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Reducing the energy consumption of space heating in buildings: design of an optimal controller

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Abstract: The reduction of the energy consumption in buildings has become a priority in every developed country. Automatic control is one of the latest techniques introduced to this purpose. This paper describes the design of a new controller which controls the internal temperature of an individual dwelling by adjusting of the heating power. First, considering the intermittency the occupation, an optimal temperature trajectory in term of control cost has been computed. Second, introducing an augmented state representation, a state feedback law has been calculated. Third, since this law required an inaccessible state, a Kalman estimator has been introduced to estimate this state. Introducing a deconvolution problematic in its design, a "virtual feed forward" based on estimation has been introduced to balance the external disturbances. Fourth, in order to take into account the control saturation of the heating system, an anti-windup compensator has been introduced to the controller. Finally, the controller has been tested in simulation on an experimental building and the interest of the virtual feed forward has been illustrated.

1. INTRODUCTION

40% of the fossil energy in France is consumed by the buildings. In order to reduce this consumption, three approaches are possible:

The first approach is to lower the consumption, by improving the insulation of the building and the efficiency of the energetic systems such as space heating devices or air conditioning devices.

The second approach is to use renewable energies. The design of these technologies already leads to significant results (Bader H., 2005), which allows producing electricity, space heating, air cooling and domestic hot water without producing greenhouse gas. The improvement of the efficiency of these technologies is constant (Jacobsson S., 2003; Foxon T.J., 2005).

The third approach is the optimisation of the energy consumption in the buildings. It is important to minimize the energy wastes in the building, especially when solar energy devices such as photovoltaic arrays or thermal control are used. The energy production contains a random part which must be taken into account during the dimensioning phase but also by an accurate control of the energy flows in the building.

This paper describes the first step of a global project driven by Laboratory AMPERE and CETHIL started in 2005 to investigate on the optimisation of the renewable energy flows in individual dwellings, using advanced automatic control techniques. Each energy aspect has been considered: the production, the storage and the consumption of the electrical and the thermal energy. Concerning the production of thermal energy, the main thermal load in French dwellings is space heating. The optimisation of space heating can be realized by the use of an accurate temperature controller.

Each heating device manufacturer has designed several temperature controllers. The technologies used for these controllers remain however quite simple. The most accurate controllers available nowadays are PID controller or Fuzzy logic controllers (Fraisse G., 1997; Raffenel Y., 2007).

This paper describes the design of a new controller and the validation of its performance in a building using simulation. Optimal control has been chosen for the control method since in contrast with usual methods, specifications on energy consumption can be explicitly introduced in the design. It was processed in four steps. The first step is the design of the temperature set point profile which guarantees the comfort of the occupants while minimizing the control costs. In particular, the inoccupation periods are explicitly introduced in the optimisation problem. The second step is the calculation of the control by the minimization of a trade-off between the error and the control cost represented in a criterion. The third state is the design of a virtual sensor using a Kalman estimator which will estimate the state value necessary to the control, and also the value of the outside disturbances. This value will be used as a "virtual feed forward". Finally, taking into account the control saturations, an anti-windup compensator will be introduced in our control structure.

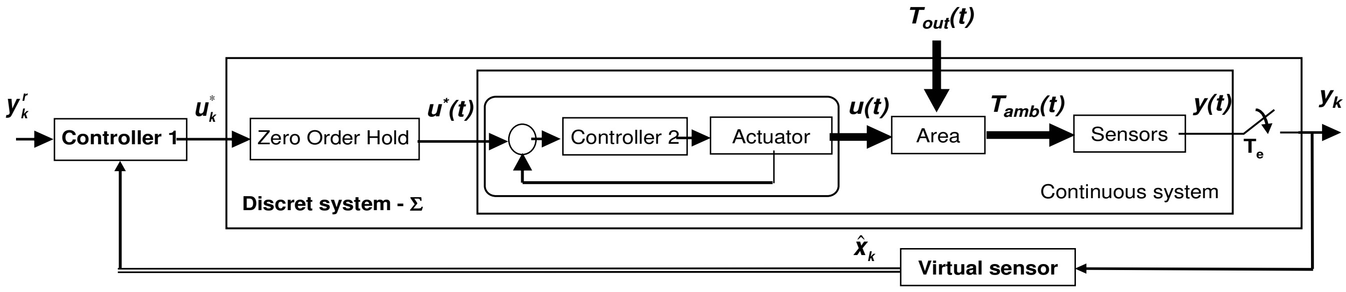

Fig. 1: Energy diagram of the dwelling

2. DESIGN OF THE CONTROLLER

2.1 Description of the problem

The purpose of the project is to design a temperature controller which optimizes the heating power of an individual dwelling. The system has a cascade structure (figure 1): in the outer loop, the controller calculates a heating power set point u_k^* for the heating system. In the inner loop, the heating system is controlled by controller 2 in order to track u_k^*. The area also undergoes the effect of the weather condition represented by the temperature disturbance $T_{out}(t)$. In this paper, we focus on the design of controller 1.

