Chapter 13
Using Dynamic Programming Optimization to Maintain Comfort in Building during Summer Periods

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Abstract. Being increasingly insulated, new buildings are more and more sensitive to variations of solar and internal gains. Controlling solar protections and ventilation is therefore becoming essential. In this publication, we study the possibility to maintain comfort in the building by controlling either mechanical ventilation for night cooling or solar protections or both of them during hot periods. The proposed energy management is a predictive set of optimal commands issued from a dynamic programming optimization knowing in advance the weather, occupation and internal gains for the next 24 hours. This method is tested on a bioclimatic house situated in Chambery, France with an annual heating demand of 26 kWh/m².

Keywords: Dynamic programming, comfort, mechanical ventilation, shutters, building.

1 Introduction

The main objective for control systems in buildings during summer is to reduce the energy consumption of air conditioning or to maintain comfort using passive cooling. Previous studies concerned the control of solar protections, e.g. [1], [2], ventilation [3], and active cooling [4], [5]. Night ventilation can be used to cool the building structure and a high thermal mass reduces the temperature elevation during the day corresponding to a passive storage [6].The stocking and destocking of heat at the right time requires a predictive controller able to anticipate the variation of ambient temperature, solar irradiance and internal loads. Many advanced control systems are reviewed in [7]. For predictive controllers, a thermal model of the building is required [8], [9], [10]. Due to the time step of this model, a combinatorial optimization is required. Among these methods, the A* [11] and the Branch and Bound algorithms [12] need an assumption of the lower or upper bound not available here. Dynamic programming is then chosen because of its exact optimization character. It has served in a building context mainly for winter operation of the heating system [9],[13]. In this publication, a dynamic programming optimization is used to set up a predictive controller knowing in advance ambient temperature, solar gains and internal loads. This

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controller serves to maintain comfort in the building by controlling mechanical ventilation during nighttime and solar protection during daytime.

2 Methodology

The main objective of this study is to maintain comfort in the building even in a worst case scenario with an important heat wave. We have first to define what kind of comfort is considered and then to present the thermal model of the building and the optimization method.

2.1 Adaptive Comfort

Comfort is difficult to define. It depends on the direct thermal environment of the inhabitants but also on their bodies' metabolism. It is usually defined as the state of mind which expresses satisfaction with a given thermal environment. Among the many parameters influencing thermal comfort, the adaptive approach states that the indoor comfort temperature depends on the ambient temperature T_C (°C) [14] or its variation over a week [15]:

$$T_C = a\ T_{RM} + b \tag{1}$$

with T_{RM} the running mean temperature over a week (°C) and a, b are constants determined experimentally in the Smart Controls and Thermal Comfort project [15]. For France, the relation becomes:

$$\begin{aligned} T_C &= 0{,}049\ T_{RM} + 22{,}\ 58 && \text{if } T_{RM} \leq 10°C \\ T_C &= 0{,}206\ T_{RM} + 21{,}\ 42 && \text{if } T_{RM} > 10°C \end{aligned} \tag{2}$$

with $T_{RMn} = 0{,}8\ T_{RMn-1} + 0{,}2\ T_{MOYn-1}$, T_{MOYn-1} being the daily mean temperature of day n-1 (°C). This is only a thermal comfort without any consideration for air velocity or humidity level. This indoor temperature cannot be maintained at this exact value at all time. The Predicted Mean Vote (PMV) [16] approach is partially used, and we consider that the comfort is maintained if:

$$T_C\text{-}2°C < T_C < T_C+2°C \tag{3}$$

T_C corresponds to an operative temperature, accounting for air but also wall surfaces because comfort is influenced by convective and radiative transfer.

2.2 Thermal Model of the Building

The building is modeled as zones of homogenous temperature. For each zone, each wall is divided in meshes small enough to also have a homogeneous temperature.

