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Control-Oriented Modelling of Thermal Zones in a House: A Multi-Level Approach

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ABSTRACT

This paper investigates the use of a multi-level simplified linear thermal modelling approach based on the electrical analogy for the development of control strategies in conventional detached residential homes equipped with convective electric heating systems. These models are developed from parameter identification of results obtained through comparison with whole building measured data. Although detailed building simulation models can be used directly for testing control strategies, this approach can be quite computationally intense and time consuming thus simplified models become advantageous. The aim of this work is to present a methodology to allow a user to switch back and forth between thermal models representing different control levels according to the modelling objectives. Different control levels include, but are not limited to, community simulation studies, whole building studies, or zone-level studies. Zone-level models take into account inter-zonal heat transfer. From these simple models, useful information can be extracted without performing any simulation, and this is also explored in this paper.

1. INTRODUCTION

This paper presents a multi-level approach to the problem of modelling different thermal zones in a house for control applications. This problem has been treated before by modelling the whole house with a single, all-inclusive RC thermal circuit which may have different levels of resolution. The core feature of the proposed methodology allows the user to switch back and forth between models representing different control levels according to the modelling objectives.

For the development of specific control algorithms for each zone, the house can be treated as a collection of interconnected zonal models, as opposed to a single, large model. This modelling approach has the advantage of maintaining a simple structure for each zone, while also taking into account the heat transfer between zones; at this control level, issues such as occupancy, thermal comfort or setpoint profiles can be examined in more detail. On the other hand, if the user is interested in a quick estimate of global variables (e.g., overall thermal load over the next 24h) then different zones or even the entire house may be combined into a single low-order model. In summary, this multi-level approach allows the user to "zoom in and out" so that models at each control level remain manageable, easy to calibrate and easy to physically interpret.

Suitable simplified multi-zone thermal models enable a rapid assessment of control strategies targeting energy reduction, or occupant thermal comfort (Bacher and Madsen, 2011; Candanedo *et al*., 2010; Lin *et al*., 2012; Wang and Xu, 2006) and advanced control strategies could greatly benefit from adequate, simple models (Sturzenegger *et al*., 2016). One common approach for simplified building modelling is grey-box RC thermal networks (Inderfurth *et al*., 2015), where system identification techniques are used to determine effective resistance and capacitance values for the model. Model predictions should be meaningful for energy and power results for the whole building level or at the zone level. Zone level detail allows for even greater potential for advanced controls. Besides energy conservation measures, there is interest in ways to reduce peak power demand (due to space heating or cooling) at critical times (Fournier and Leduc, 2014; Leduc *et al*., 2011). Simplified thermal models of buildings also offer advantages for district modelling (Baetens *et al.*, 2015; Lauster *et al.*, 2014). Simplified models allow for rapid simulation of complex and/or large systems with acceptable accuracy and benefit from quicker calibration procedures (Kummert *et al*., 2006).

This paper uses data from an existing unoccupied test house, representative of a typical family home in Québec, Canada, as a case study. Four zones are considered: basement, main floor, upper floor and attached garage. All interior doors were kept closed during experimentation and data collection, so as to minimize horizontal zonal heat transfer. For the most detailed analysis, these zones are modelled with four detailed interconnected zone models; alternative methods of connecting zones are investigated in a previous paper (Date *et al.* 2016). A global low-order whole house model is used to calculate the thermal load of the house. Results of thermal load predictions are compared and resolution of the global whole house model is investigated.

2. METHODOLOGY

The methodology employed for the identification, inspection and validation of simplified multi-zone models consists of the following steps:

- Experiments were conducted at unoccupied test homes to get data for comparison with models.
- A global low-order house model was developed and used to calculate the thermal load of the building.
- A detailed zone-level model was developed to represent the real building and used as a benchmark.
- A Simplified zone-level model was created and the connections between zones are studied.
- Unknown values of parameters of the building models were identified through system identification.
- The simplified thermal model predictions were compared with measured experimental data and the zone-level detailed model predictions.

2.1 Building Thermal Modelling Assumptions

Thermal models based on the physics of the system (typically in the form of resistance-capacitance (RC) models) are useful for control studies in buildings. Values of parameters are identified through an optimization technique, and should be interpreted as "effective" values rather than "exact" physical parameters (Candanedo *et al*., 2013). Model details could be added or taken away depending on the needs of the user. Some important assumptions used to construct simplified thermal RC networks include:

- The temperature of each surface or cross section is uniform.
- The air in each zone is well mixed.
- Radiative and convective heat transfers are combined and constant.
- Air is a non-participating medium with respect to radiation.
- Conduction between each window and window frame is neglected

An optimization algorithm is used to determine unknown parameters, therefore fewer equations is helpful. Several methods are available to reduce the complexity of a model: merging thermal zones, reducing the discretization of the walls, and merging several walls to combined surfaces.

