ghMulti-Level Approach for Model-Based Predictive Control (MPC) in Buildings: A Preliminary Overview

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ABSTRACT

Model-based predictive control (MPC) has emerged in recent years as a promising approach to building operation. MPC uses models of the system(s) under control –and knowledge about future disturbances– to select an optimal set of actions. Despite its advantages, implementing MPC in a building can be quite challenging. This is largely due to the difficulty of dealing with a detailed simulation model that may contain hundreds or thousands of variables. Simple models offer a potential solution; however, a coarser representation of the entire building is not suitable for local scales (e.g., a zone).

This paper presents an overview of a strategy to address this problem. Optimization problems are formulated by using models focusing on different control levels (building, zone, rooms, etc.), while enabling communication between them. This method allows for simpler models, facilitates programming and provides insight on building operation. Preliminary results, corresponding to a small commercial building, are presented.

INTRODUCTION

Conventional Control vs. MPC

While conventional HVAC control strategies can attain the objective of maintaining comfort, they are far from optimal in terms of load management, overall energy use and operation cost. Moreover, conventional strategies will soon become insufficient in the face of new realities, such as building-integrated renewable energy system, energy storage capabilities, and information exchange with the Smart Grid. These new conditions will require building operations to be more flexible, responsive and dynamic (Candanedo et al., 2013a).

Conventional control, based on rules of operation and basic feedback loops (PID control, ON/OFF) is "reactive" in principle. In contrast, model-based predictive control (MPC) could be seen as a "proactive" approach: calculations and preventative measures are taken as a function of expected weather and occupancy (Oldewurtel et al., 2010, Ma et al., 2010). MPC requires two elements: (i) an appropriate model and (ii) a reasonably accurate prediction of future inputs.

MPC is useful in a wide range of situations where knowledge of the future helps in decision-making. For example, MPC may be used to better take advantage of energy storage systems or to plan the opening or closing of blinds (Candanedo et al., 2011). MPC can also help in managing slow-responding components, such as radiant floors, chilled slabs or other thermally-active building systems (TABS) (Gwerder et al., 2009).

Although clear in principle and with obvious benefits, MPC must overcome some obstacles before becoming a widespread, mainstream technology. Tools to facilitate the incorporation of weather forecasts in building control systems must be developed (Candanedo et al., 2013c). Research work is still needed on the prediction and characterization of occupancy and occupants behaviour (Oldewurtel et al., 2012). This article focuses on another relevant issue: the selection of an appropriate modelling methodology for the building and its systems, taking into account the hierarchical structure of building systems.

MPC in Buildings: Detailed and Low-Order Models

As a rough generalization, two different paths to building modelling have been followed in MPC studies: (i) detailed building simulation (Corbin et al., 2013) and (ii) low-order models (Candanedo et al., 2013b). A building simulation model (e.g., EnergyPlus) consists of detailed models of indoor spaces, mechanical equipment and other building subsystems, based on first principles. On the other hand, a low order model uses a simplified representation of the building (e.g., linear thermal networks) to calculate heating and cooling loads.

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The abundance of information in detailed building simulation models makes them a valuable tool for design purposes. However, it is rather difficult to develop and prototype advanced control strategies with a building simulation model. For instance, the formulation and solution of optimization algorithms can be quite difficult with a model containing a large number of variables. Simple models often provide satisfactory descriptions of larger-scale phenomena: for example, the thermal response of a building (or even a group of buildings) has been modelled with low-order thermal networks (Bénard et al., 1992, Ma et al., 2010). Simple models are more manageable and flexible; moreover, they provide clarity and insight about the effect of different inputs. Finally, they can facilitate the management of uncertainty.

Despite their advantages, the lower resolution of simple models means that information at "smaller scales" is lost. It may occur that while a whole-building model predicts accurately that the entire building requires cooling at a given time, one of the thermal zones needs heating. This may not be a problem if the objective is to manage the energy storage inventory of the entire building, say, by charging or discharging a chilled water reservoir (Ma et al., 2010). However, when the intent is to control "local" energy storage devices or to maintain the set-point in a room with large time constants, a different tactic is needed.

