CALIBRATION OF ENVELOPE PARAMETERS USING CONTROL-BASED HEAT BALANCE IDENTIFICATION AND UNCERTAINTY ANALYSIS

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ABSTRACT

Building recommissioning in essential in the aging building stock to maintain efficient and comfortable operation as equipment ages and portions of the building are re-purposed for uses other than what was originally intended. Model-based recommissioning provides a way to evaluate payback and incentives for equipment replacement, and the response of the building to optimized operational strategies - without disturbing the comfort or productivity of current occupants. Accurate models are needed for these investigations, which must be calibrated to available sensor data. In this work, cheap wireless temperature transmitters are installed in a 40 year old building to gain information about the performance of the buildings envelope for model calibration purposes. The goal is to have a calibrated energy model that is sufficient for control system optimization. To perform this task, a detailed model is built and envelope parameters of this model are calibrated by using feedback control to identify components of zone heat balances. Uncertainty and sensitivity analysis along with optimization is used to calibrate envelope parameters so that heat transfer through the envelope is captured accurately.

INTRODUCTION

The process of building energy modeling can be broken into two different categories; modeling prior to final design and construction to assess different design measures, or modeling after the building is designed and built. In the second case, the resulting model can be used to assess retrofit candidates, for diagnostics or model predictive control, and other studies that quantify how changes in the design or operation of the building will influence energy or comfort - without disturbing occupants. In the later example, in order for the model to be effective, data should be taken from the building and used to refine the nominal estimates for the parameters in the model, resulting in a calibrated model.

In many calibration studies year-long or otherwise aggregated energy consumption is used as a metric to determine the accuracy of the model (e.g. (Reddy et al., 2007)). In (Haberl and Bou-Saada, 1998) the definition of goodness of fit based on different statistical metrics (e.g. hourly mean bias error, root mean squared error, coefficient of variation of the root mean squared error) was addressed, and many of these topics have been formalized into formal guidelines (see (ASHRAE, 2002) and (Liu et al., 2003)). Other formalized methods for model calibration were presented in (Sun and Reddy, 2006) where the applicability of candidate parameters for calibration was discussed. Sensitivity analysis can be performed to identify these dependencies and has been recently used in various studies ((Coakley et al., 2011), (Raftery et al., 2009), (Eisenhower et al., 2012), (Heo et al., 2012), and (O'Neill et al., 2011)).

The common approach of creating an energy model that contains all expected contributions to energy consumption and heat to the thermal balance makes sense when the focus of the calibration effort is to develop a model that predicts monthly utility costs. When the model is used for other purposes, as in model-based control development or tuning, utility bills may become less important. The dynamics of the thermal balance and its specific contributions at the zone level becomes an important aspect of the prediction capability of the model and hence its calibration and identification of values for uncertain parameters.

Various efforts have been made to identify different aspects of the heat balance in a building using both models and sensor data. In (ONeill et al., 2010), a Kalman filtering approach was used, in conjunction with a reduced order model to identify the HVAC load for the purpose of advanced and optimizing control. In (Schweiker et al., 2012) and (Widen et al., 2012) data was used to characterize and model occupant based influences including window states in a building, activity, and energy usage.

In most of these studies, additional sensors or surveys were used to gather needed information for the components that contribute to the heat balance in the energy model. This paper is the first in a series that will identify different aspects of the heat balance using only temperature sensors and limited information from the HVAC system. The HVAC system that we will study is a dual duct system with pneumatic mixing boxes at the zone level. Because of this, we do not know how much HVAC heating or cooling is entering each zone. In addition to this, there will be no sub-meters or occupancy logs to quantify internal loads.

The approach will be to perform data mining and pattern recognition on the data to isolate different contributions to the heat balance in time. The first step however is calibrate the heat exchanged with the outdoor environment. This is done by performing uncertainty analysis and optimization on envelope parameters when the building is not occupied and the HVAC system is shut off. Future studies will leverage this calibrated envelope model to identify typical occupancy patterns. The ultimate goal is to obtain a calibrated whole building energy model to use for recommissioning the control system for the dual duct air handling units (AHUs) - by way of optimal pre-conditioning and climate adaptive setpoints.

