An automated building energy model calibration workflow to improve indoor climate controls

by

Ipek Yilmaz

A thesis submitted to the

Faculty of Graduate and Postdoctoral Affairs

in partial fulfillment of the requirements for the degree of

Master of Applied Science

in

Civil Engineering

Department of Civil and Environmental Engineering

Carleton University

Ottawa, Ontario

December 2021

Abstract

White-box building energy models (BEM) are employed to optimize building operation and controls. Calibration improves the models' credibility by reducing the discrepancy between simulated and measured energy consumption data. However, calibrating a BEM is time-consuming and prohibitively expensive due to the large number of required model inputs and the limited availability of measurements. Moreover, this process remains challenging due to the lack of clear guidelines and a consensus on the calibration methodology. Therefore, the industry needs an efficient, low-cost, and accurate way to calibrate BEMs to actualize the benefits of operational optimization in commercial and industrial buildings. This research aims to increase the calibration efficiency by proposing an improved workflow to obtain a quick, lightweight, and parsimonious model that only requires building automation system (BAS) and energy meter data as well as simple geometric drawings. To this end, a deeper understanding of the uncertainty inherent in the BEM calibration process and the calibrated model's predictive performance on operational decisions were explored. The proposed method was demonstrated with a case study building in Ottawa, Canada, using metered energy use and actual meteorological year (AMY) data and operational parameters (e.g., HVAC system setpoints and schedules) extracted from the BAS. The results indicated more accurate parameters estimates and significantly more reliable energy consumption projections when the model is calibrated using energy meter data at a higher temporal resolution (i.e., hourly instead of monthly). Applying control interventions to calibrated case study BEM showed that up to 34% of energy could be saved through the optimized operation. Furthermore, leveraging BAS data not only overcame the overparameterization issue by reducing the number of unknown

model inputs but was also found useful to detect operational anomalies to support the operational decision-making process.

Preface

This integrated thesis consists of a conference paper that is published and a journal paper awaiting publication. Should readers wish to refer to materials from this thesis, the current thesis is required to be cited. The articles included in this thesis are as follow:

- **Article 1:** Yilmaz, I., Gunay, H. B., Newsham, G., Wills A. (2021). An inquiry into the accuracy of the energy model calibration process BS2021: 17th Conference of International Building Performance Simulation Association. [Accepted].
- **Article 2:** Yilmaz, I., Gunay, H. B., Leveraging Building Automation System (BAS) Data for Automated Building Energy Model (BEM) Calibration: An improved workflow.

The articles have been altered slightly to help the flow of this dissertation. In addition, reference is made to figures from other chapters to avoid redundancy.

Use of copyrighted material from the published articles is acknowledged as per the corresponding publisher's permission guidelines with respect to the authors' rights.

In the aforementioned articles, Ipek Yilmaz was the principal contributor to the research methodology, data analysis, and preparation of written material and figures presented in the articles, under the supervision of Drs. H. Burak Gunay. Guy R. Newsham and Adam D. Wills provided critical feedback and review on the manuscripts of their respective articles.

Acknowledgments

I extend a tremendous amount of gratitude to my supervisor Professor Burak Gunay for his unwavering patience, guidance, support, and dedication. Many thanks also go to my other co-authors and advisors, namely Dr. Guy Newsham, Dr. Adam D. Wills. I would also like to extend my appreciation to Dr. Tareq Abuimara for his valuable feedback and support.

I would like to acknowledge the Building Performance Research Centre members, especially Professor Liam O'Brien and my office mates, for coming together to create such a supportive and knowledgeable team that I am proud to be a part of. Funding for this research was provided by the National Research Council Canada and Carleton University Research Achievement Award. I would also like to acknowledge the financial support provided by the Faculty of Engineering Scholarship.

Finally, I would like to thank my mother and sister for their unconditional love, support, and sacrifice that has afforded me this incredible opportunity.

Table of Contents

List of Figures

List of Tables

Nomenclature

Abbreviation	Full name
AHF	After hours fraction
AHU	Air-handling unit
BEM	Building energy model
BPS	Building performance simulation
CV(RMSE)	Coefficient of Variation of Root-Mean Squared Error
DCV	Demand-controlled ventilation
EEM	Energy efficiency measure
EMS	Energy management system
EIU	Energy use intensity
FEMP	Federal energy management program
FDD	Fault detection and diagnosis
GA	Genetic Algorithm
SHGC	Solar heat gain coefficient
HVAC	Heating, ventilation, and air conditioning
IPMVP	International Performance Measurement and Verification Protocol
LEED	Leadership in energy and environmental design
LPD	Lighting power density
M+V	Measurement and verification
NMBE	Normalized mean bias error
ODS	Occupant distribution scenario
SAT	Supply air temperature
SATR	Supply air temperature reset
T_{oa}	Outdoor air temperature
VAV	Variable air volume
WWR	Window to wall ratio

1. Introduction

Commercial and residential buildings account for approximately 60% of the world's electricity consumption [1]. When emissions from the building construction industry are added on top of operational ones, the sector accounts for 38% of total global energy-related CO_2 emissions, according to the Emissions Gap Report 2020. Moreover, emissions from the operation of buildings hit their highest level ever in 2019, moving the sector further away from fulfilling its potential to slow climate change [2].

From 1990 to 2017, total commercial and institutional energy use in Canada increased 38%, where the sector's contribution to gross domestic product (GDP) and floor space grew nearly 102% and 48%, respectively. As a result, greenhouse gas (GHG) emissions associated with the commercial and institutional sector's energy use, including electricity-related emissions, increased about 10% over the same period. Moreover, commercial businesses and institutions spent $25.2 billion on energy in 2017 to provide heating, ventilation, air conditioning (HVAC), lighting, plug-in equipment, and domestic hot water (DHW) services. Space heating accounted for the largest share of energy use (~57%), followed by plug-in equipment (~15%) [3]. Improving the building operations can significantly reduce global energy consumption and CO_2 emissions, considering that HVAC systems in commercial and institutional buildings account for ~15% of Canada's secondary energy use and ~10% of GHG emissions [4]. However, building systems are often poorly maintained and improperly controlled despite their large gain in energy efficiency.

Although a building is designed and constructed following green building design standards, a significant portion of energy could be wasted if the energy management is not executed correctly during building operation [5], [6]. Especially in the existing buildings, operational faults are common, leading to decreased energy efficiency and occupant discomfort. For example, Bynum et al [7] reports that 68% of the deficiencies identified during retro-commissioning are related to controls and operation. It is estimated that poorly maintained and improperly controlled HVAC equipment is responsible for 15% to 30% of energy consumption in commercial buildings [8]. Moreover, the number of maintenance requests for building energy systems has increased exponentially throughout the past decades, indicating an increase in building operational faults [9]. In addition to unexpected equipment faults (e.g., malfunctioning sensors), setting improper operating conditions (i.e., setpoints and schedules) also cause inefficiencies in energy consumption. For example, Gunay et al. [10] identified that inappropriate economizer programming increased the cooling loads by 25%. Therefore, aside from technical and economic analysis for building retrofits [11], [12], the control of HVAC installations and lighting systems (i.e., building operations) [13]–[17] have been studied to improve the building energy performance.

While significant effort has been expended on improving the energy performance of new buildings through better technologies and stricter regulations, annually, new buildings replace only about 1% of the current building stock in Canada [18]. Significant effort must therefore also be invested in energy efficiency measures (EEMs) to existing buildings. Low and medium cost EEMs are comprised of modifications in HVAC control strategies (e.g., supply air pressure and temperature reset, multiple-zone variable air volume (VAV) system ventilation optimization control, economizer low and high limit configuration, optimal start

scheduling), and lighting systems (e.g., occupancy sensors, optimal daylight control, daylight control by fixture, LED lighting upgrades); adding new sensors and making algorithmic changes (e.g., demand controlled ventilation (DCV) in system and zone level, occupancy-based zone temperature setback and daylight control). Large-scale investments like improving the building envelope, renovating frames and windows, and replacing major equipment (e.g., high-efficiency boilers, chillers, pumps, and improving cooling tower fans) are considered high-cost EEMs. Considering their cost-effectiveness and ease of execution, EEMs focusing on operational optimization have the potential to achieve energy conservation targets. Likewise, 20–30% of building energy consumption can be saved through optimized operation and management without changing the structure and hardware configuration of the building energy supply system [19]. Therefore, a reliable, practical, and economical way to evaluate these operational optimization measures in the existing commercial and residential building industry is needed if the industry is ever to see the potential widespread benefit of these or similar approaches over high-cost investments.

Energy auditing is carried out to establish an energy consumption baseline, quantify energy usage according to its discrete functions, and develop recommendations to improve energy efficiency [20]. ASHRAE categorizes the energy auditing process into three groups based on the level of complexity [21]. ASHRAE Level 1 involves walk-through surveys and collecting and analyzing the energy and natural gas consumption data to prioritize energy efficiency projects. ASHRAE Level 2 includes more detailed energy calculations and financial analysis of proposed energy efficiency measures. Finally, ASHRAE Level 3 involves a more detailed analysis of capital-intensive modifications. Energy audits rely on an expert's knowledge in building systems and require on-site investigations and

measurements; thus, they can be time-consuming, labor-intensive, and cost-prohibitive, especially for small- to medium-sized commercial buildings. Thus, energy audits are typically carried out much less frequently than once per year [22]. However, due to the changes in operational characteristics (e.g., change of temperature setpoints and operating schedules due to occupant complaints) and new faults in building systems (e.g., malfunction of sensors and actuators) over time, energy efficiency initiatives should be carried out continuously. Therefore, analytical tools that can continuously monitor a building's energy performance are needed.

Inverse modeling can be used as an analytical tool to coherently monitor the energy performance of a building and identify and interpret its' energy use anomalies. Generally speaking, the two most commonly used modelling approaches suggested by the ASHRAE Guideline 14 [23] are calibrated simulation data-driven regression analysis and calibrated computer simulation tools (i.e., white-box models) such as EnergyPlus, eQuest etc. The pure data-driven model (i.e., black-box) statistically derives a relationship between a set of inputs (e.g., the ambient conditions) and outputs (e.g., energy consumption). In practice, inverse models trained by actual building energy consumption data can provide reliable estimation and have been widely adopted for measurement and verification (M+V) and ongoing commissioning of building performance [24], [25] [26]. However, since the model input coefficients have no direct link to a definitive parameter in the physical environment [27], pure data-driven models might not always reflect the physical behaviour of a building. Besides, said approaches may not be suitable for many existing buildings due to issues in obtaining metadata and limitations in the sensing and data collection infrastructure. On the other hand, white-box building energy models (BEMs) utilize a physics-based model of

building components, sub-systems, and systems. Given the availability of high-quality input data, this approach can achieve the most detailed prediction of the performance indicators since it is explicitly linked to the physical building, HVAC system, and environmental parameters. Above all, white-box models provide a platform for assessing the impact of changes to these parameters (e.g., optimize operation, commissioning building systems, and retrofit analysis). Thus in the last two decades, calibrated white-box BEMs have been frequently used in the operation, diagnostics, commissioning, and evaluation of building systems [28]–[31]. Nevertheless, two major limitations associated with white-box models can be classified as: (i) they require detailed building information which might not be available or not easy to get, and (ii) calibrating the white-box model is challenging, time-consuming, and labour-intensive.

Disagreement between simulated and metered energy consumption is common in white-box BEMs. For this reason, there is a recognized need for model calibration to improve the models' credibility. White-box BEMs are generally considered 'calibrated' if they meet the criteria set out by ASHRAE Guideline 14 [23]. Meaning that once there is reasonable agreement between measured and simulated data, the model may be deemed 'calibrated' according to current international acceptance criteria. The validation is based on a model's compliance with standard criteria for Coefficient of Variation of Root-Mean Squared Error (CV(RMSE)) and Normalized Mean Bias Error (NMBE). However, these guidelines only specify acceptable error ranges. Despite widespread interest in the community, there is no consensus on how to perform calibration using simulation programs.

Recently, significant research has been focused on developing methods for tuning model parameters to improve predictions (i.e., calibration of a BEM against measured data). As

perceived, accurate calibration fitted to the measured data subsequently allows accurate energy use prediction under operational changes to the existing building. Advanced optimization techniques are practiced to improve the performance of automated calibration methods. For instance, Hong et al. [32] developed an automatic calibration model using the genetic algorithm (GA) with the optimization objective of approaching the minimum CV(RMSE). GAs are widely used for auto-calibration in many studies [14], [33], [34]. While GAs have been used in a large number of optimization problems with objectives such as minimizing building energy use and/or life-cycle costs [35], the majority did not account for uncertainties that are involved in the process [36]. Several studies suggested using an emulator or meta-model that replaces the physical model to reduce the computational cost of the optimization algorithm. A typical application example is Bayesian calibration [37]. Bayesian calibration approaches have been successfully employed to integrate model-driven and data-driven procedures by training a Gaussian process meta-model with computer simulation data and using it in a Bayesian calibration process [8]. Monari et al. introduced CALIBRO, an R package that has the objective of facilitating Bayesian calibration of BEMs [38]. Common approaches to perform optimization are reviewed in depth by Nguyen et al. [39]. The survey in the paper ranked EnergyPlus as one of the most widely used BEM programs in calibration studies. Moreover, MATLAB toolbox as an optimization engine, and the metaheuristic search algorithm (e.g., GA) as an algorithmic technique, outweighed their alternatives.

Although calibration can be cast as an optimization problem, the fundamental obstacle is that the calibration problem is underdetermined or over-parametrized, i.e., there are many more parameters to tune than can be supported by the monitored data. Therefore, its order

has to be first reduced by using heuristic insights as well as acquiring detailed information from audits and spot measurements. However, detailed building audits and sub-metering are not available in most cases, and on-site measurements are time-consuming and cost-prohibitive. Building automation system (BAS) installed in many commercial and institutional buildings serves as an untapped existing resource to provide input data for BEMs. Simply put, operational data can be extracted from BAS to decrease the number of parameters to be estimated through calibration.

1.1. Motivation

A practical and cost-effective way to calibrate white-box BEMs is needed if the industry is ever to see the opportunity in operational optimization applications in commercial and industrial buildings. However, creating an accurate model is labour-intensive, expensive, and complex because the unknown parameters required for the calibration process exceed the number of available measured inputs. Moreover, the existing guidelines provide calibrated simulation procedures, but the lack of formal and recognized methodology still makes the calibration process highly dependent on users' skills and judgments. Through automated calibration with basic information from BAS (i.e., setpoints and schedule) engineering cost of calibration can be reduced. Furthermore, calibrated BEM can be used to evaluate low-cost controls and operation-related measures since their parameters are difficult to determine and critical for their effectiveness (e.g., parameters to configure a supply air temperature (SAT) and supply air pressure (SAP) reset). Therefore, this thesis investigates the uncertainties inherent in the calibration process and exploits the existing resources (i.e., BAS data) to increase the calibration efficiency and accuracy.

1.2. Research objectives and questions

Considering calibrated BEMs' potential on lowering energy consumption by enabling modellers to test the impacts of optimized building operations, this research aims at (i) demonstrating the imperfections inherent in the calibrated models and highlighting how these imperfections translate into the building performance simulation-based operational decision-making, (ii) introduce an improved automated calibration workflow to increase calibration efficiency. The major inquiries of this integrated thesis are broken down by chapter:

Accuracy of BEM calibration process (Chapter 2):

- How accurately can the unknown parameters of a white-box BEM be estimated through the automated model calibration process?
    - How does the temporal resolution of meter data (e.g., hourly, monthly) used for calibration affect the calibrated BEM's predictive performance and parameter stability?
- How do the imperfections in the model calibration process affect the calibrated model's ability to make operational decisions?

Improved workflow for BEM calibration (Chapter 3):

- How can BAS data be leveraged to perform a quick and low-cost white-box BEM calibration?
    - Which available operational characteristic parameters can be useful for model calibration?
- How can building geometry and calibration parameters be simplified to obtain a quick and lightweight BEM without diminishing the calibration accuracy?

  - How can BAS data address white-box BEMs' over-parameterization?
- How can calibrated BEM be employed to evaluate low-cost controls and operational measures?
  - What magnitude of energy savings can be achieved through operational interventions?

1.3. Document structure

The remainder of this integrated thesis consists of two main body chapters on (1) accuracy of the BEM calibration process and (2) improved workflow for BEM calibration, followed by the conclusion. Each chapter is outlined briefly below:

Chapter 2: This chapter quantifies the uncertainty inherent in the white-box BEM calibration process and investigates the model's predictive performance on operational decisions. In this regard, a generic building is simulated with three different occupancy and envelope scenarios using EnergyPlus. Subsequently, seven parameters (envelope and operational characteristics) are assumed unknown, and a custom MATLAB optimization (genetic algorithm (GA)) script is employed to search for these parameters. The temporal resolution of meter data's effect on the calibration accuracy and parameter stability are discussed. A simple yet effective method to improve monthly calibrations' parameter representativeness and predictive performance is recommended. Finally, the study highlighted how imperfections in the calibration process translate into the operational decision-making process.

Chapter 3: This chapter aims to develop an improved workflow to obtain a lightweight, parsimonious, calibrated white-box BEM using geometric drawings, BAS, and monthly/hourly energy meter data. The BAS data of a government office building in

Ottawa, Canada, is retrieved, and a calibrated energy model in EnergyPlus is developed using the proposed workflow. Subsequently, the model is coupled with a custom MATLAB optimization (i.e., GA) script to search for unknown model parameters by minimizing the deviation from the metered energy use data under practical and physical constraints. The case study building was calibrated with monthly and hourly meter data, and the accuracy of the proposed workflow is discussed. Finally, calibrated BEM was used to test the effect of operational modifications on the energy consumption of the building. Operational EEMs were implemented incrementally on the model, and their potential energy savings were discussed. This study's key contributions are to introduce an automated workflow to reduce the number of model parameters estimated through calibration with the use of BAS data and to demonstrate the potential of calibrated BEMs in determining building-specific optimal control sequences.

Chapter 4: This chapter summarizes the findings and conclusions from each chapter. The contributions of each portion of this research are also outlined. Recommendations for future work are provided.

Chapter 2

This chapter has been published as:

Yilmaz, I., Gunay, H. B., Newsham, G., Wills A. (2021) "An inquiry into the accuracy of the energy model calibration process" BS2021: 17th Conference of International Building Performance Simulation Association.

2. Accuracy of BEM Calibration Process

2.1. Introduction

Buildings are responsible for one-third of the total global energy consumption [40], split evenly between the commercial and residential sectors. More than 80% of building energy consumption in commercial buildings occurs during the operation phase, mostly to provide building services such as heating, cooling, ventilation, and lighting [41]. While contemporary building codes and standards are expected to improve the energy performance of the new buildings, methods to guide major retrofit decisions are needed for existing buildings, considering that the annual new construction floor area typically represents less than 2% of the total rentable floor area [42]. Therefore, energy use throughout the building systems should be understood to evaluate potential operational and retrofit decisions. In contrast, the impact of the changes on energy consumption and thermal comfort in actual buildings cannot be tested on building management systems. However, a BEM representing the entire building can help investigate and understand this energy consumption.

Many researchers have developed different reference BEMs, mainly categorized into black-box, grey-box, and physical models (white-box). Black-box BEMs are statistical models constructed from a large amount of training data. However, those models fail to represent the physical meaning while mapping strong input parameters to the energy use behaviour; therefore, they may not always reflect the physical behaviour. Besides, said approaches may not be suitable for many existing buildings due to issues in obtaining metadata and limitations in the sensing and data collection infrastructure. Grey-box models are hybrid models that combine white and black-box models. They use training data sets and simplified physical systems to define parameters. Although using the physical models reduces the training data sets needed, the same limitations with black-box models also exist in those models. On the other hand, physics-based models engage a descriptive algorithm to link the building, system, and environmental parameters [43]. Thus, physics-based energy models calibrated with metered energy use data have gained popularity among the building simulation community.

The reliability of a calibrated BEM depends on the similarity of the energy use to the target facility. Major efforts to set standards for an acceptable calibrated BEM are ASHRAE Guideline 14, International Performance Measurement and Verification Protocol (IPMVP), and Federal Energy Management Program (FEMP). They establish acceptable fitness levels to the meter energy use based on statistical indices such as the CV(RMSE) and the normalized mean bias error (NMBE). Although the existing guidelines provide calibrated simulation procedures, they do not offer a methodology to calibrate a model to measured data [44], [45]. Therefore, different calibration techniques were applied in previous studies [46]. Each technique requires different analytical tools and expertise to assist in the

calibration process. Manual and iterative calibration is performed by adjusting inputs and parameters on a trial-and-error basis until the program output matches the known data. It requires a certain level of expertise, and usually, the process is time-consuming (run simulation engines, wait for the new outputs, evaluate the match to measured data, and then change inputs once again) [43]. Automated calibration offers specific tests and measurements through analytical and mathematical procedures. Mostly, an optimization function is incorporated with a programming environment to minimize the discrepancy between the measured and simulated data (e.g., alter parameters to minimize the CV(RMSE) iteratively).

