DEVELOPMENT OF AN AUTOMATED METHODOLOGY FOR CALIBRATION OF SIMPLIFIED AIR-SIDE HVAC SYSTEM MODELS AND ESTIMATION OF POTENTIAL SAVINGS FROM RETROFIT/COMMISSIONING MEASURES

A Dissertation

by

JUAN CARLOS BALTAZAR CERVANTES

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

DOCTOR OF PHILOSOPHY

December 2006

Major Subject: Mechanical Engineering

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ABSTRACT

Development of an Automated Methodology for Calibration of Simplified Air-Side

HVAC System Models and Estimation of Potential Savings from

Retrofit/Commissioning Measures.

(December 2006)

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This dissertation provides one methodology to determine potential energy savings of buildings with limited information. This methodology is based upon the simplified energy analysis procedure of HVAC systems and the control of the comfort conditions. Numerically, the algorithm is a tailored exhaustive search over all the independent variables that are commonly controlled for a specific type of HVAC system. The potential energy savings methodology has been applied in several buildings that have been retrofitted and/or commissioned previously. Results from the determined savings for the Zachry building at Texas A&M after being commissioned show a close agreement to the calculated potential energy savings (about 85%). Differences are mainly attributed to the use of simplified models.

Due to the restriction of limited information about the building characteristics and operational control, the potential energy savings method requires the determination of parameters that characterize its thermal performance. Thus, a calibrated building is needed. A general procedure has been developed to carry out automated calibration of building energy use simulations. The methodology has been tested successfully on building simulations based on the simplified energy analysis procedure. The automated calibration is the minimization of the RMSE of the energy use over daily conditions. The minimization procedure is fulfilled with a non-canonical optimization algorithm,

the Simulated Annealing, which mimics the Statistical Thermodynamic performance of the annealing process. That is to say, starting at a specified temperature the algorithm searches variable-space states that are steadier, while heuristically, by the Boltzmann distribution, the local minima is avoided. The process is repeated at a new lower temperature that is determined by a specific schedule until the global minimum is found. This methodology was applied to the most common air-handler units producing excellent results for ideal cases or for samples modified with a 1% white noise.

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ACKNOWLEDGMENTS

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CHAPTER I

INTRODUCTION

As the energy needs of the world have been growing, and as the population has been increasing, governments and private organizations have been participating in different efforts to influence global policies that will lead to energy efficient processes and preserve the environment. For this reason in recent years in the US, energy conservation programs have become more important, both because they are seen as contributors to the solution of the environmental pollution, and because they reduce waste of non-renewable energy sources. In the United States, slightly more than one-third of the total primary energy consumption is used in the buildings sector. Commercial buildings alone consumed the equivalent of 18% of the total energy use in the US in 2004 (EIA, 2005). An energy conservation program for the building sector could embrace a variety of aspects. Among others, it may include auditing, installing retrofits, commissioning, collection of monitored energy-use data, data analysis, savings determination, fault diagnostic of the building systems, and optimization of building energy use by improving operation and maintenance practices.

The modeling of the building energy use is a significant component of the success of conservation programs; therefore, several techniques and simulation programs have been developed to accomplish this purpose. By and large, it is accepted that simulations and/or statistical modeling of daily, or monthly, energy use are appropriate for determining retrofit savings, while the hourly energy use scale may be used for performing more detailed analysis, such as fault diagnosis and optimization.

For almost four decades, energy simulation programs have been used to estimate the energy loads in buildings or to compute the individual contributions of their system components. However, simulators have not been able to determine accurately the actual energy loads in the building, because all computer programs make approximations, and

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This dissertation follows the style of the *Journal of Solar Energy Engineering*.

the building operations are often different from what is assumed. In some cases operational problems exist that may not be represented by the simulation program. Well-designed and extensively used simulation programs such as DOE-2, BLAST, etc., need a great number of inputs to accurately portray Heating, Ventilating and Air-Conditioning (HVAC) system performance. Yet, these programs cannot avoid finding departures from the measured load patterns found in real buildings. This fact has acquired more relevance, and needs to be solved, as simulations are being used to propose retrofit/commissioning measures that might lead to a more efficient energy use or to explore potential energy-use savings measures in buildings.

When a simulation tool is used for purposes of evaluating opportunities for retrofitting/commissioning an existing building, the proper HVAC model must be chosen and the simulation inputs must be accurately adjusted so the simulated energy use data closely matches the actual measured data. This process is recognized as "calibration" of the simulation. In other words, a calibration process seeks the actual characteristics and/or real operation conditions using both data from an energy simulation program and measured energy use data through a reconciliation process; the inputs of the program are modified until the obtained energy-use loads match the actual energy-use data. A fully calibrated model gives a reliable set of building operation parameters because it matches the measured data in both the monthly total and daily profiles of end-use energy use. To make the calibration a useful tool for applications like the evaluation of retrofit energy savings, the identification of operating problems, or the optimizing of system operation, the calibration of the simulation should require minimal time and effort.

Many procedures have been suggested to calibrate building energy simulations; these procedures are based on different approaches, mostly related to the measured data types and length of the measurement periods. However, the previously reported calibration processes have generally been time-consuming and, due to the open range of the variations that may be included in the process, require a user with a high level of expertise in simulating and measuring HVAC systems performance.

Due to the growing number of building energy use simulators and the engineering relevance that the calibration processes has been acquiring, it is proposed to develop and test an innovative, and inexpensive systematic approach to perform automated calibrations of HVAC systems. The proposed methodology anticipates the use of steady-state air-side HVAC engineering analysis, which may reliably resolve or tune any significant differences between the simulated and measured energy use in commercial buildings. In addition, the proposed procedure would avoid any user interaction with the calibration process. It is expected that the proposed automated calibration procedure will support the evaluation of and, in some sense, help to develop a methodology for the analysis of potential energy savings that could be obtained from retrofit/commissioning measures.

The four major generic types of commercial building air handling units (AHU) that are included in this research are: the Dual Duct Constant Volume (DDCV), the Dual Duct Variable Air Volume (DDVAV), the Single Duct Constant Volume (SDCV), and the Single Duct Variable Air Volume (SDVAV) systems. There are variations of each of these major system types, but those systems are beyond the scope of this work.

1.1   Objectives of the Research

Calibrated building simulation models can be used, as previously mentioned, to identify operational problems, and optimize system operation and control schedules. Typical procedures for calibration start with a base building model and some form of measured data from an existing building; then, various building parameters in the simulation program are changed to adjust the simulated energy use until the best possible match is achieved between these and the measured energy use data. Hence, the calibration of a model is generally a time-consuming task and, as the data interval is reduced (i.e. daily, hourly) the path to calibration typically becomes more cumbersome. That is to say, it takes longer to calibrate daily or hourly data than monthly data because the required variation in the parameters may be finer.

Historically, the calibration methodology of a building simulation is based on a trial and error procedure, or some variant of it. However, this method requires the interaction of a practitioner, or an expert on HVAC systems performance, and general rules have not been established on how it should be done to assure that the precision required to claim successful calibration is reached. Several systematic calibration procedures have been proposed, but just a few have been developed for possible automation. This task is inherently complex because of the large number of parameters that may require calibration, though this number depends on the simulation program. This complexity combined with the high precision required for a successful calibration process entails the development of alternative methodologies that would reduce the process time and that could be carried out automatically with maximum accuracy.

Three calibration methods have been developed that have been automated or are claimed to be suitable for automation. Two of the reported methods with capabilities of being implemented in an automated way (Sun and Reddy 2006, Subbarao 2000) make use of the DOE-2 program. These methodologies require that the engineering models of these simulation programs be differentiable in the operational ranges of the variables and that the code of these programs be accessible. The other automated methodology, developed by Lee and Claridge (2002) was tested on a CVRH system modeled using the ASHRAE simplified energy analysis procedure (Knebel 1983) and utilizes a commercial optimization program to achieve calibration. Although these methodologies have been successfully demonstrated, they appear to depend on access to certain details of the engineering models used to carry out the automated optimization or calibration process, and they require a high degree of expertise by the potential user.

This research seeks to achieve the following objectives:

- To develop a steady-state simulator for the four major generic types of air-handling units utilized in commercial building systems that contains an automated calibration methodology, which can serve as the basis of the potential energy saving determination methodology.

- To implement and test an accurate automated calibration algorithm for the four typical HVAC systems. The proposed algorithm is based on the minimization of the root-mean-squared error (*RMSE*) between simulated and measured data. The calibration procedure should be independent of the simulation program that is used to model the building energy use.

- To describe and demonstrate a methodology based on the automated calibration for the determination of potential energy savings that could be obtained from retrofit and/or commissioning work.

The focus of the automated calibration procedure is on the temperature-dependent energy use, such as the whole-building heating and cooling use. To fulfill these objectives, the procedure makes use of data that may be easily collected and simplified engineering models, which are used to simulate the air-side HVAC systems and building indoor conditions in steady-state operation. The simulations are based on daily average data because it is assumed that the HVAC systems are to be operated at least 16 hours per day. The automated calibration procedure minimizes the *RMSE* between the measured and simulated data. The calibrated parameters will then be used as a starting point to determine the potential energy savings according to the building characteristics and its operation conditions. The potential energy savings methodology is based on the minimization of the building energy use, while maintaining comfort conditions in the spaces of the building and adequate ventilation according to the ASHRAE standards.

CHAPTER II

LITERATURE REVIEW

For almost four decades, computers have been used as part of the energy system design process and as valuable energy analysis tools to relieve the otherwise tiresome manual energy calculations (Kusuda 1999 and 2001, Ayres and Stamper 1995, Beranek and Lawry 1989). While the level of detail offered by the actual energy simulation programs is high, the reliability of the results is frequently compromised by a lack of certainty that the simulations reflect actual performance. For building energy use analysis, some of the most complete simulation and emulation programs – such as DOE-2, BLAST, TRNSYS, and HVACSIM$^+$, have been empirically evaluated and analytically verified, albeit the performance of those validation programs can only assure a performance-map modeling of space equipment when the operation conditions are close to the design conditions (Neymark et al. 2001). In general, comparing the measured energy use data of a system to its corresponding simulated data set have always been accepted as the prime method of verifying how well the simulation model represents actual system performance. Energy simulation programs may be used for estimating potential savings as well as to help verify savings from retrofits or commissioning measures actually installed.

The simulation programs and most of the design tools used to analyze the performance of the HVAC systems in buildings are typically based on two different categories of modeling, which are characterized by the purposes of the analysis or investigation (Rabl 1988). The approaches are forward – or classical, and inverse – or data-driven. The forward approaches are based on sound engineering principles and have gained extensive acceptance by designers and the professional community. These approaches utilize detailed knowledge not only of the various natural phenomena affecting the system behavior but also of the magnitude of their interactions. On the other hand, the inverse methods are applied when the input and output variables are

known and measured. This allows the estimation of a mathematical representation of the building's energy use or the identification of the significant system parameters. Since the model parameters are deduced from actual building performance, this method is much more likely to capture accurately the as-built system performance, thus allowing more accurate predictions of future system behavior under certain specific circumstances (ASHRAE 2001). However, it is limited because it may not allow for the characterization of energy use of a specific sub-system or component.

Several factors must be considered in the selection of an energy analysis method, including among others: accuracy, versatility, speed, reproducibility, and cost. For determining energy use in buildings, experts prefer simulation programs that assemble component models into pre-assembled system models and then integrate those models with weather and occupancy data. Unfortunately, these programs require an intense computational effort, and that is hard to justify when the energy use must be estimated quickly to study trends or compare systems. For these last purposes simpler methods such as the bin or degree-day methods, and their variations, may be used (Claridge 1998, Thamilseran and Haberl 1994, Thamilseran 1999).

For the estimation of a building's energy use, inverse methods follow different approaches, such as a completely empirical approach – also known as the black–box approach; the calibrated simulation approach; and the gray-box approach which is a mixture of black-box and calibrated simulation methods. These approaches vary broadly in data requirements, time, effort, and reliability.

The empirical approach may utilize single or multi-variable regression methods based on influential environmental and/or occupancy parameters (Kissock et al. 1998, Katipamula et al. 1998, Ruch and Claridge 1991, Reddy et al. 1997a and 1997b, Claridge 1998). This approach is adequate for the evaluation of the effect of simple and conventional energy conservation measures in an actual building. In addition, this approach may be used for baseline model development to determine savings from energy conservation measures. More complex, but also beneficial models belonging to this category, are Fourier series models and Neural Networks, which are particularly

suitable when a great amount of data is available (Dhar et al. 1998, 1999a, and 1999b; Kreider and Wang 1991).

The gray-box approach is different than a black-box approach because it follows the physical representation of the building or the HVAC system, from which the most important parameters are identified by statistical analysis. This approach requires a high level of expertise in physical modeling and in estimating the parameters, but has great potential in comfort analysis, evaluation of typical meteorological years, fault detection, and diagnostics (Reddy et al. 1999, Subbarao 1988, Andersen et al. 2000, Palomo and Lefebvre 1995, Richalet and Neirac 1991).

The calibrated simulation approach commonly uses existing building simulation software and tunes its physical inputs so that the simulated energy use closely matches the measured use. Calibrating a model, or simulation, typically requires detailed information on the actual building's features and systems. In addition, the procedure requires many adjustments to achieve acceptable prediction accuracy. Calibration methods have been found useful for creating building energy baselines when little or no monitored baseline data are available (Katipamula and Claridge 1993) and as an aid in diagnosing operating problems (Liu and Claridge 1995).

2.1 Calibrated Simulation Approaches

Reconciling computer simulations to actual measured data is not a new practice. As early as 1970, recommendations were made to reconcile models based on measured data (Ayers and Stamper 1995). Historically, comparisons have been an art form that inevitably relies on user knowledge, statistical expertise, engineering judgment, and plenty of trial and error analysis. For a long time, the reconciliation of the simulation results to measured monthly utility data was the primary form of calibration implemented.

As computing technology has become affordable, users have taken advantage of hourly simulation programs on desktop personal computers that can perform loads calculations quickly and inexpensively. In addition, measurement technology has

become sufficiently inexpensive to monitor energy use and environmental data hourly, or sub-hourly, over long periods. This seems to give a broad perspective to the calibration approach. However, while it is reasonably easy to match simulation results with utility bills, it is considerably harder to match daily or even hourly data.

Many procedures have been proposed to calibrate a simulation using different periods and different types of measured data. Some of these procedures have been successful in achieving simulated results that agreed with the measured consumption within 5-15% on an annual basis (Soebarto 1996). Some procedures require on-site hourly measurements of building energy use, and others are based on monthly energy use. Several of the calibration procedures that have been developed are dedicated to the non-weather-dependent loads of the building (Bronson et al. 1991, Bronson et al. 1992). In general, all calibration processes require enormous amounts of computing time because they depend on a large number of input parameters and on the user expertise with the simulation program.

The procedures for calibration of hourly simulation models developed by Haberl and Bou-Saada (1998) have led to the inclusion of this approach in the ASHRAE Guideline 14-2002 (ASHRAE 2002), Measurement of Energy and Demand Savings and in the International Performance Measurement and Verification Protocol (IPMVP 2001), as option D for evaluating savings. Nevertheless, there is little systematic guidance available to the practitioner, either qualitative or quantitative.

Several causes may prevent the achievement of a calibrated simulation. Hsieh (1988) thoroughly listed the input parameters that may affect the accuracy of the simulation of the total building energy consumption; among them, the tenant energy use, HVAC operation schedules, and the envelope's heat loss coefficient have significant effects on the accuracy of the simulation model. In addition, other factors that must be considered in calibrations are the following:

(a) The measurement and adaptation of weather data for use by the simulation programs.

(b) The choice of the procedures used to calibrate the model. Typically when a model is established as being calibrated, i.e., the user states that the "accuracy" for electricity is approximately "5% per month", the author does not reveal the techniques used other than stating that the final result is "calibrated" or "validated". This manifests a lack of uniformity and abundance of confusion in calibrating simulations to actual data.

(c) The choice of methods used to measure the required input parameters for the simulation. Kaplan et al. (1990a and b) found significant sources of simulation model error based on their work in the Energy Edge program. These errors include: underestimation of the receptacles' power densities, overestimation of the loads using nameplate data, underestimation of the receptacle and lighting uses during the unoccupied periods, inaccuracy in describing the interior and exterior window shading coefficients, the mass of the building, infiltration coefficients, and window and wall U–values. In addition, another error usually occurs when the modelers use the as–designed building operating schedules in the model while, in fact, the real operating schedules have significantly changed.

Due to the reasons mentioned above and the associated financial resources required, totally calibrated models using full–sized simulation programs, such as DOE-2 and BLAST, have been achieved in only a few applications (Haberl and Bou-Saada 1998, Bronson et al. 1992, Kaplan et al. 1990a and b, Bou-Saada and Haberl 1995, Manke et al. 1996, and Norford et al. 1984).

Another calibration scheme, suggested by Katipamula and Claridge (1992, 1993), makes use of simplified models; this allows the calibration procedure to be carried out faster. The building is divided into two zones: an exterior zone, or perimeter, and an interior, or core, zone. This core zone is assumed insulated from the envelope heat losses/gains, and the conduction gains/losses from the roof are taken to appear as loads on the external zone only. Given the internal load schedule, the building description, the type of HVAC system, and the climatic parameters, the HVAC systems' loads can be estimated for each hour of the day and for many days of the year as needed by the

simplified system model. Since there are fewer parameters to vary, the calibration process is much faster (Liu et al. 1998b, Wei et al. 1998). This scheme is based on the ASHRAE simplified energy analysis procedure (Knebel 1983).

Although several calibration procedures have been developed and tested during the last twenty years, to date no consensus guidelines or standards have been published on calibration procedures that can generally be used on a variety of buildings and that show how to assess the comparison of the results from a building's energy simulation program against measured data from an actual building (Diamond and Hun 1981, Hsieh 1988, Kaplan et al. 1992, Hunn et al. 1992, Haberl et al. 1993, Clarke et al. 1993, Bou-Saada 1994, Bou-Saada and Haberl 1995a and b, Manke et al. 1996).

As mentioned above, in almost all the studies on calibration procedures the results fall short in providing a toolkit of procedures capable of truly rapid calibration. Most of the calibration methodologies have focused on, among others issues, defining an appropriate period for the calibration procedure, conducting sensitivity analyses to identify the parameters that have a major influence on the simulation results, investigating the variables that should be monitored, and applying suitable day-typing techniques to remove the effect of major changes in the operation schedule of the building system.

2.1.1 Calibration time periods

Testing and modifying the simulation models by using long–term data sets is expensive and time–consuming. An alternative to this is to choose short-term data sets that cover all the seasons of the year. Kaplan et al. (1990b) pointed out that a cold weather period and a hot weather period might be sufficient to calibrate models for stable weather patterns. Another method of calibrating models by using short data sets is the Short–Term Energy Monitoring (STEM) method, which has been successfully applied in residences and commercial buildings (Subbarao et al. 1990; Balcomb et al. 1993 and 1994). STEM essentially uses a Primary and Secondary Terms Analysis and Renormalization (PSTAR) method in a building. PSTAR is based on a frequency domain analysis and permits the determination of the building loss coefficient, the building

mass, and the solar heat gain without one factor interfering with the other (Subbarao 1988). STEM is based on data sets of three to five days duration and is performed with the building unoccupied. An approach using short-term data sets was also followed by Manke et al. (1996) using the BLAST program as the simulation tool to calibrate non–weather dependent loads by varying the primary parameters. The primary factors included in the study were wall and roof R-values, glass window transmittance, internal mass area, and thickness.

Soebarto et al. (1996b and 1997) developed a calibration method that makes use of monthly utility records of the building, two to four weeks of hourly monitored energy data at any period of the year, on-off "blink test" data, and a building description from site observations. These data are used to disaggregate the total energy use into the components of heating, cooling, fan motors, and domestic hot water, and then to calibrate a simulation. The calibration is performed on both hourly and monthly data.

Another calibration procedure for the building energy performance model is based on actual monthly data (Yoon and Lee 1999, Yoon et al. 2003). This procedure has been visualized as a logical flow chart and can be understood as a stepwise procedure. A key concept in this approach is the use of a mid-season base load analysis for disaggregating the energy consumption into more detailed sub-areas to examine and trace the energy use in the building. The results indicate that this approach provides a reliable and accurate computer model for the annual building energy-use.

2.1.2   Sensitivity analysis

The usefulness of a sensitivity analysis for calibrating a building energy use simulation lies in the fact that it might reduce the amount of work required to reach this goal. This can be achieved by identifying the most sensitive parameters from among those that affect the building energy use and tuning these sensitive parameters to improve the model fit. The first run of a simulation is performed to establish a base case reference, and then several runs are performed with extreme values of each parameter that significantly affects the model prediction. The results of these simulations are used to determine the most sensitive parameters. Wei et al. (1998)

described such sensitivity analysis through signatures of different parameters on the heating and cooling energy consumption of typical air handling units (AHU's). The basis of this analysis is to use the simplified engineering models based on the simplified energy analysis procedure (Knebel 1983). These signatures can then be used to aid in the calibration process through rational decisions. Claridge et al. (2001) have systematized the procedure of calibration through these signatures for potential users. This methodology has been tested with synthetic and actual data generating excellent results.

2.1.3 Monitored variables

Calibration of simulation models can be accomplished by matching simulated indoor temperatures to measured indoor temperatures. Hsieh (1988) compared DOE-2 predicted temperatures with measured temperatures to help identify the discrepancy between actual and model predicted energy use. Clarke et al. (1993) conducted similar tests under the PASSYS program. Haberl and Komor (1990c) used minimum and maximum zone temperatures to verify HVAC system operation. In general, the variables used for the calibration procedures depend on the methodology or on the criteria of the authors.

2.1.4 Day-typing

Energy use in commercial buildings is affected greatly by the systematic scheduling of the building systems; separating the data set based on major operational changes prior to model development is an important step.

The day–typing of energy data involves either a simple data sorting based on the calendar or a complex statistical analysis. Katipamula and Haberl (1991) proposed a day-typing methodology to identify diurnal load shapes using monitored end–use data. According to their technique, the day-types are generated through univariate statistical analysis that assumes that any final day-type will not have a Coefficient of Variance greater than 10%.

