Weather prediction to improve energy efficiency and climate control of the buildings

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RESUME. La gestion énergétique des bâtiments jouera un rôle majeur dans la réduction de la consommation et des coûts énergétiques globaux, car le secteur du bâtiment consomme plus d'un tiers de la consommation énergétique mondiale. En intégrant la prévision des conditions météorologiques locales au contrôle des équipements comme le CVC, on peut améliorer considérablement l'efficacité énergétique et le confort intérieur des bâtiments. Dans cet article, nous abordons la conception et la synthèse d'un contrôleur prédictif optimal couplé aux prévisions météorologiques et aux conditions de fonctionnement du bâtiment pour optimiser le couple confort/énergie afin de rendre le bâtiment plus performant. L'efficacité de notre méthodologie sera démontrée par la présentation de résultats expérimentaux sur notre banc d'essai CVC, comparant les économies d'énergie réalisées par un contrôleur prédictif optimal avec celles réalisées sans prévisions météorologiques.

MOTS-CLÉFS. Prévision météorologique, confort thermique, contrôle optimal.

ABSTRACT. The energy-efficient management of building systems will play a major role in reducing overall energy consumption and costs, as the building sector consumes more than a third of global energy consumption. By incorporating the prediction of the local weather conditions along with the equipment data like the HVAC'unit, one can improve significantly energy efficiency and indoor climate control in buildings. In this paper, we address the design and synthesis of an optimal predictive controller coupled with the weather forecasts and the building operating condition for energy efficient building climate control. Some conditions are given to verify the feasibility of the approach and the performance of the controller designed. The effectiveness of our methodology will be demonstrated by presenting experimental results on our HVAC testbed, comparing energy savings realized by an optimal predictive controller with against without weather forecasts.

KEYWORDS. Weather prediction, thermal comfort, optimal control.

1 Introduction

Residential and commercial building sector are considered today with transportation, as the largest energy savings potential. Optimizing energy consumption within these different fields of application become therefore one of the main tasks of all communities during these last decades. However, this task is not always easy to perform, particularly for buildings. There are various reasons for this ; some of which have been identified in (Hiroshi et al., 2017). For instance, it is mentioned that the thermal behaviour of the buildings can be influenced by the (i) weather conditions, (ii) building envelope, (iii) building services and energy systems, (iv) building operation and maintenance, (v) occupant activities and behaviour and (vi) indoor environmental quality provided. In this paper, we would like to focus our study and analysis especially on how much weather forecasts can impact the building thermal performances, improve energy efficiency and indoor climate control in buildings.

The use of weather predictions for building climate control has been investigated in several works (Gwerder et Tödtli, 2005), (Cho et Zaheer-uddin, 2003), (Grünenfelder et Tödtli, 1985), (Henze et al., 2005), and model predictive control (MPC) has been recognized as the suitable solution to take into account this external disturbances (Florita et Henze, 2009), regardless of MPC typology and classification. Briefly, MPC is a model-based technique widely and successfully used over the past years to improve globally control systems performance (Smarra et al., 2018), (Segovia et al., 2019) but also for building systems efficiency (Higuera et al., 2014; Kuboth et al., 2019; Wang et al., 2019) and for energy storage systems (Thieblemont et al., 2017), as well as to the optimal management of on-site renewable energy sources (Serale et al., 2018). In the other hands, (Oldewurtel et al., 2012) show in their work how MPC coupled with weather predictions can increase the energy efficiency in integrated room automation (IRA) while respecting occupant comfort. Basically, they develop a stochastic model predictive control (SMPC) strategy that takes into account the uncertainty due to the use of weather predictions. (Dong et Lam, 2014) introduce and illustrate a methodology for integrated building heating and cooling control to reduce energy consumption and maintain indoor temperature setpoint, based on the prediction of occupant behavior patterns and local weather conditions. A nonlinear model predictive control (NMPC) is designed and implemented in real-time based on dynamic programming.

