Optimised thermal zone controller for integration within a Building Energy Management System

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1. Introduction

Today's important buildings are often equipped with a Building Energy Management System (BEMS) that aims to control and optimise all the energy fluxes involving the HVAC system, but also the lighting and other appliances. The BEMS is also intended to maintain an acceptable level of comfort in the building by a proper control strategy. The notion of comfort not only means the thermal comfort but is also related to the Indoor Air Quality (IAQ) and to other discomfort sources : noise, insufficient or glaring light, ...

The trade-off between comfort and energy consumption is often realised by choosing adequate set points for the local controllers of the HVAC installation. This trade-off is sometimes left entirely to the operators, and requires much experience and a good empirical knowledge of the building.

As far as the thermal comfort is concerned, the classical control system includes a fluid temperature control at the heat exchanger outlet, associated with thermostatic regulators in each room or for each heating/cooling unit. The fluid temperature set point is often adjusted by simple laws combining a feedforward action using an external temperature sensor and a feedback action using a representative temperature of the building. The feedforward action is known as the "heating curve". These control systems have been used for a long time and have proven their ability to maintain an acceptable level of comfort in buildings, if they are correctly implemented on a well designed HVAC plant. However, they leave the door open for important energy savings and for a less conservative design while maintaining and even improving the thermal comfort, especially during the mid season and the summer. Modern buildings are indeed well insulated and often have important passive solar and internal gains, which makes them very sensitive to overheatings. Avoiding this problem requires an anticipation of the building's thermal behaviour, unless an oversized cooling plant is used, leading to unacceptable cost.

Our research's objective is to provide a control algorithm adapted to today's buildings and HVAC installations which makes possible to optimise both comfort and energy consumption according to an explicit optimisation criterion. The optimal control theory presents the ideal formalism for this purpose, offering algorithms that permit to anticipate the building's thermal behaviour to calculate the control sequence that minimises a mathematical expression of both costs involved : discomfort and energy consumption.

This paper presents the application of these principles to a simplified problem : the thermal control of a single zone. Previous papers [1] [2] [3] have shown that optimal control can lead to substantial thermal comfort improvement and energy savings. However, the simulation-based results were obtained using very simple models for the building and the

HVAC plant. Fulcheri et al. [4] and André [5] have shown that the performance of such controllers could be significantly reduced if they were evaluated on more complex models, and *a fortiori* on real buildings.

Braun [6] has considered an entire cooling plant and one building zone with more complex models, to study the possible energy savings of optimal control compared to conventional night set-up control, in the case of summer cooling. The optimisation of the cooling plant was achieved using a steady state performance map and was decoupled from the building dynamic analysis. A parametric study covering a wide range of conditions was made using synthetic weather data, and considering "steady periodic" solutions. This analysis showed that 5 factors have an influence on the possible energy savings : the building thermal inertia (a sufficient storage capacitance must be present), the utility rate structure (high ratios of on-peak to off-peak rates lead to more important gains), the part-load characteristics of the cooling plant (a good part-load performance gives a greater flexibility), the occupancy schedule (intermittent occupied buildings show a higher potential) and the weather (a relatively cold temperature during the night permits to use some free pre-cooling of the building).

Keeney and Braun [7] showed that important energy savings can be achieved for the summer cooling of buildings using a simplified control method to replace the conventional night set-up control. The optimisation of two control variables (e.g. pre-cooling period and power), combined with a classical comfort-based controller with simple rules during building occupancy, can yield about 95% of the possible energy savings using optimal control. This solution reduces drastically the computational load of the optimisation.

In our study, we have used a simplified linear state-space model developed for control purpose [8], trying to find a good trade-off between accuracy and complexity. Furthermore, the optimal controller has been tested on a more complex building model, to be closer to the real conditions (non-zero modelling error). The reference model for our simulations is the TRNSYS TYPE 46, which has the same calculation engine as the Belgian software MBDSA [9] and is very close to the official TRNSYS TYPE 56 [10] (the TYPE 46 considers a resultant temperature rather than the air temperature). The simulation scheme was completed by a compensating feedback controller (a conventional PID) which would be necessary in real conditions since the optimal controller actually works in open loop between two optimisations.

2. Problem's description

A thermal zone represents an air volume where the temperature is assumed to be uniform. Depending on the needed accuracy and on the size of the modelled building, a zone can include less than one room to several similar rooms for which the same thermal behaviour is assumed.

The temperature considered for the zone is a fictitious one combining the radiative and convective effects. It is closer to the actual comfort feeling of an occupant than the pure air temperature. This temperature, called the "resultant temperature", is adopted by several complex simulation programs, including the TYPE 46.

The zone's energy balance is given by :

$$C\frac{dT_z}{dt} = f\left(q_i, q'_i\right) \tag{1}$$

with C : thermal capacity of the zone
T_z : zone resultant temperature
q_i : radiative and convective heat fluxes from/to HVAC installation
q'_i : other conductive, radiative and convective heat fluxes

The aim of the thermal controller is to maintain the zone temperature within an acceptable comfort range during the occupation hours and to prevent the temperature to go beyond absolute lower and upper bounds at any time. If we include energy concerns at this level, the temperature control must be achieved while minimising the energy consumption Q :

$$Q = \int_{t=0}^{t=\infty} q_i \, dt \tag{2}$$

If we assume that all the heat transfers are linear, the thermal zone behaviour can be described by a set of linear equations known as the state-space system's description. Using the matrix notation, we have :

$$\begin{cases} \dot{\mathbf{X}} = \mathbf{AX} + \mathbf{BU} \\ \mathbf{Y} = \mathbf{CX} + \mathbf{DU} \end{cases} \tag{3}$$

where **X** is a vector containing the state variables (temperatures)
Y is a vector containing the outputs (e.g. some chosen measured temperatures)
U is a vector containing the controlled inputs and the disturbances

This kind of linear systems has been extensively studied in control theory and provides the ideal basis for our study. Furthermore, the state space representation has the great advantage to permit very easy extension to Multi Inputs-Multi Outputs (MIMO) systems, which is necessary if we think to the simultaneous control of several zones by mean of several energy sources.

3. Optimal control principles

We will apply the principles of optimal control theory of discrete linear systems [11]. Indeed, the use of computer control techniques implies the sampling of a continuous time system.

Using the matrix notation and separating the controlled inputs from the disturbances, the discrete-time form of the state equations (3) is :

$$\begin{aligned} \mathbf{X}_{k+1} &= \mathbf{\Phi}_k\ \mathbf{X}_k + \Gamma u_k\ \mathbf{U}_k + \Gamma v_k\ \mathbf{V}_k \\ \mathbf{Y}_k &= \mathbf{C}_k\ \mathbf{X}_k + \mathbf{D}u_k\ \mathbf{U}_k + \mathbf{D}v_k\ \mathbf{V}_k \end{aligned} \tag{4}$$

with **X** : state variables
Y : outputs
U : control signals
V : measured disturbances
Φ, Γu, Γv, **C**, **D**u, **D**v : system's matrices

the k subscript denotes the time step

We assume to know a perfect trajectory for the outputs, given by $\mathbf{Y}^s$. In our case, the output will be the zone temperature and the "set point" will be the optimum comfort temperature, which depends on many variables : humidity, air velocity, clothing, ... [12]

The purpose of optimal control is to find the optimal control sequence $U_{k\ (k=0..NH-1)}$ that minimises a given cost function J over an optimisation horizon NH.

$$J = \sum_{k=0}^{k=NH} J_k(\mathbf{U}_k, \mathrm{E}_k) \tag{5}$$

where **E** is the output error : $\mathbf{E} = \mathbf{Y}^s - \mathbf{Y}$

Note that the optimisation of the future behaviour of the building (J is evaluated at time k=0) requires the value of the future disturbances that will be applied to this system. In our simulations, we assumed that the disturbances were perfectly forecast. This will give an upper bound for the controller's performance.

