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A Multi-Level MPC Simulation Study in a School Building

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ABSTRACT

This paper discusses a proof of concept application of a multi-level modelling concept for the treatment of predictive control in an institutional building. The multi-level approach consists in tackling the control problems of a building hierarchically in several control layers. By setting aside internal details and focusing only on the problem at hand, it is possible to describe the dynamics of the system under consideration with simple low-order models; this strategy facilitates model calibration and the solution of predictive control problems. The case study building considered is a two-story school with a floor area of 24,000 m^2. A benchmark model of the building, created in EnergyPlus, was used to generate data to identify models at three different levels: building level (one model), wing (7 models) and thermal zone (46 models). The multi-level representation enables an effective treatment of the different time scales involved. An MPC strategy was investigated by optimizing the use of two energy storage devices, one for heating (brick thermal energy storage) and another for cooling (ice bank). The MPC strategy enables reducing cost under a time-of-use tariff.

1. INTRODUCTION

The use of predictive models in control strategies has emerged as a promising path to improve energy performance, load management and thermal comfort in buildings. Nevertheless, significant obstacles remain regarding the practical implementation of the concept. For instance, the issue of model development for control applications is still a challenge. One possibility is to create a detailed model of the entire building with a building simulation tool (e.g., EnergyPlus) in order to predict the dynamic response of the building. Although in principle a building simulation model enables taking into account the effect of small changes in conditions (e.g., opening a window, sudden increase in the number of occupants in a room), in practice the difficulty of calibrating hundreds or thousands of parameters so as to match the real building dynamics *at every scale* (e.g., temperature fluctuations within a room, overall heating load of the building) presents nearly unsurmountable obstacles. Assuming that the calibration of a detailed model for control purposes is possible, the question remains of how to perform this calibration within a reasonable time frame and at a reasonable cost so that it is an attractive option for building operators.

It might be helpful to reflect at this point on the role of a model. All models are imperfect representations of reality that help in making a prediction of a phenomenon with the purpose of finding a practical solution for a specific problem. Models allow comparing different "what if" scenarios, either for design (very long term planning) or control (short term planning) applications. In essence, this kind of cognitive reasoning is employed by human brains in decision-making: an approximate image of reality is used to plan actions (Battaglia *et al.*, 2013). Thus, when using a model it is essential to keep in mind the question the model intends to answer. In a building, these questions might be phrased as "what will be the heating profile over the next 24 hours", "how much will the temperature of this office rise over the next hour?", "should the motorized blinds be closed?", "when should I start pre-cooling this meeting room if the assembly is supposed to start at 2 pm?", etc. A model may perform quite well according to one criterion (e.g., long term energy use) and yet be inadequate for a control application.

The multi-level control (MLC) approach discussed in this paper (Figure 1) focuses on viewing the building in a hierarchy of control levels, so that a simple low-order model is enough to make useful predictions for control purposes (Dehkordi and Candanedo, 2014; Candanedo *et al.*, 2014; Candanedo and Dehkordi, 2013). In this sense, the MLC methodology mimics human organizations. The MLC modelling approach has the following features:

- It is recognized that different time scales may be needed for different applications. For example, the building level may require prediction horizons of 48 hours at time steps of 2 hours; at a room level, the prediction horizon may be 1 hour, with time steps of 10 minutes.
- Different kinds of low-order models ("grey box" or "black box").
- Models do not need to be of the same kind for every control level.
- Models can be easily calibrated with measured data.
- Significantly reduced computational burden in the solution of optimization problems.
- Uncertainty can be incorporated relatively easily.
- The predictions of adjacent layers (e.g., heating load) should "match" approximately, although this correspondence is not necessarily exact.
- The recognition of discrepancies between predictions at different levels requires the use of "negotiation" algorithms.
- The multi-level concept may be extrapolated to include a "building cluster" or "community layer".