2.2 Calibrated Simulation Tolerances

The iterative nature of the calibration methodologies makes it necessary to define a tolerance that allows the procedure to end with an acceptable and reasonable accuracy. The criterion to assess the calibration process can be seen in qualitative and quantitative manners. Graphical representation of the results of simulated systems is typically referred to as qualitative analysis. A decade ago, most of the procedures relied on comparisons of monthly percent difference time-series graphs, x-y scatter plots, bar charts, carpet plots, or comparative 3-D time series plots (Bronson et al. 1991, 1992). Recent efforts have compared hourly outputs of simulations to their corresponding hourly measured data, but many of the traditional statistical and graphical comparison techniques mentioned above become overwhelmed with too many data points. In some better cases, these procedures rely on temperature binned box-whisker-mean analyses to improve x-y scatter plots, 24-hour weather-daytype box-whisker-mean graphs to show hourly temperature-dependent energy use profiles, and 52-week box-whisker-mean plots to display long-term trends (Bou-Saada 1994). McCray et al. (1995a and b) developed a data visualization analysis kit for studying the total load and end-use data produced by the DOE-2 building simulation program. These data visualization techniques allow the user to quickly and easily view and analyze hourly data sets through statistical measures of fit, potentially reducing the modeling cost because it could reduce the iterative modeling process (Cohen and Bailey 1998).

To obtain reliable results, a quantitative analysis that is based on statistical metrics that assess the goodness-of-fit between modeled and measured data is needed. This quantitative assessment is perhaps the most decisive factor in determining the final state of the calibration process.

Monthly comparisons fall short of the level of accuracy that is needed when the simulation is used to quickly evaluate changes that amount to less than 10% to 20% of a building's total energy use. While both simulations and measurements may be performed with considerable resolution in time and space, all that detail is thrown away when only comparisons of aggregated monthly simulation results to monthly utility data

are carried out. The error in agreement can also be influenced by the use of average weather data in the simulation.

Discrepancies between measured data and simulation results have a direct influence on the uncertainty of a model. The greater the discrepancy, the more uncertain are the predictions of the simulation. Should the calibrated model be used to evaluate savings, the uncertainty of the model would directly affect the savings estimation.

As reported in previous works (Kreider and Haberl 1994, Haberl et al. 1998, McCray et al. 1995), the Coefficient of Variation of the Root Mean Square Error (CV-RMSE) and the Mean Bias Error (MBE) are the parameters most frequently used to establish if a model or a simulation fulfill accuracy criteria. The CV-RMSE can be thought as an estimate of the consistency of a model in predicting loads. The MBE is a linear norm that describes how well a model predicts the energy use and is generally expressed as the difference between the model predicted and the actual energy use.

Both parameters, the CV-RMSE and the MBE, must be acceptable for a model to be considered calibrated. The dilemma is on deciding what values for these parameters are acceptable to end the calibration procedure. ASHRAE Guideline 14-2002 (ASHRAE 2002) provides, without specifics, that computer models being used for calibration should be accurate to within 5% of the normalized mean bias error (NMBE) and 15% for the CV-RMSE relative to monthly data, but for hourly data the thresholds are 10% and 30%, respectively.

Palomo et al. (1991) have suggested the use of a series of statistical tools to evaluate the goodness–of–fit of the comparison between the measured energy use and the result of a simulation program. These tools include the autocorrelation function, the auto-spectrum, the cross-correlation matrix, and the spectral matrix, among others. All of the previously mentioned tools are time series statistical measures that depict the stationary behavior and the dynamics of the variations between the measured and the simulated data, but for practitioners these parameters are hard to follow.

2.3 Uses of Calibrated Simulations

The need to analyze the energy performance of commercial buildings in order to measure savings from energy efficiency retrofits, or Continuous Commissioning® (CC®)[1] measures, and to assure continued performance has increased in recent years (Claridge et al. 2000).

Calibration methods have been found useful for creating building energy baselines when little or no monitored baseline data is available (Katipamula and Claridge 1993) and as an aid in diagnosing operating problems (Liu et al. 1994).

A number of different approaches have been developed to identify operating and control problems or to detect faults in HVAC systems. These include the use of expert systems, neural networks, and fault detection using physical models. All these methods require highly detailed system information or long training periods, which limits their application, and most of them are developed for a specific building system component (Liu and Claridge 1998a). Calibrated modeling approaches perform better than regression and auto-associative neural network (ANN) approaches in determining the effect of a particular parameter, for example, cold deck temperature of a building's HVAC system, on the building's energy use.

Calibrated simulation can be a great tool for determining potential savings in a commercial building through the identification of operational improvements. Several studies have described the use of calibrated simulation for this purpose (Liu and Claridge 1995, Liu et al. 1994, Liu et al. 1996a and 1996b). This method can also be used to optimize operating strategies and control deck schedules and has served to identify malfunctioning components. The simulation of a case-study building indicated that its thermal energy consumption would be reduced by 23% using the optimized operating schedules.

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[1] Continuous Commissioning and CC are registered trademarks of the Texas Engineering Experiment Station (TEES).

2.4 Automated and Semi-Automated Calibration Procedures

During the same time that this study was being developed, three methodologies for automated calibration were developed.

Subbarao (2000) patented a method for improving building energy simulations which calibrates the simulations by introducing corrective heat flows. The original inputs of the simulator, or program, used for the building energy analysis are based on a building audit. The corrective heat flows are calculated from calibration parameters and primary heat flows, and incorporated as additional internal gains in order to minimize the differences between the predicted and measured performance. The calibration parameters are then used as a guide to modify the audit inputs to the simulator to reduce the magnitude of the corrective flows. This methodology used the DOE-2 program as the base of the work, but it is claimed that the methodology could be used on other simulators, too.

Lee and Claridge (2002) developed a calibration methodology that is based on the simplified energy analysis procedure of Knebel (1983). The calibration process is developed for just one of the most common HVAC systems (SD CVRH) and used *RMSE* minimization using a commercial program. In order to perform the calibration, the commercial program needs access to the building energy simulation equations in order to perform the required minimization. The calibration is carried out automatically in a successful manner, avoiding difficulties that any local minimum can produce.

More recently, Sun and Reddy (2006) proposed a four-step process to address the calibration of building energy simulations through mathematical and statistical formulations. Their methodology involves several distinct sub-elements, such as sensitivity analysis, identifiable analysis, numerical optimization, and uncertainty analysis. They presented their results from calibrating a synthetic example, and the calibration was based on the whole-building electricity use and demand. This proposed methodology was based on and developed using the DOE-2 simulator.

All of the methodologies presented here claim success but just one of them states clearly that the methodology is automated (Lee and Claridge 2002). Besides the

amount of information and parameters that are included in the other two procedures, the steps that are to be followed to obtain the calibrated simulation appear to involve important interaction and expertise of an analyst.

2.5 Potential Savings in Commercial Buildings

Several types of studies have been related to the assessment of energy conservation potential in commercial buildings. Some of these studies rely on comparisons among the energy conservation performance standards, which have been changing in time with the intent of improving energy efficiency in buildings. Hadley and Halverson (1993) compared the interim energy conservation standard for new commercial and multi-family high-rise buildings on a whole-building energy-use basis utilizing the 90A-1980 standard as the base building configuration and found that an average reduction of 18% in energy use would be obtained in buildings using the DOE-93 standard. They also found that the greatest potential reduction in energy use is obtained in retail buildings in the coldest climate locations. Also, it was found that for all climate locations and most building types, the greatest single source of potential reduction comes from reductions in lighting energy use.

The potential energy savings also convey the associated cost savings; moreover, the importance of energy conservation implies benefits for the environment. Harris and Johnson (1999) assessed the potential energy, cost, and CO_2 emissions savings from energy-efficient government purchasing — including federal, state, and local agencies. Of the four savings scenarios that they analyzed, the most likely case represents annual energy cost savings worth, for all three levels of government, over $1 billion/year in 2010 along with reduced CO_2 emissions of about 2.9 MMT/year. These numbers indicate that energy-efficient purchasing programs could make a major contribution to energy and environmental goals at all three levels of government while saving taxpayer dollars in the process.

2.6 Energy Benchmarking Strategies for Commercial Buildings

By and large, benchmarking is a procedure that is used for comparison against a standard. Therefore, for energy use in commercial buildings, the benchmarking technique can be used to compare either the whole-building energy use, the energy use of a specific system, or the energy use of a specific component to a comparable data set. The comparison could be performed through annual indexes, e.g., the annual energy use intensity (EUI) (Building Technology Center 2001). The EUI is the average power use normalized by the gross conditioned area of the building.

Energy benchmarking gives a global picture of how efficiently the energy is being used in a building in comparison with other similar facilities. For this reason, benchmarking is one of the first activities in the process of deciding whether to invest in energy-conservation measures in buildings. Furthermore, energy benchmarking helps to ensure appropriate energy management and could assist in the identification of potential improvements.

The most significant challenge in energy performance benchmarking is to ensure that the data are compared in the most meaningful way possible. It is important to avoid the misinterpretation of comparing data that might lead to inappropriate conclusions. In general, benchmarking methods do not sufficiently account for differing functional requirements. To unravel some of these deficiencies, several formal methodologies have been established for energy benchmarking in buildings including: statistical analysis, point-base rating, model-base rating, hierarchical end-use performance metrics, and combinations of these methods, among others (Sator et al. 2000).

The benchmarking technique based on statistical analysis is perhaps the most widespread of all. It uses an extensive energy-use building database, which may be classified in different ways and from whose energy use patterns statistical indexes can be extracted. Thus, a direct comparison between actual energy-use in a particular building may be obtained if there are buildings in the database with the same characteristics, i.e., square footage, type of building, usage of the building, etc. Statistical data, especially end-use data, may be useful for comparisons between

buildings of participating companies; however, generalization to the overall population should be avoided.

Assessment and comparison of statistical energy indicators can be considered a simple starting point for more refined procedures such as the ENERGY STAR[®] Building Label. This label is the major office building benchmarking effort in the US (Sharp 1996, Hicks and Clough 1998) and accounts for differences in the "levels of service" provided by different office buildings.

Point-based rating system benchmarking is a consensus-based rating system to evaluate specific parameters' performance from a "whole building" perspective. It is a system where credits are earned for satisfying each criterion.

Model-based benchmarking, developed at the University of California Center for Environmental Design Research (CEDR) (Federspiel et al. 2002), is a tool that calculates the minimum energy requirement for a basic set of functional facility requirements. The objective of this method is to define a benchmark related to the energy consumption of an "ideal" building that consumes the minimum amount of energy required to achieve the same indoor temperature, humidity, lighting, and ventilation conditions as the actual building. The energy consumption benchmark derived from the "ideal" building is determined using mathematical models.

Sator et al. (2002) describe a more complete, but also more laborious benchmarking scheme in which a set of hierarchical and end-use performance metrics is developed. The idea of hierarchical measurements and metrics is to start at the highest level (whole-building) and subsequently begin to "peel the onion", moving down toward the underlying system performance data. Such approach is useful for identification of specific energy efficiency opportunities for a given facility. Additionally, a set of characteristic data could be applied to help "explain" the measurements by relating the data back to the "type" of system in place, or the building characteristics. Information may also include hours of use, equipment type, and vintage, plus process and plug load descriptions.

Each benchmarking approach presents strengths and weaknesses; those that use whole-building level data may give false signals:, e.g., a low energy use intensity may not necessarily mean an energy efficient building. Disaggregated data is very useful in understanding energy consumption in buildings and allows for benchmarking of systems and components across multiple buildings. However, it requires laborious and time-consuming analyses. Obviously, the development of more sophisticated software tools in the future will help to alleviate the burden of benchmarking tasks.

2.7 Summary

Until now, only a few calibration procedures have been systematized to perform as automated or semi-automated procedures (Subbarao 2000, Lee and Claridge 2002, Sun and Reddy 2006). In general, a calibration procedure, based on the practitioner's expertise, uses an energy simulation of an existing building and tunes the inputs to the simulation so its calculated energy use matches the measured energy use. The reliability of any calibration process has always depended on the understanding and expertise of the analyst or practitioner. There is general agreement on the accuracy required for a good calibration, but little agreement on the path to follow to achieve calibration.

As the hardware for processing and collecting data have become more accessible in the HVAC field, the collection period or data interval used for calibration continues to decrease. In the 1980's, calibrations were made using utility bills; subsequently it has been possible to collect data in hourly or sub-hourly intervals that have helped to improve the accuracy of the calibration of the simulations. However, the hourly calibration schemes have also increased the required level-of-expertise and time required to produce a calibrated simulation.

The tools used to guide the analysts in carrying out calibration have also changed. Initially, the main tool used in calibration was the analyst's experience and knowledge of the building operation. This fact led many authors to try to systematize their experiences, but no consensus seems to have evolved across users. As the calibration

was carried out with hourly data, the amount of information overwhelms most practitioners. Hence, with the experience obtained from past calibration methodologies and with plots that visually help to systematize the data, such as three-dimensional plots, binned-whisker-box, and scatter plots, it was possible to usually identify which parameters were substantially affecting the simulation and in that way modify it for the next iteration. Although this makes the process simpler and more understandable, the analyst expertise remains a critical component in the use of such techniques.

An important shift in the calibration procedures was developed by researchers at the Energy Systems Laboratory (ESL) at Texas A&M University. In the effort to find ways of improving operation and control to diagnose malfunction of HVAC components, and/or predict effects on other secondary equipment of large buildings, ESL investigators (Liu and Claridge 1998a, 1998b, 1999; Liu et al. 1994a, b, 1996a, b, 1998; Wei et al. 1998) derived a procedure to calibrate building energy simulations using measurements from the building's AHU. The methodology is based on the simplified engineering models (SEAP) and was carried out using the "AirModel" simulator (Liu 1997). It emphasizes the whole-building cooling and heating thermal loads on an hourly basis. The methodology represents the building using only two-zones (interior and exterior) and assumes that the building has a few large air-handling units (AHU) in lieu of the numerous similar smaller ones for each space. The most important part of the proposed method developed at the ESL is the integration of the energy signatures of the building AHU that express the variation of the energy consumption as a function of each of the parameters included in the modeling of the secondary systems. After the signatures are generated, the calibration procedure considers the variations with weather dependence of the energy use in the building and finally on the energy use profiles.

To avoid the intervention of any user in the calibration procedure, it is desirable to formulate this process mathematically in such a way that its representation may be rigorously solved to minimize differences between simulated and measured consumption values, reducing the haphazard approaches and misinterpretation of the intermediate solutions that are inherent to manual procedures.

The recent automated (or semi-automated) methodologies presented by Sun and Reddy (2006), Lee and Claridge (2002), and Subbarao (2000) are excellent examples that fully automated calibration could be possible for a building energy simulation, that has been implemented for secondary systems, using whole-building energy simulation programs. However, it appears that these methodologies lack the simplicity, due to the complexity of the simulations, and the need to incorporate key simulation algorithms into the calibration process that would allow users without much experience to calibrate building energy simulations. Therefore, this study proposes the development of a fully automated methodology that, without loss of accuracy, will be easier for practitioners to use through the application of a global optimization algorithm.

As has been mentioned earlier in this review, there are many opportunities to apply or make use of a calibrated simulation. These uses include identifying potential retrofits or commissioning measures that save energy – promoting an efficient use of energy in buildings. Calibrated simulation could also be used to support methodologies of benchmarking or determination of potential energy savings. This study, in addition, proposes to use a calibrated building energy model to determine potential energy savings in the building. The idea is similar to that proposed by the CEDR, which is a model-based benchmarking. However, the proposed procedure does not maintain fixed interior conditions in the building; instead, the calibrated model minimizes the consumption while maintaining conditions in the comfort zone and the maintain air ventilation requirements. This process is based on the SEAP and the performance of the characteristic parameters of the secondary systems.

CHAPTER III

AUTOMATED METHODOLOGIES FOR CALIBRATION THROUGH
SIMPLIFIED AIR-SIDE HVAC SYSTEM ANALYSIS

Typical procedures for calibrated building simulation start by defining a base building model, which may be either a simulation or system of equations that represents or models the energy flows occurring in the building. Then, arbitrarily, the most influential of the building's physical parameters are decreased or increased, over a typical range of values, to obtain diverse energy use outputs. This process is repeated until, eventually, an acceptable match between the simulated and measured energy use is achieved. As may be anticipated by this type of procedure, a calibration process is generally a time-consuming task, and the time increases as the amount of data is increased, i.e. it takes longer to calibrate a model to daily or hourly data than to monthly data.

These calibration methodologies required the interaction of a user in each trial and had a clear dependence on his/her expertise. In addition, they lacked the ability to reach the point of quantitatively defining a suitable level of precision for the term "acceptable match" between the measured and simulated data.

Therefore, alternative methodologies that reduce the time and effort and that can be carried out automatically, while achieving a highly accurate match between the simulated and the measured energy data, would be very valuable and welcome.

3.1 Automated Calibration Methodology

To develop an automated calibration procedure, it is necessary to have a complete understanding of the system to be calibrated. In this case, the calibration is going to be undertaken to identify the parameter values that determine the thermal behavior in the conditioning of buildings. Thus, a model must be defined that represents this thermal behavior very well. Also, it is important that the simulation model be capable of representing the departures from ideal behavior that occur in real systems and that it be

able to detect several of the common deficiencies. This modeling can very well be an air-side energy balance of the most representative air-handler system in the building. Considerations and a complete description, and their modeling, of the air handler systems considered in this work are found in Appendix D.

The model, with a set of initial parameter values, is used to simulate the energy use of the building, according to the outside environment where the building is located. This simulated data is compared with the measured energy use data that was actually observed. Although there are several ways of doing this comparison, perhaps the most reliable for evaluating the differences between a series of data could be the Root Mean Square Error (*RMSE*), see Appendix B. The *RMSE* is a robust statistic that represents the average square root of the square of the difference between the measured value and the one that is predicted by some model, as defined in Equation 3.1. The *RMSE* is the keystone function of the calibration procedure. This function must obtain the lowest value possible, i.e. zero in an ideal case.

The procedure that carries out the search for this minimum RMSE is denoted as *calibration*. Calibration is a systematic approach for reconciling differences between the simulated and measured energy use in buildings and can be performed manually by an expert or, as has been sought in this work, in an automated manner. Numerical searches are required for doing this task in an automatic way. The numerical search has to be done until the desired value of RMSE is reached. Search methods are widely known, so it is necessary to find the most appropriate method for this purpose. Figure 3.1 is a block diagram that presents the proposed process of obtaining an automated calibration.

The calibration procedure requires that alternative values of the physical parameters be selected over a range to alter the energy use outputs. Any parameter change will produce different output (energy use), so the *RMSE* is evaluated through the following expression:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}\left(Energy_{measured,i} - Energy_{simulated,i}\right)^2}{n}} \qquad (3.1)$$

where n is the number of data points in the comparison period. It is important to recognize that the RMSE should be calculated independently for the cooling energy use and for the heating usage in the building being analyzed. Therefore, a total $RMSE_T$ should be defined in order to include, in a single function, the individual variations of all the energy uses being simulated. Perhaps the simplest way of representing a total $RMSE_T$ is the direct addition of the heating and cooling RMSE E values as follows:

$$RMSE_T = RMSE_{COOL} + RMSE_{HEAT} \qquad (3.2)$$

Although other combinations could be found to account for the individual RMSE variations, the foregoing is simple and direct enough to satisfy the criteria of the calibration methodology. Some authors suggest the convenience of evaluating a coefficient of variation of this total $RMSE_T$, which in a general sense would normalize the variations of the energy uses, but this is not possible in a straightforward way because, by definition, the CV-RMSE requires that the $RMSE$ be divided by an average value of the set being analyzed. In this case, however, the total $RMSE_T$ is compounded by two different variables, precluding the possibility of having a real normalization by just one variable; the variations are in cooling and heating energy uses, and no representative parameter has come into general use for these combined energy components.

The procedure is continued until the simulated and measured energy use values are reconciled within some predetermined level of precision.

3.2 Mathematical formulation of the Automatic Calibration methodology

The problem of calibration – automatic or manual, therefore, becomes a minimization problem; for automatic calibration, the minimization must be carried out by a numerical algorithm without intervention by the user. The proposed automated

calibration methodology, presented in Figure 3.1, is composed of two major modules, a function to be minimized (optimized) and the numerical optimization method to find the minimum. The function to be optimized is the statistical parameter $RMSE_T$, which has been defined previously. Although strictly speaking the $RMSE_T$ is an indicator of the differences between modeled and measured values, for the case of the automated calibration it is indispensable to include its relationship with the model that generates the simulated values. In this case, the model is the set of thermodynamic equations that represent the HVAC system to be calibrated and which is driven by the coincident ambient conditions. This relationship makes it necessary to think of the function to be minimized as a compound function rather than one that can be defined in a simple equation.

Compound function

| Coincident Weather Conditions | → | HVAC System Air-side Energy Calculation | ← | Variable Values |

Measured HVAC Data

Statistical Function (RMSE)

Numerical Optimization Procedure → RMSE < ε → Success: Calibrates

N · Y
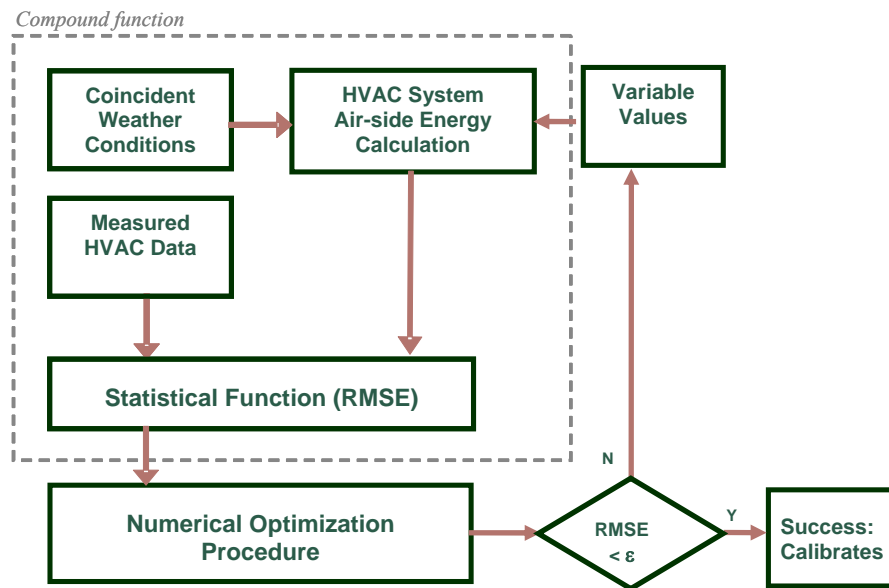
Figure 3.1 Block diagram of automated calibration methodology.