The optimisation problem is then to minimise a function of the system's variables **X**, **Y** and **U** given the constraint equations (4). Additional inequality constraints have to be added to give the upper an lower bounds on **Y** (minimum/maximum allowed temperature) and on **U** (maximum heating/cooling power).

$$\begin{aligned} \mathbf{U}\min_k \le \mathbf{U}_k \le \mathbf{U}\max_k \\ \mathbf{Y}\min_k \le \mathbf{Y}_k \le \mathbf{Y}\max_k \end{aligned} \tag{6}$$

The optimal theory has been mainly developed in the case of purely quadratic cost functions, because of the existence of analytical solutions in this case [13].
However, we consider a linear-quadratic cost function of the form :

$$\mathrm{J}_k = \mathbf{E}_k^T \, \mathbf{Q}_k \, \mathbf{E}_k + \mathbf{L}_k^T \, \mathbf{U}_k \tag{7}$$

where **Q** is a positive semi-definite matrix and **L** is any matrix.

This cost function combines a linear cost on the control signals (power of the HVAC system) and a quadratic cost on the output error. The linear cost on the control signal will insure the energy consumption minimisation since the control variable is directly proportional to the heating/cooling power in this simplified approach. Note that this implies two restrictions : no part-load characteristics of the heating and cooling plant are taken into account, and the ambient temperature has no effect on the cooling cost. In particular, the possibility of free cooling is not considered.

The quadratic function of the difference between the temperature and the optimum comfort temperature is used to model the discomfort feeling of an occupant. However, a better approximation is to consider a dead-band in this quadratic function, corresponding to a "comfort zone" in which the occupant is supposed to adapt his clothing. The discomfort feeling can be set to zero in this zone, which gives the following function for the discomfort cost $J_{d,k}$, for one temperature :

$$J_{d,k} = \begin{cases} a\left(T_k - T_{hi,k}\right)^2 & \text{if} \quad T_k > T_{hi,k} \\ 0 & \text{if} \quad T_{lo,k} \le T_k \le T_{hi,k} \\ a\left(T_{lo,k} - T_k\right)^2 & \text{if} \quad T_k < T_{lo,k} \end{cases} \tag{8}$$

where T_{lo} and T_{hi} are respectively the lower and upper bounds of the comfort zone, and a is a constant. This function is represented fig. 1 for a=1, T_{lo}=20°C and T_{hi}=24°C.

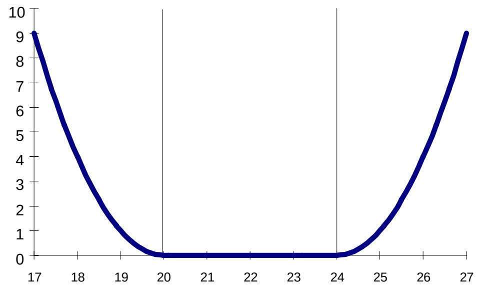

fig. 1 : discomfort cost

Such function can be expressed as in eq. (7) introducing new variables that are subject to linear constraints :

$$\begin{cases} \mathbf{E}_{lo,k} \ge \mathbf{X}_{lo,k} - \mathbf{X}_{\mathbf{k}} \\ \mathbf{E}_{hi,k} \le \mathbf{X}_{\mathbf{k}} - \mathbf{X}_{hi,k} \end{cases} \tag{9}$$

The minimisation of the square of these variables will lead to E_{lo} = 0 if T > T_{hi}, and E_{hi} = 0 if T < T_{lo}, the other variable giving the correct difference between the temperature and the comfort zone.

The cost function is then written as :

$$J_k = \underbrace{\mathbf{E}_{lo,k}^T \mathbf{Q}_k \mathbf{E}_{lo,k} + \mathbf{E}_{hi,k}^T \mathbf{Q}_k \mathbf{E}_{hi,k}}_{J_{d,k}} + \underbrace{\mathbf{L}_k^T \mathbf{U}_k}_{J_{e,k}} \tag{10}$$

where $J_{d,k}$ is the "discomfort cost" and $J_{e,k}$ is the "energy cost", J_k being the "total cost".

With these hypothesises, the optimal control problem can be written as a Quadratic Programming (QP) problem. The general form of a QP problem is :

Minimise $J = ½\ \chi^T H \chi + C^T \chi$

with the constraints $\mathbf{A}e\ \chi = \mathbf{B}e$ (11)

$\mathbf{A}i\ \chi \le \mathbf{B}i$

The problem of the minimisation of (10) with the constraints (4) and (6) can be rewritten to this form using a χ vector that includes all the system's variables (**X**, **U** and **Y**) at each time step of the optimisation period.

This kind of problem can be efficiently solved using a projected gradient method, e.g. described in details in [14]. This algorithm has been implemented in the Matlab Optimisation Toolbox, which was used for the optimal control computation [15].

4. Simplified zone model

The internal model of the controller is a state space model based on a second order wall representation. This model has been developed for control applications and realises a trade-off between the accuracy of the dynamics modelling and the complexity of the model [8]. The model is a lumped capacitance representation, which can be interpreted using the electrical analogy. Each wall is modelled by two state variables (i.e. two thermal capacitors), and two additional nodes represent the wall surfaces. The surface nodes have no associated thermal capacity and are used to introduce the radiative heat fluxes, which are distributed according to area absorptance weighted ratios. Each wall model (from surface to surface) includes 3 free parameters, if we impose the conservation of the global parameters (U-value, thermal capacitance). These parameters were chosen using physical insight and adapted to give a satisfactory dynamic response in the necessary frequency range. The reference model were detailed transfer functions. An identification procedure will be developed to guarantee a satisfactory accuracy of the model in a real controller.

The zone model consists in a star network where the wall models are connected to a central air node representing the thermal capacity of the air inside the zone. This capacity is multiplied by 5 to account for convective transfers inside the air [9]. The air node is connected to the walls by thermal resistance values which include both convective and radiative effects to give the resultant temperature. Fig. 2 shows the model obtained for the zone modelled in the simulation example.

