OPTIMAL CONTROL FOR BUILDING HEATING: AN ELEMENTARY SCHOOL CASE STUDY

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ABSTRACT

Due to the development of energy performance contracting and the needs for peak electric demand reduction, the interest for optimal building control is renewed. In this context, the real time prevision and optimization of building heat demand can help the manager to reduce the energy bill and to propose peak shaving offers. Our study aims to illustrate such heat control strategies on a one floor elementary school. The building is modeled through a second order inverse "grey box" model. The inverse model identified during a short learning period is first validated on its ability to forecast heat load and indoor temperature. Then it is used for optimal control and for that purpose two strategies are proposed. The first one consists in optimizing the night setback period with a constant electricity price. The second one aims to set a varying indoor temperature set point in a context of peak and off peak hours. The results show about 5% off electricity consumption for the first strategy and 4% off electricity bill for the second strategy. For a very cold week it appears that the optimization could lead to an over-consumption to improve the comfort.

INTRODUCTION

Buildings represent 43% of final energy consumption in France (ADEME, 2011) and electrical heating systems are accountable for a large part of this consumption. Today's standards are low-energy buildings but the buildings' renewal rate is very low (1% a year, INSEE, 2012) and in 2011 the average annual energy consumption was 209 kWh/m² (ADEME, 2011). Therefore, it is still actual to work on some solutions to reduce consumption on high-energy buildings.

Another concern with electrical heating systems is their impact on the national peak demand of electricity. Indeed, building's thermal inertia and time-of-use electricity tariffs can be used to reduce energy bills and the stress level on the electricity network.

In this article we propose to use a second order grey box model to represent the thermal behaviour of an elementary school and to use two strategies to manage heating systems. The first strategy intends to optimize the night set back period to minimize the energy consumption and respect the comfort criteria. The second strategy aims to optimize the set point temperature for 24 hours in a context of off-peak and on-peak energy prices in order to minimize the energy bills while maintaining comfort criteria.

Grey box models are well known and often used to make simple but physical and accurate building models. In the literature, we found many forms of grey box models; most of them are mono-zone and have between one (Fux et al., 2012) and 8 orders (Braun, 2002). These models are particularly well adapted to perform optimization because they run quickly and are liable to constraints (i.e. maximal power constraints). Three types of optimization objectives can be identified in the literature. The first one is consumption reduction by flux optimization (Oestreicher et al., 1996), (Palomo et al., 2000), (Mossoly and Ghali, 2009), (Morosan and Bourdais 2010), (Hazyuk et al., 2012). Flux optimization allows to minimize consumption by anticipating set point variation (optimal trajectory between each set point). The second strategy identified aims to reduce consumption peaks (Reddy et al., 1990), (Lee and Braun, 2008). This strategy is very useful to reduce stress on the electricity network but can generate additional costs for consumers. The last strategy identified in the literature is the global cost minimization by flux or set point optimization (Henze et al., 2007), (Verhelst et al., 2012). This strategy can be interesting for both the consumer and the owner of the network, but needs variable energy prices to be established.

In this study, measured data from an elementary school are used to identify a grey box model ("R6C2"). Then, two control strategies are assessed based on the identified R6C2 model.

With these strategies (i.e. optimization of set-point temperature), we assume that the multi-zone building can be driven by a mono-zone model while reducing the discomfort risk.

First, the tested building is described. Secondly, the grey box model is explained and validated. Finally, the two strategies are tested and discussed.

TEST BUILDING

Description of the building

The studied building is a one-floor elementary school built in 1975 in the east of France (continental climate). The walls are composed of 15 cm of concrete and do not contain any insulation. The windows are double glazed panels (renovation in 2010). The roof is well insulated with 15 cm of glass wool (renovation in 1986). The building is square with a heated surface of 800 m². The heating demand is provided by electrical heaters and AHU systems (Air Handling Unit with electric resistances).

