

FIRST LAW ENERGY BALANCE AS A DATA SCREENING TOOL

A Thesis

by

XIAOJIE SHAO

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 2005

Major Subject: Mechanical Engineering

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ABSTRACT

First Law Energy Balance as a Data Screening Tool. (May 2005)

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This thesis defines the Energy Balance Load (E_{BL}) as the difference between the heating requirements plus the electric gains in the building and the cooling coil loads. It then applies a first law energy balance in conjunction with the concepts of analytical redundancy (AR) and trend checking to demonstrate that measured values of E_{BL} can be compared with the simulated characteristic ambient temperature-based E_{BL} to serve as a useful tool to identify bad data. Uncertainty and sensitivity analysis are introduced to analyze the impact of each building or system parameter to the simulated values of E_{BL} . A Visual Basic for Application (VBA) program has been developed through this research work, which applies the methodology illustrated in this thesis to automatically pre-screen the measured building energy consumption data with the inputs of several key parameters. Through case studies of six on-campus buildings, the methodology and the program successfully identified monitored consumption data that appears to be erroneous, which may result from incorrect scale factors of the sensors and the operational changes to the building that may enormously affect the key parameters as the simulation inputs. Finally, suggestions are given for the on-line diagnostics of sensor signals.

ACKNOWLEDGMENTS

I would like to express my sincere gratitude to my graduate advisor, Dr. David Claridge, for his great guidance, stimulating discussions, support and encouragement throughout this research work. I also would like to acknowledge my committee members Dr. Jeff Haberl and Dr. Charles Culp for all of their careful reading and comments on this thesis.

I am especially grateful to Mr. Juan-Carlos Baltazar-Cervantes. Without his advice and help, this research would not have been possible.

The appreciation is extended to all my friends and colleagues in the Energy System Laboratory for their continuous support, invaluable discussions, and well wishes. Many thanks go to Dr. Jeff Haberl, who first introduced me to this wonderful group.

I would like to thank my parents, Yunfeng Shao and Jihong Zhang, who have always been an example and a source of encouragement.

NOMENCLATURE

α = absorptivity

A_{win} = windows area of the building, ft^2

$A_{envelope}$ = surface area of the building, ft^2

A_{wall} = walls area of the building, ft^2

A_{floor} = floor area of the building, ft^2

c_p = specific heat of air, $Btu/(lb_m \cdot ^\circ F)$

d = number of sample case

f = multiplying factor to whole building electricity

f' = multiplying factor to heat gain of building

F = solar heat gain coefficient,

h_i, h_o = inlet and outlet specific enthalpies, Btu/lb

h_{fg} = enthalpy of air, Btu/lb_m

I_{sol} = solar insolation, $Btu/(hr \cdot ft^2)$

\dot{m} = inlet or outlet mass flow amounts, lb_m

n = number of measurements

ρ_{occ} = density of occupants in the building, $ft^2 / person$

ρ = density of air, lb_m / ft^3

$q_{individual, sen}$ = sensible heat generation of each individual, $(Btu / hr) / person$

$q_{individual, lat}$ = latent heat generation of each individual, $(Btu / hr) / person$

q_{sen} = sensible load of the building, Btu / hr

q_{lat} = latent load of the building, Btu / hr

$q_{CL, sen}$ = sensible load on cooling coil, Btu / hr

$q_{CL, lat}$ = latent load on cooling coil, Btu / hr

q_{RH} = heat load on heating coil, Btu / hr

q_{gain} = heat gain of building, Btu / hr

Q_{sol} = heat load due to solar insolation, Btu / hr

Q_{air} = heat load due to air exchange, Btu / hr

Q_{con} = heat load due to conduction and convection, Btu / hr

Q_{occ} = heat load due to occupants, Btu / hr

$Q_{con, win}$ = heat load due to conduction through windows, Btu / hr

$Q_{con, wall}$ = heat load due to conduction through walls, Btu / hr

$Q_{air, sen}$ = sensible heat load due to air exchange, Btu / hr

$Q_{air, lat}$ = latent heat load due to air exchange, Btu / hr

$RMSE$ = root mean squared error

t = daily averaged number of hours occupants staying in the building, hr

T_{std} = the standard deviation of the temperature, $^{\circ}F$

T_{OA} = out-side air temperature, $^{\circ}F$

T_R = inner-side air temperature, $^{\circ}F$

T_S = supply air temperature to the buidling, $^{\circ}F$

T_{MA} = temperature of mixed return and fresh air, $^{\circ}F$

τ = transmissivity

$U_{glazing}$ = averaged U value of the single-pane windows, $Btu / (hr \cdot ft^2 \cdot ^{\circ}F)$

U_{win} = averaged U value of the windows, $Btu / (hr \cdot ft^2 \cdot ^{\circ}F)$

U_{wall} = averaged U value of the walls, $Btu / (hr \cdot ft^2 \cdot ^{\circ}F)$

U_{tot} = averaged total U value of walls and windows, $Btu / (hr \cdot ft^2 \cdot ^{\circ}F)$

V_{tot} = total air flow through HVAC system, cfm

V_{OA} = outside air intake into the building through HVAC system, cfm

V_{CL} = air volume passing through cooling coil, cfm

W_{OA} = specific humidity ratio of outside air, lb_w / lb_{air}

W_{CL} = specific humidity ratio of cooling coil, lb_w / lb_{air}

W'_R = specific humidity ratio of the air entering cooling coil, lb_w / lb_{air}

W_{MA} = specific humidity ratio of mixed return and fresh air, lb_w / lb_{air}

W_{bele} = whole building electricity usage, Btu / hr

W_{bcool} = whole building cooling energy consumption, Btu / hr

W_{bheat} = whole building heating energy consumption, Btu / hr

X_{OA} = outside air intake ration

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CHAPTER I

INTRODUCTION

1.1 Background

In the United States, energy consumed in commercial buildings is a significant fraction of that consumed in all end-use sectors. In 2000, about 17 percent of total energy was consumed in the commercial sector (EIA, 2000). However, buildings rarely perform as well in practice as anticipated during design. A recent evaluation of new construction commissioning found that 81% of the building owners surveyed encountered problems with new heating and air conditioning systems. Another study of 60 buildings found that half were experiencing controls problems, 40% had HVAC equipment problems, 15% had missing equipment, and 25% had energy management control systems (EMCS), economizers, and/or variable speed drives that were not functioning properly (Piette et al. 2001). Such problems are widely reported in the building commissioning literature, and cause a lot of energy waste. Experts claim that up to 50% reduction in energy use for commercial buildings can be achieved with more efficient technologies (Patel et al. 1993). This enormous potential savings in money and resources in existing buildings has lead to an intense interest in energy conservation. While energy efficient design of new buildings is desirable, decreasing energy use in existing buildings is likely to have a far greater impact in the near future.

Starting in 1989, the Texas LoanSTAR Program began using hourly monitored data as part of the conservation program (Verdict et al., 1990). Subsequently, monitored data has become important in numerous processes including existing building retro-commissioning, Continuous Commissioning[®] (CC[®])¹ and re-commissioning (Liu et al. 1999 and Haas and Sharp, 1999). Different from other commissioning processes, Continuous Commissioning[®] focuses on optimizing HVAC system operation and control for the existing building conditions. Based on Continuous Commissioning[®] results from more than 130 buildings, the average measured utility savings are about 20%. In addition, CC[®] improves the system reliability and building comfort and reduces O&M costs (Liu et al. 1999, Claridge et al. 2000).

It is important to verify the predicted savings or to determine why the energy savings of the buildings do not match projections. ASHRAE recently released Guideline 14 titled “Measurement of Energy and Demand Savings” (ASHRAE 2002), which defines acceptable approaches for determining the savings achieved by energy retrofits and operational improvements. The methods described in Guideline 14 generally determine energy savings using baseline models. Data from the period before the changes were made is used to develop a baseline model; this baseline model simulates the performance of the system being studied as it performed before the implementation of the changes. Then environmental data from the period after the system was changed is processed through the baseline model equation to simulate how the system would have performed if the changes had not been implemented; the actual measured energy use is then

¹ Continuous Commissioning[®] and CC[®] are registered trademarks of Texas Engineering Experiment Station. Contact Energy Systems Laboratory, Texas A&M University for further information.

subtracted from the simulated energy use to calculate the energy savings. The amount and quality of the data available to the analyst are the major limiting factors in the type and accuracy of the baseline models that can be created and the savings that are determined.

There are various classification schemes for building energy monitoring projects used to collect data for energy savings measurements and baseline model creation such as that developed by ASHRAE and found in the HVAC Applications Handbook (ASHRAE 2001). Different levels of energy monitoring are classified by these schemes, including but not limited to: monthly billing data, short-term intrusive monitoring, continuous whole building monitoring, continuous sub-metering, and high resolution single channel metering (Reddy et al. 1994). With the replacement of traditional pneumatic analog controls with direct digital controls, it has become common for a large commercial building's energy management and control system to process and record data at time intervals as short as a second from hundreds of channels (Kissock et al. 1993).

Although handling the massive amounts of data that are needed to create good models is now a relatively inexpensive and fast process due to the revolution in price and performance of microcomputers, the ability to handle massive amounts of data requires the ability to screen data for faults caused by significant instrument failures, and software errors. A good data screening methods can lead to more accurate savings determination. A complementary use of the consumption data optimizes energy savings

by allowing for early detection of various system changes that can degrade the actual performance of energy conservation measures.

1.2 Objective

This proposed research is intended to use first law energy balance in conjunction with the concepts of analytical redundancy and trend checking to develop an effective data screening method suitable for automated application. The main goal of this research is to increase the efficiency with which gross faults in sensor measurements are found and identified for correction.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction of Fault Detection and Diagnosis Methodology

Fault detection is the indication that something in the monitored system is incorrect or unacceptable in some respect; whereas, fault diagnosis is the identification or localization of the cause of faulty operation. Fault detection is easier than fault diagnosis, since knowledge of the different ways in which particular faults affect performance is not required (Haves and Khalsa 2000).

In the last decade of the 20th Century, Fault Detection and Diagnosis (FDD) capabilities have shown a very rapid development in many industries including the aircraft and aerospace industry, where safety is a major concern. While productivity and quality considerations have led to applications in intelligent vehicle highway systems (Agogino et al. 1988), manufacturing (Walker and Wyatt 1995), chemical engineering (Dunia et al. 1996, Tong and Crowe 1995), and nuclear power stations (Dorr et al. 1997).

FDD technology was introduced into building HVAC systems in the 1970s, but systematic research started in the 1980's. Early work on FDD development for HVAC systems and equipment has been conducted by individual researchers, such as Usoro et al. (1985), Anderson et al. (1989), Pape et al (1991) and Wagner and Showreshi (1992). The International Energy Agency (IEA) encouraged research in this field with Annex 25, Building Optimization and Fault Diagnosis Source Book (Hyvarinen 1995) and Annex

34, Computer-Aided Evaluation of HVAC System Performance: The Practical Application of Fault Detection and Diagnosis Techniques in Real Buildings (Dexter 1996). An advanced FDD scheme aims at assisting system operators to monitor the current sensor and control signals, which are accessible in building management systems. Application of such FDD techniques could lead to improved occupant comfort, reduction of energy consumption, prompt and economic equipment maintenance, and longer equipment life.

As most of the fault detection and diagnosis methods that have been used rely on data measured by sensors installed within the facilities, the reliability of each method is strongly associated with the precision of the measurement. Sensor faults can generally be categorized as so-called hard failures and soft failures. A hard sensor fault refers to an abruptly occurring problem or complete failure of the sensor; examples are the complete failure of a fan, control valve, or supply temperature sensor in air handling units (AHU) (Lee et al. 1997, Yoshida et al. 1996). The soft sensor fault is a rather slowly changing bias, drift or scale-factor deviation, which is typical of many faults commonly found in HVAC systems (Wang and Wang 1999). No matter what kind of sensor fault exists in the system, it provides deceptive information to control and monitoring systems and operators. The effects could be more energy consumption (Kao and Pierce, 1983), failure in applications of advanced control, optimization and system/component FDD techniques (Stylianou and Nikanpour 1996), and unreliable results in system/component performance assessments. In fact, any action or decision based on biased sensor signals could be erroneous, which can be particularly serious in HVAC systems, since the

temperature differentials are usually small, and biases of even moderate magnitudes can result in drastic errors in control, FDD and performance monitoring schemes. Therefore, validating the sensor signals in the installation or commissioning of FDD systems is a critical first step.

2.2 Development of Sensor Signal Validation

There are several possible approaches for carrying out sensor signal validation. One of the traditional strategies to detect sensor signal faults is to implement manual checking. Manual sensor checking is used to periodically compare the measurement sensor readings to those from calibrated instruments at normal operation conditions. This approach has three problems: (1) Manual sensor checking requires a large amount of labor; (2) On-site checking of some sensors can be difficult and even impossible; and (3) The accuracy of on-site manual checking is limited. It is, therefore, highly desirable to develop convenient methods for assessing the health status of the monitoring sensors.

A review of the literature on signal validation shows that an on-line or remote sensor signal validation method would help ease the burdens and difficulties in on site manual sensor checks during commissioning or recommissioning of energy management and control systems (EMCS). This method must not only be reliable; it should work in a timely manner to allow for rapid repair or replacement of the failing instrument and also provide as continuous a data stream as possible. The most commonly used approaches can be generally classified in six categories: physical redundancy, automatic sensor

validation, limit checking, live zeros, and ceiling, knowledge-based and model-based sensor validation (Deyst et al. 1981, Dexter and Pakanen 2001, Wang and Wang 2002).

Physical redundancy, which can also be called “like” sensor comparison (Deyst et al. 1981), hardware redundancy, or the voting technique, is a simple way to validate sensors by installing several sensors to measure the equivalent or symmetric process parameters. This method can work quite well for the detection of “hard” or large failures. However, the cost of redundant sensor comparison is one limitation, especially for the systems possessing a high level of hardware redundancy. Besides the cost limit, voting techniques cannot be used to detect failures that affect multiple instruments in the same way, or subtle degradations in instrument behavior. Examples include common power supply failures and common thermal effects.

A SEVA (sensor validation) sensor is designed to have a built-in micro-controller to generate information more accurately than with standard sensors. This type of sensor (smart sensor) could deliver diagnostic information, or even perform internal diagnostics, measurement correction and generate standard metrics describing the measurement quality (Henry and Clarke 1993), and this approach is not usually affected by system faults. However, most HVAC systems in commercial buildings are not equipped with state-of-the-art instruments due to their high cost, and even when sophisticated sensors are used, they are still subject to various kinds of failures such as scale factor errors, bias faults, gradual drift, etc, which are all classified as soft sensor faults.

Limit checking compares the sensor output with some preset upper and/or lower limit. A measurement outside the preset limit is defined as a measurement fault. Limit

checking can detect various faults, but only when the measured value is highly erroneous. Trend checking (Isermann 1984, Wagner and Shoureshi 1992) applies a simple limit check to a time derivative function and can detect faults earlier than limit checking. In general, limit/trend checking is useful in detecting gross failures. However, it is not sensitive to subtle degradation of sensors such as gradual sensor drifts.

The live zeros and ceilings approach scales sensor outputs to limit the range of signal during normal operations. This approach is particularly useful when the normal sensor response covers a large portion of the total sensor range, and it is suitable for identifying faults such as shorts, grounds, open circuits, and so on. Many newer instrument systems have incorporated and automated this technique. On the other hand, subtle or long-term failures, such as decalibrations, drifts, etc. are not readily detectable by this sensor validation approach.

In the knowledge-based sensor signal validation method, qualitative models of the process are built and manipulated using heuristic reasoning. This technique is particularly efficient when applied to detect and isolate faults in measurement systems integrated in control architectures (Betta et al. 1995). Techniques used include expert systems (Tzafestas 1991), neural nets (Hemmelblau 1992, Lee et al. 1997) and fuzzy logic (Vachekov and Matsuyama 1992). The limitation of this method is that its efficiency is based on the implemented knowledge used to build the qualitative model, and this approach is more suitable for steady state systems.

The model-based sensor signal validation approach is one of the most common methods used in modern FDD schemes. Many sophisticated approaches to signal

validation based on this technique have reduced or eliminated the drawbacks of the traditional techniques in the past two decades (Willsky 1976, Frank 1990, Patton and Chen 1994). One model-based technique, called “functional redundancy”, “internal redundancy”, or “analytical redundancy”(Clark 1978), has gained increasing popularity over the years. This method uses on-line data processing techniques to generate redundant signals from a single set of instruments.

Analytical or functional models are largely based on the laws of physics, such as conservation laws of mass, momentum and energy. Those fundamental relationships are easy to build up and their validity is absolute and independent of the system performance degradations and change in working conditions. One advantage of functional models is that the prior knowledge that they embody improves their ability to extrapolate to regions of the operating space for which no training data are available (Haves et al. 1996). For a given degree of model accuracy, functional models also require fewer parameters. A further feature is that the parameters correspond to physically meaningful quantities, which has two advantages: (1) Values of the parameters can be estimated from design information and manufacturers’ data and (2) Abnormal values of particular parameters can be associated with the presence of particular faults. In addition, analytical redundancy can also be used to check a system for consistent measurements by operating it without load or by stopping its flow (Dexter and Pakanen 2001).

However, it is important to realize that this method has some problems in application. The first is that signals from the estimated parameters may also suffer from inaccuracy if they are not validated. The more variables required to form an analytic measurement, the

higher the possibility that a large error will propagate into the analytic measurement, causing a higher rate of false alarms. Thus, the error in an analytic measurement is often higher than that of a direct measurement, especially when the physical relationships of actual systems have been idealized (Wei 1997).

2.3 Applications of Sensor Signal Validation to Energy Management

Analytical redundancy has been utilized to assist energy management and control system (EMCS) operation and performance verification and monitoring. By a number of investigations, energy savings and better thermal comfort can be achieved. Work related to this topic, which has been reviewed includes: (1) a nonlinear mathematical model of HVAC systems used to detect room temperature sensor errors (Usono et al. 1985); (2) a “first-principles” model and a rule-based classifier used to identify the errors in a chiller plant (Benouarets et al. 1994); (3) energy balance used to check sensor faults in a chiller (Haves and Khalsa 2000); (4) an analytical redundancy methodology used to verify boiler performance (Wei 1997); (5) a law-based strategy used for fault detection and diagnosis of drift in the temperature sensors and flow meters in a central chilling plant (Wang and Wang 2002); and (6) neural networks applied for sensor fault detection and diagnosis to a chiller model (Najafi 2003). In addition, several approaches implemented to validate the measurements of building energy consumption are reviewed as well, which include the expert system technique (Haberl and Claridge 1987), and the limit checking method (Lopez and Haberl. 1992).

Usoro et al. (1985) primarily used analytical redundancy to detect an abrupt bias in a room temperature sensor. First principles and a lumped parameter approach were used to develop a mathematical model of a typical single-zone air-handling unit. A statistical criterion as an indicator of fault occurrence is built up based on certain “features” of the system behavior, which are monitored during system operation. Statistically significant disagreements between the monitored and the corresponding estimated data based on the no-failure model of the system indicate the occurrence of failures.

Benouarets et al. (1994) used a “first principles” model and a rule-based classifier for detecting and diagnosing faults in air-conditioning systems, and examined their ability to detect water-side fouling and valve leakage in the cooling coil subsystem of an air-handling unit. “First principles” models for this research consist of equations derived from a theoretical analysis of the physical process in the subsystem – heat and mass balances, and the established empirical relationships – heat transfer coefficient correlations. Design information and manufacturer’s data were used to generate the predicted parameters based on the reference models, and the measurements from the system being monitored were compared with the prediction results to identify the data faults in the system.

Haves and Khalsa (2000) set up a steady-state detector in conjunction with the energy balance equation to check the sensor bias in a chiller. Applying the algorithm of energy balance to the chiller of an air handling unit, if heat losses from the surface of the machine are ignored, the measured heat rejected by the condenser should equal the sum of the measured electric power and the heat absorbed by the evaporator. Thus, the

electric power can be calculated in terms of the duties on evaporator and condenser, and the residual between the calculated and measured power usage can be selected as a detector to indicate instrument or sensor faults.

Wei (1997) applied analytical redundancy to detect system faults and the in-situ operating characteristics of a boiler when some metered data are either missing or obviously erroneous. Mass conservation and the combustion equation are used to develop the AR (analytical redundancy) model, which can calibrate the gas and steam flow meters without shutting down the boiler in the utility plant. Consequently, this broadly useful diagnostic methodology helps the engineer and operating staff generate a boiler characteristic curve, which will aid in the efficient operation and better maintenance of the plant.

Wang and Wang (1999) reported a law-based strategy for fault detection and diagnostics of nonabrupt biases of the temperature sensors and flow meters in a central chilling plant. According to the principles of heat and mass balance for a building primary-secondary refrigeration system, the monitored data on building supply flow meter, building supply and return temperature sensors, chilled water flow meter and supply and return temperature meters may be associated with each chiller and bypass flow meter in terms of residual functions. Ideally, these residuals should be equal to zero when there are no heat losses, thermal storage, or water leakage within each control volume. However, various errors in measurements, such as biases, drifts, noise, and failures prevent the achievement of perfect balance. Consequently the sum of the squares of the balance residuals over a certain period are deemed as the effective indicators of

the existence of flow meter and temperature sensor biases. To locate the biased sensors and estimate the magnitudes of the biases can be realized by analyzing the residuals under various operating conditions of the refrigeration plants and minimizing the sum of the squares of the corrected balance residuals. This strategy is convenient for the operator to check the accuracy of the measurement devices.

Najafi (2003) presented the Enhanced Auto Associative Neural Networks (E-AANN), an improved approach of Auto Neural Networks (AANN) for sensor diagnostics. A secondary optimization process is implemented by E-AANN to identify and reconstruct sensor faults. This approach can catch the drift error and shift or offset error, and a chiller model is generated to test E-AANN under various noise level conditions. Results show that such approach works in noisy situations, however its performance degrades as the noise level increases (Najafi 2003).

Haberl and Claridge (1987) used regression techniques and an expert system to present a prototype result for building energy consumption analysis. An expert system is a computer program that solves problems difficult enough to require human expertise by using a previously assembled knowledge-based system. With the knowledge collected through the on-site maintenance personnel and over six years' experiences, the authors developed a Building Energy Analysis Consultant (BEACON) system, which can predict energy consumption of a building and indicate abnormal consumption. The limitations of this application are the intensive labor as well as complete and thorough expertise it required for the program development.

The Energy Systems Laboratory monitors buildings at various levels of detail, ranging from monthly to hourly, in order to build baseline models and calculate energy savings by comparing projected baseline use in the post-retrofit period against measured post-retrofit energy use. The data are archived for future research use as well. Hourly data are collected from remote sites by downloading data from remote data loggers as well as collecting National Weather Service data. Once collected, these data are screened using simple automated quality control checks, and visual inspection plots. Data screening is conducted by assigning static lower and upper bounds with individual information channels. If the data are outside the specified range, the program can be set to flag the value in a diagnostic log file as well as replace the suspect value with some predefined marker in the output data (i.e., -99). After passing through the high-low check, a second check is run to find missing data, since a common occurrence is for a data logger to lose power in the field, which causes it to miss an entire data record (Lopez and Haberl 1992). Once the data has undergone this initial data screening, the screened data are circulated between the project's principal investigators and research staff in weekly graphical plots referred to as the Inspection Plot Notebook (IPN). These data are examined visually to help locate potential problems (Lopez and Haberl 1992). This process is labor-intensive, repetitive and limited by the number of experienced people available to do the examining.

From the reviewed literature described above, analytical redundancy has been applied to detect and diagnose component or instrument faults in several instances in the HVAC field. Building energy consumption has been analyzed to filter out abnormal data

by using diverse FDD approaches including limit checking and an expert system. However, no previous research has been performed on automatic on-line building energy consumption data validation in terms of the increasingly developed model-based sensor fault detection and diagnosis method—analytical redundancy (AR). Consequently, this research targets development of an accurate on-line data fault detection or so-called data screening program based on the analytical redundancy technique, which could automatically validate the recorded building energy consumption. There are many programs in the energy conservation field that could benefit from the implementation of an automated sensor validation methodology. These programs handle large amounts of data as part of their day-to-day procedures, and they rely on a commissioning engineer or operator to perform the tests and analyze the results. The main benefits of automated performance monitoring tools are that they can ‘pre-filter’ data from many points, avoiding the need for manual inspection of all the measurements from every point. Therefore, they have the potential to allow a building operator to spend less time keeping on top of performance and to allow remote operators and service companies to monitor multiple buildings efficiently. Ultimately, automated tools may be able to make reliable diagnoses, automatically contact service contractors, and direct them to replace particular components (Haves and Khalsa 2000).

2.4 Building Energy Consumption Analysis

2.4.1 Energy Analysis Methods and Tools

Although the procedures for estimating energy requirements vary considerably in their degree of complexity, they all have three common elements: the calculation of space load, secondary equipment load and primary equipment energy requirements. Secondary refers to equipment that distributes the heating, cooling, or ventilating medium to conditioned spaces, while primary refers to central plant equipment that converts fuel or electric energy to heating or cooling effects. This research is more related with the building side energy consumption; primary equipment energy requirements will not be studied in more detail.

Space load is the heat that must be supplied or removed by the HVAC equipment to maintain a constant space air temperature. The load calculation step involves the calculation of the thermal loads experienced by the building spaces. Typically, it is necessary to calculate or estimate (1) solar radiation through transparent surfaces; (2) heat conduction through exterior walls and roofs; (3) heat conduction through ceilings, floors and interior partitions; (4) heat generated in the space by occupants, lights, and appliances; (5) energy transfer as a result of ventilation and infiltration of outdoor air; and (6) miscellaneous heat gains (ASHRAE 2001). Three main methods are used for calculating the instantaneous space load: (1) the heat balance method; (2) the weighting factor method; and (3) the thermal network method.

The heat balance method relies on the first law of thermodynamics and the principles of matrix algebra. The most fundamental assumption of this method is that the air temperature of the zone is uniform everywhere. In addition, the surfaces of the interior zone (walls, windows, floor, etc.) can be assumed to have uniform surface temperatures, diffuse radiating surfaces and one-dimensional heat conduction. With these assumptions, the heat balance model can be viewed as four distinct processes: (1) outside surface heat balance; (2) walls conduction process; (3) inside surface heat balance; and (4) air heat balance (ASHRAE 2001). The heat balance method is more fundamental than the weighting factor method, but it requires more calculations.

The weighting factor method calculates the space load by using the superposition principle and response factors (Stephenson and Mitalas 1967). Heat gain and air temperature weighting factors are the two groups of weighting factors used in this method. Heat gain weighting factors represent transfer functions that relate space cooling load to instantaneous heat gains from different heat sources. Air temperature weighting factors express how the net energy load of the room can be transferred to room air temperature. This method requires that the process be linear and invariant, and it is a compromise between simple steady-state calculation and a complex energy balance calculation (ASHRAE 2001).

In many respects, the thermal network method is considered a refinement of the heat balance method. Generally speaking, the heat balance method uses one node for zone air, while the thermal network method implements multiple nodes (ASHRAE 2001). Of

these three methods used to determine space load, the thermal network method is the most flexible and has the greatest potential for high accuracy.

In the loads-systems-plants sequence, the second step translates the space load to a load on the secondary equipment. There are a variety of forward building energy analysis procedures presently available, which include but are not limited to: (1) the degree-day procedure; (2) the basic bin method; and (3) comprehensive computer programs (Knebel 1983).

As the earliest energy calculation procedure, the traditional degree-day procedure estimates the heating energy requirement and is limited to residential buildings, where the envelope transmission and infiltration are the dominant factors contributing to the building load. Further modifications take into account the interior temperature and heat gains from occupants, solar radiation and appliances, and develop into monthly (Erbs et al. 1983) and annual variable-base degree-day methods (ASHRAE 2001, Kusuda et al. 1981).

For large commercial buildings, the degree-day method is not appropriate, because of the exceedingly variable internal loads, sophisticated control systems and complex air systems or plant arrangements (Kreider and Rabl 1994). The bin method that calculates the annual energy consumption for different temperature “bins” often gives a good result. However, the principle drawback of the basic bin method is obtaining the envelope loads by linear interpolation between the design heating and cooling loads; this approach ignores the variation of the transmission solar effects, which could significantly reduce the total loads (Knebel 1983).

Comprehensive computer programs that can simulate and calculate building energy consumption hourly have been developed in order to fulfill the requirements for accurate simulation of complex buildings. Examples of such programs include DOE-2, Energy Plus and BLAST. The main limitation in implementing of computer simulations in building energy consumption calculation is the high cost as well as the complexity of the algorithms, which makes it difficult for average practicing engineers to assess the accuracy of the results obtained (Knebel 1983).

ASHRAE Technical Committee 4.7 developed the modified bin method (Knebel 1983) to fill the need for a simple yet comprehensive method of calculating the energy requirements of buildings. The modified bin method recognizes that the building and zone loads consist of time dependent loads and temperature dependent loads. The modified bin method utilizes bin weather data. In expressing building loads as a function of outdoor temperature, two major simplifying assumptions are made. One is that all exterior loads can be expressed as a linear function of outdoor temperature; the other is that on a daily basis, two calculation periods, representing occupied and unoccupied hours are sufficient. In buildings dominated by internal loads or in low mass structures the method provides reasonable results.

The first law of thermodynamics and the modified bin method will be used in this research for space load and secondary system energy consumption evaluation respectively.

2.4.2 Solar Insolation

The modified bin method as introduced by Knebel (1983) used six parameters to determine the linear equation relating insolation on a surface and ambient temperature: (1) a fraction of possible sunshine for July; (2) the solar heat gain factor for July; (3) the mid-point of the highest temperature bin; (4) a fraction of possible sunshine for January; (5) the maximum solar heat gain factor of January; and (6) the mid-point of the lowest temperature bin.

$$Q_{sol} = M \times (T - T_{ph}) + Q_{sol,Jan},$$

$$M = (Q_{sol,Jul} - Q_{sol,Jan}) / (T_{pc} - T_{ph})$$

An improved method developed by Vadon et al. (1991) used first-degree curve-fitting for the insolation data as a function of temperature. It was a simpler method, needing only two coefficients and leading to accuracy in the 90% range of the most frequent data, and it did not create any unacceptable problems in the low and high temperature ranges (Vadon et al. 1991). The linear equation is

$$Insolation_{bin} = Intercept + Slope \times T_{p,bin}$$

where $T_{p,bin}$ is the mid-bin temperature value for which the insolation is to be calculated, and the intercept and the slope in the linear regression model above were shown to depend on $\sqrt{1/T_{std}}$, the standard deviation of the annual outside air temperature.

$$Slope = A \times \sqrt{\frac{1}{T_{std}}} + B \quad (\text{Btu/h}\cdot\text{ft}^2)$$

$$Intercept = C \times \sqrt{\frac{1}{T_{std}}} + D \quad (\text{Btu/h}\cdot\text{ft}^2\cdot^\circ\text{F})$$

$$T_{std} = \sqrt{\frac{\sum_{i=1}^{N_{bin}} F_i \times (T_i - T_{avg})^2}{8759}} \quad (\text{Btu/h}\cdot\text{ft}^2\cdot^\circ\text{F})$$

where the coefficients of the equations depend on the azimuth of the vertical surface in radians, so A, B, C, D can be determined as:

$$A = 10.463 + 4.98 \times \cos(az - 1) ;$$

$$B = -1.887 - 0.9754 \times \cos(az - 0.5) ;$$

$$C = -837.73 - 398.39 \times \cos(az - 1) ;$$

$$D = 223.29 + 100.53 \times \cos(az - 0.5)$$

where T_{std} = the standard deviation of the temperature, °F

az = the azimuth of the vertical surface in radians,

F_i = the frequency of the bin, hr

T_i = the mid-point of the bin, °F

T_{avg} = the annual average temperature for the location, °F

N_{bin} = the number of bins,

This method has many advantages over the one used in the original modified bin method. When compared to actual temperature and insolation bin data, the new method gives considerably better results than the original. This is not achieved by a complicated process or a very computationally intensive method but by a simple equation that uses only one parameter, the standard deviation of the temperature distribution. As a consequent of these advantages, this research will use this improved bin method to calculate the solar contribution to the building space load.

2.4.3 First Law of Thermodynamics

The form of analytical redundancy applied in this thesis will be based on the first law of thermodynamics. As one of the constraints that nature places on processes, it is commonly called the law of conservation of energy. If we regard the entire building as a control volume, there is mass flow crossing the system boundary; thus, the steady form of the first law for open systems will be implemented as the study model. It can be expressed as

$$\dot{m}_i \left(gz_i + \frac{v_i^2}{2} + h_i \right) + \dot{Q} = \dot{m}_o \left(gz_o + \frac{v_o^2}{2} + h_o \right) + \dot{W}$$

where \dot{m}_i, \dot{m}_o = inlet and outlet mass flow amounts, lbm (kg)

z_i, z_o = inlet and outlet system port elevations, ft (m)

v_i, v_o = inlet and outlet air average velocity, ft/s (m/s)

h_i, h_o = inlet and outlet specific enthalpies, Btu/lb_m (kJ/kg)

The sign convention on heat transfer \dot{Q} is that heat added to a thermodynamics system is positive; work output by the system \dot{W} is also positive. The steady-state conservation-of-mass equation ensures that

$$\dot{m}_i = \dot{m}_o = \dot{m}$$

It will be convenient and sufficiently precise if we assume the identical inlet and outlet system port elevations as well as the identical inlet and outlet air velocities, so there is no work output by the system to environment. The first law equation is then simplified to

$$\dot{m}(h_i - h_o) = -\dot{Q}$$

The measured energy consumption including the cooling and heating supplied to the building as well as the electricity consumed by the lights and other appliances may be considered part of the heat transfer \dot{Q} . The calculated space load includes solar radiation through transparent surfaces, heat conduction through exterior walls, roofs, floors, and heat generated in the space by occupants and heat transfer as a result of ventilation and infiltration of outdoor air. Some of the space load can be the accounted for in the heat transfer term \dot{Q} , while the air flows (ventilation and infiltration/exfiltration) constitute the mass flow terms. Thus, for a steady state system, the measured and calculated energy consumption of the building should correlate with each other based on the first law energy balance equation, and this conclusion can be used for cross checking the monitored energy consumption data implementing analytical redundancy.

In principle, reference models used in FDD should treat dynamic behavior as well as steady state behavior. Static reference models are simpler to develop and configure; the dynamic behavior of HVAC equipment is often poorly understood. Static reference models can be used for FDD if it is possible to determine when their predictions are valid, and when measurements can safely be used to estimate their parameters (Haves and Khalsa 2000). Hourly energy consumption data monitored and recorded in the Energy Systems Laboratory will be transformed into daily indices, which provide sufficiently detailed information for verifying base-level consumption and energy profiles.

2.5 Summary

This chapter first discusses the importance of fault detection and diagnosis (FDD) in the control and monitoring facilities, which leads to the conclusion that accurate sensor measurement is an essential step for installation or commissioning of FDD systems. After that existing literature on a variety of methodologies that are implemented to validate instrument signals, specifically the application of fault detection in the field of energy management, have been reviewed. The advantages and limitations of each approach are noted and it is found that no study has been done on signal validation of building energy consumption in terms of analytical redundancy.

The objective of this research is to use first law energy balance in conjunction with the concepts of analytical redundancy and trend checking to develop an accurate data screening method suitable for automated application. Chapter III describes the

application of analytical redundancy in a whole building thermodynamic model. Chapter IV investigates the impacts of different HVAC systems and simulation model input parameters on the combined energy consumption of a building, using simplified energy analysis in conjunction with the modified bin method. Sensitivity and uncertainty analysis are implemented in Chapter V, and following by the determination of standard variation and confidence interval of the predicted energy consumption value, which is used to compare with the measured data and filter out the biased ones. The automatic pre-screening tool for validating on-line measured energy consumption data is illustrated in Chapter VI, and case studies by applying this tool into real data fault detecting in 10 buildings on the Texas A&M University campus are presented in Chapter VII. The conclusions and discussion of future work are presented in Chapter VIII.

CHAPTER III

METHODOLOGY

3.1 Introduction

The most commonly used measured data for evaluating the energy savings are the “purchased” energy data for the building (such as electricity, gas, chilled water, and hot water) used in conjunction with the outside air temperature. To guarantee the quality of the collected data and further provide reliable savings estimation, it is desirable to screen the data for faults caused by instrument failures and operational or mechanical changes.

This chapter is intended to explore the use of analytical redundancy in screening energy consumption data collected from large buildings. The main goal of this work is to increase the effectiveness with which gross faults in sensor measurements are found and identified for correction. Another goal of this approach is to aid in finding more subtle faults that heretofore have not been examined in any systematic way.

In this chapter, the first law of thermodynamics as a functional model from which AR derives is applied to a simplified on-campus building construction. A newly named term, Energy Balance Load, which is a redundant quantity determined from some HVAC system or building construction-related parameters, will be introduced as well.

3.2 Application of Analytical Redundancy to Data Pre-Screening for Building Energy Consumption Measurements

All of the measured data used in this work were obtained from the database of the Energy Systems Laboratory at Texas A&M University (TAMU). Flow meter, temperature meter, BTU meters were installed by the Energy Systems Laboratory to measure the electricity, cooling, and heating energy consumption for numerous individual buildings. For modern air conditioning systems, dependable measurements are required for continuous online automated schemes. Therefore, automated online sensor signal fault detection and diagnosis or data screening is desirable. In the most common data screening methods used in the energy conservation field, each individual channel is analyzed as an independent entity, or at most compared only to outside air temperature. While this does not inhibit the detection of gross faults, the more subtle faults that potentially hamper data collection and the energy conservation efforts are not easily found with such limited approaches. To screen data from multiple meters, it would be potentially more useful to use all of the available site data to cross-check each individual channel; the more channels are available, the greater the ability to detect faults on provided individual channels that are related by analytical expressions. The method that is investigated and applied in this thesis is called “analytical redundancy.”

Analytical redundancy is a method of sensor signal fault detection that uses mathematical process models to derive a set of parameters that are applied to a data filter. In the case of whole-building energy analysis, the obvious process model is derived from the first law of thermodynamics, or energy balance. It states that the energy change in a

system is equal to energy added to a system minus the energy removed from the system if no energy is stored or generated in the system (ASHRAE 2001).

A thorough understanding of the structure and algorithm of the whole-building thermodynamic model is an essential step to conduct other related studies. Building thermal loads include five main parts: heat transmission through the building structure; air ventilation and infiltration via doors, windows, or air-handling units (fresh air exchange); solar radiation through the envelope; internal heat gain from lighting, equipment, and occupants; and heat inserted into and removed from the building by the HVAC system.

To create the desired energy balance model of the commercial building, certain assumptions are made. First, the internal temperature of the building is assumed to be constant. Second, the building space serviced by the metered data is assumed constant. Third, no energy is stored in the system. Fourth, except for heat gain from occupants, no energy is generated in the system. Fifth, a fraction (f) of the measured non-chiller electricity consumption transforms to heat gains into the system. These five assumptions reduce the generalized first law of thermodynamics to a simplified thermodynamically open system. Thus, the building energy use can be represented by Figure 3.1:

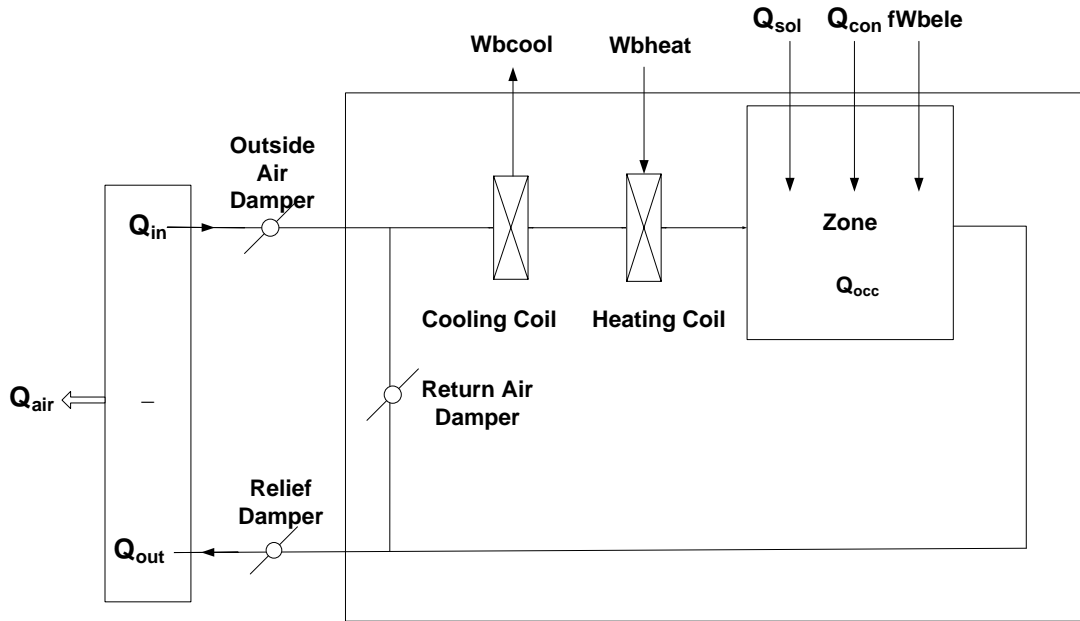


Figure 3.1 Whole building thermodynamic model

$$fW_{bele} + W_{bheat} - W_{bcool} + Q_{sol} + Q_{air} + Q_{con} + Q_{occ} = 0 \quad (3.1a)$$

Or

$$fW_{bele} + W_{bheat} - W_{bcool} = E_{BL} \quad (3.1b)$$

W_{bele} is the energy used in the building in the form of electricity, W_{bheat} is the energy added to the building by heating, W_{bcool} is the energy removed from the building by the cooling system, and E_{BL} is the remainder term. E_{BL} is a newly introduced term, herein called Energy Balance Load, which is a substitute for all terms in Equation (3.1a) that are not readily measurable. In other words, Energy Balance Load can be expressed as the negative value of the sum of occupant load and weather-related loads including solar heat gain, air infiltration/ventilation, and heat transmission through the windows and walls.

$$E_{BL} = -(Q_{sol} + Q_{air} + Q_{con} + Q_{occ}) \quad (3.2)$$

The Energy Balance Load evaluated with the measured energy consumption data of Wehner Building for year 2000 is plotted in terms of outside air temperature, shown as Figure 3.2, to give an example of the pattern of Energy Balance Load, for additional information about this building the reader is referring to Figure 6.4. From the plot, it can be seen that E_{BL} shows a largely linear function in terms of outside air temperature. Furthermore, according to Equation 3.2, E_{BL} is expected to be independent of system type and hence is a measure of the data that is not as strongly dependent on building characteristics as the individual data streams.