2.2 Benchmark Model (Detailed Model)

A benchmark detailed model (DM) has been developed consisting of 4 zones, with separated walls, windows, doors, resulting in 32 capacitances. A zone represents a level/storey of the house, shown in Figure 3. Figure 1 shows one zone (floor) of the detailed model (DM) for floor-level modelling. A zone model such as that in Figure 1 represents, for example, the main floor (Zone 2) which is connected to a model depicting the upper floor (Zone 1) and another model representing the basement level (Zone 3) via inter-zonal convection and conduction terms, thus creating a very detailed multi-zone model of the building. Several models can be connected to create a multi-zone model via "$T_{adjacent}$" terms. The thermal mass of the envelope is modeled as a single layer (i.e. one capacitance). This model can be seen as the benchmark model or used as the "real building" in MPC simulation-based studies.

Models of similar detail/structure can represent either the whole building or just a section of the building (floor, room, etc). In this study, models are connected via inter-zonal convection and conduction terms to create a multi-zone model at the floor-level detail with a total of four zones. This section outlines two modelling levels investigated in this paper: (i) the floor-level and (ii) the whole building-level. This approach can be expanded in either direction of detail, to zooming out to the community-level, or with further detail at the individual room-level.

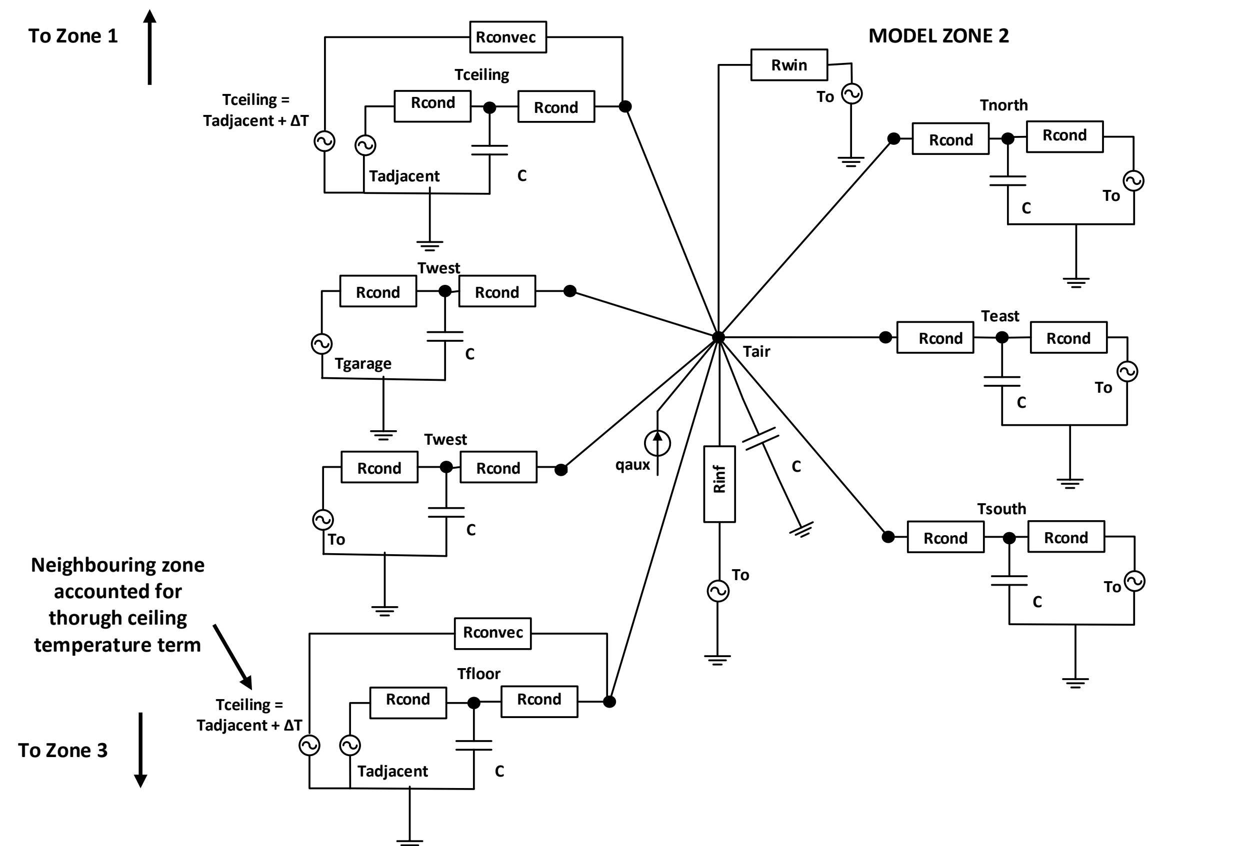

Figure 1: Thermal network of detailed model (DM) for one zone

Figure 3 depicts the system inputs and outputs for the floor-level model. Each zone (floor) is modelled separately and these individual zone models are then connected to one another via inter-zonal convective and conductive terms to create a multi-zone model of the whole building. The system outputs of one zone (i.e. zone air temperature) effectively become system inputs to another adjacent zone. For this study, solar radiation as an input was neglected since the experimental setup effectively blocked the influence of solar radiation (Date *et al.,* 2016).

