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A Bottom-up Method to Calibrate Building Energy Models Using Building Automation System (BAS) Trend Data

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Abstract

Ongoing commissioning based on calibrated building energy models is one of the most promising means to improve the energy performance of existing buildings. Many calibration methods in the literature relied on whole-building utility data to calibrate building energy models. Recent studies revealed that only using this approach could result in offsetting errors occurring at sub-utility levels. Bottom-up calibration sequentially calibrates the zone, system, plant, and whole-building levels to reduce offsetting errors at sub-utility levels. The number of candidate measurement points required for bottom-up calibration is large. Fortunately, building automation systems (BASs), common in many commercial/institutional buildings, can provide some of the required data. Using inputs generated from trend data and calibrating the zone level first often yielded a calibrated model at the system level. The paper applies the proposed method to a new research building.

Keywords – building energy model; calibration; measurements; BAS trend data

1. Introduction

A calibrated building energy model is a powerful tool that can create benchmarks for operation, perform fault detection and diagnostics [1,2], and identify optimal control of building energy use and demand response [3].

1.1 Model Calibration Methods

There are no standard methods for calibrating building energy models [4,5], which may result in modelers using different combinations of inputs to achieve a calibrated model. Overall, the iterative, pragmatic, and manual calibration methods, identified in [4], are highly dependent on user experience and knowledge and are non-transparent due to the tuning of inputs. Raftery et al. [6] addressed the non-transparency issues by advocating more explicit documentation of the tuning process.

Identifying influential inputs is time consuming due to the large search space. The signature analysis calibration method requires a large set of characteristic signatures which must be either created or found in a database for similar buildings in similar climates. There are no batch programs available that could help to create characteristic signatures; to the author's knowledge, the only set of characteristic signatures was published in [7]. The optimization-based methods have the capacity to produce a set of calibrated models using various combinations of tuned parameters. Sun and Reddy [8] developed a method that applies heuristics to monthly utility bill data to determine a set of influential inputs and estimates their range of variation; the most influential inputs are determined by using the Monte Carlo search; and the uncertainty of the calibration process is evaluated. Reddy et al. [9, 10] expanded the method by creating a small set of the most feasible calibrated models instead of choosing only one optimal solution. ExCaliBEM [11] has the capacity to tune inputs in order to minimize the residuals of variables in DOE-2 and EnergyPlus models.

1.2 Use of Trend Data in Model Calibration

One approach to overcome the issue of underdetermined models is to employ shorter interval subsystem data obtained from building automation systems (BASs), commonly installed in many commercial and institutional buildings. A few examples are listed here. The trend data used by [12] included setpoints and control signals, sub-metered electricity, air temperatures in the AHU and zones. Monfet et al. [13] used trend data to calibrate AHU supply air flow rates, and supply and return air temperatures of the HVAC system. Pang et al. [14] used trend data to create inputs for use in real-time with an already calibrated model. Gestwick and Love [15] used trend data to estimate lighting, equipment, and fan schedules and compared hourly plant heating load trend data to simulation outputs. They noted that offsetting errors would likely have occurred if hourly plant heating load trend data were unavailable. Kandil and Love [16] used trend data to generate inputs to simulate fan and pump schedules; domestic hot water schedule and capacity; boiler efficiency; AHU air flow rate and demand. Mihai and Zmeureanu [17] calibrated the models of thermal zones by using zone supply air flow rates and indoor air temperature trend data. Mustafaraj et al. [18] reported the use of several BAS trend data such as set points, on/off values, schedules, electrical consumption of heat pumps, hot water temperature, and room indoor air temperature.

It is the authors' opinion that the use of BAS trend data for the model calibration method proposed in this paper is a more cost-effective alternative to the installation of a dedicated monitoring system.

1.3 Calibration Method

This paper presents the application of a bottom-up calibration method that uses BAS trend data. The bottom-up method sequentially calibrates the zone, system, plant, and whole-building models. The method relies on inductive reasoning based on

evidence (i.e., BAS trend data) from measurements to show that if these models are calibrated, then the model will contain less offsetting errors than if it was only calibrated at the whole-building level. The approach can be applied to simulation software such as eQuest and EnergyPlus.

Measurements from BAS trend data in a case study building and simulation outputs from the energy model are compared at the thermal zone and system levels in this study. The plant and whole-building levels of the model are not calibrated because the building is connected to a campus central plant and whole-building electricity is not submetered. The comparison is carried out by using hourly rather than monthly or annual data. The paper presents the model calibration for the shoulder season, rather than over the whole year of operation to simplify the simulation when testing the method.

