IDENTIFICATION OF BUILDING MODEL PARAMETERS AND LOADS USING ON-SITE DATA LOGS

Thomas L. McKinley and Andrew G. Alleyne
Department of Mechanical Science and Engineering
University of Illinois at Urbana-Champaign
1206 West Green Street; MC-244; Urbana, IL USA 61801
E-Mail: tmckinl2@uiuc.edu / alleyne@uiuc.edu
Phone: 1-217-244-9993

ABSTRACT

To minimize energy consumption, one must understand a building's thermal characteristics, usage patterns, and local environment. This information is frequently not known a priori. Although this presents a significant barrier, a *system identification* procedure combining building simulation and on-site measurements enables the unknowns to be estimated. This paper presents two novel processes for determining time-invariant model parameters and time-varying loads. The computational effort, accuracy, and repeatability are quantified using model generated "on site" data logs for a three story office building. The resulting *self-calibrating models* are extremely valuable for controls and diagnostic purposes in *intelligent building systems*.

INTRODUCTION

About 40% of annual US energy demand is consumed by commercial and residential buildings (US DOE – 2007a, 2007b). This is a significant contributor to global warming, and reducing building energy use has been identified as one of the most promising "stabilization wedges" for limiting growth of atmospheric CO_2 concentration (Pacala and Socolow, 2004). Although new buildings can be designed to achieve very high energy efficiency, for existing buildings this was usually not a priority. High efficiency HVAC systems, high performance windows, and extra insulation allow energy consumption to be reduced, but these retrofits can be quite costly. An alternative is to deploy an energy management system (EMS) to more optimally control the building HVAC system.

Although EMS are quite prevalent for large commercial buildings, substantial opportunities for growth remain in medium commercial, small commercial, and residential market segments (Braun, 2007). However, the diversity of building designs, uses, and environments likely require site specific control methodologies (Braun, 2003). Engineering cost to tune the EMS may outweigh energy cost savings, which tend to reduce with floor area.

However, self-calibrating building thermal models, coupled with model predictive control or off-line controls optimization, may be an enabling technology for this market. These models would train themselves using on-site measurements. This approach eliminates the need for detailed construction drawings that may in some cases no longer exist.

To that end, this paper describes processes for determining a building's time invariant parameters and time-varying source terms. Moreover, these processes are developed and evaluated quantitatively using model generated data logs – providing "proof of concept" of the method.

BUILDING MODEL

In this study, the model consists of a thermal network representing the building structure, coupled to the air mass or *zone* inside the building.

The thermal network (see ***Figure 1***) is typical of several models in the literature. Gouda et al (2002), by comparing electrical analogy predictions to one-dimensional model results, recommended that three resistances and two capacitors be used to represent walls. The network is augmented by a parallel resistance for heat transfer through windows. This pattern was also used by Wang and Xu (2006) and Lee and Braun (2004), who repeated it for exterior walls, roofs, foundations, and internal partitions.

The network includes solar loads into the inside and outside surfaces of the structure. The outer load is caused by solar irradiation absorbed by exterior walls and roofs. The inner load is due to solar irradiation transmitted through windows and subsequently absorbed on interior walls, floors, and furnishings. These source terms were computed using the EnergyPlus building simulation. The calculation is fairly complicated, and takes into account beam and diffuse solar irradiation from the sun, ground, and sky in addition to building geometry, N-S orientation, time of year, time of day, latitude, cloudiness, window transmittance, and shading.

The thermal network is coupled to the zone, which is represented by a control volume (see ***Figure 2***). The dry air mass is assumed to be constant, so there is a balance between HVAC system return flow and the sum of the HVAC system supply flow and leakage of outside air into the building (infiltration). In addition to experiencing heat exchange with the structure, the zone experiences latent and sensible loads due to lights, people, and equipment. These terms can be estimated from handbook data (ASHRAE, 2005) if building use, occupancy versus time, and electricity consumption are known.

In this case, only a single instance of the thermal network and a single zone were used. Since the primary objective of this study is the development and validation of model calibration procedures, choosing a model that is representative, yet low order, is highly desirable. Assuming success with a low order model, extension to higher order models is a natural next step.