From the considerations expressed in the previous paragraph, with respect to how the function to be minimized is compounded, the mathematical formulation for the calibration of any of the HVAC systems pertinent to this work may be expressed as follows:

Objective Function:

Minimize $RMSE_T$

where $RMSE_T = RMSE_{COOL} + RMSE_{HEAT}$

$RMSE_T$ is the total root mean square error compounded from the corresponding individual heating ($RMSE_{HEAT}$) and cooling ($RMSE_{COOL}$).

Subject to the following constraints applied for each of the selected daily average ambient conditions:

a) Simulation results satisfy the system of equations that model a specific HVAC system (See Appendix D)

$$F(x_i) = 0 \qquad i=1...n$$

b) Primary variables values must fall within practical ranges

$$x_{i,1} \geq x_i \geq x_{i,2} \qquad i=1...n$$

where the subscripts *1* and *2* correspond to the lower and upper limits for each of the operational variables

The number of variables to be evaluated depends on the HVAC system identified in the building, e.g. in DDVAV systems the cold deck and hot deck temperature parameters must be specified while SDCAV systems require only the cold deck parameter to be specified.

3.3 Optimization Approaches for Calibration

In practice, many large-scale optimization problems cannot be optimally solved because the search for an optimum requires prohibitive amounts of computation time. Thus, it is necessary to use approximation algorithms or heuristics, for which there is usually no guarantee that the solution found by the algorithm is optimal, but for which bounds on the computation time can be given.

Approximation algorithms can be divided into two categories: algorithms tailored to a specific problem and general algorithms applicable to a wide variety of optimization problems.

The application of an iterative improvement algorithm assumes the definition of configurations, a cost function, and a generation mechanism, i.e., a simple prescription to generate a transition from one configuration to another by a small perturbation.

Iterative improvement is also known as a neighborhood search or a local search. The algorithm can be formulated as follows: Starting at a given configuration, a sequence of iterations is generated; each of these iterations consists of a possible transition from the current configuration to a configuration selected from the neighborhood of the current configuration. If this neighborhood configuration has a lower cost, the current configuration is replaced by this neighbor; otherwise, another neighbor is selected and compared for its cost value. The algorithm terminates when a configuration is obtained whose cost is no worse than that of any of its neighbors.

Some disadvantages of iteration improvement algorithms are:

-Iterative improvement algorithms, by definition, terminate in a local minimum, and there is generally no information as to the amount by which this minimum deviates from a global minimum.

-The local minimum obtained depends on the initial configuration, for the choice of which, generally, no guidelines are available.

-In general, it is not possible to give an upper bound for the computation time.

It is clear, however, that iterative improvement does have the advantage of being generally applicable.

In the next sections of this chapter, three approaches for automated calibration are presented. The first two approaches belong to the category of iterative improvement algorithms. One of these is the exhaustive uniform, or factorial, search, and the other is a derivative of the first one and solves the minimization problem through a one-dimensional search for all the variables by the Golden Section search.

Multivariable Optimization: Exhaustive Uniform Search
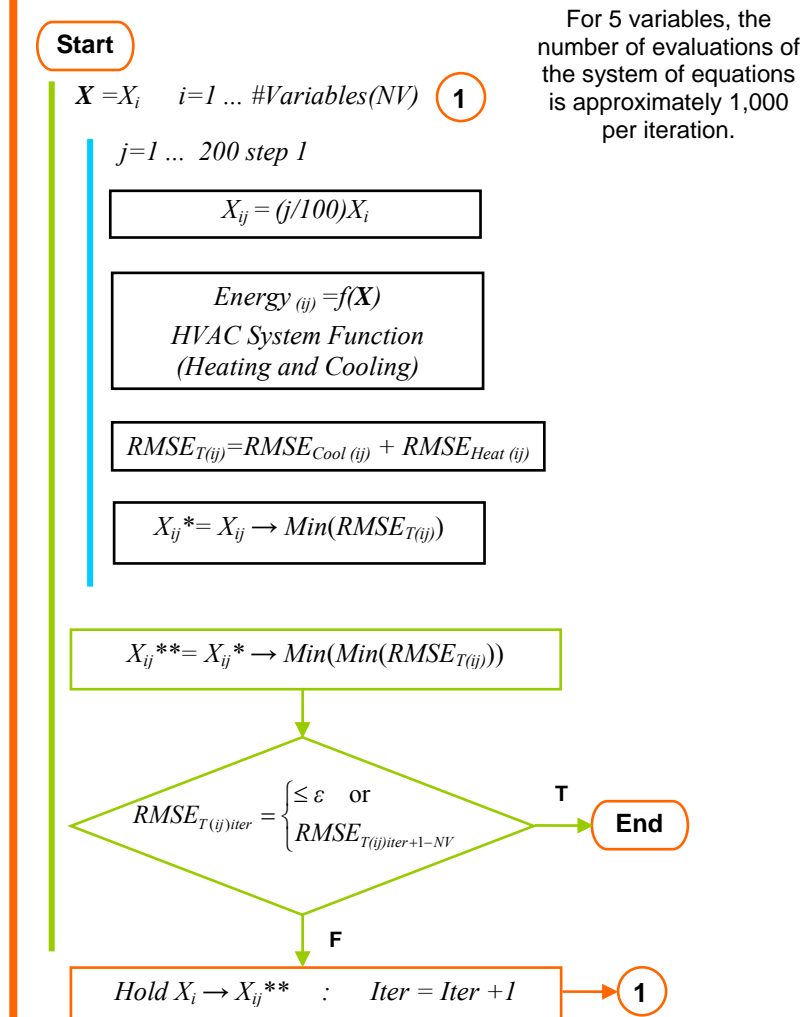
Figure 3.2 Flowchart for a multivariable optimization methodology by the exhaustive uniform search methodology.

3.4 Multivariable minimization of the $RMSE_T$ by exhaustive uniform search

The general procedure for the exhaustive uniform search for the HVAC simplified engineering models is applied as follows: every parameter to be calibrated is varied from 1% to 200% of its nominal value, in 1% increments, while the other parameters are held at the original values. For each of these variations of the parameters, the $RMSE_T$ between the energy use obtained by the model simulation and the measured

energy use is evaluated according to Equation 3.2. Through these simulations, the variable value that produces the minimum $RMSE_T$ is identified. This entire set of simulations and $RMSE_T$ calculations is called an *iteration*. Having found the minimum $RMSE_T$ in any iteration, the responsible variable's value is modified to the value that produces this minimum and is held at this value for the entire next iteration. With this new set of parameters, a new series of variations for all parameters is carried out, except for the one that generated the previous $RMSE_T$ minimum; this allows a subsequent search around the neighborhood of the minimum and a new $RMSE_T$ minimum is obtained. The new parameter that generated this last minimum is held for the next iteration and the procedure is continued until eventually the $RMSE_T$ is less than or equal to the accuracy criterion previously established. Figure 3.2 is an overall flowchart of this procedure.

3.5 Multivariable minimization by the one-dimensional Golden Section search

The second algorithm is a consequence of the first one. After having performed some simulations with the factorial methodology, as expected, it was found that the number of simulations required to carry out the calibration is very large. On the other hand, it was observed that the behavior of the factorial search follows a convex unimodal pattern in all the variables. These observations provided an advantage for refining the accuracy of the methodology and for reducing the number of iterations, and consequently, the number of evaluations of the system of equations. Thus, a one-dimensional search algorithm can be proposed instead of the exhaustive sweep. The search methodology known as "Golden Section algorithm" that can effectively search for the minimum on each of the variables over a determined individual range is suggested and implemented. After obtaining the global minimum, the iteration is completed and the $RMSE_T$ is compared to the accuracy criterion value. If the criterion is not reached, the procedure is continued until the condition is satisfied. The $RMSE_T$ precision criterion is a crucial issue for this search procedure because the results depend

on this parameter. Figure 3.3 is an overall flowchart of the Golden Section search procedure.

Multivariable Optimization: One-Dimensional Golden Section Search
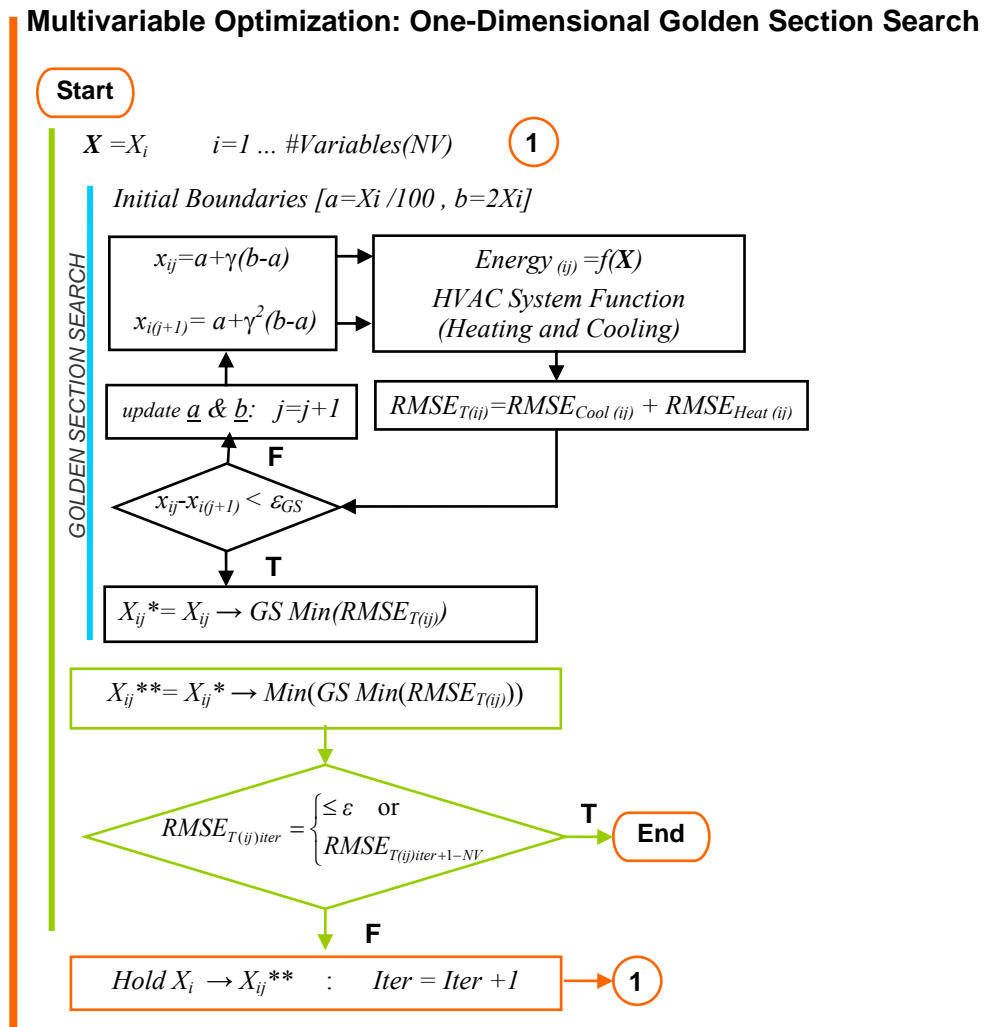
Figure 3.3 Flowchart for a multivariable optimization methodology through one-dimensional Golden Section search.

3.5.1 Golden Section search: one-dimensional search

The Golden Section search is based on an interval elimination method; thus, starting with the original boundaries on the independent variables, the interval in which

the optimum value of the function occurs is reduced to some final value, the magnitude of which depends on the desired accuracy. No derivatives are required, and the specification of the desired accuracy will determine the number of evaluations of the function. Golden Section search is the name given to this methodology because it depends on a ratio γ, known to the early Greeks as *golden mean* or *golden section*. This fraction comes from dividing a line (or area) in such a way that the ratio of the larger part to the total is the same as the ratio of the smaller to larger. This is equivalent to $\gamma = (\sqrt{5}-1)/2 \approx 0.6180339887$ and satisfies the equation $\gamma^2 = 1 - \gamma$, which represents the proportions of the line's partition (Press et al. 1992).

To perform this algorithm, at each of its steps, an interval is available from a previous iteration. It is an interval known to contain the minimum point x^*, and the objective is to replace it by a smaller one that is also expected to contain x^*. To this end, the principle of scale similarity must be used to divide the interval in the same manner at each stage.

A minimum needs to be bracketed only when there is a triplet of points, $a < b < c$, such that $f(b)$ is less than both $f(a)$ and $f(c)$. In this case, it is known that the function (if it is nonsingular) has a minimum in the interval (a, c).
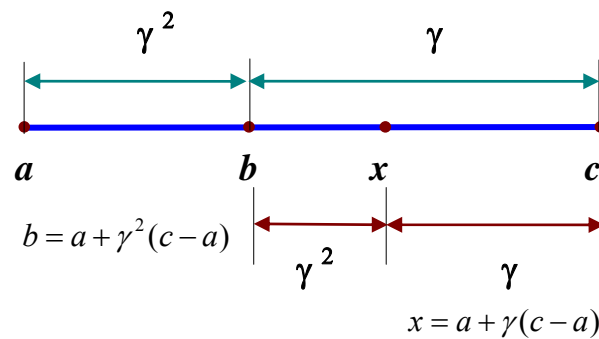
Figure 3.4 Partitioning of the search through the golden section search.

Then, based on Figure 3.4, a new point, x, must be chosen, either between a and b or between b and c. The scale similarity implies that x should be the same fraction of the way from b to c (if that is the bigger segment) as was b from c to a. Evaluate $f(x)$, if $f(b) < f(x)$, then the new bracketing triplet of points is (a, b, x); contrariwise, if $f(b) >$ $f(x)$, then the new bracketing triplet is (b, x, c). The process of bracketing continues through the self-replicating ratios until the distance between the two outer points of the triplet is tolerably small. Applying the golden section fraction, the optimal bracketing interval (a, b, c) has its middle point b a fractional distance 0.38197 from one end (say, a), and 0.61803 from the other end (say, c). The Golden Section search guarantees that each new function evaluation, after self-replicating ratios have been achieved, will bracket the minimum to an interval just 0.61803 times the size of the preceding interval.

The golden section search is a very robust method and, provided there are no discontinuities, is guaranteed to work.

3.6 Multivariable Minimization by Simulated Annealing Methodology

To avoid some of the disadvantages of iterative improvement algorithms, such as the ones presented above, one alternative that provides general applicability is the limited acceptance of transitions that correspond to an increase in the cost function. This is a variation of an iterative improvement algorithm where only transitions corresponding to a decrease in cost are accepted.

The simulated annealing (SA) methodology can be seen as such an algorithm; it is a general optimization technique for solving unconstrained optimization problems. The algorithm is based on randomization techniques, but it also incorporates a number of aspects related to iterative improvement algorithms. Simulated Annealing has primarily been explored in areas such as Operation Research, Computer Science, and Artificial Intelligence, with research and applications in the field of combinatorial optimization.

SA is a probabilistic heuristic algorithm based on thermodynamic considerations developed by Kirkpatrick et al. (1983) based on the work of Metropolis et al. (1953) in the earliest days of scientific computing. The technique is motivated by an analogy to

the statistical mechanics of annealing in solids. In this process, the solids are taken to a low energy state, a highly ordered state - such as a crystal lattice. To accomplish this, the material is first melted, then it is cooled slowly and, as the temperature is reduced, the atoms migrate to a more ordered state with lower energy. The atomic arrangement reaches a higher degree of order and the material freezes into a good crystal. Annealing, therefore, allows the obtaining of a more global energy minimum than is possible in a quick quenching process, which is equivalent to a local energy minimum. Numerically realized simulated annealing techniques use an analogous set of "cooling operations" for non-physical optimization problems in order to transform a poor, unordered solution into a highly optimized, desirable solution.

The Metropolis algorithm provides an efficient simulation of a collection of atoms in equilibrium at a given temperature. The probability $p(E_i)$ that, at a given temperature T, a system is in state i is given by the Boltzman distribution:

$$p(E_i) = \frac{1}{Z(T)} \exp(-\frac{E_i}{kT})$$

(3.3)

where k is the Boltzman constant, $Z(T)$ is a normalization factor, and E_i is the energy of state i. Numerical realization of simulated annealing is based on the theory of Markov chains, where it can be shown that, as $T \rightarrow 0$, only globally optimum states have a non-zero probability of occurrence and the algorithm converges to these optimum solutions with probability one (Laarhoven and Aarts 1987).

At a given temperature, a number of random variations of the system state are considered. If a state results in a lower energy level, it is unconditionally accepted. If, however, a higher-energy state results from the variation, it is only accepted with a probability p, defined as follows:

$$p = \exp\left[-\frac{(E_2 - E_1)}{kT}\right]$$

(3.4)

where the state E_2 corresponds to a higher-energy level than state E_1. The criterion for the avoidance of being trapped in a local minimum centers on occasional acceptance of moves that do not improve the objective. These probability-based, uphill moves are a central feature of any SA algorithm.

The simulated annealing heuristic considers two choice groups: specifics and generics. Specific choices include: (i) configuration, (ii) neighborhood of a configuration, (iii) cost of a configuration, and (iv) initial configuration. Four generic parameters must be stated for any SA: (i) initial temperature T_o; (ii) frozen state represented by the final temperature T_f; (iii) cooling ratio, the rate at which the temperature is lowered between two cooling cycles; and (iv) epoch length, the number of random variations at each temperature (N_k). The latter two parameters are collectively referred to as an annealing or cooling schedule. All of them are, however, problem-dependent, and devising a good set for a specific problem relies, to a large degree, on empirical studies. While the parameters are generic, there is no single parameter set that would be universally applicable.

3.6.1 Implementation of the Simulated Annealing algorithm

Many statistical methods rely on numerical optimization to estimate a model's parameters. Unfortunately, conventional algorithms sometimes fail. Even when they do converge, there is no assurance that they have found the global, rather than a local, optimum. According to tests, not only does the Simulated Annealing method find the global optimum, but it is also less likely to fail on difficult functions because it is a very robust algorithm (Goffe et al. 1994). Although SA is clearly superior to conventional algorithms for some difficult statistical optimization problems, the benefit does not come without a cost; SA may require substantially more execution time.

Figure 3.5 shows the flowchart of a standard simulated annealing algorithm. Using the cost function instead of the energy function, and defining by the Metropolis procedure configurations of a set of parameters $\{x_i\}$ of a given optimization problem at some effective temperature, is a straightforward process. This temperature is simply a control parameter in the same units as the cost function. The simulated annealing

process consists of first "melting", at a high effective temperature, the system being optimized, then lowering the temperature in slow stages until the system "freezes" and no further changes occur. At each temperature, the simulation must proceed long enough for the system to reach a steady state. The sequence of temperatures and the number of rearrangements of the $\{x_i\}$ attempted in order to reach equilibrium at each temperature can be considered an *annealing schedule*.

Annealing, as implemented by the Metropolis procedure, differs from iterative improvement in that the procedure is not susceptible to being caught in a local minimum, since transitions out of a local optimum are always possible at nonzero temperatures. Like most iterative improvement schemes, the Metropolis algorithm proceeds in small steps from one configuration to the next, but the temperature prevents the algorithm from being trapped by permitting uphill moves. A second, more important feature is that a sort of adaptive divide-and-conquer occurs. Gross features of the eventual state of the system appear at higher temperatures, while the small changes are deferred until low temperatures are reached.

Implementing the appropriate Metropolis algorithm to simulate annealing of a combinatorial problem is straightforward and easily extended to new problems. As mentioned previously, four ingredients are needed: a concise description of a configuration of the system; a random generator of "moves", or rearrangements of the elements in a configuration; a quantitative objective function containing the trade-offs that have to be made; and an annealing schedule of the temperatures and lengths of time for which the system is to be evolved. The annealing schedule may be developed by trial and error for a given problem or may consist of just warming the system until it is obviously melted, then cooling it in slow stages until diffusion of the components ceases. Inventing the most effective sets of moves and deciding which factors to incorporate into the objective function require insight into the problem being solved, and the solutions may not be obvious. Fortunately, existing methods of iterative improvement can provide natural elements on which to base a simulated annealing algorithm.

A more detailed development of the Simulated Annealing optimization methodology is presented in Appendix A.
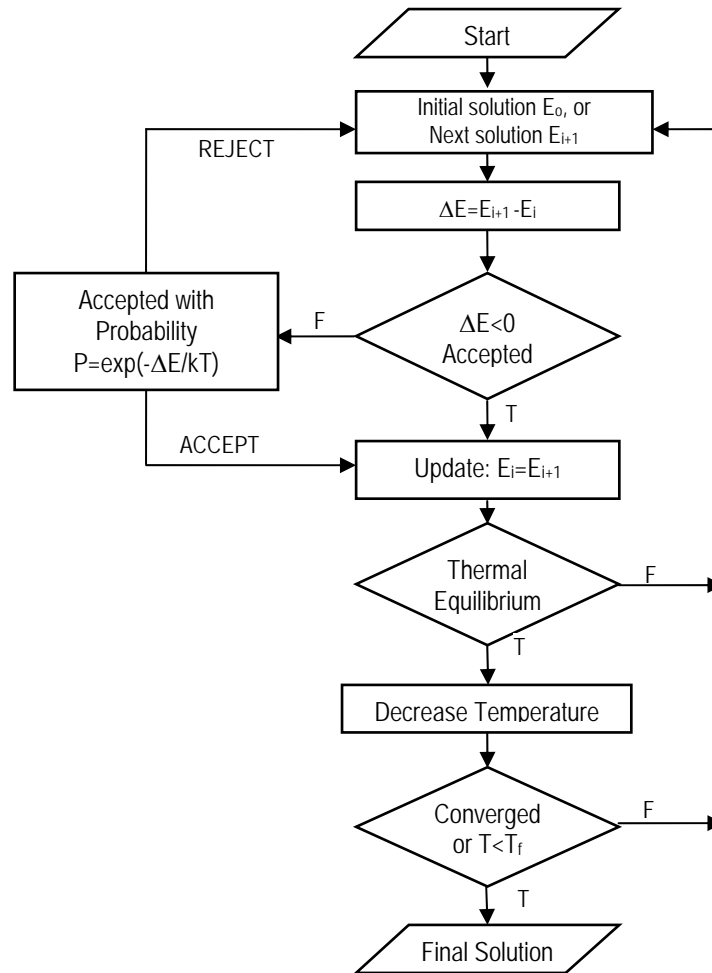
Figure 3.5   Flowchart of a canonical strategy for implementing the simulated annealing methodology.

3.6.2 Tailoring the SA algorithm for the automated calibration

The implementation of the methodology to any HVAC calibration process requires that the general "energy" function of the previously explained methodology be replaced for the objective function of the optimization problem, specifically for the $RMSE_T$

equation, whose minimization represents the calibration. This discrete mathematical–statistical function is related indirectly to a specific type of HVAC system, characteristic parameters and local environment conditions.

