Recursive thermal building model training using Ensemble Kalman Filters

Brent Huchuk[1], Cynthia A. Cruickshank[2], William O'Brien[1], and H.Burak Gunay[1]
[1] Carleton University, Dept. of Civil and Environmental Engineering, Ottawa, Ontario
[2] Carleton University, Dept. of Mechanical and Aerospace Engineering, Ottawa, Ontario

Abstract

Simplified building models have gained in popularity as a result of their practical applications in model-based predictive control (MPC); however, these models require accurate parameter estimates in order to give meaningful results. To this end, this simulation-based study proposes a recursive parameter estimation methodology — the so-called Ensemble Kalman Filter — as a method for predicting effective resistance and capacitance values of an office space. Accuracy of the proposed methodology to predict the response of the simulated-building was studied. Results indicate that the proposed methodology resembles a promising approach to learn building physics in a self-adaptive manner using simple generic sensor/meter networks; lending itself to the controls practitioners.

1 Introduction

1.1 Motivation

Buildings account for 53% of Canada's electrical energy use — split between residential and commercial buildings (NRCan 2010). Existing control networks in buildings represent significant potential for the application of predictive control strategies, which can reduce the energy use, and dampen the peak demands with little, if any, additional hardware investment.

Traditionally, comfort and energy management of the indoor climates of buildings can be maintained through HVAC systems and automated window and window shading devices, which are controlled with the sole knowledge of instantaneous stimuli. For example, heating and cooling equipment that operates when the setpoint is not met. On the other hand, by blending various control inputs (e.g., weather forecasts) with prior knowledge of building physics through heuristic and/or model-based approaches, future heating and cooling demands can be forecasted recursively. With this knowledge, automated building systems' operational inefficiencies can be predicted in advance (e.g., overheating) and the controls can be adapted accordingly (e.g., blinds' position) to avoid future discomfort/energy inefficiency.

Unfortunately, often in practice when seeking to utilize the building's physical characteristics, such as during optimal starts and stops, the commissioning is based on rules of thumb (e.g., calculations based on square footage) or estimates of the thermal capacitance. This approach relies on the experience of the technician and typically favours a conservative controls approach which does not risk potential occupant discomfort.

1.2 Forecasting future demand of heating and cooling

Forecasting the future heating and cooling demands typically involves a series of simple heuristics (May-Ostendorp, Henze, Corbin, Rajagopalan & Felsmann 2011) based on weather forecasts; e.g., *"Cooling will be needed in the next six hours, if ambient temperature will be less* *than* $15°C$ *and if solar radiation will be larger than* $50\,W/m^2$ *in the next six hours; then, close the automated blinds."* It is evident that this static rule-based approach has little scientific basis; it rather relies on the experience of the designer or operator. Meanwhile, model-based prediction of the heating and cooling demands relies on the recursive learning of building physics. A set of parameters (e.g., thermal resistance or capacitance) can be backed out from a simplified physical model of a building by employing a recursive parameter estimation technique (Fux, Ashouri, Benz & Guzzella 2012, Braun & Chaturvedi 2002). The heating and cooling demand in the near future can be predicted in advance using these calibrated parameter estimates in a simplified physical model in each timestep. However, the implementation of this approach outside academics is not as common as the heuristic approach (Candanedo & Athienitis 2010). This lack of adoption is partially a result of technical limitations in the model predictive controller communicating with the building automation system (May-Ostendorp, Henze, Rajagopalan & Corbin 2012). The other major limitation was noted as the computational requirements to implement real-time or online physical building model training methodologies (May-Ostendorp et al. 2012, Corbin, Henze & May-Ostendorp 2012). To this end, researchers have been seeking for solutions which can remove the aforementioned limitations. One solution has been the use of offline modelling, from which general models can be extracted. It was reported that by applying offline model-based rules, similar savings can be achieved to the online counterpart (May-Ostendorp et al. 2011, May-Ostendorp et al. 2012), while significantly reducing the computational requirements.