GOVERNING EQUATIONS

The governing equations for the thermal network are:

$$\frac{dT_O}{dt} = \frac{1}{R_O C_O}(T_{AMB} - T_O) + \frac{1}{R_{WALL} C_O}(T_I - T_O) + \frac{\dot{Q}_{SOL-O}}{C_O} \quad (1)$$

$$\frac{dT_I}{dt} = \frac{1}{R_{WALL} C_I}(T_O - T_I) + \frac{1}{R_I C_I}(T_{ZONE} - T_I) + \frac{\dot{Q}_{SOL-I}}{C_I} \quad (2)$$

$$\dot{Q}_{STRUC} = \frac{T_I - T_{ZONE}}{R_I} + \frac{T_{AMB} - T_{ZONE}}{R_{WIND}} \quad (3)$$

The governing equations for the zone are:

$$\frac{dW_{ZONE}}{dt} = \frac{\dot{m}_{SUP}}{m_{ZONE}}(W_{SUP} - W_{ZONE}) + \frac{\dot{m}_{INF}}{m_{ZONE}}(W_{AMB} - W_{ZONE}) + \frac{\dot{m}_{W-LATENT}}{m_{ZONE}} \quad (4)$$

$$\frac{du_{ZONE}}{dt} = \frac{\dot{m}_{SUP}}{m_{ZONE}}(h_{SUP} - h_{ZONE}) + \frac{\dot{m}_{INF}}{m_{ZONE}}(h_{AMB} - h_{ZONE}) + \frac{\dot{Q}_{SENS} + \dot{Q}_{STRUC}}{m_{ZONE}} + \frac{\dot{m}_{W-LATENT} h_{W-LATENT}}{m_{ZONE}} \quad (5)$$

Equations (1), (2), (4), and (5) are the state equations, and the model is fourth order.

DATA LOGGING ASSUMPTIONS

It is assumed the following quantities are measured:

- Temperature and humidity ratio of the ambient air, supply air, and zone air
- Supply air mass flow rate
- Solar flux, which when coupled with building simulation allows the calculation of solar loads

Measurements were recorded every 118 seconds. By sampling at a much higher rate (e.g. 1 Hz) and averaging the data over this period, excellent signal to noise ratio can be achieved.

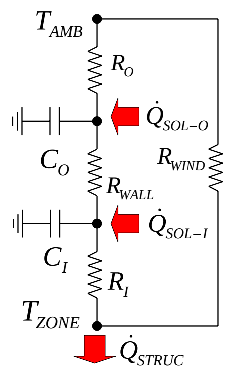

Figure 1 Building Thermal Network Model

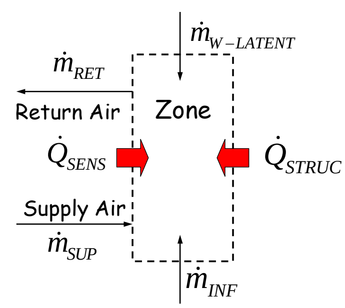

Figure 2 Zone Control Volume Model

PROBLEM DEFINITION

The "simple" fourth order model contains eight time-invariant parameters which are the zone mass, four thermal resistances, two thermal capacitances, and the infiltration rate. It also contains four time-varying source terms or loads which are inside and outside solar load, latent load, and sensible load. This suggests two classes of system identification problems:

Parameter Estimation: If the four source terms are known, find the eight parameters.

Source Term Estimation: If the eight parameters are known, find the source terms.

Solution procedures for each class of problem must be efficient, accurate, and repeatable. To quantify these characteristics, model generated "on-site" data logs were used. That is to say, the differential equations given above were solved using a known set of time-invariant parameters and time-varying source terms for a test case building. A quantitative comparison of known and estimated values is then given.

TEST CASE BUILDING

A typical three-story office building was adopted as a test case (see ***Figure 3***). Building construction, building usage, and time-invariant parameters are summarized in ***Table 1***. For this fictional building, weather data for July 15 to July 22, including ambient temperature, humidity, direct and diffuse solar flux, and solar angles were taken from the EnergyPlus database. The assumed location was Urbana-Champaign, IL.

