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## Introduction

In France, 25% of greenhouse gases emissions and 46% of global energy consumption are nowadays due to buildings. So, for trying to overcome the actual energy crisis, French government has published legal documentation [1] [2] with the aim of both regulating energy consumption in buildings and comparing different buildings, using a global energy indicator: $kWh.m^{-2}.year^{-1}$. However, the above-mentioned documentation is not sufficient for efficiently promoting energy savings. Indeed, this documentation is only about reducing energy by means of construction materials, design…A more efficient energy management needs appropriately controlling energy facilities to achieve energy savings, especially concerning heating installations. Thus, energy management entails reducing fossil energy consumption and enhancing renewable energy supply using different heating controllers [3].

For enhancing energy management according to a better control of heating energy facilities, a simulation model is used. First, a building mock-up has been modelled and, secondly, PID and fuzzy-PID controllers have been designed and characterized by indicators. The paper presents the developed simulation model, the PID, fuzzy and fuzzy-PID theories and the obtained results using the above-mentioned controllers. A conclusion ends the paper.

## Simulations model

The opportunity to instrument a real building with a set of sensors for testing heating controls is rare. In addition, the flexibility in sensors and heat sources localizations in a building mock-up is a real advantage. The lack of thermal inertia promotes the reactivity, and avoids energy waste: just a few of electricity is consummated to heat the mock-up. Thus a building mock-up was built [4].

The design of the mock up is based on (i) its scale, (ii) the building materials, and (iii) the possibility of easily knowing the thermal losses of the construction. The mock-up is build with polystyrene insulation, plasterboard for the walls and polyane for the glasses. The length is about 60 cm, the width is 30 cm and the height is 15 cm. In addition, the instrumentation is composed of 8 temperature sensors (1 outdoor and 7 indoor) and two heat sources represented by electrical resistors. The first represents the renewable energy resource (RE) and the second, the fossil one (F).

Modelling the building mock-up to develop a numerical model for simulations needs both temperature and heat power data sets. Several trainings to heat the mock-up were carried out, according to different powers and different time periods. Figure 1 shows an example of temperature acquisition during heat tests (around twenty days).

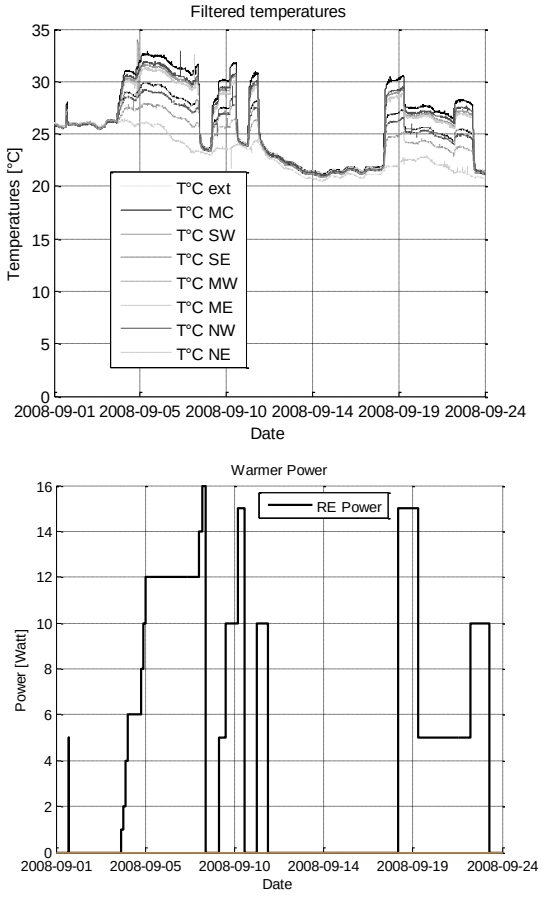


*Figure 1. Mock-up temperature acquisition and power supply.*

According to the measurements, indoor temperature behaviours show the same response time with different amplitudes. Theirs behaviours seem to be similar to a first order in reply to a power step or an outdoor temperature change. In addition, the more the power is, the less the temperature variations are. For modelling this specific comportment, a

power parameter ρ is added to the heat power influence such as 0<ρ<1. The study of the thermal mock-up behaviour, corresponding to several heat powers, leads to the model structure depicted by Equation 1. So, the model is composed of seven equations, one for each temperature.