A second approach is the simplification of physical models representing the buildings with the use of lumped resistance and capacitance (RC) models, in which effective values of resistance and capacitance are utilized (Candanedo & Athienitis 2010, Široký, Oldewurtel, Cigler & Prívara 2011, Fux et al. 2012, Radecki & Hencey 2012). The major pitfall to this approach is the potential difficulty in determining the value of these lumped parameters. They vary for every individual building and in many cases are time-variant. Thus, the choice of parameter estimation technique for inverse modelling is crucial; so that models of low complexity can be trained with minimal computational effort to yield reliable parameter estimates. Various researchers employed differing statistical approaches to solve this problem. These attempts include recursive least-square methods (Chen & Athienitis 2003, Loveday, Virk & Cheung 1992), the extended Kalman filter (EKF) (Fux et al. 2012) and the unscented Kalman filter (UKF) (Radecki & Hencey 2012). These techniques still have their shortcomings including local minimization (i.e., finding the minimal value in a certain range and not the overall minimum of the function) and need for accurate starting values; both of which are problematic in a system designed to reduce the intervention by a technician or other knowledgeable individual. Here, an alternative Bayesian methodology which utilizes the abilities of a Monte-Carlo method, namely the Ensemble Kalman Filter, is introduced to acquire meaningful parameter estimates while addressing the issues of other recursive techniques.

1.3 Research Objectives and Document structure

The current paper seeks to explore the ability of the Ensemble Kalman Filter (EnKF) as a viable training technique for online parameter estimation of a building model. Section 2 provides a brief insight about the application of the EnKF. In Section 3.1, the building model used as a source of data and a building space to be inversely modelled is described. In Section 3.2, the RC model and the EnKF approach are presented. This inverse model is established and trained to learn the building's effective resistance and capacitance terms recursively. In Section 3.3, the RC model and its forward training approach are demonstrated. This forward model is established to predict the zone's temperature over a forecast period. Both parameter estimation and forward modelling was implemented in Matlab v.R2011.a. In Section 4, the results of both the training and forecasting performances are presented. In Section 5, the results of the current study are discussed, limitations/challenges are assessed and acknowledged by comparing them with the existing literature; concluding results are summarized and future work recommendations are developed.

2 The Ensemble Kalman Filter

The Ensemble Kalman Filter, is an algorithm for recursive estimation which can be used for both parameters and states. Previously it has been used in various engineering applications and climate modelling (Evensen 2003). The EnKF relies on an *ensemble* forecasting technique in which an *ensemble* of values are used — similar to a particle filter — but its requirement of Gaussian distributions for all probabilities make it much more efficient to operate. Compared to other Kalman filtering techniques, such as the UKF and the EKF, the EnKF better handles error closure issues (Evensen 1994) and does not require the calculation of the Jacobian to deal with non-linearity (like the EKF) or deterministic sampling (like the UKF). Further the EnKF avoids the problem that the EKF and UKF can result in unreliable and unstable variable estimates, if the modelled system is highly non-linear; as it is in the building heat transfer problems (He, Liu, Zhang & Chen 2013, Ching, Beck & Porter 2006).

In general terms, the iterative process of the EnKF begins with an ensemble of q forecasted state and parameter estimates (X) based on a normal distribution for each value. These estimates are matched with estimates of the associated error covariance (P) in the prediction step, as is shown as a general concept in Figure 1. The update step begins with processing of an observation which is compared with the predictions using the calculated Kalman Gain (K). Finally the updating step is completed when state and covariance predictions are improved using the Kalman Gain. In this situation, the states estimated are the temperature of the nodes, while the parameters are the effective material properties of thermal resistance and capacitance. A more complete and thorough explanation of the EnKF and its methods can be found elsewhere, such as Evensen (2009).