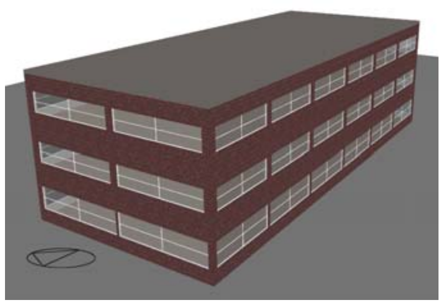

Figure 3 Test Case Building

Supply air temperature and mass flow rate were determined by two proportional type controllers. If zone temperature was above the set point of 23 deg C, supply air flow was increased, while supply air temperature and humidity ratio were maintained at 10 deg C and 0.009 kg H_2O per kg dry air. If zone temperature dropped below 20 deg C, the humidity ratio was maintained at 0.009 kg H_2O / kg dry air, but supply temperature was increased to as much as 16 deg C. This approximated the action of a variable air volume with reheat HVAC system.

Figure 4 shows zone temperature for July 17, which is typical of each day during this study. Temperature is not constant, and is somewhat representative of a system operating with night setback.

Initial conditions must also be chosen. As a starting point, all temperatures were initialized to 20 deg C and the zone humidity ratio was initialized to 0.009 kg H_2O per kg dry air. To minimize the impact of these assumptions on the results, the model was run for two consecutive days, each identical to July 15, before the period from July 15 to July 22 was simulated. These two "warm-up" days start the simulation from conditions that are approximately periodic.

Table 1 Test Case Building Parameters

Construction and Usage	
Building Type	Three-Story General Office
Building Occupancy	8 AM - 10 PM Monday through Friday Total Capacity: 85 people
Dimensions	35 m (W) x 15 m (D) x 10.5 m (H)
Orientation	Long Side (35 m) Facing South
Fraction of Wall Area as Glazing	First Floor: 50% Second Floor: 40% Third Floor: 40%
Glazing Type	Single Pane, Clear
HVAC System	Variable Air Volume With Terminal Re-Heat
Thermal Resistances (K/KW)	
Inside Structure Surface to Zone (R_I)	0.10268
Outside Structure Surface to Ambient (R_O)	0.03571
Structure Walls (R_{WALL})	2.807
Windows (R_{WIND})	0.3591
Thermal Capacitances (kJ/K)	
Inner Layer (C_I)	2.778E+04
Outer Layer (C_O)	1.574E+05
Other Model Parameters	
Zone Mass (kg)	6581.9
Infiltration Rate (kg/s)	0.7313

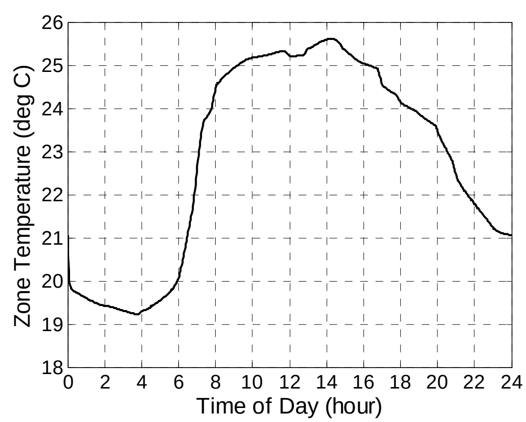

Figure 4 Zone Temperature vs Time of Day (July 17)

PARAMETER ESTIMATION PROCESS

The process for estimating model parameters is as follows. First, the simulation is applied using measured ambient and supply air conditions for an assumed set of time-invariant model parameters. For each set, an error function is calculated. An optimization procedure is used to find the model parameter set which minimizes the error function. Thus, error function and optimization procedure are important considerations.