There is one more mesh for the air and furniture of the zone. Eventually, a thermal balance is done on each mesh within the building:

$$C_{mesh}\dot{T}_{mesh} = Gains - Losses \tag{4}$$

C_{mesh} being the thermal capacity of the mesh, T_{mesh} its temperature, Gains and Losses including heat transfer by conduction, radiation and convection but also possible internal heating and cooling from equipment and/or appliances.
For each zone, repeating equation (4) for each mesh and adding an output equation leads to the following continuous linear time-invariant system [17]:

$$\left\{\begin{array}{l} C\dot{T}(t) = AT(t) + EU(t) \\ Y(t) = JT(t) + GU(t) \end{array}\right\} \tag{5}$$

with

- ✓ T mesh temperature vector
- ✓ U driving forces vector (climate parameters, heating, etc)
- ✓ Y outputs vector (indoor temperatures accounting for air and wall surfaces)
- ✓ C thermal capacity diagonal matrix
- ✓ A, E, J, G matrices relating the temperature and driving forces vectors

In order to simulate such a model, it is important to know the occupancy of the building, which defines the emission of heat by inhabitants and appliances, the thermostat set point influencing the heating/cooling equipment, and possible actions regarding ventilation and solar protections. Another important aspect is the weather model, influencing the loss due to heat transfer with the ambient temperature and the gain with solar irradiance. All the data of the occupancy and weather models are contained in the driving forces vector *U*.

A high order linear model is now available. Its state dimension is too large to allow a fast convergence of an optimization algorithm. A reduction method is applied to lower the state dimension and thus to make the algorithm faster

2.3 Optimization Algorithm

The dynamic programming algorithm is a sequential optimization method which gives the optimal set of commands over a period. A state variable describing as well as possible the system is discretised temporally:

$$x(t) = x_t \in X_t, X_t \subset R^{Ne} \tag{6}$$

with Xt the set of possible states, Ne the dimension of X_t. There is also a control vector with Nc dimension:

$$u(t) = u_t \in U_t, U_t \subset R^{Nc} \tag{7}$$

with *Ut* the set of possible control. The state equation at each time step *t* is then:

$$x(t) = x_t, x(t+1) = f(x(t), u(t), t) \tag{8}$$

We now define a value function v_t which is the cost to go from *x(t)* to *x(t+1)* :

$$v_t(x_t, x_{t+1}), x_{t+1} \in \Gamma_t(x_t) \tag{9}$$

Γt being the set of possible state variable at time *t*. The cost function is then the sum of all the value functions at each time step:

$$V_0^t = \sum_{j=0}^{t-1} v_j(x_j, x_{j+1}) \tag{10}$$

This equation gives us a set of control to go from x_0 to x_t. The optimization seeks to maximize or minimize the following objective function over *N* time steps:

$$J = Max[V_0^{N-1}] \tag{11}$$

Bellman's principle of optimality is applied to accelerate this optimization by breaking this decision problem into smaller sub-problems:

> An optimal policy has the property that whatever the initial state and initial decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision [18]

Then (11) becomes:

$$J = Max[V_0^{N-1}] = Max(v_0(x_0, x_1)) + Max(V_1^{N-1}) \tag{12}$$

To resume, we have to find a set of command $U_N = (u_0, u_1, \ldots, u_N)$ maximizing (12) from a system described in (8) with constraints on the state variable (6) and on the controls (7).

3 Application on a Case Study

3.1 Building Description

The building under study is a French single-family house. The actual building is an experimental passive house part of INCAS platform built in Bourget du Lac, France. The house has two floors for a total living floor area of 89 m². 34% of its south facade surface is glazed while the north facade has only two small windows. All the windows are double glazed except for the north façade with triple glazed windows. The south facade is also equipped with solar protections for the summer period. The external walls are made with a 30 cm-thick layer of concrete blocks and the floor is composed of 20 cm reinforced concrete. The insulation is composed of 30 cm of glass-wool in the attic, 15 cm in external walls and 20 cm of polystyrene in the floor. According to thermal simulation results using Pléiades+COMFIE [17], the heating load is 26 kWh/(m².year) which is typical for such type of house.

3.2 Optimization Parameters

The chosen state variable is the total energy of the building. This energy is calculated as follows:

$$E = \sum_{i=1}^{nbr\_meshes} E_i = \sum_{i=1}^{nbr\_meshes} C_i T_i \tag{13}$$

with E the total energy of the building, C_i the thermal capacity of the mesh i, and T_i the temperature of the mesh i. The model of the building is mono-zonal, there is only one control for the whole building.

