A multi-level architecture to facilitate MPC implementation in commercial buildings: basic principles and case study

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Abstract

This paper presents a methodology aimed at facilitating the deployment of model-based predictive control (MPC) in buildings. MPC has shown promise as an effective way to reduce utility costs associated with peak demand, and to better manage the interaction between "smart buildings" and the "smart grid". However, steps are needed to streamline the implementation of MPC in buildings and thus encourage its adoption in building operation. The proposed architecture intends to contribute to this goal by enabling a "compartmentalized", distributed, hierarchical approach to building modelling and controls.

The proposed multi-level methodology allows formulating control problems so that the planning time horizon fits the scale of the system. A model of a commercial building, including thermal energy storage devices at different control levels, is used to demonstrate the methodology. Low-order resistive-capacitance models for the thermal spaces are obtained from a detailed model created in EnergyPlus.

1 Introduction

The application of model-based predictive control (MPC) to the operation of buildings has received a great deal of attention in recent years (Ma et al., 2010, Nghiem and Pappas, 2011, Široký et al., 2011, Candanedo and Athienitis, 2011, Kim and Braun, 2012, Corbin et al., 2013). MPC has come to be recognized as an effective technique for improving load management in high-performance buildings, and as a promising approach to the incorporation of renewable energy sources. MPC and similar methods are expected to play a key role for the integration of smart buildings in the smart grid.

Despite these promising prospects, the practical implementation of a formal MPC strategy in a building –understood as the application of a model-based optimization algorithm– is a rather daunting task today. Reaching the state in which online MPC strategies can be applied in buildings in a timely and cost-effective manner requires advances in several areas. These areas include appropriate modelling (Prívara et al., 2012, Eisenhower et al., 2012, Candanedo et al., 2013a); automatic formulation and solution of optimization problems (Cigler et al., 2013); tools for obtaining weather forecast information (Candanedo et al., 2013c); data-collection and modelling of occupancy (Oldewurtel et al., 2012, Gunay et al., 2013), among others.

This paper presents the outline of an approach aimed at facilitating the testing of predictive control strategies and the implementation of MPC in buildings (Candanedo and Dehkordi, 2013). This methodology is one of core components of a four-year project at our institution[1]; it is based on the "dissection" of the complex structure of a commercial building into smaller control areas arranged hierarchically (e.g., room/thermal zone, group of zones, whole building), which may be nested into each other. With this method, relatively simple

[1] Multi-level Control for Buildings (MLCB), EcoEII program.

models (RC, state-space representations, simple ANN, etc.) suffice to represent each control region satisfactorily. The methodology, still under development, is illustrated in this paper with a case study building with five zones with active and passive thermal energy storage.

Principles of Multi-level MPC Control

The proposed methodology, summarized in Figure 1, is based on the following principles:

- **Multi-level approach**. Dividing the building spaces and the HVAC system in control regions arranged in different hierarchical levels.
- **Simplified models**. Using simple models at each control region, both for the thermal response of the spaces and the mechanical equipment. Simpler models will be preferred, provided that they are accurate enough for the task at hand. These models will be adjusted and fine-tuned with online collected data during normal operation.
- **Local control**. Setting-up local “controlling agents” at each control region. These local “agents” will operate as decision-making entities which will use the models corresponding to their jurisdiction, together with forecasts of input data (weather, occupancy, etc.), for load predictions and selection of control actions.
- **Communication**. Enabling communication and “negotiation” protocols between the controlling agents, so that discrepancies in operation policies, which will inevitably occur, are resolved.