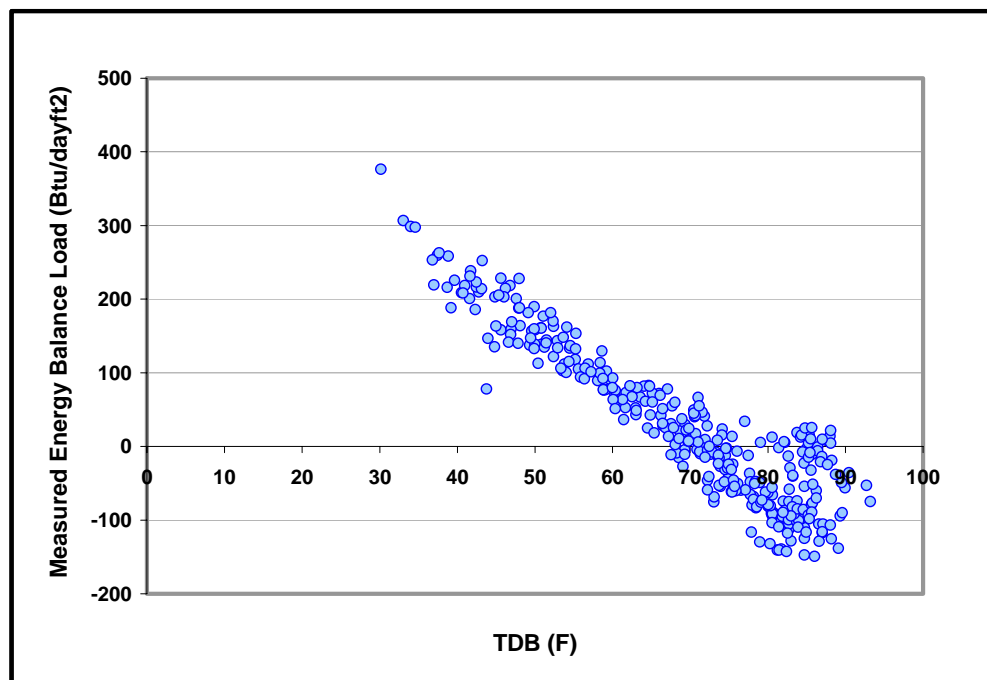


Figure 3.2 Measured Energy Balance Load vs. outside air temperature of Wehner Building for year 2000

In simplified form, each of the heat gains listed above, except Q_{occ} , may be linearly related with the outside air temperature (Knebel 1983), and the corresponding equations are expressed as follows (Vadon et al. 1991, Kreider and Rabl 1994)

$$I_{sol} = Intercept + Slope \times T_{OA} \quad (3.3)$$

$$Q_{sol} = FI_{sol} A_{win} \quad (3.4)$$

where F is a constant of proportionality called the solar heat gain coefficient, for single glazing windows that most of the TAMU buildings have, it is given by

$$F = \tau + \frac{\alpha U_{glazing}}{h_o} \quad \text{with } U_{glazing} = \frac{h_i h_o}{h_i + h_o} \quad (3.5)$$

$$Q_{cond} = Q_{cond,win} + Q_{cond,wall} + Q_{cond,ground} = U_{tot} A_{envelope} (T_o - T_R) \quad (3.6)$$

where $U_{tot} A_{envelope} = U_{win} A_{win} + U_{wall} A_{wall}$. Heat loss through the ground can be estimated by the ground unit heat loss and the difference between the building interior air temperature, building perimeter, and the average ground temperature (ASHRAE 2001). For a typical TAMU building such as Zachry Building, ground coupling is less than 20,000 *Btu/hr* approximately, which is small comparing with other heat loss through the envelope. Thus, heat loss through the building ground is neglected in the this research work.

Assuming the sensible and latent heat load generated by any individual occupant is a fixed rate $q_{individual}$, the total heat generation from occupants may be determined by floor area of the building, occupant density and the average time of the occupants stay in the building. The result is shown as Equation (3.7).

$$Q_{occ} = Q_{occ,sen} + Q_{occ,lat} = A_{floor} \rho_{occ} (q_{individual,sen} + q_{individual,lat})t \quad (3.7)$$

As for the air quality requirements, large portions of the buildings on the TAMU campus have outside fresh air intake through air handling units, which combines sensible and latent loads. The sensible load is represented in terms of the differential between the inlet and outlet air temperature, as well as the fresh air intake volume. Besides the same outside air intake volume, the latent load is determined by the difference between the humidity ratio of the fresh air and the humidity ratio of the room return air.

$$Q_{air} = Q_{air,sen} + Q_{air,lat} \quad (3.8)$$

$$Q_{air,sen} = V_{OA} \rho c_p (T_{OA} - T_R) \quad (3.9)$$

$$Q_{air,lat} = \rho h_{fg} V_{tot} [W'_R + X_{OA} (W_{OA} - W'_R) - W_{CL}] \quad (3.10)$$

Having obtained the detailed expression for each term in Equation (3.2), the Energy Balance Load can then be determined by Equations (3.11) and (3.12) for sensible and latent loads separately. For Equation (3.12), the maximum value command indicates that there is latent load only when the cold deck is wet, or in other words only when there is condensation on the cooling coil.

$$E_{BL,sen} = -[FI_{sol} A_{win} + (U_{tot} A_{envelope} + V_{OA} \rho c_p) \times (T_{OA} - T_R) + A_{floor} \rho_{occ} q_{individual,sen} t] \quad (3.11)$$

$$E_{BL,lat} = -Max\{\rho h_{fg} V_{tot} [W'_R + X_{OA} (W_{OA} - W'_R) - W_{CL}], 0\} \quad (3.12)$$

Without $E_{BL,lat}$, the latent portion of the Energy Balance Load, the sensible portion of the Energy Balance Load, $E_{BL,sen}$, is linearly related with the outside air temperature, which is consistent with what has been shown as Figure 3.2, and can be expressed as

$E_{BL} = k(T_{OA}) + l$, where $k, l = const$, while the average values of $E_{BL,dat}$ versus outside air temperature can be fit by a polynomial line of order four or less.

Summarizing Equations (3.3) through (3.12), the calculation of E_{BL} as a redundant value requires the availability of several building or HVAC system characteristics and set points. The required parameter values for the Wehner Building, located on the TAMU west campus, are listed in Table 3.1 as an example. It is proposed to use the calculated value of E_{BL} as an analytically redundant measure to cross-check the combination of measured values $fWbele$, $Wbheat$ and $Wbcool$. Simulation accuracy of the system, or in other words, the computation accuracy of E_{BL} , is dependent on the depth of knowledge captured in the model, the preciseness of the basic structure, and the function and behavior of objects included in the system.

3.3 Data Requirements

Hourly data for energy consumption and ambient temperature will be retrieved from the Energy Systems Laboratory Database. Electricity consumed by the interior lights, equipment, and other appliances contributes to the whole building electricity usage, which is represented as $Wbele$. Additionally, the terms $Wbcool$ and $Wbheat$ will denote the chilled water and hot water energy utilized by the air-handling units to satisfy the comfort requirements of the building.

Table 3.1 Input parameters of Energy Balance Load simulation (Wehener Building in 2000 is used as an example)

Input Parameters			
Wehner Building	Building #528		Year: 2000
HVAC System		3 SDVAV	6 DDVAV
Economizer		Yes	
Heat Recovery System		No	
Conditioned Floor Area		192,001	ft ²
Exterior Walls	Area	45,000	ft ²
	Uwall	0.2	Btu/hr*ft ² F
Exterior Windows	Area	30,000	ft ²
	Uwindow	0.98	Btu/hr*ft ² F
	F	0.87	
Room Temperature	Heating	75	F
Outside Air Flow	Flow rate	0.05	cfm/ft ²
Total Air Flow Rate		1.00	cfm/ft ²
Cold Deck Schedule	Tcl	60	F
	Wcl	0.01	
Occupant	Density	300	ft ² /person
	Heat	240	Btu/hr*person
	Hours	10	hr

To limit the effects of thermal storage and dynamic behavior of the building, daily data will be used for analysis in this research work, the measured energy usage will be summed to daily data and the temperature data will be averaged on a daily basis. If there are 18-23 hours of data for a day, it will be multiplied by $24/n$ where n is the number of hours of data available for the day. If there are less than 18 hours of data available for a day, the day will be omitted and set with a predefined missing data marker in the output (i.e., -99). E_{BL} represented in Equation (3.11) and (3.12) is in hourly format, corresponding daily E_{BL} calculation can be illustrated as below:

$$E_{BL, sen} = -\left[\sum_{t_i=0}^{23} FA_{win} I_{sol, t_i} + (T_{OA} - T_R) \sum_{t_i=0}^{23} (U_{tot} A_{envelope} t_i + V_{OA, t_i} \rho c_p) + \sum_{t_i=0}^{23} A_{floor} \rho_{occ} q_{individual, sen} t_i \right]$$

$$E_{BL, lat} = -Max\{[W_R + X_{OA}(W_{OA} - W_R) - W_{CL}] \sum_{t_i=0}^{23} h_{fg} V_{tot, t_i}, 0\}$$

where the temperature and specific humidity ratio are daily averaged value.

The characteristic information for the building structure and air-handling units, which are needed to calculate the analytically redundant variable, will be obtained from architectural and mechanical drawings, the EMCS (Apogee), CC[®] reports, and/or field investigation.

3.4 Summary

In this chapter, the basic concept of AR and a newly defined term called Energy Balance Load, are illustrated. It has been shown that by taking some relatively simple measurements and implementing a suitable physical relationship, an indirect measurement of energy consumption is obtained. This analytic measurement may subsequently be compared with the direct measurement to validate the data, and hence supplement hardware redundancy.

CHAPTER IV

PARAMETRIC INVESTIGATION OF ENERGY BALANCE LOAD

4.1 Introduction

This chapter is intended to investigate the impacts of different HVAC systems and simulation model input parameters on the Energy Balance Load of a building using simplified energy analysis as embodied in the modified bin method.

Four basic secondary HVAC systems and four input parameters for the simulation model are selected for this study, with various parameter values, the pattern of cooling and heating energy combination in terms of ambient temperature would change following some specific regulations. Numerical, theoretical and graphical analyses are used to assist illustrating the outcome of this section. Amplifying on this subject, which input parameter is significant to the model can be indicated, leading to the further sensitivity analysis, which is necessary or desirable for simulation model being used in this research.

The interior lighting, equipment, and other appliances contribute to the whole building electricity consumption, which is measured and collected by the Energy System Laboratory as “*Wbele*”. Extraordinary low portion of TAMU on-campus buildings have chiller installed on site, therefore the whole building electricity consumption “*Wbele*” is a factor relying on the building function and operation schedule rather than the outside

air temperature and HVAC system types. To be simplified, this type of energy usage is estimated as a constant value.

4.2 Simulation with Different Secondary HVAC Systems

The equations listed in prior chapters, which are used to calculate each item contributing to the Energy Balance Load, are very general. In reality, the equations, especially for the calculation of the latent load portion of E_{BL} , may change with different HVAC system types. Therefore, to test the effect of different HVAC types on E_{BL} , the modified bin method (Knebel 1983) will be used to simulate cooling and heating energy consumption loads on the heat transfer coils with assumed values of the building and system parameters.

There are two generic classes of the secondary systems (HVAC systems) for heating and cooling of buildings: those using air for heating and cooling and those using water and air. The former include fixed- and variable-air volume systems, while the latter include combined systems using air for ventilation along with coils at each zone for heating and cooling. There are many combinations of these systems, but an understanding of a few basic systems will permit the proper design of hybrids of the basic systems. Four representative secondary systems are selected for this research:

- Single-duct constant-air-volume with terminal reheat (CVRH)
- Dual-duct constant-air-volume (DDCV)
- Single-duct variable-air-volume (SDVAV)
- Dual-duct variable-air-volume system (DDVAV)

A diagram for each of these four HVAC systems is displayed in the following. In addition, with identical building, environmental, and HVAC system variables, how the patterns of ambient temperature dependent cooling and heating energy consumption vary with diverse secondary systems will be calculated by using the modified bin method (Knebel 1983) and corresponding plots showing the simulation results will be provided. The following sample data will be used to predict the performance of the selected air systems, which is for a two-zone problem characteristic of an interior and exterior zoned building.²

Zone 1 = Exterior Zone

$$V_e = 50000 \text{ CFM}$$

$$T_e = 75 \text{ }^\circ\text{F}$$

$$q_{e,s} = 10000 \times (T_{OA} - 30) \text{ Btu / hr}$$

$$q_{e,l} = 35,000 \text{ Btu / hr}$$

$$V_{OA} = 10\% V_{tot}$$

$$T_{CL} = 55 \text{ }^\circ\text{F}$$

$$W_{CL} = 0.00831 \text{ lbw / lba}$$

Zone 2 = Interior Zone

$$V_i = 100000 \text{ CFM}$$

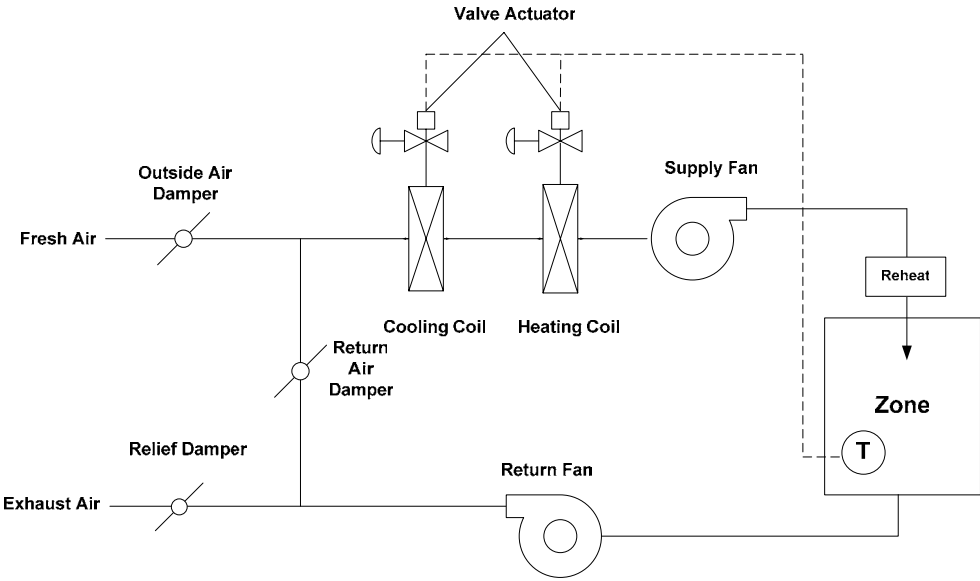
$$T_i = 75 \text{ }^\circ\text{F}$$

$$q_{i,s} = 1,000,000 \text{ Btu / hr}$$

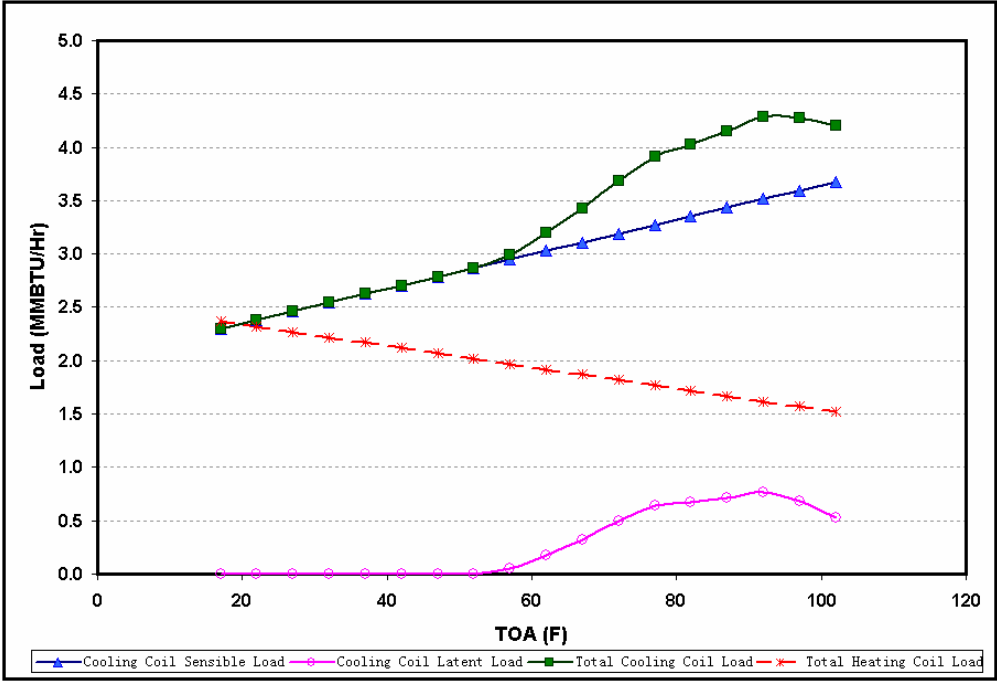
$$q_{i,l} = 70,000 \text{ Btu / hr}$$

² This example is based on one used in MEEN 664 – Energy Management in Commercial Buildings in Fall, 2001.

4.2.1 Simulation for CVRH System



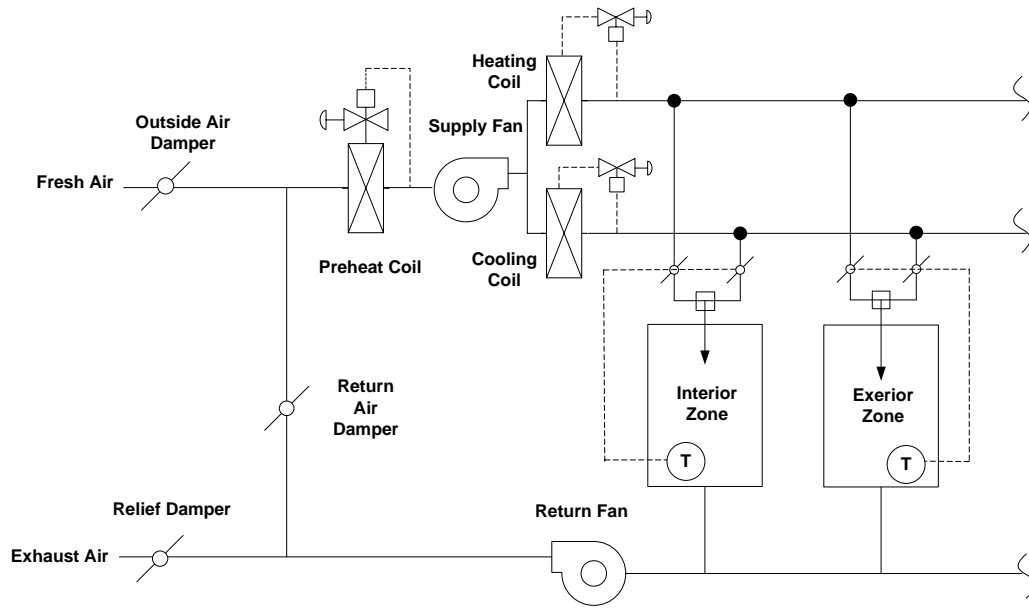
(a)



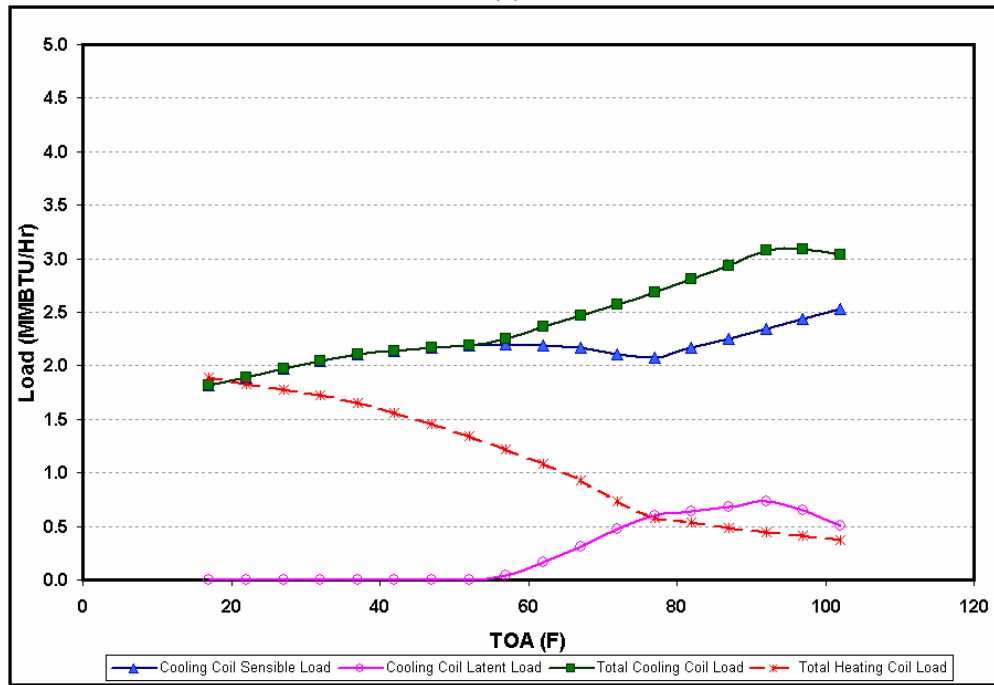
(b)

Figure 4.1 (a) Diagram of constant volume system with terminal reheat; (b) Plot of simulated energy consumption vs. outside air temperature

4.2.2 Simulation for DDCV System



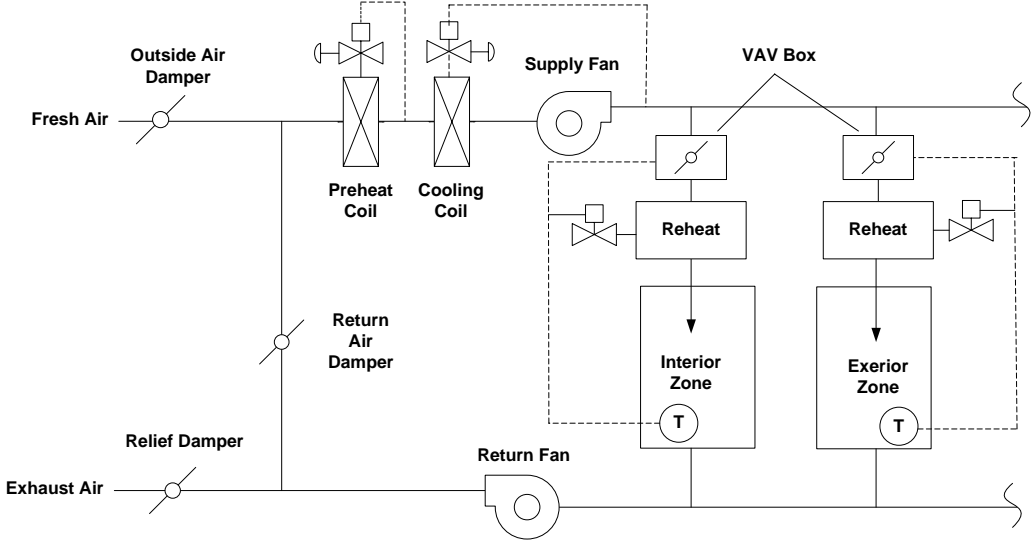
(a)



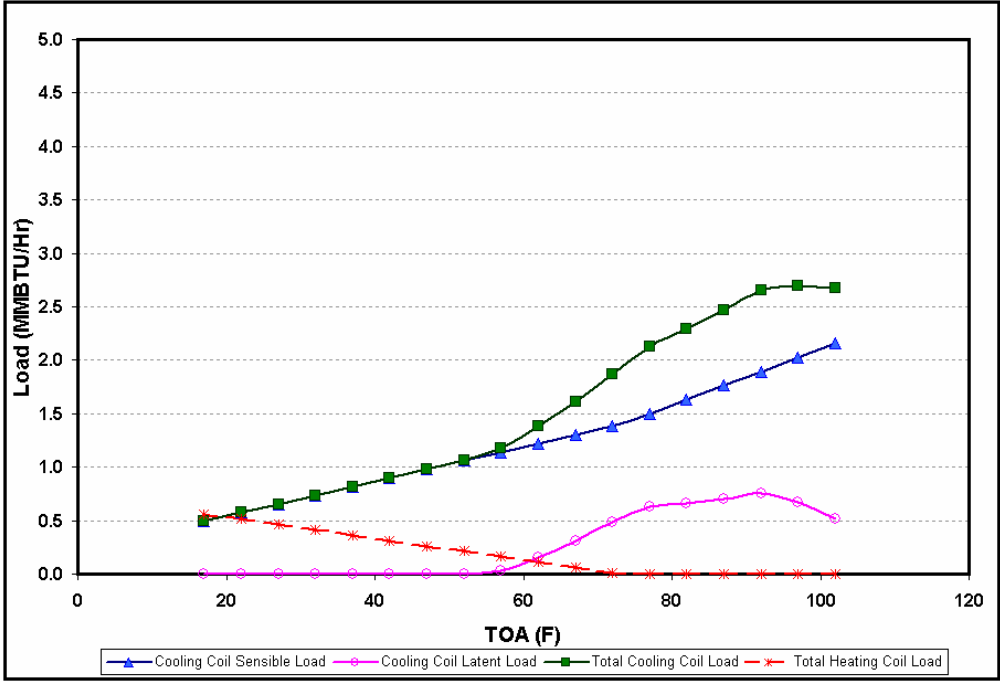
(b)

Figure 4.2 (a) Diagram of dual duct constant volume system; (b) Plot of simulated energy consumption vs. outside air temperature

4.2.3 Simulation for SDVAV System



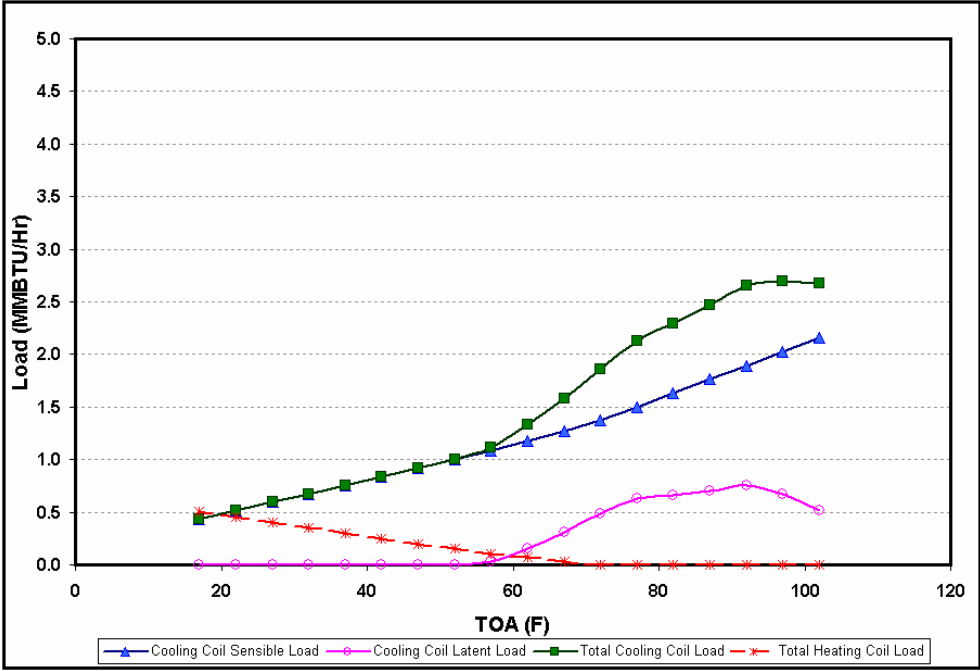
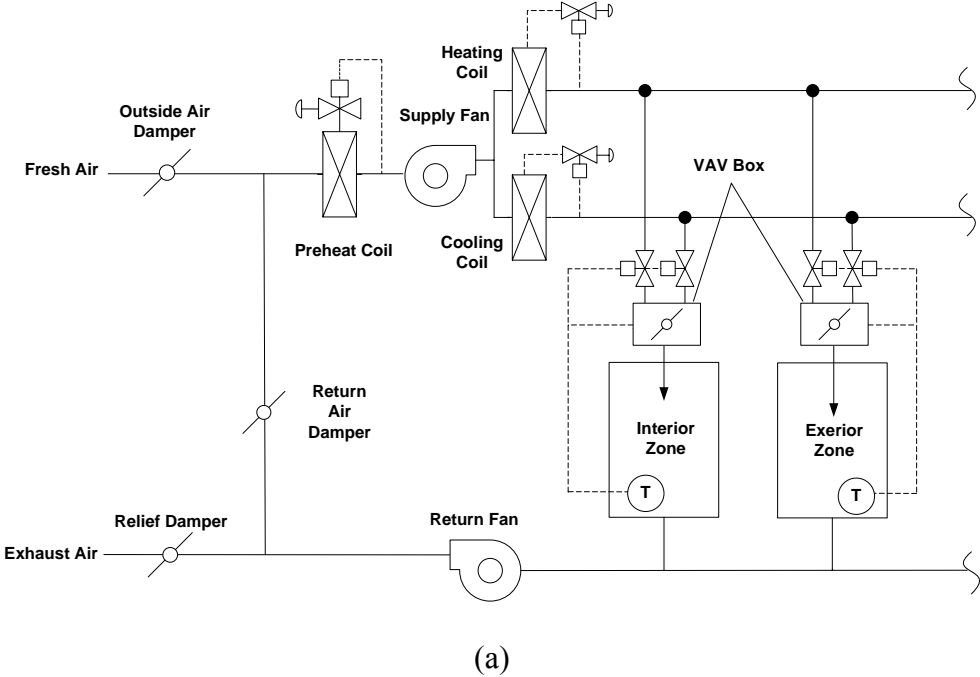
(a)



(b)

Figure 4.3 (a) Diagram of single duct variable volume system; (b) Plot of simulated energy consumption vs. outside air temperature

4.2.4 Simulation for DDVAV System

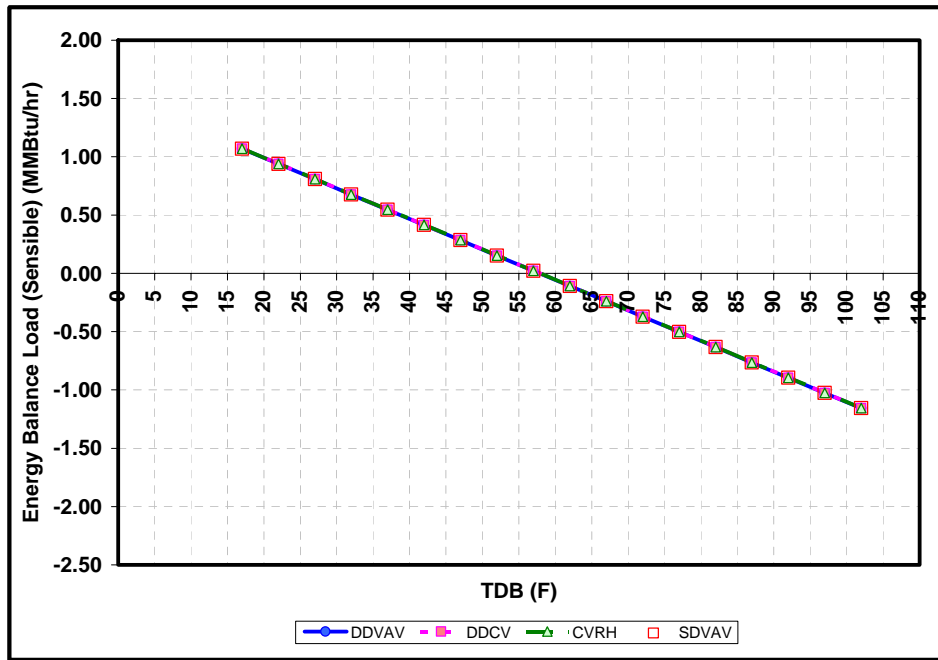


(b)

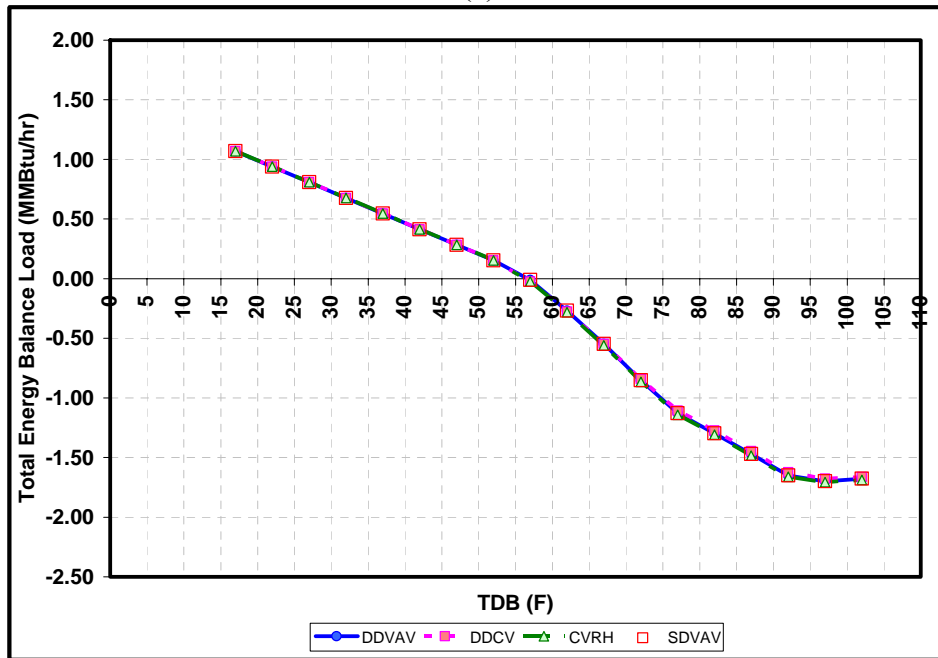
Figure 4.4 (a) Diagram of dual duct variable volume system; (b) Plot of simulated energy consumption vs. outside air temperature

Observation from Figures 4.1 through 4.4, it is obvious to see that distinct secondary systems performance different patterns of energy consumption on individual cooling or heating coil.

In succession, the impact of diverse secondary systems taken on the Energy Balance Load is investigated. Simulation analysis results into sensible only and total energy consumption by adding up heating and electricity but minus cooling. Sensible only E_{BL} for all the four types of HVAC systems show the same linear line in terms of outside air bulb temperature, as in Figure 4.5 (a). The total E_{BL} , including latent cooling energy consumption, is linear when outside air bulb temperature is lower than 55°F, but curves below the sensible only E_{BL} line as temperature becomes higher than 55°F, as shown in Figure 4.5 (b). In addition, plot of E_{BL} based on consumption for four diverse HVAC systems show no visible difference among the systems at high temperatures. It can be concluded that the influence of different system types on Energy Balance Load is negligible, or alternatively, calculating building E_{BL} does not require knowledge of the HVAC system type, which has been pointed out based on the observation at Figure 3.2.



(a)



(b)

Figure 4.5 Plot of (a) sensible and (b) total Energy Balance Load vs. outside air temperature for different types of HVAC systems

4.3 Simulation with Different Input Parameters of the Model

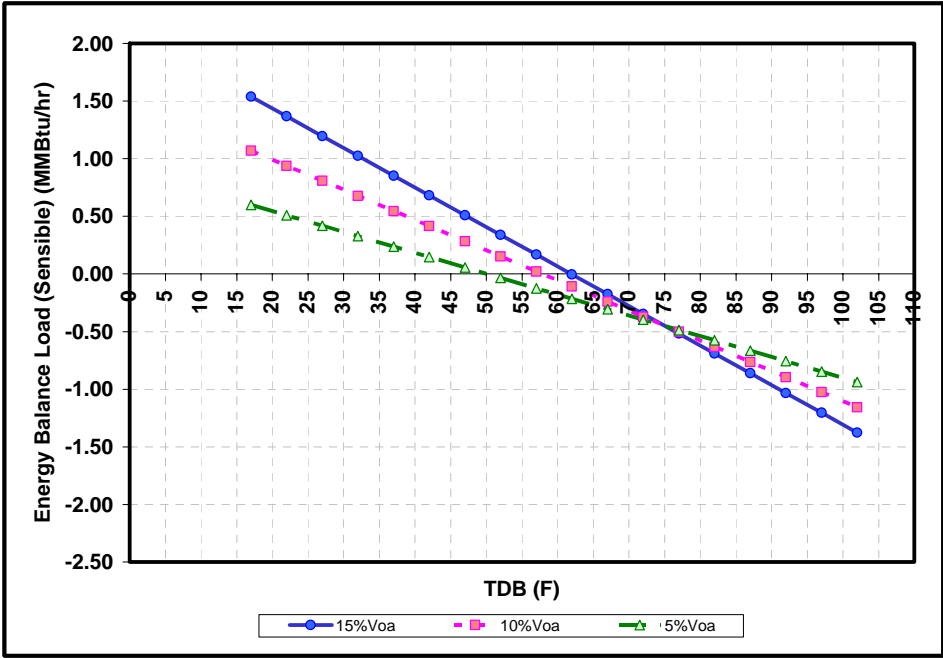
As the simulated E_{BL} is independent of the type of secondary system the building uses, a single HVAC system with simpler simulation process can be utilized to represent all four systems to dig out how model input parameters influence the simulation result of E_{BL} , therefore constant volume with terminal reheat (CVRH) is selected. Outside air intake volume, cold deck set point, heat recovery ventilator installation and other simulation model-related variables will be analyzed individually in this section to see how the pattern of the temperature dependant simulation line of E_{BL} varies with different values of these parameters. The modified bin method is utilized as a fundamental in this chapter, with which the energy consumption on the CVRH system can be calculated through the procedure shown in Table 4.1. There is latent load only when the cooling coil is wet, thus if the cooling coil is dry, the analysis results comes from the following sections will end up with sensible load portion.

Table 4.1 Relationships for calculating energy consumption of a CVRH system

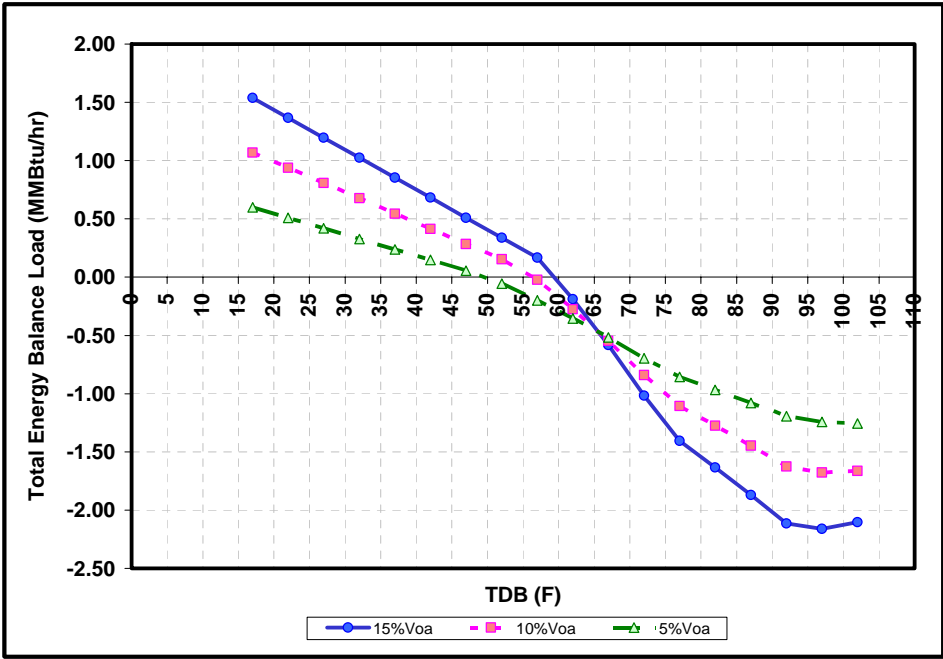
q_{sen}	$= U_{tot} A_{envelope} (T_{OA} - T_R) + q_{gain}$
q_{lat}	$= KA_{floor}$
T_s	$= T_R - q_{sen} / (1.08V_{tot})$
q_{RH}	$= Max(0, 1.08V_{tot} (T_s - T_{CL}))$
T_{MA}	$= T_R + X_{OA} (T_{OA} - T_R)$
$q_{CL, sen}$	$= 1.08V_{tot} (T_{MA} - T_{CL})$
W'_R	$= W_{CL} + q_{lat} / 4840V_{tot}$
W_{MA}	$= W'_R + X_{OA} (W_{OA} - W'_R)$
$q_{CL, lat}$	$= Max\{0, 4840V_{tot} (W_{MA} - W_{CL})\}$

4.3.1 Simulation with Different Outside Air Intake Volume

First, the impact of outside air intake volume on the simulation result is investigated. By presuming the portion of outside air volume over the total air volume the HVAC system requires is 5%, 10%, and 20%, the simulation result of E_{BL} versus bin temperature is shown as Figure 4.6: Figure (a) illustrates the sensible proportion of the Energy Balance Load, and Figure (b) displays the complete E_{BL} . Generally speaking, with more outside air intake, the simulation line performs steeper; the polynomial line, which represents there is latent loaded on the cooling coil, is more far away from the extension of the linear line, and there is a joint point of the three trend lines. Detailed investigation and discussion inducted by the plot could be described as the following three sections.



(a)



(b)

Figure 4.6 Plot of (a) sensible and (b) total Energy Balance Load vs. outside air temperature with different values of outside air intake volume

4.3.1.1 Impact of Outside Air Intake Volume on the Simulation Model

Referring to the energy consumption calculation process of constant volume with terminal reheat system (CVRH) illustrated in Table 4.1, the sensible load part of E_{BL} can be expressed first as:

$$\begin{aligned}
 E_{BL}(\text{Sensible}) &= q_{RH} + f' q_{gain} - q_{CL,sen} \\
 &= 1.08V_{tot}(T_S - T_{CL} - T_{MA} + T_{CL}) + f' q_{gain} \\
 &= 1.08V_{tot}(T_S - T_{MA}) + f' q_{gain} \\
 &= 1.08V_{tot}(T_R - \frac{q_{sen}}{1.08V_{tot}} - T_R - X_{OA}(T_{OA} - T_R)) + f' q_{gain} \\
 &= -(1.08V_{tot} X_{OA} + U_{tot} A_{envelope})T_{OA} + (1.08V_{tot} X_{OA} + U_{tot} A_{envelope})T_R + (f' - 1)q_{gain} \quad (4.1)
 \end{aligned}$$

In Table 4.1, q_{gain} represents the internal heat gain of the building, which includes the gain from occupants, lighting, and equipment, as well as the solar heat gain through the building envelope. Although the solar heat gain is linearly related with the outside air temperature as described in Equation (3.3), it is reasonable to treat solar heat gain as a constant value because it is a small amount of quantity and more stable comparing with the other heat gains through the building envelope. In order to simulate Energy Balance Load, a multiplying factor (f') is given to q_{gain} to express the heat gain from the lighting and equipment only, which substitutes fW_{bele} in the E_{BL} equation.