The optimization is done over 14 days, a very hot week for a worst case scenario and a normal summer week after (Fig.1), the simulation includes also a week initialization period. The occupancy of the building is a typical four people family. The building is non-occupied only during the working days from 8.00 a.m. to 17.00 p.m.. Each occupant emits 80 W due to his metabolism, there are also small internal loads from appliances during occupied hours.

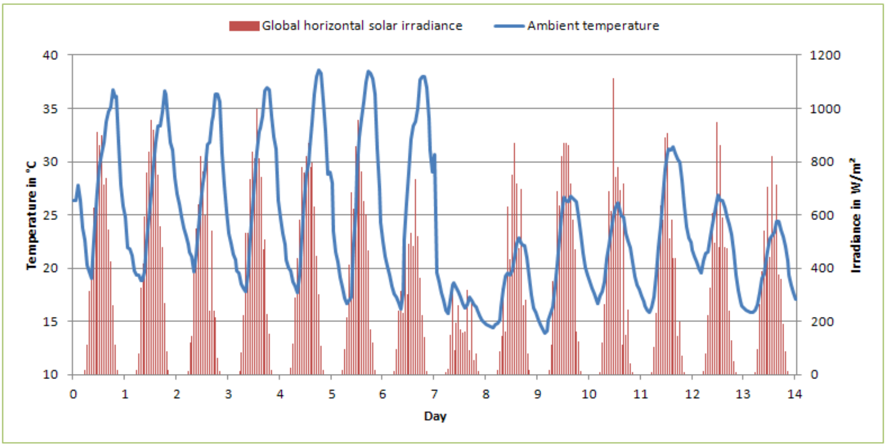

Fig. 1. Two weeks weather data used for optimization

4 Results

4.1 Mechanical Ventilation Controller

The mechanical ventilation controller is first optimized, the roller blinds being open at all time during the two weeks. The air flow rate can vary between 0.6 and 6 ach (air change per hour) with no heat recovery in summer. The mechanical ventilation consuming electricity, the objective is to maintain comfort while minimizing its use, the value function is then:

$$v_t(E_t, E_{t+1}) = abs(T_{\text{in}} - T_c) + \cos t * {vent}/{100} \tag{14}$$

with *vent* the control in percentage of the maximum ventilation, T_c the comfort temperature and T_{in} the indoor temperature. The results for *cost* = *1* are presented in Fig.2.

At the beginning of the very warm week, the indoor temperature is under the value of the comfort temperature, then the mechanical ventilation is operating during the night. The comfort condition (3) is always maintained during this very warm week. During the second week, the mechanical ventilation is more often used but at lower value. During the two first days normal ventilation is sufficient to follow the decrease of the comfort temperature. Then night ventilation allows cooling the thermal mass of the building in order to maintain comfort during daytime. Without a regulation, the night cooling is very limited because of the constant air flow rate value (0.6 ach), and the comfort condition (3) is maintained but with a high temperature.

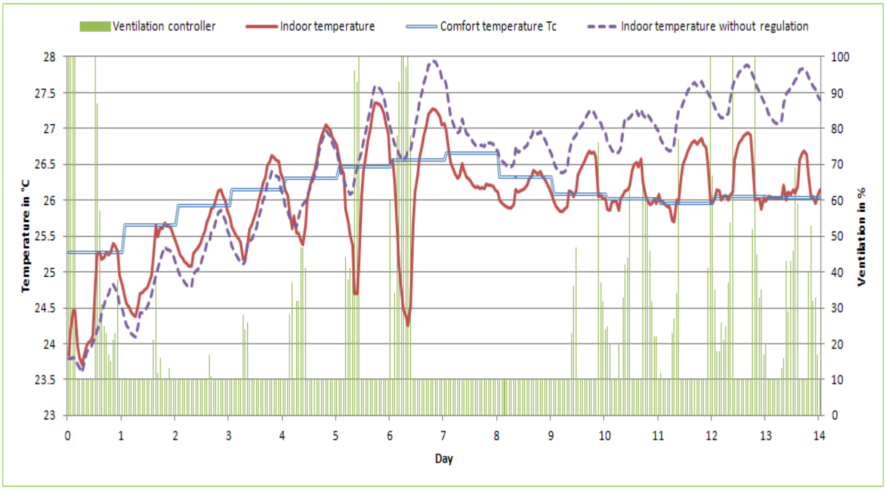

Fig. 2. Variation of indoor temperature and of the mechanical ventilation controller over the two considered weeks

