ENERGY CONSUMPTION REDUCTION IN OFFICE BUILDINGS USING MODEL-BASED PREDICTIVE CONTROL

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ABSTRACT

The system under study is an office building using two types of sources for heating: traditional gas boilers and energy-efficient, geothermal heat pumps. A Model-based Predictive Control (MPC) strategy is suggested and tested in simulation, where the building is used as an active storage in order to decrease the morning peak loads and consequently the use of the boilers. The MPC algorithm aims at maintaining the comfort temperature during the working hours while minimizing the total demand in primary energy over one day. The strategy exhibits satisfactory results in terms of control performance and energy savings when compared to a standard proportional-integral (PI) control.

INTRODUCTION

The University of Mons and the company Electrabel, GDF Suez group have been developing for a couple of years a scientific collaboration. The studies related to this collaboration are concerned with energy efficiency aspects inside the company itself, more particularly the optimization of the energy resources used for the Heating, Ventilation and Air-Conditioning (HVAC) of office buildings. Presently two new twin office blocks are being built in Brussels, Belgium, the first one is equipped with classical HVAC systems and is already occupied whereas the second one is still under construction and the associated HVAC systems are under design completion. Both HVAC systems are equipped with:

- a centralized Air-Conditioning (AC) system and well-adapted end-user AC units;
- enthalpic wheels allowing for the energy recovery from the exhaust air;
- to some extent, free cooling capabilities from the outdoor air and/or the ground.

The energy production systems consist of:

- standard gas boilers and cooling machines;
- two geothermal heat pumps;
- a complex pipe switching system allowing for many operation modes, such as the heating and/or cooling mode of the heat pumps, the geothermal cooling, the energetic regeneration of the ground when successive heat extraction and supply steps do not compensate.

At the first stage of the study, a commercial software (Trnsys, 2007) was used to develop:

- the building model, which accurately accounted for the building complexity in terms of geometry, materials, glazing, etc.;
- the model of the HVAC systems;
- a simple on-off control structure which aimed at maintaining fixed temperature and humidity during the working hours only.

The simulation results revealed the importance of the building thermal inertia (due to the internal walls), i.e., the heating needs were much higher in the early morning than during the rest of the day, especially at the beginning of the week (due to the week-end inactivity).

From these observations and since the extra energy boost is delivered by conventional machines (gas boilers) which are less efficient than heat pumps, it could be worth decreasing the peak load by raising up the inner temperature during the night, which is achieved advantageously by using heat pumps. However, this idea can only be properly implemented if the thermal behaviour of the building, the comfort (i.e., the indoor temperature) and the energy cost are evaluated over some time period, which leads to consider that the Model-based Predictive Control (MPC) technique is well-suited to the problem. The concept of using optimal/MPC control together with building thermal storage is not so recent. It was an important research topic dozens of years ago, notably in cooling applications where the electricity cost varies according to the day-night regime (Rabl and Norford, 1991; Morris et al., 1994); such literature is reviewed in (Braun, 2003). More recently, Ma *et al.* gave a comprehensive introduction to how thermal storage and MPC can be combined at several control levels in heating/cooling (Ma et al., 2012). Alternatively MPC and weather forecasts are used to save heating energy just when the building behaviour is sensitive to variable gains (Siroky et al., 2011).

In this study too the benefit of load shifting thanks to the building thermal storage is illustrated. The of-

fice storeys of the building are viewed as a Resistor-Capacitor (R-C) model with only two nodes (representing the indoor air and the concrete thermal mass). The time period is a couple of days in winter time where gains are majorily of the internal type and only heating is considered to compensate mainly the effect of the outdoor temperature. The control performance is restricted to maintaining a comfort temperature during the working hours (the control of humidity is out of scope). The strategy aims at making a compromise between control performance and energy efficiency over a 24-hour horizon by using a 3-level profile of the end-user heat flow rate (typically night, morning and afternoon regimes) and the outdoor temperature forecasts. The control performance term is based on the deviation of the inner temperature from a fixed setpoint during the working hours whereas the energy term integrates over the day the primary energy delivered by both the standard boilers and the heat pumps. The primary energy is presently calculated from the computed end-user heat flow rate by using fixed efficiencies for the energy production devices. The MPC strategy is compared with a classical proportional-integral (PI) control in terms of performance and primary energy consumption. All developments regarding modelling, solution of equations and optimization are achieved using MATLAB®.
The rest of the article is as follows. Section *Modelling* describes the simplified building, the HVAC systems chosen for the purpose of the study and the associated model. The MPC strategy and its implementation are described in Section *Model-based predictive control*. The simulation results are introduced in Section *Results* and, finally, Section *Conclusion* is devoted to the conclusions and perspectives.