The results obtained with these methodologies are particularly interesting, in the sense that concrete improvements in terms of thermal comfort are obtained from these investigations. In this paper, we discuss on the design and synthesis of an optimal predictive controller coupled with the weather forecasts and the building operating conditions (w-OPC) to improve the energy efficiency of the building as well as indoor thermal comfort. In other words, the controller developed should integrate predictively and take into account the uncertainty in the problem in order to improve the control performance. Thus, we can incorporate in the predictive modeling facility's energy needs along with weather and operating mode is used to optimize energy consumption, demand response and optimal indoor climate comfort. Some conditions are given to verify the feasibility of the approach, the performance and the convergence of the controller designed.

The remainder of the paper is as follows. Section 2 introduces the formulation of the thermal model which expresses the thermal behavior of the building according to its different operating conditions. Section 3 will describe the main results in terms of controller design, optimality analysis of the optimal predictive controller. Section 4 will present the experimental results by showing the thermal comfort and energy savings by the controller developed. Section 5 will give the conclusion of this work.

2 Thermal-model formulation

Let us recall, this paper deals with the synthesis and design of an optimal predictive controller which will take into account the evolution of the outdoor climate and building operating conditions to improve the thermal comfort and energy efficiency of building. In other words, we control the indoor thermal comfort (T_a) according to two factors, the HVAC'unit usage (I_{hv}) and the weather conditions (d_{we}), through the horizon of prediction (H_p) at each instant (k), and the building operating condition (q) :

$$T_{ak} = f_q(I_{hv}, d_{we}, k, H_p). \tag{1}$$

The affine function $f_q(.)$ can be defined by a piecewise ARX (pw-ARX) model. This last is a piecewise affine dynamic system, using a set of ARX submodels with the same model structure. Notice that this system can model a large number of linear or non-linear physical processes, including the residential buildings.

The model is obtained by splitting the state-input domain represented by their parameters $\{\theta_q\}_{q=1}^{s}$ into a finite number of polyhedral regions (or operating conditions) $\{\mathfrak{R}_q\}_{q=1}^{s}$.

PW-ARX models represent the input-output version of PWA models. They are defined by introducing the regression vector (for a MIMO system) :

$$\varphi_k = [y_{(k-1)}^T \ \cdots \ y_{(k-n_a)}^T \ \cdots \ u_{(k-n_b)}^T \ \cdots \ u_{(k-n_b-n_k+1)}^T]^T \tag{2}$$

where n_a and n_b are the model orders and n_k is the pure delay between them. u represents the set of inputs defining the activation or not of the HVAC'unit and the weather conditions. The input/output (u_k, y_k) model of the pw-ARX model is represented by the following relation :

$$y_k = f(\varphi_k) + e_k \tag{3}$$

and f is a piecewise affine map of the following form :

$$f(\varphi_k) = \begin{cases} \theta_1^T \bar{\varphi}_k & \text{if} \quad \sigma_k = 1 \\ & \vdots \\ \theta_s^T \bar{\varphi}_k & \text{if} \quad \sigma_k = s, \end{cases} \tag{4}$$

where $\bar{\varphi} = \left[\varphi^T \ 1\right]^T$ is the extended regression vector. σ_k is the switching rule defined by :

$$\sigma_k = q \quad \text{if} \quad \varphi_k \in \mathfrak{R}_q, \tag{5}$$

and $\{\theta_q\}_{q=1}^{s}$ are the parameter vectors that define the sub models. $\{\mathfrak{R}_q\}_{q=1}^{s}$ represent a complete partition of the region $\mathfrak{R} \subset \mathbb{R}^n$, with $n = n_e n_a + (n_b + 1)$, and each region is a convex polyhedron with

$$\mathfrak{R}_q = \{\varphi \in \mathbb{R}^n : H_q \bar{\varphi} \preceq \mathbf{0}\} \tag{6}$$

where H_q and $\mathbf{0}$ are respectively a matrix of appropriate dimensions defining the limit of the region partitioning the set of regression vector and the null vector.

