DEVELOPMENT AND CALIBRATION OF A REDUCED-ORDER ENERGY PERFORMANCE MODEL FOR A MIXED-USE BUILDING

Bing Dong[1], Zheng O'Neill [2]; Dong Luo [3]; Bailey Trevor[3]
[1]Department of Mechanical Engineering, University of Texas at San Antonio, U.S.A
[2]Department of Mechanical Engineering, University of Alabama, U.S.A.
[3]United Technologies Research Center, U.S.A.

ABSTRACT

Previous studies show that building HVAC systems can consume greater than 20% more electrical energy than was the design intent largely because of equipment performance degradation, equipment failures, or detrimental interactions among subsystems. A key barrier is the lack of information at sufficient detail to isolate abnormal changes in load conditions or anomalous equipment operations. One of the solutions is to develop model-based diagnostic methods. Hence, developing a calibrated energy performance model becomes the key component. In this paper, an integrated energy model for a mix-use building was developed based on a reduced-order thermal model, which includes building envelope model, and HVAC primary and secondary system models. The integrated model was validated against real-time measured data within ±15% error in terms of the load differences.

INTRODUCTION

The Department of Defense (DoD) is the largest single user of energy in the United States, representing 0.8% of the total US energy consumed and 78% of the energy consumed by the Federal government. Approximately 25% of the DoD energy use is consumed by its buildings and facilities. The DoD currently has 316,238 buildings across 5,429 sites and in 2006 its facility energy bill was over \$3.5B (DoD 2008). Due to the large energy footprint of DoD facilities, increasing building energy efficiency offers the largest opportunity for reducing DoD energy consumption. Studies show that building HVAC systems can consume greater than 20% more electrical energy than was the design intent largely because of equipment performance degradation (e.g. filter or heat exchanger fouling), equipment failures, or detrimental interactions among subsystems such as cooling and then reheating of conditioned air. A key barrier is the lack of information at sufficient detail to isolate abnormal changes in load conditions or anomalous equipment operations. One of the solutions is to develop model-based diagnostic methods. Hence, developing a calibrated energy performance model becomes the key.

Calibrated energy models received more and more attentions for better building operations in the last two decades. Claridge (Claridge, 2004) provides a detailed summary of IEA Annex 40 project, where researchers and practitioners investigated the use of whole building simulation in commissioning process from design, post-construction, on-going commissioning, retro-commissioning to the new control code. It was found that calibrated simulation models have been applied routinely for retro-commissioning.

Lee et al. (2007) investigated the usage of calibrated ASHRAE simplified energy analysis procedure (SEAP) for fault detection at the whole-building level based on three years measured data (Lee et al., 2007). It was found that the daily percentage change of the hot water or chilled water consumption for the same period of different years could be up to 400% due to control changes and equipment degradation.

O’Neill et al. (2011a) built up a calibrated EnergyPlus reference model of a DoD building for real-time energy diagnostics (O’Neill et al., 2011a). The model was calibrated based upon real-time measurements including weather, HVAC system and equipment electricity consumptions and thermal loads (e.g., chilled water and hot water consumptions) etc. The result shows that 30% of annual steam energy savings can be achieved through model-based performance monitoring and energy diagnostics (O’Neill, et al., 2011b).

Recently, Bynum et al. (2012) developed an Automated Building Commissioning Analysis Tool (ABCAT), which utilizes a calibrated first-principles based model to predict energy consumption for given weather conditions (temperature and humidity) (Bynum, et al., 2012). ABCAT uses three sensors and meters: whole building electricity usage, whole building heating usage, and whole building cooling usage. This tool focuses on detecting faults that have a significant impact if they persist for a long period of time. ABCAT has been tested on a total of 10 buildings covering over 20 building years of energy consumption data and results show the ability to identify whole building energy savings from 18% to 60 because of system faults.