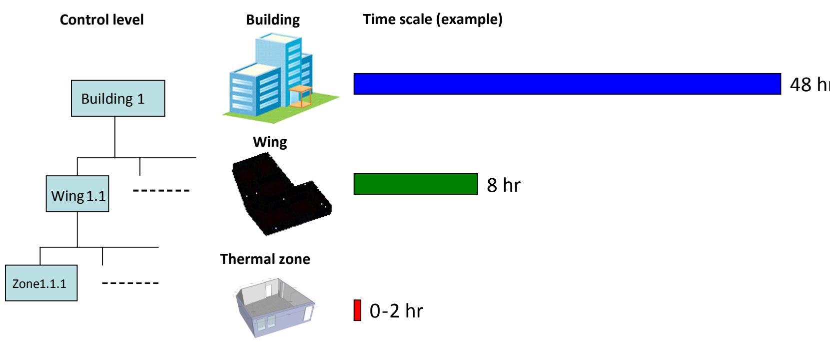

Figure 1: Multi-level control structure

In recent years, distributed MPC (a concept sharing similarities with MLC) has been used to tackle predictive control problems in buildings. In this approach, information is shared between the controllers of adjacent rooms in order to solve the predictive control between zones more effectively (Morosan *et al.*, 2010; Putta *et al.*, 2014). Distributed MPC is associated with a "horizontal" information transfer. The concept of a hierarchical control structure, implying a "vertical" arrangement was applied by Lefort *et al.* (2013) for the predictive control of a house, including the idea of different horizons for two different hierarchical layers: "scheduling control", for a long term horizon; "piloting control", for a short term horizon. A similar two-tier approach (scheduling vs short time scale) was investigated by Touretzky and Baldea (2014).

2. METHODOLOGY

2.1 Case study building

A two-story secondary school, one of DOE Commercial Reference Buildings (Deru *et al.*, 2011), was used as a benchmark model (Figure 2). The school building has a total footprint of 24,000 m^2 (258,000 ft^2) with 46 thermal zones, with a usable floor area of about 19,600 m^2 (211,000 ft^2) and a glazing fraction of 33%. This building was chosen considering its size, the diversity of thermal spaces (classrooms, offices, gymnasia, long hallways). The EnergyPlus detailed model was used to perform "virtual experiments". Output data (indoor operative temperatures) were used together with input signals (exterior temperature, solar gains, internal gains) in order to create simplified low-order models at different control levels.

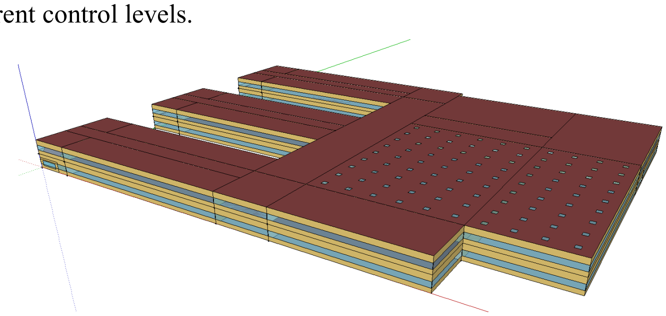

Figure 2: Secondary school building used as a benchmark.

It is assumed that the building is located in Montreal, Canada. The corresponding EnergyPlus weather file (EPW) is used to create weather inputs in MATLAB.

Three control levels were chosen for this case study building: building level (one model), "wing" level (7 models), and thermal zones level (46 models). More details about the system identification procedure are available in a complementary paper presented in this conference (Dehkordi and Candanedo, 2016). The control levels are also associated with different time scales, as shown in Table 1. The "wing models" distribution is shown in Figure 3.