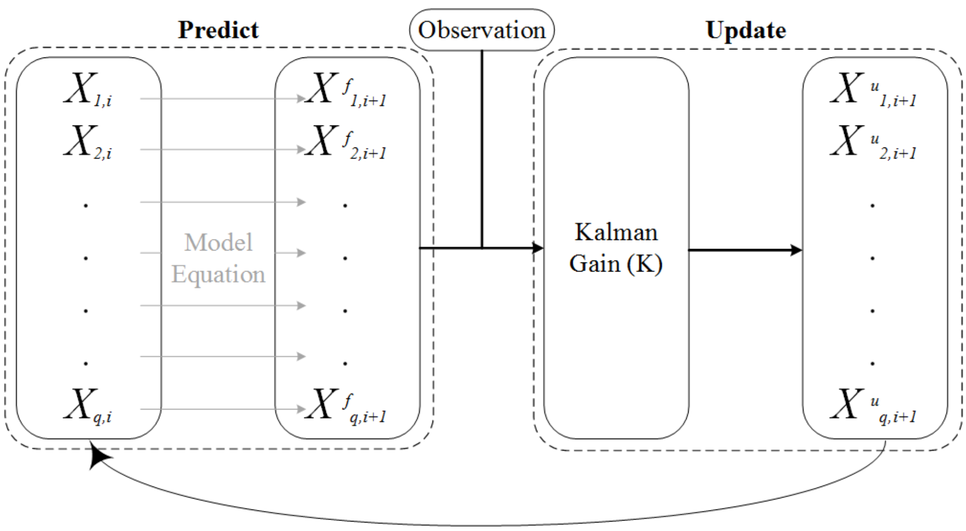

Figure 1: Schematic of the EnKF process

3 Methodology

3.1 Building Model

The intent of the EnKF is to train the model parameters based on a series of measurements made on the physical system. An RC model, an illustration of which can be found in Figure 2, is calibrated. The order of the model (i.e., the number of capacitance terms) is based on past researchers efforts. Many researchers have found that models using multiple capacitances better performed then a single R and C model (Wang & Xu 2006, Hudson & Underwood 1999, Gouda, Danaher & Underwood 2002, Nielsen 2005).

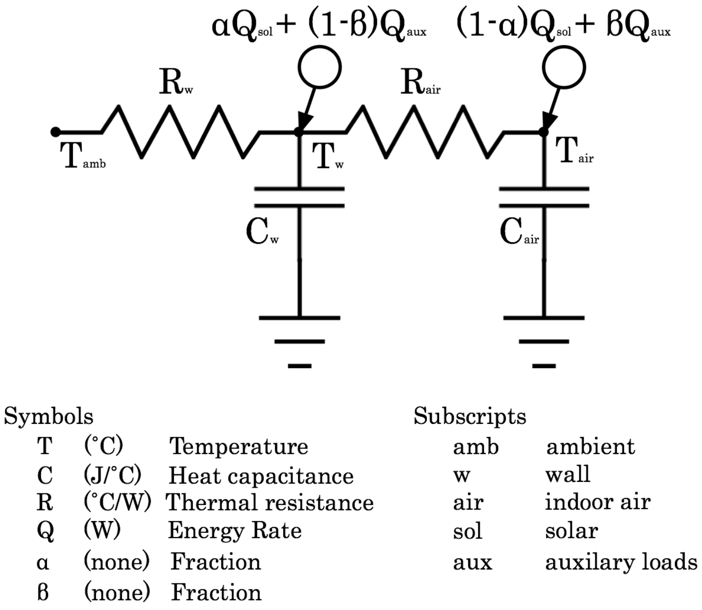

Figure 2: RC model representation of building model

The lumped resistance term, R_{air} (°C/W), represents the effective thermal resistance between the walls and the interior air. The lumped capacitance term, C_{air} (J/°C), represents the combined thermal mass of the air and contents of the room. The term R_w represents the thermal resistance between the zone and the exterior environments while C_w is the lumped capacitance of the zone construction. The Q_{sol} (W) term represents the solar gains incident on the exterior surface of the room and Q_{aux} represents the added or removed energy in the zone, either from internal load gains, or HVAC loads. The α and β are fractions to represent the fraction of the load that is injected at the air versus surface node.

The general explicit finite difference equation (Equation 1) is defined for the two nodes represented in this model as Equation 2 and Equation 3. In order to determine the indoor air temperature (T_{air}) both equations are required to be solved at each time step, and represent two states in the EnKF. In this situation the values for R and C are calibrated from an initial guess, which was based on work of others on RC modelling. The indoor air temp (T_{air}) and outdoor temperature (T_{amb}) along with the components of additional energy rates from the HVAC and solar gains are assumed to be measurable and accessible to the building control system (e.g., via the building automation system or a local weather station).

$$T_{k+1} = \frac{\Delta t}{C_i}\left[Q + \sum_j \frac{T_{j,k} - T_{i,k}}{R_{i,j}}\right] + T_k \tag{1}$$

$$T_{\mathrm{air},k+1} = \frac{\Delta t}{C_{\mathrm{air}}}\left[(1-\alpha)Q_{\mathrm{sol}} + \beta Q_{\mathrm{aux}} + \frac{T_{w,k} - T_{\mathrm{air},k}}{R_{\mathrm{air}}}\right] + T_{\mathrm{air},k} \tag{2}$$

$$T_{w,k+1} = \frac{\Delta t}{C_{air}}\left[\alpha Q_{sol} + (1-\beta)Q_{aux} + \frac{T_{amb,k} - T_{w,k}}{R_w} + \frac{T_{air,k} - T_{w,k}}{R_{air}}\right] + T_{w,k} \tag{3}$$

For use as an effective building model, the effective value of C and R must be determined based on the individual thermal zone(s). These values are unique for each set of constructions (Fux et al. 2012, Braun & Chaturvedi 2002). To successfully calibrate these parameters manually would be tedious and nearly impossible, so statistical inverse-modelling methods are often employed to automate and expedite the process.