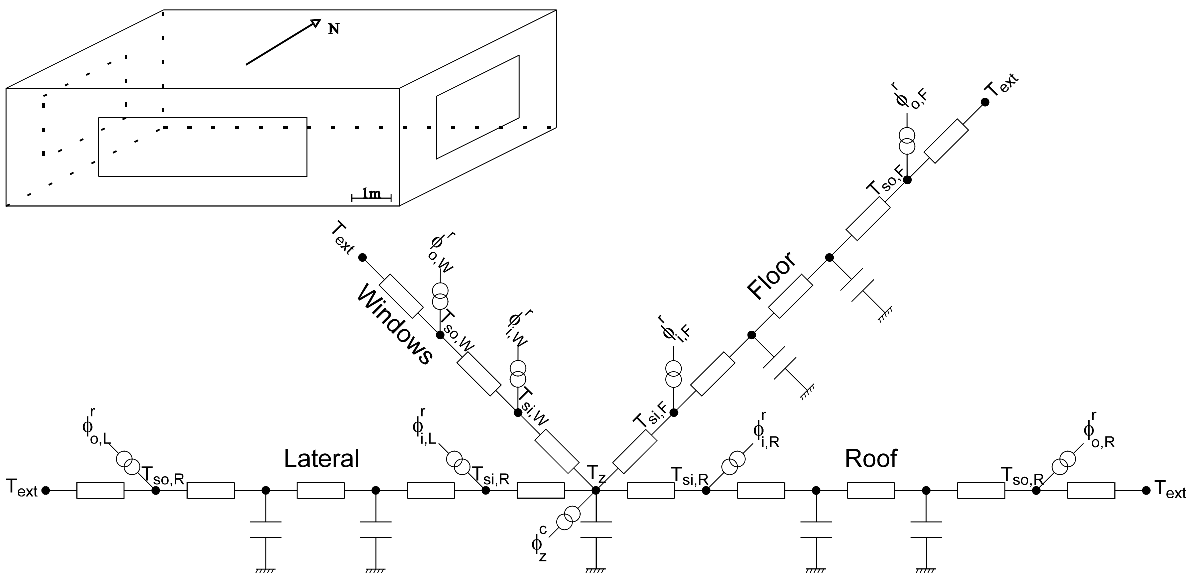

Fig. 2 : The example thermal zone and its simplified model

In the simplified approach that we adopted, the control signals are the energy flows transferred from the HVAC system to the zone. In a further study, a part of the HVAC plant will be introduced in the zone model, and use will be made of more realistic control signals. Note that these control signals could be the set points for local controllers with faster dynamics (e.g. outlet temperature of a heat exchanger).

5. Practical implementation of the optimal controller

Fig. 3 describes the information flow during the simulation of the optimal controller, as it was implemented in TRNSYS. The optimal controller was implemented in Matlab for convenience in matrix operations, but the algorithm can be easily integrated into a TRNSYS TYPE. The building is simulated by the TRNSYS TYPE 46. The measured disturbances, the inputs and the outputs of the TYPE 46 are used by a state estimator (TYPE 63) to reconstruct the state variables of the controller's internal model in order to give the initial conditions of the optimisation period. Each day, the optimal controller uses this initial state and the disturbances forecasting to calculate the optimal control sequence which is applied to the TYPE 46. To account for unexpected disturbances or model inaccuracies, a feedback controller (TYPE 37) is used. Its role is to correct the applied control to follow the optimal trajectory of the outputs.

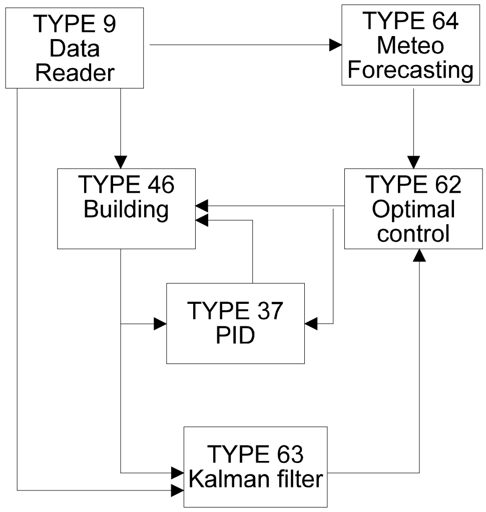

Fig. 3 : Information flow during the simulation

Complex zone model (TYPE 46)

This model plays the role of the real building in our simulation. It solves a detailed heat balance of the building, using the z-transform method to evaluate the conductive heat fluxes through walls. The only output considered in the simulation is the zone resultant temperature. This model is simulated with a time step of 0.25h, which was used for the PID and the Kalman filter.

Meteorological data forecasting

A forecasting routine based on neural networks and conventional techniques is currently under development. For this simulation, a perfect forecasting is assumed, giving the ideal conditions for the optimal controller. A comparison with less accurate forecast data will be done in a near future. Note that the development of the forecasting routine requires long periods of real data, which made us use Swiss meteorological data for this study (the real 1986 year measured in Zürich). Such a long period of real data is not easily available for Belgium.

State Estimator

This state estimator uses the zone temperature from the TYPE 46, the meteorological data and the input signals to estimate the state variables of the simplified zone model. The used algorithm is a dynamic Kalman Filter, which as been implemented as a TRNSYS TYPE by André [5].

Optimal controller

The optimal controller starts an optimisation procedure each day at 0:00 AM. The initial conditions are obtained from the Kalman Filter and the forecast disturbances are used. The QP algorithm is used to obtain a hourly control sequence and a hourly optimal temperature sequence. The inequality constraints added to the problem defined by (4) and (5) are of the form of (6), i.e. upper and lower bounds on the zone temperature ("night set points") and on the control signals (maximum heating/cooling power).

The controller can use variable matrices for the system model as well as for the cost function. However, in this simulation, constant matrices were used for the system. The quadratic cost for the zone temperature is variable, since it has to be zero when no occupants are in the building. The heating energy cost has been maintained constant, but a variable cost for cooling was considered to take into account time-of-day electricity rates.

The conversion of optimal sequences to a shorter time step (0.25h) is made assuming a zero order hold for the control signals and using a dynamic simulation for the temperature sequence. Note that the optimisation time step has not to be very short, since it is used to define an optimal response of the building, which has very large time constants.

Feedback compensating controller

The feedback controller is assumed to have a short sampling period compared to the time step (0.25 h). In a real implementation, this sampling rate should be adjusted to the HVAC installation dynamics, the only limitation being the computation time.

The implemented controller is a classical PID and its parameters have been adjusted to obtain a reasonably fast closed loop response without excessively large control signals, since they are added to the optimal ones. The set point temperature is the optimal sequence obtained by the optimal controller and, in the case of perfect modelling and perfect disturbances forecasting, the PID's output would be zero.

Computational load

The system includes 7 state variables which must be estimated by the Kalman filter. Then, the optimal control algorithm has to compute the optimal control sequence for the 24 hours to come with a hourly time step, for two control variables (the cooling and heating are separated to allow a linear cost without taking the absolute value of the power). Furthermore, two variables are added for the comfort cost (see eq. 9).

The expression of this problem as a quadratic programming problem as in eq. (11) leads to a χ vector with 24*(7+2+2) = 264 elements. The number of added constraints is 24*7 for the state equations, 24*6 for the control signals and zone temperature bounds and 24*2 for the additional discomfort variables. This gives 168 equality constraints and 192 inequality constraints.

The typical computing time for a one-day optimisation, on a Pentium-100 PC, is about 85 sec.

6. Simulation example

6.1. General hypothesises

The chosen thermal zone for the simulation is a heavy structure, well insulated single-room building with important passive solar gains through large window's. A sketch is presented fig. 2. The lateral walls have a classical structure (concrete-air-insulation foam-brick), the roof is very well insulated and quite light (insulation material-tiles) and the floor is heavy and well insulated (two concrete slabs separated by an insulation layer). The zone air volume is 225m³. The high inertia of the walls and the absence of adjacent rooms makes this configuration quite difficult to model, which was the reason to select such an example. For the sake of simplicity, no gains were introduced in the zone.