1.4 Statistical Indices Comparing the Model Simulations to Measurements

ASHRAE Guideline 14 [19] presented the thresholds of two statistical indices for the building energy model to be considered as calibrated. When hourly data are used, the mean bias error (MBE) between model simulations and measurements of whole building annual energy use must be less than 10%, and the coefficient of variation of root-mean-squared error (CV(RMSE)) must be less than 30%.

2. Case Study Building

The Research Centre for Structural and Functional Genomics, referred to herein as the Genome (GE) Building (Fig. 1) was completed in 2011 on Loyola campus of Concordia University in Montreal, Quebec, Canada. The GE Building has a floor area of 5,400 m² over five levels that houses 48 offices, three conference rooms and corridors, which account for about 53% of the total floor area, and laboratories with fume hoods that account for about 30%. The remaining space is occupied by kitchen/lounge and restrooms on each floor.



Fig. 1 Genome (GE) Building

The brick and aluminum facades have an overall effective U-value of 0.41 W/m²·K. The vision panel of the curtain wall has an overall U-value of 3.5 W/m² accounting for the edge-of-glass and frame, while the opaque part has an effective U-value of 1.7 W/m²·K. Vertical semi-transparent shading fins of 30% transparency are on the windows.

The GE Building has a variable-air-volume (VAV) system with reheat terminals. Two identical AHUs are connected in parallel. Exhaust air is extracted from fume hoods, laboratories, and restrooms through centrifugal exhaust fans. The air within the AHUs is conditioned using run-around sensible heat recovery coils, and heating and cooling coils (inactive during the shoulder season). The BAS trend data show the maximum supply air flow rate of 42,500 L/s, during that season, and the outdoor air flow rate of 33,000 L/s. The outdoor air dampers are always 100% open and close completely only during periods of maintenance or emergency shutdown.

The BAS runs Siemens APOGEE® software to control the HVAC systems. Trend data were recorded every 15 min, from which the hourly values were calculated.

3. Initial Building Energy Model and Shoulder Season Calibration

The development of the initial building energy model begins by collecting as much information about the building as possible. Sources of information included design documents, BAS trend data, site inspections, short-term measurements with data loggers, operator interviews and local weather data. Using trend data in calibration greatly increases the number of inputs and outcomes available for comparison with simulation outputs. However, trend data can provide only some of the required inputs. There are still many phenomena that may be highly influential in energy use, such as occupant heat gains, air infiltration, and envelope heat loss/gain, but are particularly difficult to measure on an ongoing basis. Lighting and equipment loads are rarely sub-metered, and occupant loads are very difficult to measure even if time clock or security card records are available, especially at the zone level. Using trend data enables one to focus the tuning on uncertain and difficult to measure inputs related to zone loads.

3.1 Building Model

This chapter describes the development of the initial building energy model for the shoulder season, from April 8 to April 23, 2013, when the AHU heating and cooling coils were off. eQUEST was chosen as the simulation software in this study because it is one of the most widely used building simulation tools in North America; it uses the DOE-2 simulation engine, which has been extensively documented and validated.

Instead of using the thermostat setpoint temperature of each thermal zone as inputs to eQuest, the hourly median zone air temperature and zone minimum supply air flow ratio schedules for weekdays and weekends, and the maximum zone supply air flow rate were extracted from BAS trend data over the shoulder season.

Lighting, equipment, and occupant peak values and schedules were estimated using values found in the literature for use as a starting point in the initial model. The

maximum occupant density by space type was estimated based on values in ASHRAE 62.1 [20], while corresponding sensible heat gains were obtained from [21]. Equipment power densities were estimated using [21], and lighting power densities were estimated using [22]. Occupant schedules were estimated using the diversity factors developed by Davis and Nutter [23] from measurements in a university building. The lighting and equipment diversity factors created by Claridge et al. [24] were used.

To simplify the calibration of internal loads because of their large uncertainty, the effect of all internal loads was replaced with one single equivalent peak load for each zone. For instance the aggregated peak load for zone Z1-S was input as 23.6 W/m². All schedules were aggregated into two schedules, one for weekdays and another for weekends/holidays, for the entire building (Fig. 2).

The HVAC system was modelled as VAV with zone hot water reheat. The two parallel AHUs, each one with two parallel fans, were modelled in eQUEST as one AHU with one fan equal to the capacity of the four fans.