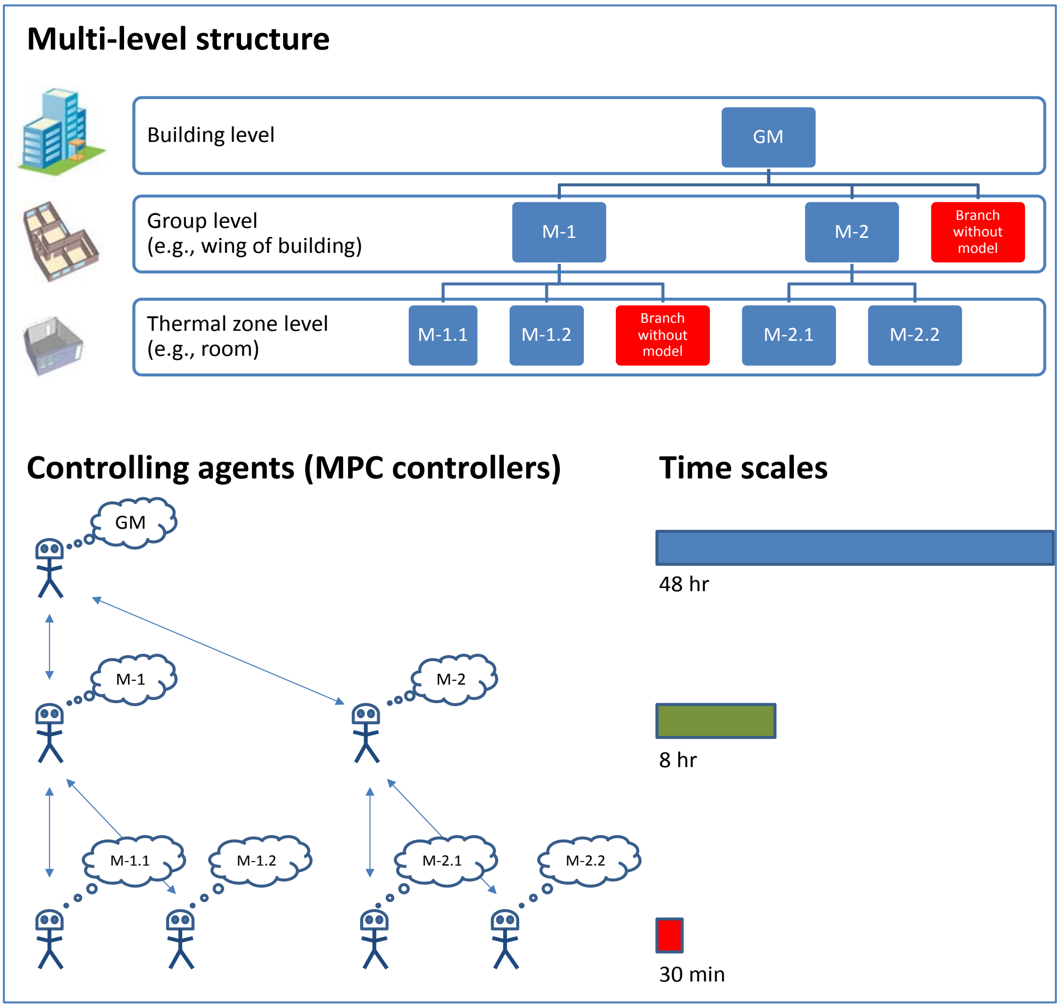

Figure 1: Conceptual description of the proposed multi-level control approach.

2 Methodology

Case study building

This investigation uses a small commercial building model created in EnergyPlus. This building model (codenamed "Chipmunk") was designed to test and develop the multi-level control approach methodology. The Chipmunk is a single-story building with a rectangular plan of 800 m^2 (40 m × 20 m), as shown in Figure 2.

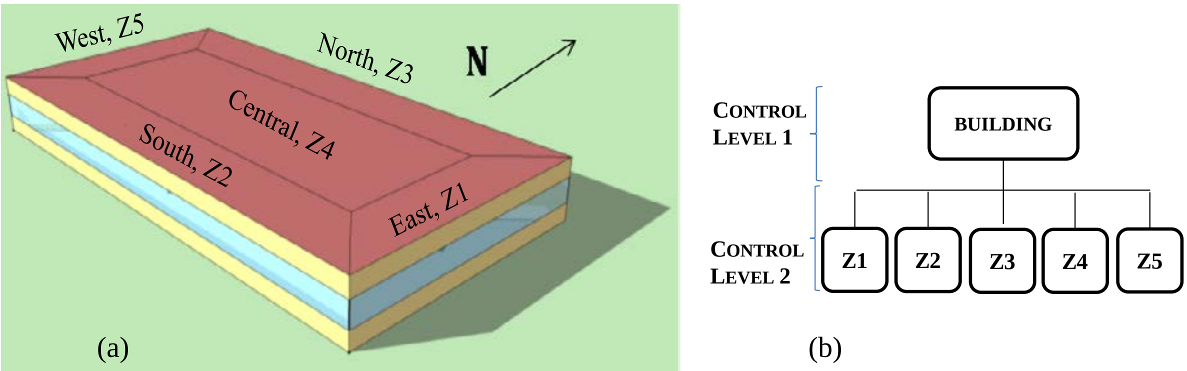

Figure 2. (a) EnergyPlus model of "Chipmunk" building; (b) control levels.

