USE OF SIMULATION FOR THE VALIDATION OF A MODEL PREDICTIVE CONTROL STRATEGY FOR ENERGY MANAGEMENT IN BUILDINGS

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ABSTRACT

In this paper, a methodology for interfacing and assessing a Model Predictive Control strategy in a building simulation tool (SIMBAD) is presented. Firstly, a system identification is performed in order to derive a suitable embedded model for the predictive controller from the simulation tool. Secondly, we assess the performance of this control strategy by introducing uncertainties on forecasted weather conditions and occupancy. Finally, we provide some simulation results in order to analyse the robustness of the controller in presence of uncertainties on forecast.

INTRODUCTION

Active energy efficiency is becoming a crucial paradigm for energy consumption reduction of buildings. As witnessed in (Dounis and Caraiscos, 2009), a lot of effort has been deployed during the last decade in order to improve energy efficiency related algorithms in buildings. Among several control techniques that have been investigated, Model Predictive Control (**MPC**) appears clearly as one of the most promising control strategies for building energy management. The reader may refer to (Gyalistras and Team, 2010) where a large study on the potential energy saving of this control strategy is presented.

Within **HOMES** program[1], assessment of such advanced control strategies in a complete simulation tool (**SIMBAD**) is a key point.

Nevertheless, some specific requirements need to be addressed for **MPC** integration and assessment in our simulation tool, they represent the main contributions of this short communication:

• Necessity of disposing of an internal model of the building. This implies that a sufficiently compact and representative simplified model has to be derived from the simulation tool. To tackle this issue, an identification procedure that takes advantage of some given properties of the model is proposed.

• Predicted weather scenarios should differ from the "real" weather data injected in the building in order to assess the robustness of the **MPC** strategy against uncertainties on weather predictions.

• Some stochastic occupation scenarios have to be introduced. As it will be discussed in the paper, modeling this uncertainty source differs from the previous one. In fact, a Markov chain parameterized with some presence probability is used to model the presence of occupants.

[1]http://www.homesprogramme.com

This paper firstly gives some recalls on **MPC** and previous developments that we carried out on this topic. The issues cited above are then addressed and the proposed solutions are shortly presented. In the last section, some simulation results are given to prove the added value of the methodology and a direct application of the designed predictive controller for HVAC dimensioning is briefly depicted. The conclusion emphasizes the main results obtained and gathers some of the further issues that will be studied within **HOMES** program.

BACKGROUND

Recalls on MPC

In this section, we briefly recall the principle of **MPC**. More detailed presentation can be found in (Mayne et al., 2000).

Consider a general dynamical system governed by the following set of discrete-time equation:

$$x(k+1) = f(x(k), u(k), w(k)) \tag{1}$$

where $(x, u, w) \in \mathbb{R}^n \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_w}$ stand for the state, the control and the exogenous signal, respectively. MPC feedback control at instant k is computed by first finding the optimal sequence of future open-loop controls $\tilde{u}^\star(x(k)) := [u^{\star^t}(k), \dots, u^{\star^t}(k+N-1)]^t \in \mathbb{R}^{N\cdot n_u}$ that minimizes some cost function $J(\tilde{u}, x(k))$ defined over the prediction horizon $[k, k+N]$ starting from the initial state $x(k)$, namely:

$$\tilde{u}^\star(x(k)) = \underset{\tilde{u}\in\mathbb{R}^{N\cdot n_u}}{\text{Argmin}}\; J(\tilde{u}, x(k)) \quad \text{s.t} \;\; \mathcal{C}(\tilde{u}, x(k)) \leq 0$$

where $\mathcal{C}(\tilde{u}, x(k)) \leq 0$ gathers the set of operational constraints. The feedback at instant k is then defined to be the first control $u^\star(k)$ in the optimal sequence $\tilde{u}^\star(k)$, namely:

$$u(k) = K_{MPC}(x(k)) = \Pi_1^N \cdot \tilde{u}^\star\big(x(k)\big) \tag{2}$$

where $\Pi_j^N \in \mathbb{R}^{n_u \times (N \cdot n_u)}$ is the matrix that selects the j-th vector $u^\star(k+j-1)$ in the sequence of N concatenated vectors $\tilde{u}^\star(x(k))$. At the next sampling instant $k+1$, the new optimal sequence $\tilde{u}^\star(x(k+1))$ is computed and the first control $u^\star(k+1)$ is applied during the sampling period $[k+1, k+2]$ and so on.

