# A CONTROL-ORIENTED SIMPLIFIED BUILDING MODELLING STRATEGY

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## ABSTRACT

This paper discusses the development of a control-oriented simplified modelling strategy (COSMOS) for model-based predictive control (MPC) in buildings. In MPC, a model of the system is used along with forecast information for optimal planning. A model that is as simple as possible –but accurate enough for the purpose at hand– facilitates the implementation of an MPC strategy. This paper discusses desirable features of models intended for the specific needs of advanced control applications. A path for the creation of such models is presented, based on low-order resistance-capacitance (RC) thermal networks and their equivalent state-space formulation; such an approach provides physical insight while facilitating the treatment of the problem. The model parameters are found by applying an optimization to match the output of a building simulation model. Results include an assessment of the uncertainty of the model outputs.

## INTRODUCTION

In most buildings, the operation of mechanical and electrical systems is continuously adjusted in response to weather variations and the demands and behaviour of the building occupants. In this "reactive" approach, little or no planning takes place. However, this prevalent control paradigm is expected to evolve in the near future, given that factors such as the integration of renewable energy, real-time pricing and electric vehicles will require a flexible and dynamic interaction between buildings and the grid. On-site renewables (e.g., BIPV), energy storage and advanced controls will enable a better temporal match between energy supply and demand, thus reducing the cost associated with peak demand charges or real-time pricing profiles. To provide a closer link between the Smart Grid and Smart Buildings, a new approach to controls is needed.

With a reasonably accurate forecast of future weather and occupancy conditions, building models can be used to calculate building energy needs over a prediction horizon of up to a few days. This knowledge can then be used to decide on the optimal allocation of resources over time. A control approach using formal optimization algorithms to choose an optimal operation sequence based on a system model and forecast data (Figure 1) is called model-based predictive control, or MPC (Camacho and Bordons, 2004). MPC has successfully been used for decades in process control and chemical engineering (Qin and Badgwell, 2003).

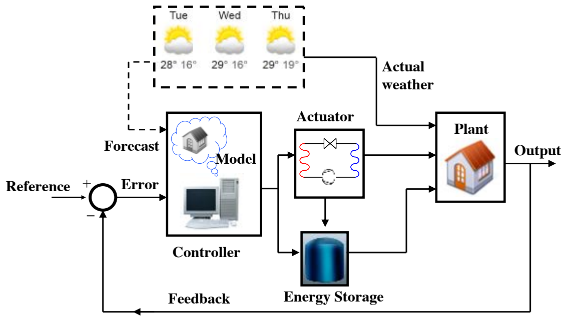


*Figure 1. Model-based predictive control (Candanedo et al., 2013) .*

Despite numerous research efforts on the application of MPC and other advanced control techniques in buildings, there is still a large gap between the potential of these techniques on one hand, and current control practices on the other hand (Cigler et al., 2012). This is due to multiple factors: among others, the lack of tools to easily incorporate weather forecasts into building automation systems; the scarcity of user-friendly software to test and develop control strategies in buildings; and the limited familiarity of building professionals with control engineering methods. Unlike other industries in which controls must work flawlessly at all times (e.g. aerospace), buildings are relatively more resilient to control faults. Although *conventional* control may not be up the task of managing a dynamic buildings/grid interaction, it is robust, inexpensive, easy to implement and often sufficient for maintaining comfort. Nevertheless, new realities will require advanced control strategies.

This paper discusses desirable features of appropriate models for advanced control in buildings, and proposes a method for their development by using building performance simulation as the starting point.

## CONTROL-ORIENTED MODELLING

Mathematical models are, primarily, problem-solving tools that may have many different objectives: feasibility studies, design, comfort assessment, optimization, development of controls, or simply better understanding of the system under study. Accordingly, modelling should be tailored to suit the needs of a given application. The approach proposed for a control-oriented simplified modelling strategy (COSMOS) is based on these guiding principles:

- Preference towards simple and physically meaningful models.
- Selection of modelling resolution considering objectives, controllable variables, and time constants involved.
- Parameters chosen to improve predictions for control-appropriate time-scales (minutes-days).
- Adjustment of model parameters in real time.
- Rapid generation of control-oriented models, often with limited information.
- Facilitation of automatic formulation of optimal control problems.
- Quantitative assessment of output uncertainty.
- Allowance for stochastic representations of inputs (e.g., weather, occupancy, etc.).
- Common language for communication between building specialists and control engineers.