MODELLING

Physical description

Figure 1 represents the office building, of which the offices occupy 12 storeys. For each storey the floor surface area is $2280\,\mathrm{m}^2$ (A_{st}) and the height is $3.35\,\mathrm{m}$ (h_{st}). The inter-floor separation is a concrete slab of thickness $0.35\,\mathrm{m}$ (h_{if}). The office zone considered is assumed to be in thermal equilibrium with the storeys above and below. The total facade wall has a surface area of $13850\,\mathrm{m}^2$ (A_f), essentially made of well-insulating glass, so that the heat transfer coefficient equals $1.1\ \mathrm{W/m^2\ K}$ (K_{io}) and the thermal capacity is negligible.

[ht] 

Figure 1: Office building under study, facing North (Source: Officine Tosoni).

The building is occupied during the working days from 8.00 to 18.00 and this activity causes an internal gain heat flow rate of $806\ \mathrm{kW}$ (Φ_{ig}). The solar gains are neglected, due to the the poor sunny radiation in winter, the glazing properties of the facade and the orientation of the glass walls (mainly West, North and East). The building is ventilated (in standard operation, only during the working days from 7.00 to 19.00) with a fresh air flow rate of $34.5\ \mathrm{m^3/s}$ ($\dot{V}_v$). However, an enthalpic wheel allows for recovering part of the exhaust air heat, so that the net heat loss due to ventilation can be calculated by assuming that the fresh air temperature is taken at the enthalpic wheel outlet (fresh air side). The enthalpic wheel is viewed as a heat exchanger with efficiency equal to 0.6 (ϵ_{rec}). The fresh air out of the enthalpic wheel is then heated through a heating coil. In the heat production process, the heat pump is prioritized, however with a maximum heat flow rate of $352\ \mathrm{kW}$ ($\Phi_{HP;max}$).

Model equations

Two differential equations (1-2) express the energy conservation of the indoor air node and of the concrete node.

$$
\begin{aligned}
C_i \frac{dt_i}{d\tau} &= (KS)_{io}(t_e - t_i) + (KS)_{ic}(t_c - t_i) \\
&\quad + \Phi_{ig}(\tau) + KV(\tau)(t_r - t_i) \\
&\quad + \Phi_h(\tau) \qquad (1) \\
C_c \frac{dt_c}{d\tau} &= (KS)_{ic}(t_i - t_c) \qquad (2)
\end{aligned}
$$

where

- t_i and t_c are the indoor air and concrete temperatures, respectively;
- t_e is the outdoor air temperature, t_r is the fresh air temperature at the recovery wheel outlet;
- $\Phi_h(\tau)$ is the net heat flow rate delivered to the fresh air in the heating coil;

- C_i and C_c are the indoor air and concrete thermal capacities, respectively;
- $(KS)_{io}$ and $(KS)_{ic}$ are the global heat transfer coefficients (in $\mathrm{W/K}$) from the indoor air node to the outdoor air and concrete nodes, respectively;
- $KV(\tau)$ is the global heat transfer coefficient (in $\mathrm{W/K}$) due to ventilation.