Measurement setup

The indoor temperature is measured with 11 sensors, one in each room. The electrical power is measured with three clamp ammeters, one for all electrical heaters and one for each AHU system. The heating is ensured by the AHU system and electrical heaters during occupancy period and AHU are switched-off during vacant period. Electrical heaters ensure the peak needs during the day and the night setback. All devices are on/off and controlled with a set point temperature. The ventilation airflow is constant and has the same schedule as AHU systems.
Table 1 summarises all the data obtained from the building every 10 minutes.

Table 1
List of recorded data

NAME	UNIT	SOURCE
Outdoor temperature (Te)	°C	Measured
Indoor temperature (Ti)	°C	Measured
Set-point temperature (Tc)	°C	Controlled data
AHU and electrical heater power (P)	W	Measured
Electrical heater power	W	Measured
Ventilation set-point (Ve)	0 or 1	Deduced from AHU Power
Domestic Water consumption	litre	Measured

We assume that the electrical heaters and the AHU systems have an efficiency of 100%. Therefore, the heating power is equivalent to the electrical power. In addition, we assume that secondary HVAC systems are entirely convective.

MODEL DESCRIPTION AND VALIDATION

Building model description

The building is modelled by a nonlinear second order differential equation ("R6C2"). The non-linearity comes from the heating power's upper bound. We use an electrical analogy to represent the set of equations (figure 1). The model has been built to have a little number of parameters, simple enough to be identifiable but complex enough to represent all physical phenomena. Hazyuk (Hazyuk et al., 2011) proposes to use a two-order model. The representation of solar gains can be improved by separating the solar flux arriving on the external wall from the solar flux reaching the internal wall. Bacher (Bacher and Madsen, 2011) also proposes a two-order model where internal gains and variable ventilation are not taken into account.
The particularities of our R6C2 model are double. First, the solar radiation reaching the building is divided in two parts, one hits directly the outdoor surface wall (Th), and the second goes on the indoor surface wall node (Ts). We introduce a node (Ts) between the indoor temperature node and the wall node.
Secondly, the model can handle changes in mechanical ventilation thanks to the variable resistance Rv (Rv is proportional to the airflow rate).
Table 2 describes the sources of not measured inputs of the R6C2 model and Table 3 describes all identified physical parameters of the R6C2 model.

Table 2
List of other data

NAME	UNIT	SOURCE
Cloud cover	okta	Professional meteorological data (from Meteo France)
Occupancy ratio (OCC)	%	Standard profile (validated with domestic water consumption data)

Table 3
Model parameters description

NAME	DESCRIPTION
Ci (J/K)	Internal air capacity
Cw (J/K)	Wall capacity
Ri (K/W)	Interior convective resistance
Rs and Rw (K/W)	Wall conductive resistance
Re (K/W)	External convective resistance
Rg (K/W)	Infiltration and glazing equivalent resistance
Rv (K/W)	Mechanical ventilation equivalent resistance (variable)
G (W)	Maximum heat gain due to occupancy
α (%)	Radiative ratio of internal gains

All identified parameters have a lower bound and an upper bound. Their values are based on the French thermal standard (CSTB, 2005) or on geometrical observations.