Former studies of buildings behaviours (Inard C., 1997) reveal that the thermal behaviour of the building can be modelled by a linear MIMO state model. The building is divided in q zones with an homogeneous temperature y_i. Each zone is heated by a heating power u_i and heat transfers from the outside and the adjacent zones. The parameters are calculated from the characteristics of the building. The model is then programmed in specific thermal sciences software. A reduced model is then obtained by identification of the programmed model.

Since temperature controllers are usually implemented on low memory and low calculation capacities hardware, we will consider a discrete state system with a sampling period of 1000 seconds.

$$\Sigma = \begin{cases} x_{k+1} = Fx_k + Gu_k \\ y_k^m = Cx_k + d_k \end{cases} \tag{1}$$

With $x_k \in \Re^n$ the state vector, $u_k \in \Re^q$ the control vector, $y_k^m \in \Re^q$ the temperature measurement, $d_k \in \Re$ the contribution of outside sources. F, G and C are matrices with appropriate dimensions with (F,G) controllable and (F,C) detectable.

It is correct to assume that the inside temperature of a zone is the sum of all sources contributions (heating device, adjacent zones, outside temperature or solar radiance). The corresponding model d_k will be considered in a first assumption as a white stochastic process. In this paper, the variance of such process will be considered as constant.

2.2 Set point profile design

Generally, an individual dwelling is only by intermittency occupied: in many cases, the house is empty during the day and the occupants are present during the evening and the night. There is no need to heat the house when it is empty; this represents an interesting energy saving potential. However, the comfort of the occupants cannot be neglected and the controller has to make sure that the temperature remains above the occupation temperature set point which depends of the zone. The first step of the design process will be the calculation of a temperature set point for each zone during the inoccupation which will minimize the energy consumption. We know that these profiles start and end on a specific high set point temperature which is for example 20°C for a zone gathering the living room, the kitchen and the dining room.

Since these profiles will be ideal profiles, we will consider the model without disturbance:

$$\begin{cases} x_{k+1} = Fx_k + Gu_k \\ y_k^m = Cx_k \end{cases} \tag{2}$$

The aim is to define the optimal couple (u*,y*) for the inoccupation phase respecting initial and final set point value. So a quadratic cost criterion is used

$$J_1 = 0.5\left[y_{N_2}^r - y_{N_2}\right]^T Q_{N_2}\left[y_{N_2}^r - y_{N_2}\right] + 0.5\sum_{k=N_1}^{N_2-1} u_k^T R_k u_k \tag{3}$$

with N_1 and N_2 the first and the last sample of inoccupation phase. $R_i \in \Re^{q\times q}$ and $Q_{N_2} \in \Re^{q\times q}$ are matrices respectively definite positive and semi-definite positive. The first term of the criterion is used to find the optimal restart instant. The second allows the determination of the output trajectory that requires the lowest command.

Introducing the Hamiltonian $H_k \in \Re$ such as:

$$H_k = -0.5 u_k^T R_k u_k + \beta_{k+1}^T [F x_k + G u_k] \quad (4)$$

with the adjoint state $\beta_k \in \Re^n$.

Using the Discrete Maximum Principe (Ramirez W.F., 1994), we obtain the minimal control u_k^* :

$$\beta_k = -\frac{\partial H}{\partial x_k} \Rightarrow \beta_k = F^T \beta_{k+1} \quad (5)$$

$$\frac{\partial H}{\partial u_k} = 0 \Rightarrow u_k^* = R_k^{-1} G^T \left(F^T\right)^{N-k-1} \beta_{N_2} \quad (6)$$

Using (6) in (1), some manipulations lead to:

$$\beta_{N_2} = \left(\sum_{k=N_1}^{N_2-1} F^k \; G R_k^{-1} G^T \left(F^T\right)^k \right)^{-1} \left(I - F^{N_2}\right) x_{N_2}^r \quad (7)$$

with $x_{N_2}^r$ the desired final value of state.