Other key features of the case study building are:

- Double-glazed windows, window/wall ratio ≈ 40%
- R-20 (RSI-3.53) in walls
- 0.80 ACH (infiltration + ventilation)
- Façades oriented towards the cardinal points

Proposed RC structures for thermal models

A previous preliminary paper by our team made use of sets of transfer functions (i.e., SISO systems) to model the response of the building and its zones (Candanedo and Dehkordi, 2013), which were obtained by using the MATLAB System Identification Toolbox. Such an approach, based on sets of transfer functions, has been used in previous studies on MPC for radiant floor heating systems (Candanedo and Athienitis, 2011) and ice storage devices (Candanedo et al., 2013b).

Instead of transfer functions, the present study uses 3rd order, grey-box, RC thermal networks to model the response of the building and its zones. Low-order RC networks represent a compromise between accuracy and physical significance (Candanedo et al., 2013a). Two slightly different RC structures are proposed for the two control levels (Figure 3).

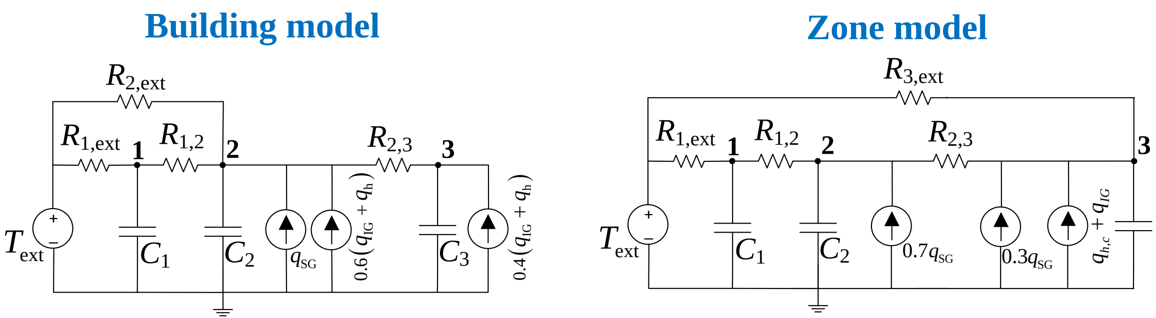

Figure 3. RC thermal networks for the building and zone levels.

These structures are not fixed. The selection of the structure and complexity level of the thermal network is left to the good judgment of the user, depending on the application.

From RC thermal network to state space representation

To find the values of the RC parameters in Figure 3, the first step was to develop a MATLAB code to convert the RC network into an equivalent canonical state-space representation. This state-space formulation was presented in a previous paper (Candanedo et al., 2013a). Three elements are needed in order to carry out this conversion: (a) information on the RC configuration; (b) information on the inputs (type of input, on which node they are acting); (c) information on the outputs (the information we are interested about).

First, the RC circuit configuration is described by following this convention in a text file: type of device (R or C), first node, second node and value of the element. The units for each of the elements are given in a consistent set of units. In this case, resistance is given in K/kW, and capacitance in kJ/K (resistances could be given in K/W and capacitances in J/K). For example, the zone model is described as:

```
C 1 0 99845.92
C 2 0 5751.61
C 3 0 1000.00
R 1 4 5.00
R 1 2 50.00
R 2 3 1.72
R 3 4 8.16
```

In this case, “C 1 0” refers to the capacitance connected between node 1 and the ground (namely C_1). Node #4 is the one to which the outdoor temperature (T_{ext}) signal is connected. The ground node or earth node (node 0) is the reference. The thermal capacitances connected to the ground node define the states of the system.

After describing the circuit, it is important to indicate: *inputs* (whether they are temperature or heat sources, and whether they act totally or partially on each of the nodes; and *desired outputs*. For the case of the inputs of the zonal model, the text file has this format:

```
T,4
Q,2,0.65,3,0.35
Q,3,1
Q,3,1
```

In this case, the file indicates that there are four inputs: (a) a temperature source connected to the 4^{th} node; (b) a heat source of which 65% goes to node 2 and 35% goes to node 3; (c) a heat source that is received in its entirety (100%) by node 3 and; (d) another heat source received by node 3. These sources represent, respectively, outdoor temperature, solar gains, internal gains and heating (the last two sources are interchangeable).

Finally, the desired outputs are defined by the following brief text file which simply means that there is a single output: the temperature of node 3.

```
T,3
```

Formulation of optimization problem

Once the circuit structure and the position inputs and outputs are defined, the state space representation can be readily found, and put into an optimization loop to determine the optimal RC values according to a given objective function.