The meteorological data is the real 1986 year measured in Zürich, for the reasons explained here above. The occupancy schedule is from 8 AM to 6 PM on weekdays, and none during weekends. All the controllers were set to maintain at any time the zone temperature within the range [10°C, 35°C].

The heating and the cooling units are assumed to be purely convective with a maximum power of respectively 6000W and 4000W. To have a common basis for controllers comparisons, the energy cost is set to 1 10^{-5} Wh^{-1} for heating, 1.5 10^{-5} Wh^{-1} for cooling during off-peak period and 3 10^{-5} Wh^{-1} for on-peak cooling. This represents an electricity cost with a on-peak to off-peak ratio equal to 2. Off-peak rates are applied from 11 PM to 7 AM.

6.2. Cost function

In our example, the cost function (10) reduces to :

$$J_k = a\left(E^2_{lo,k} + E^2_{hi,k}\right) + L_{h,k}\ U_{h,k} - L_{c,k}\ U_{c,k} \tag{12}$$

$E_{lo,k}$ and $E_{hi,k}$ are defined in eq. (9) and reduce to scalars since only one temperature is considered. $U_{h,k}$ is the heating power, $U_{c,k}$ is the cooling power ($U_{c,k} < 0$). $L_{h,k}$ and $L_{c,k}$ are respectively the linear cost of heating and cooling ($L_{h,k}$ and $L_{c,k}$ are >0).

We impose the value of $L_{h,k}$ and $L_{c,k}$ to 1 10^{-5} and 1.5 10^{-5} during off-peak period and to 1 10^{-5} and 3 10^{-5} during on-peak period, to express the chosen energy cost. In the following text, the "energy cost" will refer to :

$$J_e = \begin{cases} 1\ 10^{-5}\ \ U_h + 1.5\ 10^{-5}\ \ U_c \quad (\text{off - peak}) \\ 1\ 10^{-5}\ \ U_h + 3\ 10^{-5}\ \ U_c \quad (\text{on - peak}) \end{cases} \tag{13}$$

The "discomfort cost" will refer to :

$$J_d = \left(E^2_{lo,k} + E^2_{hi,k}\right) \tag{14}$$

This means that, in eq. (8), the parameter "a" is set to 1. T_{lo} and T_{hi}, respectively the lower and upper bounds of the "comfort zone", are set to 20°C and 24°C.

The "total cost", or "weighted cost" will refer to :

$$J = \alpha\ J_d + J_e \tag{15}$$

The parameter α is the mathematical expression of the trade-off between comfort and energy concerns. A larger value for α is the translation of a greater importance given to the comfort.

6.3. Compared controllers

Different optimal controllers are simulated, with different values for α (see eq. 15). The values adopted were 0.025, 0.05, 0.1, 0.2, 0.4 and 0.8. A controller using a very large value for α is also tested. In the following sections, these controllers will be referred as 'OPT' followed by the decimal part of the α-value (e.g. OPT025 for the controller using $\alpha = 0.025$). The last controller will be referred as 'OPTinf'.

Four other control systems are compared with the optimal controller : a perfect thermostatic heating with two different fixed on/off schedules (referred as 'T46PH1' and 'T46PH2') and standalone PID controllers using the same start/stop schedules (referred as 'PID1' and 'PID2').

The perfect heating is performed by the TRNSYS TYPE 46. The exact needed energy to maintain the set point temperature is computed by successive iterations and applied if it does not overrule the maximum allowed power. The heating and the cooling are used to keep the temperature between the fixed bounds (10°C - 35°C) at any time and at the set point during occupation time. The used set points are 20°C for heating and 24°C for cooling. They correspond to the lower and upper bounds of the "comfort zone" defined for the discomfort cost.
The two different schedules are :
- T46PH1, PID1 : comfort heating start at 3 AM on Monday, at 5 AM on other weekdays
- T46PH2, PID2 : comfort heating start at 0 AM on Monday, at 3 AM on other weekdays

The comfort heating/cooling is always switched-off at 6 PM, which is the end of the occupation period.

The standalone PID starts heating as soon as the zone temperature goes below its lower set point temperature (20°C if the building is occupied, 10°C else), and starts cooling if the zone temperature reaches the upper set point temperature (24°C if the building is occupied, 35°C else)

We did not consider the combination of an optimal start controller with a conventional PID. A further study will include the comparison with an optimal start controller based on simple algorithms for predicting the recovery time from night setback described by Seem et al. [16].

7. Results

Fig. 4 shows obtained optimal temperature profiles and optimal heating curves for three different days representing the summer, the winter and the mid season typical situation. It can be seen that the optimal controller (in this case, OPT1) can maintain the desired comfort temperature with a very good accuracy when the resulting energy cost is not too high, and respecting the fixed bounds.

Note that the optimal controller should always start the heating as late as possible to obtain a desired temperature at a given time. However, during the first heating hour of the winter day, the heating power is less than the maximal allowed value. This is due to the discrete nature of the optimisation process. The "real" optimal starting time for this day is between 5 AM and 6 AM. The summer day shows the ability of the optimal controller to take advantage of the time-of-day rates to pre-cool the building. This particular operation mode will be discussed later.

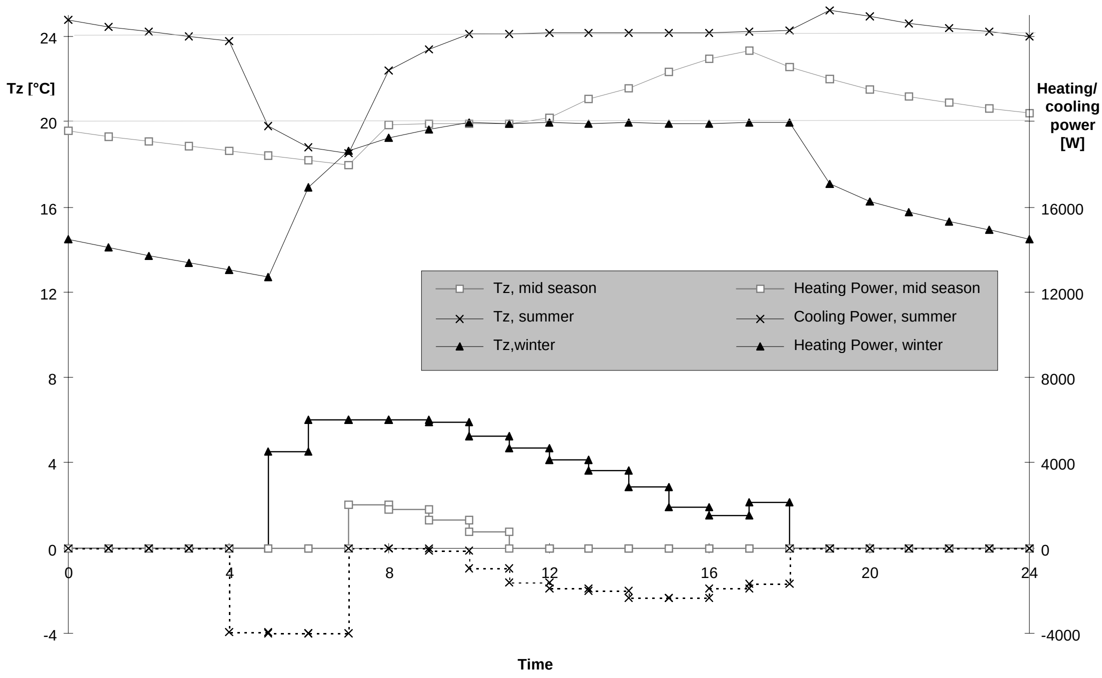

Fig. 4 : Three typical days, optimal temperature and heating/cooling profiles

Comfort / Energy trade-off

Fig. 5 shows the energy (J_e, eq. 13) and discomfort (J_d,eq. 14) costs obtained for the whole year using different weighting factors (α, eq. 15). The naming convention is explained in sec. 6.3.

