T_i referring to a comfort temperature (see Part I), is constrained within a comfort interval I_{comf}, the superior limit is set at 23 °C. The inferior limit varies with the occupancy (19 °C for occupied periods and 16 °C for the remaining time),
- cost: the FHS power is calculated by Eq. (12) and integrated over time to obtain the FHS energy consumption.

This is equivalent to minimize the following cost function on the prediction horizon (Eq. (13)), where J_{comf} is an assessment of comfort and J_{eco} is a cost estimation (Eq. (14)).

$$T_{ws} \in [20^\circ\,\mathrm{C}; 25^\circ\,\mathrm{C}] \tag{11}$$

$$P_{fhs} = \dot{m} C_p (T_{ws} - T_{wr}) \tag{12}$$

$$J = \int_{t_0}^{t_{horiz}} J_{comf}(t) \cdot dt + \int_{t_0}^{t_{horiz}} J_{eco}(t) \cdot dt \tag{13}$$

$$\begin{cases} J_{comf} = \left| \begin{array}{ll} \left(T_i - T_{comfort,\max}\right)^2 & if \quad T_i \geq T_{comfort,\max} \\ \left(T_i - T_{comfort,\min}\right)^2 & if \quad T_i \leq T_{comfort,\min} \\ 0 & if \quad T_i \in I_{comf} \end{array} \right. \\ J_{eco} = P_{fhs} \end{cases} \tag{14}$$

3.3. Potential estimation method

The overall method is summarized in the diagram in Fig. 4. Firstly, the three strategies are compared experimentally for one month measurement series. The first reference strategy was applied from 19/12/2015 to 22/01/2016 and the second from 23/01/2016 to 21/02/2016. The predictive strategy is implemented between 11/04/2016 and 06/05/2016.

Thereafter, strategies are simulated in the Simulink environment using the MPC toolbox [16]. The 5R4C model allows simulating the thermal response of the building for the three strategies and also serves as internal model for MPC. The results are compared to the experimental results to ensure that the simulation models are reliable.

Finally, the three control strategies are simulated over a complete heating season from 05/10 to 29/04. The room is occupied every work day (Monday-Friday) from 8:00 am to 12:00 pm and from 1:30 pm to 6:00 pm. The building is unoccupied for two weeks (Christmas holidays) from 19/12 to 02/01 and one week (winter holidays) from 20/02 to 27/02. The simulations are carried out from normalized meteo files for three different cities of France: Clermont-Ferrand, Agen and Strasbourg. Two quantities can be compared: the unified degree-day (UDD) which reflects the harsh of the climate and the number of hours of sunshine per year (Fig. 5). These data are provided by the national service of meteorology and are averaged over 30 years (1951–1980) for UDD and 20 years for sunlight (1991–2010). Agen's climate is the mildest with weak annual UDDs and high sunshine rate. Conversely, Strasbourg climate is the roughest with high UDDs and lower sunshine rate. Clermont-Ferrand is an intermediary.

Control strategies are compared on the basis of energy consumption and comfort. The energy consumption of the FHS and FCU are calculated by integrating their respective power signals. For comfort evaluation the literature distinguishes two approaches: rational approach independent of occupant actions and adaptive approach where the occupant is an actor of his comfort and able to carry out actions. It is difficult to use adaptive methods to evaluate comfort for optimal control because it depends on unmeasurable data. The rational method commonly used for papers dealing with optimal control is the discomfort rate calculated from a temperature interval. It is used by Ghiaus [17], Sourbron [18] and Gweder et al. [19] for the control of heating floors and ceilings. Thus, a discomfort rate between 19 °C and 23 °C is chosen during the occupied periods.

Table 2
Comparison of strategies.

	Ref 1	Ref 2	MPC
FHS	T_{ws} basic 16°C	T_{ws} comfort 20°C + weekly	T_{ws}
anticipative effect	null	fixed	optimized
FCU	$\dot{m}_{fcu} \begin{cases} if \quad T_{comfort,\min} - 1°C \le T_i \le T_{confomt,\min} + 1°C & low.speed \\ if \quad T_{comfort,\min} - 3°C \le T_i \le T_{confomt,\min} - 1°C & medium.speed \\ if \quad T_i \le T_{comfort,\min} - 3°C \quad high.speed \end{cases}$ (Eq.9)		
AHU	$\dot{m}_{ahu} \begin{cases} vacancy: 20\% \\ occupancy: 100\% \end{cases}$ (Eq.10)		