With increasing ratio of outside air intake, the absolute value of the simulation line's slope is getting bigger. In other words, the fitting curve of the simulated data is steeper.

For the purpose of examining the total E_{BL} , latent load is studied as well.

$$\begin{aligned}
& q_{CL,lat} \\
&= 4840V_{tot} (W_{MA} - W_{CL}) \\
&= 4840V_{tot} \left[W_{CL} - W_{CL} + \frac{q_{lat}}{4840V_{Tot}} + X_{OA} \left(W_{OA} - W_{CL} - \frac{q_{lat}}{4840V_{Tot}} \right) \right] \\
&= [-q_{lat} + 4840V_{tot} (W_{OA} - W_{CL})] X_{OA} + q_{lat} \tag{4.2}
\end{aligned}$$

Within a limited range of ambient temperature (50-90° F), the average specific humidity is approximately linearly related with the outside air temperature (Knebel 1983), which can be displayed as $W_{OA} \approx C_1 T_{OA} + C_2$, C_1 and C_2 will be various for different locations, Texas constitute many locations with very different values for these two constants. For typical College Station weather, the outside air temperature is located within this range most of the time, therefore this assumption is applicable to this research. By substituting W_{OA} with $C_1 T_{OA} + C_2$, the alternative expression of $q_{CL,l}$ and its derivative are expressed as Equation (4.4).

$$q_{CL,lat} = C_1 4840V_{tot} X_{OA} T_{OA} + (4840V_{tot} C_2 - W_{CL} - q_{lat}) X_{OA} + q_{lat} \tag{4.3}$$

$$\tan_{q_{CL,l}|T_{OA}} = \frac{\partial q_{CL,lat}}{\partial T_{OA}} = C_1 4840V_{tot} X_{OA} \tag{4.4}$$

More fresh air intake will lead to more latent load on the cooling coil and a steeper incline of the tangent of the polynomial simulation curve. Therefore, two conclusions can be made. One is that by increasing the amount of outside air intake, E_{BL} through a HVAC system has a steeper slope as a function of outside air temperature. The other is that the tangent of the polynomial simulation model of the situation when there is latent load on the cooling coil will be farther away from the extension of the linear model part.

4.3.1.2 Point A Which is Independent of Outside Air Intake Volume

As the previous section presented, the sensible load part of E_{BL} over outside air temperature could be expressed as Equation (4.1), for this specific study principle, the formation of the equation is changed to the following:

$$\begin{aligned} E_{BL}(Sensible) &= q_{RH} - q_{CL,sen} + f' q_{gain} \\ &= (1.08V_{tot} X_{OA} + U_{tot} A_{envelope})(T_R - T_{OA}) + (f' - 1)q_{gain} \end{aligned} \quad (4.5)$$

when $T_R - T_{OA} = 0$ or $T_{OA} = T_R$, the first term will be zero, therefore no matter what value X_{OA} is, $E_{BL}(Sensible)$ will be constant at $(f' - 1)q_{gain}$. Consequently, latent load on the cool coil is added to it, where

$$q_{CL,lat} = (1 - X_{OA})q_{lat} + 4840V_{tot} X_{OA}(W_{OA} - W_{CL}) \quad (4.6)$$

The total Energy Balance Load can be represented as:

$$\begin{aligned} E_{BL}(Total) &= (1.08V_{tot} X_{OA} + U_{tot} A_{envelope})(T_R - T_{OA}) + (f' - 1)q_{gain} - q_{CL,lat} \\ &= X_{OA}[1.08V_{tot}(T_R - T_{OA}) + q_{lat} - 4840V_{tot}(W_{OA} - W_{CL})] \\ &\quad + U_{tot} A_{envelope}(T_R - T_{OA}) - q_{lat} + (f' - 1)q_{gain} \end{aligned} \quad (4.7)$$

Similarly to the sensible load analysis, when the sum of all terms multiplying X_{OA} is equal to zero, $E_{BL}(Total)$ will be $U_{tot} A_{envelope}(T_R - T_{OA}) - q_{lat} + (f' - 1)q_{gain}$ constantly. The equation representing the requirement can be expressed as Equation (4.8).

$$1.08V_{tot}(T_R - T_{OA}) + q_{lat} - 4840V_{tot}(W_{OA} - W_{CL}) = 0 \quad (4.8)$$

The equation above can be used to determine the point A as well, where

$$T_{Point A} = T_R + \frac{q_{lat}}{1.08V_{tot}} - \frac{4840}{1.08}(W_{OA} - W_{CL}) \quad (4.9)$$

It can be concluded that, with higher room temperature, higher cold deck set point which leads to higher cold deck humidity ratio, and higher latent load generation density, the point A moves rightward along the temperature axis; in other words the simulation lines for various outside air intake volumes cross at a higher temperature.

4.3.1.3 Point B Where the Simulation Lines Turns from Linear into Polynomial

For point B, where the simulation line turns from linear into polynomial, the sensible only and total Energy Balance Load are equal, so that the latent load on cooling coil $q_{CL,lat}$ is zero. Consequently, $4840V_{tot}(W_{MA} - W_{CL}) = 0$ or $W_{MA} = W_{CL}$ is fulfilled, and follows with the deduction below:

$$W_{MA} = W_{CL} + \frac{q_{lat}}{4840 \times V_{tot}} + X_{OA} \left(W_{OA} - W_{CL} - \frac{q_{lat}}{4840 \times V_{tot}} \right) = W_{CL} \quad (4.10)$$

$$X_{OA} = \frac{\frac{q_{lat}}{4840V_{tot}}}{\frac{q_{lat}}{4840V_{tot}} - (W_{OA} - W_{CL})} \quad (4.11)$$

Therefore, the average specific humidity ratio at point B can be determined by

$$W_{Point B} = \frac{X_{OA} \left(\frac{q_{lat}}{4840V_{tot}} + W_{CL} \right) - \frac{q_{lat}}{4840V_{tot}}}{X_{OA}} = \frac{q_{lat}}{4840V_{tot}} + W_{CL} - \frac{q_{lat}}{4840V_{tot}X_{OA}} \quad (4.12)$$

It can be concluded that, with more outside air intake volume, humidity ratio of temperature point B, where the simulation line of E_{BL} turns into polynomial from linear gets higher, so that a higher temperature point B is indicated indirectly. Additionally,

because the ratio of outside air to the total air volume that goes through the HVAC system has an upper limit of 1, it is easy to see from the previous equation that W_{PointB} would never be higher than W_{CL} . Its pattern along with the various outside air intake ratios is shown in Figure 4.7.

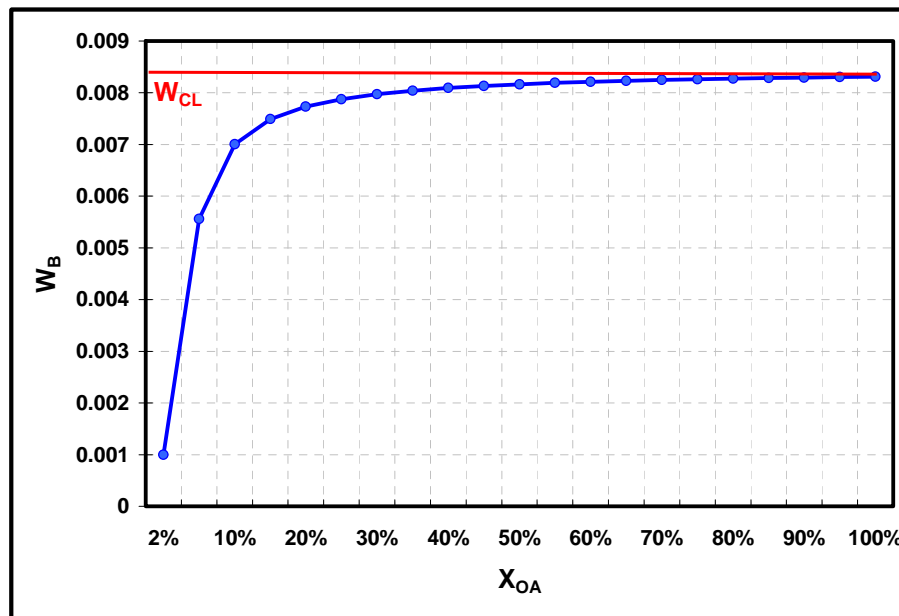


Figure 4.7 Correlation between the humidity ratio at Point B along with different outside air intake ratios

4.3.1.4 Conclusions and Discussion – Impact of Outside Air Intake Volume

Summarizing the simulation results and theoretical analysis above, there are two characteristics showing the impact of various outside air intake volumes on the Energy Balance Load. First, with variable outside air intake volume, the simulation lines representing the sensible load proportion of E_{BL} meet at the point where $T_{OA} = T_R$. While

the total E_{BL} for both sensible and latent load meets at point A, which satisfies Equation (4.9), and with higher T_R and W_{CL} , point A will move rightward. Second, as more fresh air is brought into the simulation system, point B where the simulation line of E_{BL} turns from linear into polynomial occurs at higher outside air temperature, and the line through the points B is almost linear dependent on the outside air temperature.

4.3.2 Simulation with Different Cold Deck Set Temperature

Second, the impact of cold deck set temperature on the simulation result is investigated. By presuming that the cold deck set point of the HVAC system is constant at 45°F, 55°F, and 65°F with other parameters remaining the same, the simulation result of E_{BL} is shown in the following Figure 4.8. As seen in the figure, the previous mentioned change point B, which indicates the ambient temperature where the latent load appears on the cooling coil shifts rightward with higher cold deck set point. Moreover, with higher cold deck temperature, less latent cooling load results in a smaller magnitude of E_{BL} at the same outside air temperature. Again, more detailed theoretical demonstration is provided in the following three sections.

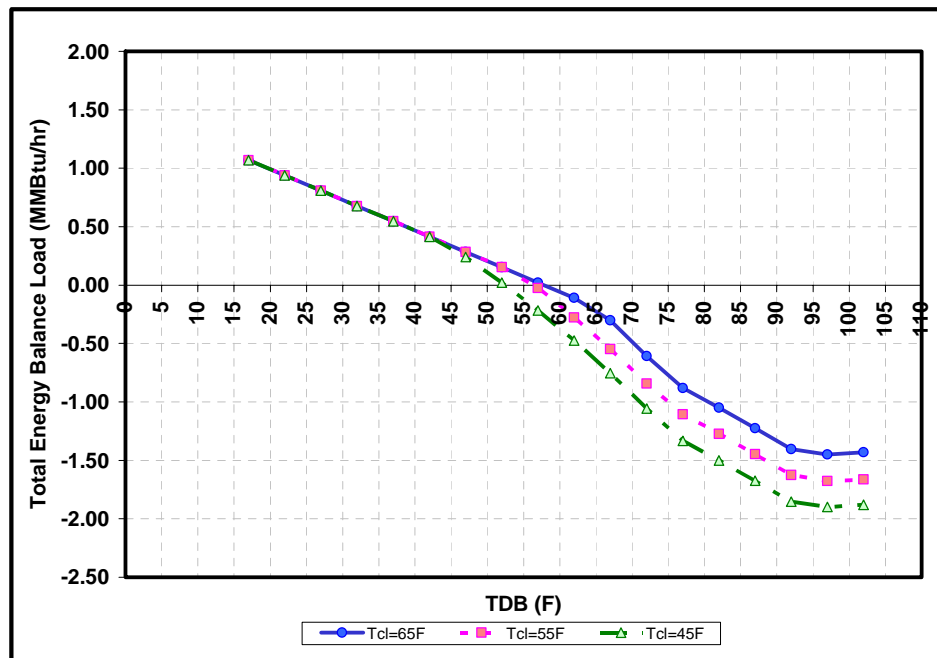


Figure 4.8 Plot of total Energy Balance Load vs. outside air temperature with different values of cooling coil set temperature

4.3.2.1 Impact of Cooling Coil Set Temperature on the Simulation Model

As the previous section discussed, the sensible only Energy Balance Load for a building with the constant volume terminal reheat system (CVRH) can be expressed by Equation (4.5)

$$\begin{aligned}
 E_{BL}(\text{Sensible}) &= q_{RH} - q_{CL, \text{sen}} + f' q_{\text{gain}} \\
 &= (1.08V_{\text{tot}} X_{OA} + U_{\text{tot}} A_{\text{envelope}})(T_R - T_{OA}) + (f' - 1)q_{\text{gain}}
 \end{aligned}
 \tag{4.5}$$

Having no term related with cold deck set temperature in the equation above indicates that sensible only E_{BL} is independent of T_{CL} . Alternatively, no matter how the set point of T_{CL} changes in the system, the simulated data falls on a straight line. By

taking the latent load into account of the load simulation, the entire Energy Balance Load can be expressed as Equation (4.7).

$$\begin{aligned}
 E_{BL}(Total) &= X_{OA}[1.08V_{tot}(T_R - T_{OA}) + q_{lat} - 4840V_{tot}(W_{OA} - W_{CL})] \\
 &+ U_{tot}A_{envelope}(T_R - T_{OA}) - q_{lat} + (f' - 1)q_{gain}
 \end{aligned} \tag{4.7}$$

With other parameters fixed, the value of E_{BL} is a linear function of W_{CL} . As noted in section 2, a plot of E_{BL} versus the outside air temperature is no longer linear once the coil becomes wet; it can be fit by a polynomial line when typical values of W_{CL} are used. How the slope of the polynomial part E_{BL} 's tangent at point B changes as the cold deck temperature varies can be figured out by looking at the first derivative of E_{BL} with respect to T_{OA} , and the result is shown in Equation (4.13). As the equation is independent of T_{CL} , it may be concluded that T_{CL} has no impact on the tangent of the polynomial simulation line.

$$\tan_{E_{BL}|T_{OA}} = \frac{\partial E_{BL}}{\partial T_{OA}} = -1.08V_{tot}X_{OA} - U_{tot}A_{envelope} - 4840V_{tot}X_{OA}C_1 \tag{4.13}$$

Summarizing the analysis, different cooling coil set point takes would not make changes to E_{BL} if there is no latent cooling load on the coil. On the other hand, higher T_{CL} results in less latent load or a larger E_{BL} .

4.3.2.2 Point B at Where the Simulation Line Turns from Linear to Polynomial

Similarly as the investigation of V_{OA} 's influence, it is desirable to study how point B moves along with variable cold deck set point. As what has been described in section 3.1.3, the relationship between W_{PointB} and W_{CL} can be expressed by Equation (4.12).

$$W_{PointB} = \frac{q_{lat}}{4840V_{tot}} + W_{CL} - \frac{q_{lat}}{4840V_{tot}X_{OA}} \quad (4.12)$$

It is able to see that with a higher cooling coil set temperature, point B moves toward higher outside air temperature. The same as what has been pointed out previously W_{PointB} would never be higher than W_{CL} , in that the maximum ratio of outside air to the total air volume goes through the HVAC system is 1.

4.3.2.3 Ambient Temperature Dependent Cold Deck Set Point Schedule

For the purpose of minimizing combined fan power and thermal energy consumption or cost, the cold deck set point is often varied as a linear function of the outside air temperature over a limited temperature range. This section is intended to study how E_{BL} acts with variable T_{CL} schedules. In the example treated here, the cold deck temperature is assumed to vary from 65°F to 55°F as the ambient temperature increases from 50°F to 80°F, which can be described as Equation (4.14) and Figure 4.9. With this optimization, the retrieved simulation result of the Energy Balance Load can be displayed as Figure 4.10.

$$T_{CL} = \begin{cases} 65^{\circ}F & T_{OA} \leq 50^{\circ}F \\ -\frac{1}{3}T_{OA} + 81.67^{\circ}F & 50^{\circ}F < T_{OA} < 80^{\circ}F \\ 55^{\circ}F & T_{OA} \geq 80^{\circ}F \end{cases} \quad (4.14)$$

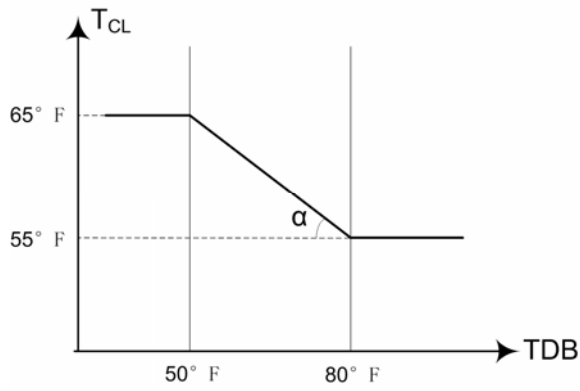


Figure 4.9 Diagram of cooling coil set temperature schedule reliant on the outside air temperature

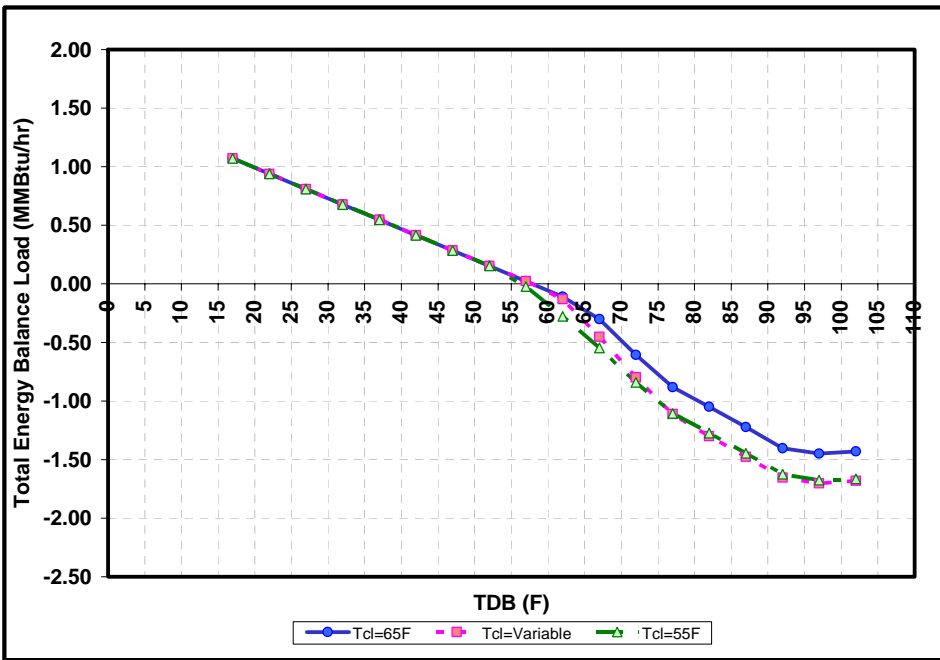


Figure 4.10 Impacts of variable cooling coil set temperature on the simulation result of Energy Balance Load vs. outside air temperature

Point B where the simulation line in the example changes into polynomial mode locates between 55°F and 65°F. Given that the cold deck temperature would be 55°F as the ambient temperature is 80°F, the simulation line for the AHU with optimized cold deck schedule will be the same as that of the systems with cold deck set temperature of 55°F when the ambient temperature is higher than 80°F. In addition, the slope of the T_{CL} function in terms of T_{OA} , expressed as α , will affect how fast the simulation line drops on that of the line with $T_{CL} = 55^\circ F$.

4.3.2.4 Conclusions and Discussion – Impact of Cold Deck Set Temperature

The impact of cold deck set temperature on the Energy Balance Load can be categorized by three points. The first one is with variable cold deck temperature, the sensible E_{BL} is unchanged from its behavior with fixed cold deck temperature. The second one is that with higher set point of T_{CL} , point B where the simulation line of E_{BL} changes from linear into polynomial moves forward down along the sensible only simulation line. Finally, if the cold deck set temperature is optimized to an outside air temperature reliant variable, point B will occur at the temperature which is between the upper and lower limits of the T_{CL} , and the simulation line will overlap with that of the system with constant cold deck set point equal to the lower limit value of optimized T_{CL} .

4.3.3 **Impact of Other Input Parameters**

Beside of outside air intake volume and HVAC cold deck set temperature, there are several supplementary input parameters of the energy consumption simulation model.

Compared with those two factors, the other parameters have more intuitive and quite similar consequences on E_{BL} . Therefore, this section put all these kind of parameters together and the illustration for the confounded or homologous features of corresponding factors will be provided. Graphics and theoretical analysis are mainly used in this section, which enable the qualitative analysis to be carried out.

A significant number of air handling units are equipped with a heat recovery ventilator, with the aim of decreasing the energy use of a building for heating and cooling. A heat recovery ventilator uses two fans to exhaust return air and supply fresh outside air via the heat exchanger core. The fresh outside air flows at approximately the same rate as the return air is exhausted. In the core, the fresh air stream is automatically preheated or precooled by the exhausted air. This device can significantly improve the energy efficiency of the building and recover 60 to 75 percent of the heat in the exhausted air.

4.3.3.1 Parameters Associated with the Slope of the Simulation Model

To find out which parameters of the system or the building may affect the slope of the simulation line, alternatively speaking the angle between the simulation line and the horizontal axes, the multiplier of T_{OA} is subjected to analysis. From the expression equation of E_{BL} , besides the impact from outside air intake volume, the total air flow (V_{tot}), as well as the total heat transmission coefficient of the envelope components ($U_{tot}A_{envelope}$) contribute a negative multiplier to T_{OA} .

$$\begin{aligned}
 E_{BL}(Total) &= (-1.08V_{tot}X_{OA} - U_{tot}A_{envelope})(T_{OA} - T_R) + (X_{OA} - 1)q_{lat} \\
 &\quad - 4840V_{tot}X_{OA}(W_{OA} - W_{CL}) + (f' - 1)q_{gain}
 \end{aligned} \tag{4.7}$$

Therefore, with larger value of any coefficient consisting of the $U_{tot}A_{envelope}$, the simulation line of the E_{BL} will result in a more tilted slope, and vice versa, which can be shown as Figure 4.11.

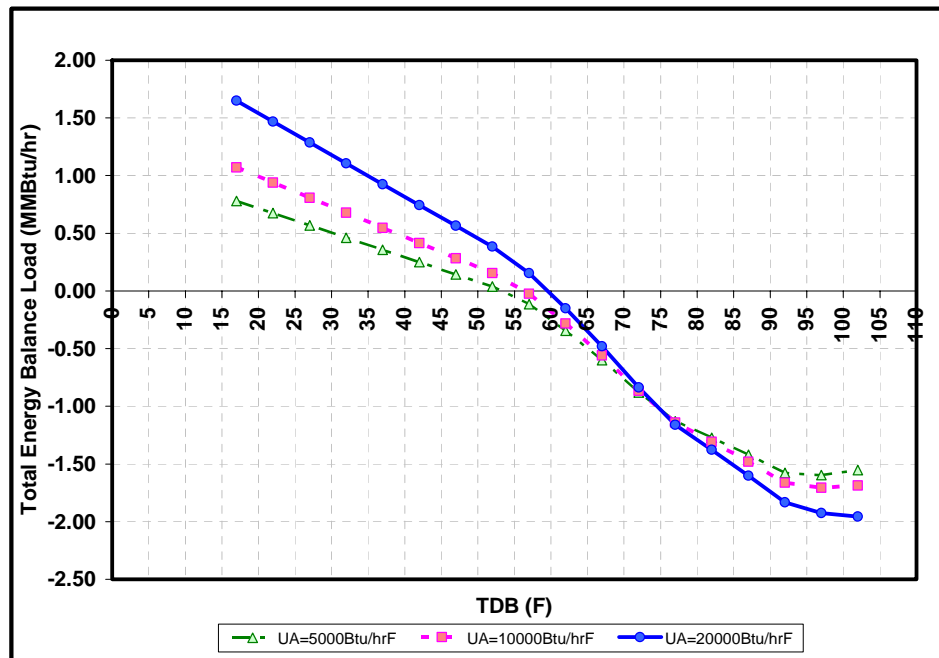


Figure 4.11 Impacts of simulation model slope related variables on the simulation result of Energy Balance Load vs. outside air temperature

4.3.3.2 Parameters Associated with the Vertical Movement of the Simulation Model

Similar to the analysis in the prior section, parameters impact how the simulation line of E_{BL} moves along the vertical axes can be identified through the expression equation, which should be the terms without T_{OA} involved. Besides the two parameters (X_{OA}, T_{CL}) that have been analyzed, $U_{tot}A_{envelope}$, V_{tot} , T_R , q_{lat} and q_{gain} are also associated with the move of the simulation line along the vertical axes, higher values of these parameters, upward moves the simulation line, shown in Figure 4.12.

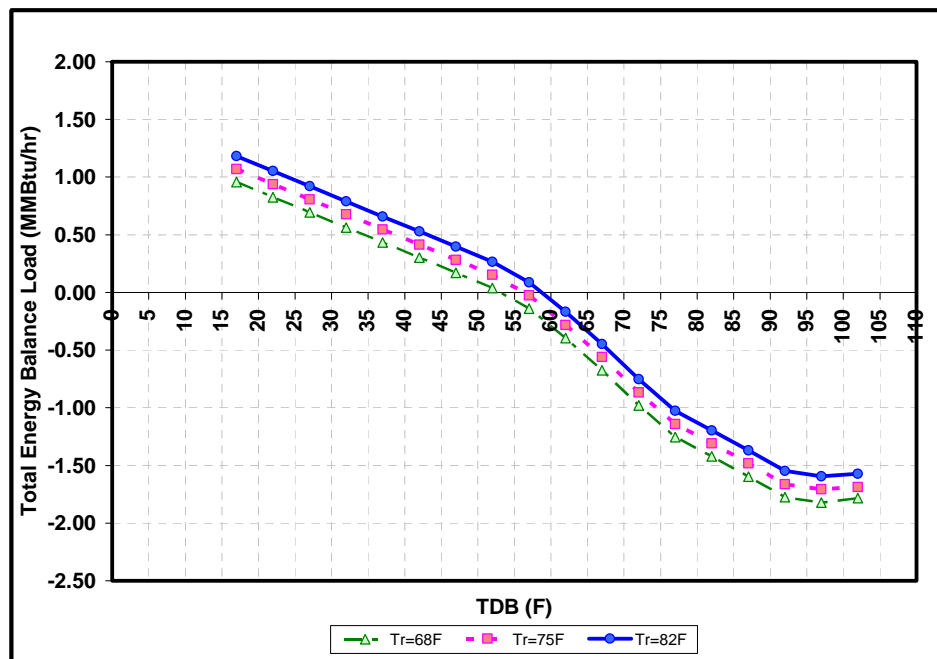


Figure 4.12 Impacts of simulation model intercept related variables on the simulation result of Energy Balance Load vs. outside air temperature

4.3.3.3 Economizer

Economizer cycles are a standard energy conservation feature in most HVAC systems. Their basic principle is to use the cooling which ventilation air can provide to the building (Stoecker and Jones 1982). Generally speaking, economizers can be categorized as temperature-controlled or enthalpy-controlled. The latter is more efficient but more expensive and prone to failure, so most economizer cycles are temperature-controlled.

A common control strategy for the temperature-controlled economizer of a constant air volume system is illustrated in Figure 4.13. T_e is determined as $T_e = T_R - dT_e$, where the temperature differential dT_e is introduced to reduce or eliminate the latent cooling loads on the cold deck that would often be present when the outside air temperature T_{OA} is close to room temperature T_R . Normally dT_e is in the range of 2°F to 6°F (Reddy et al. 1995). When $T_{OA} > T_e$, outside air intake volume is kept at the minimum amount; as T_{OA} progressively decreases before reaching T_{CL} , outdoor air intake is maintained constant equal to the total building airflow rate. As $T_{OA} < T_{CL}$, the outside air flow rate is gradually decreased to the minimum amount requested by the building, which intends not to increase the heating energy consumption. The temperature point where the outside air intake volume ramp to the minimum amount can be determined by Equation (4.15), and the variation of the outside air intake volume with the temperature can be represented by Equation (4.16).

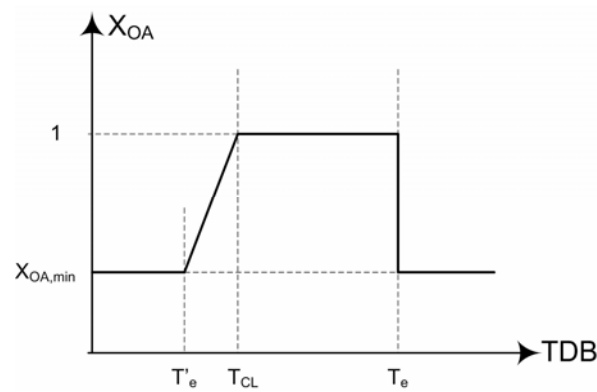


Figure 4.13 Variation of outside air intake fraction with outside air temperature for constant air volume system with economizer cycle

$$T'_e = T_R - (T_R - T_{CL}) / X_{OA,min} \quad (4.15)$$

$$X_{OA} = \frac{1 - X_{OA,min}}{T_{CL} - T'_e} T_{OA} + X_{OA,min} \quad (4.16)$$

The four types of HVAC systems being analyzed in this chapter are simulated with a temperature-controlled economizer implemented in order to examine its impact on the Energy Balance Load. dT_e is presumed as 4°F, and results are shown in Figure 4.14. Variable and constant air volume systems display different performance of E_{BL} at temperatures lower than T_e , and both of them have higher E_{BL} values than the system without an economizer.

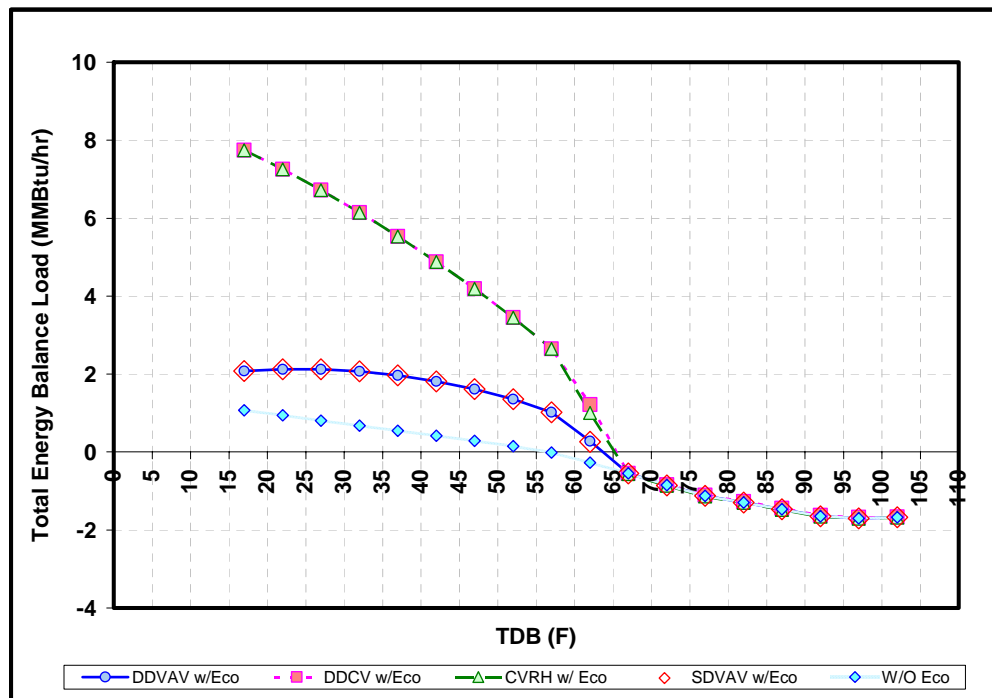


Figure 4.14 Plot of Energy Balance Load vs. outside air temperature with economizer cycle

To study the impacts of the temperature economizer introduced to the building energy savings, different deck reset and economizer measures are implemented in the HVAC system of Harrington Tower, Texas A&M University, from February 8 through April 2 of 2001 by Giebler (2003). The data for year 2001 are obtained and the Energy Balance Load with different modes is compared, shown as Figure 4.15.

Mode 1 is the typical DDVAV HVAC system without economizer implemented, while Mode 3 is the operation mode with temperature economizer operated, where data left in this year is marked as “normal”. From Figure 4.15, the Energy Balance Load under operation Mode 3 is higher than that under operation Mode 1, which proves the

impact of temperature economizer observed through simulation, though it shows limited change. For simplification, the impact of the utilizing economizer on E_{BL} is neglected in the remainder of this research.

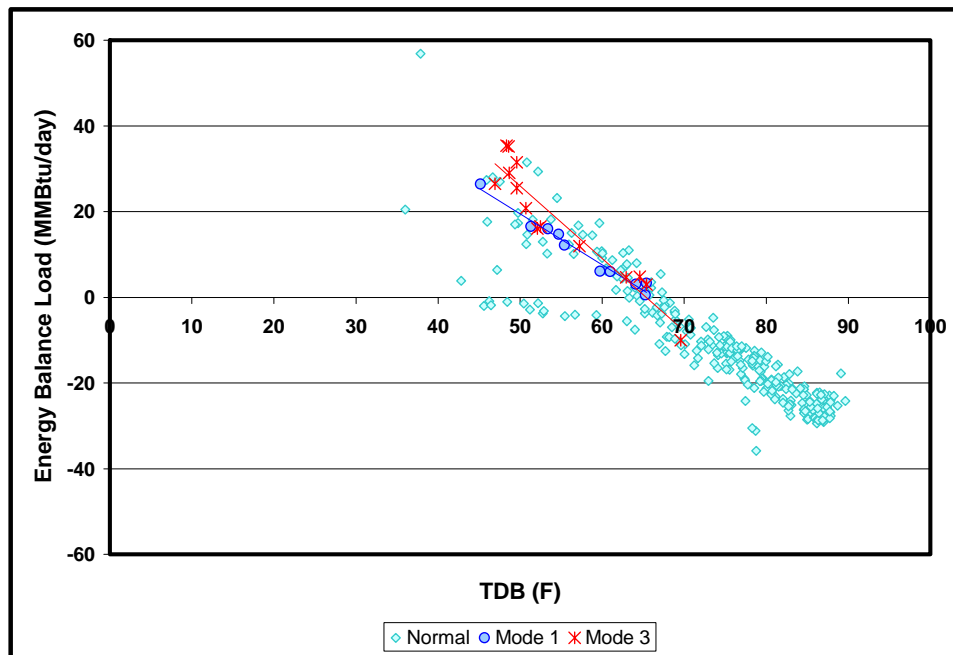


Figure 4.15 Plot of Energy Balance Load vs. outside air temperature with economizer cycle

4.3.3.4 Heat Recovery Ventilator

According to the principle of the heat recovery ventilator for the air handling unit, a heat exchanger inside the ventilator extracts the warmth from the indoor air sent out of the building and uses it to pre-heat the incoming fresh air in the winter season. During the summer, the heat exchanger works in reverse to expel heat from the incoming air as

it heads toward the air conditioner, and humidity control is not available for this device, a temperature controlled economizer installed in a constant volume air handling unit can be displayed as Figure 4.16.

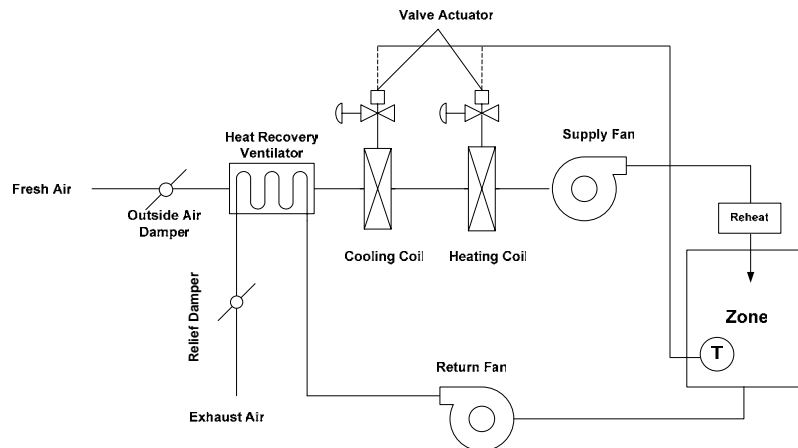


Figure 4.16 Diagram of single duct constant volume system with heat recovery ventilator

The temperature set point of the heat recovery ventilator is defined as $T_{HR,win}$ and $T_{HR,sum}$, as the outside air temperature is lower than $T_{HR,win}$ in the winter or higher than $T_{HR,sum}$ in the summer, the fresh air will be heated up or cooled down to the set point through the ventilator. There is only heat transfer through the heat recovery ventilator, so that the latent load brought by the fresh air remains the same as if there is no ventilator. Therefore, for the building with heat recovery ventilator installed, the sensible load taken into the building by the fresh air intake should be modified as follows:

$$Q_{air, sen} = \begin{cases} V_{OA} 1.08(T_{OA} - T_R), & T_{HR, win} < T_{OA} < T_{HR, sum} \\ V_{OA} 1.08(T_{HR} - T_R), & T_{OA} < T_{HR, win} \text{ or } T_{OA} > T_{HR, sum} \end{cases} \quad (4.17)$$

This diversity enables the reduction of the Energy Balance Load when the outside air temperature is either lower than $T_{HR, win}$ or higher than $T_{HR, sum}$, and the simulation line is closer to the X-axis as the ambient temperature is located in these two ranges. An example is given in Figure 4.17 to compare the simulation result of a CVRH system with and without a heat recovery ventilator installed, where $T_{HR, win} = 55^\circ F$ and $T_{HR, sum} = 75^\circ F$.

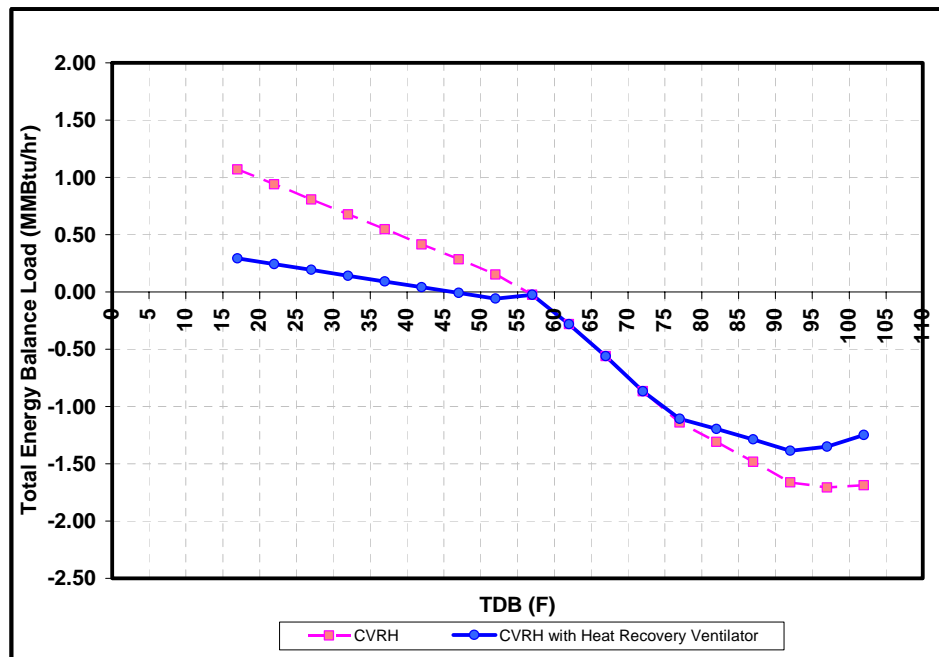


Figure 4.17 Impacts of heat recovery ventilator installation on the simulation result of Energy Balance Load vs. outside air temperature

4.4 Key Parameters of the Simulation Model

Based on the simulation results of the previous research work, there are four main characteristics identified to structure the simulation line relating the Energy Balance Load with the ambient temperature, shown as Figure 4.18:

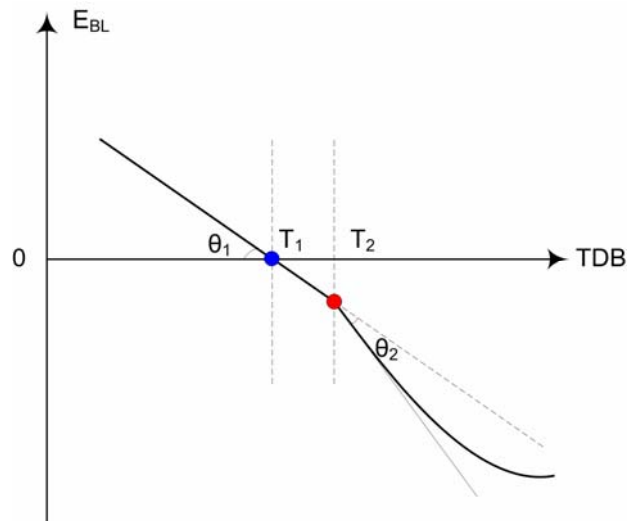


Figure 4.18 Key characteristics of simulated results of Energy Balance Load

- T_1 : Joint point where the simulation line goes across the X-axis.

$$E_{BL}(Sensible) = 0$$

$$(1.08V_{tot} X_{OA} + U_{tot} A_{envelope})(T_R - T_1) + (f' - 1)q_{gain} = 0$$

$$T_1 = T_R - \frac{(f' - 1)q_{gain}}{1.08V_{tot} X_{OA} + U_{tot} A_{envelope}} \quad (4.18)$$

$$T_1 \propto \{T_R, q_{lat}, -V_{tot} X_{OA}, -U_{tot} A_{envelope}\} \quad (4.19)$$

- T_2 : Change point where the simulation line of E_{Bl} turns from linear into

polynomial line.

$$W_{T_2} = \frac{q_{lat}}{4840V_{tot}} + W_{CL} - \frac{q_{lat}}{4840V_{tot}X_{OA}} \quad (4.20)$$

$$W_{T_2} \propto \left\{ q_{lat}, \frac{1}{V_{tot}}, -\frac{1}{X_{OA}}, W_{CL} \right\} \quad (4.21a)$$

$$T_2 \propto \{ q_{lat}, -V_{tot}X_{OA}, W_{CL}, RH_{OA} \} \quad (4.21b)$$

And $T_2 \in [0, T_{OA}(W = W_{CL}, RH = 95\%)]$

- θ_1 : The slope of the linear part simulation line.

$$\tan \theta_1 = 1.08V_{tot}X_{OA} + U_{tot}A_{envelope} \quad (4.22a)$$

$$\theta_1 \propto [V_{tot}X_{OA}, U_{tot}A_{envelope}] \quad (4.22b)$$

- θ_2 : The angle between the polynomial part's tangential line at point T_2 and the extension line from the linear part.

$$\tan \theta_2 = \frac{\partial q_{CL,lat}}{\partial T_{OA}} = C_1 4840V_{tot}X_{OA} \quad (4.23a)$$

$$\theta_2 \propto [V_{tot}X_{OA}, C_1] \quad (4.23b)$$

With knowledge of the parameters for building characters and HVAC system, such as X_{OA} , V_{tot} , T_{CL} , q_{lat} , etc., three parameters of the simulation line of the Energy Balance Load including θ_1 , θ_2 , T_1 , and T_2 could be calculated and used as the screening tool for data verification.

