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CONTROL STRATEGIES FOR MANAGING ENERGY IN A BUILDING MOCK-UP

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ABSTRACT

The present work focuses on investigating ways to enhance the energetic performance of buildings i.e. on proposing control strategies for managing energy in buildings. Therefore, control algorithms were tested using a prototype, composed of a building mock-up, a monitoring system and a data post-treatment software. The data acquisition system allows recording both mock-up indoor/outdoor temperatures and energy consumption. Two resistors serve as renewable and fossil fuel energy sources respectively. The aim of this work is controlling the mock-up indoor temperature subject to outdoor disturbances by means of the power supply applied to the two resistors, while minimizing fossil energy consumption.

INTRODUCTION

The starting point in developing control strategies allowing efficiently managing energy in buildings is understanding the way the current French legal documentation promotes energy efficiency. Its study reveals the use of a global energy indicator, $kWh.m^{-2}.year^{-1}$, with the aim of quantifying energy consumption and classifying buildings. Both “Réglementation thermique 2005” (French Republique, 2006b) and “Diagnostic de Performance Energétique” (French Republique, 2006c) documentations explain how calculating this indicator and limit the energy consumption for buildings. However, ways to reach the above-mentioned objective using renewable energy, measuring the real energy consumption and finally controlling energy facilities are missing. Consequently, three control schemes, the standard Proportional Integral Derivate (PID), the Model Predictive Control (MPC) and finally the Fuzzy Logic Control (FLC), have been tested with the objective of completing the legal documentation and enhancing both energy savings and renewable energy contribution, using the global energy indicator.

Another observation leading to the present work is the state of the art about energy management in buildings (Dounis et al., 2008). Mathews et al. (2008), Levermore et al. (1992), Bernard et al. (1982), Kolokotsa et al. (2005), Ben-Nakhi et al. (2001), Kalogirou et al. (2000) and Gonzalez et al. (2005) mainly worked on both energy management strategies through cost reduction and energy consumption forecast, while Chen et al. (2006), Calvino et al. (2004), Kummert et al. (2001), Morel et al. (2000), Nygard (1990), Lute et al. (2000), Liang et al. (2005) and Argiriou et al. (2001) worked on controlling thermal conditions in buildings. However, considering many energy sources and relating energy management and performance criteria are not recurrent themes. That is why defining new criteria allowing qualifying energy management in buildings and comparing the previously mentioned control schemes was of great interest. These criteria are the following ones: the share of consumed energy being fossil energy ($\%_{FE}$) (to be minimized) and both comfort (I_C) and performance (I_P) criteria (to be maximized). Because of its impact on energy consumption in buildings, heating is the key-point.

Finally, and because being able to instrument real buildings with a set of sensors and implementing control schemes for managing energy is not easy, a building mock-up has been built then modelised to test the proposed controllers using Matlab simulations. A real one-floor house of approximately 120 m^2 has been used as reference for designing the mock-up. The scale is 1:27 and materials remain the same as for the real house: polystyrene for insulation and tiling for the floor.

The first section of the current paper focuses on the mock-up model, the second one presents all the used control schemes while the last one is dedicated to the obtained control results.

SIMULATION MOCK-UP MODEL

Building mock-up and experimental data

After performing preliminary studies focusing on the development of a theoretical model based on the heat equation (Paris et al., 2008b), heating control strategies were tested using an experimental data model.

Collecting data from real buildings being really difficult, a building mock-up has been built and instrumented (Paris et al., 2008c). It allows flexibility concerning both sensors and heat sources localizations. The lack of thermal inertia favors reactivity and avoids energy waste; a small amount of electricity is being consumed for heating the mock-up. Instrumentation for acquiring experimental data consists of eight temperature sensors (one outdoor sensor and seven indoor sensors) and two resistors serving as heat sources. Temperature and heat power datasets being useful to model the building mock-up, several tests have been carried out according to different both resistor powers and periods. Figure 1 depicts examples of temperature acquisition during these tests (for about twenty days).

