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HEAT TRANSFER INVERSE MODELING OF BUILDINGS USING REAL TIME SENSOR DATA FOR OPERATIONAL ENERGY EFFICIENCY IMPROVEMENT

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ABSTRACT

Development of an accurate heat transfer model of buildings is very important. This model can be used for analyzing energy efficiency of buildings, predicting energy consumption and providing decision support for energy efficient operation of buildings. Commercially available building energy simulation such as EnergyPlus, eQuest and TRNSYS can be used to develop the heat transfer models, but they require substantial effort to collect the needed data, which in some cases is not possible. In this study, we have developed an inverse approach, which, if properly set up, can calibrate heat transfer models for many buildings in automatic fashion based on mostly sensor data collected from each building. We have tested our approach using simulated and real sensor data and we demonstrate superior results using our approach.

INTRODUCTION

The building sector, which includes commercial and residential buildings in the Unites States, accounts for 40% of the nations total energy consumption (DOE, 2006). It has also been responsible for 45% of the green-house gas (GHG) emissions. The prediction of energy usage in the building is useful for identifying opportunities for improving energy performance, saving energy consumption and for reducing greenhouse gases (GHG). However, it is difficult to develop a model that accurately predicts energy consumption in buildings because the energy consumption is influenced by building characteristics, HVAC systems, operations, occupants behavior, weather condition and many other factors. Therefore, many approaches for building energy models that estimate building energy consumption in various conditions has been proposed and used from building design phase to operation and control and to retrofitting.

These approaches can be classified into two major types: forward and inverse modeling. Although the inverse modeling generally requires high level of mathematical techniques and expertise, it would be more feasible to predict energy consumption of existing building at a certain circumstance because the method needs a smaller set of input data comparing with the forward modeling and the key thermal parameters are deduced from actual building performance data (ASHRAE, 2009). Dynamic inverse model as one of data-driven modeling for building energy performance is a method that allows estimation of thermal parameters of a building or space using differential equations that describe the heat transfer phenomena (Andresen and Brandemuehl, 1992).

A number of papers has been published for the dynamic inverse modeling that aim at estimating key heat transfer parameters of building using sensor and meter data. Previous studies have applied a simplified thermal-network model (Wang and Xu, 2006; Braun and Chaturvedi, 2002; Fraisse et al., 2002) or thermal response model (Armstrong et al., 2006), but many of them used simulated data to recover the thermal parameters or tested the model under a small laboratory setting (Park et al., 2011). One of the most common models is the simplified building internal mass model 3R2C (Schultz and Svendsen, 1998), which from our experience, may not produce neither accurate nor robust prediction which is good enough in realistic settings with real sensor data.

Development of an inverse model for building energy that can calibrate models for many buildings in automatic fashion based on mostly sensor data collected from each building is of high importance. However, reasonably accurate inverse models in practical commercial environment is very difficult to develop. Deriving a common and reasonably simple set of heat transfer equations that produce realistic energy prediction of many buildings of interest is very challenging, since the sensor data that are used to calibrate the heat transfer model can be inaccurate; and building operation (and/or behavior of building occupants) changes over time.

In this paper, we present an approach for developing a dynamic inverse modeling tool that can handle uncertainties by sensor data and can be used as an energy management system (EMS) for commercial buildings. The developed model is constructed in an automatic fashion by using parameter estimation algorithms which is incorporated with real-time data from building management system (BMS).

To date, the common practice in heat transfer simulations for buildings was to use forward modeling approach combined with possible black box type optimization. This approach typically requires substantial manual efforts and the developed model is limited to one particular building. Additionally, a lot of data for building envelopes, materials and HVAC system information are needed to construct such a model and to calibrate the model based on the actual building thermal performance (Haberl and Bou-Saada, 1998).

In this paper, we present an approach for developing inverse modeling tool that can handle uncertainties of sensor data and can be used as EMS for commercial buildings. The inverse model is calibrated in an automatic fashion using real time sensor and meter data coming from BMS. The recovered parameters of heat transfer reflect the current properties (not necessarily the design properties) of building's structures resulting from aging and degrading, and they can be used to determine a dynamic profile of building's energy consumption, to evaluate energy impact of operational alternatives of HVAC systems, and to compute optimal operational settings that optimize the balance between occupant comfort and energy consumption. In this paper, we also describe techniques for calibrating the inverse model and performing sensitivity analysis to improve and assess the model accuracy. The proposed method has been applied and implemented for a midsized commercial building to study the effectiveness.