3. MULTI-LEVEL THERMAL MODELLING APPROACH

3.1 Simplified Floor-Level Model

The simple floor-level model combines surfaces into effective areas, creating 14 capacitances for the whole house model. The thermal mass layer (gypsum board, concrete foundation etc) of the envelope is modeled as a single capacitance. Figure 2 shows an example for the main floor (Zone 2). In a previous study (Date *et al.,* 2016) it was found that a simple floor-level model should include a thermal mass term for the structure between zones (i.e. ceiling/floor material) and the convective and conductive terms should be separated, if one is interested in accuracy at the floor level (rather than building level).

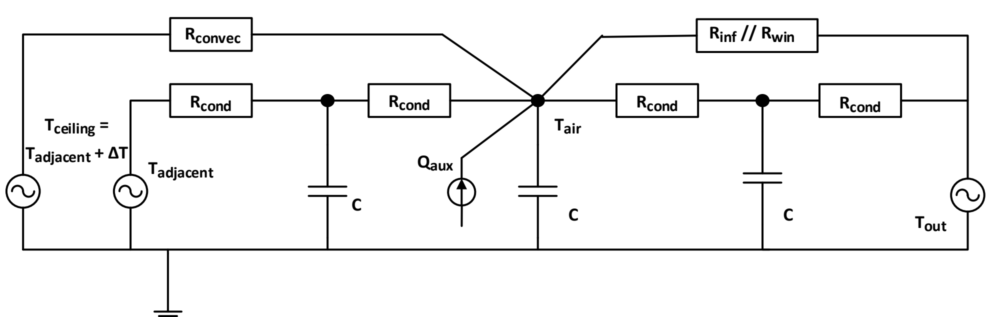

Figure 2: Thermal network of floor-level model (one zone)

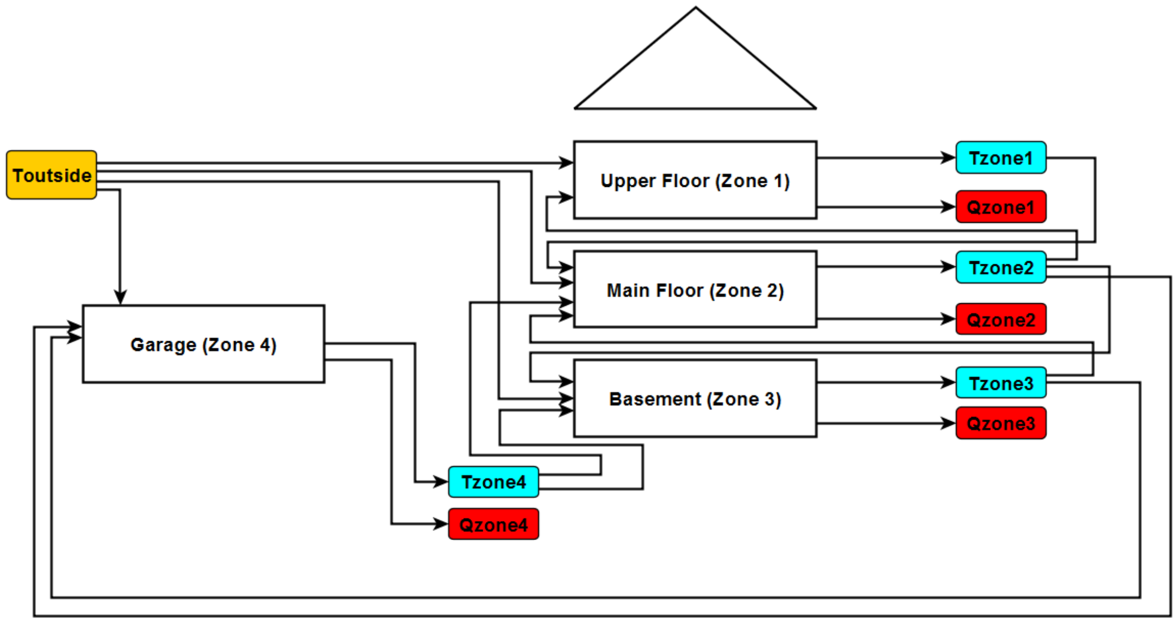

Figure 3: Inputs and outputs of all zones

In all models, experimentally determined data of the zone air temperature stratification was used for the calculation of one-way vertical inter-zonal convective heat transfer (heat transfer driven by a temperature difference). In this case, the models uses a T_{ceiling} term instead of T_{adjacent} temperature. Therefore, in this study, ΔT represents the average temperature difference between the center of the room (height = 1220mm) and the temperature measured near the ceiling (height = 2440mm) obtained from experimental measurements. This is used for temperature difference convective energy flow from vertically adjacent connected zones (i.e. Zone 1 to Zone 2, or Zone 2 to Zone 3). This approach is an attempt at a simplified method for the convective heat transfer between floors in a multi-story building. Further work on simplified inter-zonal modelling for controls includes taking into consideration the techniques and correlations developed by Riffat (1989).