MULTI-LEVEL CONTROL STRATEGY

Basic Principle

The approach proposed herein attempts to make use of the advantages of simplified modelling while enabling the treatment of a complex building system. The basic idea consists of creating *control models* by looking at the building and its systems in a hierarchical arrangement, in which every control level is associated with its own time scale (Figure 1).

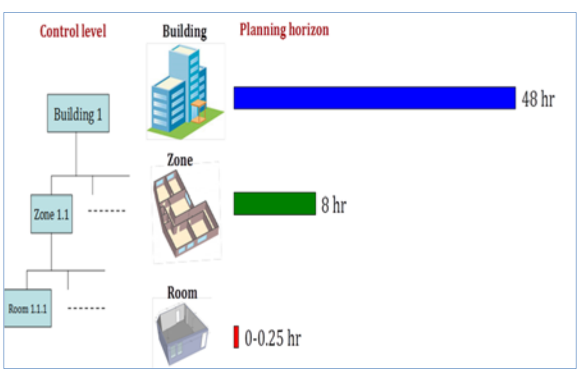

Figure 1. Multilevel control structure and corresponding time-scales.

With this method, it is possible to use relatively simple control models to describe the dynamics of each subsystem. This approach makes it possible to write algorithms for each level with different control horizons (e.g., several days for a large building; minutes for a small zone). These models are interconnected within control levels, as well as with upper and lower levels. For example, heat transfer between two adjacent rooms must be accounted for in the models of both rooms. Similar multi-level approaches have been investigated for residential buildings (Lefort et al., 2013).

When the predictions of the models do not coincide, a "negotiation" protocol –based on a pre-defined set of rules– is necessary.

Simulation Model vs. Control Model

In simulation studies of model-based control strategies, building models play two related, but clearly distinct roles:

a) Simulation. The cost and logistical challenges associated with running experiments in buildings imply that building research relies considerably on *simulation* models. A simulation model is the "next best thing" to a real building. It can be used for "virtual experiments". It is meant to reproduce reality (e.g., heat transfer phenomena, mechanical systems, electrical loads) as accurately as possible, or at least as accurately as required for a given objective. By programming a control algorithm within the simulation model, or by linking it to a control software tool, it may also be used to test the performance of control strategies.

b) Control. A *control* model refers to the model used by the controller. The optimization algorithm and operation rules are based on the predictions of the control model. Although the control model should make reasonably accurate predictions, these predictions do not need to be *identical* to those made by the simulation model. Ease of implementation and calibration, user friendliness, computational speed, flexibility, clarity and other practical issues are also relevant. The decisions of the controller can be sent periodically to the simulation model, which in turn sends feedback signals (e.g., temperatures) to the update the state of the controller.

The distinction between simulation model and control model should always be kept in mind, and it should be stated explicitly. Although it is possible to use the same model for both functions (which is often the case), this is not strictly necessary. When model-based control strategies are implemented on-site studies in actual buildings, only the control model is required.

METHODOLOGY

Case Study Building

This investigation makes use of a small, case-study commercial building. The simulation model was created in EnergyPlus (Figure 2).

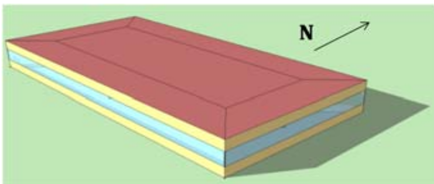

Figure 2. EnergyPlus model.