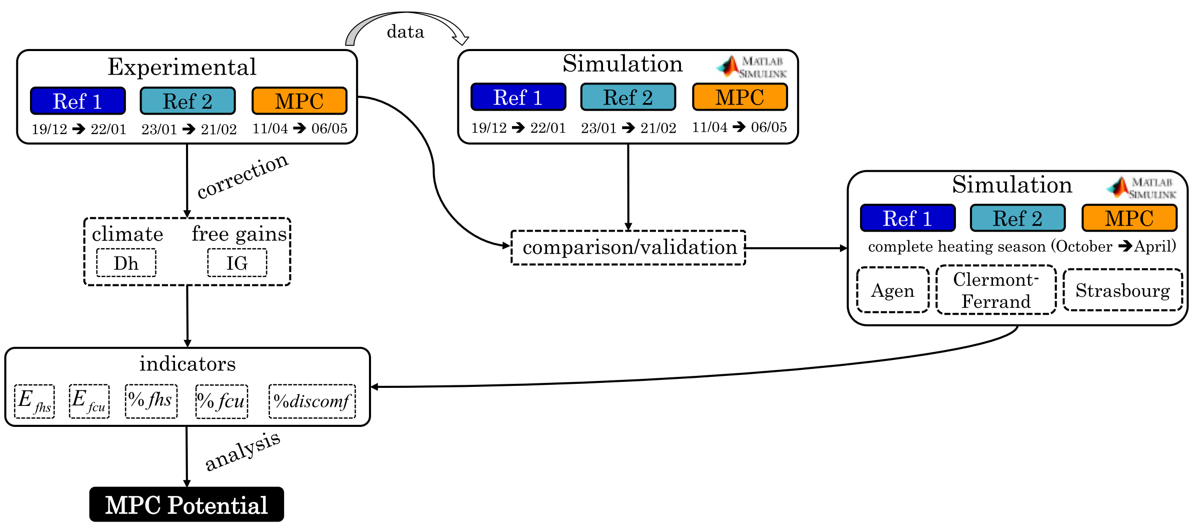

Fig. 4. Procedure for potential estimation of MPC control.

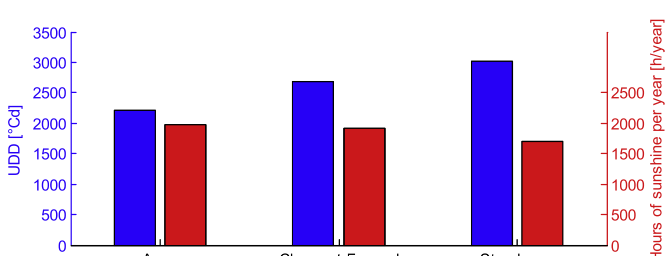

Fig. 5. Temperate climate compared.

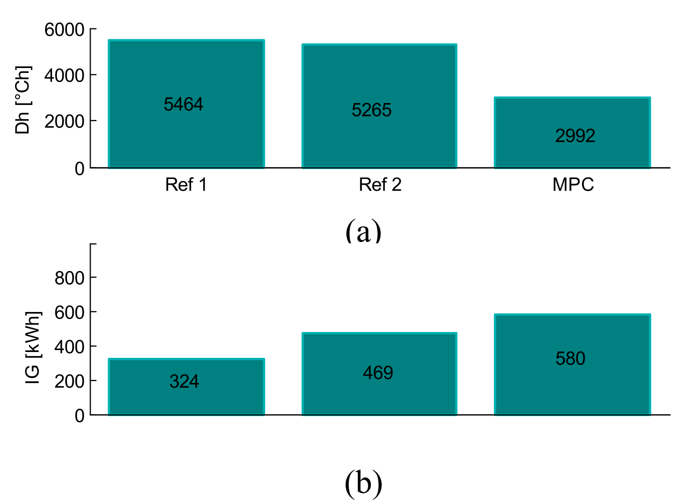

Fig. 6. (a) Degree-hours and (b) internal gains of experimental measurement series.