This chapter advances our understanding of the uncertainty in the automated energy model calibration process. Specifically, the following research questions are investigated: (a) how accurately the unknown parameters of a calibrated energy model can be estimated through the model calibration process; (b) how the imperfections in the model calibration process affect the calibrated model's ability to make operational decisions. A generic three-story office building in Ottawa, Canada, is simulated with three different occupancy and envelope scenarios to generate synthetic metered energy data for calibration to answer these questions. Subsequently, several input parameters (e.g., air infiltration, window, and exterior wall thermal conductance) are then assumed unknown. The model is coupled to a custom optimization script that searches for these unknown parameters by minimizing the deviation to the metered energy use data subject to practical and physical constraints. The process is repeated with monthly and hourly metered energy data. The calibration process's performance is assessed based on the optimization algorithm's ability to estimate the unknown parameters. Further, the calibrated energy models are used to evaluate

operational decisions related to air handling unit (AHU) supply air temperature (SAT) reset and demand control ventilation (DCV) to examine the effects of the imperfections in the model calibration process on operational decisions.

2.2. Methods

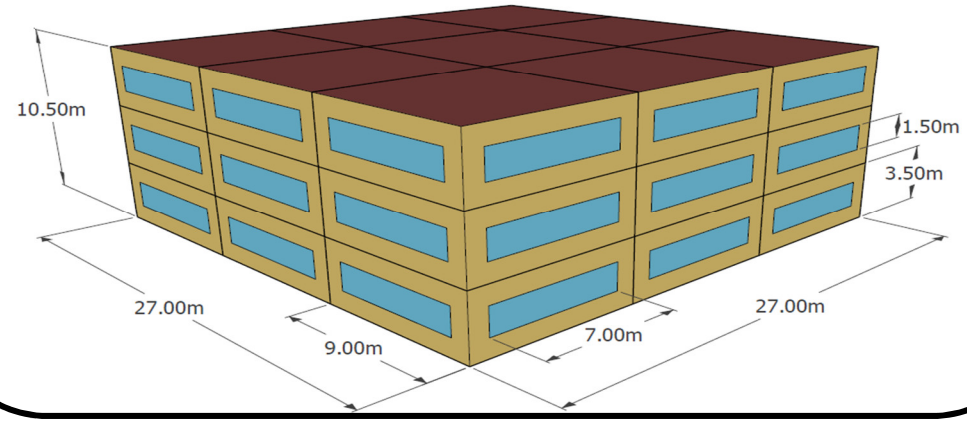
This section discusses the calibration steps followed in detail. First, establishing a BEM to generate synthetic metered energy data for calibration is demonstrated. Subsequently, identifying a list of input parameters that will be assumed unknown for the optimization script to estimate is discussed. Also, three different envelope and occupancy scenarios are presented. Next, customizing the objective function and a search space for a genetic algorithm (GA) to find the model parameters with the least CV(RMSE) value are elaborated. Finally, we discussed the details of performing optimization-based calibration.

2.2.1. Establishing BEM and Synthesizing Meter Data

The calibration process starts with creating a building with all thermophysical properties precisely characterized. An office building model was initially developed in SketchUp 2017 and then exported to EnergyPlus v9.3.0 to carry out the simulations. EnergyPlus has many advantages for this study. The data file, i.e., the IDF file, uses a text format that easily allows the model parameters to be edited. Furthermore, a large number of EnergyPlus models can be created automatically by using the command line, and simulation results are obtained in formats that are suitable to be processed in Excel. The target facility is a generic three-story office building located in Ottawa, Canada, with a 2187 m^2 total floor area.

Model Geometry

27m by 27m per floor; 3 floors; 9 zones each floor (four on cardinal directions, four corner zones, one core zone); 3.5-floor height; 1.5 m x 7 m centered windows on each exterior wall



System Architecture

3 AHUs serving each floor

- Differential dry bulb-based economizer program
- Supply and return fans
- Heating and cooling coils without humidifier

24 VAV terminals with reheat coil

- No other perimeter heating

3 VAV terminals without reheat serving core zones

Figure 2.1: An overview of the model geometry.

An overview of the model geometry and system architecture is presented in Figure 2.1. For simplicity, the 27m-by-27m floor is divided into nine thermal zones: eight perimeter and one core zone. Since our emphasis was on uncertainty in the calibration process in a given design, this study does not study the impact of various zoning decisions. The floor height is 3.5 m, and windows (1.5 m x 7 m) are centered in all cardinal directions.

Three AHUs, which contained heating and cooling coils, were modelled to serve all building zones, where each of them served a different floor. Cooling equipment gross rated coefficient of performance was assumed to be three. EnergyPlus defines rated conditions for the coefficient of performance for cooling as air entering the cooling coil at 19.4°C wet-bulb and 26.7°C dry-bulb temperatures, and air entering the outdoor condenser coil at 35°C. The natural gas-based heating equipment was assumed to operate at 80% efficiency. A built-in economizer type in EnergyPlus, differential dry bulb, is used. It increases the outdoor airflow rate when there is a cooling load, and the outdoor temperature is below the zone exhaust air temperature. Twenty-seven VAV units supplied heating and cooling to thermal zones, where twenty-four of them were perimeter zones with reheat coils. There was no other perimeter heating. Three terminals serve the core zones without reheat, and the maximum discharge air temperature with reheat is set as 35°C.

EnergyPlus automatically sized HVAC equipment and systems in the simulation models. The minimum airflow fraction of the VAVs is considered 20%. The outdoor air method is defined as a flow per area. The AHUs operate from 4 am to 6 pm on weekdays and remain off during the weekends. The AHU heating coil and VAV reheat coils were set to be available from October to April. During the heating season, the supply air temperature setpoint is 18°C; the zone temperature setpoint is 22°C. Analogously, the AHU cooling

coil was set to be available from May to September. During the cooling season, the supply air temperature setpoint is 13°C; the zone temperature setpoint is 23.5°C. Both heating and cooling season temperature setpoints are kept constant across all simulations.

Supply fan pressure was set to 500 Pa. Internal loads are generated by the occupants, lighting, plug-in appliances, and any other heat-generating equipment within a building. Unless lighting and plug loads are separately sub-metered, the optimizer cannot separate them. In practice, metered data is not usually available for lighting and plug loads; therefore, occupant density is linked to combined lighting and plug load intensity for practical concerns [17], [47]. Occupant heat gains depend on their activity level. An EnergyPlus activity schedule and clothing insulation schedule were used to estimate occupant heat gain. We created a custom EMS (energy management system) script coupled with a constant schedule to increase the flexibility of creating a customized schedule. Plug and lighting load intensity was assumed to be 300 W/person [48]. Subsequently, three different occupancy and envelope property scenarios were created. As shown in Table 2.1, the envelope scenarios were generated by varying the common envelope performance metrics systematically – e.g., increasing the heat transfer coefficient of the window (U-value), decreasing the unit thermal resistance of the walls (R-value), and reducing the airtightness [13]. Also, varying internal load and ventilation rates were examined while keeping envelope properties constant – e.g., decreasing the people density (PPL) and increasing the after-hours fraction (AHF) and ventilation.

Table 2.1: Actual parameters for the test scenarios.

Parameters used in calibration	Units	Scenario 1	Scenario 2	Scenario 3	Lower bound for GA search	Upper bound for GA search
U-value	*(W/m^2-K)*	2	2.5	2	1.5	3
SHGC	-		0.5		0.3	0.6
R-value	*(W/m^2-K)*	4	3	4	2	5
Infiltration	*(L/s-m^2)*	0.25	0.5	0.25	0.1	1.0
AHF	-	0.3	0.3	0.5	0.1	0.7
PPL	*(m^2/person)*	20	20	15	10	40
Ventilation	*(L/s-m^2)*	0.5	0.5	1	0.2	2.0

2.2.2. Identifying calibration parameters and scenarios

A simulation model's accuracy depends on how accurate the inputs can describe the design conditions of building envelopes and HVAC systems and operation practices; thus, the outputs compare with available measured energy use data. Therefore, identifying the calibration parameters is critical to improving the accuracy of the calibration. Some previous studies considered window and wall characteristics, minimum outdoor and supply airflow, air infiltration rate, and lighting and plug loads as influential parameters [31], [49]–[52]. Cipriano et al. [49] identified the envelope thermal transmittance and infiltration rate as critical parameters. Heo et al. [31] emphasized the importance of lighting and plug loads in calibration. In the light of previous studies, U-value, and solar heat gain coefficient (SHGC) of the window, R-value of the wall, air infiltration rate, AHF, people density (m^2/person), and outdoor airflow rate (ventilation)

are selected as calibration parameters. Note that after-hours plug loads and lighting ratio, i.e., AHF, is defined as the fraction of the lighting and plug load power draw that remains on after the work hours. Building's actual parameters for different scenarios are listed in Table 2.1. Finally, the BEM generated the target building's heating and cooling coil and electricity (fan, interior light, interior equipment) loads monthly and hourly for one year, for each scenario as explained in the following section. The optimization algorithm treats these results as synthetic meter data while we attempt to estimate the parameters assumed unknown during calibration.

2.2.3. Defining objective function and genetic algorithm

The objective function should be defined in a way to guide the algorithm to find the best possible solution. Uncertainty analysis is necessary to verify these models' resemblance to the real building. In other words, it is required to determine the variability degree and data fitness with the actual building. In this research, the CV(RMSE) was selected as an error-minimizing objective function aiming to reduce the difference between measured heating, cooling, and electricity data to simulated data (i.e., taking the average heating, cooling, and electricity CV(RMSE).

The process of calibrating a set of parameters was carried through a custom MATLAB script that read and write from the base EnergyPlus model. MATLAB genetic algorithm function is used as an optimization method. This analysis permits assessing the degree of variability and how the data fit in the actual building. The selection of an appropriate objective function helps the algorithm more rapidly find the best solutions. Actual Meteorological Year (AMY) data is used as historical weather data. A GA operates on a finite set of simulations (population) as an evolutionary algorithm. In each iteration

(generation), there is a competition between the different subjects (particular models) of the population, and the algorithm selects the ones that fit best with the objective. It then generates a new population in a given space for the next generation with the best subjects and new random ones. In each result evaluation, the best ranking parameters get updated. When all generations are performed, the process stops, and the best model is stored as the calibrated model. Search space was created by defining threshold values for parameters, which are shown in Table 2.1.

This work's selected stopping criterion runs a maximum number of five generations for all calibration approaches (monthly and hourly) until the optimal solution is obtained. Population size is an important parameter affecting the performance of optimization methods based on genetic algorithms. The population sizes recommended are twice or four times the number of variables [53]. In this study, the population size is chosen as 50. The crossover fraction was set to 0.5. The number of elite individuals (stall gen) to pass to the next generation was set to five.

After establishing calibration parameters, objective function, and setting up the optimization algorithm, optimization-based calibration is performed for each scenario. The optimization process stops when maximum generations are reached and stores the best-calibrated model with heating, cooling, and electricity consumption closely matching the monitored data. For each of the three scenarios listed in Table 2.1, the seven parameters that minimize the objective function was determined using the genetic algorithm. The optimization algorithm is repeated five times for each scenario without changing any settings to evaluate model parameter variations for different runs. This process is repeated

with monthly and hourly metered energy data for all scenarios. In total, 30 optimization runs are analyzed.

2.3. Results and Discussion

This section first investigates the variation of model parameters among different optimization runs and the effect of the calibration method's temporal resolution (monthly/ hourly). Next, it offers an approach to increase monthly calibration accuracy and compares the selected model results with the measured consumption data using CV(RMSE) criteria. Finally, operational decisions like AHU supply air temperature (SAT) reset and DCV are demonstrated with accurately and poorly calibrated models. Discrepancies among those results are examined.

2.3.1. Parameter and Load Estimates

Figure 2.2 shows the variational range obtained for each monthly and hourly analysis parameter for five optimization runs. The minimum and maximum threshold values limit the variational range. Blue scatters are the monthly, orange ones are the hourly calibration estimates, and the black line represents the real building parameters. It should be noted that all calibrated models (all scenarios) satisfied ASHRAE Guideline 14 CV(RMSE) acceptance criteria. ASHRAE Guideline 14 limits the monthly CV(RMSE) value to 10% and hourly to 30%. This study presented the maximum and minimum $CV(RMSE)_{monthly}$ and $CV(RMSE)_{hourly}$ as 5.37%, 1.36%, and %17.64, %5.81 respectively. It should be noted that all calibrated models (all scenarios) satisfied ASHRAE Guideline 14 CV(RMSE) acceptance criteria. ASHRAE Guideline 14 limits the monthly CV(RMSE) value to 10% and hourly to 30%. Through this study, the maximum and minimum

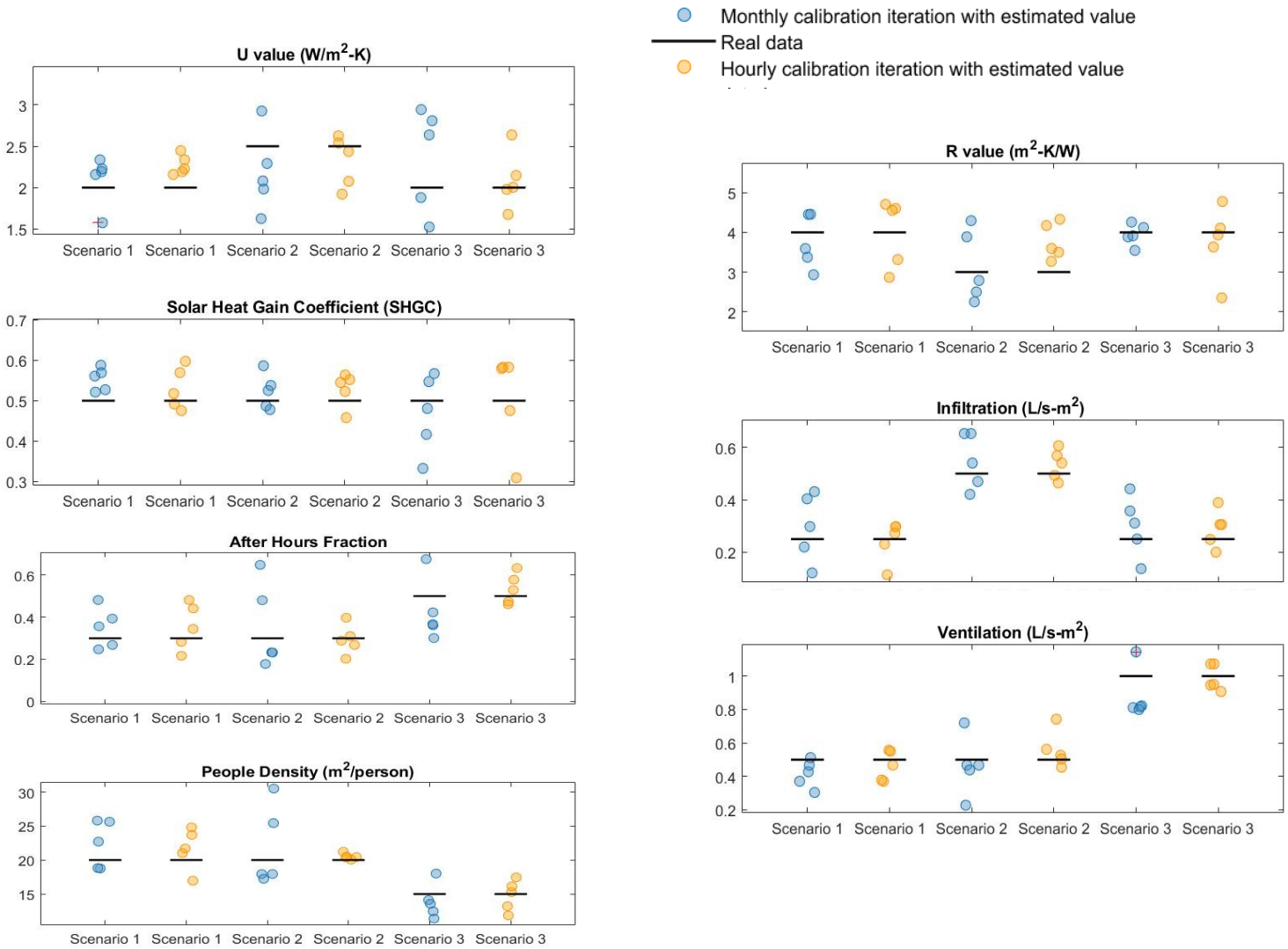


Figure 2.2: Parameter estimates of five runs.

$CV(RMSE)_{monthly}$ and $CV(RMSE)_{hourly}$ were presented as 5.37%, 1.36%, and 17.64%, 5.81%, respectively.

In most cases, hourly calibration estimates were tightly clustered, whereas monthly estimates were more spread out. 75% of the hourly parameters had a narrower standard deviation and variance than monthly estimates. Monthly energy use data does not generate as accurate estimates as hourly data of the unknown parameters – even though the goal was to estimate only seven parameters. Due to the multicollinearity amongst many parameters, it was challenging to acquire correct estimates, particularly for the window and wall thermal transmittances and the air infiltration rate. It is essential to mention that these are the results for five optimization runs per scenario. Due to space constraints, all the presented results and performed operational decisions will be based on Scenario 1.

Note that the optimization approach is stochastic, not deterministic, and that is why each run arrives at different results. In an effort to increase the monthly calibration accuracy, average parameters (running the calibration several times, i.e., five runs and averaging the estimates) are adopted as final calibrated model estimates. Results showed that using those average parameters could improve the monthly calibration accuracy up to 58% with a 2% $CV(RMSE)_{monthly}$. Figure 2.3 shows the monthly heating, cooling, and electricity energy loads (MWh) obtained at each run, and the red line represents the average parameter estimate. The results show how this method balances the discrepancies among optimization runs; thus, CV(RMSE) tolerance criteria could be achieved in a narrow margin; however, it should be noted that the performance of this approach is assessed based on this case study.

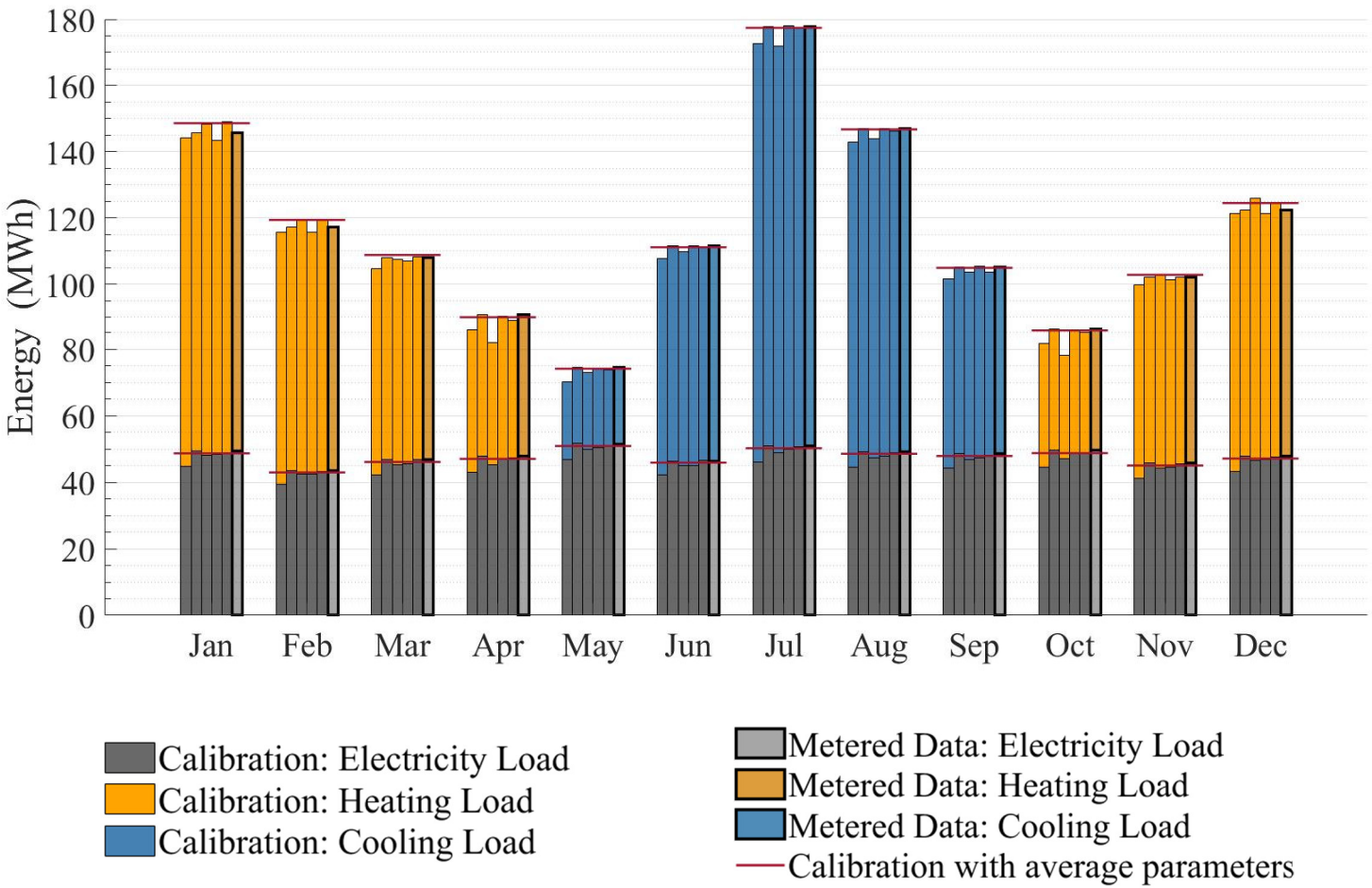


Figure 2.3: Comparison of monthly load estimates to metered data.