Zone MPC

As it has been briefly depicted, the core component of **MPC** lies in the model of the process $x^+ = f(x, u, w)$. In previous works, we designed Multi-Input/Multi-Output zone **MPC**'s (Lamoudi et al., 2011). Namely, in our framework each zone controller is responsible of maintaining a certain comfort level in the zone by controlling temperature, CO_2 level and indoor illuminance (see fig. 1). Moreover, each zone takes directly into account forecast on disturbances and occupancy predicted profiles in order to optimally manage its local actuators. Table 1 gathers all inputs and outputs related to one zone, where N_f is the number of external facades of the zone, N_b is the number of blinds and N_{adj} the number of adjacent zones. Therefore, accessing to a dynamical representation of each zone in the building is a crucial requirement. In the next section, we describe the technique used in deriving the zone models from our simulation tool. Once these models are identified, we will briefly describe the zone **MPC** algorithm for completeness of the presentation.

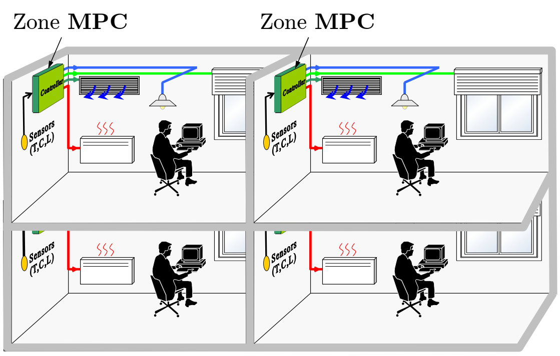

Figure 1: Each zone MPC manages the actuation of its local actuators in order to ensure comfort

ZONE MODELS IDENTIFICATION

A brief description of SIMBAD simulation tool

We provide in the section a brief description of the simulation tool, the reader can find more information in (P. Riederer, 2002; Riederer et al., 2000) or (http://kheops.champs.cstb.fr/Simbadhvac/index.html). SIMBAD (SIMulator of Building And Devices) is a Matlab/Simulink toolbox dedicated to building simulation (temperature, IAQ[2], Lighting). It is developed by CSTB[3]. In SIMBAD, each building is described by an XML file that contains all the information related to:

Table 1: Description of controlled inputs, outputs and exogenous variables of each zone

Variables	Description	unit
u_h	Heating control	$[-]$
u_c	Cooling control	$[-]$
u_v	Ventilation control	$[-]$
u_l	Lighting control	$[-]$
$\{u_b^j\}_{j\in N_b}$	blind control	$[-]$
T^{ex}	Outdoor temperature	$[^oC]$
$\{T_{adj}^i\}_{i\in N_{adj}}$	Adjacent zones temp.	$[^oC]$
$\{\phi^j\}_{j\in N_f}$	Global irr.* flux per facade	$[\frac{W}{m^2}]$
γ	Number of occupants	$[-]$
CO_2^{ext}	Outdoor CO_2 level	$[ppm]$
T^{in}	Indoor air temperature	$[^oC]$
C^{in}	Indoor CO_2 level	$[ppm]$
L^{in}	Indoor illuminance	$[Lux]$

*: irradiance

- **the architecture** of the building in terms of physical characteristics of the envelope, physical interconnections between zones (common walls), facades and windows orientations of each zone of the building;
- **the systems** involved in the building, this includes HVAC systems, lighting as well as all auxiliary systems (pumps, valves etc.) and their respective dimensioning;
- **the location** which is mainly used to determine the related weather station and for the calculation of solar position.

Knowledge related to the topology of the building is essential in order to determine:

- all temperatures impacting the zone in interest (determination of the physically linked zones),
- number and nature of each actuator in each zone,
- disturbances impacting each zone (orientation of each facade, number and orientations of windows).

This information enables to build the structure of the model of each zone in terms of inputs/outputs. Table 1 shows a typical zone input/output description.

In the following, an identification procedure is used to derive the dynamical model of each zone on any building described in SIMBAD.

Zone model Identification

SIMBAD has been delivered as a black box simulink library. Therefore, the building mathematical model is not explicitly accessible and has to be deduced from this simulation tool in order to be integrated in the Model Predictive Controllers.

Hopefully, the embedded model has only to represent inputs/outputs transfers and therefore any dynamical

[2]Indoor Air Quality

[3]Centre Scientifique et Technique du Bâtiment, France.

representation that captures the dynamical behavior of SIMBAD can be used. This means that it is unnecessary to derive a physical model form SIMBAD and greatly simplifies the task since physical models are generally more difficult to identify than non physical ones even in simple cases.

A key point in system identification is the choice of an appropriate mathematical structure. This choice is generally linked to the form of the first principle equations used in the description of the system.

Once this structure is fixed, one can perform an identification procedure in order to find the set of parameters involved in the parametrization of the model structure.