The Euclidean norm is often used to compare vectors. The Euclidean norm (or Euclidean distance) is defined as the square root of the sum of the square of the elements, i.e.:

$$\|\mathbf{x}\| = \sqrt{x_1^2 + x_2^2 + \cdots x_M^2} = \sqrt{\sum_j x_j^2} \tag{1}$$

The Euclidean norm of the difference between the reference and the output of the simplified model can be used as one of the criteria to select the "best match" for an RC circuit response. In this case, the objective function is defined based on a comparison of the response of the RC and the EnergyPlus benchmark under three situations: (i) free floating conditions (outdoor temperature, solar gains and internal gains acting together); (ii) response to solar gains; (iii) response to internal gains.

$$J = 0.50\left\|\mathbf{y}_{\mathrm{ff,E+}} - \mathbf{y}_{\mathrm{ff,RC}}\right\| + 0.25\left\|\mathbf{y}_{\mathrm{SG,E+}} - \mathbf{y}_{\mathrm{SG,RC}}\right\| + 0.25\left\|\mathbf{y}_{\mathrm{IG,E+}} - \mathbf{y}_{\mathrm{IG,RC}}\right\| \tag{2}$$

In this case, more weight is given to the response under free floating conditions. Figure 4 summarizes the system identification procedure for the identification of RC parameters.

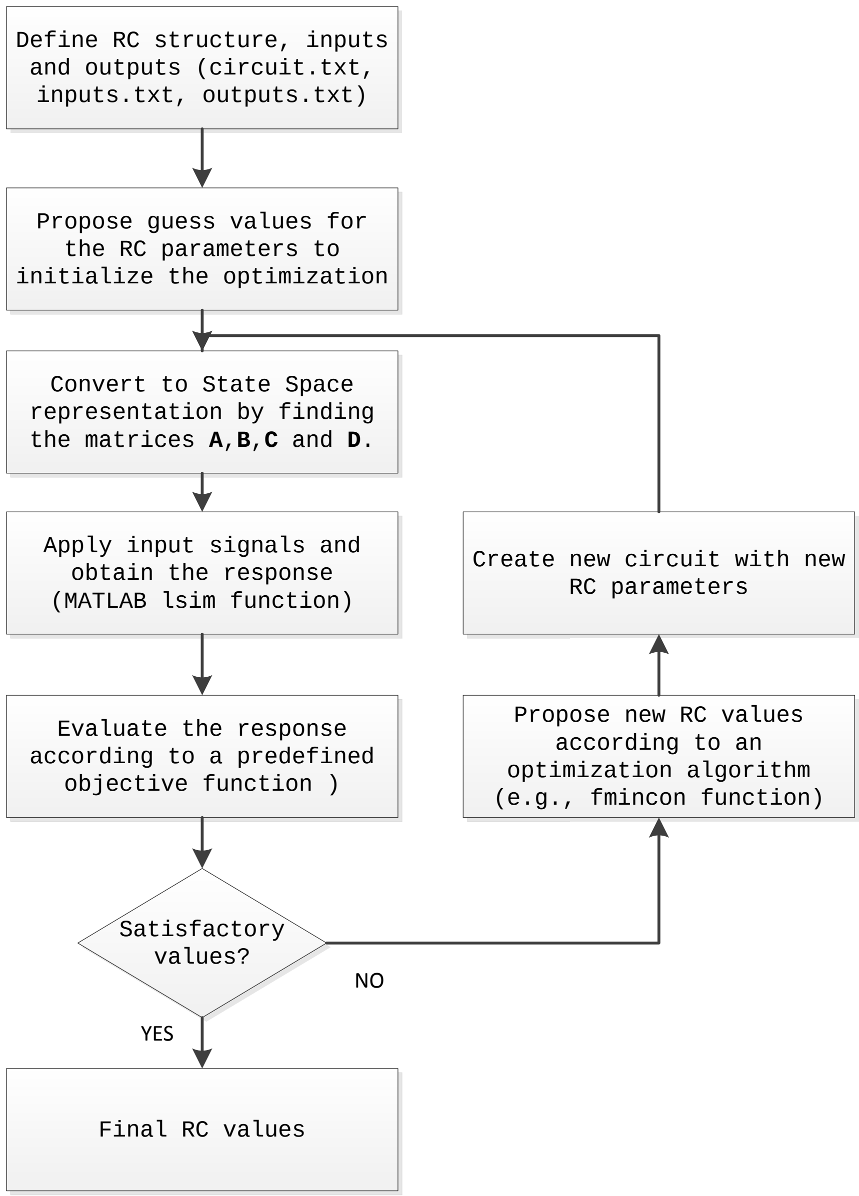

Figure 4. System identification procedure for RC parameters.

Figure 5 shows a comparison between the EnergyPlus and the RC models under free-floating conditions. The distribution of the error approaches a normal distribution with a mean value of $\mu \approx -0.15$ °C and a standard deviation of $\sigma \approx 1$°C.