It is worth noting that the last 3 terms of equation 1 are explicitly time-dependent, which especially indicates that they are zero apart from the application period.
Temperature t_r is calculated using the enthalpic wheel efficiency

$$\epsilon_{rec} = \frac{t_r - t_e}{t_i - t_e} \tag{3}$$

The thermal capacities are described as follows

$$\begin{aligned} C_i &= V_i \rho_i c_i && (4)\\ C_c &= V_c \rho_c c_c && (5)\\ V_i &= 12 A_{st} h_{st} && (6)\\ V_c &= 11 A_{st} h_{if} && (7) \end{aligned}$$

where ρ_i and c_i are the density and the specific heat at constant pressure, respectively, of the indoor air node. ρ_c and c_c are the corresponding parameters for the concrete node.
The global heat transfer coefficients are described as follows

$$\begin{aligned} (KS)_{io} &= A_f K_{io} && (8)\\ (KS)_{ic} &= 11(2A_{st})K_{ic} && (9)\\ KV(\tau) &= \dot{V}_v(\tau)\rho_i c_i && (10)\\ 1/K_{ic} &= \frac{h_{if}}{2\lambda_c} + \frac{1}{K_h} && (11) \end{aligned}$$

where

- λ_c is the heat conductivity of the concrete slab;
- K_h is the global heat transfer coefficient from the surface of the slab to the indoor air (subscript *h* stands for *horizontal*).

PI-control equations

The PI scheme is designed to control the indoor air temperature t_i by using the control variable Φ_h. Here the continuous form of the controller is employed, i.e., the differential-equation system is augmented by one state equation (12), and by one state variable, $v(\tau)$,

$$\frac{dv}{d\tau} = t_i^* - t_i \tag{12}$$

The net heat flow rate Φ_h is given by

$$\Phi_h = G_{PI}\left((t_i^* - t_i) + \frac{v}{T_{PI}}\right) \tag{13}$$

where G_{PI} and T_{PI} are the proportional gain and integral time constant of the PI controller, respectively. Here classical techniques are employed to compute the controller parameters, which guarantee performance and stability by setting the closed-loop bandwidth and the phase margin, respectively (see (Aström and Hägglund, 1995)). Detailed calculations are beyond the scope of this article.
Table 1 summarizes the parameters and their values.

[ht]

Table 1: Model parameters and values

Parameter	Value	Unit
A_{st}	2280	$\mathrm{m^2}$
h_{st}	3.35	m
h_{if}	0.35	m
A_f	13850	$\mathrm{m^2}$
ρ_i	1.204	$\mathrm{kg/m^3}$
c_i	1012	$\mathrm{J/kg\ K}$
ρ_c	2300	$\mathrm{kg/m^3}$
c_c	1000	$\mathrm{J/kg\ K}$
K_{io}	1.1	$\mathrm{W/m^2\ K}$
K_h	8	$\mathrm{W/m^2\ K}$
λ_c	1.7	$\mathrm{W/m\ K}$
Φ_{ig}	806	kW
$\dot{V}_v$	34.5	$\mathrm{m^3/s}$
ϵ_{rec}	0.6	(-)
t_i^*	22.0	$^\circ\mathrm{C}$

All programs have been developed by using standard MATLAB language and the associated libraries for the solution of the differential equation systems (ODE15s).

Heat production

The heat production is based on two important assumptions:

- the heat pump is prioritized, given a maximum heat flow rate $\Phi_{HP;max}$;
- the cost is expressed in terms of the primary energy consumed.

In this way the net and primary heat flow rates are calculated from the total end-user heat flow rate Φ_h as follows:

$$\begin{aligned} \Phi_{HP} &= min(\Phi_h, \Phi_{HP;max}) && (14)\\ \Phi_{Bo} &= \Phi_h - \Phi_{HP} && (15)\\ \Phi_{HP;p} &= \frac{\Phi_{HP}}{COP\ \eta_{ps}} && (16)\\ \Phi_{Bo;p} &= \frac{\Phi_{Bo}}{\eta_{Bo}} && (17) \end{aligned}$$

In equations (14-17),

- Φ_{HP} and Φ_{Bo} are net heat flow rates delivered by the heat pump and by the boiler, respectively;
- $\Phi_{HP;p}$ and $\Phi_{Bo;p}$ are the corresponding primary heat flow rates;

- COP is the (electrical) coefficient of performance of the heat pump;
- η_{ps} is the global efficiency associated to the power station;
- η_{Bo} is the efficiency associated to the boiler.

The heat production parameters chosen here are listed in Table 2.

