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A PROTOCOL-BASED, INVERSE-MODEL-DRIVEN METHODOLOGY FOR BUILDING AUDITING AND FORWARD ENERGY MODEL FORMULATION

A Dissertation in

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by

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ABSTRACT

The commercial and residential building sectors consume approximately 40% of all U.S primary energy each year and 70% of all generated electricity. In the commercial building sector, office buildings use the largest percentage of primary and derived energy. System upgrades and renovations are applied in office buildings to achieve energy reduction. To estimate energy savings after a renovation or equipment retrofit, measurement and verification (M&V) is conducted. Various methods have been established which use energy models and benchmarking tools to track and assesse savings.

This dissertation demonstrates two methods to formulate inverse regression models of a building's as operated energy utilization. Two advanced and robust variable selection techniques -Least Absolute Shrinkage and Selection Operator (LASSO), and Variable Selection though Smoothly Clipped Absolute Deviation Penalty (SCAD) - are implemented as part of the regression based model development. It is established that independent variables determined to be important in influencing building energy models use should be metered prior to the building retrofit or audit.

A medium sized office building developed by U.S Department of Energy (DOE), also known as the DOE commercial reference buildings is utilized to develop the model formulation methodology. The building represents an average condition of numerous buildings in the US medium size office building sector. The "typical" office building condition is established as a baseline model case for the analysis. Input data variation, models generations and independent variable selections are determined using the baseline building through the use of EnergyPlus and Matlab tools. Multi-variant regression models are formulated for whole building energy utilization, the cooling system and heating sub-system utilization. Statistical indices indicate that the models developed though the two methods are valid and effective in confidently predicting

building energy utilization. Though the LASSO and SCAD variable selection techniques, key variables that are statistically significant to building energy use are identified. Those variables should be given priority in any building monitoring plan as their characterization with assist in energy utilization analyses to continuously improve building energy performance.

In addition to establishing inverse model formulation though variable selection techniques, this investigation developed a variation bin method to identify “inefficient” sub-system utilization in building energy use. The idea of bin method is to compare energy variation of sub-systems’ data by excluding impacts from ambient weather conditions. The advantages of this method are obvious. Firstly, it is easy and straightforward to apply. Secondly, it can be applied to the entire metered sub-systems data.

The methodology is used to formulate as-operated, low variance forward building energy models. Forward building energy models enables parametric analysis to evaluate design or renovation strategies. It allows energy efficiency estimates that can be achieved by implementation of energy standards or codes and assists in application for design certifications. As-operated building energy models are often developed to assist energy conservation measures (ECMs) design and evaluation. The methodology developed in this investigation results in an actual data based, sub-system focused energy model. The methodology avoids trial and error, time consuming, labor intensive approaches. The model is considered calibrated when simulated heating, cooling, plug and lighting sub-systems end use and whole building energy use meet predefined statistical criteria. Two medium size office buildings in Pennsylvania are selected as case studies and show that the method is valid and efficient. Monthly and weekday daily comparisons indicate that simulated results satisfy statistical criteria and models are considered as calibrated.

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There are millions of wonderful things ahead in life; another step is taken from here.

Chapter 1

Introduction

In 2010, the building sector in the US consumed 7% of global primary energy in the world and accounts for approximately 40% of primary energy in the US (DOE 2011). In Figure 1, it shows variety types of buildings based on the percentage of floor area. From the figure, office buildings are the largest type in commercial buildings which is 17%; the second largest is ware house and storage type which is 14.1% floor area. From commercial building energy survey (EIA 2012), office buildings consumed 19% of primary energy which is the largest energy consumer in commercial building sector. Design and built of green and sustainable office buildings are encouraged to provide low energy use, sustainable buildings for the nation and society. In the office building sector, retrofit current system is a cost-effective, feasible way to reduce energy consumption in the nation. The energy retrofits are typically implemented by installing several energy conservation measures (ECMs) in buildings. Energy reduction is estimated based on types of ECMs applied. In this dissertation, the research mainly focuses on medium size office buildings sector because they are the largest building type by floor area (%) and has immediate need for energy reduction.

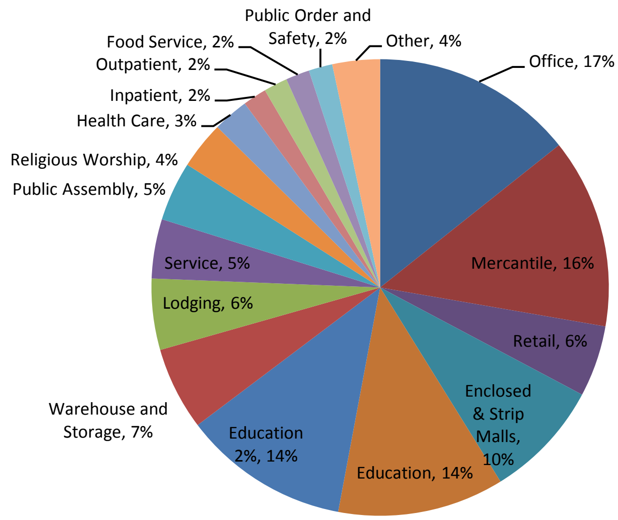


Figure 1-1. Building floor percentage by type.

In building industry, there is an increasing recognition for the importance of ECMs' validation, measurement and verification (M&V) process. Building auditing and M&V process allows building owners and researchers to detect causes of energy inefficiency and saving opportunities. The energy inefficiency can be caused by different reasons such as fault settings in control system, HVAC system degradation, operators' overwrite, irresponsible occupants' behavior. Building auditing and implement ECMs are widely applied in buildings to improve energy performance. The M&V process quantifies energy and capital savings from installation of corresponding ECMs. Common methods for assessing ECMs performance and savings are (1) direct comparison measured or estimated energy use in baseline (pre-retrofit) and post –retrofit period with weather normalization. (2) Formulate baseline empirical model with post retrofit conditions. (3) Detailed hourly energy modeling for baseline and after-retrofit conditions. Different modeling methods divide energy models into two categories: forward energy model and inverse energy model.

The forward energy model is typically applied for design to-be-built buildings and calibrated existing building models. The model requires comprehensive detailed input variables that describe building ambient weather conditions (dry bulb temperature, solar radiation etc.), geometry, envelop construction (material thermal properties, glazing information etc.), operational and occupants inputs (plug loads schedule, occupancy density etc.) and HVAC system characteristics, etc. The calibrated forward energy model is capable of predicting energy savings from installing specific ECMs and select optimal ECMs package. The critical step is model calibration to reduce degree of freedom with high certainty. In chapter 2, model calibration methods have been reviewed; corresponding benefits and problems are summarized.

Inverse energy model is a data driven, steady state analytical approach. It has been widely used in building retrofit projects. The model uses measured data as inputs and develops the relationship between empirical driving variables and energy use. Benefits of inverse model are obvious, it requires much less input variables than forward model and physical relationship is easy to understand. A well-developed inverse model saves labor effort on tuning and effectively assesses energy savings. Popular methods of the inverse model are reviewed in chapter 2 and problems are discussed.

1.1 Statement of problems and research questions

In general, two major energy modeling approaches are widely adopted: forward model and inverse model. The forward energy simulation provides energy use breakdown and considers complex interactions between building components. Given the data from energy monitor and utility bills, analyst is able to calibrate energy model and identify operational problems in buildings. A calibrated energy model is capable to quantify ECMs' savings and optimize retrofit plan. The inverse model is derived from actual measured data and expresses relationship between driving variables and dependent variable. Popular inverse models are: (1) single and multiple variants regression models. (2) Thermal network and artificial neural network. (3) Constant base and variable base degree day method. (4) Bin methods.

From previous research (Ahmad and Culp 2006), an un-calibrated forward model can have up to 75% of difference from actual data. Many efforts have been have been spent on developing "as-operated" building model. Conventional approach uses a top-down approach that matches building total energy use with utility bills by satisfying statistical criteria. The approach is not robust for several reasons. The calibration is an underdetermined problem which there is more "unknowns" than "knowns". An overall energy use match can't guarantee sub-level calibration. Building components and systems have interactions and corresponding errors mask each other at sub-system levels. Simulated sub-system end uses can vary from actual data significantly while total use shows a "fake" good match. The saving predictions for ECMs are unreliable if as-operated conditions are not well presented in the model. There is no consensus on specific steps reconciling the simulation results with actual data or lack of systematic validation of "as-operated" model. Energy modeler's personal judgement and experience plays an important role in practice. The detailed hourly energy simulation has numerous variables, it is imperative to find critical variables that are most influential to system end uses and overall energy use.

Traditional sensitivity analysis has limitations for example the interrelationship between variables can bias results or piecewise effect exits among variables and outcomes. Therefore, data screen and variables selection methods should be adopted to identify critical variables for system end use and whole building energy end use. Monitoring and tuning critical variables with great care can improve the confidence level of model prediction.

For inverse model development, popular methods are regression models, thermal network, artificial neural network, degree days. The model is based on historical performance (actual data) of buildings therefore it has no need for calibration. Among different inverse model approaches, regression model is convenient and widely accepted method. The key to a successful regression model is the selection of predictors. Conventionally, temperature is considered as one of the driving variables. However, when daily overall energy use is plotted against ambient dry bulb temperature, large scatters were found for example in two medium buildings in figure 1-2 and 1-3.

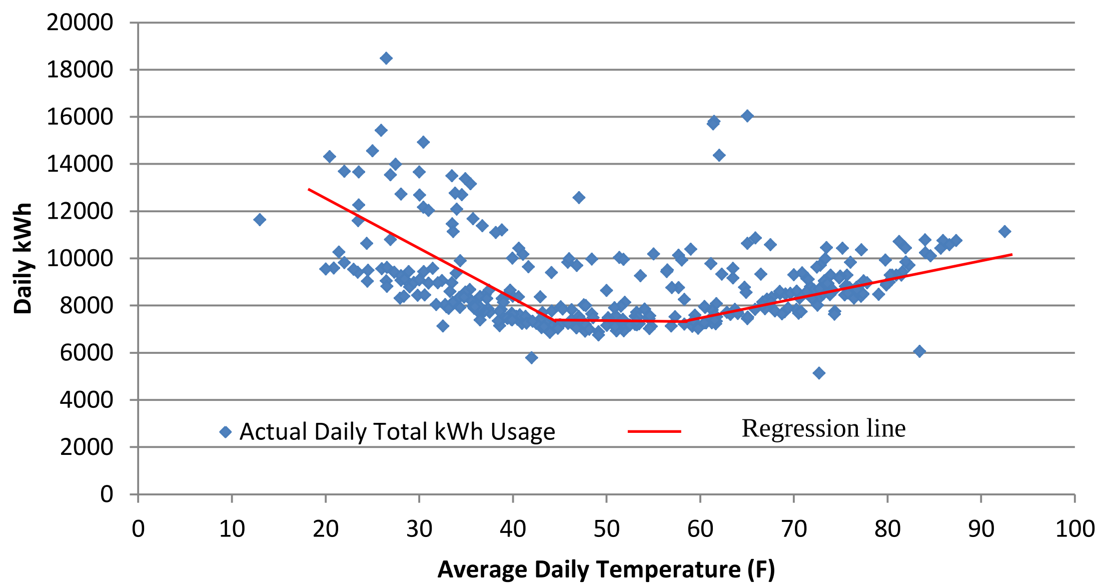


Figure 1-2. Case study building I electricity use vs. temperature.

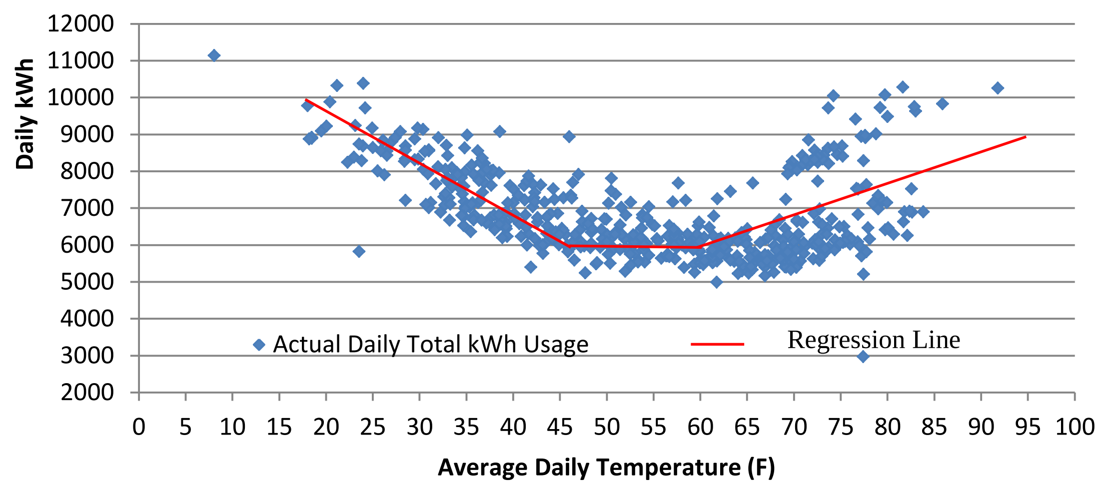


Figure 1-3. Case study building II electricity use vs. temperature.

From figures 1-2 and 1-3, under given temperature or a close temperature interval, building total energy use varies significantly. They show that large variation occurred along the inverse regression model, it appears to be two independent modes of operation which has very similar response to the ambient temperature but at different levels of energy use. Temperature is apparently an energy use driving variables, but the energy use is driven by other key independent variables as well. In current researches, little effort was spend on eliminating the discrepancies or explaining causes of variance. It is important to break down system end use to explain discrepancies and understand the variance. By including and monitoring critical variables, it helps setting up a more comprehensive model to simulate energy use and explain or eliminate the variance and discrepancy. Specific research questions are summarized to answers problems in statement above.

1. What independent variables in addition to dry bulb temperature should be monitored, auto-metering acquired to establish an inverse model formulation capable of reducing “scatter” in inverse model whole building energy formulation?
2. What protocoled methodology can be utilized to form a low variance inverse model of a building and an as-operated forward model to asses ECMs savings?

1.2 Research hypothesis and assumptions

The building energy and performance analysis is a critical method to reduce energy use, carbon emission and cost. Detailed forward energy modeling and inverse model techniques are widely adopted based on the goal of project or research. Inverse modeling techniques typically include regression model, thermal network, neural network, degree days and etc. Regression model is widely adopted because of its simplicity and convenience to understand. It finds the relationship between empirical key variables and dependent variables for example whole building energy use. However, the choice of key independent variables is based on user's personal judgement or experience. The ambient dry bulb temperature is intuitively considered relating to whole building energy use pattern. However, the reason for such large scatter of variation needs to be studied. Therefore, the first research hypothesis is that the building inverse model variance can be reduced or explained by adding more key variables or monitor several other variables in addition to dry bulb temperature.

The detailed energy modeling technique is typically applied in isolating savings from individual ECMs or design ECMs options to achieve best saving results. It involves 8760 hours simulation for a year, popular simulation software are EnergyPlus, eQUEST, IES VE etc. A complex building energy model has thousands of variables from different aspects of building, such as geometry, construction materials, mechanical system, control strategies etc. After the model is initially built, calibration is imperative and necessary to be performed before conducting calculation of energy savings from ECMs. From literature review, there is no consensus or well accepted method for model calibration. To answer the second research question in chapter 1.1, the second hypothesis is that a protocoled based model calibration method can be developed to continuously calibrate forward building energy model. While at meantime, the simulated results can formulate low variance inverse model that enables assessment of savings from ECMs.

This research adopts detailed hourly energy simulation software EnergyPlus as the simulation tool to provide detailed data, perform variable selection, regression inverse model investigation and case study validation. The EnergyPlus is an open source, fully integrated building simulation software developed by US Department of Energy (DOE). It is a robust, simultaneously simulation of primary and secondary systems. It can provide sub-hourly, user defined time steps simulation; modular systems, zone heat balance calculation, multi-zone air flow calculation and water usage and natural ventilation simulation. The EnergPlus is frequently upgraded and extensively validated. (Judkoff and Neymark 2006) summarized several ways of testing the validity and accuracy of detailed whole building simulation software and EnergyPlus has been tested for example: (a) Analytical tests: ASHREA Research Project 865 tested the HVAC simulation capability. ASHRAE Research Project 1052 tested EnergyPlus building fabric calculations. (b) Comparative tests: ANSI/ASHRAE Standard 140-211, International Energy Agency Solar Heating and Cooling Program (IEA SHC) BESTest (Building Energy Simulation Test Methods). EnergyPlus is adopted as the primary building simulation tool in this dissertation. The research assumes that: The energy simulation program is able to provide accurate, as-operated simulation results when the input variables are well selected and determined to represent the reality. The difference between simulation and actual conditions is caused by software limitation or approximation instead of the problems in coding or algorithm.

The second assumption is: the building energy consumption is only influenced by its inner system and variables. Neighbors, micro-weather creates negligible influence on system end uses and whole building energy use.

1.3 Research objectives

From the research questions and hypothesis, objectives are summarized as follows:

1) Identify key variables in addition to dry bulb temperature that lead to the formulation of an office building energy use inverse regression models.
2) Explain key variables or causes in buildings that results in significant scatters of energy use under same temperature or close temperature interval.

3) Develop a method that can improve the accuracy and confidence level of a forward building energy model for energy conservation measure (ECM) prioritization and selection.
4) Provide strategies that can develop low variance inverse model from calibrated forward energy model simulation results.

1.4 Dissertation outline

Chapter 2 is the literature review for inverse model and forward modeling techniques. Advantages and shortcomings of each approach is summarized and compared. Chapter 3 introduces two variable selection methods in inverse model development. Chapter 4 introduces the frame work and steps of inverse model establishment. Chapter 5 presents the developed Bin-method to explore causes of energy variation in building inverse model with case study analysis. Chapter 6 discusses the iterative forward energy model calibration loop. In this chapter, two medium-size office buildings are demonstrated as case studies to validate model calibration method. Inverse models are formulated based on simulated results. Chapter 7 summarizes results and provides conclusions in this dissertation. Future research recommendations and suggestions are also discussed.

Chapter 2

Literature Review

2.1 Forward modeling techniques

Energy simulation provides an insight of energy flow inside the building. In measurement and verification (M&V) process, forward energy model gives an approach to isolate savings from each ECM. The first step is to build up an as-operate model via calibration. The discrepancies between simulated model and actual utility data could be influenced by many factors, for example input variables uncertainty, faulty operation or control in the building. (Ahmad and Culp 2006) believes the discrepancies can be 30% of the total energy consumption with one outlier. At individual component level, the un-calibrated model could have ± 90% difference from the actual use. (Judkoff, Wortman et al. 2008) believes at monthly level, an un-calibrated model results in 50% -100% variations from the actual use. Calibrating the energy model is significant in estimating energy consumption and calculation of ECMs' savings.

(Judkoff, Wortman et al. 2008) conducted a comprehensive study on validating building energy simulation analysis. The report covers the methods and approaches for model validation, analytical verification and comparative case studies for different energy simulation software and has a discussion on the numerical solutions. The report claimed seven main sources of error: 1) Actual weather conditions and typical meteorological year (TMY) difference. 2) Human behavior in reality is different from the assumptions or schedules in simulation software and it is a main source of discrepancy 3) Input error by individual user (Energy Modeler). 4) As-built building thermal characteristics are different from the assumed or handbook values. 5) The actual heat transfer process is more complicated than the calculation mechanism or algorithm in the software.

6) At component level, the interactions are different from actual heat transfer mechanisms. 7) Possible coding errors in simulation engine.

In practice, simulated building energy consumption is compared with real building utility bill data with little or no effort to solve the difference. This is not an easy task, the masking effect at certain time interval will cover errors from above sources. A good match between simulated and actual data at monthly or annual level can't guarantee the model is valid. The report divided error sources into external and internal category. The control of external error has higher priority than internal errors. The external sources of error are errors that result from inaccurate user input or data measurement. The internal error is defined as the energy simulation software limitation or calculation approximation. External errors are major sources of discrepancy between simulated results and real data. The report considered occupants is the largest source for discrepancy. The simulated heat transfer mechanism in simulation engine provides less error than sources 1, 2 and 3. The validation of simulated results is often constrained by the limited number of data. Extrapolation should be avoided as much as possible. The study reported several extrapolation errors in the practice.

Table 2-1 Model simulation source of errors.

Real Data	**Extrapolation**
A few climates	Many climates
Short-term(Monthly) total energy usage	Long-term(yearly) total energy usage
Short-term(hourly) temperature or fluxes	Long-term(yearly) total energy use and temperature extremes
A few buildings representing a few sets of variable mixes	Many buildings representing many sets of variable mixes
Small-scales, simple test cells and buildings	Large-scale complex buildings

The weather data file should cover enough range to represent heat transfer conditions in the building. The study found out that the weather data resulted error could be 50% of the total energy consumption. Extrapolation error 4 and 5 is hard to overcome in reality, but this is an acceptable extrapolation. The study also compared the advantages and disadvantages of comparative, analytical and empirical modeling techniques and concluded that the existing data base is not enough to identify influential input data for particular building type. The analytical approach showed the conduction heat transfer at component level is accurate. The study also suggested that code-to-code comparison is necessary, especially for solar-driven buildings with large thermal mass. From the research, a clearly defined method of energy model validation and system level comparison are necessary to unveil the ambiguity between simulated results and actual use.

(Reddy, Maor et al. 2007) described the methodology in calibrating building energy with measured data in (Reddy, Maor et al. 2007) presents the application of the methodology on three case study buildings. The methodology is concluded as 1) based on the type and functions of target building, heuristically find a group of influential variables and schedules inputs that clearly match building characteristics and have reasonable guesses for unmeasured data. 2) A coarse grid search is used to find influential variables and the bound of variability. 3) A guided grid search to further improve selected influential variables' vectors. 4) Using a group of solutions to predict the energy consumption and uncertainties of the calibration. The previous calibration process heavily depends on users' knowledge, judgment and expertise. Sensitivity analysis has been widely used in tackling such issue for example in (Saltelli 2002), (Frey 2002) and (Christopher Frey and Patil 2002). In(Reddy, Maor et al. 2007), the methodology is applied to find a group appropriate solution is shown in figure 2-1 below.

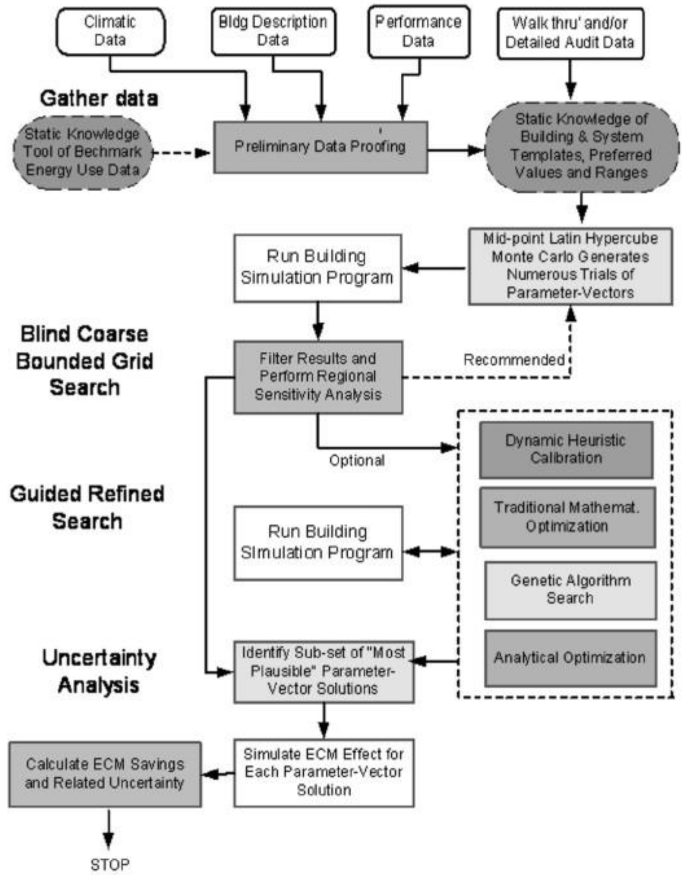


Figure 2-1. Process of calibration method.

The basic procedures include collecting baseline performance data, the data should be validated by visual or statistical methods. The energy modeler needs to define multiple influential input variables based on personal knowledge, experience. A coarse grid searching method is used to find the search space. After coarse search, a refined, guided method will find plausible solutions of each variable from the coarse grid search. The calibration process is an underdetermined issue; the modeler has to estimate the group of influential variables. This conclusion agrees with (Oliva 2003), (Saltelli 2002). The last step is the calculation of uncertainty in a “well-tuned” energy model. Traditionally, statistical criteria for determining the quality of a mode is R square value. The paper suggested coefficient of variation (CV) and normalized mean bias error (NMBE) to determine if the model is lack-of-fit. The goodness of fit index is shown below:

$$\mathrm{GOF_{CV}} = \left[\frac{\left(\mathrm{w_{kWh}^2 CV_{kWh}^2 + w_{kW}^2 CV_{kW}^2 + w_{th}^2 CV_{therms}^2}\right)}{\mathrm{w_{kWh}^2 + w_{kW}^2 + w_{th}^2}}\right]^{1/2}$$

$$\mathrm{GOF_{NMBE}} = \left[\frac{\left(\mathrm{w_{kWh}^2 NMBE_{kWh}^2 + w_{kW}^2 NMBE_{kW}^2 + w_{th}^2 NMBE_{therms}^2}\right)}{\mathrm{w_{kWh}^2 + w_{kW}^2 + w_{th}^2}}\right]^{1/2}$$

A sensitivity analysis is proposed to identify the “strong” and “weak” variables. The determination of influential and weak variables is reflected in the indexes CV and NMBE. The estimated influential variables will be tuned with great care while the weak variables will be set based on engineering judgment. The sensitivity analysis has limitations that when variables are correlated or final result doesn’t show a linear relationship with the dependent variable, the selected variables are not inclusive. The calibration is an underdetermined process that means there are multiple possible solutions that could satisfy the goodness of fit criteria with similar error range. (Clarke 2001) states the performance problem could have offsetting issue which covers the error at the whole building energy use level. In (Reddy, Maor et al. 2007), three case study office buildings have been studied to validate the calibration strategy. The general approach to validate the success of ECM retrofit is to compare simulated results with actual utility bills. In (ASHRAE 2002), the impact of each ECM could be determined by the making changes to one of several input variables. From (Reddy, Maor et al. 2007), this approach tends to be erroneous, because the interacting variables will mask the effect of bias, the variable should be calibrated at component level. A so called “calibrated model” should not be used to estimate the savings from implement ECMs when the saving percentage is less than 5%. The paper investigated a small size office building and two medium size office buildings. The criteria for determining variables values are based on indexes in the previous study CV, NMBE. The calibration steps follow the procedures in (Reddy, Maor et al. 2007). From the research results, when the energy saving is less than 5%, the overall building simulation results are less reliable. Increasing the number of trials could effectively reduce the bias. The conclusion from the case study buildings indicates that the proposed calibration methods are robust and effective.

(Sun and Reddy 2006) results showed in the calibration process, the actual measured data is important in the validation of energy model for representing the actual building and system end uses. When measured data in unavailable, the analyst has to manipulate the input variable and via trial and error process to find the optimal value thus the simulation results matches the actual daily or monthly data. This process is labor intensive and requires a lot of engineering judgment and expertise. Another shortcoming for this methodology is no consensus about the steps should take at each stage; it acts like a black box for the analyst. The validity of the results has been jeopardized. This paper proposes a general analytic framework for calibration. The approach is based on the recognition that although calibration can be seemed as an optimization problem, the core issue is that the calibration problem is underdetermined or over-parameterized. Furthermore, detailed simulation programs are made up of nonlinear, implicit and computationally demanding models. The proposed methodology involves several methods for example sensitivity analysis, numerical optimization and uncertainty analysis. A synthetic example involving an office building is used to illustrate the methodology with the DOE-2 simulation program.

Assumptions made for the operation conditions could be used to calibrate the energy model. (Monfet, Charneux et al. 2009) presented this path way to calibrate the energy model in educational science building in Canada in terms of supply and return flow rate and overall energy consumption calibration. In (Monfet, Charneux et al. 2009)'s study, the calibration was carried based on two operational periods A and B (A from May 4 to Jun 20, 2006; B from March 20 to May 3, 2006). Separating the simulation into different sections can avoid error compensation effect. The case study building has a floor area of 344,445ft^2. The supply air is provided by

AHUs in VAV system. The energy model for this building includes 97 thermal zones, 26 air plenums and more than 1700 surfaces. Geographical information and thermal characteristics information were obtained from building design drawings. The primary calibration step is to implement sensitivity analysis to find the variables that are sensitive to the total energy consumption. In this paper; sensitivity analysis was conducted based on two different weeks in two operational periods. The results showed that internal load has more impact on the cooling loads and supply air flow rate than ambient dry bulb temperature and building envelope characteristics. The infiltration rate has negligible effects in two periods. Graphical comparison of supply air flow rate vs. temperature exhibited the problems in the building operation. The simulated energy consumption is 10% higher in teaching sector and 12 % lower in student area, the results is less than compliance value 25% in (Kaplan, Michael, Phoebe Caner, and G. W. Vincent 1992). The proposed procedures showed the energy model is calibrated.

A fundamental problem in the energy model calibration is lack of comprehensive, consistent data base and information structure(O'Donnell 2009). The original design drawing or equipment manual can't represent the actual building accurately. Many critical input values are missing or estimated by the modeler or from the default value in the engineering reference book. This shortcoming makes the energy calibration highly subjective. Modeler has to determine the input value without sufficient confidence in tuning the model (Troncoso 1997). Actual sub-metered data and set points in building automation systems (BAS) need to be used to calibrate the energy model in (Raftery, Keane et al. 2011). The research suggested the energy modeler should have access to "building information model (BIM), as built drawings, operation and maintenance (O&M) manuals, EMS, BAS" and conduct surveys and interviews when necessary. The so called as-built drawings should be verified by on-site inspection or surveys. The understandings of night and after work periods operations are also very important in the calibration. Many buildings have set back algorithms or night purge control. For different data input sources, measured data is superior to the estimated or referenced value. Data obtained from benchmark analysis is better than values in standards and educated guess. In case study model, the measured internal load values were used in the simulation, schedules are determined from the measurement. The author found several problems are caused by the limitation of energy simulation. Once initial energy model was set up, the modeler should use carpet and surface plots, scatter matrix and plot (Baumann 2004) to compare simulated results, conduct outlier identification (Seem 2007), and calculate CVRMSE at annually, monthly and daily basis.

(Haves and Kim 2005) and (Wang, Yoshida et al. 2005) agree with previous literature review that the underlying issue causes the difference between simulation and actual data is insufficient building data to build up an as operated model. Thus there are more unknown variables than known equations. The top-down method can give satisfied overall prediction but at sub-system level, the energy use goes far away from the actual usage. This is a typical error compensating effect. An overall utility bill calibrated model can't simulate an as-operated situation. The bottom up method requires more data to implement. The fundamental solution to the model calibration process is to increase sub-metering of building data.

(Maile 2010) divided simulation problems into three categories: measurement problem, simulation problem and operational problem. The measurement problem originated from the sensor error or data measurement. Simulation problem came from the software which can be corrected easily. The operational problem shows problems in the operation or control defects in actual buildings. For example energy modeler should be aware of the influence of holidays or events in the building. The change of operation schedule or control should be updated in the model. The research presented a method to compare, identify and solve the difference between the energy simulation results and actual performance data. The difference is divided into three categories: measurement, software limitation and building operation problem. The author also summarized the assumptions in the measurement and limitations in the software. When difference occurred between simulated results and measurement, the first step is to determine if this is caused by the measurement error or simulation software simplification/approximation. The difference can't be explained by those two reasons is considered as the operational problems in the building. The shortcoming of this method is that it requires well-detailed sub-metered data which is not available in every building during the analysis.

Energy audit is a common approach to understand the building energy performance and identify energy saving potentials. In a deep level of energy audit, detailed hourly simulation program is effective to optimize the ECMs installation package and predict the thermal and energy-wise performance (Sterling, Collett et al. 1992) (Rahman, Rasul et al. 2010). (ASHRAE 2002) defined three levels of energy audit. The level-one walk through. The major purpose is to understand building operations and identify potential for energy savings via conducting interviews with building operator and collecting utility data. The level 2 is "energy survey and analysis" aiming at the different energy conservation measures potential. The work scope includes building envelop system, HVAC system, general service load, domestic hot water and so on. The level 3 is "Detailed analysis of capital intensive modifications". The findings in level 2 analysis may require a large amount of capital, personnel's investment. The feasibility and predicted output should be validated to understand the benefits, risks and costs. The level 3 analysis is considered as the continuation of level-2 audit. At this level of energy audit, detailed building energy simulation is involved. The energy audit steps have been proved to be very effective in (Li 2008), (Eskin and Türkmen 2008), (Iqbal and Al-Homoud 2007) and (Rahman, Rasul et al. 2010). The standard didn't give clear or specific procedures to implement auditing at different level. (Alajmi 2012) did an energy audit mainly focus on building mechanical system in Kuwait. The building is a 2 story educational facility with 7020 square meters. The HVAC system consists of 14 constant air volumes (CAV) air handling units (AHU). The workshop is served by fan coil units. The energy team conducted level-1 and level-2 audit in the building.

After retrofit process, the energy service team submitted a series of energy improvement recommendations to the owner including repairing building envelope, replace current lighting fixture into T-5 fluorescent lights, installing occupancy sensors etc. From the final analysis, the energy service team concluded if all the recommendations are implemented, 52% of total energy consumption could be saved and annual CO2 emission reduction is 648 tons.