In this study, we focus on the energy performance models used for supervisory optimal controls and HVAC system/equipment Fault Detection and Diagnostics (FDD), which requires flexible access to the models. Building models incorporated within whole building simulation programs such EnergyPlus, TRNSYS and ESP-r are not explicit and would require significant computational effort when integrated with control and diagnostics algorithms for an on-line implementation in buildings. An integrated reduced-order energy performance modelling approach, derived from building physics, is presented in this paper. The whole building energy model was developed in MATLAB (MATLAB, 2011b) environment. It includes a reduced-order building envelope model, and HVAC primary and secondary system models. The internal heat gains/losses were estimated using real-time measurements coupled with Extended Kalman Filter (O'Neill et al., 2010). The simulation coupling between HVAC systems and building zones is modelled through a ping-pong coupling approach.

TECHNOLOGY APPROACHES

The technologic approaches include building envelope model, HVAC equipment model, internal load estimation, building data acquisition system and integrated whole building modelling.

1. Building envelope model

A thermal network model (3R2C) was adopted in this study. This modelling framework has been widely used to represent the heat transfer and thermal dynamics process through building envelope and the subsequent effects on indoor air temperature (ASHRAE 2009). The 3R2C model has been successfully used to model building envelopes for building thermal load prediction (Braun and Chaturyedi, 2002; O'Neill et al., 2010). One major assumption used by this approach is that the zonal air is well mixed, with only one temperature node and one humidity node. Figure 1 shows a typical energy flow in buildings for the reduced-order model (ROM) approach. Table 1 lists out all the modules that have been developed and validated with measured data in this study. The infiltration and ground heat transfer modules were not validated due to unavailable data at the time of this study.

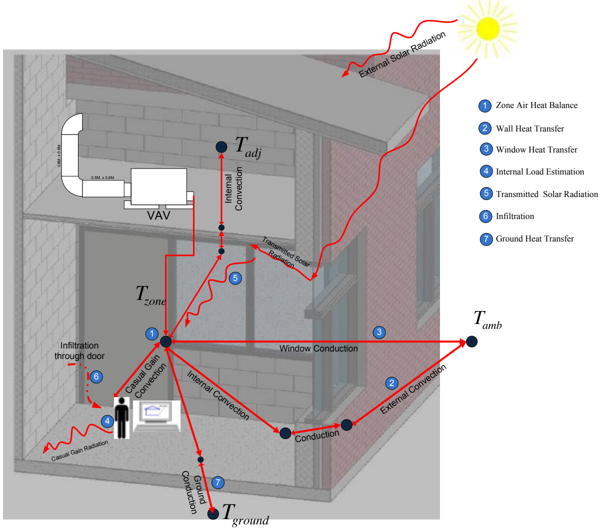

Figure 1. Energy Flow in Buildings

Table 1 Individual Modules in the Building Envelop Model

Component	**Module**	**Validation/Verification**
Air Heat Balance	(1)	√
Wall Heat Transfer	(2)	√
Window Heat Transfer	(3)	√
Internal Load Estimation	(4)	√
Transmitted Solar Radiation	(5)	√
Infiltration	(6)	N/A*
Ground Heat Transfer	(7)	N/A*
Automatically Model Extraction		√

*N/A No data available for validation/verification at the time of this study

The sensible zone air balance, module (1) in Figure 1, assuming air is well mixed, can be presented as:

$$ma_{zone}C_{pa}\frac{dT_{zone}}{dt} \tag{1}$$
$$= \dot{m}_{\sup}C_{pa}\left(T_{\sup}-T_{zone}\right)+\dot{m}_{\inf}C_{pa}\left(T_{amb}-T_{zone}\right)+$$
$$\psi_{\text{int}}+\sum_{i}^{N_{surface}}\psi_{structure\_i}+\sum_{i=1}^{N_{adjzone}}\dot{m}_iC_{pa}(T_{zonei}-T_{zone})$$

For the building envelope part (i.e., modules 2 and 3 in Figure 1)