Table 2: Heat production parameters

Parameter	Value	Unit
$\Phi_{HP;max}$	352	kW
η_{Bo}	0.9	(-)
COP	4.5	(-)
η_{ps}	0.4	(-)

MODEL-BASED PREDICTIVE CONTROL

Principle

In this section the basic principle and the major definitions of the Model-based Predictive Control (MPC) scheme are summarized. More comprehensive information is found in the dedicated literature, see (Camacho and Bordons, 1999; Maciejowski, 2001) among others.
The main feature of MPC is that some control variable $u(\tau_k)$ at sampling time τ_k is calculated by solving an optimization problem, i.e.,

$$u_k(\tau) = \min_{\hat{u}(\tau)} \int_{\tau_k}^{\tau_k+H} CF(\hat{x}(s), \hat{u}(s))ds \qquad (18)$$

given

$$\begin{aligned} \frac{d\hat{x}}{d\tau} &= f(\hat{x}, \hat{u}) && (19) \\ \hat{x}_0 &= x(\tau_k) && (20) \\ g(\hat{x}, \hat{u}) &<= 0 && (21) \end{aligned}$$

Equation (18) expresses that

- a cost function $CF(.)$ depending on the predicted state variables $\hat{x}$ and on the control variable $\hat{u}$ is integrated over a fixed-time horizon H, named *prediction horizon*;
- the integral is minimized in order to find the *best* $\hat{u}(\tau)$ profile.

The solution must verify constraints (21) (a typical constraint is the saturation of the control variable). Variable $\hat{x}(\tau)$ is evaluated by solving system (19) with initial condition (20) and input $\hat{u}(\tau)$.
The second feature is that the control variable is applied *over one sampling period only* (from τ_k to τ_{k+1}). Then, based on a new measurement $x(\tau_{k+1})$ as initial condition, a new problem is solved over the same time horizon H, however from time τ_{k+1}.

Implementation

The first aim is control performance, i.e., to maintain the indoor air temperature close to the setpoint value during the working hours. The second aim is primary energy saving, i.e., to minimize the sum of the energies produced by the heat pump and by the boiler, once appropriately converted to primary energy. Therefore function $CF(.)$ is expressed as

$$CF(.) = f_{WH}(t_i^* - t_i)^2 + w_E(\Phi_{HP;p} + \Phi_{Bo;p}) \qquad (22)$$

where f_{WH} equals 1 during the working hours, 0 otherwise. w_E is a weighting factor allowing for the tuning of the optimization algorithm. $\Phi_{HP;p}$ and $\Phi_{Bo;p}$ are the primary energy heat flow rates of the heat pump and of the boiler, respectively. Due to the cyclic behaviour of the building (day-night regime imposed by the outdoor temperature and by the occupancy), the prediction horizon H is naturally $24\,\mathrm{h}$. The sampling time, T_s, equals $1\,\mathrm{h}$.

Here the control variable $u(\tau)$ is obviously $\Phi_h(\tau)$. A delicate task is the time profile parameterization of Φ_h since a complex profile may lead to serious optimization difficulties. However, one must account at least for:

- the difference between the night and day regimes;
- the difference between the morning boost and the afternoon regime.

This led us to consider 3 degrees of freedom (or heat flow rate levels) as follows:

- night regime, from 19.00 to 7.00 (of the next day): $\Phi_h = \Phi_{night}$;
- morning regime, from 7.00 to 13.00: $\Phi_h = \Phi_{morning}$;
- afternoon regime, from 13.00 to 19.00: $\Phi_h = \Phi_{afternoon}$;

Additionally, during the night regime, in order to reduce the night losses, the ventilation flow rate is set to half the working regime value, that is $17.25\,\mathrm{m}^3/\mathrm{s}$.

The optimization algorithm is implemented by using MATLAB's OPTIMIZATION TOOLBOX (LSQNONLIN).

RESULTS

The simulation experiments are performed for a few days in winter time from Monday at 0.00 onwards. The outdoor temperature is taken from standard weather files for Western Europe (see (Trnsys, 2006)) and is represented in figure 2.