Assuming that $\mathbf{x}=\{x_i \in R^k\}$ is a set of independent variables each ranging in a finite, continuous interval $a_1<x_1<b_1$, … , $a_k<x_k<b_k$, that control the operation of an HVAC system, the energy equation – $RMSE_T$ can be expressed by

$$RMSE_T(\{x_i\}) = \frac{1}{\sqrt{n}}\left(\sqrt{\sum_{j=1}^{n}\left(E_j^{C,m} - E_j^{C,s}(\{x_i\})\right)^2} + \sqrt{\sum_{j=1}^{n}\left(E_j^{H,m} - E_j^{H,s}(\{x_i\})\right)^2}\right) \qquad (3.5)$$

where E represents the HVAC energy requirement, the super-indexes C and H indicate the cooling and heating loads, respectively, and the m and s are associated, in that order, with the measured and the simulated energy use. Because the energy loads, cooling and heating, are functions of a given number of parameters $\{x_i\}$, then, from similarity with the annealing process, the probability of obtaining a parameter set $\{x_i\}$ that satisfies Equation 3.5 for $RMSE_T$ is

$$p(RMSE_T;\{x_i\}) \propto \exp\left[\frac{-RMSE_T(\{x_i\})}{T}\right] \qquad (3.6)$$

where T is a control parameter, analogous to temperature in statistical physics, which is directly proportional to the energy. As the SA methodology is based in the concept of a random walk in the parameters vector $\{x_i\}$ (Metropolis et al. 1953), each point has an associated $RMSE_T$ value and an associated probability (from Equation 3.6). The transition probability between two states with values $RMSE_{T,i}$ for an initial $\{x_i\}$ parameter set and $RMSE_{T,c}$ for a $\{x_c\}$ candidate parameter set is defined as:

$$p(RMSE_{T,i} \rightarrow RMSE_{T,c}) = \exp\left[-\frac{(RMSE_{T,c} - RMSE_{T,i})}{T}\right] \qquad (3.7)$$

The sequence of randomly generated $\{x_k\}$ parameter values will converge as defined by Equation 3.6. If at any time in the sequence the $p(RMSE_{T,i} \rightarrow RMSE_{T,c}) > 1$, then the probability is set to one. The region of more "acceptable" parameter sets will be visited more frequently. Expressed as a criteria, the parameter set is accepted or rejected according to the Metropolis criteria (Metropolis et al. 1953; Mailhot et al. 1997), i.e. if $\Delta(RMSE_T) = [RMSE_{T,c} - RMSE_{T,i}] \leq 0$, then the "*new*" $\{x_{i+1}\} = \{x_c\}$ set is accepted, else accept the "*new*" set with the probability of Equation 3.7; in practice this is accomplished by comparing this probability with a pseudo-random probability generated in this evaluation step.

The most frequent method of generating a candidate parameter set $x_i^{new} = \{x_c\}$ is based on seeking a random configuration within the neighborhood of the current configuration x_i. One possibility based on variable step distribution starts with the initial, feasible parameter set x_i, and the next parameter set is generated using the following relation:

$$x_i^{new} = x_i + rv_h \qquad (3.8)$$

where r is a random number generated in the range $[-1,1]$, and v_h is the component of the step vector along the hth direction. If the hth component of x_i^{new} falls outside the bounded domain given by the constraints, then a fresh random search takes place until a feasible point x_i^{new} is obtained. The magnitude of the vector v is related to the acceptance ratio $acc \equiv n/N_k$, where n is the number of accepted moves and N_k is the total number of evaluated moves ($\equiv$ epoch length). Both n and N_k are at a given temperature, and they have a great influence on the robustness and the number of function evaluations, since they control how quickly the temperature declines and the number of function evaluations performed at each temperature. For each direction, h, the new step vector component is taken as:

$$v_h = \begin{cases} v_h^o(1 + c(n/N_k - 0.4)/0.4) & n > 0.6N_k \\ v_h^o/(1 + c(0.4 - n/N_k)/0.4) & n < 0.4N_k \\ v_h^o & \text{Otherwise} \end{cases} \qquad (3.9)$$

where c is a constant parameter which should be tuned and v_h^o correspond to the initial, or the previous component of the step value in the iterative process for the hth direction. The initial status is chosen arbitrarily and for the next iteration the component step is replaced by the v_h obtained in the immediately previous iteration. The purpose of these variations in step length, at a given temperature, is to maintain the average percentage of accepted moves at about 50% of the total number of moves (Corana et al. 1987).

Given the main structure on the decision rules and key features of the SA methodology, the iterative process implementation starts at some arbitrarily selected "high temperature". A series of parameter sets are randomly generated until "equilibrium" is reached; that is to say, the value of the objective function, $RMSE_T$, reaches a steady value as the number k of generated parameter sets increases. The solution that produces the "thermal equilibrium", is named the optimum parameter set for that "temperature".

The "temperature" parameter, T, is reduced every time that "thermal equilibrium" occurs and a fresh complete sequence of iterations is made starting with the "optimum" parameter set previously found and ends when equilibrium is reached again, and so forth. The process is stopped at a temperature low enough that no more useful improvements can be expected according to a convergence criterion.

The algorithm is tuned by setting heuristic rules on the number of times that the accuracy is satisfied after finding equilibrium on a complete sequence of configurations $\{x_i\}$; the number of evaluations of the objective function before any step adjustment in a new configuration is suggested and the number of times the previous loop allowed before any reduction in the "temperature" term is made, before claiming success. All of these parameters should be specifically determined for use in this study for the calibration of HVAC systems.

The SA methodology, as could be expected in most of the numerical algorithms, has a more stable performance when the variables are normalized. The variables for the SA methodology were normalized accordingly to the span of their finite and continuous

range of operation, so the extreme values of those ranges are *-1* for the lower and *+1* for the upper. On this basis, any variable can be normalized by the next expression:

$$X(i) = \frac{[2x(i) - x_U(i) - x_L(i)]}{x_U(i) - x_L(i)} \tag{3.10}$$

where $X(i)$ is the corresponding normalized variable of $x(i)$, and the subscripts U and L refer to the upper and lower extremes of $x(i)$ variables, respectively.
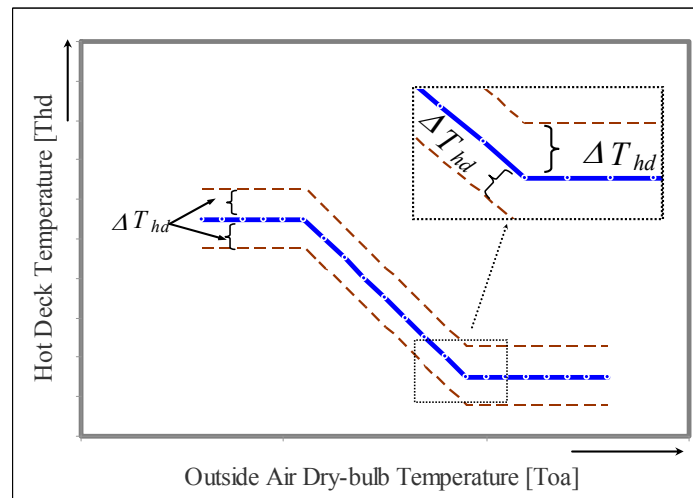
Figure 3.6 Schematic representation of the ΔT_{hd} variable used in the calibration methodology.

Table 3.1 Range of typical values for variables sought in an automated calibration.

Min	Variable	Max
65	T_e and/or T_i (°F)	85
45	T_{cd} (°F)	80
-3	ΔT_{hd} (°F)	3
0.01	x_{oa}	1
0.01	$x_{oa\ min}$	1
500	Occupancy(#persons)	10,000
1,000	UA (Btu/hr °F)	100,000

The number of variables that can be evaluated differs from type to type of HVAC system, based on the kind of thermal modeling used for the representation of the system. Thus, the variable-air-volume systems generally have, in contrast with the constant air volume systems, a variable schedule for the temperature of the hot (or cold) deck. While there is some variation depending on the HVAC system type being analyzed, the parameters that can generally be identified from the calibration process as key variables that determine the operation of a HVAC system are: the building heat transfer coefficient, the average interior/exterior temperature set point, the outside air fraction, the occupancy heat load, and cold (and hot deck, if present) temperature. The variation of the hot deck schedule, ΔT_{hd}, is based on a constant change of a practical schedule pattern as indicated in Figure 3.6.

Table 3.1 shows the ranges for the variables that were sought through the minimization process – or automated calibration of a DDVAV system; the variables for other HVAC systems analyzed in this study are correspondingly presented in the next chapter, but the variable ranges are the same as those shown in this table.

CHAPTER IV

ANALYSIS OF RESULTS OF THE AUTOMATED CALIBRATION
METHODOLOGIES

The performance of the optimization methodologies with the objective of generating an automated calibration procedure for HVAC systems is presented in this chapter. An analysis of the opportunity for implementing the calibration of the HVAC system simulations by multivariable optimization, through the factorial method, the one-dimensional Golden Section search, and the Simulated Annealing (SA) procedure, is presented. The performance of the techniques, especially the SA, is evaluated for ideal cases and with variations on these ideal conditions, by adding to the samples variation in the form of random noise – also called white noise (WN). In addition, a description of the validation tests applied and in-depth observations on the performance of the implemented simulated annealing minimization technique as applied to the four most common HVAC systems are given.

4.1   Description of the Samples

The data samples used for this study were generated from simulations of the HVAC systems through the simplified energy analysis method (Knebel 1983). The simplified analysis of the air-side HVAC systems for the variable and constant air volume systems used for the generation of the data sets, in their dual-duct and single duct with re-heat arrangements, are presented in Appendix D. To get a closer estimate of the physical performance of the actual energy-use loads that may be found in a building, in addition to the actual environmental conditions, some measured electricity use data was included as input parameters. Thus, to generate the data sets, samples of the measured whole building and the motor control center (MCC) electricity usage were considered in the simulation together with the actual ambient conditions of the building location (Zachry Engineering Center at Texas A&M University-College Station). By and large, these generated datasets are denoted "synthetic data," because they are artificially made using

a simulation, and correspond to the energy use loads based on known conditions (Reddy and Claridge 1994). These data sets have been used to test the auto-calibration methodologies described in Chapter III.

The main focus of the tests is assessing the performance that a minimization technique could have in a real case. Thus, the synthetic data sets were modified with normal white noise (WN(sd%)) at different levels; energy use data modified samples with standard deviations of 1%, 3%, 5%, and 10% white noise were generated. These samples could be comparable to measured data samples, which are expected to find some disagreement with their equivalent simulated data set samples, due to unknown operational conditions, weakness in the assumptions of the simplified analysis, or misleading information about the characteristics of the building being analyzed. Figure 4.1, for example, shows an example of a synthetic data set and its modification by normal white noise (WN(10%)) for both heating and cooling loads of a dual-duct variable air volume system. The plots of the most significant data set samples generated for each HVAC system considered in this study are found in Appendix F.

4.2   General Performance of the Minimization Techniques

As has been pointed out in Chapters I and III, a major objective of this study is to find and assess an algorithm that performs a calibration of any HVAC system in an automated manner. It has also been explained in the previous chapters that "calibrate" is a term that is used in the sense of finding the actual operational parameter values of a building HVAC system. As pictured in Figure 4.2, initially the cooling and the heating loads are measured and a trial parameter set is used in the simplified algorithm to determine the simulated loads. Typically, in this step there exist clear differences between the measured and the simulated loads obtained with the initial parameter set (see Figure 4.2a). Should an ideal calibration process be applied over the sample, the energy-use loads simulated and measured would match perfectly (see Figure 4.2b). Though this process may seem likely, in most real samples, there is no guarantee that

this match can be obtained. The definition of the criteria to determine when the calibration is finished should be determined before the methodology is selected.
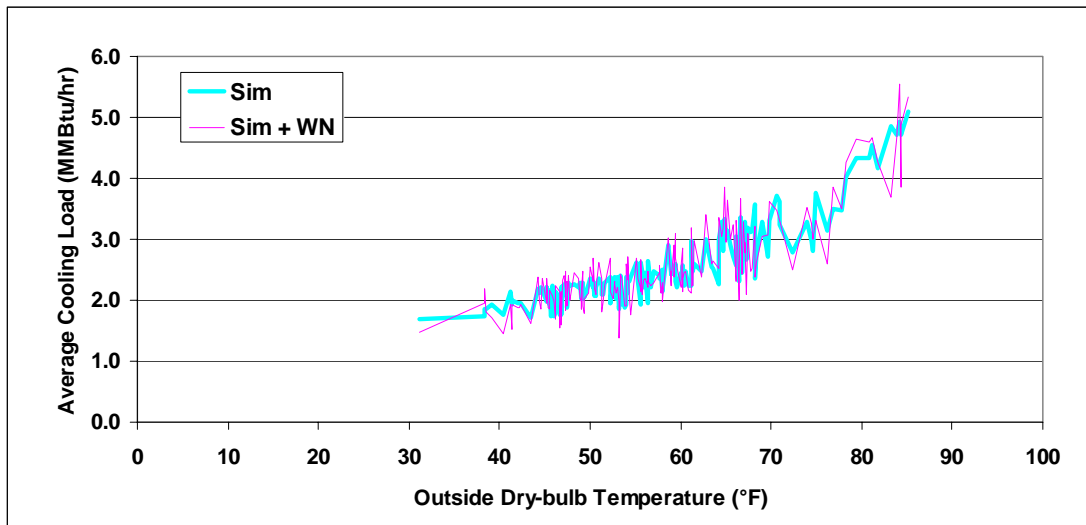
(a)
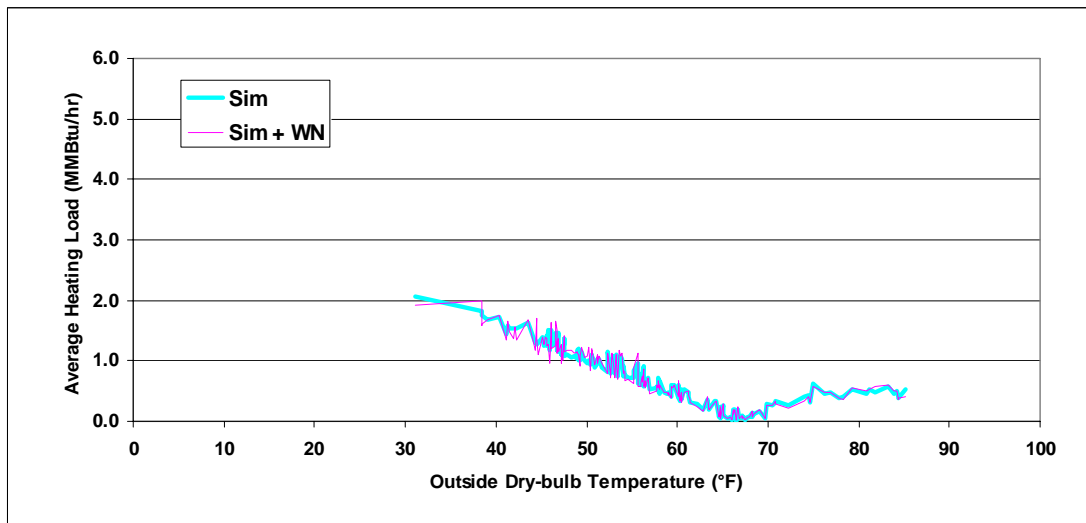
(b)

Figure 4.1   Synthetic data set and the same data modified by addition of ten percent white noise (WN(10%)): samples of (a) cooling and (b) heating loads obtained from a dual-duct variable air volume system simulation plotted vs. outside dry-bulb temperature.
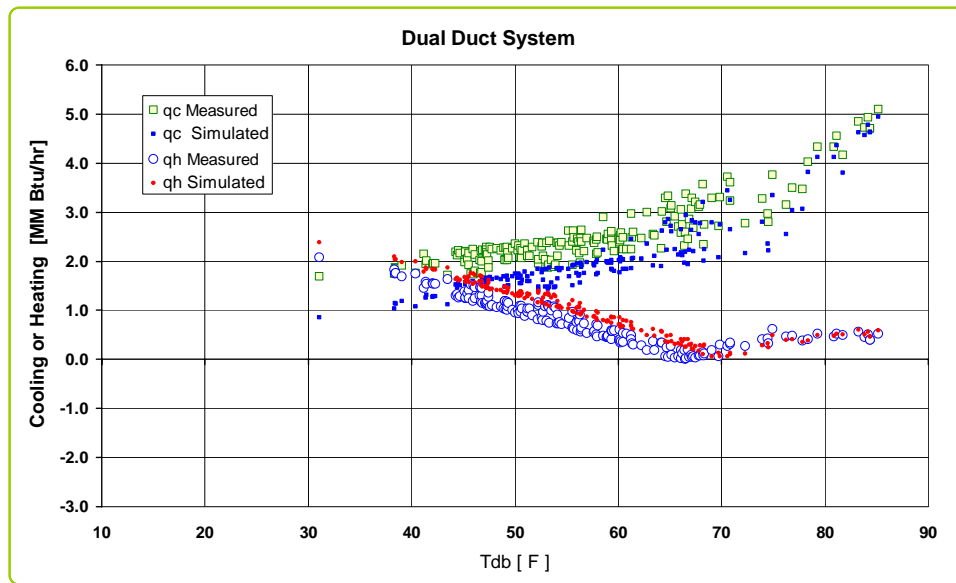
(a)
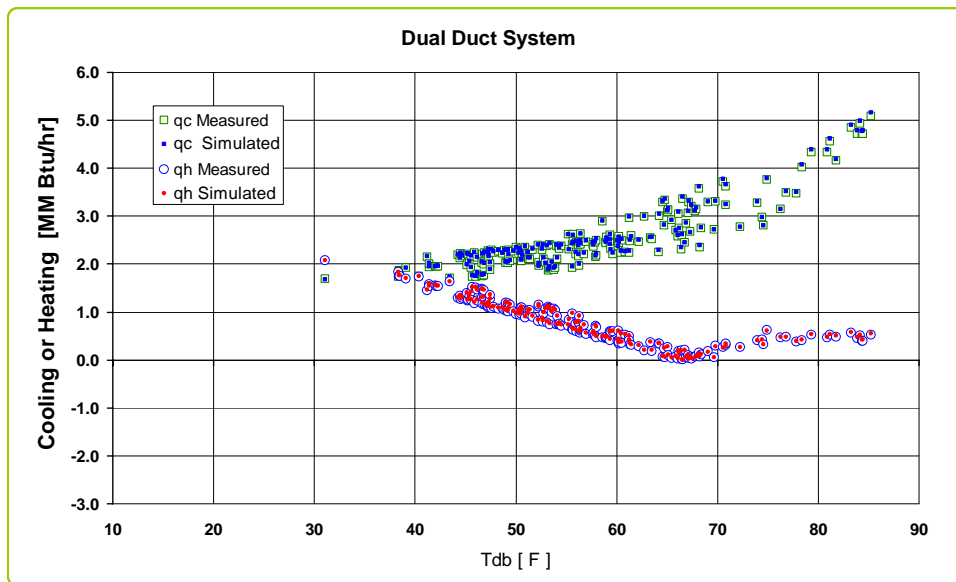
(b)

Figure 4.2   Example of measured and simulated cooling and heating loads for a dual-duct
variable air volume system (a) before calibration and (b) after calibration.

The main characteristics a methodology must have to be capable of performing a

calibration process are accuracy and stability. On the other hand, for the purpose of

analysis, a simple and easy-to-use algorithm will always be appreciated. The computer time that is related to the resources utilized in carrying out the algorithm is also a factor that should be considered. Thus, for practical purposes it is recommended that the algorithm be completed in a reasonable time.

The ideal performance of any multivariable optimization process, should lead quickly and reliably to its objective. In real problems, nevertheless, it can be found that the goal of the search, the minimum in this study, is not always easy to locate; in some cases there is a narrow margin where it can be found or there is a shallow-shape region in the function close to the objective. The performance of a well-designed algorithm for the last instance is illustrated in Figure 4.3; all of these plots are exactly equivalent with the only difference being that each of them have different x and y axes.

The search algorithms are primarily based on "iterations" – a numerical device that sequentially makes a number of evaluations of the function and uses smart decisions to improve the search. Therefore, the curves in Figure 4.3 show the algorithm performance based on the number of evaluations of the function. As seen in part (a), the regular Cartesian representation of the algorithm performance does not permit clear recognition of a variable set that satisfies the function objective. Changing one of the axes, as in part (b), or both of them, as in part (c), to the logarithmic scale makes a big difference in graphically vizualizing when the optimum has been obtained. In contrast to (c), (b) gives no indication that the algorithm is converging.