The outside surface heat flux balance is given by:

$$\frac{\rho_{ow}C_{p\_ow}l_{ow}A_{ow}}{2}\frac{dT_{osurf}}{dt}=h_oA_{ow}\left(T_{amb}-T_{osurf}\right) \tag{2}$$
$$+\frac{T_{isurf}-T_{osurf}}{l_{ow}}(k_{ow}A_{ow})+\psi_{surfo}$$

The inside surface heat flux balance is given by:

$$\frac{\rho_{iw} C_{p\_iw} l_{iw} A_{iw}}{2} \frac{dT_{isurf}}{dt} = h_i A_{iw} \left(T_{zone} - T_{isurf}\right) + \frac{T_{osurf} - T_{isurf}}{l_{iw}} (k_{iw} A_{iw}) + \psi_{surfi} \quad (3)$$

The total heat flux through the building structure is given by:

$$\psi_{structure} = h_i A_{iw} (T_{isuf} - T_{zone}) + \frac{(T_{amb} - T_{zone})}{R_{win}} \quad (4)$$

Where:

C_{pa}	Specific heat of the air [J/kg·°C]
ma_{zone}	Air mass of the zone [kg]
T	Temperature[°C]
ψ	Load from different sources [W]
A	Surface area [m^2]
l	Length of the surface [m]
k	Thermal conductivity of surface [W/m·°C]
h	Overall heat transfer coefficient of surface, which includes both radiation and convection [W/m^2·°C]

The subscripts, *amb, zone, sup, ow,iw, osurf, isurf, win,* refer to ambient, zone, supply, outside wall, inside wall, outside surface, inside surface and window respectively.

2. HVAC Equipment Model

Table 2 List of HVAC ROMs

System	Equipment	Quantity	Model	Validation/ Verification
Primary	Absorption chiller	2	√	**
	Cooling tower	1	√	Verification
	Condenser pump	3	√	√
Secondary (AHU)	Cooling coil	10	√	N/A
	Heating coil	8	√	N/A
	Heat recovery coil	4	√	N/A
	Supply fan	10	√	√
	Return fan	10	√	√
	CHW pump	3	√	√
	HW pump	4	√	√
	Heat recovery pump	4	√	N/A
	Economizer	10	√	*
Terminal	VAV	238	√	N/A
Other	Unit heater (hot water)	5	√	N/A
	Unit heater (electric)	6	√	N/A
	Exhaust fans	39	√	VFD fans

HVAC subsystem models have been created for the equipment in this study as listed in Table 2. These models are lumped steady-state reduced-order models. The models can be used for energy monitoring and trend analysis. Those models have been calibrated and validated when appropriate measured data were available. For equipment without measured data or with low-quality data, models have been examined with trends and ranges based on fundamental physics.

* Inconsistent controls for some units. (e.g., minimal damper positions specified by the control design document were not in actual operation)

** Measured data of condensate flow rate for heat input to the absorption chiller needs to be improved

Two examples given here are cooling coil and fan models.

Cooling coil model

The cooling coil model is based on approach to the saturation line in the heat and mass transfer process (Brandemuehl et al., 1993). As an equivalent psychrometric calculation, coil UA values were derived from the bypass factor and effectiveness-NTU method. Dry-bulb temperature for dry coil and enthalpy for wet coil conditions were used during the calculation.

$$UAt = e\_NTU(\dot{m}_a, h_{ai}, \dot{m}_w * C_{pw} / C_{psat}, T_{wi}) \quad (5)$$

$$UAo = -\log(BPh) * \dot{m}_a * C_{pa} \quad (6)$$

$$UAi = C_{psat} / (1/UAh - C_{pa}/UAo) \quad (7)$$

where,

UAt,o,i	UA values for total, external and internal heat transfer rate [W/ °C];
$\dot{m}_a$	Air mass flow rate [kg/s]
$\dot{m}_w$	Water mass flow rate [kg/s]
C_{pw}	Specific heat of water [J/kg·°C]
C_{psat}	Specific heat of water and air at equivalent saturation condition [J/kg·°C]
BPh	Bypass factor [-]

For the cooling coil model, eight functions for coil and fifteen psychrometric functions have been created in MATLAB.