Choice of Error Function

In previous work, rms error in zone temperature (Dewson, 1993) or sensible zone load (Lee and Braun, 2004; Wang and Xu, 2006) have served as error functions. In the course of this study, it was found that rms error in zone temperature admitted multiple combinations of window resistance and infiltration rate having the same error. This happens because building leakage and heat flow through windows both allow energy transport between the zone and ambient through paths unfiltered by thermal capacitance.

However, infiltration affects the zone humidity ratio while window thermal resistance does not. Therefore, parameter confounding can be eliminated if the error function includes both temperature and humidity effects. This perspective has not been documented in previous work and in fact many of the previous building models did not even consider conservation of zone water mass (equation (4)).

Although rms error in <u>total</u> (sensible plus latent) load may address this issue, in this study a more direct approach was chosen. Specifically, the *error function* is the Euclidean norm of the two *error diagnostics* – one for temperature and one for humidity effects:

$$e = \sqrt{\left(e_T\right)^2 + \left(e_{m_{INF}}\right)^2} \tag{6}$$

The temperature diagnostic is a normalized rms error in zone temperature:

$$e_T = \sqrt{\frac{\int_{t_i}^{t_f} (T_{ZONE(MEAS)} - T_{ZONE(PRED)})^2\, dt}{\int_{t_i}^{t_f} (T_{AMB(MEAS)} - T_{ZONE(MEAS)})^2\, dt}} \tag{7}$$

A novel error diagnostic for humidity effects is:

$$e_{m_{INF}} = \frac{\left|\hat{\dot{m}}_{INF(PRED)} - \hat{\dot{m}}_{INF(MEAS)}\right|}{\left|\hat{\dot{m}}_{INF(MEAS)}\right|} \tag{8}$$

where:

$$\hat{\dot{m}}_{INF} = \frac{\int_{t_i}^{t_f} \dot{m}_{SUP}(W_{ZONE} - W_{SUP})dt - \int_{t_i}^{t_f} \dot{m}_{W-LATENT}\, dt}{\int_{t_i}^{t_f} (W_{AMB} - W_{ZONE})dt} \tag{9}$$

In equations (7) and (8), the subscripts MEAS and PRED correspond to measured and predicted values, respectively.

Equation (9) was specifically designed with parameter estimation in mind. Note that the numerator is the difference between supply air and latent load effects on zone humidity. In so doing, the impact of infiltration is isolated. Our testing shows this to provide a much more sensitive measure of infiltration rate than rms error in zone humidity ratio. This would also be an advantage over rms error in latent or total zone load. Also, the quantity on the left hand side of equation (9) is an average infiltration rate where storage effects are neglected (compare to equation (4)). This is analogous to the degree day method for estimating the UA product.

As further proof that the error function described in equation (6) is effective, the individual error diagnostics in equations (7) and (8) were calculated for 100 random parameter sets within the search space (see the following section). The correlation coefficient between the two error diagnostics was -0.0728, with a p-value of 0.47. This shows there is no significant correlation between the two diagnostics, so they have the desirable trait of assessing different aspects of the model.

Choice of Optimization Procedure

The best optimization procedure is problem dependent (Goldberg, 1989). This application is an unconstrained optimization over a convex region of comparatively low dimension. Since the model is coded in double precision, numerical noise should be minimal. These characteristics suggest that, if a single global optimum exists, a hill climbing algorithm is preferred.

With these thoughts in mind, a subspace trust region solver based on the interior-reflective Newton method (Coleman and Li, 1996) was chosen. This hill climbing algorithm is available in the MATLAB 7.1 Optimization Toolbox. Gradients were computed by finite differences, and iteration continued until the relative step size was less than 1.0e-6.