The experimental results are not directly comparable since the external and internal conditions are different. Thus, two corrections must be made to the experimental results. The ref 1 strategy serves as the basis of calculation:

- gains correction: the sum of the powers generated by the solar contribution, occupants and AHU is integrated to calculate the contribution of free internal gains on energy balance (Eq. (15)). They decrease the energy to be provided by the heating system. Thus the gain difference with the ref 1 strategy is added to the initial consumption.
- correction on climatic conditions: heat losses are approximately proportional to the indoor-outdoor temperature difference. A

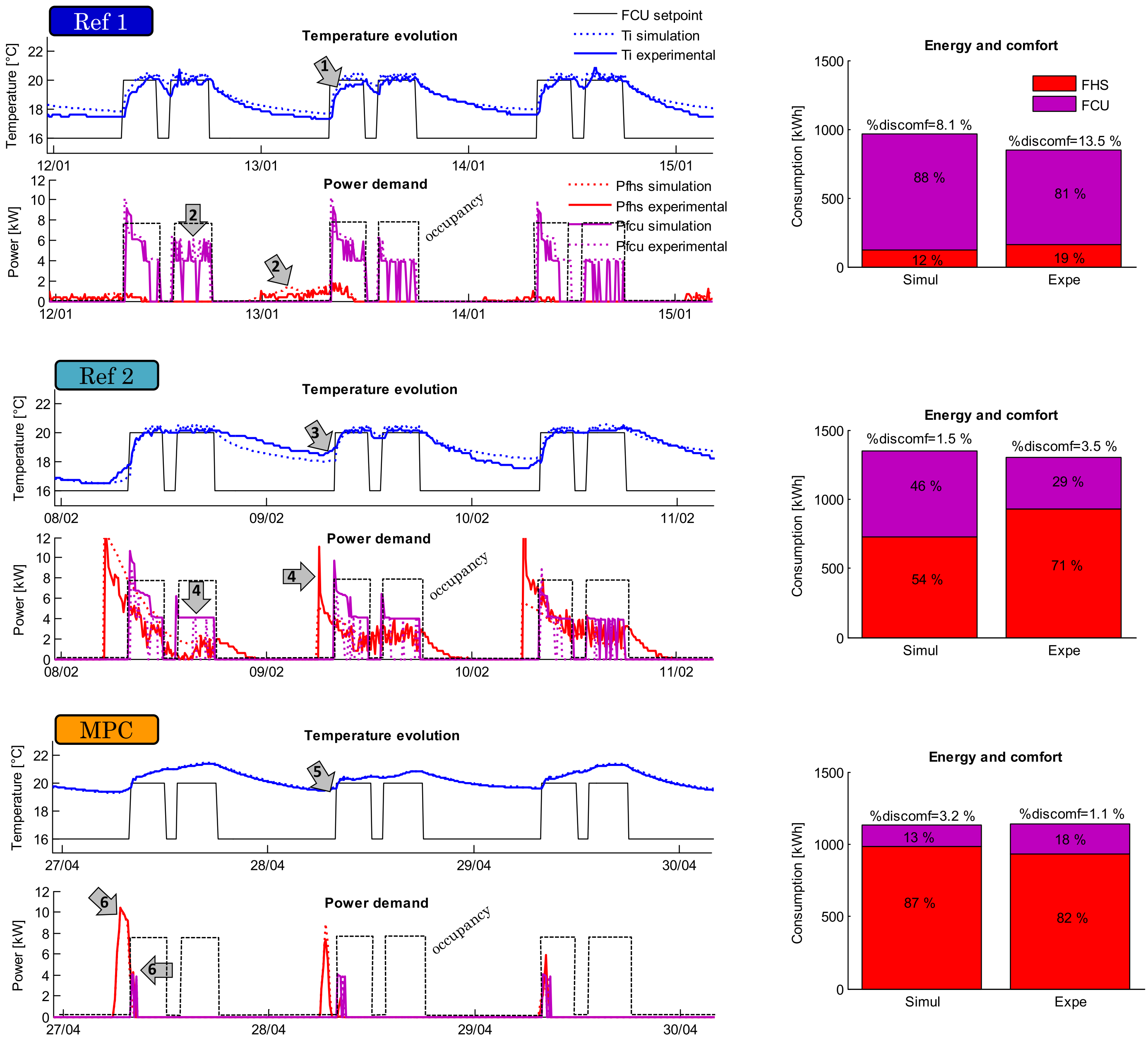

Fig. 7. Experimental and simulated results with on-site measurement series.