CHAPTER V

SENSITIVITY AND UNCERTAINTY ANALYSIS OF THE SIMULATION OF THE ENERGY BALANCE LOAD

5.1 Introduction

Most of the building or HVAC system information listed in Table 3.1 could be obtained through building blueprint observation, document investigation and, field visit, etc. As less information is required to be known, the time and effort expended on obtaining the information can be saved. Consequently, the proposed pre-screening program should be widely accepted. Because of its simplicity and ease of use, decreasing the input parameters of the data fault detection program is important.

The available knowledge of the model input is subjected to many sources of uncertainty, including errors of measurement, inadequate sampling resolution, etc. Additionally, the model itself can include conceptual uncertainty, for example uncertainty in model structures, assumptions, and specifications (Crosetto et al. 2000, Wallach and Genard 1998). Both of these situations impose a limit on the confidence to the response or output of the model, so that sensitivity quantification of this model-based method in use is necessary.

Statistical approaches, specifically uncertainty analysis and sensitivity analysis, in association with the DataPlot program (NIST 2003), are implemented to fulfill the

requirements described previously, and corresponding analysis results and conclusions are illustrated in this chapter.

5.2 Uncertainty Analysis and Sensitivity Analysis

Uncertainty analysis and sensitivity analysis are needed in any field where models are used. In that, if the input variables to the models either are measured quantities or derived from measured quantities, there will be an uncertainty in the input variable values, which in turn implies that there will be uncertainty in the output variable value. Uncertainty analysis allows assessing the uncertainty associated with the model response as a result of uncertainties in the model input. Sensitivity analysis studies how the variation in the model output can be apportioned to different sources of variations, and how the given model depends upon the information it is fed.

The objective of sensitivity analysis of the model output can be defined as “to ascertain how a given model depends on its input factors” (Saltelli et al. 1999). Sensitivity analysis relates to the problem of investigating the contribution of the uncertainty in the input factors to the uncertainty in the model response, which helps to understand the behavior of a model, the coherence between a model and the world, and how different parts of the model interplay. Accordingly, the factors that need to be measured accurately in order to achieve a given precision in the model output can be determined. The advantages of implementing sensitivity analysis where a model is used include two aspects. First, results of sensitivity analysis do not depend on the true

uncertainty in the inputs and parameters. In addition, sensitivity analysis is not explicitly related to the quality of model predictions.

Two distinct schools of thought for sensitivity analysis can be found in practice, the local sensitivity analysis school and the global one (Saltelli et al. 1999). For local sensitivity analysis, the sensitivity of any input factor to the output can be obtained by changing its value, while keeping other factors fixed at a central value. Global sensitivity analysis investigates the variation of the output induced by a factor in terms of averaging over the variation of all the factors. Global sensitivity analysis is often selected for use when there is difficulty building an effective and rigorous measure within a finite region of input factors. By using some screening methods, a qualitative global sensitivity analysis is introduced, which aims to rank all the factors of the model in order of their importance with low computing cost; however, the percentage of the output variation that each factor accounts for can not be quantified. This qualitative global sensitivity analysis will be mainly used in this research work.

In summary, sensitivity analysis can be used to identify the parameters to which the system is most sensitive, with a view toward changing the true values of those parameters in order to modify system behavior. Sensitivity analysis can also be used as an exploratory tool to aid in understanding model behavior, by indicating which parameters have the largest effect on the model outputs. Consequently, as a result of sensitivity analysis, minor factors may be neglected and taken out of the model, and the objective of decreasing input parameters for the pre-screening program can be achieved.

Uncertainty analysis attempts to quantify the effects of uncertainty in input or parameter values on the quality of model predictions. Uncertainty analysis is important in two respects. First, uncertainty analysis assists in identifying the contributions of uncertainty in different inputs and parameters to the errors in model prediction, which is useful to the overall investigation of the model predictive quality. Secondly, uncertainty analysis helps determine whether additional information or more precise measurement would be valuable, and how the lack of these input factors affects the prediction model.

Two main types of uncertainty influence estimates of the Energy Balance Load. One major cause of uncertainty is the omission of influencing variables from the simulation model. The sensitivity analysis permits the important and unimportant factors to be distinguished. For the purpose of easy application, the less important factors will be eliminated from the simulation model, with default parameter values being used instead. Because of the non-random nature of these variables, their omission from the simulation model can consequently cause uncertainties. Additionally, the available knowledge of the model input is subjected to many sources of uncertainty, including errors of measurement, inadequate sampling resolution, etc. For this reason, the response or output of the model will result in more limits on the confidence.

Associated uncertainty analysis implemented in this chapter targets to provide a confidence interval to the outcome of the model according to the two kinds of uncertainties described above. Next, the confidence interval will be used to filter out the faulty measured data. For example, with a presumed confidence coefficient $1 - \alpha$, if an infinite number of random samples are collected and a $100(1 - \alpha)$ percent confidence

interval for E_{BL} is computed from each sample, then there is $100(1 - \alpha)$ percent certainty that these intervals will contain the true value of the estimated parameter, which can be represented as Equation (5.1).

$$E_{BL}^- \leq E_{BL} \leq E_{BL}^+ \quad (5.1)$$

The left and right parts of the inequality are called the lower- and upper-confidence limits respectively, which are correlated with the confidence coefficient $1 - \alpha$. The data outside these two boundaries are considered as sufficiently suspicious to require further investigation.

In order to interpret the trigger band more clearly, a cross-check plot of the measured vs. simulated Energy Balance Load will be generated to provide a visual aid in understanding the screening criteria. This type of check would typically be expected to produce a linear trend line; the more linear the trend line the better the model. In addition, it is proposed to investigate the confidence interval of E_{BL} presented as two linear trend lines parallel to that of the simulated E_{BL} , and the “bad” data may then be easily identified as the data outside these two boundaries.

5.3 Methodology and Software Implementation for Sensitivity Analysis

Exploratory Data Analysis (EDA) is an approach/philosophy for data analysis that employs a variety of techniques to: (1) maximize insight into a data set; (2) uncover underlying structure; (3) extract important variables; (4) detect outliers and anomalies; (5)

test underlying assumptions; (6) develop parsimonious models; (7) determine optimal factor settings (NIST 2003).

The primary differences between classical data analysis and EDA is that the classical approach imposes models (both deterministic and probabilistic) on the data. Deterministic models include, for example, regression models and analysis of variance (ANOVA) models, while the Exploratory Data Analysis does not impose deterministic or probabilistic models on the data. By contrast, the EDA approach allows the data to suggest models that best fit the data. In this way, EDA is proposed to maximize the analyst's insight into a data set and its underlying structure.

Statistics and data analysis procedures can broadly be categorized as quantitative and graphical. Quantitative techniques are the set of statistical procedures that yield numerical or tabular output. A large collection of statistical tools regarded as graphical techniques include, but are not limited to scatter plots, histograms, probability plots, residual plots, box plots, and block plots. Most of the techniques EDA employs are graphical with a few quantitative techniques. The reason for the intense reliance on graphics is that graphics enable the analyst to open-mindedly explore the data, entice the data to reveal its structural secrets, and to gain some new, often unsuspected, insight into the data. With the advantages EDA has comparing to the classical data analysis, this research work selects EDA to approach uncertainty and sensitivity analysis.

A powerful and flexible software program developed and normally used at the National Institute of Standards and Technology (NIST), named Dataplot (NIST 2003), is implemented in this research work to carry out Exploratory Data Analysis (EDA).

DataPlot is a public domain, multi-platform (Unix, VMS, Linux, Windows 95/98/ME/XP/NT/2000, etc.) software for performing engineering, statistical, and graphical analysis. It is an interactive, command-driven language/system with English-like syntax, which can do Exploratory Data Analysis (EDA), time series analysis, process control, and reliability analysis. The target Dataplot user is the researcher and analyst engaged in the characterization, modeling, visualization, analysis, monitoring, and optimization of scientific and engineering processes. The original version was released by Filliben in 1978 (NIST 2003), with continual enhancements to present.

In order to investigate the sensitivity of the input factors to the target dependent variable, deliberately changing one or more process variables (or factors) is desired to observe the effect the changes have on one or more response variables. For this purpose, a statistical experiment or series of tests becomes an important approach, and the validity of the conclusions that are drawn from the experiment depends to a large extent on how the experiment was conducted. Therefore, the design of the experiment, laying out of a detailed experimental plan in advance of conducting the experiment, plays a major role in the eventual solution of the problem that initially motivated the experiment. Well-chosen experimental designs maximize the amount of "information" that can be obtained for a given amount of experimental effort.

The choice of an experimental design depends on the objectives of the experiment and the number of factors to be investigated. Types of distinct experimental objectives include: (1) comparative objective, which is to select one dominant factor among several factors under investigation and identify how it is significant to the output of the model;

(2) screening objective, which is to select or screen out the few main effects from the many less important ones; and (3) response surface (method) objective, which allows us to estimate interaction and even quadratic effects, and therefore gives us an idea of the (local) shape of the response surface we are investigating.

Combined with the number of factors to be investigated, the selection of an experimental design could be directed by the guidelines illustrated in Table 5.1 (NIST 2003).

Table 5.1 Guidelines for selection of experimental design

Number of Factors	Experimental Objective		
	Comparative	Screening	Response Surface
1	1-factor completely randomized design	—	—
2 - 4	Randomized block design	Full or fractional factorial design	Central composite or Box-Behnken design
5 or more	Randomized block design	Fractional factorial design	Screen first to reduce number of factors

The proposed sensitivity analysis and uncertainty analysis scheme for this research is intended to distinguish the few crucial factors out of all input parameters required by the process model. This information will be used to reduce the number of input parameters to make the pre-screening program more applicable. Thus, the projected experiment can be categorized with the screening objective. Additionally, by assuming that the floor, windows, and walls area, whether the HVAC systems have an economizer and heat recovery system in use are required and easily obtained information, 7 parameters listed in Table 3.1 are left for sensitivity analysis. As a result, with the screening objective and

7 factors to be investigated by the experiment, fractional factorial experimental design is recommended by the guideline. The reason for using a fractional factorial experimental design is because for a two-level, full factorial design with 7 factors, $2^7 = 128$ runs are specified, which is a large number that will cost considerable time and effort to accomplish. The solution to this problem is to use only a fraction of the runs specified by the full factorial design. In general, a fraction such as $\frac{1}{2}$, $\frac{1}{4}$, etc. of the runs called for by the full factorial design will be selected with an appropriate strategy that ensures the experiment will have a modest number of operations to fulfill the requirement of the full factorial design.

A $\frac{1}{8}$ fraction or a 2^{7-3} design is considered to be implemented for this 7-factor experiment, which contains 16 runs, and with 15 degrees of freedom, this experimental design would allow all 7 main effects and some 2-factor interactions to be estimated. The standard layout for a 2-level design uses +1 and -1 notation to denote the “high level” and the “low level” respectively, for each factor. The use of +1 and -1 for the factor settings is called coding or orthogonal coding the data. This aids in the interpretation of the coefficients fit to any experimental model. After factor settings are coded, center points have the value “0”, and all the columns of a coded 2-factor design matrix are typically orthogonal as the dot product for any pair of columns is zero. The orthogonality property is important because it eliminates correlation between the estimates of the main effects and interactions.

For this 7-factor experiment, the 2^{7-3} 2-level fractional factorial design is expressed as shown in Table 5.2. The matrix describes an experiment in which 16 trials (or runs)

were conducted with each factor set to high or low values during a run according to whether the matrix had a +1 or -1 set for the factor during that trial. Next, Table 5.3 lists the denoted values for the “+1” and “-1” codes for each of the 7 factors, which refer to the practical building construction characteristics and HVAC setting parameters.

Table 5.2 2^{7-3} two level fractional factorial experimental design

Random Order	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6	Factor 7
1	-1	-1	-1	-1	-1	-1	-1
2	+1	-1	-1	-1	-1	+1	+1
3	-1	+1	-1	-1	+1	-1	+1
4	+1	+1	-1	-1	+1	+1	-1
5	-1	-1	+1	-1	+1	+1	+1
6	+1	-1	+1	-1	+1	-1	-1
7	-1	+1	+1	-1	-1	+1	-1
8	+1	+1	+1	-1	-1	-1	+1
9	-1	-1	-1	+1	+1	+1	-1
10	+1	-1	-1	+1	+1	-1	+1
11	-1	+1	-1	+1	-1	+1	+1
12	+1	+1	-1	+1	-1	-1	-1
13	-1	-1	+1	+1	-1	-1	+1
14	+1	-1	+1	+1	-1	+1	-1
15	-1	+1	+1	+1	+1	-1	-1
16	+1	+1	+1	+1	+1	+1	+1

Table 5.3 Denoting codes for the 2^{7-3} fractional factorial design

	Parameter	-1	+1	Unit
Factor 1	F	0.25	0.87	
Factor 2	U_{window}	0.1	1.04	$Btu / hr \cdot ft^2 \cdot ^\circ F$
Factor 3	U_{wall}	0.1	0.2	$Btu / hr \cdot ft^2 \cdot ^\circ F$
Factor 4	T_R	65	80	$^\circ F$
Factor 5	V_{OA}	0.05	0.8	cfm / ft^2
Factor 6	T_{CL}	50	70	$^\circ F$
Factor 7	Q_{occ}	3	8	$Btu / ft^2 \cdot day$

To explore the sensitive construction and air-handling unit factors for a generic commercial building, the 2^{7-3} fractional factorial design with 16 runs is applied to four Texas A&M University (TAMU) campus buildings by implementing the Dataplot program. As daily ambient temperature data are used for the Energy Balance Load (E_{BL}) estimation, the output of the simulation process is daily format as well, which will make the sensitivity analysis to be carried out complex due to the large amount of data. The solution to this problem is to use a yearly base root mean squared error (RMSE) comparing the simulated data with measured data as the response variable in the

$$\text{experiments, } RMSE = \sqrt{\frac{\sum_{d=1}^n (E_{BL,d} - \hat{E}_{BL,d})^2}{n}}.$$

$E_{BL,d}$ is the Energy Balance Load value predicted by the simulation model for the sample case d (out of n sample cases); $\hat{E}_{BL,d}$ is the target value or the measured Energy Balance Load in this research; and n is the number of measurements, for a yearly base simulation with daily data $n = 365$.

Detailed analysis results for these four buildings are described in the following section.

5.4 Sensitivity Analysis Results

The four buildings selected for the sensitivity analysis, all located on the Texas A&M University campus, are the Eller Oceanography & Meteorology Building, the Veterinary Research Center, the Wehner Building, and the Harrington Tower. With one of the 16

sets of values for the 7 input parameters subjected to sensitivity analysis, each of these four buildings is used to simulate the Energy Balance Load in terms of daily ambient temperature for year 2000. Comparing the simulated results with the monitored data, a yearly base RMSE is estimated, which will then be used as the response variable in the fractional factorial design. Consequently, four groups of experiments in combination with 16 trials for each group, are ready for the sensitivity analysis. According to the implementation of DataPlot in terms of the concept of Exploratory Design Analysis (EDA), the experiment on each of the four buildings goes through the following five steps:

- (1) Data input. To run the 16 experiments, the values of the 7 factors for each experiment listed in Table 5.2 will be applied to the simulation, and other parameters values not listed in Table 5.2 will be obtained by referring to the blueprints and other documents with information of the building, for example Cho's master's thesis (2002). The RMSE between the simulated and measured E_{BL} will then be used as the input file to the DataPlot program;
- (2) Initial plots/main effects. The Main Effect plot is generated to more clearly show the main effects. A factor can be important if it leads to a significant shift in the location of the response variable as we go from the "-" setting of the factor to the "+" setting of the factor. Alternatively, a factor can be important if it leads to a significant change in variation (spread) as we go from the "-" to the "+" settings. Both definitions are relevant and acceptable. The default definition of "important" in engineering/scientific applications is the former (shift in location);

- (3) Interaction effects. In addition to the main effects, it is also important to check for interaction effects, especially 2-factor interaction effects. For a k-factor experiment, the effect on the response could be due to main effects and various interactions all the way up to k-term interactions. In practice, the most important interactions are likely to be 2-factor interactions. The total number of possible 2-factor interactions is $n = \frac{k(k-1)}{2}$. For this experimental design where $k = 7$, the number of 2-factor interactions is equal to 21. The interaction effects matrix plot generated by DataPlot is an extension of the Main Effect plot to include both main effects and 2-factor interactions. The interaction effects matrix plot can provide a ranked list of factors (including 2-factor interactions), ranked from most important to least important.
- (4) Important factors (|Effects| plot). The |Effects| plot displays the results of the 2^{7-3} fractional factorial design in both a tabular and a graphical format. The least squares estimation criterion is implemented in the analysis to determine the estimated effect of a given factor or interaction and its rank relative to other factors and interactions. Based on such an estimation criterion, the |Effects| plot yields both the plot itself, as well as the tabular list of the factors and interactions ordered by the effect magnitude. The plot is expected to have an L-shape, where the factors or interactions having large effects on the response variable locate on or near the vertical axis, while the ones showing small effects fall down on the horizontal direction. Consequently, it is easy to distinguish the important and unimportant factors and interactions.

Furthermore, the plot also presents auxiliary confounding information, which is necessary in forming valid conclusions for fractional factorial designs;

- (5) Summary of conclusions. The results on every building will be displayed one by one in the following section.

5.4.1 Analysis Results on the Eller Oceanography & Meteorology Building

5.4.1.1 Data Input

Table 5.4 Input parameters of the Energy Balance Load simulation

Input Parameters			
Eller O&M Building	Building #511		Year: 2000
HVAC System		4 DDVAV	2 CVRH
Economizer		Yes	
Heat Recovery System		No	
Conditioned Floor Area		180,316	ft ²
Exterior Walls	Area	63,248	ft ²
	U _{wall}	0.2	Btu/hr*ft ² F
Exterior Windows	Area	26,208	ft ²
	U _{window}	0.98	Btu/hr*ft ² F
	F	0.87	
Room Temperature	Heating	70	F
Outside Air Flow	Flow rate	0.22	cfm/ft ²
Total Air Flow Rate		1.30	cfm/ft ²
Cold Deck Schedule	T _{cl}	55	F
	W _{cl}	0.00825	
Occupants	Density	300	ft ² /person
	Heat	240	Btu/hr*person
	Hours	10	hr

Table 5.5 Simulation results for the Eller Oceanography & Meteorology Building

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
151.49	-1	-1	-1	-1	-1	-1	-1

166.51	1	-1	-1	-1	-1	1	1
723.31	-1	1	-1	-1	1	-1	1
246.93	1	1	-1	-1	1	1	-1
218.41	-1	-1	1	-1	1	1	1
684.27	1	-1	1	-1	1	-1	-1
115.21	-1	1	1	-1	-1	1	-1
91.29	1	1	1	-1	-1	-1	1
319.74	-1	-1	-1	1	1	1	-1
505.77	1	-1	-1	1	1	-1	1
162.43	-1	1	-1	1	-1	1	1
144.11	1	1	-1	1	-1	-1	-1
145.79	-1	-1	1	1	-1	-1	1
183.28	1	-1	1	1	-1	1	-1
544.91	-1	1	1	1	1	-1	-1
381.99	1	1	1	1	1	1	1

5.4.1.2 Initial Plots/Main Effects

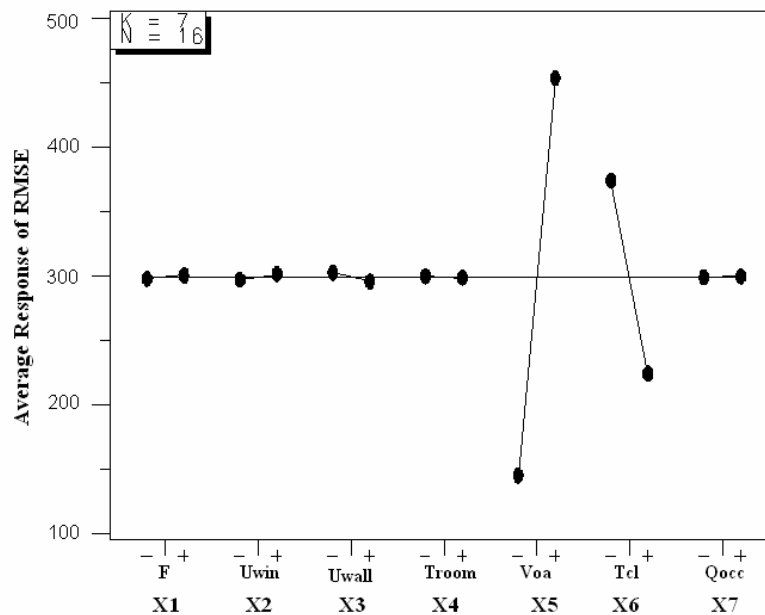


Figure 5.1 Main Effect plot for the Eller Oceanography & Meteorology Building

From the Main Effect plot shown in Figure 5.1, it can be concluded that:

- Important Factors: X5 (effect = large: about 308); X6 (effect = large: about -150)

5.4.1.3 Interaction Effects

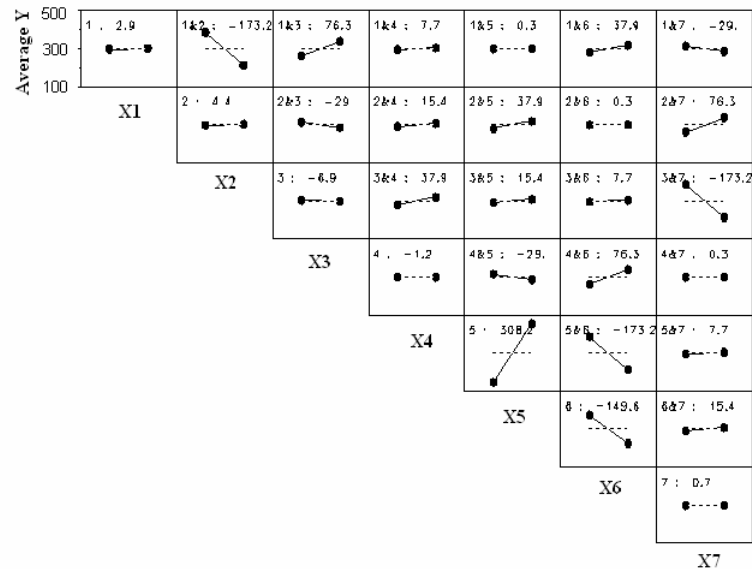


Figure 5.2 Interaction Effects plot for the Eller Oceanography & Meteorology Building

From the Interaction Effects plot shown in Figure 5.2, it can be concluded that:

- Important Factors: Looking for the plots that have the steepest line, as well as the estimated effect given in the legends on each subplot.
 - ✓ The diagonal plots are the main effects. The important factors are X5 and X6. These two factors have $|\text{effect}| > 140$. The remaining five factors have $|\text{effect}| < 10$.
 - ✓ The off-diagonal plots are the 2-factor interaction effects. Of the 21 2-factor interactions, 9 are nominally important and fall into 3 groups:
 - X1*X2, X3*X7, X5*X6 (effect = -173.2)

$X1*X3, X4*X6, X2*X7$ (effect = 76.3)

$X1*X7, X2*X3, X4*X5$ (effect = -29)

- All remaining 2-factor interactions are small, having an $|\text{effect}| < 10$. In this case, the fact that $X1*X2, X3*X7$ and $X5*X6$ all have effect estimates identical to 173.12 is not a mathematical coincidence. It is a reflection of the fact that for this design, the three 2-factor interactions are confounded.

5.4.1.4 Important Factors: |Effects| Plot

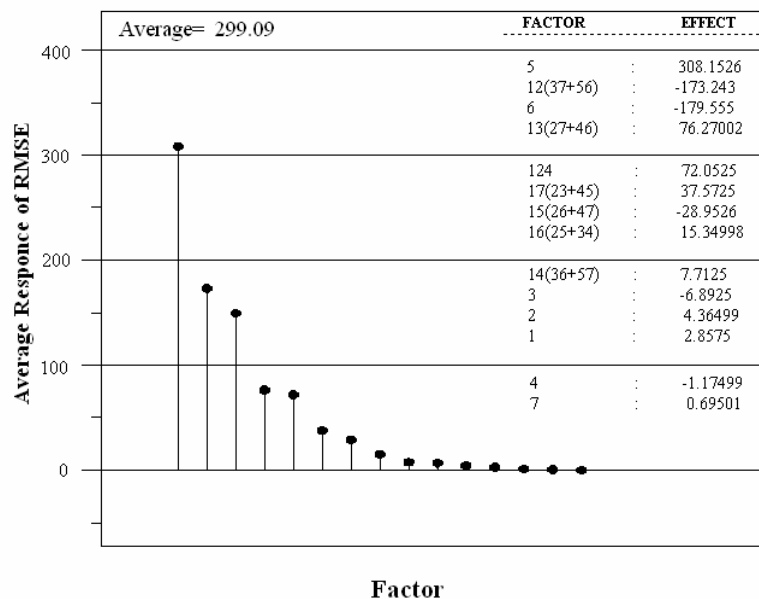


Figure 5.3 |Effects| plot for the Eller Oceanography & Meteorology Building

From the |Effects| plot shown in Figure 5.3, it can be concluded that:

- A ranked list of main effects and interaction terms is:

X5; X1*X2 (confounded with X3*X7 and X5*X6); X6; X1*X3 (confounded with X2*X7 and X4*X6); X1*X2*X4 (confounded with other 3-factor interactions); X1*X7 (confounded with X2*X3 and X4*X5); X1*X5 (confounded with X2*X6 and X4*X7); X1*X6 (confounded with X2*X5 and X3*X4); X1*X4 (confounded with X3*X6 and X5*X7); X3; X2; X1; X4; X7

- From the graph, there is a clear dividing line between the first 3 effects (all $|\text{effect}| > 170$) and the last 11 effects (all $|\text{effect}| < 80$). This suggests we retain the first 3 terms as "important" and discard the remaining as "unimportant".

5.4.1.5 Conclusions

The primary goal of this experiment was to identify the most important factors in minimizing the RMSE of simulated and measured E_{BL} . Based on the preceding graphical analysis, the following conclusions can be made:

- Two factors and one group of 2-factor interactions are important. A rank-order listing of factors is:
 - ✓ X5: V_{OA} —Outside air intake volume (effect = 308.15)
 - ✓ X1*X2: $F*U_{window}$; X3*X7: $U_{wall}*Q_{occ}$; X5*X6: $V_{OA}*T_{CL}$ (effect = -173.24)
 - ✓ X6: T_{CL} —Outside air intake volume (effect = -179.55)
- Thus, of the 7 factors and 21 2-factor interactions, it was found that 2 factors and at most 3 2-factor interactions seem important, with the remaining 5 factors and 18 interactions apparently being unimportant for the Eller O&M Building.

5.4.2 Analysis Results on Wehner Building

5.4.2.1 Data Input

Table 5.6 Input parameters of the Energy Balance Load simulation

Input Parameters			
Wehner Building	Building #528		Year: 2000
HVAC System		3 SDVAV	6 DDVAV
Economizer		Yes	
Heat Recovery System		No	
Conditioned Floor Area		192,001	ft ²
Exterior Walls	Area	45,000	ft ²
	U _{wall}	0.2	Btu/hr*ft ² F
Exterior Windows	Area	30,000	ft ²
	U _{window}	0.92	Btu/hr*ft ² F
	F	0.87	
Room Temperature	Heating	75	F
Outside Air Flow	Flow rate	0.06	cfm/ft ²
Total Air Flow Rate		1.00	cfm/ft ²
Cold Deck Schedule	T _{cl}	58	F
	W _{cl}	0.00921	
Occupants	Density	300	ft ² /person
	Heat	240	Btu/hr*person
	Hours	10	hr

Table 5.7 Simulation results for the Wehner Building

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
88.36	-1	-1	-1	-1	-1	-1	-1
85.04	1	-1	-1	-1	-1	1	1
866.82	-1	1	-1	-1	1	-1	1
387.54	1	1	-1	-1	1	1	-1
355.20	-1	-1	1	-1	1	1	1
827.45	1	-1	1	-1	1	-1	-1
72.49	-1	1	1	-1	-1	1	-1
108.63	1	1	1	-1	-1	-1	1
333.04	-1	-1	-1	1	1	1	-1
637.63	1	-1	-1	1	1	-1	1
40.46	-1	1	-1	1	-1	1	1
39.01	1	1	-1	1	-1	-1	-1
57.42	-1	-1	1	1	-1	-1	1
54.14	1	-1	1	1	-1	1	-1

Table 5.7 Continued

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
671.80	-1	1	1	1	1	-1	-1
400.70	1	1	1	1	1	1	1

5.4.2.2 Initial Plots/Main Effects

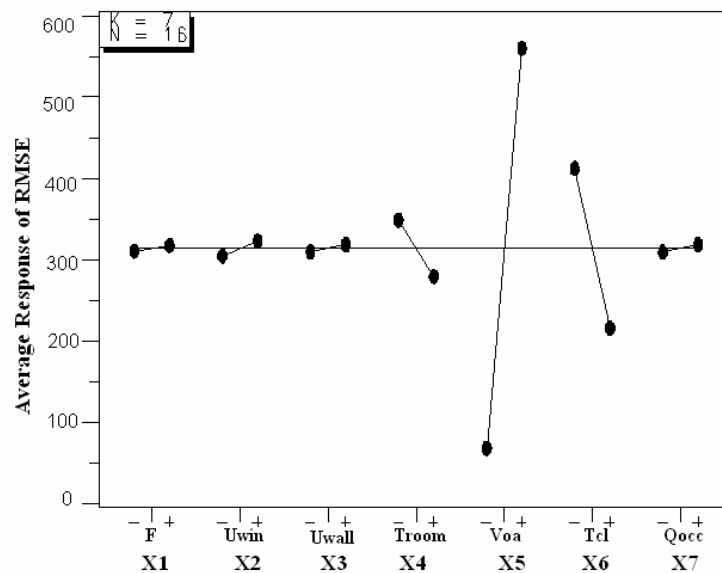


Figure 5.4 Main Effect plot for the Wehner Building

From the Main Effect plot shown in Figure 5.4, it can be concluded that:

- Important Factors: X5 (effect = large: about 491.8); X6 (effect = large: about -196.1)

5.4.2.3 Interaction Effects

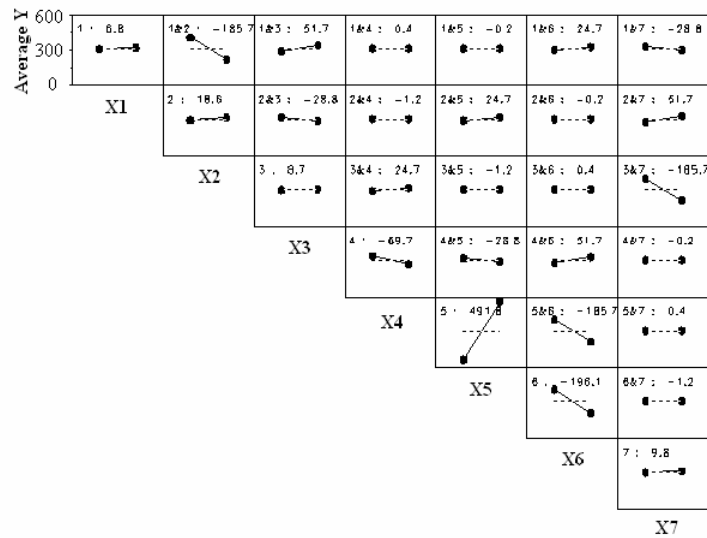


Figure 5.5 Interaction Effects plot for the Wehner Building

From the Interaction Effects plot shown in Figure 5.5, it can be concluded that:

- Important Factors: Looking for the plots that have the steepest lines, as well as the estimated effect given in the legends on each subplot.
 - ✓ The diagonal plots are the main effects. The important factors are X5 and X6. These two factors have $|\text{effect}| > 190$. The remaining five factors have $|\text{effect}| < 70$.
 - ✓ The off-diagonal plots are the 2-factor interaction effects. Of the 21 2-factor interactions, 3 are nominally important:
 - X1*X2, X3*X7, X5*X6 ($|\text{effect}| = -185.7$)
- All remaining 2-factor interactions are small, having an $|\text{effect}| < 30$.

5.4.2.4 Important Factors: |Effects| Plot

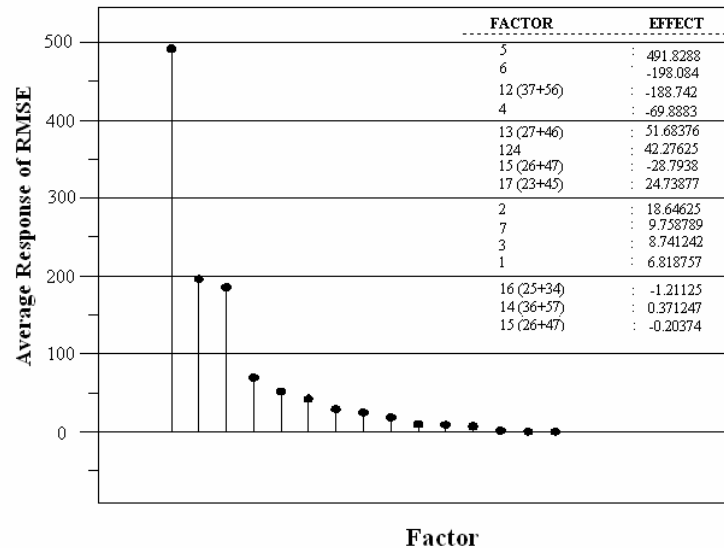


Figure 5.6 |Effects| plot for the Wehner Building

From the |Effects| plot shown in Figure 5.6, it can be concluded that:

- A ranked list of main effects and interaction terms is:

X5; X6; X1*X2 (confounded with X3*X7 and X5*X6); X4; X1*X3 (confounded with X2*X7 and X4*X6); X1*X2*X4 (confounded with other 3-factor interactions); X1*X5 (confounded with X2*X6 and X4*X7); X1*X7 (confounded with X2*X3 and X4*X5); X2; X7; X3; X1; X1*X6 (confounded with X2*X5 and X3*X4); X1*X4 (confounded with X3*X6 and X5*X7); X2*X4 (confounded with X3*X5 and X6*X7);

- From the graph, there is a clear dividing line between the first 3 effects (all |effect| > 190) and the last 11 effects (all |effect| < 70). This suggests we retain

the first 3 terms as "important" and discard the remaining as "unimportant".

5.4.2.5 Conclusions

Based on the preceding graphical analysis, the following conclusions can be made:

- Two factors and one group of 2-factor interactions are important. A rank-order listing of factors is:
 - ✓ X5: V_{OA} —Outside air intake volume (effect = 491.8)
 - ✓ X6: T_{CL} —Outside air intake volume (effect = -196.1)
 - ✓ X1*X2: $F*U_{window}$; X3*X7: $U_{wall} * Q_{occ}$; X5*X6: $V_{OA} * T_{CL}$ (effect = -188.7)
- Thus, of the 7 factors and 21 2-factor interactions, it was found that 2 factors and at most 3 2-factor interactions seem important, with the remaining 5 factors and 18 interactions apparently being unimportant for Wehner Building.

5.4.3 Analysis Results on Harrington Tower

5.4.3.1 Data Input

Table 5.8 Input parameters of the Energy Balance Load simulation

Input Parameters			
Harrington Tower	Building #509		Year: 2000
HVAC System		1 DDVAV	3 SDVAV
Economizer		No	
Heat Recovery System		No	
Conditioned Floor Area		130,844	ft ²
Exterior Walls	Area	41,200	ft ²
	U _{wall}	0.2	Btu/hr*ft ² F
Exterior Windows	Area	19,017	ft ²
	U _{window}	0.80	Btu/hr*ft ² F
	F	0.87	
Room Temperature	Heating	72	F
Outside Air Flow	Flow rate	0.13	cfm/ft ²
Total Air Flow Rate		1.00	cfm/ft ²
Cold Deck Schedule	T _{cl}	58	F
	W _{cl}	0.00921	
Occupants	Density	300	ft ² /person
	Heat	240	Btu/hr*person
	Hours	10	hr

Table 5.9 Simulation results for the Harrington Tower

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
98.21	-1	-1	-1	-1	-1	-1	-1
118.84	1	-1	-1	-1	-1	1	1
863.68	-1	1	-1	-1	1	-1	1
312.85	1	1	-1	-1	1	1	-1
283.54	-1	-1	1	-1	1	1	1
821.21	1	-1	1	-1	1	-1	-1
75.04	-1	1	1	-1	-1	1	-1
59.83	1	1	1	-1	-1	-1	1
258.50	-1	-1	-1	1	1	1	-1
575.86	1	-1	-1	1	1	-1	1
138.42	-1	1	-1	1	-1	1	1
114.00	1	1	-1	1	-1	-1	-1
108.88	-1	-1	1	1	-1	-1	1
146.85	1	-1	1	1	-1	1	-1

Table 5.9 Continued

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
590.53	-1	1	1	1	1	-1	-1
300.10	1	1	1	1	1	1	1

5.4.3.2 Initial Plots/Main Effects

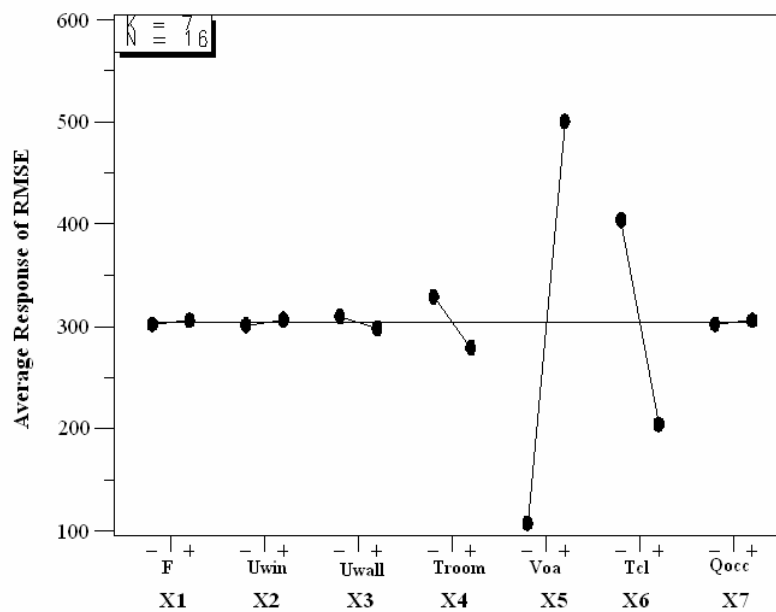


Figure 5.7 Main Effect plot for the Harrington Tower

From the Main Effect plot shown in Figure 5.7, it can be concluded that:

- Important Factors: X5 (|effect| = large: about 393); X6 (|effect| = large: about 200)

5.4.3.3 Interaction Effects

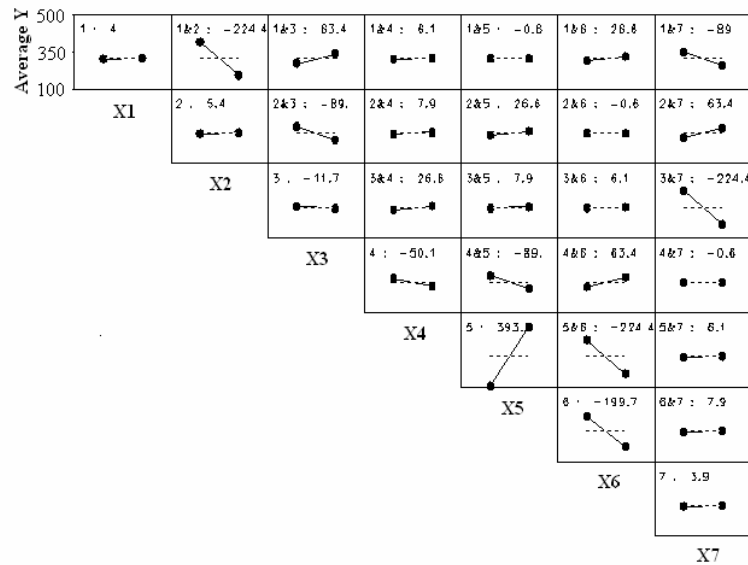


Figure 5.8 Interaction Effects plot for Harrington Tower

From the Interaction Effects plot shown in Figure 5.8, it can be concluded that:

- Important Factors: Looking for the plots that have the steepest lines, as well as the estimated effect given in the legends on each subplot.
 - ✓ The diagonal plots are the main effects. The important factors are X5 and X6. These two factors have $|\text{effect}| > 198$. The remaining five factors have $|\text{effect}| < 50$.
 - ✓ The off-diagonal plots are the 2-factor interaction effects. Of the 21 2-factor interactions, 3 are nominally important:
 - X1*X2, X3*X7, X5*X6 ($|\text{effect}| = -224.4$)
- All remaining 2-factor interactions are small, having an $|\text{effect}| < 63$.

5.4.3.4 Important Factors: |Effects| Plot

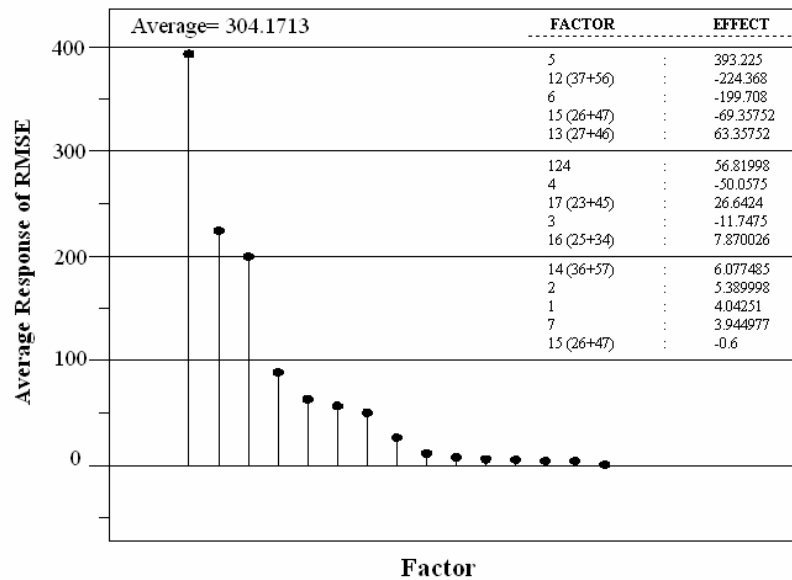


Figure 5.9 |Effects| plot for the Harrington Tower

From the |Effects| plot shown in Figure 5.9, it can be concluded that:

- A ranked list of main effects and interaction terms is:
 X5; X1*X2 (confounded with X3*X7 and X5*X6); X6; X1*X5 (confounded with X2*X6 and X4*X7); X1*X3 (confounded with X2*X7 and X4*X6); X1*X2*X4 (confounded with other 3-factor interactions); X4; X1*X7 (confounded with X2*X3 and X4*X5); X3; X1*X6 (confounded with X2*X5 and X3*X4); X1*X4 (confounded with X3*X6 and X5*X7); X2; X1; X7; X2*X4 (confounded with X3*X5 and X6*X7);
- From the graph, there is a clear dividing line between the first 3 effects (all |effect| > 190) and the last 11 effects (all |effect| < 70). This suggests we retain

the first 3 terms as "important" and discard the remaining as "unimportant".