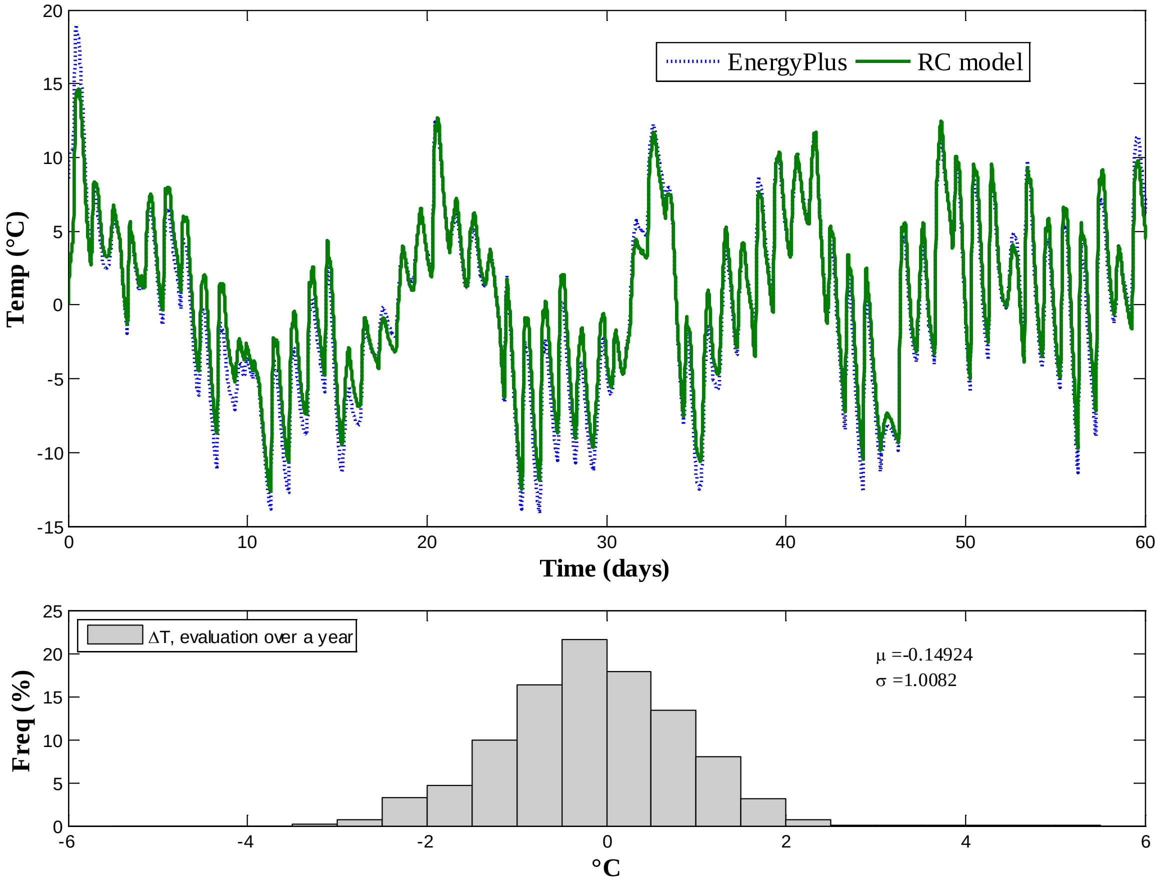

Figure 5. Free floating response of EnergyPlus and simplified RC model, zone 1.

Additional considerations in model performance

The performance of the identified RC circuits is quite satisfactory. However, there is significant room for improvement to reduce the discrepancies observed.

- **Updating of model states**. A direct comparison between EnergyPlus and the RC circuit, *while acting independently from each other*, is a conservative criterion to assess the performance of the RC circuit. In practice, the predictions of the RC circuit would be compared periodically with on-site measurements. In other words, by collecting data from the real building the new states (and outputs) predicted by the RC model can be corrected. This correction could be done either by simply introducing the new values or by using a more sophisticated method to weigh the confidence on the sensor measurements (e.g. a Kalman filter). This approach of continuous state correction would effectively result in better predictions, especially at shorter prediction horizons.
- **Design of system identification experiments.** While there has been interest in using simplified controls for many years, there is a need to develop a systematic procedure for the selection of the model order, structure and value of parameters. In particular, apart from the criteria proposed in Equation (2), other "virtual experiments" could be designed to test the validity of the model. These

experiments could include the response at particular frequencies (response at one-cycle per day), steady-state response ("effective R-value"), etc.