Basically, the physical presentation of thermal behaviour of indoor air T_a by considering the q^{th} mode and with m input variables is defined by (Benzaama et al., 2019) :

$$T_{ak} = \sum_{j=1}^{n_a} a_{j,q} T_{a(k-j)} + \sum_{v=1}^{m} \sum_{j=1}^{n_b} b_{j,q}^{v} u_{(k-j)}^{v}, \tag{7}$$

and by considering :

$$u^v = \{P_w \ \ T_o \ \ H_o \ \ R_a\}, \quad \text{with} \quad v = (1, \cdots, 4)$$

where P_w is the controlled heating power, and both T_o the outdoor air temperature, H_o the outdoor humidity and R_a the solar radiation are uncontrolled inputs. According to this configuration, equation (7) can be presented as :

$$\begin{aligned} T_{ak} = \sum_{j=1}^{n_a} a_{j,q} T_{a(k-j)} + \sum_{r=1}^{n_b} [& b_{r,q}^1 T_{o(k-r)} + b_{r,q}^2 H_{o(k-r)} \\ & + b_{r,q}^3 P_{w(k-r)} + b_{r,q}^4 R_{a(k-r)}]. \end{aligned} \tag{8}$$

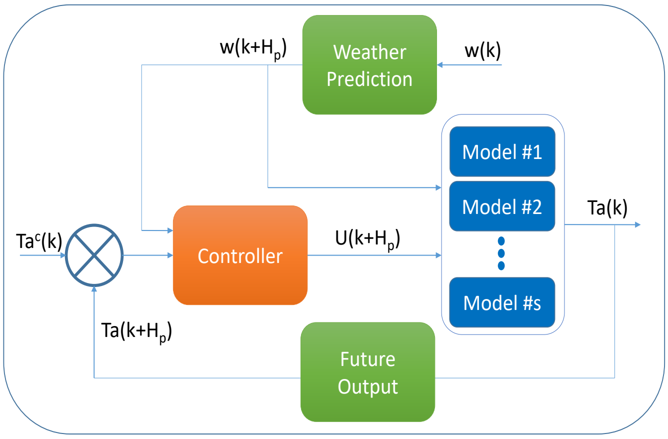

FIGURE 1. System block diagram.

The definition of the structure, input parameters and identification of the pw-ARX model are not discussed in this paper. For further information, the reader may refer to (Benzaama et al., 2020).

3 Predictive controller design

The overview of control setup is illustrated in Figure 1. Herein, we can see as time varying parameters, the comfort temperature setpoint and the weather prediction, which are considered as inputs of the optimal predictive controller. In addition, the weather prediction is the input of the set of thermal model in order to optimize both the prediction of the current/future temperature felt and the predictive control strategy. Notice that the set of thermal model describes the building thermal behaviour according to its operating condition. This architecture is adopted to maximize thermal comfort and minimize the energy consumed.

So, let us define the desired thermal comfort is represented by the setpoint y_k^d at each instant k, therefore the control objective is to design a predictive optimal output feedback controller defined by :

$$\Delta u_k = K^T E_k^T + \Gamma^T W_k^T \tag{9}$$

where respectively E_k and W_k give the error vector and the weather forecasting values. K is the controller gain and Γ is a weight vector used to make robust the control action against the outdoor climate impact. The notation M^T means the transpose of the matrix (resp. vector) M.

According to the prediction horizon H_p, each parameter can be written as follows :

$$E_k = [\epsilon_{k|k} \quad \epsilon_{k+1|k} \quad \dots \quad \epsilon_{k+H_p-1|k}], \tag{10}$$

and

$$W_k = [w_{k|k} \quad w_{k+1|k} \quad \dots \quad w_{k+H_p-1|k}]. \tag{11}$$

Each term of E_k is obtained by the error target :

$$\epsilon_{i|k} = y_k^d - y_{i|k}, \tag{12}$$

and

$$w_{i|k} = \{T_{o(i|k)} \quad H_{o(i|k)} \quad R_{a(i|k)}\}, \tag{13}$$

where $i \in \{k,\ k+1,\ \dots,\ k+H_p-1\}$. In other terms, this error target can be used as the performance index in terms of thermal comfort needs by the occupant at the observation time k.