### Some Advantages of Simplified Models

Models with fewer parameters facilitate setting-up initial conditions, a key consideration in controls. In simulations intended for design, a long "warming up period" is applied; furthermore, when the main goal is the calculation of annual energy use, initial conditions are relatively secondary. In contrast, since a control-oriented model is intended to predict the system response over a short term (e.g., hours), precisely knowing the "starting point" precisely is important. In an actual control installation, sensor measurements (e.g., temperatures) can be used to easily set the initial states of a simplified model at the beginning of each prediction horizon.

In the case of linear models, a straightforward biunivocal correspondence can be established between a set-point profile and a cooling/heating curve. Simpler models facilitate code debugging and interpretation of results. They also reduce the number of calculations required by optimization algorithms.

As discussed below, simplified models have been applied before to the study of advanced building controls. However, a systematic methodology to generate simplified models for control applications is still needed.

## LITERATURE REVIEW

### Building Modelling for Optimal Control

Optimal control for buildings has been investigated at least since the 1980s. It has often been based on simplified models. Nizet et al. (1984) described an optimal control strategy for air conditioning based on a simple thermal network and its equivalent state-space representation. Approaches based on simplified linear models were followed by Paassen (1988) and Vinot (1989). Braun (1990) proposed an optimal control strategy for cooling, taking advantage of the building thermal mass; Braun used a comprehensive room transfer function to model the building, as developed by Seem et al. (1989). Also, typical load profiles have been used in optimal control for cooling systems with ice storage (Henze et al., 1997).

### Simple RC Networks and Other Linear Models

Bénard et al. (1992) used system identification techniques to create low-order RC models. Kummert et al. (1996) proposed the use of simplified RC thermal networks for solar buildings. Madsen and Holst (1995) proposed a second-order RC circuit and a state-space representation for a residential building. Antonopoulos and Koronaki (1998) investigated the concept of effective thermal capacitance, a useful notion for simplified modelling. Gouda et al. (2002) investigated how to reduce the order of complex RC networks by applying optimization algorithms. Fraisse et al. (2002) investigated simple RC circuits for wall models. Wang and Xu (2006) studied the identification of a simple RC network for a commercial building. Recently, Bacher and Madsen (2011) investigated an iterative method for the determination of RC models.

Although not specifically focused on control applications, Jiménez et al. (2008) investigated the system identification of time-series models and building parameters. Other studies on simplified models include Mustafaraj et al. (2009), and Berthou et al. (2012). A review on simplified building models, not necessarily control-oriented ones, was recently published (Kramer et al., 2012).

### Recent Studies on MPC for buildings

Over the last decade, numerous studies have investigated MPC for small and mid-size buildings by using linear models in any of their different formulations: state-space models (Kummert et al., 2001, Kim and Braun, 2012); simple RC networks (Gyalistras and OptiControl Team, 2010, Lee and Braun, 2004, Verhelst et al., 2011); time-series (Freire et al., 2008, Donaisky et al., 2007, Morosan et al., 2010); or continuous or discrete transfer functions (Candanedo and Athienitis, 2010).

In recent years, the control engineering community has shown significant interest on MPC for buildings, e.g. Oldewurtel et al. (2012), Ma et al. (2010), Nghiem and Pappas (2011), Siroký et al. (2011), and Balan et al. (2011), among many others.

The direct linking of building simulation and control software (co-simulation) has been proposed for MPC in buildings (Wetter and Haves, 2008, Nghiem, 2010, Hoes et al., 2012). Other studies have pointed out the importance of modelling for predictive control, and the use of simplified models as a viable alternative (Prívara et al., 2012, Kim and Braun, 2012).

## METHODOLOGY

The procedure presented here for the creation of control-oriented models is based on the assumption that the building behaves mainly as complex linear network that may be approximated with a simpler linear one (Bacher and Madsen, 2011). The methodology consists of the following steps:

a. A detailed model is created with a building simulation tool (e.g., EnergyPlus).
b. A simplified model is proposed, in which the building response depends on a few key input variables with significant impact.
c. Virtual experiments are used to study the effect of these inputs on the building.
d. With the resulting input and output vectors, system identification techniques are used to find the parameters of a proposed RC structure.
e. The RC circuit model is written in a standardized state-space formulation. The temperatures of the nodes with capacitances are selected as the state variables to facilitate physical interpretation.
f. The simplified model predictions are compared with those of EnergyPlus. The uncertainty of the simplified model predictions is then assessed.
g. The simplified model is validated by comparing its predictions with the results of EnergyPlus with a different weather file.