Table 1

Control level	Prediction horizon	Time step	Vector length	Recalculation frequency
Zone level	2 hours	10 min	12 samples	30 min
"Wing" level	8 hours	1 hour	8 samples	4 hours
Whole Building	48 hours	2 hours	24 samples	12 hours

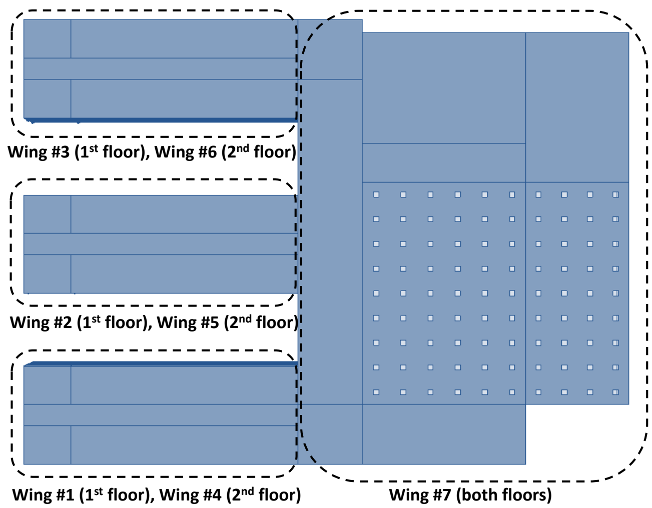

Figure 3: Wing models**.**

2.2 HVAC and heat distribution system

To illustrate the concept of multi-level control, a simple mechanical system is assumed. Heating and cooling are distributed to the thermal zones by means of a piping system connected to local air handling units. It is assumed that two energy storage devices are available at the building level (i.e., for the entire school): a large ice bank (over 15,000 kWh of storage capacity) for storing cooling energy, and a hot water tank (100 m^3) for storage of heating energy. Cooling is provided by a centralized 3-stage chiller with a maximum cooling capacity of 850 kW (2,900 kBTU/hr). The electricity power use of the chiller and its cooling output are both functions of the "partial load ratio" (PLR) requested by the user. Heating energy is provided, for the purposes of this exercise, with an electric furnace of 1,000 kW (3,410 kBTU/hr).

The heating/cooling load is calculated independently for each of the 46 thermal zones, for the 7 wings and for the entire building by using the models developed through the system identification routine. For the purposes of this study, in which no co-simulation is conducted with a building simulation tool, the loads calculated by the 46 zonal models are used as the benchmarks (i.e., it is assumed that the "real loads" are those calculated by the zonal models). The heating/cooling is distributed to the different wings proportionally according to the loads calculated by each of the wing models (Figure 4).

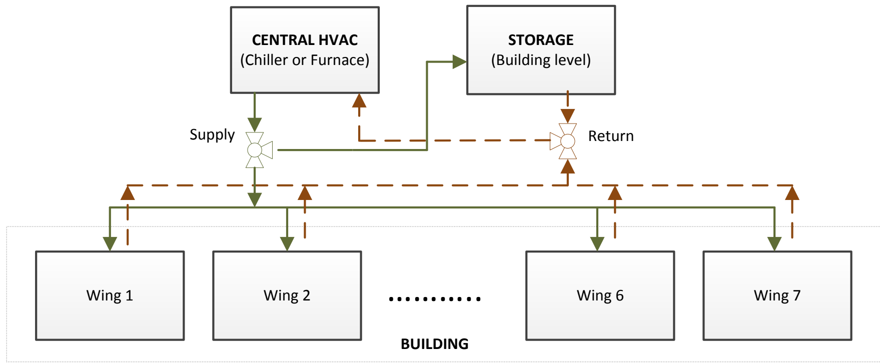

Figure 4: Connection of central plant heating and cooling plant, thermal storage and building "wings".

2.2 Role of different control levels: negotiation rules

The hierarchical division in control layers simplifies the optimization calculation required by predictive control, while at the same time there is a continuous corroboration of the comfort conditions at the zonal level. This facilitates calculations, and provides a mechanism to implement a negotiation between economic optimization and comfort requirements. The simulation can be summarized as follows:

A. Load calculation and optimization carried out at the "building level"

The "building level" model is used along with the weather forecast to run the optimization algorithm (see description in section 2.3). The prediction horizon in this case is 48 hours, and the "states" of the furnace, chiller, ice bank and hot water tank are calculated a 2 hour intervals, thus yielding vectors with 24 elements each.