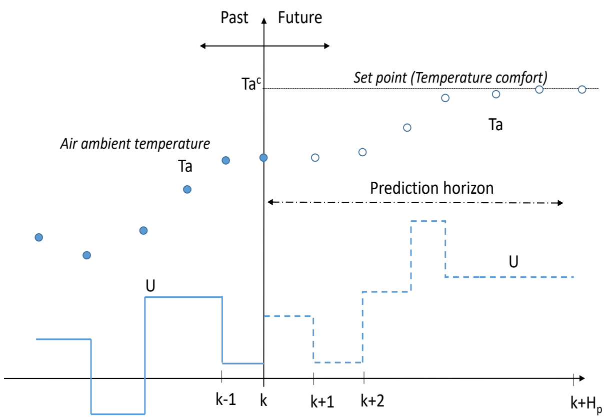

FIGURE 2. Basic concept for predictive controller.

Figure 2 illustrates a basic concept of predictive controller to have a further information about the notion defined above. We can see here that at the k^{th} sampling instant, the values of manipulated variables $u(k)$, at the next horizon prediction H_p sampling instant, $[u_{k|k} \;\; u_{k+1|k} \;\; \dots \;\; u_{k+H_p-1|k}]$, are calculated. In our case, the operation is done with the future evolution of the indoor (resp. error vector $[\epsilon_{k|k} \;\; \epsilon_{k+1|k} \;\; \dots \;\; \epsilon_{k+H_p-1|k}]$) and outdoor climate conditions $[w_{k|k} \;\; w_{k+1|k} \;\; \dots \;\; w_{k+H_p-1|k}]$.
Thus to guarantee the convergence of the controller, the optimal gain K and the weighting parameter Γ will be chosen by solving the optimization problem :

$$(K, \Gamma) \rightarrow \arg \min_{y,u} J(y, u) \tag{14}$$

and, which allows to get the following update corresponding to the data-driven optimal controller designed

$$(K^\star, \Gamma^\star) \equiv g[f(\varphi_{i|k}), J^\star]. \tag{15}$$

So, we can write finally the optimal predictive controller based on weather and operating conditions (w-OPC) assigned to the system (3) solves the following problem :

$$\min_{\{y_{i|k}\}_{i=k}^{k+H_p-1},\ \{u_{i|k}\}_{i=k}^{k+H_p-1}} J_k(y_{i|k}, u_{i|k}) \tag{16}$$

subject to :

$$y_{i+1|k} = f(\varphi_{i|k}) + e_{i|k} \tag{17}$$
$$\varphi(i|k) \in \Phi, \;\; i \in \{k, k+1, \dots, k+H_p-1\} \tag{18}$$
$$y(j|k) \in \Psi, \;\; j \in \{k, k+1, \dots, k+H_p\} \tag{19}$$
$$y_{k|k} = y_k \tag{20}$$
$$\underline{u} \preceq u_{i|k} \prec \overline{u} \tag{21}$$
$$\underline{w} \preceq w_{i|k} \prec \overline{w} \tag{22}$$

with $(\underline{u}, \underline{w})$ and $(\overline{u}, \overline{w})$ are respectively the minimum and maximum value that the control signal and the disturbance inputs $(u_{i|k}, w_{i|k})$ can take. Moreover, we define the set of control inputs considered into the prediction horizon H_p by $\{u_{i|k}\}_{i=k}^{k+H_p-1} \equiv \{u_{k|k}, u_{k+1|k}, \dots, u_{k+H_p-1|k}\}$. The output prediction $\{y_{i|k}\}_{i=k}^{k+H_p-1}$ as well as the weather prediction $\{w_{i|k}\}_{i=k}^{k+H_p-1}$ will be defined in the same manner.
The performance of the predictive controller is then reflected on the measures of the tracking error and the actuator efforts. In other terms, the fact of minimizing the cost function J_k, thanks to the error target and the variation of the control action, allows us to guarantee the maximization of thermal comfort and the minimization of the energy consumed.