Using (6), (7), we obtain the ideal set point trajectory y_k^* for the inoccupation phase:

$$\begin{cases} x_{k+1}^* = F x_k^* + G R_k^{-1} G^T \left(F^T\right)^{N_2-k-1} \beta_{N_2} \\ y_k^* = C x_k^* \end{cases} \quad (8)$$

The global trajectory of temperature is illustrated figure 2. The evolution is finally composed by 3 parts. In part 2, if a regulator ensures y*, the corresponding control is equivalent to the lowest u* (Anderson B. D. O., 1990). As illustrated, constant set points are used (high and low set point) in parts 1 and 3 according to occupation and inoccupation constraints. The official rule indeed imposes a minimal temperature in the building during inoccupation [RT 2005].

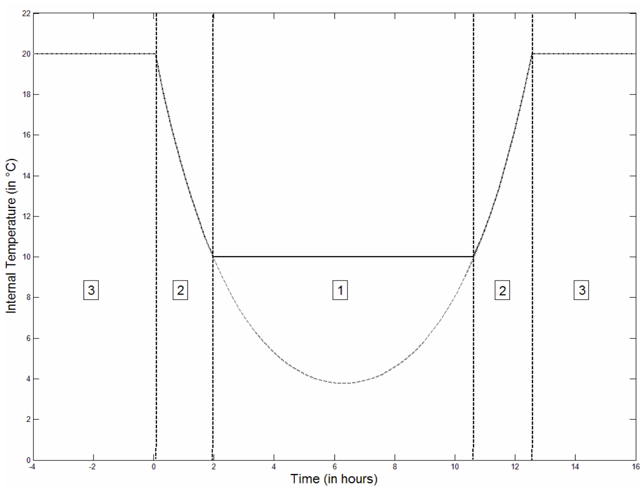

Fig. 2: Set point trajectory for single zone building Minibat (solid line: with constraint; dashed line: without constraint) with Q_{N2}=1 and R_k=3,55*10^{-6}

2.3 Design of control parameters

For tracking the global set point profile defined in step 1 and on figure 2, we design the discrete controller. Thus, let us consider the following criterion:

$$\begin{aligned} J &= 0.5\left[y_N^r - y_N\right]^T Q_N \left[y_N^r - y_N\right] \\ &+ 0.5 \sum_{k=N_1}^{N_2-1} \left\{ \left[y_k^r - y_k\right]^T Q_k \left[y_k^r - y_k\right] + u_k^T R_k u_k \right\} \end{aligned} \quad (9)$$

where y_N^r is the high set point and N is the total number of samples included in the whole cycle.

In order to ensure the reduction of the effect due to smoothed disturbances, an integrator is introduced on the error by the addition of a new state ζ_k. This leads to an augmented discrete representation Σ_a :

$$\begin{cases} \tilde{x}_{k+1} = \begin{bmatrix} x_{k+1} \\ \zeta_{k+1} \end{bmatrix} = F_a \tilde{x}_k + G_a u_k \\ y_{k+1} = C_a \tilde{x}_k \end{cases} \quad (10)$$

with $F_a = \begin{bmatrix} F & 0 \\ -C & I \end{bmatrix}$, $C_a = \begin{bmatrix} C & 0 \end{bmatrix}$ and $G_a = \begin{bmatrix} G \\ 0 \end{bmatrix}$

With I the identity matrix, $\tilde{x}_k \in \Re^{n+1}$ the increased state, and the subscript "a" to identify the increased representation for control. We introduce the income function Ω_k defined by:

$$\Omega_k = 0.5\left[\tilde{x}_k^* - \tilde{x}_k\right]^T C_a^T Q_k^a C_a \left[\tilde{x}_k^* - \tilde{x}_k\right] + 0.5 u_k^T \varphi_k u_k \quad (11)$$

with $Q_k^a = \begin{bmatrix} Q_k & 0 \\ 0 & R_k \end{bmatrix}$

and $\varphi_k \in \Re^{q \times q}$.

Using the *Bellman Optimisation Principle* (Anderson B. D. O., 1990), we obtain the optimal control:

$$u_k^* = -K_k^c X_k + L_k \lambda_{k+1}$$

with $K_k^c = -\left(F_a - G_a K_k^c\right)^{-1} G_a^T P_{k+1} F_a \quad (12)$

and $L_k = \left(F_a - G_a K_k^c\right)^{-1} G_a^T$

With $\lambda_k \in \Re^{n+1}$ an adjoint vector and $P_k \in \Re^{(n+1)\times(n+1)}$ a definite positive and symmetrical matrix such that:

$$P_k = \left(F_a - G_a K_k^c\right)^T P_{k+1} \left(F_a - G_a K_k^c\right) + K_k^{c\,T} \varphi_k K_k^c + C_a^T Q_k^a C_a \quad (13)$$

with $P_N = C_a^T Q_{N_1}^a C_a$

$$\lambda_k = \left(F_a - G_a K_k^c\right)^T \lambda_{k+1} - C_a^T Q_k^a C_a \tilde{x}_k^r \quad \text{with } \lambda_{N_1} = C_a^T Q_{N_1}^a C_a \tilde{x}_{N_1}^* \tag{14}$$