In the context of identifying algorithm performance, the next sections deal with the implementation of the multivariate optimization methodologies examined in this study: exhaustive search, golden section, and simulated annealing.
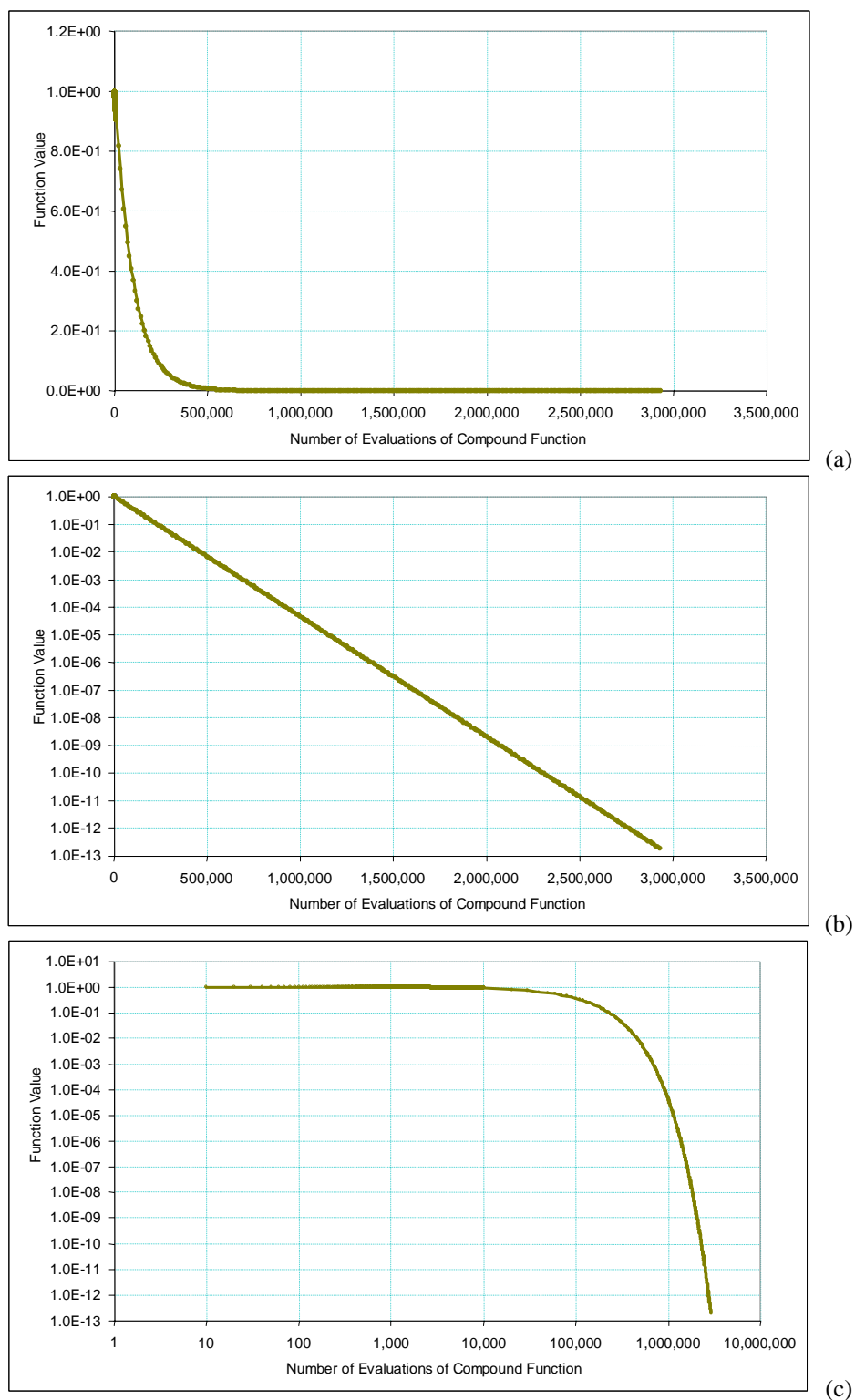
Figure 4.3 Ideal performance of a multivariable minimization search (a) x-y plot, (b) semi-log
plot, and (c) log-log plot.

4.2.1   Performance of the multivariable minimization of the RMSE by exhaustive
          uniform search

As established in Chapter III, the objective function for a calibration process is the statistical compound function of the root mean square error between the HVAC system simulated data set and the measured data set.

To develop a multivariable minimization algorithm that consistently reaches its goal, the approach that the method uses to select the path toward the minimum must be understood. One way to do this is to observe the effect of each of the variables on the value of the function to be minimized. This is very helpful in determining which variables are causing significant changes.

Figure 4.4 presents the behavior of five variables at the beginning of the multivariable minimization of the RMSE applied to a DDVAV system by exhaustive uniform search. This procedure thoroughly examines the effect that each variable has on the function before making any decision on the path to be followed. In this case, one parameter is varied a specified number of times, and the corresponding function objective evaluation is conducted, holding the other parameters constant. After the minimum is identified, the procedure is repeated for the other variables. Finally, the minimum of the minimums is obtained and kept until the variation of the variables in subsequent iterations produces a lower minimum. This procedure is continued until the objective function reaches the sought minimum within some established tolerance.

Also in Figure 4.4, one important fact is observable: the pattern of the function related to each variable follows a parabolic curve. Therefore, the one-dimensional representation of the function has a unimodal pattern for each variable and has a convex curvature; that is why its minimum is easily perceptible.

Figure 4.5 confirms everything mentioned above and presents the performance of the methodology when the process is at the 70th iteration. The behavior is similar to that in Figure 4.4, but now the patterns are more defined for each variable and the minimum of each pattern is closer to the minimum of the objective function. As the

algorithm progresses, eventually the procedure will converge at the minimum of the objective function according to an established criterion.
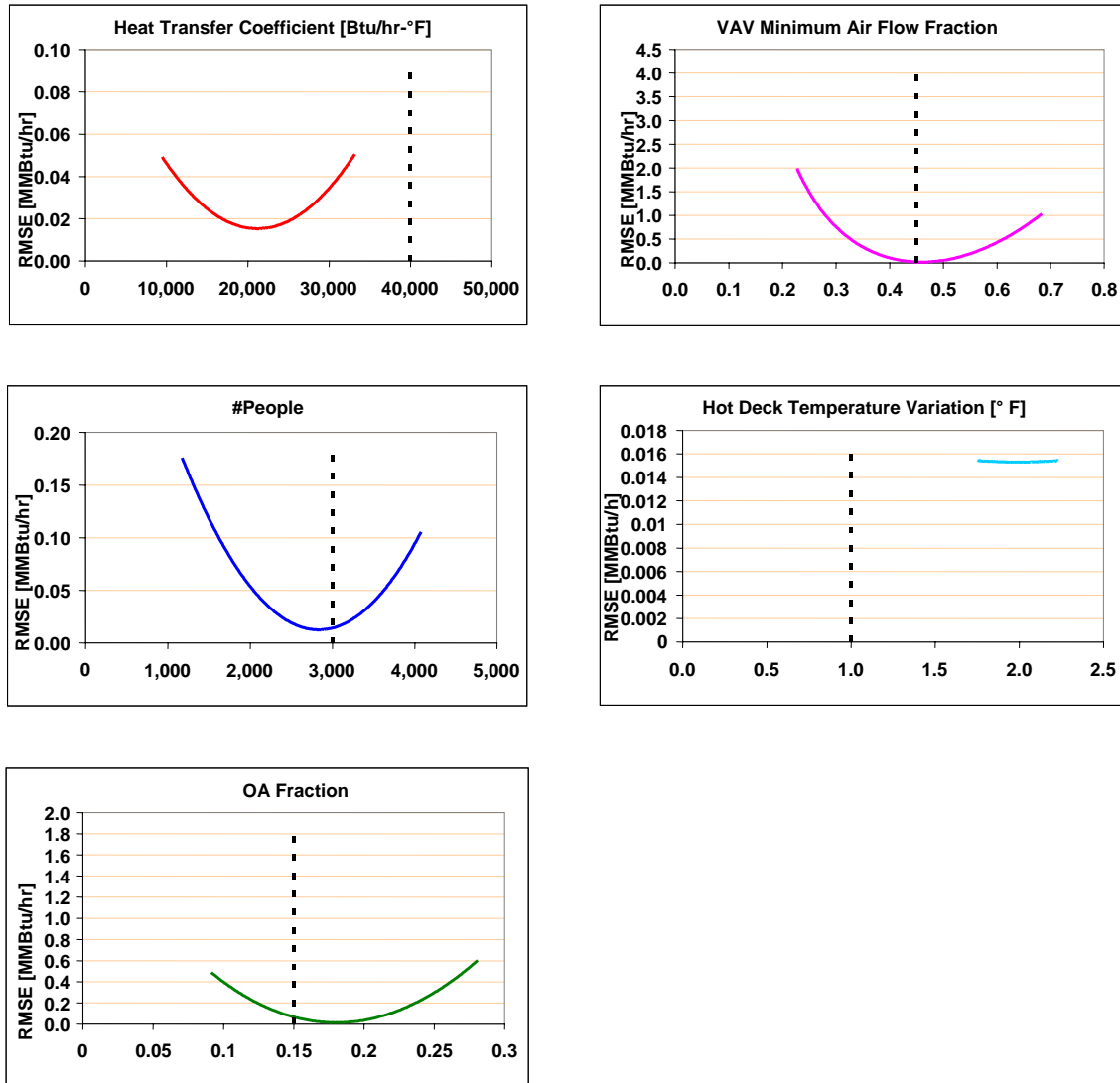
Figure 4.4 Graphical representation of the behavior of five parameters in the multivariable minimization of the RMSE applied to a DDVAV system by exhaustive uniform search at iteration 20 (vertical dashed lines represent the expected parameter value).
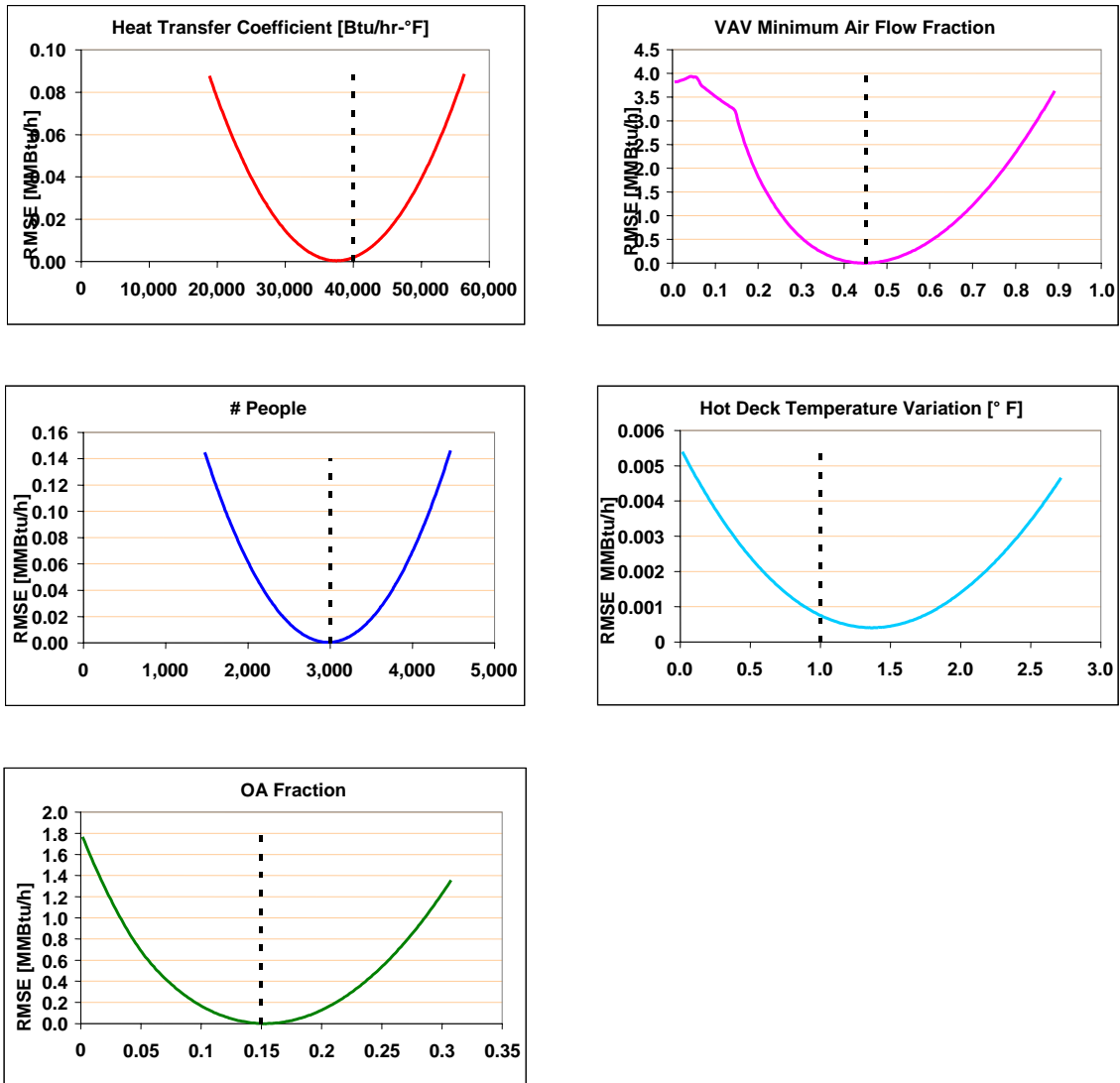
Figure 4.5 Graphical representation of the behavior of five parameters in the multivariable minimization of the RMSE applied to a DDVAV system by exhaustive uniform search at iteration 70 (vertical dashed lines represent the expected parameter value).

4.2.2 Performance of the multivariable minimization methodology using one-dimensional Golden Section search.

As a consequence of the time-consuming performance of the exhaustive search methodology, a modification was examined to reduce the number of evaluations of the objective function. Thus, the Golden Section (GS) search was used to find the minimum *RMSE* for each dimension – for each variable. The procedure is exactly as described for exhaustive search, but, due to the numerical search technique used, the number of evaluations of the function is significantly reduced. Figure 4.6 shows the behavior of some variables at the beginning of the procedure following this approach. The curves in this case do not look completely parabolic, but that is because, in contrast to the exhaustive search, they are generated from a smaller number of points that the GS methodology uses. In any case, the minimum is easily distinguishable and, as the number of iterations increases, the variables are definitely on the path to reaching the minimum (see Figure 4.7).

The overall performance of both the exhaustive and the GS search methodologies in a sample could present the pattern of Figure 4.8. The difference would be a much larger number of evaluations of the objective function by the exhaustive search. This chart is a typical problem-free response or converging minimization path of the RMSE in this class of problems. Figure 4.9 is the representation corresponding to the normalized variable convergence patterns. On the other hand, Figures 4.10 and 4.11 show the RMSE response for the case when a local minimum is displayed around iteration 2000. The last case implies that the methodologies can fail in obtaining the global minimum depending on the path followed by the methodology. As previously explained, due to the problems in discerning the global minimum, the plots of Figures 4.8 and 4.10 are presented in logarithmic axes, and Figures 4.9 and 4.11 with semi-logarithmic axes. The variable behavior plots of the complete iterative *RMSE* minimization process through the GS search for the last instance, which belongs to a DDVAV system simulation, are included in Appendix C.
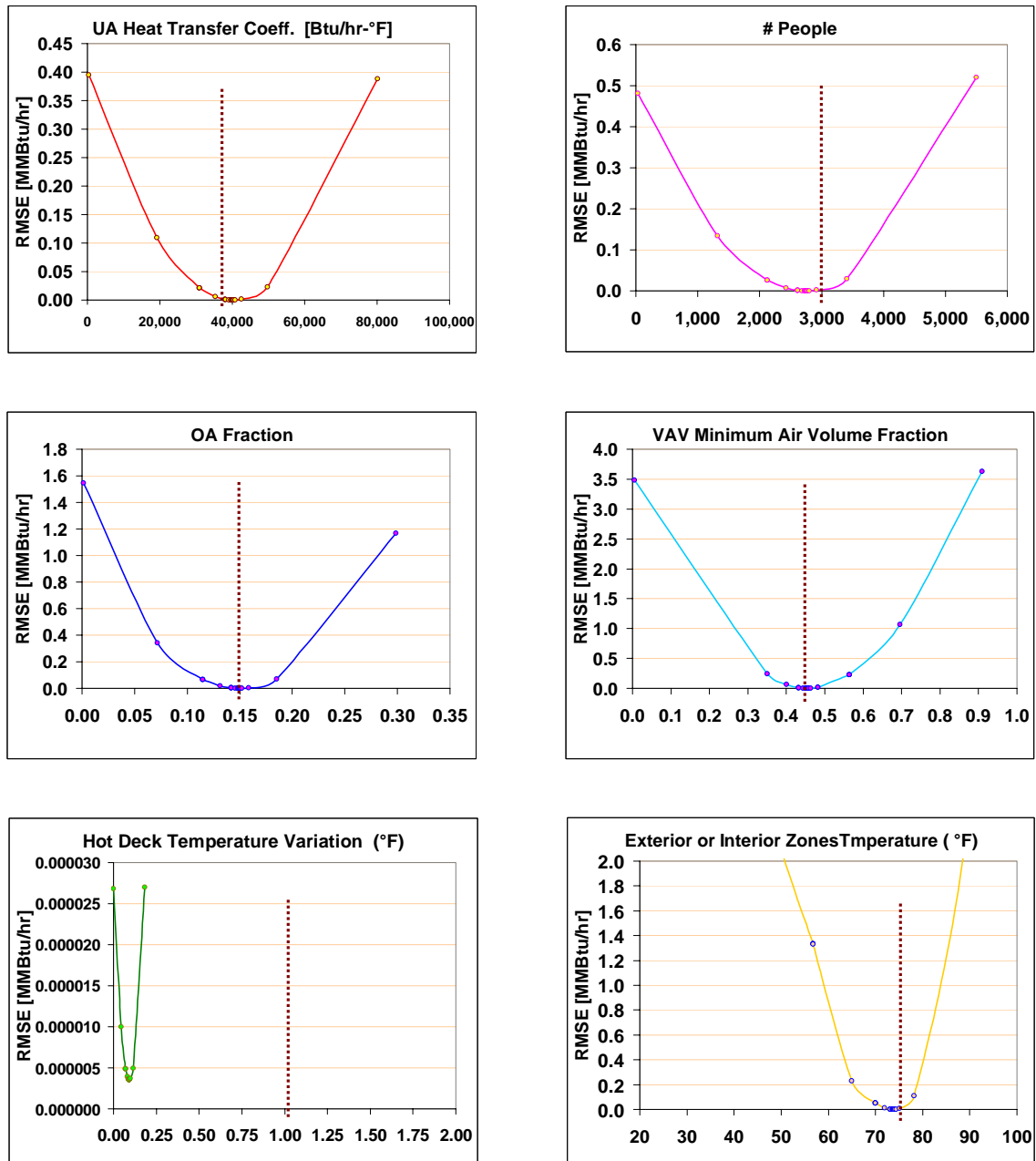
Figure 4.6   Graphical representation of the behavior of six parameters in the multivariable minimization of the RMSE applied to a DDVAV system by Golden Section search at iteration 3010 (vertical dashed lines represent the expected parameter value).
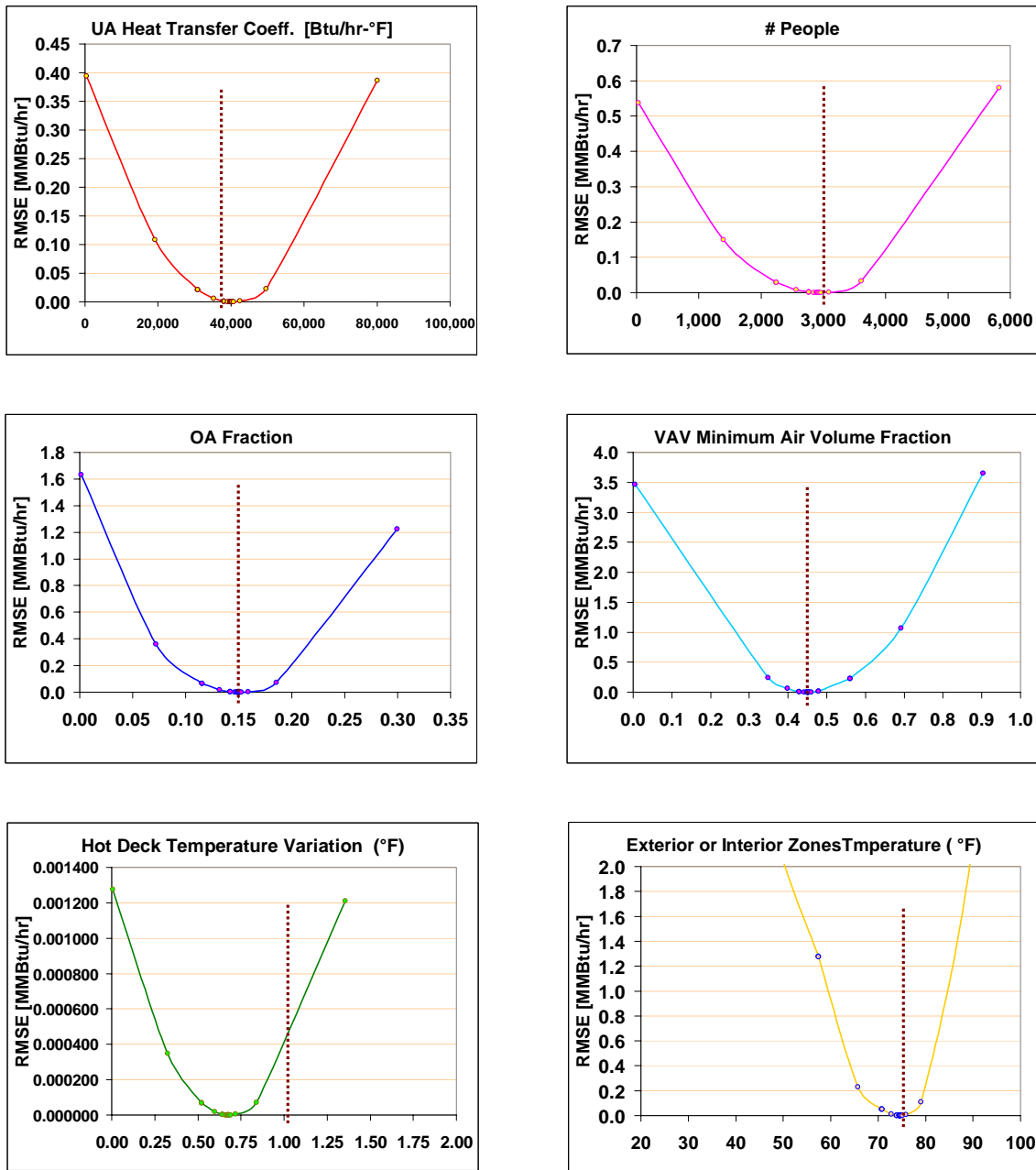
Figure 4.7 Graphical representation of the behavior of six parameters in the multivariable minimization of the RMSE applied in a DDVAV by Golden Section search at iteration 13110 (vertical dashed lines represent the expected parameter values).
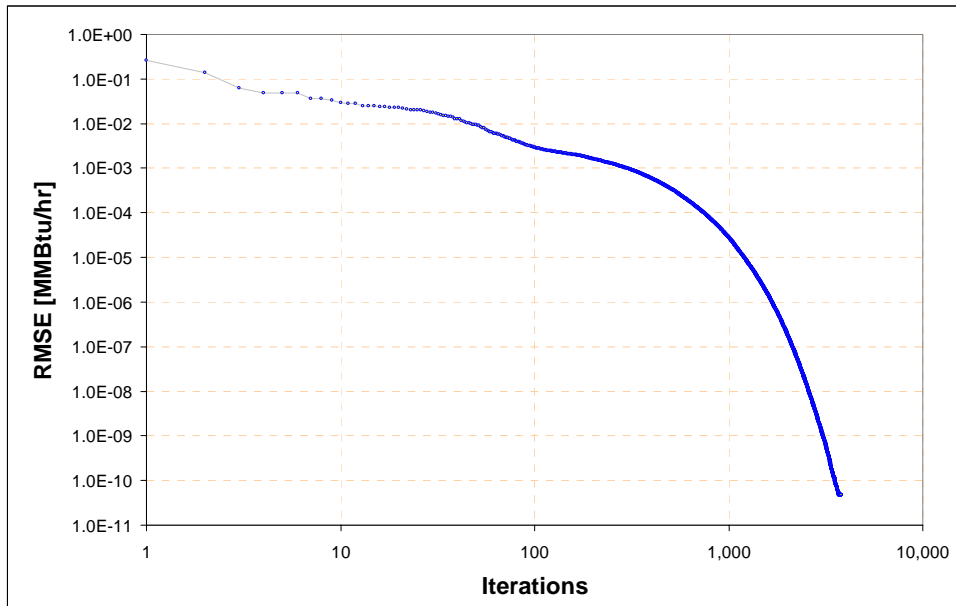
Figure 4.8 Typical problem-free search path for the minimization of the RMSE by the GS search applied to a DDVAV system.
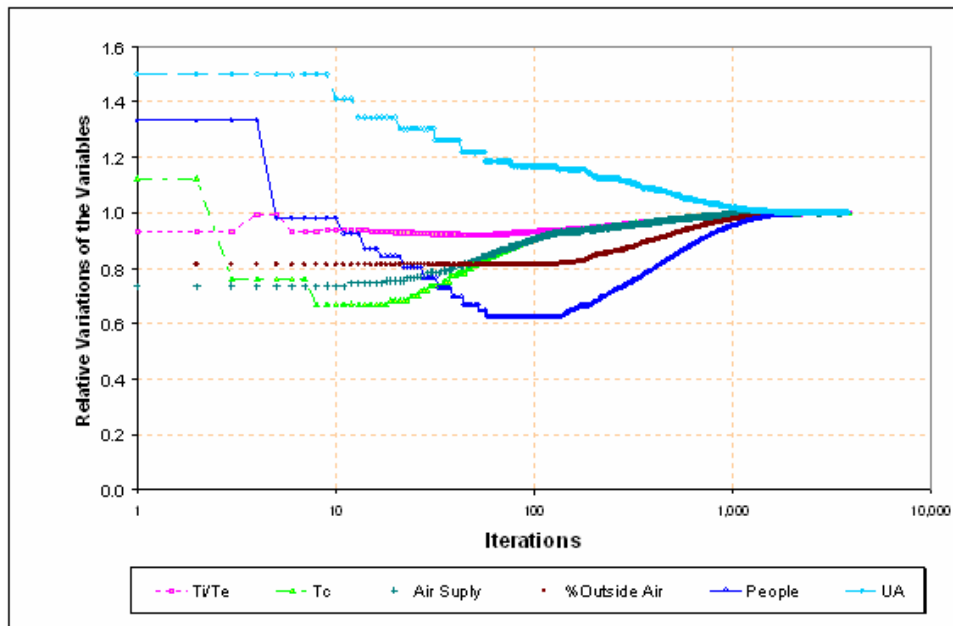
Figure 4.9 Corresponding normalized variable convergence patterns for the RMSE minimization path presented in Figure 4.8.
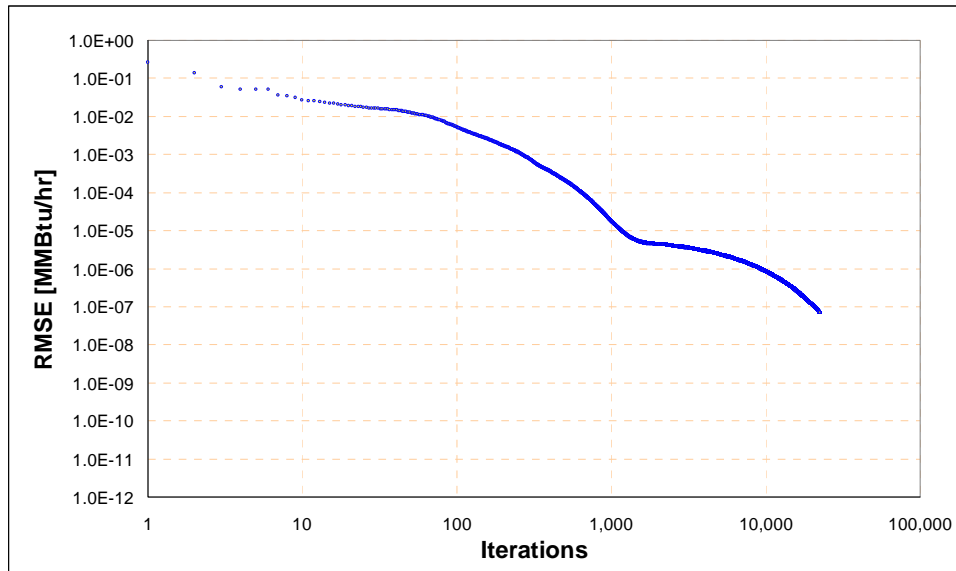
Figure 4.10   Search path of the RMSE minimization process by the GS methodology applied to a DDVAV system.
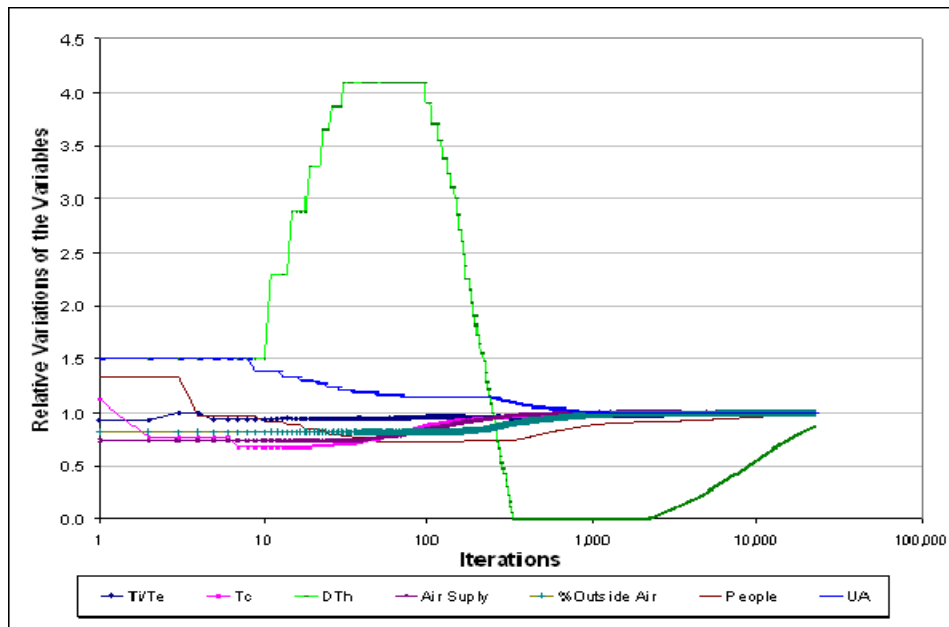
Figure 4.11   Corresponding variable convergence patterns for the RMSE minimization path presented in Figure 4.10.