In the next section we will describe the approach used to identify a portion of the zone heat balance that will lead us to information regarding the envelope parameters. The approach will be described in a general way while the case study which follows will describe specifics of this approach.

APPROACH

The method to calibrate the envelope of a building model described in this paper is different than traditional methods as it requires less assumptions and has fewer degrees of freedom on uncertain inputs. Traditional calibration approaches require the user to make assumptions on all stationary parameters (e.g. envelope parameters) as well as parametric influence that varies in time. These time dependent influences include schedule-based internal loads (equipment, occupancy, etc.), lighting operation, and HVAC operation. Assumptions on all of these parameters are chosen and typically an optimizer is used to automatically adjust these parameters to minimize a difference between the model and data acquired from the building.

Two issues with this approach are 1) the number of uncertain parameters grows very quickly, especially when parameterizing time variant influences (e.g. hourly schedules for each type of internal load or HVAC operation), and 2) the influence of these parameters is not orthogonal - the same model response can be achieved by having a high internal heat load as with having high amount of HVAC heating. The approach in this paper helps to alleviate these concerns by isolating portions of the heat balance in a way that reduces the numbers of parameters and assumptions on these parameters while reducing the impact of the non-uniqueness in parameter combinations.

The approach used to calibrate envelope properties of the building energy model begins by comparing the temperature output between sensors in the building and the model, and identify heat that is necessary to drive the difference in these temperatures to zero. Envelope parameters are then varied to minimize the error between the estimated heat flow and measured/intuited heat flow. The general steps to this process are outlined below:

1. **Collect Data.** Data from the Building Management System BMS was selected for archiving, which includes very few actuator and thermal sensors at the AHU level. In addition to this, additional temperature sensors were placed into the building to measure comfort, approximately 75% of the zones in the building were equipped with inexpensive wireless temperature transmitters.

2. **Energy Modeling.** An energy model was built for the building using original drawings which were updated to accommodate for changes in the design since construction. An actual meteorological year (AMY) weather file was obtained to capture conditions current to the study. The model contains no HVAC systems or internal loads.

3. **Heat Identification.** A control loop is connected to the energy model using co-simulation which identifies the necessary heat input that is needed to match the operative temperatures of the energy model with the measured temperatures in the building. This heat may include internal loads (including occupants), HVAC heat, and any error in the envelope portion of the model. The heat balance for each zone is:

$$C_i \frac{dT_i}{dt} = \dot{Q}_{\text{Env}} + \dot{Q}_{\text{Int}} + \dot{Q}_{\text{HVAC}} \ , \qquad (1)$$

where C_i is the thermal capacitance of the zone, T_i is zone temperature, $\dot{Q}_{\text{Env}}$ is heat transfer within the envelope (including interior partitions), $\dot{Q}_{\text{Int}}$ is heat transfer from internal loads (and occupants) and $\dot{Q}_{\text{HVAC}}$ is heat transfer from the HVAC system. The heat transfer within the envelope can be partitioned as:

$$\dot{Q}_{\text{Env}} = \sum_{j=1}^{N_{\text{part}}} \dot{Q}_{\text{part}_j} + \dot{Q}_{\text{Amb}} + \dot{Q}_{\text{Env}_\varepsilon} \ . \qquad (2)$$

N_{part} is the number of internal partitions and thermal mass elements ($\dot{Q}_{\text{part}_j}$ is heat transfer exchanged in these partitions), $\dot{Q}_{\text{Amb}}$ is the heat transfer with the ambient outdoor environment, and $\dot{Q}_{\text{Env}_\varepsilon}$ is the error in envelope heat transfer. If the envelope of the model is calibrated well, $\dot{Q}_{\text{part}_j}$ and $\dot{Q}_{\text{Amb}}$ will match the real building and this error will be zero. In the process of matching the temperature output of the model with the sensors, an identified heat transfer is found as

$$\dot{Q}_{\text{ID}} = \dot{Q}_{\text{Int}} + \dot{Q}_{\text{HVAC}} + \dot{Q}_{\text{Env}_\varepsilon} \ . \qquad (3)$$

With knowledge of how the HVAC system is operated and intuition on internal loads, $\dot{Q}_{\text{Env}_\varepsilon}$ can be assessed using a PID controller that identifies $\dot{Q}_{\text{ID}}$. Optimization is used to minimize $\dot{Q}_{\text{Env}_\varepsilon}$ so that the heat transfer with the ambient environment through the envelope in the model is close to what occurs in the real building.