It was found that the optimizer converged prematurely if the range in parameter set values was large. This scaling problem was overcome by mapping parameters to a vector x and then having the optimizer operate on x:

$$R_I = R_{I(NOM)} \cdot x_1 \tag{10}$$

$$R_O = R_{O(NOM)} \cdot x_2 \tag{11}$$

$$R_{WALL} = R_{WALL(NOM)} \cdot x_3 \tag{12}$$

$$R_{WIND} = R_{WIND(NOM)} \cdot x_4 \tag{13}$$

$$C_I = C_{TOT(NOM)} \cdot x_5 x_6 \tag{14}$$

$$C_O = C_{TOT(NOM)} \cdot x_5 (1 - x_6) \tag{15}$$

$$\dot{m}_{INF} = \dot{m}_{INF(NOM)} \cdot x_7 \tag{16}$$

$$m_{ZONE} = m_{ZONE(NOM)} \cdot x_8 \tag{17}$$

Here, the subscript NOM refers to a nominal or engineering estimate for the parameter. In this study the nominal values were the same as the known values listed in Table 1, but in practice any approximate value would suffice. Engineering judgment permits us to set reasonable bounds on the vector x (see ***Table 2***), and the optimizer was constrained to search only this space, starting from a random point within it.

EVALUATION OF PARAMETER ESTIMATION PROCESS

Since the data logs were model generated, "true" parameter values are known and accuracy can be quantified by comparing to estimated values. To quantify repeatability, the optimizer was run for ten randomly selected starting points and the coefficient of variation (COV) in parameter estimates was calculated. As shown in ***Table 3***, the process described above was able to determine all eight model parameters both accurately and repeatably.

These results are noteworthy. Specifically, Dewson (1993) conducted a similar study using a comparable model, model generated data logs, and a hill climbing optimizer. He reported finding multiple optima, leading to parameter errors as high as 27%.

Another performance measure is computational effort. Using an ordinary desktop computer (four CPU Pentium R @ 2.80 GHz, 504 MB RAM @ 2.79 GHz), the mean time for each of the ten runs was 1.6 hours. Because of the excellent repeatability and accuracy of the process, in practice it would likely only be executed once. Keeping in mind that the data log covers eight days of operation, run time is less than 1% of the time required to log the data.

SOURCE TERM ESTIMATION PROCESS

The process for estimating time varying source terms is now described. For the sake of brevity, we consider only the case where inside solar load is unknown. However, with appropriate modification it can be applied to other source terms as well.

Inside solar load is of great practical interest since it is affected by the position of blinds and shades. Simply stated, the building's solar collection efficiency can be varied dynamically by building occupants, which is clearly a source of uncertainty.

We also restrict our attention to finding the inside solar load for a single day, which in this case was July 17. This choice is arbitrary, as longer periods of time would just require longer run times.

Table 2 Search Space Limits

Component	Meaning	Maximum	Minimum
x_1	Scale factor on $R_{I(NOM)}$	1.300	0.700
x_2	Scale factor on $R_{O(NOM)}$	1.300	0.700
x_3	Scale factor on $R_{WALL(NOM)}$	1.300	0.700
x_4	Scale factor on $R_{WIND(NOM)}$	1.300	0.700
x_5	Scale factor on $C_{TOT(NOM)}$	2.000	0.500
x_6	Ratio of C_I to C_{TOT}	0.500	0.010
x_7	Scale factor on m_{INF}	3.000	0.333
x_8	Scale factor on m_{ZONE}	1.300	0.700

Table 3 Parameter Estimate Accuracy and Repeatability

Parameter	Mean Error	Coefficient of Variation
R_I	-0.123%	0.003%
R_O	-0.228%	0.011%
R_{WALL}	-0.078%	0.017%
R_{WIND}	0.013%	0.002%
C_I	0.085%	0.005%
C_O	0.009%	0.023%
m_{INF}	-0.007%	0.019%
m_{ZONE}	0.149%	0.013%

Choice of Solution Procedure

Three possible solution procedures were considered. First, inside solar load can be represented using a characteristic curve. The coefficients defining that curve are the unknowns, which can be found using the same error function and optimization procedure described above. Although results are not presented here, this method worked reasonably well. Using a piecewise linear curve with fifteen breakpoints (on the hour for each hour between sunrise and sunset), solar load was determined accurately and efficiently with a run time of about 1.0 hour on a desktop computer.