- **Free-floating versus controlled-conditions response.** The vast degree of fluctuation of a free-floating system (i.e., without a control system) implies that a model most perform very well under a wide range of conditions. In practice, the control model would operate in a much more restricted range of states.
- **Control-oriented model vs. simulation model.** The simplified RC circuit proposed is intended as a *control model*, in the sense that it will be used for decision-making over a limited prediction horizon (ranging from a few minutes up to a couple of days). Unlike a building simulation model, a control model is not intended to replicate the behaviour of a real building, but to serve as a tool to make better informed decisions.

Development of a multi-level architecture: prototype of emulator

Once the models for the building and the zones have been identified, they can be arranged in a multi-level architecture in a simulation environment. In this study, the models have been in a Simulink platform, with the goal of developing an emulator for testing and developing control strategies. The Simulink environment, an offshoot of MATLAB used for dynamic simulations, contains several drag-and-drop blocks for signal processing and control decisions. Other advantages include the possibility of selecting the method for the treatment of the differential equations (Euler, Runge-Kutta, etc.), the large availability of control tools (e.g., PID controls, system identification). While Simulink is a general tool that does not contain specific models building systems, programs developed in MATLAB can easily be incorporated.

This environment is comprised of the following elements:

- *Simulation models*, representing the response of the real building and zone. As a first attempt, these models are slight modifications of the previously identified RC circuits. Ideally, and planned for a later development, the simulation model will be replaced by an EnergyPlus simulation model, or at the very least a higher order state-space representation.
- *Control agents*, in charge of decision making. Each of these control agents contains its own *control model* (i.e., a previously identified RC model), which is then used to calculate loads, and then make control decisions for the allocation of resources in the energy storage elements. Figure 6 compares the two types of models to be used in the emulator.

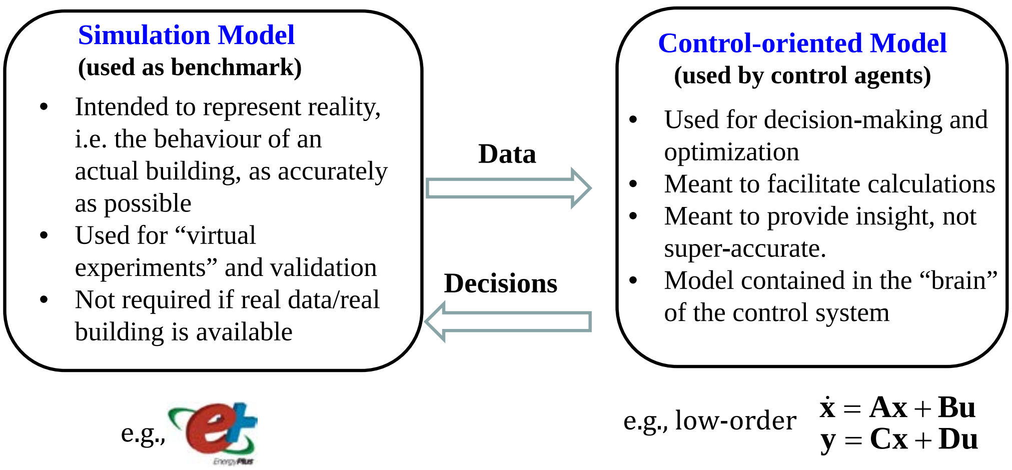

Figure 6. Types of models used in emulator.

- *Metronome or “time-keeper”*. This is a critical element that sends trigger signals to each of the control agents at regular intervals. These signals are sent to the control agents, which then proceed to execute an optimization exercise within its own jurisdiction and for its respective control horizon time scale. Table 1 shows typical time scales for different control levels.

Table 1. Example of time scales used.

Control level rank	Control level	Control horizon	Sampling time	Number of intervals
1	Building	24 h	1 h	24
2	Group control horizon	6 h	½ h	12
3	Room	½ h	5 min	6
NA	Simulation time step	1/24 h (2.5 min)	----	----

A screenshot of the prototype emulator under development is shown in Figure 7.