This building was conceived in the context of a project on MPC carried out at our institution. Some of the salient features of the case study building are:

- Rectangular plan, single story
- Floor area = 800 m^2 (40 m × 20 m)
- Window/wall ratio ≈ 40%
- Double-glazed windows
- R-20 (RSI-3.53) in walls
- 0.80 ACH (infiltration + ventilation)

The four façades of this building are oriented towards the cardinal points. The EnergyPlus model is divided in 5 thermal zones (North, East, South, West and a Central Zone).

Multilevel-Control Approach (Two Levels)

Two hierarchical levels are considered in this case: building level and zone level (Figure 3).

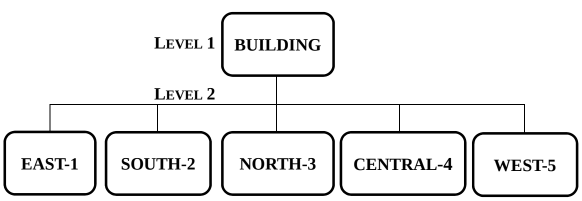

Figure 3. Hierarchical levels used.

Although there should be some agreement in the predictions of the models at the building level and zone level, they do not have to match with absolute accuracy in order to be of practical value. Indeed, as a result of the assumptions made in the creation of simplified models, some small disagreements are to be expected. It is then necessary to establish a "negotiation protocol" to decide how much heating/cooling will be delivered.

Models for Whole Building and Zones

In this study, the models used for the whole building and for the zones are state-space models obtained from system identification. These models, simple but of relatively high order, were built from a set of transfer functions obtained by system identification of EnergyPlus virtual experiments.

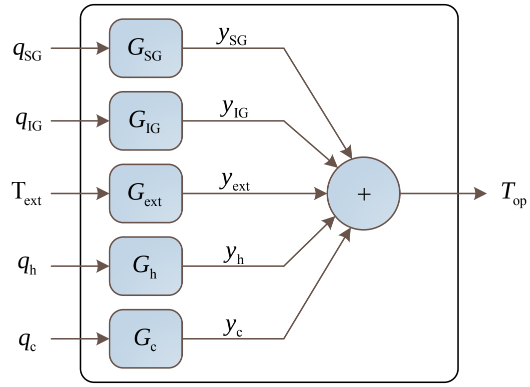

Figure 4. Whole building model (level 1).

The inputs selected for the building model (Figure 4) were the solar gains (q_{SG}), internal gains (q_{IG}), outdoor temperature (T_{ext}) and the thermal output of the heating and cooling systems (q_h and q_c, respectively). The output selected, T_{op}, is the arithmetic mean of the *operative* temperature of each of the zones; the operative temperature is used because it is a better indicator of thermal comfort than air temperature (T_{op} considers the effect of both the air temperature and the mean radiant temperature of the surrounding surfaces).

The zone models are developed in a similar way. Each zone model includes the mean temperature of the adjacent zones as an additional input. The model corresponding to zone *i* is shown in Figure 5.

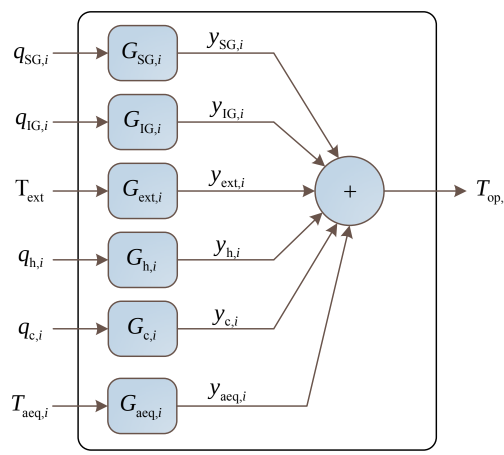

Figure 5. Model for zone *i* (level 2).

In this preliminary study, the EnergyPlus simulation model is only used to generate the simplified control models used in the development of MPC strategies.

Active TES Devices

Two types of thermal energy storage (TES) devices are considered in this study. Each of these systems is intended for different control levels.