(Tian and Choudhary 2012) used a probabilistic bottom up engineering approach to implement M&V in secondary schools. (Kavgic, Mavrogianni et al. 2010),(Huang and Brodrick 2000) and (Heiple and Sailor 2008) categorized the building energy models into top-down and bottom-up approach. The top-down method investigates the relationship between energy consumption and aggregated data. The bottom-up method starts the calibration processes by examine the system components. The first step is to create an energy model with detailed building data for example floor area, percentage of glazing, internal heat gains, detailed schedules of occupants, lighting and HVAC systems. Two methods for sensitivity analysis have been applied: Standardized Regression Coefficient (SRC) and Multivariate Adaptive Regression Splines (MARS). The description of two methods can be found in (Storlie, Swiler et al. 2009) and (Storlie, Swiler et al. 2009). The third step is to estimate the probability distribution functions of variables from sensitivity analysis. In the last step, different ECMs are evaluated by altering variables coefficients from the previous step. The research implemented the proposed method into school buildings in London. The paper also states that input variables correlation is a cause of deviation from the actual usage. This should be considered in the sampling process.

(Raftery, Keane et al. 2011) proposed a systematic, data-driven method to calibrate building energy model. The method suggested using well-documented building decision file, hourly interval data to calibrate large office buildings. A dedicated information system stored all the electrical consumption information at each major building panel. The model was built as operated building configuration based on the documentation and drawing. The schedule for internal load was derived from the hourly building automation system (BAS). In the final update of the model, the author checked the error results from the modeler input error. After 15 iterative updates, the model meets the statistical criteria. The mean bias error (MBE), cumulative variation of root mean square error (CVRMSE), biased percentage error and absolute percentage error are calculated as the compliance statistical indexes. The author also believes that the model assumption and simplification from the software caused the discrepancy. For example air flow in VAV box in the simulation is more responsive to the cooling load than actual conditions. The author recommends energy model calibration based on the hourly sub-metered data. System level end use calibration is necessary to detect error compensating effect.

Three standards govern the bounds within which a simulation model can be considered calibrated –these are ASHRAE Guideline 14 2002 (ASHRAE 2002), the International Performance Measurement and Verification Protocol (IPMVP) (Efficiency Valuation Organization 2007) and the Federal Energy Management Program (FEMP) Monitoring and Verification Guide (DOE 2008). These documents primarily apply to Measurement and Verification (M&V) projects and recommend calibrated simulation as one of several means by which to quantify savings due to proposed ECMs. These guidelines and standards aim to match overall building simulation results to utility bills instead of sub-level end uses. They failed to stipulate a clear method to systematically calibrate the energy model. For most of conditions, the calibration process is still under the personal judgment. The general and subjective approaches are not appropriate for ECM analysis which requires high-confidence level. Those standards and codes define hourly and monthly comparison criteria and are given in table below.

Table 2-2 Calibration statistical criteria for different standards.

	Hourly Comparison		**Monthly Comparison**	
Name	CVRMSE	MBE	CVRMSE	MBE
ASHRAE Guideline 14	30%	10%	15%	5%
FEMP	20%	5%	Not Given	20%
IPMV	30%	10%	15%	9%

The simple fulfillment of monthly or hourly comparison criteria is insufficient to determine that model is capable to simulate an as-operated condition in actual building. Those standards should have explanation or effort to state the need for this accuracy based on purpose of research. Specific method should be given based on the function of energy model and purpose of the project. There is no guarantee by adopting the overall monthly comparison criteria can result in an accurate prediction in ECM savings. It is important to know (1) which variables are more influential for system end use and overall building energy consumption. (2) What steps are necessary to quickly and accurately improve model accuracy thus modeler can quickly and efficiently predict the savings from ECMs.

The top down approach has been widely studied; however the uncertainty and limitations of this approach are obvious. The final results meet the statistical criteria don't guarantee a well representation of actual conditions inside the building, especially when multiple internal errors mask each other and yield a "calibrated" simulation results. With more sub-metering data, a bottom up, actual data based approach should be used to accurately and efficiently build up a forward energy model. Critical variables should be identified before installing measurement equipment in the building for example sensors. Direct measurement of critical variable and input with great care is more accurate than given multiple mathematical solutions for example in (Reddy, Maor et al. 2007). The component or system end use should be calibrated with specific compliance criteria.

2.2 Inverse modeling techniques

Inverse model is developed from the historical monitored data and empirical behavior of the building by including one or several critical variables. The building type and system configuration should be understood first to determine the driving variables, then for example statistical approach or artificial neural network is applied to forecast whole building energy use or sub-system use breakdown. This calculation is performed in backward direction so it is known as inverse model. Popular inverse models include variable-base degree models, bin methods, single or multivariate regression methods, thermal network and artificial neural networks. Different from the forward energy modeling, inverse model is empirical data orientated, non-dynamic simulation.

2.2.1 Regression models

Inverse model is measured data-driven, actual data based modeling of the existing building. It generates a model to describe the relationship between the output variable and independent variables. (Ruch, Chen et al. 1993) presented a method to predict overall building energy consumption called Change Point Principal Component Analysis (CP/PCA). Basic PCA procedures and results with a change-point model are discussed. Detailed PCA methods can found in (Dunteman and Ho 2006),(Jolliffe 2002). Conventional inverse modeling for example change-point linear regression or multivariate regression are often complicated by the diurnal effect in the influential variable or seasonal variation. (Hadley and Tomich 1986) used PCA to verify the heating energy saving in a meteorological study. (D. Ruch and Claridge 2013) combined empirical physical model with PCA methods to validate the saving percentage in M&V process. (Haberl and Vajda 1988) used PCA as a method to find the operation and maintenance problems inside a building. Besides diurnal effect or seasonal effect, collinearity between variables or linear dependence between variables will results in unstable regression models. The coefficient of the variables can be physically impossible. PCA corrected two issues above. (D. Ruch et al. 2013) implemented PCA on a grocery store as a case study. The multi-linear regression (MLR) mode was the first attempt, but the correlation between variables cause the large variance of certain variable coefficients. This MLR model is unstable and confusing prediction of building energy usage. Non-linear effect in model was also observed; therefore PCA combined with change point model tackles two problems together. A case study in (Reddy, Kissock et al. 1998) found that dry bulb temperature and specific humidity are identified as the major ambient variables. In the building cooling dominant region, strong correlation was found between temperature, solar radiation and humidity. Wind factor is not considered in this research. From PCA calculation, PC (principal component) 1 and PC2 could cover 94.67% of original information which is higher than the 70% requirement. In shoulder season, solar radiation is less significant than in the cooling season because at this time of the year cooling is unnecessary, the building is operating at base load which consisting of plug loads, lights and other equipment end use. In the shoulder season, PC1 and PC3 are selected because PC2 has high standard error. After the model was developed, it was used to validate its goodness of fit. The results showed the model is accurate especially in cooling season. The PCA is superior to MLR in terms of robustness of model and ability to understand the true influence of individual variables for example temperature, humidity and solar radiation.

(Kwok and Lee 2011) use a probabilistic entropy-based neural (PENN) method as a data-driven approach and studied the impact of occupants in the load calculation. The occupancy activity in the building a significant contributor in the building load calculation, but the current model or simplification of occupant behavior in the simulation engine can’t accurately reflect the complexity and influences of human behavior. The most complex impact from occupants is the interaction with the building. This interaction affects the indoor environmental quality and energy end use (Robinson 2006). For example, people have different perception about the temperature, humidity and tend to control the temperature by their own. The occupants’ schedule is hard to predict if measurement is unavailable. From (Mahdavi, Kabir et al. 2006), the general purpose of human activity is to increase the indoor environmental quality for example thermal and visual comfort. The relationship of individual person and building interactions are hard to quantify, for example turn on/off lights, the time spends in the office, open/close blinds. However, the relationship could be quantified by measuring long-term data (Mahdavi and Pröglhöf 2009).

(Reddy, Deng et al. 1999) proposed an inverse model to estimate building and ventilation parameters with limited intrusive monitor in commercial buildings. The paper provides three basic methodology categories in the measurement and verification (M&V) procedures, including empirical method, calibrated energy simulation and Marco-inverse model variable identification. The conventional empirical inverse model approach is statistically determining the energy consumption for a building with its appropriate driving variables. The savings is to compare the energy consumption before and after retrofit period. The direct comparison is inappropriate because the saving is not only caused by the retrofit. It is also caused by weather, internal loads or other factors. The typical approach is to compare after retrofit conditions to the building if the retrofit had not occurred. The regression model is a widely applied inverse model analysis, because it is simple, replicable and easy to understand. The Marco-model with variable identification has been discussed for a long period for example (Sonderegger 2010),(Sinha and Rao 2012). The variable estimation method provides additional insights to the forward modeling. It estimates physical or HVAC parameters of the building and data. In (Reddy and Claridge 1994) also presented a building energy efficiency index called energy deliver efficiency (EDE) which is similar to Carnot efficiency to describe multi-zone effect in commercial buildings and assets the HVAC system performance in a score. (Kreider, Curtiss et al. 2009) proposed a Multi-zone Efficiency Index (MEI) to account for the energy waste caused via simultaneous heating and cooling. The ideal HVAC system should consume minimum energy to neutralize the net building heat gains and at mean time satisfied the indoor environmental requirement. The EDE therefore is defined as

$$\mathrm{EDE}_{1-\mathrm{zone}} = \frac{\text{Thermodynamic minimum energy use}}{\text{Actual energy use}} = \frac{(\mathrm{E_C} - \mathrm{E_H})}{(\mathrm{E_C} + \mathrm{E_H})}$$

Where $\mathrm{E_c}$ is whole building cooling energy from the cooling coil, $\mathrm{E_H}$ is the heating energy from the heating coil.

The EDE is a measurement of HVAC aspect efficiency, MEI considered about the energy waste in simultaneously heating and cooling. The cooling and heating MEIs are defined as below.

$$\text{Cooling MEI} = \frac{\mathrm{E_{C,ideal}}}{\mathrm{E_{C,HVAC\ system}}} \quad \text{Heating MEI} = \frac{\mathrm{E_{H,ideal}}}{\mathrm{E_{H,HVAC\ system}}}$$

Where $\mathrm{E_{c,ideal}}$ and $\mathrm{E_{H,ideal}}$ are the "ideal" heating and cooling energy for one zone. $\mathrm{E_{C,HVAC\ system}}$ and $\mathrm{E_{H,HVAC\ system}}$ are the actual observed cooling and heating energy for a zone.

The two energy efficiency indexes have very clear limitations. EDE cannot provide accurate reflection of HVAC efficiency in transition period. When the outside air temperature is extreme, for example in the peak of summer of winter, MEI is zero. More importantly, the drawback of these two indexes is that the model is too simplified and ideal, it is very hard to use in a large, multi-functional commercial buildings.

(Kissock, Reddy et al. 1998) describes several models and procedures to implement measurement and verification process using ambient temperature as the primary variable in the regression analysis. The regression analysis is an empirical approach because energy consumption is statistically determined by one or several driving variables. The general method to confirm the energy saving is to compare the consumption before and after retrofit periods. The building energy consumption is driven by different factors, for example weather conditions, occupancy rate, internal plug load, HVAC system control and operation. It is important to normalize retrofit unrelated factors. Using temperature as the variable in the regression model is most appropriate for weather related energy consumption. For weather independent energy consumption, such as lighting retrofit, weather conditions before and after retrofit is not essentially related to the savings. Two saving calculation methods are discussed in the paper: actual and normalized savings. The normalized saving is more appropriate in the calculation of savings from forward energy simulation models, but the uncertainty is higher.

Weather conditions are influential variables in building energy consumption; it includes ambient dry bulb temperature, specific humidity, relative humidity, dew point, wind, solar radiation. From (Kissock, Reddy et al. 1998) and (Ruch, Kissock et al. 1999) their research believes ambient temperature, humidity and solar radiation are linearly related and including those variables simultaneously in the model will cause multicollinearity issue. This issue cause variables' coefficient physically unreasonable or unstable. Principal component analysis in (Reddy and Claridge 1994), (Lam, Wan et al. 2010),(Lam, Wan et al. 2008), (Ndiaye and Gabriel 2011) have been used to tackle multicolinearity issue in the equation.

Several studies have shown that ambient temperature is easy to collect, simple and understandable. Given all advantages above, the temperature is considered as the single variable in several studies for example (Kissock, Claridge et al. 1992), (Greely, Harris et al. 1990) and (Reynolds, Komor et al. 1990). Extrapolation error is a major problem for using temperature as the single variable. So as to minimize the error, the baseline period temperature should cover a full year or at least extend to cover cooling, heating and shoulder season. The saving uncertainty is reduced with the increase baseline periods increases. (Reddy, Kissock et al. 1998) states the diurnal effect will cause strong correlation within variables, the paper argues that the minimum time scale is at least 24 hours. Weekly cycle is also appropriate for many commercial buildings especially in office buildings. No one regression model is suitable for all types of buildings, (Reddy, Kissock et al. 1998), (Kissock, Haberl et al. 2002) introduced five regression models to analyze different types of buildings: two-parameter, three-parameter, four-parameter and five-parameter regression models.

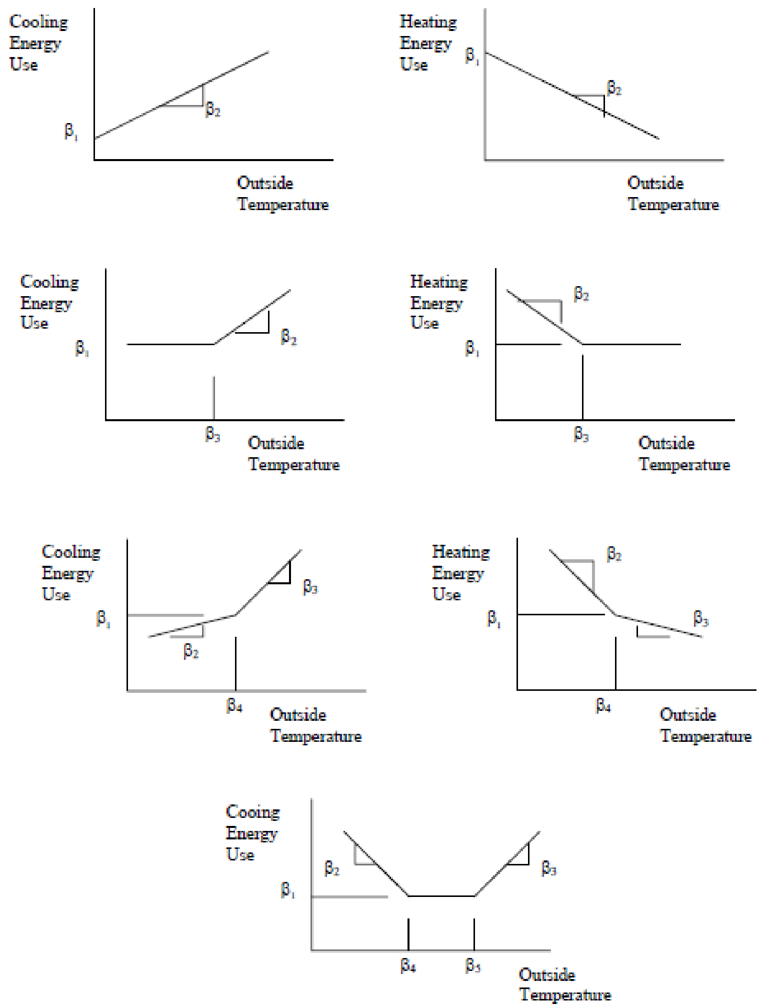


Figure 2-2. Types of regression models.

The "best-fit criteria" (Kissock, Reddy et al. 1998) will lead the selection of five-parameters model because it has the largest number of variables. The conventional R^2 value criterion cannot give enough insights of underlying relationships. (Katipamula and Claridge 1993) and (Reddy, Katipamula et al. 1995) studied the relationship between ambient dry bulb temperature and different cooling and heating systems. The research results showed that latent load has huge impact on the overall energy consumption especially in humid climates. When the dew point of cooling coil is lower than the dew point of ventilation air, latent ventilation load increases the overall building energy consumption. The study in (Kissock, Reddy et al. 1998) shows the humidity is significant to the total energy consumption and a change point effect on dry bulb temperature. The influence from other factors for example internal load, occupancy area, space set points should also be normalized and accounted in the calculation of energy savings.

(Ruch and Claridge 1993) provided a study of the normalized annual consumption (NAC) index with statistical error diagnostics for regression models. From the research, the NAC is defined as “the total building energy consumption for a normal year.” The normal means an average year over a long period. Let $\widehat{E_\imath}$stands for the energy consumption on day I in a normal condition. The total energy consumption for a whole year is defined as below (Ruch and Claridge 1993)

$$\mathrm{NAC} = \sum \widehat{E_\imath}$$

This definition is suitable for any model calculating the overall energy consumption. The research believed the cooling and heating energy in large buildings are linearly increased with ambient dry bulb temperature. The NAC for linear, four-parameter change point models are discussed in the paper. The annual linear NAC model based on daily temperature is given below.

$$\widehat{E_\imath} = a + bT_i \text{ Thus}$$

$$\mathrm{NAC} = \sum \widehat{E_\imath} = \sum (a + bT_i) = 365a + b \sum T_i$$

The NAC uses ambient average temperature as the variable instead of degree day because the model is not a change point model which has no piece-wise impact at baseline temperature (Kissock, Claridge et al. 1992). The simultaneous cooling and heating effect also makes degree day method less reliable. When the long term average temperature is close to the centroid of data temperature, the NAC model will be stable and provide good prediction. The four-parameter model of NAC is given as below.

$$E = a + b_2(T - t)^+ - b_1(t - T)^+$$

Where T is the average daily temperature, t is the change point temperature, b_1 is the low temperature slope, b_2 is the high temperature slope and "+" indicates zero if the term inside the parentheses is negative.

(Katipamula, Reddy et al. 1994) studied reasons of difference between prediction based on short and long term data. The dry bulb temperature is one the driving ambient variables in the model. The dew point, solar radiation and internal gains are also considered. The latent load in the commercial building is generally created from the ventilation. The study shows in regression model, it is better to use dew point temperature minus mean surface temperature of the cooling coil. The annual electricity consumption is a function of multiple variables. The research developed a change of slope with indicator model as shown below.

$$E_c = \propto + \beta_o T_o + \beta_1 I + \beta_2 I T_o + \beta_3 T_{dp}^{+} + \beta_4 q_i + \beta_5 q_{sol}$$

Whereα β_0 β_1 β_2 β_3 β_4 and β_5 are regression coefficients.

The research finds that that collinearity caused by model is misleading. The conclusion is that dry bulb temperature and dew point temperature varies significantly at monthly level, if the inverse regression data is not enough to cover entire period, the mean bias error is high. The mean bias error varies from 15% to 40%.

(Reddy, Kissock et al. 1994) studied the multiple linear regression models on large commercial buildings. The building is a complex entity that has dynamic reactions to the ambient weather conditions, internal loads, control algorithms etc. The building operation is different from hour to hour for example in VAV system the fresh air intake volume is different, but at daily level it is relatively constant. The daily level regression model is appropriate and reliable if the data could cover entire weather conditions. In the study, the total cooling energy consumption in a VAV system is expressed as

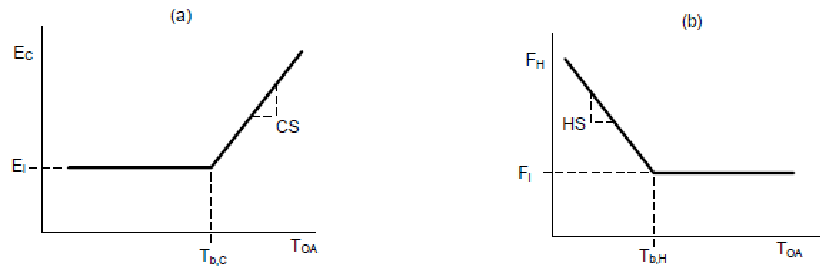
$$E_c = a + bT_O + cI + dIT_O + e(w_m - w_c) + fq_{sol} + gq_i$$

Where T_O is the ambient air temperature, w is the humidity ration, q_{sol} and q_i are solar heat gain and internal heat gain respectively. I is the indicator variable when T_o is greater than the change point temperature and 0 otherwise. The latent load term$(w_m - w_c)$ can be replaced by $(T_{dp} - T_s)$ and it is set to zero when it is negative. Thus the regression model is modified as follows:

$$E_c = a + bT_O + cI + dIT_O + eT_{dp}^{+} + fq_{sol} + gq_i$$

The simulation results show the outdoor dry-bulb temperature in dual duct constant volume and VAV models accounts for over 80% of energy variation. The dew point temperature and q_{sol} solar radiation in the VAV model explains more than twice variation in DDCV cooling model. The q_{sol} solar radiation in the regression model is insignificant. The daily regression model was also compared with hourly model. The daily model has higher R2 value and lower CV and RMSE than hourly model. The study concludes that T_o and T_{dp} explains most of the variation in cooling energy consumption. The daily model performs better than hourly model because the energy consumption is less scatter and has lower coefficient of variation.

(Lammers, Kissock et al. 2011) described a multivariate three-parameter change point regression model to estimate the retrofit energy saving in industrial buildings. In Princeton Scorekeeping method, variable degree days is the variable in the model (Pels 1986). In three-parameter change point model, temperature is the single factor. This model was based on (Kissock, Reddy et al. 1998) and (Ruch and Claridge 1992). The first step is to use ambient dry bulb temperature as the predictor to set up a three-parameter change point model. The next step modifies regression model coefficients to estimate the energy consumption with suggested retrofit scopes. The final step is to use typical weather data to calculate the energy consumption in the baseline and after-retrofit period. Energy saving is calculated as the difference between the baseline model and post retrofit model with a typical weather data file. Typical three-parameter model for cooling and heating are shown below.



ure 1 *(a) 3PC (Cooling) and (b) 3PH (Heating) regression models*

Figure 2-3. Three-parameter regression models.

Where E is the building electricity usage. $T_{b,c}$ is the cooling change point temperature and $T_{b,H}$ is the heating change point temperature.

In large commercial buildings with simultaneous cooling and heating, five-parameter regression model are discussed in detailed in (Kissock, Reddy et al. 1998, Kissock, Haberl et al. 2002) and (Haberl, Sreshthaputra et al. 2003). In (Kissock and Eger 2008) the working production was introduced in the regression model to represent the electricity or energy consumption on the production. Appling energy conservation measures will change the value of energy signature model. The coefficients of regression model are calculated in below.

$$CC = UA + V\rho c_p \qquad HC = UA + V\rho c_p$$

$$CS = \frac{cc}{\eta_c} \qquad HS = \frac{HC}{\eta_H}$$

$$T_{b,c} = T_{set} - \frac{Q_i}{cc} \qquad T_{b,H} = T_{set} - \frac{Q_i}{HC}$$

Where CC and HC are cooling coefficient and heating coefficient. U is the building envelop conductivity, A is the envelop area, V is the ventilation rate, ρ is the air density, c_p is the air specific heat. η_c and η_H are the efficiency of cooling and heating equipment. $T_{b,c}$ and $T_{b,H}$ are the cooling and heating balance temperature. Q_i is the internal load. The calculated difference between baseline model and planned ECMs is the energy savings. The proposed energy model is tested in an industrial facility. Different from detailed forward model simulation, inverse model doesn't require model calibration with moderate effect on the data collection. In the model, scatter effect of data was found around the regression line.

(Lammers, Kissock et al. 2011) described a method to analyze utility bill, weather and energy data to calculate the normalized energy intensity for a company. The method used "sliding NEL" analysis accomplished in four steps. The first step is to generate a three-parameter change point model to describe the cooling or heating conditions in a facility. The algorithm and software are discussed in (Kissock and Eger 2008) and (Kissock 2005). The horizontal intercept describes weather independent energy use. The change point model could be extended by adding an additional term "production" and its coefficient in the equation. Adding production term is based on modeler's experience, other related terms could be added as well. By using three-parameter change point model, overall energy consumption could be divided into weather dependent and independent part. The interpretation of the cooling or heating slope can be found in (Kissock, Seryak et al. 2004), (Kissock and Seryak 2004) and (Kissock and Eger 2008). The second step to normalize annual energy consumption. The third step is to compare a normalized annual consumption (NAC) during 12 month periods. The sliding NAC shows the change of energy consumption trend over time. The final step is to calculate the "Normal energy intensity (NEI)" and compare the energy flow inside the building. The paper described a four-step method to calculate the normalized building energy intensity index. The shortcoming of this method is that a time lag was found between energy efficiency changes and reflection in NEI. From the analysis, 12 months data is necessary to adequately manifest the saving from efficiency improvement.

In inverse model analysis, the residuals might not be independent; instead it shows a pattern or correlation which is called autocorrelation. This phenomenon would cause the over-fit issue in energy prediction. The mean square error, variance of the model is smaller than the actual value. The autocorrelation might be caused by omission of important variables or operational change of building in a time series manner (Reynolds, Komor et al. 1990) (MacDonald and Wasserman 1989). Autoregressive model is proposed by (Katipamula, Reddy et al. 1994), but the method is constrained by practical issues. (Ruch, Kissock et al. 1999) proposed a “hybrid” model using the ordinary linear regression (OLS) method to estimate the regression coefficient but autocorrelation method to estimate the variance and predictor error. The method split the data into baseline and post retrofit. The baseline data is used to set up the model and the post retrofit data is for testing. The model was tested in several buildings with the method mentioned above. The model prediction and uncertainty calculation are compared with OLS and actual values. The case study buildings proved the autoregressive model improves the estimation of energy consumption. The prediction uncertainty can be effectively reduced by hybrid model. The research should follow up annual energy consumption normalization because the comparison between baseline and post retrofit is meaningful only after normalization.

Inverse regression models also have been successfully used in many studies for example (Lam, Hui, and Chan 1997)(Chung, Hui, and Lam 2006)(Sever et al. 2011)(Kissock, K. et al. 1992). The overall energy consumption is predicted as linear change-point relationship to weather conditions for example heating/cooling degree days, ambient dry bulb temperature, wet bulb, solar radiation intensity. In commercial or educational internal load dominant buildings, the high plug load made the building more independent on the ambient weather conditions. Several researches adopted multiple linear regression for example (Katipamula, Reddy, and Calridge 1994) to include the other effects on the building energy consumption. This approach highly depends on the building function and HVAC system type, for example in retail story, it was found that energy consumption is highly related to the customer count or in a factory it is related to the factory production rate (Sever et al. 2011).

The success of a multiple regression model highly depends on variables chosen in the model. The selected variables should have critical impact on the energy use and independent from each other. The benefit of regression model is its simplicity and physical meanings in coefficients. Although each building is special and no model is perfect to model every building type, it is important to develop a general strategy to identify “outliers” from normal variation in operation. The problem might results from 1) omission of certain significant variables, 2) linear dependency between predictors and response, 3) time series effect. It is important to diagnose reasons and causes of scatter by correctly select important predictors in the model and screen faulty operation periods. A key point of this research is to determine which group of variables is valid to develop the energy signature model.

2.2.2 Thermal network & artificial neural network

(Lee and Braun 2004) described a thermal network method to simulate demand-limiting (DL) control process. This control strategy is used to precool the building before the occupancy hours, set the temperature at low boundary in the unoccupied period. In the peak cooling hour, the DL control limits the peak cooling load. The night-setup point is a popular control strategy to adjust the temperature so the HVAC is operating at minimum energy consumption. (Braun 1990) (Braun and Chaturvedi 2002) (Braun, Montgomery et al. 2001) and (Keeney and Braun 1997) researched on the space set point selection and adjustment strategies. They all agree precooling in the unoccupied period and increase the set point during occupied period is a good strategy to reduce energy consumption. (J. E. Braun, Montgomery, and Chaturvedi 2001) studied on an inverse gray-box model to simulate the load-shift in commercial buildings. The model consists of resistors and capacitors in the thermal network. The training data group teaches the resistor and capacitors to simulate the actual data while minimizing the errors. (Gouda, Danaher, and

Underwood 2002) implemented a nonlinear optimized, lumped parameter model to predict energy consumption. The research used Kuhn-Tucker equation to calculate the temperature set point. Results showed 2nd-order thermal capacity wall losses minimum calculation accuracy but improves calculation efficiency considerably. (Lee 2004) tested the thermal network model in case study building named Energy Resource Station (ERS) in Iowa. The interior room is modeled as single zone. The calculated cooling load is the total cooling load for the case study building. The first principal energy balance equation is stated below.

$$\frac{-dx_b}{dt} = A_b x_b + B_b u_b$$

$$Y_b = Q_b = C_b x_b + D_b u_b$$

Where Q_b is rate of instantaneous heat gain to the building air.

(J. E. Braun and Chaturvedi 2002) described a detail study of a hybrid “gray box” approach to simulate energy flow in the building. The research used three steps to find optimal parameter values. 1st step is to estimate the physical values from building geometry or material descriptions. 2nd step implemented a global search algorithm with physical constraints to search for the optimal value. The last step is to use a nonlinear regression algorithm to determine the value while minimize the errors between prediction and measurement. The model formulation is based on the basic energy balance equation formed by (J. Braun 1990) and (J. E. Seem et al. 1989). At any time step, the cooling load of a zone is below:

$$Q_{zs,k} = \sum_{i=0}^{N} \left(a_i T_{a,k-i} + b_i T_{z,k-i} + c_i Q_{g,s,k-i} + d_i Q_{sol,k-i}\right) + \sum_{i=1}^{M} e_i Q_{zs,k-i}$$

The electrical circuits are commonly analogized to building thermal configuration. The building wall is represented by the thermal network as shown in below.

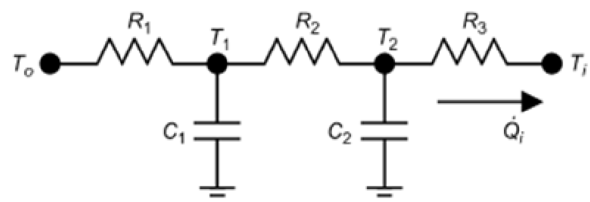


Figure 2-4. Thermal network models.

The overall building thermal network is complex than a wall thermal network. It includes external walls, roof, floor, internal partition and windows.

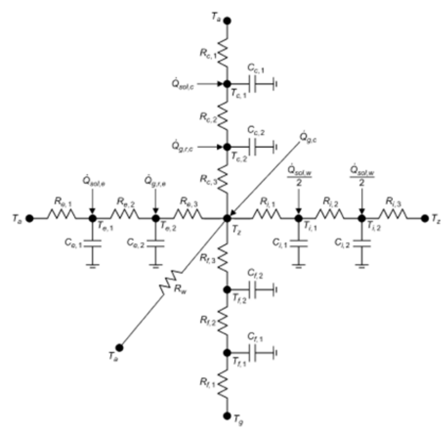


Figure 2-5. Overall building thermal network.

The model training process starts with the collection of information in terms of thermal, geometric information of the building. Global and local training algorithms are implemented sequentially to find the optimal values of the parameters. The “grey box” model was tested in a commercial building near Chicago, IL. The building is four stores office building. The envelop material is mainly constructed by heavy concrete materials. 16 air handling units with VAV system provides cooling and heating to the building. It was found that the internal heat gain has the largest impact on the model errors. The large commercial building is internal load dominant and less sensitive to the ambient weather conditions. In the case study building, one or two week’s data is considered enough to provide training in thermal network model.

The artificial neural network (ANN) model has been used widely to dynamically represent human behavior in inverse modeling. ANN is not required to meet the strict assumption in regression or employ different program to reflect human activity. In the training data, ANN will adapt itself to the human behavior (Zhang, Patuwo et al. 1998) The ANN is a data-driven, self-learning method, it is capable to simulate non-linear model (Kwok and Lee 2011). The input for ANN is divided into external and internal parameters. (Papalexopoulos, Hao et al. 1994) predicted energy consumption of a building for a short period and adopted predicted temperature as input. (Yalcinoz and Eminoglu 2005) used short term and medium term data to predict the building electricity consumption. The ANN model was trained with historical data to understand the peak load, daily load and monthly electricity consumption. (Osman, Awad et al. 2009) used ANN model and onsite weather condition data to predict building energy consumption. The research used the weather data to train the model. (Kreider, Curtiss et al. 2009) implemented ANN to validate a retrofit project of a building. The input data (layers) include weather data for example dry-bulb temperature, humidity ratio, wind, and other variables such as chilled water consumptions. The research assumed human activity and interaction in a deterministic way for instance a fixed schedule of working hours in ANN model. The random effect of human is hard to capture, this may explain the difference between simulated and measured results. (González and Zamarreno 2005) used an ANN model to predict hourly load in a building. The research developed a hybrid training method to give input in the model. (Amjady 2001) used a time series ANN model to forecast short term load and power demand in buildings. The research divided a week into weekdays, weekends and holidays. The author also studied the peak load in a building. In (Kwok and Lee 2011) includes two extra variables to represent occupancy: the hourly occupancy area and the occupancy rate (power consumption in AHUs). The hourly occupancy area varies with schedule and human activity inside the building. The percentage of building occupancy area is recorded as the input to the model. The occupancy rate is calculated via CO2 concentration level. The fresh air provided in the AHU with demand ventilation control indicates the CO_2 level thus the reflection of occupancy level. The fresh air supply rate is calculated by the electrical power consumption in the AHUs with variable frequency drive fans. The amount of electricity consumption is directly proportional to the air supply rate. The paper tested the model with occupancy area and occupancy rate in a mega office building in Hong Kong. The office building occupancy varies with the function, schedule and number of tenants. The simulation results show that by including occupancy area and rate increases model accuracy considerably. The paper didn't discuss how to define occupancy area; besides not all the demand ventilation control is available and correctly operated in the building.

2.2.3 Degree days

Many research used cooling degree days or heating degree days to correlate the building energy consumption (Sarak and Satman 2003) and (Layberry 2008). It is considered as one of the most popular methods in inverse model.