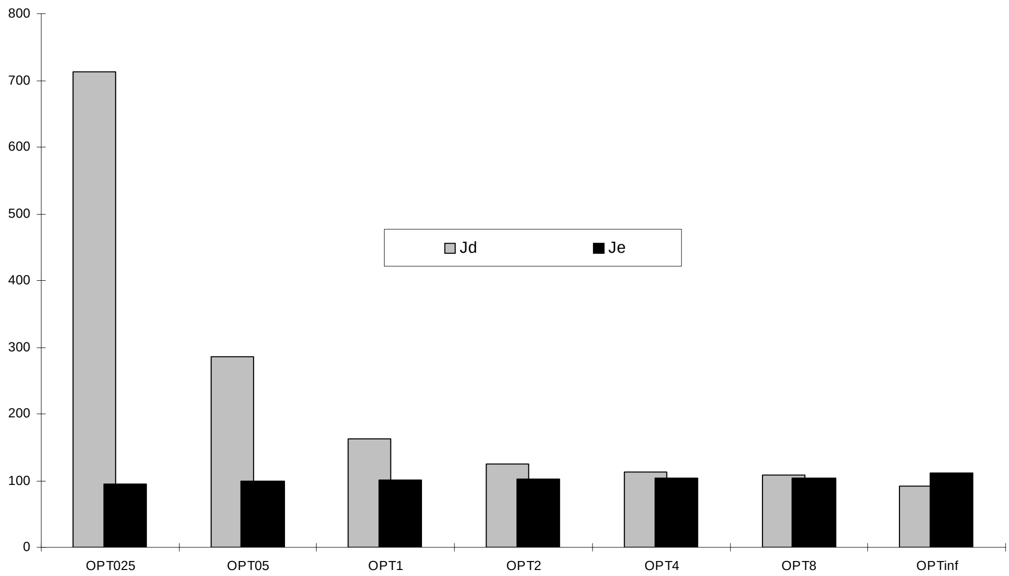

Fig. 5 : Energy and comfort cost for different optimal controller settings

Varying α from 0.025 to 0.8 gives a wide variation in the obtained discomfort cost, which illustrate the capability of optimal control to satisfy different users concerns. With an increasing α, the remaining discomfort cost comes from periods for which the heating or cooling power is insufficient to maintain the desired temperature in the zone. During extremely cold periods, after long a set-back time (i.e. after a week-end), the heating start at

0 AM does not lead to a satisfactory thermal comfort on the beginning of the occupation period. In this case, the optimal controller cannot find a better solution than heating with the maximum power from midnight until the comfort is sufficient. This is a limitation of the used algorithm, which starts the optimisation at 0 AM each day. An improvement of the method could be to use a receding horizon, i.e. to calculate the optimum sequence every hour. With this solution, the optimum sequence is calculated over a 24h horizon but only the first hour is applied. The optimal controller could then decide to start the heating before midnight. Another advantage of this method is the improvement of the meteorological forecasts during the day (with the adopted method in this study, the forecasting is realised at 0 AM each day and used till 11 PM).

When α increases, the energy cost increases and tends to reach a limit corresponding to the energy requirements to maintain a perfect thermal comfort (excepted when the heating/cooling power is insufficient).

The reference optimal controller for the comparison with perfect heating and standalone PID will be OPT2. For α values lower than 0.2, the energy gains do not compensate the discomfort increase. On the other side, if α is increased above 0.2, the small comfort improvement does not compensate the energy cost increase.

Compensating PID action

Fig. 6 shows the optimal zone temperature (Tz, Opt) and the optimal control sequence (U, Opt) as computed by the controller, and the corrected signal (U,corrected) based on the TRNSYS TYPE 46 zone temperature (Tz, TRNSYS). The compensating PID tracks Tz,Opt and gives a correction (Upid) to U,Opt.

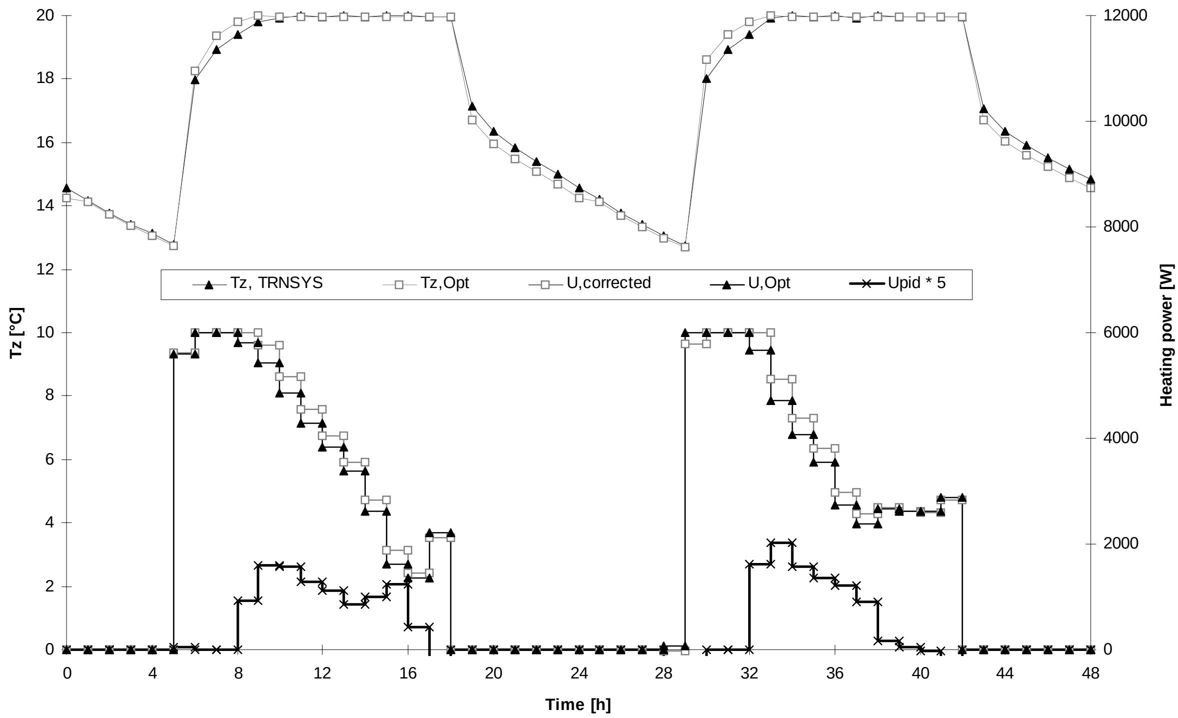

Fig. 6 : Optimal temperature and control signal and PID correction

The PID signal was forced to zero when the optimal control signal was not significant to prevent useless energy consumption. At the heating start, the TYPE 46 temperature is a little lower than the predicted value, because the simplified model slightly underestimate the time constant of the response to a heating step. However, at this time, the PID cannot correct the control signal since it is at the maximum allowed value (6000W). Later, the heating is increased to adjust the zone temperature to the desired value. At the heating stop, the building has again a slower response than the predicted one, but the PID does not correct the control signal since the optimal value is zero. At 0 AM, the optimal controller computes the new optimal control sequence for the next day. The Kalman filter estimates the building state using the actual zone temperature, which gives the small "bump" in the optimal temperature. This process "resets" the error prior to the optimal algorithm computations.