- An ice bank, used for storage of cooling energy for the entire building (level 1)
- Five brick TES system, used for the storage of heating energy for each of the zones (level 2)

Ice bank. The ice bank has been modelled as a heat exchanger by solving a system of two equations: (a) one corresponding to the energy balance in the coil; (b) and another corresponding to the description of heat transfer. The second equation includes an effectiveness factor represented by two curves: one for “charging mode” (i.e., ice making) and one for “discharging mode” (i.e., ice melting). Previous publications provide details on the ice bank model (West and Braun, 1999, Candanedo et al., 2013b).

Brick TES. Brick thermal energy storage systems are used to store sensible heat at high temperatures (in the order of hundreds of °C). As their name indicates, bricks of high density and high specific heat are used. The brick TES is charged (i.e., heated) with electric wires and discharged with water pipes, which are then used to deliver heat to the space. The energy storage capacity of brick TES, in the order of a few hundred kWh, makes them suitable for thermal zones and peak load shaving when electricity is used for heating, as is the case in Québec. Details of the brick TES model will be presented in a future article.

Input Signals

An EnergyPlus weather file corresponding to Montréal, QC, was used to generate the weather signals (solar gains and outdoor temperature) used in each of the models. The internal gains were modelled with a simple schedule (Figure 6).

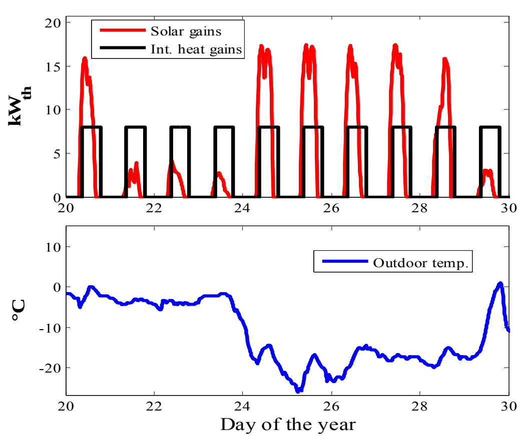

Figure 6. Inputs used for whole building model.

PRELIMINARY MODEL ASSESSMENT

Free-floating Response

The free-floating response (i.e., the operative temperature without heating or cooling delivered to the space) is examined to assess the performance of the models. Figure 7 shows the free-floating response of the five zone models over a 15-day period in late January and early February.

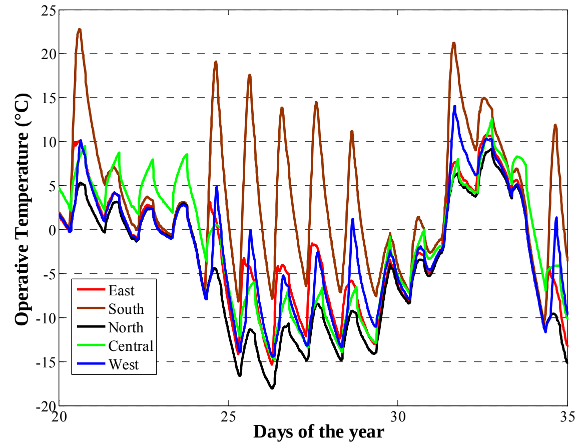

Figure 7. Free-floating response, five zones.

As expected, the South zone overheats due to its solar gains even despite low winter temperatures. The temperatures of the other zones are similar to each other; however, there are still clear differences between them. The North zone is the coldest.

Figure 8 compares the response predicted by the whole building model and the average temperature of the five zonal models. The extreme temperatures in the zones tend to “cancel out”. As a result, both curves coincide almost exactly. This figure indicates that the whole building model accurately predicts the mean temperature of the entire building.