Figure 4 shows the overall thermal network schematic of a whole building of the simple floor-level model structure. It shows the individual zone models (rectangles) and how each zone model is connected to adjacent zone models by convection and/or conduction terms. In all models, experimentally determined data of the zone air temperature stratification was used for the calculation of vertical inter-zonal convective heat transfer (heat transfer driven by a temperature difference), depicted by the ΔT source terms. Parameters are identified using the simplex algorithm.

3.2 Whole Building-Level Model

At the whole building-level, a first order (i.e. one capacitance) model is developed and model parameters are identified using the optimization algorithm. Figure 5 depicts the system inputs and outputs for the whole building thermal model. Figure 6 shows the thermal circuit at the whole building-level, where the building is modeled as one equivalent zone with one effective capacitance and one effective resistance, thus creating a 1R1C model.

As the setpoint of each zone within the house may not be the same, an effective whole house setpoint temperature can be defined as:

$$T_{eff,setpoint} = \sum_{j=1}^{n} \left(\frac{T_{setpoint_j} \cdot A_j}{A_{total}} \right) \tag{1}$$

Using equation (1) to estimate the effective setpoint for the building (when individual zones are controlled differently), this model structure can be useful to obtain quick estimates of whole building loads and operation or for district/community scale simulation studies.

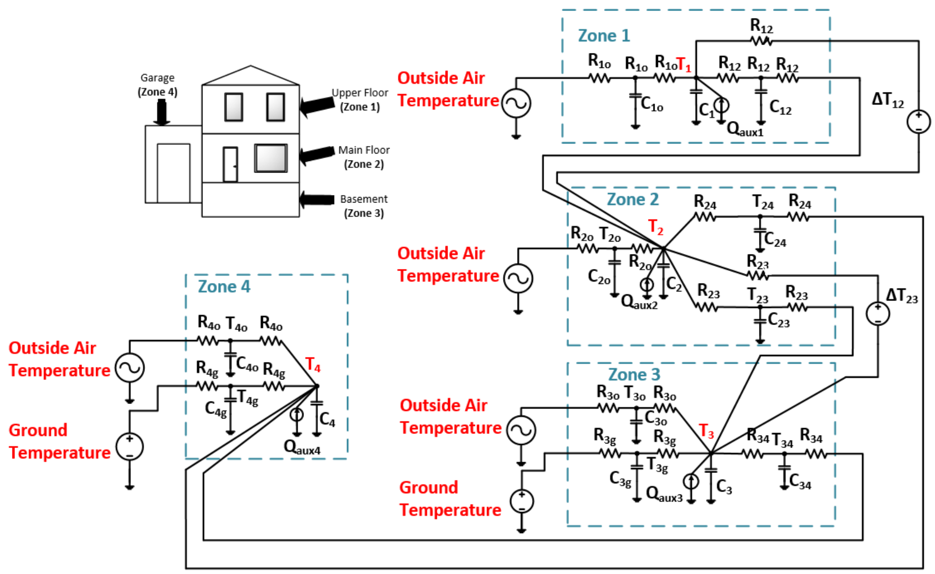

Figure 4: Multi-zone thermal network whole building schematic

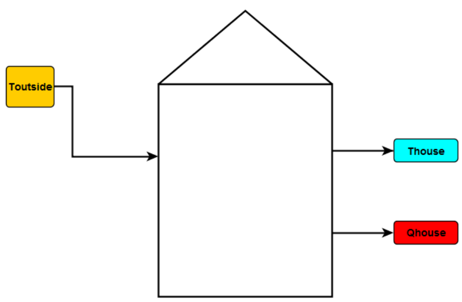

Figure 5: Inputs and outputs of whole house model

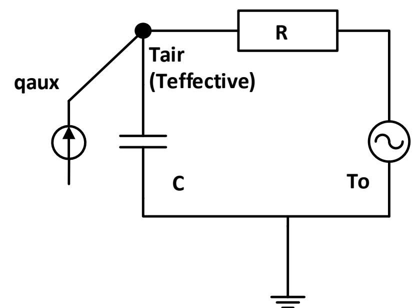

Figure 6: 1R1C thermal network of whole house

4. CALIBRATION OF MODELS

An optimization routine is used to find the parameter values that minimize an objective function. In this case, the objective function chosen was the coefficient of variation of the root-mean-square error (CVRMSE) between measured power and the prediction at 15 minute intervals, similar to (Lavigne *et al.*, 2014). The training data length was 5.4 days of data. Nelder-Mead Simplex was used for this study using the Python programming language. The Simplex algorithm is used here; other algorithms can replace it depending on the user's preference. Since the individual results of each zone and whole building power use are of importance, the CVRSME of each individual zone was minimized (for the floor-level models), and then whole building results were investigated. The objective function (CVRMSE) used is shown in:

$$J(y,\hat{y}) = \frac{1}{\bar{y}}\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)^2} \tag{2}$$

where y is the experimentally measured data (thermal power) and $\hat{y}$ represents the model predictions. The building was modeled using the fully explicit finite difference method to solve the energy balance equations. Initial values of model parameters are based off of the known building material properties and estimates for infiltration, inter-zonal convective transfer and air capacitance multipliers.