The degree day or variable degree day regression method has been studied widely in building industry, for example the method was presented and discussed in (Day and Karayiannis 1999) (Day and Karayiannis 1999), (Sinha 1991). The degree day method is easy to understand the effect from ambient weather condition, but results sometimes are misunderstood or overestimated. The misinterpretation will raise concerns and uncertainty in the measurement and verification process. (Day et al. 2003) studied the degree day method on actual building data and the uncertainty of the results in the base line temperature selection. Many uncertainties and problems can be eliminated by correctly choosing baseline temperature. The heating baseline temperature calculation is shown below.

$$\theta_b = \theta_i - \frac{Q_G}{\left(\sum UA + \frac{1}{3}NV\right)}$$

Where U is the fabric transmittance, A is the fabric area in m^2, N is the infiltration rate in air changes per hour, V is the volume of the room in m^3, $\theta_i$is the internal temperature, Q_G is the solar heat gain.A problem in calculating baseline temperature is the baseline temperature varies through the operation. For example solar radiation and occupancy varies will change the prevailing heat gains. A constant baseline temperature will lead to scatter in the degree day regression. From the regression analysis it might show that heating system is in poor operation, but actually, the heating system is making wise decision based on the heat gain of the building. The paper advocated using daily building energy data and outdoor temperature to estimate the baseline temperature. The cooling load contains sensible and latent loads. The overall degree day calculation is shown below from (Hitchin 1983)

$$D_m = \frac{N(\theta_b - \overline{\theta_O})}{1 - e^{-k(\theta_b - \overline{\theta_o})}}$$

Where D_m is the monthly degree days, N is the number of days in a month, θ_b is the base temperature, $\overline{\theta_O}$ is the monthly average temperature, K is a constant coefficient calculated by 2.5 over the standard deviation of the hourly temperature distribution.

This formula can be used with daily, weekly or monthly average temperature. The degree day method is inappropriate when there is a poor correlation between energy consumption and degree days. It is important calculate the base temperature especially it varies with time and load conditions, this will indicate the operation or thermal characteristics change in the building and gain more confidence in the saving calculation.

(Day and Karayiannis 1999b) discussed a quantification process of degree day uncertainty and revised understanding of degree day results. From (Day, A. R and Karayiannis,T.G 1997), the energy demand for heating is calculated as

$$E = U' \int (\theta_b - \theta_o)\, dt$$

Where E is the energy demand from heating system. U' is the overall heat loss coefficient of the building. θ_b and θ_o are the internal and ambient temperature.

This equation is the definition of degree day calculation. Several issues have to be addressed before using this equation for the calculation. (1) Internal temperature varies with time especially in intermittently heated building. (2) External heat gain changes with time and operation. (3) The previous two issues results in non-constant baseline temperature. (4) Thermal storage effect will influence the base temperature. The paper develops several equations to calculate the balance temperature with different input data. For example daily balance temperature with set point is calculated below

$$\overline{\theta_{b,d}} = \theta_{sp} - \frac{\overline{Q_{g,d}}}{U'}$$

Daily base with mean daily temperature is calculated below

$$\overline{\theta_{b,d}} = \overline{\theta_{\imath,d}} - \frac{\overline{Q_{g,d}}}{U'}$$

Hourly base temperature is calculated below

$$\overline{Q_{b,h}} = \overline{\theta_{\imath,d}} - \frac{\overline{Q_{g,h}}}{U'}$$

Where θ_{sp} is the set point temperature, $\overline{\theta_{\imath,d}}$ is the internal temperature, $Q_{g,d}$ is the heat gains in building, $U'$is the overall building heat loss coefficient.

After the base temperature is determined, the degree day is calculated using equation below

$$D_d = \frac{\sum_{24}(\theta_b - \theta_{o,b})}{24}$$

Where D_d is the daily total degree days. θ_b is the base temperature and $\theta_{o,b}$ is the outside temperature. The energy consumption is estimated in the equation below

$$\hat{E} = 24U'D$$

After determine equations to calculate the base temperature under different data resolution and building characteristics, the research use simulated building energy data to test the equation. The results showed using mean internal temperature is better than implementing correction factors. Uncertainties have been quantified for each base temperature calculation in the synthetic building data validation process. The uncertainty decreases when data periods increase. The degree day should not be calculated at hourly and daily level.

The degree day method is to predict building energy consumption with degree day calculation. General discussion about the degree day methods showed little or no attempt to avoid uncertainties in the estimation. Degree day method is easy to understand and employ, it can be calculated at different time scale. It effectively relates energy consumption with ambient effects on the thermal energy consumption. However, many problems have been found in this method. The balance temperature should be determined with caution. Each building is unique therefore the heating set point and supply air temperature varies from each building. The degree day method is a weather normalization technique. The balance temperature will have different base load estimation. Base load is considered as independent of ambient weather. Another major issue with degree days is that it assumes building has a thermal demand 24/7; this is rarely the case in the building. A lot of buildings only provide heating/cooling during occupied period. During shoulder season, the building has minimum thermal demand. The degree day calculation is very sensitive to balance temperature. Discontinuous operation of HVAC system causes additional uncertainty of degree day calculation. To summarize, the degree days method should be used with caution and might not be appropriate for most of the complex commercial buildings.

2.3 Conclusions of literature review

Overall, in building energy analysis, two major modeling approaches from the literature are widely adopted: forward modeling and inverse modeling. The forward energy simulation provides usage breakdown and allows complex interactions between building components. Given from the actual usage and utility bill, analyst can calibrate the energy model and identify the operational problems in the building. A well calibrated forward model is capable of estimating the savings from installing ECMs and optimize retrofit plan. Inverse model is data driven, steady state simulation by one or several driving variables. The major inverse modeling approaches are: (1) single and multiple variants regression models (2) thermal network and artificial neural network (3) constant base and variable base degree day method and (4) bin methods. A well-developed inverse model can accurately simulate the building performance in the baseline and post-retrofit period and helps calculate the savings in M&V process.

An un-calibrated forward model can have up to 75% of difference from the actual data (Ahmad and Culp 2006). Many efforts have been spent on creating "as-operated" building model. The conventional approach uses a top-down approach to match the overall utility bill by satisfying statistical criteria. This approach is not robust for several reasons. This calibration is an underdetermine problem which there are more "unknowns" than "knows". An overall calibration doesn't guarantee the sub-level calibration and it has a high degree of freedom. All components and systems in a building have interactions among each other; system errors can mask each other at sub-system levels. Simulated end use varies significantly from actual data. The saving predictions from ECMs is less reliable if the model cannot well represent the as-operate conditions. The data availability is another issue for the calibration. There is no consensus on specific steps reconciling simulation results with actual data or lack of systematic validation of "as-operated" model. A lot of times this is based on personal judgment and experience. The accuracy and confidence level of such approach is always a concern. Several studies implement mathematical approach for example coarse grid search to find the optimal numerical value for the variable. This approach gives a group of solutions instead of one true measurement from the reality. The optimal value for the variable is only mathematically correct but is not the actual condition in a building.

From the literature review, the detail hourly simulation has numerous variables and it is imperative to find critical variables that are most influential, dominant to components' performance, system end uses and building overall consumptions. Conventional sensitivity analysis has limitations for example the interrelationship between variables could affect the results and piecewise effect among variables and outcomes is observed. Data screen and variables selection methods should be adopted to identify critical "knobs" for the system end uses and overall building energy. Monitoring and tuning the critical variables with great care can provide enough data base and continuously improve the energy model. After critical variables are determined for different types of systems, a protocol based forward model formulation method should be investigated. This can help setting up an accurate as-operated forward energy utilization model. The discrepancies' between components, systems and actual data should be investigated to find the problem in the building operation. From above summary, variable selection at sub-systems' level is necessary. A sub-system focused, sub-meter data based forward model formulation method needs to be studied.

Chapter 3

Variable Selection Methods for Inverse Model Development

To answer research question 1, this chapter reviews current variable selection techniques. Two robust variable selection techniques: Smoothly Clipped Absolute Deviation (SCAD) penalty and Least Absolute Shrinkage and Selection and Operator (LASSO) method are described in detail.

3.1 Variable selection techniques

In inverse model formation, ambient dry bulb temperature is intuitively known critical; however, it is insufficient to drive the energy use pattern for many buildings especially in internal load dominated buildings such as office buildings (figure 1-2) or mixed use buildings (Ruch and Claridge 1993, Piper 1999, Kissock, Haberl et al. 2002, Matson and Piette 2005, Chung, Hui et al. 2006, Bohdanowicz and Martinac 2007, Kissock and Eger 2008, Spyrou, Shanks et al. 2014). To find key variables that drive energy use, it is necessary to apply variable selection to determine key variables that relate to energy end use. Current popular and widely adopted variable selection techniques include stepwise and best subsets variable selection.

Stepwise selection generally has three approaches: (1) forward selection, (2) backward elimination and (3) bidirectional elimination. Three approaches have very similar concepts. The backward elimination begins a full model including all variables. A predefined F-test or t-test index will eliminate unnecessary variables at each step till the final is model achieved. (Chung, Hui et al. 2006) used this method to benchmark energy use in commercial buildings. Their research initially includes twelve variables such as wet-bulb temperature, number of customers and etc. After backward elimination, the final model contains five variables which are building age, floor area, operational schedule, customer account and behavior. Other researches (Bohdanowicz and Martinac 2007, Spyrou, Shanks et al. 2014, Valovcin, Hering et al. 2014) applied this method in food retail buildings, hotels and residential buildings. Forward selection is reversed steps of backward elimination. The initial model has zero variable, each variables is tested to add into the model. The step will stop when no further improvement can be made by adding more variables. The criteria to add a variable can be simple such as $\alpha_{critical}$(alpha to add). Bidrectional elimination is a hybrid method of forward and backward elimination.

The advantage of adopting stepwise variable selection is obvious. The method is easy to compute and time saving. Much commercial software such as Minitab® or SAS® has full package that can generate the result less than one minute. The theory and procedures behind the result is clear and convenient to understand. User can define the threshold based on the purpose of research and preference. However, shortcomings are obvious as well. The method adds or deletes a variable "one-at-a-time." In fact, the final model can have large chance miss key predictors. The significance of certain variables can be amplified and dropped variables are still possibly correlated to the dependent variable (Roecker 1991).

Best subsets variable selection is another important field of variable selection in practice. The method automatically generates "best fit" of models based on predefined statistical index. Popular indexes include highest R^2 value, smallest mean square error (MSE), Mallows' C_p statistic. Each index emphasizes different aspect or performance of model. R^2 is a commonly applied index, it is coefficient of determination which is a percentage of variance that can be predicted or explained by independent variables. R^2 index will always prefers models with more variables, while in practice, monitoring extra variable might be cost-prohibitive or impossible. It is unworthy to add new variable if improvement of model is insignificant. Adjusted R^2 is another criterion which is similar to R^2. It adds penalty for adding more variables in models. Mean square error (MSE) is another approach. It estimates deviation of predicted value from actual data. Bias of model prediction value can be evaluated by Mallows' C_p. A smaller C_p value means model is less biased. The method starts with different combinations of variables and categorizes models based on the number of independent variables. In each category, the model is compared by the previously discussed model comparison index. The last step is to compare the best model within each category. The best subsets variable selection model has similar advantages of stepwise method. However, it should be use with caution as well. The selected "best of fit" is not global optimal model because the definition of "best" is not unique. As previously discussed, each index emphasizes different aspects of model evaluation. Index can be selected based on user's opinion or purpose of model. Another shortcoming is that if certain or several key variables are missing in the original data set, the derived model can be misleading or underspecified (Weisberg 2014).

3.2 LASSO method

Given the shortcomings of best subsets method, stepwise variable selection methods, this research adopted two methods called Least Absolute Shrinkage and Selection and Operator (LASSO) and Smoothly Clipped Absolute Deviation (SCAD) penalty methods to generate regression models. Calculated results from two methods can cross validate each other. Variables that are selected in both methods are considered most important. They should be monitored in actual buildings and included in inverse model development. The brief method description of LASSO is given below. Statistical detailed steps and theory discussion can be found in (Tibshirani 1996).

A typical mathematical description of liner regression model is given below.

$$\mathrm{y} = \beta_0 + \mathrm{x}_1\beta_1 + \mathrm{x}_2\beta_2 + \cdots + \mathrm{x}_\mathrm{p}\beta_\mathrm{p} + \varepsilon = \mathrm{x}^\mathrm{T}\beta + \varepsilon \qquad (1)$$

In model, $x = (x_1, x_2, \cdots, x_p)^T$ are initial independent variables, $\beta = (\beta_0, \beta_1, \cdots, \beta_p)$ are the corresponding coefficients and ε is random error or noise. In practice, it is cost-prohibitive or physically impossible to measure all variables. Therefore, researchers tend to conduct variable reduction which means use less variables to predict dependent variable. The problem in practice is that we can't know which variables are more important than others in advance, thus the initial variable data should be as comprehensive as possible. If we assume variables in equation (1) with n times of observations are descried in equation (2)

$$Y = X\beta + \varepsilon \tag{2}$$

The Y is nth sample response and X is nth observation value from predictor $x = (x_1, x_2, \cdots, x_p)^T$. The ordinary least squares estimate the coefficient in equation (3).

$$\widehat{\beta_{LS}} = (X^T X)^{-1} X^T y \tag{3}$$

When the number of sample is less than the number of independent variables (n<p), the classic least square is unavailable. When n is larger than p, penalized square in equation (4) is introduced to estimate coefficients.

$$\widehat{\beta} = \underset{\beta \in \mathbb{R}^p}{\operatorname{argmin}} \|\mathbf{y} - \mathbf{X}\beta\|_2^2 \qquad \text{subject to } \|\beta\|_1 \leq \gamma. \tag{4}$$

$\ell_1$norm is a constrain of coefficients vector. Vector γ is the prefix threshold. The definition is given below.

$$\|u\|_1 = \sum_{i=1}^{p} |u_i|, \quad \|u\|_2 = \sqrt{\sum_{i=1}^{p} u_i^2}\,, for\ all\ u \in R^p \tag{5}$$

The corresponding Lagrangian optimization is in equation (6).

$$\widehat{\beta} = \underset{\beta \in \mathbb{R}^p}{\operatorname{argmin}} \|\mathbf{y} - \mathbf{X}\beta\|_2^2 + \lambda \|\beta\|_1 \tag{6}$$

Sparsity is one of properties of ℓ_1 constrained least square. It means coefficients solution for proper positive λ value, several elements can be set exact to zero. When λ equals to 0, it is a classical least square problem. When λ is infinite, every variable coefficient is zero. The technique and proof of sparsity is beyond the scope of this research. The sparsity property derives a large class of statistical method called regularization regression or penalized regression. SCAD is a member of the family and will be discussed in the next section.

By convention, equation (1) includes all initial variables is considered as full model. Assume variable $x_k, k = 1, \cdots, p$ are redundant, the corresponding coefficient is set to zero and deleted from full model. The resultant model is shown in equation below.

$$y = \beta_0 + x_{(1)}\beta_1 + x_{(2)}\beta_2 + \cdots + x_{(s)}\beta_p + \varepsilon = \hat{x}^T\tilde{\beta} + \varepsilon \qquad (7)$$

A special statistical procedure needs to be designed to accurately estimate significant coefficients and shrink none-important into zero. The procedure is called regularization method which is defined in below.

$$\widehat{\beta} = \underset{\beta \in \mathbb{R}^p}{\operatorname{argmin}} \sum_{i=1}^{n} \rho(y_i - \mathrm{x}_i^T \beta) + n \sum_{j=1}^{p} \mathrm{P}_\lambda(|\beta_j|). \qquad (8)$$

In equation, i stands for data from i-th sample and j represents j-th predictor. $P_\lambda()$ is a specially designed penalty function, $\rho()$ is a loss function and λ is a tuning parameter to control the complexity of the model. By regularization regression, variable selection and coefficient estimation can be done simultaneously.

In practice, $\ell_1$penalty function is widely applied, which called" Least Absolute Shrinkage and Selection and Operator" and LASSO for abbreviation (Tibshirani 1996). Variable coefficient estimate is combined with $\ell_1$penalty function in LASSO, which is descried in equation below.

$$\widehat{\beta}_{\text{Lasso}} = \underset{\beta \in \mathbb{R}^p}{\operatorname{argmin}} \sum_{i=1}^{n} (y_i - \mathrm{x}_i^T \beta)^2 + n \sum_{j=1}^{p} \lambda_j \, |\beta_j| \qquad (9)$$

An advantage of LASSO approach is that its convexity guarantees global optimal result. From the last decade, statisticians and mathematicians spend great effort on improving the algorithm of LASSO. Nowadays, it can be conveniently applied in C, C++, Matlab® and R language.

3.3 SCAD method

SCAD approach is a member of penalty regression family and an improvement of LASSO approach. It utilizes a penalty function to estimate and keep significant variables and leave insignificant predictors into zero. Variable selection and estimation of corresponding coefficient in model is done simultaneously by the algorithm.

Consider a classic linear regression model.

$$y = X\beta + \varepsilon \tag{10}$$

In equation, y is an $\times$ 1vector and X is an n $\times$ d matrix. Conventional least square algorithm estimate confidents though $||\hat{\beta} - \beta||$. In penalized regression, constrains are added to the parameter to solve the least squares or maximal likelihood. The equation is below (11)

$$\widehat{\beta} = \underset{\beta \in \mathbb{R}^p}{\operatorname{argmin}} \sum_{i=1}^{n} (y_i - \mathrm{x}_i^T \beta)^2 + n \sum_{j=1}^{p} \mathrm{P}_\lambda(|\beta_j|). \tag{11}$$

Where i is the number of samples and j is j-th predictor. P_λ is designed penalty function and λ is the tunning parameter to control the complexity of the model. When λ is zero, the model is original full model, when λ equals infinity,no variables are selected.

(Fan and Li 2001) proposed three criteria to assess an appropriate penalty function.

1. Unbiasedness: Bias should be minimized or avoid when number of significant variables is large.
2. Sparsity: Model will set insignificant variable's coefficient into zero for proper λ value.
3. Continuity: Developed model stability and smooth is guaranteed by continuity property.

A well-developed penalty function is appropriate to address above three properties. (Fan and Li 2001) proposed Smoothly Clipped Absolute Deviation (SCAD) penalty functions and is defined in equation 12-14.

$$P_\lambda(|\beta|) = \begin{cases} \lambda|\beta|, & 0 \le |\beta| \le \lambda; \quad (12) \\ \frac{a\lambda|\beta| - (\beta^2+\lambda^2)/2}{a-1}, & \lambda \le |\beta| \le a\lambda; \quad (13) \\ \frac{(a+1)\lambda^2}{2}, & a\lambda < |\beta| \quad (14) \end{cases}$$

Resulting SCAD estimator solutions are given in equations below.

$$\left|\widehat{\beta}\right| = \begin{cases} \operatorname{sgn}(z)(|z|-\lambda)_+, & 0 \le |z| \le 2\lambda, \quad (15) \\ \frac{\{(a-1)z - \operatorname{sgn}(z)a\lambda\}}{a-2}, & 2\lambda < |z| \le a\lambda, \quad (16) \\ z, & a\lambda < |z|. \quad (17) \end{cases}$$

Parameter a is set to 3.7. SCAD doesn't compress large number of parameters; the selected variable is more concise and reliable. From (Fan and Li 2001, Fan and Li 2006), it has been proven that SCAD can exactly select all true variables and shrink non-significant variables into zeros. (Zou and Li 2008) further developed SCAD algorithm by proposing a local linear approximation algorithm to obtain one-step sparse SCAD estimation. Approximation SCAD penalty with ℓ_1 constrain is shown in equation (18).

$$P_\lambda(|\beta_j|) \approx P_\lambda\left(\left|\beta_j^{(0)}\right|\right) + P_\lambda{}'\left(\left|\beta_j^{(0)}\right|\right)\left(|\beta_j| - \left|\beta_j^{(0)}\right|\right), \quad \text{for} \quad \beta_j \approx \beta_j^{(0)}. \qquad (18)$$

Where $\beta_j^{(0)}$ is the initial value. LASSO estimator determines $\widehat{\beta}_j^{\mathrm{Lasso}}(\lambda)$ as $\beta_j^{(0)}$. One-step sparse SCAD estimator is derived from equation below.

$$\widehat{\beta}_n^{\mathrm{OSE}}(\lambda) = \underset{\beta \in \Theta}{\operatorname{argmin}} \frac{1}{n}\sum_{i=1}^{n}(Y_i - x_i^T\beta)^2 + \sum_{j=1}^{p} P_\lambda{}'\left(\left|\widehat{\beta}_j^{\mathrm{Lasso}}\right|\right)|\beta_j|. \qquad (19)$$

A high dimensional Bayesian information criterion (HBIC) is proposed by (Wang, Kim et al. 2013) to choose an global optimal tuning parameter to control the complexity of model. A calibrated Local Linear Approximation (LLA) to calculate the estimator. The definition of HBIC is in equation (20).

$$\mathrm{HBIC}(\lambda) = \log\left(\hat{\sigma}_\lambda^2\right) + |\mathrm{M}_\lambda| \frac{\mathrm{C_n} \log(\mathrm{p})}{\mathrm{n}} \qquad (20)$$

Where $M_\lambda = \{j: \hat{\beta}_j(\lambda) \neq 0\}$, $|M_\lambda|$ is the number of elements of M_λ and $\hat{\sigma}_\lambda^2 = n^{-1}\rho(y - X\hat{\beta}(\lambda))$. C_n is a sequence of number that diverges to ∞. In the calculation, set $C_n = \log(n)$. The tuning parameter is set as

$$\widehat{\lambda} = \operatorname*{argmin}_{\lambda \in \Lambda_n} \mathrm{HBIC}(\lambda). \qquad (21)$$

Following steps are from LLA algorithm to estimate optimal tuning parameter $\hat{\lambda}$

1. Set initial value $\beta^0 = \hat{\beta}^{Lasso}(\lambda^2)$ where

$$\widehat{\beta}^{\mathrm{Lasso}}(\lambda^2) = \operatorname*{argmin}_{\beta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} (Y_i - x_i^T \beta)^2 + \sum_{j=1}^{p} \lambda^2 |\beta_j| \qquad (22)$$

2. Let

$$\widehat{\beta}_n^{\mathrm{OSE}}(\lambda) = \operatorname*{argmin}_{\beta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} (Y_i - x_i^T \beta)^2 + \sum_{j=1}^{p} P_\lambda{}' \left(\left| \beta_j^{(0)} \right| \right) |\beta_j| \qquad (23)$$

3. Evaluate HBIC and obtain optimal $\hat{\lambda}$ value.

$$\widehat{\lambda} = \operatorname*{argmin}_{\lambda \in \Lambda_n} \log\left(\widehat{\sigma}_\lambda^2 (\widehat{\beta}_n^{\mathrm{OSE}}) \right) + \left| M_\lambda (\widehat{\beta}_n^{\mathrm{OSE}}) \right| \frac{\log(n) \log(p)}{n}. \qquad (24)$$

The optimal value of λ is serached among interval $\left[{}^{C_1}/_{n}, c_2 \log(n)/n\right]$, then value of $\hat{\lambda}$ is derived for given λ. Value of C_1 and C_2 is determined by empirical studies.

Chapter 4

Frame Work, Steps of Analysis and Inverse Model Development Results

The frame work and steps to an inverse model formulation will be discussed in this chapter. Each step is explained based on the sequence followed. Baseline building information is introduced and data preparation method is discussed. The developed frame work and steps are shown in figure 4-1.

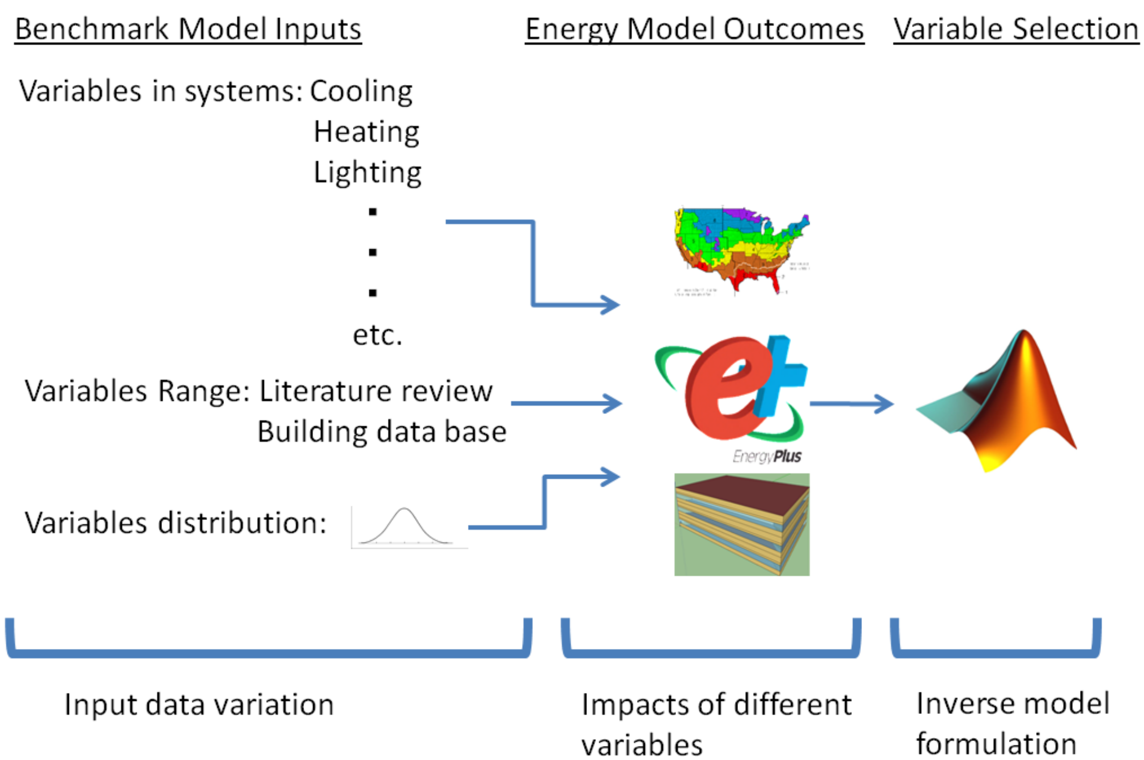


Figure 4-1. Schematic steps diagram for inverse model development.

4.1 Baseline building and candidate variables

The Department of Energy (DOE) benchmark office building is selected as the baseline building for analysis. Candidate variables are selected from this building based on the category of sub-system energy usage. There are several reasons for choosing this building as the baseline building. It reflects a generic office building conditions in the US, such as size, geometry layout, envelope construction materials, mechanical system type and settings, plug loads, etc. Although no one building can represent all building types, research steps in this investigation can be applied to other building types. This benchmark building represents typical characteristics of numerous buildings in the medium office building sector. Findings and results from the analysis is assumed that can be applied to buildings with similar conditions.

The DOE benchmark medium size office building is a three-story office building. The construction material set is considered as “post-1980” type this means it resembles typical newly-built office buildings. The building shape is shown in figure 4-2 which is rectangular shape with flat roof. In data variation, building orientation is kept the same. This is because rectangular shape has no self-shading effect. Typical building location and ambient weather data are retrieved from ASHRAE 90.1 weather zones. Sixteen weather zones are included (Table 4-1). Typical meteorological weather (TMY3) file provides sub-hourly weather conditions such as dry bulb, wet-bulb temperature, solar radiation etc. TMY 3 data is preferred over actual meteorological year (AMY) data for this research; it is an averaged generic condition for past 15 years.

Table 4-1 Location weather zone information.

Location	ASHARE 90.1- 2004 Climate Zone	Location	ASHARE 90.1- 2004 Climate Zone
Miami	1A	Albuquerque	4B
Houston	2A	Seattle	4C
Phoenix	2B	Chicago	5A
Atlanta	3A	Boulder	5B
Los Angeles	3B-CA	Minneapolis	6A
Las Vegas	3B	Helena	6B
San Francisco	3C	Duluth	7
Baltimore	4A	Fairbanks	8

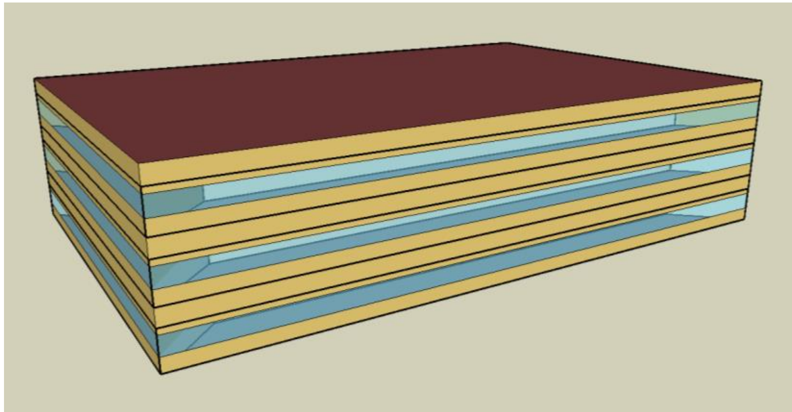


Figure 4-2. Benchmark office building shape

The total building floor area is 53626 ft^2; total conditioned space area is 53604 ft^2. The length and width ratio is 1.5. Each floor has standard five thermal zones which include one core zone and four perimeters zones as shown in figure 4-3. Zone 1 is the core zone in the middle, which is dominated by internal load. Zones 2 to 5 are perimeter zones which are more sensitive to ambient weather conditions. In the top of each floor, a plenum is setup as the return for the supply air. The plenum is simulated separately in the model. Based on ambient condition, interior and exterior boundary conditions are automatically generated. The exterior wall construction materials include wood siding, 2-inch steel frame, insulation and 0.5 in gypsum board inside. In each façade, the window to wall ratio is 0.33. The mechanical-side of system, the building designs adopts a multi-zone variable air volume (VAV) system. A packaged air condensing system provides cooling energy to offset demand. Heating energy is mainly provided by a gas furnace, while supplemental heat is offered by electric heater. Occupancy and operating schedules are setup for a typical office building. In practice, the number of occupants and activity are hard to measure. In the model, the tenants' behavior is defined by the schedule and occupants' density.

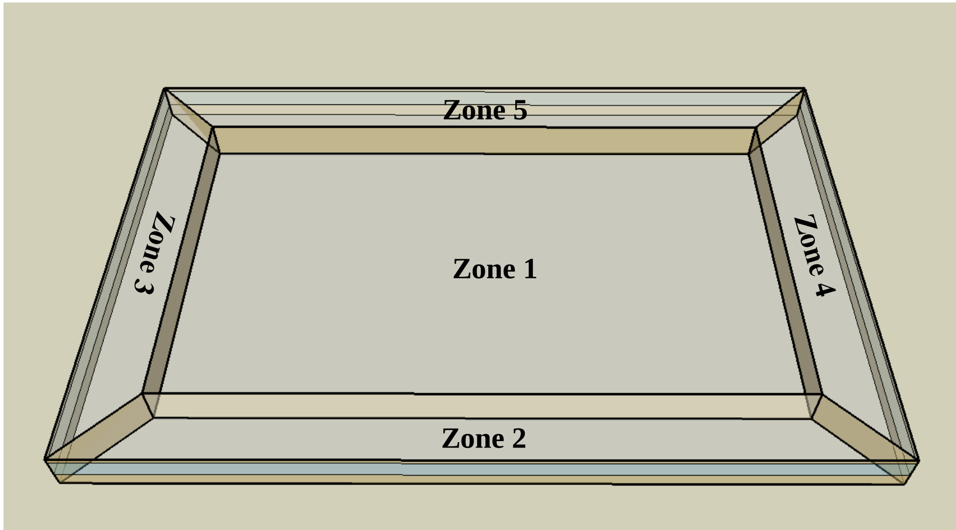


Figure 4-3. Baseline building thermal zones layout.

Table 4-2 Benchmark building mechanical system summary.

Building Heating, Ventilation and Air Conditioning (HVAC) System	**Air System Type**	**Variable Air Volume System in each floor**
	Cooling Type	**Two-Speed-Air-Cooled Direct Expansion (DX) Coil**
	Heating Type	**Gas Furnace in Air Handling Unit(AHU) and electric reheat in terminal box**
Building Domestic Hot Water (DHW) System	**DHW System Type**	**Gas Fired Water Heater**

A building has numerous variables such as thermal characteristics of envelop material, mechanical system parameters, set-points, plug load operation etc. Given the time and cost to comprehensively measure those data, benchmark office building is an ideal candidate for couple of reasons. The model is setup in EnergyPlus in numerical numbers; perturbation and access to every variable are possible. Another reason is that in actual metered data, meter reading error and data storage error happens frequently. In simulated EnergyPlus results, data is error free which provides more robust conclusion. The purpose of variable perturbation is to examine the effect of different variables on energy use. The selection of initial key variables is based on sub-system category such as envelop, mechanical system, plug loads system etc. In input variables' perturbation, the probability distribution function is important and needs to be defined. Current building information data based such commercial building energy survey (2003) and building performance data base (DOE, 2014) do not provide distribution percentage of variables. Normal distribution is a popular assumption in many research fields, however based on the purpose of this research, it might bias the results. Currently no public data is available to indicate that the distributions of variable are near the center value. Instead, the purpose of variables' perturbation is to exam the impact of each variable on energy outcome. Thus input variables are taken as continuous uniform distribution with equal probability for selection. This means input variables are spread out evenly between upper and lower boundary with equal chance to be selected. The impact of each variable at different levels is considered comprehensively though the entire range space. To make the data more closely to represent actual building conditions in the US, the upper and lower boundaries' values are derived from literature, open-public building data base and educated estimation. The input candidate variables are summarized in table below.

Table 4-3 Candidate variables table, distribution functions and boundaries.