### a. Building Simulation Model

Figure 2 shows the building model used for system identification. This 800-$m^2$ building is simulated in EnergyPlus with five zones (central, north, east, west and south). Similar models are commonly used in building simulation studies, including recently on modelling for controls (Radecki and Hencey, 2012). The insulation, schedules and other features of the building correspond to typical office buildings.

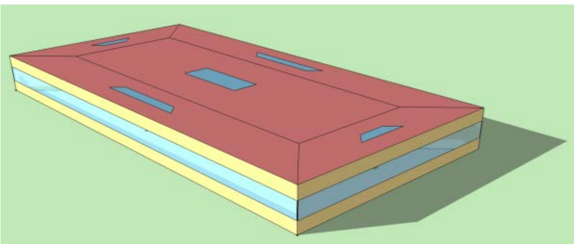

*Figure 2. E+ model used for system identification.*

### b. Input and Output Variables

In the present study, the selected outputs are the average *operative temperature* of the perimetral zones ($T_{op,per}$) and the operative temperature of the central zone ($T_{op,cent}$). The chosen inputs are: solar gains ($q_{SG}$), sensible internal gains ($q_{IG}$), outdoor temperature ($T_{ext}$), heating power ($q_h$) and sensible cooling power ($q_c$). For the zone models, the mean temperature of adjacent zones ($T_{adj,i}$) is also used. Cooling power is not considered in the current paper. Figure 3 shows the input and output variables used.

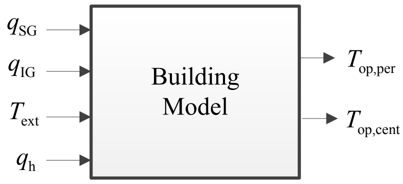


*Figure 3. Inputs and output for the building model.*

Evidently, other factors have an impact on the indoor temperature: e.g., infrared heat loss to the sky, ground temperature, solar radiation on exterior surfaces and wind speed. They are not used as inputs since they are either (a) strongly correlated with other variables; (b) can be easily accounted for, if required, as a temperature offset (the case of ground temperature); (c) or can be included as part of the noise. Furthermore, choosing a few relevant and easily measurable variables, while quantifying uncertainty, makes the model more flexible and practical for control applications.

### c. Virtual Experiments

The model created with EnergyPlus can be used to run "virtual experiments" that provide significant insight on the thermal dynamics of the building and the effect of the input variables.

While it is possible to study the building response with several inputs acting simultaneously, it is useful to consider the independent effect of each input. This can easily be done in a simulation tool by "turning off" other inputs. For example, to determine the effect due to solar gains, the temperature in the weather file is set to a constant 0 °C, internal heat gains are set to zero and the HVAC equipment is turned off. After running the EnergyPlus simulation, the results become available as vectors of inputs and outputs. Figure 4 shows a plot of the input (solar gains) and outputs of interest: (i) the average of the operative temperatures in the perimeter zones ($T_{op,per}$) and (ii) the operative temperature of the central zone ($T_{op,cent}$). The effect of several inputs can be obtained by superposition.

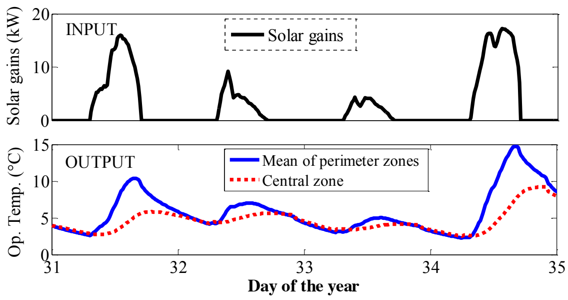


*Figure 4. Solar gains forcing function (input) and corresponding response (output).*

In this study, the operative temperature response of the building under free floating conditions (without heating) is used as the main criterion for system identification.