$$T_i(k+1) = \alpha_i T_i(k) + \beta_{1i} u_1^{\rho_{1i}}(k) + \beta_{2i} u_2^{\rho_{2i}}(k) + \gamma_i T_{out}(k)$$

*Equation 1.*

Table 1. References for model equations.

| | | |
|---|---|---|
| T | Indoor temperature | °C |
| i | $i^{th}$ sensor | |
| β | Heat power influence | |
| α | Temperature inertia | |
| γ | Outdoor temperature influence | |
| k | Time index | |
| Ts | Sampling time | 60 s |
| u | Heat power | W |
| $T_{out}$ | Outdoor temperature | °C |
| ρ | Heat power influence | |

The main objective is to identify for each temperature the optimal $\alpha$, $\beta_1$, $\beta_2$, $\rho_1$, $\rho_2$ and $\gamma$ parameters which minimize an error criterion $J$ as defined in Equation 2. Optimization is completed thanks to a classical iterative algorithm of minimization.

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

$$s.a. \begin{cases} 7 \text{ indoor thermal equations} \\ -1 < \alpha < 1 \\ -10 < \beta_1 < 10 \\ -10 < \beta_2 < 10 \\ 0 < \rho_1 < 1 \\ 0 < \rho_2 < 1 \\ -10 < \gamma < 10 \end{cases}$$

*Equation 2.*

$T_{mes}$ is the measured temperature and $T_{mod}$ is the indoor temperature given by the thermal model. $k$ represents the time index on which is computed the error.

Once optimization is done, a curve-fitting is computed (Equation 3) to highlight clearly how each model temperature fits the experimental one. Curve-fitting results are given in Table 2.

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

*Equation 3.*

Table 2. Modelling fits.

| Modeled variables | $fit$ [%] |
|---|---|
| $T_{South\_East}$ | 92.22 |
| $T_{South\_West}$ | 91.52 |
| $T_{North\_East}$ | 88.80 |
| $T_{North\_West}$ | 91.45 |
| $T_{Middle\_East}$ | 90.69 |
| $T_{Middle\_West}$ | 86.59 |
| $T_{Middle\_Ceiling}$ | 91.15 |

With a mean of similarity above 90%, the identification results are very significant. The 7 equations are afterwards used in simulation for estimating the average indoor temperature of the mock-up. For example, South West temperature parameters are:

- ✓ $\alpha = 0.98$
- ✓ $\gamma = 0.019$
- ✓ $\beta_1 = 0.033$
- ✓ $\rho_1 = 0.48$
- ✓ $\beta_2 = 0.019$
- ✓ $\rho_2 = 0.54$

**Data simulation sets**

External temperatures are recorded at an office of the University of Perpignan during a few years. Temperature sensors are placed on north of the building and these data are used in simulation to deal with real external conditions. A sample of 8 days of 2008 allowed carrying out the simulations presented in this paper. For more realistic results and balance the lower thermal inertia of the mock-up, the 8 days of the external temperature variations are condensed in 24 hours. With this time acceleration, the proportion between transitory and stationary stage are closer of a real building behavior.

In addition, temperature set-point instructions are required to test the different heating controllers. The study of the French legal documentation gives answers. Once again, the aim is to be as realistic as possible. Thus, two temperature set-point instructions are defined: (i) office temperature instructions, (ii) accommodation temperature instructions (Table 3).

Table 3. Temperature set-points.

| Hours for set-points changing | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 2 | 4 | 6 | 8 | 10 | 12 | 14 | 16 | 18 | 24 |
| 19 | 16 | 19 | 16 | 19 | 16 | 19 | 16 | 19 | 7 | |
| 21 | 18 | 15 | 18 | 21 | 18 | 15 | 18 | 21 | 7 | |
| Temperature set-points [°C] | | | | | | | | | | |

**Strategies criteria**

Two different kinds of controllers are compared in this paper, classical PID and fuzzy-PID using objective criteria.