4. **Parameter Perturbation.** To perform the calibration using optimization, uncertainty analysis is initiated by perturbing all numerical parameters in the model by sampling them around their nominal value. A large number of perturbed models are created and simulated creating a database of data that is used to fit a meta-model.

5. **Sensitivity Analysis and Model Reduction.** A metric is defined that indicates how well the model is calibrated (the variance of $\dot{Q}_{\mathrm{ID}}$ during unoccupied hours is used, as explained later). This metric is calculated for all of the 500 parameter samples, and sensitivity analysis is performed to identify which parameters are critical to this metric. Once these parameters are isolated, a reduced order meta-model is fit to the data using only these critical parameters.

6. **Optimization** Numerical optimization is performed on the reduced order meta-model to identify which numerical combination of critical parameters are needed to get the best agreement between model predictions and data. The optimized parameters are placed into the original model and simulated to confirm their performance in the real model.

CASE STUDY

In this section the building which is used as a case study is explained, along with the setup for data acquisition. The energy model and how it is implemented into the co-simulation environment is then explained including the development of a discrete-time PID controller for heat balance identification. Parameter sampling, sensitivity analysis and model reduction is then explained. This section is concluded with the discussion of the calibration of the envelope parameters of the model.

The building and its usage

The building used as an example in this study is a student healthcare center on a university campus. The building was designed and constructed in the 1970's and acts as an outpatient facility with services ranging from optometry and dentistry, to wellness and counseling. The building is a single story and is conditioned with a dual duct fresh-air only system. The layout of the building is fairly symmetrical (see Figure 1) and two air handling units (AHUs) are used for each half of the building, both with 1.13 $\mathrm{m^3/s}$ (2400 CFM) fans. Two Trane 110 ton chillers, and two 651 (input) 516 (output) kW (2,220,000 / 1,760,000 $\mathrm{BTU/Hr}$) Bryant boilers are used for heating and chilled water production.

This building was chosen as a candidate for a recommissioning audit as it stands out as being one of the largest normalized energy consumers of the 100 or so buildings on campus. In addition to this, occupants are rarely comfortable, wearing winter jackets and using electric space heaters when needed in some areas of the building, and complaining of extreme heat in others. At the zone level, cold and hot air mixing boxes (44 in the upper wing, 54 in the lower wing) are operated using pneumatic thermostatic controls with no data acquisition on how these are functioning.

Data Acquisition

Because of the vintage of the building, very little data existed regarding its operation and performance - other than comfort complaints, which aren't logged. With this in mind, 82 temperature sensors were strategically placed (Figure 1) to ensure temperature data is representative of the whole building (Inovonics EN 1723 dual temperature transmitters (Inovonics, 2013)). This wireless transmitter can accurately record temperatures ranging from -25 to 60 °C (-13 to 140 F) with a typical accuracy of 0.44 °C (0.80 F). The EN 1723 sensors are capable of recording data at a variety of time intervals ranging from fifteen minutes to half of a second, while for our implementation, we chose a 5 minute interval, or a temperature change of 0.28 °C (0.5 F), whichever came first. The equipment cost was approximately $50 (USD in 2012) per sensor including the single receiver which operates at a frequency of 900 MHz. The wireless sensors come in a compact format (about half the size of a deck of playing cards) and were mounted using adhesives near the existing pneumatic thermostatics (i.e. no tools or equipment were needed for the network installation).