**d. System Identification**

Once the vectors of inputs and output values are collected, a system identification procedure is applied. A third-order thermal network structure is proposed (Figure 5). Although a data-driven set of transfer functions or a "black-box" state-space model would be sufficient for the mathematical operations used in controls, RC circuits facilitate the physical interpretation of the results. Nevertheless, one must keep in mind that rather than "exact" parameters, the R and C values may be considered "equivalent" or "effective" numbers.

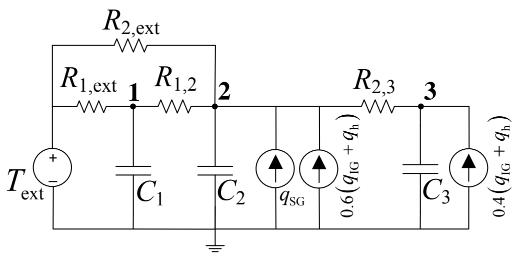


*Figure 5. Equivalent RC network, whole building.*

In Figure 5, $C_1$ stands for the equivalent thermal capacitance of the building envelope, $C_2$ represents the equivalent thermal capacitances of the perimetral zones, and $C_1$ is the equivalent thermal capacitance of the central zone. $T_2$ and $T_3$ respectively represent the operative temperatures of the perimetral and central zones. Solar gains are received by the perimetral zones (node 2). Node 2 also receives 60% of the internal gains and heating power, while 40% is received by node 3. These percentages are an approximation based on the zone floor area; other splits are possible. The outdoor temperature is connected to the lumped capacitance of the building envelope (node 1) through $R_{1,\text{ext}}$; it is also connected to node 2 through elements with negligible thermal mass (windows, doors) and the effect of infiltration, both represented with $R_{2,\text{ext}}$. The equivalent thermal resistances between nodes are $R_{1,2}$ and $R_{2,3}$.

The circuit in Figure 5 should not be understood as a perfect representation of first principles, but as a compromise between simplicity and the preservation of physical sense. More details could be added to the model depending on the needs of the user.

Let the "measured" outputs from EnergyPlus be $\mathbf{y}_1$ (operative temperature of node 2) and $\mathbf{y}_2$ (operative temperature of node 3), where the bold font indicates a *vector* of values. The outputs of the RC circuit are represented with a circumflex accent (^). To find the RC parameters, the outputs of the simplified RC circuit and the EnergyPlus models are compared. Considering $q$ output variables, the objective function is defined in this paper as:

$$J(\mathbf{y}_1, \hat{\mathbf{y}}_1, \cdots, \mathbf{y}_q, \hat{\mathbf{y}}_q) = \sum_{i=1}^{q} \left\| \mathbf{y}_i - \hat{\mathbf{y}}_i \right\| = \sum_{i=1}^{q} \left\| \mathbf{e}_{T_i} \right\| \quad (1)$$

where the vertical bars represent the Euclidean or 2nd norm operator. The Euclidean norm of a vector $\mathbf{x}$ with $M$ elements is defined as:

$$\|\mathbf{x}\| = \sqrt{x_1^2 + x_2^2 + \cdots x_M^2} = \sqrt{\sum_j x_j^2} \quad (2)$$

In this case, in which only two outputs are taken into account ($T_2$ and $T_3$), the objective function is:

$$\begin{aligned} J(\mathbf{y}_1, \hat{\mathbf{y}}_1, \mathbf{y}_2, \hat{\mathbf{y}}_2) &= \|\mathbf{T}_2 - \hat{\mathbf{T}}_2\| + \|\mathbf{T}_3 - \hat{\mathbf{T}}_3\| \\ &= \|\mathbf{e}_{T_2}\| + \|\mathbf{e}_{T_3}\| \end{aligned} \quad (3)$$

The objective function of equation (3) may be modified to emphasize the fitting at specific times of the year, to attribute more weight to some inputs, or to account for the response at specific frequencies (e.g. daily cycles or steady state). The resulting optimization problem may be solved by any suitable method. In this case, a commercial software package, MATLAB Optimization Toolbox™, was used (Mathworks, 2012).