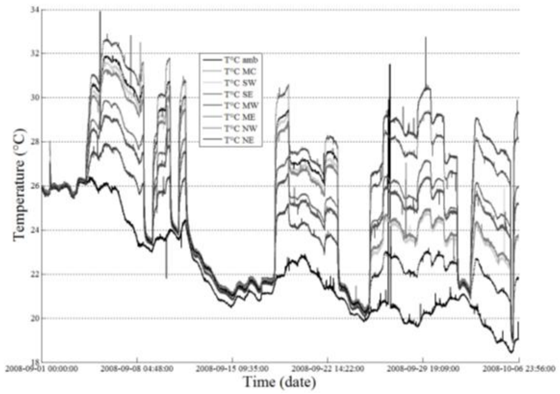

Figure 1. Mock-up temperatures acquisition.

Modelling and identification

The study of the thermal behaviour of the mock-up, corresponding to several heat powers, leads to the following model structure:

$$T_i(k+1) = \alpha_i T_i(k) + \beta_{i1} u_1^{\rho_{i1}}(k) + \beta_{i2} u_2^{\rho_{i2}}(k) + \gamma_i T_{out}(k) \quad (1)$$

Each temperature sensor is identified with the different parameters seen in Equation 1, using an iterative method of error minimization (Equation 2):

$$\min_{\alpha,\beta_1,\beta_2,\rho_1,\rho_2,\gamma} \left[J = \sum_{k=1}^{N} \left(T_{mes}(k) - T_{mod}(k) \right)^2 \right]$$

$$s.a. \begin{cases} Seven\ indoor\ thermal\ equations \\ -1 < \alpha < 1 \\ -10 < \beta_1 < 10 \\ -10 < \beta_2 < 10 \\ 0 < \rho_1 < 1 \\ 0 < \rho_2 < 1 \\ -10 < \gamma < 10 \end{cases} \quad (2)$$

For each temperature, the fit between experimental and modelled data is compute with Equation 3. With a mean of similarity above at 90%, the identification results are very significant.

$$fit = 100 \times \left(1 - \frac{\| T_{mod} - T_{mes} \|}{\| T_{mes} - < T_{mes} > \|} \right) \quad (3)$$

Identification results

Table 1 shows the different results of identification and table 2 shows the different parameters of identified building mock-up model.

Table 1
Fit results for each temperature

Modelled variables	fit [%]
T_{South_East}	93.12
T_{South_West}	92.41
T_{North_East}	92.76
T_{North_West}	92.59
T_{Middle_East}	91.40
T_{Middle_West}	88.07
$T_{Middle\_Ceiling}$	92.00

Table 2
Parameters of the mock-up model

	α	γ	β_1	ρ_1	β_2	ρ_2
T_{SE}	0.981	0.0193	0.0209	0.516	0.0329	0.501
T_{SW}	0.981	0.0192	0.0327	0.478	0.0188	0.540
T_{NE}	0.982	0.0179	0.00859	0.573	0.0530	0.447
T_{NW}	0.984	0.0161	0.0314	0.443	0.0107	0.467
T_{ME}	0.984	0.0160	0.0248	0.480	0.0170	0.513
T_{MW}	0.984	0.0163	0.0150	0.489	0.0267	0.460
T_{MC}	0.979	0.0209	0.0408	0.485	0.0516	0.461

Figure 2 shows the South West temperatures.

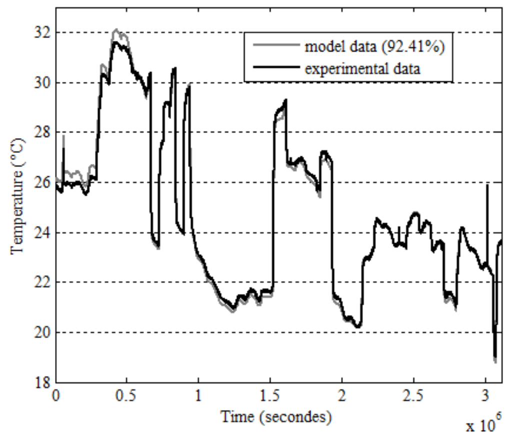

Figure 2. Comparison of experimental and model data for South West temperatures.