Fan model

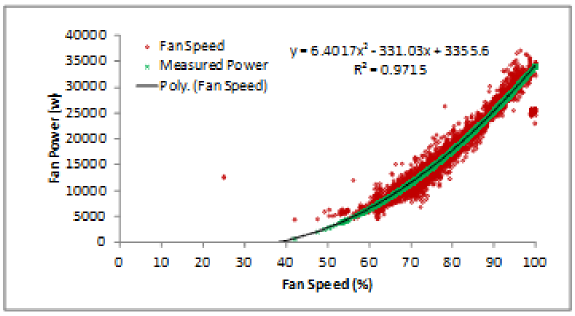

Figure 2 Building 7114 AHU2 Supply Fan Power vs. Fan Speed

Figure 2 shows the measured fan power vs. fan speed for the supply fan of AHU2 in Building 7114 (building used for the case study), from June to August, 2011. The fan power has a strong 2^{nd} order polynomial relationship with the speed, with an coefficient of determination (R^2) of 0.97. Hence, the fan power model was created as a function of fan speed signal, depending on availability of data.

$$P_{fan} = C_0 + C_1 * x + C_2 * x^2 \quad (8)$$

where,
C_0-C_2: coefficients created from measured data;
x: fan/pump speed signal (%)

3. Load Estimation

In the absence of direct measurement of some exogenous inputs, a model-based estimation approach was used to provide information about unmeasured data relative to building energy performance, internal loads in this study. Estimation was performed using extended Kalman filters (O'Neill et al., 2010). The system model was augmented with states defining the internal load and driven with white noise (Equation 9). The extended Kalman filter was then employed to estimate the internal load.

$$X = \begin{bmatrix} \dot{x} \\ \dot{Q}_{\text{int}} \end{bmatrix} = \begin{bmatrix} f(x,u) + f(x,\theta) + Q_{\text{int}} + w_x \\ w_Q \end{bmatrix} \quad (9)$$

$$Y = C^T x + v$$

Compared with previous study (O'Neill, et al., 2010), additional capabilities/ flexibilities extended in this study are:

1. Constraint Handling: The EKF implementation was extended to handle time-varying lower and upper bound constraints on the internal load. The algorithm requires the user to specify these bounds a-priori, otherwise a default value of zero lower bound is used to reflect the fact that internal loads (physically) can only be non-negative. The bound specification is required to be a Ndata by Nzones matrix, where Ndata is number of data points and Nzones is the number of zones for which load estimates is required.

Any available information on the internal load can easily be incorporated in to the constraints. For example, if the lighting load is known, the lower bound will be set to a minimum value equal to the lighting load for each zone. Otherwise, the model can be modified to include the known component of the load while the estimator only computes the unknown component. The constrained load estimation is handled with an algorithm that projects the unconstraint estimate unto the user defined constraint surface.

2. Consolidation of Output Model: The original KF code requires one function file per output, resulting in unnecessary many function files for large buildings with many zones. Since the output measurements in the buildings is usually the zone temperature. The KF is revised to accept one single function file for all the specified outputs.

3. Automatic calculation of Jacobian: EKF requires the calculation of the partial derivative matrices or Jacobian (Equation. 10) at the current state estimate.

$$A = \left. \frac{\partial f}{\partial x} \right|_{\hat{x},\, \hat{u}} \quad (10)$$

Since the functional form of the building 3R2C model is not available for analytical computation of the Jacobian, it is computed numerically by finite difference. The advantage of this is that the user only need to provide the building model and the Jacobian is calculated as a part of the estimation routine of EKF.