**e. Canonical State-Space Representation**

State-space representations, which describe systems of linear differential equations in a compact manner, are often used in control applications. They have been used in building modelling (Madsen and Holst, 1995) A state-space model consists of a set of two matrix equations written in terms of three vectors: a state vector $\mathbf{x}$ with $n$ elements; an input vector $\mathbf{u}$ with $p$ elements; and an output vector $\mathbf{y}$ with $q$ elements. These vectors are linked by four matrices, $\mathbf{A}$ ($n \times n$), $\mathbf{B}$ ($n \times p$), $\mathbf{C}$ ($q \times n$) and $\mathbf{D}$ ($q \times p$):

$$\begin{aligned} \dot{\mathbf{x}} &= \mathbf{A}\mathbf{x} + \mathbf{B}\mathbf{u} \\ \mathbf{y} &= \mathbf{C}\mathbf{x} + \mathbf{D}\mathbf{u} \end{aligned} \quad (4)$$

Although the possibilities for choosing the state variables are technically infinite, in RC thermal networks it is convenient to use the temperatures of the nodes with thermal capacitances. Such a state-space formulation, equivalent to the well-known finite difference method, facilitates the mathematical treatment of the problem.

A third order model, such as the one in Figure 5, is defined by three state variables. With this state-space formulation, initial conditions can be easily set-up since they are equal to the nodal temperatures at the beginning of the simulation. The state, input and output vectors are:

$$\mathbf{x} = \begin{bmatrix} T_1 \\ T_2 \\ T_3 \end{bmatrix}, \quad \mathbf{u} = \begin{bmatrix} T_{\text{ext}} \\ q_{\text{SG}} \\ q_{\text{IG}} \\ q_{\text{h}} \end{bmatrix}, \quad \mathbf{y} = \begin{bmatrix} T_2 \\ T_3 \end{bmatrix} \quad (5)$$

The matrices $\mathbf{A}$ and $\mathbf{B}$ can be found by writing the energy balance differential equations for each node in terms of thermal conductance ($U$). For example, considering the energy balance in node 1:

$$\frac{dT_1}{dt} = \frac{1}{C_1}\left[U_{1,\text{ext}}\left(T_{\text{ext}} - T_1\right) + U_{1,2}\left(T_2 - T_1\right)\right] \quad (6)$$

By writing the energy balance for the all the nodes:

$$\mathbf{A} = \begin{bmatrix} -\frac{U_{1,\text{ext}} + U_{1,2}}{C_1} & \frac{U_{1,2}}{C_1} & 0 \\ \frac{U_{1,2}}{C_2} & -\frac{U_{2,\text{ext}} + U_{1,2} + U_{2,3}}{C_2} & \frac{U_{2,3}}{C_2} \\ 0 & \frac{U_{2,3}}{C_3} & -\frac{U_{2,3}}{C_3} \end{bmatrix} \quad (7)$$

$$\mathbf{B} = \begin{bmatrix} \frac{U_{1,ext}}{C_1} & 0 & 0 & 0 \\ \frac{U_{2,ext}}{C_2} & \frac{1}{C_2} & \frac{0.6}{C_2} & \frac{0.6}{C_2} \\ 0 & 0 & \frac{0.4}{C_3} & \frac{0.4}{C_3} \end{bmatrix} \quad (8)$$

The matrices **C** and **D** depend on the outputs of interest. In this case, the outputs are $T_2$ and $T_3$ (equal to states 2 and 3), and there is no *direct* impact from the input variables on the outputs.

$$\mathbf{C} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}; \quad \mathbf{D} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad (9)$$

For the general case of RC thermal networks whose states are the temperatures of nodes with capacitances, the matrix A is given by:

$$\mathbf{A} = \mathbf{M}_{\text{cap}}^{-1}\mathbf{U} \quad (10)$$

where the matrix $\mathbf{M}_{\text{cap}}$ is given by:

$$\mathbf{M}_{\text{cap}} = \underbrace{\begin{bmatrix} C_1 & 0 & \cdots & 0 \\ 0 & C_2 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \cdots & 0 & C_n \end{bmatrix}}_{\text{Capacitance matrix}} \quad (11)$$

A particularity of RC thermal networks is that all the capacitances are connected to the ground (i.e., the reference temperature, which is often 0 °C). As a result, the capacitance matrix $\mathbf{M}_{\text{cap}}$ is a diagonal matrix, since it only has non-zero elements in its main diagonal, which also means that it is always invertible. The inverse of a diagonal matrix is found by simply replacing each of the elements in the main diagonal by its reciprocal ($C_1$ by $1/C_1$, etc.).