Variable Name	Unit	Distribution Function	Lower Boundry	Upper Boundry
Interior Lighting Power Density	$W/_{m^2}$	Continues uniform	0	17
Interior Lighting Schedule	$Hour$	Continues uniform	3.45	16.7
Lighting Return Fraction	$\%$	Continues uniform	0	40
Exterior Lighting Power	$Watt$	Continues uniform	0	22206
Plug Load Density	$W/_{m^2}$	Continues uniform	0	34
Plug Load Schedule	$Hour$	Continues uniform	0	21.4
Plug Load Convective Fraction	$\%$	Continues uniform	0	100
Boiler Efficiency	$\%$	Continues uniform	65	95
Boiler Heat Loss	$W/_{K}$	Continues uniform	3	9
Water System Peak Flow Rate	$m^3/_{s}$	Continues uniform	1.56E-7	4.6E-8
DHW User Demand Schedule	$Hour$	Continues uniform	2.78	7.5
DHW Ambient Temperature	℃	Continues uniform	11	28
DHW Boiler Outlet Temp	℃	Continues uniform	40	65
External Wall Overall U Value	$W/_{m^2K}$	Continues uniform	1.5	0.2
External Wall Capacitance	$W/_{m^2K}$	Continues uniform	0.34	1.0875
Ground Floor Overall R value	$m^2K/_{Win}$	Continues uniform	2.43	1.28
External Roof R value	$m^2K/_{Win}$	Continues uniform	17	6
External Roof Capacitance	$W/_{m^2K}$	Continues uniform	0.96	0.56
Window U value	$W/_{m^2K}$	Continues uniform	4.8	1
External Window SHGC	$\%$	Continues uniform	0.585	0.195
Infiltration Rate	$m^3/_{sm^2}$	Continues uniform	0.0001	0.0006
Occupancy Density	$Area/Person$	Continues uniform	4.9	700

Occupancy Schedule	*Hours*	Continues uniform	2	14.7
Thermal Cooling Set Point	℃	Continues uniform	22	25
Thermal Heating Set Point	℃	Continues uniform	17	22
Cooling Reset Temperature	℃	Continues uniform	24	27
Heating Reset Temperature	℃	Continues uniform	16	21
Design Fan Head	*Water Inch*	Continues uniform	2.22	6.68
Fan Nominal Efficiency	*%*	Continues uniform	50	88
Fan Motor Efficiency	*%*	Continues uniform	50	95
Fan Minimum Air Flow Rate	$m^3/_s$	Continues uniform	0.2	2
Motor Air Stream Fraction	*%*	Continues uniform	0	100
Fan Operating Schedule	*Hours*	Continues uniform	3	24
Outside Air Intake Ratio	*%*	Continues uniform	0	100
Economizer	*On/off*	Categorical	0	1
Supply Air Temperature	℃	Continues uniform	6	20
Terminal Box Minimum Position	*%*	Continues uniform	2	45
Night Cycle Thermal Stat Tolerance	*Delta* ℃	Continues uniform	1	4
Cycling Run Time	*Minute*	Continues uniform	5	10
Gas Furnance Efficiency	*%*	Continues uniform	60	90
Reheat Coil Efficiency	*%*	Continues uniform	90	100
DX Coil COP		Continues uniform	2	5
Occupants Radiant Fraction	*%*	Continues uniform	30	50
Design Outdoor Air Flow	$m^3/_s$	Continues uniform	0.0065	0.0185
Elevator No.	*No.*		1	3
Elevator Power	*Watt*	Continues uniform	16054	48164
Pump Head	*Pa*	Continues uniform	269028	89676

Pump Motor Efficiency	%	Continues uniform	70	95
Pump Motor Inefficiency to fluid stream	%	Continues uniform	10	40
Preheat Design Temperature	℃	Continues uniform	5	10
Precool Design Temperature	℃	Continues uniform	6	19
Water Heater Dead Band	℃	Continues uniform	1	5
Yearly Average Dew Point	℃	TMY3	-8	18
Yearly Average Relative Humidity	%	TMY3	34	74
Yearly Average Solar Radiation Intensity	$Wh/_{m^2}$	TMY3	107.93	239.06
Yearly Average Wind Speed	$m/_{s}$	TMY3	2.4	4.7

Variables in table 4-3 are candidate variables that will vary at different levels to simulate building energy end use. Unlike many previous researches (Gustafsson 1998, Westphal and Lamberts 2005, Sun and Reddy 2006, Lam, Wan et al. 2008, Sanchez, Lacarrière et al. 2014), variable is only changed “one-at-time”. This research not only change variable “one-at-time” but also varies “two-concurrent” simultaneously. An “one-at-time” approach might ignore the interacting effects among variables; “two-concurrent” variation avoids such shortcoming. Around 2000 samples of building variables are generated from table4-3 within the parameter boundaries and compiled into input variable data base. The next step is to initiate the runs of the EnergyPlus engine for simulation. Each simulation period is 8760 hours which is a whole year period. This covers year-around weather conditions including building energy performance under different weather conditions. The simulation time step is set as 4 which keeps the simulation running time from too long while maintain the accuracy of results. During data generation, computational time can be significant. With current computer technology, parallel simulation is very helpful for time saving. EnergyPlus is capable of running batch of simulations at one time to expedite the process.

Simulated building energy corresponding to sample data matrix is exported into Matlab® and prepared for LASSO and SCAD analysis.

4.2 Variable selection via LASSO and SCAD penalty

As mentioned in chapter 3, the LASSO and SCAD penalty method are two methods that will implement the variable selection process on the data. Simulated data from the reference building is standardized before running the algorithm. Standardization is an important procedure for data preparation. It removes the difference from the units of measurement which helps the research comparing “apple to apple” instead of “apple to orange.” After standardization, LASSO and SCAD penalty results are generated in Matlab®.

4.2.1 LASSO variable selection results

LASSO variable selection is conducted in Matlab®, significant variables that relate to whole building energy use (kWh) are kept and shrink non-significant ones into zero. The LASSO selection results indicate that total energy use (kWh) is a function of averaged ambient temperature, interior (ILPD)/exterior lighting power density (ELPD), plug load power density (PLPD), thermal cooling (CSP)/heating set point (HSP) and supply air temperature (SAT). The mathematical equation is given in equation 25. The overall R^2 value is 94.4% which means 94.4% variance in building total energy use can be explained by variables above. The correlation coefficient is 0.971.

$$\boldsymbol{Total\ Energy\ Use = -0.05 * Temperature + 0.38 * ILPD + 0.06 * ELPD + 0.85 * PLPD + 0.05 * HSP - 0.06 * CSP - 0.06 * SAT} \quad (25)$$

It is important to realize the physical meanings of coefficients do not need to be over-interpreted. Each building is unique and will generate new coefficients when the model is developed. It should be noticed, the variable selection result will be very different if standardization is not conducted before the calculation. The procedure removes units of measurement in variables and bandwidth of variations. For example, the absolute number of plug load power variation range is much larger than space air temperature set point variation.

Therefore, the model selection technique will invariably select plug load power if standardization is not considered.

The final model only contains eight variables out of sixty eight initial variables. The R^2 value indicates a very strong correlation between energy use and selected variables. The result gives building owners an insight about sub-metering priorities. Variables selected in the model are statistically more significant than others which mean they should be monitored, auto-metering stored by the building data management system. Instead of measuring “minor” variables, collecting key data makes much more sense to evaluate whole building energy use and performance.

A primary finding from the model is that most key variables are internal load and space condition related. This helps us to realize focusing on building internal load reduction and monitor indoor space conditions. The building energy use is less sensitive to the variation of ambient weather conditions. Mechanical system is generally being considered as the largest energy consumer in a building; however selected mechanical system factors are less than expected. There are several reasons to explain. Most of mechanical system end uses are dependent variables. They can’t be included or selected by the model as independent variables. Another possible cause is that mechanical system operation is mainly driven by internal load system. The system is operating when there is a need to offset the heat generated by plug loads or inner zones have a demand to maintain comfort conditions. Internal load is the main driver for mechanical system operation.

Another finding is that weather condition variables are minimized to zero in the selection except dry bulb temperature. This is partially due to, as previously mentioned, office building energy use is primarily driven by internal loads and less responsive to ambient weather conditions. Another key reason is many weather parameters are linearly related to dry bulb temperature as can be seen in figure 4-3. For example, wet bulb temperature and relative humidity are highly correlated to dry bulb temperature. Including those variables will cause multicollinearity issue. In another word, this shows the robustness of LASSO algorithm. It automatically detects linear dependent relationship between variables and only selects key independent variable.

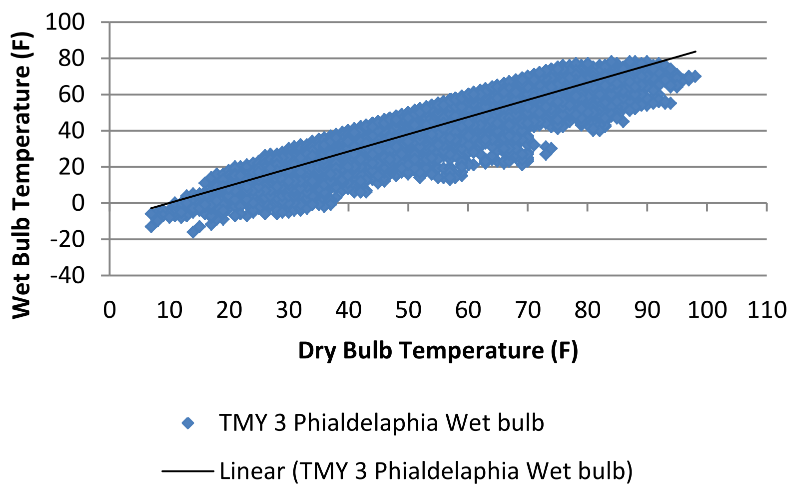


Figure 4-4. Philadelphia TMY3 wet bulb temperature vs. dry bulb temperature.

The research conducted variable selection for building cooling energy and heating energy as well. The procedure is very similar to total building energy variable selection. The only difference is to change whole building energy data into overall cooling and heating energy use respectively. This will help researcher to find key variables that are significantly relevant to cooling and heating sub-systems. The benefits are: (1) identify key variables that helps monitor performance of cooling/heating system. (2) Help to calibrate mechanical system energy use in forward building energy model (Chapter 6). (3) Assist the formation of mechanical system inverse model.

For whole building cooling energy use variable selection, LASSO algorithm result shows dry bulb temperature, interior lighting power density (ILPD), plug load power density (PLPD), window solar heat gain coefficient (SHGC), space cooling set point (CSP) , supply air temperature (SAT) and system COP are selected in the model. The final equation is shown in equation 27.

$$\textit{Cooling use} = 0.1919 * Temp + 0.3161 * ILPD + 0.8089 * PLPD + 0.1648 * SHGC - 0.1486 * CSP - 0.2298 * SAT - 0.0483 * COP$$

The overall R^2 value is 92.4% which means 92.4% variance in cooling energy use can be explained by variables above. The correlation coefficient is 0.96.The statistic index indicates the model is acceptable and capable to simulate cooling energy use with selected variables.

For whole building heating energy use, the LASSO variable selection shows ambient dry bulb temperature, ILPD, PLPD, window U value, occupancy density (OD), space heating set point (HSP), space cooling set point (CSP) and SAT are more important than other variables. The generated regression model is shown in equation 28.

$$\textit{Heating use} = -0.3159 * Temp - 0.2936 * ILPD - 0.616 * PLPD + 0.2883 * U\ value - 0.1131OC - 0.1832 * SAT - 0.1094 * CSP + 0.1775HSP$$

The overall R^2 value is 75.5 % which accounts 75% of variation in heating energy use. Two models for cooling and heating energy regression model are considered equally good with high coefficient of relation. Selected variables are statistically significant and number of variables is reduced to seven and eight. The temperature, interior lighting power density, plug load power density have largest coefficient in both models. This indicates building mechanical system energy use is primarily driven by ambient weather condition (primary dry bulb temperature) and internal loads (plug and lighting load) together. In commercial use or mixed use buildings, high office equipment load operates long hours in a day. The start and operation of mechanical system primarily depends on the schedule of occupants and internal loads. Two models both strongly show that including dry bulb temperature alone in the model is insufficient, collecting building internal load factors and data is critical to model building energy use.

Space conditions such as set points and supply air condition are considered important in the model as well. Both models select similar variables in terms of space conditions. Indoor environment partially determines the magnitude of thermal demand in the building. Mechanical system needs to response to the load quickly and accurately. More importantly, inner space or zones thermal demands are virtually ambient weather independent. The inner space might have constant annual cooling demand that has little dependency on ambient weather variation. Since weather condition has small influence on core zones, mechanical system component factors are less influential than other variables and consequently not selected. It is reasonable to assume correlation exists but not strong enough to statistically “stand out” from other variables at aggregate annual system end use.

Several previous researches (Spyrou, Shanks et al. 2014) show building square footage is significant to energy end use. In this research, it is not being considered for couple of reasons. For an existing building, the size and geometry are fixed conditions which can’t be altered. The only variable that can be considered is conditioned floor area. In most commercial buildings, especially high end office space, the whole building is conditioned including stairs. Another reason is building plug or lighting load increases linearly with floor area. For similar building type, although total plug or lighting end use varies constantly, the power density is very similar. This is because most buildings have to obey energy standards such as ASHARE 90.1 or similar regulations. Plug or lighting end use will increase linearly when floor area increases. Therefore, plug and lighting loads are good surrogates of floor area. This will also avoid multicollinearity issue between variables.

4.2.2 SCAD penalty variable selection results

SCAD algorithm is compiled in Matlab® and standardized data matrix is imported. The variable selection is conducted on whole building energy use, annual cooling energy use and heating energy use. Results are discussed in below.

Total building energy use is selected to be a function of dry bulb temperature, interior plug load and lighting load. The resultant regression model is shown in equation 29. The coefficient of determination is 92%; the correlation coefficient is 0.96 which is a very strong correlation.

$$\boldsymbol{Total\ Energy\ Use = -0.25 * Temperature + 0.3828 * ILPD + 0.8562 * PLPD} \quad (29)$$

From the model, plug and lighting load have stronger influence on total energy use. Temperature is influential but less significant. When compared to LASSO algorithm, SCAD penalty results show less number of selected variables in the model. This is resulted from the difference in two algorithms. SCAD doesn't compress large parameters like LASSO algorithm, therefore the result is more conservative and fewer variables are allowed in the final model. Although fewer variables are selected, the final model generates great insight about building energy use. Plug load and lighting load are selected in both LASSO and SCAD penalty regression model. In SCAD penalty method, they are the only two variables selected by both algorithms in additions to dry bulb temperature. It means plug and lighting load data are very critical for inverse model development. More importantly, they are selected by both algorithms. It is safe to conclude that, in a medium-sized office building, lighting and plug load are the most important factors that influence building energy use. Dry bulb temperature is another factor that impacts energy end use. Dry bulb temperature represents the majority influence of ambient weather conditions. By including plug, lighting load and dry bulb temperature, the regression model includes both internal (plug and lighting) and perimeter (dry bulb temperature) influential factors that drives building energy use. It suggests that by only including dry bulb temperature in the regression model is not enough.

For SCAD penalty cooling energy variable selection, the method finds ambient dry bulb temperature, interior lighting power, plug load, window SHGC, space cooling set point (CSP), supply air temperature and mechanical system COP are significant and kept. Equation 30 shows the regression model for cooling energy use.

$$\boldsymbol{Cooling\ Use} = -\mathbf{0.1919} * \boldsymbol{Temperature} + \mathbf{0.3161} * \boldsymbol{ILPD} + \mathbf{0.8059} * \boldsymbol{PLPD} + \mathbf{0.1648} * \boldsymbol{SHGC} - \mathbf{0.1486} * \boldsymbol{CSP} - \mathbf{0.2298} * \boldsymbol{SAT} - \mathbf{0.0483} * \boldsymbol{COP} \quad (30)$$

Though SCAD penalty selection, above variables are found significant to annual cooling energy use. 92% of variability in cooling energy use is explained by equation above, the coefficient of correlation is 0.96 which indicates a very strong correlation between dependent variable (annual cooling energy use) and selected independent variables. From the coefficient, interior lighting and plug loads are the largest contributors which indicate they have strong capability to explain variation in cooling energy use. Ambient dry bulb temperature is the second strongest variable which is intuitively reasonable because in summer, most buildings have a high cooling load. In commercial buildings, they might have cooling load in winter for example data center. Other factors include window characteristic (SHGC), indoor space conditions factors (CSP,SAT). Space condition is influenced by internal loads, on the other hand, is controlled by set points. Mechanical system has to turn on constantly to keep the space in set point's range which make space condition factors important and are selected in regression model.

Similar to previous variable selection results, dry bulb temperature is the only weather condition factor selected. The reason is other weather variables are correlated to dry bulb temperature; including dry bulb temperature alone will cover other weather effects. The results show that SCAD penalty method has same robustness like LASSO and avoids multicollinearity issue between variables.

For annual heating energy use, SCAD penalty method has very similar result to LASSO method. The final model includes ambient dry bulb temperature, interior lighting, plug load, window SHGC, occupancy, space cooling set point, heating set point and supply air set point. The model is shown in equation 31 below.

$$\boldsymbol{Heating\ use} = -\mathbf{0.3159} * \boldsymbol{Temp} - \mathbf{0.2936} * \boldsymbol{ILPD} - \mathbf{0.616} * \boldsymbol{PLPD} + \mathbf{0.1648} * \boldsymbol{SHGC} - \mathbf{0.1131}\boldsymbol{OC} - \mathbf{0.1832} * \boldsymbol{SAT} - \mathbf{0.1094} * \boldsymbol{CSP} + \mathbf{0.1775}\boldsymbol{HSP} \tag{31}$$

The model can explain 75% of variance (R^2) in annual heating use. Coefficient of correlation is 0.87 which represents strong correlation between selected variable and dependent value. Similar to findings in LASSO algorithm, interior plug, lighting load and ambient dry bulb temperature has largest coefficient which means strong influence of those variables on heating energy use. Space condition factors (CSP, HSP, SAT), window characteristics also have strong influence.

4.3 LASSO and SCAD penalty variable selection result summary

LASSO and SCAD penalty methods conducted variable selection respectively on reference building energy data. Dependent variables are total whole building energy use, annual cooling energy use and heating energy use.

In whole building inverse model development, LASSO selects interior, exterior lighting power, plug load power, thermal cooling/ heating set point and supply air temperature in final model. 94% of variability in total energy use can be explained by the model. SCAD penalty algorithm is relatively conservative than LASSO. In its final model, dry bulb temperature, interior lighting and plug loads are selected. The coefficient of determination is 92%; the correlation coefficient is 0.96 which indicate a very strong correlation relationship between selected variables and dependent variable.

Overall, two models have good coefficient of determination and strong correlation coefficient. This indicates high confidence of model validity and accuracy of modeling building energy use. From selected variables, three variables are occurred in both methods which are: ambient dry bulb temperature, interior lighting and plug load. Those three variables are selected in two algorithms which mean among all selected candidate variables, ambient dry bulb temperature, interior lighting and plug loads are the most significant. They represent two driving factors that control building energy use pattern: ambient condition driver and internal driver. For many commercial buildings, the building base load is relatively higher compared to weather-related load. Many inner spaces require whole year precise temperature and humidity control such as storage room or has constant cooling demand, for example data center. Those spaces' loads show very little dependencies on ambient weather variation. More importantly, they are spaces with the highest energy use intensity in entire building. To answer the first research question in chapter one, in addition to dry bulb temperature, interior lighting and plug loads data should be collected and included. Other important variables are space cooling heating/cooling set point, supply air set point temperature which concluded as space condition variables. Space condition variables determine the thermal conditions in space and energy demand. Mechanical system is turned on to keep space at desired temperature ranges.

For mechanical cooling/heating subsystem end use, LASSO and SCAD penalty results are very similar. For cooling system annual end use, final model selected by LASSO includes temperature, interior lighting power, plug load, window SHGC, cooling set point, supply air temperature and mechanical system COP. Statistical index shows R square value is 92.4% and correlation coefficient is 0.961. SCAD penalty selects ambient temperature, interior lighting power, plug loads, window SHGC, cooling set point, supply air set point and mechanical system average COP are important. Two models have exactly the same selected variables which cross validate each other. Space condition variables such as set points are included because set points define thermal environment in spaces and mechanical system has to operate to meet the demand. Window SHGC indicates building glazing materials are sensitive to cooling energy use. Glazing system in current buildings is not only for aesthetic purpose, but also help to provide free day lighting, reduce cooling load in space. SHGC is under glazing system material data category. Knowing building window material well is critical to space cooling energy use.

For space heating energy end use, two algorithms have similar results. LASSO selects dry bulb temperature, interior lighting power, plug load, window U value, number of occupancy, supply air temperature, cooling and heating set point in space. SCAD penalty results show temperature, interior lighting power, plug load, window SHGC, supply air temperature, cooling/ heating set points are relative. Two models both have a coefficient of correlation of 0.87 which indicate strong correlation between heating energy endues and selected variables. The only difference in two algorithms is window SHGC and window U value selection. However, both variables are under glazing material category. Other variables in two variable selection techniques are the same.

In summary, variable selection results based on different sub-system for two algorithms are included in table 4-1, variable selection matrix. Two methods show very similar findings on key variables determination. For whole building energy end use, interior lighting and plug loads are selected in both methods. In cooling/heating model, they are all being selected as well. Therefore, interior lighting and plug loads are the two most significant variables. From cooling and heating selected model, space conditions variables are also critical, such as cooling and heating set point, supply air temperature. Those variables determine space thermal environment and drives mechanical system to meet the load. Other variables selected are window material information such as SHGC or U value. It means glazing materials have huge impact on system energy use. The last variable selected is mechanical system's COP, which is obvious because it is ratio between energy output and input of mechanical system. System with a higher COP will always has better energy performance while maintaining the same space comfort conditions. From model statistical index, all models show strong correlation between selected variables and dependent variable. This means models are valid with high degree of confidence.

Table 4-4 Summary of variable selection results.

Variable Name	Dry Bulb Temp	Lighting Power	Plug Load	Occupants	Window SHGC	Window U value	Space Cooling Set Point	Space Heating Set Point	Supply Air Temp	System COP
Total Energy Use (LASSO)	√	√	√		√		√	√	√	
Total Energy Use (SCAD)	√	√	√							
Cooling System (LASSO)	√	√	√		√		√		√	√
Cooling System (SCAD)	√	√	√		√		√		√	√
Heating System (LASSO)	√	√	√	√		√		√	√	
Heating System (SCAD)	√	√	√	√	√			√	√	

Chapter 5 Variation Bin Method

5.1 Method introduction

Chapter 3 and Chapter 4 identify key variables that in addition to dry bulb temperature that are significant to whole building energy use, heating system energy use and cooling system energy use. From results, ambient dry bulb temperature, lighting power and plug load are the most important variables because they are selected by two algorithms in all regression models. However, in Figure 1-2, 1-3, large scatter was found alone ambient temperature profile. Besides, it is unfair to compare or investigate system performance at different ambient conditions. This research develops a variation bin method to isolate impacts from weathers and investigate the cause of large scatter in building energy use.

The bin method is a procedure where daily metered energy use is sorted into discrete groups (bins) of weather conditions. The idea of this analysis is to compare metered energy use data within each bin to exclude impacts from temperature. Each bin contains number of days during a year in a particular range of dry bulb temperature (5°F degrees). It means when averaged daily temperature difference is less than 5 degrees, those days will be grouped into one bin. The selection of bin bandwidth can be different; it can be 3 degrees, 5 degrees, 10 degrees or any number. However, large bandwidth will jeopardize the accuracy of the analysis. The theory for the bin method is that when daily averaged temperature is close enough (under one bin); variation of energy use (scatter) is caused by weather independent factors. This allows isolating weather impacts from two discrete days. It enables fair comparison of building energy performance analysis under different weather conditions.

The whole building daily energy use variation, sub-metered data variation are calculated to find the cause of scatter. In statistic field, common measurements of data dispersion metrics include variance and standard deviation. Variance and standard deviation calculations are in equation 32 and 33.

$$\sigma^2 = \sum(X - \mu^2) \qquad 32$$

Where μ is the population mean, X is the expectation value. It quantifies averaged square difference of expectation from mean value.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2} \qquad 33$$

Where $\mu = \frac{1}{N}\sum_{i=1}^{N} x_i$, standard deviation is the square root of variance. Low values of standard deviation and variance indicate that data are closer to the sample average value. A variance will always be positive number but the unit will be different from original data. On the contrary, standard deviation expresses dispersion of data in the same original unit, it is intuitively better to know the spread of data in the same unit. Thus in the bin variation method, standard deviation is more appropriate to describe variation of data dispersion in this investigation.

Two medium size office building data (figure1-2, figure1-3) have been collected for at least twelve months. Two buildings locate very close to each other and have very similar design features. Both buildings have three floors with a square footage of 103,500 ft^2 and 108,676 ft^2. The building mechanical system is roof top units with VAV system. Heating demand is met by electric resistant heater inside the AHUs and terminal boxes. Supply air temperature is supplied around 50 °F to 60 °F. Space thermostat is programmed to around 73 °F. Energy metered is installed to measure whole building energy use, lighting and plug load energy, total HVAC system energy use at 15 minute interval. The data collection period is more than one year, this helps analyze different weather conditions though an entire year.

5.2 Data preparation and time scale determination

Commercial buildings especially office buildings have very distinctive patterns of operation between weekdays and weekend (figure 5-1, figure 5-2). In weekdays, tenants start to work in office at very similar hours in a day. Plug loads and interior lighting energy use follows occupants' activities closely. The mechanical system is turned on at full capacity to maintain the thermal environment in spaces. While in weekends, many buildings have thermostat reset that space temperature is different from working days. Space plug and interior lighting load is kept at minimum level. However, careless tenants might show ignorance of energy conservation that leave computers or lights on during the weekend. Some employees might have occasional overtime work in weekend. This will lead to mechanical system operation and energy use. Interior lighting and plug loads will also have different levels of energy use from weekdays. More importantly, statistically building operations in weekends are unpredictable. Analyst can't accurately estimate the number of overtime working in the weekend and its' level of energy use.

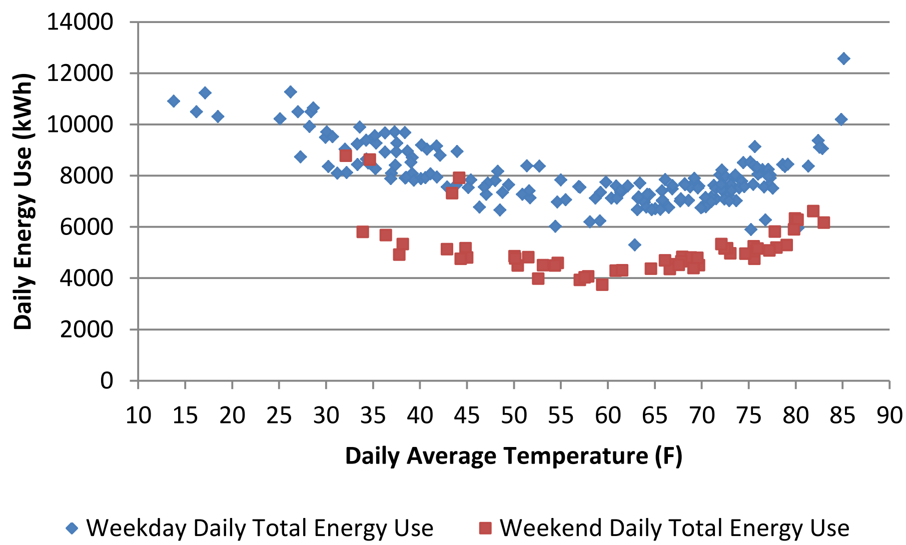


Figure 5-1. Case study building I weekday & weekend daily energy use.

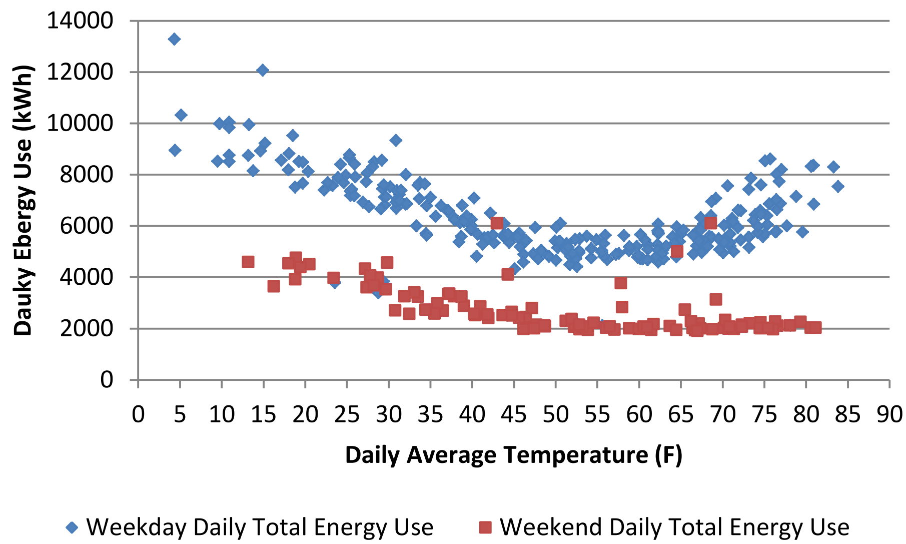


Figure 5-2. Case study building II weekday & weekend daily energy use.

From figure5-1, 5-2, weekends and weekdays show very dissimilar pattern of energy use. Weekend use is relatively independent of temperature because most of buildings have weekend operation scheme that energy use is kept at minimum. However, several weekends end uses are significantly higher than others. Possible causes are weekend events were held in the building, tenants' weekend overtime work and etc. Therefore, it is necessary to divide building data into weekday and weekend category. The bin variation is mainly conducted on weekday analysis because weekdays have larger energy consumption than weekends.

The case study building sub-metered data is collected at 15-minute interval, original data can be grouped into different time scale such as an hour, a day, a week or a month. During a whole day operation, system changes or operational changes can happen at different times, such as supply air temperature reset, static-pressure reset, on/off of interior equipment. However, most of changes are similar in a whole day cycle. The scheduled change can be regarded as a constant variation if time interval is at least equal or larger than cycling period. For example, weekly averaged data comparison can ignore set point changes within one day because that same change happens every day therefore canceling each other. Another factor that should pay attention is building thermal delay effect. Many buildings have a time-lagging effect of peak cooling/heating load. For example, the moment of highest cooling or heating load is latter than the hottest or coldest ambient weather condition. Building's thermal response is slower than ambient weather variations. Mechanical system can't responses to building loads spontaneously. For example, the sensor detects a space has a heating demand; it may take time for water start to flow. In a cold season, warming up the air or coil material will take extra time. Delay can also be caused by air traveling time to supply diffuser and heating up the space. The length of lagging effect has dependencies of building thermal mass, material and indoor/ ambient conditions. Thermal mass varies with building locations, type and size. Modeling such dynamic effect requires detailed software such as EnergyPlus. Linear regression model is unable to simulate. To solve this issue, an appropriate selected data time scale allows enough time for stored energy to release from thermal mass and mechanical system responses to the load. From (Kissock 1993), the research suggested a simplified thermal network to estimate the time for building thermal mass to achieve steady state. A time constant had been introduced to describe the rate of thermal mass radiates. From the results, space will achieve 99% of its steady state after 24 hours. This conclusion strongly recommends appropriateness of choosing 24-hours (daily) as minimum time scale. It allows thermal mass to fully radiate its stored energy and mechanical system has sufficient time to response. Daily cycling operational changes are also removed if 24-hours are the data time scale.

To summarize, 24 hours (daily) interval is appropriate for data analysis because it avoids problems with thermal mass effect, mechanical system response time and daily cycling changes.

5.3 Variation bin method results

The bin interval is selected as 5 degrees, dates that averaged daily temperature less than 5 degrees are grouped into same bin. Standard deviation of whole building energy use, sub-metered data are shown in figure 5-3, 5-4. The vertical axis is standard deviation (kWh/Day) and horizontal axis is the sequence of bins based on averaged daily temperature.

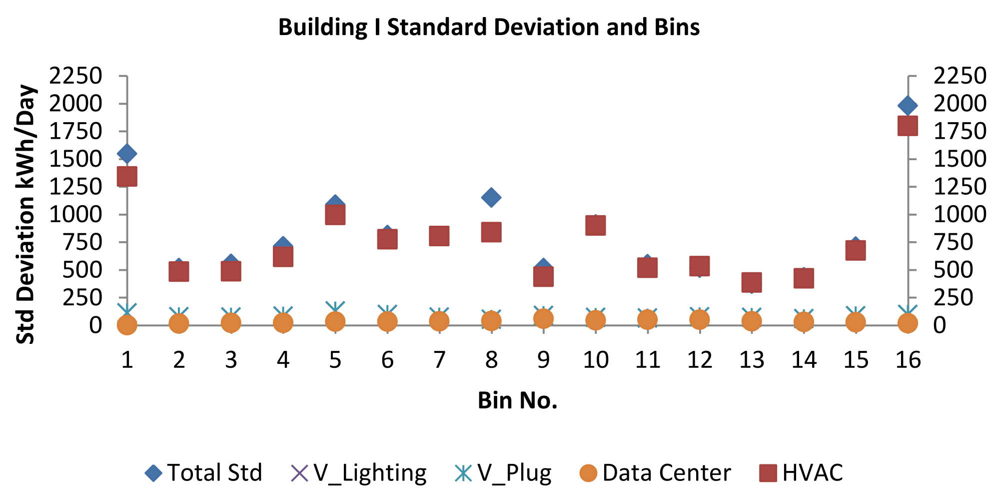


Figure 5-3. Case study building I bin method result.

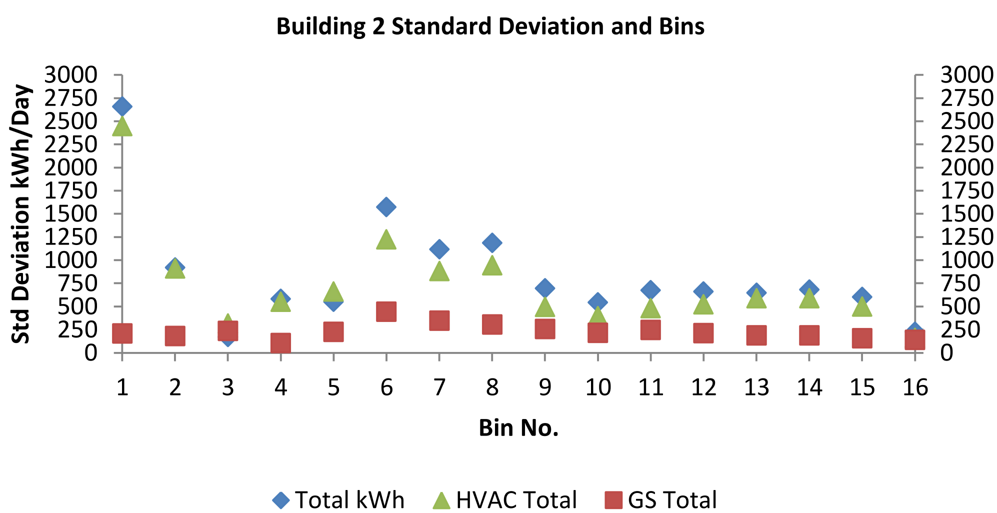


Figure 5-4. Case study building II bin method result.