An alternative is to use a greedy algorithm (Cormen, 2001). In the first approach, the dimension of the search space equals the number of unknowns, and the simulation must be run for the entire time period for each set of breakpoints. However, with suitable initial conditions, the optimization can be performed over a segment of the total time period, with the final conditions for each segment becoming the initial conditions for the following segment. This permits the fifteen dimensional optimization problem described above to be transformed into a series of fifteen sequential one dimensional problems, each covering a time segment of one hour rather than 24 hours. Thus, the greedy algorithm could be used to shorten run time.

Although both approaches are capable, they require iteration and gradient estimation by finite differences, and as such are only feasible for off-line data reduction. However, we propose a new approach called the *direct inversion method* that eliminates these limitations and enables on-line estimation.

The Direct Inversion Method

The direct inversion method is now described in a step-by-step fashion. First, the zone humidity ratio is differentiated with respect to time. In this study, simple one sided and center finite difference operators were used.

Next, rearranging equation (4) gives:

$$\begin{aligned}\dot{m}_{W-LATENT} &= m_{ZONE}\frac{dW_{ZONE}}{dt} - \dot{m}_{SUP}(W_{SUP} - W_{ZONE}) \\ &\quad -\dot{m}_{INF}(W_{AMB} - W_{ZONE})\end{aligned} \tag{18}$$

This equation is used to compute the time varying latent load, noting that all terms on the right hand side are either known or measured from data logs. Although not presented here, by correlating occupancy to latent load, it is possible to concurrently estimate inside solar load and building occupancy. Correlations of this type are available for various physical activities (ASHRAE, 2005). The resulting building occupancy estimates would be particularly useful for buildings where internal loads due to people are a significant fraction of total load (e.g. office buildings, schools).

Zone internal energy is then computed from property relationships and the measured zone temperature and humidity ratio. Next, the time derivative of internal energy is calculated, again using a finite difference operator.

Rearranging equation (5):

$$\begin{aligned}\dot{Q}_{STRUC} &= m_{ZONE}\frac{du_{ZONE}}{dt} - \dot{m}_{SUP}(h_{SUP} - h_{ZONE}) \\ &\quad -\dot{m}_{INF}(h_{AMB} - h_{ZONE}) \\ &\quad -\dot{m}_{W-LATENT}h_{W-LATENT} - \dot{Q}_{SENS}\end{aligned} \tag{19}$$

Assuming the sensible load is known, so are all of the other terms on the right hand side, and the heat transfer rate between the structure and the zone can be computed.

Then, rearranging equation (3):

$$T_I = T_{ZONE} + R_I\left[\dot{Q}_{STRUC} - \frac{(T_{AMB} - T_{ZONE})}{R_{WIND}}\right] \tag{20}$$

This allows the inside surface temperature to be calculated. Again, using finite difference operators its time derivative can be computed.

Assuming an initial condition for the outside surface temperature (T_O), equation (1) can be integrated to find T_O at each instant of time. Just as before, we choose the initial condition to be 20 deg C and apply the inversion method through two warm-up days. In this study, a common Runge-Kutta integrator was employed.

Rearranging equation (2):

$$\dot{Q}_{SOL-I} = C_I\frac{dT_I}{dt} - \frac{(T_O - T_I)}{R_{WALL}} - \frac{(T_{ZONE} - T_I)}{R_I} \tag{21}$$

This gives us the inside solar load estimate we seek.

EVALUATION OF SOURCE TERM ESTIMATION PROCESS

Again, since the data logs were model generated, the "true" inside solar load is known and accuracy can be quantified by comparing to estimated values. As shown in ***Figure 5***, except for a short periods of noise, the two traces are virtually identical. Since the direct inversion method does not require a random starting point, the method is repeatable. This technique is also very efficient. Using the same desktop computer, the total run time was about 22 seconds, including time spent modeling the two warm-up days. This is quite an improvement from the 1.0 hour run time needed by the optimization based method.

The direct inversion method requires that all model parameters be known, but this is also true of the other approaches mentioned above. As a measure of robustness, each parameter was perturbed +/- 10% and the analysis was repeated. An uncertainty envelope was constructed from the worst case deviations from the known solar load at each instant of time (see ***Figure 6***). Differences are noticeable, but slight.