method for comparing climatic conditions consists in calculating the degree-hours. This indicator corresponds to the sum of the deviations between the interior setpoint temperature and the hourly mean outside temperature (Eq. (16)). The ratio of the degree-hours with the ref 1 strategy defines a corrective factor to increase or decrease the heat losses of the other two strategies.

$$IG = \int_0^t (P_{solar}(t) + P_{ahu}(t) + P_{occupant}(t)) \cdot dt \tag{15}$$

$$Dh = \sum_{h=0}^{n} T_{set\,point,h} - \left(\frac{T_{\max,h} - T_{\min,h}}{2} \right) \tag{16}$$

$$E_{tot,init} = L - IG \tag{17}$$

$$\begin{cases} E_{tot} = L^* - IG + \left(IG - IG_{ref1}\right) \\ L^* = L * \frac{Dh_{ref1}}{Dh} \\ L = E_{tot,init} + IG \end{cases} \tag{18}$$

$$\begin{cases} E_{tot} = (E_{tot,init} + IG) * \dfrac{Dh_{ref1}}{Dh} - IG_{ref1} \\ E_{fhs} = \dfrac{E_{fhs,init}}{E_{tot,init}} * E_{tot} \\ E_{fcu} = \dfrac{E_{fcu,init}}{E_{tot,init}} * E_{tot} \end{cases} \tag{19}$$

The energy need is equal to the heat losses L minus free gains (Eq. (17)). The correction on the climatic conditions allows to calculate a corrected heat loss L^*. The gain correction is done by adding the gain difference with ref 1 (Eq. (18)). The corrected energy consumption, denoted E_{tot}, is therefore determined by the calculation of Eq. (19). The using ratio values of FHS (E_{fhs}) and FCU