More specifically, we derive an integrated PDE-ODE model that describes thermal energy balance in various zones in a building, and propose an inversion procedure to estimate physical parameters associated with the enclosure of the zones. In addition, we estimate a time-dependent function associated with the internal load of the zones by minimizing the misfit between simulated and measured sensor data. Since the model is designed to work with real sensor data in addition to simulated data, the set of parameters which are recovered must be carefully chosen to handle uncertainties in the real settings of commercial buildings. For instance, the building under study may be surrounded by other buildings, and due to shading, solar radiation on different sides of wall can be different from one another; dynamics profile of internal load might not be available; supply air temperature may not be clearly defined with different HVAC systems. Some sensor data, such as inner or outer surface temperature of wall, may not be accurate and may require reinstallation of the sensors. When recovered parameters are used in simulation, a weighted averaging of the parameters recovered from different calibration periods is properly considered. We design our calibrating procedure in two steps. Firstly, multiple initial values are randomly chosen for the optimization procedure to reduce chances of getting a local minimum. Then, a validation step is taken to choose a proper regularization coefficient to avoid data over-fitting. We add a regularization term to our objective misfit function in order to avoid over-misfit of our solution to the noise level, in addition by adding regularization we restrict our solution space and favor a more smooth temperature profile, which is reasonable assumption for this problem.

The paper is organized as follows. Firstly, we present a formulation of PDE-ODE model that describes heat transfer equations through the building envelope and interior zone. Next, we describes our calibration and simulation procedure, followed by presentation of a case study on how the model was applied to a commercial building. Lastly, we provide conclusion and summary of the study.

PDE-ODE HYBRID MODEL

The enclosure, which includes wall, windows, floor and roof of a building (or a zone) provides insulation for the occupied space. Based on thermodynamics principles, heat can transfer through the enclosure (building envelope) in the form of conduction, convection and solar radiation.

Mathematically, wall temperature T_{ws} for the side $s \in \{N, E, S, W, R\}$ satisfies the following PDE

$$\rho_w C_{wp} d_{ws} \frac{\partial T_{ws}}{\partial t} = \frac{\partial}{\partial x}\left(\lambda_k K \frac{\partial T_{ws}}{\partial x}\right), \quad (x,t) \in (0, d_{ws}) \times (t_0, t_f) \tag{1}$$

with boundary conditions

$$\lambda_k K \frac{\partial T_{ws}}{\partial x}(0,t) = -\lambda_{eh} h_{os} (T_{amb}(t) - T_{ws}(0,t)) - \lambda_{ws} Q_{sol}(t) + (\lambda_{eos} - 1)\sigma (T_0 + T_{ws}(0,t))^4 \tag{2}$$

$$\lambda_k K \frac{\partial T_{ws}}{\partial x}(d_{ws},t) = \lambda_{ih} h_{is} \left(T_{zone}^{sen}(t) - T_{ws}(d_{ws},t)\right) - (\lambda_{eis} - 1)\sigma (T_0 + T_{ws}(d_{ws},t))^4 \tag{3}$$

The heat flux at wall surfaces consists of the convection driven by the difference between ambient air temperature and surface temperature, solar radiation on wall and heat radiated from wall. In equation (1), ρ_w is wall density, C_{wp} is specific heat of wall, h_{os}, h_{is} are convection coefficients which are functions of surrounding wind speed and temperature difference. K is wall conductivity; Q_{sols} solar radiation; d_{ws} thickness of wall, subscript s means that its value is different for each wall direction; σ is the Stefan-Boltzmann constant. $T_0 = 273.15°K$ is the absolute temperature corresponds to $0°C$. T_{amb}, T_{zone}^{sen} are ambient and zone temperature respectively. Multipliers $\lambda_k, \lambda_{ih}, \lambda_{eh}$ are for conductivity and internal and external convection respectively. Note that no side of wall dependence is assumed here. Multiplier λ_{ws} is for heat absorption coefficient, which is different for different sides, since each wall might be under different shading effect from nearby buildings or trees and with different color and smoothness. The multipliers $\lambda_{eos}, \lambda_{eis}$ are used to adjust external and internal wall heat radiation. Assuming we have a good estimation for the physical parameters, we expect all λ's value to be close to 1. In such case, the whole factor for heat radiation could be negative. As a matter of fact, wall surface temperature reading from sensor is most likely to be inaccurate, and strongly depend on sensor location. We would like to treat this term as some kind of artificial term to handle a systemic and consistent error resulting from improper-emplacement of surface sensors.