3.2 Training Method

To illustrate a building measurement situation an EnergyPlus building model provided a test bed for the recursive inverse parameter-learning model. Using a simplified lumped-parameter model the buildings thermal response can be represented. The model parameters of the RC model are given as an initial estimation and are trained to a correct value online using the EnKF. A generic thermal model for a perimeter office space in Ottawa, Ontario (a Zone 6 climate) was created based on the schematic seen in Figure 3.

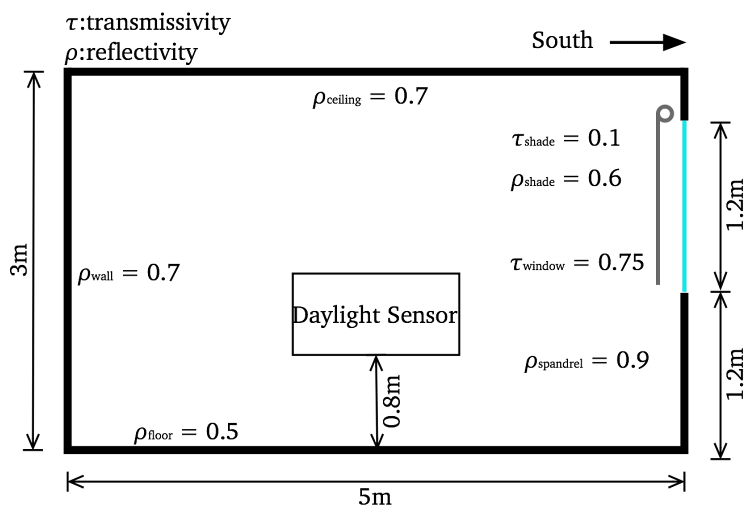

Figure 3: Elevation view of office space modelled in EnergyPlus

The office was modelled with 8 m^2 of exterior, south-facing exterior window and 7 m^2 of exterior wall area. The concrete floor slab was set to have an area of 25 m^2 and a thickness of 0.15 m. The remaining interior walls were set as adiabatic; an assumption based on the symmetric boundaries with the rest of the building. Windows were modelled using a simplified method, and were specified to have a solar heat gain coefficient (SHGC) of 0.6 and a corresponding U-factor of 2 $\mathrm{W \cdot m^{-2} \cdot K^{-1}}$. Infiltration and ventilation were set to have a combined air change rate of 0.5 ach. Heating and cooling demands were met using an ideal forced air system using set-back thermostat settings. For cooling, temperatures were set at 24°C and 28°C for occupied and unoccupied periods respectively. For heating, temperatures were set at 20°C and 16°C for occupied and unoccupied periods respectively. Occupancy was assumed to a fixed 9 : 00am – 5 : 00pm weekday routine for a single occupant who provided an internal heat gain of 100 W (with a sensible fraction of 0.6). Other internal gains were included for lighting at a power density of 10 $\mathrm{W \cdot m^{-2}}$ and miscellaneous equipment at 5.4 $\mathrm{W \cdot m^{-2}}$ (ASHRAE 2010). Lights were automated in a strictly binary matter (i.e., they can only be on or off), and were designed to provide 500 lx at the workplane defined 0.8 m above the floor in the centre of the room.

3.3 Forward Modelling

Forward modelling was performed to demonstrate the effectiveness of the training methods and the simplified model at capturing the thermal performance of the building space. In order to demonstrate the capabilities, the mean value after convergence (i.e., the model had been trained for an adequate amount of time to attain a perceived converged value based on visual inspection of the data) was placed in for the parameters of the RC model. The data collected from the EnergyPlus model in terms of loads and ambient conditions was fed into the model to determine how close the RC model could determine the interior temperature of the space (in EnergyPlus) through the solving of the set of Equation 2 and Equation 3. Since an ensemble of values is used in the training of the parameters, the converged values are left with a mean and variance. As such the forward modelling was performed using a Monte Carlo method in which an ensemble of N simulations was run each with a stochastically determined value for the R and C based on the results of the training.