4.1 Calibration of Benchmark Model and Floor-Level Model

The parameter values of the benchmark (detailed) floor-level model and simplified floor-level model were identified and the power use predictions were compared. The focus was on accuracy of power prediction rather than room temperature prediction, as most building simulation models are calibrated against power or energy consumption of the whole building. Results after calibration using 5.4 days of model training data are found in Table 1.

Table 1: Calibration results for detailed (benchmark) and simple floor-level models

	Detailed Model	Floor Level Model
CVRMSE – Zone 1 (Top Floor)	23%	26%
CVRMSE – Zone 2 (Main Floor)	25%	23%
CVRMSE – Zone 3 (Basement)	19%	26%
CVRMSE – Zone 4 (Garage)	7%	6%
CVRMSE – Whole Building	13%	15%

4.2 Calibration of Building-Level Model

Table 2 shows the values for the parameters R and C of the 1R1C thermal model of the whole house (Figure 6). Initial and second guesses were made based on geometry and material properties of the building and then an optimization routine was conducted to identify R and C values which results in the lowest CVRMSE, when model predictions are compared to experimentally measured data of 5.4 days. For the initial guess of the 1R1C model, R and C were determined by adding the resistances according to the series and parallel circuit laws and the capacitances were simply added together. In the second guess, a capacitance multiplier of 15 was chosen.

Table 2: 1R1C whole building thermal network model parameter values before and after identification

	Initial Guess	Second Guess	After Identification
R (Kelvin/kW)	7.1	7.1	6.4
C (MJ/Kelvin)	49.1	57.7	17.2
Effective air capacitance multiplier	1	15	N/A
CVRMSE	51%	55%	20%
Time Constant (τ = RC)	97 Hours	114 Hours	31 Hours

One interesting result from the identification process of the 1R1C model is the value of the C parameter, as it is much smaller (almost 3 times smaller) than what the expected "effective" C value should be based on the geometry and material properties of the building. These results suggest that new, revised methods are needed to estimate effective capacitances of buildings. Figure 7 shows the predictions of the floor-level model and experimental heating power data. For visual clarity, only one day of data and predictions is shown here. The predictions of each zone's power demand contribution are shown, and the simple whole house 1R1C power profile is overlaid (dashed line).

The concept of the multi-level thermal modelling approach for different control applications can be summarized as follows. The top benchmark model is the most detailed version of the building thermal model. From there, one can choose to look at optimal control at the zone level by using the simplified zone-level models or at global whole building operation by using the building level model. It is a simple procedure to interchange between the different modelling levels depending on the needs or interests of the model user. The characteristics and results of the three thermal modelling levels are summarized in Table 3.

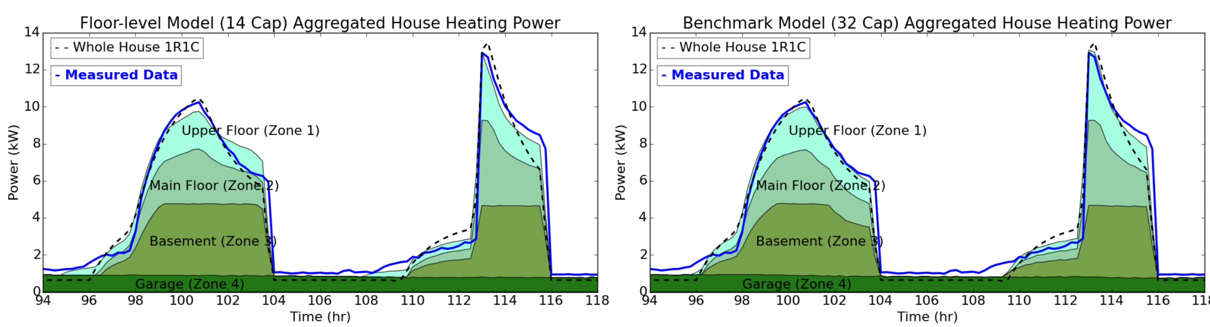

Figure 7: Model verification results of left: simplified floor-level model, and right: benchmark detailed model

Table 3: Summary of three thermal modelling levels

	Benchmark Model	Zone-Level Model	Building-Level Model
Model Order (number of capacitances)	32	14	1
Number of Resistances	69	26	1
Building CVRMSE	13%	15%	20%

5. WHOLE-BUILDING MODEL: IS 1R1C ENOUGH?

From the preceding discussion, it seems apparent that a 1R1C model provides an accurate representation of the heating load of the whole house over a period of several days (and when calibrated with training data of several days). Several questions arise: Is there a need to add more capacitances (e.g. 2 or 3) to the model? Do these models predict the heating load accurately in the short term (say, the next 3 hours)? How does the model training period affect the accuracy of the model? What kind of information can be obtained about the house dynamics from a quick inspection of the models (i.e. without simulation)?