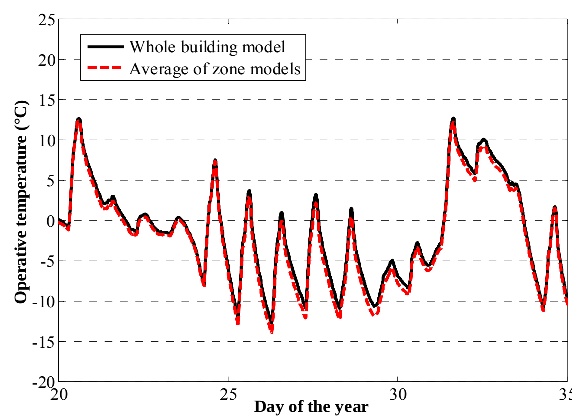

Figure 8. Response of the whole building model (level 1) and average of zone models (level 2).

<u>Heating/Cooling Predictions</u>

Apart from the "free-floating" response without intervention of the HVAC system, the models were also used to calculate how much heating or cooling is required given a fixed operative temperature set-point of 23.0 °C.

Figure 9 shows the thermal load predicted by the whole building model, as well as the total load predicted by each of the zones for April 11th and 12th (t = 100.00 is April 11th at 0:00; t = 100.25 is April 11 at 6:00 a.m., and so forth).

Both heating (+) and cooling (−) are required. Again, both curves nearly coincide. The maximum difference between the two is about 1.3 kW (about 5%). The whole building model tends to slightly overestimate the heating load.

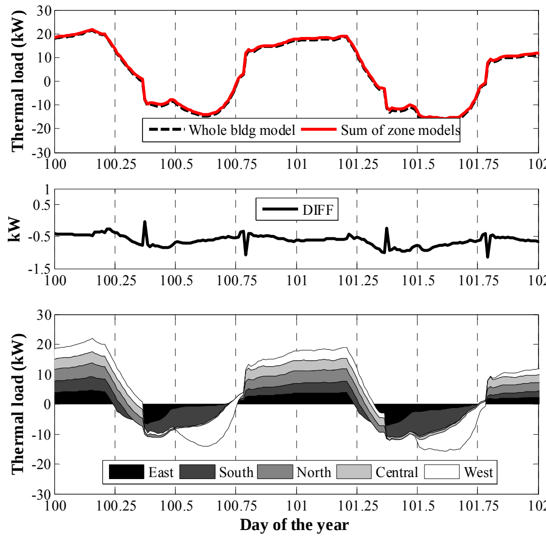

Figure 9. Thermal load predictions.

As expected, the load predictions of the whole building largely coincide with the sum of the energy needs calculated by the models for each of the zones

Note that there are brief periods in which some of the zones require heating while simultaneously others require cooling (e.g., early morning). All the zones require heating at night. As expected, the South zone has the highest cooling requirements. The East zone requires cooling earlier in the day, while the West zone requires cooling in the afternoon. The Central and North zones require very little cooling.

Figure 10 shows the heating/cooling energy needs for the period from April 10th to April 30th, inclusive. This graph confirms the agreement between the building model and the zone models.

MPC STRATEGY FOR ACTIVE TES SYSTEMS

The main purpose of developing models at different hierarchical levels is to facilitate the development of control strategies. The models obtained have been used in the development of MPC algorithms for the control of the active TES systems at the building and zone levels. The MPC algorithms are calculated with the following procedure:

- At time t, the heating/cooling loads are calculated for a prediction horizon of 24 hours. The weather information from the weather file (assuming a "perfect" forecast), and the internal gain profile, are used in the calculation of the loads. Load calculations are carried out by assuming a constant temperature set-point of 23 °C.
- <u>Negotiation protocol</u>. As an elementary rule, it is assumed for the purposes of this study, that whenever a discrepancy is observed