5.4.3.5 Conclusions

Based on the preceding graphical analysis, the following conclusions can be made:

- Two factors and one group of 2-factor interactions are important. A rank-order listing of factors is:
 - ✓ X5: V_{OA} —Outside air intake volume (effect = 393.23)
 - ✓ X6: T_{CL} —Outside air intake volume (effect = -199.708)
 - ✓ X1*X2: $F*U_{window}$; X3*X7: $U_{wall}*Q_{occ}$; X5*X6: $V_{OA}*T_{CL}$ (effect = -224.37)
- Thus, of the 7 factors and 21 2-factor interactions, it was found that 2 factors and at most 3 2-factor interactions seem important, with the remaining 5 factors and 18 interactions apparently being unimportant for the Harrington Tower.

5.4.4 Analysis Results on the Veterinary Research Center

5.4.4.1 Data Input

Table 5.10 Input parameters of Energy Balance Load simulation

Input Parameters			
VMC	Building #523		Year: 2000
HVAC System		SDVAV	
Economizer		Yes	
Heat Recovery System		Yes	
Conditioned Floor Area		117,666	ft2
Exterior Walls	Area	33,560	ft2
	Uwall	0.1	Btu/hr*ft2F
Exterior Windows	Area	22,370	ft2
	Uwindow	0.81	Btu/hr*ft2F
	F	0.87	
Room Temperature	Heating	70	F
Outside Air Flow	Flow rate	0.62	cfm/ft2
Total Air Flow Rate		1.15	cfm/ft2
Cold Deck Schedule	Tcl	56	F
	Wcl	0.00888	
Pre-Heat Deck Schedule	Thl,win	50	F
	Thl,summer	75	F
Occupant	Density	200	ft2/person
	Heat	240	Btu/hr*person
	Hours	10	hr

Table 5.11 Simulation results for the Veterinary Research Center

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
441.51	-1	-1	-1	-1	-1	-1	-1
465.63	1	-1	-1	-1	-1	1	1
206.40	-1	1	-1	-1	1	-1	1
347.11	1	1	-1	-1	1	1	-1
374.42	-1	-1	1	-1	1	1	1
185.62	1	-1	1	-1	1	-1	-1
413.91	-1	1	1	-1	-1	1	-1
379.37	1	1	1	-1	-1	-1	1
459.65	-1	-1	-1	1	1	1	-1
167.01	1	-1	-1	1	1	-1	1
455.20	-1	1	-1	1	-1	1	1
429.68	1	1	-1	1	-1	-1	-1

Table 5.11 Continued

Y	X1	X2	X3	X4	X5	X6	X7
RMSE	F	U _{win}	U _{wall}	T _R	V _{OA}	T _{CL}	Q _{occ}
437.76	-1	-1	1	1	-1	-1	1
473.05	1	-1	1	1	-1	1	-1
224.42	-1	1	1	1	1	-1	-1
475.72	1	1	1	1	1	1	1

5.4.4.2 Initial Plots/Main Effects

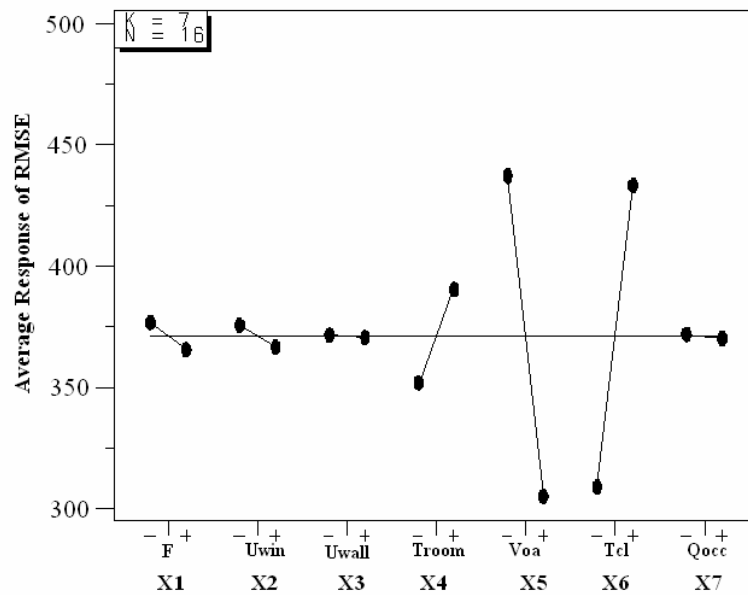


Figure 5.10 Main Effect plot for Veterinary Research Center

From the Main Effect plot shown in Figure 5.10, it can be concluded that:

- Important Factors: X5 (effect = large: about -130); X6 (effect = large: about -120);

5.4.4.3 Interaction Effects

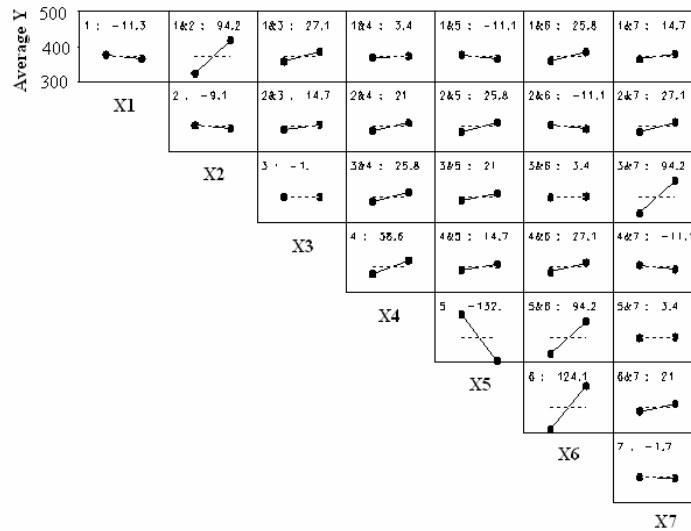


Figure 5.11 Interaction Effects plot for the Veterinary Research Center

From the Interaction Effects plot shown in Figure 5.11, it can be concluded that:

- Important Factors: Looking for the plots that have the steepest lines, as well as the estimated effect given in the legends on each subplot.
 - ✓ The diagonal plots are the main effects. The important factors are X5 and X6. These 2 factors have $|\text{effect}| > 120$. The remaining 5 factors have $|\text{effect}| < 40$.
 - ✓ The off-diagonal plots are the 2-factor interaction effects. Of the 21 2-factor interactions, 3 are nominally important:
 - X1*X2, X3*X7, X5*X6 (effect = 94.2)
- All remaining 2-factor interactions are small, having an $|\text{effect}| < 30$.

5.4.4.4 Important Factors: |Effects| Plot

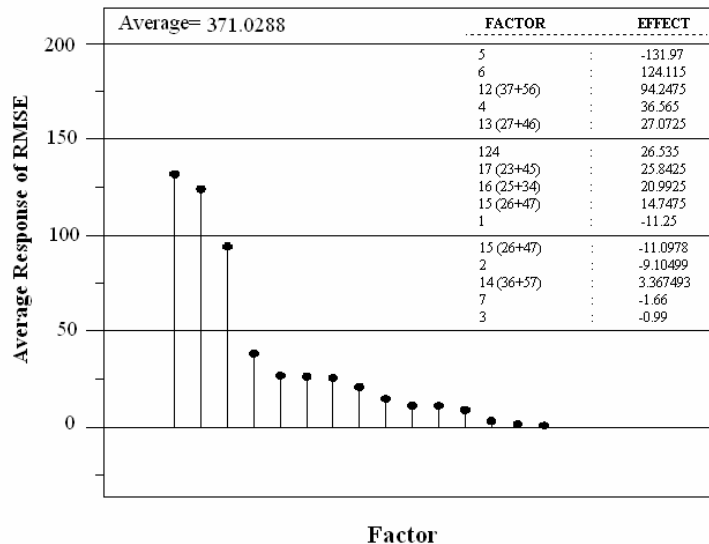


Figure 5.12 |Effects| plot for the Veterinary Research Center

From the |Effects| plot shown in Figure 5.12, it can be concluded that:

- A ranked list of main effects and interaction terms is:

X5; X6; X1*X2 (confounded with X3*X7 and X5*X6); X4; X1*X3 (confounded with X2*X7 and X4*X6); X1*X2*X4 (confounded with other 3-factor interactions); X1*X7 (confounded with X2*X3 and X4*X5); X1*X6 (confounded with X2*X5 and X3*X4); X1*X5 (confounded with X2*X6 and X4*X7); X1; X2*X4 (confounded with X3*X5 and X6*X7); X2; X1*X4 (confounded with X3*X6 and X5*X7); X7; X3

- From the graph, there is a clear dividing line between the first 3 effects (all |effect| > 90) and the last 12 effects (all |effect| < 40). This suggests we retain the first 3 terms as "important" and discard the remaining as "unimportant".

5.4.4.5 Conclusions

Based on the preceding graphical analysis, the following conclusions can be made:

- Two factors and a group of 2-factor interactions are important. A rank-order listing of factors is:
 - ✓ X5: V_{OA} —Outside air intake volume (effect = -131.97)
 - ✓ X6: T_{CL} —Outside air intake volume (effect = 124.12)
 - ✓ X1*X2: F*Uwindow; X3*X7: Uwall*Qocc; X5*X6: $V_{OA} * T_{CL}$ (effect = 94.25)
- Thus, of the 7 factors and 21 2-factor interactions, it was found that 2 factors and at most 3 2-factor interactions seem important, with the remaining 5 factors and 21 interactions apparently being unimportant for the Veterinary Research Center.

5.4.5 **Block Effects**

In many experimental design problems, it is necessary to design the experiment so that the variability arising from a nuisance factor can be determined and controlled. For this research, the simulation results from four different buildings on the TAMU campus are used to analyze the significance of different input factors'. Different buildings may have a noticeable effect on the response values, and therefore should be considered when comparing the groups. On the other hand, such effects are generally presumed to exist; testing them is of secondary importance. Thus, the Box Plot in EDA is a good tool for conveying the location and Box plots (NIST 2003) are an excellent tool for conveying location and variation information in data sets, particularly for detecting and illustrating

block effects in different groups of data. As Figure 5.13 shows below, the box plot compares four buildings for RMSE of simulated and measured $-E_{BL}$, where

- Building 1—Eller O&M Building
- Building 2—Harrington Tower
- Building 3—Wehner Building
- Building 4—Veterinary Research Center

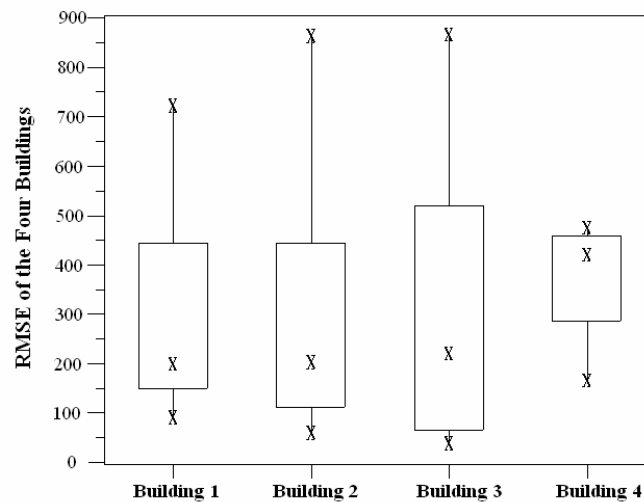


Figure 5.13 Box plot of the four buildings used for sensitivity analysis

The following conclusions can be made:

- The median for Building 4 is around 400, while the other 3 buildings have a similar median at 200;
- The spread (whiskers within 1.5 interquartile ranges from the first and third

quartiles) for Buildings 1, 2, and 3 is reasonably similar, and is larger than that of Building 4;

- Buildings 1, 2, and 3 are right skewed (asymmetric, with a long tail to the right), while Building 4 is left skewed.

There does appear to be a building effect. However, it mainly depends on whether or not the building has a heat recovery ventilator. In other words, if the building does not have a heat recovery system, the factor's significance order, variance of the response factor, and the fitting of the model should be similar to the Buildings 1, 2, and 3; If the building does have a heat recovery system, the situation should be similar with Building 4. Therefore, being notified whether the building has an installed heat recovery system should be important to the simulation.

5.4.6 Conclusions on Sensitivity Analysis

In this section, Exploratory Data Analysis (EDA) is implemented to perform sensitivity analysis on the Energy Balance Load simulation model, for which the 2^{7-3} fractional factorial experimental design is explored for four commercial buildings making use of the DataPlot program. Upon the sensitivity analysis results described above, two identical single factors and one set of confounded 2-factor interactions display sensitive impacts on the response variable, which include X5 (V_{OA}), X6 (T_{CL}), and X1*X2 (F*Uwindow) confounded with X3*X7 (Uwall *Qocc) as well as X5*X6 (V_{OA} * T_{CL}). Therefore, it can be concluded that parameters V_{OA} and T_{CL} are 2 key factors in the simulation of the Energy Balance Load, and change of their values will cause major variation of the RMSE. Although 3 confounded 2-factor interactions contribute

significantly large effects on the model output as well, the individual factors will be ignored in the simulation for simplicity. Thus, among the 7 factors tested by the experiments, V_{OA} and T_{CL} will be selected as the input parameters for the pre-screening program. Meanwhile, the remaining 5 parameters can be omitted, and these 2 factors need to be measured accurately in order to achieve a given precision in the model output. As for the building with heat recovery ventilator utilized such as the Veterinary Research Center, the main effects plot indicates that, besides V_{OA} , and T_{CL} , T_R has more effects on the model output than what it has on the 3 buildings without a heat recovery ventilator installed. Thus, it can be defined as a minor important factor in minimizing the simulation RMSE.

Consequently, V_{OA} and T_{CL} are the most important factors in Energy Balance Load calculation, and T_R should also be an important factor if the HVAC system of the building uses a heat recovery system. In other words, these 3 parameters in combination with the information including the area of floor, windows, and walls; and whether the HVAC systems have an economizer and heat recovery ventilator should be available as the input parameters while using the program to pre-screen measured data. The remaining 4 parameters, U_{win} , U_{wall} , F , and Q_{occ} could be set as default numbers in the program, and used to calculate the confidence interval of the simulation results.

5.5 Methodology for Uncertainty Analysis

Following the sensitivity analysis, uncertainty analysis is conducted as the next step in the research to determine the uncertainty influence caused by omitting several

unimportant variables from the simulation model. In addition, it is also desired to detect how the uncertainty of the input parameters affects confidence in the output of the simulation model.

Generally speaking, there are two statistical uncertainty analysis techniques. One is categorized as structured and the other one as a non-structured method (MacDonald and Strachan 2001). The structured method is derived from experimental techniques, in which a series of experiments are designed to analyze the outcome for predetermined models. Non-structured methods are stochastic in nature, and the most popular method for application is Monte Carlo Analysis (MCA).

MCA relies on the central limit theorem to provide an overall assessment of the uncertainty in the predictions being made. The Monte Carlo technique generates an estimate of the overall uncertainty in the predictions due to all the uncertainties in the input parameters, regardless of interactions and quantity of parameters. In the application of MCA, a probability distribution is first assigned to each input parameter under consideration. Values from within their probability distribution are randomly selected and simulations are run repeatedly. Given a large number of simulations, the uncertainty in the output parameter of interest will have a Gaussian distribution, irrespective of how the input parameter probability distributions appear. The main difficulty in employing MCA is the identification of the distributions that the input parameters are likely to have.

Comparing with the Monte Carlo method, the structured method does not require determining the probability distribution for each of the input parameters. To examine the uncertainties subjected to many resources, the analysis simply starts with operating a

base case simulation in which input parameters are set with the best estimates of the parameters under consideration. Then the simulation is repeated with lack-of-fit variables or any input parameter value changed within its possible variation limits, and the effect on the output parameter of interest noted.

The simpler approach for uncertainty analysis – the structured method based on experiments – will be employed in this research. The four buildings on the university campus selected for sensitivity analysis will have uncertainty analysis performed in this section as well. Consequent quantitative results will then be used as a general criteria to determine the confidence intervals with the data screening tool; this will make it possible to detect the measurement faults.

5.6 Uncertainty Analysis Results

The three major causes of the uncertainty to the response variable of the simulation model include the omission of influencing variables from the simulation model, the uncertainties of the input parameters obtained through observation or measurements, and the incomplete model due to the simplification or assumption made to the simulation model. Uncertainty analysis results according to the different error sources are developed and represented in the section below, and then the confidence interval of the simulation result under the consideration of the uncertainties is provided.

5.6.1 Uncertainties Due to Simpler Model

According to the conclusions retrieved from sensitivity analysis, 3 of the 7 factors picked for sensitivity experiments, including the room temperature, the cold deck set

point, and the outside air intake volume, are shown to be the most important input parameters to the Energy Balance Load (E_{BL}) simulation. The more accurate these 3 parameters values, the closer the outcome variable of the simulation model to the true value. On the other hand, as the remaining input parameters are not dominant factors to the simulation model, and their values change little from building to building, they can be omitted for detailed exploration and default numbers will replace the corresponding numbers used in the simulation model instead. For the typical construction materials of the buildings on the campus of Texas A&M University (for example 1/8-inch clear single glazing with aluminum frame, insulated frame walls with 1/2-inch gypsum wallboard, steel framing members, and mineral fiber insulation), default parameter values can be set based on values in the ASHRAE Handbook of Fundamental (ASHRAE 2001). Moreover, the area of the exterior walls and windows can be approximately set as fractions of the total floor area (A_{wall} is 30% of A_{total} , and A_{window} is half of the A_{wall}), and heat gain from occupants is set as a fixed number as $6 \text{ Btu} / \text{ft}^2 \cdot \text{day}$, where assumes $\rho = 400 \text{ ft}^2 / \text{person}$, $t = 10 \text{ hr} / \text{day}$, and $q_{individual, sen} = 240 \text{ Btu} / \text{person}$). Default parameter values are represented in Table 5.12.

Table 5.12 Default value settings for the unimportant parameters to the simulation model

	Parameter	Default Value	Unit
Factor 1	F	0.87	
Factor 2	U_{window}	0.98	$Btu / h \cdot ft^2 \cdot ^\circ F$
Factor 3	U_{wall}	0.2	$Btu / h \cdot ft^2 \cdot ^\circ F$
Factor 7	Q_{occ}	6	$Btu / ft^2 \cdot day$
Exterior Walls Area	A_{wall}	$0.3A_{floor}$	ft^2
Exterior Windows Area	A_{window}	$0.15A_{floor}$	ft^2

Simulation with the reduced factor model in terms of the default values for the unimportant parameters will be run for each of the four buildings, respectively. The root mean squared error (RMSE) between the outcomes from the simpler and the complete simulation models will be provided as an index, which can evaluate whether or not the reduced input parameters of the Energy Balance Load calculation model are suitable, and how much uncertainty it contributes to the prediction of the Energy Balance Load.

Table 5.13 Test results on the four buildings with reduced factor model

Building Name	RMSE ($Btu / ft^2 \cdot day$)
Eller Oceanography & Meteorology Building	3.7
Veterinary Research Center	10.9
Wehner Building	4.3
Harrington Tower	18.9

Table 5.13 above records the results of the reduced factor model on the Eller Oceanography & Meteorology Building, Veterinary Research Center, Wehner Building,

and Harrington Tower in terms of outside air temperature in year 2000. The difference between the outcome from the complete and the simplified model, which can be represented by RMSE, is less than $20 \text{ Btu} / \text{ft}^2 \cdot \text{day}$ and about $9.45 \text{ Btu} / \text{ft}^2 \cdot \text{day}$ as an average. Consequently, it can be concluded that if the lack-of-fit model with omission of several influencing variables is applied to the prediction of the Energy Balance Load, the implementation of the lack-of-fit model instead of the complete simulation model may contribute about $10 \text{ Btu} / \text{ft}^2 \cdot \text{day}$ uncertainty to the response variable.

5.6.2 Uncertainties Due to Variation of Input Parameters

With the omission of the unimportant factors, there are 3 input parameters left in the Energy Balance Load simulation model, which include the room temperature, outside air intake volume, and the cold deck set temperature of the HVAC system. Operation documents checking and field measurements are typical approaches to determine the values of these 3 variables. However, the actual operation schedule is often different from what is set under the design conditions, and measurement errors usually exist, both of which will lead to uncertainties in these values.

In this section, the effect of uncertainties in the input parameters on the model prediction error is evaluated approximately. The method employed here assumes the uncertainty limit of the input parameters from their measured values is $\pm 1\text{-}3^\circ\text{F}$ for the room temperature (T_r) and cold deck set point (T_{CL}), while $\pm 10\%$ for fresh air intake volume (V_{OA}) respectively. Simulation is run by changing any of the 3 parameters one at a time to the maximum within its presumed uncertainty limits, and then comparing the

response variable with the original measured input parameter values to investigate the uncertainty effect of each factor on the simulated result. As in previous sections, the analysis will be performed on the Eller Oceanography & Meteorology Building, Veterinary Research Center, Wehner Building, and Harrington Tower using outside air temperatures in year 2000 to produce a more general criterion.

Table 5.14A Effects of variation of input parameters on prediction errors

Building Name	Input Parameter	Original Values	Variant Values	RMSE (<i>Btu / ft² · day</i>)
Eller Oceanography & Meteorology Building	T_R	70	73	27.6
	T_{CL}	55	58	21.6
	V_{OA}	0.22	0.242	17.2
Veterinary Research Center	T_R	70	73	63.1
	T_{CL}	56	59	62.6
	V_{OA}	0.62	0.682	43.3
Wehner Building	T_R	75	78	17.1
	T_{CL}	58	61	3.8
	V_{OA}	0.06	0.066	6.2
Harrington Tower	T_R	72	75	22.5
	T_{CL}	58	61	6.5
	V_{OA}	0.13	0.143	11.9

The root mean square error of the predicted Energy Balance Load developed with variant input parameter values listed in Table 5.14A represents the effect of uncertainties in individual variables on the simulation result. By assuming that the errors from different variables are independent of each other, the uncertainty of the simulated Energy Balance Load that relies on the input parameters can be determined as:

$$RMSE_{E_{BL, var}} = [(RMSE_{T_R})^2 + (RMSE_{T_{CL}})^2 + (RMSE_{V_{OA}})^2]^{1/2} \quad (5.2)$$

Consequently, the uncertainty analysis results presented in Table 5.14(a) can be updated to Table 5.14B, where the root mean square error (RMSE) of the four buildings is no larger than $100 \text{ Btu} / \text{ft}^2 \cdot \text{day}$, and the average value is $45.7 \text{ Btu} / \text{ft}^2 \cdot \text{day}$.

Table 5.14B Effects of variation of input parameters on prediction errors

Building Name	RMSE ($\text{Btu} / \text{ft}^2 \cdot \text{day}$)
Eller Oceanography & Meteorology Building	38.9
Veterinary Research Center	98.86
Wehner Building	18.55
Harrington Tower	26.3

5.6.3 Uncertainties Due to Other Sources

Due to the simplified methodology used in the research to analyze the Energy Balance Load, some factors that affect the accuracy of the simulation model have not been investigated, therefore corresponding adjustment is explored here.

In the research, solar radiation is assumed to be a linear function of the average daily outside air temperature, which in reality is a reasonable approximation for time periods, but on cloudy days, it may be as little as 20% of this value and as much as 150% of this value on clear days. Thus, 0.2 and 1.5 times of the current calculated solar radiation is

applied respectively to the simulation model, which results in an average RMSE of 25 $Btu / ft^2 \cdot day$.

The solar radiation on the opaque surface of the building is excluded from the simulation. To adjust for this, a solar heat gain coefficient factor, F_{wall} , similar to what has been used for solar radiation through the windows is introduced, which can be presented as $F_{wall} = \tau_{wall} + \alpha \frac{U_{wall}}{h_{o,wall}} \approx 0.124$. By adding this part of the heat gain simulation to the original model, an RMSE of 11.6 $Btu / ft^2 \cdot day$ can be estimated.

The heat gain from the occupancy in the building is assumed as a fixed factor, which is independent of the different building operation hours for weekdays and weekends. If the Q_{occ} is averaged to 5 $Btu / ft^2 \cdot day$ by considering the weekday/weekend distinction, the simulation result has an RMSE of 1.6 $Btu / ft^2 \cdot day$ compared to that from the initial set up.

Factors due to wind forces that affect the infiltration rate can be estimated by knowing the opening area, the pressured difference across it, and the discharge coefficient of the opening area (ASHRAE 2001), which can be illustrated as follows:

$$V_{OA} = C_A A_{opening} \sqrt{\Delta p} \quad (5.3)$$

where C_A = airflow coefficient, approximately 700-1000 $cfm / ft^2 \cdot (in. \text{ of water})^{0.5}$

$A_{opening}$ = free area of inlet openings, assumed to be $0.0002A_{floor}$, ft^2

Δp = pressure difference across the building, which can be determined by

$$\Delta p = \Delta C_p \frac{\rho}{2} v_{wind}^2, \text{ in. of water}$$

By selecting an average wind speed of 9.4 *mph* (Texas Climate 2004), a typical pressure coefficient of 0.5, and a standard air density of 0.075 *lb_m / ft³*, an estimated value of Δp is approximately 0.025 *in. of water*. Applying these values to Equation (5.3), the air infiltration rate to the building is within the range of 0.022 to 0.032 *cfm / ft²*. The simulation model is modified to include the impact from the infiltration due to the air pressure across the building, and results in an average RMSE of 31 *Btu / ft² · day*.

The uncertainty of the simulated Energy Balance Load, due to the factors analyzed in this section, can be merged into one factor defined as $RMSE_{E_{BL}, \text{other}}$, which is around 41 *Btu / ft² · day*.

5.6.4 Confidence Interval of Simulated E_{BL}

To provide the necessary information with which to make engineering or scientific decisions, predictions from process models are usually given as intervals of plausible values that have a probabilistic interpretation. In particular, intervals that specify a range of values that will contain the value of the predicted value with a pre-specified probability are often used. These intervals are called confidence intervals (Montgomery and Runger 1999). The probability with which the interval will capture the true value of the regression function is called the confidence level, and is most often set by the user to

be 0.95, or 95% in percentage terms. The higher the confidence level is set, the more likely the true value is to be contained in the interval. The trade-off for high confidence, however, is wide intervals. The confidence level of an interval is usually denoted symbolically using the notation $1-\alpha$, with α denoting a user-specified probability, called the significance level, that the interval will not capture the true value of the model function. The significance level is most often set to be 5% so that the associated confidence level will be 95%.

Confidence intervals are computed using the estimated standard deviations of the predicted response variable values and a coverage factor that controls the confidence level of the interval and accounts for the variation in the prediction of the residual standard deviation. The standard deviations of the predicted values of the response variable depend on the standard deviations of the random errors in the data, the experimental design used to collect the data and fit the model, and the values of the predictor variables used to obtain the predicted values. With this concept, the confidence interval of E_{BL} could be determined through:

$$E_{BL} - \varepsilon_{E_{BL}} \leq E_{BL} \leq E_{BL} + \varepsilon_{E_{BL}} \quad (5.4)$$

For an approximately linear simulation model of the Energy Balance Load (E_{BL}), with temperature (T) as the independent variable, the uncertainty associated with predicting E_{BL} is:

$$\varepsilon_{E_{BL}} = t_{\frac{\alpha}{2}, n-2} RMSE_{E_{BL}} \left[1 + \frac{1}{n} + \frac{(T_d - \bar{T})}{\sum_{d=1}^n (T_d - \bar{T})^2} \right]^{1/2} \quad (5.5)$$

The t-statistic, $t_{\frac{\alpha}{2}, n-2}$, is a function of the level of significance (α), the total number of sample cases in the simulation process (n), and the number of parameters in the mode (p). The level of significance (α) indicates the fraction of predictions that are likely to fall outside of the prediction confidence intervals. In reality, the value of the parenthesis term is usually very close to unity, and the value of the t-statistic is close to 1.96 for a reasonable number of 1 year round measured data set and a 5% significance (95% confidence). Thus, $\varepsilon_{E_{BL}}$ can be closely approximated as:

$$\varepsilon_{E_{BL}} = 1.96 RMSE_{E_{BL}} \left[1 + \frac{2}{n} \right]^{1/2} \quad (5.6)$$

The uncertainty of the simulated E_{BL} is subjected to 3 major causes: (1) the omission of influencing variables from the simulation model; (2) the uncertainties of the input parameters obtained through observation or measurements; and (3) the incomplete model due to the simplification or assumptions made to the simulation model. If the errors caused by those 3 sources are assumed to be independent between each other, the root mean square error of the simulated E_{BL} relative to the true value, $RMSE_{E_{BL}}$, can be written as:

$$RMSE_{E_{BL}} = \left[(RMSE_{E_{BL}, \text{model}})^2 + (RMSE_{E_{BL}, \text{var}})^2 + (RMSE_{E_{BL}, \text{other}})^2 \right]^{1/2} \quad (5.7)$$

The average values of $RMSE_{E_{BL},model}$ and $RMSE_{E_{BL},var}$ for the four buildings selected for sensitivity and uncertainty analysis are applied to Equation (5.7) to generate a more general criterion of $RMSE_{E_{BL}}$, which turns out to be $62.2 \text{ Btu} / \text{ft}^2 \cdot \text{day}$.

Consequently, the normalized $RMSE_{E_{BL}}$ can be used in the Equation (5.5) to determine the confidence interval of the simulated E_{BL} and then screen out the sensor measurement faults. The pre-screening method, in terms of the confidence interval applied to the Wehner Building with the data in year 2000, is given as an example in Figure 5.14. The two linear lines parallel to the line crossing the point “0” the represent the confidence intervals, and the measured Energy Balance Load locating outside of these two boundaries are regarded as suspicious data requiring for further investigation.

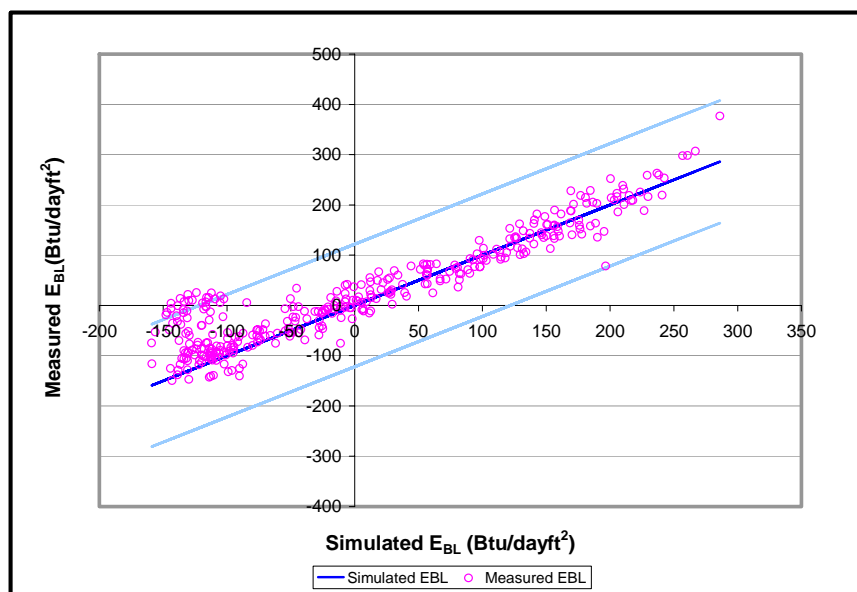


Figure 5.14 Cross-check plot of the measured and simulated Energy Balance Load of the Wehner Building for year 2000

5.7 Summary

This chapter applies the sensitivity and uncertainty analysis to the methodology of analytical redundancy implemented in the pre-screening of sensor measurement faults. The most important input factors to the simulated Energy Balance Load are identified through sensitivity analysis, and the uncertainties in the outcome of the simulation model, according to the omission of unimportant factors and the errors of the measured or estimated input parameters, are evaluated via uncertainty analysis. Consequently, a confidence interval with an approximate value has been developed in this chapter as well, which will be used in the automatic pre-screening program introduced in the following chapter to filter out the faulty measured data.

CHAPTER VI

PRE-SCREENING PROGRAM

6.1 Introduction

The main goal of this research is to use first law energy balance in conjunction with the concept of analytical redundancy to develop an accurate data screening method suitable for automated application; it should also increase the efficiency of gross fault checking in sensor measurements.

Based on the conclusions from the previous chapters, the newly introduced outside air temperature dependent term, Energy Balance Load (E_{BL}), can be implemented as the analytically redundant variable to the measured building energy consumption, and comparison between E_{BL} and measured data can be used to pre-screen the signal faults. A detailed and simplified simulation process of the Energy Balance Load, as well as the sensitivity and uncertainty analysis to the methodology, has been studied. If these procedures are programmed into a file to pre-screen the energy use data, it can perform the data analysis, identify the faulty measurements automatically, and then improve the accuracy and efficiency of the data screening method.

Microsoft® Office Excel is the first development tool to provide the advantages of both spreadsheets and visual programming tools. It contains various types of worksheet functions such as mathematical, financial, lookup, and database for application in its

spreadsheet. Visual Basic for Applications (VBA) is a programming language that allows users to program complex tasks within an application. Excel VBA, a general purpose programming language, which comes standard with Microsoft Excel 2000[®] or Microsoft Office 2000[®], can be used to construct high-end engineering tools. Excel VBA can be used for such tasks as communicating with databases, scanning and analyzing worksheet data, automating chart construction, performing calculations, performing simulations, communicating with other languages such as FORTRAN and C, creating wizards (i.e., dialog boxes), creating GUIs, etc.

Thus, for the fault detection for building energy consumption data in association with analytical redundancy, which involves a complicated simulation and data analysis process, a program developed with Microsoft Excel 2000[®] with VBA would probably satisfy the requirements of handling huge amounts of data easily and accurately. This chapter deals with the description and implementation of the VBA program named the “Energy Balance Pre-Screening Toolkit.”

6.2 Overview

The simulation program is mainly made up of four parts: (1) information input; (2) Energy Balance Load prediction; (3) data pre-screening; and (4) outputs. These four parts of the process are operated in order.

A Microsoft Excel[®] file is developed as the carrier of the Energy Balance Pre-Screening Toolkit. A user interface (UI), which should be the means by which an end user communicates with the program, will show up automatically as the Excel[®] file

opens, and requires the user to input the values of the necessary parameters for the simulation process. This interface is built with the consideration that even the audience that consists of the relatively inexperienced can apply it, which can be seen in Figure 6.1. The information gathered in the interface is used to initiate collecting the daily weather data for the specific time period and to load the weather data into a worksheet which is invisible to the user. The daily weather information, which includes the outside dry bulb and wet bulb temperature, as well as the calculated solar insolation data, in conjunction with the building and system information, is used to predict the Energy Balance Load. Measured data is also required to be input in the program file, and faulty data can be screened out with the comparison of the measured and predicted energy consumption data. The outputs provided by the program include the time series and temperature-based plots for each type of the energy consumption data, the summary table containing the building and system information, the temperature-based and cross-check plot of the measured and predicted Energy Balance Load, and the list of all suspicious data identified through the pre-screening process.

The simulation program is organized in a way to be easily understood and operated.. The user-friendly interface helps to correlate the four major parts tightly, and orient the operation process to pre-screen out the measured data faults. It requires only simple parameter input, and then most of the other data tables and figures involved in the simulation and screening process will be created automatically. The functions and the relationships among these four parts are presented in detail in the following section.

Energy Balance Pre-Screening Toolkit

Building Name: Site Number: Year:

HVAC System:

Floor Area: ft² Heat Recovery System: Yes No

Room Temperature: °F Economizer: Yes No

Out Side Air Flow Rate: CFM/ft²

Preheat Deck Schedule:

Constant °F

Variable Toa °F

Thl °F

Cold Deck Schedule:

Constant °F

Variable Toa °F

Tcl °F

Apply *Simulate* *Reset* *Exit*

Data Plot *Pre-Screening Plot* *Summary Report*

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Figure 6.1 User interface of the Energy Balance Pre-Screening Toolkit

6.3 Program Description

Described in the following section are the four parts of the simulation program and how they are related to each other to complete the whole pre-screening process.

6.3.1 Information Input

Information input is the first step of the entire simulation program. By opening the Energy Balance Pre-Screening Toolkit, the user interface shown in Figure 6.1 jumps out to the user automatically, where the building and HVAC system information and parameter values, which are used to collect weather data and predict the Energy Balance Load, are required to be input here. The information or parameter values that users are required to input in the interface include:

- **Building Name:** The name of the building;
- **Site Number:** A three-digit number that corresponds to the building in the Energy Systems Laboratory Database;
- **Year:** Which year of data to test; user can choose the year through the drag down box;
- **HVAC System:** Type and number of the HVAC systems the building has installed; user can select the number from the spin button, and choose the system type from the drag down box;
- **Floor Area:** Total floor area of the building;
- **Room Temperature:** Room temperature set point of the building;
- **Outside Air Flow Rate:** Flow rate of the outside air intake into the building through the HVAC system;

- **Heat Recovery Ventilator:** Check the option box to indicate whether the building has a heat recovery system in use;
- **Economizer:** Check the option box to indicate whether the building has an economizer in use;
- **Preheat Deck Schedule:** This option is specific for the system with a heat recovery ventilator; if it is checked as “No,” input for the preheat deck schedule will be disabled. The preheat deck set point could be constant or variable. The constant preheat deck schedule could be entered if option box “Constant” is checked. Assuming the variable deck schedule is linearly related with outside air temperature, the lowest and highest temperatures at which the preheat deck schedule turns to constant, as well as the corresponding deck set points, are both required for this simulation program;
- **Cold Deck Schedule:** Similar to the Preheat Deck Schedule input, though it is not for any specific system.

There are seven click buttons at the bottom of the user interface, as shown in Figure 6.1, including “Apply,” “Simulate,” “Reset,” “Exit,” “Data Plot,” “Pre-Screening Plot,” and “Summary Report.” Among them, “Apply” and “Reset” are designed for the first step. By clicking the button called “Reset,” all information inputted will be cleaned from the screen, and then the user can type in the new set of information. By clicking the button named “Apply,” the program will be given a command to collect the weather

information as daily data of the year, with which the user incline to detect the signal faults.

The ambient weather data of College Station, TX is used for this research project, since it is the closest weather station to Texas A&M University. Hourly weather data is recorded in the Energy Systems Laboratory Database as Channels 707 and 708 consisting of dry bulb and wet bulb temperature. To efficiently and easily service the simulation program, a Microsoft® Office Access file is created as an attachment, in which the hourly dry bulb and wet bulb ambient temperature data from years 1992 through 2003 has been converted into daily data. When the program receives the requirement of collecting weather data, corresponding codes will guide the system to retrieve data from the Microsoft® Office Access file and place it into a worksheet, which is invisible to the user.

6.3.2 Energy Balance Load Prediction

By clicking the button “Simulate,” the program will automatically initiate the following calculation in a worksheet of the Excel® file: solar insolation to the building, heat transfer through the windows, the walls, and air ventilation, and heat gain from the occupants. As shown in Chapter III, each of the loads to the building except that from occupants can be expressed as a function of ambient temperature. Thus, the building load data for each daily time interval can be predicted in terms of the temperature data and building and/or system information. The Energy Balance Load then can be predicted by appropriately combining all term of the building loads.

Subsequent to this process, a message box will show up instructing the user to input the measured energy consumption data in three designated columns, as shown in Figure 6.2.

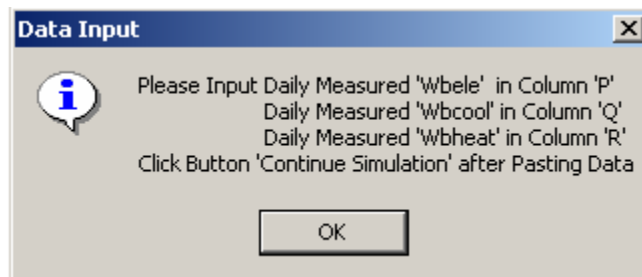


Figure 6.2 Message box indicating input of the measured data

After the user has pasted the measured data in the worksheet, shown in Figure 6.3, and clicked the “Continue Simulation” button, the program will routinely validate the pasted measured energy consumption data by criteria of numerical and non-blank data. If all data is valid, daily simulated and measured Energy Balance Load becomes visible instantly, as well as the yearly base root mean square error (RMSE) between them. Meanwhile, the confidence intervals of the simulated Energy Balance Load can be determined by assuming the confidence coefficient is 95%, and the measured data outside the confidence intervals will be noted as suspicious data requiring for further investigation. Additionally, a clickable button shown as “Return to Menu” can lead the user back to the program interface.

Date	Outdoor F	Indoor %	Measured Whole MMBtu/day	Measured Wcool MMBtu/day	Measured Wheat MMBtu/day	Continue Simulation	Simulated EBL Btu/#2/day	Measured EBL Btu/#2/day	Residual*2	RMSE
1/1/2000	64.40	66.93	14.20	14.62	16.86		64.14	70.79	44.16	42.65
1/2/2000	71.77	81.51	14.50	18.22	11.66		-2.60	26.25	832.57	
1/3/2000	66.20	38.36	20.30	17.42	14.11		52.01	67.32	234.55	
1/4/2000	44.25	42.19	20.99	11.22	32.06		199.29	196.00	10.77	
1/5/2000	46.18	43.76	21.60	11.71	33.83		186.35	205.17	354.19	
1/6/2000	52.48	90.79	21.47	13.02	25.19		144.09	152.84	76.58	
1/7/2000	51.22	98.65	21.32	12.32	27.15		152.54	166.07	183.14	
1/8/2000	50.99	97.55	17.64	10.52	30.59		154.09	178.04	573.24	
1/9/2000	57.43	80.96	17.49	13.02	26.66		110.88	143.95	1093.94	
1/10/2000	61.60	30.52	22.49	16.13	22.45		82.89	126.64	1913.77	
1/11/2000	68.28	64.00	23.12	18.63	20.29		38.09	104.97	4472.83	
1/12/2000	74.53	77.76	23.50	24.23	12.64		-24.95	37.56	3907.31	
1/13/2000	68.99	60.50	23.06	20.43	14.99		33.31	67.77	1187.28	
1/14/2000	57.15	23.20	22.27	15.72	21.96		112.72	125.27	157.43	
1/15/2000	60.10	67.23	17.24	15.62	22.35		92.98	106.83	191.91	
1/16/2000	65.76	77.76	17.13	16.82	18.03		54.97	77.66	514.97	
1/17/2000	66.06	79.59	19.64	18.33	17.35		51.51	76.72	635.09	
1/18/2000	68.73	78.33	26.39	29.75	18.52		28.51	51.50	528.42	
1/19/2000	66.23	71.42	26.96	27.04	14.90		51.82	49.12	7.33	
1/20/2000	54.73	41.48	26.49	19.33	18.33		128.97	105.17	566.25	
1/21/2000	48.51	54.78	25.42	15.12	24.31		170.69	153.79	285.51	
1/22/2000	65.54	85.42	18.16	16.22	13.72		51.53	62.66	123.92	
1/23/2000	60.71	66.75	19.10	15.22	16.27		88.88	85.06	14.57	
1/24/2000	48.29	53.45	26.59	16.43	23.62		172.17	148.29	570.21	
1/25/2000	48.15	45.65	26.44	15.62	23.13		173.07	149.26	566.85	
1/26/2000	42.88	41.99	26.34	12.62	29.32		208.49	196.74	138.15	
1/27/2000	38.85	77.01	25.98	10.92	36.77		235.47	242.87	54.72	
1/28/2000	33.31	89.56	24.73	9.02	44.51		272.63	287.91	233.52	
1/29/2000	34.39	77.42	18.69	7.01	45.88		265.37	280.35	224.39	

Figure 6.3 Simulation worksheet

6.3.3 Data Pre-screening

“Data Plot” and “Pre-Screening Plot” are two options giving the user some graphical views focusing on the data characterization aspect. By doing so, it may help the user have the most natural and direct insight into the trend of data variation based on time or outside air temperature.