Figure 2.4: Comparison of monthly simulated estimates (red dashed line) to measured data (solid blue line).

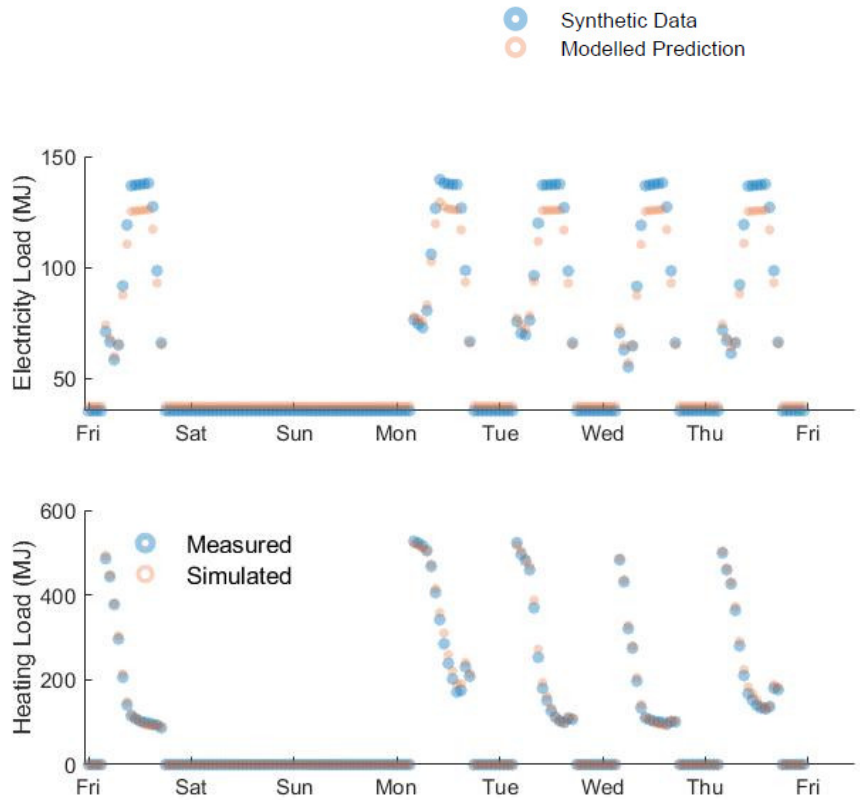


Figure 2.5: Comparison of hourly simulated estimates to measured data (February 4 to 10).

Figure 2.4 presents the monthly predicted electricity, cooling, and heating load profiles using the calibrated model (with average parameters) compared with the actual measured load profile all year round. It shows that the model can dynamically predict loads, which agreed well with the actual measured data, that could accurately follow energy consumption trends.

Figure 2.5 shows the dispersion between the measured and calibrated electricity and heating load for seven days (4–10 February) during the heating season. The model with the median CV(RMSE) is presented as the calibrated model among five runs. The calibrated model accurately captures seasonal patterns and peak demands. The analyses covered all year round, but only heating season results are presented due to space constraints.

It should be highlighted that accuracy increases significantly when the average parameter is selected as the final model inputs for monthly calibration. This method is beneficial when hourly metered data is not available, or monthly calibration is practiced for a specific task.

2.3.2. Implementing Operational Decisions

This section deals with the actions performed to investigate how inaccuracies in model parameters impact operational decisions. Energy savings can be attained by applying SAT reset and DCV. Most AHUs in commercial buildings have an air economizer cycle for free cooling under certain outside air conditions. The outside and return air dampers are regulated during the economizer cycle to seek SAT at its setpoint. Meanwhile, spaces may have less cooling load, and if the SAT is too low, it may cause excessive use of reheat in the economizer mode. In other words, a building might enter into the economizer mode

while the majority of the perimeter heating devices are operating. Further information on SAT reset strategies can be found elsewhere [14], [17].

In this chapter, the EnergyPlus SAT reset function, OutdoorAirTemperatureReset, was utilized. Function resets the SAT based on the following default rules: (i) when the outdoor dry-bulb temperature (ODB) is at or below 6.7ºC; the heating coil design setpoint is applied (which was 18°C), (ii) when the ODB is at or above 10.0ºC the heating coil design setpoint minus 5.2ºC is applied (18 – 5.2°C), (iii) in between, the setpoint varies linearly.

Another way to improve HVAC systems' operation is to provide heating, cooling, and ventilation only when and where they are needed, in the amount that they are required [54]. Note that this is inevitably dependent upon having access to system-level occupant count information, knowing the number of occupants, ventilation rates can be adapted (i.e., DCV). The minimum outdoor air schedule is set to the occupancy schedule to examine the savings.

SAT reset, DCV, and a combination of SAT reset and DCV decisions are performed with poorly and accurately calibrated models, and discrepancies among energy-saving predictions (energy use intensity (MJ/m^2)) were reported (Table 2.2 and Table 2.3). Note that the poorly calibrated model is the model with the highest CV(RMSE) for both monthly and hourly calibration. In contrast, the accurately calibrated model corresponds to the model obtained with mean parameter estimates for monthly calibration and the model with the median CV(RMSE) for hourly calibration. Results indicated that percentage error for savings could go as low as 8% (accurate model) to as high as 24% (poor model) for hourly simulated models. Where savings percentage error could be reduced to 4% (accurate

model) from 50% (poor model) using the mean of parameter estimations for monthly calibrated models.

Table 2.2: Comparison of actual and hourly calibrated models' predicted energy load intensity per total building area ((MJ/m^2)) under applied operational optimization interventions.

Operational Decision / Savings	Actual building	Poorly calibrated	Accurately calibrated
Default	573.58	534.21	583.52
SAT reset	539.27	504.34	547.8
Savings	34.31	29.87	35.72
DCV	566.11	532.24	573.44
Savings	7.47	1.97	10.08
SAT reset and DCV	531.43	502.34	537.2
Savings	42.15	31.87	46.32

Table 2.3: Comparison of actual and monthly calibrated models' predicted energy load intensity per total building area under applied operational optimization interventions.

Operational Decision / Savings	Actual building	Poorly calibrated	Accurately calibrated
Default	573.58	559.93	577.7
SAT reset	539.27	539.35	544.49
Savings	34.31	20.58	33.21
DCV	566.11	559.29	570.9
Savings	7.47	0.64	6.8
SAT reset and DCV	531.43	538.7	537.3
Savings	42.15	21.23	40.4

Results demonstrated that imperfections in the calibration process translate into the operational decision-making process distinctly. The discrepancy among the poorly calibrated models can be significant enough to lead to inappropriate decisions. For example, one may advise against investment to purchase occupant sensing technologies or hire controls engineer to implement the SAT reset strategy based on the poorly calibrated model's estimated savings. Similarly, overestimation and underestimation of the parameters could lead the inappropriate retrofit decisions. For example, overestimation of u-value can cause high-cost window retrofit investments, and underestimation of R-value can cause high-cost insulation investments. Hence, for high-cost investments, further investigation might be required.

2.4. Summary

In this chapter, uncertainties in the model calibration process were determined, and the effect of imperfections on the accuracy of building performance simulation-based operational decision-making process was diagnosed.

First, a building with all thermophysical properties accurately characterized is simulated with three different occupancy and envelope scenarios in EnergyPlus v 9.3.0. A synthetic metered energy data is generated monthly and hourly to investigate the effect of temporal resolution on calibration validity. Accordingly, input parameters like U-value and SHGC of the window, R-value of the wall, air infiltration rate, AHF, people density, and outdoor airflow rate were assumed unknown. Subsequently, a custom optimization (GA) script in MATLAB searched for these unknown parameters by minimizing the CV(RMSE). The optimization algorithm was repeated five times for each scenario without changing any settings to evaluate parameter estimates' variations for different runs.

Results demonstrated that calibration with hourly meter data yielded more accurate and stable parameter estimates than monthly data. However, repeating the calibration a few times with monthly data and averaging the parameter estimates appeared to increase the accuracy by up to 58%. Monthly calibrated models obtained by averaging the parameter estimates of multiple calibration runs were very similar to those calibrated with hourly data. Poorly calibrated models that cannot represent the building's thermophysical properties properly yielded misleading operational decisions. In contrast, accurate models were able to support the operational decision-making process adequately. Therefore, for projects where hourly metered data is unavailable or when the monthly calibration is preferred, parameter accuracy can be increased by running the calibration a few times, averaging the estimated parameters, and using them as an input for the final calibrated model.

Key findings of this chapter are:

- Calibration with hourly meter data yields more accurate results than monthly data.
- If calibration is performed with monthly energy use data, one should repeat calibration a few times and use the parameter estimates' average to obtain final calibrated parameters.
- Imperfectly calibrated energy models cannot support the operational decision-making process with acceptable accuracy.

Chapter 3

3. Improved Workflow for BEM Calibration

3.1. Introduction

Buildings are responsible for approximately 40% of the global energy [55], and 51% of the total electricity consumption [56]. The majority of this energy is used to provide occupants with a comfortable and healthy indoor environment. According to the International Energy Outlook [57], energy consumption is anticipated to increase by nearly 50% by 2050, and worldwide energy-related carbon dioxide (CO_2) emissions are expected to grow at an annual average rate of 0.6% for the same period. Although the building sector holds the greatest potential and lowest cost for carbon reductions [58], building systems are often poorly maintained and improperly controlled [26], [59]–[61], leading to vast amounts of avoidable energy waste.

Although new buildings replace only about 1% of the current building stock in Canada annually [4], most studies [62]–[64] focus on improving the energy performance of new constructions through advanced technologies and stricter regulations. Significant effort must therefore be invested in applying energy EEMs to existing buildings. Enhancing building efficiency represents one of the easiest, most immediate, and most cost-effective ways to reduce global CO_2 emissions. EEMs can be low and medium cost, such as modifying HVAC control strategies and lighting systems, installing new sensors and actuators accompanied by new software or algorithmic changes, and making minor equipment changes. On the other hand, high-cost EEMs include large-scale investments

like improving wall and roof insulation, renovating frames and windows, and major equipment replacements. Various studies have demonstrated that building operation-based low-cost EEMs can significantly mitigate the issue of high energy consumption in buildings. For example, 20–30% of building energy consumption can be saved through optimized operation and management without changing the structure and hardware configuration of the HVAC system and its components [19].

As building ages, equipment degrades, faults and anomalies occur, demands vary, and operators change control settings for various reasons that often detrimentally affect building performance. Operators' decisions are often made without having access to information regarding building characteristics, occupancy ratio, occupant comfort preferences, building envelope, and HVAC equipment characteristics [13]. Therefore, although a building is assumed to be designed and constructed in an energy-efficient manner, a significant portion of energy could still be wasted due to improper operation.

Energy use throughout a building should be understood to optimally operate a building. However, the impact of these operational interventions on energy consumption and thermal comfort in actual buildings cannot be quantified in building management systems. In this case, BEMs serve as an essential tool. BEMs are used to simulate heat and air mass transfer through the building envelope, calculate HVAC system loads, and predict energy and comfort performance under the influence of various inputs such as weather, building geometry, internal loads, HVAC systems, operational schedules, and simulation specific parameters. Subsequently, through BEMs, EEMs can be simulated prior to their execution, and improvements in building energy performance can be observed without exhaustive field testing. Thus, although BEMs are initially intended for use during the design phase,

they are increasingly used throughout a buildings' lifecycle [65]. White-box BEMs use descriptive algorithms to explicitly link the physical building, system, and environmental parameters. Given the availability of high-quality input data, this approach can achieve the most detailed building performance prediction. EnergyPlus is widely used in the literature as the simulation engine for automated calibration studies [39].

Despite the widespread usage of BEMs within the building industry, there are increasing concerns about the model's credibility as significant discrepancies between simulated and measured energy use become more apparent with the rapid deployment of smart energy meters and internet of things (IoT) sensors [66], [67], [67], [68]. For instance, Turner and Frankel [69] analyzed 121 LEED buildings and found that measured energy was between 0.5 and 2.8 times the predicted energy use. Likewise, Menezes et al. [67] suggested that the measured energy use can be as much as 2.5 times the predicted energy use. Consequently, model calibration is often undertaken to match simulation predictions to actual observations to better increase the model's credibility for making predictions. The International Energy Agency's Energy in Buildings and Communities (IEA-EBC) Annex 53 also reported the significance of the development and application of model calibration and uncertainty analysis for BEMs [70]. Therefore, calibrated white-box BEMs (i.e., calibrated simulation approach) are employed to commission building systems, optimized operation (e.g., model-based predictive controls, model-based fault detection, and diagnostics), and measurement and verification (M+V) of building retrofit projects.

Model calibration refers to tuning the input parameters to narrow down the mismatch between the simulated and the metered energy use data. Calibration approaches can be classified as either manual or automated [27]. Automated approaches utilize computerized

processes to tune model parameters by fitting the model to observations. In contrast, manual approaches rely on iterative pragmatic intervention by the modeller, which can also be time-consuming, costly, and requires extensive expertise. Therefore, researchers have shifted focus to automated calibration [71].

In most cases, physics-based energy models are calibrated against measured data (e.g., electricity, natural gas). With the improvement of monitoring systems in buildings, sub-metered energy usage data (e.g., electricity submetering data (e.g., lighting, equipment, AHU fans), HVAC cooling/heating loads, etc.) has become available to modellers. Although calibration with sub-metered data can yield more accurate BEMs, a universal calibration method and a standard calibration procedure are still lacking in the literature [72]. A recent review by Chong et al. [71] pointed out that calibration against electricity and gas/steam energy is generally carried out with monthly resolution data. However, along with other studies [28], [73], Chapter 2 (Accuracy of BEM Calibration Process) demonstrated that BEMs calibrated with monthly energy use data might fail to represent the actual conditions of the building; hence using hourly or even sub-hourly energy consumption data is encouraged for operational optimization studies.

BEM calibration includes estimating independent and interdependent unknown parameters representing the correlations and dynamic interactions among building envelope properties, HVAC systems, internal/casual gains (e.g., light, equipment, occupant-related internal heat gains), and exterior impacts (e.g., solar radiation). Therefore, model calibration is a mathematical search problem for an over-parameterized model in an underdetermined search space [74]. Likewise, obtaining necessary data and identifying the accurate simulation input values for a particular BEM requires significant time, effort, and

cost [75]. One effective way of addressing this issue is to increase the amount of available measured data (i.e., operational data) used in model creation. For example, BAS provides data on actual building operations that can be used as BEM inputs. BAS offers hourly, daily, or monthly inputs such as AHU supply air temperature and humidity setpoints, airflow rates, differential pressures, zone air temperature setpoints, and equipment operating states. Intuitively, while extracting calibration parameters, analysts can also identify faults in operation and fix them once a calibrated model is created.

Detailed measurements for thermal properties of the building envelope (e.g., air infiltration, window, roof, and exterior wall thermal transmittances, SHGC) are not typically performed for each building. Additionally, in most cases, manufacturers' data is not available to the energy modellers during the retrofit process as well as published information does not represent the actual building properties. Building energy performance is highly dependent on energy gain/loss through the envelope. Therefore, together with occupant-related parameters, unknown building envelope parameters are usually chosen as key calibration indices [68].

A practical, low-cost, yet accurate way to calibrate BEMs is needed for the industry to realize the potential benefits of operational optimization applications in commercial and industrial buildings. To this end, this study presents a workflow to calibrate a BEM to measured energy use data by incorporating operational parameters (HVAC system setpoints and schedules) from the BAS and estimating the unknown parameters (envelope properties, occupant-related internal heat gain, infiltration characteristics, and setback temperatures) through white-box automated calibration. Additionally, the BAS data can be utilized to detect operational anomalies (i.e., fault detection and diagnostics (FDD)) and

further support the operational decision-making process. This chapter also included implementing operational optimization interventions to the calibrated BEM to predict potential low-cost energy savings.

The objective of this study is to develop an improved calibration workflow to obtain a lightweight, parsimonious BEM by using only basic drawings, BAS, and monthly/hourly energy use data. The geometry of a case study building in Ottawa, Canada, is generated on DesignBuilder v6 and extracted to EnergyPlus v9.3 to run simulations. Available HVAC system setpoint and schedule characteristics were extracted from the BAS database, and unidentified characteristics were calibrated along with other unknown design parameters. Subsequently, the model is coupled to a MATLAB custom optimization script to search for these parameters by minimizing the deviation to the metered energy use data subject to practical and physical constraints. Selected calibration parameters include U-value and SHGC of the window, R-value of the wall, air infiltration rate, ventilation rate, lighting and plug load profiles, and after-hours temperature setpoints to engage the setback/setup mode. The case study building is calibrated with monthly and hourly meter data to test the workflow on both approaches. Finally, operational EEMs (e.g., DCV, Supply air temperature reset (SATR), economizer settings) were applied to the hourly calibrated model to distinguish potential savings.

The remainder of this chapter is structured to have a literature review followed by the methodology section that thoroughly explains the calibration workflow. Subsequently, the results of implementing this workflow in the case study are provided.

3.2. Literature Review

The 2013 ASHRAE Handbook-Fundamentals [76] classified modelling approaches into two basic categories: forward (classical) modelling and inverse (data-driven) modelling. The forward modelling approach generally takes the physical parameters describing the building as input, including building coordinates, geometry, envelope materials, operational schedule, HVAC system type, and local weather, etc., and the objective is to predict the output. The forward modelling approach is typically used in the design phase to facilitate building designers to make early design decisions [77]. Inverse models take the monitored building energy consumption data (and available other monitored behaviour data) as inputs and are expressed in terms of one or more driving variables and a set of empirical parameters [77]. Typically, a base model is a priori assumed, and measured data are used to find the parameters that provide the best fit for the chosen base model and data set. The data-driven approach includes three categories as: (i) black-box, (ii) grey-box, and (iii) white-box (physics-based). Black-box BEMs are statistical models with a short development time and provide accurate building performance predictions, given quality prior training data [78]. These models do not require any information about physical phenomena, but they are based on a function deduced only by means of sample data connected to each other and which describe the behaviour of a specific system. Heo et al. [31] proposed a calibration methodology based on Bayesian calibration of normative models, and correctly evaluated energy retrofit options, and supported risk-conscious decision-making by explicitly inspecting risks associated with each retrofit option. Gunay et al. [24] developed a systematic method to select an inverse black-box model that parsimoniously characterizes the building-level heating and cooling load patterns. Model

performance was assessed through cross-validation and residual analysis to select the most accurate model. Nagpal et al. [79] proposed a methodology that uses a data-driven approximation technique to reduce the computational effort. Instead of brute-force simulations using detailed engineering models, their study employed statistical surrogate models with an optimization algorithm to estimate properties of unknown building parameters. They obtained sufficiently accurate estimates of hard to observe building characteristics about 500 times faster than traditional approaches, as long as the envelope information is available. Hou et al. [80] conducted a comprehensive review on BEM calibration by Bayesian inference. Ciulla & D'Amico [81] applied the multiple linear regression method to develop some simple relationships to determine the thermal heating or cooling energy demand of a generic building as a function of only a few well-known parameters; where the reliability of the results are supported by statistical analysis of the error indices. The approach was not targeted at replacing a dynamic simulation model but represented a simple decision support tool for the preliminary assessment of the energy demand related to any building and any weather condition. Subbarao et al. [82] proposed a new scientific yet pragmatic methodology, called enhanced parameter estimation, that allows physically relevant parameter estimation rather than a brute-force model fit to energy use data. Although black-box models are fast in execution, they require a large amount of training data and fail to represent the physical meaning while mapping strong input parameters defining the energy use behavior. Besides, black-box modelling approaches may not be suitable for many existing buildings due to issues in obtaining metadata and limitations in the sensing and data collection infrastructure. Grey-box models [83] are hybrid models that combine features of white and black-box models. They use

training data and a simplified physical representation of the thermophysical processes to define parameters. Although grey-box models tend to require less training data than black-box models, the same limitations with black-box models also exist in those models.