From figure 5-3, figure 5-3, most of variations in whole building energy use is caused by mechanical system. General service load (primarily plug load and interior lighting load) has a relatively flat variation though different bins. Whole building energy use and HVAC system energy end use achieve maximum variation in extreme weather conditions. It is obvious and clear to tell that mechanical system energy end use is the main factor that cause large data scatter under same temperature or similar averaged temperature days. However, mechanical system energy use is a dependent variable and can't be added as an independent variable in whole building regression model.

The research further looked into load profiles of mechanical systems in each bin. The 15-minute interval data is summed into days. Different days within one bin are plotted in the same figure. Figure 5-5, 5-6 are the HVAC load profiles for case study building I. Figure 5-7, 5-8 are the HVAC load profiles for case study building II.

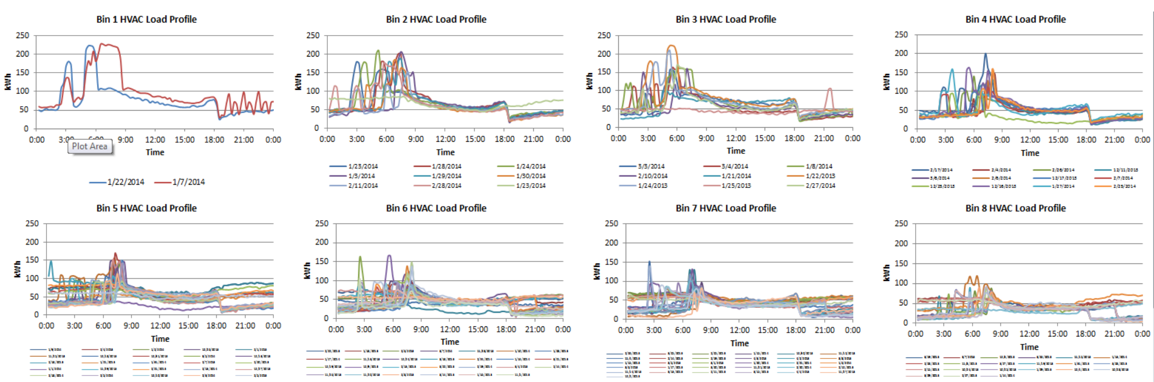


Figure 5-5.Case study building I HVAC load profiles for Bin 1 to 8.

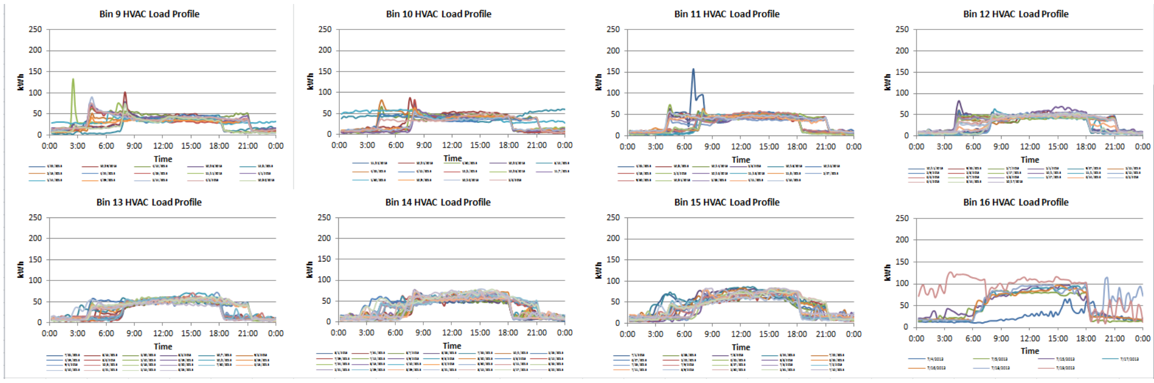


Figure 5-6.Case study building I HVAC load profiles for Bin 9 to 16.

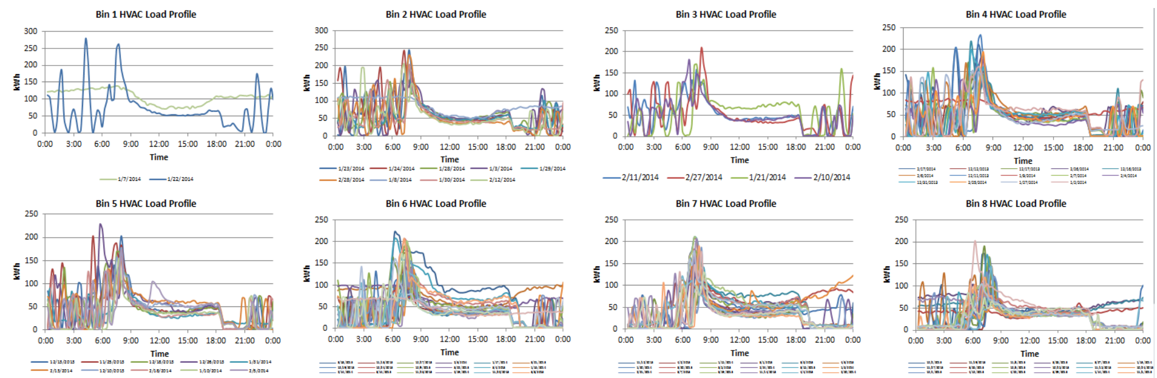


Figure 5-7.Case study building II HVAC load profiles for Bin 1 to 8.

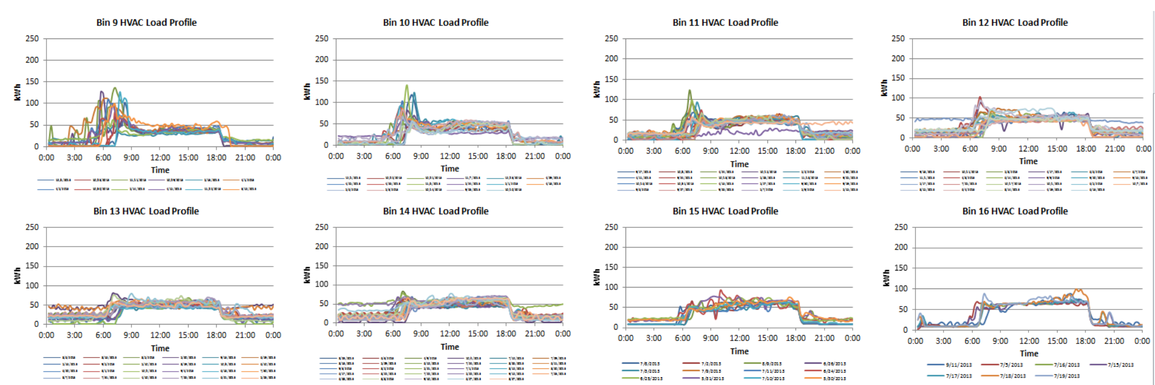


Figure 5-8.Case study building II HVAC load profiles for Bin 9 to 16.

From figure 5-5, figure 5-6, HVAC system has relatively constant load profiles in working hours (9:00 am to 6:00 pm) and shows very little dependency on ambient weather variations. The magnitude of mechanical system energy use is very close across entire bins. This agrees with previous LASSO and SCAD penalty variable selection results. Office building is typically internal load dominated and less responsive to ambient weather conditions. Mechanical system operation is mainly to offset thermal demand generated by internal loads. However, in morning warm-up hours (0:00 to 8:00 am), high degrees of irregularity of operations were found. Within each bin, morning hour period mechanical system energy use varies significantly with the time. Spikes and valleys happened frequently during a short time, this indicates system might cycle on and off constantly. The morning irregularity conditions are found more frequent in heating season. In summer, the morning warm-up energy use is relatively compact. Same conclusions are found in figure 5-7, figure 5-8, that during working hours mechanical system energy use is almost constant and compact though the entire year. It means mechanical system is well controlled at that time and building is internal load driven. The morning warmup period shows high frequency of irregular operations. It is safe to conclude that variations of mechanical system in figure 5-3, 5-4 are mainly caused by irregular operations in morning warm-up period. Due to unavailability of detailed sub-metered data of mechanical system, such as fans, air flows etc., so this research can’t identify causes of irregular operation in morning warm-up period. Buildings need to commission or monitor system control strategies in morning warm-up period especially in the heating season. Possible reasons for warm-up irregularity can be manual overwrite or change in building management system, mechanical system optimal start scheme, night-time set back schedules and so on.

Chapter 6
Forward Energy Model Calibration Loop and Inverse Model Development

6.1 Introduction and method

The shortcomings of current methods reconciling actual data with simulated results have been reviewed and summarized in chapter 2. In this chapter, a reproducible, measured-data based, sub-system focused method is proposed and serves as a guideline to quickly develop a forward energy model and calibrate simulated results with actual data. The calibrated model is capable of estimating savings from corresponding ECMs and evaluates its performance.

The first step of creating energy model is data collection. To begin from the scratch, building information should be collected from as-built design drawings, building energy audits/reports, property manager interviews, occupants complains. Any changes or retrofit made inside the building should be recorded carefully especially the starting and ending dates. Local weather conditions should be collected as well without missing any significant variables or periods. Holiday or special events that take place inside the building, tenants move in/out dates and number should be documented with time, duration and so on.

In developing the model, input data has a variety of source, the hierarchy of input data source needs to be defined. The credibility of this method relies on building evidence: actual measured data. It has the highest hierarchy among entire data source. Actual measurement represents actual conditions in the building. Unless data is not available from measurement or drawings, information derived from onsite survey or interview are the second order in the hierarchy, then benchmark building assumptions, then buildings' standards and the educated estimation.

A criticism in conventional model calibration is the unavailability of building data (Sun and Reddy 2006). Nowadays, with more intensive sub-metered data available, more detailed, in depth study is feasible. It allows starting calibration procedure from the bottom which is called bottom-up calibration. Instead of comparing whole building energy use with actual data, bottom-up approach starts from components or sub-system energy end use calibration. It acts like building "anatomy" which enables thorough isolation of sub-system or component energy consumption. Error masking effects in conventional top-down approach is avoided. In following sections, detail steps are discussed.

Overview steps in the method are model initiation, components/systems matching and overall evaluation. The model initiation includes collecting relevant data to develop building energy mode. Measured data source always has the highest priority. Component matching is detecting the difference between building simulated component's performance and actual data if measurement is available. System matching compares system level end use with actual use. Key variables list generated in chapter 4 should be tuned with care with high confidence level. The final step is matching overall simulated result with actual whole building energy use. Method overview is illustrated in figure 6-1 and discussions of steps are below.

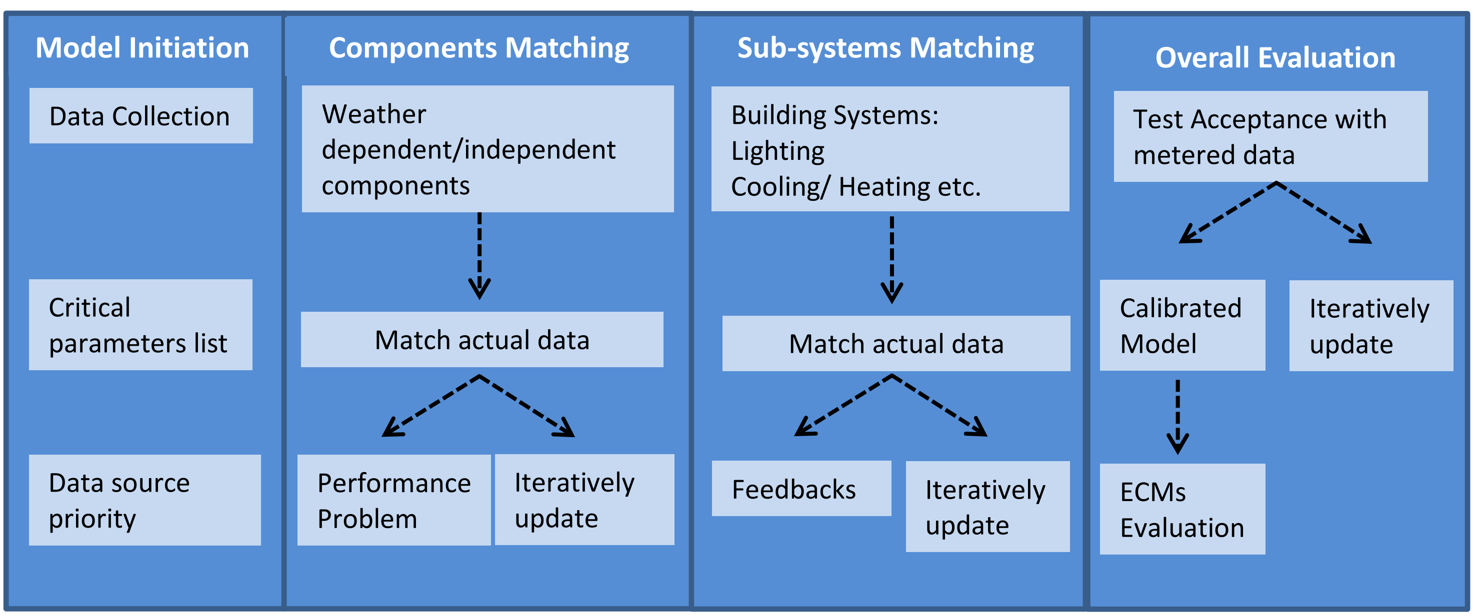


Figure 6-1. Overall as-operated model formation method.

Step 1 model initiation: Data collection for model development includes actual sub-metering data, design drawings, site visit, as-operate documentation, building automation system (BAS), BIM model, benchmark building data, industry standards, component specifications, local weather information etc. Critical variables generated in chapter 4 require special attentions from the modeler. For whole building energy use calibration, the critical variable list includes **local actual metrological weather (AMY) data, interior lighting energy, plug system energy, glazing system information, space cooling/heating set point, supply air temperature.** For cooling and heating system end use calibration, AMY weather data, interior lighting energy, plug system energy, occupancy information, window material information, space cooling/heating set point temperature, supply air temperature and system overall COP are important. If measurement is not available, follow the hierarchy of data source to find an optimum value. After model is set up in the software, modeler runs an initial whole building simulation and archive components' and systems' simulated results. At this stage, simulated results will generally diverge from actual metered use.

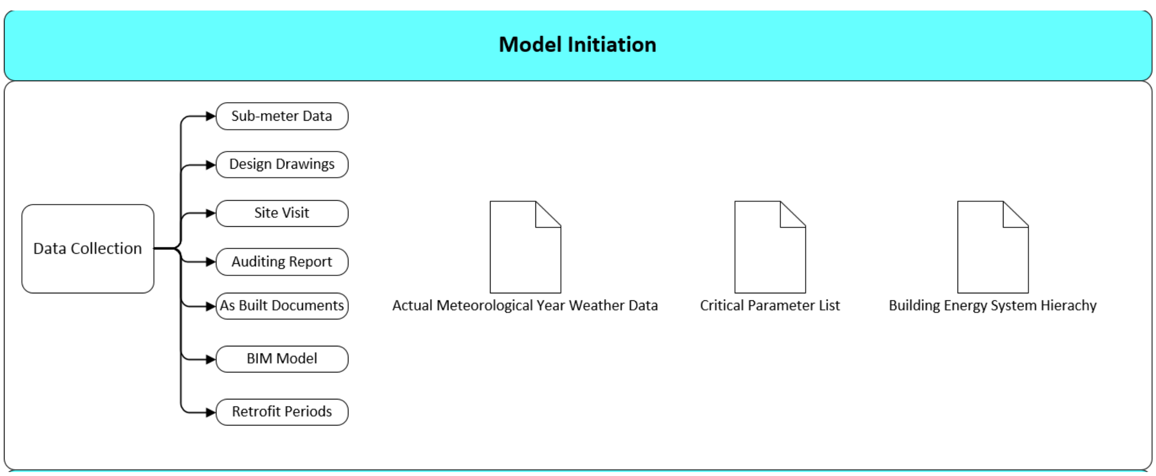


Figure 6-2. Flowchart of model initiation.

Step 2 component and sub-systems matching: after model initiation, next step is to tune component and system level variables. In many actual building sub-metered data, component‘s level data might not be available. This step can be merged into system matching step. The purpose of system and component matching steps are comparing energy end use at its corresponding level, for example compare simulated general service energy end use with actual general service meter data.

A building simulated energy use can be divided into two periods: shoulder season and cooling/heating season. In shoulder season, ambient weather condition has minimum influence on building energy use. The base load causes the majority of building energy load and needs to be calibrated first. Simulated discrepancies caused by poor building operations or settings need to be documented and inform building owner. Unresolved discrepancy goes into the continuous improvement loop. The system level critical variable list needs to be checked first. This avoids efforts on adjusting trivial variables while maintain minimum level of efforts to increase the accuracy of model. Actual measured value in the critical variable list should be assigned to the input. If not available, analyst follows data source hierarchy till statistical criteria are met. The iterative loop keeps improving the accuracy of model at system level. The detailed flow chart is shown in below.

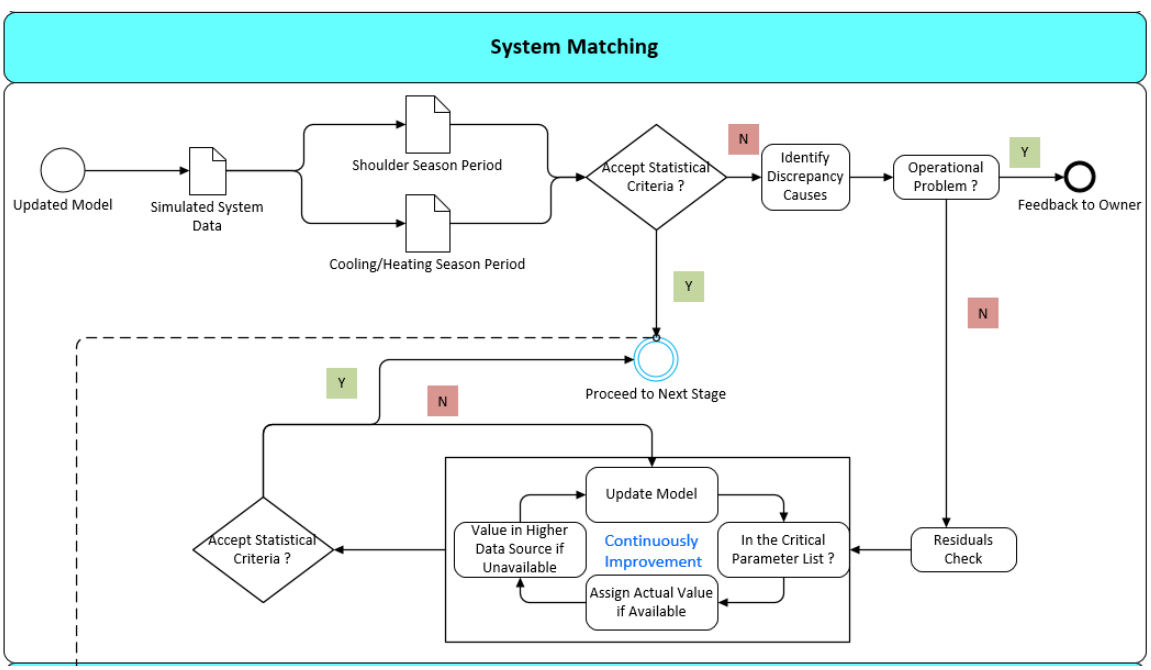


Figure 6-3. Flowchart of component and system matching.

Overall evaluation: After model is updated from previous step, sub-system energy use is assumed to be calibrated. The next step is to compare whole building energy use with actual data. Previous steps for example component matching and system matching avoid sub-system energy convolution and error compensating effects. The residual of discrepancy should be at a small magnitude. If the whole building energy use fails to meet statistical criteria, the modeler restarts the improvement loop with more stringent criteria till total building energy use matches actual data. When criteria are met, the model is claimed as calibrated model at this time.

Energy conservation measures design and estimation is based on varying ECM related variables in the model to simulate the condition after retrofit. The difference between baseline and post retrofit model is the saving caused by installed ECMs. Detailed guidelines and steps can be found in ASHRAE Guideline 14 (ASHRAE 2002) and International performance measurement and verification protocol (IPMVP) (Organisation 2007). The flowchart of step is shown in figure 6-4 in below.

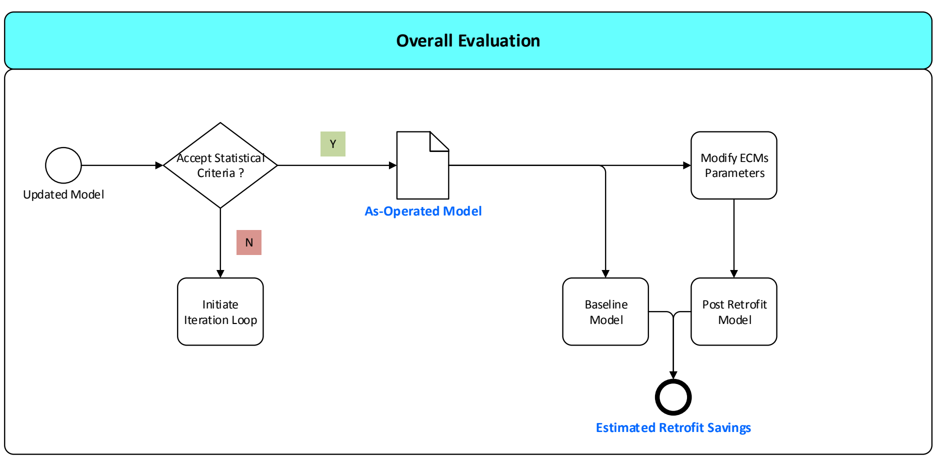


Figure 6-4. Flowchart of overall evaluation.

Figure 6-2 to figure 6-4 demonstrates model calibration loop. It is a bottom-up, measured data based approach which means the method starts from matching energy use in components or sub-systems. The critical variables identified in chapter 4 generate a critical variable list that informs modeler that those variables are significant to energy simulation. The whole building energy use is the sum of sub-system end use. Therefore, a confident, well calibrated sub-system end use will result in an accurate whole building energy simulated results. The more sub-metered data specification (lighting, heating, cooling, plug) and finer resolution of energy use data, the more efficient and effective calibration of this iterative improvement loop. The benefits of sub-metered data are two folds: it allows one to determine what specific end-use sub-system might be responsible for the problematic whole building energy use. It also enables calibrating sub-system energy use in forward model with high level of confidence. The proposed iterative calibration loop establishes a cost effective, time saving plan for energy conservation measure optimization and inverse model development. It minimizes the financial cost and labor hours to acquire irrelevant data in the building. The data acquisition and analysis can be modified to different types of buildings. In following sections, two medium size buildings have been selected to demonstrate the implementation of calibration loop.

6.2 Case study building I and II

Case study building I and II have very similar features in terms of space geometry, mechanical systems, tenants etc. Two buildings located near the city of Philadelphia, PA, and only 8.3 miles away from each other. The weather difference between two locations is considered negligible. Two buildings energy models' have been developed and followed calibration loop.

Case study building I is a four-story, medium sized commercial office building located in Wayne, PA with a gross area of 103,500 ft^2. The building was originally built in 1971 and fully renovated in 1997. The building has two major tenants; an engineering company and IT service company. The average occupancy area is 99% in 2012 and 98% in 2013. The building's exterior wall uses a Dryvit stucco system. The windows are double-paned, tinted glass with aluminum frames. The original roof was a black rubber material surface and was partially replaced with Tremco built-up gravel roofing in 1987. In 2013, a section of roof was replaced with a RubberGard EPDM roof system during the renovation. Four variable-air-volume (VAV) rooftop units (RTUs) and four Libert ® units along with several supplemental DX units provide conditioned air to building spaces. Direct Expansion (DX) unitary systems are used for cooling and electric resistant heating coils are used for heating. The building has night time setback set points and startup mode controlled by building automation system (BAS). The building is lit primarily by 2ft× 4ft three-lamp, 32-watt T-8 and 2ft×2ft two-lamp U-bent, 32-watt T-8 fluorescent fixtures. Figure 6-5 shows building pictures during auditing process.

Figure 6-5. Pictures of case study building I.

Case study building II is a three-story, medium size office building located in Malvern, PA with a gross area of 101,700 ft^2. The building was originally built in 2004. Mechanical system is almost identical to case study building I. It has variable air volume system with direct expansion (DX) system for cooling and electric resistant coils for heating. Some zones in the building have fan powered terminal boxes that has an electric coil for supplemental heating. The lighting system design is also very close to case study building I. Multiple tenants occupied the building including IT company, bank, engineering firms etc. The occupied area is 100% for three consecutive years. Therefore, the influence of tenants and leasing area change can be ignored.

Figure 6-6. Pictures of case study building II.

The building owner intentionally designed the whole building with electric energy use, three meters measure building energy uses which include: whole building energy use, general service energy and HVAC system energy use. General service load typically consists of plug energy and lighting energy use. All the measurements were taken in the unit of kWh. The researcher walked into two case study buildings with building operators, engineers to conduct building audit. During the audit, the team gathered data from building management system; provide surveys to operators, tenants; check mechanical system operations and compared with information from drawings. During walk through, findings and questions have been recorded, especially building operating schedules, control strategies have been documented with great detail. 15-minute interval sub-metered data (whole building energy use, lighting energy, plug energy, HVAC energy) are downloaded and "filtered". To ensure the quality of sub-hourly data, quality check is performed. The first step is to ensure blank periods and overlapped periods are cleaned. Secondly, compare date-to-date monthly sub-metered total use with actual utility bill provided by the local electricity company. Another factor needs additional attention is that no significant changes should be occurred inside the building during simulated months. For example system upgrades, significant change of tenants, large occupancy area change should not be taken place during simulation periods. A valid building energy modeling needs at least twelve-month period to cover all weather conditions though a year. After data quality and operational period monthly check, simulating period is selected from May 2013 to April 2014.

Model creation work flow is shown in below.

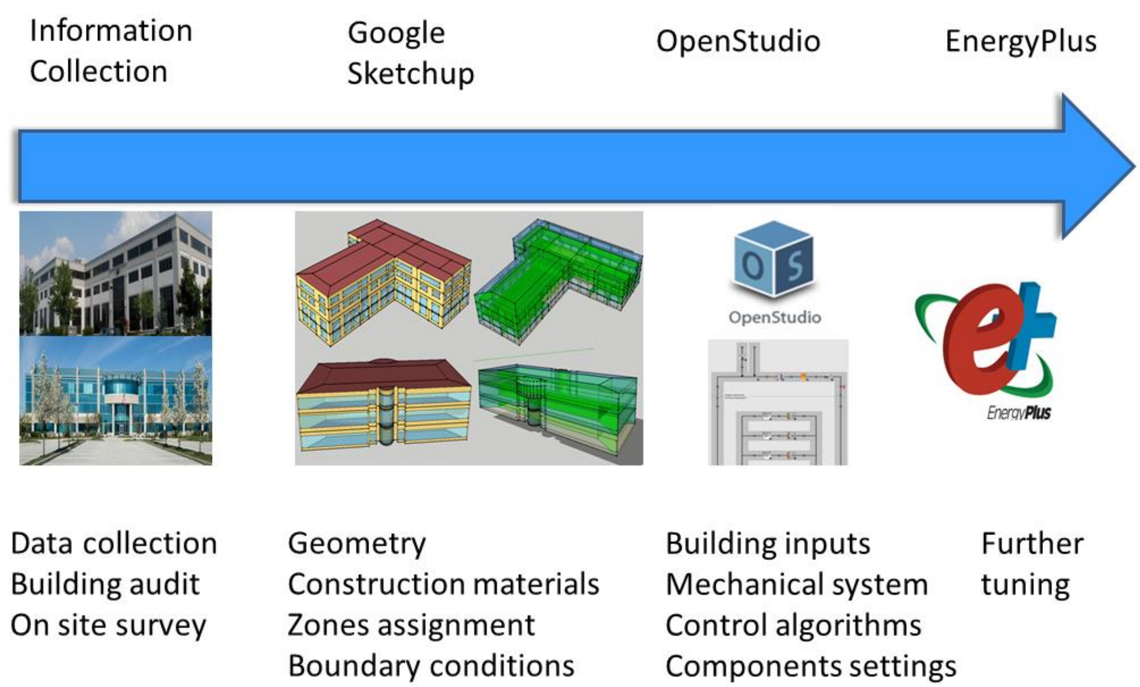


Figure 6-7. Model creation work flow.

Two building models are initially developed in Sketchup®, geometry models are shown in figure 6-8 and 6-9. In model creation, thermal zones are set up that close to actual zoning conditions inside the building. However, some very similar zones are grouped into one zone because it is convenient to develop and save calculation time. The research focus on calibrating whole building energy use instead of estimating one floor or specific zone energy performance, therefore such simplification is appropriate. For case study building I, around 80 thermal zones are generated according to architectural and mechanical drawings. Similarly, case study building II has more 100 zones inside the model.

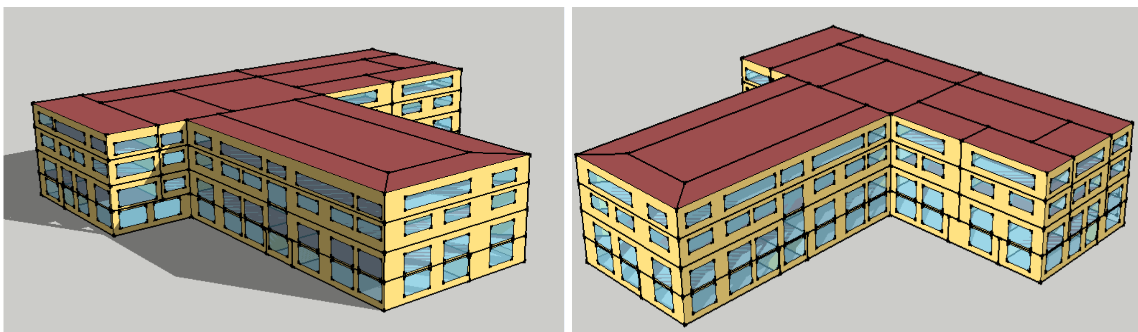


Figure 6-8. Model geometry for case study building I.

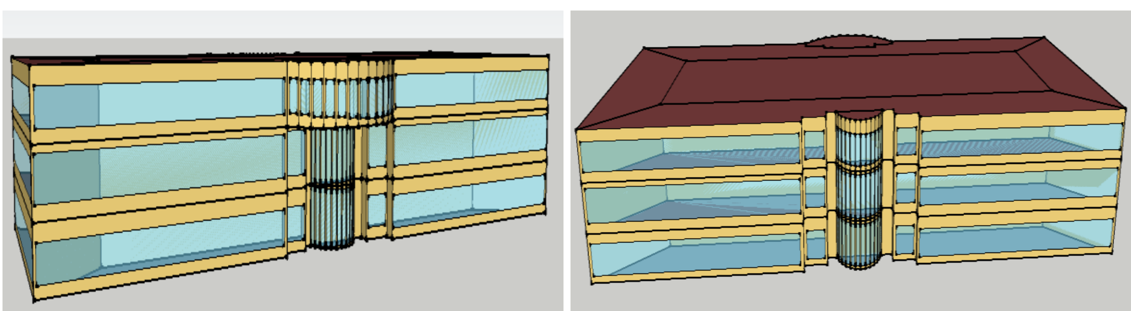


Figure 6-9. Model geometry for case study building II.

Once upon the model geometry is developed, envelop construction materials, glazing type are collected and assigned to model. Boundary conditions are automatically generated to identify exterior and interior boundaries. Figure 6-10 and 6-11 illustrate different boundary conditions. Inside the building, each space has different functions such as offices, corridors etc. Template information from ASHRAE standard 90.1 was input as default settings for further modification. This will also help researcher understands the difference between default settings and actual measurement settings of simulated results.

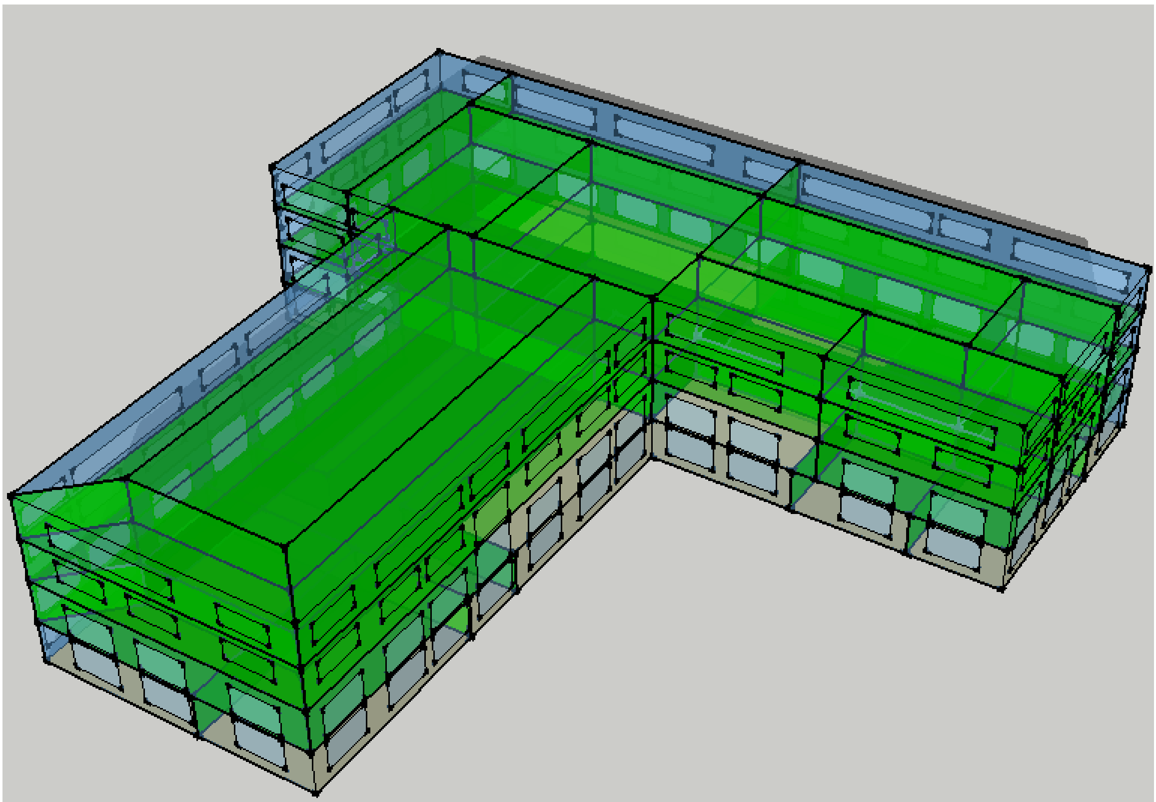


Figure 6-10. Boundary conditions for case study building I.