Then, the seven equations are afterwards used in simulation, to estimate the average indoor temperature of the mock-up.

Outdoor temperature data

After the dynamic model definitions, outdoor temperature data set is required with the aim of performing simulations. That is why outdoor temperature has been recorded during one week, at the University office.

HEATING CONTROL

Heating systems control

The chosen control methods, for the mean temperature, are, first, the PID control, a generic control loop feedback mechanism widely used in buildings engineering, secondly, the Model Predictive Control (MPC) and, finally, the fuzzy-PID control. Both MPC and fuzzy-PID control are advanced methods of process control. These controls are described in details in the following sections.

Simulation: set-points and models

For simulations, a temperature set point based on legal documentation and the function of office buildings was defined (French Republique, 2006a). The choice to work with this temperature instruction is explained by the aim of testing the robustness of ours different controllers in a concrete way. Figure 3 depicts the temperature instruction used with the mock-up model. Eight days of set-point temperature have been compressed in 24 hours to ensure a good ratio between transitory and stationary phases representative of a real building. Indeed the inertia of the mock-up is very short due to its small size.

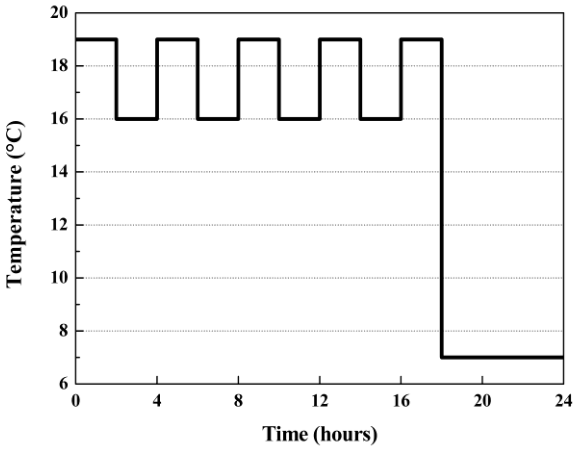

Figure 3. Temperature set-points for office buildings.

Control criteria

Tools are needed for comparing the controllers' performance. The global energy performance indicator is only able of expressing the amount of energy consumption but without any explanation. It does not dissociate the various energy consumptions components in buildings and does not explain how energy is consumed. That is why additional criteria, the share of consumed energy being fossil energy (criterion to be minimized) and both comfort (I_C) and performance (I_P) criteria (criteria to be maximized), were developed. These criteria incorporate the way energy is in-time used and controlled. Let us note that common criteria for human feeling in heated rooms or buildings such as both "Predictive Mean Vote" and "Percentage of Dissatisfied" criteria (ISO 7730, 1983), are found in the literature but do not match with objectives. First, the $\%_{FE}$ criterion is the percentage of the fossil energy consumed compared with the total energy used:

$$\%_{FE} = 100 \times \frac{E_{FE}}{E_{tot}} \tag{4}$$

Then, the I_C comfort criterion represents the mean relative error of the temperature set-point follow up:

$$I_C = 100 \times \left(1 - \frac{\|T_{sp} - T_m\|}{\|T_{sp} - < T_{sp} >\|}\right) \tag{5}$$

Finally, the I_P criterion focuses on the performance of the controller comparing the two other criteria:

$$I_P = (I_C - \%_{FE}) \tag{6}$$

Heating power repartition

Simulations for evaluating and testing heating controls using developed model are based on a unique set of outdoor temperatures and allows computing the above-mentioned energy performance indicators thanks to the consumptions of the two warmers and the set-point tracking. Let's remember that the developed model incorporate two heat sources, (i) a renewable energy warmer (W_{RE}) and (ii) a fossil energy warmer (W_{FE}). Respective powers are 80 W and 34 W.