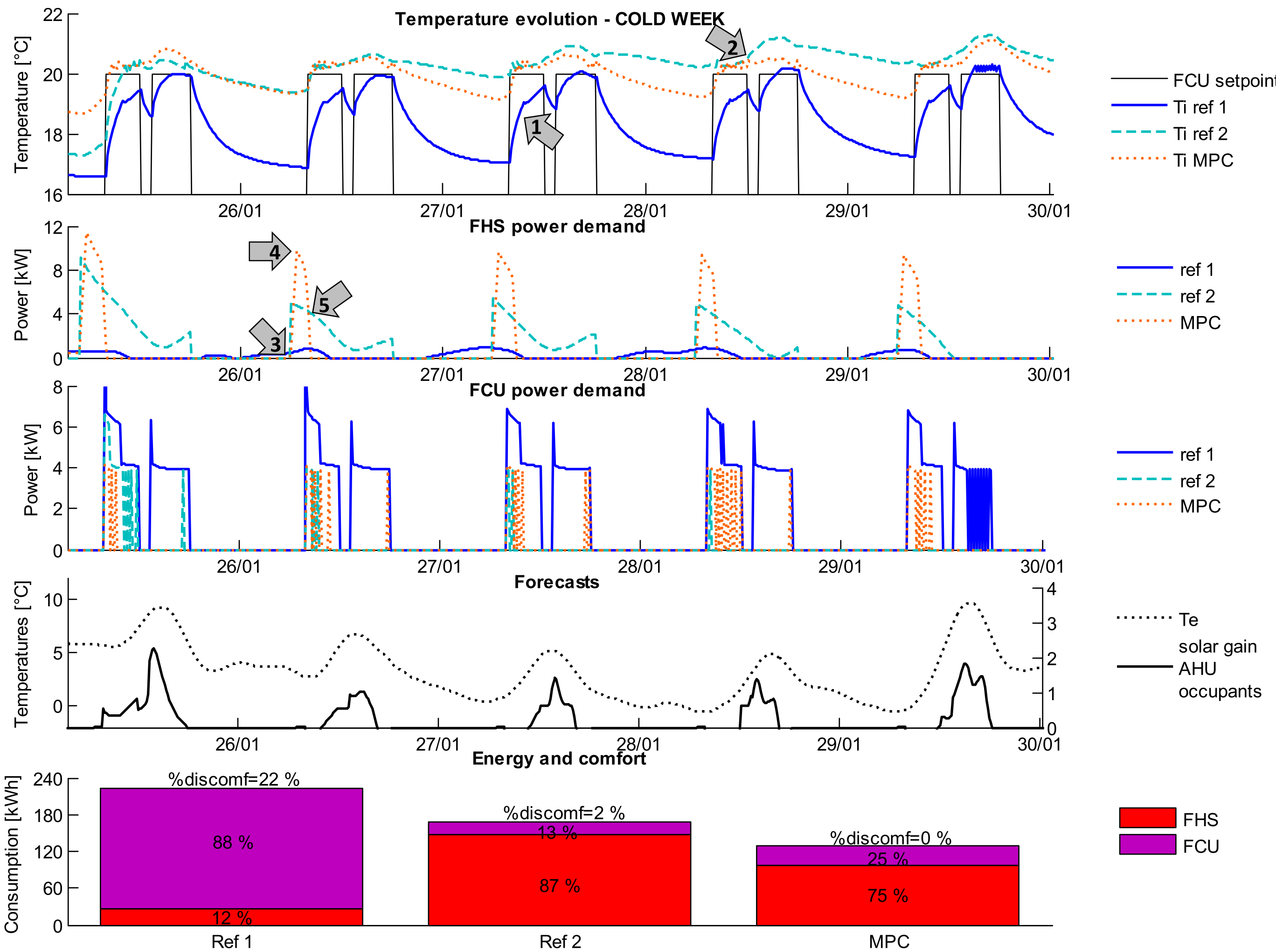

Fig. 8. Behavior of ref 1, ref 2 and MPC strategies for a typical cold week.

(E_{fcu}) are the same after the correction. The degree-hours and internal gains values are presented in Fig. 6.

4. Results and analysis

The experimental results highlight the behavior of the three controllers.

- ref 1: the energy consumption over the studied period is 848 kWh. This strategy has the worst comfort indicator (13.5%). The discomfort mostly occurs during the restart period in the morning. The temperature of 20 °C is reached only in the middle or at the end of the morning (arrow 1). The FCU are strongly used (81%) compared to the FHS (19%) which operates as basic heating (arrows 2),
- ref 2: the corrected energy consumption over the studied period is 1300 kWh. The fixed restart time penalize the energy consumption indicator but logically allows a relative improvement in comfort (3.5%) below the symbolic value of 10% mainly used in eco-labels. This strategy ignores the weather forecasts but the fixed anticipation of 2 h makes it possible to reach the comfort quickly in the morning (arrow 3). The FHS is much more solicited since it represents 71% of consumption and the use of FCU is therefore less (arrows 4),
- MPC: the corrected energy consumption over the studied period is 1137 kWh. The predictive controller makes maximum use of the FHS (82%). The optimal strategy is to thermally load the floor slab upstream of the occupied period (arrow 5). Then the inertia of the floor slab allows a slow decrease in temperature and the FCU are switched on only at the beginning of the occupation period (arrows 6). The predictive strategy allows a high level of comfort (1.1%) for a moderate energy consumption. It is lower than ref 2 but greater than ref 1 (thanks to a degraded comfort). This result is consistent with the predictive control philosophy of making a compromise between comfort and energy consumption.

The experimental sequences are simulated by inserting the input data (weather, occupancy, gains) into Matlab/Simulink environment. The results are also given in Fig. 7. The ref 1 controller is well simulated since the deviations are small for all the compared values. A slight over-use of FCU (88%) is observed compared to the experiment (81%), which justifies the difference of 14% on the total energy consumption and a slightly lower discomfort rate. Nevertheless, it is complicated to obtain better results that are linked to the uncertainties of the 5R4C model of Part I. The calculated discomfort rates are also similar since the evolutions of interior temperature are close. The ref 2 controller has more differences between the experimental and simulation results. There is also an overconsumption of the FCU in simulation (46% versus 29%). This may be due to the delay between action and measurement with the sensor in experimentation while in simulation the effect is instantaneous. In addition, the FCU manual remote control may have been modified by students (no locking possible) and creates un-