FIGURE 3. Lavoisier student Residence in Douai

The methodology of the developed controller can be summarized by the steps described in Algorithm 1 as shown subsequently.

Algorithm 1 w-OPC design

Input : Initialization

σ : the number of operating modes ; n_a and n_b : the system orders ; α : control weighting ; β : optimal convergence rate ; N : the observation horizon ; H_p : the prediction horizon ; y^r : the output target and $\hat{\theta}_\sigma$: the regression vector.

for $(k \leftarrow max(n_a, n_b) : N - n_a + H_p)$ **do**
  Step 1 : Output estimation
  for $(i \leftarrow k - n_a : k + H_p - 1)$ **do**
    $y_{i+1|k} \leftarrow f(\varphi(i|k)) + e(i|k)$
    $\epsilon_{i|k} \leftarrow y_k^d - y_{i|k}$
    $E_i \leftarrow [\epsilon_{i|k} \quad \epsilon_{i+1|k} \quad \dots \quad \epsilon_{i+H_p-1|k}]$
  Step 2 : Compute the controller gain by optimizing
  $J_k \leftarrow \frac{1}{2}E_k^T E_k + \frac{1}{2}\alpha \Delta u_k^T \Delta u_k - \frac{1}{2}(Q^T \Delta\Gamma_k^T \Delta\Gamma_k Q)$
  $(K, \Gamma) \leftarrow \arg\min_{\epsilon,u} J_k(\epsilon, u)$
  Step 3 : Controller convergence
  Choose the best controller gain and weighting parameters $(K^\star, \Gamma^\star)$ minimizing the cost function

Output : Best controller gain $(K^\star, \Gamma^\star) \equiv g[f(\varphi_{i|k}), J^\star]$

4 Results and discussion

4.1 Case study

To validate our methodology, we apply it onto the Lavoisier student residential building, located in Douai, in the north of France (Figure 3). This building is characterised by the following parameters. The total area is approximately $3500m^2$ and it is subdivided into 2 sub-buildings. The main difference between this two parts is the number of rooms composing each sub-building. The first is made of 10 rooms on each floor while the second one by 32 rooms. Each room is $11m^2$ with a double glazed window size ($135cm \times 110cm$). Note that for this building, the envelop is composed by brick walls with a thickness $22cm$ and a glass wool insulation with a thickness $14cm$. We have deployed a network of smart meters in each room to collect data from the building

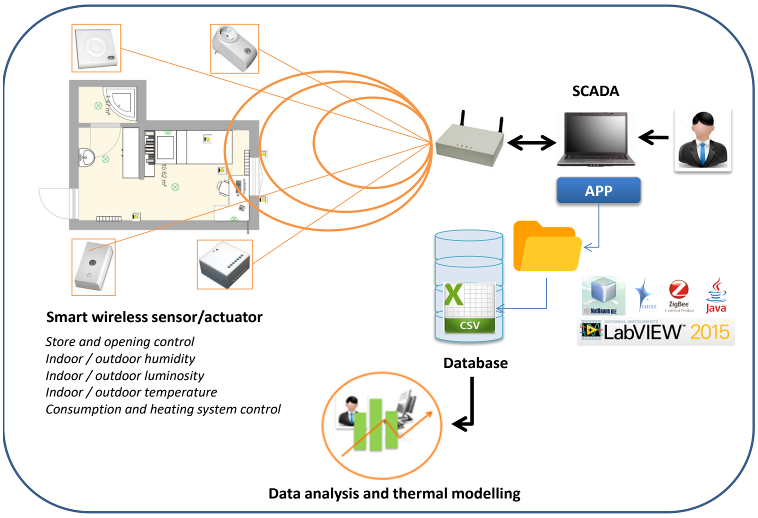

FIGURE 4. Smart meters deployed into the student's room

and control the heating system (Figure 4). The technology adopted is a wireless sensor networks (WSN) platforms based on a universal solution of the CLEODE company (Made in France), and each smart meter/device is configured with a sampling time of $T_s = 2.4mn$.