B. Wings-Zones interaction ("negotiation")

At this step, a negotiation takes place between the heating/cooling required by the zones and the estimate made by the wing models. The 46 zones are used as the calculation benchmark (i.e., the "accurate" temperature calculation). The order of the models depends on factors such as their exposure to neighboring zones, solar radiation, geometry, etc. (Dehkordi and Candanedo, 2016). The zonal models employ a prediction horizon of 2 h at 10 min intervals (also used as the basic simulation time step), while the wing models use a prediction horizon of 8 h at intervals of 1 hour. Therefore, the "time overlap" occurs only over the first two hours predicted by the wing model.

If the difference between the heating/cooling load predicted by a wing model and the aggregated heating/cooling load predicted by its zones is more than a certain threshold (in this case 20 kW), then the wing model prediction is adjusted to match the aggregated load. If the difference is $\leq$ 20 kW, then this "discrepancy" is tolerated, and the zones having a non-zero heating or cooling load share the difference evenly. In essence this will result in some minor deviations from optimal comfort. The trade-off between economics and comfort can be adjusted by playing with the threshold value.

C. Wing models used to correct building level prediction

It is assumed that the "right value" for the heating and cooling loads is provided by the wing models as determined in the previous step. This corrected heating/cooling load calculation is then used to revise the scheduling of the operation of the main equipment.

- In heating mode:
  - If *more* heating is needed, then the electric furnace provides the difference
  - If *less* heating is needed, then (a) first, reduce heating provided by furnace; (b) if necessary, reduce heat taken from the hot water tank
- In cooling mode:
  - If *more* cooling is needed, then increase the cooling provided by the chiller
  - If *less* cooling is needed, then (a) first, reduce the contribution of the chiller; (b) if necessary, reduce the contribution from the ice bank.

This algorithm is summarized in Figure 5.