Let us note that these two last equations must be solved backward in time. We must pay attention to solve them outline. The structure of our augmented state representation (10) leads to:

$$\forall k \in [0, N_1],\ \lambda_k = 0 \tag{15}$$

Furthermore, the fast convergence of K_k^c (the state model and the weighting matrix are invariant) during the backward solving allows us to consider a stationary case with the final value $K_0^c = [K_1 \quad K_2]$

The real command of the process is then defined by

$$u_{k+1}^* = -K_0^c \begin{bmatrix} x_k \\ \zeta_k \end{bmatrix}. \tag{16}$$

The controller structure can be seen on figure 3.

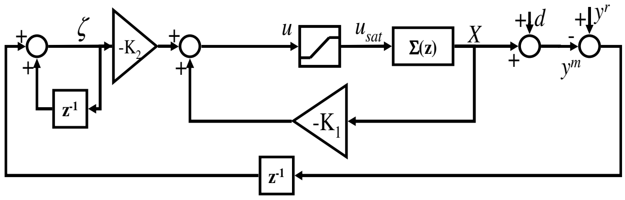

Fig. 3: Scheme of the linear control structure

2.4 Design of virtual sensor

At this step of design, x_k is required but not measurable, only the measurement y_k^m is available. Since the measurement noise can be used, a Kalman estimator will be designed (Gelb A., 1974) to obtain an estimate of real trajectories followed by the states of the system (Anderson B. D. O., 1990). Besides, the structure of the estimator will be used to estimate the external contribution d_k to the building. Thus, we assume that there exists a representation in which the output variation is the result of an additive stochastic input disturbance. The output of this representation must be similar to the output of the system:

$$\begin{cases} x_{k+1} = Fx_k + Gu_k \\ y_k^m = Cx_k + d_k \end{cases} \rightarrow \begin{cases} x_{k+1} = Fx_k + Gu_k + Gw_k \\ y_k^m = Cx_k + v_k \end{cases} \tag{17}$$

where w_k is a non zero mean white noise with constant variance and v_k the noise measurement considered as a zero mean white noise with constant variance. As a result, we need to compute this unknown input and thus, solve a deconvolution problem (Thomas G., 1980). To estimate this unknown input, we need to introduce a model of this disturbance: we can consider that w_k is the output of a Wiener process generator driven by a zero mean Gaussian white noise with constant variance. It leads to the following representation Σ_e :

$$\begin{cases} x_{k+1}^e = \begin{bmatrix} x_{k+1} \\ w_{k+1} \end{bmatrix} = F_e x_k^e + G_e u_k + M_e \omega_k \\ y_k^e = C_e x_k^e \end{cases} \tag{18}$$

with $F_e = \begin{bmatrix} F & G \\ 0 & I \end{bmatrix}, G_e = \begin{bmatrix} G \\ 0 \end{bmatrix}$ and $M_e = \begin{bmatrix} 0 \\ I \end{bmatrix}$ with $C_e = [C \quad 0]$

with subscript "e" to identify the increased representation for estimation. From (18), an optimal estimator in the sense of the minimum variance of the estimation error can be defined (Kalman Theory). Thus, in the stationary case, we obtain:

$$\Pi = F_e \Pi F_e^T + M_e Q_\omega M_e^T - F_e \Pi C_e^T \left[C_e \Pi C_e^T + R_v\right]^{-1} C_e \Pi F_e^T \tag{19}$$

with $\Pi \in \Re^{(n+1)\times(n+1)}$ a definite positive and symmetrical matrix, $Q_\omega \in \Re^{(n+1)\times(n+1)}$ and $R_v \in \Re^{(n+1)\times(n+1)}$ are respective input and measurement noise variance.

$$K_e = \Pi C_e^T \left[C_e \Pi C_e^T + R_v\right]^{-1} \tag{20}$$

With $K_e \in \Re^{n+1}$ the estimator gain.

The "a priori" estimation is defined by:

$$\hat{x}_{k/k-1}^e = F_e \hat{x}_{k-1/k-1}^e + G_e u_{k-1} \tag{21}$$

And the "a posteriori" estimation is defined by:

$$\hat{x}_{k/k}^e = \hat{x}_{k/k-1}^e + K_e \left[y_k^m - C_e \hat{x}_{k/k-1}^e\right] \tag{22}$$

At this point, our linear controller has the following expression:

$$u_k^* = -K_{k-1}^c \begin{bmatrix} \hat{x}_{k-1/k-1} \\ \zeta_{k-1} \end{bmatrix} - \hat{w}_{k-1/k-1} \tag{23}$$

We withdraw the term $\hat{w}_{k-1/k-1}$, just like we would for a feed forward is the measurement of the disturbance and its transfer were available. That is why we called this process "virtual feed forward". The estimator structure into the global control structure is presented on figure 11.