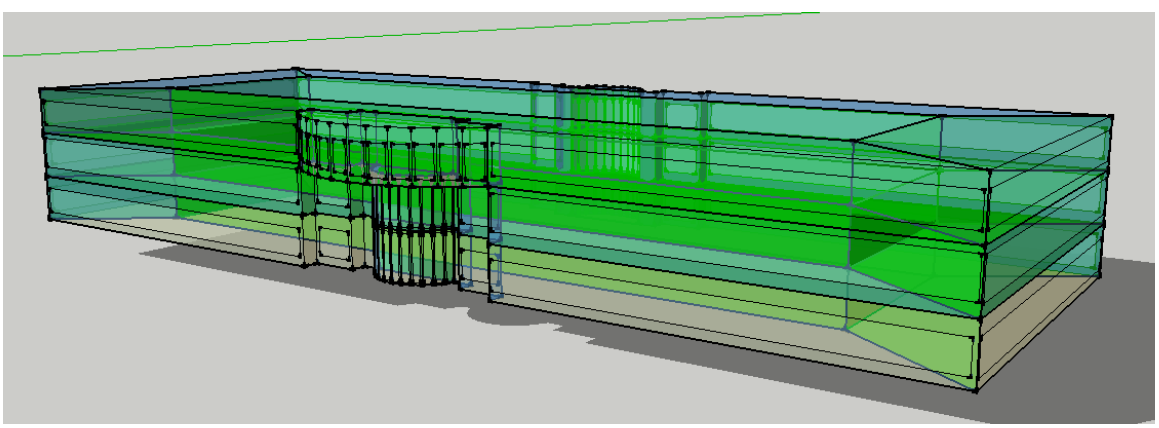


Figure 6-11. Boundary conditions for case study building II.

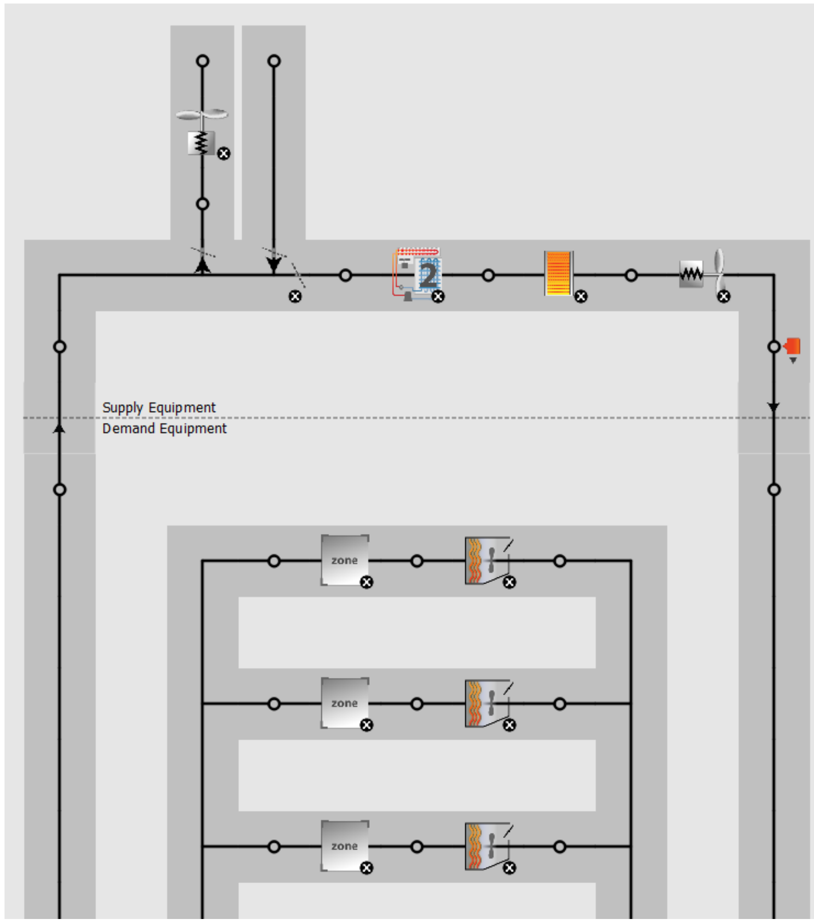


Figure 6-12. Typical VAV system layout with terminal box within RTU.

Two buildings mechanical system information with design specifications and technical details are summarized in table 6-1.

Table 6-1 Building mechanical system specifications and details.

Building No	Case Study I	Case Study II
Number of units	4	3
Type	RTU-VAV	RTU-VAV
Unit Schedule	100 Tons(Three) 20 Tons(One)	130 Tons(Three)
Supply fan air flow (CFM)	35,000(Three) 7,000(One)	42,000(Three)
Outside air flow(CFM)	3,500(Three) 700(One)	4,200(Three)
Supply fan horsepower	50(Three)	60(Three)

	10(One)	
Heating coil capacity	553 kW(Three)	190 kW(Three)
Cooling coil capacity	370 kW(Three) 74(One)	404 kW(Three)
Return fan horsepower	45(Three) 10(One)	40(Three)
Return fan head	1.7 in w.g.	1.5 in w.g.
Motor general efficiency	0.9	0.9
Return fan airflow	30,000(Three) 6,000(One)	40,000(Three)

Building model initial version is set up with actual information and data from building management system collection, drawings, walk through, surveys etc. Variables in critical variable list generated in chapter 4 are set as default template value from ASHRAE 90.1. In component and system matching step, they will further be tuned with actual value. In iterative loop, critical variables will be accumulatively updated till statistical criteria are met.

The initial model is generated to match all aspects of actual building characteristics, such as construction materials, thermal zoning layout, and mechanical system parameters except key parameters. The initial simulated result is shown in Figure 6-13 and 6-14.

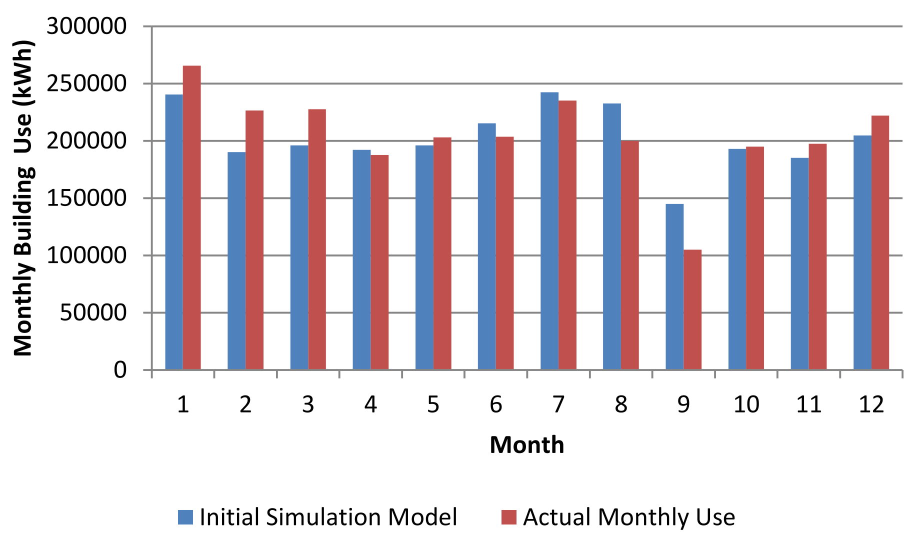


Figure 6-13. Case study building I monthly energy use comparison initial results.

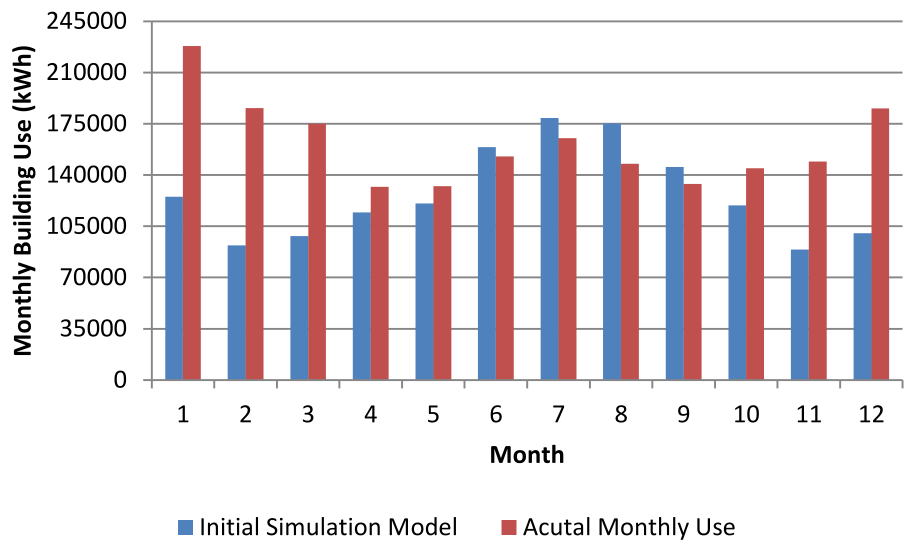


Figure 6-14. Case study building II monthly energy use comparison initial results.

ASHRAE guideline 14 introduces two statistic indexes to measure data variability that is described by the model or quantify model uncertainty. Coefficient of variation of root mean square error (CVRMSE) and normalized mean bias error (NMBE) are given in equations below.

$$CVRMSE = 100 \times \left[\sum (y_i - \bar{y}^2)/(n-1)\right]^{1/2} / \bar{y} \qquad (34)$$

$$NMBE = \frac{\sum (y_i - \hat{y}_i)}{(n-p) \times \bar{y}} \times 100 \qquad (35)$$

For whole year building simulation results, n is 12, p is considered as 1. Where $y_i, \bar{y}$ and $\hat{y}_i$ are actual monthly use, averaged monthly use and simulated monthly use. ASHRAE also gives recommend values for CVRMSE and NMBE as statistical criteria for calibrated model. For monthly calibration comparison, NMBE should be less than 5% and CVRMSE of 15%. For hourly calibration they are 10% and 30% respectively.

In initial simulation results, NMBE and CVRMSE indexes for case study building I are 0.86% and 11.14% respectively. For case study building II, they are 23.36% and 36.65%

respectively. Although building I has very low NMBE which is 0.86%, sub-system endues varies significantly from actual data for example in figure 6-15. It is clear to see that actual mechanical system differs substantially from actual data. This agrees with this research's conclusion that an overall use agreement can't guarantee that model is calibrated.

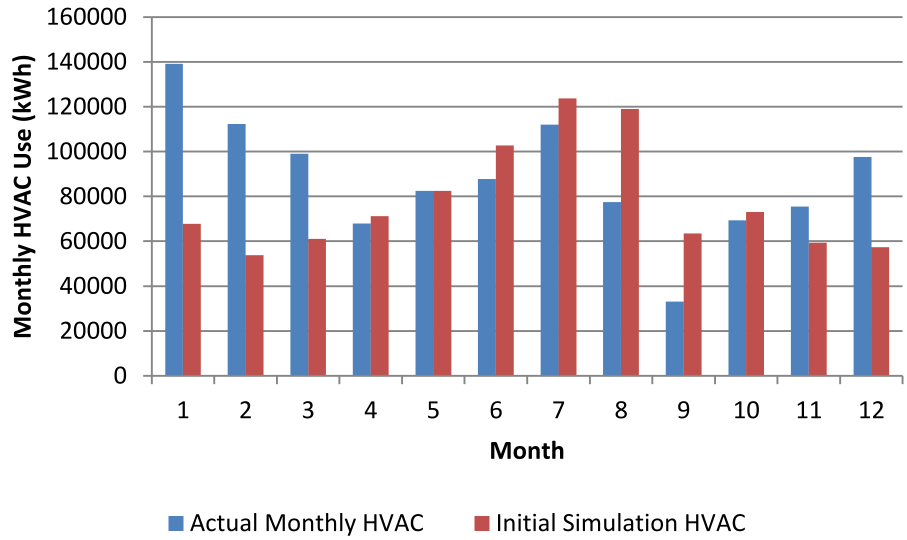


Figure 6-15. Case study building I initial HVAC simulation results.

After initial run, two case study buildings' models are calibrated based on critical variables list. Following sections discuss the determination procedures for those inputs. Critical variable list includes **local actual metrological weather (AMY) data, interior lighting energy, plug system energy, glazing information, space cooling/heating set point, and supply air temperature.**

In building energy modeling, typically two kinds of weather files are available: typical metrological weather (TMY) and actual metrological weather (AMY) data. TMY weather described an averaged condition in past 15 years or 30 year. It is widely used in design mechanical systems. However, past 15 years averaged condition is not similar to weather condition in a particular year. The average monthly temperature might be close, but at daily interval or 15 minutes interval the difference is significant. In LASSO and SCAD penalty variable selection results, ambient dry bulb temperature is very important. Therefore, in modeling two existing case study buildings, actual weather conditions especially actual dry bulb temperature data needs to be selected. From sub-metered data quality check and building operational condition survey, May 2013 to April 2014 is selected as simulation period and AMY weather file for the same period is purchased from the third party website. The AMY file is compatible with EnergyPlus engine and simulate the model seamlessly. Daily averaged temperature of AMY file in the simulating period is shown in figure 6-16.

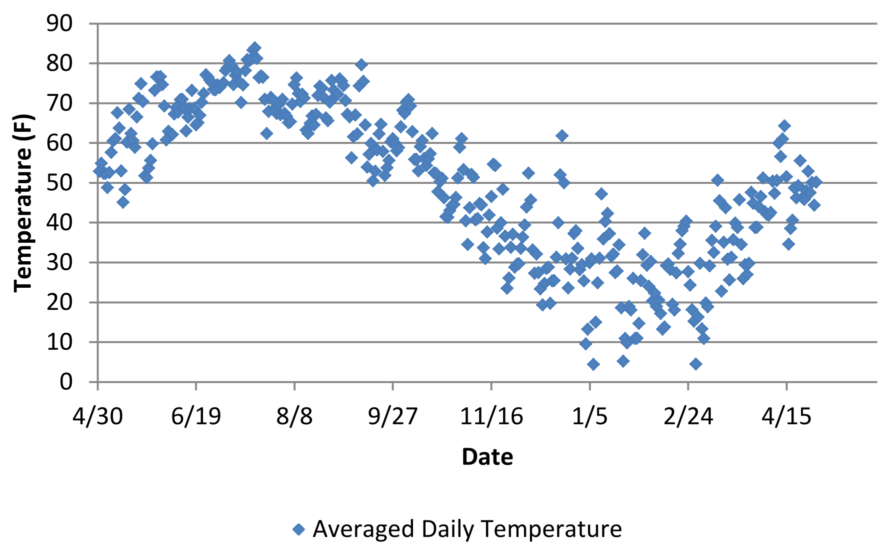


Figure 6-16. AMY daily averaged dry bulb temperature vs. dates.

Interior lighting energy input is very different from AMY weather data. As previously discussed (for example figure 5-1), office building has very distinctive energy use in weekdays and weekend. According to sub-metered interior lighting energy meter, data is grouped into weekdays and weekends.

The method to develop energy use profile for weekdays and weekends are very similar. Though lighting fixture counting and wattage calculation from fixtures' schedule, averaged lighting power density is 1.1 watt/square ft. Lighting fixture counting is achieved by estimating number of fixtures (for example Figure 6-17) in a zone and collects power information from schedule.

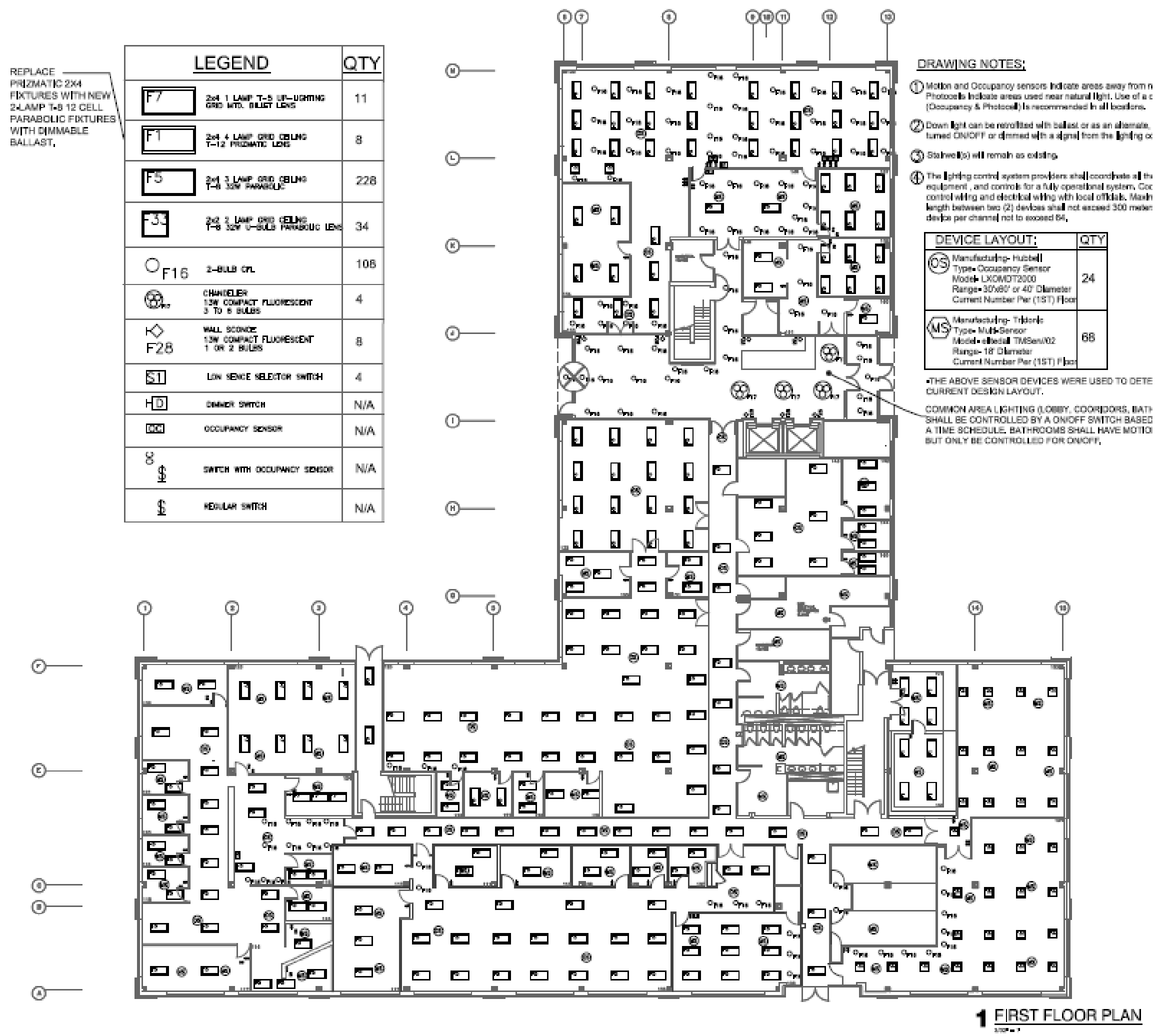


Figure 6-17. Lighting electrical drawing for building I (First floor).

Ideally, lighting energy use profile should be based on each zone or per-floor space. However, metered data only measure whole building lighting use. For the research purpose, this dissertation tries to model whole building energy use. It is appropriate to use one averaged lighting energy use profile to represent the entire building lighting use profile. Excel spreadsheet is helped to generate monthly profiles. Figure 6-18, 6-19 shows generated monthly interior lighting diversity factors. Figure 6-20 shows default weekday lighting diversity factors in the software. It is obvious that generated monthly lighting diversity factors are different from default settings. The building lighting schedules show a variation at different months of a year.

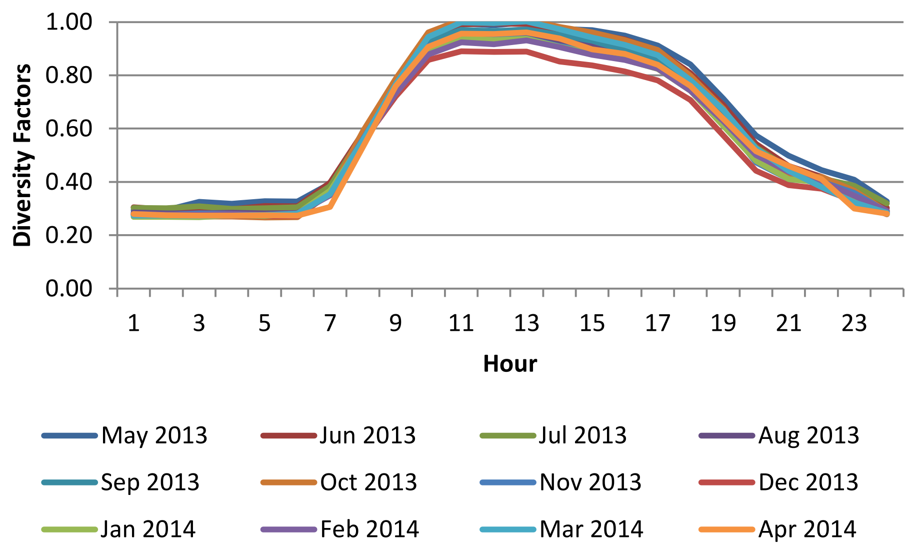


Figure 6-18. Monthly lighting diversity factors in building I.

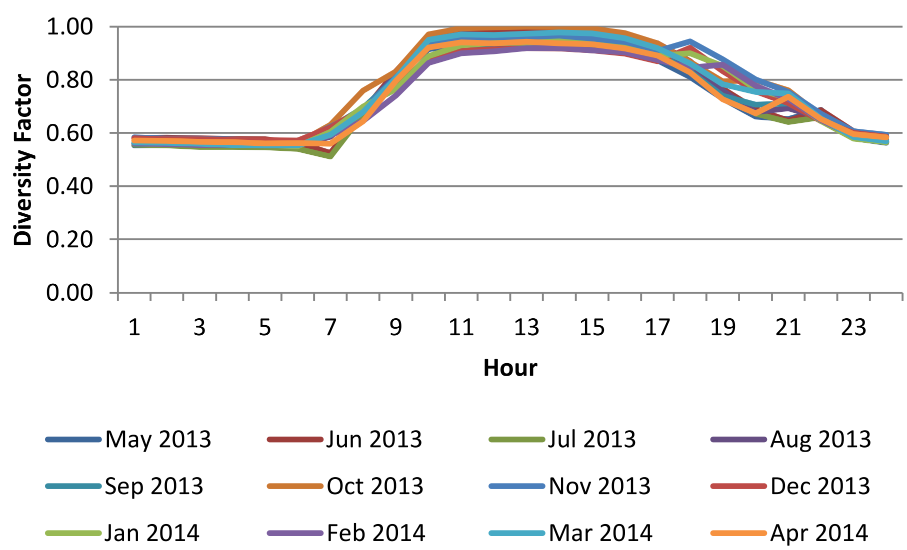


Figure 6-19. Monthly lighting diversity factors in building II.

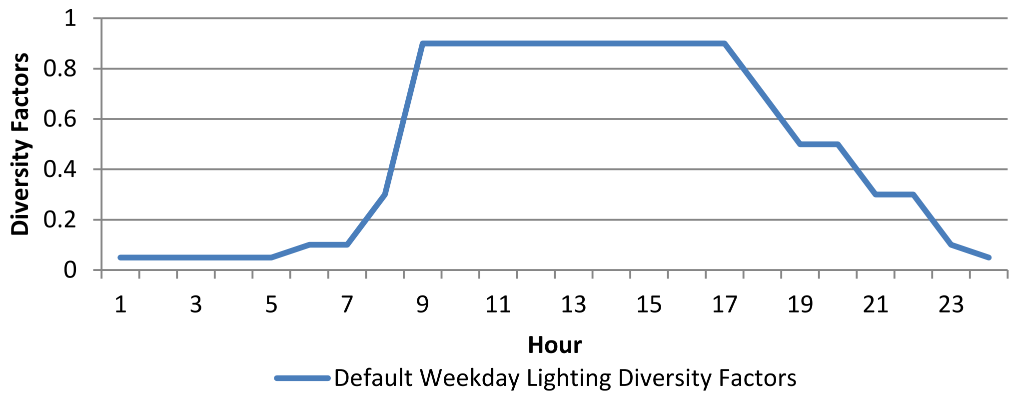


Figure 6-20. Default weekday lighting diversity factors.

After interior lighting input parameters are updated, simulated 15-mintue lighting energy use and daily weekday lighting energy use comparison are shown in Figure 6-21 and 6-22.

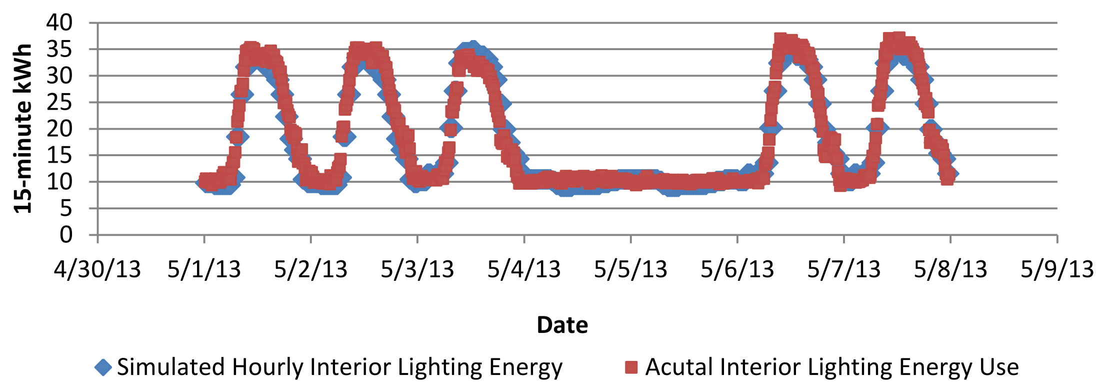


Figure 6-21. 15-minute interval lighting energy use comparison.

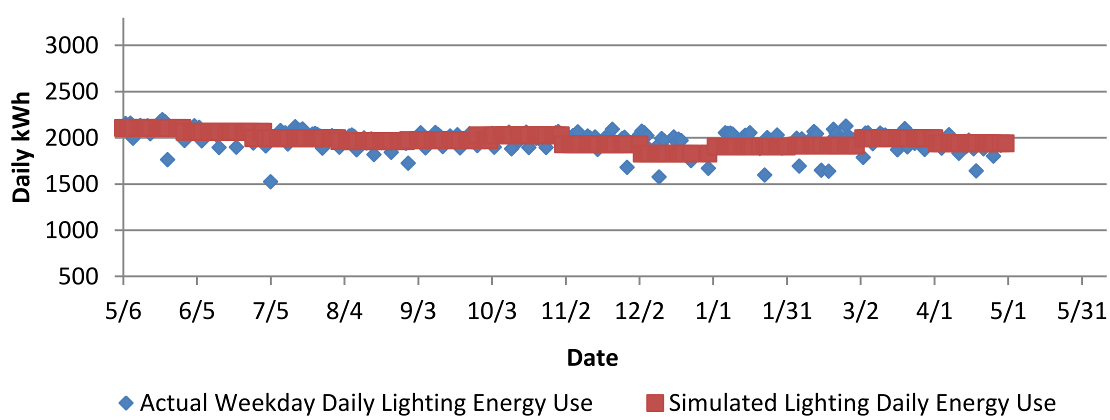


Figure 6-22. Daily weekday lighting energy use comparison.

Interior lighting energy weekend use and plug load energy use diversity factor generation is very similar to weekday lighting energy use diversity factor generation.

Both buildings have a data center inside and they are separately metered. The data center energy use profiles are shown in figure 6-23.

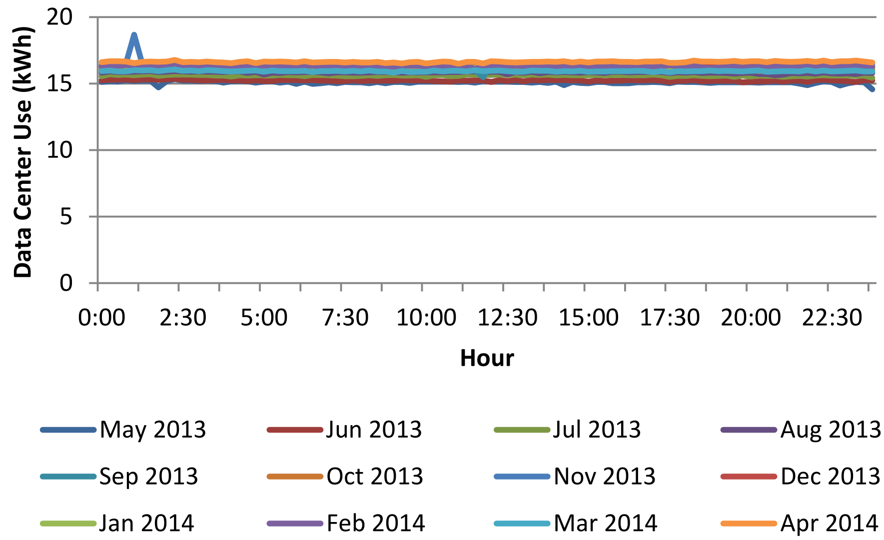


Figure 6-23. Monthly data center energy use profiles.

Data center daily total energy use with dates is plot in figure 6-24.

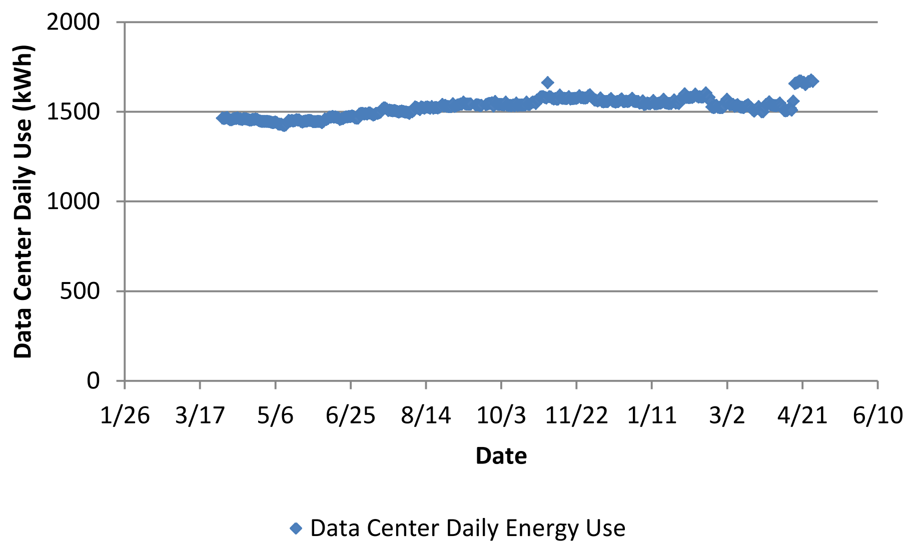


Figure 6-24. Data center daily total energy use.

Figure 6-24 clearly indicates operational characteristics of data center. It has a constant load though the whole year. No significant weekdays, weekends and holidays difference is detected. It is reasonable to assume data center has a constant diversity factor. The resultant power density estimation is straightforward. It is calculated as averaged daily use divided by the area of data center.

From above discussion, interior lighting, plug load and data center inputs are calibrated based on actual building measurement, the simulated results for interior lighting, plug load and data center is shown in below.

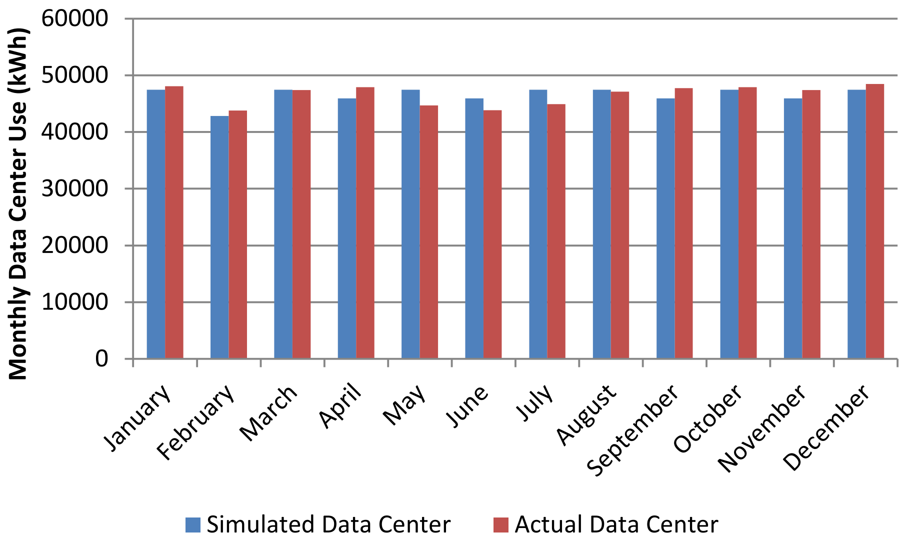


Figure 6-25. Comparison of simulated monthly data center energy use (building I).