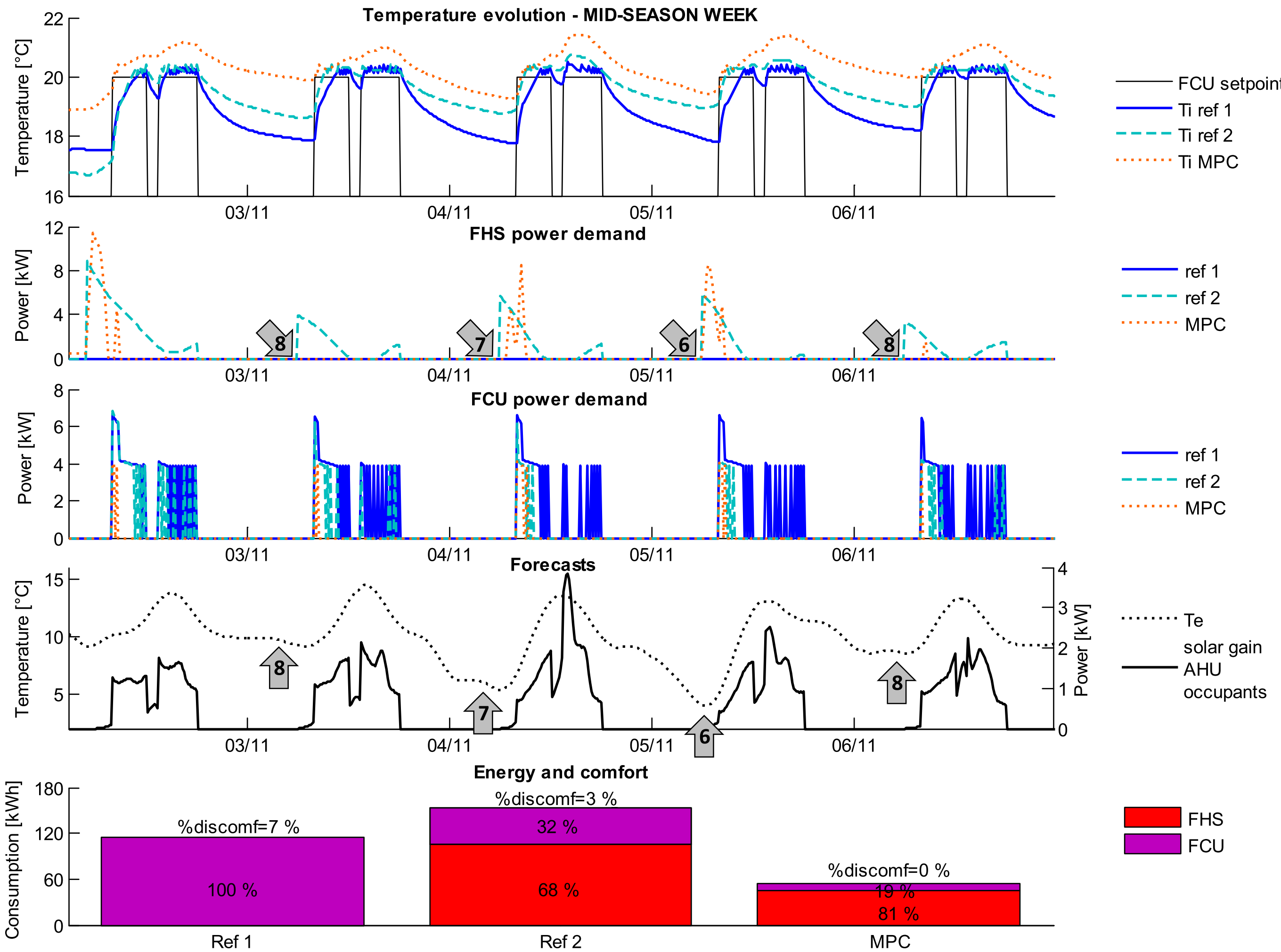

Fig. 9. Behavior of ref 1, ref 2 and MPC strategies for a typical mid-season week.