Temperature T_{zone} inside a zone satisfies the following ODE

$$\lambda_{ac}\rho_{air}C_{ap}V_{zone}\frac{dT_{zone}(t)}{dt} =$$
$$\lambda_{ih}\sum_s h_{is}A_{ws}\left(T_{ws}(d_{ws},t) - T_{zone}(t)\right) +$$
$$\sum_s(\lambda_{eis}-1)\sigma(T_0 + T_{ws}(d_{ws},t))^4 +$$
$$\lambda_{gu}\sum_s U_{gs}A_{gs}\left(T_{amb}(t) - T_{zone}(t)\right) +$$
$$\lambda_{inf}\rho_{air}C_{ap}\dot{M}_{inf}\left(T_{amb}(t) - T_{zone}(t)\right) +$$
$$\lambda_{shgc}\sum_s \lambda_{ws}Q_{sol}A_{gs} + \lambda_{load}Q_{load} +$$
$$\rho_{air}C_{ap}\dot{M}_{sys}\Big(T_{sys}(t) - T_{zone}(t)\Big) \qquad (4)$$

Where ρ_{air} is density of air, C_{wp} is specific heat of air, V_{zone} is zone volume, A_{ws} and A_{gs} are areas of wall and window respectively, U_{gs} is U-value of window, $\dot{M}_{inf}$ is infiltration rate and $\dot{M}_{sys}$ is Air Handling Unit (AHU) supply air flow rate. Q_{load} is internal load, including contribution from lighting, electric equipment and occupants, T_{sys} is the system supply air temperature. Multipliers $\lambda_{ac}, \lambda_{gu}, \lambda_{inf}, \lambda_{shgc}, \lambda_{load}$ are for air heat capacity, for U-value of window, for air infiltration rate, for solar heat gain coefficient through window and for internal load respectively.

The first two terms in the right hand side represent convection and heat radiation contribution from different walls. The internal wall temperature T_{ws} and the multipliers λ_{is} and λ_{eis} were established during calibrating of the above PDE system. The third term stands for heat conduction through windows. The fourth term stands for air infiltration through building enclosure. The fifth term is for solar radiation contribution through window. The sixth term is for internal load. The multiplier λ_{load} can be vary depending on time of a day. A piecewise constant function is chosen with a constant value for every three hours in a day. The seventh term is for system supplied energy, which is used to maintain the comfort level of zone temperature. Note that heat contribution through window is modeled differently compared with the heat transfer through wall, and is modeled directly through the third and fifth terms in equation (4), because window heat capacity is much smaller than wall heat capacity. The value of λ_{ac} will reflect wall partition, furniture and equipment layout inside the zone. Both λ_{gu} and λ_{inf} are factors of terms containing $T_{smb}(t) - T_{zone}(t)$, and would be correlated in current model.

We implement a numerical PDE solver for the parabolic equation using Crank-Nicolson scheme and an ODE solver using implicit Euler scheme. Both numerical algorithms for solving our PDE and ODE equations with given multipliers' value are unconditionally stable due to implicit nature on time-step evolution.

CALIBRATION PROCEDURE

In this section we describe the calibration procedure for the inverse model. The multipliers are estimated through solving minimization problem. The overall procedure consists of two steps to overcome correlations among multipliers.

Minimization with PDE constraint

Inversion procedure for parameters estimation is posed as a minimization the objective function defined by

$$\min_{\lambda_i}\sum_k\sum_s\Big[\left(T_{ws}(0,t_k;\lambda) - T^{sen}_{wos}(t_k)\right)^2 +$$
$$\Big(T_{ws}(d_{ws},t_k;\lambda) - T^{sen}_{wis}(t_k)\Big)^2\Big] + \eta\sum_i(\lambda_i - 1)^2 \qquad (5)$$

by choosing proper multipliers

$$\{\lambda_i\} = \{\lambda_k, \lambda_{ih}, \lambda_{eh}, \lambda_{ws}, \lambda_{eos}, \lambda_{eis} || s \in N, S, E, W, R\} \quad (6)$$

where $T_{ws}(x,t;\lambda)$ is a solution of PDE defined in (1) with boundary conditions (2), $T^{sen}_{wos}(t)$ is sensor data of outside wall surface temperature and $T^{sen}_{wis}(t)$ is sensor data for inside wall surface temperature. The first term represents the sum of squared differences between simulated outside wall surface temperature and measured outside wall surface temperature – a misfit measure for outside wall surface temperature. Similarly, the second term represent the same misfit measure for inside wall surface temperature. Our goal is to find a set of multipliers so that the misfit defined by first two terms is minimized. In order to avoid over-fit to the noisy available data, a regularization term, the third term in the objective function (5), is included. Since those multipliers are multiplying factors of well-defined nominal physical value, they are expected to be close to one.