4.2.3 Performance of the multivariable RMSE minimization by Simulated Annealing technique

Of the characteristics that an optimization or minimization algorithm methodology should have, reliability and speed are the most significant. The RMSE minimization carries the intrinsic problems that appear in the minimization of a statistical function. Furthermore, in this study the function is dependent on environmental parameters, which makes the solution more complex. Therefore, it is imperative that the methodology for solving the RMSE minimization, which would be the "automated calibration", avoid problems that are being experienced with the exhaustive and Golden Section search. These methodologies are not one hundred percent reliable; they could tend to obtain a local minimum, and spend significant time completing the optimization process.

One alternative that is proposed and tested in this study belongs to the so-called intelligent algorithms. The suggested methodology is the Simulated Annealing optimization technique; this may be the first time it has ever been applied to the field of heating, ventilation, and air conditioning system analysis. The procedure has previously been explained in Chapter III, and is described in more detail in Appendix A. The algorithm is based on the physical meaning of the thermodynamics of the annealing process. In brief, the method of simulated annealing is an analogy to the way that liquids freeze and crystallize, or metals cool and anneal. At high temperatures, the molecules of a liquid move freely with respect to one another. If the liquid is cooled slowly, thermal mobility is lost. The algorithm consists of the identification of an initial set of possible system solutions; an objective function analogue of energy, the minimization of which is the goal of the procedure; the definition of a generation mechanism of random changes in the neighborhood, a critical control parameter analogue of temperature; and an annealing schedule that advises how the control parameter should be lowered from high to low values.
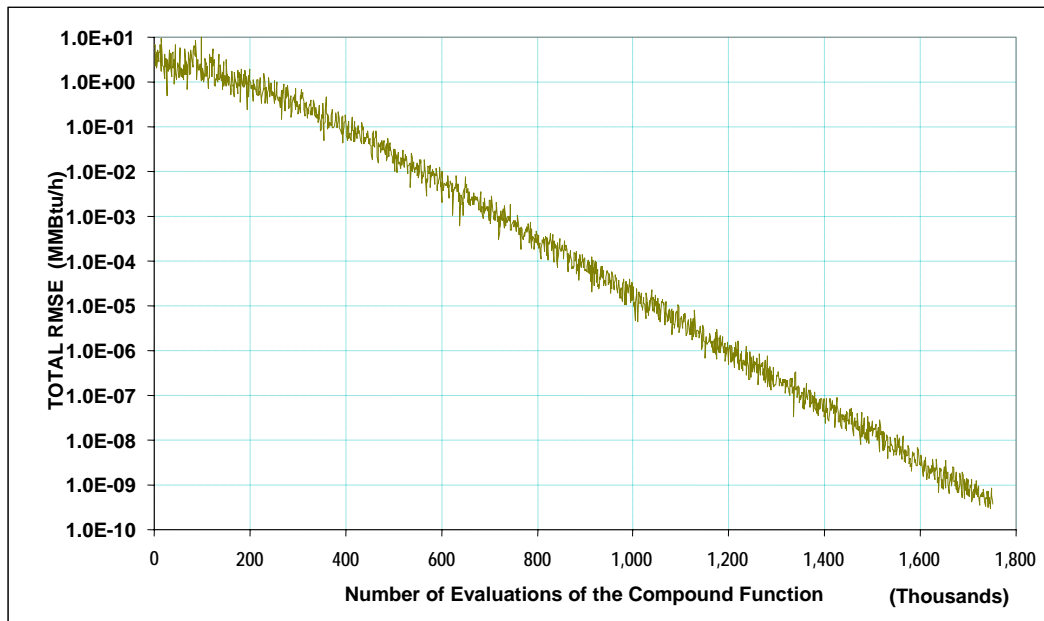
(a)
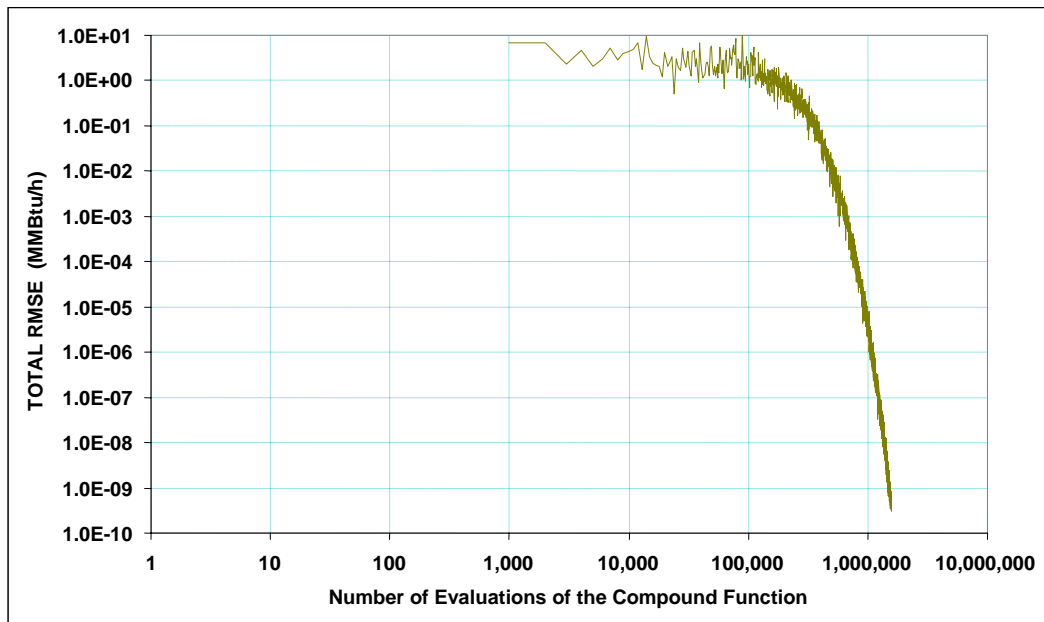
(b)

Figure 4.12   Typical performance of the Simulated Annealing multivariable RMSE minimization for a dual-duct variable air-volume system with synthetic data, (a) with a semi-log scale, and (b) with a log-log scale.

Figure 4.12 illustrates the RMSE pattern that is obtained from the simulated annealing minimization process for a DDVAV system using a synthetic data set. In general, the RMSE minimization performance looks as expected in a very well-designed multivariable optimization procedure. There are still some differences between this pattern and the one observed in Figure 4.3, which corresponds to a perfect multivariable optimization, in that the SA algorithm generates a wiggly pattern. That is anticipated because it is the intrinsic nature of this algorithm, that randomly generates a solution set and because of the fact that it does not always follow the descendent path from the location of local minimum, as done by typical optimization. The SA algorithm accepts solutions that produce a greater local minimum depending on the Boltzman distribution. This is precisely what is depicted in Figure 4.12.

By and large, it has been proven by many authors (Kirkpatrick et al. 1983, Laarhoven and Aarts 1987) that the algorithm is reliable and steady in most cases. Ingber (1989, 1993, 1998) has also found that the algorithm works reasonably well in badly conditioned problems, although, instead of obtaining a clear annealing in the final process, the procedure in these cases is better explained as a quenching process. Figure 4.13 depicts the performance of the SA algorithm when this process appears in the RMSE minimization of a DDVAV system. The same pattern is very likely to occur when the SA methodology is applied to data modified by white noise.
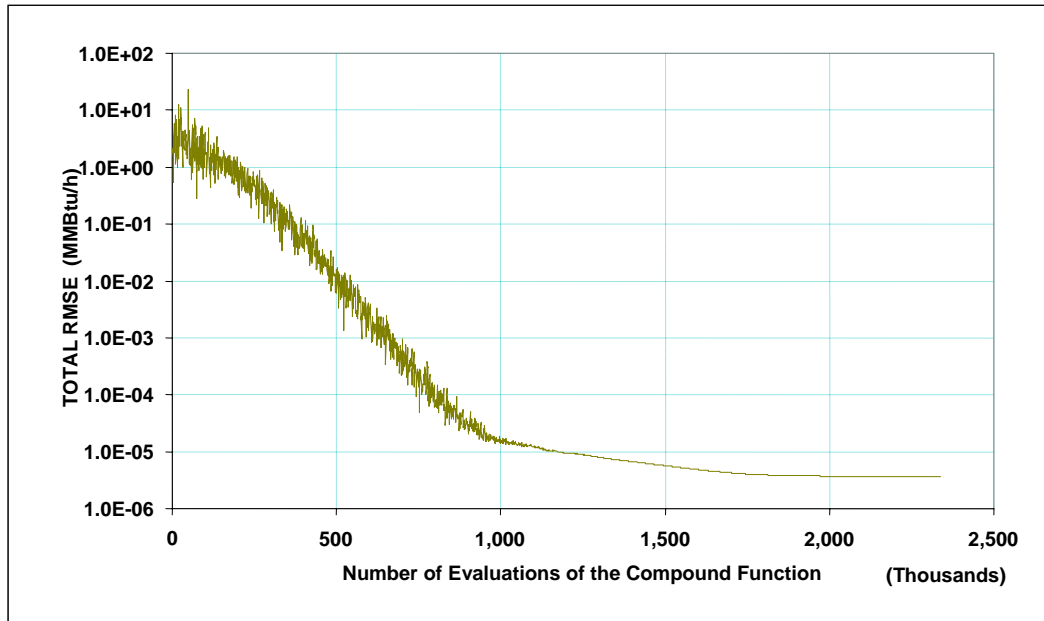
(a)
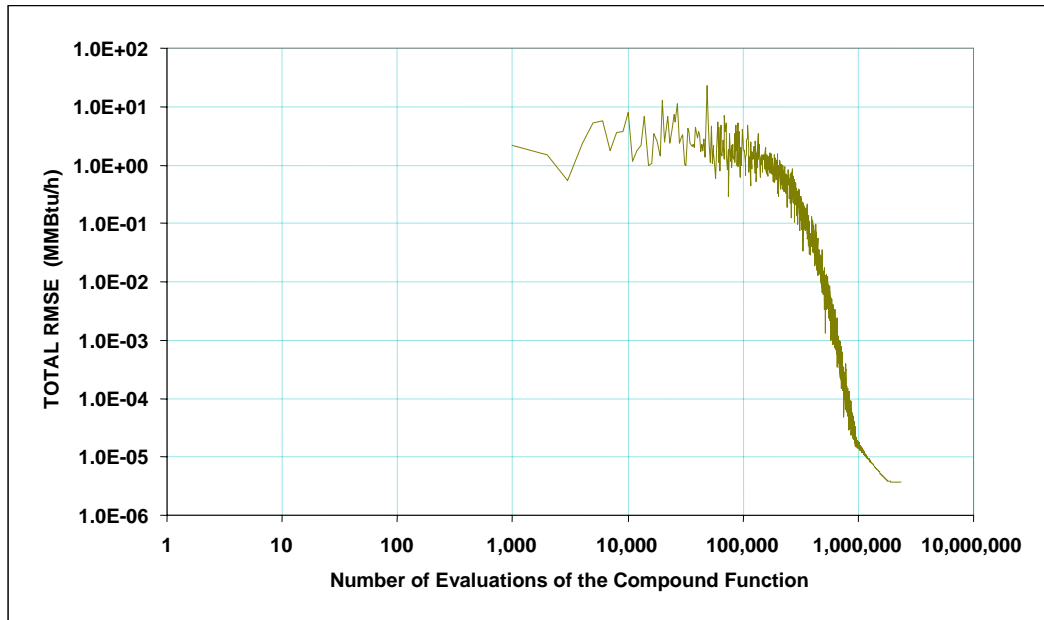
(b)

Figure 4.13   Typical performance of the Simulated Annealing multivariable minimization of the RMSE for a dual-duct variable air volume system with white noise modified synthetic data, (a) with a semi-log scale, and (b) with a log-log scale.

4.3   Methodology Tests Description

The assessment of a computerized or analytical methodology involves applying several tests to the methodology to validate and understand its performance. Perhaps the most significant tests for evaluating the performance of an algorithm are the accuracy and stability tests, which should be designed and developed according to the characteristics of the methodology to be assessed.

The accuracy test consists of evaluating the performance of a methodology in obtaining the correct values of the "input" variables when the objective function is minimized. In a minimization methodology applied to a function, this corresponds to entering the variable values that give the global minimum. In terms of a *calibration*, when this test is applied to a synthetic data set, the goal of the algorithm is to retrieve the variable values from which this data set was generated.

The stability test assesses the repeatability and steadiness of the accuracy of a methodology independent of the initial input parameter values that are entered. In an optimization methodology, this stability test implies that the output of the methodology always must be the same independent of the initial values that have been entered. This test is very significant because it gives an assessment of the methodology's reliability.

4.4   Analysis of the Results of the Tests

As explained in Chapter III, the methodology to be tested is a "calibration" algorithm of a data set based on the performance of simplified analysis of HVAC systems. Mathematically this calibration process becomes a minimization of a statistical function, the root mean square error (RMSE).

The tests were carried out for all the data samples, including synthetic data and white noise modified synthetic data for the constant and variable air volume systems in both dual-duct and single duct with re-heat. A complete set of embodiments tables with results for all the HVAC systems tested and with complete information on all the tests can be found in Appendix G.

Each accuracy test consists of multiple runs of the methodology with random inputs over one data set sample. For uniformity and statistical purposes, six runs are presented for each system. The statistical summary of the results for the plain synthetic data sets for a dual-duct variable air volume, a dual-duct constant air volume, a single duct variable air volume, and a single duct constant air volume with re-heat system are presented in Tables 4.1, 4.2, 4.3 and 4.4, respectively.

Table 4.1 presents the average values of the input parameters and the results obtained from the RMSE minimization by the simulated annealing methodology for the plain synthetic data sample of a dual-duct variable air volume HVAC system. From the statistical results, it is shown that the test of accuracy is totally satisfied. The coefficient of variation of the standard deviation (CV-StDev) and the mean bias error (MBE), both based on the initial parameter values that generate the synthetic data samples of the inputs, are high for all the variables. This fact demonstrates that each of the input variable values was varied completely over a broad range. In contrast, the parameter set values, obtained after the RMSE minimization is complete, present a solid performance as expected in an accuracy algorithm. The CV-StDev and the MBE are very low; the maximum value of any statistical index for all the variables is far below 1%, which is an excellent sign of success in this type of test.

The data in Table 4.1 also validates the stability test. The very low values of both the CV-StDev and the MBE indicate that the variation in each of the variables considered is successfully retrieved in all cases. No deviations from the variables' values were found from test to test. Therefore, the accuracy and the stability of the SA methodology are confirmed for the plain synthetic data of a dual-duct variable air volume HVAC system. Similar analyses have been done for the other HVAC systems.

Table 4.1 Statistical indexes, input parameters, and average values of results obtained for six runs of the *RMSE* simulated annealing minimization methodology for the synthetic data sample of the dual-duct variable air volume HVAC system.