Moreover, and with the aim of being in agreement with common behaviors, in any case, the renewable energy warmer is used until power saturation is reached. At this point, the fossil energy warmer starts working. U_{RE} and U_{FE} are the heat power of W_{RE} and W_{FE} respectively, u is the unsaturated total heat power computed by the feedback controller, while k is the time index:

$$U_{RE}(k) = u(k) \ and \ U_{FE}(k) = 0$$

- $if \ u(k) \geq U_{RE\_max} \ then \ U_{RE}(k) = U_{RE\_max}$
  $and \ U_{FE} = u(k) - U_{RE}(k)$ (7)
  $if \ U_{FE}(k) \geq U_{FE\_max} \ then \ U_{FE}(k) = U_{FE\_max}$
  $else \ if \ U_{FE}(k) \leq 0 \ then \ U_{FE}(k) = 0$
- $else \ if \ u(k) \leq 0 \ then \ U_{RE}(k) = U_{FE}(k) = 0$

As a consequence, renewable energy is firstly used. Moreover, all the controllers' parameters can be optimized to maximize the I_P criterion. In the same way, a constraint (explained later) have been considered with the aim of adjusting the advanced controllers (MPC) as required for taking into account the different uses of buildings.

Proportional Integral Derivate

Figure 4 shows the reference control structure. Standard PID controller is a generic heating control mechanism widely used in buildings engineering. Thus, it's the reference. Let's just remind its structure for discrete time control with anti-windup considerations (Equation 8).

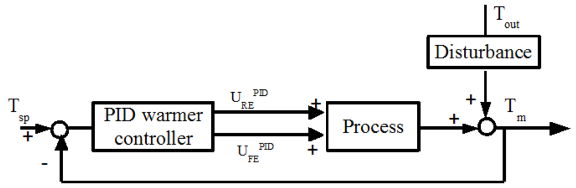

Figure 4. PID control framework.

$$\begin{cases} U_{max} = U_{RE\_max} + U_{FE\_max} \\ T_{aw} = \frac{T_e}{K_I} \\ x_I(k) = x_I(k-1) + K_I \cdot \left(T_{SP}(k) - T_m(k)\right) \\ x_D(k) = K_D \cdot x_D(k-1) + \left(T_m(k-1) - T_m(k)\right) \\ u(k) = K_P \cdot \left(T_{SP}(k) - T_m(k) + x_I(k) + x_D(k)\right) \\ u\_sat_{PID}(k) = u_{PID}(k) \\ if\ u_{PID}(k) > U_{max}(k)\ then\ u\_sat_{PID}(k) = U_{max} \\ if\ u_{PID}(k) < 0\ then\ u\_sat_{PID}(k) = 0 \\ x_I(k) = x_I(k) + \left(\frac{T_e}{K_P \cdot T_{aw}}\right) \cdot \left(u\_sat_{PID}(k) - u_{PID}(k)\right) \end{cases} \quad (8)$$

With the aim of optimizing the performance criterion I_P, Equation 9 allows finding the most accurate coefficients of the PID controller.

$$\max_{K_P, K_I, K_D} (I_P = I_C - \%_{FE})$$

$$s.a. \begin{cases} Thermal\ equations \\ PID\ controller \\ 0 < K_P < 100 \\ 0 < K_I < 1 \\ 0 < K_D < 1 \end{cases} \quad (9)$$

Model predictive control and PID

The model predictive controller (MPC) (García et al., 1989) is a model based and discrete controller allowing calculating an optimal command sequence. To elaborate this sequence, one needs a linear model and a working point of the system to be controlled. Knowing the future setpoint and predicting external disturbances allows anticipating setpoint changes and considering the consequences of these disturbances. The MPC controller estimates the way the temperature is evolving on a prediction horizon H_P and computes optimal increments on a command horizon H_C (shorter than H_P). So, a new optimization is carried out for each time step.

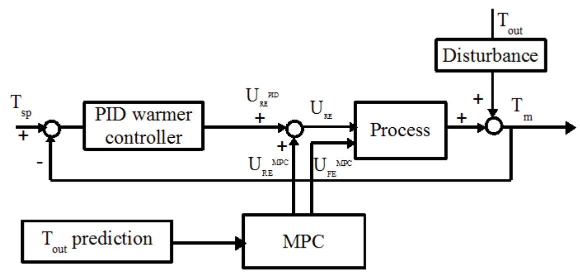

Figure 5. MPC control framework.