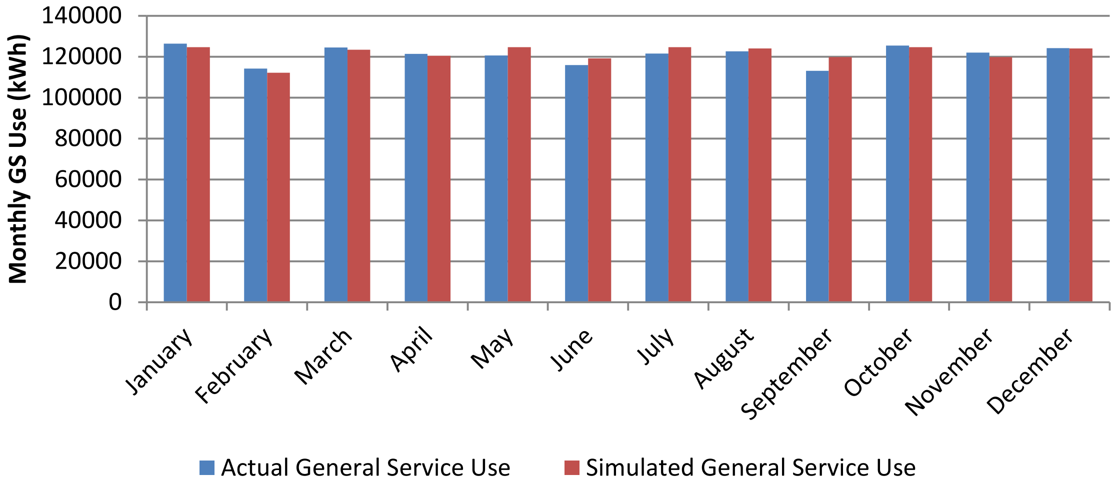


Figure 6-26. Comparison of simulated monthly GS energy use (building I).

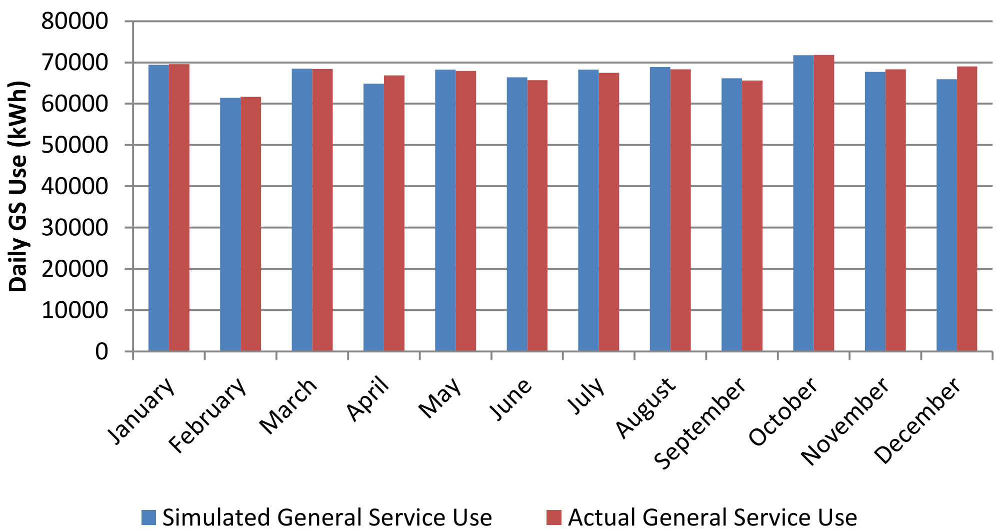


Figure 6-27. Comparison of simulated monthly GS energy use (building II).

According to ASHRAE guideline 14, equation 34 & 35 define calculation of NMBE and CVRMSE. NMBE ensures that model results will not be over or under predicted from the actual data. CVRMSE measures the dispersion of simulated results' distribution. In ASHRAE guideline 14, they are used as criteria to qualify if a model is calibrated. In case study building I, NMBE and CVRMSE for general service load is -1.40% and 2.44% respectively. In case study building II, NMBE and CVRMSE are 0.41% and 1.77% respectively. From ASHRAE guideline 14, monthly comparison should have NMBE less than 5% and CVRMSE less than 15%. Calculated NMBE and CVRMSE for building I&II are far smaller than defined criteria. It is safe to conclude that building's general service load is well calibrated in both case study buildings.

After interior lighting, plug load energy use have been calibrated, next step is to adjust window characteristics to match the actual performance of glazing system. Buildings envelop and glazing system information is mainly gathered from architectural drawings and manufacture website. Sections of architectural drawings are in figure 6-26 below.

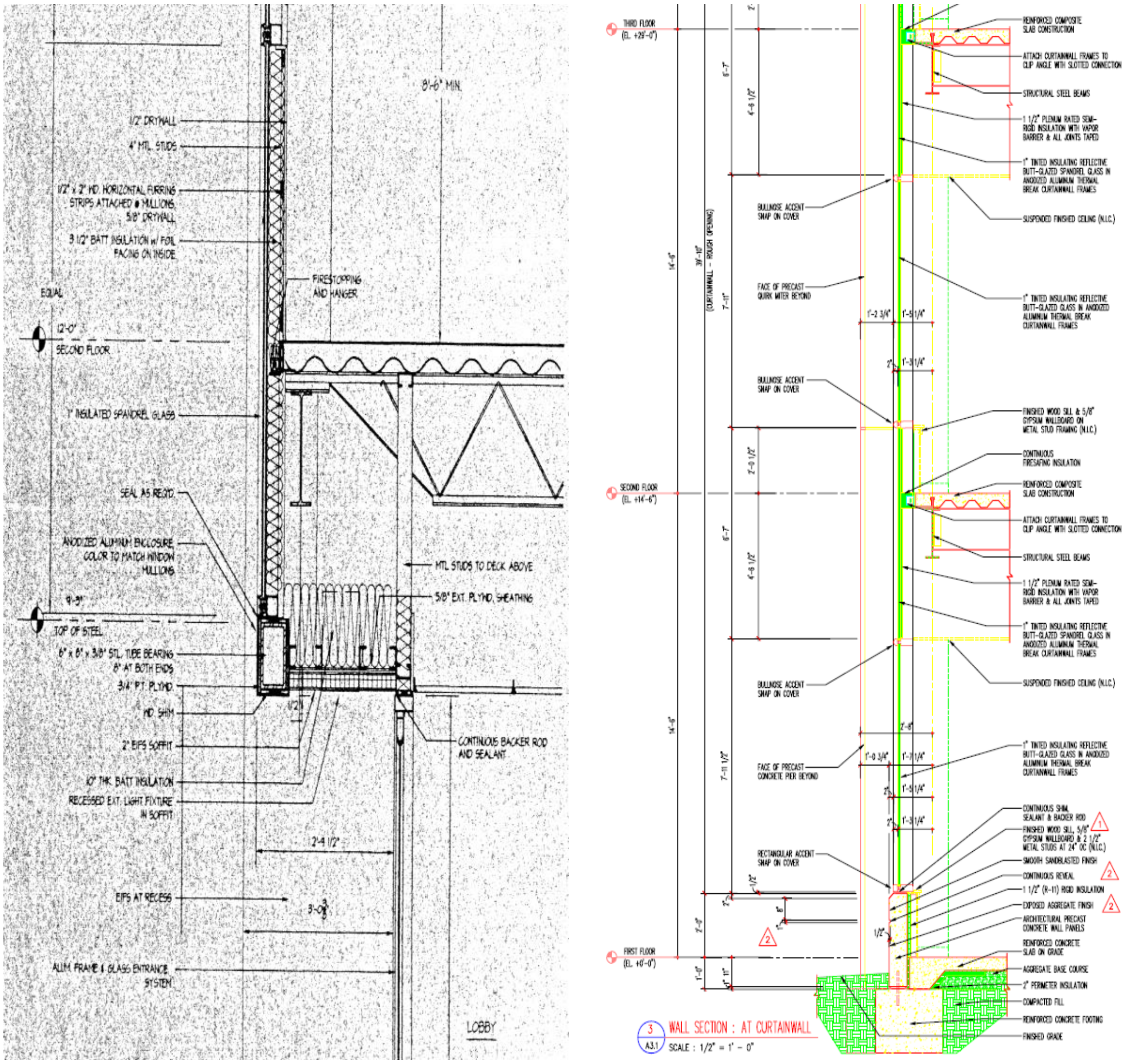


Figure 6-28. Section views of case study building I (left) and building II (right).

Table 6-2 Glazing materials' layer information.

Case Study Building	I	II
Glazing materials	6 mm reflective C tint window Air gap 3mm Clear window 6mm	6 mm reflective D tint window Air gap 6 mm Clear window 6mm

Thermal characteristics of glazing materials are in table 6-3 below.

Table 6-3 Glazing materials properties.

Material	Clear 3mm	Clear 6mm	REF C Tint 6mm	REF D Tint 6 mm
Data Type	Spectral Average	Spectral Average	Spectral Average	Spectral Average
Thickness (m)	0.003	0.006	0.006	0.006
Solar Transmittance at normal incidence	0.837	0.775	0.1	0.3
Front side solar reflectance	0.075	0.071	0.1	0.14
Back side solar reflectance	0	0.071	0.42	0.36
Visible transmittance	0.898	0.881	0.11	0.25
Front Side visible reflectance	0.081	0.08	0.1	0.18
Back side visible reflectance	0	0.08	0.38	0.45
Infrared Transmittance	0	0	0	0
Front side infrared hemispherical emissivity	0.84	0.84	0.84	0.84
Back side infrared hemispherical emissivity	0.84	0.84	0.51	0.82
Conductivity (Btu-in/h-ft2-F)	6.24	6.24	6.24	6.24
Solar diffusing	No	No	No	No

Glazing materials' properties are set up according to architectural drawings and curtain wall data from the manufacture. In critical variable list, next variables that need to be tuned are space cooling/ heating set point and supply air set point. During building walk through, screen shots were taken from building energy management system and documents. Figure 6-29 shows screen shots for cooling supply air temperature and Figure 6-30 shows cooling supply air temperature reset algorithm.

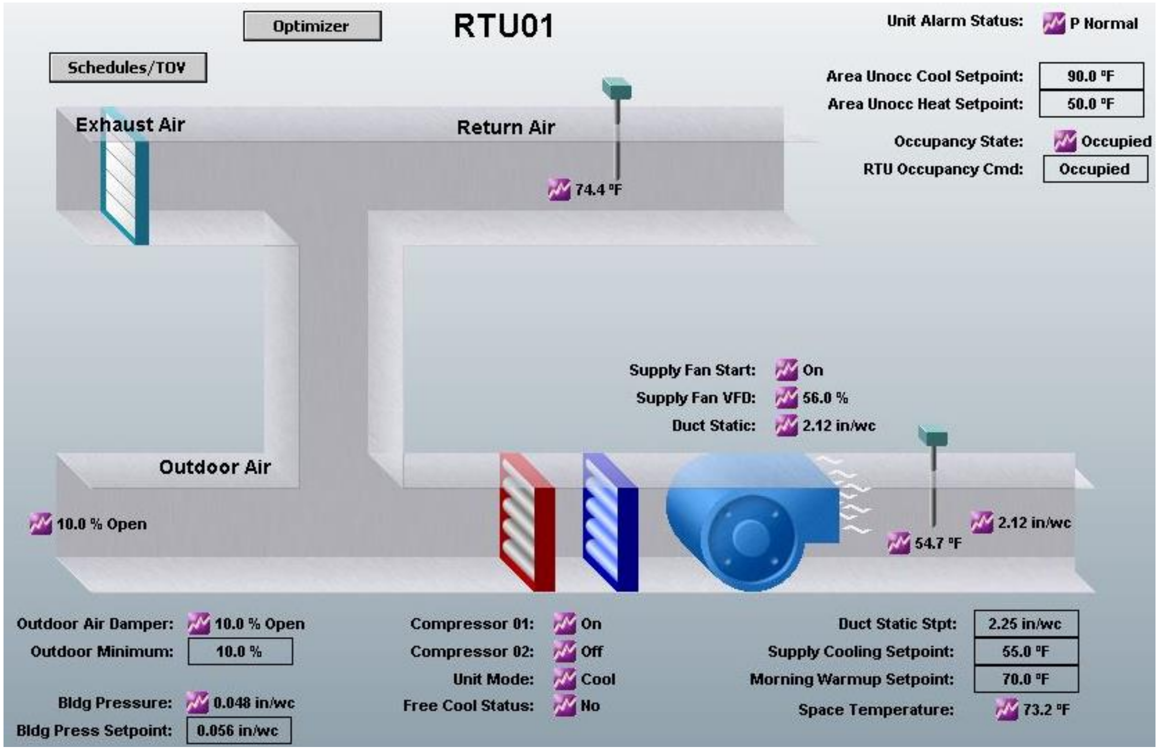


Figure 6-29. Screenshot of supply air temperature (Cooling).

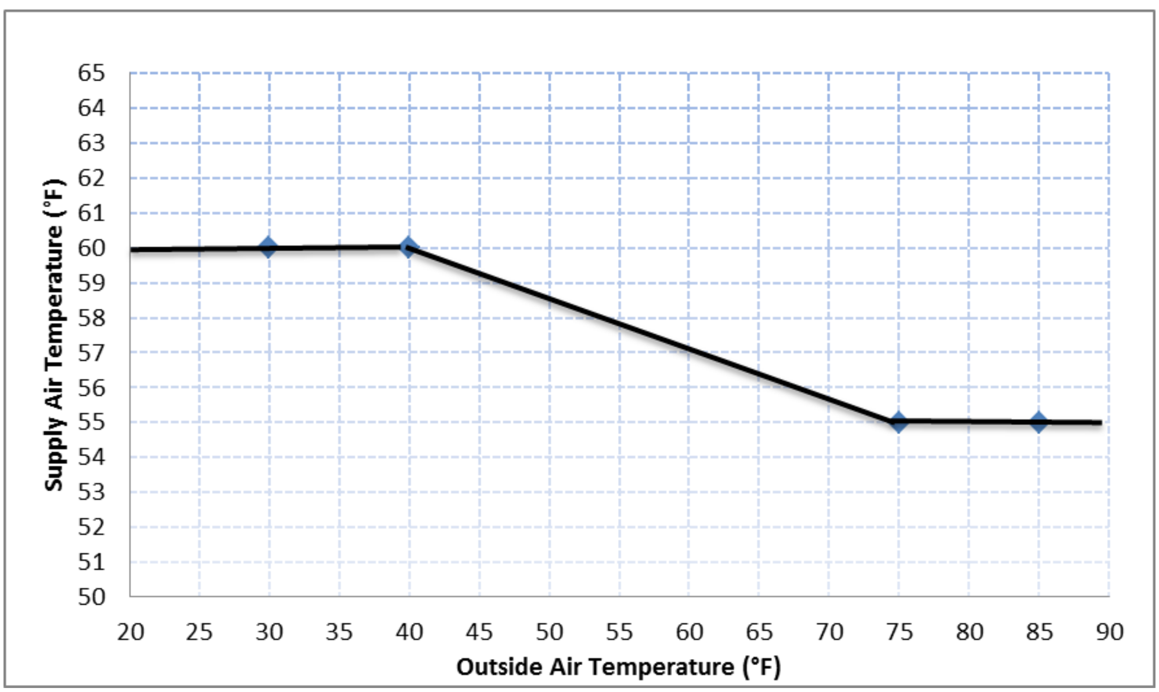


Figure 6-30. Supply air temperature reset scheme (Cooling).

The supply air temperature reset scheme is applied in the building. For example, in cooling period, when the outdoor air temperature is lower than 40 degrees, supply air temperature is set as 60 degrees. When outdoor air temperature is higher than 75 degrees, the set point is 55 degrees. In other conditions, supply air temperature set point varies linearly with outside air temperature. Space set point is set 75 degrees for occupied period and 85 degrees for unoccupied period.

Now variables from critical variable list are adjusted based on actual measurement or drawings from building, final models are simulated for the period from April, 2013 to May, 2014 with AMY weather data. Monthly building simulated energy use and actual energy use comparison is shown in figure 6-31 and 6-32.

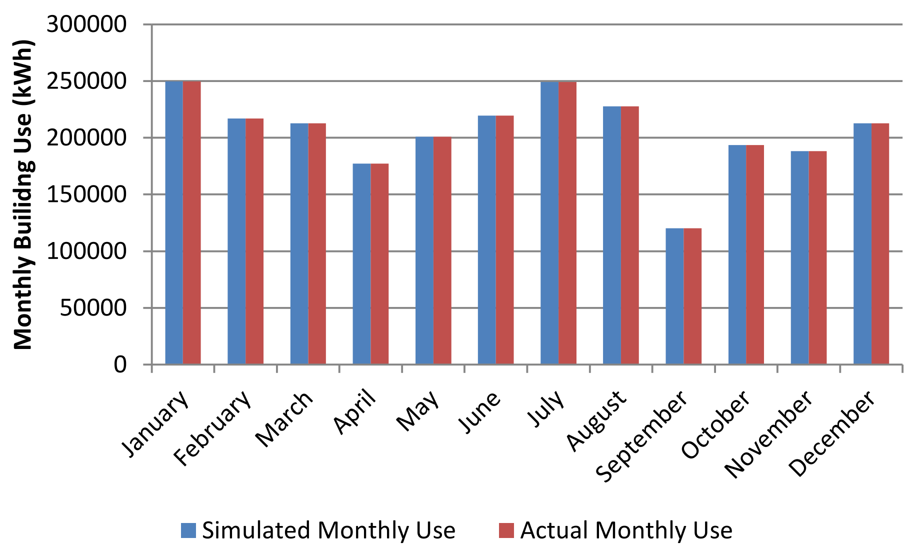


Figure 6-31. Case building I simulated monthly energy use comparison.

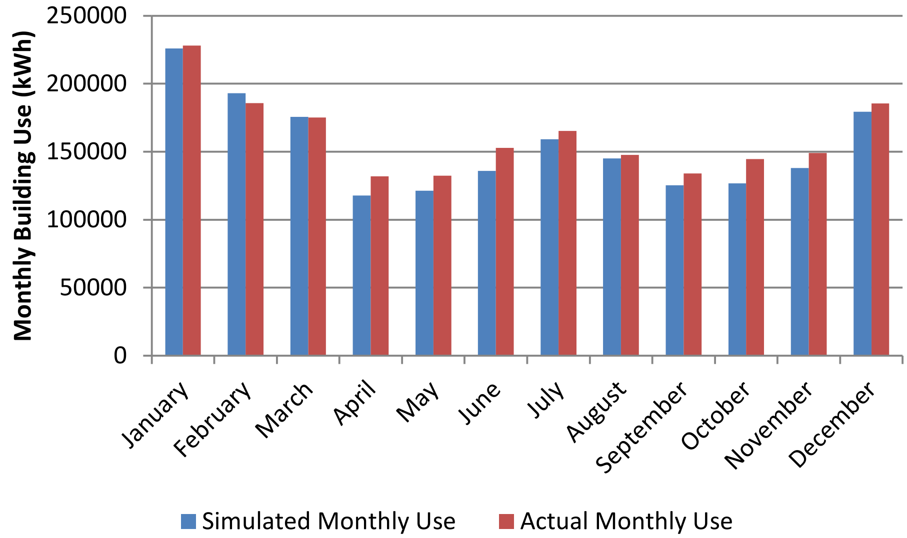


Figure 6-32. Case study building II simulated monthly energy use comparison.

Table below shows simulation results and comparison statistic indexes.

Table 6-4 Summary of monthly simulation results.

Building No.	Starting Month	Ending Month	Actual Whole Year Use (kWh)	Simulated Whole Year Use (kW)	Difference Percentage (%)	NMBE (%)	CVRMSE (%)
I	April,2013	May,2015	2,467,248	2,468,113	0.04%	-0.02%	6.99%
II	April,2013	May,2015	1,931,407	1,842,930	4.58%	5%	6.65%
ASHRAE Guideline 14						5%	15%

According to ASHRAE guideline 14, both buildings monthly simulated results satisfy the criteria. NMBE and CVRMSE for building I is -0.02% and 6.65%% respectively, for building II is 5% and 6.65% respectively. In case study building, month by month comparison shows very great agreement with actual measurement data. Total percentage difference is less than 1%. In case study building II, energy use from January to March is slightly over estimated than actual data, while in the rest of the year the number is marginally under estimated. It might be caused by some system change or building operational change that it is hard to predict in the model. For example buildings weekend operation in figure below or morning irregular operation in morning warm-up period (Figure 5-5 to Figure 5-8). Although a small discrepancy is identified in building II, the whole building energy use is still well calibrated.

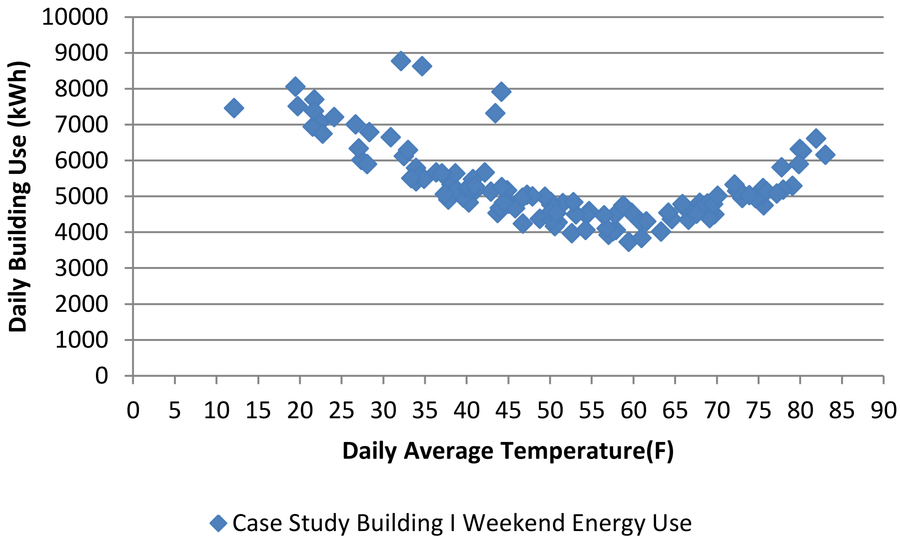


Figure 6-33. Case study building I weekend actual daily energy use.

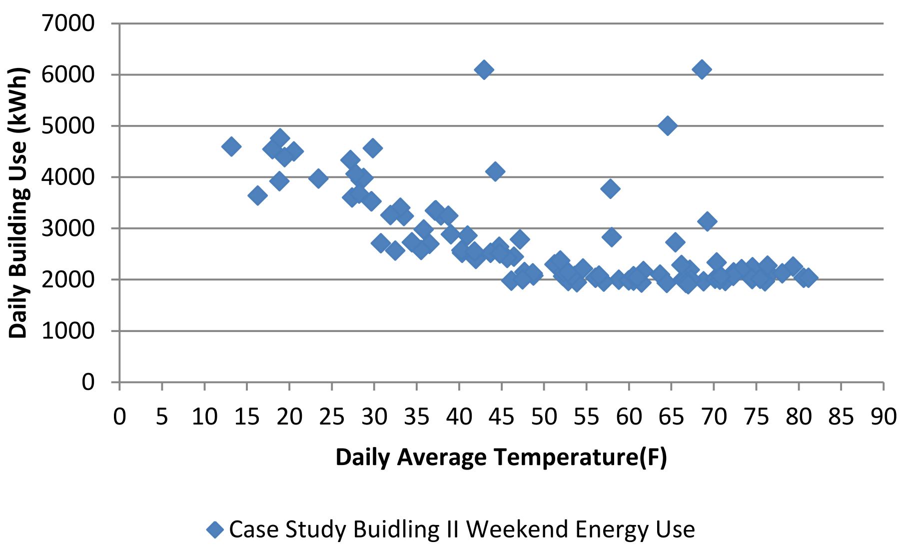


Figure 6-34. Case study building II weekend actual daily energy use.

Figure 6-33 and 6-34 shows “random” operation of weekend energy use in two buildings. The random operation might be caused by weekend overtime work or events. However, the occurrence of such conditions is unpredictable. Therefore, it is reasonable to only compare weekday simulated results and actual data.

The simulated overall HVAC system energy use and actual mechanical system end use comparison is shown in two figures below.

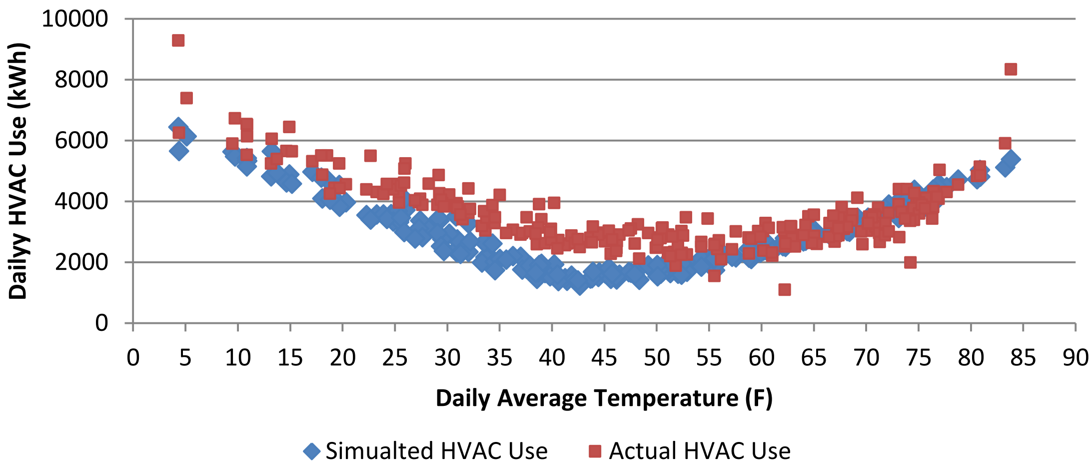


Figure 6-35. Case study building I HVAC weekday daily energy use comparison.

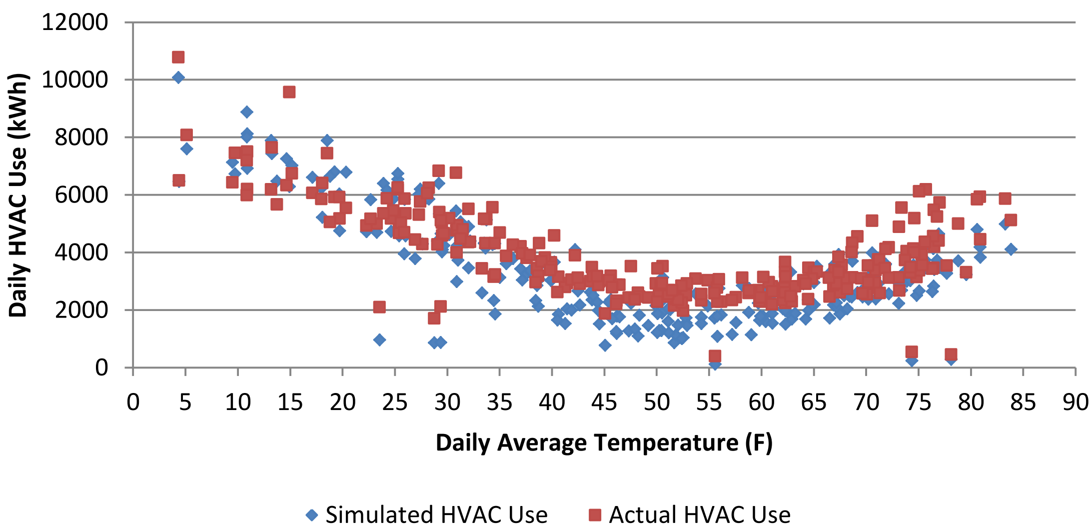


Figure 6-36. Case study building II HVAC weekday daily energy use comparison.

The statistic indexes for HVAC simulation results are summarized in table below.

Table 6-5 Summary of monthly HVAC simulation results.

Building No.	Actual Total HVAC Use (kWh)	Simulated HVAC Use (kWh)	Total Difference Percentage (%)	NMBE (%)	CVRMSE (%)
I	862574	712102	17.44%	18%	26%
II	1008454	863518	14.37%	14.43%	23.41%

ASHRAE guideline 14 defines uncertainty criteria at monthly level and hourly level which is showed in table below. However, at daily interval the statistical indexes are not defined. This dissertation assumes criteria at daily interval are in between of monthly and hourly levels.

Table 6-6 Summary of ASHRAE Guideline 14 criteria.

Index	Monthly	Hourly
NMBE	5%	15%
CVRMSE	10%	30%

For case study building I, weekday HVAC daily energy simulation results has a NMBE value of 18%, CVRMSE is 26%. In case study building II, NMBE and CVRMSE are 23.41% and 14.43% respectively. The CVRMSE values of both buildings satisfy criteria of daily CVRMSE, however, the NMBE values indicate the criterion is not met. In figure 5-5 to figure 5-8, high frequency of irregular operations in mechanical system in the morning warm-up period are detected. Due to unavailability of more detailed sub-metered data, the cause of such behavior can’t be located. However, this is a clue to suggest comparing simulated results and actual data excluding “random” morning hours. Comparisons of two case studies mechanical system energy use from 9:00 am to midnight are shown in figures below.

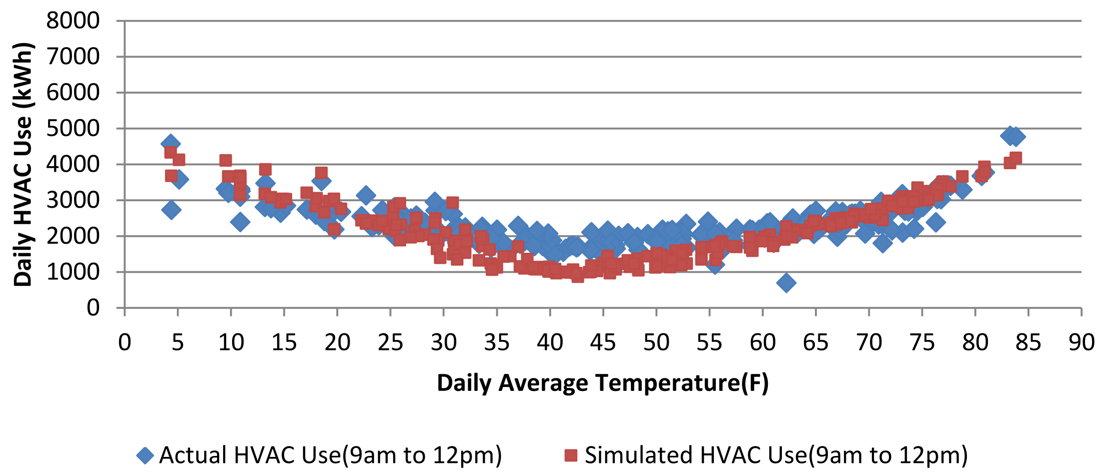


Figure 6-37. Case study building I HVAC weekday 9am to 12pm comparison.

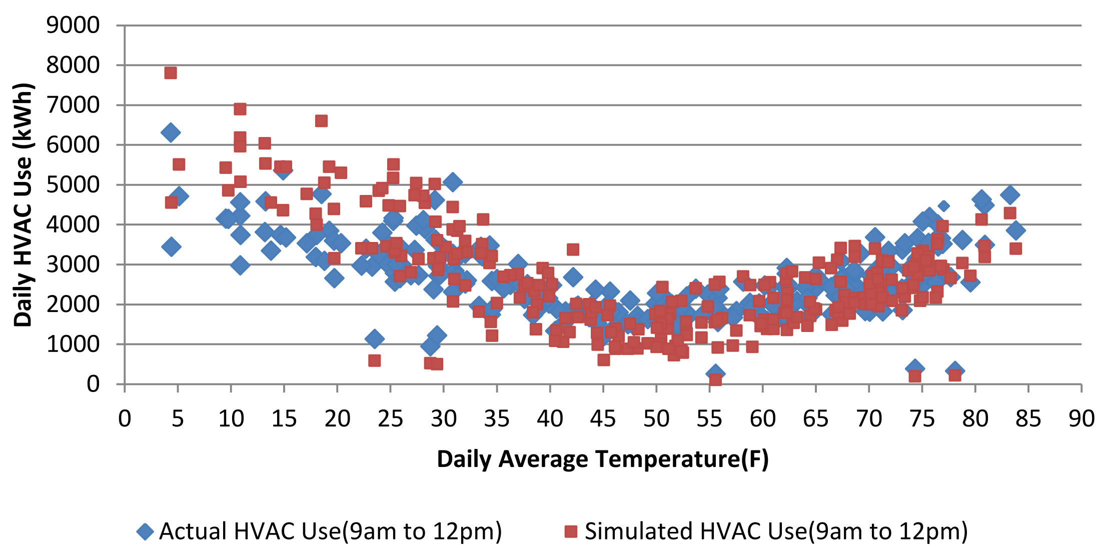


Figure 6-38. Case study building II HVAC weekday 9am to 12pm comparison.

By excluding morning warm-up period mechanical system energy use, NMBE and CVRMSE for building I are 0% and 9% respectively. For building II they are -0.94% and 18.02% respectively. From table 6-5, statistical criteria are met. It is safe to conclude that the majority of discrepancy between simulated and actual data is caused by “random” operation of mechanical system in the morning. NMBE and CVRMSE for both buildings show that mechanical system energy use is calibrated.

Figure 6-21 to 6-27 show general service (interior lighting, plug load and data center) energy use are well-matched with actual data. At this point, sub-system end uses are calibrated. Figure 6-26, 6-27 show monthly whole building energy use is calibrated. The next step is to compare daily whole building energy use with actual data. Case study building I weekday daily energy use and actual data is shown in figure below.