White-box models use detailed physics-based equations to model building components, sub-systems, and systems to predict whole buildings and their sub-systems behaviours, such as their energy consumption and indoor comfort. Due to the detailed dynamic equations in white-box models, they have the potential to capture the building dynamics well. However, their predictive strength highly depends on the quality of input data. Thus, physics-based energy models calibrated with metered energy use data have been used among the building simulation community [14], [22], [43], [50], [74], [84]. There are various BEM tools, including DOE-2, ESP-r, EnergyPlus, and TRNSYS, and the most common specifications for model calibration are IPMVP [85] and ASHRAE Guideline 14 [23]. EnergyPlus has a large support community of active users and is used internationally to model HVAC, lighting, and water consumption.

Model calibration and validation are essential for physics-based BEMs to ensure that the building and HVAC systems are properly modelled and integrated to predict the building energy performance. In addition, calibrated BEMs are helpful for building system commissioning, estimating potential savings from EEMs, and M+V of building retrofit projects [86]. Coakley et al. [27] published a review of 129 publications of calibration of physics-based BEMs to measured data. They concluded that, at one extreme, there is the optimization-based calibration that identifies solutions by systematically and automatically searching the parameter space; at the other extreme, there is the ad hoc calibration with the manual tuning of inputs until an acceptable solution is reached. Moreover, there is no

consensus on a standard calibration approach, nor is there a widespread acceptance of the validation criteria necessary for calibrating different building energy models depending on purpose. Study grouped the issues related to the model calibration as follows: (i) lack of consensus on a calibration standard, (ii) significant expenses for building auditing, metering, and model development which is necessary as a starting point for the calibration process, (iii) calibration of detailed models is an over-specified and under-determined problem, (iv) quantification of inputs without or less accurate measured values, (v) uncertainty of inputs versus accuracy of the model outputs, (vi) procedures for the identification of required model changes, and (vii) automation of the calibration process.. The main constraint in calibration, as mentioned above, is that the problem is under-determined or over-parametrized, i.e., there are many more parameters to tune than can be supported by the monitored data.

Sensitivity and uncertainty analyses are used to identify the BEM parameters with the most influent on energy consumption [87]. Some applications take advantage of this kind of analysis to reveal the most critical operational decisions in terms of their impact on building performance [13] or in the selection of the most efficient EEMs [88]. Sensitivity analysis techniques in building simulation tools are also practiced to help the user in the calibration step [51], [89]. In these cases, the common task relies on the simulation of a hundred cases applying a systematic disturb on predefined inputs, which is a time-consuming task that sometimes slows down the use of simulation software as a design tool [89].

The genetic algorithm is a common meta-heuristic optimization algorithm belonging to the evolutionary algorithms based on Darwin's theory of evolution where the weakest in parameter population are eliminated at each generation [35], [87]. The survival principle

governs the population, and the best individuals, those that best match the objective function, survive. Common GA parameters are population size, probability of crossover, and probability of mutation. Both the absolute value used for these parameters and their relative values determine how a GA finds new solutions and, ultimately, the quality of the final solution found [90]. Several studies have been conducted on choosing the most optimal GA parameters [90]–[93]. GA first creates a random population of candidate solutions for the proposed optimization. Then, selection occurs by evaluating the fitness of the solutions using a fitness function. Thereafter, a new population is generated based on the outcomes of the first generation and the generation and evaluation process continues until the termination criteria are met [94]. The process stops when all generations are performed, and the best model is stored as the calibrated model In most cases, the quality of the obtained solutions was improved when the number of generations was increased [53]. The study conducted by Hamdy et al. [53] also found that The study also found that at a minimum of 1400–1800 evaluations are required to stabilize optimization results of the BEM. The calibration technique used in this study is based on the optimization of models' uncertainty indices where measured data is introduced in the model. This technique uses the simulated energy use data at the end of each simulation to compare against the measured data. This comparison is called uncertainty analysis, and the uncertainty analysis outcomes are used as an objective function by the algorithm to select a new set of parameters.

The use of BAS data in calibration appears to have first been reported by Carling et al. [95]. They identified multiple faults that might have been missed without BAS data like set points and control signals, sub-metered electricity, air temperatures in the AHU and

zones, and slab temperatures. Pang et al. [96] used BAS data to create inputs for real-time use of an already calibrated model. Kandil and Love [84] used BAS data to generate inputs to simulate fan and pump electrical demand and schedules, DHW schedule and capacity, boiler efficiency, and AHU air flow rate. They noted that hourly data were essential to calibrate the model reliably. Mustafaraj et al. [50] developed a method for model calibration using BAS data, including setpoints, on/off values, schedules, underfloor heating flow rate, hot water temperatures, indoor air temperatures, and pump electrical use. They noted that the use of BAS data improved the fitness of the predictions to the measured data. Coakley et al. [27] anticipated that integrating building operation data with building simulation software may reduce the calibration time. Zibin et al. [97] suggested a bottom-up calibration approach sequentially calibrates the zone, system, plant, and whole-building level models. The approach was applied to an eQUEST model at the zone and system level of a university building using BAS data. Zibin et al. [97] focused on the shoulder season when the heating and cooling coils in AHUs were inactive. An automated calibration tool was developed that couples BAS data with building commissioning tasks. This tool reduced the time required to manually process and analyze large sets of BAS data for use in calibrated simulation considerably [98]. Mihai and Zmeureanu [99] proposed a bottom-up calibration technique using eQUEST and BAS data, which starts with zone level calibration with supply airflow rate to each zone, indoor air temperature, and cooling load, followed by AHU level calibration. The results show that the AHU model was calibrated naturally on top of most calibrated zones, which avoids any additional tuning through the trial-and-error method.

Literature review shows that no single approach has been reported to have the ability to tackle all the outstanding issues in the calibration problem, and it is clear that the industry seeks practical and low-cost methods to calibrate BEMs to evaluate EEMs. In addition, despite their potential to increase the efficiency of the calibration process, the literature review demonstrates that there is currently little use of BAS data in calibration. To this end, this study aims to develop a workflow utilizing BAS data to reduce the number of unknown parameters. This approach is promising due to its simplicity since the measured data can be acquired from the BAS that is typically installed in institutional and commercial buildings as a cost-effective alternative to installing a dedicated monitoring system. Moreover, this research also involved studying the savings through operational changes on the calibrated model.

3.3. Methodology

In this study, we are presenting a white-box BEM calibration method that aims to reduce labour (i.e., no on-site measurement), computational (i.e., lightweight model), and engineering (i.e., automated calibration) cost by enhancing the information that is usually available to the modeller, with BAS data. Specifically, parameters defining the thermophysical characteristics of the envelope, internal heat gains, ventilation, zone heating, and cooling setback temperatures are chosen for calibration. The proposed improved calibration workflow can be applied with any detailed building energy modelling tool. Due to its simplicity and compatibility with the latest EnergyPlus versions, DesignBuilder was used to create the geometry and the zones. EnergyPlus v9.3.0 was used to carry out the simulations. The advantages of using EnergyPlus for this study are (i) the data file, i.e., the IDF file, uses a text format that easily allows the model parameters to be

edited, (ii) a large number of EnergyPlus models can be created automatically by using a command line, (iii) simulation results are obtained in formats that are suitable to be processed in Excel. The process described in this article follows the scheme shown in Figure 3.1.

First, the basic geometry of the building was generated by using available design specifications and drawings. Subsequently, the thermal zones were represented by separating the perimeter and core zones, different façade orientations for perimeter zones, different HVAC systems, and different space use types. Then, information about the HVAC systems was extracted from the operation staff and past energy audits. Selection of measurements in the BAS database was made and transferred to the CSV format for preprocessing (i.e., removal of outliers and abnormal operation data). Hourly values of operation variables like zone temperatures, scheduled hours of operation of AHUs, AHU supply air temperatures, and duct static pressures were extracted to become inputs in the EnergyPlus model. Instead of using hypothetical or default lighting and plug loads schedules, occupant-driven load profiles were used where the intensity was altered as a function of the number of occupants [14], [17]. Concurrently, occupancy schedule profile parameters including the first and last arrival and first and last departure times are included in the calibration process.

Once the development of the initial model was completed, a customized objective function and a search space for the optimization algorithm (i.e., GA) were defined to find the model parameters with the least CV(RMSE) value. The calibration process was applied for both monthly and hourly calibration approaches to test the method accuracy for various temporal resolutions, yet operational improvements are only outlined for hourly estimation.

The scope of the proposed approach is limited to the calibration of the thermal performance of the envelope, internal heat gain characteristics, and unknown operational parameters (e.g., unoccupied mode heating and cooling temperature setpoints).

3.3.1. Proof-of-concept demonstration

This section elaborates on applying the suggested methodology to a government building located in Ottawa, Canada, in ASHRAE Climate Zone 6 [100].

3.3.1.1. Base model

The case study building, constructed in 1955, has two stories above grade plus a basement, with a total conditioned floor area of about 4,463 m^2. The core zones of the above-grade floors are used as laboratories, offices are located along the perimeter, and a large laboratory is in the basement area. The remaining space consists of corridors and restrooms on each floor. Most of the building tenants occupy the office space on the second floor and around the first-floor perimeter. According to the previous energy audit, the window-to-wall ratio (WWR) is approximately 25%, where the front entrance is equipped with a full vestibule with glass doors and spandrel assemblies. Note that, since the building was completed in the late 1950s, the building's envelope predates the National Energy Code of Canada for Buildings [101]. Also, building envelope characteristics were not well documented. Previous energy audit indicated that the facility houses 80 full-time workers between 08:00 and 17:00 Monday through Friday; however, some workers frequently stay late or come in on weekends to finish tasks, some laboratories are used at different times as well. A district heating and cooling system meet the building's heating and cooling demands. The hot water supplied by the plant is distributed to the VAV terminal box reheat

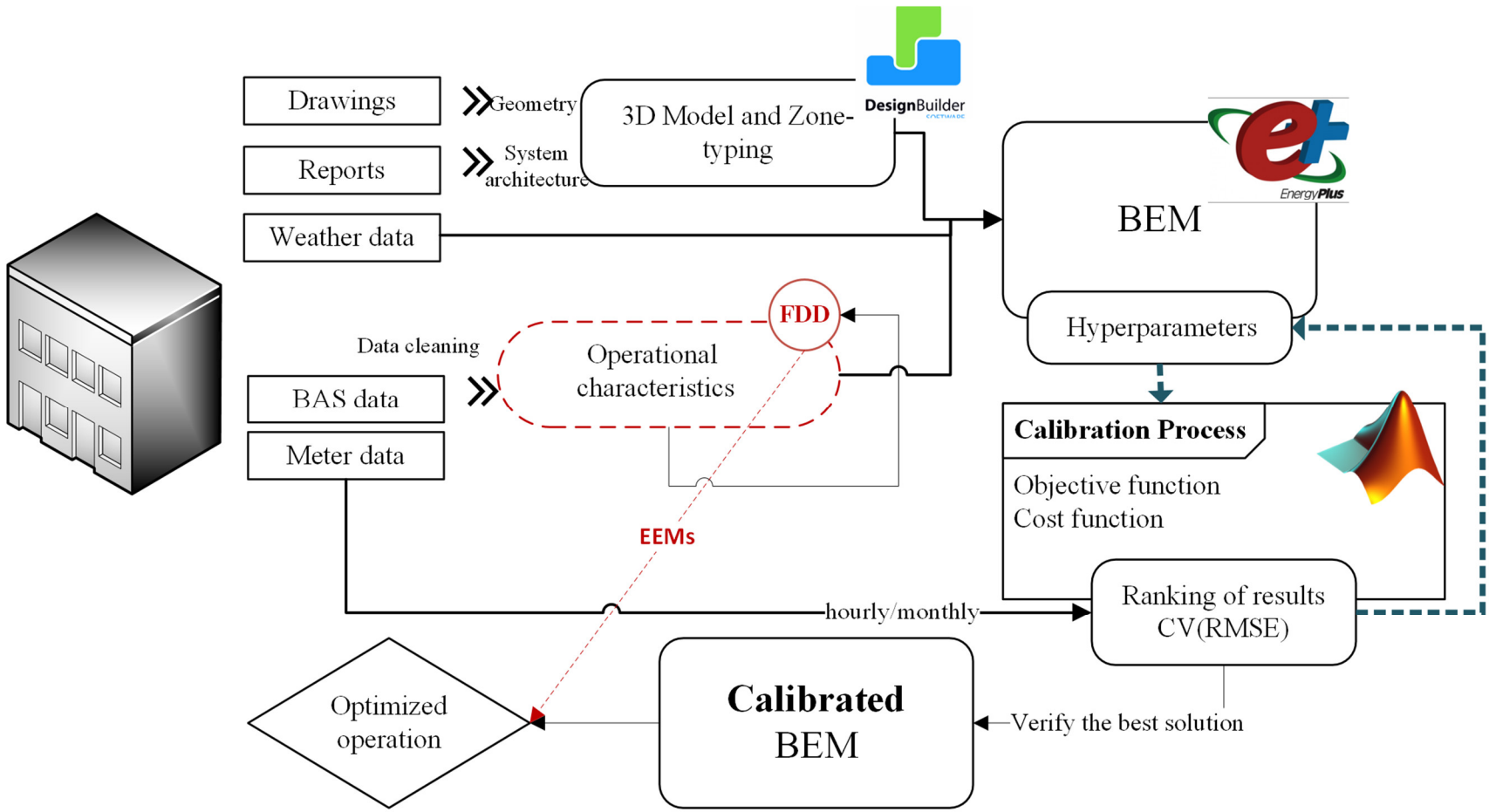


Figure 3.1: An overview of the improved workflow.

coils, baseboard heaters, and AHU heating coils; the chilled water is distributed to the AHU cooling coils.

To improve the comprehensiveness, thermal zones in BEM should accurately represent the actual zone conditions (i.e., using multiple zones instead of a single large zone). However, zoning simplifications are required to keep the model's size and computation time reasonable. Four major criteria were considered to assign thermal zones in the model, (i) space HVAC characteristics, (ii) position relative to the exterior, (iii) different façade orientations for perimeter zones, (iv) space function (similar energy usage/requirements). Accordingly, this method reduced a large model into 16 thermal zones (e.g., core, perimeter, offices, labs). Architectural geometry is created on DesignBuilder v6.1.8.021. Once the geometry was modelled, an EnergyPlus input file (IDF file) with all geometry information was exported, and the EnergyPlus IDF Editor was used to create the HVAC system model. Figure 3.2. presents rendered geometry and zoning generated in DesignBuilder.

The facility has ten AHUs serving different zones and floors. AHU 3 and 10 are 100% outdoor air units serving AHU 5 and 7, AHU 4 and 6, respectively, where AHU 9 is a return air unit with 0.47 m^3/s capacity. Those AHUs were not included in the model for simplicity. Following notation was used for 16 thermal zones: Zabc; where a is the AHU a serving the zone, b is the floor number, c is the orientation (Figure 3.2). The AMY data in EPW format were used at hourly intervals from January 1st, 2017 to January 1st, 2018. In addition, hourly and monthly heating, cooling, and electricity use measurements for the same period were extracted.

More than 500 relevant data points were identified in the BAS database. Since only the schedule and setpoint related parameters were chosen as model inputs, a MATLAB script was created to extract the selected variables from the BAS database to CSV format. Parameters exported from BAS are supply (SAT) and return air (RAT) temperature, supply (SF) and return (RF) fan state, supply (SAH) and return (RAH) air humidity, supply volumetric airflow rate, supply, and return air delta pressure of 10 AHUs; as well as thermal zone room temperatures and VAV supply volumetric airflow rate and damper and valve position signals.

In any modelling environment, the accuracy and reliability of outputs are determined by the measured input quality. BAS data quality usually involves uncertainties, sensor faults, and measurement noises; therefore, data preparation is required. Two typical problems regulated with BAS data considered in this study were (i) missing values and (ii) outliers, hence prior to analyzing operational characteristics, missing values and outliers were cleaned from the exported data set.

AHU supply air temperatures and pressures for the heating and cooling season were extracted from BAS data and presented in Figure 3.3 and Figure 3.4. Table 3.1 presents the setpoints and schedules obtained from BAS data. During the heating season, the SAT setpoint was set to 18.5°C for all AHUs besides AHU 5 and 6. Supply fan maximum flow rates were obtained through building reports and verified with BAS data. The AHU heating coil and VAV reheat coils were set to be available all year-round. Analogously, the AHU cooling coil was set to be available from April to December. During the cooling season, the supply air temperature setpoint is 13.5°C for all AHUs besides AHU 5 and 6.

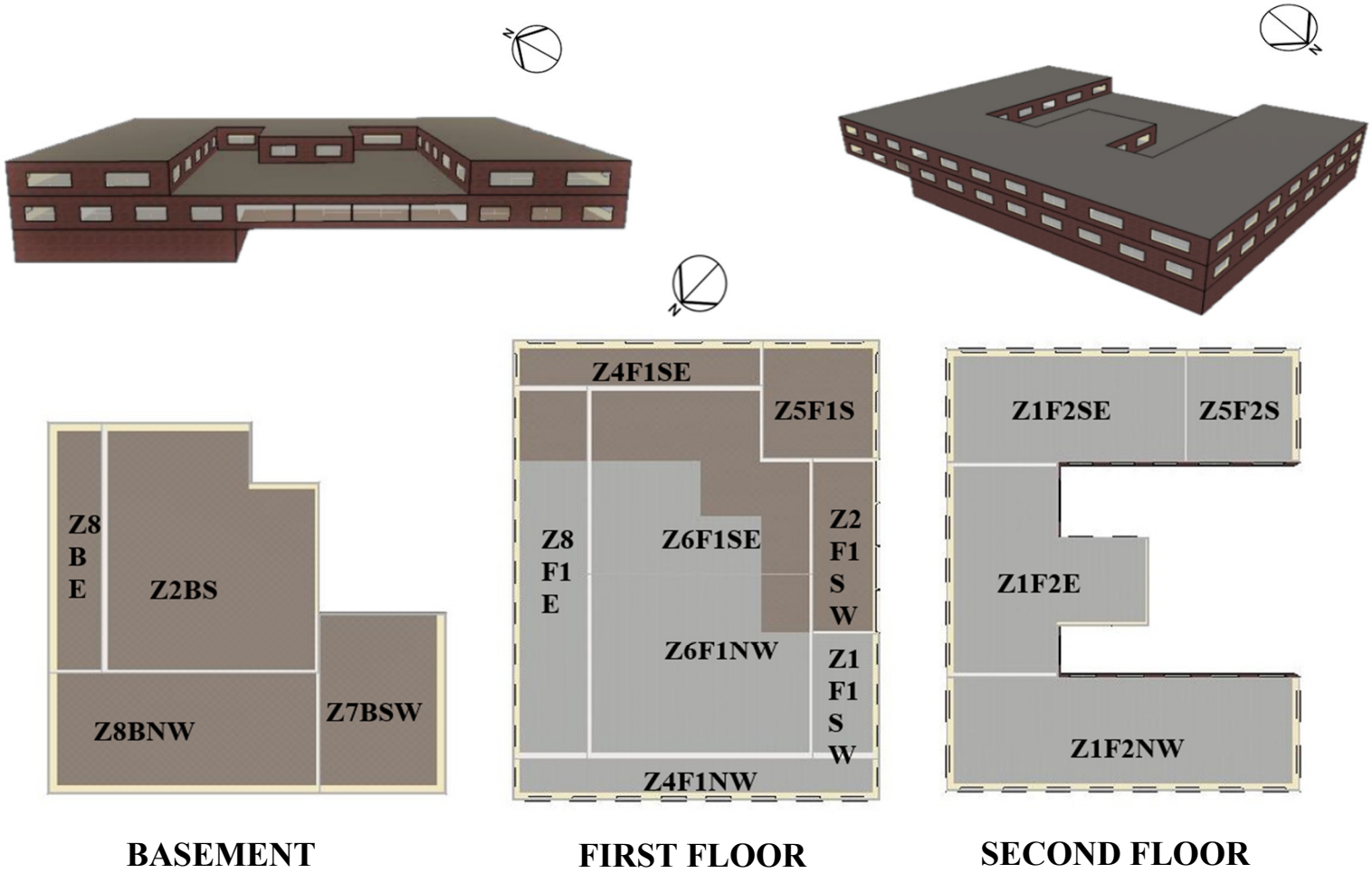


Figure 3.2:An overview of the EnergyPlus model.