For the entire year (case OPT2), the mean absolute optimal power is 863 W, with a standard deviation of 1763W. The PID correction standard deviation is 97W (5% from the original signal). The corrected signal has a mean absolute value of 874W, with a standard deviation equal to 1787W. This confirms that the PID action can be considered as small compared to the optimal control signals. However, only the modelling error is present in our simulation, and the situation would be different in a real situation with incorrect weather or internal gains forecasts

Controllers comparison

To assess the optimality of the building's control throughout the year, we will consider the comparison with the three other controllers described in sec. 6.3.

Simulation results are summarised for the entire year and partial results are also given for three periods of the year : the "warm" period, the "cold" period and the mid season. The meteorological characteristics of these periods are given in table 1 (Igh is the global horizontal solar radiation).

Table 1 : Meteorological data summary					
Period	Months	Text [°C]			Igh [W/m^2]
		Min	Max	Avg	Avg
Cold period	Jan, Feb, Nov, Dec	-15.6	13.9	0.5	48
Mid season	Mar, Apr, May, Sep, Oct,	-7.8	27.2	9.8	131
Warm period	Jun, Jul, Aug	4.4	32.2	17.3	217
Year		-15.6	32.2	8.7	125

Table 2 presents the results for 5 simulated controllers, over the three periods defined here above and for the entire year. The results of the TYPE 46 perfect heating (T46PH1 and T46PH2) were found to be within 5% from the corresponding standalone PID's (i.e. the PID's using the same schedules), PID1 and PID2. The perfect heating results will not be discussed here.

Fig. 6 gives a graphical representation of the energy cost, the weighted discomfort cost (i.e. the discomfort cost multiplied by the correct α value), and the total weighted cost. As in table 2, the α values for PID1 and PID2 are respectively taken to these of OPT025 and OPT2, i.e. 0.025 and 0.2.

Table 2 : Year simulation results						
		OPT025	**OPT2**	**OPT8**	**PID1**	**PID2**
Cooling energy (on-peak) [kWh]	Cold period	0	0	0	0	0
	Mid season	190	260	268	384	376
	Warm period	720	839	854	1319	1271
	Year	**910**	**1100**	**1122**	**1703**	**1647**
Cooling energy (off-peak) [kWh]	Cold period	0	0	0	0	0
	Mid season	107	119	121	28	49
	Warm period	688	674	673	153	239
	Year	**795**	**793**	**794**	**181**	**288**
Heating energy [kWh]	Cold period	4209	4328	4344	4446	4668
	Mid season	1319	1380	1387	1471	1586
	Warm period	54	60	61	56	68
	Year	**5583**	**5768**	**5792**	**5972**	**6323**
Total energy consumption [kWh]	Cold period	4209	4328	4344	4446	4668
	Mid season	1615	1759	1776	1884	2011
	Warm period	1463	1574	1587	1528	1579
	Year	**7288**	**7660**	**7707**	**7857**	**8258**
Energy Cost *(see eq 13)*	Cold period	42	43	43	44	47
	Mid season	20	23	24	27	28
	Warm period	32	36	36	42	42
	Year	**95**	**103**	**103**	**114**	**117**
Discomfort Cost *(see eq.14)*	Cold period	254	95	87	269	70
	Mid season	205	8	4	5	3
	Warm period	253	21	17	134	46
	Year	**712**	**124**	**108**	**408**	**119**
Weighted Cost *(see eq.15)*[1]	Cold period	48	62	113	51	61
	Mid season	26	25	27	27	28
	Warm period	39	40	50	46	52
	Year	**113**	**127**	**190**	**124**	**141**

If we compare the results of OPT2 and PID2, which lead to the same discomfort cost, we can see that the total weighted cost is 10% lower for the optimal controller. The energy cost is actually 12% lower. This gain is partly realised by a smaller heating energy consumption, especially during the mid season (13% savings), which is conform to the expectations, as it was the case in previous work [17]. The cost reduction is also realised by a better use of the time-of-day electrical rates. The cooling energy consumption is approximately the same, but the optimal controller uses off-peak electricity for 42% of the cooling load, while this proportion is 15% for the PID. Even though the energy load is not minimised as such (but rather the energy cost), the total energy consumption is 7% lower for the optimal controller.

[1] for PID1 and PID2, the weighted cost of respectively OPT025 and OPT2 are used (i.e. $\alpha = 0.025$ and 0.2)

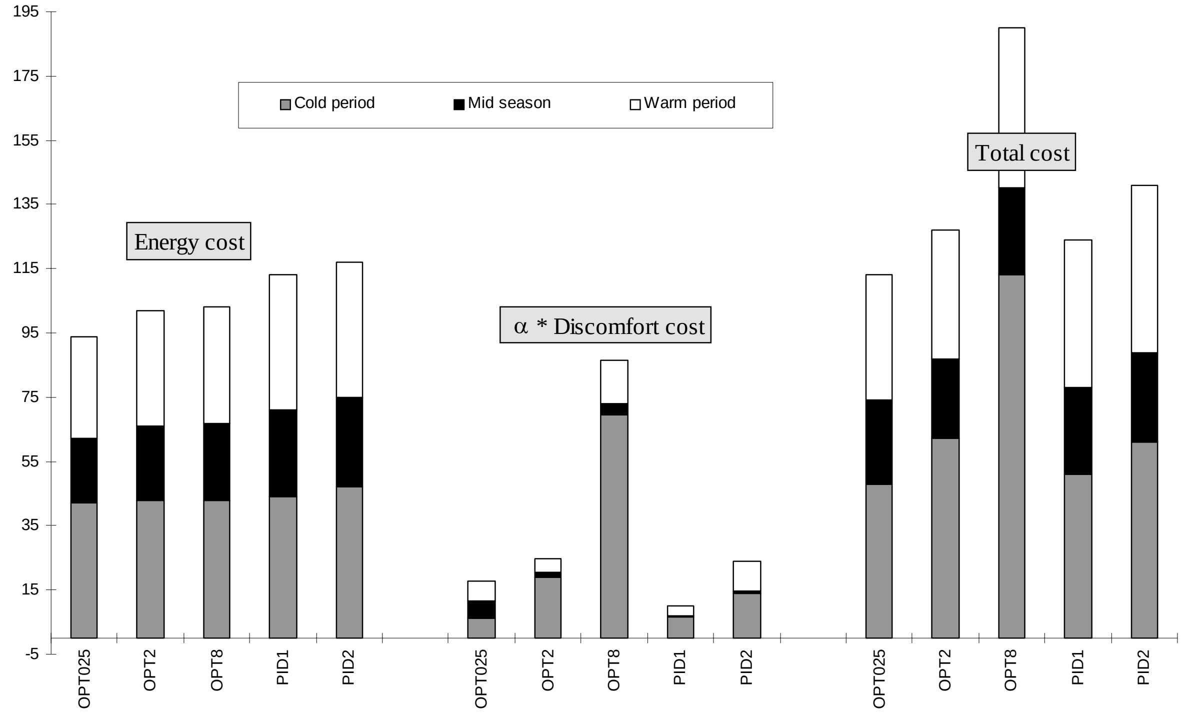

Fig. 6 : Simulation results summary

The results of OPT025 and PID1 can be compared in the same manner. Both controllers lead to a higher discomfort associated to an energy consumption reduction. The discomfort cost is higher for the optimal controller, but, as the importance accorded to this concern is reduced, the total weighted cost is 9% lower than for the PID. In this case, the energy savings are of the same magnitude (7%), but the energy cost reduction amounts to 17%. This is due to a greater part of off-peak electricity in the consumption (47% of the total load instead of 10% for the PID).