When selecting the “Data Plot,” a worksheet containing 6 plots will be automatically created, as shown in Figure 6.4. All of these 6 plots are derived from the measured energy consumption, among which the time series plot of daily measured electricity, cooling energy and heating energy consumption, as well as the outside air dry bulb temperature, are individually provided. The other two plots represent the behavior of

each kind of energy consumption as a function of the outside air temperature, and a time series plot of the Energy Balance Load.

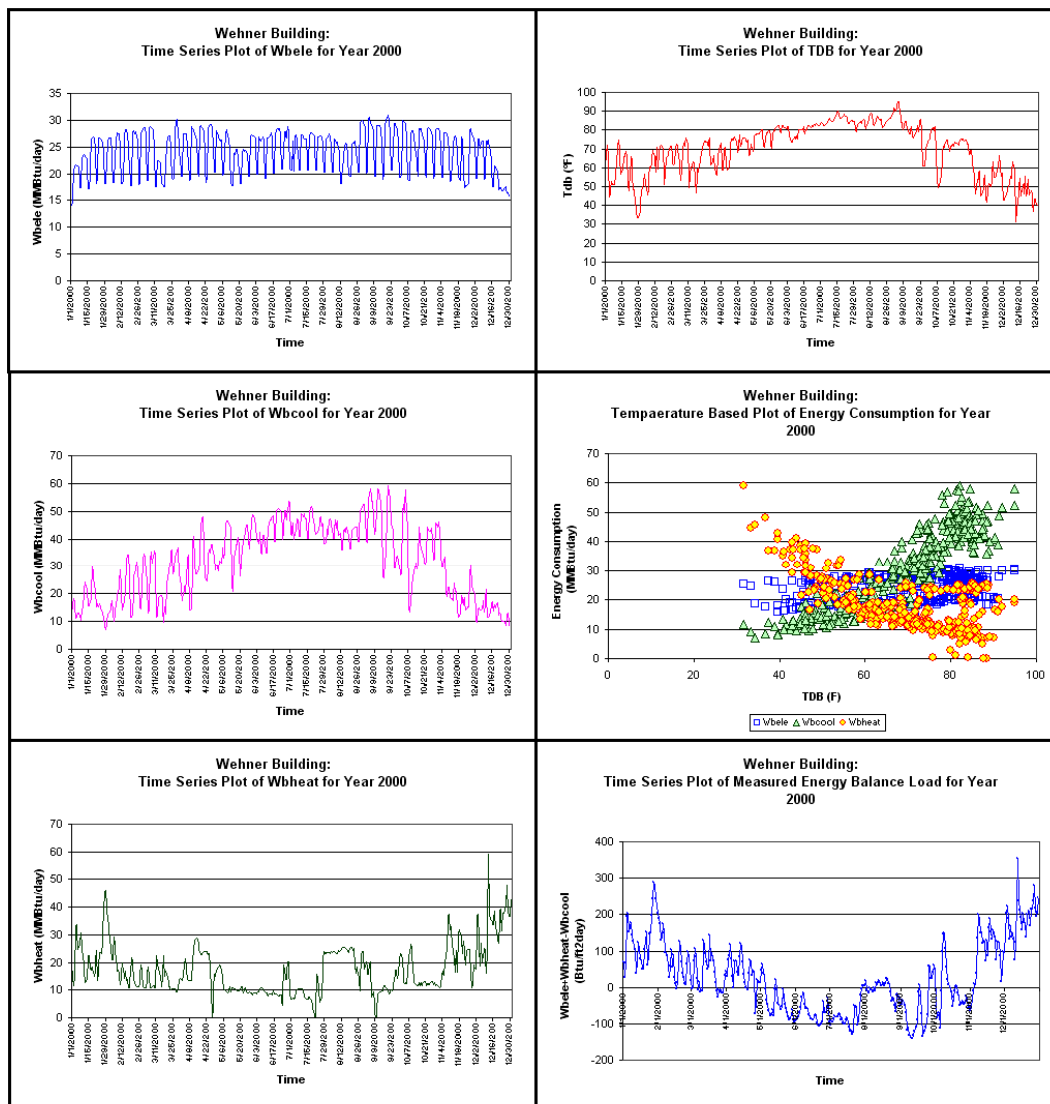


Figure 6.4 Data plot

Similarly, the “Pre-Screening Plot” consists of two graphs. One of them is the comparison plot of simulated and measured Energy Balance Load as a function of the

outside air temperature. Besides the data series representing simulated and monitored Energy Balance Load, the suspicious data rejected by screening is also marked by different color and style. The other plot is the cross-check plot, which displays the measured Energy Balance Load as a function of the simulated E_{BL} . This type of check would typically be expected to produce a linear trend line, the more linear the trend line the better the model. Two boundaries referring to the upper and lower limit of the confidence intervals filter the data outside it as suspicious enough to investigate with 95% confidence. From either pre-screening plot, the user can select to print the plot, switch to the other plot, or return to the main menu by clicking the buttons set at the right corner of the plot, shown in Figure 6.5.

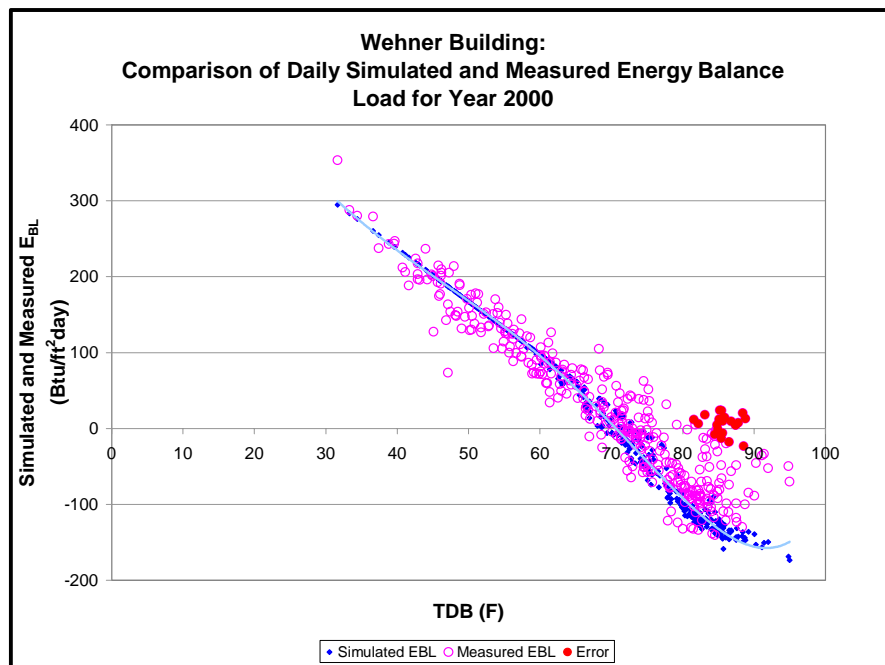


Figure 6.5 Pre-Screening plot

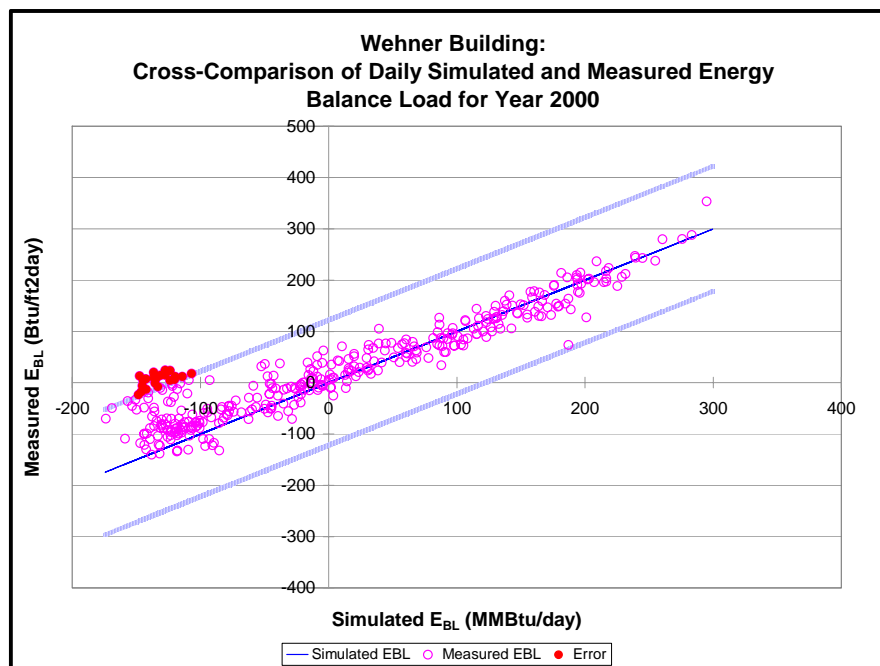


Figure 6.5 Continued

6.3.4 Summary Report

One desired feature of this program is to create a summary report for the user automatically, which intends to give the user a complete and well organized table covering all information the pre-screening program requested for the simulation process, the pre-screening plots the program carried out, and detailed unreliable data detected for further investigation. For example, in Figure 6.6, the first part of the summary report is an input parameter table. Generally, parameter values, building, and HVAC system variables inputted in the interface are shown in the table in addition to the program default values utilized in the Energy Balance Load calculation. The second part of the summary report is formatted pre-screening and cross-check plots, with suspicious data

clearly marked. In Figure 6.7 is a detailed list of the “bad” data in as a time order, including daily outside air temperature, relative humidity, measured electricity, cooling and heating energy consumption, and Energy Balance Load derived from thermal energy equation and monitored data. Two functional buttons are available for the user to print the summary report or return to the main menu.

Date	Oadrybulb	Oarh	Measured Wbele	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Btu/ft2day	Btu/ft2day
1/1/2000	64.40	66.93	14.20	14.62	16.86	66.89	70.79
7/29/2000	84.83	63.18	20.23	38.46	23.13	-123.73	4.45
8/1/2000	83.11	63.94	26.82	41.66	23.62	-106.82	17.78
8/5/2000	84.91	68.89	20.38	40.26	23.81	-135.18	-0.74
8/6/2000	85.58	70.29	20.39	41.26	23.81	-145.21	-5.93
8/7/2000	85.42	69.74	26.42	47.07	23.42	-142.37	-13.11
8/9/2000	84.49	70.40	26.00	46.57	24.21	-133.26	-8.13
8/10/2000	85.87	59.23	24.93	41.26	24.11	-127.40	14.55
8/11/2000	87.81	56.53	24.12	42.16	24.30	-142.57	7.52
8/12/2000	88.80	53.78	18.31	37.05	24.89	-147.37	12.96
8/13/2000	88.43	50.37	18.17	36.05	25.38	-136.54	20.14
8/14/2000	85.11	59.40	23.97	42.46	25.58	-119.76	11.94
8/15/2000	82.20	77.52	24.53	43.57	25.09	-120.25	5.99
8/16/2000	85.68	62.30	25.68	42.56	24.79	-131.22	14.46
8/17/2000	87.42	59.65	25.56	44.17	24.50	-144.67	4.06
8/18/2000	86.80	57.80	24.27	41.06	23.42	-134.45	9.25
8/19/2000	85.44	59.58	19.69	36.35	25.09	-123.57	23.39
8/20/2000	85.22	62.91	19.46	36.45	25.48	-127.40	23.95
8/21/2000	85.64	65.40	25.39	42.96	24.50	-136.48	9.64
8/22/2000	81.57	77.97	25.77	43.47	25.09	-113.98	11.64
8/29/2000	86.51	65.36	29.79	50.77	23.52	-146.04	-17.82
8/30/2000	88.57	55.47	29.96	52.37	23.91	-148.41	-23.40

Figure 6.6 Suspicious data list detected by Pre-Screening Toolkit

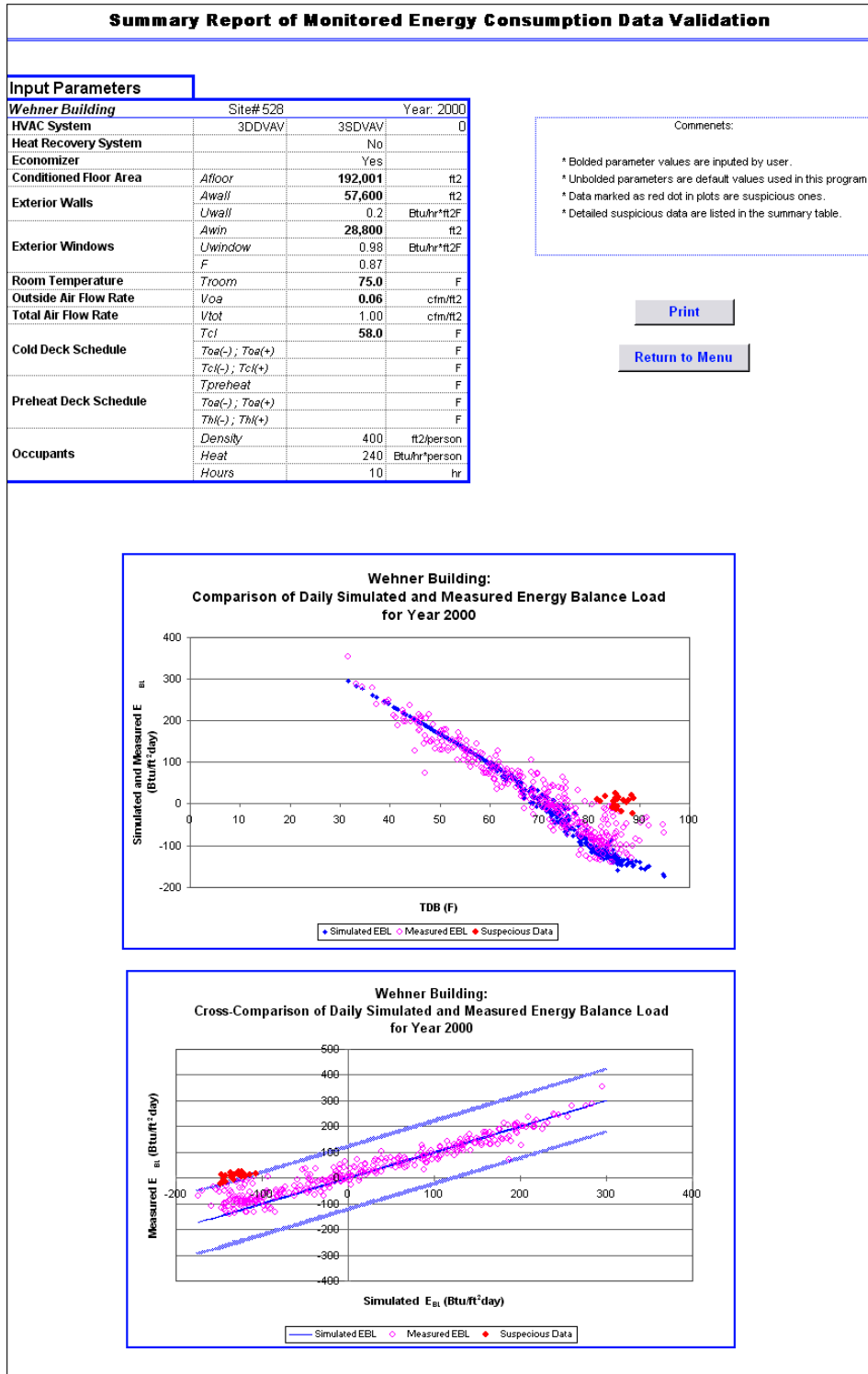


Figure 6.7 Summary report

6.3.5 Others

The “Exit” option will lead the user to quit the Energy Balance Pre-Screening Toolkit, “Save the changes to file” will be asked for the user before completely closing the file.

Opening the file will initiate the program to load specific menu bars of its own, all functions the Pre-Screening Toolkit can provide, are listed in the menu bar. From the menu bar, the user can switch to wherever he/she would like to investigate.

The VBA codes created for this Energy Balance Pre-Screening Toolkit are documented as Appendix A, and the copyright belongs to the Energy Systems Laboratory, Texas A&M University.

CHAPTER VII

CASE STUDIES

7.1 Introduction

As stated in previous chapters, the quality of the measured building energy consumption data is essential to apply the advanced control, assess the system/component performance, and evaluate the saving resulting from the implementation of energy retrofits and operational improvements. First law energy balance, in conjunction with the concepts of analytical redundancy and trend checking, has been discussed in this research to validate the sensor signals. Moreover, an Excel[®] VBA program named the Energy Balance Pre-Screening Toolkit has been developed, which aims to detect the faulty measured consumption data automatically with knowledge of a few building and system characteristics.

To test the performance of the methodology and the program, the measured data of six buildings on the Texas A&M University campus are selected to be pre-screened by the program. They are the Harrington Tower, Eller O&M (Oceanography and Meteorology) Building, Veterinary Medical Center, Wehner Building, Zachry Engineering Center, and Halbouty Geosciences Building.

The measured electricity, cooling energy, and heating energy consumption of these buildings can be retrieved from the Energy Systems Laboratory Database. The database

also records a small amount of information about the building, for example, the floor area and construction data. Unfortunately, it does not contain the specific information about the building and HVAC system, which is required for the Energy Balance Load simulation. Thus, field observation, document investigation, and interviews and discussions with CC[®] engineers are necessary for this research to obtain the required parameter values.

7.2 Pre-Screening Case 1: Harrington Tower

7.2.1.1 Site Description

Harrington Tower is located on the main campus of Texas A&M University. Harrington Tower is an eight story building consisting of classrooms, offices, and computer centers, which has a gross area of 130,844 square feet. The indoor environment comfort (72°F) is maintained by the operation of 1 large dual duct variable volume and 3 small single duct variable volume air handling units, where the cold deck set point averages 58°F, and the outside air intake volume is $0.13 \text{ cfm} / \text{ft}^2$. The energy consumed in this building is measured and monitored by the Energy Systems Laboratory, and the site number used as identification of this building is 509. With this information, the Energy Balance Load can be simulated and used as a fault detection factor; the measured data for year 2000 is selected to be pre-screened for signal faults.

7.2.1.2 Application of Energy Balance Pre-Screening Toolkit

The Energy Balance Pre-Screening Toolkit is used to automatically detect the data faults of Harrington Tower for year 2000, and the summary report is shown in Figure 7.1.

It may be concluded that the measured energy consumption data of the Harrington Tower had suspicious data in some parts of July and August 2000.

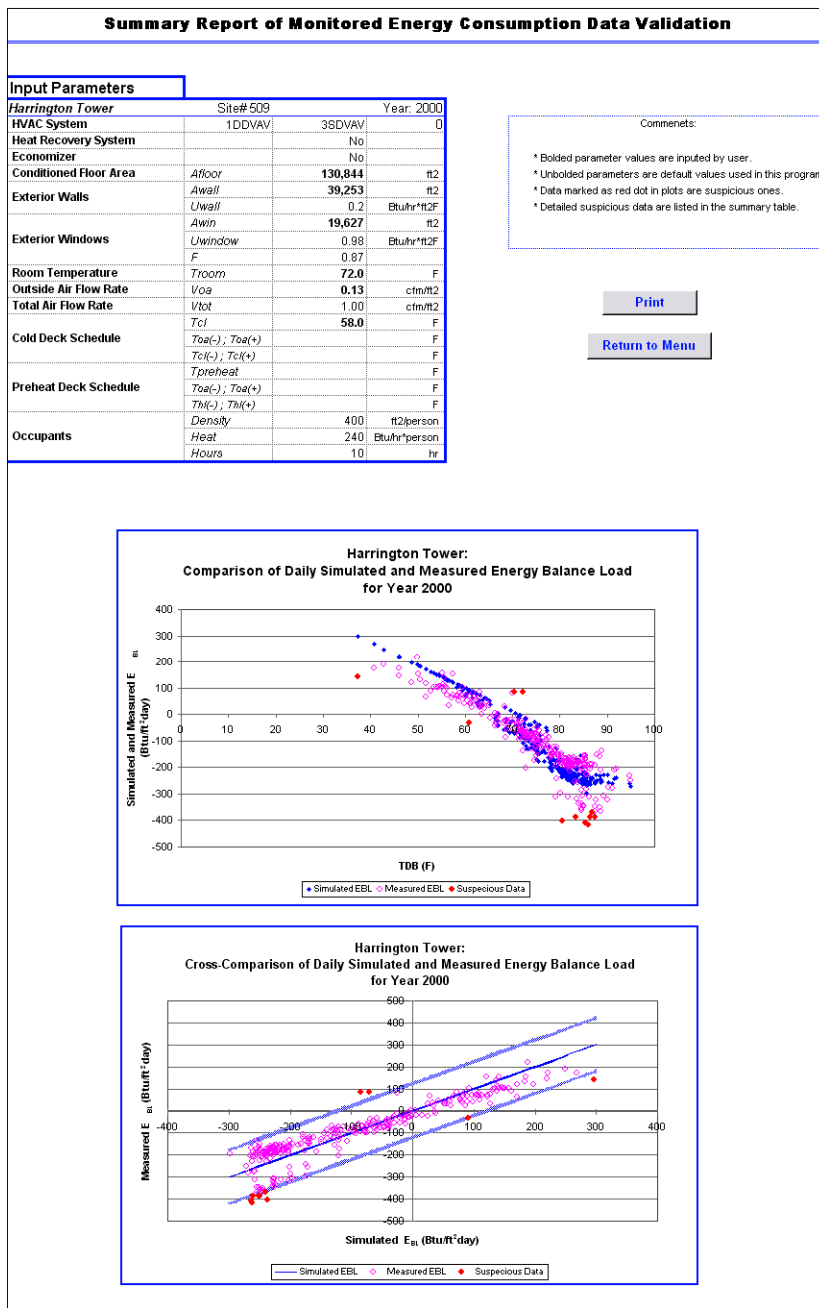


Figure 7.1 Summary report of data fault detection for the Harrington Tower for year 2000

Date	Oadrybulb	Oarh	Measured Wbele	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Btu/ft2day	Btu/ft2day
2/16/2000	70.29	90.19	13.85	0.00	0.00	-70.18	84.70
2/17/2000	72.22	83.62	13.90	0.00	0.00	-84.92	85.00
7/17/2000	86.41	62.44	14.46	64.09	1.90	-251.03	-386.88
7/18/2000	86.04	66.78	15.16	70.98	4.41	-262.63	-416.07
7/19/2000	87.51	60.22	14.99	64.37	1.88	-260.35	-385.89
7/23/2000	86.80	58.47	11.89	60.03	1.98	-240.75	-370.93
8/4/2000	83.37	75.34	13.76	63.65	2.09	-249.12	-386.30
8/7/2000	85.42	69.74	15.27	66.97	1.23	-263.85	-409.04
8/8/2000	80.63	85.61	13.98	64.74	0.86	-236.58	-402.74
9/25/2000	60.85	66.44	13.81	15.45	0.10	91.21	-32.90
12/13/2000	37.40	96.50	13.07	4.01	12.28	297.07	143.13

Figure 7.1 Continued

To test the applicability of the methodology and program in the consecutive years, measured data of year 2002 is pre-screened as follows. As there have been no energy conservation measures or construction activities in this building since year 2000, the parameters used for the simulation of year 2000 are assumed the same as that of year 2002. The simulation result is shown in Figure 7.2. From the report, it can be concluded that most of the data faults for 2002 happened in January and February, which is most likely because of the unreasonably low heating energy values.

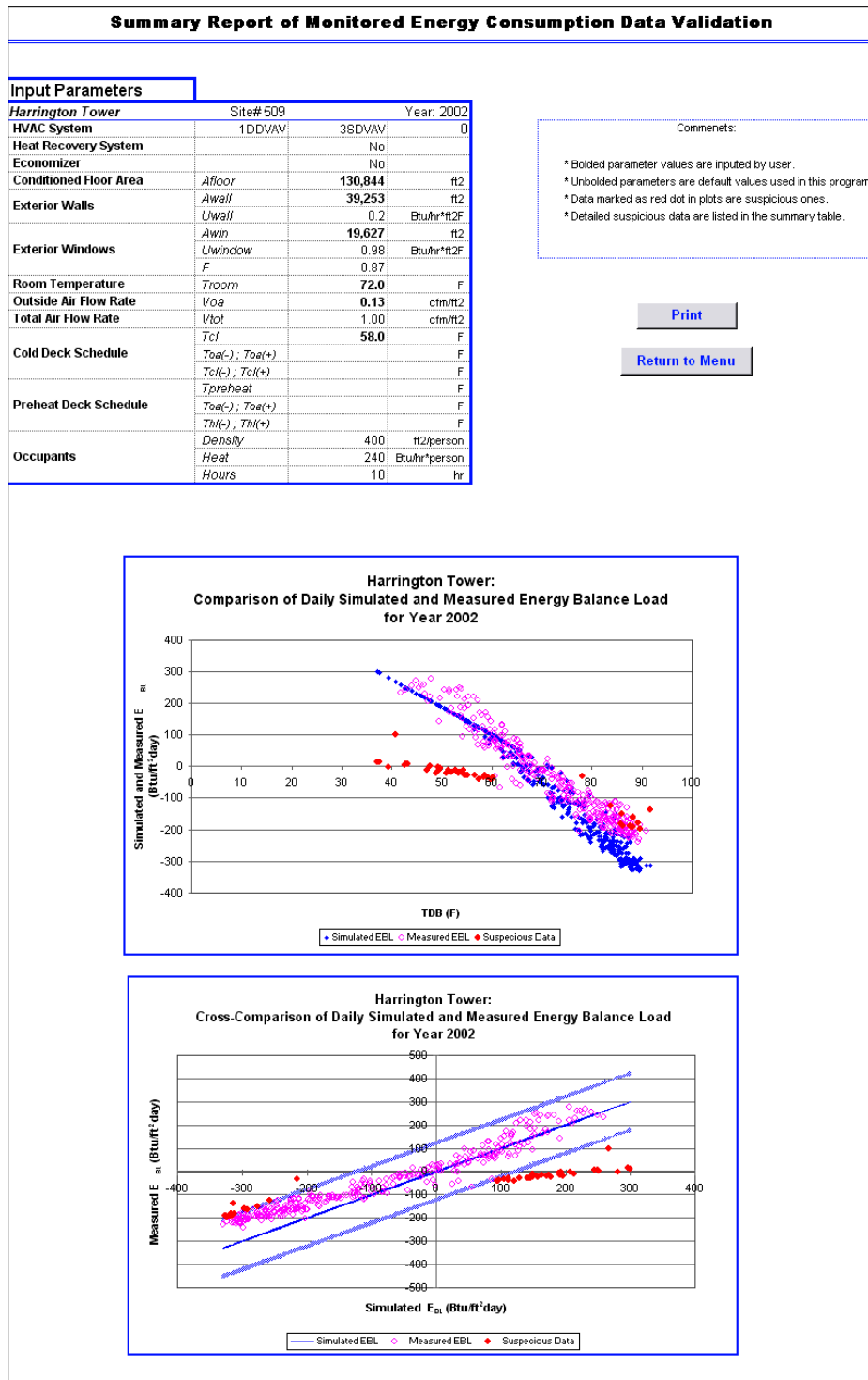


Figure 7.2 Summary report of data fault detection for the Harrington Tower for year 2002

Date	Oadrybulb	Oarh	Measured Wbele	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Btu/ft2day	Btu/ft2day
1/1/2002	39.32	62.14	8.99	7.48	0.00	280.17	-2.18
1/2/2002	37.03	64.71	12.23	8.26	0.00	300.29	11.89
1/3/2002	37.48	53.67	13.13	8.78	0.00	296.35	13.19
1/4/2002	42.76	61.50	12.91	9.44	0.00	250.01	6.82
1/5/2002	49.33	96.24	10.47	8.65	0.00	192.36	-2.08
1/6/2002	49.64	65.22	10.30	8.96	0.00	189.57	-5.45
1/7/2002	47.69	50.25	13.16	10.67	0.00	206.73	-1.08
1/8/2002	52.71	56.98	13.26	12.41	0.00	162.62	-13.79
1/11/2002	54.30	63.14	13.01	11.91	0.00	148.75	-11.51
1/12/2002	53.45	49.98	10.42	11.44	0.00	156.20	-23.75
1/13/2002	54.80	49.81	10.23	11.85	0.00	144.28	-28.03
1/14/2002	56.57	48.12	14.22	15.00	0.00	128.76	-27.72
1/15/2002	54.61	38.94	14.12	14.92	0.00	146.01	-27.67
1/16/2002	58.52	79.34	14.25	16.04	0.00	111.69	-35.47
1/17/2002	59.76	87.82	14.09	16.52	0.00	93.34	-40.10
1/18/2002	51.84	85.28	12.73	12.54	0.00	170.33	-17.97
1/19/2002	50.99	79.70	10.30	11.28	0.00	177.75	-23.26
1/20/2002	48.97	74.22	10.01	10.86	0.00	195.53	-21.75
1/21/2002	59.32	64.95	10.28	12.75	0.00	104.63	-34.56
1/24/2002	55.19	95.46	14.05	15.16	0.00	140.94	-30.02
1/25/2002	49.41	47.43	13.53	12.58	0.00	191.64	-13.44
1/26/2002	54.34	39.97	10.33	11.57	0.00	148.36	-25.30
1/27/2002	60.19	50.75	9.76	12.58	0.00	97.01	-36.47
1/31/2002	57.50	87.74	13.73	16.57	0.00	120.60	-42.67
2/1/2002	43.29	58.22	13.62	10.25	0.00	245.35	4.96
2/2/2002	46.97	53.70	10.87	10.17	0.00	213.07	-11.27
2/3/2002	53.60	51.23	10.43	10.95	0.00	154.82	-19.95
2/4/2002	51.33	72.51	14.01	13.06	0.00	174.79	-14.19
2/5/2002	42.62	101.51	14.68	11.19	0.00	251.18	4.20
2/6/2002	40.77	92.85	14.97	10.99	11.79	267.43	97.64
4/28/2002	83.74	75.84	10.56	29.86	5.19	-257.78	-124.00
7/1/2002	77.99	93.67	14.90	17.49	1.56	-214.55	-30.71
7/6/2002	88.29	65.23	10.58	32.65	3.21	-296.17	-160.33
7/20/2002	87.63	73.10	9.90	36.10	3.38	-318.97	-189.50
7/21/2002	87.93	73.18	9.91	36.41	3.37	-324.92	-191.89
8/2/2002	89.69	65.68	12.96	38.71	2.40	-323.73	-198.25
8/3/2002	89.19	65.19	10.43	34.94	3.06	-312.29	-179.94
8/4/2002	88.16	64.68	10.11	32.91	3.29	-291.60	-164.60
8/7/2002	91.75	55.95	13.77	30.98	1.95	-313.62	-137.73
8/8/2002	85.97	70.18	12.95	33.12	2.89	-275.61	-151.79
8/17/2002	85.89	80.52	10.06	35.22	3.23	-317.24	-182.90
8/18/2002	86.20	78.55	9.97	35.86	3.13	-315.06	-189.17
8/25/2002	88.22	72.12	9.71	36.22	3.45	-325.84	-191.02
12/21/2002	60.30	73.88	9.62	12.85	0.00	96.04	-39.36
12/22/2002	58.60	57.19	9.14	11.26	0.00	111.00	-30.16

Figure 7.2 Continued

7.3 Pre-Screening Case 2: The Eller O&M Building

7.3.1 Site Description

The Eller O&M (Oceanography and Meteorology) Building is located on the main campus of Texas A&M University. It is a 14 story building consisting of classrooms, offices, and laboratories, and has a gross area of 180,316 square feet. The indoor environment comfort (70°F) is maintained by the operation of 4 dual duct variable volume air handling units, where the cold deck set point averages 55°F, and the outside air intake volume is $0.22 \text{ cfm} / \text{ft}^2$. The energy consumed in this building is measured and monitored by the Energy Systems Laboratory, and the site number used as identification of this building is 514. With this information, the Energy Balance Load can be simulated and used as a fault detection factor, and the measured data for year 2000 is selected to be pre-screened for signal faults.

7.3.2 Application of Energy Balance Pre-Screening Toolkit

The Energy Balance Pre-Screening Toolkit is used to automatically detect the data faults of the Eller O&M Building for year 2000, and the summary report is shown in Figure 7.3. Generally speaking, the measured energy consumption of the Eller O&M Building for year 2000 is of good quality, except for several suspicious data in January, February, and December.

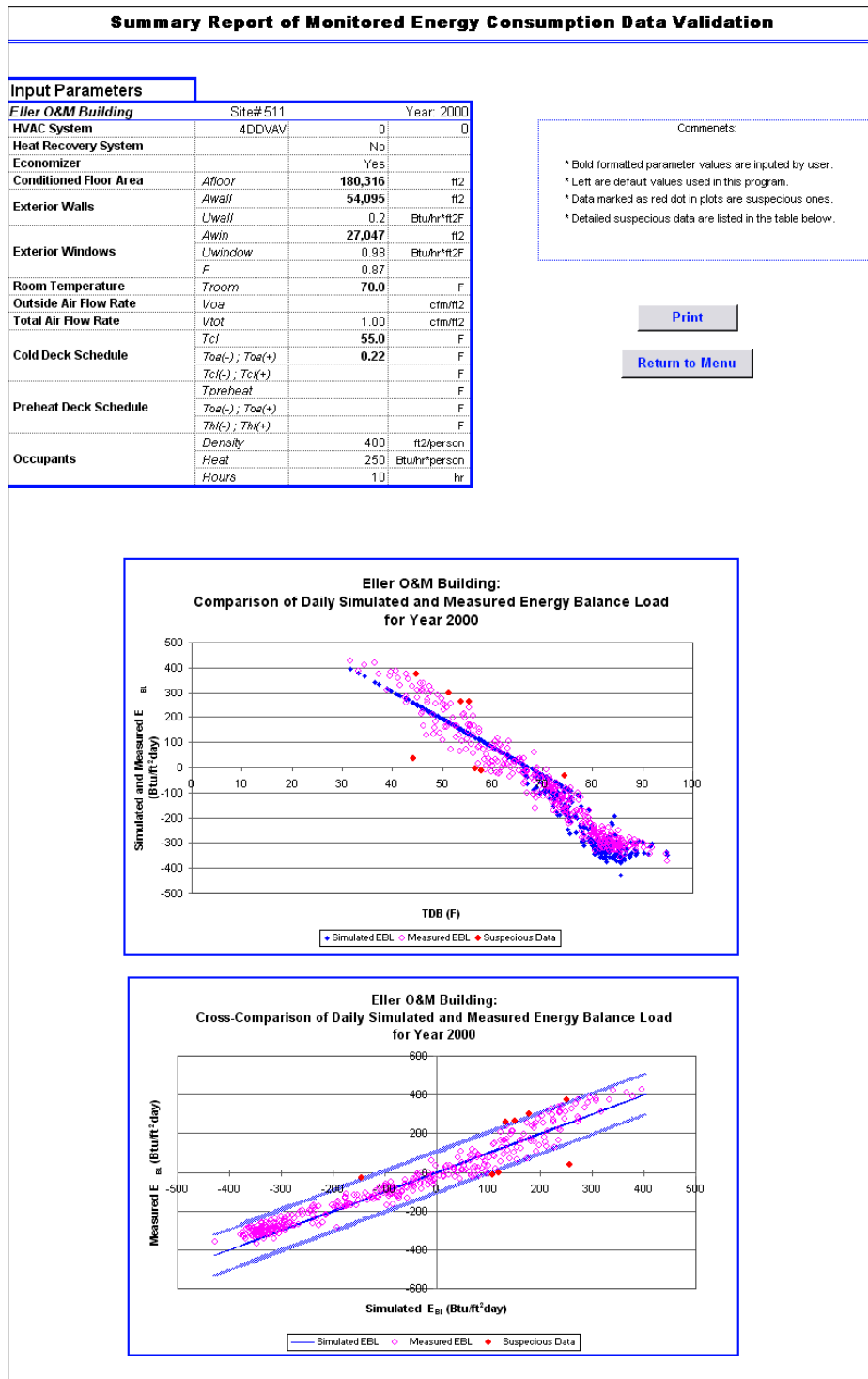


Figure 7.3 Summary report of data fault detection for the Eller O&M Building for year 2000

Date	Oadrybulb	Oarh	Measured Wbele	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Btu/ft2day	Btu/ft2day
1/1/2000	64.40	66.93	28.38	32.06	13.44	33.20	22.60
1/4/2000	44.25	42.19	34.39	21.18	0.31	257.11	36.87
1/12/2000	74.53	77.76	36.53	49.35	14.47	-144.75	-31.34
2/12/2000	57.73	71.55	31.62	35.35	7.71	107.27	-13.03
10/7/2000	56.69	80.58	29.47	24.07	0.00	118.84	-2.76
12/17/2000	44.82	40.87	33.52	26.87	67.51	250.69	374.10
12/18/2000	51.37	58.84	39.57	36.06	58.48	177.91	299.89
12/20/2000	55.46	58.47	36.71	34.76	52.59	132.47	261.72
12/23/2000	53.76	68.90	31.33	32.67	54.95	151.44	262.55

Figure 7.3 Continued

As there were energy conservation measures in Eller O&M Building from 2/3/1997 through 3/18/1997, the parameters used for the simulation of year 2000 are assumed the same as that of year 1998. The simulation result is shown in Figure 7.4. From the report, it can be concluded that most of the data faults happened in colder months of 1998, which is most likely because of the unreasonably low heating energy consumption.