The heating control strategy is defined according to the following guidelines: the PID controller estimates the power of the W_{RE} (U_{RE}^{PID}), while the MPC specifies the optimal sequence to be applied to the W_{FE} (U_{FE}^{MPC}) and if the power of the W_{RE} needs to be adjusted U_{RE}^{MPC} (Paris et al., 2008a). Figure 5 shows this heating control struture.

Being a model based controller is one of the main drawbacks of the MPC, jointly to its extensive on-line computational effort, but, in the other hand, it can inherently handle constraints. Equation 10 describes both the objective function used for optimizing I_P and how constraints are applied to fossil energy.

$$\min_{\Delta u(k/k),\dots,\Delta u(k+c-1/k)} \sum_{i=0}^{p-1} \left(\left| \left(T_{m(k+j+1/k)} - T_{SP(k+j+1)}\right) \right|^2 + \left| \omega \cdot U_{FE\,(k+j/k)}^{MPC} \right|^2 \right)$$

$$Constraints \begin{cases} Model\ equations \\ PID\ control\ equations \\ 0 \leq U_{RE(k+j/k)} \leq U_{RE\_max} \\ 0 \leq U_{FE(k+j/k)} \leq U_{FE\_max} \\ \Delta u(k+h) = 0, h = \{c, \dots, p-1\} \end{cases} \quad (10)$$

The result depends of the fossil energy minimization regarding the temperature setpoint follow-up, using several values of ω.

To obtain the optimal ω maximising the I_P criterion, the resolution of the following optimization problem is needed (Equation 11).

$$\max_{\omega} (I_P = I_C - \%_{FE})$$

$$s.a. \begin{cases} Thermal\ equations \\ Best\ PID\ controller \\ MPC\ controller \end{cases} \quad (11)$$

Fuzzy logic control and PID

The last heating control scheme used is the fuzzy logic control (FLC) (Fraisse et al., 1997). Fuzzy logic is a well-known problem-solving methodology with many applications in both control and information processing. It provides a remarkably simple way to draw definite conclusions from vague, ambiguous, imprecise, noisy or missing information. Fuzzy logic incorporates a simple and rule-based approach to a solving control problem rather than attempting to model a system mathematically (Zadeh, 1965, Huang et al., 2008). Both the structure of the control tool and the heating control strategy remain the same as when using MPC and PID controllers (Figure 6). From the difference between the setpoint temperature and the current mean indoor temperature (ε), the PID controller estimates the power of the W_{RE} (U_{RE}^{PID}) while a first fuzzy module determines if this power needs (or not) to be corrected (U_{RE}^{FLC}). From both ε and U_{RE}, a second fuzzy module evaluates the power of the W_{FE} (U_{FE}^{FLC}).

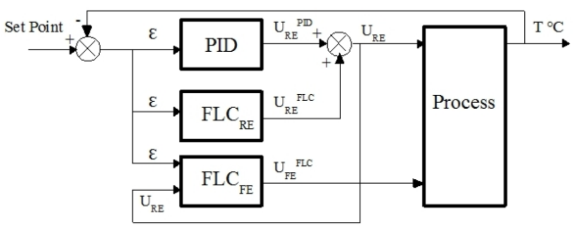

Figure 6. *FLC control framework.*

Because of thermal inertia, heat transfer and heating dimensioning, indoor temperatures in buildings (ΔT) may be in the 0°C-30°C range. Moreover, and according to the "Règlementation thermique" documentation, temperature setpoints (ΔT_{SP}) may be in the 7°C-22°C range. As a result, values for the difference between the setpoint temperature and the current mean indoor temperature range between -24°C and +24°C ($\varepsilon = [-24°C; +24°C]$). Values of U_{RE}^{FLC} and U_{FE}^{FLC} are normalized between -1 and +1 ($U_{RE}^{FLC} = [-1; +1]$) and 0 and +1 ($U_{FE}^{FLC} = [0; +1]$) respectively then denormalized using the K_{RE} and K_{FE} gains. Finally, U_{RE} being saturated at 80W, U_{RE} variations are defined as $U_{RE} = [0W; 80W]$. Based on these considerations, one needs, first, to characterize all the above-mentioned parameters and their respective "universes of discourse" using fuzzy sets and membership functions (Figures 7-10) and, secondly, to define an appropriate base of fuzzy rules that maps inputs to outputs, with the aim of maximizing the global performance indicator.