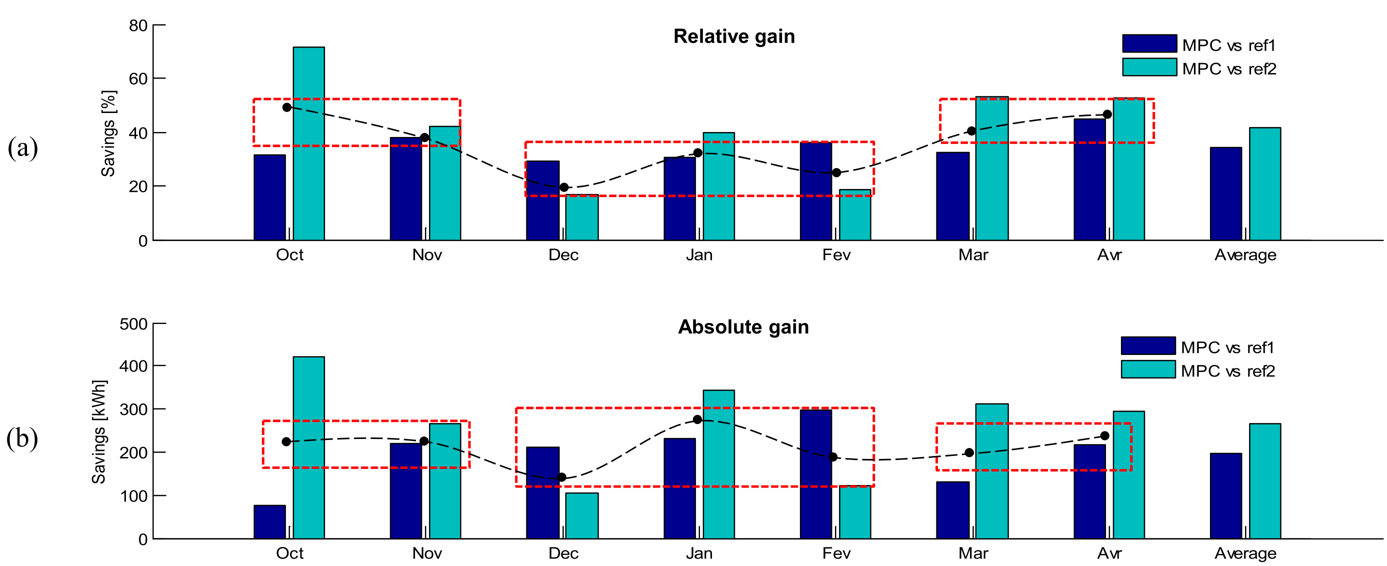

Fig. 10. (a) Relative and (b) absolute energy savings with MPC.

certainty on the real use level of FCU. This seems to be confirmed by the observed deviations in the FCU power signals. In the experiments, the FCU are less used in comparison with the simulation. However, the results for this controller are correct since the temperature variations remain similar. The predictive controller is correctly simulated (1130 kWh compared to 1137 kWh) since the optimal experimental control sequence is very close to the simulated one. It is therefore consistent that temperature evolutions are close. The simulation models are considered reliable despite deviations due to modeling errors and relative uncertainty in the use of FCU. Indeed, the trends are the same for the three strategies:

- ref1: poor comfort, low consumption but strong use of FCU,
- ref2: good comfort, high consumption, shared use of both systems,
- MPC: good comfort, intermediate consumption and high use of FHS (comfort feeling improved by low air velocities compared to FCU).

These strategies are used to obtain results over a complete heating season with three climates. Fig. 8 and Fig. 9 present the behavior of each controller, respectively on a representative cold week (January) and mid-season week (November). For these two weeks, five graphs are plotted: indoor temperature evolution, FHS and FCU power signal, forecast of outdoor temperature and gains, and energy/comfort indicators. For the cold week, the ref 1 controller has a high level of discomfort (22%). Insufficient power of the FHS and the delayed effect of FCU leads to discomfort hours at the beginning of the day (arrow 1). FCU are heavily solicited with a ratio of 88%. The ref 2 controller tends to overheat the building (arrow 2) which logically increases the energy need but reduces the rate of discomfort (2%). In this case, the FHS has a utilization rate of 87%. The predictive controller achieves the best energy performance. For this week, the gain of the predictive controller is 43% and 24% respectively compared to the ref 1 and ref 2 controllers. The energy consumption is thus lower for an improved comfort (ref 1) or equivalent (ref 2). This energy gain is explained by the anticipation of heat gains (solar, occupant). The graph of power demand demonstrates that the FHS starts at the same time between the predictive controller and ref 2 (arrow 3). However, the predictive controller has a higher peak demand on the FHS (arrow 4) and is turned off at mid-morning (arrow 5) in anticipation of solar contributions in particular. The ref 2 controller anticipates only the restart time but not the external conditions. The optimal strategy of predictive controller could permit to refine the ref 2 controller with an important load only in the morning.