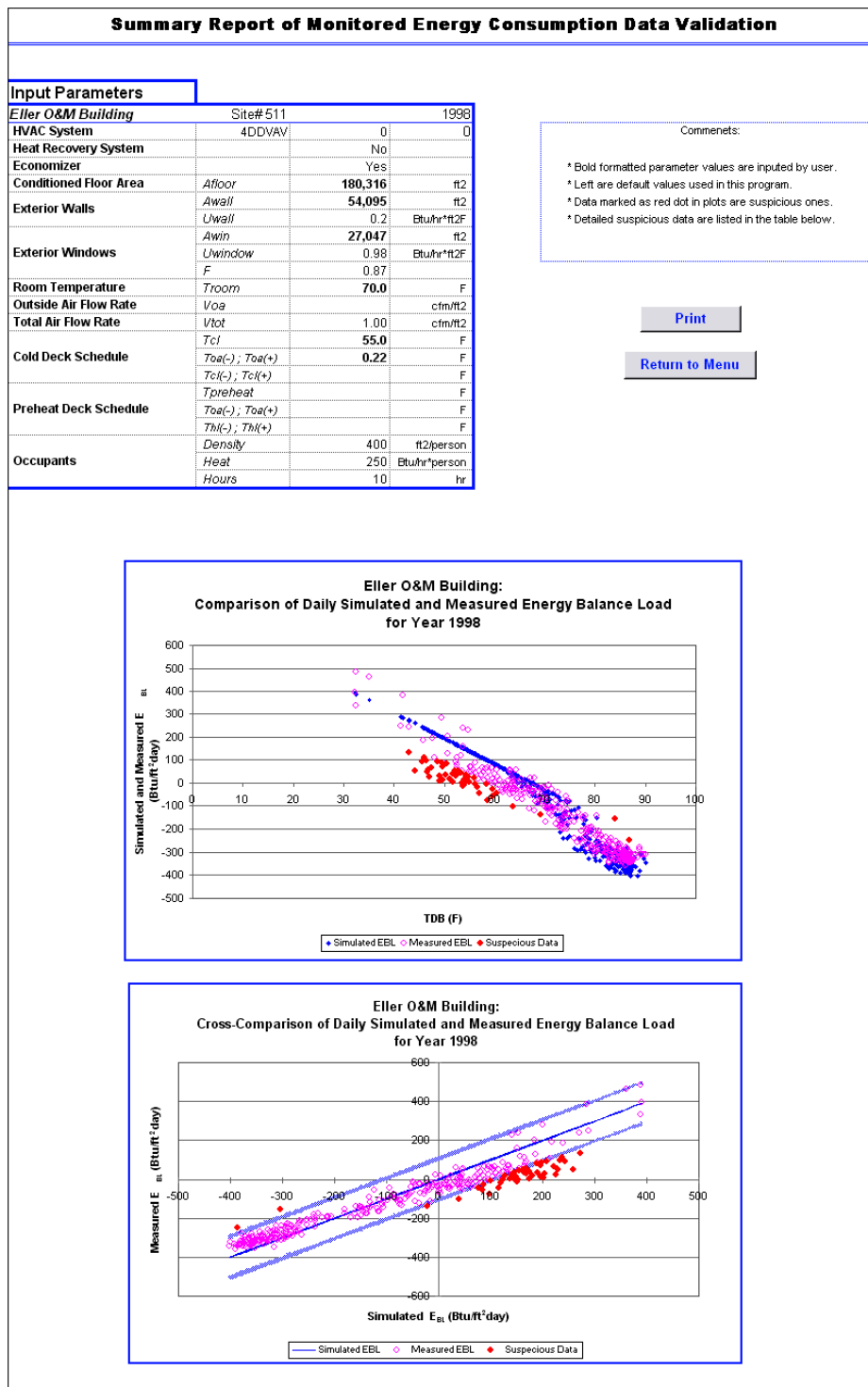


Figure 7.4 Summary report of data fault detection for the Eller O&M Building for year 1998

Date	Dadrybulb	Oarh	Measured Wbclc	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Etu/ft2day	Etu/ft2day
1/1/1998	53.97	71.51	27.26	25.97	2.36	149.07	-9.98
1/7/1998	44.14	90.63	35.27	19.08	0.00	258.32	50.67
1/8/1998	46.92	64.56	35.81	18.48	0.00	227.37	56.37
1/9/1998	50.26	74.87	34.49	23.08	1.48	190.30	33.24
1/10/1998	53.78	88.05	27.14	24.48	0.00	151.25	-15.32
1/13/1998	49.67	95.36	36.35	27.07	0.00	196.95	11.13
1/14/1998	47.11	100.12	36.03	24.17	0.00	225.34	25.81
1/15/1998	46.69	63.88	35.45	21.58	1.99	229.96	48.60
1/16/1998	56.00	53.90	34.71	24.77	0.75	126.53	20.75
1/17/1998	53.60	56.33	27.35	22.08	0.00	153.15	-1.11
1/19/1998	49.17	67.81	30.26	22.48	0.00	202.48	9.61
1/20/1998	58.32	85.00	35.73	29.57	0.00	100.72	-5.46
1/23/1998	46.04	69.06	34.23	8.89	1.64	237.22	111.67
1/27/1998	51.69	64.36	36.34	24.67	2.29	174.40	37.09
1/31/1998	59.57	86.77	29.08	31.06	2.87	86.86	-27.32
2/1/1998	55.00	90.09	28.60	28.77	6.60	137.62	3.97
2/2/1998	54.28	85.73	37.56	30.16	6.35	145.60	34.60
2/4/1998	52.61	57.69	37.61	28.37	4.77	164.20	35.99
2/5/1998	52.17	61.69	37.57	28.77	8.30	169.09	53.21
2/6/1998	46.42	55.84	36.32	26.07	14.50	233.00	97.00
2/7/1998	47.38	60.52	28.54	22.68	11.73	222.28	65.90
2/11/1998	52.73	59.19	37.15	27.17	6.53	162.83	50.40
2/13/1998	52.70	81.47	36.02	29.97	8.08	163.23	38.44
2/14/1998	54.57	79.53	27.15	26.97	7.87	142.43	14.50
2/17/1998	49.66	78.43	37.12	24.58	7.80	196.99	71.62
2/18/1998	54.73	69.49	37.26	28.97	3.79	140.64	25.71
2/19/1998	53.43	85.00	37.44	26.27	4.00	155.11	42.60
2/21/1998	53.78	81.28	27.54	21.48	0.02	151.25	3.16
2/22/1998	51.66	91.81	26.94	20.68	0.00	174.72	4.83
2/28/1998	54.51	38.97	29.23	22.38	0.12	143.10	6.26
3/1/1998	51.13	35.53	29.46	20.98	0.74	180.59	18.42
3/3/1998	52.15	41.05	37.55	24.37	2.37	169.27	44.58
3/6/1998	53.94	82.12	37.30	33.06	5.48	149.43	12.55
3/7/1998	56.22	97.77	29.21	28.57	4.33	124.09	-4.82
3/8/1998	45.56	67.37	29.31	18.98	11.75	242.53	89.96
3/12/1998	42.91	61.23	39.16	23.18	15.53	272.01	131.34
3/13/1998	49.53	84.93	36.78	23.08	9.69	198.45	88.95
3/20/1998	48.66	57.36	28.25	7.89	1.71	208.07	91.05
4/18/1998	60.44	68.77	30.05	31.76	0.00	77.19	-42.82
6/2/1998	83.98	65.31	33.63	54.54	0.00	-303.73	-153.27
6/6/1998	69.27	75.99	29.39	48.15	0.00	-20.93	-136.61
7/13/1998	86.87	66.53	35.50	73.12	0.00	-386.42	-248.02
11/6/1998	50.41	74.25	36.52	14.58	0.28	188.69	82.68
12/7/1998	58.60	94.43	37.93	44.16	0.18	97.63	-75.61
12/8/1998	49.05	74.93	37.48	24.50	0.00	203.75	30.43
12/14/1998	52.27	64.34	37.74	30.57	5.68	167.98	29.44
12/16/1998	54.30	60.70	35.75	27.07	3.35	145.39	27.06
12/17/1998	53.92	54.03	34.61	27.57	0.00	149.62	0.65
12/18/1998	56.55	80.28	34.29	30.46	0.00	120.43	-16.82
12/19/1998	57.00	94.72	27.54	29.97	0.00	115.44	-44.00
12/20/1998	59.73	99.61	27.07	31.87	0.00	85.05	-56.63
12/21/1998	63.66	93.34	32.26	45.05	0.73	40.04	-102.73

Figure 7.4 Continued

7.4 Pre-Screening Case 3: The Veterinary Medical Center

7.4.1 Site Description

The Veterinary Medical Center is located on the west campus of Texas A&M University. It is a 5 story building, mostly comprised of classrooms and laboratories, which has a gross area of 114,666 square feet. The indoor environment comfort (70°F) is maintained by the operation of 5 single duct variable volume air handling units, where the cold deck set point averages 56°F, and the outside air intake volume is $0.62 \text{ cfm} / \text{ft}^2$. As the building is a medical center, the indoor air quality is maintained by the large amount of outside air intake, which would cause high energy consumption. The approach to decrease the energy consumption caused by using more fresh air is implementing the heat recovery ventilator, and the pre-heat deck set point is approximately 50°F. The energy consumed in this building is measured and monitored by the Energy Systems Laboratory, and the site number used as identification of this building is 523. With this information, the Energy Balance Load can be simulated and used as a fault detection factor, and the measured data for year 2000 is selected to be pre-screened for signal faults.

7.4.2 Application of Energy Balance Pre-Screening Toolkit

The Energy Balance Pre-Screening Toolkit is used to automatically detect the data faults of the Veterinary Medical Center for year 2000, and the summary report is shown in Figure 7.5. Generally speaking, the measured energy consumption of the Veterinary Medical Center for year 2000 is good, except for several scattered suspicious data.

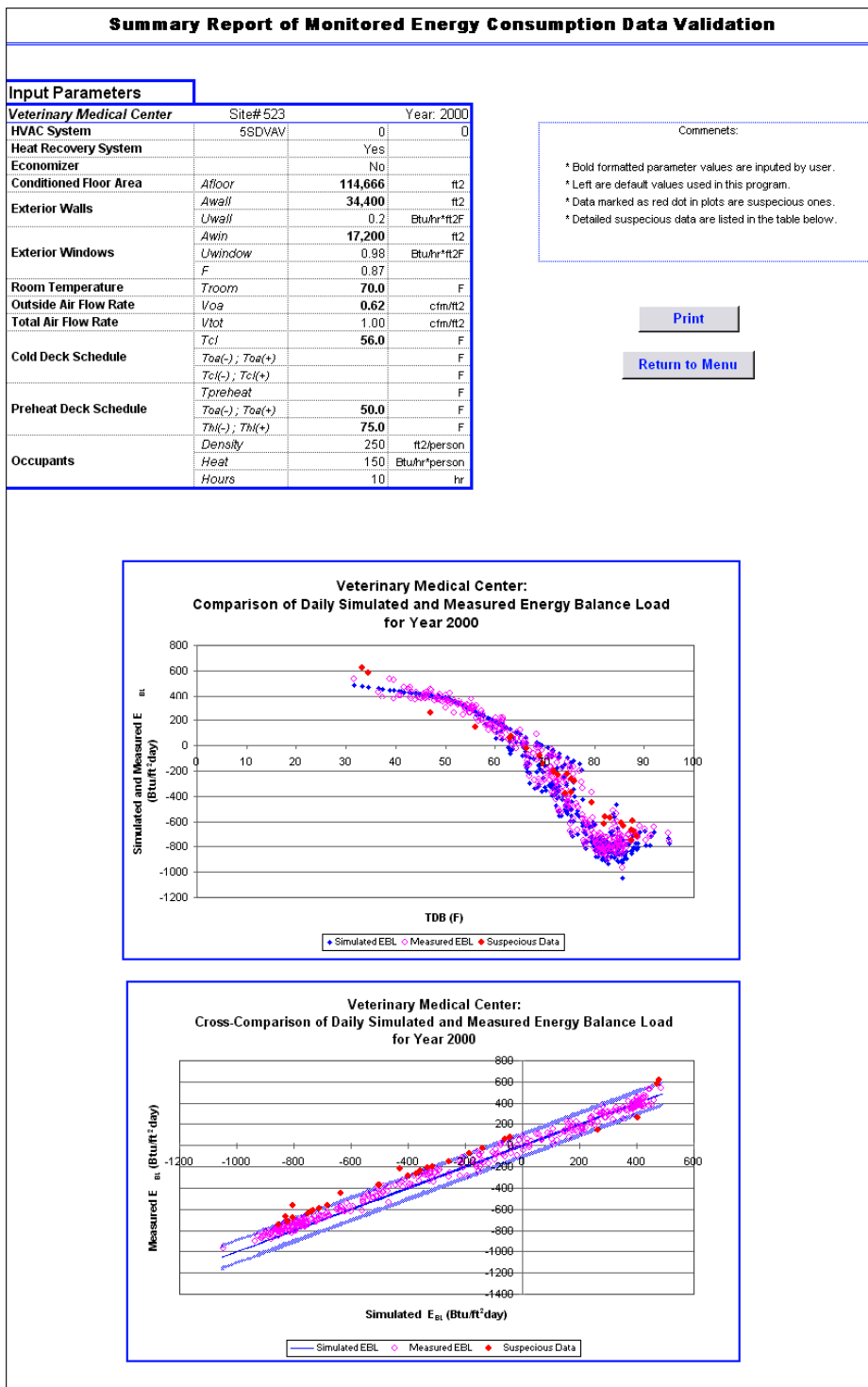


Figure 7.5 Summary report of data fault detection for the Veterinary Medical Center for year 2000

Date	Oadrybulb	Oarh	Measured Wbele	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Btu/ft ² day	Btu/ft ² day
1/1/2000	64.40	66.93	30.92	28.51	10.27	103.63	56.64
1/2/2000	71.77	81.51	31.91	52.97	3.89	-333.75	-205.35
1/12/2000	74.53	77.76	40.70	64.94	6.98	-429.84	-221.52
1/28/2000	33.31	89.56	38.46	3.47	43.69	476.92	619.18
1/29/2000	34.39	77.42	34.20	2.97	42.40	471.08	582.45
2/10/2000	68.97	80.10	38.93	46.53	6.49	-184.37	-77.61
2/24/2000	69.70	83.92	40.60	49.50	0.20	-257.42	-146.68
3/1/2000	72.71	79.55	40.75	59.70	0.20	-358.82	-234.57
3/2/2000	71.86	79.33	40.69	55.54	0.20	-314.67	-198.75
3/9/2000	75.91	69.63	39.44	64.15	0.20	-398.85	-282.53
3/29/2000	75.26	69.86	39.33	61.88	0.20	-370.19	-263.44
4/16/2000	75.32	80.41	36.67	72.27	0.30	-502.84	-371.79
6/24/2000	82.09	75.21	35.51	93.27	0.00	-803.32	-565.66
7/19/2000	87.51	60.22	42.29	119.91	0.20	-854.68	-748.89
7/21/2000	87.58	52.17	38.41	98.80	0.00	-710.70	-593.69
7/22/2000	87.48	58.84	35.43	105.34	0.00	-827.70	-671.50
8/1/2000	83.11	63.94	40.22	97.32	0.00	-682.26	-568.11
8/10/2000	85.87	59.23	39.85	105.14	0.20	-748.86	-637.20
8/11/2000	87.81	56.53	41.52	111.09	0.20	-802.27	-677.37
8/19/2000	85.44	59.58	38.85	101.48	0.10	-732.62	-613.07
8/30/2000	88.57	55.47	39.72	113.66	0.10	-822.59	-713.27
9/15/2000	81.89	71.69	39.94	103.56	0.20	-737.73	-622.75
10/2/2000	79.40	73.90	40.72	84.05	0.20	-634.40	-447.18
10/15/2000	74.11	85.66	36.40	72.27	0.20	-501.60	-374.57
11/14/2000	47.12	53.89	36.11	7.33	8.18	402.24	259.36
11/23/2000	63.13	96.87	34.70	26.33	5.08	-59.82	56.75
11/28/2000	66.39	88.11	39.30	35.15	0.90	-138.59	-24.48
12/10/2000	63.19	94.24	36.37	23.86	3.59	-41.28	76.97
12/11/2000	56.15	84.06	37.90	27.23	13.57	265.68	145.29

Figure 7.5 Continued

With the same input parameter values, measured data of year 2002 for the Veterinary Medical Center is selected to be pre-screened; results are shown in Figure 7.6. From the simulation result, most of the data for that year is out of the predicted confidence intervals, but the trend of the measured Energy Balance Load has a good pattern in terms of outside air temperature. Investigation of the building finds that there were CC[®] measures implemented in it during 3/2/2002 and 7/2/2002. Consequently, the analytical redundancy method can also be used to detect the operation changes, which make changes to the input parameters, for example T_{CL} or V_{OA} .

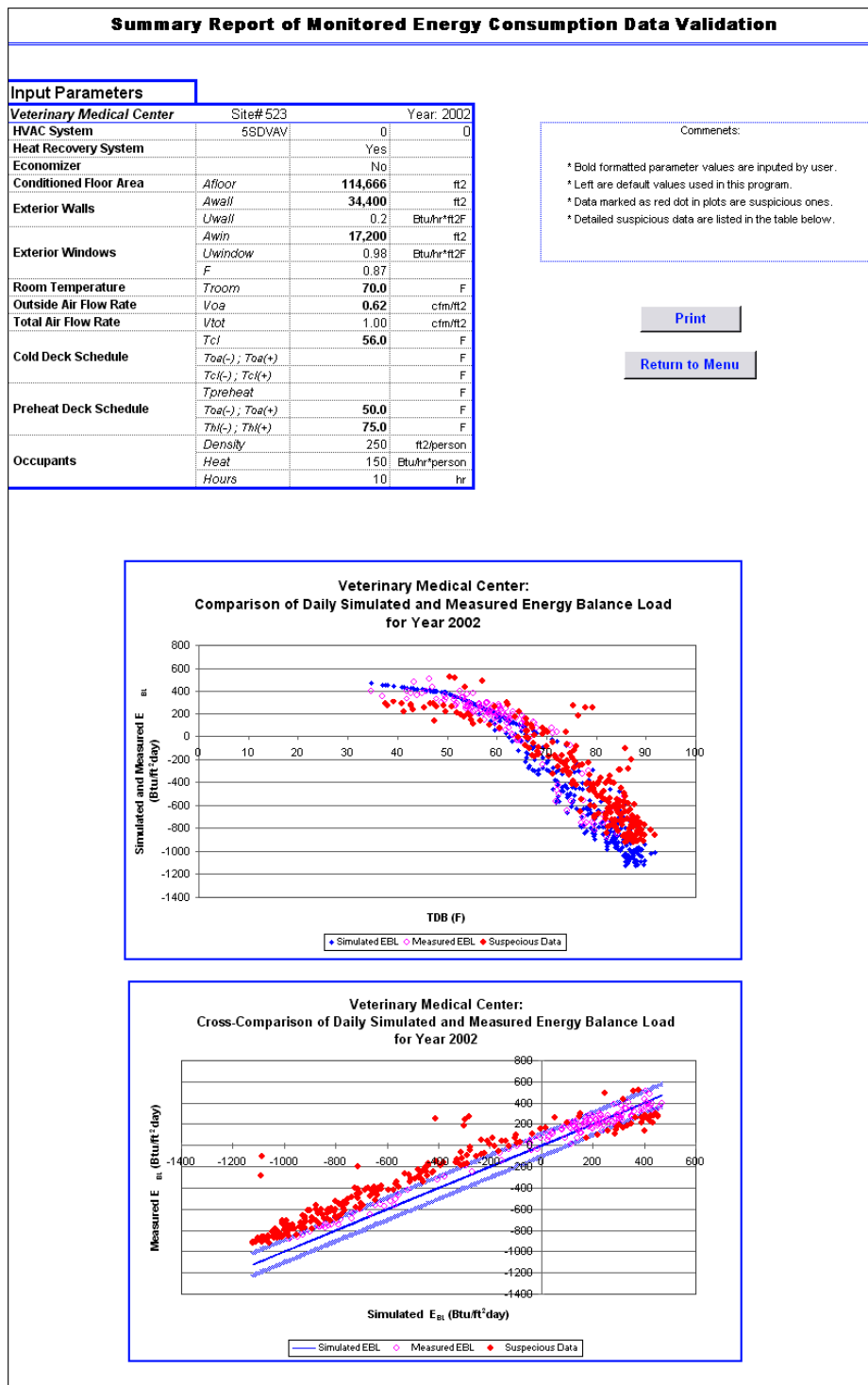


Figure 7.6 Summary report of data fault detection for the Veterinary Medical Center for year 2002

7.5 Pre-Screening Case 4: The Wehner Building

7.5.1 Site Description

The Wehner Building is located on the west campus of Texas A&M University. It is a 4 story building consisting of classrooms and offices, and has a gross area of 192,001 square feet. The indoor environment comfort (75°F) is maintained by the operation of 4 dual duct variable volume air handling units, where the cold deck set point averages 58°F, and the outside air intake volume is $0.06 \text{ cfm} / \text{ft}^2$. The energy consumed in this building is measured and monitored by the Energy Systems Laboratory, and the site number used as identification of this building is 528. With this information, the Energy Balance Load can be simulated and used as a fault detection factor, and the measured data for year 2000 is selected to be pre-screened for signal faults.

7.5.2 Application of Energy Balance Pre-Screening Toolkit

The Energy Balance Pre-Screening Toolkit is used to automatically detect the data faults of the Wehner Building for year 2000, and the summary report is shown in Figure 7.7. Generally speaking, the measured energy consumption of the Wehner Building of year 2000 is good. The data in August 2000 is filtered out as suspicious measurement, which is very possibly because of the questionable high heating energy consumption.

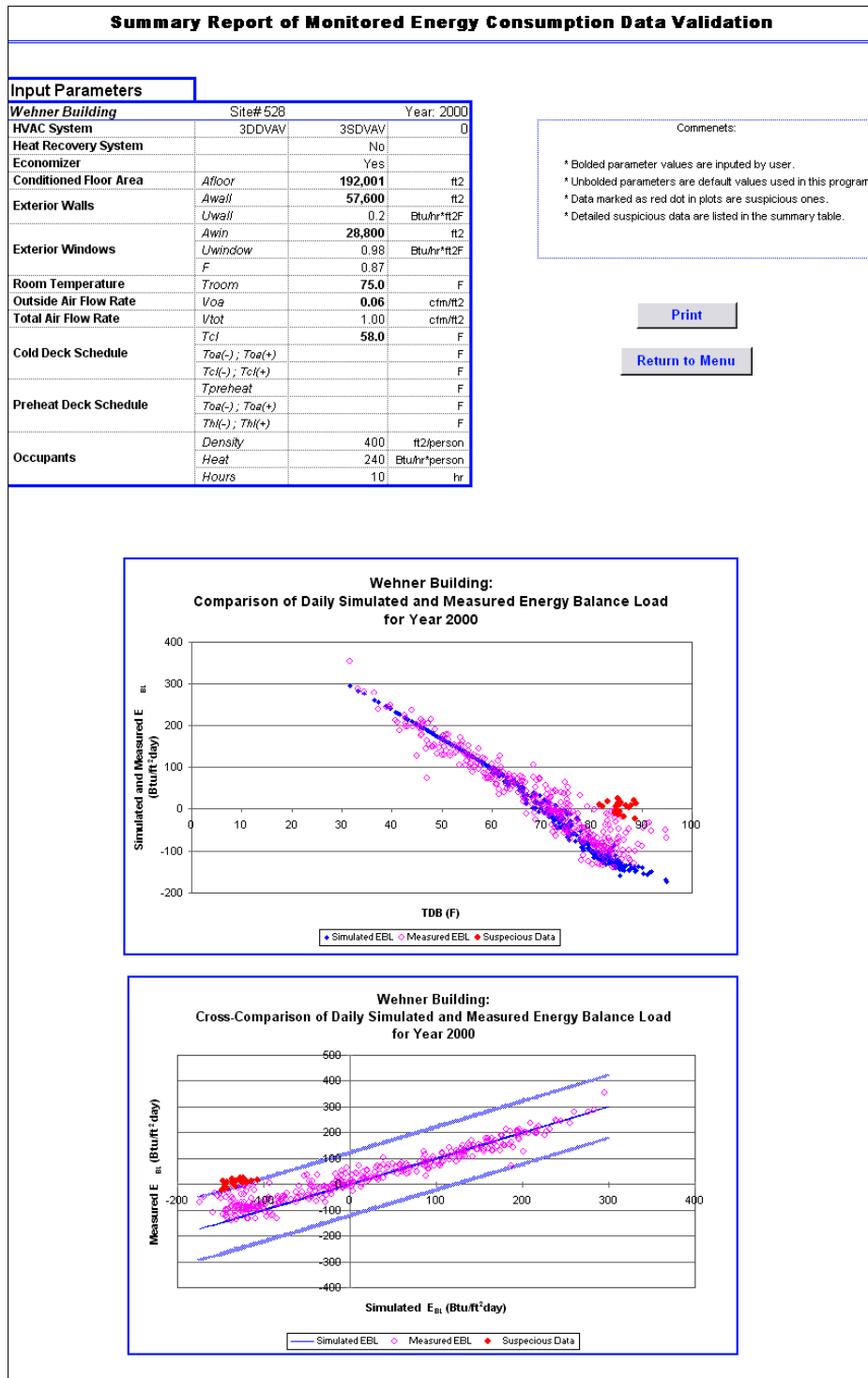


Figure 7.7 Summary report of data fault detection for the Wehner Building for year 2000

Date	Oadrybulb	Oarh	Measured Wbele	Measured Wbcool	Measured Wbheat	Simulated EBL	Measured EBL
	F	%	MMBtu/day	MMBtu/day	MMBtu/day	Btu/ft2day	Btu/ft2day
1/1/2000	64.40	66.93	14.20	14.62	16.86	66.89	70.79
7/29/2000	84.83	63.18	20.23	38.46	23.13	-123.73	4.45
8/1/2000	83.11	63.94	26.82	41.66	23.62	-106.82	17.78
8/5/2000	84.91	68.89	20.36	40.26	23.81	-135.18	-0.74
8/6/2000	85.58	70.29	20.39	41.26	23.81	-145.21	-5.93
8/7/2000	85.42	69.74	26.42	47.07	23.42	-142.37	-13.11
8/9/2000	84.49	70.40	26.00	46.57	24.21	-133.26	-8.13
8/10/2000	85.87	59.23	24.93	41.26	24.11	-127.40	14.55
8/11/2000	87.81	56.53	24.12	42.16	24.30	-142.57	7.52
8/12/2000	88.80	53.78	18.31	37.05	24.89	-147.37	12.96
8/13/2000	88.43	50.37	18.17	36.05	25.38	-136.54	20.14
8/14/2000	85.11	59.40	23.97	42.46	25.58	-119.76	11.94
8/15/2000	82.20	77.52	24.53	43.57	25.09	-120.25	5.99
8/16/2000	85.68	62.30	25.68	42.56	24.79	-131.22	14.46
8/17/2000	87.42	59.65	25.56	44.17	24.50	-144.67	4.06
8/18/2000	86.80	57.80	24.27	41.06	23.42	-134.45	9.25
8/19/2000	85.44	59.58	19.69	36.35	25.09	-123.57	23.39
8/20/2000	85.22	62.91	19.46	36.45	25.48	-127.40	23.95
8/21/2000	85.64	65.40	25.39	42.96	24.50	-136.48	9.64
8/22/2000	81.57	77.97	25.77	43.47	25.09	-113.98	11.64
8/29/2000	86.51	65.36	29.79	50.77	23.52	-146.04	-17.82
8/30/2000	88.57	55.47	29.96	52.37	23.91	-148.41	-23.40

Figure 7.7 Continued

As there was no energy conservation measures in the Wehner Building during year 2001, the parameters used for the simulation of year 2000 should be the same as that of year 2001. The simulation result of year 2001 is shown in Figure 7.8, from which it can be seen that all the measured data is within the confidence intervals, and there is no fault data for this case.

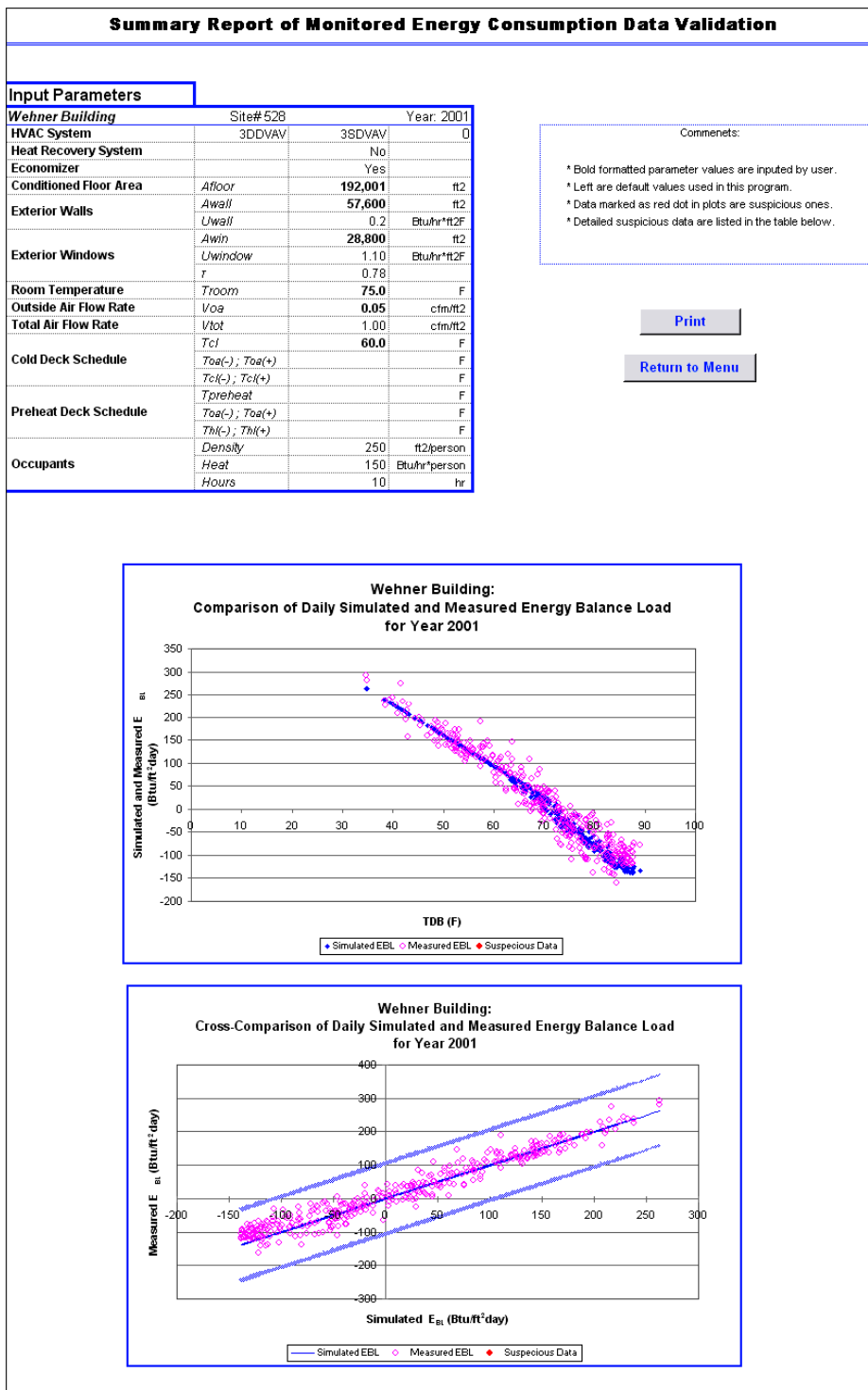


Figure 7.8 Summary report of data fault detection for the Wehner Building for year 2001

7.6 Pre-Screening Case 5: The Zachry Engineering Center

7.6.1 Site Description

The Zachry Engineering Center is located on the main campus of Texas A&M University. It is a 4 story building consisting of classrooms, offices, and laboratories, which has a gross area of 324,400 square feet. The indoor environment comfort (70°F) is maintained by the operation of 12 large dual duct variable volume and 6 small constant volume air handling units, where the cold deck set point averages 58°F, and the outside air intake volume is $0.05 \text{ cfm} / \text{ft}^2$. The energy consumed in this building is measured and monitored by the Energy Systems Laboratory, and the site number used as identification of this building is 500. With this information, the Energy Balance Load can be simulated and used as a fault detection factor, and the measured data for year 2000 is selected to be pre-screened for signal faults.

7.6.2 Application of Energy Balance Pre-Screening Toolkit

The Energy Balance Pre-Screening Toolkit is used to automatically detect the data faults of the Zachry Engineering Center for year 2000, and the summary report is shown in Figure 7.9. Though the measured data filtered out by the program is a limited amount, the trend of the measured and simulated Energy Balance Load in terms of outside air temperature displays obviously different pattern. The time series plots of electricity, cooling energy and heating energy consumption, as well as the measured Energy Balance Load, are investigated as assistance for trouble shooting, which is shown in Figure 7.10.

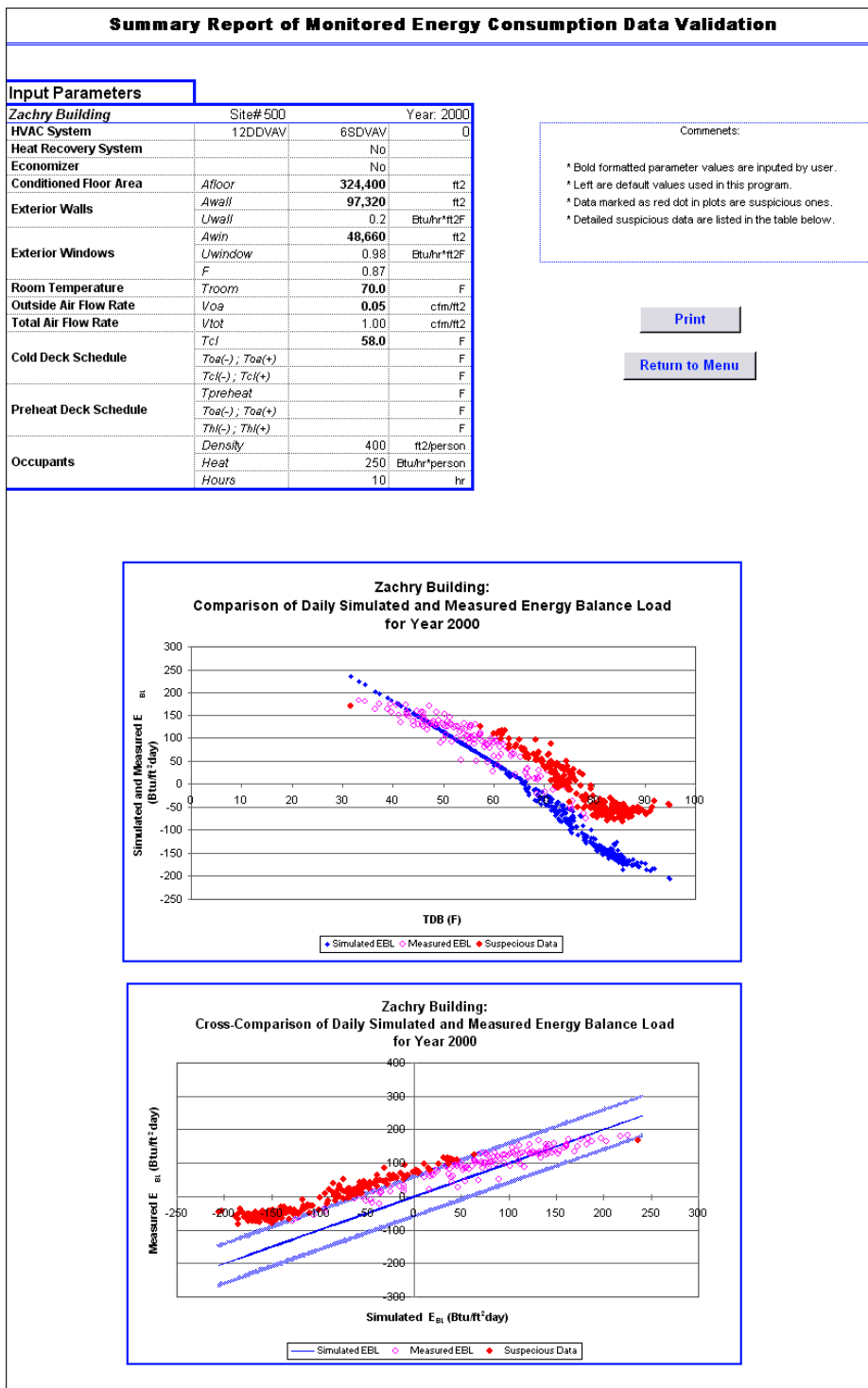


Figure 7.9 Summary report of data fault detection for the Zachry Engineering Center for year 2000

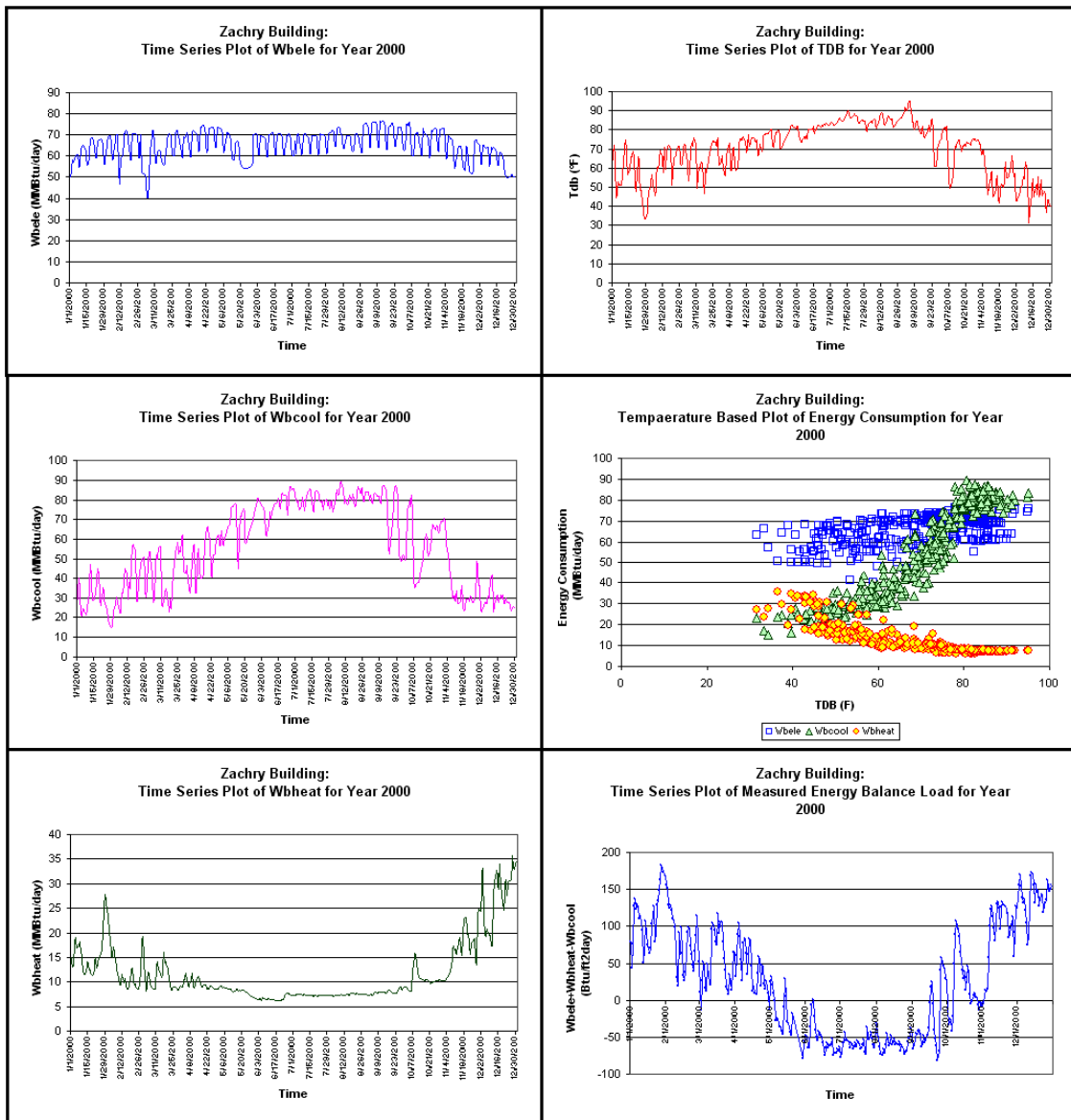


Figure 7.10 Data plots for the Zachry Engineering Center for year 2000

The cooling energy consumption of the Zachry Engineering Center has a good performance vs. outside air temperature; however, it has a much lower magnitude than that of most other buildings that have been analyzed, approximately one-half less.

Additionally, the historical Energy Balance Load composed of the three types of energy consumption presents a high frequency of positive values, which is quite suspicious too. Therefore, the time series and temperature-based plots of the measured energy consumption, in addition to the cross-check plot of the simulated and measured Energy Balance Load, indicate a scale problem of the measured cooling energy consumption for the Zachry Engineering Center for year 2000.

From this case, it can be concluded that the method of analytical redundancy is a useful approach to detect the scale problem of the signals, which is not easy to identify through the ordinary visual observation of the time series or temperature-based plot for individual energy consumption measurement. Furthermore, improvement may be necessary for the pre-screening program, which will enable the program to identify the bad scale data automatically.

7.7 Pre-Screening Case 6: The Halbouty Geosciences Building

7.7.1 Site Description

The Halbouty Geosciences Building is located on the main campus of the Texas A&M University. It is a 4 story building consisting of classrooms, offices, and laboratories, which has a gross area of 120,874 square feet. The indoor environment comfort (75°F) is maintained by the operation of 2 dual duct variable volume and 1 single duct variable volume air handling units, where the cold deck set point averages 55°F, and the outside air intake volume is $0.1 \text{ cfm} / \text{ft}^2$. The energy consumed in this building is measured and monitored by the Energy Systems Laboratory, and the site

number used as identification of this building is 519. With this information, the Energy Balance Load can be simulated and used as a fault detection factor, and the measured data for year 2000 is selected to be pre-screened for signal faults.

7.7.2 Application of Energy Balance Pre-Screening Toolkit

The Energy Balance Pre-Screening Toolkit is used to automatically detect the data faults of the Halbouty Geosciences Building for year 2000, and the summary report is shown in Figure 7.11. The program filters out most of the measured data, and the trend of the measured and simulated Energy Balance Load in terms of outside air temperature displays quite different pattern. The scale problem with the measured data is a concern, so that the time series plots of electricity, cooling energy, and heating energy consumption, as well as the measured Energy Balance Load, are investigated as assistance for trouble shooting, which is shown in Figure 7.12.