The global energy indicator used in legal documentation in several countries and labels is already presented: kWh.m$^{-2}$.year$^{-1}$. It only displays the global energy consumption, per square meter of the building, during a year of functioning. However, this indicator is not sufficient for comparing the different heating controllers. That is why new indicators were created. The first one, the $\%_{FE}$ criterion, is the percentage of the fossil energy consumed in comparison to the total energy used (Equation 4):

$$\%_{FE} = 100 \times \frac{E_{FE}}{E_{Tot}}$$

*Equation 4.*

The second one, the $I_c$ comfort criterion represents how the mean of the indoor temperatures fit the set-point temperature (Equation 5).

$$I_{C[\%]} = 100 \times \left( 1 - \frac{\left\| T_{sp} - T_{mean} \right\|}{\left\| T_{sp} - < T_{sp} > \right\|} \right)$$

*Equation 5.*

Finally, the $I_p$ criterion focuses on the performance of the controller comparing the two previously-mentioned criteria (Equation 6).

$$I_P = \left( I_C - \%_{FE} \right)$$

*Equation 6.*

To ensure that indoor temperatures correctly follow the temperature set-points, 10 constraints were added. They assure that at the middle of each step of the temperature set-points, the indoor mean temperature is equal to the set-point (Equation 7).

$$C_{1:10} : \left| T_{sp}(j) - T_{mean}(j) \right| < 0.1°C$$
$$j \in \{1h\,;\,3h\,;\,\ldots;\,17h\,;\,21h\}$$

*Equation 7.*

Table 4. References for criteria definition.

| | | |
|---|---|---|
| $E_{FE}$ | Fossil energy | kWh.m$^{-2}$ |
| $E_{RE}$ | Renewable energy | kWh.m$^{-2}$ |
| $E_{Tot}$ | Total energy | kWh.m$^{-2}$ |
| $\%_{FE}$ | Fossil energy index | % |
| $I_c$ | Comfort index | % |
| $I_p$ | Performance index | % |
| $T_{mean}$ | Mean temperature of the model | °C |
| $T_{sp}$ | Temperature set point | °C |

Then, constrains on energy resources are added: each warmer can put a limited power out. The renewable one can only afford 80 W and the fossil one only 34 W. So the model is constrained by Equation 8.

$$\begin{cases} u_{RE} < U_{\max\_RE} \quad s.a. \quad U_{\max\_RE} = 80\,W \\ u_{FE} < U_{\max\_FE} \quad s.a. \quad U_{\max\_FE} = 34\,W \\ U_{\max} = U_{\max\_RE} + U_{\max\_FE} = 114\,W \end{cases}$$

*Equation 8.*

**Proportional Integral Derivate (PID)**

Standard PID controller corresponds to the "classical" heating controller in engineering of buildings [5]. Thus it serves of reference. So, its standard structure for discrete time control with anti-windup considerations is just reminded (Equation 9).

$$\begin{cases} x_i(k) = x_i(k-1) + K_i \cdot \left( T_{sp}(k) - T_{mean}(k) \right) \\ x_d(k) = K_d \cdot x_d(k-1) + \left( T_{mean}(k-1) - T_{mean}(k) \right) \\ u(k) = K_p \cdot \left( c(k) - y(k) + x_i(k) + x_d(k) \right) \\ u\_sat_{PID}(k) = u_{PID}(k) \\ if \;\; \left( u_{PID}(k) > U_{\max}(k) \right) \;\; then \;\; u\_sat_{PID}(k) = U_{\max} \\ if \;\; \left( u_{PID}(k) < 0 \right) \;\; then \;\; u\_sat_{PID}(k) = 0 \\ x_i(k) = x_i(k) + \left( T_e / K.T_{aw} \right) \cdot \left( u\_sat_{PID}(k) - u(k) \right) \end{cases}$$