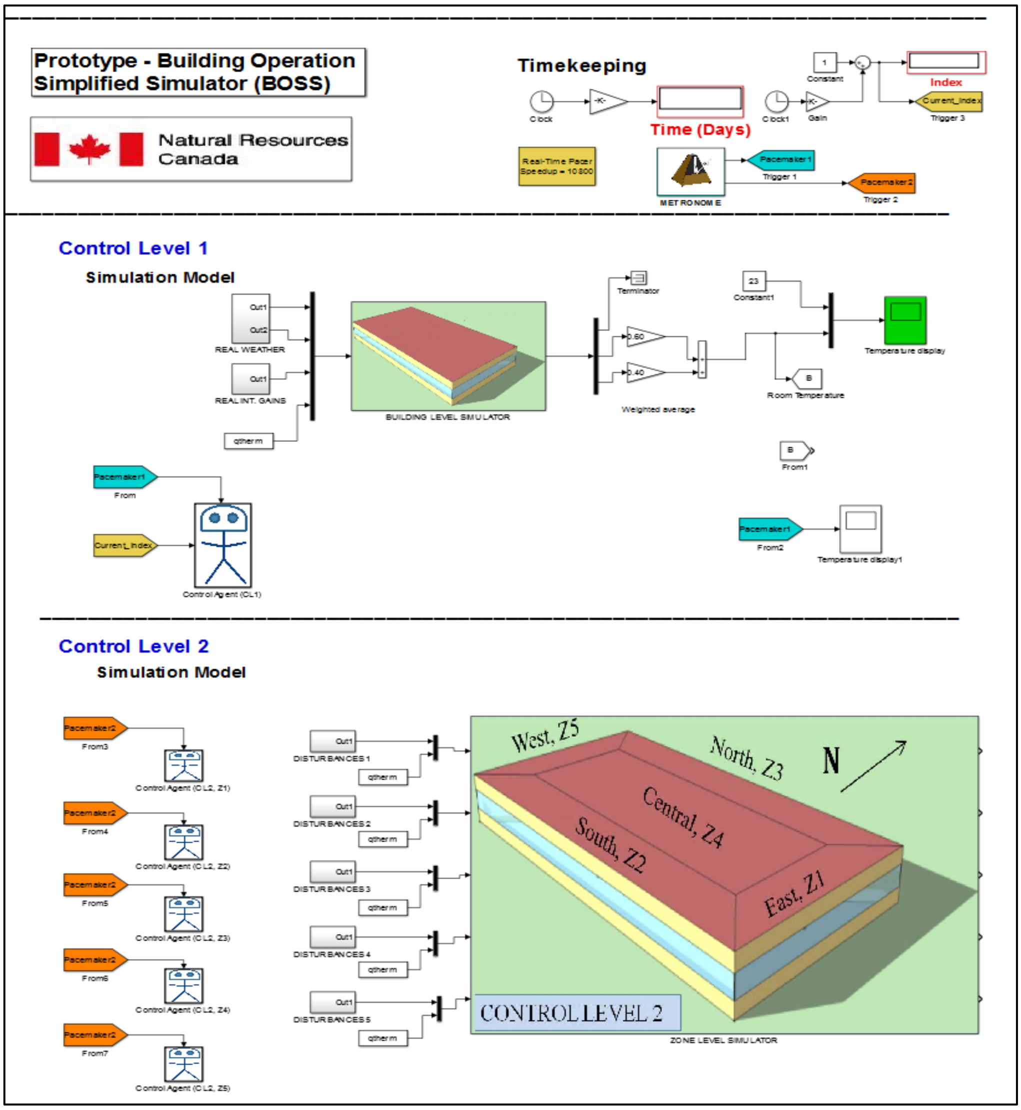

Figure 7. Screenshot of emulator prototype (under development).

The prototype emulator proposed in this study makes use of a Real-Time Pacer block (Vallabha, 2010), which allows the human operator to “slow down” the simulation to take a closer look at the response of the controllers and the building. For example, the simulation can be made to run so that 1 second of simulation time is equivalent to 1 day of “real time”.

Treatment of uncertainty

Several sources of uncertainty are present in the modelling of dynamic response of buildings for predictive control applications:

- **Uncertainty in the model**
    - *Source information*. construction details, thermal properties of materials, optical properties of surfaces, geometric details, furniture layout, etc.
    - *Simplifying modelling assumptions*. Even if perfect information were available, physical modelling –even the most detailed one– requires simplifications and approximations (e.g., , level of spatial discretization, etc.).
- **Uncertainty in the dynamic inputs**
    - *Weather forecast.* Although increasingly reliable (especially over a period of a few days) weather forecasts are obviously not exact. However, abundant information on the degree of confidence, based on the output of several weather forecast models, is becoming available.
    - *Occupancy and user loads forecast.* Perhaps the most difficult input to predict is the number of occupants and their energy consumption patterns. Nevertheless, in the case of control applications in existing buildings, occupancy patterns can be *observed* (e.g., how many people are present during weekdays). User loads (lighting or electric appliances) can be monitored if sub-metering is in place. This information becomes more reliable as more data is gathered during normal operation. Both occupancy and user load information can be presented in terms of probabilistic descriptions (Figure 8). Recent publications follow a stochastic approach (Widén and Wäckelgard, 2010).