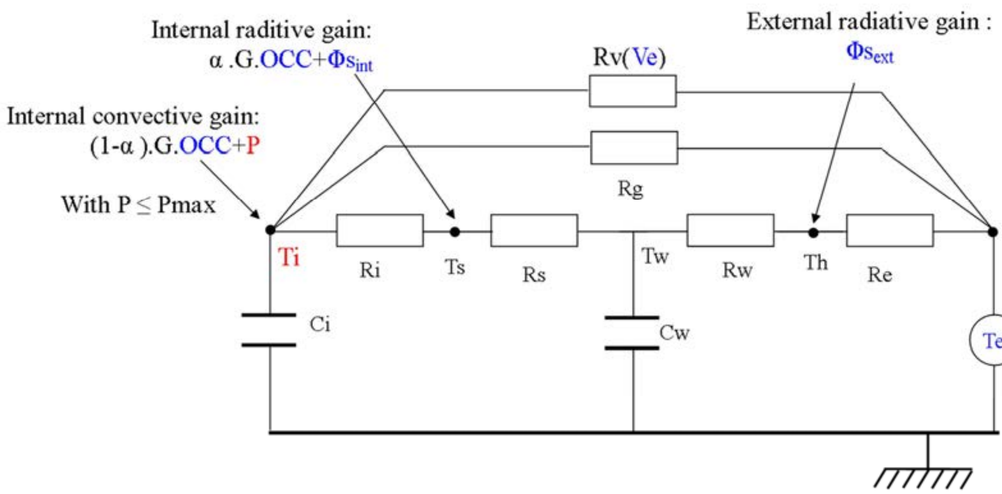

Figure 1: R6C2 model presented as an electrical analogy

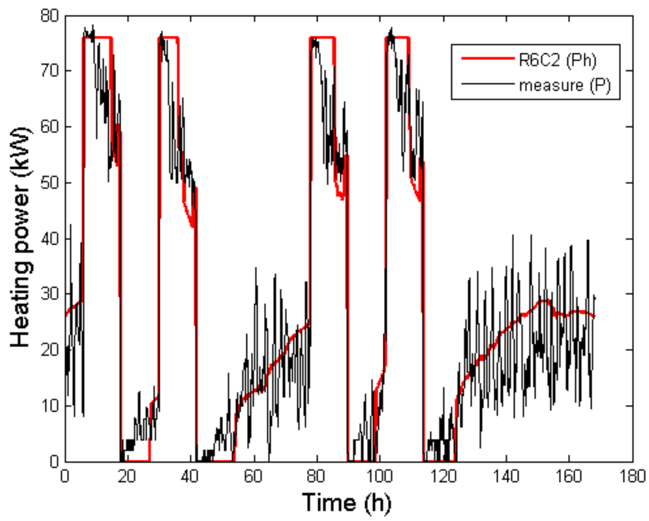

Figure 2 : Heat power measured (black) and predicted (red) compared during 1 week in December

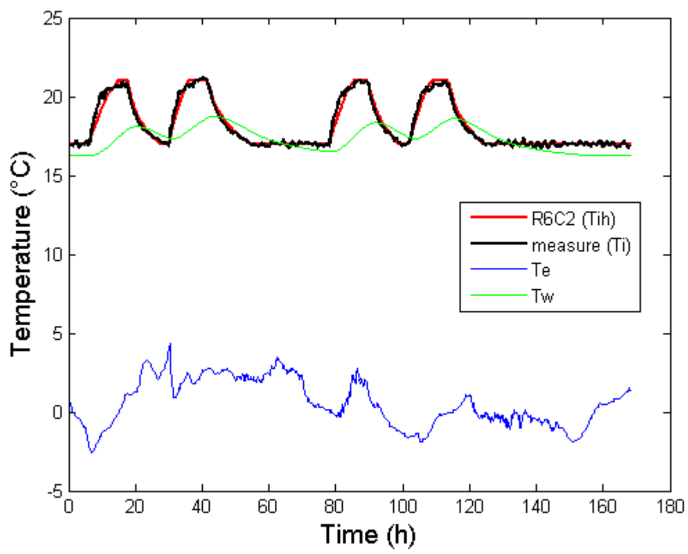

Figure 3: Indoor temperature measured (black) and predicted (red) compared on 1 week in December. The green and the blue curves represent the calculated wall temperature and the measured outdoor temperature, respectively.

Solar flux calculation

The direct and global solar radiations are calculated with the well-known Kasten model (Kasten and Czeplak, 1980), which has been adopted by Scharmer (Scharmer and Greif, 2000) in the European Solar Radiation Atlas.