*Equation 9.*

Power repartition between renewable enegy and fossil energy is made as follow (Equation 10):

$$\begin{aligned} & u_{RE\_PID} = u_{sat\_PID} \\ & u_{FE\_PID} = 0 \\ & if \;\; u_{RE\_PID} > U_{\max\_RE} \;\; then \\ & \quad u_{RE\_PID} = U_{\max\_RE} \\ & \quad u_{FE\_PID} = u_{sat\_PID} - U_{\max\_RE} \\ & \quad if \;\; u_{FE\_PID} > U_{\max\_FE} \;\; then \;\; u_{FE\_PID} = U_{\max\_FE} \\ & end \end{aligned}$$

*Equation 10.*

Parameters $K_p$, $K_i$, and $K_d$ that maximized the $I_p$ criterion according to the following optimization problem have to be found (Equation 11).

$$\min_{K,K_i,K_d} \left( I_p = I_C - \%_{EF} \right)$$
$$s.a. \begin{cases} 7 \text{ indoor thermal equations} \\ \text{PID controller} \\ 1000 < K_p < 0 \\ 1 < K_i < 0 \\ 1 < \mathrm{K_d} < 0 \\ 10 \text{ set} - \text{point constraints } C_{1:10} \end{cases}$$

*Equation 11.*

Optimization results are introduced in the last part of the paper and compared to the fuzzy-PID controller described in the following part.

**Fuzzy control**

The general structure of a fuzzy logic controller (FLC), or fuzzy controller (FC), consists of three basic portions: the fuzzification unit at the input terminal, the inference engine built on the fuzzy logic control rule base in the core, and the defuzzification unit at the output terminal [6] [7] (Figure 2).

The Fuzzification Module transforms the physical values of the process signal, e.g. the error signal which is an input to the fuzzy logic controller, into a normalized fuzzy subset. This subset consists of a interval for the range of the input values and a normalized membership function describing the degree of confidence of the input belonging to this range. It selects reasonable and good, ideally optimal, membership functions (noted $\mu_X$) under certain convenient criteria meaningful to the application.

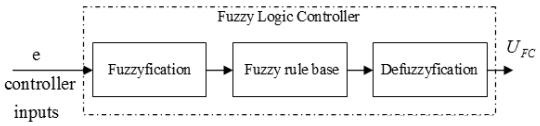


*Figure 2. General structure of a fuzzy logic controller.*

**The fuzzy logic rule base**

Designing a good fuzzy logic rule base is key to obtaining a satisfactory controller for a particular application. Classical analysis and control strategies should be incorporated in the establishment of a rule base. A general procedure in designing a fuzzy logic rule base includes the following:

- ✓ determining the process states and control variables,
- ✓ determining input variables to the controller,
- ✓ establishing a fuzzy logic IF-THEN rule base,
- ✓ establishing a fuzzy logic inference engine.

**The defuzzification module**

The defuzzification module is in a sense the reverse of the fuzzification module: it converts all the fuzzy terms created by the rule base of the controller to numerical values. Then it sends them to the physical system, so as to execute the control of the system. The defuzzification module performs the following functions:

- ✓ it creates a control signal, *u*, by combining all possible control outputs from the rule base into a weighted average formula,
- ✓ it transforms the control output, *u,* obtained in the previous step, to the corresponding physical values.

This converts the fuzzy logic controller's numerical output to a physical means that can actually drive the given plant to produce the expected outputs.

There are several defuzzification formulas, and the most commonly used is the "center of gravity" formula, and the discrete-time version is the following one (Equation 12).

$$u(k+1) = \frac{\sum_{i=1}^{N} \mu_{Ui}(u_i(k)) \times u_i(k)}{\sum_{i=1}^{N} \mu_{Ui}(u_i(k))}$$

*Equation 12.*

Where $u_i$ are fuzzy subsets consisting of some bounded intervals with their associated membership functions $\mu_{Xi}$.

**Fuzzy-PID**

Fuzzy control showed its effectiveness when it is applied only but also makes it possible to regulate the existing parameters of regulation. Studies in applied research show that it is even more interesting to combine the use of fuzzy logic with traditional controllers in order to make these controllers more robust. It is a question, for example, of working on a existing PI or PID loop on processes which one knows the behavior in closed loop. The fuzzy order makes it possible to improve the behavior in closed loop directly, while being superposed on the existing controller.