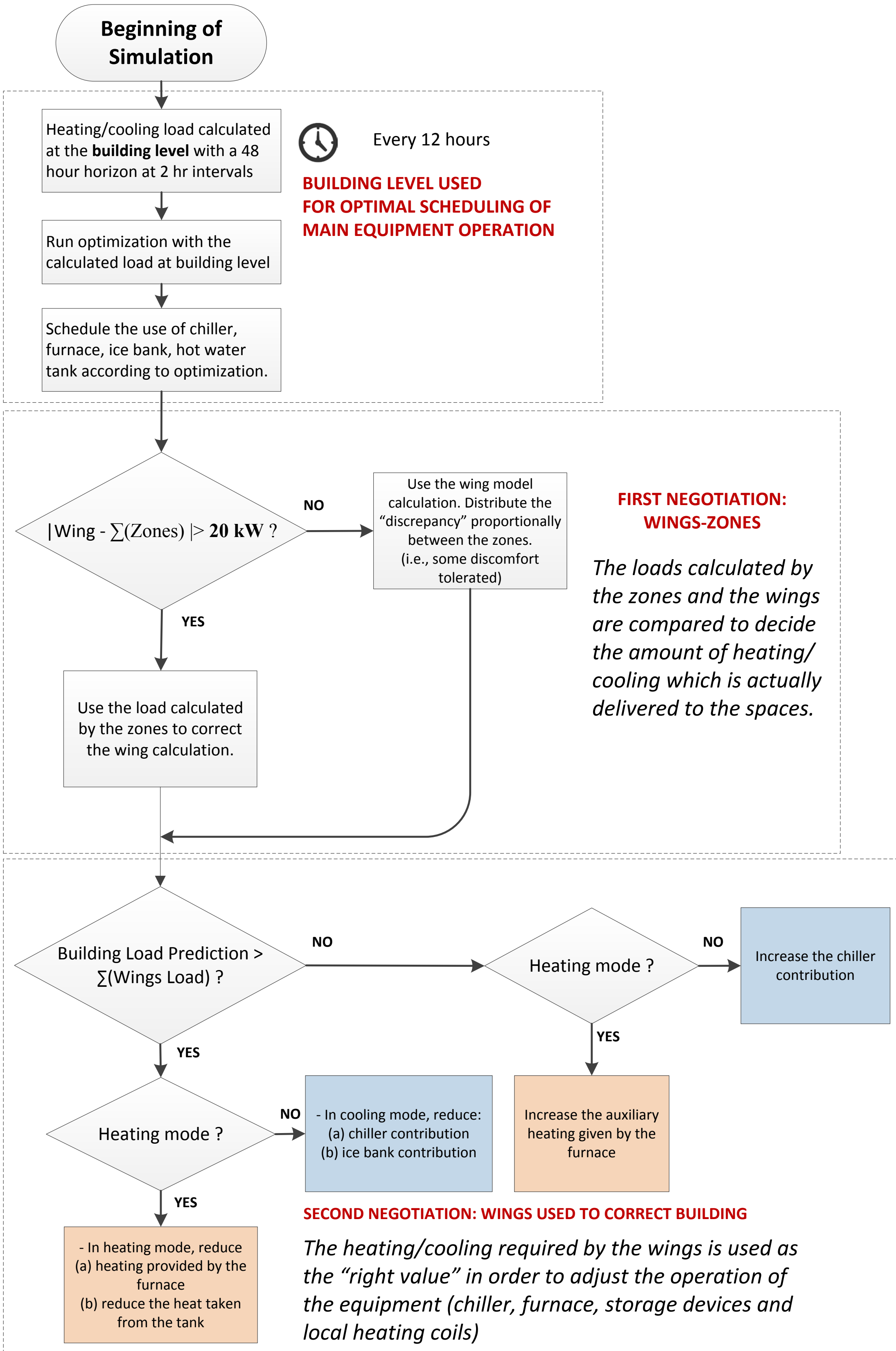

Figure 5: Summary of algorithm used in the simulation.

2.3 Cost function and optimization

A time-of-use rate (TOU) profile, with 24 different hourly rates is used in the calculation of the energy cost in the building by using the "building level" model. The optimization problem to be solved is then:

$$\min \sum_{\langle N \rangle} C(n) \cdot P(n) \cdot \Delta T \tag{1}$$

For the **cooling loop**, both the latent and sensible cooling loads must be provided. The latent load is estimated based on some typical schedules for occupancy rate. At any given time step:

$$\begin{aligned} q_{\text{bldg,c}} &= q_{\text{bldg,sens}} + q_{\text{bldg,lat}}, && \text{at any given time step} \\ \mathbf{q} &= \mathbf{q}_{\text{sens}} + \mathbf{q}_{\text{lat}}, && \text{in vector form} \end{aligned} \tag{2}$$

Considering that the total cost is the dot product of the hourly cost vector and the average electric power of the chiller, the total cost can be calculated as:

$$\text{cost}(\mathbf{P}_{\text{c}}) = \mathbf{c}^{\text{T}} \cdot \mathbf{P}_{\text{c}}, \quad \mathbf{P}_{\text{c}} = f(\mathbf{q}_{\text{ch}}) \tag{3}$$

The optimization can then be written as follows:

$$\begin{aligned} &\min_{\mathbf{q}_{\text{h}}, \mathbf{q}_{\text{hwt}}} \mathbf{c}^{\text{T}} \cdot \mathbf{P}_{\text{h}}, \\ &\text{s.t.} \begin{cases} \mathbf{q}_{\text{ch}} + \mathbf{q}_{\text{IB}} = -\mathbf{q}_{\text{c}}^{*} \\ \mathbf{q}_{\text{ch}} \le 850\text{kW} \\ 0 \le \mathbf{PLR} \le 1 \\ 0 \le \mathbf{x}_{\text{v}} \le 1 \\ 0 \le \mathbf{x}_{\text{IB}} \le 1 \\ 150\dfrac{\text{kg}}{\text{s}} \le \dot{\mathbf{m}}_{\text{ch}} \le 450\dfrac{\text{kg}}{\text{s}} \\ -7^{\circ}\text{C} \le \mathbf{T}_{\text{chwr}} \le 15^{\circ}\text{C} \\ -7^{\circ}\text{C} \le \mathbf{T}_{\text{chws}} \le 10^{\circ}\text{C} \end{cases} \end{aligned} \tag{4}$$

The optimization constraints make sure that the cooling load is provided by the sum of the ice bank and the chiller, the respect of the operational limits of the chiller (maximum capacity and PLR), the positions of the three-way valves remain between 0 and 1. This also makes sure that the flow rates, and return and supply temperatures remain within realistic limits. The ice banks and chiller models used by the authors in a smaller buildign (Candanedo *et al.*, 2013) were properly scaled for the school building.