Thus, these configurations allow us to remotely monitor and control the thermal dynamics of the building. Figure 5 bellow illustrates for instance the evolution of the outdoor climate during the experimentation (from 09/02/2019 to 11/02/2019). On the top we have the evolution of the outdoor temperature which can take value between 2^oC to 10^oC. In the middle we have the outdoor humidity which can take value between 75% to 100% and bottom the solar radiation that brings energy between $0W/m^2$ to $15W/m^2$ on the floor.

4.2 CONTROLLER PERFORMANCE ANALYSIS

Applying algorithm 1 given before, we obtain the following values for each controller gain between the controller type considered (Table 1), for a prediction horizon $H_p = 20T_s \simeq 45mn$:

TABLE 1: The best controllers optimal gain

K^*(w-OPC)	K^*(OPC)	K^*(COC)
68.59	68.40	37.24

Let us recall, in this table w-OPC means by optimal predictive controller which takes into account the weather prediction. OPC stands for optimal predictive controller (without weather prediction), and COC is a classical optimal controller, well-known by LQR controller. The thermal comfort control results is illustrated on the top of Figure 6 for each controller considered. The black line represents the thermal comfort setpoint defined by the user, while the red, blue and green lines are respectively the tracking realised by COC, OPC and w-OPC controller. Accordingly, the heating control activation is illustrated on the middle of the same figure for each controller.

Concerning the operating mode illustrated on the bottom of Figure 6, three indoor thermal behaviors were detected and identified (Benzaama et al., 2020). For instance, as shown in Table 2, the first sub-configuration (associated to Mode 1) corresponds to the indoor thermal dynamic where the heating system is active (ON). The second one (associated to Mode 2) corresponds to the indoor thermal dynamic where the heating unit is inactive (OFF) and the solar radiation is greater than $2.19W/m^2$, while the last one (associated to Mode 3) corresponds to the indoor