4 Results

4.1 Parameter Training Results

Using the data collected from the EnergyPlus model, the RC model was trained using the EnKF. The convergence of the values was effected by the selection of initial values along with the prescribed estimates for measurement error and variances on the value of interest. The amount of data required to achieve a converged value was investigated using differing timestep lengths, representative of the frequency of measurements taken within the simulated building. A comparison in the time required for convergence is seen in Figure 4, for the indoor air node resistance (R_{air}). Each training period was started from the same time instant, experienced a quick drop off and began to reach a steady value. Visually it appears that by 3000 timesteps, the values have converged. The converged values meanwhile are not all the same, but are all of the same order of magnitude and are similar.

The convergence of all the parameters, while utilizing a 1 hour timestep is shown in Figure 5. The converged values for the 1 hour timestep are shown in Table 1 along with their variance. Each parameter has a different trajectory towards convergence. The more dramatic paths of the capacitance values reflect initially very low estimates on their value. A shorter timestep would be better in an application where the converged values were required as a piece of the building automation system as the training period would be on the order of weeks and not months, but in this ideal situation, this was not a critical concern. These values are the ones on which the forward modelling in Section 4.2 was carried out.

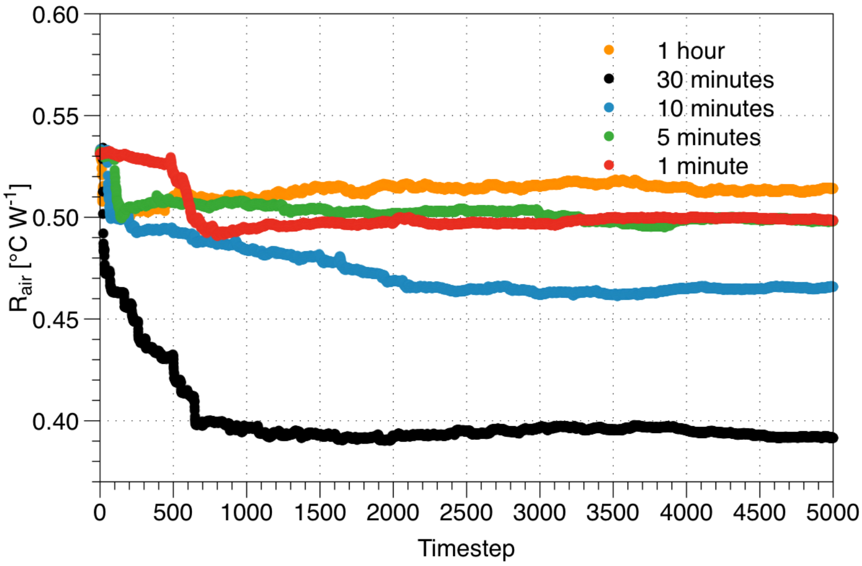

Figure 4: Variation to the duration of timesteps

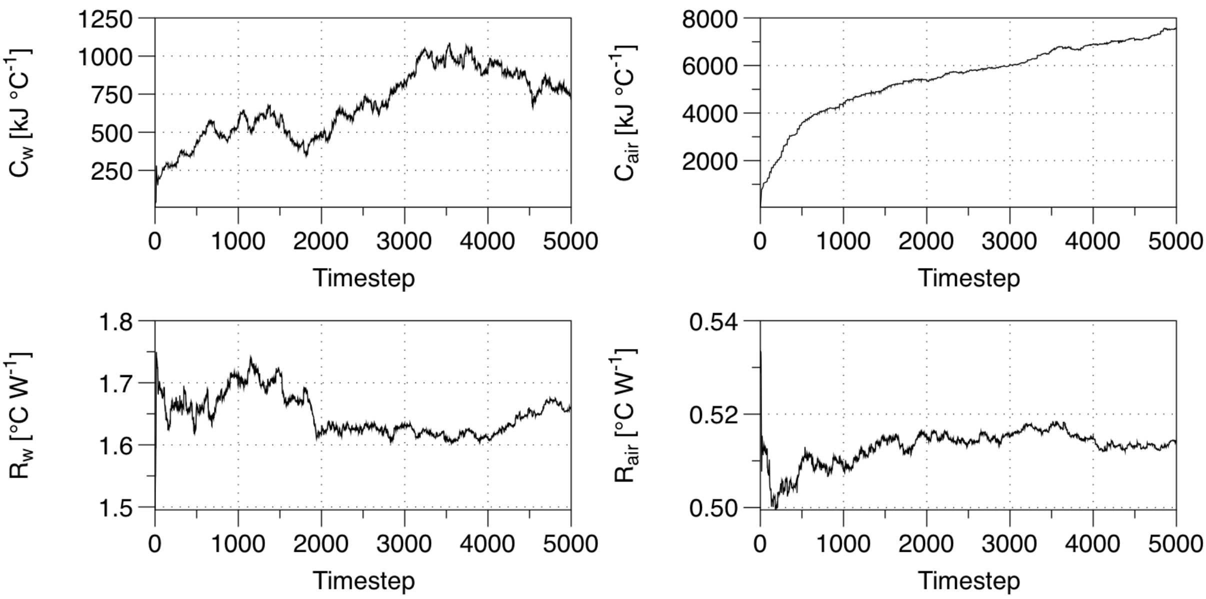

Figure 5: Time evolution of parameter estimates using the 1 hour timestep

Table 1: Converged Values using a 1 hour timestep

Component	Unit	Value	Variance
C_w	$J \cdot {}^{\circ}C^{-1}$	8.72×10^5	2.61×10^3
R_w	${}^{\circ}C \cdot W^{-1}$	1.65	2.76×10^{-4}
C_{air}	$J \cdot {}^{\circ}C^{-1}$	7.84×10^6	2.41×10^3
R_{air}	${}^{\circ}C \cdot W^{-1}$	0.51	2.33×10^{-5}

4.2 Forward Modelling Results

The forward modelling was intended to gauge the validity and abilities of the converged values for the building model parameters. Using weather and auxiliary load data, which was not used in the training interval, the indoor air node's temperature was forecasted and compared to the measure values, as seen in Figure 6. The resulting temperature had a Root Mean Square Error (RMSE) of Figure 6(a) is 0.8279 while the RMSE of Figure 6(b) is 0.7571.