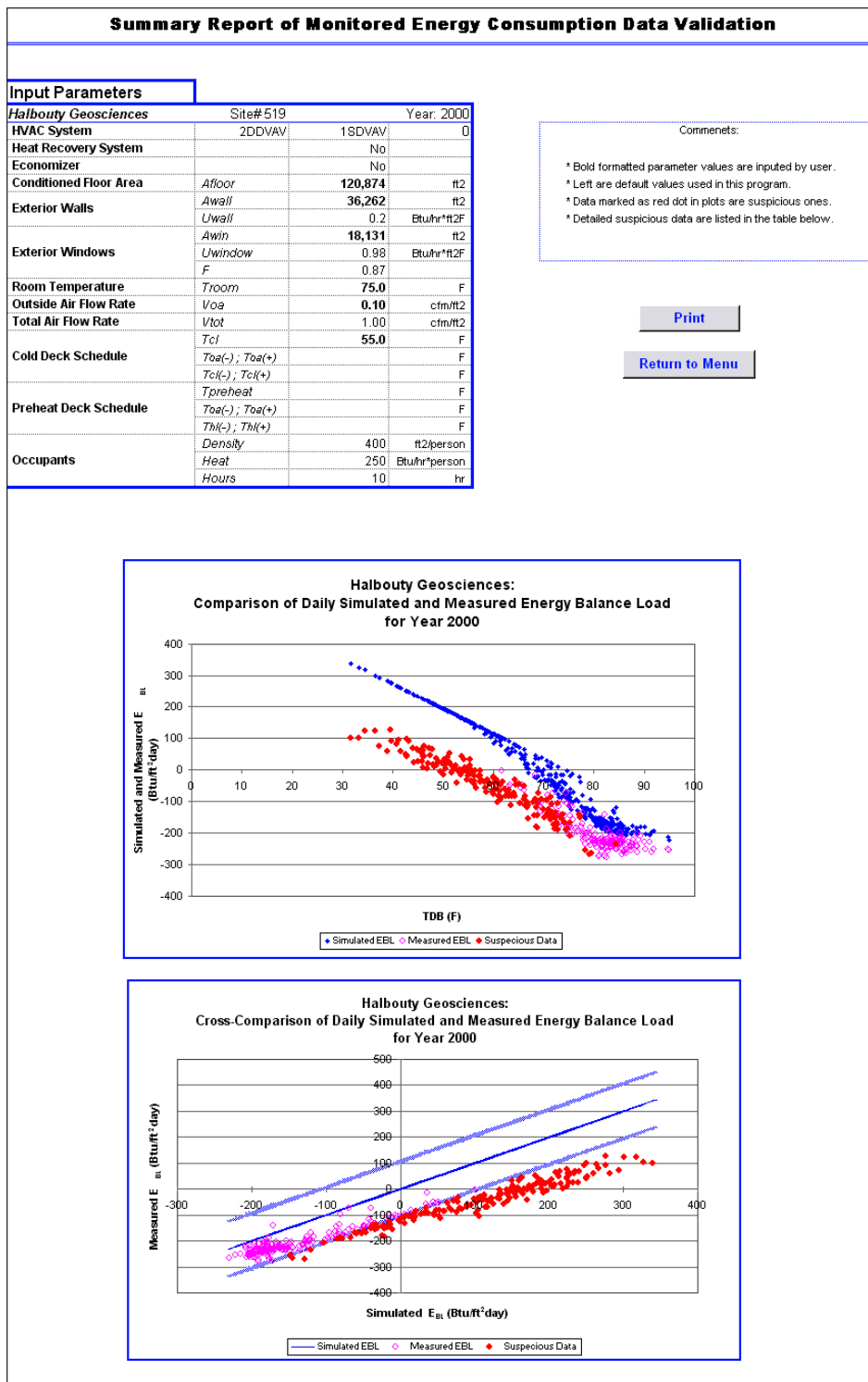


Figure 7.11 Summary report of data fault detection for the Halbouty Geosciences Building for year 2000

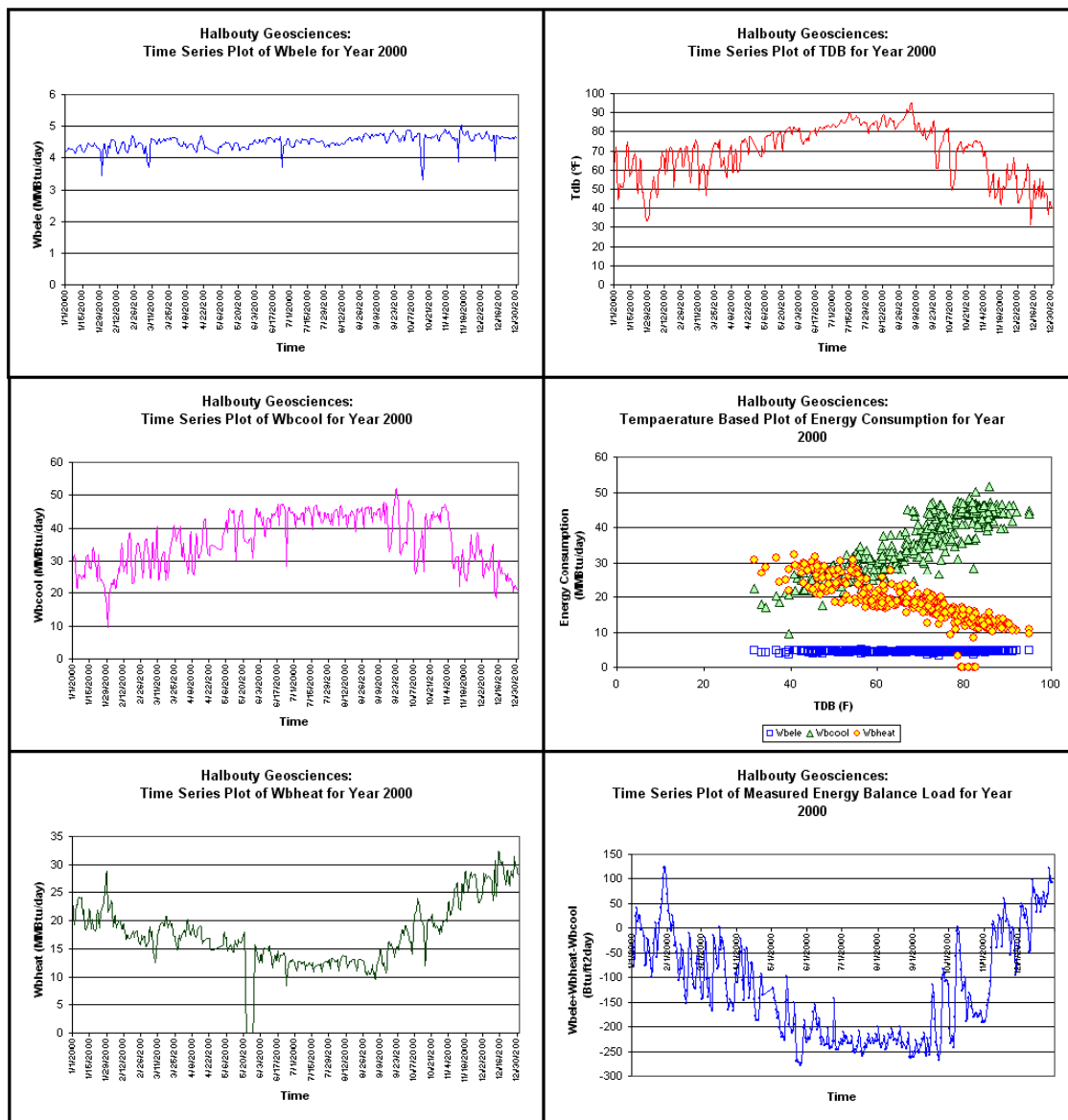


Figure 7.12 Data plots for the Halbuty Geosciences Building for year 2000

The electricity consumption of the Halbuty Geosciences Building has a good performance vs. outside air temperature; however, it has a much lower magnitude than that of most other buildings that have been analyzed, approximately one-half less.

Additionally, the historical Energy Balance Load, composed of the three types of energy consumption, presents a high frequency of negative values, which is quite suspicious too. Therefore, the time series and temperature-based plots of the measured energy consumption, in addition to the cross-check plot of the simulated and measured Energy Balance Load, indicate a scale problem of the measured electricity consumption for the Halbouty Geosciences Building for year 2000.

7.8 Conclusions

Measured data from six buildings on the Texas A&M University campus are screened using the Energy Balance Pre-Screening Toolkit in this chapter. The program, using simulation in conjunction with the analytical redundancy concept, was able to identify numerous outliers in the data sets that have a probability approaching 95% of being erroneous data. It also appears that the methodology, with some further development will be able to automatically identify and correct scaling problems in the data. This is not easy to recognize through normal visual observation of the data. It also appears that it will be able to identify operational changes in the building, which will enormously affect the key parameters as the simulation inputs, such as the cold deck set point, room temperature and heat recovery ventilator renovation. The pre-screening program appears to be a useful and effective tool for detecting measurement faults in the energy consumption data from commercial buildings.

CHAPTER VIII

SUMMARY AND CONCLUSIONS

Analytical redundancy has been used to develop a method to screen building energy consumption data for erroneous measurements when data for heating, cooling, and electricity that primarily contributes to internal gains is available. The process model needed to implement the analytic redundancy concept is derived from the first law of thermodynamics, or energy balance.

Energy Balance Load (E_{BL}) is defined as the sum of the heating requirements and the electric gains in the building minus the cooling coil loads. Measured values of E_{BL} can be obtained by combining the measured building electricity, cooling and heating energy usage using the E_{BL} definition. Simulated values of E_{BL} are determined based on the first law of thermodynamics by building and system parameter values for a particular building. Sensitivity and uncertainty analysis have determined that the set point of the cooling coil leaving air temperature and the outside air intake volume are the key parameters that strongly influence values of the simulated E_{BL} . Comparison of the E_{BL} values obtained through these two approaches helps to identify the questionable measurements in the building energy use data sets with a prescribed confidence level. The methodology also takes account of the uncertainties introduced by uncertainties in the input parameters and the incomplete model used for the simulation.

A pre-screening toolkit based on the methodology developed in this thesis was developed with Visual Basic for Application (VBA). This toolkit may be utilized to automatically pre-screen measured building energy consumption data with the input of five parameters. Its application increases the efficiency with which gross faults in sensor measurements may be found and identified for correction.

The methodology as implemented in the program successfully identified monitored consumption data that appears to be erroneous in case studies using data from six buildings on the Texas A&M campus. With knowledge of five key parameters of the building and its systems, daily measurements of the building energy consumption data can be screened out for probable errors with at a specified confidence level. It also appears that the methodology, with some further development will be able to automatically identify and correct scaling problems in the data and that it will be able to identify operational changes in cold deck set point and outside air intake volume. Some non-consecutive days of data, which are just outside the detection bands, may not be due to either sensor problems or operational changes. Consequently, further investigation on these topics is recommended.

The methodology as implemented in this thesis used daily average ambient temperature measurements and an implementation of the ASHRAE Simplified Energy Analysis Procedure sometimes called the modified bin method which assumes solar insolation on the building is linearly related with the outside air temperature. The implementation used here assumes that the weekday and weekend energy consumption difference is negligible and that average ambient specific humidity is linearly related to

the outdoor temperature. In reality, the building operation normally has different operating schedules on weekdays and weekends and the latter is true for a limited temperature range. Consequently, future work to improve the methodology should investigate the error introduced by these assumptions. Application of the AR methodology and the concept of E_{BL} to various time interval based measurements such as example weekly or monthly data should also be investigated.

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APPENDIX

VISUAL BASIC APPLICATION CODES OF THE PRE-SCREENING TOOLKIT

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For more information about this program, please contact Xiaojie Shao at jshao@utilities.tamu.edu.

Userform Shows up and Retrieve Hourly Environmental Data

```
Public Connection As ADODB.Connection
Dim DBFullName As String
Dim DBOption As Integer
Dim StrConn As String
Dim msg As String
Private Sub JessyMacro_Open()
UserForm1.Show
End Sub
```

```
Public Sub DataRetriever()
' Retrieve hourly and DataBase_Daily TDB&Oarh data based on the date input
Call ConnectToDB
    InitialInputs
    DisconnectToDB
End Sub
```

```
Public Sub ConnectToDB()
    DBFullName = ThisWorkbook.Path & "\TDB.mdb"
    StrConn = "provider=Microsoft.Jet.OLEDB.4.0; "
    StrConn = StrConn & "Data Source=" & DBFullName & ";"
    Set Connection = New ADODB.Connection
    Connection.Open ConnectionString:=StrConn
    If Err <> 0 Then
        msg = "An error occurred trying to connect to the TDB database:" & vbCrLf
        msg = msg & "Error number: " & Err & vbCrLf
        msg = msg & "Description: " & Err.Description
        MsgBox msg
        Err.Clear
    End If
End Sub
```

```

Public Sub DisconnectToDB()
    If Not (Connection Is Nothing) Then
        Connection.Close
        Set Connection = Nothing
    End If
End Sub

Public Sub InitialInputs()
    On Error Resume Next
    ' Var Declair
    Dim DBYear
    ' Dim DBTime
    ' Dim DBHour As String
    Dim Recordset_H As ADODB.Recordset
    Dim Recordset_D As ADODB.Recordset
    Dim strSQL As String
    DBYear = UserForm1.YearSelect.Value
    ' DBHour = DBinput.HourSelect.Value
    ' DBTime = DBinput.Calendar1.Value & " " & DBinput.HourSelect.Value
    ' DATA worksheet value clear
    Worksheets("DataBase_Hourly").Range("A3:J65536").ClearContents
    Worksheets("DataBase_Daily").Range("A3:G65536").ClearContents
    ' Connect to the Database
    If Connection Is Nothing Then ConnectToDB
    ' Create an empty Recordset.
    Set Recordset_H = New ADODB.Recordset
    ' Create the SQL statement. and open the recordset
    With Recordset_H
        strSQL = "SELECT Date, Hour, [Dry Bulb Temperature], [Relative Humidity] from
[Hourly Weather Data] Where Year = "
    '     strSQL = strSQL + "#" + DBTime + "#"
        strSQL = strSQL + DBYear
    '     MsgBox strSQL
        .Open Source:=strSQL, ActiveConnection:=Connection
    End With
    ' Test if the Record is empty
    If Recordset_H.EOF And Recordset_H.BOF Then
        MsgBox "No matching records found. Please Choose again"
        Exit Sub
    Else
    ' Copy Recordset to Worksheet Hourly DATA
    Worksheets("DataBase_Hourly").Range("A3").CopyFromRecordset Recordset_H
    ' Clear ADO vars
    Set Recordset_H = Nothing
    strSQL = ""
    End If
    ' Create an empty Recordset.
    Set Recordset_D = New ADODB.Recordset

```

```

' Creat the SQL statement. and open the recordset
With Recordset_D
    strSQL = "SELECT Date, [Dry Bulb Temperature], [Relative Humidity] from [Daily
Weather Data] Where Year = "
'    strSQL = strSQL + "#" + DBTime + "#"
    strSQL = strSQL + DBYear
'    MsgBox strSQL
    .Open Source:=strSQL, ActiveConnection:=Connection
End With
' Test if the Record is empty
If Recordset_D.EOF And Recordset_D.BOF Then
    MsgBox "No matching records found. Please Choose again"
    Exit Sub
Else
' Copy Recordset to Worksheet Hourly DATA
Worksheets("DataBase_Daily").Range("A3").CopyFromRecordset Recordset_D

' Clear ADO vars
Set Recordset_D = Nothing
strSQL = ""
' Disconnect to the data base
If Not Connection Is Nothing Then DisconnectToDB
End If
End Sub

```

```

Public Sub Bin()
' Find Minimum, Maximum and Average hourly temperature
Dim Maximum As Integer
Dim Minimum As Integer
Dim RCount As Integer
Dim BinMin As Integer
Dim BinMax As Integer
Dim MRoundMin As Integer
Dim MRoundMax As Integer
Worksheets("DataBase_Hourly").Activate
Range("C3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Set myRange = Selection
RCount = Selection.Rows.Count
Maximum = Application.WorksheetFunction.Max(myRange)
Minimum = ActiveCell.Value
Average = Application.WorksheetFunction.SumIf(myRange, "<>-99") /
Application.WorksheetFunction.CountIf(myRange, "<>-99")
Do While ActiveCell.Value <> ""
    If ActiveCell.Value <> -99 And ActiveCell.Value < Minimum Then
        Minimum = ActiveCell.Value
    End If
    ActiveCell.Offset(1).Activate

```

```

Loop
' Calculate the temperature Bin
Worksheets("DataBase_Hourly").Activate
Range("F3").Activate
MRoundMin = MRound(Minimum, 5)
If Minimum <= MRoundMin Then
    BinMin = MRoundMin - 5
Else
    BinMin = MRoundMin
End If
MRoundMax = MRound(Maximum, 5)
If Maximum >= MRoundMax Then
    BinMax = MRoundMax + 5
Else
    BinMax = MRoundMax
End If
' Set the hourly temperature into Bin
ActiveCell.Value = BinMin
ActiveCell.Offset(0, 2).Value = Application.WorksheetFunction.Frequency(myRange,
ActiveCell.Value)
Do
    ActiveCell.Offset(1).Value = ActiveCell.Value + 5
    ActiveCell.Offset(0, 1).Value = Application.WorksheetFunction.Average(ActiveCell.Value,
ActiveCell.Offset(1).Value)
    ActiveCell.Offset(1).Activate
    ActiveCell.Offset(0, 2).Value = Application.WorksheetFunction.Frequency(myRange,
ActiveCell.Value)
    ActiveCell.Offset(-1, 3).Value = ActiveCell.Offset(0, 2).Value - ActiveCell.Offset(-1, 2).Value
    ActiveCell.Offset(-1, 4).Value = ActiveCell.Offset(-1, 3).Value * (ActiveCell.Offset(-1,
1).Value - Average) ^ 2
Loop Until ActiveCell.Value = BinMax
Worksheets("DataBase_Hourly").Range("J3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Range("L3") = (Application.WorksheetFunction.Sum(Selection) /
Application.WorksheetFunction.CountIf(myRange, "<>-99")) ^ 0.5
Range("L4") = Average
' Hourly solar insolation calculation
Worksheets("DataBase_Hourly").Range("E3").Activate
Do While ActiveCell.Offset(0, -2).Value <> ""
    If ActiveCell.Offset(0, -2).Value <> -99 Then
        ActiveCell.Value = ActiveCell.Offset(0, -2).Value * (41.854 * (1 / Range("L3").Value) ^ 0.5
+ (-7.547)) + (1 / Range("L3").Value) ^ 0.5 * (-3351.112) + 893.096
    Else
        ActiveCell.Value = -99
    End If
    ActiveCell.Offset(1).Activate
Loop
End Sub

```

```

Public Sub DateToDaily()
' List the DataBase_Daily date
Worksheets("DataBase_Hourly").Activate
Range("A3").Activate
Range("A2").AutoFilter Field:=2, Criteria1:="0"
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Selection.Copy Worksheets("DataBase_Daily").Range("A3")
Selection.AutoFilter
End Sub

Public Sub InsoToDaily()
' Autofilter the hourly data into rang: 600-1800
Worksheets("DataBase_Hourly").Activate
Range("A:B").AutoFilter Field:=2, Criteria1:="<=1800", Operator:=xlAnd, Criteria2:=">=600"
Range("A3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Selection.Copy Worksheets("DataBase_Daily").Range("E3")
Range("B3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Selection.Copy Worksheets("DataBase_Daily").Range("F3")
Range("E3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Selection.Copy Worksheets("DataBase_Daily").Range("G3")
' Cancel the autofilter in worksheets("DataBase_Hourly")
Selection.AutoFilter
' Get the DataBase_Daily average solar insolation
Worksheets("DataBase_Daily").Activate
Range("E3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Set DateRange = Selection
Range("G3").Activate
Range(ActiveCell, ActiveCell.End(xlDown)).Select
Set InsoRange = Selection
Range("A3").Activate
Do While ActiveCell.Value <> ""
    If ActiveCell.Offset(0, 1).Value <> -99 Then
        ActiveCell.Offset(0, 3).Value = Application.WorksheetFunction.SumIf(DateRange,
ActiveCell, InsoRange) / Application.WorksheetFunction.CountIf(DateRange, ActiveCell)
    Else
        ActiveCell.Offset(0, 3).Value = -99
    End If
    ActiveCell.Offset(1).Activate
Loop
End Sub

```


Simulate Energy Balance Load Based on the Input Parameter Values

```

Public Sub CopyDaily()
' Copy the daily data into Worksheets("Simulation")
Worksheets("Simulation").Activate
Range("A3:W65536").ClearContents
Sheets("DataBase_Daily").Activate
Range("A3:D3").Select
Range(Selection, Selection.End(xlDown)).Select
Selection.Copy Worksheets("Simulation").Range("A3")
Worksheets("DataBase_Daily").Activate
Range("D3").Select
Range(Selection, Selection.End(xlDown)).Select
Selection.Copy Worksheets("Simulation").Range("E3")
End Sub

Public Sub Woa()
Worksheets("Simulation").Activate
Range("B3").Activate
Do While ActiveCell.Value <> ""
R = ActiveCell.Value + 459.67
K = 4.39553 - 3.469 * (R / 1000) + 3.0728 * (R / 1000) ^ 2 - 0.8833 * (R / 1000) ^ 3
P = 3226 * 10 ^ (K * (1 - 1165.67 / R))
If ActiveCell.Value <> -99 Then
ActiveCell.Offset(0, 2).Value = 0.622 * (ActiveCell.Offset(0, 1) / 100 * P) / (14.696 -
ActiveCell.Offset(0, 1) / 100 * P)
Else
ActiveCell.Offset(0, 2).Value = -99
End If
ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub Qwin()
' Calculate Qwin based on floor are and room temperature information
' Assume Awin/Afloor=0.15;Uwin=0.98;F=0.87
Worksheets("Simulation").Activate
Range("F3").Activate
Do While ActiveCell.Offset(0, -4).Value <> ""
If ActiveCell.Offset(0, -4).Value <> -99 Then
ActiveCell.Value = 0.87 * ActiveCell.Offset(0, -1).Value * UserForm1.AreaText.Value *
0.15 / 1000000 + 24 * 0.98 * (ActiveCell.Offset(0, -4).Value - UserForm1.TroomText.Value) *
UserForm1.AreaText.Value * 0.15 / 1000000
Else
ActiveCell.Value = -99
End If
ActiveCell.Offset(1).Activate
Loop

```

End Sub

Public Sub Qwall()

' Calculate Qwall based on floor are and room temperature information

' Assume Awall/Afloor=0.3; Uwall=0.2

Worksheets("Simulation").Activate

Range("G3").Activate

Do While ActiveCell.Offset(0, -5).Value <> ""

 If ActiveCell.Offset(0, -5).Value <> -99 Then

 ActiveCell.Value = 24 * 0.2 * UserForm1.AreaText.Value * 0.3 * (ActiveCell.Offset(0, -5).Value - UserForm1.TroomText.Value) / 1000000

 Else

 ActiveCell.Value = -99

 End If

 ActiveCell.Offset(1).Activate

Loop

End Sub

Public Sub Qinf()

' Calculate Qinf based on floor are and room temperature information

Worksheets("Simulation").Activate

Range("H3").Activate

Do While ActiveCell.Offset(0, -6).Value <> ""

 If ActiveCell.Offset(0, -6).Value <> -99 Then

 If UserForm1.HeatRecoveryNo.Value = True Then

 ' Qinf without heatrecovery system

 ActiveCell.Value = 0.075 * 0.24 * UserForm1.AreaText.Value * UserForm1.VoaText.Value * 60 * 24 * (ActiveCell.Offset(0, -6).Value - UserForm1.TroomText.Value) / 1000000

 Else

 ' Qinf with heatrecovery system

 If ActiveCell.Offset(0, -6).Value < UserForm1.ThlToaText1.Value Then

 ActiveCell.Value = 0.075 * 0.24 * UserForm1.AreaText.Value * UserForm1.VoaText.Value * 60 * 24 * (UserForm1.ThlThlText1.Value - UserForm1.TroomText.Value) / 1000000

 ElseIf ActiveCell.Offset(0, -6).Value < UserForm1.ThlToaText2.Value Then

 ActiveCell.Value = 0.075 * 0.24 * UserForm1.AreaText.Value * UserForm1.VoaText.Value * 60 * 24 * (ActiveCell.Offset(0, -6).Value - UserForm1.TroomText.Value) / 1000000

 Else

 ActiveCell.Value = 0.075 * 0.24 * UserForm1.AreaText.Value * UserForm1.VoaText.Value * 60 * 24 * (UserForm1.ThlThlText2.Value - UserForm1.TroomText.Value) / 1000000

 End If

 End If

 Else

 ActiveCell.Value = -99

 End If

```

    ActiveCell.Offset(1).Activate
  Loop
End Sub

```

```

Public Sub Qoccsen()
' Calculate Qoccc
' Assume density is 400ft2/person; heat is 240Btu/h*person; Operation hour is 10 hours
Worksheets("Simulation").Activate
Range("I3").Activate
Do While ActiveCell.Offset(0, -7).Value <> ""
  If ActiveCell.Offset(0, -7).Value <> -99 Then
    ActiveCell.Value = UserForm1.AreaText.Value / 400 * 240 * 10 / 1000000
  Else
    ActiveCell.Value = -99
  End If
  ActiveCell.Offset(1).Activate
Loop
End Sub

```

```

Public Sub Qsen()
' Calculate Qsen
Worksheets("Simulation").Activate
Range("J3").Activate
Do While ActiveCell.Offset(0, -8).Value <> ""
  If ActiveCell.Offset(0, -8).Value <> -99 Then
    ActiveCell.Value = -ActiveCell.Offset(0, -1).Value - ActiveCell.Offset(0, -2).Value -
ActiveCell.Offset(0, -3).Value - ActiveCell.Offset(0, -4).Value
  Else
    ActiveCell.Value = -99
  End If
  ActiveCell.Offset(1).Activate
Loop
End Sub

```

```

Public Sub Thl()
' Decide whether Thl is variable with Toa
Worksheets("Simulation").Activate
Range("K3").Activate
If UserForm1.ThlVariable.Value = True Then
  TclToa1 = UserForm1.ThlToaText1.Value
  TclToa2 = UserForm1.ThlToaText2.Value
End If
Do While ActiveCell.Offset(0, -9).Value <> ""
  If ActiveCell.Offset(0, -9).Value <> -99 Then
    If UserForm1.ThlConstant.Value = True Then
      ActiveCell.Value = UserForm1.ThlConstantText.Value
    ElseIf ActiveCell.Offset(0, -9).Value <= ThlToa1 Then
      ActiveCell.Value = UserForm1.ThlThlText1.Value
    End If
  End If
End Sub

```

```

    ElseIf ActiveCell.Offset(0, -9).Value <= ThlToa2 Then
        ActiveCell.Value = (UserForm1.ThlThlText1.Value - UserForm1.ThlThlText2.Value) /
        (UserForm1.ThlToaText1.Value - UserForm1.ThlToaText2.Value) * ActiveCell.Offset(0, -
        9).Value + (UserForm1.ThlThlText2.Value * UserForm1.ThlToaText1.Value -
        UserForm1.ThlThlText1.Value * UserForm1.ThlToaText2.Value) /
        (UserForm1.ThlToaText1.Value - UserForm1.ThlToaText2.Value)
    Else
        ActiveCell.Value = UserForm1.ThlThlText2.Value
    End If
Else
    ActiveCell.Value = -99
End If
ActiveCell.Offset(1).Activate
Loop
End Sub
Public Sub Tcl()
' Decide whether Tcl is variable with Toa
Worksheets("Simulation").Activate
Range("L3").Activate
If UserForm1.TclVariable.Value = True Then
    TclToa1 = UserForm1.TclToaText1.Value
    TclToa2 = UserForm1.TclToaText2.Value
End If
Do While ActiveCell.Offset(0, -10).Value <> ""
    If ActiveCell.Offset(0, -10).Value <> -99 Then
        If UserForm1.TclConstant.Value = True Then
            ActiveCell.Value = UserForm1.TclConstantText.Value
        ElseIf ActiveCell.Offset(0, -10).Value <= TclToa1 Then
            ActiveCell.Value = UserForm1.TclTclText1.Value
        ElseIf ActiveCell.Offset(0, -10).Value <= TclToa2 Then
            ActiveCell.Value = (UserForm1.TclTclText1.Value - UserForm1.TclTclText2.Value) /
            (UserForm1.TclToaText1.Value - UserForm1.TclToaText2.Value) * ActiveCell.Offset(0, -
            10).Value + (UserForm1.TclTclText2.Value * UserForm1.TclToaText1.Value -
            UserForm1.TclTclText1.Value * UserForm1.TclToaText2.Value) /
            (UserForm1.TclToaText1.Value - UserForm1.TclToaText2.Value)
        Else
            ActiveCell.Value = UserForm1.TclTclText2.Value
        End If
    Else
        ActiveCell.Value = -99
    End If
    ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub Wcl()
' Calculate Wcl
Worksheets("Simulation").Activate

```

```

Range("M3").Activate
Do While ActiveCell.Offset(0, -10).Value <> ""
  If ActiveCell.Offset(0, -11).Value <> -99 Then
    R1 = ActiveCell.Offset(0, -1).Value + 459.67
    K1 = 4.39553 - 3.469 * (R1 / 1000) + 3.0728 * (R1 / 1000) ^ 2 - 0.8833 * (R1 / 1000) ^ 3
    P1 = 3226 * 10 ^ (K1 * (1 - 1165.67 / R1))
    ActiveCell.Value = 0.622 * (90 / 100 * P1) / (14.696 - 90 / 100 * P1)
  Else
    ActiveCell.Value = -99
  End If
  ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub Qocclat()
' Calculate Qocc
' Assume density is 400ft2/person; heat is 240Btu/h*person; Operation hour is 10 hours
Worksheets("Simulation").Activate
Range("N3").Activate
Do While ActiveCell.Offset(0, -12).Value <> ""
  If ActiveCell.Offset(0, -12).Value <> -99 Then
    ActiveCell.Value = UserForm1.AreaText.Value / 400 * 240 * 10 / 1000000
  Else
    ActiveCell.Value = -99
  End If
  ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub Qlat()
' Calculate Qlat caused by infiltration
Worksheets("Simulation").Activate
Range("O3").Activate
Do While ActiveCell.Offset(0, -13).Value <> ""
  If ActiveCell.Offset(0, -13).Value <> -99 Then
    Wet = ActiveCell.Offset(0, -2).Value - ActiveCell.Offset(0, -11).Value - ((1 -
UserForm1.VoaText.Value) / UserForm1.VoaText.Value * ActiveCell.Offset(0, -1).Value / (4840
* 1 * UserForm1.AreaText.Value * 24 / 1000000))
    If Wet > 0 Then
      ActiveCell.Value = Application.WorksheetFunction.Max((1 - UserForm1.VoaText.Value) /
UserForm1.VoaText.Value * ActiveCell.Offset(0, -1).Value + 4840 * 1 *
UserForm1.AreaText.Value * 24 / 1000000 * (ActiveCell.Offset(0, -11).Value -
ActiveCell.Offset(0, -2).Value), 0)
    Else
      ActiveCell.Value = Application.WorksheetFunction.Max(1 - UserForm1.VoaText.Value /
UserForm1.VoaText.Value * ActiveCell.Offset(0, -1).Value + 4840 * UserForm1.VoaText.Value
* UserForm1.AreaText.Value * 24 / 1000000 * (ActiveCell.Offset(0, -11).Value -
ActiveCell.Offset(0, -2).Value), 0)
    End If
  End If
  ActiveCell.Offset(1).Activate
Loop
End Sub

```

```

    End If
Else
    ActiveCell.Value = -99
End If
ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub DataInput()
' Calculate -EBL
Worksheets("Simulation").Activate
Range("P3").Activate
MsgBox "Please Input Daily Measured 'Wbele' in Column 'P'" & Chr(13) + Chr(10) & _
"      Daily Measured 'Wbcool' in Column 'Q'" & Chr(13) + Chr(10) & _
"      Daily Measured 'Wbheat' in Column 'R'" & Chr(13) + Chr(10) & _
"Click Button 'Continue Simulation' after Pasting Data", vbOKOnly + vbInformation, "Data
Input"
End Sub

Public Sub DataValidation()
' Determine whether the input measured EBL is valid
Dim ValidateCode As Variant
Dim msg As String
Worksheets("Simulation").Activate
Range("P3").Activate
Do While ActiveCell.Offset(0, -1).Value <> ""
    ValidateCode = EntryIsValid(Cell)
    If ValidateCode <> True Then
        msg = "Cell" & ActiveCell.Address(False, False) & ":"
        msg = msg & vbCrLf & vbCrLf & ValidateCode
        MsgBox msg, vbCritical, "InvalidEntry"
        Exit Sub
    End If
    ActiveCell.Offset(1).Activate
Loop
Worksheets("Simulation").Activate
Range("Q3").Activate
Do While ActiveCell.Offset(0, -2).Value <> ""
    ValidateCode = EntryIsValid(Cell)
    If ValidateCode <> True Then
        msg = "Cell" & ActiveCell.Address(False, False) & ":"
        msg = msg & vbCrLf & vbCrLf & ValidateCode
        MsgBox msg, vbCritical, "InvalidEntry"
        Exit Sub
    End If
    ActiveCell.Offset(1).Activate
Loop
Worksheets("Simulation").Activate

```

```

Range("R3").Activate
Do While ActiveCell.Offset(0, -3).Value <> ""
  ValidateCode = EntryIsValid(Cell)
  If ValidateCode <> True Then
    msg = "Cell" & ActiveCell.Address(False, False) & ":"
    msg = msg & vbCrLf & vbCrLf & ValidateCode
    MsgBox msg, vbCritical, "InvalidEntry"
    Exit Sub
  End If
  ActiveCell.Offset(1).Activate
Loop
Call EBL
  RMSE
End Sub

Private Function EntryIsValid(Cell) As Variant
' Returns True if cell is a number
' Otherwise it returns a string that describes the problem
' Blank?
If Not ActiveCell.Value <> "" Then
  EntryIsValid = "Blank Entry" & Chr(13) + Chr(10) & "Replace Blank with -99"
  Exit Function
' Numeric?
ElseIf Application.WorksheetFunction.IsText(ActiveCell.Value) = True Then
  EntryIsValid = "Non-numeric Entry"
  Exit Function
' It passed all the tests
Else
  EntryIsValid = True
End If
End Function
Public Sub EBL()
' Sum up all heat gains to get simulated -EBL
Worksheets("Simulation").Activate
Range("T3").Activate
Do While ActiveCell.Offset(0, -18).Value <> ""
  If ActiveCell.Offset(0, -5).Value <> -99 And ActiveCell.Offset(0, -10).Value <> -99 Then
    ActiveCell.Value = (ActiveCell.Offset(0, -10).Value - ActiveCell.Offset(0, -5).Value) /
UserForm1.AreaText.Value * 1000000
  Else
    ActiveCell.Value = -99
  End If
  ActiveCell.Offset(1).Activate
Loop
' Calculate the measured -EBL
Worksheets("Simulation").Activate
Range("U3").Activate
Do While ActiveCell.Offset(0, -19).Value <> ""

```

```

    If ActiveCell.Offset(0, -5).Value <> -99 And ActiveCell.Offset(0, -4).Value <> -99 And
ActiveCell.Offset(0, -3).Value <> -99 Then
        ActiveCell.Value = (ActiveCell.Offset(0, -5).Value * 0.8 + ActiveCell.Offset(0, -3).Value -
ActiveCell.Offset(0, -4).Value) / UserForm1.AreaText.Value * 1000000
    Else
        ActiveCell.Value = -99
    End If
    ActiveCell.Offset(1).Activate
Loop
End Sub

```

```

Public Sub RMSE()
    Worksheets("Simulation").Activate
    Range("V3").Activate
    Do While ActiveCell.Offset(0, -1).Value <> ""
        If ActiveCell.Offset(0, -1).Value <> -99 And ActiveCell.Offset(0, -2).Value <> -99 Then
            ActiveCell.Value = (ActiveCell.Offset(0, -2).Value - ActiveCell.Offset(0, -1).Value) ^ 2
        Else
            ActiveCell.Value = -99
        End If
        ActiveCell.Offset(1).Activate
    Loop
    Range("V3").Activate
    Range(ActiveCell, ActiveCell.End(xlDown)).Select
    Range("W3").Value = (Application.WorksheetFunction.SumIf(Selection, "<>-99") /
Application.WorksheetFunction.CountIf(Selection, "<>-99")) ^ 0.5
End Sub

```

```

Public Sub Filter()
' Filter out -99 in daily data file for the plot
    Worksheets("Data Plot Data").Activate
    Cells.ClearContents
    Worksheets("Simulation").Activate
    Cells.Select
    Selection.AutoFilter
    Selection.AutoFilter Field:=2, Criteria1:="<>-99.00", Operator:=xlAnd
    Selection.AutoFilter Field:=16, Criteria1:="<>-99.00", Operator:=xlAnd
    Selection.AutoFilter Field:=17, Criteria1:="<>-99.00", Operator:=xlAnd
    Selection.AutoFilter Field:=18, Criteria1:="<>-99.00", Operator:=xlAnd
    Range("A3:C3").Select
    Range(Selection, Selection.End(xlDown)).Select
    N = Application.WorksheetFunction.CountIf(Selection, "<>-99")
    Selection.Copy Worksheets("Data Plot Data").Range("A1")
    Range("P3:R3").Select
    Range(Selection, Selection.End(xlDown)).Select
    Selection.Copy Worksheets("Data Plot Data").Range("D1")
    Range("T3:U3").Select
    Range(Selection, Selection.End(xlDown)).Select

```



```

Selection.Copy Worksheets("Data Plot Data").Range("G1")
Selection.AutoFilter
' Error band evaluation
Worksheets("Data Plot Data").Activate
Range("I1").Activate
Do While ActiveCell.Offset(0, -1).Value <> ""
    ActiveCell.Value = ActiveCell.Offset(0, -2) - 1.96 * 62.2 * (1 + 2 / N) ^ 0.5
    ActiveCell.Offset(0, 1).Value = ActiveCell.Offset(0, -2) + 1.96 * 62.2 * (1 + 2 / N) ^ 0.5
    ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub ErrorIdentify()
' Identify the faulty measured data
Worksheets("Data Plot Data").Activate
Range("H1").Activate
Do While ActiveCell.Value <> ""
    If ActiveCell.Value < ActiveCell.Offset(0, 1).Value Or ActiveCell.Value > ActiveCell.Offset(0,
2).Value Then
        ActiveCell.Offset(0, 3).Value = ActiveCell.Value
    End If
    ActiveCell.Offset(1).Activate
Loop
End Sub

Public Sub Result()
Worksheets("Simulation").Activate
End Sub

Public Sub NewEntry()
Worksheets("Sheet1").Activate
UserForm1.Show
With UserForm1
    .NameText.Value = ""
    .NumberText.Value = ""
    .YearSelect = ""
    .HVAC1_Number.Value = "0"
    .HVAC2_Number.Value = "0"
    .HVAC3_Number.Value = "0"
    .HVAC1.Value = ""
    .HVAC2.Value = ""
    .HVAC3.Value = ""
    .AreaText.Value = ""
    .TroomText.Value = ""
    .VoaText.Value = ""
    .HeatRecoveryYes = False
    .HeatRecoveryNo = False
    .EconomizerYes = False

```

```

.EconomizerNo = False
.ThlConstant = False
.ThlConstantText = ""
.ThlVariable = False
.ThlToaText1 = ""
.ThlToaText2 = ""
.ThlThlText1 = ""
.ThlThlText2 = ""
.TclConstant = False
.TclConstantText = ""
.TclVariable = False
.TclToaText1 = ""
.TclToaText2 = ""
.TclTclText1 = ""
.TclTclText2 = ""
End With
End Sub

```

Create Plots for Individual Energy Consumption

```

Public Sub ModifyChart1()
Worksheets("Data Plot").ChartObjects("Chart 3").Activate
With ActiveChart
.ChartTitle.Text = UserForm1.NameText & "." & Chr(13) & "Time Series Plot of Wbele for
Year " & UserForm1.YearSelect.Text
End With
End Sub

```

```

Public Sub ModifyChart2()
Worksheets("Data Plot").ChartObjects("Chart 4").Activate
With ActiveChart
.ChartTitle.Text = UserForm1.NameText & "." & Chr(13) & "Time Series Plot of Wbcool
for Year " & UserForm1.YearSelect.Text
End With
End Sub

```

```

Public Sub ModifyChart3()
Worksheets("Data Plot").ChartObjects("Chart 8").Activate
With ActiveChart
.ChartTitle.Text = UserForm1.NameText & "." & Chr(13) & "Time Series Plot of Wbheat
for Year " & UserForm1.YearSelect.Text
End With
End Sub

```

```

Public Sub ModifyChart4()
Worksheets("Data Plot").ChartObjects("Chart 5").Activate
With ActiveChart

```

```
.ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Time Series Plot of TDB for  
Year " & UserForm1.YearSelect.Text  
End With  
End Sub
```

```
Public Sub ModifyChart5()  
Worksheets("Data Plot").ChartObjects("Chart 2").Activate  
With ActiveChart  
.ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Tempaerature Based Plot of  
Energy Consumption for Year " & UserForm1.YearSelect.Text  
End With  
End Sub
```

```
Public Sub ModifyChart6()  
Worksheets("Data Plot").ChartObjects("Chart 9").Activate  
With ActiveChart  
.ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Time Series Plot of Measured  
Energy Balance Load for Year " & UserForm1.YearSelect.Text  
End With  
End Sub
```

```
Public Sub PlotPrint()  
ActiveWindow.SelectedSheets.PrintPreview  
End Sub
```

```
Public Sub DataPlot()  
Sheets("Data Plot").Activate  
End Sub
```

```
Public Sub MenuReturn()  
UserForm1.Show  
End Sub
```

```
Public Sub ModifyChart7()  
Sheets("Cross Check").Activate  
With ActiveChart  
.ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Cross-Comparison of Daily  
Simulated and Measured Energy Balance Load for Year " & UserForm1.YearSelect.Text  
End With  
End Sub
```

```
Public Sub ModifyChart8()  
Sheets("Pre-Screening Plot").Activate  
With ActiveChart  
.ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Comparison of Daily  
Simulated and Measured Energy Balance Load for Year " & UserForm1.YearSelect.Text  
End With  
End Sub
```

```
Public Sub CrossPlot()
  Sheets("Cross Check").Activate
End Sub
```

```
Public Sub ScreeningPlot()
  Sheets("Pre-Screening Plot").Activate
End Sub
```

Create Summary Reports

```
Public Sub Parameter()
' Retrieve the input parameters into the summary report
  Worksheets("Summary Report").Activate
  Range("A6").Value = UserForm1.NameText.Value
  Range("B6").Value = "Site# " & UserForm1.NumberText.Value
  Range("D6").Value = "Year: " & UserForm1.YearSelect.Value
  Range("B7").Value = UserForm1.HVAC1_Number.Value & UserForm1.HVAC1.Value
  Range("C7").Value = UserForm1.HVAC2_Number.Value & UserForm1.HVAC2.Value
  Range("D7").Value = UserForm1.HVAC3_Number.Value & UserForm1.HVAC3.Value
  If UserForm1.HeatRecoveryYes.Value = True Then
    Range("C8").Value = "Yes"
  Else
    Range("C8").Value = "No"
  End If
  If UserForm1.EconomizerYes.Value = True Then
    Range("C9").Value = "Yes"
  Else
    Range("C9").Value = "No"
  End If
  Range("C10").Value = UserForm1.AreaText.Value
  Range("C11").Value = Range("C10").Value * 0.3
  Range("C13").Value = Range("C10").Value * 0.15
  Range("C16").Value = UserForm1.TroomText.Value
  Range("C17").Value = UserForm1.VoaText.Value
  If UserForm1.TclConstant.Value = True Then
    Range("C19").Value = UserForm1.TclConstantText.Value
  Else
    Range("C20").Value = UserForm1.TclToaText1.Value & UserForm1.TclToaText2.Value
    Range("C21").Value = UserForm1.TclTclText1.Value & UserForm1.TclTclText2.Value
  End If
  If UserForm1.ThlConstant.Value = True Then
    Range("C22").Value = UserForm1.ThlConstantText.Value
  Else
    Range("C23").Value = UserForm1.ThlToaText1.Value & UserForm1.ThlToaText2.Value
    Range("C24").Value = UserForm1.ThlThlText1.Value & UserForm1.ThlThlText2.Value
  End If
End Sub
```

```

Public Sub SummaryPlot()
    Worksheets("Summary Report").ChartObjects("Chart 7").Activate
    With ActiveChart
        .ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Comparison of Daily
Simulated and Measured Energy Balance Load for Year " & UserForm1.YearSelect.Text
    End With
    Worksheets("Summary Report").ChartObjects("Chart 3").Activate
    With ActiveChart
        .ChartTitle.Text = UserForm1.NameText & ":" & Chr(13) & "Cross-Comparison of Daily
Simulated and Measured Energy Balance Load for Year " & UserForm1.YearSelect.Text
    End With
End Sub

```

```

Public Sub SuspeciousData()
' Copy the suspicious data identified previously into the summary report
    Worksheets("Data Plot Data").Activate
    Cells.Select
    Selection.AutoFilter
    Selection.AutoFilter Field:=11, Criteria1:="<>", Operator:=xlAnd
    Range("A1:H1").Select
    Range(Selection, Selection.End(xlDown)).Select
    Selection.Copy Sheets("Summary Report").Range("K3")
    Selection.AutoFilter
    Selection.End(xlUp).Select
End Sub

```

```

Public Sub ReportPrint()
' Select the print area automatically
    Worksheets("Summary Report").Activate
    ActiveSheet.PageSetup.PrintArea = "$A$1:$I$79,$K$1:$R$85"
    Range("K1").CurrentRegion.Select
    With Selection.Borders(xlEdgeLeft)
        .LineStyle = xlContinuous
        .Weight = xlThick
        .ColorIndex = 41
    End With
    With Selection.Borders(xlEdgeTop)
        .LineStyle = xlContinuous
        .Weight = xlThick
        .ColorIndex = 41
    End With
    With Selection.Borders(xlEdgeBottom)
        .LineStyle = xlContinuous
        .Weight = xlThick
        .ColorIndex = 41
    End With
    With Selection.Borders(xlEdgeRight)

```

```
.LineStyle = xlContinuous  
.Weight = xlThick  
.ColorIndex = 41  
End With  
End Sub  
  
Public Sub SummaryReport()  
    Worksheets("Summary Report").Activate  
End Sub
```

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