These results show that for a equivalent discomfort cost, the optimal controller achieves significant energy and cost savings compared to the PID using a fixed schedule. From the comparison with the PID's using two different schedules, we can say that the optimal controller is able to find the best building's behaviour with respect to the chosen optimisation criterion. However, these results must be taken with care, keeping the hypothesises in mind. Further simulations with more realistic conditions are necessary to quantify the possible energy savings and comfort improvement on existing buildings. These simulations should include the heating and the cooling plant, to take the part-load performance of the plants and the possibility of free cooling into account.

Mid season performance

Fig. 7 shows the building behaviour with four different control strategies (OPT025, OPT2, PID1 and PID2) for two mid season days (25^{th} and 26^{th} of April). It can be seen that, for this period, the start times used for both PID cases lead to useless preheating of the building and to an increased energy demand. Furthermore, this useless heating causes a more important need for cooling at the end of the occupation period. The temperature profile for the optimal controller illustrates its ability to apply a minimal heating to the building in order to prevent an excessive cooling in the afternoon. Even in the case of a simultaneous start of the PID and optimal heating, the optimal controller could decide to slightly under-heat the building in the morning to decrease the cooling load in the afternoon.

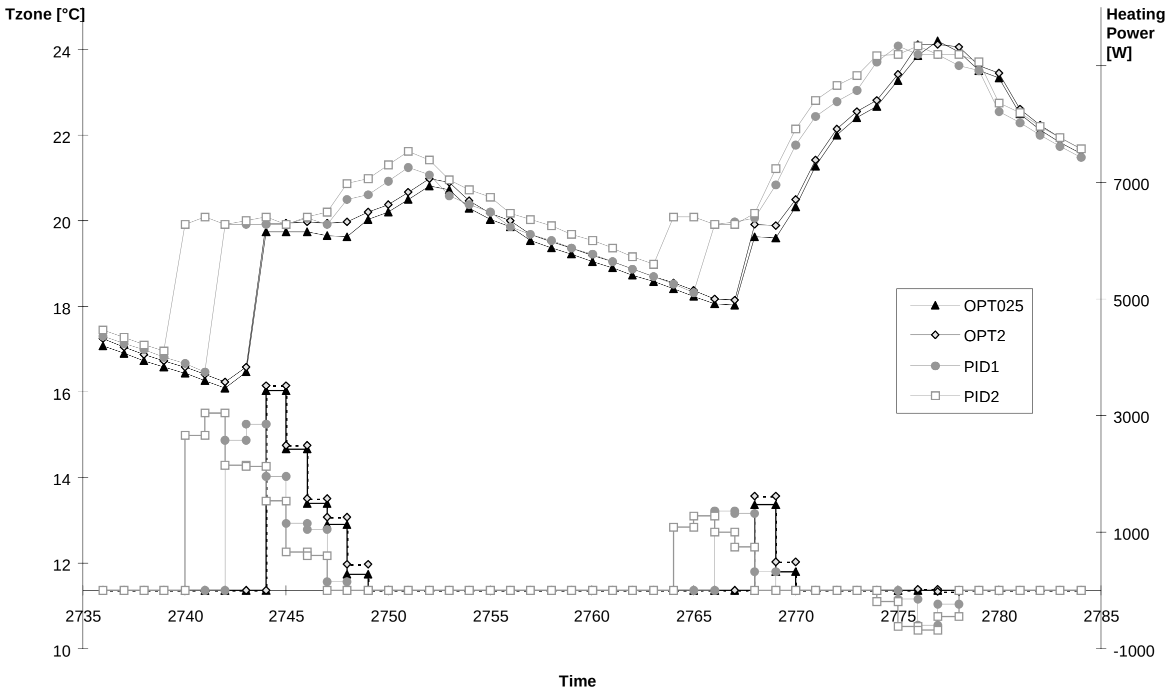

Fig. 7 : 25th and 26th of April

Summer cooling

Fig. 8 gives the temperature and cooling load profile for OPT2 and PID1, during a typical summer week.

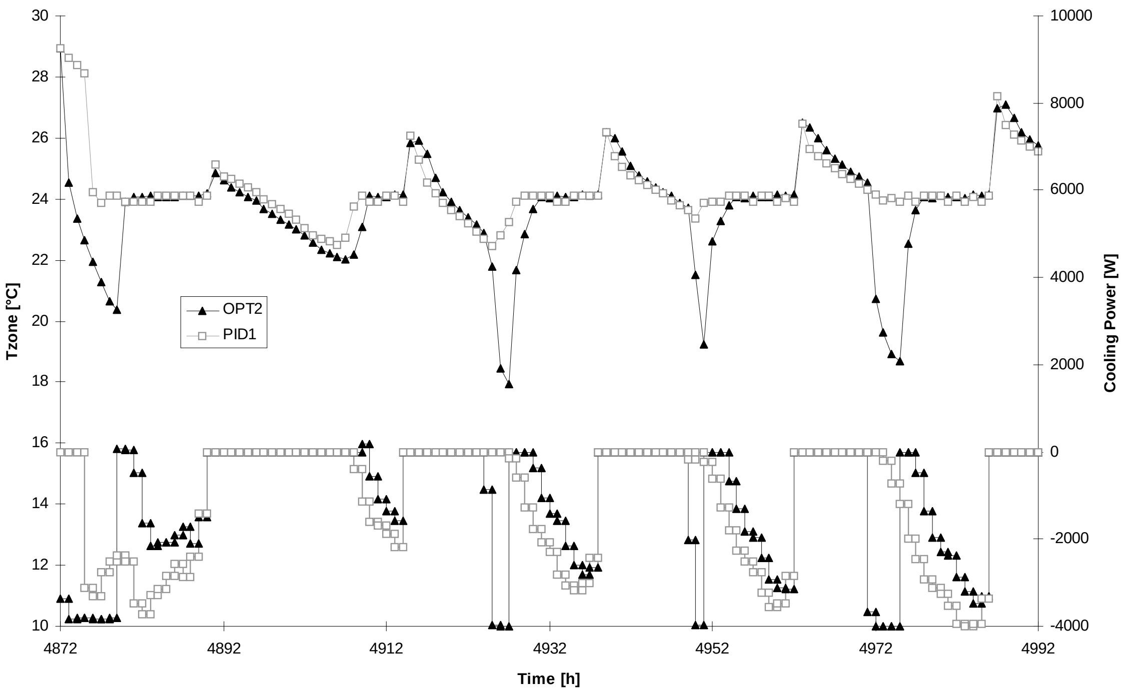

Fig. 8 : 23th to 27th of July

The optimal controller uses the time-of-day rates to decrease the energy cost by pre-cooling the building prior to its occupation. The pre-cooling take place during the last hours of the off-peak period, with a duration and a power depending on the initial building state and on the forecast weather evolution. The energy consumption is not minimised strictly speaking, since the cold stored in the building is partly lost to the ambience. The storage efficiency can be expressed as the ratio of the energy saved during the on-peak period to the energy needed for the pre-cooling, during off-peak period. This efficiency depends on the building structure and is related to the pre-cooling start time [7]. It has been estimated for the whole summer period to 0.7 for OPT2, and to 0.78 for OPT025. These relatively high values can be explained by the heavy and well-insulated structure of the building and by the optimal controller performance. The optimal algorithm ensures that the pre-cooling is started as late as possible and adjusts the pre-cooling load to its optimal value.