According to the modeling hypotheses considered in SIMBAD (P. Riederer, 2002; Mustafaraja et al., 2010; Kolokotsa et al., 2009; Freire et al., 2005) it comes that the dynamical model of each zone can be expressed by the following bilinear state-space representation:

$$M(\theta) : \left\{ \begin{array}{lcl} x^+ & = & A_\theta x + [B_\theta(y,w)]u + G_\theta w \\ y & = & C_\theta x + [D_\theta(w)]u + F_\theta w \end{array} \right. \tag{3}$$

where:

- $A_\theta, B_\theta, C_\theta, D_\theta, G_\theta, F_\theta$ are matrices of appropriate sizes parameterized by a set of parameter θ;
- x is the state vector of the identified model and has a priori no physical meaning (during simulation, it is recovered using a Kalman observer);
- $y := (T^{in}, C^{in}, L^{in})^t \in \mathbb{R}^3$ is the output vector (see table 1);
- $u := (u_h, u_v, u_l, u_b^1, \dots, u_b^{N_b})^t$ regroups all the controlled inputs (see table 1);
- $w := (T^{ex}, \{T^i_{adj}\}_{i\in N_{adj}}, \{\phi^j\}_{j\in N_f}, \gamma, C^{ex})^t$ is the vector of exogenous variables (see table 1);

Remarks:

- The term $[B_\theta(y,w)]u$ is a bilinear term ($B_\theta(y,w)$ is affine in y and w) and is explained by the fact that the temperature and CO_2 level depend not only on the actuator position u but also on the difference between indoor and external quantities ($T^{in} - T^{ex}$) (convective heat introduced by the mechanical ventilation) and ($C^{in} - C^{ex}$). Moreover, the blinds positions impact the temperature of the zone through the terms $(T^{ex} - T^{in})u_b^1, \dots, (T^{ex} - T^{in})u_b^{N_b}, \phi^1 u_b^1, \dots, \phi^{N_b} u_b^{N_b}$.
- In SIMBAD the radiative exchanges are linearized. This explains that the terms on the form T^4 are non-existent in (3).

For the given model structure $M(\theta)$, the identification problem consists of finding the best set of parameters denoted $\theta^\star$ so that the error between the output of the identified model $M(\theta)$ noted y^θ_{Id} and the output of the simulator y_{sim} for the same inputs is minimized. This is expressed by the following optimization problem:

$$\theta^\star = \underset{\theta}{\text{Argmin}} \sum_{k=0}^{k=T_{sim}} \|y_{sim}(k) - y^\theta_{Id}(k)\|_2 \tag{4}$$

where T_{sim} is the simulation duration.

$M(\theta)$ is a Multi-Input/Multi-Output dynamical system with coupled dynamics. In order to simplify the identification task, this system is (virtually) split into three Multi-Input/Single-Output systems, each one corresponds to an output (temperature, CO_2 rate, indoor illuminance).

The temperature behavior can be described using the following Multi-Input/Single-output Nonlinear Auto Regressive model (which is strictly equivalent to dynamical relation linking T^{in} and u, w expressed by $M(\theta)$):

$$T^{in}(k) = \mathbf{A^T}(q^{-1})T^{in}(k) + \sum_i^{n_v} \mathbf{B_i^T}(q^{-1})\mathbf{v}_i^{\mathbf{T}}(k) \tag{5a}$$

with:

$$\begin{aligned}\mathbf{v^T} := [&u_h, (T^{ex} - T^{in})u_v, u_l, \phi^1 u_b^1, \dots, \phi^{n_f} u_b^{n_f}, \\ &(T^{ex} - T^{in})u_b^1, \dots, (T^{ex} - T^{in})u_b^{n_f}, T^{ex}, \\ &\phi_1, \dots, \phi_{n_f}, \gamma]\end{aligned} \tag{5b}$$

where:

- $\mathbf{v}_i^{\mathbf{T}}$ is the i^{th} component of the vector $\mathbf{v^T}$;
- $\mathbf{A^T}(q^{-1}) := a_1^{\mathbf{T}} q^{-1} + \cdots + a_{n_a}^{\mathbf{T}} q^{-n_a}$ is a polynomial of order n_a;
- $\mathbf{B}_i^{\mathbf{T}}(q^{-1}) := b_{i,1}^{\mathbf{T}} q^{-1} + \cdots + b_{i,n_b^i}^{\mathbf{T}} q^{-n_b^i}$ is the input polynomial related to the i^{th} component of vector $\mathbf{v^T}$ and is of order n_b^i;
- q^{-1} is the delay operator defined for any time dependant $\mathbf{x}(k)$ by: $q^{-n}\mathbf{x}(k) := \mathbf{x}(k-n)$.

Notice that the vector $\mathbf{v^T}$ gathers all affine contributions on temperature (i.e. such that the transfer between each input $\mathbf{v}_i^{\mathbf{T}}$ and the output T^{in} is linear).