4. Building Data Acquisition System

A Building Data Acquisition System (BDAS) was developed to acquire data from the Building Management System (BMS). This BDAS includes three layers: a) Data Communication Protocol for Building Automation and Control Networks (BACnet) reader utility, which reads data from BACnet compatible Building Energy Management System (BEMS); b) StoreBACnetDatatoBIMdatabase, which convert the raw data from BACnet into a structured query language; c) DatabaseManager, which stores the raw data into a building information model database. For example, the thermal boundary conditions including outside air temperature, solar radiation, and wind speed and direction were stored in the database, then passed to the ROM in real-time. In a summary, the following functions are supported by the BDAS system: 1) Get real-time operational data from BMS that support BACnet protocol: this is done through BACnet reader in the BCVTB (Wetter, 2011) and 2) Store data in a database. The details can refer to Dong et al. (2012).

5. Integrated Whole Building Modelling

The integrated building system model was developed based on pre-described building envelope and HVAC equipment ROM models. The integrated model has four parts: 1) model initialization; 2) HVAC control logic; 3) coupling of the building envelope model with HVAC equipment models; and 4) interface with the building database and BMS. The overall schema of the integrated system model is illustrated in Figure 3.

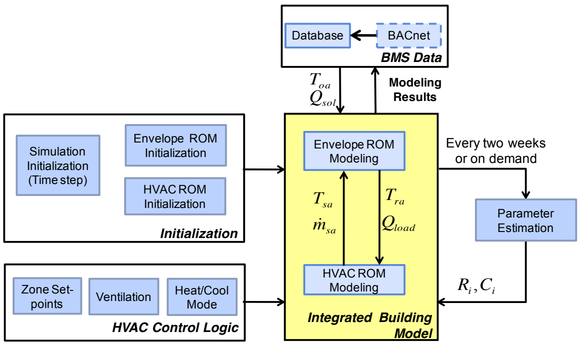

Figure 3. Overall Schema of Integrated System Model

The integrated system model runs in the MATLAB simulation environment. The co-simulation involves both inter-domain (coupling coil model and chiller model) and intra-domain (coupling building envelope model and HVAC model) coupling. The coupling between the building envelope and the HVAC equipment models uses a "loose-coupling" approach.

6. Automatic Model Generation (BIM to BEM)

In this study, the building energy models (BEM) including building envelope and HVAC was created automatically from a tool chain that seamlessly convert building information model (BIM) to BEM. First, a BIM-based database was created and implemented for building properties. This includes: a) static information directly from a building Industry Foundation Classes (IFC) file which is generated by a) Revit model and b) dynamic information from building operation data. The development of this database scheme is composed of four elements: 1) Building static information; 2) Operational information; 3) Simulation information; and 4) Fault detection and diagnostics (FDD) information. Second, the information from both Revit architecture and mechanical drawings were exported to IFC and gbXML files, and stored in the BIM database. Third, necessary input information, including building geometry, building envelope materials properties, and thermal zoning etc., was automatically extracted from the BIM-based database and then the ROMs were created automatically in MATLAB environment. Details for this tool chain can be found from Adetola et al. (2013).

CASE STUDY

1. Case Description

The test facility is Building 7114, which is 149,875 ft^2 recruit barracks at Naval Station Great Lakes, Great Lakes, IL, It is a long rectangular building, consisting of a large block of berthing compartments, heads (bathrooms), laundry rooms, classrooms, a quarterdeck with a two-story atrium and office spaces, and a large cafeteria/galley. Building 7114 shares the absorption chillers, cooling tower, heating hot water heat exchangers, chilled water pumping system, heating hot water pumping system, and the condenser water pumping system with another similar building. The compartment area is served by two variable air volume (VAV) Air Handling Units (AHU) with VAV terminal units (with hot water reheat).The details of this test facility can be found in Dong et al. (2012).