There are two major challenges in this optimization problem. First, our objective may not be convex function and a local minimum may be achieved. To address this, we randomize the initial guess for these multipliers and perform the optimization multiple times. We choose the solution that obtained the minimal objective function value. Second, the solution may result from over-tuning the model from sensor data for the chosen period, since real sensor data is likely to contain errors and operation condition might different from our expected one. The solution corresponding to the least misfit for specific period is not necessarily good solution for other periods and the misfit could become larger when applying the recovered multipliers on other periods. The regularization term helps us to address this issue through choosing a proper regularization coefficient. We first separate the collected data into two parts: training and validating sets. For each chosen regularization coefficient, a solution corresponding to the least objective value on the training set is found. Then the misfit value is calculated on the validate set with the solutions from different regularization coefficients. Finally, the solution corresponding to the least misfit on the validating set with certain regularization coefficient is chosen. Since it is impossible to test all different regularization coefficients over a large range, we pick the coefficient η from a discrete set $\{0.1, 0.01, 0.001, 0.0001, 0.00001\}$ that covers different order of values.

Note that our objective function includes misfits from all walls, but subject to the same multipliers for conductivity and convection. In this way, we also reduce chance to over-fit certain biased sensor data. Even doing so, we might not fully resolve the over-tuning issue and will propose better statistical sampling in the conclusion section.

Minimization with ODE constraint

The additional multipliers

$$\{\lambda_i'\} = \{\lambda_{ac}, \lambda_{gu}, \lambda_{inf}, \lambda_{shgc}, \lambda_{load}\} \tag{7}$$

are chosen to minimize the following objective function, i.e.

$$\min_{\lambda_i'} \sum_k \left(T_{zone}(t_k;\lambda') - T_{zone}^{sen}(t_k)\right)^2 + \eta' \sum_i (\lambda_i' - 1)^2 \tag{8}$$

where $T_{zone}(t;\lambda')$ is the ODE solution of equation (4) and $T_{zone}^{sen}(t)$ is sensor data of zone temperature. The first term in the objective (8) represents a misfit of zone temperature between simulated and measured and the second term is for regularization term. We use a similar procedure described in the last subsection to find these additional multipliers defined in (7). Note that, the multiplier λ_{ac} could be greater than one, since there are internal partitioning walls, furniture inside a zone and etc., and the multiplier λ_{load} is a function of time in a day.

Stepwise calibration

The whole calibration procedure is shown in Figure 1. First, the minimization problem with PDE constraint is solved and a set of multipliers related to building envelope are recovered. Second, the minimization problem with ODE constraint is solved and additional multipliers are recovered to estimate internal load impact. The second minimization will use some information coming from the first minimization problem, like thermal energy consumption related to building envelope.

The left part of Figure 1 shows calibration procedure through minimization with PDE constraint. There are two loops in the procedure. The inner loop is used to get a solution with the least objective value on the train data for multiple random initial guesses with a given regularization coefficient in order to achieve a global minimum. The outer loop is used to get a solution with the least misfit on the validation data with different regularization coefficients in order to avoid an over-fitting situation. The right part of Figure 1 shows calibration procedure through minimization of the objective with ODE constraint.

For the solution of the minimization problem we are using constrained nonlinear multivariable optimization method within MATLAB, namely *fmincon*.

When solving the minimization problem with PDE constraint, we not only estimate multipliers related to building envelope, but also find out heat-contribution from the internal walls to the zone. Heat gain or loss through building envelope will be substituted into the ODE model. With measured system contribution from AHU data, we can actually estimate internal load change during the day. In other words, the load multiplier is found as a function of time of the day. In fact, our proposed stepwise calibration reduces impact from correlation among multipliers. It helps us to discover energy consumption distribution between building envelope and internal load more accurately.

SIMULATION METHOD

After recovering multipliers through calibration using sensor data, we can use the integrated PDE-ODE model to simulate zone temperature dynamics and conduct what-if analysis, in addition different control strategies can be evaluated to meet comfortable level requirement.