2.5 Design of anti-windup compensator

Until this step, the constraints of the actuator have not been taken into account yet. The actuator is a heating system which supplies heating power to the building. The consequence is that the control can only be positive. There also is a maximal constraint which depends of the actuator:

$$0 \le u_k \le u_{\max} . \tag{24}$$

An anti-windup compensator is necessary to minimize the non-linear effect of these constraints: it will ensure that the saturated system is internally stable and that the response of the saturated system deviates as little as possible from that of the nominal linear system, using the distance described in the next paragraph. The method used is described in (Turner M., & al. 2003). It is proposed to consider a classical structure for the compensator $\theta = [\theta_1 \quad \theta_2]$ represented on figure 12.

Considering u^{lin} the output of the controller, $y^{lin} = \Sigma(u^{lin})$ and $y^d = y - y^{lin}$, the efficiency of the anti-windup compensator will be measured by the square distance μ, defined by:

$$\forall u^{lin} \in \Re^N , \sum_{k=1}^{N} \left(y_k^d\right)^T y_k^d < \mu \sum_{k=1}^{N} \left(u_k^{lin}\right)^T u_k^{lin} . \tag{25}$$

To build θ, the following theorem is used:

Theorem (Turner M., & al. 2003)

If there exist matrices $\Psi > 0$, $L \in \Re^{(q+q)\times q}$ (with q the length of u and y) and positive real scalars $\mu>0$ and $U > 0$ such that the following LMI is satisfied:

$$\begin{bmatrix} -\Psi & -\Psi \overline{C}_1^T & 0 & \Psi \overline{C}_2^T & \Psi \overline{F}^T \\ * & -\eta & I & 0 & UG_a^T + L^T \overline{G}^T \\ * & * & -\mu I & 0 & 0 \\ * & * & * & -I & 0 \\ * & * & * & * & -\Psi \end{bmatrix} < 0 \tag{26}$$

where $\eta = 2U + \overline{D}_1 L + L^T \overline{D}_1^T$, then a suitable static compensator $\theta = [\theta_1 \quad \theta_2]$ given by $\theta = LU^{-1}$ guarantees the internal stability of the system and verifies (25).

The definitions of the sub matrix are:

$$\overline{F} = \begin{bmatrix} F - GK_1C & -GK_2 \\ T_e C & I \end{bmatrix}, \ \overline{G} = \begin{bmatrix} G & -GK_1 \\ 0 & -T_e \end{bmatrix} \tag{27}$$

$$\overline{C}_1 := [-K_1 C \quad -K_2], \ \overline{C}_2 := [C \quad 0], \ \overline{D}_1 := [I \quad K_1]$$

Constraint (26) defines an LMI feasibility problem. In the next section, this problem is solved for our benchmark problem, using the LMI control toollbox of Matlab.

3. TESTING ON A VIRTUAL BUILDING

The controller will now be tested on a building called Minibat. This building was built by the CETHIL and is used inter alia for the testing and design of temperature controller. However, the controller has only been tested for the moment on its numerical model programmed on TRNSYS (a thermal phenomena modelling software) and adapted for Matlab.

3.1 Description of the building

This test installation is a 2 identical contiguous area with a controlled climatic environment (temperature, sunning). The rooms dimensions are 3.*10 m × 3.10 m × 2.50 m* (L x l x h). The external jacket consists of standard insulating concrete (Siporex) with *20 cm* thickness and has the following dimensions: *7.5 m × 4.50 m × 3.43 m*. Walls of the cell are composed of agglomerated wood panels of *5 cm* thick, covered with a pressure-sealed plasterboard of *1 cm*. Only the southern wall is equipped with a window of *1 cm* thickness. The floor is made of a concrete flagstone of *20 cm* thickness.