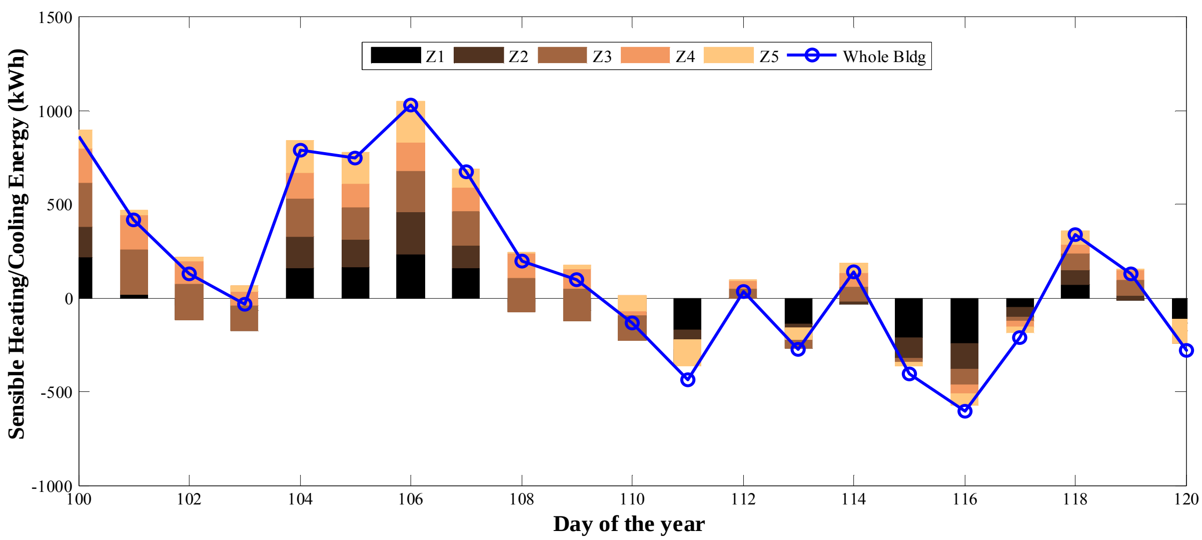

Figure 10. Daily energy needs, as calculated with the whole building model and the zone models.

between the total of the zone models and the whole building model, the result of the zone models is given first priority.

- The state of charge of the TES devices is determined by obtaining the solution that minimizes the cost of electricity over the prediction horizon.

$$\min J = \int_{t}^{t+24h} P_{elec}(t)C(t)dt \quad (1)$$

where $P_{elec}(t)$ is the electric power use $c(t)$ is the time-dependent electricity cost. The heating/cooling load is supplied by combining the primary source (heating coils, chiller) with the storage device (ice bank, brick TES):

$$q_{\text{load}} = q_{\text{primary}} + q_{\text{TES}} \quad (2)$$

This optimization is solved *independently* at the building level (level 1) and at the zonal level (level 2). The optimization problem is solved by respecting a set of constraints defined by the physical parameters of the problem (maximum and minimum water flow rates, chiller performance, maximum and minimum temperatures, etc.).

- The calculated heating/cooling are delivered to the system, and the calculation is repeated at 6-hour intervals.

MPC Preliminary Results

Figure 11 shows some preliminary results corresponding to the optimal state of charge of the brick TES devices for the East, South and Central zones, late in the heating season. The state of charge of fluctuates more at the Central zone, since this zone does not receive solar heat gains. The state of charge corresponding to the South zone (with high solar gains) has the least fluctuation. The state of charge of the East zone takes intermediate values.

Figure 11 shows some preliminary results corresponding to the optimal state of charge of the ice bank from April 10th to July 4th. As can be expected, as the cooling season sets in, the ice bank is required more and more often.

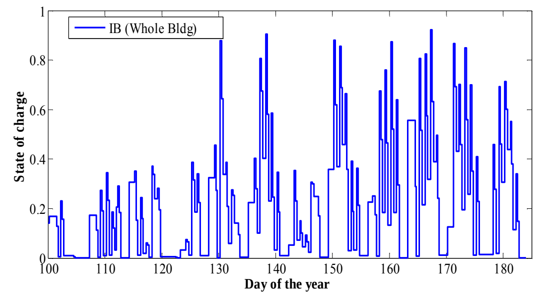

Figure 11. Ice bank state of charge.