Makovicka (Makovicka and Berthou, 2012) developed an original dynamical method specially designed for simple physical models. The main function of this algorithm is to calculate the solar flux on the façade of the building while taking into account the shading effect. It is based on the use of a clinometer to measure the surrounding obstacles' shadows on windows and geometrical considerations for solar protection. A simplified representation of the solar gain model is presented in figure 4. This algorithm aims to calculate the solar flux on indoor walls (Φs_{int}) and the solar flux on outdoor walls (Φs_{ext}).

This solar flux calculation method was validated during summer when the building is empty and the indoor temperature is not controlled. In these conditions only the outdoor temperature and the solar flux affect the building (the wind and night sky radiation are neglected). The model was tested for two months during summer 2012. The model fits very well the measured data and is adapted to R6C2 modelling.

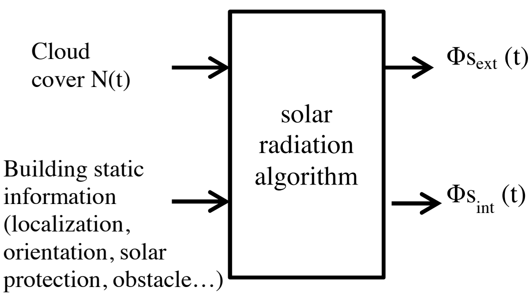

Figure 4: Simplified representation of solar radiation model

Identification method

The Interior Point algorithm is well adapted to handle nonlinear constrained minimization problems (Byrd et al, 2000), (Waltz et al., 2006). Two weeks of December (winter 2012) were used to identify the 10 parameters. The initial value of each parameter is approximated with values of the French thermal standards (CSTB, 2005) and the Interior Point algorithm is used to minimize heating power and mean indoor temperature prediction error. The objective function is mono-objective (equation 1).

$$f(x) = \sum (P - P_h(x))^2 \times \sum (T_i - T_{ih}(x))^2 \qquad (1)$$

- f(x) is the minimized function
- x is the vector of identified parameters
- P_h et T_{ih} are the predicted heat power and mean indoor temperature, respectively.
- P et T_i are the measured heat power and mean indoor temperature, respectively.

For identification, we tried several levels of maximal power (corresponding in theory to the installed heating power). Finally, we use a limitation of heating power corresponding to maximum power observed during the learning period (76 kW), which gives the best results.

Model validation

The R6C2 model is validated ex-post with the following week data. All model inputs are known and we compare the calculated outputs (P_h and T_{ih}) with the measured data (P and T_i). We use the fitting formula (equation 2) as a likelihood criterion.

$$fit(\%) = 100 \times \left(1 - \frac{|y_h - y|}{|y - \bar{y}|}\right) \qquad (2)$$

Where y is the reference vector and y_h is the vector of calculated data.

Figure 2 compares one week of calculated heating power (red) and measured heating power (black).

(1) The model cannot predict high frequency oscillations due to on-off control strategies on each electrical heater.
(2) The saturation phenomenon is not well modelled because the mono-zone model cannot handle local saturation. Indeed the R6C2 model is mono-zone and the regulation is supposed perfect.
(3) The energy balance is well respected since there is less than 2% error during the tested week.
(4) The fitting reaches 66% which is quite good given the previous remarks

Figure 3 compared one week of calculated indoor temperature (red) and measured indoor temperature (black).

(1) The dynamic variation of indoor temperature is very well respected
(2) The fitting reaches 84%

Considering these tests, the R6C2 model gives a good representation of the building's thermal behaviour. We assume R6C2 model is well adapted to handle optimization strategies.

PRESENTATION OF OPTIMIZATION STRATEGIES

Reference case

The building is occupied all weekdays except Wednesday. The first occupants start arriving at 8 a.m. and leave no later than 5:30 p.m. Therefore, thermal comfort must be reached from 8 a.m. to 5:30 p.m.. Since the inertia of the studied building is high and the installed power is quite low, it is necessary to switch on the heater a few hours before the occupants arrive. For this purpose, the set point temperature is raised from 17 to 21 °C at 4 a.m. This schedule was chosen by a trial and error process by the building manager. The night setback starts at 5:30 p.m. (with a set point temperature of 17°C) when all occupants have left. The ventilation schedule is linked to the AHU schedule and works from 4 a.m. to 5:30 p.m.