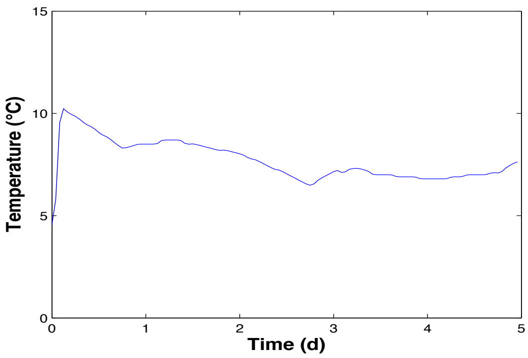

Figure 2: Outdoor temperature during the experiment

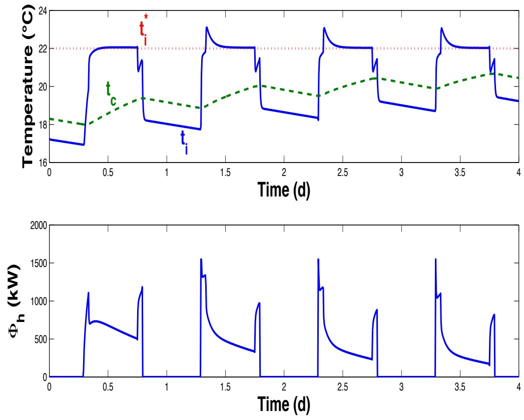

Figure 3: PI-control: evolution of the state variables and of the setpoint (upper) and of the control variable Φ_h (lower)

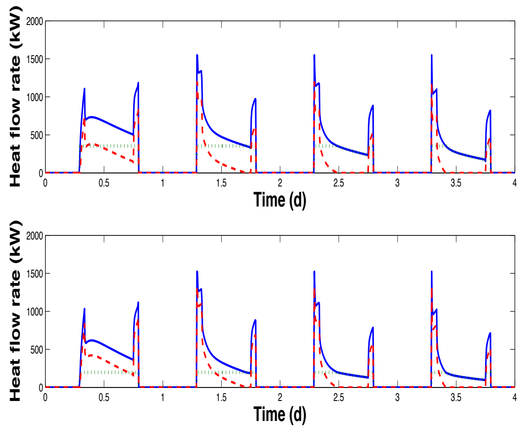

Figure 4: PI-control: total and per source heat flow rates (upper: net heat flow rates, lower: primary heat flow rates; solid: total, dashed: boiler, dotted: heat pump)

Classical PI-control

A PI-control has been designed, which aims at maintaining the indoor temperature $t_i(\tau)$ close to the setpoint value t_i^* by using the end-user heat flow rate $\Phi_h(\tau)$. The traditional criteria of bandwidth and phase margin led to a controller gain $G_{PI} = 303.4\,\mathrm{kW/K}$ and time constant $T_{PI} = 0.57\,\mathrm{h}$. The results obtained are represented in figure 3, which shows the controlled variable (indoor temperature) and the control variable (net heat flow rate). One notes that the controller performs nicely as the indoor temperature correctly fits the setpoint during the working hours. Small jumps of the temperature but mostly of the heat flow rate are due to the internal gains, i.e., there is a 1h-delay between the start (or stop) of the HVAC system and the incoming (or outcoming) of the working people, this latter phenomenon acting as a perturbation in the control loop. Furthermore one notes that, each day, a heating boost is required in the morning and that, during the week, the boost magnitude and also the daily energy decrease. This observation is clearly related to the increase of the concrete floor temperature during the week. In figure 4 (upper graph), it appears that the heat pump is not sufficient in the beginning of the week (first two days) and conversely, the boiler is less used towards the end of the week (last two days). Figure 4 (lower graph) illustrates the evolution of the primary heat flow rate (considered here as the real cost). Values from the beginning towards the end of the week decrease even more drastically than on the upper graph. In conclusion higher values of the concrete slab temperature allow for a minor boost in the morning, moreover a major use of the heat pump instead of the more expensive gas boiler.

Model-based predictive control

An MPC algorithm has been designed and implemented by using the parameter values listed in Table 3.