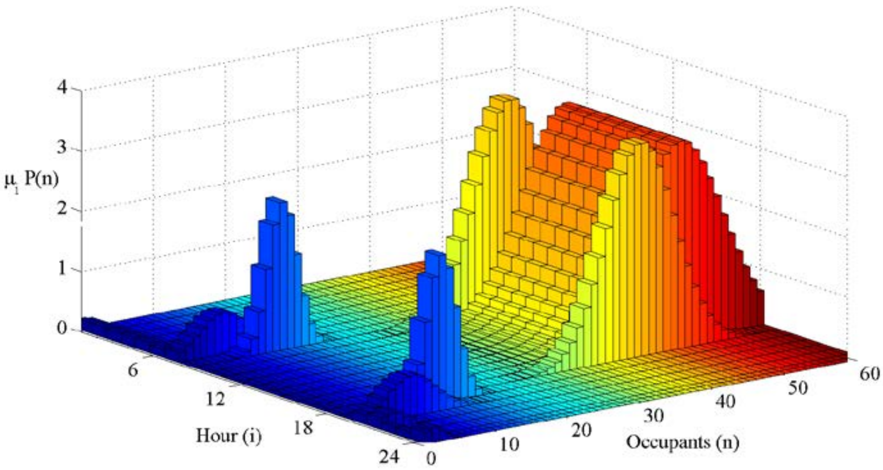

Figure 8. Example of occupancy modelling (sample values). A different probability distribution can be used for each hour of the day.

A key advantage of a distributed, hierarchical approach based on low-order models is that it facilitates the incorporation of uncertainty, and crucially, how to deal with it when making a decision concerning the operation of the building. A model with fewer parameters makes it easier to compare scenarios (for example, by running Monte Carlo simulations).

Ongoing work

At the time of writing, a number of tasks are under development for the emulator:

- Implementation of models for active thermal energy storage devices (e.g., brick thermal energy storage for heating and ice-storage for cooling).
- Implementation of automatic optimization algorithms that will be triggered at regular intervals according to signals received from the "metronome", according to the different prediction horizons. These optimization algorithms have already been tested "off-line" with M-files (Candanedo et al., 2013b).
- Formulation of the "negotiation" protocol between levels. Different "priorities" will be considered.
- Investigation of different approaches to deal with uncertainty, due to model inaccuracies and forecast errors; development of input signals related to occupancy and occupant behaviour.
- Implementation in a larger-scale model ("Elephant" model).

3 Conclusions

This paper has presented an overview of the basic principles of a multi-level architecture for the study of MPC and other advanced control concepts in building systems. This architecture is currently being applied in the development of an emulator tool. Also, this architecture will also be used in the development of "control agents" in charge of a control region.

Model-based control applications require continuous verification with data obtained on-site. Models for the building and its equipment should be made so that they can be easily modified when online data collection is available. Given the inherent complexity of buildings, it is difficult to assess *a priori* every possible factor having an impact on the building response. Rather than attempting to create a complex model with a "perfect" prediction, it is preferable to rely on a model with relatively few parameters. These parameters may receive kick-start guess values that may be easily corrected as soon as on-site data from the real building is available. Simpler models facilitate the mathematical treatment of uncertainty. As mentioned in the paper presented at ICEBO "rather than perfect accuracy, the goals pursued are logical structure and coherence" (Candanedo and Dehkordi, 2013).

Although low-order RC networks have been presented, the proposed multi-level architecture does not depend on a given kind of model. First-principle models, grey-box or artificial neural networks may be applied, although grey-box models may be more amenable for practical implementation. Using simplified models also allows shifting the attention of the control engineer towards the often-neglected issue of the quality of the dynamic input data. The emerging interest in the development of better models for prediction of occupancy and occupant behaviour is encouraging.

Apart from thermal models represented with linear networks, it is also necessary to incorporate models for other relevant phenomena (e.g., electric energy use, lighting, etc.). The multi-level control scheme will also be useful in this case.

This multi-level, distributed architecture also enables the study of fault scenarios. For example, if one of the zone control agents fails, the heating/cooling power calculated by the building model can be used to provide an estimate of the requirements of the zone.

An essential element in the concept of multi-level control is the incorporation of the different time scales and prediction horizons for each of the control levels. This methodology acknowledges the presence of patterns or cycles (weather, occupant behaviour) which repeat themselves at different periodic intervals, forming a juxtaposition of different "rhythms".

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