A certain number of controllers are actually only fuzzy PID, i.e. the coefficients of the PID are taken as fuzzy variables, so as to increase the effectiveness by it. This work concentrates on the improvement of the performances of the previous existing PID controller, while adding to the control, a fuzzy control, having for goal to act on the residual error. Fuzzy controller inputs are then defined in the derivative successive space of the closed-loop error. Figure 3 illustrates an example of fuzzy-PID composite control loop [8].

The objective of this work is improving the use of renewable energy, so the fuzzy controller contribution is only added to RE_PID output. This makes it possible increasing the performance of the PID controller and providing an optimal control.

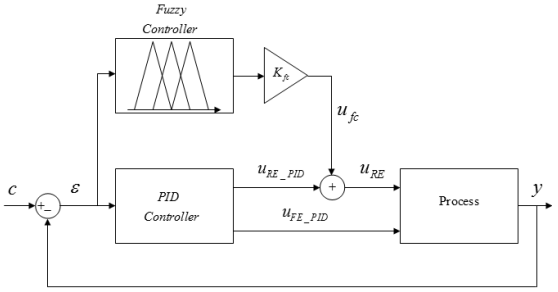


*Figure 3. Fuzzy PID control example.*

It is necessary to work with a closed loop stabilized system and with a small error. The goal of this control is to increase the behavior in regulation. The methodology of this type of control is the following:

- ✓ determining a controller in closed loop (PI or PID, etc.),

- ✓ determining the fuzzy rules starting from the knowledge of the operator on the controlled system, to refine the corrector by regulating the parameters of the fuzzy control.

So another parameter $K_{fc}$ is useful to maximize the $I_p$ criterion and it becomes (Equation 13):

$$\min_{K,K_i,K_d,K_{fc}} \left(I_p = I_C - \%_{EF}\right)$$

$$s.a. \begin{cases} 7 \text{ indoor thermal equations} \\ \text{Fuzzy - PID controller} \\ 1000 < K < 0 \\ 1 < K_i < 0 \\ 1 < K_d < 0 \\ 1 < K_{fc} < 2000 \\ 10 \text{ set} - \text{point constraints } C_{1:10} \end{cases}$$

*Equation 13.*

This gain comes from the fuzzy controller output, and makes it possible to let the fuzzification of the variable unchanged while optimizing the range of the output values.

The standard structure for discrete-time control becomes (Equation 14):

$$u_{RE}(k) = u_{RE\_PID}(k) + u_{fc}\left(e^i_{BF}(k)\right)$$

*Equation 14.*

**Results for optimization**
The fuzzy controller is a MISO controller type :

- ✓ Input 1 : error, *ε(t) = c(t)-y(t)*
- ✓ Input 2 : d_error, *Δε(t) = ε(t) – ε(t-1)*
- ✓ Output : out (eq. 12)

Fuzzy controllers achieve fuzzification of the control inputs using two triangular memberships functions (Positive: Pos, and Negative: Neg) and using three for the output (Positive: Pos, Zero, Negative: Neg). Recent literature has suggested that other forms of input, like gaussian for instance, can be used to provide different properties for the controller. However, the triangular membership functions provide an ideal means of developing control capability and are so used in general.

Fuzzy rules can be expressed as follows :

$R_1$ : **IF** ε is Neg **AND** Δε is Neg **THEN** out is Neg
$R_2$ : **IF** ε is Neg **AND** Δε is Pos **THEN** out is Zero
$R_3$ : **IF** ε is Pos **AND** Δε is Neg **THEN** out is Zero
$R_4$ : **IF** ε is Pos **AND** Δε is Pos **THEN** out is Pos

Figure 4 shows rules surface of the fuzzy controller. All of the inputs and output variables are described in a [-1 1] range because of the small error on the closed loop PID structure.
This is modified and so optimized by the $K_{fc}$ gain at the fuzzy controller output.