5 Discussion and Conclusions

5.1 EnKF for parameter estimation

The training functionality of the EnKF was demonstrated along with aspects of the training method. The number of timesteps required to achieve convergence (the *burn in period*) was found to be be approximately 3000, as shown in Figure 4 in Section 4.1. In practical applications this means during training, the timestep could be decreased during commissioning to reduce the time the building model is uncalibrated and any MPC controls would be sub-optimal. In any application of the approach it would be thought that the parameter estimation would continuously be updated and not stopped after a set number of timesteps. This would help capture any changes to the environment which could effect any systems reliant on a calibrated model. It can also be seen in Figure 4 that all values do not converge to the same value. This is explained both with the variance of each value (which is not represented) and that in terms of use in the equation the R values are combined in a product with the C. This means that if the R value might converge lower then the C might converge higher but their product will be consistent.

Analysis of the converged R and C values and their related variances (shown in Table 1, Section 4.1) reveal two interesting points. First, it should be noted that these are not values that could be derived from only material knowledge but rather effective values, meaning its not straightforward in a a repeatable way. Second, the variances on the wall nodes are higher then on their air node counterparts. This is reflective of the fact that the wall node values are continually estimated and have no corresponding observation like the air node or the ambient temperature.

5.2 EnKF for forward modelling

The ability of the simplified model to track the temperature profile was considered to be acceptably good — in terms of a RMSE value and ability to follow the general trend. This is consistent with the conclusions made by Sourbron, Verhelst & Helsen (2013) and Candanedo, Dehkordi & Lopez (2013) with regards to the abilities of simple models over a short time frame. The representative 24-hour simulations, in Figure 6, show a general trend similarity between the forecasts to what actually occurred but do not fully capture the maximum and minimum values. Part of this struggle is the dual state estimation in this model. Both the T_{air} and T_w nodes are being forecasted while errors on both compound each other. In the training portion, with the