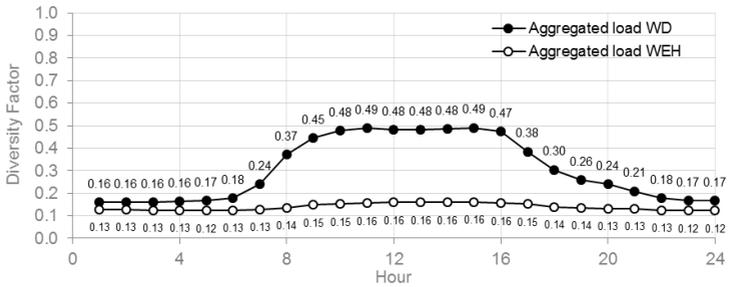


Fig. 2 Aggregated diversity factors for occupant, lighting, and plug loads

3.2 Weather data file

Weather data were obtained from SIMEB [25] using data collected at the Montreal-Pierre Elliot Trudeau International Airport, located approximately 9 km of the GE Building. The difference between the outdoor air temperature (T_{OA}) trend data recorded at an adjacent building and at the airport had an MBE of -16% and RMSE of 1.8 °C. The T_{OA} of the original data file was replaced with the trend data.

3.3 Tuning of Initial Model

After the initial model was created, and the initial model errors and limitations of the initial model were addressed, the predictions were compared with trend data. Statistical indices indicated that 11 zones out of 17 zones of the initial model were calibrated according to the thresholds in [19]. The thresholds in [19] are given for the calibration of whole building annual energy use only and do not recommend thresholds for the calibration of variables used in this study (e.g., supply air flow rate to each zone,

indoor air temperature). The thresholds in [19] were used to determine if the zone variables were calibrated because no threshold has been recommended for variables such as flow or temperature. The calibrated zones cover 62% of the floor area and 72% of the supply air flow. This result demonstrates how effective trend data utilization can be to assist in the calibration process.

The initial model was modified by changing the diversity factors of internal gains (Fig. 2) with a constant schedule with diversity factor equal to 1.0 during the occupied hours for all zones, and by tuning the aggregated peak value for each zone. For instance, the peak value of zone Z1-S was reduced from 23.6 W/m² to 19 W/m². The tuning improved the model fit of the zones tuned but resulted with no additional calibrated zones (Table 1), where \checkmark shows if the zone was calibrated.

Table 1. Statistical indices of the zone level calibration after tuning

Zone	Calib (yes)	Indoor air temperature		Supply air flow rate	
		MBE (%)	CV(RMSE) (%)	MBE (%)	CV(RMSE) (%)
Z1-S		-1.8	4.8	83	125
Z1-NE		-0.7	4.4	13	37
Z1-NW	\checkmark	-0.9	4.3	0.2	0.7
Z1-CORR	\checkmark	-1.7	3.1	-0.4	3.5
Z1-CONF		-1.4	3.6	-6.5	33
Z2-SW	\checkmark	-3.2	5.3	1.1	15
Z2-E		-1.1	4.1	12	30
Z2-INT	\checkmark	-0.7	3.4	4.4	22
Z2-NE	\checkmark	-2.6	3.5	0.4	9.1
Z2-S	\checkmark	-2.9	3.9	0.1	0.5
Z2-W		-1.1	2.8	15	65
Z3-SW	\checkmark	-0.7	4.5	-0.6	14
Z3-E	\checkmark	-1.4	3.8	5.3	15
Z3-INT	\checkmark	-0.8	3.1	7.0	21
Z3-NE	\checkmark	-2.7	3.5	-0.5	10
Z3-S	\checkmark	-2.4	3.7	0.5	22
Z3-W		-0.8	3.8	5.1	37

The tuning was done for all thermal zones to calibrate for the indoor air temperatures (T_Z), supply air flow rates (V_{zs}), and zone HVAC load. Tuning this load represented tuning uncertain zone loads from lighting, equipment, occupants, infiltration, and envelope gains/losses. Each of these uncertain loads were initially input into the model using as much information as possible; however, it was clear that offsetting errors in the original estimations caused this aggregated load to be refined.

Since a large fraction of thermal zones, in terms of floor area and supply air flow rate, met the calibration criteria, the system level model was calibrated next. The system level model is considered to be calibrated (Table 2), as the statistical indices for some important outcomes are below the thresholds from [19]. The calibration was achieved by using only trend data and short term measurements, and no tuning of the system level model was required. Overall the supply air temperature T_S closely follows the pattern in the trend data. Large differences in the peak supply air temperature T_S (Fig. 3) occurs when outdoor air temperatures were high.