Regarding the **heating loop**, the problem is formulated in a similar way, except that in this case an electric furnace linked to a hot water tank is employed. In this case, only sensible heating is considered. The total cost over a period of time is:

$$\text{cost}(\mathbf{P}_{\text{h}}) = \mathbf{c}^{\text{T}} \cdot \mathbf{P}_{\text{h}} \tag{5}$$

Then, the optimization problem can be written as:

$$\min_{\mathbf{q}_h, \mathbf{q}_{hwt}} \mathbf{c}^T \cdot \mathbf{P}_h \,, \quad \text{s.t.} \begin{cases} \mathbf{q}_h + \mathbf{q}_{hwt} = \mathbf{q}_h^* \\ 30\dfrac{kg}{s} \le \dot{\mathbf{m}}_h \le 100\dfrac{kg}{s} \\ \dot{\mathbf{m}}_{hwt} \in \{0, 10\}\dfrac{kg}{s} \\ 19^\circ C \le \mathbf{T}_{hwt} \le 40^\circ C \end{cases} \tag{6}$$

At any given moment, the heating load is provided by combining the heat provided by the furnace and the hot water tank. The hot water tank is modeled according to the procedure presented in (Candanedo *et al.*, 2015). Minimum and maximum flow rates are established for the furnace. Limits for the hot water tank temperature are also defined.

3. RESULTS AND DISCUSSION

3.1 Wing/zones interaction

According to the algorithm presented in Figure 5, the heating/cooling load is calculated for each of the wings, and their corresponding zones. Figure 6 shows the results of the load calculation at Wing #2 for a period of 3 hours in January, and the aggregated load of the first two hours for its zones (the prediction horizon at the zone level is 2 h). Note that the calculations for the zone level take place at 10 min intervals, whereas the load prediction at the wing level yields results at hourly intervals. The wing level prediction horizon is 8 h, of which only 3 hours are shown.

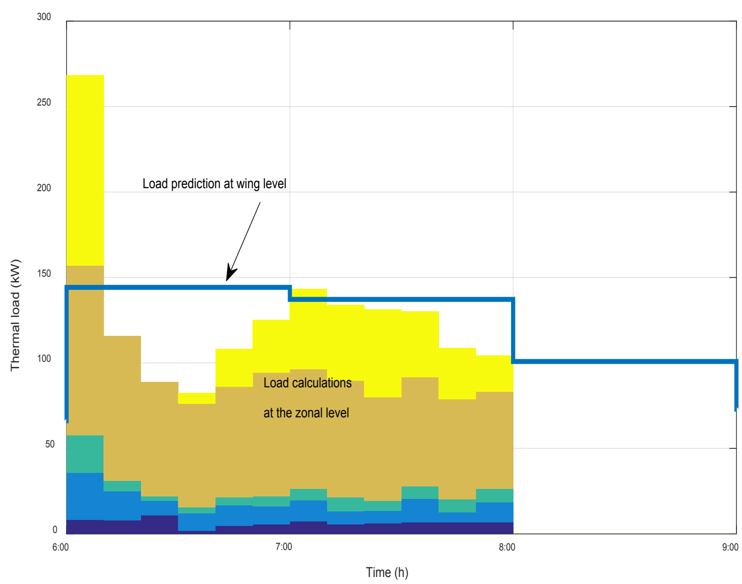

Figure 6: Load prediction for wing #2 and the aggregated load of its zones (before "negotiation")

These calculations for the wing/zone level are then revised according to the "negotiation" rules explained above. The revised calculations are shown in Figure 7. When the difference between the wing load and the aggregated load is larger than the 20 kW threshold, the aggregated load prevails. In contrast, when the difference is smaller than the threshold, the wing calculation is used as the "right value", and the load for the zones is adjusted accordingly.