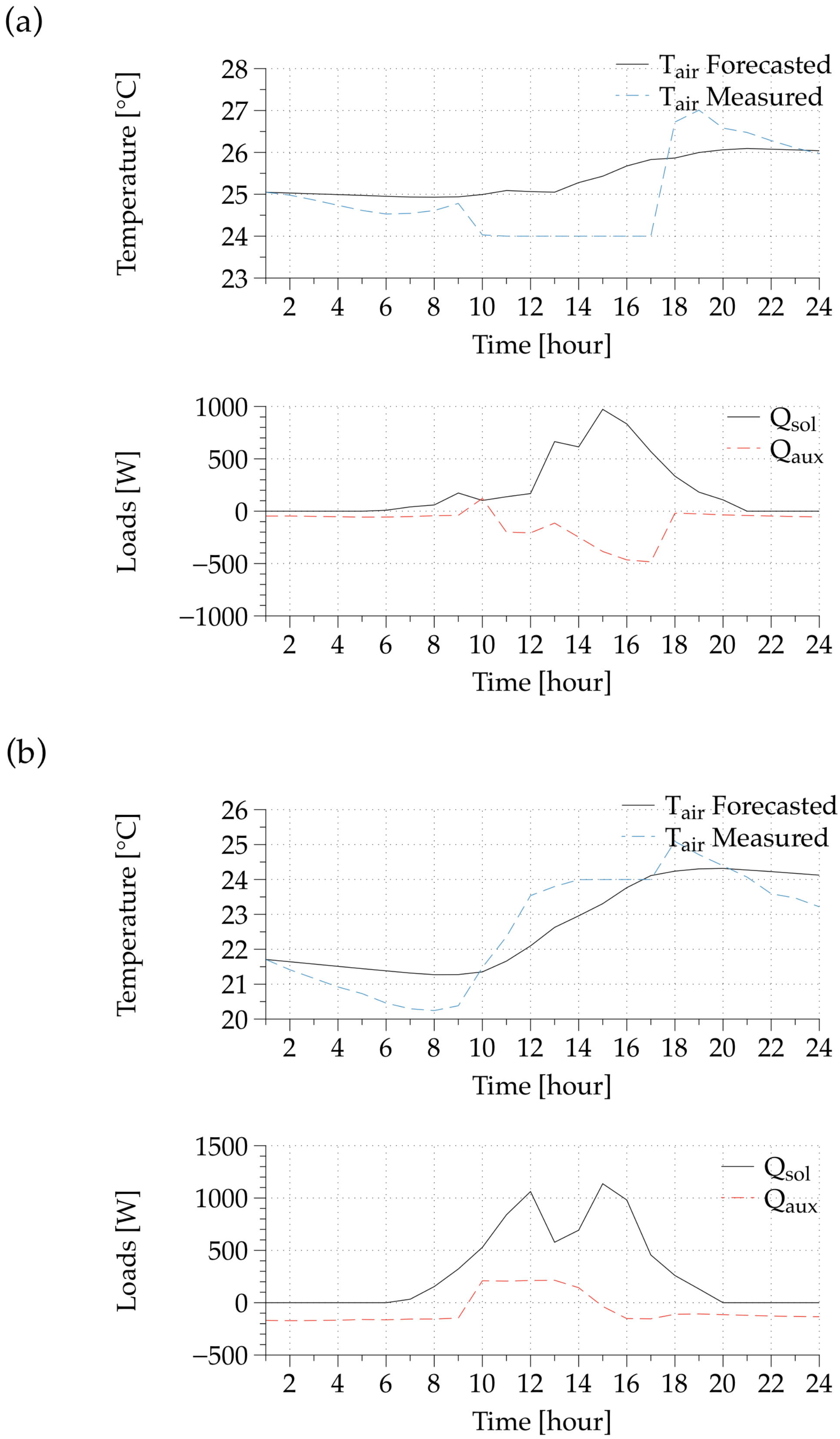

Figure 6: Temperature response for (a) an occupied day (b) an unoccupied day including the loads added to the zone

continual validation against the measured value of the room temperature to correct it at every timestep this problem is less pronounced. Unfortunately since the T_w node is an effective node with no true physical representation (and subsequently no true way to measure it), the estimation of the state continuously cannot be avoided. Further fractions were brought in to split how the loads affect each node. The approach here saw the loads only split between Q_{aux} and Q_{sol}, a further investigation would be to see if the loads require to be split further with their own fractional adjustment included (i.e., the HVAC loads and the internal heat gains might have their own fractions).

The fact remains that in terms of providing the potential model accuracy to be used as a functioning element for model-based predictive controls, in which the window or prediction often is much shorter (e.g., 4-6 hours) than the 24 hours investigated here, needs to be fully (and is intended to be) investigated. Regardless, the EnKF managed to show its merits as an inverse-modelling technique which has potential in applications regarding building parameter estimation. Moving forward the next step in its validation is a more thorough investigation both simulation-based and using data from real buildings, in which data availability is limited, to determine its feasibility as part of an advanced building automation system.