Algorithm used

For the strategies presented hereafter, the vector to optimize is the set point temperature. We use same optimization algorithm as the one for the identification process (Interior Point Algorithm). In case of a non-converged calculus, a Genetic algorithm is employed since the previous algorithm used for identification did not converge all the time (only for optimal strategy study). Genetic Algorithms are well adapted for complex non-linear models but have high CPU costs (Mitchell, 1999).

Strategy 1: Energy minimization

The first strategy aims to reduce 24h energy consumption and guarantee an indoor temperature of 19 °C at 8 a.m. when the first occupants arrive. To achieve this objective, the set point temperature vector (Tc) can be modified between a lower bound of 15 °C and an upper bound of 22°C.

The objective function (equation 3) is written so as not to penalize indoor temperature above T_{set} (i.e. 19 °C) at 8 a.m..

$$S1(x) = \sum (P_h(x)) \times (\max(0, T_{set} - T_{ih}(x_{8\,p.m.})) + 1) \qquad (3)$$

In this strategy, we suppose the electricity prices constant. Experiments show that the comfort condition is always respected with this objective function and under the tested weather data.

Table 3 sums up strategy 1.

Table 3
Presentation of strategy 1

Variables to be optimized :	- Set point temperature (Tc) between 0 and 8 a.m.
Constraints :	- Tc can vary between 15 °C and 22°C
Objectives :	- to minimize the 24h heating energy consumption - to reach the indoor temperature of 19°C at 8 a.m.

Strategy 2: Cost minimization

Since the price of energy varies during a day, it is possible to reduce the energy bills by modifying the building set point. The principle is to anticipate the price peaks by loading the building walls with thermal energy. To illustrate this strategy, an electricity ‘green price” will be used. The “green price” varies from 4.23 c€/MWh to 6.91 c€/MWh and contains on-peak/off-peak periods. This structure price is valuable from December to February in France.

The objective function (S2) is presented below in equation 4.

$$S2(x) = \sum P_h(x) \times price \qquad (4)$$

To allow load shedding during high price periods we authorize a limited discomfort during a short period. For that, we impose a discomfort surface limit. This is equivalent to assume that reducing indoor temperature by 1°C during 8 hours creates the same discomfort as reducing the indoor temperature by 2 °C during 4 hours.

So as not to complexify the objective function, the indoor temperature is constraint-free. To guarantee 19°C at 8 a.m the set point temperature variation is limited to 0.5°C per hour. In this way the indoor temperature follows the set point temperature and constraints are applied on optimized variables.

Table 4 sums up strategy 2.

Table 4
Presentation of strategy 2

Variables to be optimized :	- Set point temperature (Tc) between 0 a.m. and 5:30 p.m.
Constraints :	- Tc can vary between 15 °C to 22°C from 0 to 8 a.m. - Tc can vary between 19 °C and 22°C from 8 a.m. to 5:30 p.m. - The maximum set point temperature variation is 0.5°C in one hour
Objectives :	- to minimize the energy bill on 24h - to limit the discomfort surface of 8 °C.h

RESULTS AND ANALYSIS

Strategy 1

The results of strategy 1 are presented through two examples. A given week of data is the base of each example. The first week is relatively warm with an average outdoor temperature of 7.4 °C. The optimized solution (figures 5&6) shows that it is not necessary to rise the set point temperature at 4 a.m.: doing it later is better. Strategy 1 is able to reduce the weekly energy consumption by 5%. On the other hand, the second week studied is very cold with an average outdoor temperature of -6°C. The comfort temperature is not reached with the reference set point. In such conditions, strategy 1 ensures an indoor temperature of 19°C at 8 a.m. every working day, but causes a weekly overconsumption of 1%.