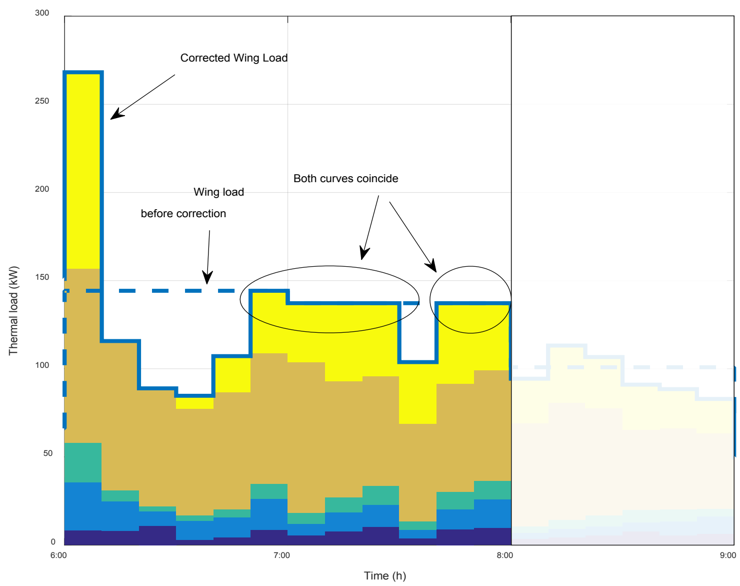

Figure 7. Revised calculations after "negotiation"**.**

3.2 Building/wings interaction

Figure 8 shows the load prediction for the building level and the aggregated load of the wings. To make it consistent with the previous graph, the graph is shown starting at 6:00. There is, however, a non-zero load from 4:00 to 6:00 (preheating). The calculations at the building level are used in the optimization algorithm described in Section 2.3. The building load calculation extends much longer than shown, since a prediction horizon of 48 h is used.

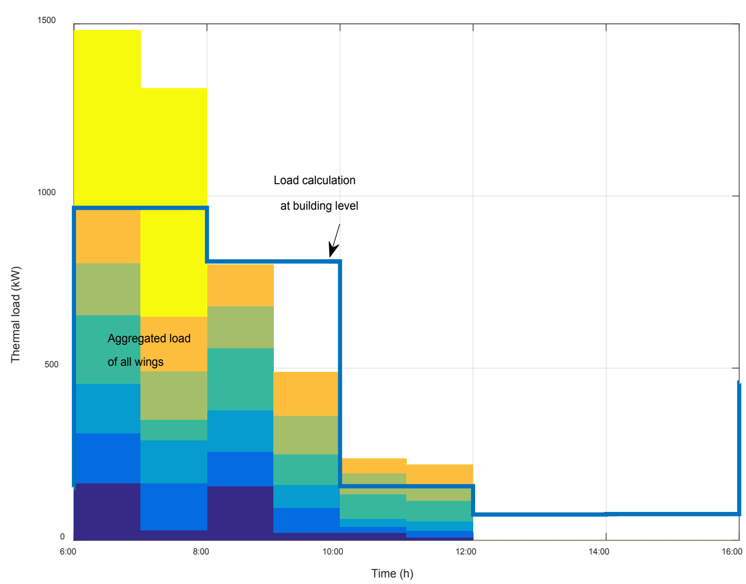

Figure 8: Load calculations at the building level (before negotiation) vs aggregated load of the wings.

As a result of the optimization for the building level, the optimum states of operation for the main mechanical equipment (total heating load, heat delivered to the hot water tank, heat taken from the hot water tank, and heat provided by the furnace) are given at 2-hour intervals (Figure 9).