The matrix **U** is the well-known conductance matrix (note: $r$ is the number of temperature source nodes):

$$\mathbf{U} = \underbrace{\begin{bmatrix} -\sum_j^{n+r} U_{i,j} & U_{1,2} & \cdots & U_{1,n} \\ U_{2,1} & -\sum_j^{n+r} U_{2,j} & \cdots & U_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ U_{n,1} & U_{n,2} & \cdots & -\sum_j^{n+r} U_{n,j} \end{bmatrix}}_{\text{Conductance matrix}} \quad (12)$$

The state matrix **A** defined in equation (10) has a useful property for simulations: its main diagonal defines the time constants associated with each capacitance, and thus the critical time step of the system. The elements of the main diagonal are:

$$a_{i,i} = \frac{-\sum_j^{n+r} U_{i,j}}{C_i} = -\frac{\text{sum of the conductances connected to this node}}{C_i} \quad (13)$$

The critical time step is:

$$\Delta t_c = \min\left(\frac{1}{|a_{i,i}|}\right) \quad (14)$$

The matrix **B** is given by:

$$\mathbf{B} = \mathbf{M}_{\text{cap}}^{-1}\mathbf{S} \quad (15)$$

where the matrix **S** is a “source matrix”. Each element $s_{i,j}$ describes the effect of a source $j$ acting on a node $i$. For a *heat source*, the element ($i$, $j$) of the matrix is given by:

$$s_{i,j} = \alpha_{i,j} \quad (16)$$

where $\alpha_{i,j}$ is the fraction of the source $j$ absorbed by node $i$. For a *temperature source* $j$ linked to the node $i$ with a conductance, the element ($i$, $j$) is given by:

$$s_{i,j} = U_{i,j} \quad (17)$$

The matrices **C** and **D** will be chosen depending on which outputs the user is interested about.

### f. Comparison and Uncertainty Estimation

Once the R and C values are determined, a statistical comparison of the outputs of the model and the detailed simulation is performed. Such a comparison gives *an idea* of the simplified model uncertainty, since a true uncertainty assessment implies a comparison with the *real* building response.

### g. Validation

Finally, the performance of the simplified model is tested with a different data set. This can be done by running an EnergyPlus simulation with a different weather file, and comparing its results with those of the simplified model.

## RESULTS

Table 1 shows the RC values providing the best agreement with the results of an EnergyPlus simulation (training data: Montreal weather file).

*Table 1. Parameter values for simplified model.*

| **Capacitances (kJ/K)** | | **Resistances (K/kW)** | |
|---|---|---|---|
| $C_1$ | $8.745 \times 10^7$ | $R_{1,ext}$ | $5.926 \times 10^{-4}$ |
| $C_2$ | $7.864 \times 10^3$ | $R_{1,2}$ | 5.743 |
| $C_3$ | $3.048 \times 10^4$ | $R_{2,3}$ | 0.468 |
| | | $R_{2,ext}$ | 1.388 |

Valuable insight may be gained from these values. The effective capacitance of node 2 is only 25% of that of node 3, which indicates that the temperature of central zone changes more slowly than that of the perimetral zones. The resistance $R_{2,ext}$ (infiltration + windows) is also about one-quarter of the resistance of the opaque parts of the building envelope.

The free floating responses (i.e., without heating) for $T_{op,per}$ ($T_2$) of the EnergyPlus and RC models, using a Montreal weather file, are shown below in Figure 6. In general, there is good agreement between them.

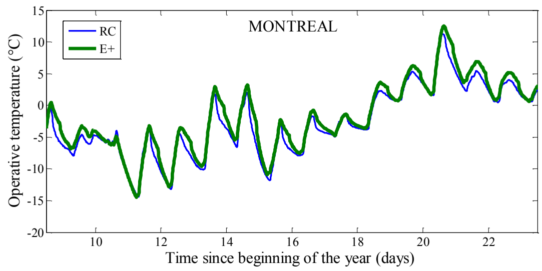


*Figure 6. Free floating response (Montreal), average of perimetral zones (EnergyPlus) and $T_2$ (RC).*

Figure 7 compares the daily heating energy found by EnergyPlus and the RC circuit for a few days in January (Montréal weather file), with an operative temperature set-point of 21 °C. It was found that the error of daily heating needs has a mean value of nearly 0%, and a root mean square error deviation (RMSD) of 5%. This information could be used to model the error as a random variable having a normal probability distribution with $\mu \approx 0$ and $\sigma \approx 5\%$. Error bars for this uncertainty margin are also shown.