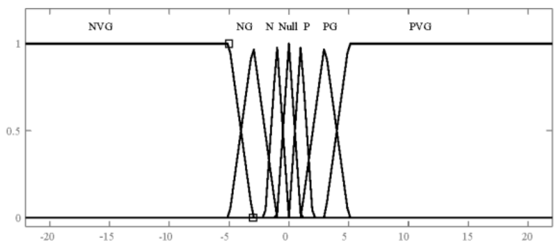

Figure 7. Fuzzification of ε.

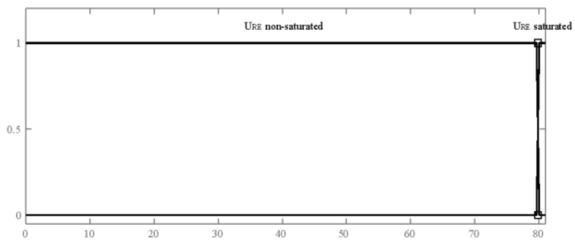

Figure 8. Fuzzification of U_{RE}.

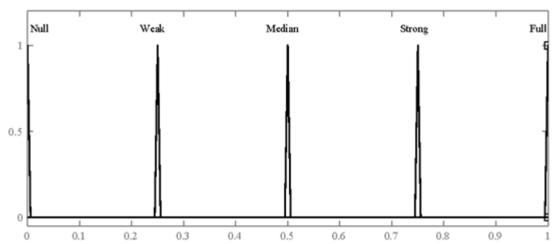

Figure 9. Fuzzification of normalized U_{FE}^{FLC}.

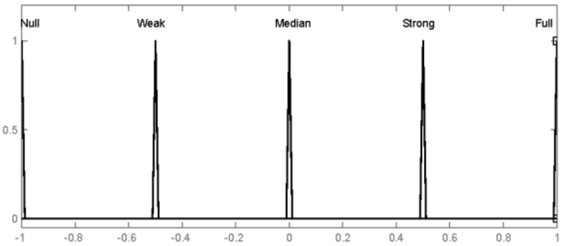

Figure 10. Fuzzification of normalized U_{RE}^{FLC}.

Equation 12 describes the way this indicator can be maximized i.e. optimizing the various controllers' gains.

$$\max_{K_P, K_I, K_D, K_{RE}, K_{FE}} (I_P = I_C - \%_{FE})$$

$$s.a. \begin{cases} Thermal\ equations \\ PID\ controller \\ FLC\ controller \\ 0 < K_P < 100 \\ 0 < K_I < 1 \\ 0 < K_D < 1 \\ 0 < K_{FE} < 1000 \\ 0 < K_{RE} < 1000 \end{cases} \quad (12)$$

DISCUSSION AND RESULT ANALYSIS

Comparative results

Table 3 presents the best results obtained using the PID, MPC and FLC schemes.

Table 3
Office simulation results for mock-up model

	E_{RE} $[Wh.m^{-2}]$	E_{FE} $[Wh.m^{-2}]$	$\%_{FE}$ [%]	I_C [%]	I_P [%]
Office temperature set-point					
PID	7494	521	6.5	72.0	65.5
MPC	7339	381	4.9	73.6	68.7
FLC	7731	470	5.7	72.4	66.7

Whatever the considered criteria, the optimal PID controller obtains the worst results over the other control schemes. On the other hand, the model predictive controller is the best performer: I_P and I_C criteria are respectively 4.9% and 2.2% higher than when using the PID controller. Concerning energy consumption, savings of fossil energy using the MPC are about 26.9%. This represents 140 $Wh.m^{-2}$. However, developing a MPC is harder and longer than developing a classical PID controller and as previously mentioned requires an accurate linear model of the building. Furthermore, implementing this kind of advanced controller needs an embedded numerical optimizer and a fast microprocessor.