DISCUSSION AND CONCLUSION

This paper has presented a multi-level modelling and control methodology aimed at facilitating the development of MPC strategies in commercial buildings. The concept has been illustrated with a simple example consisting of models organized in a two-level structure: whole building + zonal models. These models were obtained from virtual experiments with an EnergyPlus model of a case study building.

The mechanical system of the building includes active thermal energy storage (TES) devices for each thermal space. This article discusses preliminary results of potential MPC applications, including the optimal management of the brick TES devices used to store heating energy for each of the zones. This exploration is among the first instances of an investigation on an MPC algorithm applied to storage heater devices.

The predictions of the zonal models agree well

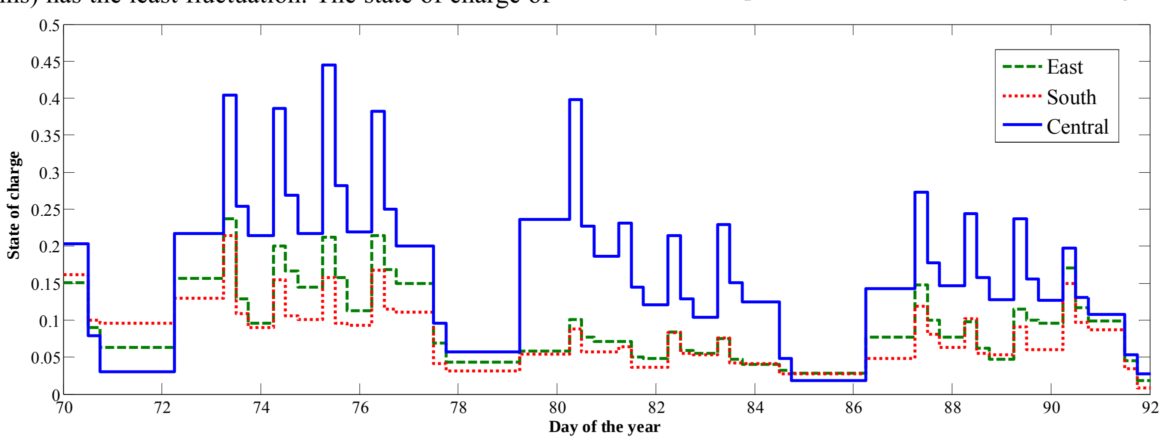

Figure 12. State of charge of brick TES devices (March 12th to April 2nd).

with those of the whole building model. Consequently, it has been shown that these models can be used with confidence to develop optimal control strategies independently for each subsystem. The “negotiation” protocol was called for very infrequently because of the good agreement between predictions. Nonetheless, it must be recalled that the models used in this preliminary investigation are data-driven state-space models of relatively high order, and high accuracy is to be expected.

Ongoing work by our research team explores the development of models that, while intuitive and simple (for example of 3rd or 4th order thermal circuits) lend themselves to physical interpretation (Candanedo et al., 2013a). While simple RC thermal networks may not reach the degree of accuracy of data-driven, higher order models, they provide flexibility to varying conditions, ease of use and accessibility to building operators and could be more readily tuned with monitored data. With coarser models, negotiation rules will become more important. A straightforward and systematic approach to the creation of simple RC models is required.

This paper has presented a basic example (only two levels) of the concept behind the proposed methodology. This methodology is meant to simplify the implementation of MPC in larger buildings, which may have many more control zones and hierarchical levels. Future work will examine the application of this methodology in a significantly larger building with more zones, more control levels and diversity in space utilization and occupant loads.

The predictions of different models in a large commercial building do not have to coincide as accurately as in the example presented in this paper. Rather than perfect accuracy, the goals pursued are logical structure and coherence.

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