Using the same notations for indoor CO_2 level, it comes that:

$$C^{in}(k) = \mathbf{A^C}(q^{-1})C^{in}(k) + \sum_i^{n_v} \mathbf{B_i^C}(q^{-1})\mathbf{v}_i^{\mathbf{C}}(k) \tag{6}$$

where $\mathbf{v^C} := [(C^{in} - C^{ex})u_v, \gamma]^t$

Concerning the indoor illuminance level, the following static model is assumed:

$$\begin{aligned} L(k) &= a_L u_l(k) + \sum_{j=1}^{j=N_b} b_L^j \phi_j(k) u_b^j(k) \\ &\quad + \sum_{j=1}^{j=n_f} \bar{b}_L^j \phi_j(k)(1 - u_b^j(k)) \end{aligned} \tag{7}$$

The model mathematical structure being now described, one can identify the polynomials $\mathbf{A^T}$, $\mathbf{B_i^T}$,

$\mathbf{A^C}$, $\mathbf{B_i^C}$ and constants a_L, b_L^j, $\bar{b}_L^j$ in order to fully describe the model. Noting the set of the unknown coefficients cited above θ, it is easy to recover the model $M(\theta)$.

It can be shown that (4) is in our case a linear least square problem (Landau and Zito, 2006), this problem is efficiently solved using some dedicated optimization tool (we used Matlab optim. toolbox).

Even if this identification problem seems to be quite simple given that no noise affects the measurements and no unmeasured disturbance is present, one has to mention that the following precautions must be taken in order to ensure the success of the identification:

1− Appropriately chosen excitation signals have to be injected in the simulator. This in order to ensure that inputs are not correlated. Moreover each excitation signal has to be sufficiently rich in frequencies to excite all the modes of the simulation model (Landau and Zito, 2006);

2− The initial state of the process (SIMBAD) is forced to zero (equilibrium);

3− Let us finally notice concerning the thermal aspect that adjacent zones air temperatures are considered as disturbance from the point of view of the zone in concern, therefore local zone controllers must be inserted in each adjacent zone in order to control each adjacent zone temperature.

The identification procedure described above has been applied on SIMBAD for different buildings. It has been noted that the simulation model (SIMBAD) can be identified quasi perfectly (mean error less than 0.01 %) for sufficiently high model orders (typical value was $n_a = n_b = 6$ concerning temperature and a first order for CO_2 level).

Design of the zone MPC

In this section, the cost function $J(\cdot, x(k))$ and the constraints $\mathcal{C}$ that are used at each instant k to compute the optimal sequence (as recalled in the first section) are described. The **MPC** optimization problem is defined at each decision instant k based on the following knowledge:

- The current state $x(k)$ of the system model (obtained via classical dynamic observer),
- The prediction of disturbances $\tilde{w}$,
- The normalized characteristic power consumption p_j of each actuator j ($p_j \cdot u_j$ represents the power)
- The prediction of the normalized energy rate profile $\tilde{r}_j$ for each actuator type j.
- The comfort related bounds profiles $\underline{y}(k+i)$ and $\overline{y}(k+i)$ for $i \in \{1, \dots, N\}$

It is generally admitted that occupant comfort can be described by an admissible set to which the output y has to belong (please refer to existing standard (EN1). This admissible set obviously depends on the occupancy of the zone, the current season and the nature of the zone under consideration. These consideration leads to the following constraints:

$$y(k) \in [\underline{y}(k), \overline{y}(k)] \quad (8)$$

where $\underline{y}(k) \in \mathbb{R}^3$ and $\overline{y}(k) \in \mathbb{R}^3$ are lower and upper bounds that implicitly depends on the occupancy indicator (through the time argument k). Table 2 shows typical values of $\underline{y}$ and $\overline{y}$ depending on the occupancy indicator.

Table 2: Nominal comfort region

	T_{in}		C^{in}		L^{in}	
	min	max	min	max	min	max
Occup.	20	23	–	900	500	–
Vacant	5	30	–	–	–	–

Moreover, saturation constraints on the actuators are also considered using standard constraints of the form:

$$\big[A_{sat}\big]u(k) \le b_{sat} \quad (9)$$

which may include both saturation the value of u as well as on its rate of change. For convenience, normalized vector are considered, then all inputs u must be comprised in $[0, 1]$.

The cost function at instant k is affine in the control sequence and defined over the prediction horizon $[k, k+N]$ by the total energy invoice:

$$J(\tilde{u}, x(k)) := \sum_{i=0}^{N-1} \sum_{j=1}^{n_u} r_j(k+i)\big[p_j u_j(k+i)\big] \quad (10)$$

$$= R(k) \cdot \tilde{u} \quad ; \quad R(k) \in \mathbb{R}^{1 \times N \cdot n_u} \quad (11)$$

and the MPC-related optimization problem at instant k becomes:

$$\min_{\tilde{u}} \; [R(k) \cdot \tilde{u}(k) + \rho \cdot \sum_{i=1}^{i=N} \tilde{\delta}^+(i) + \tilde{\delta}^-(i)] \quad (12a)$$