There are two approaches for solving the system. The first approach is to solve PDE and ODE together and to obtain wall surface temperature and zone temperature under a given ambient temperature from weather forecast. The second approach is to solve PDE and ODE iteratively. First, with an initial guess of zone temperature, we solve the PDE and obtain internal wall surface temperature. Second, we solve the ODE with the internal wall surface temperature obtained from the solution of the PDE and obtain a new zone temperature. Then we solve the PDE again with the new zone temperature coming from solution of the ODE. That procedure will be iterated several times until convergence. When solving the ODE, we need to know AHU supply air flow rate and supply temperature $\dot{M}_{sys}, T_{sys}$ for these simulations. The purpose of air handling units is to adjust temperature and humidity inside a zone and maintain a comfortable climate for occupants. For a constant air volume (CAV) system, we only need to determine supply air temperature. In order to achieve this, we define the following objective function as

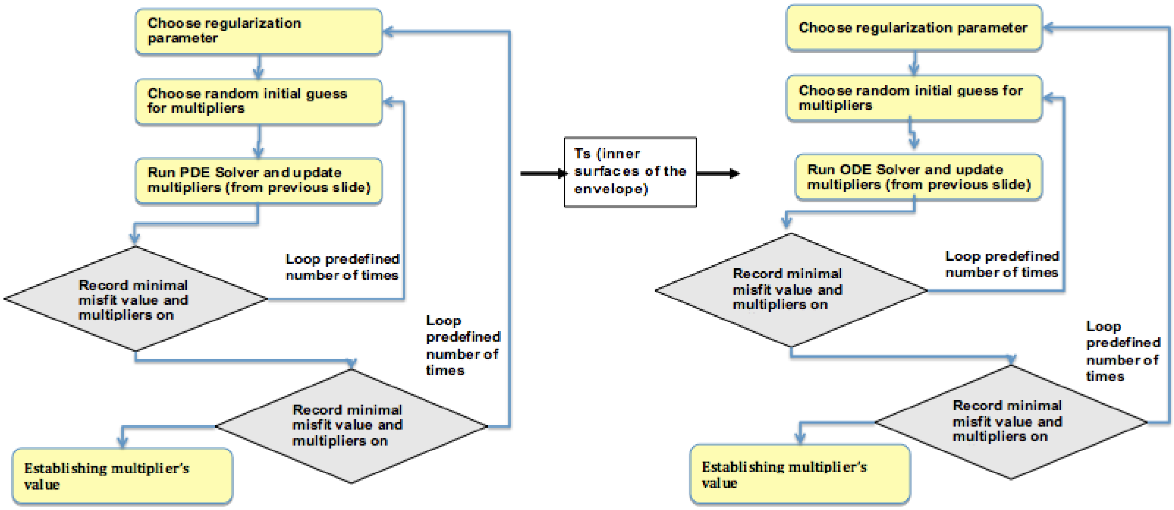

Figure 1: Stepwise calibration procedure

$$\mathrm{Func}(T_{sys}) =$$
$$C_{cp}\int_{t_1}^{t_2}(1-p(t))\dot{M}_{sys}(T_{sys}(t)-T_{zone}(t;T_{sys}))^{\pm}dt+$$
$$C_{cp}\int_{t_1}^{t_2}p(t)\dot{M}_{sys}\left(T_{sys}(t)-T_{amb}(t)\right)^{\pm}dt+$$
$$\mu\int_{t_1}^{t_2}sign\left(\dot{M}_{sys}\right)|T_{zone}(t;T_{sys})-T_{sp}(t)|^2dt+$$
$$\mu\int_{t_1}^{t_2}\left(1-sign(\dot{M}_{sys}\right)|T_{sys}|^2dt \qquad (9)$$

Here $T_{zone}(t;T_{sys})$ stands for zone temperature resulting from the ODE corresponding to a given T_{sys}. T_{sp} is a specified temperature set point which may vary over time. p is fresh air fraction when both ventilation and circulation are in operation and can be specified based on ventilation strategy. μ is the weight for meeting set point requirement. The first two terms represent thermal energy requirement and it can be either cooling or heating energy depending on either positive or negative part of the difference in the integrand. The first term represents air circulating, which is driven by the difference between return air temperature and supply air temperature T_{sys}; the second term represents air ventilation, which is driven by the difference between ambient air temperature and supply air temperature T_{sys}. The third term in the objective measures the difference between zone temperatures and set point temperature. $sign(\dot{M}_{sys})$ is an indicator function, whose value is 1 if $\dot{M}_{sys} > 0$ and 0 otherwise. With this factor in the third term, it implies that set point temperature is targeted only during system being on period. The fourth term is used to force $T_{sys} = 0$ during system being off. By choosing an appropriate μ value, we balance between energy saving and comforting level of the zone. The objective function can be modified to incorporate other consideration, like humidity requirement, pre-cooling and pre-heating, and entropy control.