The electricity consumption is reasonable because the average flow rate over the period is 1.2 ach. If the objective function isn't minimizing the utilization of mechanical ventilation (cost = 0), the air flow rate over the period is 1.9 ach (Fig. 3.).

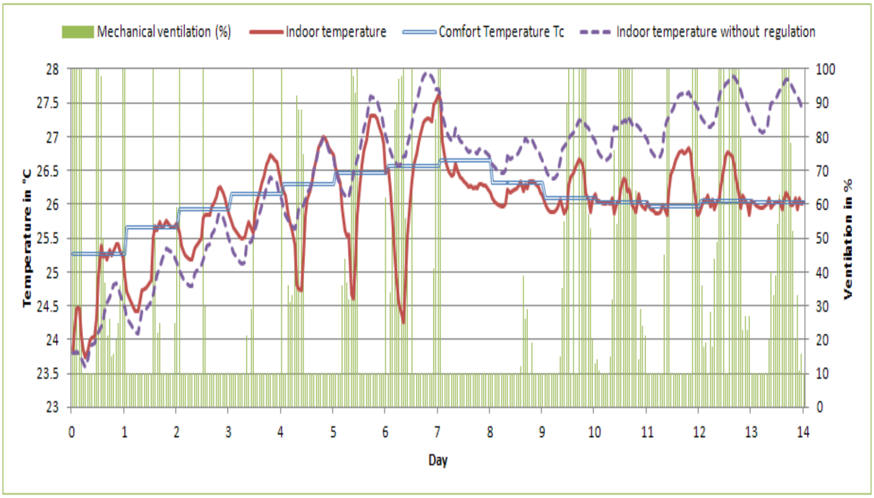

Fig. 3. Variation of indoor temperature and of the mechanical ventilation controller with no cost of use of ventilation

Figure 4 presents the results relating comfort and ventilation depending on the cost of use of ventilation. The more the weight is put on minimizing the use of ventilation, the bigger is the thermal discomfort. Further studies will concern Pareto frontiers and natural ventilation.

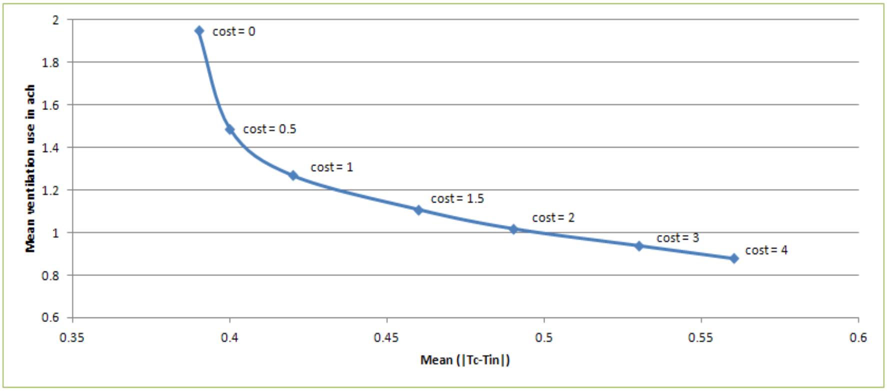

Fig. 4. Balance between ventilation use and thermal comfort depending on the cost of use of ventilation

4.2 Solar Protection Controller

The roller blind control is now studied, considering a constant 0.6 ach mechanical ventilation. The opening interval is from 0% to 100%. In the value function the electricity consumed for opening or closing the roller blades is supposed negligible.

$$v_t(E_t, E_{t+1}) = abs(T_{\text{in}} - T_c) \tag{15}$$

The results of this optimization are presented in Fig. 5. :