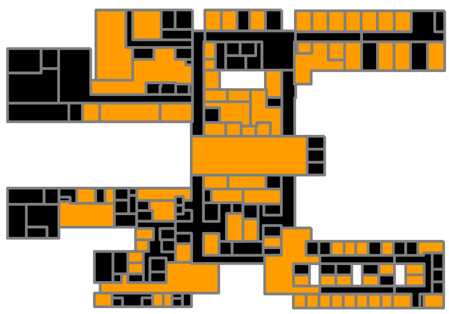

Figure 1: Floor plan highlighting the locations of 82 wireless temperature sensors installed (light color). The rooms colored black (no sensor) in many cases are unoccupied, or equipment rooms.

To accompany the wireless data, limited equipment data was archived from the Johnson Controls Meta-Sys system that operates the chiller, boiler, and AHUs. This data includes hot and cold deck temperatures, outdoor temperatures, AHU damper and coil commands for the hot and cold deck, as well as the command for the supply fan. Additional sensor values were available for the boiler and chilled water loop including supply and return temperatures and pump commands. The combination of all of these variables was used to ascertain the operation schedules and relative heating/cooling that was provided to the building for each of the two AHUs.

Building Model

An energy model was constructed of the building using EnergyPlus (version 7.2.0). The architectural layout was obtained from original drawings while information about updates to the building design were gathered by walk-through discussion with the building manager. The model consists of eight basic constructions types: exterior walls, doors, windows, roof, flooring, interior walls, doors and furnishings. Each construction is built of at least one layer from 12 different materials. The materials were taken from the commercial reference building model for existing buildings constructed before 1980 for the *outpatient health care* building type developed by (U.S. Department of Energy, 2013). An R16 insulation layer was added to the envelope of the building as it was found that the insulation in the template file was not sufficient. These template materials are only a starting guess, as the exact properties of the building are not known. The material parameters are later varied in parallel simulations to get a model that behaves the same way as the real building. In total 182 zones were created, which account for every room in the building and sectioned hallways.

No HVAC systems or internal loads (i.e. people, equipment, and lighting) were accounted for in this model. For this reason we focus on unoccupied hours such as nights and weekends - when the building is empty and systems are off. The intent at the initial stages of this project is to identify characteristics of the envelope, followed by detailed characterization of loads in each zone.

Sensor installation began in September 2012, while data for January 2013 was used for this study.

Developing the controller to determine $\dot{Q}_{\mathrm{ID}}$

To perform the identification of the heat balance, the Building Controls Virtual Test Bed (BCVTB version 1.2.0) was integrated with EnergyPlus and the temperature data that was obtained from the wireless sensor network. A discrete proportional-integral-derivative (PID) controller which was implemented with Ptolmey II's graphical modeling environment was used to identify the energy input to the model. The controller and the model were connected to form the feedback control loop shown in Figure 2. There is one controller for each of the 182 thermal zones. The measured sensor temperatures is the reference to each PID controller, and the output of the model for these same zones is the feedback signal. For the rooms where there was no temperature sensor installed (black rooms in Figure 1), data from an adjacent with similar behavior was assigned to it. The PID controller then calculates the

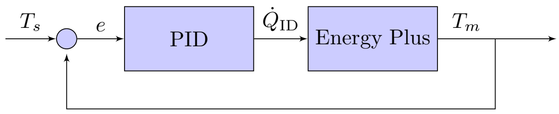

Figure 2: Diagram of the heat flow ($\dot{Q}_{ID}$) identifier. The PID block is implemented in the BCVTB and T_s are measured sensor temperatures, while T_m are modeled operative temperatures.

energy $\dot{Q}_{\mathrm{ID}}$ from Equation 3

$$\dot{Q}_{\mathrm{ID}}(t) = K_P e(t) + K_I \int_0^t e(\tau)\, d\tau + K_D \frac{d}{dt} e(t) \quad (4)$$

needed to drive this error e to zero. Equation 5 is used for the simulations is the discrete form of Equation 4

$$\dot{Q}_{\mathrm{ID}}[k] = K_P e[k] + K_I t_s \sum_{i=0}^{k} e[i] + K_D \tfrac{e[k]-e[k-1]}{t_s} \quad (5)$$

with K_P, K_I, and K_D being the PID coefficients and t_s the sampling time (in this case, the sample time is 5 minutes). The controller is implemented in its state space representation in the controller canonical form. The transfer function of a general infinite impulse response (IIR) filter in the z-domain