In this particular case of summer cooling, the controller action can be approximated by the optimisation of a pre-cooling power and a pre-cooling period. Indeed, a brief look at fig. 8 shows that the controller action can be separated in two distinct phases : building pre-cooling, and comfort-based control. Keeney and Braun established a simplified method for this purpose and showed that a high fraction of the possible cost savings can be realised using this simplified method [7].

8. Practical aspects. Integration within a Building Energy Management System

All results presented here above were based upon numerical simulations of the building and its associated control system. Furthermore, it was applied to ideal systems: the output of the optimal controller are given in terms of the requirements (heating and/or cooling) of a thermal zone, no matter the technical device that would meet these requirements. Before concluding about the relevancy of the approach, it is important to examine how these developments could be implemented on real buildings, for instance within a Building Energy Management System (BEMS).

Indeed, major modern buildings are systematically equipped with a BEMS that is able to perform the following functions [18] :

1. Basic functions : time scheduled operations, duty cycling, demand control, heating system cut-off, night cycle temperature.
2. Optimising functions :
   - economiser cycle (optimisation of the re-circulated air fraction)
   - air distribution (optimisation of VAV openings)
   - chiller and boiler plant operation
   - start/stop of heating and cooling plant
   - secondary water loop (optimisation of the water temperature at the inlet of the Air Handling Units).
3. Operational functions : boiler and chiller profiles, trouble diagnosis, metering, maintenance, safety alarms.
4. Other functions : lighting control, access control, smoke and fire management.

This non-exhaustive list points out that the optimising functions of a BEMS appear as essential. This function would consequently be the ideal "niche" for the theoretical and simulation-based developments undertaken and related here above.

Optimised management of the energy release to the zone could be engineered in real buildings by means of one of the following systems :

1. For heating applications:

Air systems :

- optimisation of the temperature at the outlet of the air handling units with respect to the ambient temperature and/or availability of free gains (internal and solar loads)
- in this case, the correction action, PID controlled, could be performed by the local action of the Variable Air Volume (VAV) boxes (PID control of VAV is quite common) and/or by the water temperature control of the water entering the heating coil.

Water systems :

- optimisation of the water temperature leaving the boiler. "Classical" systems are based upon an open loop tuning of the building heating curve to the ambient temperature. Neither solar gains nor internal loads are taken into account to modify the position of the heating curve when a deviation from nominal conditions occurs. Furthermore, the dynamics of the building and of the HVAC plant are not considered.

2. For cooling operation:

Air systems :

- optimisation of the temperature at the outlet of the air handling units with respect to the ambient temperature and/or availability of free gains (internal and solar loads)
- The correction action, PID controlled, could be performed by the local action of the VAV boxes and/or by the water temperature control of the water entering the cooling coil.

Compared to existing operational optimisation systems, the present approach seems to offer the following advantages (to be confirmed by, first, non ideal simulations, and then by experiments on real buildings) :

- the approach is based upon a **model** which should take into account the major dynamics of the building and of the system. In particular, the thermal mass temperature of the building is taken into account.
- The knowledge of the building's dynamics associated with a forecasting of the meteorological variables makes it possible to replace fixed schedules chosen by trial and error and with empirical knowledge, especially for the **start of the heating plant**.
- the availability of this model leaves the door open to the implementation of **auto-adaptive** procedures that should tune the model all along the building life and take possible modifications of the building behaviour into account.
- the Multi Input-Multi Output formalism permits to simultaneously control several state variables by means of several control actions. A maximum **flexibility** is offered by the control calculation thanks to the user-defined (and possibly variable) weighting factors to be applied to the different contributions to the cost function.

Of course, the results presented here above ask for further verification. Operational **limitations** can also be identified at this stage and ask for further research :

- Need for a good **weather forecasting** method. The savings involved by the optimisation heavily rely on the quality of this algorithm.
- Need for a better appraisal for the **comfort definition**: the used cost function models the comfort as a quadratic function of the difference between the zone resultant temperature and the closest bound of a comfort zone. It should take the humidity into account, since it

is known to have an influence on the comfort feeling in a building. Authors have used the PMV defined by Fanger [12] to control the building temperature (see, e.g. [6] and [7]).

- Need for a good representation of the **whole HVAC** system in the numerical optimisation. This could be done step by step, according to the following possible strategy :
  a. Introduction of the heat/cool emitter associated with its local loop control (VAV boxes, thermostatic valves,...)
  b. Introduction of the AHU's (for air systems), including their local loop control.
  c. Introduction of the primary systems : boiler and chiller.
  Note that an accurate model is necessary to have a good controller performance. In a real application, the parameters of the model should be identified on-line to ensure a minimum modelling error.

Most of these additional features correspond to BEMS functions or potentialities as well.

9. Conclusions

We tested an optimal controller based on a simplified model on a simulation example using a complex building model (TRNSYS TYPE 46). In spite of some major simplifications, we tried to apply a simulation scheme that was close to the real implementation of such an optimising controller in a BEMS, including a compensating feedback controller. The major improvement in this respect will be to introduce a part of the HVAC installation in the simplified model, in order to use more realistic control variables, to introduce the interaction with local controllers in the simulation and to use a more accurate estimate of the energy cost.

The controller was found to be perfectly able to control the temperature in the thermal zone, and the computed optimal control sequences effectively minimised the objective function compared to other control methods. The comparison was not meant to prove the possible superiority of the optimal controller but showed a fairly good performance compared to an ideal thermostatic control and to a pure feedback controller. Further comparisons will need the consideration of heating and cooling plants part-load performance as well as the consideration of free cooling and a better definition of the thermal comfort. Note that the optimal control permits to extend the notion of comfort to other domains such as IAQ, thanks to the ability to cope with MIMO systems and to realise a trade-off between opposite concerns.

Finally, a brief look at existing BEMS features showed that the optimal controller could be efficiently integrated into such a system to perform the optimisation and control tasks. Optimal control presents real advantages for this purpose, like the ability to control MIMO systems, the possibility to become auto-adaptive and to integrate different concerns in a comfort definition. Note that the choice of this definition is not a trivial problem and opens the door to other domains such as Indoor Air Quality control, which can be integrated in the optimal controller. The strongest limitations at this stage are the need for a forecasting of the meteorological variables and for a reliable model of the building including the HVAC installation. In the same time, the use of a receding optimisation horizon could permit a greater flexibility in the start/stop operation and insure a correction of the optimal control sequence if the meteorological forecasting is inaccurate. These problems will be tackled in our future research.

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