While this robustness is encouraging, results will be problem dependent. In this case, glazing is a fairly large percentage of the building envelope, so system response is highly linked to solar load. This may partially explain the good robustness observed here.

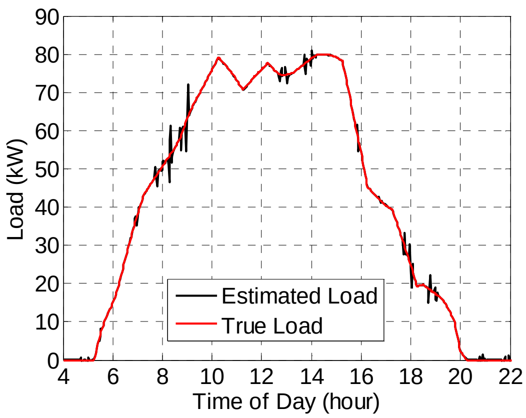

Figure 5 Estimated and True Inside Solar Load

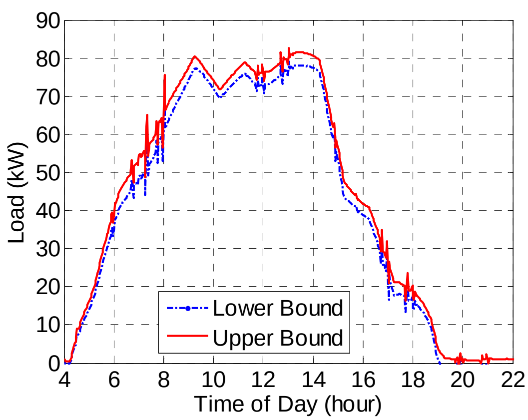

Figure 6 Uncertainty Envelope of Inside Solar Load

CONCLUSION

Improved controls hold the promise of reducing energy consumption and CO_2 emissions from existing buildings. For EMS technology to become pervasive, implementation cost must be reduced. Self-calibrating building models enable on-line or off-line controls optimization with minimal human intervention, and are part of the solution to this challenge.

To that end, a process for determining building model parameters such as zone mass, thermal resistances, thermal capacitances, and infiltration rate has been developed and validated against model generated data. The method uses novel error diagnostics and error functions to eliminate confounding of parameters. Accuracy and repeatability are well below 1% and run time on an ordinary desktop computer is only 1% of data logging time.

A novel *direct inversion method* for estimating time varying source terms or loads was shown to be accurate and robust. This technique is suitable for either on-line or off-line use, and is capable of finding both inside solar load and building occupancy. It can serve a number of purposes, among them checking the assumed load used to estimate model parameters.

The processes detailed and evaluated in this paper lay an important foundation for optimizing building energy system controls. In that regard, this work complements the developing body of research on that subject (see Braun, 2003; Lee and Braun, 2004; Lee and Braun, 2007; and Norford and Xing, 2006)

Future work will include application to real buildings, extension to higher order and multiple zone models, and controls optimization using these models.

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REFERENCES

ASHRAE (2005). ASHRAE Handbook: Fundamentals (SI Edition). Atlanta, GA: American Society of Heating, Refrigerating, and Air-Conditioning Engineers.

Braun, JE (2003). Load Control Using Building Thermal Mass. Journal of Solar Energy Engineering, 125, 292-301.

Braun, JE (2007). Intelligent Building Systems – Past, Present, and Future. Proceedings of the 2007 American Controls Conference, New York, NY: IEEE, 4374-4381.

Coleman, TF, and Li, Y (1996). An Interior Trust Region Approach for Nonlinear Minimization Subject to Bounds. SIAM Journal on Optimization, 6, 418-445.

Cormen, TH, Leiserson, CE, Rivest, RL, and Stein, C (2001). *Introduction to Algorithms, Second Edition*. Cambridge, MA: MIT Press.

Dewson, T, Day, B, and Irving AD (1993). Least Squares Parameter Estimation of a Reduced Order Thermal Model of an Experimental Building. Building and Environment, 28(2), 127-137.