In the mid-season the temperatures are milder and the ref 1 controller only uses FCU since the water supply temperature calculated from the outside temperature is low. Like the cold week, a higher level of discomfort than with the other strategies (7%) is observed with a comfort temperature reached during the morning. The ref 2 controller reduces the discomfort rate to 3%, but the energy consumption remains higher than the ref 1 controller. The predictive controller saves energy and improves significant comfort by activating three levers:

- when the nights are still cold, the behavior is similar to the cold week, that is the restart is done at the same time as the ref 2 strategy 2 (2 h before) but in a shorter and intense way (arrows 6),
- when the temperatures are milder, the restart is done later (arrows 7),
- when the temperatures are mild and important gains are forecasted, the FHS is not used (arrows 8).

For this mid-season week, the gain of the predictive controller is 53% and 65% respectively compared to the ref 1 and ref 2 controllers.

The MPC allows a significant improvement on both aspects: energy and comfort. The aim of conducting simulations over a complete heating season is to see when the energy savings are realized. For this purpose, a monthly average of the energy consumption (for the three climates) is established. The monthly relative energy gains of the MPC compared to the reference strategies is calculated (Fig. 10(a)). It appears that the predictive strategy always offers the best results in particular in October, March and April. The efficiency of the predictive control in the mid-season is highlighted. On the October-November and March-April periods, the relative gain is higher (45% on average) than that during the coldest months in winter (December-February) with an average gain of 25%. The absolute gain is relatively constant throughout the heating season (Fig. 10(b)). In winter, the interest is all the greater as the temperatures are low (January). Over the whole heating season (October-April), 60% of the economy is done in the mid-season and 40% during winter. Differences in climatic conditions do not lead to significant changes in the analysis of the three strategies in terms of consumption, comfort or utilization ratio. The overall energy saving (average versus ref 1 and ref 2) is 41% for Agen, 39% for Clermont-Ferrand and 37% for Strasbourg. The usefulness of predictive control in temperate climate is therefore proved.

5. Conclusion and outlines

The three controllers presented were first compared for the experimental building over periods of one month and then simulated over a heating season. After the climatic correction, the comparison was made from three indicators: energy consumption of the two systems, utilization ratio and discomfort rate:

- through complete heating season for three climates. The predictive controller demonstrates the best performance on the indicators with an equivalent or improved comfort situation, the energy consumption can be reduced by 30% to 40%,
- the monthly distribution of energy savings shows a greater relative gain in the mid-season (45%) compared to the two reference controllers, it is 25% on average over the winter months,
- the absolute gain is all the greater as the climate is temperate.

The conclusions presented for MPC are only permitted under three essential conditions. The first one is to have a low-order model that reproduces the dynamic response of the building to controllable and uncontrollable inputs. The second one is to properly set-up the optimization procedure with the cost function, the prediction and control horizon. The last one requires to have knowledge about future indoor and outdoor conditions with reliable forecasts.

This work therefore provides a new demonstration for a particular case of the potential for energy savings achievable by predictive control. Nevertheless, it is necessary to relativize the value of the gains for the predictive controller since these results are obtained for a given building but compared with classical management strategies. It would be interesting to determine if it is possible, thanks to the predictive control, to dispense with auxiliary heating systems and evaluate the associated impact on comfort. Indeed, the results indicate that comfort is slightly degraded for a greatly improved energy management. This work highlights that MPC maximizes the use of the FHS and limits the on/off cycles of the FCU reducing the wear and tear. It could be accompanied by an economic study to evaluate a return on investment period. Privara et al. [5] estimated this duration to be two years. It has been shown that several control strategies can present an acceptable level of comfort but a very different energy consumption from single to double. Although improving the thermal properties of the envelope remains the most effective way to reduce energy bills, it is possible to achieve significant savings without envelope refurbishments or changing the system. It is thus an interesting means of action in addition to the panel of existing solutions for energy efficiency.

In order to complete this work, it would be relevant to reproduce this study for a whole range of performance, from old buildings (before the first thermal regulation) to contemporary buildings. Thus, it would be possible to quantify a potential at the district scale. Predictive control could also be deployed on a neighborhood scale for power peak reduction. The presented predictive control technique is flexible and can take into account other criteria depending on the model and the writing of the cost function. Indeed, it is possible to integrate other physical equations in the internal model of MPC (economic, acoustic or physiological constraints for example). Finally, the potential of such a controller is not limited to the framework of these works since its application is multi-scale, multifunction and multicriteria.

Acknowledgments

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