$$\begin{aligned} H(z) &= \tfrac{Y(z)}{U(z)} = \tfrac{b_0+b_1 z^{-1}+\cdots+b_{N_b} z^{-N_b}}{1+a_1 z^{-1}+\cdots+a_{N_a} z^{-N_a}} \\ H(z) &= b_0 + \tfrac{(b_1-b_0 a_1)z{-1}+\cdots+(b_N-b_0 a_N)z^{-N}}{1+a_1 z^{-1}+\cdots+a_{N_a} z^{-N_a}} \\ H(z) &= b_0 + \tfrac{\beta_1 z^{-1}+\cdots+\beta_N z^{-N}}{1+a_1 z^{-1}+\cdots+a_{N_a} z^{-N_a}} \end{aligned} \quad (6)$$

is transformed to the transfer function in state-space

$$C(zI - A)^{-1}B + D \quad (7)$$

with the matrices

$$A = \begin{bmatrix} -a_1 & -a_2 & \cdots & -a_{N-1} & -a_N \\ 1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & \cdots & 0 & 0 \\ & & \cdots & & \\ 0 & 0 & \cdots & 1 & 0 \end{bmatrix} \qquad B = \begin{bmatrix} 1 \\ 0 \\ 0 \\ \cdots \\ 0 \end{bmatrix}$$

$$C = \begin{bmatrix} \beta_1 & \beta_2 & \cdots & \beta_N \end{bmatrix} \qquad D = \begin{bmatrix} b_0 \end{bmatrix} \quad .$$

This applied to a PID controller

$$\begin{aligned} H(z) &= K_P + K_I \tfrac{z}{z-1} + K_D \tfrac{z-1}{z} \\ H(z) &= \tfrac{(K_P+K_I+K_D)z^2+(-K_P-2K_D)z+K_D}{z(z-1)} \\ H(z) &= \tfrac{(K_P+K_I+K_D)+(-K_P-2K_D)z^{-1}+K_D z^{-2}}{1-z^{-1}} \end{aligned} \quad (8)$$

leads to the coefficients

$$a_1 = -1 \qquad \beta_1 = K_I - K_D$$
$$a_2 = 0 \qquad \beta_2 = K_D$$

to realize the PID in its controller canonical form

$$A = \left[\begin{smallmatrix} 1 & 0 \\ 1 & 0 \end{smallmatrix}\right] \qquad B = \left[\begin{smallmatrix} 1 \\ 0 \end{smallmatrix}\right]$$
$$C = \begin{bmatrix} K_I - K_D & K_D \end{bmatrix} \qquad D = \begin{bmatrix} K_P + K_I + K_D \end{bmatrix} \quad .$$

Each of the 182 PID controllers needs to be tuned due to different dynamics in every room. Because that would be too time consuming, for a start one room was selected and tuned by applying the Ziegler-Nichols method, which is an automated way to obtain PID coefficients for a particular system (G.F. Franklin, 2006). To gain information about the dynamics of the system, both the integral (K_I) and derivative (K_D) gains of the PID were set to zero while increasing the proportional (K_P) gain until the system oscillates with a constant amplitude and frequency as shown in Figure 3. For this test, the outdoor temperature was held constant and a step was used as reference temperature because the system may or may not be initially stable. The gain at which the system begins to oscillate is called the ultimate gain K_u. This and the period of the oscillation P_u are used to identify the PID gains using the Ziegler-Nichols' rules

$$K_P = \frac{K_u}{1.7}, \ K_I = \frac{2K_u}{1.7P_u}, \text{ and } K_D = \frac{K_u P_u}{1.7 \cdot 8}. \quad (9)$$

With this, the coefficients for the PID controller for one zone are established. To determine the coefficients for the other zones, these coefficients are scaled based on relative difference in the volume of each zone as compared to the zone in which the controller was tuned for. The coefficients increase all by the same ratio with increasing zone volume.