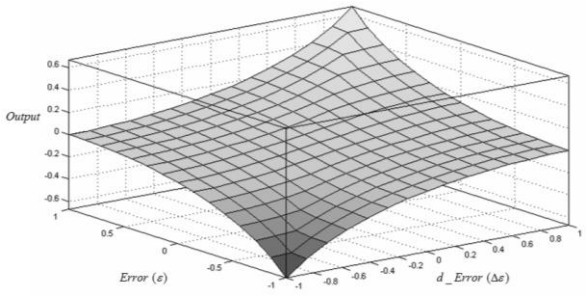


*Figure 4. Fuzzy control rules surface.*

Table 6 presents the optimal gains found with the optimization procedure for the two temperature set-points exposed in Table 3.

Table 6. Optimal gains for PID and fuzzy-PID.

| PID | | | Fuzzy-PID | | | |
|---|---|---|---|---|---|---|
| $K_p$ | $K_i$ | $K_d$ | $K_p$ | $K_i$ | $K_d$ | $K_{fc}$ |
| Gains for office temperature set-point | | | | | | |
| 51.3 | 0.391 | 1.00 | 52.8 | 0.223 | 1.00 | 761 |
| Gains for accommodation temperature set-point | | | | | | |
| 80.0 | 0.993 | 0.596 | 52.3 | 0.378 | 1.00 | 60.8 |

Coefficients are substantially different for the two temperature set-points.

**Results for temperature instructions**
Simulations are done with the optimal gains for PID and fuzzy-PID controllers. Results for criteria and energy consumptions are given in Table 7.

Table 7. Criteria for PID and fuzzy-PID controllers.

| | $RE_{\left[Wh.m^{-2}\right]}$ | $FE_{\left[Wh.m^{-2}\right]}$ | $\%_{FE}$ | $I_{C[\%]}$ | $I_{p[\%]}$ |
|---|---|---|---|---|---|
| Office temperature set-point | | | | | |
| PID | 7500 | 533 | 6.64 | 71.9 | 65.3 |
| FC-PID | 7555 | 494 | 6.14 | 72.0 | 65.8 |
| Accommodation temperature set-point | | | | | |
| PID | 7431 | 882 | 10.6 | 69.8 | 59.2 |
| FC-PID | 7496 | 819 | 9.9 | 69.5 | 59.7 |

This table shows that fuzzy-PID and PID have almost the same $I_c$ criterion. However, the $I_p$ criterion is quite better for the fuzzy-PID. This result can be explained by a lower $\%_{FE}$ for the fuzzy-PID.

The more interesting result is the Fossil Energy consumption. Indeed, for the office simulation, 7.4% of fossil energy is saved with a fuzzy-PID; this represents 39 $Wh.m^{-2}$ less than with the PID controller that consumes 533 $Wh.m^{-2}$. For the accommodation simulation the result is quite identical, 7.1% of fossil energy is saved by the fuzzy-PID which consumes 63 $Wh.m^{-2}$ less than the PID (882 $Wh.m^{-2}$).

Figure 5 shows the comparison of the indoor temperature controlled by a PID and a fuzzy-PID, subject to an outdoor perturbation temperature.

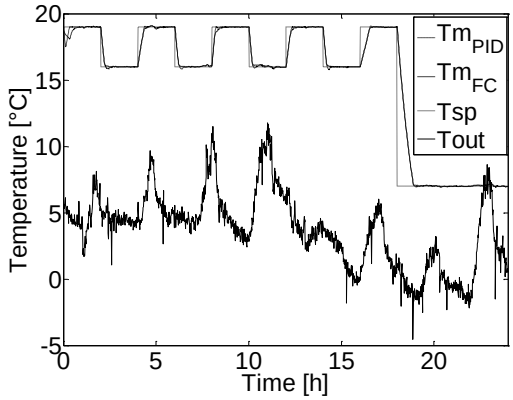


*Figure 5. Office indoor temperatures for PID and fuzzy-PID controllers with temperature set-point and outdoor temperatures.*

As it is shown by Figure 5 and Table 7, PID and fuzzy-PID controllers have similar behaviors in term of temperature set-point tracking. Differences appear on the energy consumption repartition between renewable and fossil resources. Figure 6 and 7 present both renewable energy and fossil power supplied by a system controlled using PID and fuzzy-PID regulator respectively.