6 Acknowledgements

This research was supported by the Natural Sciences and Engineering Research Council of Canada and Regulvar Controls.

7 References

ASHRAE (2010), '90.1-2010 standard-energy standard for buildings except low-rise residential buildings'.

Braun, J. & Chaturvedi, N. (2002), 'An inverse gray-box model for transient building load prediction', *HVAC&R Research* **8**(1), 73–99.

Candanedo, J. A., Dehkordi, V. R. & Lopez, P. (2013), A control-oriented simplified building modelling strategy, *in* '13th Conference of international Building Performance Simulation Association'.

Candanedo, J. & Athienitis, A. (2010), Simplified linear models for predictive control of advanced solar homes with passive and active thermal storage, *in* 'International High Performance Buildings Conference'.

Chen, T. Y. & Athienitis, A. K. (2003), 'Investigation of practical issues in building thermal parameter estimation', *Building and Environment* **38**(8), 1027–1038.

Ching, J., Beck, J. L. & Porter, K. A. (2006), 'Bayesian state and parameter estimation of uncertain dynamical systems', *Probabilistic Engineering Mechanics* **21**(1), 81 – 96.

Corbin, C., Henze, G. & May-Ostendorp, P. (2012), 'A model predictive control optimization environment for real-time commercial building application', *Journal of Building Performance Simulation* **6**(3), 159–174.

Evensen, G. (1994), 'Sequential data assimilation with a nonlinear quasi-geostrophic model using monte carlo methods to forecast error statistics', *Journal of Geophysical Research: Oceans* **99**(C5), 10143–10162.

Evensen, G. (2003), 'The ensemble kalman filter: theoretical formulation and practical implementation', *Ocean Dynamics* **53**(4), 343–367.

Evensen, G. (2009), *Data assimilation: the ensemble Kalman filter*, Springer.

Fux, S., Ashouri, A., Benz, M. & Guzzella, L. (2012), 'Ekf based self-adaptive thermal model for a passive house', *Energy and Buildings* (0).

Gouda, M., Danaher, S. & Underwood, C. (2002), 'Building thermal model reduction using nonlinear constrained optimization', *Building and Environment* **37**(12), 1255 – 1265.

He, Y., Liu, X., Zhang, C. & Chen, Z. (2013), 'A new model for state-of-charge (soc) estimation for high-power li-ion batteries', *Applied Energy* **101**(0), 808 – 814. Sustainable Development of Energy, Water and Environment Systems.

Hudson, G. & Underwood, C. (1999), A simple building modelling procedure for matlab/simulink.

Loveday, D., Virk, G. & Cheung, J. (1992), 'Advanced control for bems: A model-based predictive approach', *Building Services Engineering Research and Technology* **13**(4), 217–223.

May-Ostendorp, P., Henze, G., Corbin, C., Rajagopalan, B. & Felsmann, C. (2011), 'Model-predictive control of mixed-mode buildings with rule extraction', *Building and Environment* **46**(2), 428–437.

May-Ostendorp, P., Henze, G., Rajagopalan, B. & Corbin, C. (2012), 'Extraction of supervisory building control rules from model predictive control of windows in a mixed mode building', *Journal of Building Performance Simulation* **6**(3), 199–219.

Nielsen, T. R. (2005), 'Simple tool to evaluate energy demand and indoor environment in the early stages of building design', *Solar Energy* **78**(1), 73 – 83.

NRCan (2010), 'Energy use data handbook'.
URL: *http://oee.nrcan.gc.ca/publications/statistics/handbook10/pdf/handbook10.pdf*

Radecki, P. & Hencey, B. (2012), Online building thermal parameter estimation via unscented kalman filtering, *in* 'American Control Conference (ACC), 2012', pp. 3056–3062.

Široký, J., Oldewurtel, F., Cigler, J. & Prívara, S. (2011), 'Experimental analysis of model predictive control for an energy efficient building heating system', *Applied Energy* **88**(9), 3079–3087.

Sourbron, M., Verhelst, C. & Helsen, L. (2013), 'Building models for model predictive control of office buildings with concrete core activation', *Journal of Building Performance Simulation* **6**(3), 175–198.

Wang, S. & Xu, X. (2006), 'Simplified building model for transient thermal performance estimation using ga-based parameter identification', *International Journal of Thermal Sciences* **45**(4), 419 – 432.