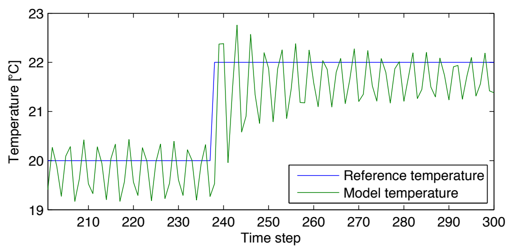

Figure 3: Tuning of a PID controller with the Ziegler-Nichols method. The proportional gain is increased until the system oscillates with constant amplitude and period. The integral gain is set to zero, hence the steady state error, and so is the derivative gain. The found gain and period are put into Equation 9 to obtain the PID coefficients.

The structure of the control system in Figure 2 is a simple way to identify the heat necessary for the zone thermal balance. Other structures were tested including disturbance rejection acting on the outdoor temperature in addition to the reference tracking. This was found to not have much influence on the controlling quality, hence unnecessary and was removed for the model analysis.

An example of how well the controller identifies the heat necessary to drive the model temperature to match the sensor temperature is illustrated in Figures 4 and 5. Monitoring the norm of the error in Figure 5 for all zones is a quick way to establish how well the PID

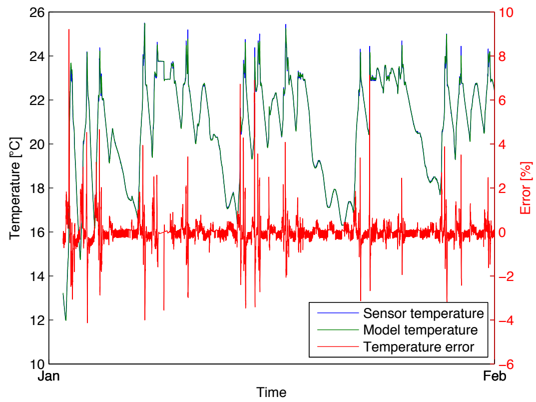

Figure 4: Sensor and model temperature for a typical zone (practically on top of each other). The PID controller manages to identify the heat needed to maintain a model temperature that is very close to the actual temperature. On the right y-axis is the tracking error in percent with a standard deviation (from zero error) of only 0.73 pp.

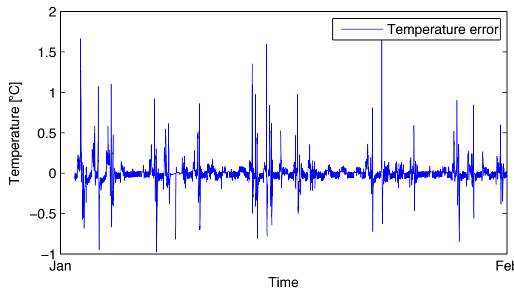

Figure 5: The error between reference and model temperature is kept between ±1.7 °C for this typical zone, the root mean squared error is only 0.16 °C.

controllers are tuned for each zone without investigating time traces for all 182 zones.

Parameter Sampling

Parameter sampling was used to characterize the behavior of the model with parameter values different than the nominal values. Because there is no environmental systems, occupancy, lighting, or equipment loads in the model, there was only 69 parameters that were candidates for envelope calibration. These parameters include material properties for walls, and internal mass, as well as window properties and infiltration rates. Other numerical parameters in the model that were not included for calibration were architectural dimensions and simulator parameters.

Most of the parameters that were selected were varied by ±75 % of their nominal value using a uniform distribution (all parameters were positive and non-zero), the solar heat gain coefficient was varied by ±10000 % because of large uncertainty in the modeling of the shading devices, and the material thicknesses were varied by ±1000 %. Regardless of the desired perturbation range, the range was ultimately constrained as necessary (e.g. [0,1] if fractional, etc.). A matrix of 500 values for each of these 69 parameters was created using a deterministic sampling algorithm (similar to (Burhenne et al., 2011) or (Eisenhower et al., 2012)). Simulations were performed in parallel on a 16-core desktop workstation, which took about 8 hours to complete the entire batch of simulations. A single simulation for this month with twelve time steps per hour, i.e. every five minutes, takes about four minutes on an Intel Xenon E5-2650 CPU running at 2 GHz.