5.1 Alternative Whole House Models

Three model structures for the whole house load calculation are shown below in Figure 8, Figure 9 and Figure 10. The first model on the left corresponds to the 1R1C presented in the previous section. As more capacitances are introduced, the model is more capable to capture the shorter term dynamic behavior of the system outputs based on inputs. CVRMSE values shown correspond to calibration using 5.4 days of training data, and evaluated over a prediction horizon of the same length.

5.2 Effect of (i) Training Data Period and (ii) Length of Prediction Horizon

The three whole building models were trained with datasets of different lengths: 5.4 days (the entire measurement period), 1 day, 6 hours and 3 hours. Different R and C parameters are found depending on the training data period. The predictions of the models were then evaluated in terms of their CVRSME values over different prediction horizons; results are shown in Figure 11. Each bar graph in Figure 11 corresponds to the different training data lengths and the models are then evaluated for different prediction horizon lengths shown in the four tables.

One notable result seen in Figure 11 is that with just 3 hours of training data, two of the simple whole building models (3R2C and 5R3C) can predict the total 5.4 days of operation with acceptable accuracy, while the simplest 1R1C performs poorly. In general, long training data periods result in a model that is satisfactory for long time scales, but not necessarily good for short term predictions (although this is largely dependent on the particular calibration period chosen). In a control application of a real building, simple models could prove useful when short lengths of training data for calibration are available, particularly if the models could be "checked" and systematically re-calibrated at specific times (e.g. once per week or once per day) with the buildings sensor data.