2. Building Envelope Model Validation

The Building 7114 envelope model was calibrated against measured data. For each zone, the total cooling or heating load was computed from the ROM building envelope model for a given month, and a percentage error was computed, with respect to the measurements. The comparison at the AHU level is summarized in Table 3, which shows that indeed, the model predictions are within 10-11% of the measurements for all the AHUs.

Table 3 Comparisons of Building 7114 Cooling Load at the AHU Level between Data and Thermal Network Models for July and August 2011

AHU	Loads, data (kWh)	Loads, model (kWh)	% error
1	112.1	104.6	11.1
2	103.8	98.4	11.7
3	54.4	51.8	9.7

3. Building HVAC Model Validation

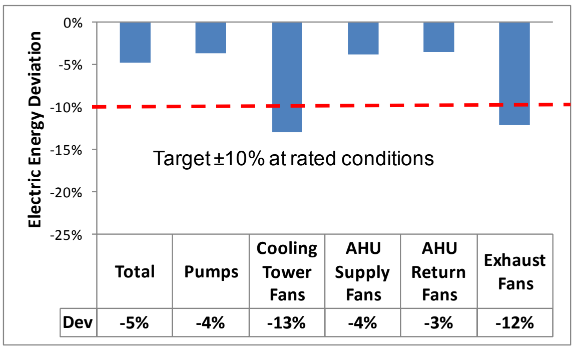

Figure 4 Building 114 equipment models validation

Figure 4 shows the results for equipment level model calibration. HVAC Model parameters were first calibrated with one set of data that covered an appropriate range of operation (e.g., data from May, 2011) and then applied to other sets of data (e.g., data from June/July, 2011). Most of the results show model accuracies within +/- 5%.

4. Internal Load Estimation

The comparison of lighting and plug loads between model predictions and measurements are presented below. The EKF was first used to get a pattern of the loads, and then the loads were adjusted based on the measurement and adjusted slightly for each month accordingly.

Lighting load

For the lighting load, electric sub-meters were installed for emergence, compartments, classrooms and mechanical rooms. Since most of the occupant's activities happen in the compartments and classrooms area, the comparison is conducted for those two areas. Figure 5 shows an example of the usage pattern of the compartment lighting from Aug.6th to Aug. 9th. 2011. The red line shows the measured lighting load, while the blue line shows the estimated pattern. They are very close to each other, although with some fluctuations during the afternoon time. If such estimation was applied on all other months, Figure 6 shows the totally monthly loads comparisons from June to December, 2011, with accuracies on the right vertical axis. The worst case is the December with a difference of 1.78%, while the best case is the July with a difference of -0.22%.

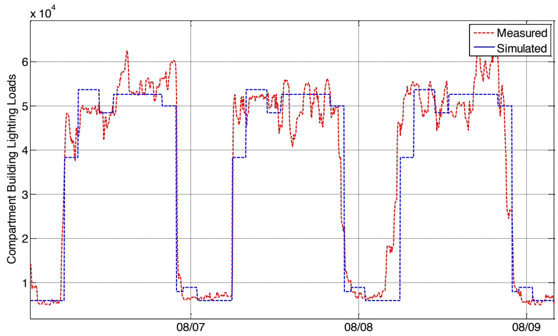

Figure 5 Comparisons between Measured and Estimated Lighting Loads in Building 7114 from 08/06/2011 to 08/09/2011

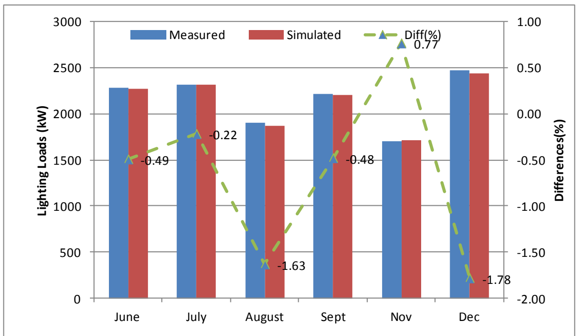

Figure 6 Comparisons between Measured and Estimated Lighting loads of Compartments and Classroom Areas in Building 7114 from June to December, 2011.