CASE STUDY

The heat transfer inverse modeling approach described in the earlier sections was applied to a commercial building and the performance was evaluated. The approach was applied to a medium-sized five story office building in Korea. The exterior of the test building and geometry of a typical floor and other building's characteristics are illustrated in Figure 2 and Table 1. To satisfy indoor thermal requirement of the space, each floor has both constant air volume (CAV) system and electric heat pump (EHP) system. A main BMS system controls the CAV system, while occupants are allowed to operate individual indoor unit of EHP system for local thermal control. A two-stage absorption chiller is operating to produce chilled and hot water for heating and cooling coils in the air handling unit (AHU). Using this information, an EnergyPlus model was developed to validate the values of the parameter recovered by the inverse model.

*Table 1: Building characteristics of test building. [*1] Design condition, [*2] Field measurement.*

Exterior wall[*1]	Gavanium STL plate (0.0012m) Air cavity (0.1 m) Insulation panel (0.1m) Air cavity (0.1 m) Gypsum board (0.012m)
Interior wall[*1]	Gypsum board (0.012m) Insulation panel (0.03m) Gypsum board (0.012m)
Fenestration[*1]	Double pane clear glass U value = 2.670 W/m^2K
Infiltration	0.22 ACH
Occupancy density[*2]	0.097 $person/m^2$
Lighting density[*2]	10 W/m^2
Plug load density[*2]	10 W/m^2
Operation schedule[*2]	6 AM - 10 PM

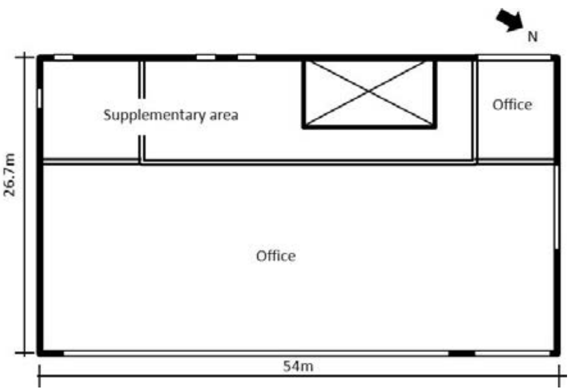

Figure 2: Typical floor layout of test case.

As described in the previous sections, the approach for parameter estimation requires sensor and meter data for model calibration. Eight surface temperature sensors were installed on inside and outside of each exterior wall. Over 120 sensor or measurement data of both CAV and EHP system for each floor are collected. A relational database stores all the dynamic data in 15 minutes intervals and the static data set which includes hourly occupants density and lighting power pattern. A local weather data for the next 72 hours with 3 hours resolution is also tabulated into the database by incorporating with an on-line local weather forecasting service of national weather administration in Korea.

When working with real sensor data from on-site measurement, we face with data quality, uncertainty issues of weather forecasting and sensor/meter data errors. Wall surface and zone temperature reading may not correctly be recorded depending on where the sensors are installed. In addition, there are two HVAC systems, AHU and EHP systems, that are operating simultaneously, so it is not simple to capture the operational characteristics of different systems independently. Data quality of weather forecasting also impacts the model performance. Although local weather station generates data of outdoor air temperature, relative humidity, wind speed, sky condition, and precipitation, the information of direct and diffuse solar radiation were not available from the weather forecasting service. Therefore, a typical metrological year (TMY) data of the location was used, these data was adjusted based on the provided forecasted of the sky condition.

Nevertheless, our proposed calibration procedure generated reasonable results. Figures 3 and 4 show comparison for the inside and outside wall surface temperature between calculated temperature from the PDE model with the recovered multipliers and the temperature recorded by the wall sensors. Figure 5 shows comparison between calculated zone temperature from ODE model with the recovered multipliers and the zone temperature recorded by the zone temperature sensor in a typical floor, for seven days.

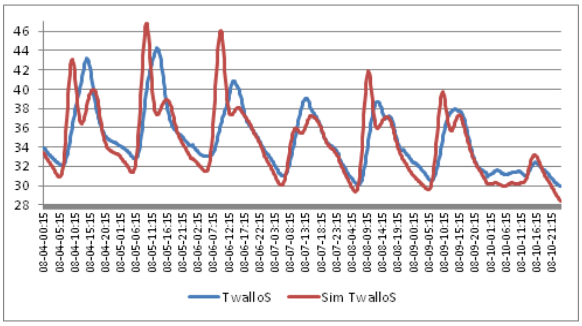

Figure 3: Comparison of outside wall temperature between simulated and sensor data