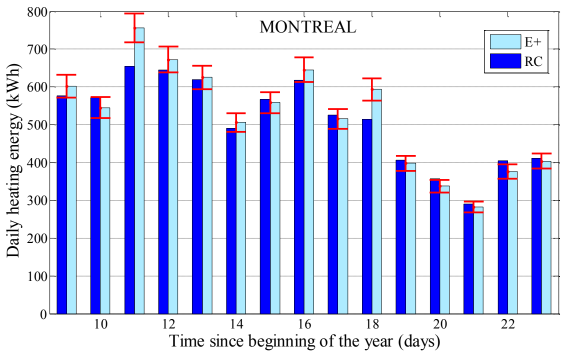


*Figure 7. Daily heating energy with EnergyPlus and simplified RC circuit, training data set (Montréal).*

A validation exercise was carried out with a different weather file (Ottawa, Canada). The free floating responses in this case are shown in Figure 8.

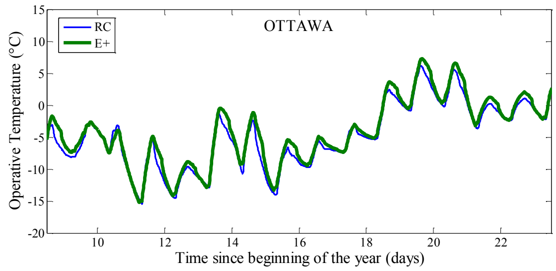


*Figure 8. Free floating response (Ottawa), average of perimetral zones (EnergyPlus) and $T_2$ (RC).*

Figure 9 shows good agreement between the heating energy needs predicted for the Ottawa weather, as calculated with EnergyPlus and the RC circuit.

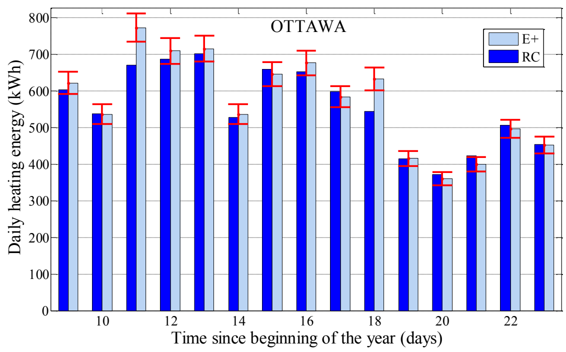


*Figure 9. Daily heating energy with EnergyPlus and simplified RC circuit, validation data set (Ottawa).*

## FINAL REMARKS

This paper has presented an example of a control-oriented simplified modeling strategy (COSMOS). This strategy, developed in the context of a long-term MPC research project, proposes: (i) using "grey-box", thermal network models; (ii) determining equivalent (rather than strictly physical) parameters; (iii) finding these parameters through an optimization routine; (iv) using a standardized state-space representation, as a link between building modelling and control engineering; (v) estimating uncertainty. This methodology may be easily implemented in building simulation tools to automatically generate simplified models. While analytical mathematical order-reduction techniques may be used to derive simpler models from complex networks, numerical optimization suffices to accomplish this task.

The RC thermal circuit presented in this paper is intended to illustrate the methodology. The layout of the circuit is, of course, not fixed; the number of nodes and their arrangement may vary depending on the requirements of the control strategy and other factors (e.g., time scale, energy storage device). The use of simple, partially data-driven models does not imply sacrificing insight: on the contrary, these models should be based on a sound understanding of the physics of the problem being studied.

A low-order linear network in which each of the states and parameters has a physical interpretation is not an absolute requirement, but it does offer some advantages. For example, having a small number of physically-meaningful state variables facilitates the task of setting-up the initial state vector ($\mathbf{x}_o$) at the beginning of each prediction horizon, by making use of sensor measurements.

Further research is needed on simplified models for building control applications. Building simulation tools can certainly play an essential role in this effort. The potential for scalability of this method is worth exploring: e.g., it may be used for load prediction of building clusters or communities or for modelling parts of a building (zonal models). Also, statistical analysis of large databases of building simulation models may allow the identification of archetypical thermal networks, and determine correlations between the building geometry and material properties and the corresponding RC parameters.

## ACKNOWLEDGEMENTS

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