Subject to: $\forall i \in \{1, \dots, N\}$

$$Y(k+i, \tilde{u}(k), \tilde{w}(k), x(k)) \le \overline{y}(k+i) + \tilde{\delta}^+(i) \quad (12b)$$

$$Y(k+i, \tilde{u}(k), \tilde{w}(k), x(k)) \ge \underline{y}(k+1) - \tilde{\delta}^-(i) \quad (12c)$$

$$A_{sat}u(k+i) \le b_{sat} \quad (12d)$$

$$\tilde{\delta}^+(i) \ge 0 \quad , \quad \tilde{\delta}^-(i) \ge 0 \quad (12e)$$

where the notation $Y(\cdot, \tilde{u}(k), \tilde{w}(k), x(k))$ is used to denote the trajectory of the output vector for given sequences $\tilde{u}(k)$ and $\tilde{w}(k)$ of future evolutions of u and w respectively. $x(k)$ is the initial state. The positive slack variables $\tilde{\delta}^+(\cdot)$ and $\tilde{\delta}^-(\cdot)$ are heavily weighted through $\rho > 0$ in order to avoid unnecessary constraint violation. Moreover, they unsure the feasibility of the problem (12). Discussion about the resolution of the optimization problem (12) (which is not necessarily convex) lies beyond the scope of this article, the reader can refer to (Lamoudi et al., 2011) for more details concerning this point.

INTRODUCING UNCERTAINTIES

At this point, zone model predictive controllers have been designed and integrated in SIMBAD. Nevertheless, it is worth underlining that within our framework, it is crucial to take into account uncertainties on predictions during the assessment of this control strategy, since predictions are directly integrated in the process of decision making (Gyalistras and Team, 2010). This is the reason why we propose to study the effect of uncertainties related to weather and occupancy.

Weather uncertainties

It is unrealistic to model exactly the errors introduced by meteorological forecast service due to its complexity. Therefore, let us assume that a meteorological forecast service (with in situ correction feature[4]) can be modeled by:

$$\tilde{w}(k) = \alpha \cdot \tilde{w}_P(k) + (1-\alpha) \cdot \tilde{w}_F(k) \tag{13}$$

where $\tilde{w}_P(k)$ is the perfect prediction profile, $\tilde{w}_F(k)$ is the prediction given by the n_d-**bin** predictor defined in (14), $\alpha \in [0,1]$ is used to weight the perfect profile and the unperfect one. This way, we can easily control the error on forecast (if $\alpha = 1$ the weather is perfectly known).

The n_d-**bin** that we use is a slightly modified version of the one given by (Henze et al., 2004), namely:

$$\begin{aligned} \tilde{w}_F(k) &:= \frac{1}{n_d} \sum_{d=1}^{d=n_d} \tilde{w}_P(k - 24 \cdot d) \\ &+ w_P(k) - \frac{1}{n_d} \sum_{d=1}^{d=n_d} w_P(k - 24 \cdot d) \end{aligned} \tag{14}$$

This simply means that the predicted temperature for the next $24hours$ is the mean temperature profiles observed on the n_d previous days and adjusted to fit the current measured temperature (this explains the term $w_P(k) - \frac{1}{n_d}\sum_{d=1}^{d=n_d} w_P(k - 24 \cdot d)$). Remark that the first temperature is always perfectly known.

This procedure is used for the prediction of outdoor temperature and irradiance fluxes.

Fig. 2 shows the mean error distribution probability with a 20-Bin predictor for Paris weather station for one year. It is interesting to notice that the proposed simple model (13) gives unbiased predictions

[4]The current weather forecast is corrected based on in situ measurements

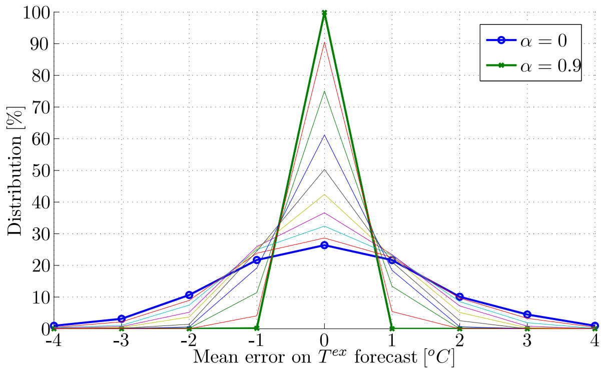

Figure 2: Mean error distribution probability of the meteo. forecast service for different values of α.

with gaussian like error distribution. This is in accordance with the generally admitted models used in other related works (Gyalistras and Team, 2010).