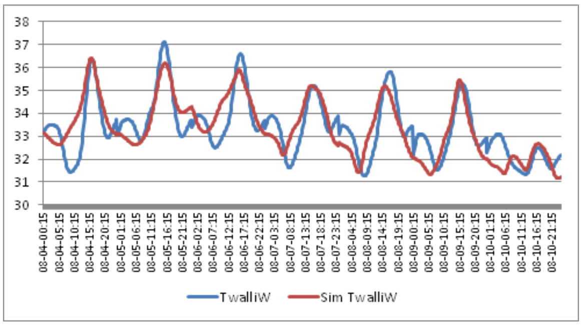

Figure 4: Comparison of inside wall temperature between simulated and sensor data

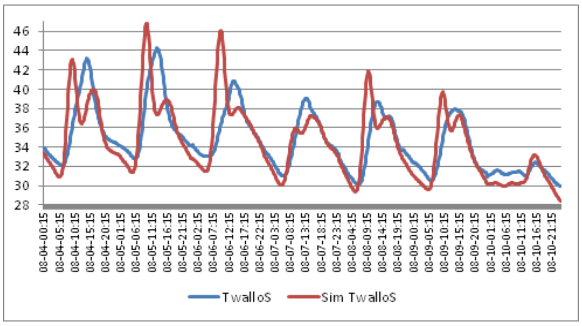

Figure 5: Comparison of zone temperature between simulated and sensor data during calibration procedure

With the recovered parameters from the calibration for seven days (June 23-29, 2012), the model computes thermal energy demand of the typical floor which is required to maintaining the set point temperature specified by BMS. It has been tested for 20 normal work days in a typical cooling season (July 2-27, 2011). Both zone air temperature and thermal energy consumption were used to evaluate the model performance.

Comparison of simulated zone air temperature with the actual measured temperature in 15 minute resolution is shown in Figure 6. During occupied hour, zone set point varies from 26.2^{o}C to 27.2^{o}C. The actual space temperature fluctuates more than the set point temperature due to the control logic of BMS and occupants request, both of which were not modeled, but the deviation from the set point temperature is within 2^{o}C during occupied hours. Although the model predicts the space temperature is 2-3^{o}C higher than the actual room temperature at the operational transition of the system, the overall temperature profiles are in good agreement.

Figure 7 illustrates comparison of simulated thermal energy requirement with the actual supplied energy from the on-site measurement with hourly resolution during the test period. Except July 24th -25th, during which the forecasted outdoor air temperature was quite different to the actual on-site measurement, both hourly energy consumption and daily profile are in good agreement. The Mean Bias Error (MBE) and the coefficient of variance of root mean square error (Cv(RMSE)) with the hourly results for the period were -8.24% and 23.9%, respectively. It is within the acceptable tolerance criteria (MBE +/- 10%, CV(RMSE) 30%) of ASHRAE Guideline 14 (ASHRAE, 2002)

Simulation provides user the capability to specify various operation conditions and requirement and conduct what-if and trade-off analysis. The simulation helps users identifying appropriate balance between energy saving and comfort level in various operational conditions.

CONCLUSION

We presented an integrated PDE-ODE model to describe heat transfer through building envelope and thermal balance inside zones. This model captures heat transfer phenomena in buildings more accurately than the reduced order models. Multipliers of parameters are introduced to the system and are estimated through a proposed calibration procedure. By defining an objective function with misfit term from all sides of walls and a regularization term, we improved the robustness of the procedure and avoided over-fitting to a certain set of sensor data. By separating calibration and parameters recovery procedure into two step processes, with first step as wall surface PDE calibration and second step as zone temperature ODE calibration, we reduced the chance for parameter correlation. Simulation procedure, that utilizes the PDE-ODE model with the recovered multipliers and realized zone temperature control, is also formulated through optimization. This procedure generates energy demand profile under a given weather condition. We applied our inverse modeling approach to a commercial building in Korea. We used sensor data for PDE-ODE model calibration and then simulated thermal energy requirement in various operating conditions. An initial study shows that the inverse modeling approach produces results with reasonable accuracy.

We plan to extend our work in the following two ways. Firstly, we would like to integrate our model with statistical tools and to get a distribution of the misfit value and obtain a response surface, based on the most likelihood calculation. When new sensor data becoming available, the respond surface would be updated using Bayesian updating procedure. In this way we can achieve the robustness of the inversion procedure. The simulation would not use a point value but use distribution associated with the parameters. Secondly, we would like to combine the analyses from different scales: thermal energy demand in daily level, and dynamical behavior in hourly level. Statistical forecast can generate daily level energy demand with reasonable accuracy. A PDE-ODE model simulates energy consumption profile in finer resolution than the statistical model. The objective function for the simulation consists of not only meeting hourly specified temperature set point but also aligning daily thermal energy consumption with the forecasted one from statistical method.