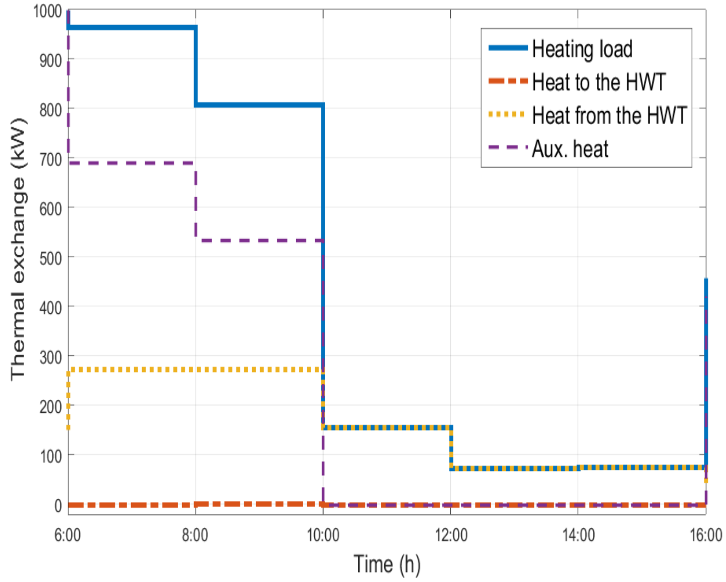

Figure 9: State of the thermal exchanges (heating load, heat delivered to the hot water tank, heat taken from the hot water taken, and auxiliary heating provided by the furnace)

Finally, when running the actual simulation at 10 min time steps, the load delivered to the wings is the sum of the load of the zones, and the *actual* building load is the sum of the heat delivered to the wings (Figure 10).

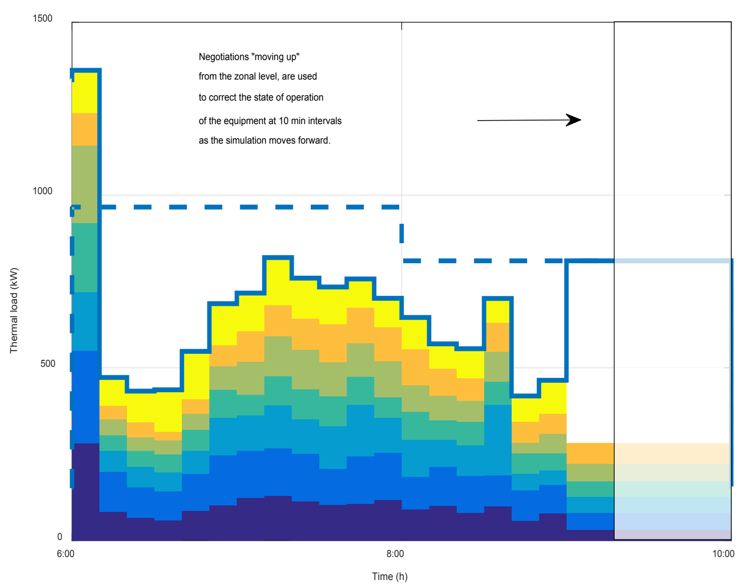

Figure 10: Adjustment of the load according to the zonal/wing negotiation.

6. CONCLUSIONS

This paper has illustrated the concept of multi-level control as an alternative to the more conventional method of modeling the entire building with a high-resolution, detailed, all-encompassing representation. It has been shown that this multi-level approach makes it possible to use a simple model for the planning of an optimization strategy (predictive control) while simultaneously tackling issues at local control levels. Minor discrepancies in the predictions of controllers at different levels are addressed through a "negotiation" algorithm, which implements a trade-off between the long-term planning intended for cost optimization, and the immediate needs of local zones to guarantee thermal comfort. Although, the proposed methodology works well, an issue that adds some complexity is the handling of the time scales; a specifically designed simulation environment could significantly simplify this task.

NOMENCLATURE

The nomenclature should be located at the end of the text using the following format:

C	total cost	(CAN$)
$\dot{m}$	mass flow rate	kg/s
P	electric power	
q	heat flux	(W)
T	temperature	(°C)

Subscript

bldg	building
c	cooling, cooling power from chiller
chwr	return water into chiller
chws	supply water from chiller
h	heating, heat from furnace

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