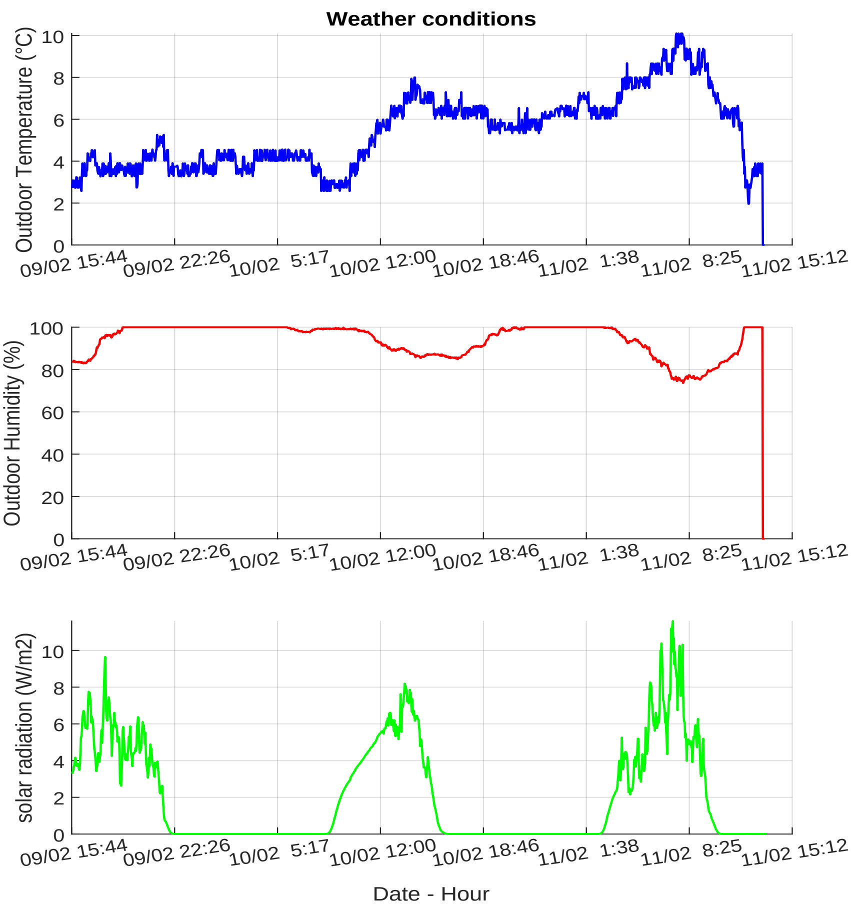

FIGURE 5. Weather measurement

thermal dynamic associated with heating device on OFF position and the solar radiation is less than $2.19 W/m^2$.

Modes	Pw	Ra
Mode 1	ON	–
Mode 2	OFF	$> 2.9\ W/m^2$
Mode 3	OFF	$< 2.9\ W/m^2$

TABLE 2: Switching conditions

In the other hand, to quantify the effectiveness of our methodology, we present in Table 3, the controllers efficiency by comparing the performance obtained with different types of controller. This leads to the analysis of a statistical properties (the variance and the standard deviation as well as the mean) of the thermal comfort and the energy consumed for different horizon of prediction. For this last, we consider two other values in this study, which are $H_p = 25Ts \simeq 60mn$ and $H_p = 30Ts \simeq 75mn$.

Thus, table 3 shows us that the prediction horizon and the weather forecasting improve any among others the variation of the control effort (statistical performances according to the variation around the mean value of the "Electrical Power consumed"). For instance between $20Ts$ and $30Ts$ the power consumed variance is from 91.3 to 83.1 for OPC controller while it is from 69.9 to 67.6 for w-OPC controller. This is particularly interesting in terms of energy saving