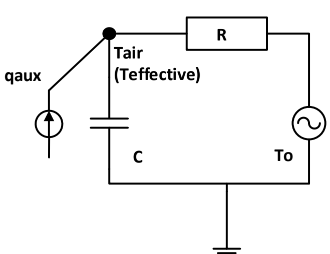

Figure 8: 1R1C Whole House Model, CVRMSE = 21%

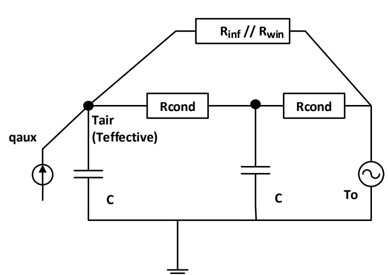

Figure 9: 3R2C Whole House Model, CVRMSE = 20%

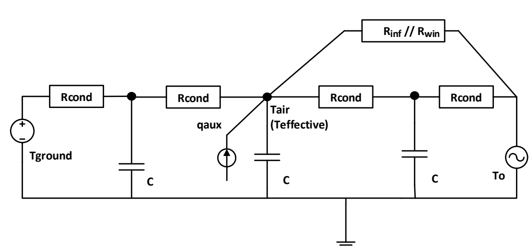

Figure 10: 5R3C Whole House Model, CVRMSE = 19%

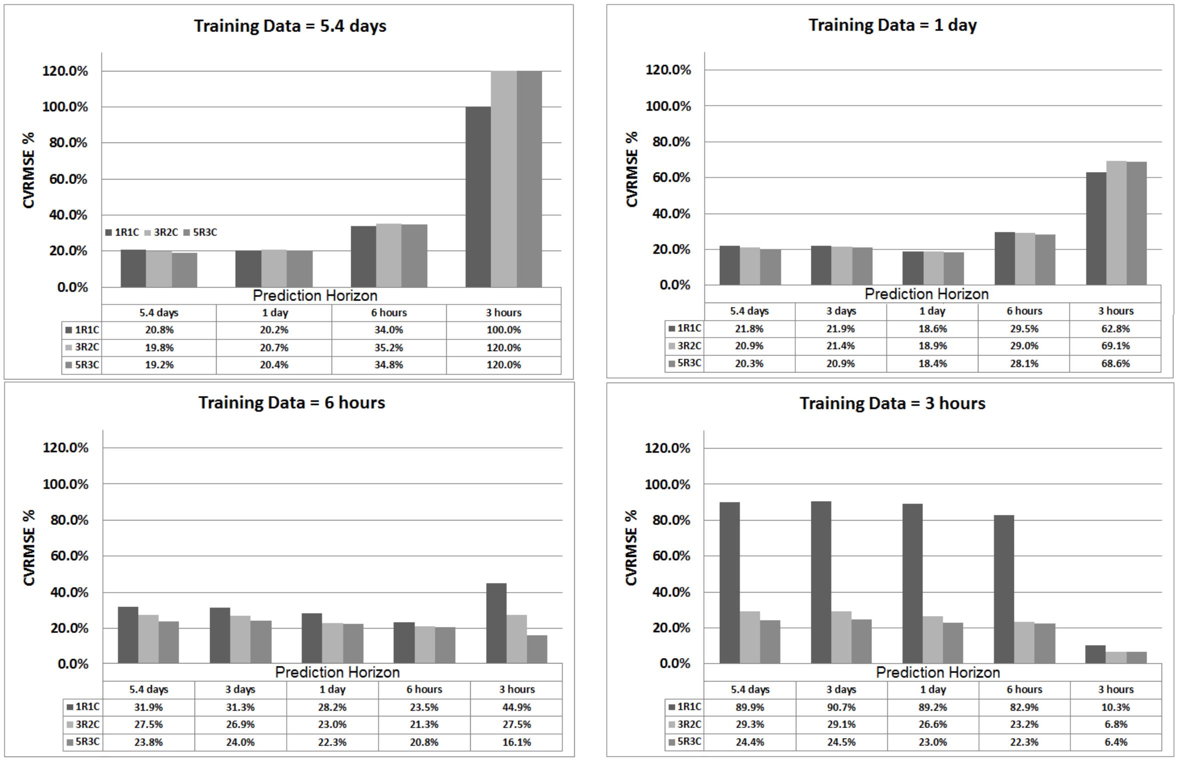

Figure 11: Model Error (CVRMSE) for different prediction horizons and training data lengths

5.3 Frequency Domain Analysis

Frequency domain analysis of these systems could prove useful in evaluating a model's accuracy in a comparative manner, almost by inspection, without the need for a simulation. After solving for the state-space representation of the three models (see Candanedo *et al.* (2013) for procedure), the frequency response of the indoor air temperature (T_{in}) output to the electric heating input (q_{HVAC}) for the three whole-house models were plotted and are shown in Figure 12. The first graph on the left shows the results of the 1R1C model for different training period lengths, the middle graphs shows results for the 3R2C model and the third graph corresponds to the 5R3C model. The magnitude on the left axis refers to °C/Watt.

The following example illustrates how frequency domain analysis enables a quick and simple assessment of a model. The 1R1C model based on 3-hour long training data predicts that, while keeping other inputs at zero, a continuous heating input of 1000 W would result in a steady room air temperature of roughly 16°C (Figure 12). Of course, it is not realistic that such little amount of heating would result in such a high air temperature; this result indicates that 1R1C model trained with only 3 hours of data is far from accurate to represent steady-state or low-frequency effects phenomena. This important result is found without performing any simulation.

In the 1R1C models calibrated with different training periods (Figure 12) there are significant differences in the steady state values predicted (e.g., 16°C/kW vs 8°C/kW); nevertheless, the lines nearly overlap for training data periods of 6 hours and longer. For the 3R2C and 5R3C models, there is significant variation in the phase angle results (corresponding to different time delays) between different training data lengths.

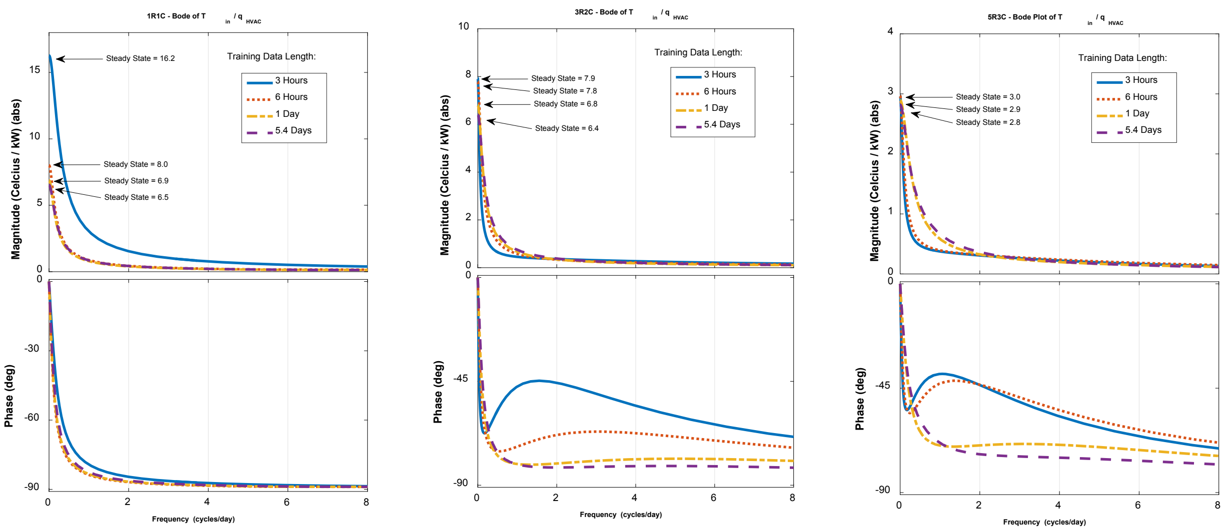

Figure 12: Frequency response - indoor air temperature to heating power

6. CONCLUSIONS

This paper outlined a methodology for multi-level control-oriented modelling for buildings with several zones. This multi-level approach allows the user to "zoom in and out" so that models at each control level remain manageable, easy to calibrate and easy to physically interpret. A global low-order model (1R1C) is developed and used to rapidly calculate the thermal load of the building, while a very detailed benchmark floor-level model is developed and can be used for verification and MPC-based simulation studies. For the development of specific control algorithms for each zone, an adequate simplified zone-level model must be identified. It was found that if zone-level accuracy is of importance, one must incorporate into the model the thermal mass of the structure between zones.