Table 2. Statistical indices of the first iteration of the system level calibration

Variable	MBE (%)	RMSE	CV(RMSE) (%)
T_S (°C)	2.7	2.1	15
T_M (°C)	1.8	1.6	14
V_S (L/s)	5.1	1208	11
\dot{Q}_{hr} (kW)	3.3	8.6	18
ϵ_{hr} (%)	-6.9	2.6	17
T_{hr} (°C)	0.5	47	4.7

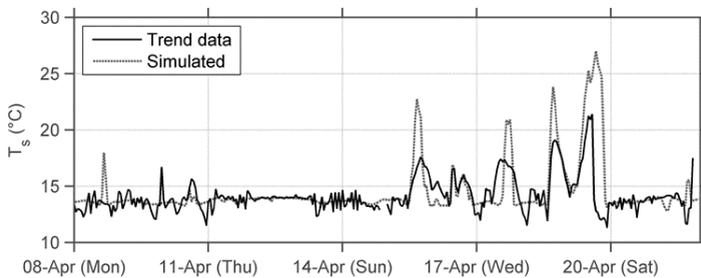


Fig. 3 Supply air temperature (T_S): simulation vs. trend data

The simulated supply air flow rate from AHUs (V_S) follows the pattern in the trend data well but with some exceptions during weekends and evenings (Fig. 4). The

air temperature leaving the heat recovery coil (T_{hr}) (Fig. 5) and heat recovery flow rate (Q_{hr}) (Fig. 6) follows the pattern in the trend data well. The simulated heat recovery effectiveness (ϵ_{hr}) (Fig. 7) is slightly higher than trend data when $T_{OA} < 2^\circ\text{C}$.

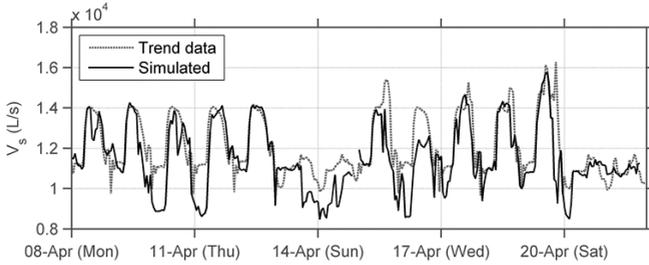


Fig. 4. Supply air flow rate (V_s): simulation vs. trend data

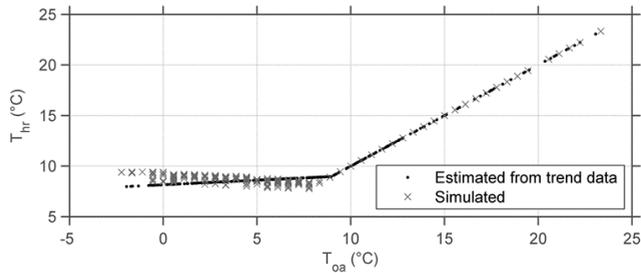


Fig. 5 Air temperature (T_{hr}) exiting heat recovery: simulation vs. trend data

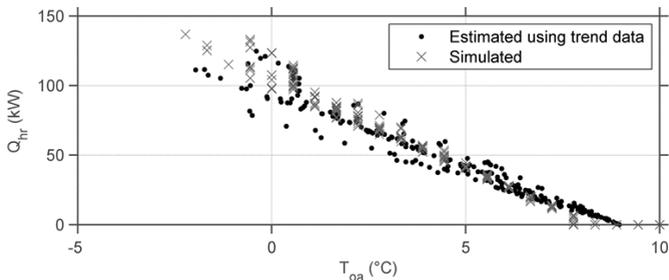


Fig. 6 Heat recovery heat flow rate (Q_{hr}): simulation vs. trend data

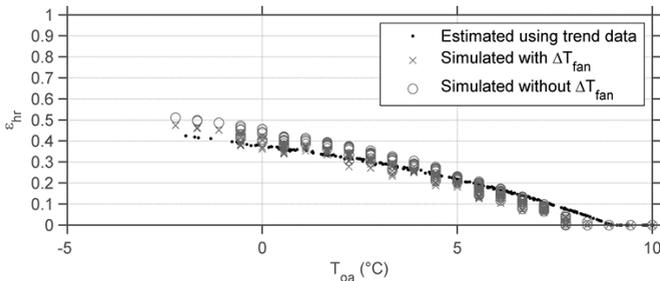


Fig. 7 Heat recovery effectiveness (ϵ_{hr}): simulation vs. trend data

4. Conclusions

Trend data provided a substantial amount of information that was useful to apply the bottom-up calibration method; however, it could not provide all the information required to model a building. It is clear that the most uncertain and difficult to measure variables in buildings are the ones affecting zone loads. An equivalent internal load per zone was created that represented the lumped loads of lighting, equipment, occupants, and heat gain/losses through the envelope. This aggregated load was tuned until a large fraction of zones were calibrated in terms of their air flows and indoor air temperatures. Trend data provided the necessary information to model the system level models without requiring any tuning once the zone level was calibrated.

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