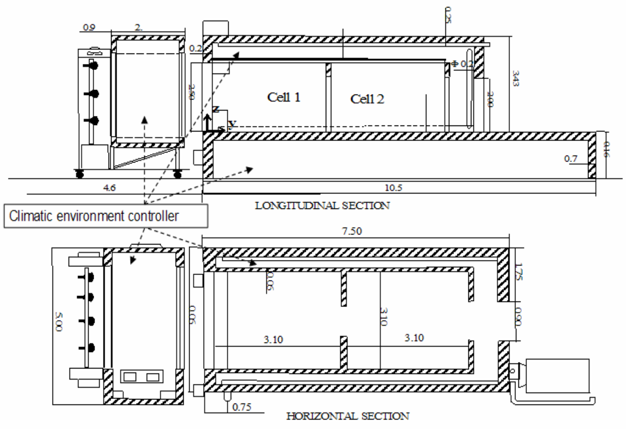

Fig. 4: The Minibat test cell

A single zone model of its thermal behaviour was developed by the CETHIL (Kuznik F., & al. 2005) for the software TRNSYS. We performed then an identification of this model: a set of runs was carried out with the cell in order to identify its dynamic and static behaviour. The heating system is an electric heating system, whose power is directly controlled. A first order continuous model was obtained:

$$F = e^{-\frac{T_e}{\tau}}, \ G = b\left[1 - e^{-\frac{T_e}{\tau}}\right] \text{ and } C = 1 \tag{28}$$

with T_e=1000s, τ=9564s and b=0.008413

The identification of the model parameters is the first part of the computation of the controller. The second part is the calculation of the gains K_1, K_2, K_e, θ_1 and θ_2. They should both be performed by the operator or the manufacturer. In the Minibat case, the following values have been computated:

K_1=2275,7; K_2=-1,197; $K_e = \begin{bmatrix} 0{,}481 \\ 227{,}6 \end{bmatrix}$;

$\theta = [-1{,}8 \quad 8{,}4.10^{-4}]$, with weights:

$Q^a = \begin{bmatrix} 10^{-3} & 0 \\ 0 & 10^{10} \end{bmatrix}$, $\varphi = 10^{-3}$ and noises:

$Q_\omega = \begin{bmatrix} 0 & 0 \\ 0 & 10^2 \end{bmatrix}$, $R_v = 10^{-1}$

3.2 Simulation conditions

The controller was designed for inoccupation periods between 7 A.M. and 8 P.M., from Monday to Friday. The low temperature level is set to 10°C and the high temperature level to 20°C. The weather data used were recorded in Lyon Bron, France, the simulation scenario is planned during two days of the first week of January. The time step is 1000 seconds.

There will be three specifications to evaluate the performance of the controller:

The first is the “high set point condition”: during occupation, the temperature must track the high set point, 20°C, with a tolerance of plus or minus 0.5°C.

The second is the “restart condition”: on the beginning of each occupation period, the temperature must equal the high temperature set point, 20°C.

The third is the “low temperature set point”: during the inoccupation, the temperature must remain above the low temperature set point, 10°C. A tolerance of -0.5°C is admitted.

3.3 Simulation results

We monitored the evolution of the temperature and the evolution of the heating power. To illustrate the interest of the virtual feed forward and of the anti-windup compensator, two other simulations have been run without these processes.

Figure 5 and 6 illustrate the behaviour of the controller without the anti-windup compensator and the virtual feed forward.

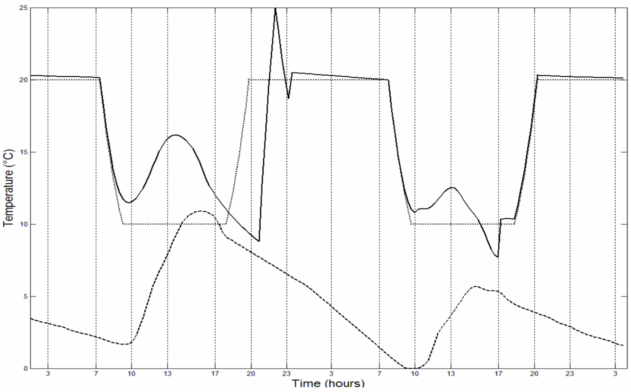

Fig. 5: Evolution of the temperature without anti-windup compensator and virtual feed forward (solid line: Internal temperature – dotted line: set point profile – dashed line: external temperature)

It is striking that the controller is unable to deal with the non linearity of the command during the inoccupation period. Since this period is planned during the day, it is strongly disturbed by the influence of the solar gains which causes an important deviation from the set point profile and leads to a negative value of u^{lin} and a saturation. We note that this deviation is not contrary to the three evaluation specifications. But when the effect of the solar gain disappears, the tracking of the set point profile remains disturbed and needs a few hours to restore its operation. The anti-windup compensator avoids these effects.