Table 3: MPC parameters and values

Parameter	Value	Unit
T_s	1	h
H	24	h
w_E	0.4	(-)

Every hour the optimization computes the *best* control time profile, i.e, 3 heat flow rate values, which are represented in figure 5. Depending on the actual time only one of these values is applied to the real system until the next sampling time. The result of this strategy is represented in figure 6, which shows the controlled variable (indoor temperature) and the control variable (net heat flow rate). In agreement with the strategy, one can note that the values of the control variable match exactly the predicted values of the corresponding regime in figure 5. For example, from 0.00 to 7.00 (or from 7.00 to 13.00 or from 13.00 to 19.00), the control variable in figure 6 corresponds to the dotted (or solid or dashed) plot in figure 5. The main observation is that the magnitude of the net heat flow rate (less than 600 kW) is smaller than with the PI-control (where extra boosts led to more than 1000 kW). On the other hand, despite that the performance was not the only objective, the behaviour of the indoor temperature is very acceptable.

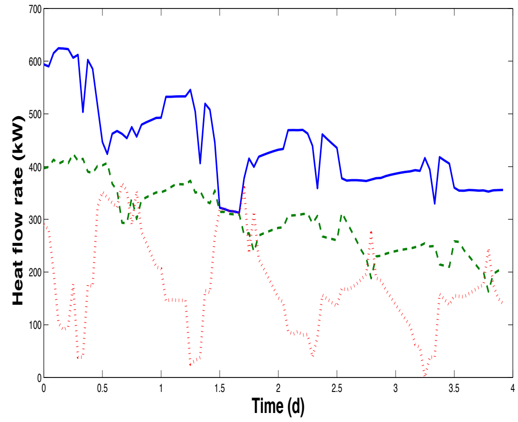

Figure 5: MPC strategy: predicted profile of the control variable (solid: morning, dashed: afternoon, dotted: night)

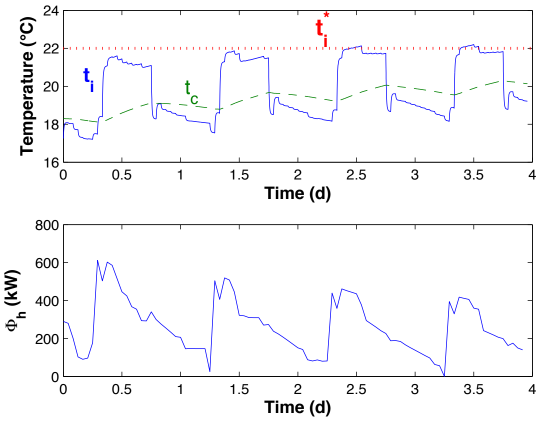

Figure 6: MPC control: evolution of the state variables and of the setpoint (upper) and of the control variable Φ_h (lower)

Comparison

The interest of the MPC strategy clearly appears when the indicators in Table 4 are compared. The indicators are mean and/or integration results over the 4 winter days under study. The temperature deviation (TD) is calculated by

$$TD = \sqrt{\sum_{i=1}^{N_{wh}} \frac{(t_i - t_i^*)^2}{N_{wh}}} \tag{23}$$

where N_{wh} is the total number of working hours. TD is lower with the PI-control, however acceptable with the MPC strategy. In regard of the energy consumption, it is important to note that the total net energy consumption has not decreased. In fact, if compared to the PI control strategy, the MPC strategy allows for energy savings due to a better heat flow rate management but higher heat losses during the night. But the total primary energy is drastically lower with the MPC strategy, essentially due to a reduced use of the gas boilers.

Table 4: Comparative performance and consumption indicators (over the 4 days under study)

	PI	**MPC**
Temperature deviation (°C)	0.66	1.27
Heat pump energy (kWh)	7042	10045
Boiler energy (kWh)	3076	112
Total energy (kWh)	10118	10157
Heat pump primary energy (kWh)	3912	5581
Boiler primary energy (kWh)	3418	124
Total primary energy (kWh)	7330	5705

CONCLUSION

Based on a simplified model of an office building and of the associated HVAC system, simulation results show how the MPC strategy can help saving heating energy while maintaining acceptable comfort conditions compared to a traditional control strategy. Either the time profiles of the temperature/heat flow rates or their integrated values on a week confirm the benefit of the MPC scheme. From this stage of simple illustration of the idea, the next steps of the study should be:

- to consider the week-end gap;
- to develop the cooling aspects (where the fresh air properties are modified in temperature but also in humidity);
- to evaluate the strategy robustness, notably against the inaccuracies of the model and of the weather forecasts.

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