Occupancy Modeling

In order to enrich the occupancy profiles, the following Markov chain based model is used to describe the presence of each occupant in a given zone. This model has been proposed in (Page, 2007) and is defined by its transition matrix $\mathcal{T}(k)$:

$$\mathcal{T}(k) = \begin{bmatrix} T_{00}(k) & T_{01}(k) \\ T_{10}(k) & T_{11}(k) \end{bmatrix} \tag{15}$$

where $\{T_{ij}(k)\}_{i\in\{0,1\},j\in\{0,1\}}$ are time dependent transition probabilities of the Markov chain describing the presence/absence of the occupant in the zone (0:absent,1:present), and are given by:

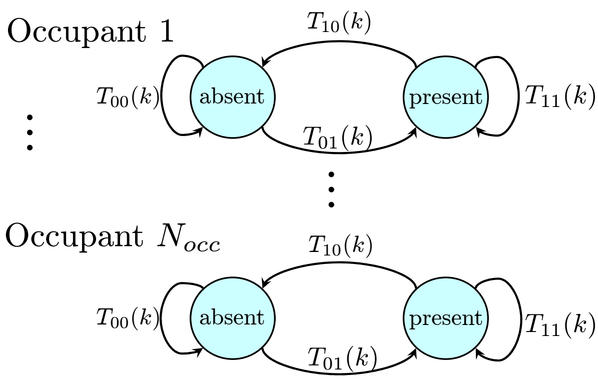

Figure 4: Markov chain with states. The transition probabilities are time varying. Each occupant can be characterized using its own Markov chain.

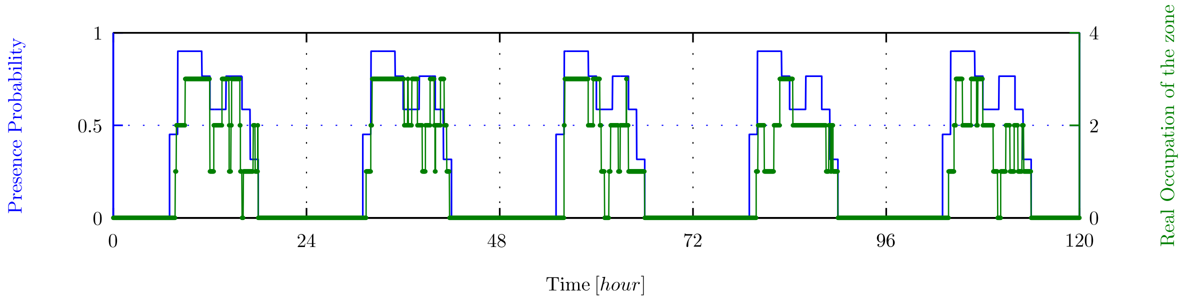

Figure 3: Presence probability (blue) and corresponding generated stochastic occupancy profile (green).

$$T_{01}(k) = \frac{\mu-1}{\mu+1}\cdot P(k) + P(k+1) \quad (16a)$$

$$T_{11}(k) = \frac{P(k)-1}{P(k)}\cdot[\frac{\mu-1}{\mu+1}\cdot P(k)+P(k+1)] + \frac{P(k+1)}{P(k)} \quad (16b)$$

$$T_{00}(k) = 1 - T_{01}(k),\ T_{10}(k) = 1 - T_{11}(k) \quad (16c)$$

where μ is the parameter of mobility and is used to adjust the moving frequency of the occupant. $P(k)$ is the presence probability of the occupant in the zone. Given a nominal number of occupants in each zone N_{occ}, one can define for each occupant a presence/absence model. Fig. 3 depicts a typical result given by 15. The presence probability profile (blue curve) is defined in accordance with the occupation schedule of the zone. One can refer to (Page, 2007; Mahdavi and Pröglhöf, 2009) to find some elements regarding appropriate choices of μ and $P(k)$.

SIMULATION RESULTS

We propose in this section some simulations performed on a simple case study. We consider a 500 m^2 office building located at Paris. Because of lack of space, only results related to one zone of this building are provided. The zone in consideration is a 20 m^2 office and has two facades (west and south), each of them has a window equipped with blinds. The controlled actuators consist of a heater (u_h), a mechanical ventilation (u_v), a lighting system (u_l) and two blinds u_{b1}, u_{b2}. Their respective power consumptions are $(1.5, .15, .5, 0, 0)$ $[kW]$.

Adjacent zones temperatures are perfectly known.

Numerical values of the identified model are omitted, however let us mention that the identification phase leaded to a 7^{th}(6 states for temp. and 1 for CO_2) order model with a sampling period of 1 min that fits exactly SIMBAD. The number of occupants $N_{occ} = 3$. **MPC** prediction horizon is 24 hours and a new optimal solution is computed each min. The energy rate $r(k)$ is two times higher between $6a.m$ and $10p.m$ (Fig. 5).

Perfectly known occupation

In this first simulation, only uncertainties on weather conditions are introduced. This leads to the results depicted on fig. 5. Simulations for 3 values of α has been conducted (0, 0.5 ,1). Unsurprisingly, degradation of weather forecast quality generates an increase of the invoice (table 3). In this case study, a maximum of 4% of increase (corresponding to $\alpha = 0$) has been noted. Let us notice that, independently of the energy invoice, the comfort of the occupant is maintained since temperature , CO_2 level and indoor illuminance are kept within their respective prescribed bounds (red and cyan).