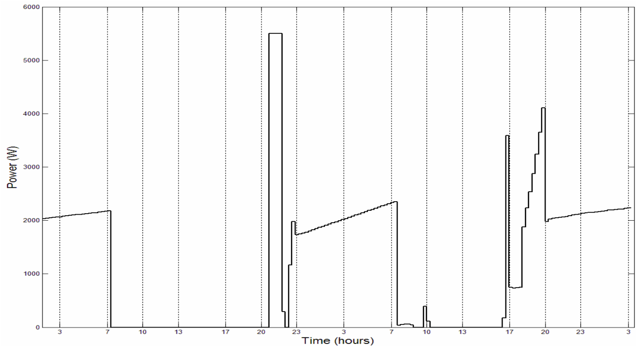

Fig. 6: Evolution of the heating power without anti-windup compensator

The figure 7 and 8 illustrate the behaviour of the controller with the anti windup compensator, but without the virtual feed forward.

In this simulation, a standard Kalman estimator has been used in the command law to estimate the state:

$$u_k^* = -K_{k-1}^c \begin{bmatrix} \hat{x}_{k-1/k-1} \\ \zeta_{k-1} \end{bmatrix} \tag{29}$$

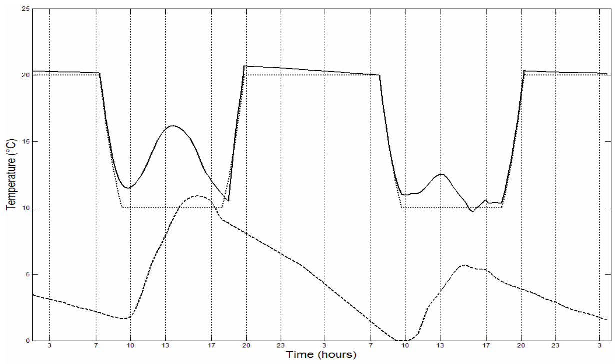

Fig. 7: Evolution of the temperature without the virtual feed forward (solid line: Internal temperature – dotted line: set point profile – dashed line: external temperature)

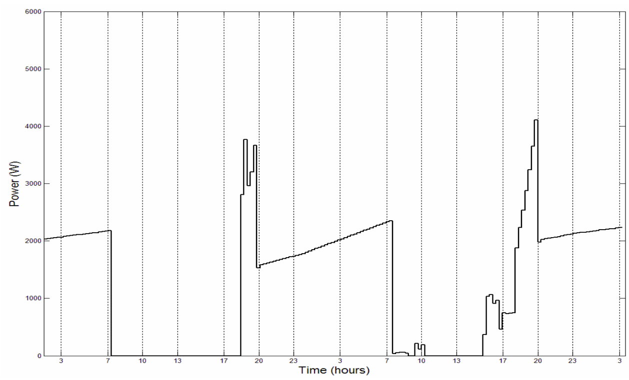

Fig. 8: Evolution of the heating power without virtual feed forward

The quality of the tracking is strongly improved with the anti-windup compensator. However, a static error can be noted on the beginning of each occupation period. The Kalman theory implies the assumption that the stochastic process which generates the signal of the external gains has a zero mean, which is not the case. The consequence is a bias in the estimator which leads to an underestimation of the state and an overheating of the building (Gelb, A., 1974). The use of an augmented state ζ in our controller allows its correction, but it remains too slow. The virtual feed forward allows a faster rejection of the static error.

The figure 9 and 10 illustrate the behaviour of the system with the whole controller. We note that the results cover the evaluation specifications.

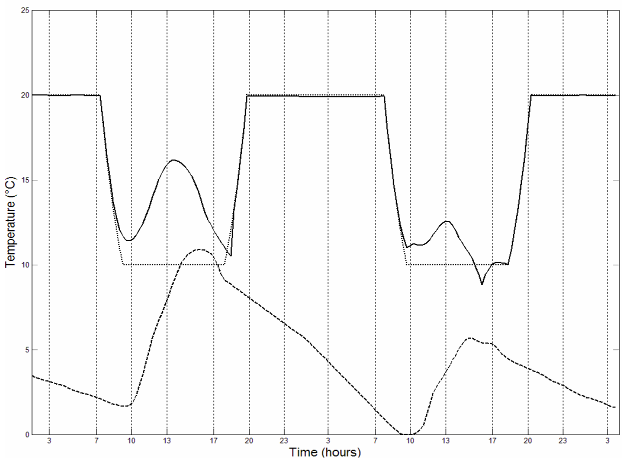

Fig. 9: Evolution of the internal temperature (solid line: Internal temperature – dotted line: set point profile – dashed line: external temperature)

The temperature tracks the set point profile during the whole occupation period. The high set point condition is then fulfilled. During inoccupation periods, the important impact of the solar radiations can be noted: the temperature increases during the middle of the day. But when the effect of the solar radiation disappears and the temperature reaches the set point profile back, then its profiles perfectly matches the set point profile during the end of the inoccupation period. The restart condition is on every time fulfilled. Finally the low set point condition is also fulfilled.