Plug load

There is only one total building sub-meter for the plug loads, which makes the estimation difficult. The estimation follows three steps: 1) Plug loads after the mid-night are mostly from computers in the two classrooms; 2) Before dinner time (around 5 pm), the plug loads are mainly from compartments and classrooms; 3) During the dinner time, the plug loads are from compartments, classrooms and kitchen/dining areas. The patterns were adjusted based on these rules, and the comparison is shown in Figures 7 and 8. Figure 7 shows the measured plug loads have spikes in the late afternoon but not for all days. Figure 8 shows the total building plug load comparison from June to December, 2011. The best case is the December with a difference of -0.1%, while the worst case is the July with a difference of 2.91%. This could be due to a lower building occupancy in December and a relatively higher building occupancy in July. With the high occupancy, there are more uncertainties in the plug load estimation.

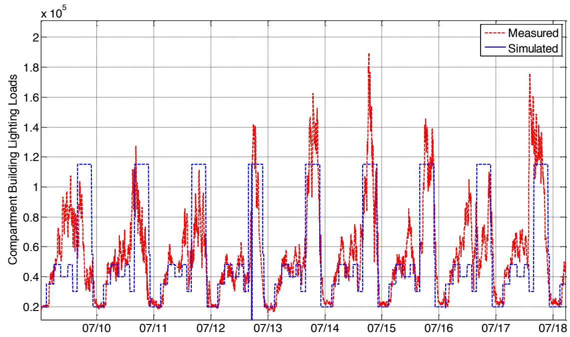

Figure 7 Comparisons between Measured and Estimated Plug Loads in Building 7114 from 07/09/2011 to 07/18/2011

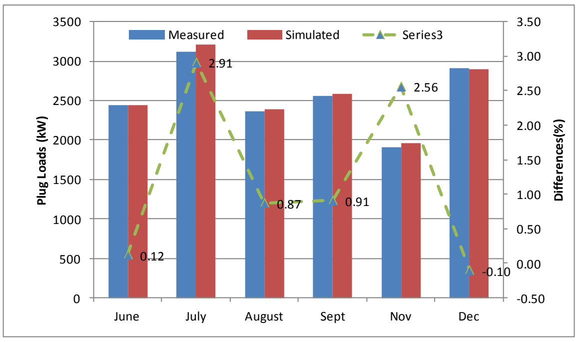

Figure 8 Comparisons between Measured and Estimated Plug Loads in Building 7114 from June to December, 2011.

5. Integrated Model Validation

The whole building heating and cooling load are defined as:

$$Q_{load\_total} = \dot{m}_{w\_c} C_{pw}(T_{ws\_c} - T_{wr\_c}) \qquad (11)$$

Where, water mass flow rate, $\dot{m}_{w\_c}$, supply water temperature, T_{ws_c} and return water temperature T_{wr_c} are computed from the integrated model. As illustrations of the model accuracy, the results of the integrated model validation are shown from some selected cooling and heating periods. During the cooling season, the zone daily occupied set-point is 21.1 ºC (70 ºF) and night set-back is 25.6 ºC (78 ºF). During the heating season, the zone daily occupied set-point is 22.2 ºC (72 ºF) and night set-back is 18.3 ºC (65 ºF). Those set-points are derived from BMS measured data. Model validation results in two periods are discussed as follows:

1) Building 7114 cooling period
The cooling model validation for Building 7114 was performed from July 6th to July 9th, 2011 as shown in Figure 9. About 85% of the data is within the ±15% error band in each time step (5 minutes). During the day time, the predicted loads from the model are very close to the ±10% error band. However, the model did not behave well during the middle of night due to the low load conditions.