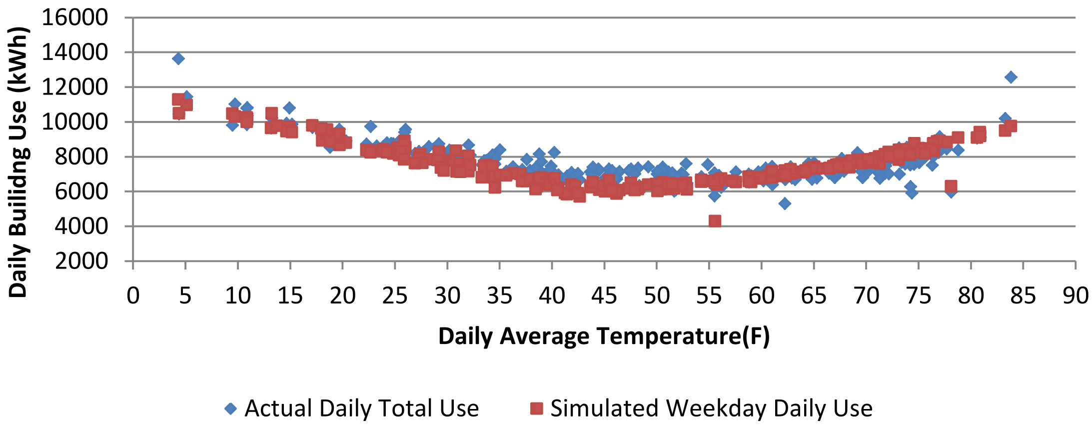


Figure 6-39. Case study building I weekday daily energy use comparison.

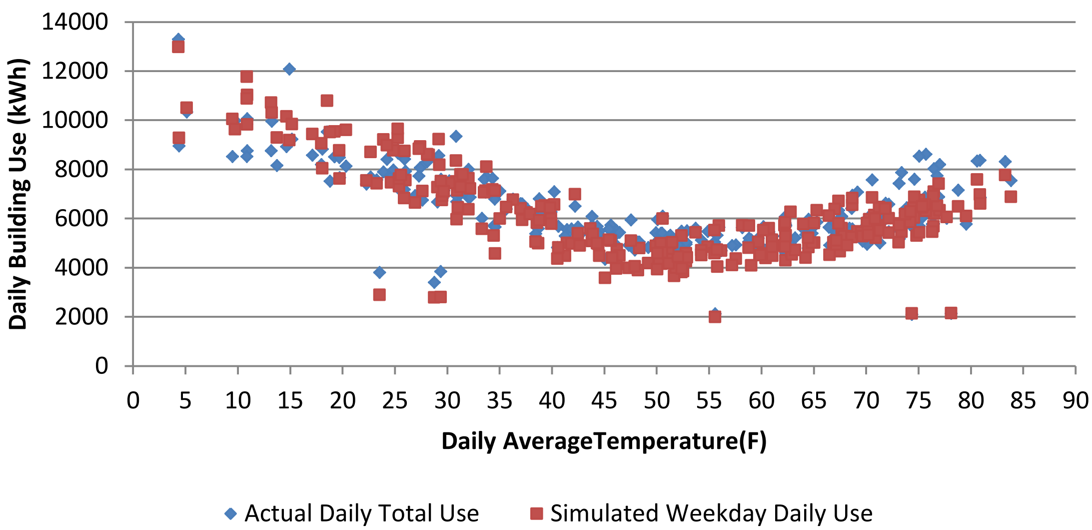


Figure 6-40. Case study building II weekday daily energy use comparison.

NMBE and CVRMSE for weekday whole building energy use in case I is 2% and 12%. In building II they are 3% and 12% respectively. Two indexes for both buildings meet the most stringent criteria from ASHARE guideline 14 (5%, 15% respectively). Two models are now confident to be claimed as calibrated models. By following steps of the method, sub-system energy end uses are well-tuned, whole building energy use is calibrated. The method has been proven to be valid.

6.3 Inverse model development from simulated results

Inverse model has some advantages that are very beneficial in actual practice. The formation of model is very time saving. Unlike running a detailed energy model, it can be formed within several minutes. A well-developed inverse model can predict building energy use with high accuracy. In this section, inverse model is developed from simulated detail modeling results. This offers several benefits in practice, for example if software is incapable of modeling applied ECMs, post retrofit conditions can be applied in inverse model and compared with actual post retrofit period energy use to quantify savings. Two case study buildings are calibrated in previous sections and the data will be used for inverse model development.

Section 5.2 discussed the selection data time scale, daily interval is considered most appropriate. In this section, daily simulated data and actual data are selected to develop inverse model. Whole building daily energy use is collected from simulation results and compare inverse model developed from actual data. Inverse model developed from simulation results and actual data equations are described below (Case study building I).

Inverse model developed from actual data:

When OAT≤42.5 $Y = 6987 - 104.58(OAT - 42.5)$

When 42.5<OAT<72.1 $Y = 6987$

When 72.1≤OAT, $Y = 6987 + 286.5(OAT - 72.1)$

Where OAT is averaged daily outdoor air temperature, Y is model dependent variable which is whole building energy use (kWh)

Inverse model developed from simulated results:

When OAT≤39.5 $Y = 6325 - 134(OAT - 39.5)$

When 39.5<OAT<57.3 $Y = 6325$

When 57.3≤OAT, $Y = 6325 + 115(OAT - 57.3)$

Figure 6-36 shows two inverse models, actual data plot against temperature.

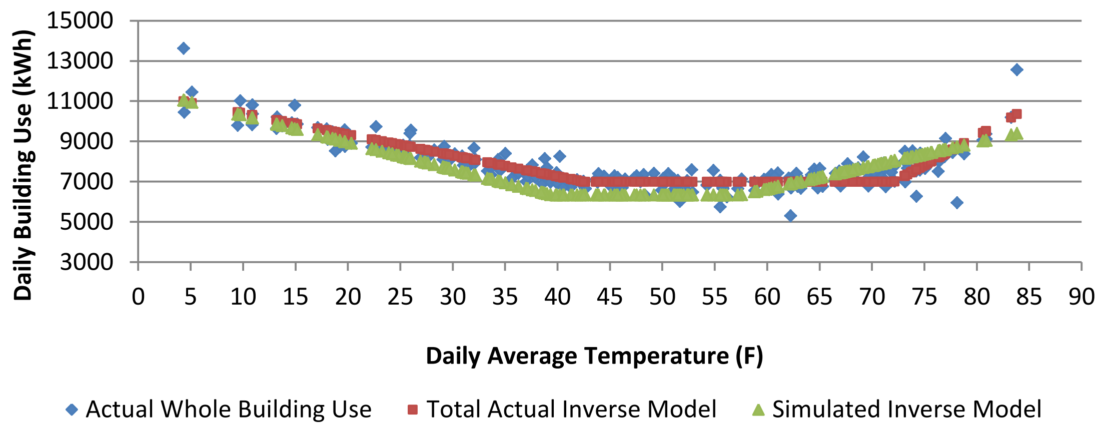


Figure 6-41. Case study building I inverse model comparison.

R^2 values for simulated IM and Actual IM are 0.93 and 0.8 respectively. CVRMSE values are 4.2% and 6.8%. Statistical p value indicates in both models the independent variable is significant. R^2 and CVRMSE indexes show that both IM model has great ability to interpret the variance in whole building energy use. The summary of two IM is shown in table below.

Table 6-7 Summary of developed inverse model in building I.

Data	R^2	CVRMSE	Annual Total (kWh)	Annual Total Difference (%)
Actual Data IM	0.789	6.863%	1,889,762	0.1%
Simulated Data IM	0.927	4.199%	1,831,302	3.19%
Actual Data			1,891,644	

Residuals for both models are shown in figure below.

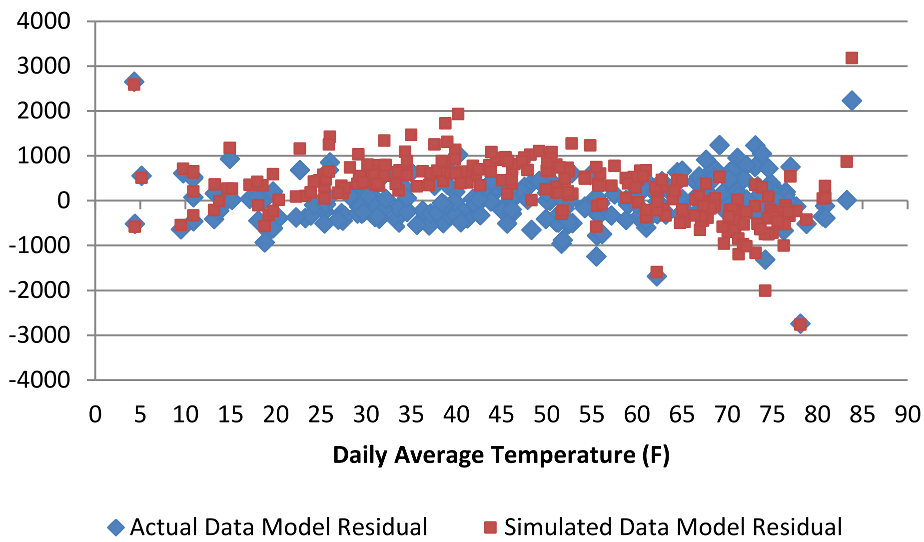


Figure 6-42. Building I inverse model residuals comparison.

From figure 6-42, most residuals "bounce randomly" around line 0. This suggests linear relationship between independent and dependent variable is appropriate. The shape of residual distribution is similar to a "horizontal rectangle" around line 0. It means variance of errors is equal. Inverse models developed from case study building II are shown in below.

Inverse model developed from actual data:

When OAT≤45.5 °F $Y = 5165.61 - 131.24(OAT - 45.5)$

When 45.5 °F <OAT<63.26 °F $Y = 5165.61$

When 63.26 °F ≤OAT, $Y = 5165.61 + 123.64(OAT - 63.26)$

Where OAT is averaged daily outdoor air temperature, Y is model dependent variable which is whole building energy use (kWh)

Inverse model developed from simulated results:

When OAT≤48.4 °F $Y = 4451.93 - 157(OAT - 48.4)$

When 48.4 °F <OAT<57.3 °F $Y = 4451.93$

When 57.3 °F ≤OAT, $Y = 4451.93 + 100(OAT - 57.3)$

Figure 6-43 shows two inverse models and actual daily energy use data plot against temperature for case study building II.

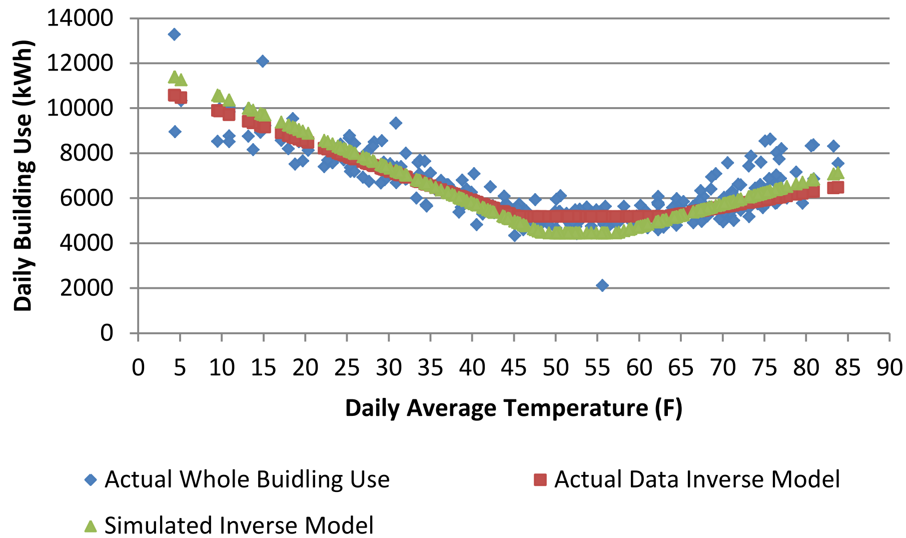


Figure 6-43. Case study building II inverse model comparison.

R^2 values for simulated IM and Actual IM are 0.84 and 0.78 respectively. CVRMSE values are 11.27% and 10.92%. Statistical p value indicates in both models the independent variable is significant. R^2 and CVRMSE indexes show that both IM model has great ability to interpret the variance in whole building energy use. The summary two IMs are shown in table below.

Table 6-8 Summary of developed inverse model in building II.

Data	R^2	CVRMSE	Annual Total (kWh)	Annual Total Difference (%)
Actual Data IM	0.78	10.92%	1,583,151	2.50%
Simulated Data IM	0.84	11.27%	1,577,551	3.19%
Actual Data			1,623,821	

Residuals for both models are shown in figure below.

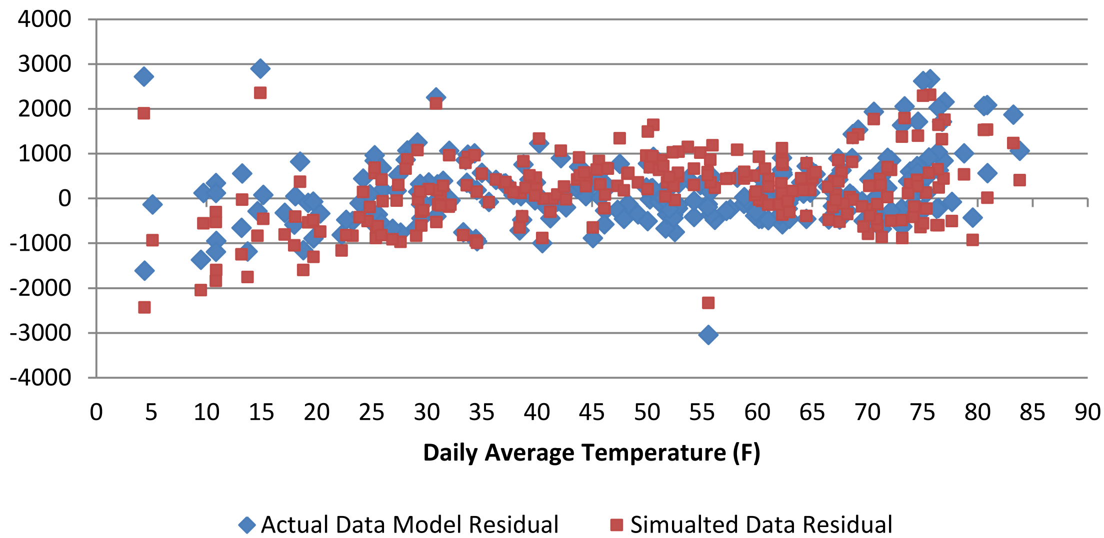


Figure 6-44. Building II inverse model residuals comparison.

In residual plot, no “fanning” effect or “funneling” effect are detected. Most of points “bounce back and forth” around line 0. When temperature gets colder or hotter, residual becomes larger. However, the trend is not very significant while most of residuals’ points form a “horizontal band.” RMSE and NMBE in table 6-8 shows both model have great goodness of fit. Inverse model developed from actual data and simulated results both are capable of simulating actual whole building energy with high certainty.

Inverse model developed from simulated results in both buildings show that when whole building energy model is well calibrated with actual data, the inverse model has same form of IM developed from actual data with equal or greater goodness of fit and certainty. This emphasizes the importance of model calibration in the model development. The calibration should not only compare whole building overall use, sub-system end uses should be taken with great care as well. For example, mechanical system (HVAC), interior lighting, plug load etc.

Chapter 7

Conclusions and Future Study Recommendations

7.1 Research conclusions

The dissertation aims to answer the proposed research questions in Chapter one. The dissertation is divided into two major sections that focus on each question. To solve the questions, constructed a research conducted advanced statistical analysis; implemented a forward detailed building model calibration method development and performed case studies validations. In chapter one, the two proposed research questions were:

1. What independent variables, in addition to dry bulb temperature, should be monitored in an auto-metering method should be acquired to establish an inverse model formulation capable of reducing "scatter" in the inverse whole building energy model formulation?
2. What protocoled method can be utilized to form a low variance inverse model of a building energy use and an as-operated forward model to asses ECMs savings?

In commercial buildings, for example office buildings, ambient weather is a driving variable for energy use, at mean time it is driven by many other factors together. To answer the first research question, this research adopted the DOE benchmark office building as the baseline building. This building has obvious advantages. It represents typical conditions of numerous medium size office buildings in the U.S, such as geometry, floor area, mechanical system, occupancy etc. More importantly, most of variables in this building are numerical and measurable. It possesses enough candidate variables for variable selection process. Assume a candidate building with limited number of measured data or missing several key variables, the derived results can be underspecified. Selection of initial candidate variables is based on sub-system categories or type such as geometry, cooling system, heating system, plug load system etc.

In order to represent actual medium office building characteristics in the U.S, the range of each variable is estimated from the current building data base, literature review and educated estimation. More than 2000 simulations are performed to simulate building energy use outcome under different input values. 16 typical TMY weather files for different weather zones are tested with the building. This aims to test building energy responses for different weather conditions within the U.S.

The literature review of previous variable selection techniques summarizes current research findings and shortcomings. This research conducted LASSO and SCAD penalty variable selection techniques to generate key variables that are critical to building energy use. Theories and algorithms of methods are briefly discussed in the dissertation. Simulated results from the baseline building were imported into Matlab®. The two algorithms performed the calculation on the same data set separately. The research also performed variable selection on cooling and heating system energy uses as well. Key variables generated by the two algorithms are similar and cross validate each. The generated key variable list also guides the development of model calibration steps in the second research question. For whole building energy use, key variables are ambient dry bulb temperature, interior lighting energy, plug load energy, space cooling/heating set point, supply air temperature and glazing information. The primary finding is that internal load related factors such as interior lighting energy use, plug equipment energy use are the most critical factors for building energy use. In commercial buildings, for example office building shows less dependency on ambient weather conditions. Dry bulb temperature is the only selected weather variable identified. On the other hand, this shows two algorithms effectively removing any collinearity effects between variables. Space related factors such as cooling/ heating set points and supply air temperature are selected. Those factors define space thermal conditions and drives mechanical system energy use.

Upon finding key variables for building energy use, the dissertation developed a variance based bin method to find the causes of large scatters in building energy use profiles. A building energy use can be divided into two categories, weather related and weather independent. The convoluted effect from ambient weather and building internal loads complicate building energy use analysis. Via the variance bin method, days with similar ambient conditions are grouped into one bin. Thus in each bin, energy variations are assumed to be caused by weather independent factors. This approach isolates the weather impact on the energy use, and enabling a fair comparison of energy uses at different ambient conditions. Figure 5-3, and figure 5-4 show HVAC energy use is the main component of energy scatters. In order to find what factors result in irregular mechanical system energy end uses, hourly load profiles within each bin are generated and compared. Through generated figures, it is very obvious that during working hours, mechanical system HVAC energy use is predictable and organized. While in the morning warmup period, a high frequency of irregular mechanical system operations was found. In case study buildings, the meter is only installed to measure entire HVAC system energy use; the research cannot go deeper to find time dependent reasons for morning irregular operations.

In the second part of this dissertation a sub-system focused, measured-data based building energy model calibration method has been developed. Complete detail steps to develop calibrated an energy model was discussed. Unlike previous research findings, this developed method not only focuses on whole building energy use, but also calibrates sub-system end uses. The sub-system focused approach disassembles convoluting effects between sub-systems. The sub-system energy uses are calibrated though the process, therefore the whole building energy use accuracy is guaranteed. The input data source is measured data oriented (evidence based), actual measured variables has the highest priority. Previous research methods advocate applying mathematical optimization algorithms to find an appropriate value for input values thus manipulate the overall use. The derived value is mathematically correct but not representing actual conditions.

The method adopts a critical variables list which is generated in LASSO and SCAD penalty variables selection results. By updating inputs in the critical variables list, the simulated results are iteratively updated. An important finding is that for buildings like office buildings separately metered interior lighting and plug load energy uses are critical for model calibration. Commercial office buildings often have a very high constant base load energy use. Data centers, interior lighting systems, and plug loads are main components of the base load. A HVAC system responds to meet thermal load or keep interior spaces at very precise conditions. Consequently, HVAC system energy use shows less variation with ambient weather conditions in terms of energy use. Plug load and interior lighting systems are basically weather independent, building core zones might and may have constant 24/7 uninterruptable operations. Most energy models assume hypothetical schedules and power levels. In this dissertation, plug load system, interior lighting and data center schedules and power levels are inversely developed. The office buildings have very distinctive operational schemes for weekdays and weekends. Separate schedules need to be set up for weekdays and weekends in any model simulation methods. In weekdays, data-based interior lighting and plug load schedules differentiate from default schedules considerably. Default/assumed schedules will result in inaccurate estimation or underestimation of loads and consequently simulated whole building energy use deviates from actual use. Underestimated or overestimated lighting and plug loads can be very problematic for an energy model. It will impact the selected size of HVAC systems and resultant mechanical energy end use prediction will be inaccurate.

To achieve better model performance, instead of applying one averaged load profile for a whole year, monthly profiles are generated. Weekly profiles can also be generated to further improve building model accuracy. However, this will be very time consuming and model improvement is not very significant. This is a tradeoff between accuracy improvement and model time investment.

After interior lighting and plug system energy uses are calibrated, the next step it to update inputs for space cooling, heating set point and supply air temperature. Three set points are considered as space condition variables. The estimation of set points is from the building management system, surveys from building operators and owners. In the case of study buildings, space set points have set back strategies to relate ambient dry bulb temperatures. Supply air temperature is collected from screen shots provided by building operator. Window/ glazing thermal characteristics are derived from architectural drawings or manufacture broachers. Glazing systems is no longer only serving a building for aesthetical purpose because they significantly impacts on building cooling and heating energy use. Double pane, triple pane, tinted, low-E coating glazing system and so on make a more sustainable and aesthetical friendly environment. Special care should be given to determine appropriate input data values for the glazing systems.

The building energy model is iteratively updated by modifying critical variable inputs. The final model's sub-systems are calibrated and ASHRAE guideline 14 statistical indexes are met. Simulated monthly whole building energy use also satisfies ASHRAE guideline 14 criteria. The research further examined into daily simulated energy use and compared with this actual daily use. Although ASHRAE guideline 14 only defines criteria at monthly and hourly level, this research assumes daily criteria are within the range of monthly and hourly criteria. Two buildings simulated on daily basis show a close match of actual measured daily use data. In case study building I, NMBE and CVRMSE are 2% and 12% respectively. In building II, they are 3% and 12% respectively. From simulated results, it shows that the proposed method is very efficient and an effective use of the proposed method of calibrating energy simulation models. Unlike previous research, the proposed method starts by calibrating energy use at sub-systems level. Instead of only comparing monthly whole building energy use data with utility bill, this research compares simulated results with actual data at daily interval. The results show that the energy model development methodology successfully captures actual building energy use trends. Therefore, two case studies suggest that proposed method is valid and effective.

The dissertation studied inverse model development from simulated building data. Generated inverse models are compared with inverse models generated from actual data. The comparison shows when the building energy model is calibrated, inverse model generated from simulated results have a similar capability of predicting energy use as an IM developed from actual data. This highly emphasizes the importance of calibrating a building energy model.

7.2 Future study recommendation

This research conducted variable selection methodology for inverse model development and forward model calibration methodologies development for medium size office buildings. Research results are primarily applicable to the same building type. Other building types such as convenience stores, large residential apartments etc. maybe to apply similar steps and methodology. LASSO and SCAD penalty are two statistical techniques to identify key variables that are important to building energy use. Other variable selection techniques are also encouraged; the resultant variables should be compared with key variables that are found in this research. Each method has its limitations and advantages, it is advisable to apply multiple methods and compare the difference.

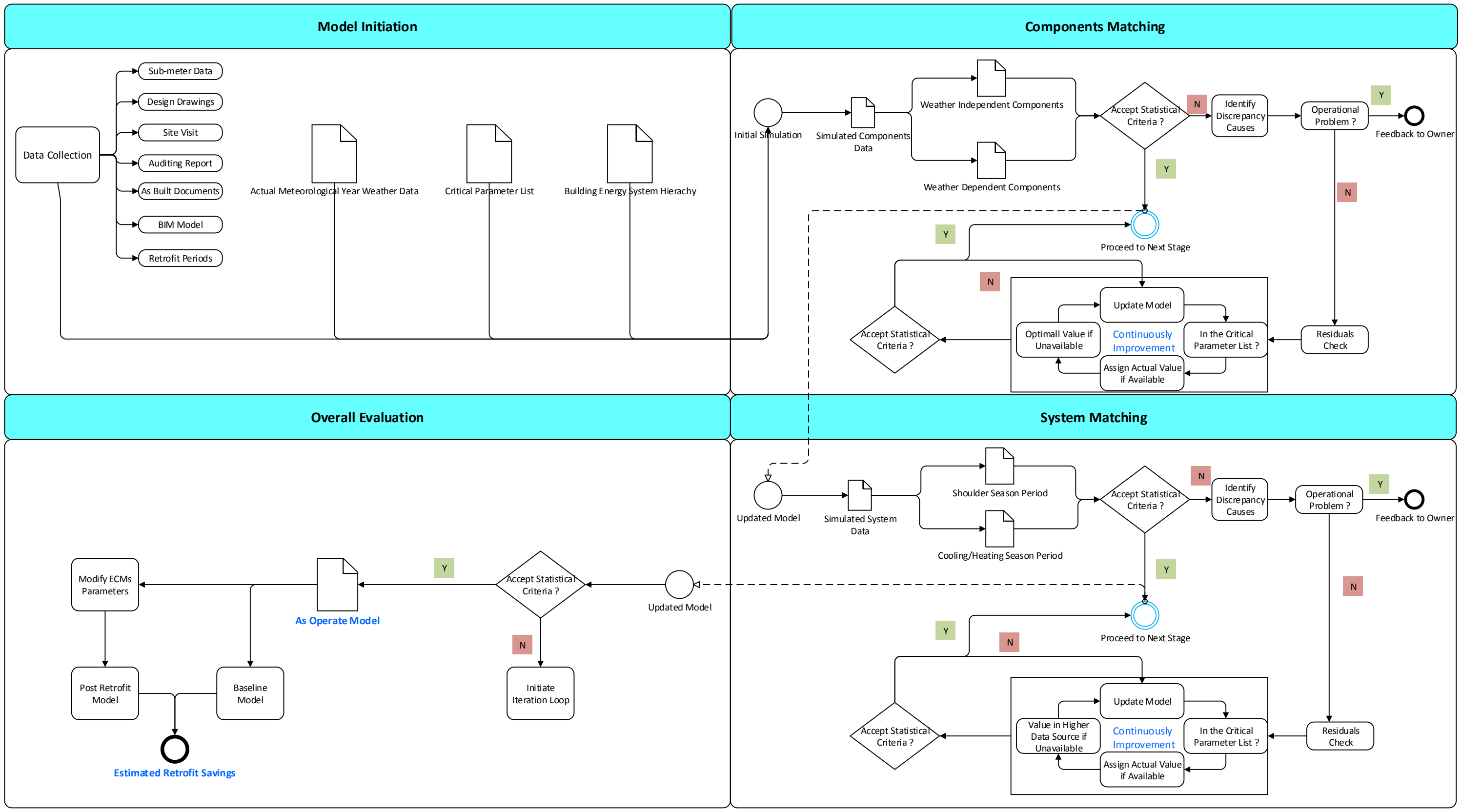
The LASSO and SCAD penalty variable selection methods' results strongly indicate that certain degrees of end-use sub-meters (direct or virtual) are very necessary for establishing inverse energy model of buildings. The sub-metered data allows analysts to determine what sub-systems or components are responsible for interruptive, irregular energy utilization performance.

Financial investment and metering priorities can be applied to the critical variable lists generation methods generated in this research as guidelines. Sub-metering minimizes the resource costs associated with required data monitor and storage and enables a cost effective, time saving analysis for the owner. For office buildings, electrical distribution systems should be isolated by sub-panels or end-use. Interior lighting and receptacle equipment should be separately measured. It is very beneficial if building energy codes/regulations recommend or mandate separate/isolate electrical panel design in new buildings. For existing buildings that have mixed end-use panels, it is advisable to install permanent meters to directly measure sub-system end use especially for interior lighting, receptacle equipment and data center (If available). However, this might increase costs because the number of installed meter will be higher compared to an isolated electrical panel design. The meter should record and store hourly or sub-hourly for example 15 minutes interval or one minute interval data. Large time scales such as monthly data can't provide enough insight to building operational characteristics. The finer the resolution of metered data the better. In section 5.3, the variation bin method found that HVAC morning warm up period shows high frequency of irregular operations. This cannot be accomplished without sub-hourly HVAC metered data. For whole building detailed energy model calibration, sub-metering key variables are also very important. It helps inversely deriving the input for the model. For example in two case study buildings, the number of fixtures can be counted from electrical drawings; however the schedules (diversity factors) cannot be determined. Default diversity factors give erroneous prediction of simulated loads. Thus, isolated electrical panels by end-use or sub-metering sub-systems are very important for both inverse model development and whole building energy model calibration.

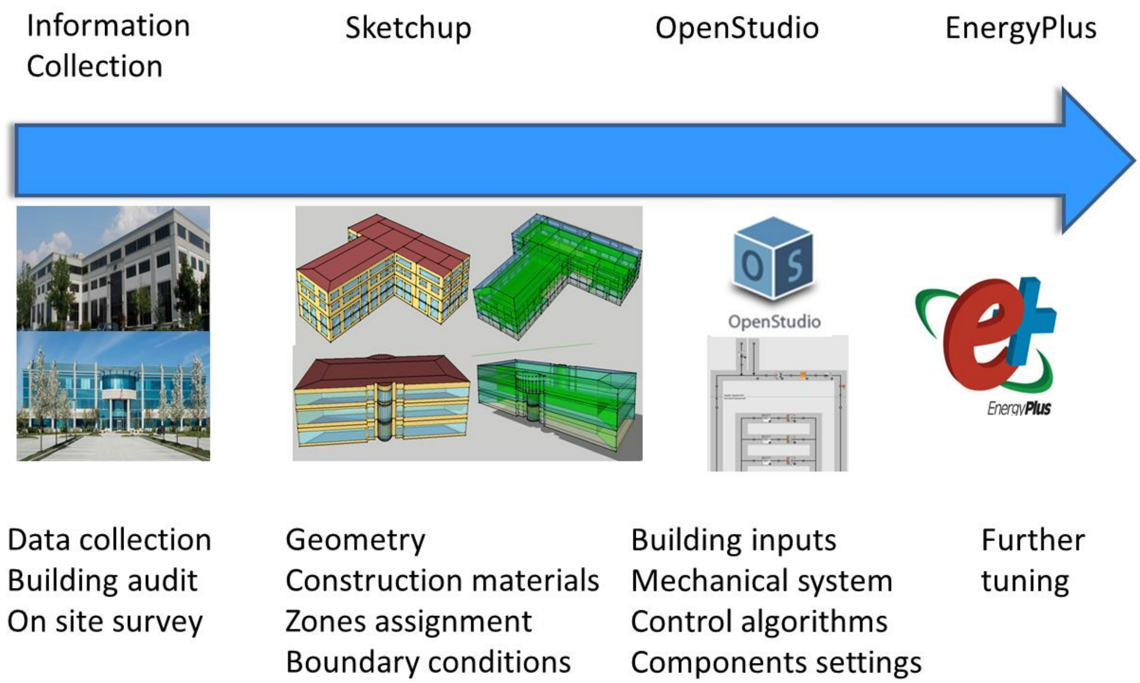
Building automation system (BAS) or management system (BMS) are encouraged to be installed in buildings. Many commercial new buildings now have BMS installed and many existing buildings have BMS installed during renovation. It is a computer based system that controls and monitors building lighting, receptacle, occupancy, air handling units, VAV terminal box etc. Researches by (Roth, Westphalen et al. 2002, Brambley, Haves et al. 2005) indicate that BMS that relates to 70 % energy consumption in buildings. A properly installed BMS provides space lighting control, electrical system control, HVAC system monitor and control and so on. In building inverse models and model calibration, BMS is very useful. Key variables, for example space cooling set points, heating set points, supply air temperatures in AHUs are retrieved from BMS. A BMS also contains information about control algorithms and set back strategies which are very beneficial and informative to the building owner, operator and analyst. From the variation bin method, it is highly recommended to store components' performance data such as fans, AHUs, terminal boxes. The stored data will assist in the investigation for causes of poor or irregular efficiency operations. For building owners, a BMS provides an alarm system that notifies erroneous operation of sub-systems or sub-systems demands in a timely manner. The system provides extra flexibility changing building operational strategies or schedules depending on conditions or events.

Appendix

Flowchart of as-operated model formulation method



Model Development Work Flow



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VITA

Bo Lin

Bo Lin is From Hunan province, People's Republic of China where he received his early education and life experience. He was dreamed to be a world class soccer star when he was little. He soon realized that the realization of the dream is almost impossible; therefore he decided to study structure option in civil engineering for his undergraduate study. Upon finished his bachelor degree, Bo quickly finds favorite study interest in building energy and mechanical system option.

In 2010, Bo started his graduate student life in Architectural Engineering Department, The Pennsylvania State University. During his master degree, he conducted research on building combined heat and power (CHP) system and served as research assistant in Mid-Atlantic Clean Energy Center under the direct supervision of Dr. Freihaut. He innovatively applied statistical concepts on CHP system at nation-wide scale. Several projects and publications were finished during his work in the Mid-Atlantic Clean Energy Center.

In 2012, Bo kept working towards his Ph.D. degree in Architectural Engineering Department, The Pennsylvania State University. During this period, Bo conducted research on building energy inverse model development, model calibration, benchmark, audit, measurement and verification. He worked as the research assistant for Energy Efficient Buildings Hub (led by the Department of Energy) and teaching assistant of AE 497F for three years.

Bo is also passionate about a lot of great of things in life. He enjoys hiking, cooking, biking and sports. He is a life-long supporter of Manchester United football club. In addition to that, Bo spends significant amount of leisure time reading historical novels and playing soccer.