			Base	Average	CV-StDev	MBE
Initial Guess	**Te | Ti**	°F		71.1559	18.11%	-3.844144
	Tc	°F		62.7094	18.37%	7.559432
	DTh	°F		0.3662	293.71%	-0.633797
	%min			0.5272	54.26%	0.077210
	Xoa			0.6496	37.40%	0.499622
	#Persons			5,146	38.25%	2,146
	UA	Btu/hr-ft^2-°F		51,066	57.64%	11,066
Optimized	**Te | Ti**		75.00	74.9959	0.0155%	-0.004147
	Tc		55.15	55.1481	0.0098%	-0.001937
	DTh		1.00	0.9971	0.8110%	-0.002889
	%min		0.45	0.4500	0.0049%	0.000008
	Xoa		0.15	0.1500	0.0019%	-0.000001
	#Persons		3,000	2,999	0.1316%	-1.409530
	UA		40,000	40,000	0.0008%	0.117223
	RMSE			6.22E-06		
	Run Time			3:47:13		
	Annealings			151		

Tables 4.2, 4.3, and 4.4 present the average values of the input parameters for the HVAC systems analyzed. These tables also contain the results obtained from the RMSE minimization by the simulated annealing methodology for the synthetic data sample of a DDCV, a CVRH, and a SDVAV HVAC system, respectively. The statistical indexes show that the methodology satisfies accuracy and stability requirements for each system. In fact, the results of both tests may be comparable with those of a DDVAV system.

The results for all the systems verify that the simulated annealing methodology is found reliable for a minimization, or calibration process, when it is applied to plain synthetic data sets.

Table 4.2 Statistical indexes, input parameters, and average values of results obtained for six runs of the *RMSE* simulated annealing minimization methodology for the synthetic data sample of the dual-duct constant air volume HVAC system.

			Base	Average	CV-StDev	MBE
Initial Guess	**Te | Ti**	°F		65.1016	20.13%	-9.898449
	Tc	°F		63.4095	14.25%	8.259528
	DTh	°F		0.2223	937.42%	0.222255
	Xoa			0.5224	54.27%	0.372431
	#Persons			4,986	61.90%	1,986
	UA	Btu/hr-ft^2-°F		61,092	57.17%	21,092
Optimized	**Te | Ti**		**75.00**	**74.9995**	**0.0013%**	**-0.000514**
	Tc		**55.15**	**55.1496**	**0.0014%**	**-0.000427**
	DTh		**0.00**	**-0.0004**		**-0.000434**
	Xoa		**0.15**	**0.1500**	**0.0001%**	**0.000000**
	#Persons		**3,000**	**3,000**	**0.0088%**	**-0.141433**
	UA		**40,000**	**40,000**	**0.0000%**	**-0.002777**
	RMSE			7.20E-07		
	Run Time			2:09:22		
	Annealings			121		

As has been mentioned in previous sections, in contrast to the synthetic data samples, the measured data set samples are expected to differ from the simulated data sets. To assess the performance of any methodology on measured data sets, the measured data will be approximated as composed of two parts. One part is the synthetic data corresponding to the results from the simplified analysis, and the second part is a random variation that could correspond to the differences due to unknown real operation conditions. These data sets intend to emulate the behavior of a building with modified operation conditions, which are correlated to how much white noise is added to the synthetic samples. These synthetic data sets modified with white noise will be the target of the minimization procedure.

The same stability and accuracy test types were applied to the white noise modified synthetic samples to assess the performance of the simulated annealing minimization technique and to analyze the effects of the white noise levels. Tables 4.5 to 4.18 contain all the results of the tests applied to the HVAC systems included in this study.

Table 4.3 Statistical indexes, input parameters, and average values of results obtained for six runs of the *RMSE* simulated annealing minimization methodology for the synthetic data sample of the single duct constant air volume with re-heat HVAC system.

			Base	Average	CV-StDev	MBE
Initial Guess	**Te | Ti**	°F		75.8019	18.83%	0.801920
	Tc	°F		64.6578	20.58%	9.507774
	Xoa			0.5665	56.25%	0.416547
	#Persons			6,746	43.05%	3,746
	UA	Btu/hr-ft²-°F		41,721	59.24%	1,721
Optimized	**Te | Ti**		75.00	75.0003	0.0018%	0.000338
	Tc		55.15	55.1503	0.0021%	0.000281
	Xoa		0.15	0.1500	0.0002%	0.000000
	#Persons		3,000	3,000	0.0124%	0.092500
	UA		40,000	40,000	0.0000%	0.000000
	RMSE			9.74E-07		
	Run Time			1:55:25		
	Annealings			109		

Table 4.4 Statistical indexes, input parameters, and average values of results obtained for six runs of the *RMSE* simulated annealing minimization methodology for the synthetic data sample of the single duct variable air volume with re-heat HVAC system.

			Base	Average	CV-StDev	MBE
Initial Guess	**Te | Ti**	°F		72.3174	13.55%	-3.245053
	Tc	°F		67.2221	10.47%	9.548623
	%min			0.6403	44.99%	0.172258
	Xoa			0.5378	54.17%	0.303245
	#Persons			3,600	96.65%	989
	UA	Btu/hr-ft²-°F		44,275	76.70%	13,707
Optimized	**Te | Ti**		75.00	74.9886	0.037%	-0.011415
	Tc		55.15	55.1447	0.024%	-0.005340
	%min		0.45	0.4500	0.020%	0.000036
	Xoa		0.15	0.1500	0.001%	-0.000001
	#Persons		3,000	2,996	0.320%	-3.913365
	UA		40,000	40,000	0.000%	0.000000
	RMSE			1.05E-05		
	Run Time			4:26:42		
	Annealings			228		

In Table 4.5, the performance of the accuracy and stability tests can be seen. The stability assessment is presented through the outputs of three selected tests for the sample modified with WN(1%). The results indicate that the performance of the methodology for this sample is successful; no significant differences were found among the tests. On the other hand, the accuracy test assesses how close the outputs are from those variable values used to generate the synthetic data. For this case of the DDVAV sample modified with WN(1%), the results can be considered a success even though some small differences are evident between the final parameters and the expected values.

Table 4.5   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a dual-duct variable air volume system carried out on synthetic data modified with WN(1%).

WN - 1%		Stability Test					
		Test 1		Test 2		Test 3	
Variable	Base	Input	Output	Input	Output	Input	Output
Te | Ti	75.00	82.1104	75.2695	79.1605	75.2706	56.5362	75.2685
Tc	55.15	79.5062	55.3332	66.4600	55.3338	63.6457	55.3328
DTh	1.00	-1.8914	1.2289	-2.9115	1.2296	-1.8326	1.2282
%min	0.45	0.3425	0.4498	0.5280	0.4498	0.3001	0.4498
Xoa	0.15	0.3335	0.1495	0.3023	0.1495	0.6866	0.1495
#Persons	3,000	9,608	3,076	7,854	3,077	6,603	3,076
UA	40,000	44,207	40,097	89,169	40,097	81,383	40,097
RMSE			3.3833E-02		3.3833E-02		3.3833E-02
Run Time			2:24:40		2:22:40		2:26:08
Annealings			107		106		108

Although the samples have been modified with a small fraction of white noise, because the white noise is generated randomly, no two samples modified with the same fraction of white noise are identical to each other. Adding a fixed amount of white noise to a synthetic data sample is just a random variation that, by its own nature, is not related to any specific operational or physical behavior. That is why samples with the

same level of white noise might lead to different results. This is exemplified in Table 4.6 with three different 1% white noise generated samples. Even though the output values are close, not all the variables respond in the same manner, because the white noise samples are different and they lead to distinct apparent operational conditions. The statistical indexes of these 1% white noise modified samples are shown in Table 4.7.

Table 4.6 Accuracy of automated calibration by the Simulated Annealing methodology for a dual-duct variable air volume system carried out on synthetic data modified with three different samples of WN(1%).

WN - 1%		White Noise Dataset					
		Sample I		Sample II		Sample III	
Variable	Base	Input	Output	Input	Output	Input	Output
Te | Ti	75.00	82.1104	75.2695	84.6730	75.4246	68.6598	77.5997
Tc	55.15	79.5062	55.3332	65.6461	55.5136	78.3324	56.5808
DTh	1.00	-1.8914	1.2289	-2.7779	1.1657	-2.6574	2.6528
%min	0.45	0.3425	0.4498	0.9741	0.4518	0.6571	0.4483
Xoa	0.15	0.3335	0.1495	0.2733	0.1510	0.8208	0.1509
#Persons	3,000	9,608	3,076	3,055	3,179	4,258	3,912
UA	40,000	44,207	40,097	6,893	40,046	63,953	40,277
RMSE			3.3833E-02		3.5816E-02		3.4585E-02
Run Time			2:24:40		2:27:44		2:40:14
Annealings			107		107		113

Table 4.8 contains the outputs for the DDVAV sample with WN(5%). Although the values obtained for most of the variables approximate the expected values some of the values are significantly different from the expected values. This is the case for the hot-deck schedule increment parameter, where the value obtained is far from the expected value and is the limit of the variation permitted rather than the optimum value.

The more white noise in the sample, the more variation from the expected values is found in the outputs from the methodology (see Table 4.9). This is understandable

because the variation in the pattern widens as the white noise increases, and the algorithm, most likely, tends to a very different minimum.

Table 4.7 Statistics of three samples of 1% white noise applied over a data set of a dual-duct variable air volume system.

Dataset Sample I [WN(1%)]			DDVAV
	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0000030134	1.0000122449	
MEAN w/wn	2.5266024246	0.7687960433	
RMSE	0.0246073390	0.0093358007	0.0339431397
CV-RMSE	0.97%	1.21%	
MBE	0.0002637875	-0.0002965670	-0.0000327796
NMBE	0.01%	-0.04%	

Dataset Sample II [WN(1%)]			DDVAV
	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0007180588	1.0002098492	
MEAN w/wn	2.5291743928	0.7685314641	
RMSE	0.0271060809	0.0091984209	0.0363045017
CV-RMSE	1.07%	1.20%	
MBE	-0.0023081807	-0.0000319879	-0.0023401686
NMBE	-0.09%	0.00%	

Dataset Sample III [WN(1%)]			DDVAV
	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0001435692	1.0001411961	
MEAN w/wn	2.5273563811	0.7688112533	
RMSE	0.0267376709	0.0084199722	0.0351576431
CV-RMSE	1.06%	1.10%	
MBE	-0.0004901690	-0.0003117770	-0.0008019460
NMBE	-0.02%	-0.04%	

Table 4.8   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a dual-duct variable air volume system carried out on synthetic data modified with WN (5%).

WN - 5%		Stability Test					
		Test 1		Test 2		Test 3	
Variable	Base	Input	Output	Input	Output	Input	Output
Te | Ti	75.00	94.8744	79.2533	70.1206	79.2533	70.8160	79.2533
Tc	55.15	53.9067	58.5985	62.4261	58.5986	47.1934	58.5985
DTh	1.00	0.1544	3.0000	2.3758	3.0000	-0.3324	3.0000
%min	0.45	0.1316	0.4636	0.5898	0.4636	0.0331	0.4636
Xoa	0.15	0.7887	0.1540	0.0616	0.1540	0.0605	0.1540
#Persons	3,000	3,992	4,630	5,095	4,630	8,708	4,630
UA	40,000	10,380	41,436	39,038	41,437	18,298	41,436
RMSE			1.7265E-01		1.7265E-01		1.7265E-01
Run Time			2:31:25		2:30:06		2:28:41
Annealings			111		110		109

Table 4.9   Variation of parameter values as a function of the white noise added to a DDVAV system sample.

WN		White Noise		
		1%	5%	10%
Variable	Base	Output	Output	Output
Te | Ti	75.00	75.2695	79.2534	69.4849
Tc	55.15	55.3332	58.5987	52.4874
DTh	1.00	1.2289	3.0000	-2.9999
%min	0.45	0.4498	0.4636	0.4623
Xoa	0.15	0.1495	0.1540	0.1486
#Persons	3,000	3,076	4,630	1,172
UA	40,000	40,097	41,436	41,006
RMSE		3.3833E-02	1.7265E-01	3.7004E-01
Run Time		2:24:40	3:03:29	2:19:13
Annealings		107	109	103

Simulated Annealing RMSE minimization of samples of a dual-duct constant air volume system (DDCV) modified with different percentages of white noise are presented in Tables 4.10 to 4.12. From these tables it may be seen that the stability test is

successful, but the accuracy test fails. Just as in the sample for a DDVAV system, the accuracy of the variables gets worse as the white noise added to the sample is increased.

Tables 4.13 to 4.15 contain the results of the tests applied to a CVRH system. In the same manner, Tables 4.16 to 4.18 have the results of the tests applied to a SDVAV system. The performance of both accuracy and stability tests are very similar to other HVAC systems. This indicates that the Simulated Annealing methodology produces stable results, but, with white noise added to the sample the accuracy of the results decreases and gets results accurate to 1–2% only when the white noise is at a comparable level. The complete sets of statistical indexes of the white noise samples and the results of the tests applied over the entire group of systems studied in this study are found in Appendix G.

Table 4.10   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a dual-duct constant air volume system carried out on synthetic data modified with WN(1%).

DDCV

WN - 1%		Stability Test			
		Test 1		Test 2	
Variable	Base	Input	Output	Input	Output
Te | Ti	75.00	59.9821	73.7586	91.9056	73.7591
Tc	55.15	53.8993	54.1376	62.6833	54.1380
DTh	1.00	1.8457	-1.0123	2.5834	-1.0118
Xoa	0.15	0.4390	0.1483	0.3189	0.1483
#Persons	3,000	4,168	2,648	4,138	2,648
UA	40,000	97,556	40,224	96,212	40,224
RMSE			4.4739E-02		4.4739E-02
Run Time			2:15:05		2:22:13
Annealings			104		108

Table 4.11 Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a dual-duct constant air volume system carried out on synthetic data modified with WN (5%).

DDCV

WN - 5%		Stability Test			
		Test 1		Test 2	
Variable	Base	Input	Output	Input	Output
Te | Ti	75.00	83.5752	77.1013	83.0647	77.1013
Tc	55.15	54.1408	65.1181	74.9494	65.1181
DTh	1.00	-2.1332	-3.0000	-2.3601	-3.0000
Xoa	0.15	0.4805	0.2834	0.0484	0.2834
#Persons	3,000	7,421	4,331	6,437	4,331
UA	40,000	67,285	40,673	41,246	40,673
RMSE			2.1873E-01		2.1873E-01
Run Time			2:18:40		2:18:14
Annealings			107		110

Table 4.12 Variation of parameter values as a function of the white noise added to a DDCV sample.

DDCV

WN		White Noise		
		1%	5%	10%
Variable	Base	Output	Output	Output
Te | Ti	75.00	73.7586	77.1013	71.4052
Tc	55.15	54.1376	65.1181	52.0564
DTh	1.00	-1.0123	-3.0000	-3.0000
Xoa	0.15	0.1483	0.2834	0.1460
#Persons	3,000	2,648	4,331	2,022
UA	40,000	40,224	40,673	40,444
RMSE		4.4739E-02	2.1873E-01	4.6720E-01
Run Time		2:15:05	2:18:40	2:18:51
Annealings		104	107	108

Table 4.13   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a constant air volume with re-heat system carried out on synthetic data modified with WN (1%).

CVRH

WN - 1%		Stability Test			
		Test 1		Test 2	
Variable	Base	Input	Output	Input	Output
Te | Ti	75.00	58.5037	74.2758	50.1965	74.4544
Tc	55.15	45.5943	54.5549	64.7869	54.7043
Xoa	0.15	0.6881	0.1492	0.0249	0.1493
#Persons	3,000	7,554	2,806	4,789	2,854
UA	40,000	32,964	40,152	23,086	40,152
RMSE			6.2803E-02		6.2803E-02
Run Time			2:18:02		2:16:14
Annealings			105		104

Table 4.14   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a constant air volume with re-heat system carried out on synthetic data modified with WN (10%).

CVRH

WN - 10%		Stability Test			
		Test 1		Test 2	
Variable	Base	Input	Output	Input	Output
Te | Ti	75.00	69.8568	79.8576	87.3646	79.8580
Tc	55.15	67.6155	59.0708	67.3594	59.0711
Xoa	0.15	0.6820	0.1549	0.7612	0.1549
#Persons	3,000	6,952	4,366	7,174	4,366
UA	40,000	7,998	40,170	89,894	40,170
RMSE			6.5721E-01		6.5721E-01
Run Time			2:22:34		2:21:18
Annealings			108		107

Table 4.15   Variation of parameter values as a function of the white noise added to a CVRH sample.

CVRH

WN		White Noise		
		1%	**5%**	**10%**
Variable	**Base**	**Output**	**Output**	**Output**
Te | Ti	**75.00**	**74.2758**	**74.5135**	**79.8576**
Tc	**55.15**	**54.5549**	**54.7040**	**59.0708**
Xoa	**0.15**	**0.1492**	**0.1516**	**0.1549**
#Persons	**3,000**	**2,806**	**2,854**	**4,366**
UA	**40,000**	**40,152**	**39,475**	**40,170**
RMSE		6.2803E-02	3.0831E-01	6.5721E-01
Run Time		2:18:02	2:21:36	2:22:34
Annealings		105	107	108

Table 4.16   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a single duct variable air volume system carried out on synthetic data modified with WN (1%).

SDVAV

WN - 1%		Stability Test			
		Test 1		Test 2	
Variable	**Base**	**Input**	**Output**	**Input**	**Output**
Te | Ti	**75**	87.5190	**70.2090**	59.8451	**70.2094**
Tc	**55.15**	54.4891	**52.6145**	53.5055	**52.6146**
%min	**0.45**	0.8761	**0.4606**	0.9627	**0.4606**
Xoa	**0.15**	0.5082	**0.1495**	0.4250	**0.1495**
#Persons	**3,000**	5,123	**1,376**	6,599	**1,376**
UA	**40,000**	37,448	**39,934**	88,186	**39,934**
RMSE			6.05E-02		6.05E-02
Run Time			3:56:33		4:00:49
Annealings			222		226

Table 4.17   Performance of the accuracy and stability tests of the automated calibration methodology by Simulated Annealing for a single duct variable air volume system carried out on synthetic data modified with WN (10%).

SDVAV

WN - 10%		Stability Test			
		Test 1		Test 2	
Variable	Base	Input	Output	Input	Output
Te | Ti	75	68.3821	69.2101	66.7669	69.2101
Tc	55.15	54.8531	49.5922	54.2374	49.5922
%min	0.45	0.1408	0.4031	0.2856	0.4031
Xoa	0.15	0.2487	0.1380	0.2791	0.1380
#Persons	3,000	6,381	1,079	8,752	1,079
UA	40,000	31,467	41,168	29,149	41,168
RMSE			6.18E-01		6.18E-01
Run Time			3:54:40		4:17:11
Annealings			216		219

Table 4.18   Variation of parameter values as a function of the white noise added to a SDVAV sample.

SDVAV

WN		White Noise		
		1%	5%	10%
Variable	Base	Output	Output	Output
Te | Ti	75	70.2090	67.5471	69.2101
Tc	55.15	52.6145	50.7208	49.5922
%min	0.45	0.4606	0.4526	0.4031
Xoa	0.15	0.1495	0.1459	0.1380
#Persons	3,000	1,376	500	1,079
UA	40,000	39,934	41,116	41,168
RMSE		6.05E-02	3.07E-01	6.18E-01
Run Time		3:56:33	4:28:06	3:54:40
Annealings		222	228	216

4.5   Summary

Great interest has been shown in performing calibrated simulations. The possibilities they could bring to the HVAC field seem to be extensive, from energy management services to detecting potential for improvements or fault detection. In this study, a methodology was proposed to carry out a calibration of building thermal simulations in an automated manner, which avoids the interaction of an engineer or practitioner in the calibration process and improves the accuracy of the process. The automated process has the objective of helping in the determination of the potential savings that could be found in a building, considering that it has just one type of HVAC system.

An automated calibration methodology was implemented using ASHRAE Simplified Energy Analysis procedure algorithms. The calibration was numerically solved by the Simulated Annealing algorithm. To assure the reliability of the methodology, two tests were performed: 1) test of the numerical performance of the Simulated Annealing algorithm, before being tailored to the thermodynamic equations of the simplified energy analysis, the test consisted in solving general mathematical optimization problems that are commonly used for benchmarking; and 2) test for the performance of the algorithm; the analysis of the performance was made with synthetic data samples, which for a broader testing were modified with white noise (WN). These assays, of the performance, were very important because they tested the reliability of the methodology for ideal and non-ideal samples.

Two types of tests were carried out: accuracy and stability or consistency. For ideal conditions with synthetic data, the performance of the methodology was found to be excellent, showing both stability and accuracy for all four types of HVAC systems included in this study. For non-ideal cases, when the synthetic data is modified with white noise, the tests showed that the algorithm has stability but not accuracy. The algorithm's lack of accuracy is due to the addition of the white noise to the sample; the larger the percentage of the white noise the larger the RMSE obtained. A sample of synthetic data with a larger white noise bandwidth means that the sample is modified to the point where it no longer represents the characteristics of the synthetic data sample.

The foregoing fact is confirmed with the results for the samples modified with 1% of white noise; in those cases the parameters obtained are still within 1-2% of the synthetic parameters. The calibrated values for room temperature, *Te* or *Ti*, cold deck temperature, *Tc*, and number of persons consistently give unreliable values when white noise is added, but the other variable values remain quite reliable.

The results seem favorable as a starting point, because they show a real possibility for carrying out automated calibrations through the Simulated Annealing algorithm.

CHAPTER V

METHODOLOGY FOR THE DETERMINATION OF POTENTIAL ENERGY
SAVINGS IN COMMERCIAL BUILDINGS

Many study opportunities can be identified for using calibrated models to lower energy use in buildings. Calibrated models can be used as a case base for innumerable operation conditions in a building, i.e. the calibrated model may be used as a reference to diagnose misbehavior of significant variables, to alert to out of range operation conditions, and to assist in the optimization of HVAC systems operation (Liu and Claridge 1998a). Another opportunity related to the calibration of an HVAC system model is the determination of potential savings from improved operation of such systems. A calibrated simulation could be used to estimate the potential savings from a proposed retrofit or to explore the potential savings from changing operational strategies of HVAC systems – similar to, or in replacement of, energy audits.

This chapter includes a proposed methodology for the determination of potential savings, its basis and a description of its components.

5.1 Potential Savings Estimation Methodology

For any energy system, theoretical and technical estimates of prospective conservation measure savings estimates are usually derived from physical and technical analyses of end-use energy flows. The theoretical potential represents achievable energy savings based on theoretical considerations of thermodynamics; in a process where final energy consumption is kept constant, the energy losses should be minimized through process operation changes, heat re-use, and/or avoiding heat loss. The technical potential energy savings represent achievable energy savings that result from implementing energy-efficient commercial and near-commercial technology available at a given time, regardless of cost considerations and the reinvestment cycle.