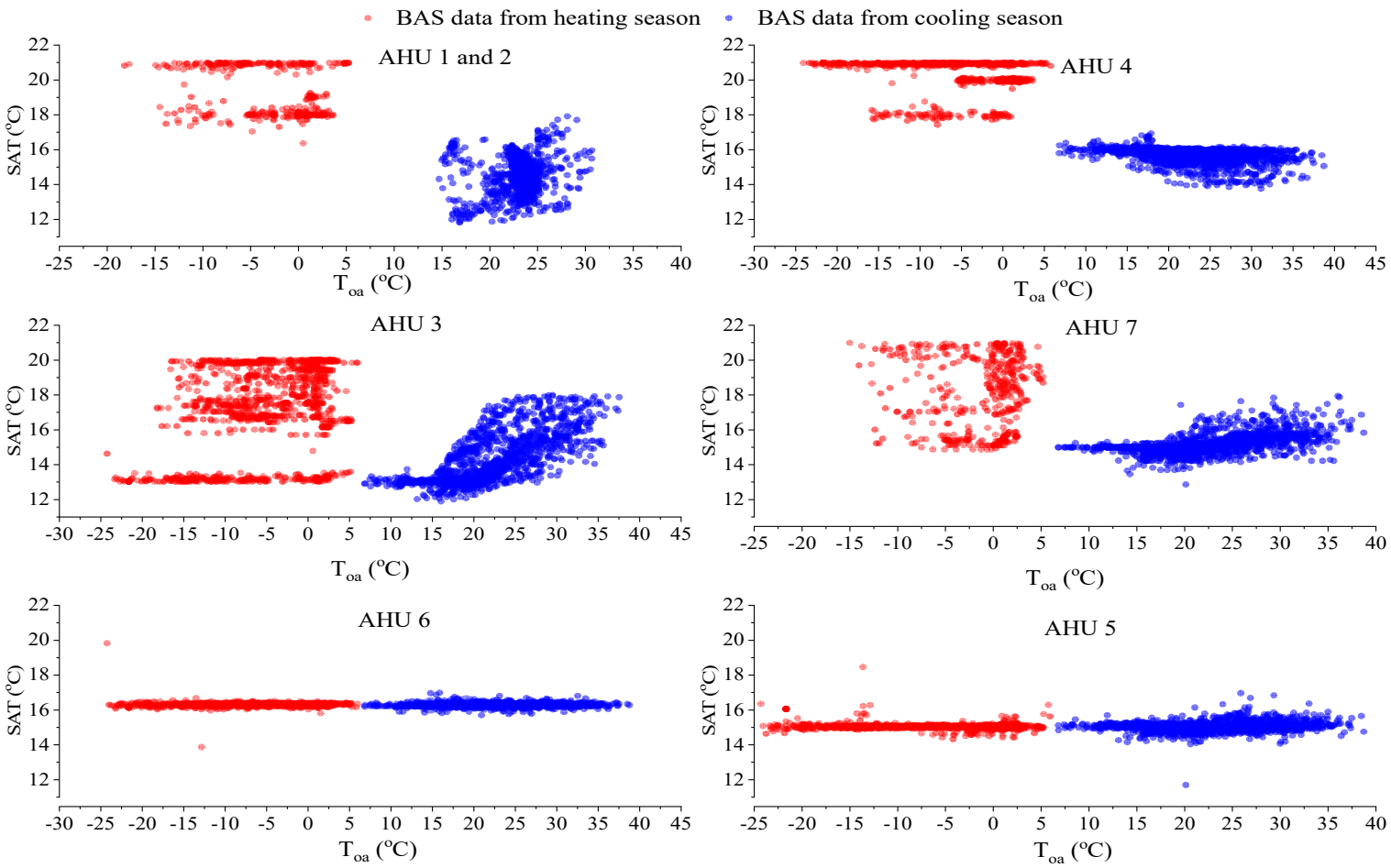


Figure 3.3: Supply air temperature BAS setpoints.

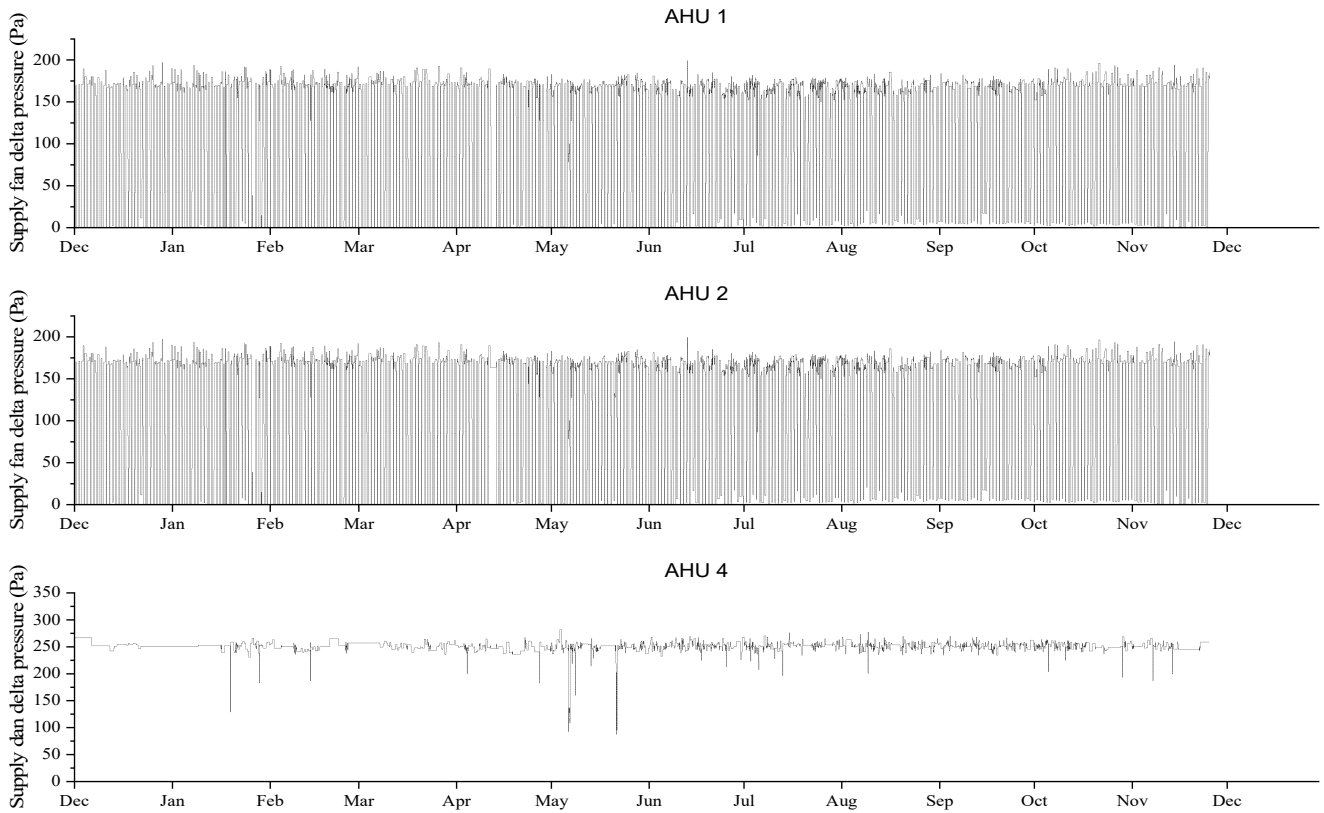


Figure 3.4: Supply fan delta pressure BAS setpoints.

Table 3.1: Base model schedule and setpoint inputs extracted from BAS.

	Supply fan maximum flow rate (m^3/s)	Supply fan delta pressure (Pa)	Supply air temperature (°C)		System availability schedule			
					November-January		February-October	
			Heating	Cooling	Weekday	Weekend	Weekday	Weekend
AHU 1	6.56	200	18.5	14.5	01:00-22:00	07:00-16:00	05:00-23:00	09:00-17:00
AHU 2	2.86	200	18.5	14.5	01:00-22:00	07:00-16:00	05:00-23:00	09:00-17:00
AHU 4	6.13	300	18.5	14.5	Always on			
AHU 5	0.72	400	16.5	16.5	Always on			
AHU 6	7.12	400	16.5	16.5	Always on			
AHU 7	0.33	400	18.5	14.5	Always on			
AHU8	1.73	400	18.5	14.5	Always on			

According to the BAS data, the supply fan pressure was set to 200 Pa for AHU 1 and 2 and 300 Pa for AHU 4. AHU 5, 6, 7, and 8 supply fan pressure was not recorded in BAS data and assumed 400 Pa. Similarly, AHU operation schedules were obtained for different seasons and workdays. All AHUs, besides AHU 1 and 2, remained on constantly, whereas AHU 1 and 2 had the same daily on-off schedule depending on the hour of the day and holidays. For example, for November, December, and January, AHU 1 and 2 operate between 5 am to 11 pm during the weekdays, and on the weekends, they operate between 9 am to 5 pm. Similarly, from February to November, AHUs operate between 1 am to 10 pm on weekdays, and on the weekends, they operate from 7 am to 4 pm during the cooling season.

By verifying from the BAS, the minimum airflow fraction of the VAVs was assumed as 20% of their design capacity. Sixteen VAV units supplied heating and cooling to thermal zones, where all zones were modeled with reheat coils and perimeter heating. The maximum discharge air temperature with reheat was set as 35°C. EnergyPlus automatically sized HVAC equipment and systems in the simulation models. Heating and cooling season average thermal zone temperature setpoints were extracted individually for heating and cooling season and weekends and weekdays by taking the average of corresponding room temperatures. For simplification, the heating season zone temperature was set to 22.5 °C, and the cooling season zone temperature was set to 23 °C. Both heating and cooling season temperature setpoints were kept constant and the night cycle kept activated across all simulations. Night cycle manager is used for cycling on an air system when one or more zones become too hot or too cold, where the usual situation is that the central air handler

is turned off at night. For the zones Z5F1S, Z5F2S, Z7BSW additional 15 W/m^2 [102] load intensity was implemented due to the existence of heavy equipment.

Although applying simple daily AHU schedules can be one of the most cost-effective ways to achieve significant energy savings [13], the facility did not have an efficient operation schedule. Moreover, Figure 3.4 demonstrates that the supply air pressure setpoint is fixed to constant values, meaning that the building does not have a supply air pressure reset strategy (i.e., AHU static pressure control). When a building's supply fan system is operational, the supply fan's static pressure setpoint can be automatically adjusted to load conditions that allow the supply fan to operate more efficiently. Outdoor air damper position data relative to outdoor temperature was analyzed to investigate economizer configurations. Results showed that only AHU 1 and 2 have an air-side economizer program. Therefore, a built-in economizer type in EnergyPlus, differential dry-bulb, was used for the model, where it increases the outdoor airflow rate when there is a cooling load, and the outdoor temperature is below the zone exhaust air temperature. This section demonstrates that analyzing BAS data gives preliminary insight to the modeller to identify some of the operational inefficiencies inherent in the building, and once the calibrated model is achieved, these issues can be fixed to achieve a more efficient building operation.

3.3.1.2. Calibration parameters

A calibrated simulation model's accuracy depends on the capability of the inputs to describe the design conditions of building envelopes and HVAC systems and operation practices; thus, the outputs are in line with available measured energy use data. The calibration problem is over-specified (i.e., too many inputs) and under-determined (i.e., too few validation points). Addressing this problem requires using hypothetical values or

simplifications without diminishing the accuracy. This study's key aspect is maintaining the model accuracy by feeding the model with the utmost amount of easily accessible inputs (i.e., BAS data) and merely calibrating unknown indices.

As mentioned before, the case study building's structure and envelope construction predate the National Energy Code of Canada for Buildings, and envelope characteristics were not well identified. Accordingly, U-value and SHGC of the windows, R-value of the wall, and air infiltration rate were chosen as calibration parameters. In the actual building, the amount

Table 3.2: Average zone temperature setpoints obtained from BAS

Average zone temperature (°C)				
Zone	Heating season		Cooling Season	
	Weekday	Weekend	Weekday	Weekend
Z1F2NW	22.5	21.3	22.8	23.5
Z1F2E	22.7	22	22.7	24
Z1F2SE	22.2	22	22.7	23.6
Z5F2S	22.7	22.5	23.1	24.3
Z5F1S	22.7	22.5	23.1	24.3
Z2F1SW	22.6	22.6	23.2	27
Z1F1SW	22.5	22.5	23.2	27
Z4F1SE	22.7	21.3	23.5	24.5
Z4F1NW	22.7	21.3	23	24
Z6F1SE	22.5	22.5	23.1	24
Z6F1NW	22.5	22.5	23.1	24
Z8F1E	22.6	22.5	23	23.2
Z8BE	22.6	22.5	23.5	23.5
Z8BNW	22.7	22.6	23.6	24
Z7BSW	22.5	22.5	23.6	24.5
Z2BS	22.5	22.5	23.6	24.5

of outdoor air in the supply air was not measured. The outdoor air method was defined as flow per area, and the ventilation rate (outdoor air rate per thermal zone floor area L/s-m^2) was also included as a calibration parameter.

At any given time of day, only a fraction of the people will be present in the building, and only a fraction of the lights and plug-in equipment will be switched on, and this diversity schedule is assumed to recur in weekly patterns in a steady-periodic fashion [103]. This study aims to use an occupancy schedule template to estimate the internal loads stimulated by occupants through calibration. A fixed template assuming the building occupants' first arrival/departure as ‘first arrival/departure’ and the last expected arrival/departure as ‘last arrival/departure’ was used. The building was assumed to remain at a peak occupancy level between ‘last arrival’ and ‘first departure. Then, the occupants were assumed to depart between ‘first departure’ to ‘last departure. The transition to full-occupancy during arrival periods and the transition from full-occupancy during departure periods were assumed linear [104]. Note that this schedule is only valid for weekdays, and no occupancy is assumed during the weekends. All parameters of the schedule (‘first arrival, ‘last arrival, ‘first departure, ‘last departure’) were included in the calibration problem. Occupancy was homogenously distributed throughout the zones based on each zone’s area for simplicity. Internal loads are generated by the occupants, lighting, plug-in appliances, and any other heat-generating equipment within a building. In practice, metered data is not usually available for lighting and plug loads separately, and unless they are separately sub-metered, the optimizer cannot separate them. Therefore, occupant density was linked to combined lighting and plug load intensity for practical concerns in this study [17], [104]. Usually, during the unoccupied hours, 20 to 70 % of the daily peak lighting and plug load power

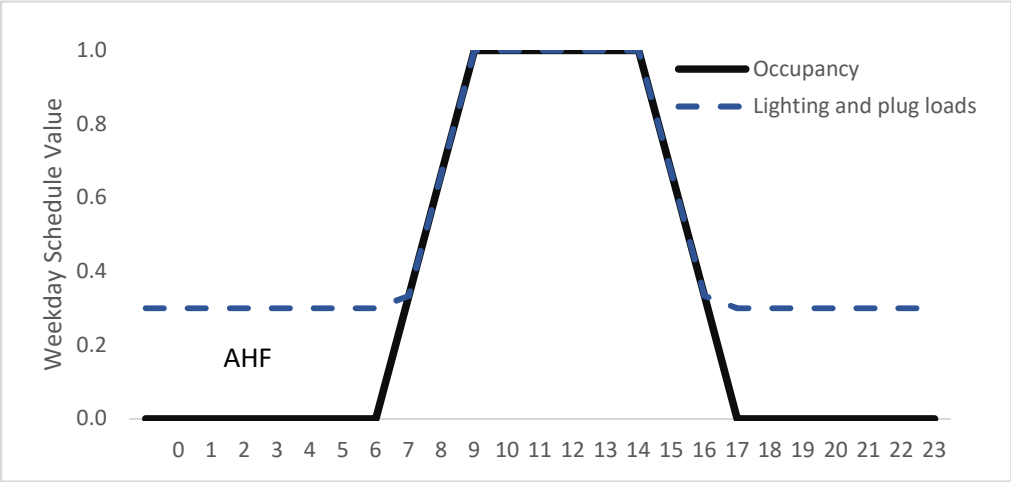


Figure 3.5: Illustration of AHF implementation during a day.

draw remains after hours in office buildings [105]. Where buildings with automated lighting and plug load management software, this value approaches the lower end of this range, and manually controlled buildings approach the higher end of this range. Recall that after-hours plug loads and lighting ratio, i.e., AHF, is defined as the fraction of the lighting and plug load power draw that remains on after the work hours (Figure 3.5). Masaso and Grobler [106] conducted an energy audit on more than five buildings, and results indicated that more energy is used during non-working hours (56%) than during working hours (44%). Therefore, calibrating the AHF is critical in increasing models' fitness to the measured data. Over the weekend, the facility is assumed vacant; thus, the plug loads and lighting electricity use remained at calibrated AHF value of the full-occupancy levels. Occupant heat gains depend on their activity level. An EnergyPlus activity schedule was used to estimate occupant heat gain. A custom EMS script (in the EnergyPlus Runtime Language ERL) coupled with a constant schedule is generated to increase the flexibility of creating a customized schedule. Plug and lighting load intensity was assumed to be 300

W/person [48], [107]. Note that, for simplification, this model neglected inter-zonal diversity of the lighting and plug loads, and occupant-driven loads are assumed to be proportionally distributed across the floor. This approach aims to effectively search for internal gains (each occupant is assumed with 300 W demand for lighting and plug loads combined) by linking them to the occupancy level. Therefore, an EMS script was created to link the occupancy with lighting and plug loads through calibrated people density value. Simply put, the purpose of calibrating people density and AHF is to search for internal heat gains rather than to search for the current occupancy rate in the facility. Similarly, 'first arrival,' 'last arrival, 'first departure, 'last departure' were mainly calibrated to obtain the occupancy-related heat gain schedule. Similarly, schedules for AHU 1 and 2 were implemented as a custom model within EMS application where this script dynamically overwrote the operating hours during the simulation.

Setback control is usually used to lower space-heating thermostats and increase the space-cooling thermostats for office buildings during unoccupied hours. Since the building's setback control strategy -if the building has one- was not well identified from BAS data, heating and cooling setback temperatures were added to the calibration problem to further investigate the building operation characteristics.

Evidently, many other parameters could not be established along with the parameters investigated; however, the focus of this study is to calibrate unknown envelope properties and operational characteristics. Intuitively, increasing the number of parameters to calibrate is expected to increase the performance accuracy; however, it also increases the computational cost and the risk of over parametrization. The relationship between the

number of operational parameters to optimize and the incremental performance benefits should be studied in detail.

3.3.1.3. Determining the threshold values for calibration parameters

The process of calibrating a set of parameters was carried through a custom MATLAB script that read and write from the base EnergyPlus model, iteratively changing the calibration parameters based on the optimization criteria and cost function. Search space was created by defining threshold values for parameters, summarized in Table 3.3. Published code values were also provided to contextualize the upper and lower bounds.

Envelope parameters

Recall that the building was constructed before the introduction of commercial building energy codes; therefore, envelope parameters were searched in a broad search space. In the optimization problem, a window with a U-value of 1.5 (W/m^2-K) and SHGC of 0.3 represents a triple-glazed insulated low emissivity window; a window with a U-value of 3.5 (W/m^2-K) and SHGC of 0.6 represents a single glazed clear window [108], [109]. Likewise, insulation with an R-value of 8 m^2-K/W represents a well-insulated construction, and an R-value of 1 (m^2-K/W) represents a poorly insulated building. National Energy Code of Canada [102] defines the air leakage value of 0.25 L/(s-m^2) as a typical infiltration rate at 5 Pa. In this case, a building with a 1 L/(s-m^2) infiltration rate is considered a highly leaky building.

Operation parameters

Internal loads include heat gains from interior lighting, plug-loads, and occupants. As a result, internal loads reduce space-heating loads and increase space-cooling loads. AHF lower bound was set to 0.2, and the upper bound was set to 0.8 due to the facility function

(labs and heavy equipment running during the off hours) [47], [106]. People density (PPL) was calibrated to search for a combined effect of lighting and plug load internal heat gain between the range of 7.5 W/m^2 to 30 W/m^2. Note that, those values were identified considering lighting power density (LPD) and equipment power density (EPD) values defined by ASHRAE Standard 90.1 [110]. Note that ASHRAE sets LPD and EPD to 10.76 W/m^2 for the base case. For the high internal load case, LPD and EPD are set 50% higher than the base case, and for the low internal load case, they are set 50% lower. The case study building work-hours were reported as from 08:00 to 17:00. Therefore, the occupancy 'first arrival' time was calibrated between 05:00 to 09:00, and accordingly, the 'late arrival' time was calibrated between 08:00 to 12:00. Similarly, the 'first departure' time was calibrated between 13:00 to 17:00, and the 'last departure' time was calibrated between 16:00 and 20:00. Search range for lighting and plug load density and schedule are presented in Figure 3.6.