Goldberg, DE (1989). *Genetic Algorithms in Search, Optimization, and Machine Learning*. New York, NY: Addison-Wesley.

Gouda, MM, Danaher, S, and Underwood, CP (2002). Building Thermal Model Reduction Using Nonlinear Constrained Optimization. Building and Environment, 37, 1255-1265.

Lee, K, and Braun, JE (2004). Development and Application of an Inverse Building Model for Demand Response in Small Commercial Buildings. Proceedings of SimBuild 2004, Boulder, CO: IBPSA-USA National Conference.

Lee, K, and Braun, JE (2007). Reduced Peak Cooling Loads through Model-Based Control of Zone Temperature Set-Points. Proceedings of the 2007 American Controls Conference, New York, NY: IEEE, 5070-5075.

Norford, LK, and Xing, HY (2006). A Multiple-Building Optimization Scheme Based on Statistical Building-Load Models. Proceedings of SimBuild 2006, Cambridge, MA: IBPSA-USA National Conference.

Pacala, S, and Socolow, R (2004). Stabilization Wedges: Solving the Climate Problem for the Next 50 Years With Current Technologies. Science, 305(5686), 968-972.

US DOE (2007a). Annual Energy Outlook 2007 With Projections to 2030. Retrieved December 1, 2007 from United States Department of Energy Web site: http://www.eia.doe.gov/oiaf/aeo/index.html.

US DOE (2007b). Buildings Energy Data Book. Retrieved December 1, 2007 from United States Department of Energy Web site: http://buildingsdatabook.eren.doe.gov/.

Wang, S, and Xu, X (2006). Simplified Building Model for Transient Thermal Performance Estimation Using GA-Based Parameter Identification. International Journal of Thermal Sciences, 45, 419-432.

NOMENCLATURE

$C_I =$ thermal capacitance of the inner layer of the building structure

$C_O =$ thermal capacitance of the outer layer of the building structure

$C_{TOT} =$ total thermal capacitance of the building

$e =$ error function

$e_{m_{INF}} =$ error diagnostic for infiltration rate

$e_T =$ error diagnostic for zone temperature

$h_{AMB} =$ enthalpy of ambient air (per unit mass of dry air)

$h_{SUP} =$ enthalpy of supply air (per unit mass of dry air)

$h_{W-LATENT} =$ water mass flow rate to zone due to latent loads

$h_{ZONE} =$ enthalpy of zone air (per unit mass of dry air)

$\dot{m}_{INF} =$ infiltration dry air mass flow rate

$\hat{\dot{m}}_{INF} =$ estimated infiltration mass flow rate (assuming zero net change in zone water mass)

$\dot{m}_{SUP} =$ supply dry air mass flow rate

$\dot{m}_{W-LATENT} =$ water mass flow rate to zone due to latent loads

$m_{ZONE} =$ mass of dry air in the zone

$\dot{Q}_{SENS} =$ heat transfer rate to zone due to sensible loads

$\dot{Q}_{SOL-I} =$ solar load into the inside surfaces of the building structure

$\dot{Q}_{SOL-O} =$ solar load into the outside surfaces of the building structure

$\dot{Q}_{STRUC} =$ heat transfer rate from the building structure to the zone

$R_I =$ thermal resistance between the inside surfaces of the structure and the zone

$R_O =$ thermal resistance between the outside surfaces of the structure and ambient

$R_{WALL} =$ thermal resistance of the structure walls

$R_{WIND} =$ thermal resistance of the windows

$T_{AMB} =$ ambient air temperature

$T_I =$ temperature of inside surfaces of the structure

$T_O =$ temperature of the outside surfaces of the structure

$T_{ZONE} =$ temperature of the zone

$t =$ time

$t_f =$ final simulation time

$t_i =$ initial simulation time (after completion of "warm-up" days)

$u_{ZONE} =$ internal energy of zone air (per unit mass of dry air)

$W_{AMB} =$ humidity ratio of ambient air

$W_{SUP} =$ humidity ratio of supply air

$W_{ZONE} =$ humidity ratio of zone air

$x_i =$ ith component of the model parameter set