Strategy 2

The reference case is designed to have the same discomfort surface as the optimized case. Therefore, the set point temperature during occupancy periods becomes 20.16 °C instead of 21 °C in order to have a discomfort surface of 8 °C*h.

Strategy 1, warm week :

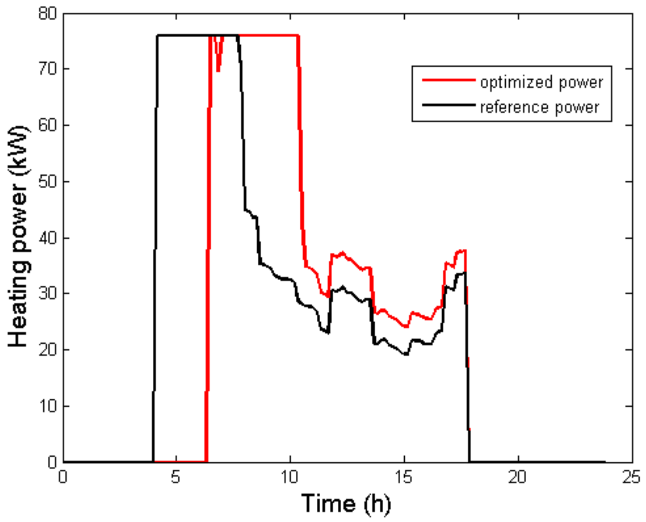

Figure 5: Comparison between the reference heating power (black) and the optimized heating power (red) with strategy 1, during one day of December.

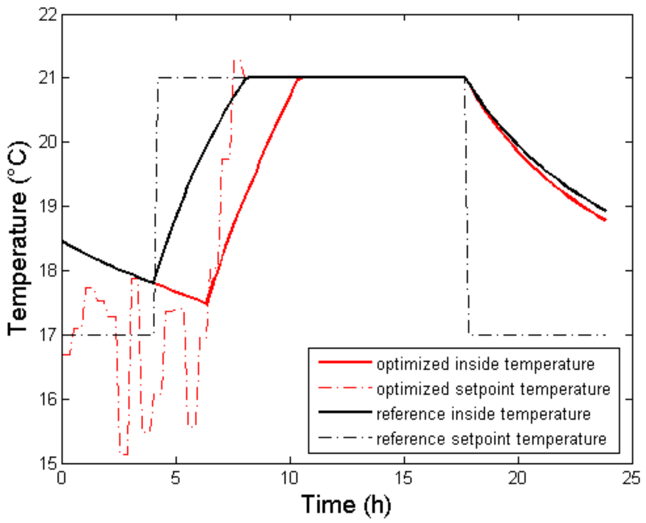

Figure 6: Comparison between the reference indoor temperature (black) and the optimized indoor temperature (red) with strategy 1, during one day of December. The doted curves are the set point corresponding to both indoor temperatures.

Results of 24 h optimization with strategy 1 :

- 24 h energy saving : 6.4%
- Indoor temperature at 8 a.m. : 19.1 °C

Strategy 2 :

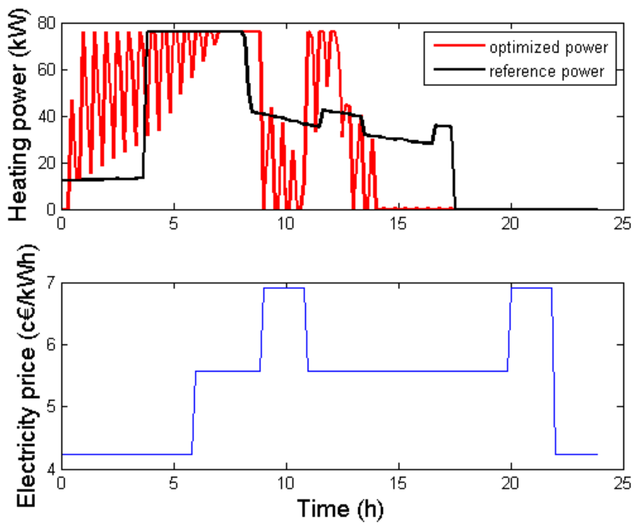

Figure 7: Comparison between the reference heating power (black) and the optimized heating power (red) with strategy 2, during one day of December. The electricity price structure is presented below in blue.