Table 3: Energy invoice for different values of α

α	0	.5	1
Invoice (Euro)	10.17	9.88	9.78
%	104%	101%	100 %

Uncertainty on both weather and occupation

Let us now introduce in addition uncertainties on the number of occupants in the zone. In this case, the predicted number of occupants (used by the **MPC**) corresponds to occupancy schedule used in the previous simulation, however the real number of occupants in the zone (injected in SIMBAD) is generated using the stochastic procedure cited above. Notice in this case that the invoice is enlarged comparing to the "perfectly known forecast" case by 18% (table 4). This enables us to give a quite realistic potential gain given a known quality of weather forecast for a realistic occupancy profile. Let us finally mention that comfort requirement is always ensured (Fig. 6) attesting the robustness of the control strategy in providing comfort for occupants.

Table 4: Invoices with the introduction of errors on occupation and weather forecast

α	0	.5	1	$\star$
Invoice (Euro)	9.57	8.98	8.92	8.13
%	118 %	110	109 %	100 %

$\star$: weather and occupancy perfectly known.

Some elements on HVAC dimensioning

We give in this last part some elements on the dimensioning of HVAC systems using the designed **MPC**. For simplicity of the presentation, let us consider that

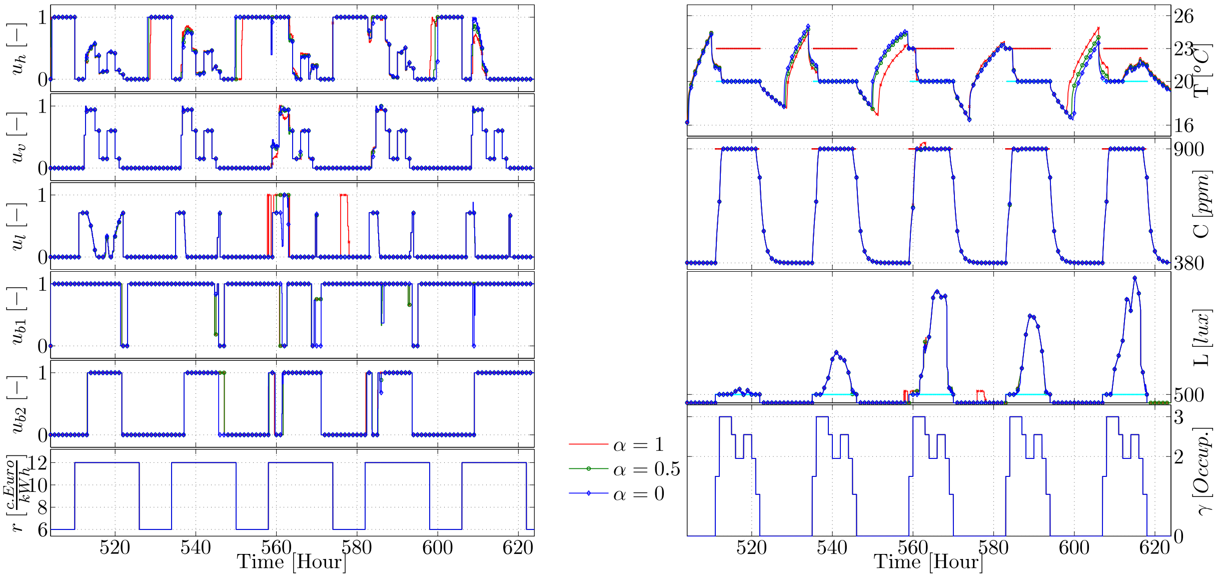

Figure 5: Simulation results for $\alpha = \{0, 0.5, 1\}$ with perfectly known occupation profile. Remark that uncertainties on predictions mainly induce a bad estimation of the heating optimal start time (top-left). Comfort bounds are always respected.

we are interested in studying the effect of a modification of the size of the electrical heater on the invoice (related to the case described above). As it has been mentioned in the first section, **MPC** is based on the resolution of the optimization problem (12). Remind that saturations on actuators are introduced in (12) through the set of constraints expressed by (12d): $A_{sat} \cdot u(k+i) \leq b_{sat}$ which includes the constraint on heater control $u_h \in [0\ 1]$ (we consider normalized inputs). Suppose now that this last constraint is modified in order to let the control u_h lies in $[0, \bar{u}_h]$, $\bar{u}_h \geq 0$ (this means that the heater dimension has been increased - or decreased- by a factor $\bar{u}_h$), then one can solve the resulting optimization problem for different values of $\bar{u}_h$. The results are provided on (fig. 7) for perfectly known weather and occupancy.

Notice that the sensitivity curve (fig. 7) considers only sensitivity of the energy invoice and doesn't include the price of the electrical heater. This consideration can be easily included further. Moreover, only admissible values of $\bar{u}_h$ (those that ensure that comfort is always provided) are considered, $\bar{u}_h \geq 0.7$ (fig. 7).