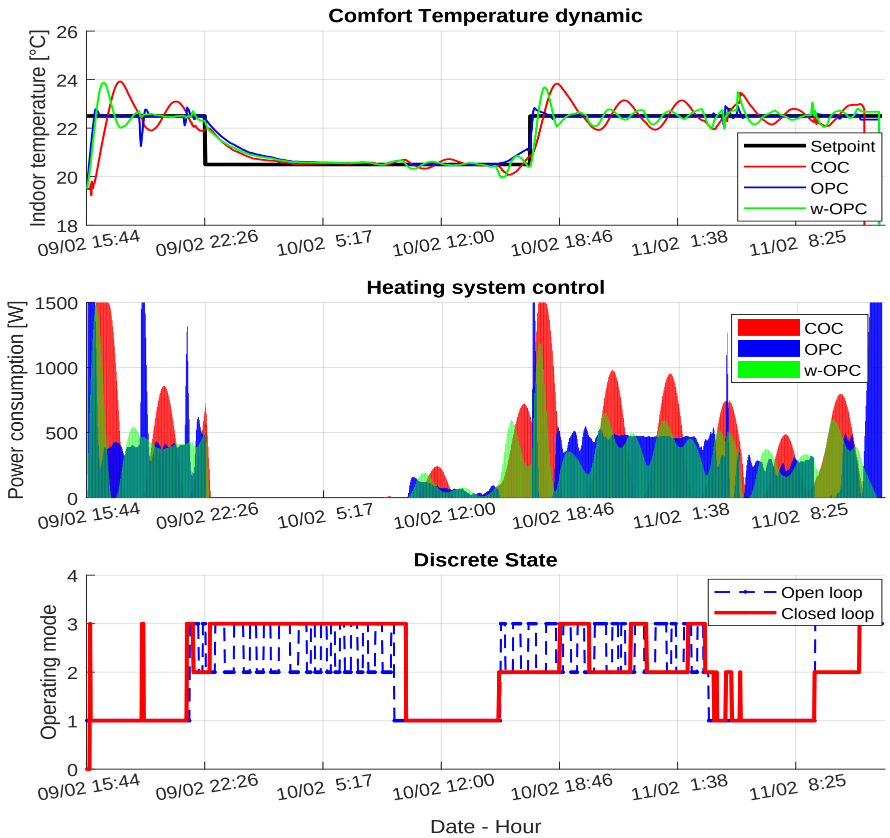

FIGURE 6. (top) Temperature comfort control. (middle) Power consumption. (bottom) Operating mode evolving

Controller	Horizon prediction	Variables	Statistical performances		
			Variance	Standard deviation	Mean
COC	Ts	Temperature [°C]	9.77	3.38	21.26
	Ts	Power [W]	134.3	366.4	269.9
OPC	$20Ts$	Temperature [°C]	2.74	1.65	21.7
	$25Ts$		2.74	1.65	21.7
	$30Ts$		2.75	1.66	21.7
	$20Ts$	Power [W]	91.3	302.1	256.5
	$25Ts$		84.7	291.1	250.3
	$30Ts$		83.1	288.3	242.7
w-OPC	$20Ts$	Temperature [°C]	2.63	1.62	21.69
	$25Ts$		2.63	1.62	21.7
	$30Ts$		2.64	1.62	21.7
	$20Ts$	Power [W]	69.9	264.4	253.4
	$25Ts$		67.3	259.5	249.2
	$30Ts$		67.6	260	242.1

TABLE 3: Thermal comfort and energy consumption variation around the mean value

because it measures how far a set of control actions are spread out from their average value. It is the same conclusion for the comfort temperature. Indeed, by comparing OPC controller with w-OPC controller the thermal comfort is better for w-OPC controller with a 4% difference.

In terms of economic gain, w-OPC and OPC controller allow respectively energy savings of

6% to 10% and 5% to 8% when compared with a COC controller. Table 4 gives a measure of just how important the use of w-OPC to maximize thermal comfort and save energy. Indeed, with a COC we have to pay for instance 1 500€ per year, while respectively with OPC and w-OPC we can save 130€ and 150€.

Horizon prediction	w-OPC	OPC	COC
$20Ts$	1 404€	1 425€	1 500€
$25Ts$	1 385€	1 400€	1 500€
$30Ts$	1 350€	1 370€	1 500€

Table 4: Estimated energy consumption cost per year

Therefore, one can see improving the energy-efficiency of HVAC systems by taking into account the weather prediction and building operating conditions has potential economic and societal benefits.

5 Conclusion

In this paper, we address the design and synthesis of an optimal predictive controller coupled with the weather forecasts and the building operating conditions in order to guarantee an energy-efficient building climate control. The performance of such controller depends on the one hand on how large is the prediction window of the weather, which have inherent uncertainty, and on the other hand, how the building thermal behaviour evolves. The formulation and description of the controller have completely given in this paper. In the end, we show the effectiveness of our methodology by presenting results from experiments on the heating system of a student residential, by comparing the thermal comfort and energy savings obtained by an optimal predictive controller coupled or not with the weather prediction between a classical optimal controller. Thus, we confirmed both we can maximize thermal comfort while minimizing the energy consumed with the developed controller. In terms of economic gain, w-OPC controller allows the energy savings until 10% by comparing with a COC controller.

Moreover, the predictive approach developed in this article has allowed us to understand the effect of weather conditions on the energy efficiency of the building, coupled with its use and characteristics. This information will be useful in the future for the implementation of a strategy for the efficient operation of energy-consuming installations. In other words, the work initiated here will enable us to study the effects of weather conditions on the use of heating, ventilation and air-conditioning systems.

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