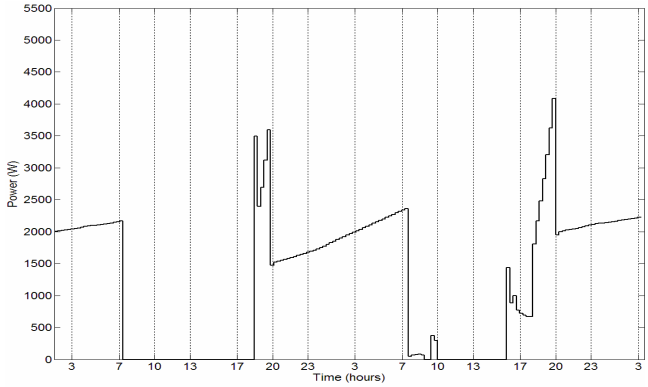

Fig. 10: Evolution of the heating power

Considering the heating power evolution on figure 10, three operation steps can be distinguished. During occupation, the heating system is on normal operation mode. It provides a heating power between 1.5 kW and 2.5 kW with slow variations. During inoccupation, the first step is the "shut down step". The heating system is shut down during the decreasing part of the set point profile during the inoccupation and also when the impact of the solar radiation is noticeable. It switches to the "restart step" when the set point trajectory moves back to the high set point temperature. The heating power increases quickly from zero to its maximal power which is 4500 W. Retrospectively, the study of this final operation step allows setting the maximal power of the heating system.

The global energy consumption is 62.2 kWh.

4. CONCLUSION

The controller fulfils all the evaluation specifications. The virtual feed forward allows a high accuracy of the tracking of the set point profile. We note that this profile depends on the model of the building and especially of its inertia.

This work will be completed in the future by the study of the robustness of the controller and of the estimator. A comparison with a standard controller, the fuzzy controller, will be made to characterize the gain of the proposed controller.

The controller should then be tested in real conditions on the Minibat cell, and in simulation on multi zone buildings models with a higher inertia.

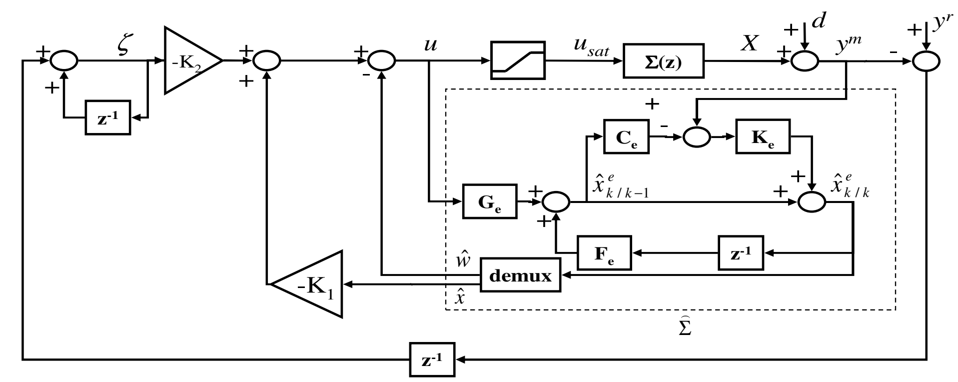

Fig. 11: Scheme of the control and estimator structure

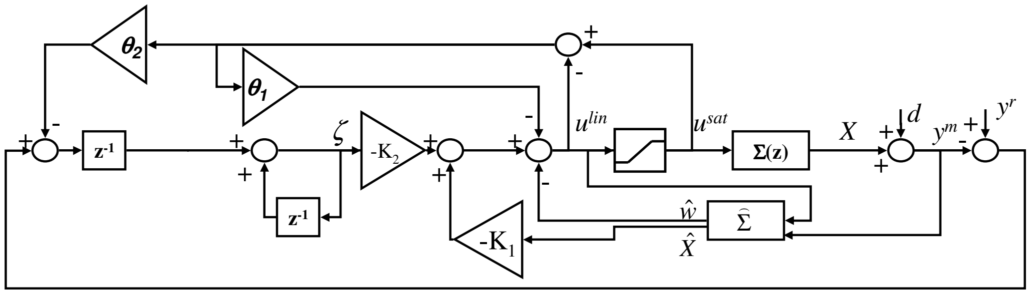

Fig. 12: General representation for an anti-windup compensator

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