Three building-level models were then evaluated to investigate the effect of incorporating additional capacitance terms. Using these three building-level models, the effects of different lengths of training data periods on the accuracy of different prediction horizons were explored. It was found that a 1R1C whole house model can perform well for either longer horizon or short ones, but not simultaneously for both. Frequency analysis was used to quickly evaluate the whole building models without the need to perform a simulation. Interesting differences emerged in the phase angle predicted by the different models. Work remains to be done on how to improve the guidelines for the initial guess of the grey-box model parameters.

NOMENCLATURE

R	thermal resistance	(K/watt)
C	thermal capacitance	(Joule/K)
T	temperature	(K/°C)
A	floor area	(m^2)
J	objective function	(-)
τ	building time constant	(hour)
CVRMSE	coefficient of variation of the root-mean-square error	(%)
MPC	model predictive control	(-)

Subscript

j	zone
i	time interval

REFERENCES

Bacher, P., and Madsen, H. (2011). Identifying suitable models for the heat dynamics of buildings. *Energy and Buildings*, 1511–1522. http://doi.org/10.1016/j.enbuild.2011.02.005

Baetens, R., De Connick, R., Jorissen, F., Picard, D., Helsen, L., and Saelens, D. (2015). OPENIDEAS - An Open Framework for Integrated District Energy Simulations. *14th International Building Simulation Conference*.

Candanedo, J. A., Allard, A., and Athienitis, A. K. (2010). Predictive Control of Radiant Floor Heating and Transmitted Irradiance in a Room with High Solar Gains. *ASHRAE Transactions*.

Candanedo, J. A., Dehkordi, V. R., and Lopez, P. (2013). A control-oriented simplified building modelling strategy. In *13th Conference of International Building Performance Simulation Association* (pp. 3682–3689). Chambery, France.

Date, J., Candanedo, J., Athienitis, A., and Fournier, M. (2016). Simplified Multi-Zone Thermal Modelling of a House for Demand Reduction & Control Applications. *CLIMA Conference 2016*, 1–10.

Date, J., Fournier, M., Chen, Y., and Athienitis, A. K. (2016). Impact of Thermal Model Resolution on Peak Heating Demand Calculation under Different Setpoint Profiles. *ASHRAE Transactions*, *122*, 1–11.

Fournier, M., and Leduc, M.-A. (2014). Study of Electrical Heating Setpoint Modulation Strategies for Residential Demand Response. In *Proceedings of eSim Conference 2014*. Ottawa, Ontario.

Inderfurth, A., Nytsch-geusen, C., and Ribas Tugores, C. (2015). Parameter Identification for Low-Order Building Models Using Optimization Strategies. *14th Building Simulation Conference*.

Kummert, M., André, P., and Argiriou, A. (2006). Comparing control strategies using experimental and simulation results: Methodology and application to heating control of passive solar buildings. *HVAC and R Research*, 553–575.

Lauster, M., Brüntjen, M., Leppmann, H., Fuchs, M., Teichmann, J., Streblow, R., and Müller, D. (2014). Improving a Low Order Building Model for Urban Scale Applications. *Fifth German-Austrian IBPSA Conference RWTH Aachen University IMPROVING*, 511–518. Retrieved from http://www.ibpsa.org/proceedings/bausimPapers/2014/p1192_final.pdf

Lavigne, K., Daoud, A., Sansregret, S., and Leduc, M.-A. (2014). Demand Response Strategies in a Small All-Electric Commercial Building in Quebec. In *Proceedings of eSim Conference 2014*. Ottawa, Ontario.

Leduc, M., Daoud, A., and LeBel, C. (2011). Developing winter residential demand response strategies for electric space heating. In *Proceedings of 12th Conference of IBPSA* (pp. 1111–1118). Sydney, NSW, Australia.

Lin, Y., Middelkoop, T., and Barooah, P. (2012). Issues in identification of control-oriented thermal models of zones in multi-zone buildings. *51st IEEE Conference on Decision and Control*, 6932–6937. http://doi.org/10.1109/CDC.2012.6425958

Riffat, S. (1989). Measurement of heat and mass transfer between the lower and upper floors of a house. *International Journal of Energy Research*, *13*(January 1988), 231–241. Retrieved from http://onlinelibrary.wiley.com/doi/10.1002/er.4440130212/abstract

Sturzenegger, D., Gyalistras, D., Morari, M., and Smith, R. S. (2016). Model Predictive Climate Control of a Swiss Office Building. *Implementation, Results, and Cost–Benefit Analysis*, *24*(1), 1–12. http://doi.org/10.1109/TCST.2015.2415411 Y3 - 07.01.2016 U6 - http://ieeexplore.ieee.org/ielx7/87/7361777/07087366.pdf?tp=&arnumber=7087366&isnumber=7361777 M4 - Citavi

Wang, S., and Xu, X. (2006). Simplified building model for transient thermal performance estimation using GA-based parameter identification. *International Journal of Thermal Sciences*, 419–432. http://doi.org/http://dx.doi.org/10.1016/j.ijthermalsci.2005.06.009

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