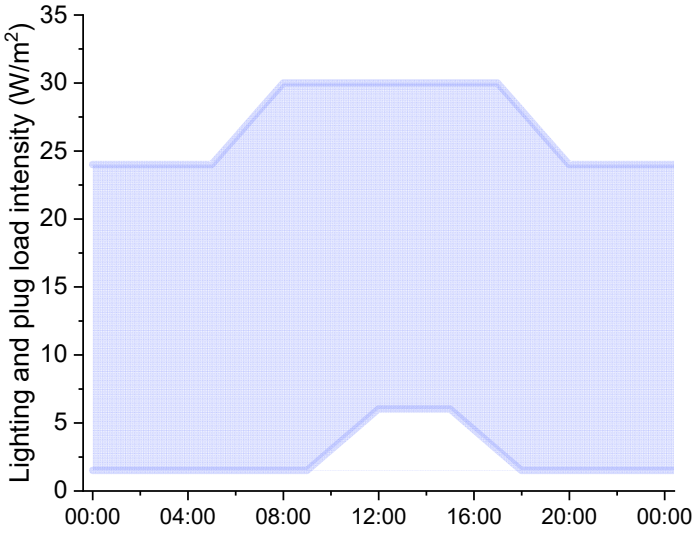


Figure 3.6: Illustration of the lighting and plug load density and schedule search space.

Considering the majority of the building is used as an office space with few laboratories, threshold values are defined considering ASHRAE 62.1 (2019b) [111] ventilation rate (L/s-m^2) for office and laboratory spaces. In this case, a building with a 2 L/(s-m^2) ventilation rate is considered a highly ventilated building, whereas a building with a 0.2 L/(s-m^2) ventilation is considered a poorly ventilated building.

Setback temperature control is setting the heating setpoints a few degrees lower and the cooling setpoints a few degrees higher for unoccupied hours at night and during weekends. Hence, two heating and cooling setback cases are considered. For the heating season: one is set back to 15 °C to represent the typical operation of most office buildings [112], and the other is to have no setback at all. For the cooling season: one is set back to 28°C [113], and the other is to have no setback at all.

3.3.1.4. Defining the objective function and genetic algorithm simulation

The calibration technique uses the CV(RMSE) value as an error-minimizing objective function aiming to reduce the difference between measured heating, cooling, and electricity data to simulated data (i.e., taking the average heating, cooling, and electricity CV(RMSE). This comparison is called uncertainty analysis, and the uncertainty analysis outcomes are used as an objective function by the GA to select a new set of parameters. Common approaches to perform optimization are reviewed in depth by Nguyen et al. [39], and this study asserted that as simulation engine EnergyPlus, and as the optimization algorithm GA is the most common approaches.

A BEM is often deemed calibrated if it meets the CV(RMSE) and NMBE limits specified by ASHRAE Guideline 14 [23], International Performance Measurement and Verification

Protocol (IPMVP) [85], and Federal Energy Management Program (FEMP) [114]. ASHRAE Guideline 14 gives the acceptable limits for calibration to hourly meter data as $CV(RMSE)_{hourly} \leq 30\%$ and $-10 \leq NMBE_{hourly} \leq 10\%$, and monthly meter data as $CV(RMSE)_{monthly} \leq 15\%$ and $-5 \leq NMBE_{monthly} \leq 5\%$. In this chapter, the accepted fitness level of ASHRAE Guideline 14 Standard is targeted to reach. Therefore, CV(RMSE) was selected as an error-minimizing objective function. Additionally, for the final model (i.e., 'calibrated model'), NMBE was calculated (to verify if the acceptable ASHRAE Guideline 14 Standard limits are satisfied), but it has not been used as the objective function for the algorithm. The formulas of these indices are set down by the ASHRAE Guideline 14.

Genetic algorithm model hyperparameters were selected such that the results between several optimization runs varied negligibly. This work's selected stopping criterion runs a maximum number of ten generations [90] until the optimal solution is obtained. Population size is an important parameter affecting the performance of optimization methods based on genetic algorithms. The population sizes recommended are twice or four times the number of variables [53]. Consequently, the population size is chosen as 100 [91]. The crossover fraction was set to 0.5. The number of elite individuals to pass to the next generation was set to ten [92]. In brief, the process starts with the first parameters defined among boundary conditions with GA and MATLAB script reads and writes from the base EnergyPlus model and iteratively alters the parameters to obtain the ones that fit best with the objective function. It then generates a new population in a given space for the next generation with the best subjects and new random ones. In each result evaluation, the best ranking parameters get updated. Finally, the process stops when all generations are performed, and the best model is stored as the calibrated model. This process is summarized in Figure 3.7.

Table 3.3: Unknown calibration parameters, published values, optimization upper, and lower bounds, and calibration parameter estimates.

Parameters used in calibration	Units	Published values	Lower bound	Upper bounds	Hourly calibration	Monthly calibration
Window U-value	*(W/m^2-K)*	1.9[1]	1.5	3.5	1.7	2.1
Window SHGC	-	-	0.3	0.6	0.35	0.34
Wall R-value	*(m^2-K/W)*	4[1]	1	8	1.8	3.3
Infiltration rate	*(L/s-m^2)*	0.25[1]	0.1	1.0	0.3	0.3
AHF	-	-	0.2	0.8	0.65	0.3
PPL_{office} / $PPL_{manufacturing\ facility}$	*(m^2/person)*	25[1]/30[1]	10	40	36	39
$Ventilation_{office}$ / $Ventilation_{laboratories}$	*(L/s-m^2)*	0.3[2]/0.9[2]	0.2	2.0	0.8	1
Occupancy first/last arrival	*hr*	-	5:00/8:00	9:00/12:00	05:20/08:20	05:10/08:10
Occupancy first/last departure	*hr*	-	13:00/16:00	17:00/20:00	13:50/16:50	13:40/16:40
Heating SAT setback	*(^{o}C)*	-	15	22.5	21.5	21.6
Cooling SAT setback	*(^{o}C)*	-	23.5	28	25.6	29.7

[102][1], [23][2]

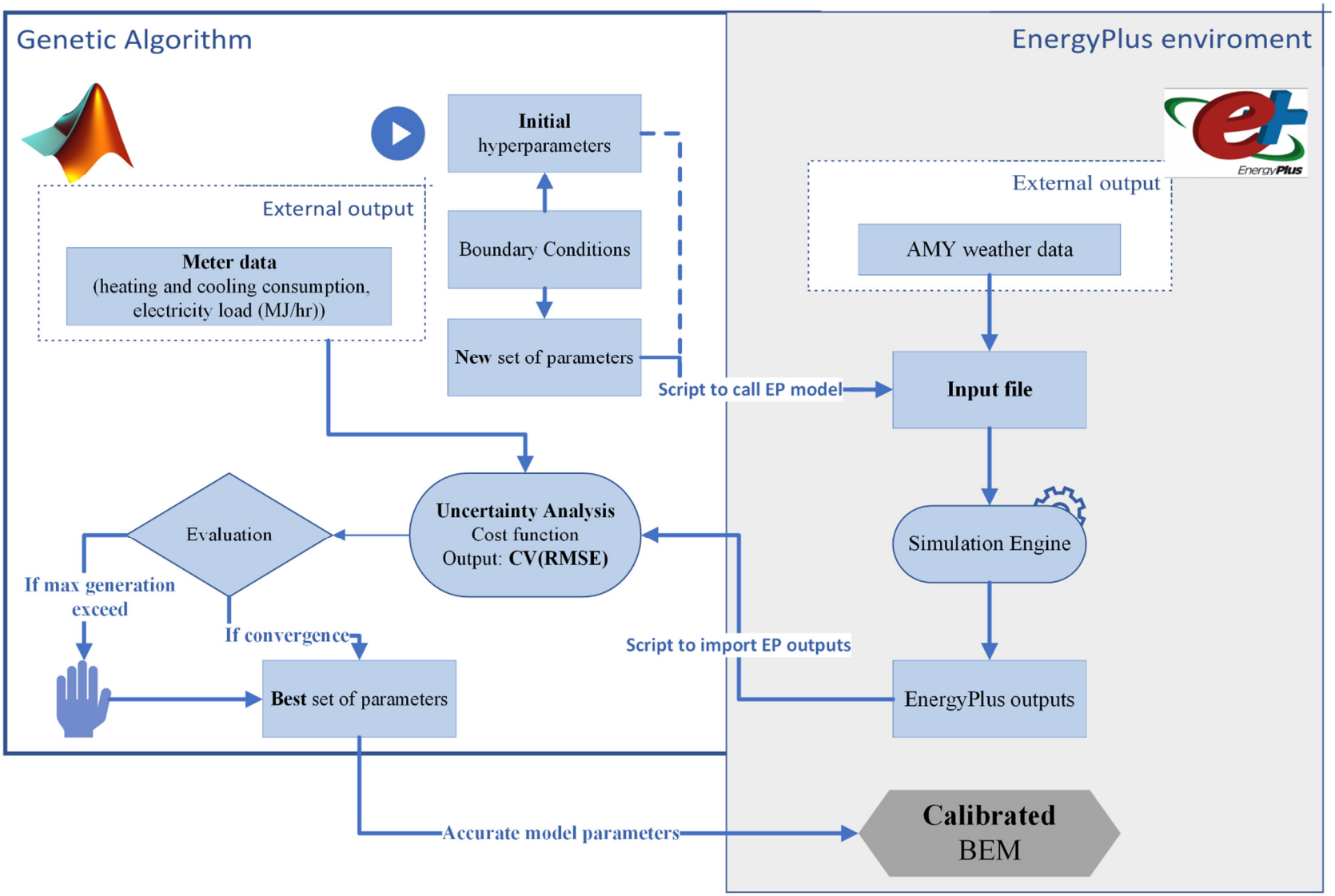


Figure 3.7: An overview of the optimization-based calibration environment.

3.4. Results and discussion

This section presents the hourly and monthly calibrated model parameters and investigates the calibrated models' accuracy and load estimations. The model with the least CV(RMSE) value was selected as the calibrated model. Note that CV(RMSE) value was obtained during the optimization process, and NMBE was calculated by comparing the final calibrated model with the measured data. Note that both hourly and monthly calibrated model's CV(RMSE) and NMBE indices were within the acceptable tolerances defined by ASHRAE. The CV(RMSE) value was calculated as 29% for the hourly calibration, and NMBE was calculated as 3.3%. The monthly calibration CV(RMSE) value was calculated as 13%, and NMBE was calculated as 1.8%. Figure 3.8 and Figure 3.9 presents the monthly and hourly predicted heating, cooling, and electricity loads compared to the measured load profiles, respectively. Results demonstrate that calibrated model can dynamically predict loads (Figure 3.8) and capture seasonal patterns and peak loads (Figure 3.9).

Calibrated parameter estimations are presented in Table 3.3. Both monthly and hourly calibration results indicated that the building's opaque assembly had lower R-values for the wall than what is stipulated in NECB, causing a significant amount of heat transfer through the façades. Given the WWR of 25%, the window U-values were calculated to be in an acceptable range, 1.7 W/m^2K for hourly and 2.1 W/m^2K for monthly calibration. A window with predicted U-values can be considered as a double-glazed window. Predicted SHGC values (i.e., 0.34-0.35) most likely indicate that 30-50% of the blinds kept closed in the actual building; hence the effect of SHGC is lower. Additionally, infiltration was estimated to be higher than the NECB value per above-grade surface area, characterizing

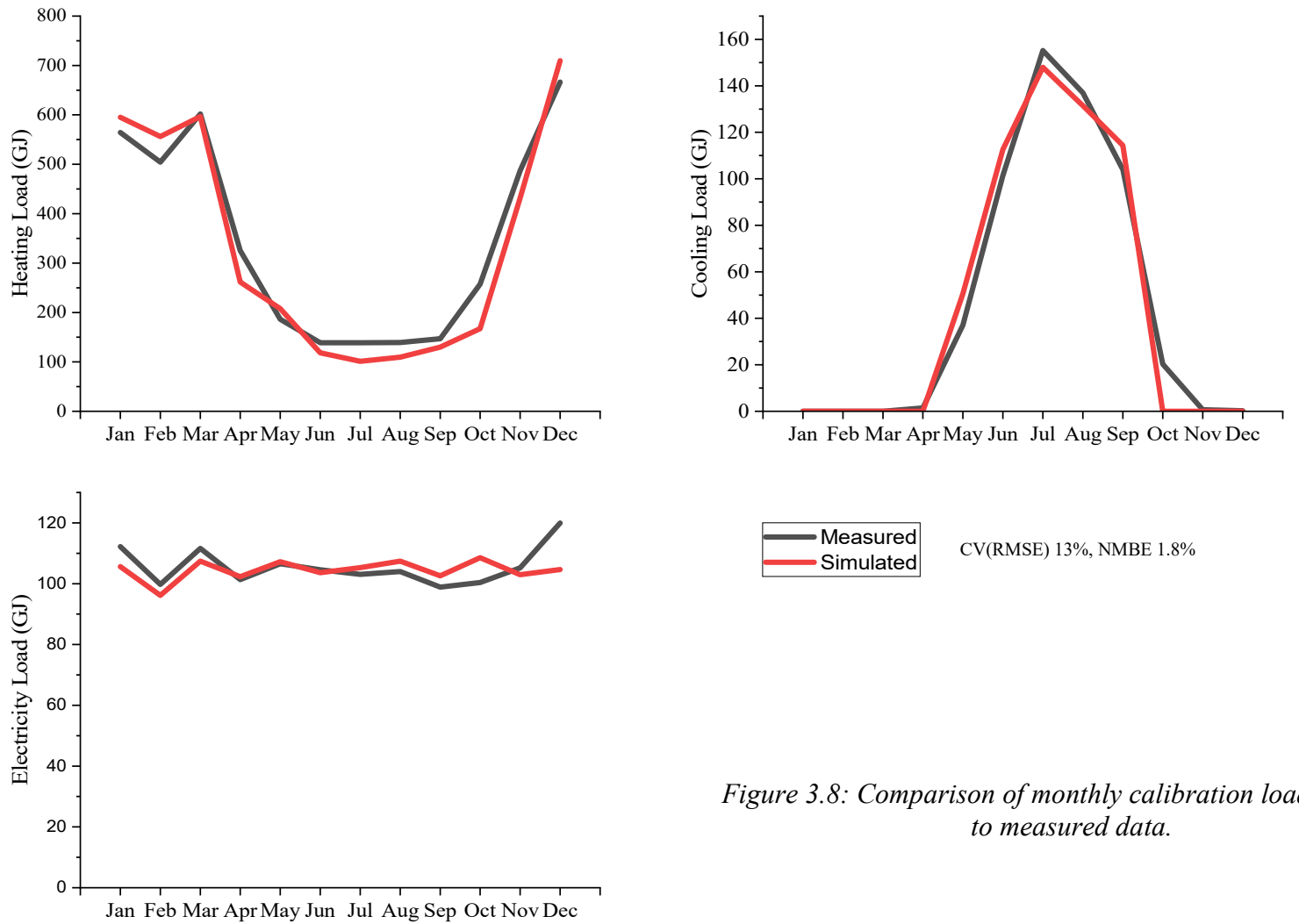
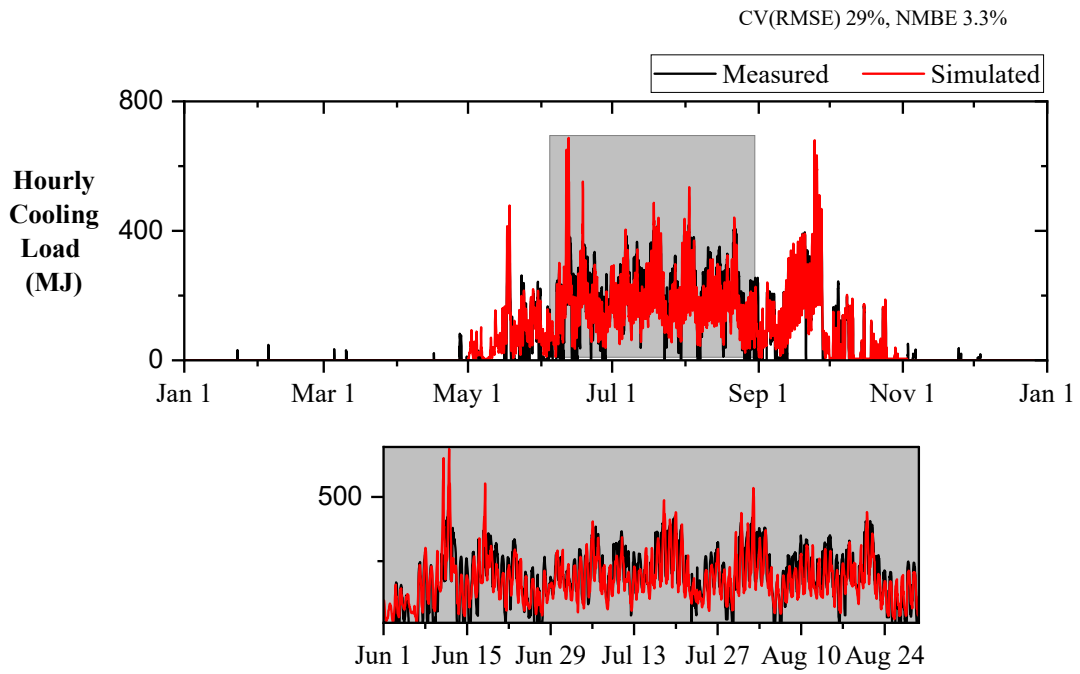
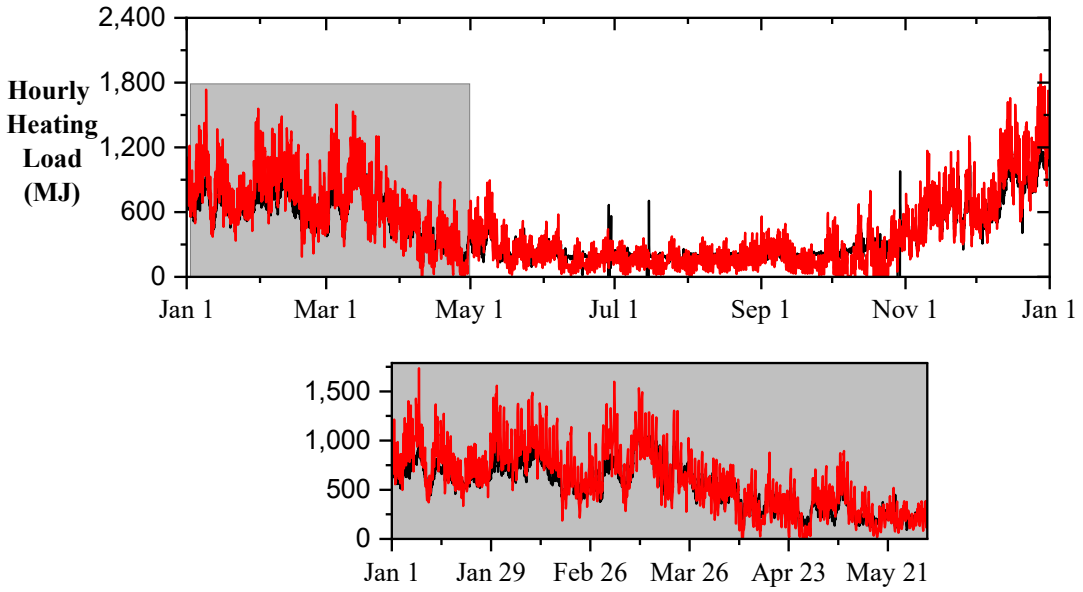


Figure 3.8: Comparison of monthly calibration load estimates to measured data.