Data Analysis

To calibrate parameters for the envelope, the heat balance is calculated during times when the building is not occupied and when the equipment is off ($\dot{Q}_{\mathrm{Int}}$ and $\dot{Q}_{\mathrm{HVAC}}$ from Equation 3 are near zero), and the variance of the remaining identified portion of the heat balance is minimized. As mentioned in the introduction, at any time, the heat identified by the PID controller includes heat from internal loads, the HVAC system, and any heat that is not accurately captured in the envelope model. When the building is not occupied and the HVAC system is turned off, we expect there to be a relatively constant load from remaining equipment (e.g. idle office equipment or refrigerators, etc.). It is expected that these loads are constant and do not track outdoor conditions.

If the envelope model is calibrated correctly, all of the heat transfer between the building and the outdoors will be accurately captured in $\dot{Q}_{\mathrm{Amb}}$ and $\dot{Q}_{\mathrm{part}}$ in Equation 2. Any identified heat from the PID controller that tracks outdoor conditions is expected to be errors or residuals in this heat flow to the ambient. Therefore, the goal is to minimize any variance or tracking of outdoor conditions when it is expected that there is no variable internal load or HVAC heat addition (small constant loads are expected from idle equipment). A formal metric for how this is being accomplished was established by calculating the variance for the sum of all $\dot{Q}_{\mathrm{ID}}$ in the building (summed over all zones for each time step) over the hours 20-4 each night, additionally 11-20 on Saturdays, and all day on Sundays.

With a metric for how accurate the envelope portion of the model is, this variance is calculated for all 500 simulations from the sampled set. From this data, a meta-model is calculated using support vector regression which is then used to identify critical parameters of the model using sensitivity analysis. The critical parameters are parameters that have a strong influence on the variance discussed above. Figure 6 illustrates the sensitivities for the 69 parameters with the top 10 most critical parameters highlighted in color.

Once critical parameters are identified (10 of the total 69) a reduced order meta-model is calculated that only accounts for this reduced set of parameters. This reduced model is then used to in conjunction with a numerical optimizer to identify which values for these parameters is needed to calibrate the model based on

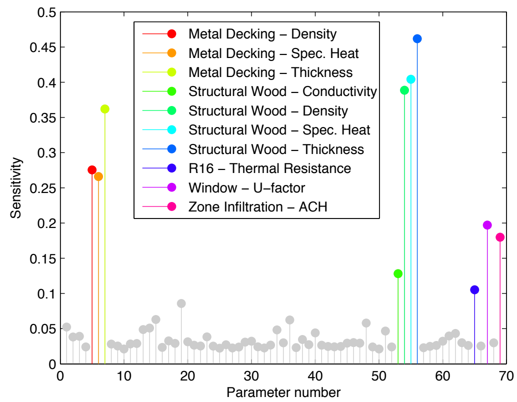

Figure 6: Sensitivities for the 69 parameters that are related to the envelope portion of the model. These sensitivities indicate the influence on the variance of the residual heat calculated during unoccupied hours.

minimizing the variance of $\dot{Q}_{\mathrm{ID}}$ during unoccupied hours. An interior point optimizer was used to perform this optimization, and since the optimization process takes only a fraction of a second, two optimizations were performed: minimizing the variance of $\dot{Q}_{\mathrm{ID}}$ and maximizing the same (which is not desired). Figure 7 illustrates $\dot{Q}_{\mathrm{ID}}$ for the nominal case and these two optimized cases (Table 1 presents the values for the critical parameters for these three EnergyPlus simulations - all other parameters remained the same as the nominal case).

Table 1: The 10 critical parameters' values for the reduced order meta-model.