Finally, taking a look at the FLC performance, one can conclude that this controller is more efficient than the PID controller but not as good as the MPC. I_P and I_C criteria are respectively 1.8% and 0.6% higher than when using the PID controller. Savings of fossil energy are about 9.8% (51 $Wh.m^{-2}$).

Implementing a FLC on an embedded control system is nearly as easy as a PID controller. Figure 11 presents the results of the indoor mean temperature control.

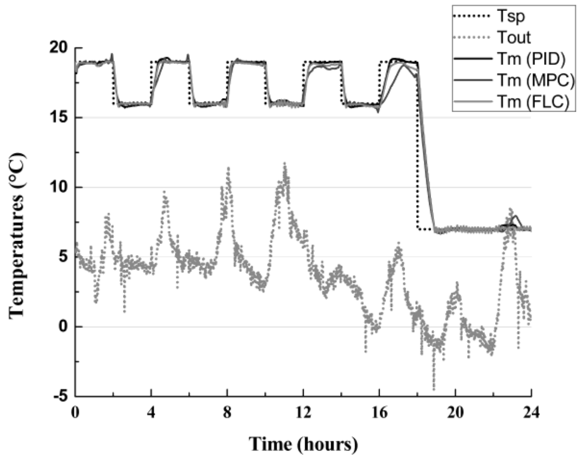

Figure 11. Simulation of indoor temperature.

MPC application

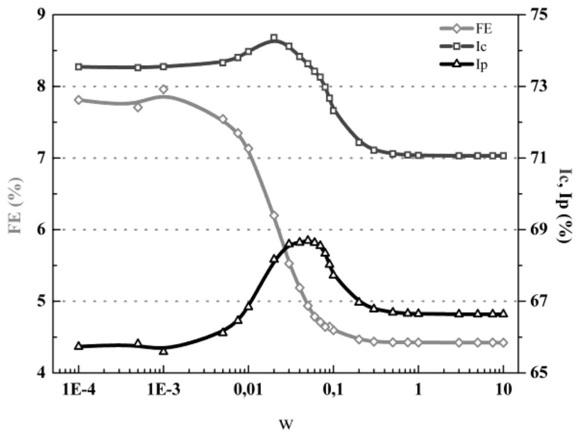

Figure 12. Influence of the constraint applied to W_{FE}.

As previously mentioned, the MPC can inherently handle constraints. This is a real advantage in heating control. So, the present subsection of the paper focuses on applying a constraint (ω) on W_{FE} with the aim of limiting the use of fossil energy (Equation 10) and on quantifying its influence on the various considered indices. One can confirm that a weak ω favours comfort while a strong ω promotes fossil energy savings. However, the use of a building determines which constraint can be applied: for example, a bad comfort index is not suitable for hospitals while a scholar building can promote energy savings during holidays.

Figure 12 depicts the influence of the constraint applied to W_{FE} on the previously-defined indices. As an important result, one can notice that ω = 0.05 leads to the best compromise between comfort and fossil energy use, the performance index being maximal.

CONCLUSION

Following a strong European will, the present paper focuses on investigating ways for improving the energetic performance of buildings. That is why various heating control strategies are proposed and tested with the aim of reducing the fossil energy consumption and enhancing the renewable energy contribution. Thinking about and proposing a global performance criterion for comparing the controllers' efficiency was the starting point of the work. As a more in-depth approach and because only considering a global performance does not allow dissociating the various energy consumptions components in buildings and does not explain how energy is consumed, criteria such as the share of consumed energy being fossil energy ($\%_{FE}$) and both comfort (I_C) and performance (I_P) criteria were added. Because being able to instrument real buildings with a set of sensors and implementing control schemes for managing energy is not easy, a building mock-up has been built and instrumented then modelised, using experimental data, with the aim of testing the proposed control schemes.

The first and referent controller used is a classical PID controller. Despite some limitations due to specific features, it is widely used in industrial control systems and commonly used for heating control in buildings. A fast and easy development is the main advantage of this controller. Its performance is the worst over the other control tools.