CV(RMSE) 29%, NMBE 3.3%
Measured
Simulated
Hourly Cooling Load (MJ)
800
400
0
Jan 1
Mar 1
May 1
Jul 1
Sep 1
Nov 1
Jan 1
500
Jun 1
Jun 15
Jun 29
Jul 13
Jul 27
Aug 10
Aug 24


Hourly Heating Load (MJ)
2,400
1,800
1,200
600
0
Jan 1
Mar 1
May 1
Jul 1
Sep 1
Nov 1
Jan 1
1,500
1,000
500
0
Jan 1
Jan 29
Feb 26
Mar 26
Apr 23
May 21

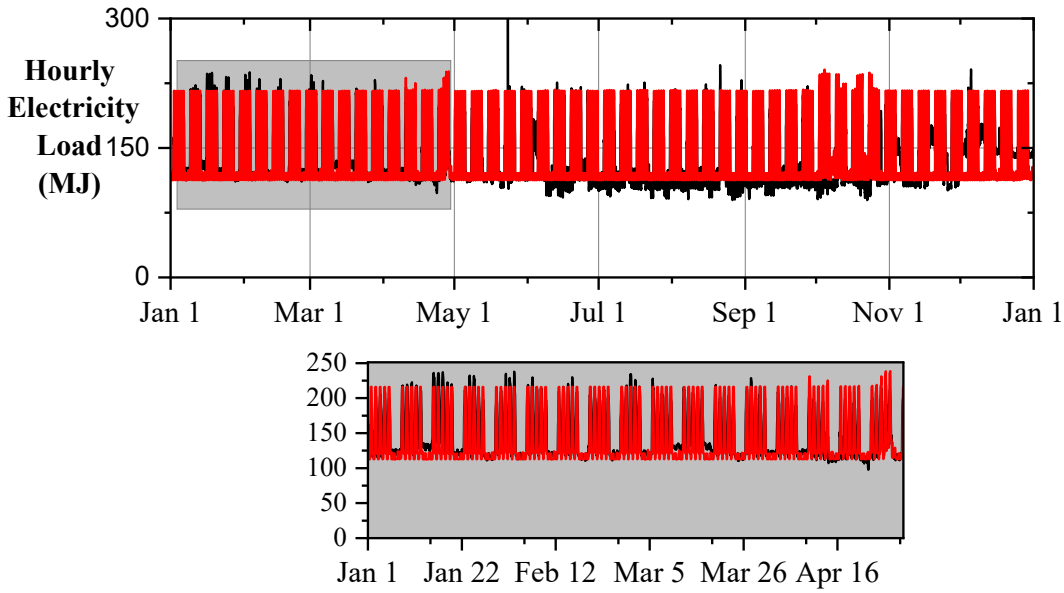


Figure 3.9: Comparison of hourly calibration load estimates to measured data.

the building as a leaky and poorly insulated building. Considering that the perimeter of the first floor and the entire second floor – the majority of the building- is used as an office area (i.e., assuming office-type occupancy throughout the building), the ventilation of the building can be considered higher than ASHRAE [111] requirements. Results indicate that implementing an occupancy-based ventilation scheme (DCV) in the building could be considered an important step to reduce energy waste, given the extent of chronic over-ventilation. According to the AHF, PPL, and first/last arrival and first/last departure parameters obtained from hourly calibration, internal heat gain load and schedule were obtained as shown in Figure 3.10. With full occupancy, the combined effect of lighting and plug loads was calculated as 8.33 W/m^{2,} and AHF was found to be 0.65, yielding 5.41

W/m^2 of combined lighting and plug load during off-hours. Accordingly, results indicated that 'first arrival' occurs at 05:20, and 'last arrival' is at 08:20 am; 'first departure' is at 13:50 and 'last departure' is at 16:50. Likewise, for monthly calibration, with full occupancy, the combined effect of lighting and plug loads were calculated as 7.7 W/m^{2,} and AHF was found to be 0.3, yielding 2.31 W/m^2 of combined lighting and plug load during off-hours. Accordingly, results indicated that 'first arrival' occurs at 05:10, and last arrival' is at 08:10 am; 'first departure; is at 13:40 and 'last departure' is at 16:40. Finally, heating SAT setback temperature was found as 21.5°C for hourly and 21.6°C for monthly calibration, indicating almost no space heating setback control during the heating season. On the other hand, the cooling SAT setback temperature was found to be 25.6°C and 29.7°C for hourly and monthly calibration, respectively, indicating that space-cooling setback control was implemented during the cooling season.

3.4.1. Implementing Operational Energy Efficiency Measures

The impact of several operational interventions on energy performance was predicted by using the calibrated energy model. These interventions are adding AHU supply air temperature reset (SATR) control, DCV, and introducing a high limit to the economizer mode to the calibrated model. Note that operational decisions are only demonstrated on the hourly calibrated model. This is because Chapter: Accuracy of BEM Calibration Process indicated that hourly calibrated models yield more precise and stable parameter estimates than monthly models by accurately representing the actual building's thermophysical properties.

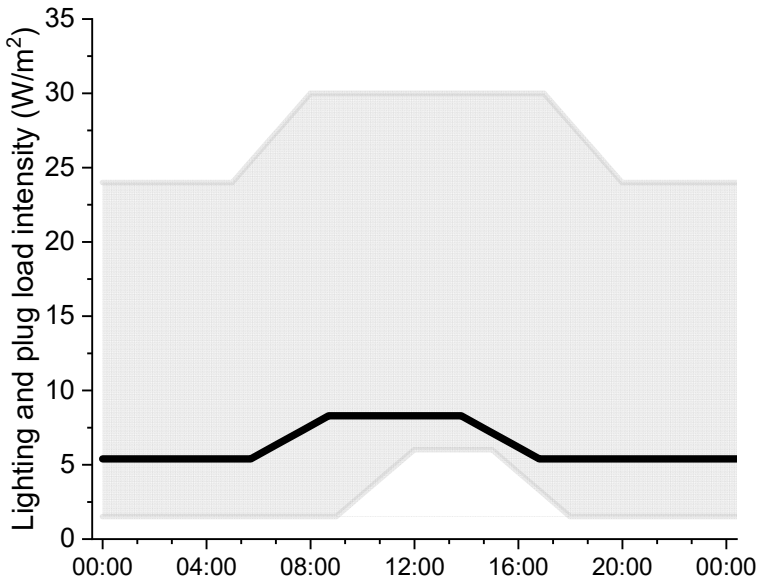


Figure 3.10: A representation of hourly calibrated models' lighting and plug load intensity and schedule in the search space.

Providing excessive ventilation to under-occupied or vacant spaces wastes a significant portion of energy. Therefore, this study aims to implement a system-level DCV that adjusts the minimum outdoor airflow rate based on occupant counts. Moreover, in the case study building, the potential benefits of implementing a DCV are evident given the extent of predicted over-ventilation. Therefore, this study set the minimum outdoor air schedule to the calibrated occupancy schedule to examine the savings through DCV.

Instead of using a constant supply air temperature setpoint, the heating coil SATR aims to set an automatic reset control for the central heating supply air temperature model. The supply air temperature is reset based on outdoor air temperature to minimize perimeter heater use in the economizer state. The parameters $T_{sa,high}$ (°C) and $T_{sa,\ low}$ (°C) represent the highest and lowest limits for the supply air temperature setpoint. $T_{sa,highsa}$ (°C) is applied

only when the outdoor temperature is less than $T_{oa,high}$ (°C); and $T_{sa,low}$ (°C) is applied when the outdoor temperature is more than $T_{oa,lowsa}$ (°C). Between $T_{oa,highsa}$ (°C) and $T_{oa,lowsa}$ (°C), the SAT setpoint linearly varies between $T_{sa,high}$ (°C) and $T_{sa,low}$ (°C). EnergyPlus SAT reset function, 'OutdoorAirTemperatureReset, was utilized for heating SATR. EnergyPlus function resets the heating SAT based on the following default rules: (i) when the outdoor dry-bulb temperature (ODB) is at or below 6.7ºC; the heating coil design setpoint is applied as 18°C, (ii) when the ODB is at or above 10.0ºC the heating coil design setpoint minus 5.2ºC is applied (18 – 5.2°C), (iii) in between, the setpoint varies linearly. Cooling coil SATR aims to set the cooling supply air temperature to the highest supply air temperature that will meet the cooling requirements of all the zones, where the minimum setpoint allowed is the cooling coil design setpoint ($T_{sa,\ design}$), and the maximum setpoint is allowed defaulted to 18ºC. EnergyPlus SAT reset function, 'Warmest,' was utilized for cooling. The Warmest setpoint manager resets the cooling supply air temperature of a central forced-air HVAC system according to the cooling demand of the warmest zone. For each zone in the system at each system timestep, the manager calculates a supply air temperature to meet the zone cooling load at the maximum zone supply airflow rate. The lowest possible supply air temperatures become the new SAT setpoint, subject to minimum and maximum SAT constraints. The resulting temperature setpoint is the highest supply air temperature that will meet the cooling requirements of all the zones. Compared to a fixed cooling supply air temperature setpoint, this strategy minimizes zone reheat coil energy (or overcooling) and central chiller energy consumption (if the chilled water temperature is also reset) at the cost of possible increased fan energy.

Analyzing the BAS data indicated that economizer high limit was not implemented on AHU 1 and 2, resulting in high loads on the fan devices and failing to lower the supply air temperature. The high limit switch is used to inactivate the economizer when cooling return air uses less mechanical cooling energy than cooling outdoor air, i.e., utilization of economizer increases the energy used by the cooling coil. Determining when the changeover occurs is complicated because cooling coils both cool and dehumidify supply air. With a fixed dry-bulb high limit, outside air temperature is measured and compared to a fixed setpoint, enabling the economizer if the outdoor air temperature is below the setpoint. The fixed dry-bulb high limit is the simplest and least expensive high limit control, requiring only a single temperature sensor or thermostat mounted in the outdoor airstream. Therefore, EnergyPlus's maximum dry bulb temperature limit is utilized for the analysis.

DCV, SATR, the economizer high limits strategies were incrementally introduced to the calibrated energy model, and the simulations were repeated for the whole year period. The energy use intensity results per total building area (EUI (MJ/m^2) and potential savings for the hourly calibrated model are summarized in Table 3.4. DCV strategy lowered the minimum outdoor air requirements during heating and cooling operating states; hence the most significant savings (~22%) were observed with that implementation. SAT reset yielded to ~7% decrease in total energy consumption solely and up to ~33% decrease when implemented with DCV. Adding an economizer high limit did not increase the efficiency notably since only AHU 1 and 2 have an economizer configuration, but it can still be considered as an efficient and cost-effective practice for alternative situations. The insights provided by this simulation exercise not only emphasized the benefit of improving building

operation but also helped to address the inefficiencies in the operating system. The magnitude of the energy savings with controls interventions in the facility emphasized how buildings of all vintages can benefit significantly from operational implementations, regardless of envelope quality. This is critical given the high average age of the commercial office building stock. Demonstrating such savings may help stakeholders justify the funding required to upgrade BASs and sensing infrastructure to achieve calibrated BEMs and facilitate these energy efficiency measures. This cost is modest in comparison to whole-building envelope retrofits.

Table 3.4: Operational EEMs and projected savings for hourly calibrated model

Operational Decision / Savings %	**EUI (MJ/m^2)**
Base case	958.8
DCV **Savings %**	748.3 **22**
SATR **Savings**	892.7 **7**
DCV +SATR **Savings**	637.9 **33**
DCV +SATR + Economizer high limit **Savings**	634.9 **34**

3.5. Summary

This chapter suggested an improved workflow to obtain a quick, light-weight, and accurate white-box calibrated BEM. Workflow overcomes the over-parameterization by decreasing the number of unknown calibration parameters by taking advantage of the available BAS,

meter, and weather data and geometric drawings. Interpreting BAS data also allows the modeller to detect the operational anomalies and fix them once the calibrated model is achieved.

A building located in Ottawa, Canada, was used as a case study building, and the proposed workflow was implemented on an hourly and monthly basis. First, the building geometry and thermal zones were created on DesignBuilder. Next, operational parameters such as supply air setpoints (e.g., temperature, humidity, pressure, etc.) and schedules, zone temperature setpoints were extracted from BAS, and outliers and abnormal operation data were removed. Furthermore, a preliminary analysis was conducted on outdoor air damper positions, economizer control settings, AHU supply airflow rate, and temperature measurements to detect possible operational anomalies. Finally, unknown envelope characteristics (i.e., U-value and SHGC of the window, R-value of the wall, air infiltration rate), and operational indices (lighting and plug load profiles, ventilation rate, after-hours temperature setpoints) were calibrated through the optimization algorithm. A customized objective function and a search space for GA were defined to find the model parameters with the least CV(RMSE) value. Eleven parameters were calibrated with a CV(RMSE) value of 29%, an NMBE value of 3.3% for hourly calibration, and 13% and 1.8% for the monthly calibration, respectively.

Calibration results of envelope properties characterized the building as an over-ventilated, leaky, and poorly insulated facility. This study linked occupant density to combined lighting and plug load intensity, searched the generated internal heat gain in the range from 7.5 W/m^2 to 30 W/m^2 and assumed a ratio of this value (i.e., AHF) stays on during the non-working hours. A fixed weekday template taking the first/last arrival and departure as input

and assuming peak occupancy level between the last arrival and the first departure was created to represent the occupancy schedule. At peak occupancy, the combined effect of lighting and plug loads were calculated as 8.3 W/m^2, and AHF was found to be 0.65 for hourly calibration yielding 5.4 W/m^2 of combined lighting and plug load during off-hours. Accordingly, for monthly calibration during peak occupancy, expected internal heat gain was obtained as 7.7 W/m^2, and for off-hours, it was obtained as 2.31 W/m^2.

Calibrated BEM is employed to evaluate the operational changes in the energy consumption of the building. Three operational optimization methods (SATR, DCV, and economizer high limit) were implemented incrementally on the model. Results indicated DCV as the most effective strategy with approximately 22% savings in total, where SATR decreases energy consumption by approximately 7% alone and up to 33% when implemented with DCV. Given that the only two AHUs (AHU 1 and 2) had an economizer adding an economizer high limit on top of those strategies decreased energy consumption by approximately 34%. Results indicated that the facility's energy savings with controls interventions emphasized how buildings of all vintages can benefit significantly from operational implementations, regardless of envelope quality. Demonstrating such savings may help stakeholders justify the funding required to upgrade BASs and sensing infrastructure to achieve calibrated BEMs and facilitate these energy efficiency measures. This cost is modest in comparison to whole-building envelope retrofits.

4. Conclusions

This research project aimed to understand the uncertainty inherent in the white-box BEM calibration process and accordingly suggest an improved workflow to obtain a low-cost, lightweight, and accurate calibrated energy model. Suggested workflow aimed to lower labour and computational costs and increase the model efficiency by increasing the amount of data inputted in the model by exploiting the existing resources (i.e., BAS data). The proposed workflow was demonstrated in a case study building in Ottawa, Canada. Hourly and monthly calibrated models satisfied ASHRAE Guideline 14 fitness criteria. Finally, operational EEMs were applied to the calibrated models to examine the low-cost energy savings.

4.1. Accuracy of BEM calibration process

The main findings from this chapter are summarized as follows:

- Calibration with hourly meter data yielded more stable and accurate parameter estimates than monthly data. When the calibration process is repeated with hourly and monthly energy use data, parameters estimated with hourly meter data were clustered more tightly compared to parameters calibrated with monthly data. 75% of the parameter estimates through hourly meter data had a narrower standard deviation and variance than monthly estimates.
- Results indicated that monthly calibration accuracy could be increased by adopting average parameters (repeating the calibration several times and averaging the parameters) as final calibrated model parameters. Results showed that using those average parameters could improve the monthly calibration accuracy by up to 58%.

- Poorly calibrated energy models can delude the operational decision-making process. Results showed that percentage error for predicted energy savings could go as high as 24% for the poorly calibrated hourly model and 50% for the poorly calibrated monthly model.

To sum up, this chapter showed that monthly calibrated models satisfying ASHRAE Guideline 14 fitness criteria can still lead to unreliable energy-saving predictions. Consequently, models calibrated with hourly meter data yielded more accurate outcomes than monthly calibrated models. Therefore, models with more stable parameter estimates should be used for EEMs. Nevertheless, the accuracy of the monthly calibrated model can be improved by running the simulation a few times and using the average estimates as the calibrated model parameters.

4.2. Improved workflow for BEM calibration

The main findings from this chapter are summarized as follows:

- Through automated calibration with operational schedules and setpoints extracted from BAS, labour (reducing or eliminating the need for on-site measurements) and computational cost (decreased number of unknown parameters) of white-box BEMs can be lowered.
- Operational parameters like SAT and RAT, SF and RF, SAH and RAH, supply volumetric airflow rate, supply, and return air duct static differential pressure, thermal zone room temperatures, VAV supply volumetric airflow rate, and damper and valve position signals were used in the base model to decrease the number of unknown parameters to be estimated through calibration.

- Several different models can meet the ASHRAE Guideline 14 acceptance criteria and may be considered "calibrated" for the same building; non-unique solutions, therefore, remain a crucial issue with model calibration. However, BAS data provides actual data on a building's operation system; hence a unique and accurate model can be achieved.
- To illustrate the proposed workflow, a building in Ottawa, Canada, was calibrated. For both monthly and hourly calibration, both models satisfied ASHRAE Guideline 14 fitness criteria to meter data. Improved workflow achieved a simple and accurate model that broadly captures the dynamic heat behavior of the building.
- If calibrated white-box BEMs can be developed rapidly, they can be useful to evaluate low-cost controls and operation measures to lower energy consumption at no capital cost.
- The magnitude of the energy savings possible (34%) with controls interventions (DCV, SATR, economizer configurations) in the case study building emphasized how buildings of all vintages can benefit significantly from operational implementations, regardless of envelope quality.
- Demonstrating up to 34% savings by operational optimization may help stakeholders justify the funding required to upgrade BASs and sensing infrastructure instead of considering high-cost EEMs. Operational optimization interventions are cost-effective and non-intrusive.

Therefore, this chapter showed that exploiting BAS data to decrease the number of unknown model parameters can reduce the engineering cost of the calibration. These quick and automatically calibrated models can be employed to evaluate operational EEMs.

4.3. Research contributions

4.3.1. Accuracy of BEM calibration process

The analysis presented in this chapter contributes to a growing body of literature on the uncertainty of the automated calibration of white-box BEMs and their operational decision-making capability. This particular study focused explicitly on the automated calibration of white-box energy models. Although the existing guidelines provide calibrated simulation procedures, the literature review showed that they do not offer a methodology to calibrate a model to measured data [51], [115]. To this end, this study aimed to demonstrate the imperfections in the model calibration process and highlighted how these imperfections translate into the building performance simulation-based operational decision-making process. The results of this study were presented in BS2021: 17th Conference of International Building Performance Simulation Association. In addition, the findings of this study have been shared with our collaborating industry partners.

4.3.2. Improved workflow for BEM calibration

The research review showed that the industry needs practical and low-cost methods to calibrate BEMs to evaluate EEMs. Despite their potential to increase the efficiency of the calibration process, there is currently little use of BAS data in calibration [50], [99]. Hence, this chapter study aimed to take advantage of BAS data to achieve a low-cost, lightweight, and accurate BEM. Moreover, this research also involved studying the savings through operational changes on the calibrated model. The findings of this study have been shared with collaborating industry partners.

4.4. Recommendations for future work

Over the course of this thesis, several research topics arose that warrant further study, including:

- The performance of the model calibration process is assessed based on the optimization algorithm's ability to estimate the unknown parameters. Therefore, other optimization algorithms need to be tested. The effect of changing the optimization algorithm and comparing the estimation accuracy would be a worthy research question.
- The computational load and run time and the performance of the GA highly depend on the hyperparameter selection. Therefore, alternating the GA hyperparameters and comparing the estimation stability and computational load should be examined.
- Increasing the number of design and operation parameters to calibrate is expected to increase a model's fitness; however, it is also expected to increase the computational cost and the risk of over-parametrization. The relationship between the number of parameters to optimize and the incremental performance benefits should be studied in detail.
- The impact of the representation of thermal zones in the BEM on the calibration performance was not studied in this thesis; therefore, the impact of zoning on calibration accuracy should be investigated.
- It should be noted that the findings of this research are explicitly related to the case study building's HVAC configuration and operational characteristics. The benefits of such an approach should be thoroughly explored for other case study buildings.

References

[1] Araya, Daniel B., Katarina Grolinger, Hany F. ElYamany, Miriam AM Capretz, and Girma Bitsuamlak. "An ensemble learning framework for anomaly detection in building energy consumption." Energy and Buildings 144 (2017): 191-206.

[2] UN Environment Programme, "2020 Global Status Report for Buildings and Construction," Glob. Status Rep., pp. 20–24, 2020, [Online]. Available: www.iea.org.

[3] NRCan, "Energy Efficiency Trends in Canada, 1990 to 2017.," 2017. https://oee.rncan.gc.ca/publications/statistics/trends/2017/commercial.cfm (accessed Nov. 12, 2021).

[4] Natural Resources Canada. (2019). Survey of Commercial and Institutional Energy Use - Buildings 2014 - Detailed Statistical Report 2019.

[5] Afroz, Zakia, H. Burak Gunay, and William O'Brien. "A review of data collection and analysis requirements for certified green buildings." Energy and buildings (2020): 110367.

[6] Newsham, Guy R., Sandra Mancini, and Benjamin J. Birt. "Do LEED-certified buildings save energy? Yes, but…." Energy and Buildings 41.8 (2009): 897-905.

[7] Bynum, J., D. E. Claridge, W. D. Turner, S. Deng, and G. Wei. "The Cost-Effectiveness of Continuous Commissioning® Over the Past Ten Years." (2008).

[8] Hong, Tianzhen, Jared Langevin, and Kaiyu Sun. "Building simulation: Ten challenges." In Building Simulation, vol. 11, no. 5, pp. 871-898. Springer Berlin Heidelberg, 2018.

[9] Roper, Kathy, and Richard Payant. The facility management handbook. Amacom, 2014.

[10] Gunay, Burak, Weiming Shen, and Chunsheng Yang. "Characterization of a building's operation using automation data: A review and case study." Building and Environment 118 (2017): 196-210.

[11] Parker, James, Paul Cropper, and Li Shao. "A calibrated whole building simulation approach to assessing retrofit options for Birmingham airport." Proceedings of the IBPSA—England (2012).