Let us also mention that this procedure can be applied for the sizing of other actuators (ventilation, lighting, cooling etc.). Many improvements can be imagined concerning this point. For instance: based on the fact that the actions of some actuators may affect more than one output (e.g lighting influences indoor illuminance and temperature), one could optimally dimension these actuators simultaneously.

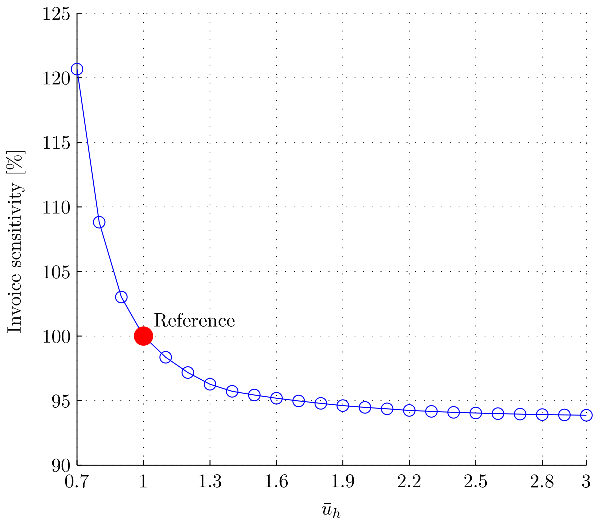

Figure 7: Sensitivity function of the invoice with respect to $\bar{u}_h$. Remark that tripling the size of the heater induces a maximum diminution of 7% of the total invoice, however a diminution of 30% increases increases the invoice with 21%.

CONCLUSION

In this paper, a methodology for interfacing and assessing **MPC** strategy with an existing building simulator has been proposed. This approach enables to give a gain potential of this control strategy in quite realistic conditions. It consists of deriving embedded models in order to design zone predictive controllers. The control strategy is then assessed in quite realistic situations thanks to the introduction of errors on predictions. These uncertainties gather the uncertainty on meteorological forecast and on occupancy of the zone. For the simulation of the meteorological forecast service, a simple weather station model has been proposed. Moreover, we presented an application of the designed predictive controller for heater dimensioning. This last point will be more detailed and enhanced

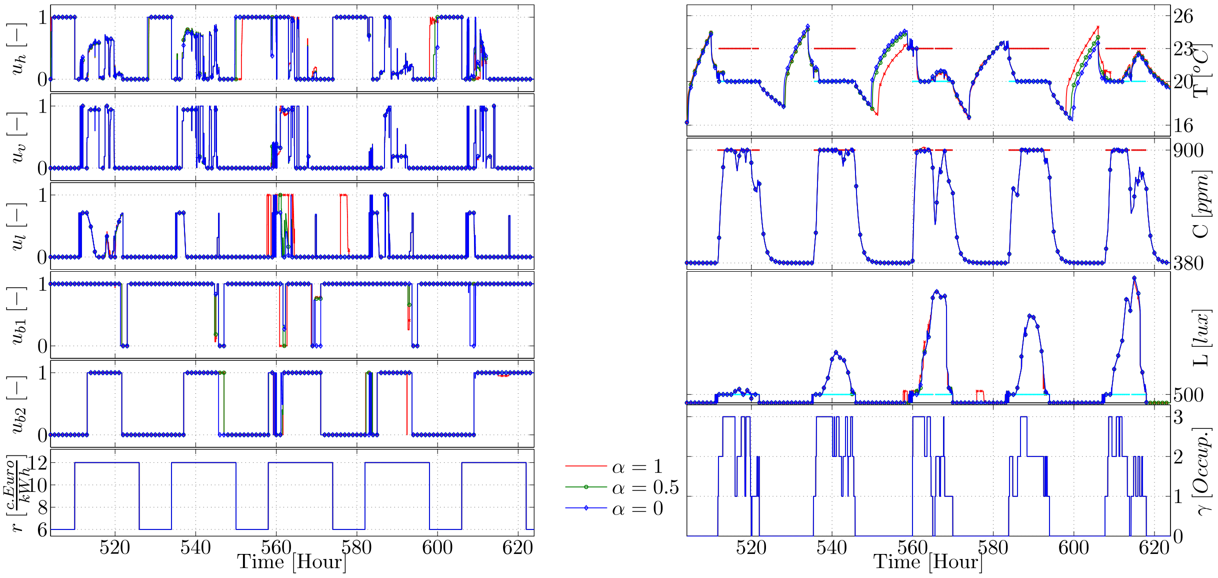

Figure 6: Simulation results with uncertainties on weather ($\alpha = \{0, 0.5, 1\}$) and occupation profile. Notice that comfort bounds on the three controlled variables are always respected.

in further studies that will also focus on designing robust predictive controller as well as studying the effect of uncertainties introduced on embedded models.

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