Parameter	Nominal	Min var	Max var
Metal Decking			
- Density [$\mathrm{kg/m^3}$]	7680	1932	13176
- Spec. Heat [$\mathrm{J/kgK}$]	418	238	733
- Thickness [m]	0.0015	0.0082	0.0147
Structural Wood			
- Conductivity [$\mathrm{W/mK}$]	0.1200	0.1705	0.1825
- Density [$\mathrm{kg/m^3}$]	100	106	175
- Spec. Heat [$\mathrm{J/kgK}$]	1210	1204	2118
- Thickness [m]	0.0100	0.0001	0.1101
R16 insulation			
- Thermal Resistance [$\mathrm{m^2K/W}$]	16	23	20
Window			
- U-factor [$\mathrm{W/m^2K}$]	4	1	5
Zone Infiltration			
- ACH [$\mathrm{1/h}$]	0.2100	0.1551	0.2512

In Figure 7, it is evident that the optimization process reduces the variance of the $\dot{Q}_{\mathrm{ID}}$ during unoccupied hours when this is the goal. It is also evident that by maximizing the variance, the $\dot{Q}_{\mathrm{ID}}$ tracks outdoor conditions to a larger degree. This suggests that the envelope properties of the model are calibrated (in the minimized case). Further work is needed to verify with new data that the response is the same for new time periods and that these envelope parameters calibrate the

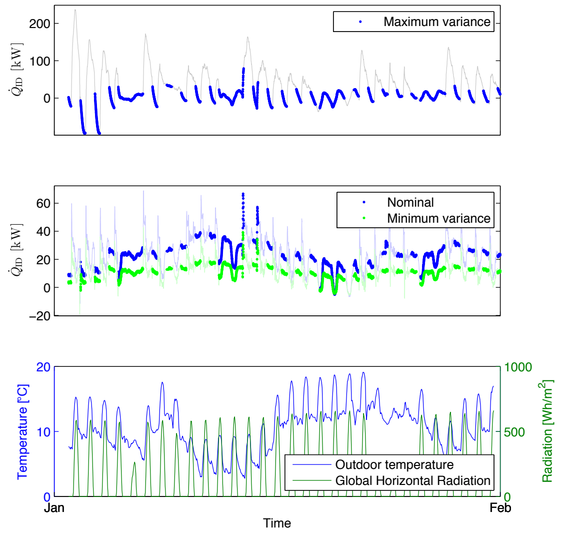

Figure 7: The sum of the identified heat ($\dot{Q}_{ID}$) over all zones for the month of January that is needed to drive the operative temperatures in each zone to match the sensor values. The first plot shows $\dot{Q}_{ID}$ for the nominal and the minimum variance optimized case. In the middle is the maximum variance case, note that this is plotted in a different scale. The bottom plot shows the outdoor temperature and the global horizontal radiation from the sun for the simulated period.

model for other seasons.

CONCLUSION

In this paper we discussed an approach to calibrate envelope parameters of a building energy model using cheap thermal sensors, a PID control loop in a co-simulation environment, and uncertainty and sensitivity analysis coupled with numerical optimization. By identifying the amount of supplemental heat that is needed in the energy balance for each zone, we calibrate parameters of the model so that this variance is minimized. This is only the first step in the formal calibration of the building energy model which will be used for model-based recommissioning. The next steps will be to use the identification of the elements of the heat balance to capture typical time dependent loads in the building (from occupants and internal equipment) and investigate how the calibrated model performs on new data in a validation step. With this information, optimized control strategies will be sought to maintain and enhance comfort in the building while minimizing energy used. This work was performed using EnergyPlus and the Buildings Control Virtual Test Bed, while the methods can be used in many other software environments.

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NOMENCLATURE

ACH	Air changes per hour
AHU	Air handling unit
Amb	Ambient
AMY	Actual meteorological year
BCVTB	Building Controls Virtual Test Bed (software)
BMS	Building management system
C	Thermal capacitance
D	Derivative coefficient
Env	Envelope
ε	Error
HVAC	Heating, ventilation, and air conditioning
I	Integral coefficient
i	Zone number i
ID	Identified
IIR	Infinite impulse response
Int	Internal
K	Gain
K_u	Ultimate gain (Ziegler-Nichols)
N	Total number (of subscript)
P	Proportional coefficient
part	Internal partitions and thermal mass elements
PID	Proportional-integral-derivative (controller)
P_u	Ultimate oscillation period (Ziegler-Nichols)
$\dot{Q}$	Heat transfer rate
T_m	Model temperatures
T_s	Sensor temperatures
t_s	Sampling time

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