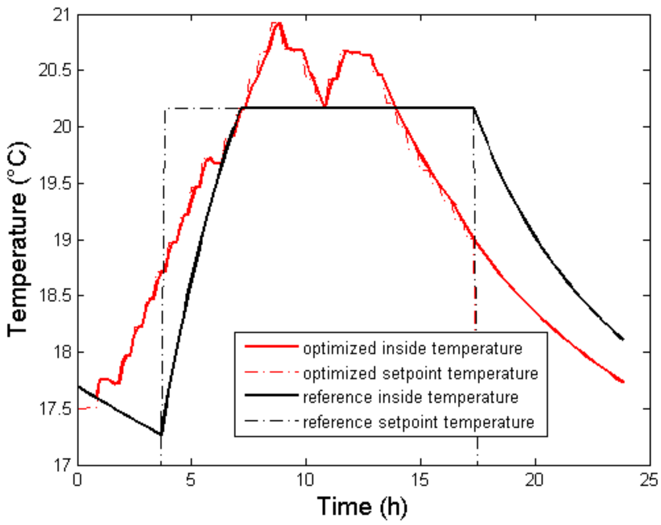

Figure 8: Comparison between the reference indoor temperature (black) and the optimized indoor temperature (red) with strategy 2, during one day of December. The doted curves are the set point corresponding to both indoor temperatures.

Results of 24 h optimization with strategy 2 :

- 24 h energy saving : 5.6%
- Indoor temperature at 8 a.m. : 20.7 °C
- 24 h economic gain : 10.6%

The cost optimization enables to reduce monthly energy bills by 4% in December. During the same period, the energy consumption remains the same.

We observe load shedding during high price periods and load shedding during the last hours of occupancy periods. Stopping heaters a few hours before 5:30 p.m allows to use building inertia to keep the indoor temperature above 19 °C. Figures 7&8 illustrate 24h of optimized temperature and power. They allow to view the load shedding during the first electricity peak and a second one during the last hours of the day. Warm and cold weeks have been tested and whatever the outdoor temperature, the percentage of cost reduction with strategy 2 is almost the same.
It is interesting to measure the impact of price ratio on energy bill reduction. Table 5 shows that cost savings increase with price ratio. With low price ratio, the gain is in order of magnitude of the model error, but with higher price ratio, the gains are quite certain. Moreover, with a high price ratio, this strategy creates an overconsumption.

Table 5
Price ratio influences on strategy 2 gains

PRICE RATIO	MONTHLY COST REDUCTION	MONTHLY ENERGY OVERCONSUMTION
1.6*	4%	0%
2.1	12%	1%
2.7	18%	4%

*Actual ratio price

CONCLUSION

An R6C2 building model was developed to represent an elementary school's thermal behaviour. After an identification process, the model is assessed on its capacity to predict heat power and average indoor temperature. Apart a few non-modelled phenomena, the model gave full satisfaction with 66% and 84% of fitting for power prediction and indoor temperature prediction, respectively. The R6C2 model allows to test two optimization strategies. The first strategy optimizes the set-point temperature in order to reduce energy consumption during night setback and the morning restart of heating. On this particular building, this strategy could save 5% of energy during cold weeks and guarantee a comfortable indoor temperature every morning on workdays. The second strategy optimizes 24h set-point temperature vector during workdays with variable electricity prices to minimize the energy bill. On this particular building, this strategy could reduce the heating bill by 4% during a winter month.

To go further, we will optimize the building in live and run optimization with predicted input.

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