Using the MPC for heating control proved that an optimal and predictive control is able to improve the performance of the controlled system and to save an important part of fossil energy in comparison to a classical PID controller. The MPC allows focusing on a specific performance i.e. favouring fossil energy savings or temperature setpoint tracking or adapting to specific buildings, periods of the year or building residents. However, and because the MPC is a linear model based controller which on-line computational effort is extensive, developing and implementing this kind of controller is a quite hard task. This explains why MPC is not commonly used for heating control of buildings but generally used for controlling complex and costly industrial processes.

Finally, the FLC proved that also fuzzy logic is suitable for enhancing the performance of PID controllers, although the way of building a complete rule base with the aim of improving performance is not always straightforward. While the best performance remains MPC's, the FLC is a good compromise between the easy to develop but not very efficient PID and the efficient but hard to develop MPC.

Let us note that the three developed and implemented controllers were tested in simulation and need now to be tested in real experimental environment as well (mock-up and real buildings).

ACKNOWLEDGEMENT

Thanks to all the people who have contributed to the present work, especially Dr. Grégory François of the Automatic Control Laboratory at the EPFL (Ecole Polytechnique Fédérale de Lausanne, Switzerland) for his help concerning the simultaneous use of both model-based predictive and PID controllers.

NOMENCLATURE

E_{FE}	Fossil energy [kWh.m^{-2}.year^{-1}]
E_{RE}	Renewable energy [kWh.m^{-2}.year^{-1}]
E_{tot}	Total energy [kWh.m^{-2}.year^{-1}]
W_{FE}	Fossil energy warmer [-]
W_{RE}	Renewable energy warmer [-]
U_{FE}	Heat power of W_{FE} [W]
U_{RE}	Heat power of W_{RE} [W]
U_{FE}^{PID}	U_{FE} computed by the PID controller [W]
U_{RE}^{PID}	U_{RE} computed by the PID controller [W]
U_{FE}^{MPC}	U_{FE} computed by the MPC controller [W]
U_{RE}^{MPC}	U_{RE} computed by the MPC controller [W]
U_{FE}^{FLC}	U_{FE} computed by the FLC controller [W]
U_{RE}^{FLC}	U_{RE} computed by the FLC controller [W]
T_{mes}	Experimental temperature data [°C]
T_{mod}	Model temperature data [°C]
T_m	Indoor model mean temperature [°C]
T_{SP}	Temperature set point [°C]
T	Current mean indoor temperature [°C]
u	Unsaturated total heat power computed by the feedback controller [W]
u_{PID}	Unsaturated total heat power computed by the PID controller [W]
u_sat_{PID}	Saturated total heat power computed by the PID controller [W]
Δu	Command increment on FE and RE [W]
U_{max}	Maximum total heat power [W]
U_{FE_max}	Maximum heat power of W_{FE} [W]
U_{RE_max}	Maximum heat power of W_{RE} [W]
K_{FE}	Denormalization gain of U_{FE}^{FLC} [-]
K_{RE}	Denormalization gain of U_{RE}^{FLC} [-]
ε	Difference between the setpoint temperature and T [°C]
ω	Constraint applied on W_{FE} [W]
$\%_{FE}$	Share of consumed energy being fossil energy [%]
I_C	Comfort criterion [%]
I_P	Performance criterion [%]
i	i^{th} sensor [-]
β	Direct heat power [-]
α	Temperature inertia [-]
γ	Outdoor temperature influence [-]
k	Time index [-]
T_e	Time sampling (60s) [s]
T_{out}	Outdoor temperature [°C]
ρ	Heat power exponent [-]
J	Cost error criterion [-]
N	Sample number [-]
K_P	Proportional gain [-]
K_I	Integral gain [-]
K_D	Derivate gain [-]
$k+j/k$	Predictive value for associated variable at $k+j$ time using k time value [-]
H_P	MPC prediction horizon [s]
H_C	MPC command horizon [s]
x_I	PID integral state [-]
x_D	PID derivate state [-]
T_{aw}	PID anti-windup time constant [s]

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