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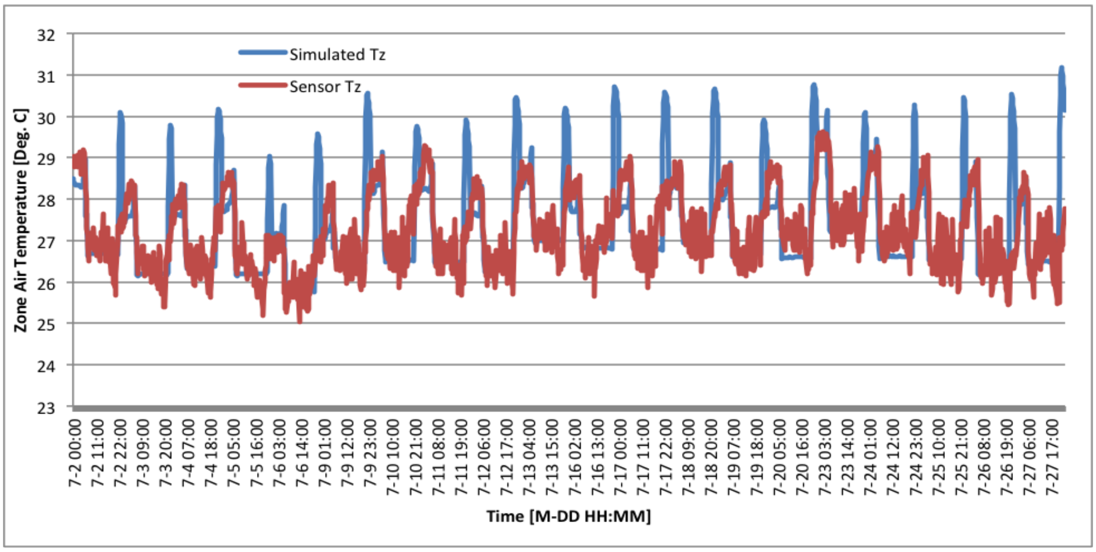

Figure 6: Comparison between computed and actual zone air temperature (July 02-July27, weekdays)

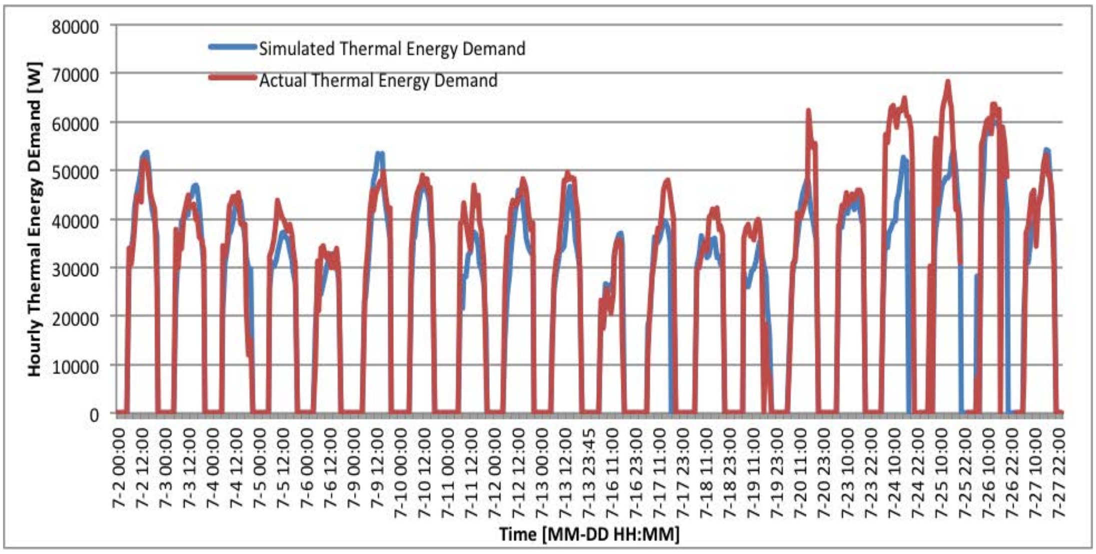

Figure 7: Comparison between computed and actual thermal energy demand (July 02-July27, weekdays)

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