2) Building 7114 heating period
The heating model validation for Building 7114 was conducted from Dec 8th to Dec 10th, 2011 as shown in Figure 10 below. About 75% of the data is within the ±15% error band in each time step (5 minutes). The main reason that the model prediction in the heating season is not as good as that in the cooling season is due to the fluctuation of water flow rate measurements.

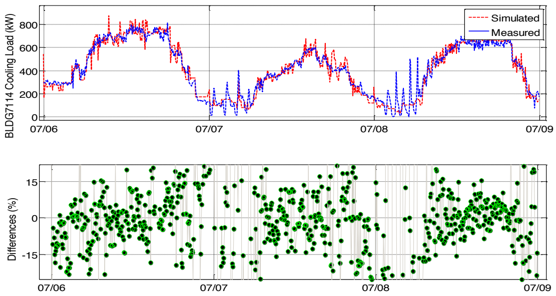

Figure 9 Building 7114 Cooling Season Integrated Model Validation from 07/06/2011 to 07/10/2011

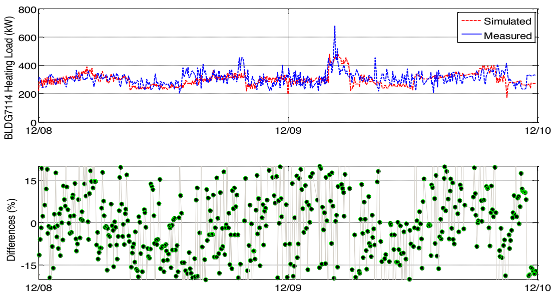

Figure 10 Building 7114 Heating Season Integrated Model Validation from 12/08/2011 to 12/10/2011

CONCLUSIONS

In this paper, an integrated building envelope and HVAC model was developed and calibrated for a mix-use building with measured data. The total building load comparisons show that the differences between measurements and predictions for the integrated ROM are within the ±15% target for the majority of time. The model prediction errors are outside the ±15% error band when there are low load conditions. This is as expected because the HVAC system/equipment ROM performance degrades at non-rated conditions. The lessons we have learned in this study are:

- The design control logic in the HVAC control system could be different from what is actually implemented locally. Such local control logic is usually proprietary and unknown to the users, which makes it difficult to establish a validated baseline model.
- Continuous and consistent data quality is the key for a good model validation process. Due to BMS communication faults, local control panel offline events and data traffic, the collected data is often interrupted or invalid for a long time period. Such data quality makes model validation process difficult. Furthermore, considerable time was spent dealing with issues related to sensor data quality (e.g., sensor bias and drifting) for modelling and diagnostics.
- Difficulties in getting real-time data effectively for the model validation. In this study, all the data mapping from the BMS to the database was done manually which increased the implementation cost. It is desirable to develop a secure, scalable and industry standard oriented storage mechanism and application interface (API) for both static and real time dynamic building operational data.

NOMENCLATURE

C_p	Specific heat [J/kg·°C]
T	Temperature [°C]
$\dot{m}$	Mass flow rate [kg/s]
ma	Air mass [kg]
ψ	Load from different sources [W]
A	Surface area [m^2]
l	Length of the surface [m]
k	Thermal conductivity of surface [W/m·°C]
h	Overall heat transfer coefficient of surface, which includes both radiation and convection [W/m^2·°C]
UAt,o,i	UA values for total, external and internal heat transfer rate [W/ °C];
BPh	Bypass factor [-]
Q	Building load [W]
Subscripts	
amb	Ambient condition
wr_c	Calculated return water
ws_c	Calculated supply water
pw	Water

pa	Air
$psat$	Water and air at equivalent saturation condition
C_{pw}	Specific heat of water [J/kg·°C]
sup	Supply
sa	Supply air
ra	Return air
oa	Outside air
ow	Outside wall
iw	Inside wall
$osurf$	Outside surface
$isurf$	Inside surface
sol	Solar
win	Window
int	Internal
$structure$	Building structure/envelope
fan	Fan
$zone$	Zone

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