[12] Chantrelle, Fanny Pernodet, Hicham Lahmidi, Werner Keilholz, Mohamed El Mankibi, and Pierre Michel. "Development of a multicriteria tool for optimizing the renovation of buildings." Applied Energy 88, no. 4 (2011): 1386-1394

[13] Gunay, H. Burak, Mohamed Ouf, Guy Newsham, and William O'Brien. "Sensitivity analysis and optimization of building operations." Energy and Buildings 199 (2019): 164-175.

[14] Gunay, H. Burak, Guy Newsham, Araz Ashouri, and Ian Wilton. "Deriving sequences of operation for air handling units through building performance optimization." Journal of Building Performance Simulation 13, no. 5 (2020): 501-515.

[15] Yan, Da, William O'Brien, Tianzhen Hong, Xiaohang Feng, H. Burak Gunay, Farhang Tahmasebi, and Ardeshir Mahdavi. "Occupant behavior modeling for

building performance simulation: Current state and future challenges." Energy and buildings 107 (2015): 264-278.

[16] Abuimara, T., William O'Brien, B. Gunay, Aly Abdelalim, Mohamed Ouf, and Sara Gilani. "Modelling occupants in buildings: Stakeholders' workshop on current Barriers, challenges and needs." IBPSA-Canada eSim 2018 (2018): 312-320.

[17] Hobson, Brodie W., Daniel Lowcay, H. Burak Gunay, Araz Ashouri, and Guy R. Newsham. "Opportunistic occupancy-count estimation using sensor fusion: A case study." Building and environment 159 (2019): 106154.

[18] Natural Resources Canada, Survey of Commercial and Institutional Energy Use - Buildings 2009 - Detailed Statistical Report 2012. 2012.

[19] Guan, Xiaohong, Zhanbo Xu, and Qing-Shan Jia. "Energy-efficient buildings facilitated by microgrid." IEEE Transactions on smart grid 1, no. 3 (2010): 243-252.

[20] NRCan, "Energy savings toolbox: An energy audit manual and tool," Ottawa, Canada, 2011.

[21] ASHRAE, Procedures for Commercial Building Energy Audits, 2nd edition Atlanta: ASHRAE, 2011.

[22] O'Neill, Zheng, Xiufeng Pang, Madhusudana Shashanka, Philip Haves, and Trevor Bailey. "Model-based real-time whole building energy performance monitoring and diagnostics." Journal of Building Performance Simulation 7, no. 2 (2014): 83-99.

[23] ASHRAE, "ASHRAE Guideline 14: Measurement of Energy, Deamnd, and Water Savings," vol. 8400, pp. 1–165, 2014.

[24] Gunay, Burak, Weiming Shen, and Guy Newsham. "Inverse blackbox modeling of the heating and cooling load in office buildings." Energy and Buildings 142 (2017): 200-210.

[25] Burak Gunay, H., Weiming Shen, Guy Newsham, and Araz Ashouri. "Detection and interpretation of anomalies in building energy use through inverse modeling." Science and Technology for the Built Environment 25, no. 4 (2019): 488-503.

[26] Zhu, Jin, Yingjun Shen, Zhe Song, Dequn Zhou, Zijun Zhang, and Andrew Kusiak. "Data-driven building load profiling and energy management." Sustainable Cities and Society 49 (2019): 101587.

[27] Coakley, Daniel, Paul Raftery, and Marcus Keane. "A review of methods to match building energy simulation models to measured data." Renewable and sustainable energy reviews 37 (2014): 123-141.

[28] Raftery, Paul, Marcus Keane, and Andrea Costa. "Calibrating whole building energy models: Detailed case study using hourly measured data." Energy and buildings 43, no. 12 (2011): 3666-3679.

[29] O'Neill, Zheng, and Bryan Eisenhower. "Leveraging the analysis of parametric uncertainty for building energy model calibration." In Building Simulation, vol. 6, no. 4, pp. 365-377. Springer Berlin Heidelberg, 2013.

[30] Liu, Simeng, and Gregor P. Henze. "Calibration of building models for supervisory control of commercial buildings." Proc. (IBPSA)'05 (2005).

[31] Heo, Yeonsook, Ruchi Choudhary, and G. A. Augenbroe. "Calibration of building energy models for retrofit analysis under uncertainty." Energy and Buildings 47

(2012): 550-560.

[32] Hong, Taehoon, Jimin Kim, Jaemin Jeong, Myeonghwi Lee, and Changyoon Ji. "Automatic calibration model of a building energy simulation using optimization algorithm." Energy Procedia 105 (2017): 3698-3704.

[33] Ruiz, Germán Ramos, and Carlos Fernández Bandera. "Validation of calibrated energy models: Common errors." Energies 10, no. 10 (2017): 1587.

[34] Huang, W., and H. N. Lam. "Using genetic algorithms to optimize controller parameters for HVAC systems." Energy and Buildings 26, no. 3 (1997): 277-282.

[35] Evins, Ralph. "A review of computational optimisation methods applied to sustainable building design." Renewable and sustainable energy reviews 22 (2013): 230-245.

[36] Lu, Yuehong, Shengwei Wang, Chengchu Yan, and Zhijia Huang. "Robust optimal design of renewable energy system in nearly/net zero energy buildings under uncertainties." Applied energy 187 (2017): 62-71.

[37] Manfren, Massimiliano, Niccolò Aste, and Reza Moshksar. "Calibration and uncertainty analysis for computer models–a meta-model-based approach for integrated building energy simulation." Applied energy 103 (2013): 627-641.

[38] Monari, Filippo, and Paul Strachan. "CALIBRO: An R package for the automatic calibration of building energy simulation models." Building Simulation 2017 (2017).

[39] Nguyen, Anh-Tuan, Sigrid Reiter, and Philippe Rigo. "A review on simulation-based optimization methods applied to building performance analysis." Applied Energy 113 (2014): 1043-1058.

[40] International Energy Agency (IEA), "Transition to Sustainable Buildings. Strategies and Opportunities to 2050," Paris, France, 2013.

[41] United Nations Environment Programme. Buildings can play key role in combating climate change. SBCI-Sustainable Construction and Building Initiative. Updated:2007. <http://www.unep.org/Documents.Multilingual/ Default.Print.asp>. [accessed 09.21].

[42] NECB, "National Energy Code of Canada for Buildings," Ottawa, Canada, 2017.

[43] Chaudhary, Gaurav, Joshua New, Jibonananda Sanyal, Piljae Im, Zheng O'Neill, and Vishal Garg. "Evaluation of "Autotune" calibration against manual calibration of building energy models." Applied energy 182 (2016): 115-134.

[44] Chong, Adrian, and Khee Poh Lam. "Uncertainty analysis and parameter estimation of HVAC systems in building energy models." In Proceedings of the 14th IBPSA building simulation conference, vol. 1, no. 1.4, p. 3. 2015.

[45] Reddy, T. Agami. "Literature review on calibration of building energy simulation programs uses, problems, procedures, uncertainty, and tools." ASHRAE transactions 112 (2006): 226.

[46] Tahmasebi, Farhang, Robert Zach, Matthias Schuß, and Ardeshir Mahdavi. "Simulation model calibration: An optimization-based approach." In Proceedings of Fourth German-Austrian IBPSA Conference, BauSIM, pp. 386-91. 2012.

[47] Mahdavi, Ardeshir, Farhang Tahmasebi, and Mine Kayalar. "Prediction of plug

loads in office buildings: Simplified and probabilistic methods." Energy and Buildings 129 (2016): 322-329.

[48] Gunay, H. Burak, William O'Brien, Ian Beausoleil-Morrison, and Sara Gilani. "Modeling plug-in equipment load patterns in private office spaces." Energy and Buildings 121 (2016): 234-249.

[49] Cipriano, Jordi, G. Mor, D. Chemisana, D. Pérez, G. Gamboa, and X. Cipriano. "Evaluation of a multi-stage guided search approach for the calibration of building energy simulation models." Energy and Buildings 87 (2015): 370-385.

[50] Mustafaraj, Giorgio, Dashamir Marini, Andrea Costa, and Marcus Keane. "Model calibration for building energy efficiency simulation." Applied Energy 130 (2014): 72-85.

[51] Sun, Jian, and T. Agami Reddy. "Calibration of building energy simulation programs using the analytic optimization approach (RP-1051)." HVAC&R Research 12, no. 1 (2006): 177-196.

[52] Westphal, Fernando Simon, and Roberto Lamberts. "Building simulation calibration using sensitivity analysis." In Ninth International IBPSA Conference, pp. 1331-1338. 2005.

[53] Westphal, Fernando Simon, and Roberto Lamberts. "Building simulation calibration using sensitivity analysis." In Ninth International IBPSA Conference, pp. 1331-1338. 2005.

[54] Shen, Weiming, Guy Newsham, and Burak Gunay. "Leveraging existing occupancy-related data for optimal control of commercial office buildings: A review." Advanced Engineering Informatics 33 (2017): 230-242.

[55] Deng, Qianli, Xianglin Jiang, Qingbin Cui, and Limao Zhang. "Strategic design of cost savings guarantee in energy performance contracting under uncertainty." Applied Energy 139 (2015): 68-80.

[56] IPCC, "Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Synthesis Report.," 2014.

[57] U.S. Energy Information Admnistration, "International Energy Outlook 2019," U.S. Energy Inf. Adm., vol. September, no. 09, pp. 25–150, 2019.

[58] Venterea, Rodney T. "Climate Change 2007: Mitigation of Climate Change." Journal of Environmental Quality 38, no. 2 (2009): 837.

[59] Schmidhuber, Jürgen. "Curious model-building control systems. In [Proceedings] 1991 IEEE International Joint Conference on Neural Networks." IEEE, Singapore (1991): 1458-1463

[60] Katipamula, Srinivas, and Michael R. Brambley. "Review Article: Methods for Fault Detection." Diagnostics, and Prognostics for Building Systems—A Review, Part II Methods for Fault Detection, Diagnostics, and Prognostics for Building Systems—A Review, Part II 9669 (2005): 37-41.

[61] Abuimara, Tareq, Brodie W. Hobson, Burak Gunay, William O'Brien, and Michael Kane. "Current state and future challenges in building management: practitioner interviews and a literature review." Journal of Building Engineering (2021): 102803.

[62] Jason Glazer PE, B. E. M. P. "Development of maximum technically achievable energy targets for commercial buildings." ASHRAE Transactions 123 (2017): 32.

[63] Kneifel, Joshua. "Life-cycle carbon and cost analysis of energy efficiency measures in new commercial buildings." Energy and buildings 42, no. 3 (2010): 333-340, 2010, doi: 10.1016/j.enbuild.2009.09.011.

[64] Morrissey, John, and Ralph E. Horne. "Life cycle cost implications of energy efficiency measures in new residential buildings." Energy and buildings 43, no. 4 (2011): 915-924.

[65] Hensen, Jan LM, and Roberto Lamberts. "Building performance simulation–challenges and opportunities." In Building Performance Simulation for Design and Operation, pp. 1-10. Routledge, 2019.

[66] De Wilde, Pieter. "The gap between predicted and measured energy performance of buildings: A framework for investigation." Automation in construction 41 (2014): 40-49.

[67] Menezes, Anna Carolina, Andrew Cripps, Dino Bouchlaghem, and Richard Buswell. "Predicted vs. actual energy performance of non-domestic buildings: Using post-occupancy evaluation data to reduce the performance gap." Applied energy 97 (2012): 355-364.

[68] Imam, Salah, David A. Coley, and Ian Walker. "The building performance gap: Are modellers literate?" Building Services Engineering Research and Technology 38, no. 3 (2017): 351-375.

[69] Turner, Cathy, Mark Frankel, and U. G. B. Council. "Energy performance of LEED for new construction buildings." New Buildings Institute 4, no. 4 (2008): 1-42.

[70] Yoshino, Hiroshi, Tianzhen Hong, and Natasa Nord. "IEA EBC annex 53: Total energy use in buildings—Analysis and evaluation methods." Energy and Buildings 152 (2017): 124-136.

[71] Chong, Adrian, Yaonan Gu, and Hongyuan Jia. "Calibrating building energy simulation models: A review of the basics to guide future work." Energy and Buildings (2021): 111533.

[72] Ji, Ying, and Peng Xu. "A bottom-up and procedural calibration method for building energy simulation models based on hourly electricity submetering data." Energy 93 (2015): 2337-2350.

[73] Li, Wancheng, Zhe Tian, Yakai Lu, and Fawei Fu. "Stepwise calibration for residential building thermal performance model using hourly heat consumption data." Energy and Buildings 181 (2018): 10-25.

[74] Chaudhary, Gaurav, Joshua New, Jibonananda Sanyal, Piljae Im, Zheng O'Neill, and Vishal Garg. "Evaluation of "Autotune" calibration against manual calibration of building energy models." Applied energy 182 (2016): 115-134.

[75] Hong, Tianzhen, Le Yang, David Hill, and Wei Feng. "Data and analytics to inform energy retrofit of high-performance buildings." Applied Energy 126 (2014): 90-106.

[76] ASHRAE Standard Committee, Ashrae handbook: fundamentals 2013. 2013.

[77] Zhang, Yuna, Zheng O'Neill, Bing Dong, and Godfried Augenbroe. "Comparisons of inverse modeling approaches for predicting building energy performance."

Building and Environment 86 (2015): 177-190.

[78] Coakley, Daniel, Paul Raftery, and Marcus Keane. "A review of methods to match building energy simulation models to measured data." Renewable and sustainable energy reviews 37 (2014): 123-141.

[79] Nagpal, Shreshth, Caitlin Mueller, Arfa Aijazi, and Christoph F. Reinhart. "A methodology for auto-calibrating urban building energy models using surrogate modeling techniques." Journal of Building Performance Simulation 12, no. 1 (2019): 1-16.

[80] Hou, D., I. G. Hassan, and L. Wang. "Review on building energy model calibration by Bayesian inference." Renewable and Sustainable Energy Reviews 143 (2021): 110930.

[81] Ciulla, G., and A. D'Amico. "Building energy performance forecasting: A multiple linear regression approach." Applied Energy 253 (2019): 113500.

[82] Subbarao, Kris, Srijan Didwania, T. Agami Reddy, and Marlin Addison. "The Enhanced Parameter Estimation (EPE)--A New Calibration Methodology for Building Energy Simulations." arXiv preprint arXiv:2103.07283 (2021).

[83] Braun, James E., and Nitin Chaturvedi. "An inverse gray-box model for transient building load prediction." HVAC&R Research 8, no. 1 (2002): 73-99.

[84] Kandil, Alaa-Eldin, and James A. Love. "Signature analysis calibration of a school energy model using hourly data." Journal of Building Performance Simulation 7, no. 5 (2014): 326-345. [85] "International Performance Measurement and Verification Protocol (IPMVP), vol. 1, 2002."

[86] Harmer, Lincoln C., and Gregor P. Henze. "Using calibrated energy models for building commissioning and load prediction." Energy and Buildings 92 (2015): 204-215.

[87] Fabrizio, Enrico, and Valentina Monetti. "Methodologies and advancements in the calibration of building energy models." Energies 8, no. 4 (2015): 2548-2574. [88] S. I. Gustafsson, "Sensitivity analysis of building energy retrofits," Appl. Energy, vol. 61, no. 1, pp. 13–23, 1998, doi: 10.1016/S0306-2619(98)00032-4.

[89] Westphal, Fernando Simon, and Roberto Lamberts. "Building simulation calibration using sensitivity analysis." In Ninth International IBPSA Conference, pp. 1331-1338. 2005.

[90] Gibbs, Matthew S., Holger R. Maier, Graeme C. Dandy, and John B. Nixon. "Minimum number of generations required for convergence of genetic algorithms." In 2006 IEEE International Conference on Evolutionary Computation, pp. 565-572. IEEE, 2006.

[91] Vrajitoru, Dana. "Large population or many generations for genetic algorithms? Implications in information retrieval." In Soft Computing in Information Retrieval, pp. 199-222. Physica, Heidelberg, 2000.

[92] Hassanat, Ahmad, Khalid Almohammadi, Esra Alkafaween, Eman Abunawas, Awni Hammouri, and V. B. Prasath. "Choosing mutation and crossover ratios for genetic algorithms—a review with a new dynamic approach." Information 10, no. 12 (2019): 390.

[93] Hong, Taehoon, Jimin Kim, Jaemin Jeong, Myeonghwi Lee, and Changyoon Ji. "Automatic calibration model of a building energy simulation using optimization algorithm." Energy Procedia 105 (2017): 3698-3704.

[94] Zang, Hongnian, Shujun Zhang, and Kevin Hapeshi. "A review of nature-inspired algorithms." Journal of Bionic Engineering 7, no. 4 (2010): S232-S237.

[95] Carling, Par, Isakson, Per, Blomberg, Per, and Eriksson, Jorgen. "Experiences from evaluation of the HVAC performance in the Katsan building based on calibrated whole building simulation and extensive trending, 2003 (Accessed January 2021, http://www. commissioning-hvac.org/files/doc/A40-D-M6-SWE-%C3%85F_KTH-2.pdf)," IEA Annex40Work.Paper, [Online].

[96] Pang, Xiufeng, Michael Wetter, Prajesh Bhattacharya, and Philip Haves. "A framework for simulation-based real-time whole building performance assessment." Building and Environment 54 (2012): 100-108.

[97] Zibin, Nicholas, Radu Zmeureanu, and James Love. "Bottom-up simulation calibration of zone and system level models using building automation system (BAS) trend data."

[98] Zibin, N., Zmeureanu, R. and Love, J., 2016. Automatic assisted calibration tool for coupling building automation system trend data with commissioning. Automation in Construction, 61, pp.124-133.

[99] Mihai, Andreea, and Radu Zmeureanu. "Bottom-up evidence-based calibration of the HVAC air-side loop of a building energy model." Journal of Building Performance Simulation 10, no. 1 (2017): 105-123.

[100] ASHRAE, ASHRAE Standard, "55, Thermal environmental conditions for human occupancy." (2013).

[101] Evans, M., H. Chon, B. Shui, and S. E. Lee. "Country report on building energy codes in Republic of Korea." Pacific Northwest National Laboratory (2009): 1-26.

[102] National Research Council Canada. (2017). National Energy Code of Canada for Buildings 2017. Government of Canada.

[103] Gunay, H. Burak, Araz Ashouri, Weiming Shen, Guy Newsham, and William O'Brien. "A Preliminary Analysis on the Use of Low-Cost Data Streams for Occupant-Count Estimation." ASHRAE Transactions 125, no. 2 (2019).

[104] Mahdavi, Ardeshir, Farhang Tahmasebi, and Mine Kayalar. "Prediction of plug loads in office buildings: Simplified and probabilistic methods." Energy and Buildings 129 (2016): 322-329.

[105] O'Brien, William, Farhang Tahmasebi, Rune Korsholm Andersen, Elie Azar, Verena Barthelmes, Zsofia Deme Belafi, Christiane Berger, et al. "An international review of occupant-related aspects of building energy codes and standards." Building and Environment 179 (2020): 106906.

[106] Mososo, O. T., and L. J. Grobler. "The dark side of occupants' behaviour on building energy use." Energy and Buildings 42 (2010): 173-177.

[107] Bennet, Isis E., and William O'Brien. "Office building plug and light loads: Comparison of a multi-tenant office tower to conventional assumptions." Energy and Buildings 153 (2017): 461-475. [108] T. Culp, S. Widder, and K. Cort,

"Thermal and Optical Properties of Low-E Storm Windows and Panels," Pacific Northwest Natl. Lab., no. July, p. 79, 2015, [Online]. Available: https://www.pnnl.gov/main/publications/external/technical_reports/PNNL-24444.pdf.

[109] National Resources Canada, "Energy Efficiency Ratings," 2011. https://oee.nrcan.gc.ca/pml-lmp/index.cfm?action=app.search-recherche&appliance=WINDOWS_GH.

[110] ASHRAE, "ANSI/ASHRAE/IES 90.1-2019: Energy Standard for Buildings Except Low-Rise Residential Buildings," Atlanta, GA, 2019.

[111] ASHRAE, "ANSI/ASHRAE Standard 62.1-2019: Ventilation for Acceptable Indoor Air Quality," 2019.

[112] Lin, Hung-Wen, and Tianzhen Hong. "On variations of space-heating energy use in office buildings." Applied Energy 111 (2013): 515-528.

[113] Wang, Liping, Paul Mathew, and Xiufeng Pang. "Uncertainties in energy consumption introduced by building operations and weather for a medium-size office building." Energy and Buildings 53 (2012): 152-158.

[114] "Federal Energy Management Program (FEMP), Measurement and Verification Guideline, (Chapter 25), 2000."

[115] Chong, Adrian, Weili Xu, and Khee Poh Lam. "Uncertainty analysis in building energy simulation: a practical approach." In 14th International IBPSA Conference, edited by J. Mathur and V Garg, pp. 2796-2803. 2015.