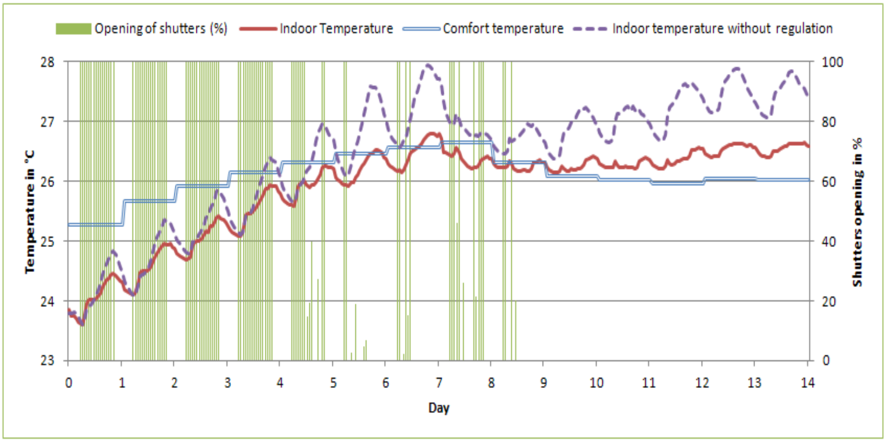

Fig. 5. Variation of indoor temperature and of the shutters controller over the two considered weeks

The roller blinds reduce efficiently the solar gains; therefore the temperature variation is reduced during the day compared to the ventilation control. But during the second week, even if the roller blinds are always closed, the indoor temperature is always higher than the comfort temperature because no important night cooling is possible. This controller allows reducing the amount of gains but can't clear it off once in the building. Still, the comfort condition (3) is always maintained.

4.3 Controlling Solar Protection during the Day and Mechanical Ventilation during the Night

The mechanical ventilation is 0.6 ach during the day and it is controlled as soon as the global solar irradiance is under 200 W/m², globally at night. Solar protection is controlled during the day and closed at night. The optimization is done using the value function described in (14). The main goal is to increase the comfort condition even further while decreasing the use of mechanical ventilation (Fig.6).

Combining of the two controllers is very effective. Except for the first day the difference between the indoor temperature and the target comfort temperature is under 1°C. During the second week this difference is even under 0.5°C. Solar protection control is the most used because there is no cost for operating it. The operating of mechanical ventilation is minimized, with a mean value of 0.72 ach.

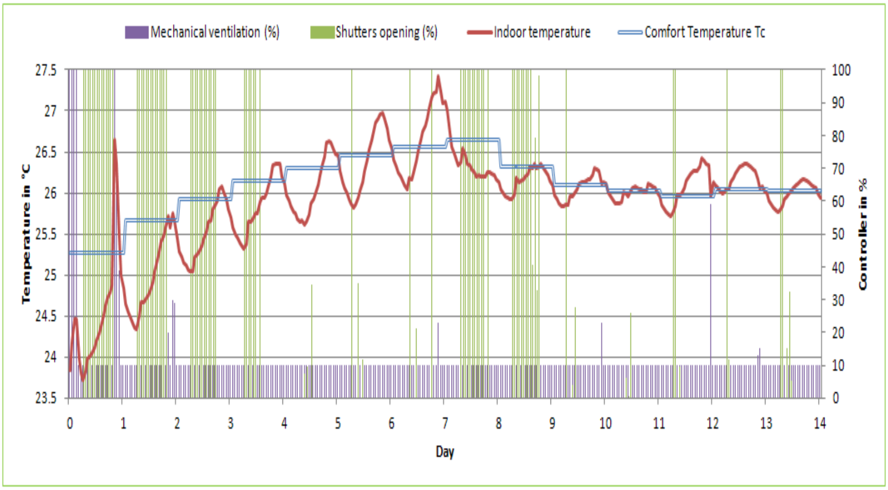

Fig. 6. Variation of indoor temperature and of the two controllers over the two considered weeks

5 Conclusion

Dynamic programming optimization has been used to study the control of ventilation and solar protections in a low energy building. A control strategy can be identified to optimize comfort and minimizing energy consummation. Further studies will address natural ventilation.

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