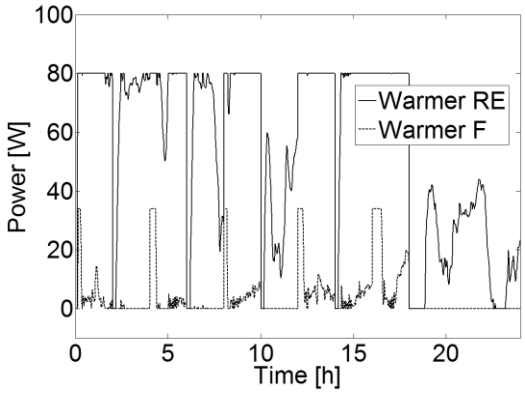


*Figure 6. Warmer power for PID control.*

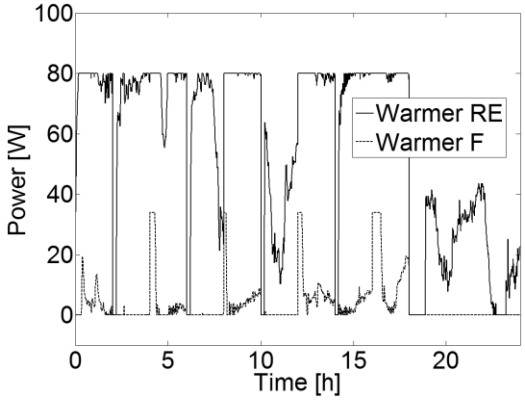


*Figure 7. Warmer power for fuzzy-PID control.*

**Conclusion**

The aim of the present paper is proposing an heating control strategy for efficiently managing energy in buildings. This management focuses on promoting both (i) energy savings and (ii) renewable energy. For reaching this objective, a building mock-up model has been developed using both temperature and heating power recorded data sets. PID and fuzzy-PID controllers have been designed and tested with the above-mentioned model according to temperature set-points. The legal energy indicator ($kWh.m^{-2}.year^{-1}$) being insufficient for comparing and optimizing the controllers, some additional criteria based on both part of fossil energy consumed and comfort were created.

In comparison to a classical PID controller, the obtained results allow highlighting that the fuzzy-PID controller is able to save 7% of fossil energy without any set-point tracking degradation. So, using a performance criterion based on energy consumption and tracking is essential for optimizing regulator parameters in the field of building warming. It also allows comparing different kinds of controllers and concluding that fuzzy-PID is a valid option. Future work will focus on testing the developed controllers on real buildings.

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**References**

1 The French Republic, Official Paper, Decree n°2006-592 of the 24, May 2006 « relatifs aux caractéristiques thermiques et à la performance énergétique des constructions », (2006).

2 The French Republic, Official Paper, Decree n°2006-1147 of the 14, September 2006, « relatif au diagnostic de performance énergétique et à l'état de l'installation intérieure », (2006).

3 B. Paris and al, A prototype for on-line monitoring and control of energy performance for renewable energy buildings, ICINCO 2008, 5th International Conference on Informatics in Control, Automation & Robotics, Funchal, Portugal, page 125-130, (2008).

4 B. Paris and al, « Travaux pratiques sur la gestion optimale d'un bâtiment Enr », 7th « Colloque sur l'Enseignement des Technologies et des Sciences de l'Information et des Systèmes », Université Libre de Brussel, Belgium, page 23, (2008).

5 Dounis, and al. Advanced control systems engineering and comfort management in building environment-A review. Renew Sustain Energy Rev (2008), doi:10.1016/j.rser.2008.09.015.

6 Guanron. Chen and al, Introduction to fuzzy sets, fuzzy logic, and fuzzy control systems, CRC Press, ISBN 0-8493-1658-8, (2001).

7 Traore A., Logique flou et contrôle supervisé des procédés biologiques de dépollution. Thèse de doctorat, Université de Montpellier II (2003).
8 P. Borne and al, Introduction à la commande floue, Sciences et technologies, Editions TECHNIP, ISBN 2-7108-0721-1, (1998).