The energy use in a commercial building is dependent on the outdoor environmental conditions, the building's physical characteristics and the operation

conditions of its systems. The main objectives of the operation of buildings' HVAC systems are to provide overall comfort for their occupants or to preserve a comfortable ambiance for their work. Comfort is an important factor that is related with productivity and health; buildings should be maintained with adequate levels of clean air, luminance and temperature.
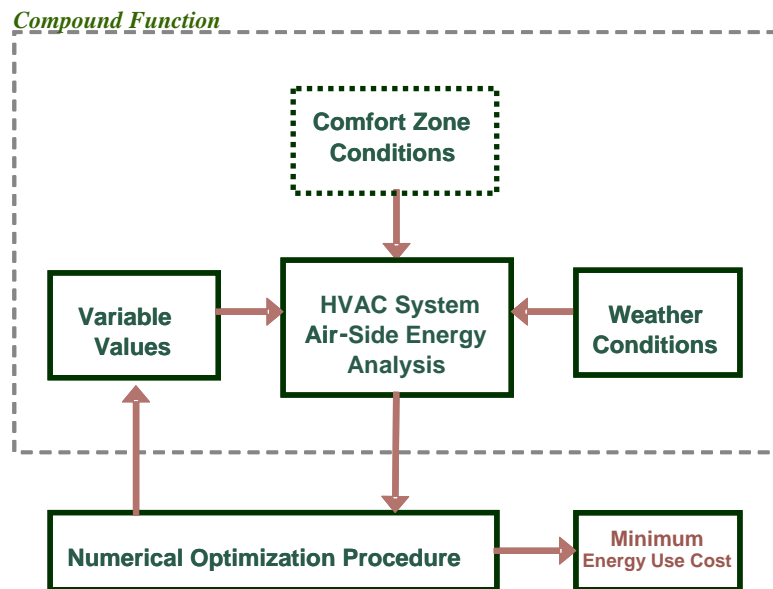
Figure 5.1   Block diagram of the methodology for determination of potential savings.

Thus, it is recognizable that the potential energy savings in a building may be obtained from the minimization of its energy loads/use, but while complying with the comfort conditions required for the specific occupant activities and/or type of building. Therefore, the minimum energy needed to provide comfort conditions in a building may be obtained through an optimization algorithm. Figure 5.1 presents a block diagram of the proposed/developed minimization methodology. Two major components are identified: a numerical procedure for the minimization of the energy use and the

compound function that thermodynamically represents the built-in HVAC system's performance.

The potential energy savings can be defined as the difference between the actual energy use during the *period of calibration* and the minimum energy use to obtain indoor comfort conditions under the same weather conditions.

$$Potential\ Energy\ Savings = Energy\ Use_{ACTUAL} - Energy\ Use_{MINIMIZED} \qquad (5.1)$$

The compound function includes the simplified energy analysis modeling for the major-representative HVAC system in the building, the ambient conditions where the building is located and the psychrometric definition of the comfort zone. The numerical methodology seeks and generates the parameter values that will produce the minimum building energy use.

The methodology consists of the ordered interaction between the HVAC system modeling and the numerical modules, until the minimum is obtained. Since the compound function is dependent on ambient conditions, which are time and location dependent, the minimization cannot be determined as in regular functions. The methodology should be applied to representative ranges of these ambient conditions; therefore, the scheme fits perfectly to a bin sorting algorithm. Thus, the methodology to determine the potential savings will be applied to the total range of the ambient conditions — average outside dry-bulb temperature as the main variable, and the outputs have to be integrated based on its bin distribution.

5.2 Mathematical Formulation of the Potential Savings Methodology

As mentioned above, the methodology for the determination of potential savings may be very well formulated as an optimization scheme. Also, due to the functional dependence on ambient conditions, the optimization should be carried out throughout that weather bin distribution, assuring an equivalent and appropriate representation of the problem.

The potential energy savings methodology is based on two main parts: the definition of the optimization scheme and the numerical algorithm to solve it. While an optimization algorithm seeks a solution in the feasible region that has the minimum value of the objective function, the optimization scheme is the mathematical formulation of the objective function and the specification of the constraints that define the feasible region. In this study, the mathematical representation for the potential savings methodology may be expressed as follows:

Objective Function:

minimize C_T

> where $C_T = C_{HHW} + C_{CHW} + C_{EF}$

> C_T is the total cost of energy use in the building, C_{HHW} is the cost of the heating loads, C_{CHW} is the cost of the cooling load, and C_{EF} represents the electricity cost of the electricity of fans.

Subject to the following constraints:

> a) System of equations that model a specific HVAC system (See Appendix D)
> $$F(x_i) = 0 \qquad i=1...n$$

> b) Primary or control variables values must fall within practical ranges
> $$x_{j,1} \geq x_j \geq x_{j,2} \qquad j=1...m$$

> where the subscripts *1* and *2* correspond to the lower and upper limits for each of the operation variables and $n > m$

> c) Secondary or resultant variables must have a positive value that is physically reasonable
> $$x_k \geq 0 \qquad k=1...q$$

> where $q = n - m$

> d) In addition to meeting these conditions, comfort parameters must fall within the comfort zone limits
> $$\{T_z, w_z\} \in \text{Comfort zone}$$

> where the subscript *z* refers to all zones in the building. The boundaries of the comfort zone utilized in this procedure are those defined in *ASHRAE Standard 55* (ASHRAE, 2001); these boundaries are illustrated in Figure 5.2 and described in a section below.

The number of variables to be evaluated, control and resultant, depends on the HVAC system assumed or identified in the building, e.g. in DDVAV systems, in contrast to SDCAV systems, both the cold deck and hot deck temperature schedules must be considered in the minimization.

From the solution of this optimization problem, the minimum heating and cooling requirements can be calculated. It should be remembered that the results are related to a particular ambient condition, and in order to obtain the whole minimize energy use loads, the procedure should be repeated for all the conditions that represent the environmental conditions at the location of the building — the optimization also needs to be performed for each bin of weather data.

5.2.1 Comfort zones – psychrometric description

The comfort conditions have been specified to provide an acceptable thermal environment for occupants wearing typical indoor clothing while engaged in near sedentary activity. These conditions are generally plotted on a psychrometric chart in terms of bounded areas as depicted in Figure 5.2. From a thermal point of view, a comfortable environment is one which at least 80% of the active persons would find acceptable. (ASHRAE 1992 and 1995). Due to the changes in clothing for seasonal weather, the comfort zones are specified for winter and summer for clothing insulation levels of 0.5 and 0.9 clo[1], respectively. The warmer and cooler temperature borders of the comfort zones are affected by humidity and they coincide with the lines of constant effective temperature[2] (Kreider and Rabl 1994). Spaces below 68 °F and 30% relative humidity in the winter, and zones above 78 °F and approximately 60% relative humidity in the summer are expected to produce discomfort in larger portions of the population (see Figure 5.2). Low relative humidity environments dry out the skin and mucous membranes, and high humidity limits the body's ability to shed excess heat. High humidity is also favorable to mold growth.

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[1]1 clo = 0.88 °F·ft^2·h/Btu (0.155 m^2 K/W)
[2]Effective temperature is the temperature of an isothermal black enclosure with 50% relative humidity where the body surface would experience the same heat loss as in the actual surface.

The parameters that can be used to indicate whether the state of a process, or condition, falls in the comfort areas may be two of the following variables: the relative humidity, the humidity ratio, and the operative temperature. Evidently, knowing the physical properties of the humid air could also be used in the determination of fulfillment of comfort conditions, but for simplicity and for concordance with the way the HVAC system is modeled, thermodynamic states are used in this study.
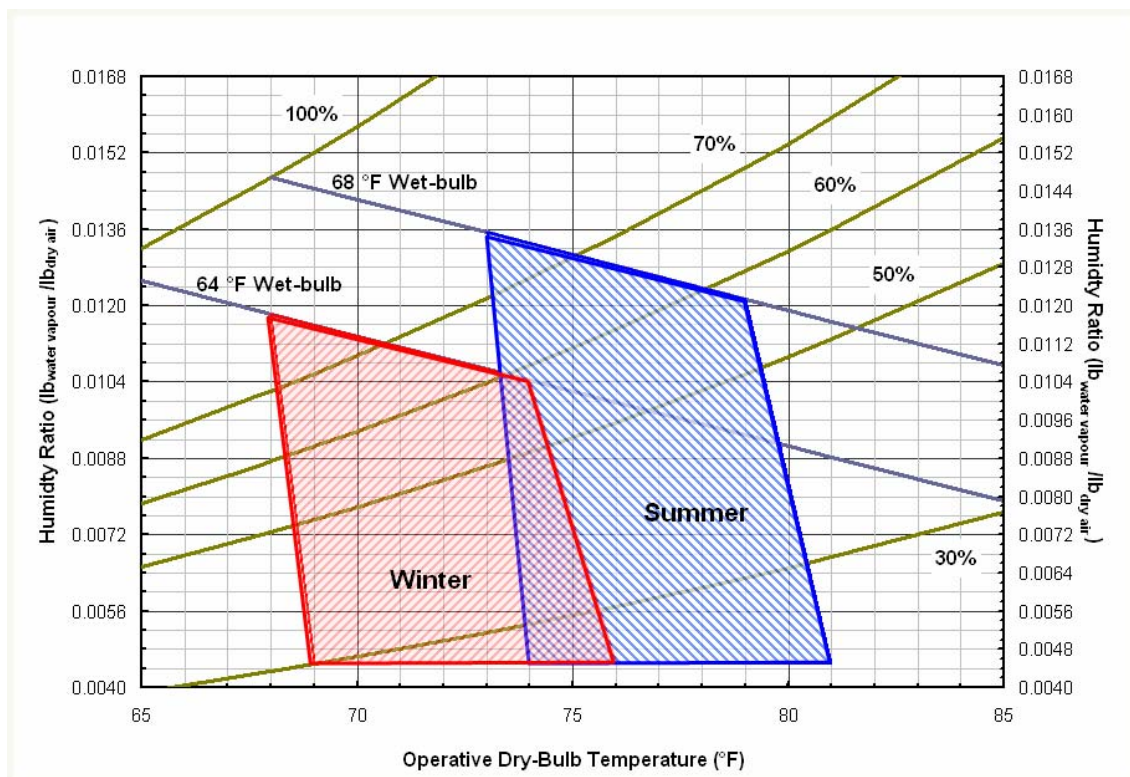
Figure 5.2 Acceptable ranges of operative temperature and humidity for people in typical summer and winter clothing during light, primarily sedentary activity (<1.2 met). The operative temperature ranges are based on a 10% dissatisfaction criterion (adapted from ASHRAE 1995)[3].

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[3] 1 met = 18.4 Btu/h·ft^2 (58.2 W/m^2), Metabolic heat generation unit.

5.2.2 Bin data for air conditioning calculations

The energy use necessary to generate indoor comfort conditions in a building is dependent on the ambient conditions, which are presented hourly, daily, or seasonally. Therefore, as has been mentioned previously, the minimization methodology should be managed through representative conditions obtained from those outdoor conditions. The most common algorithm to obtain representative equivalent ambient conditions is "bin sorting". Thus, the optimization should be carried out for each bin of weather conditions data.

The bin sorting algorithm is based on the classification of one variable that could be identified as "guide", or "key" variable, through a range separation. At the same time that the classification is carried out, the variables related in time and location to that key variable are separated in a corresponding manner. At the end of the arrangement, the averages of the coincident data related to the guide variable can be generated. This can be expressed as follows:

1. Set up an array of "bins" – one for each range of the key variable, generally the outdoor temperature, in order.
2. Examine each item of the dataset (y_{uv}) and use the value of the key variable to place it in the appropriate bin.
3. Inspect each u-bin to count the m_u elements in it, $m_u \geq 0$.
4. For each of the related variables y_u related to the key variable, the averages are evaluated through

$$\bar{y}_u = \sum_{v=1}^{m_u} y_{uv} \bigg/ m_u$$

This process can be conditioned to perform in place and does not require the use of additional memory. However, for data sets with a large number of elements the performance of the algorithm is slow. The bin sorting strategy may appear rather limited, but it can be generalized into a strategy known as Radix sorting, which for the number of data that are taken in account in this study ($<10^4$) is not justified.

The representation of ambient conditions by the common bin sorting, by any combination of the dry-bulb temperatures, wet bulb temperatures or humidity ratios, especially in hot and humid climates, has been questioned because any of the possible

sets of those combinations, using a single-parameter bin representation, is deprived of extremes (Cohen and Kosar 2000). Perhaps a joint-frequency bin representation could pick those extremes, but, for this study that is intended to be used with limited data, the extremes could also very well be missed. The subroutine developed for the bin sorting algorithm is presented in Appendix E.

5.3 Implementation of the Minimization Algorithm to Determine the Potential Energy Savings

The formulation of the minimization problem to determine potential energy savings requires an algorithm that would be reliable and manageable in the integral range of the ambient conditions available. The intrinsic formulation of some of the HVAC systems requires that the minimization be carried out with functions that may not be differentiable in a straightforward manner. Therefore, it may be convenient to establish a methodology that does not use derivatives.

Another aspect to be considered is that there are two kinds of constraints on the minimization problem for the determination of potential energy savings, one of linear – one variable and other of area - two variables. In addition, the algorithm to be used has to be repeated for each of the representative conditions of the binned ambient conditions, so the algorithm should be chosen to be as fast and simple as possible.

Several numerical algorithms to carry out the minimization were reviewed, and tested, among others, a modified simulated annealing algorithm and the simplex optimization method, which failed mainly because they are designed to work without constraints. Due to the complexity of the restrictions, the algorithm recommended is a tailored exhaustive search. Although the methodology is not sophisticated, it allows the control of the minimization constraints and the managing of the sequence of the procedure in a versatile manner.

The following diagram, in Figure 5.3, illustrates the procedure of the implementation of the methodology to determine potential energy savings.
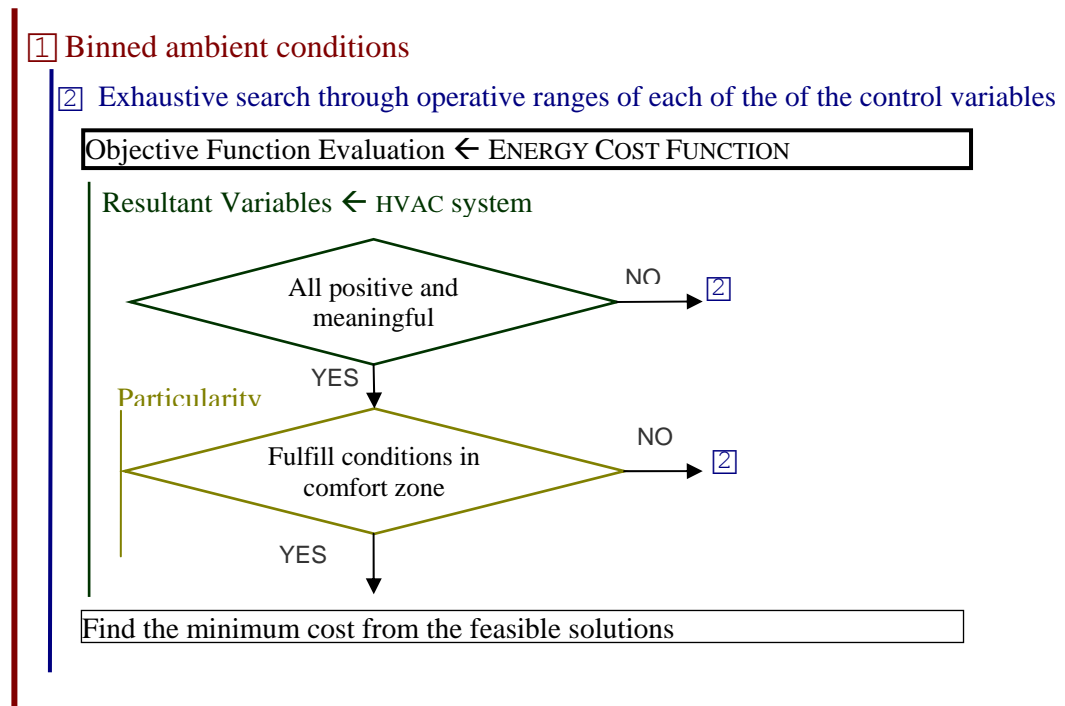
Figure 5.3 Flowchart of the methodology for evaluating potential energy savings in a building through binned ambient conditions. The total potential savings will be the sum of the individual products of the energy savings in each bin multiplied by its frequency.

The methodology is implemented to work bin by bin, individually, until all of the conditions are evaluated. The total potential savings are then the sum of all the individual products of the potential energy savings found in each bin, multiplied by the frequency of each bin.

The frequency of each bin of ambient conditions plays an important role in the determination of the potential energy savings. Although the minimization could be obtained with limited data related with a particular period, the yearly potential energy savings should be obtained from ambient conditions that reflect the average, or the "typical", ambient conditions for the location of the building. One alternative is to use the meteorological year already very well defined for use in major simulations such as DOE-2. Therefore, it is recommended in this study that the weather conditions be

obtained from the TMY2 weather files so the potential energy savings have a more solid base in this respect. In case the TMY2 file does not exist for a particular location, the TMY2 weather file closest to that location could be used or a weather year for the location with a complete record close to the period of analysis could be used.
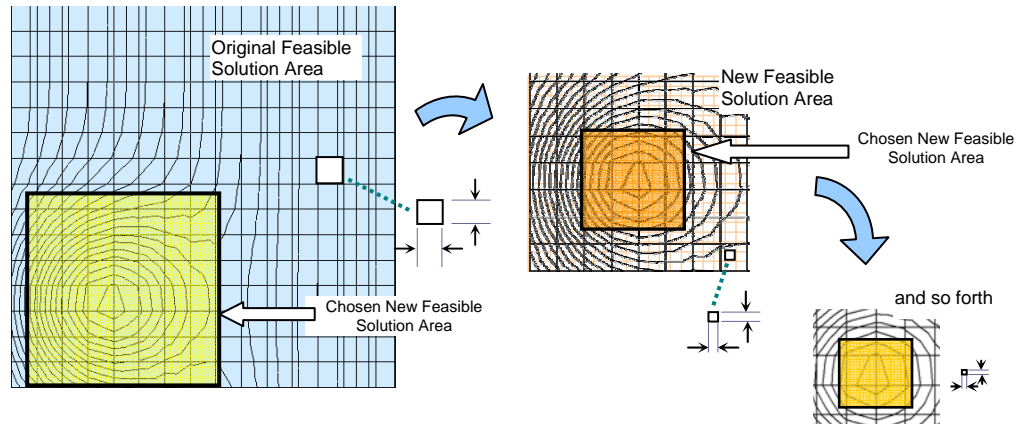
Figure 5.4   Representation of the sequential exhaustive methodology for a two-dimensional generic case.

5.4 Description of the Exhaustive Search Minimization

As mentioned above, the minimization followed to determine the potential cost savings is based on a tailored exhaustive search. The procedure consists of an exhaustive evaluation of the constrained objective function, which depends on the HVAC system in the building, through the control variables. In this case, the term exhaustive refers to a total sweep of the span of each of the control variables, under specific increments. The increments are sized in a way that the number of evaluations is not enormous, but also not so large that the minimum can be missed or mistaken. In other words, the range of each control variable should be divided in a moderate increment size for generating a grid where a minimum can be clearly detected without expending an intense computational effort. When the minimum is found, the exhaustive search is reestablished for all the control variables with new narrowed ranges, generating a new

finer grid, around the reached minimum. The procedure is started again for the new grid and looks for a new minimum in the new ranges. The procedure is continued until a defined criterion for steadiness in the minimum is fulfilled. Figure 5.4 depicts the sequence of the algorithm for a two-dimensional problem.

5.5 Application of the Methodology: Eller Oceanography and Meteorology Building

The Eller Oceanography and Meteorology (O&M) Building is the tallest building on the Texas A&M University campus (See Figure 5.5). This building is fifteen-stories high and houses the Department of Meteorology and the Department of Ocean Engineering. It is a building with diverse activities; it includes offices, laboratories, and classrooms. The total conditioned area is 180,316 square feet.

The building has 4 major DDVAV systems and the heating and cooling loads are covered from the chilled water and the hot water of the campus' central utilities plant.

The building was commissioned in the first months of 1997, and the major adjustments were tuning control valves, optimization of cold and hot decks, resets of static pressures, tuning of the minimum supply air, and tune-up for chilled and hot water pumping.

Figure 5.5   The Eller Oceanography and Meteorology Building on the Texas A&M University Campus.
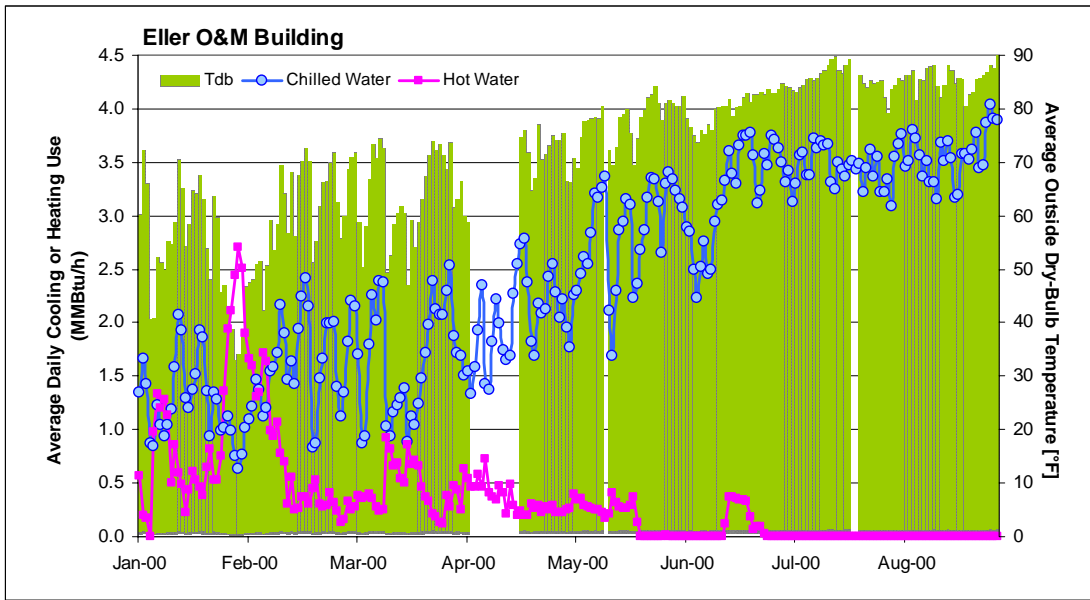
Figure 5.6 Average daily chilled and hot water consumption measured for the Eller O&M Building and daily average outside dry-bulb temperature for the period of January to August for 2000.
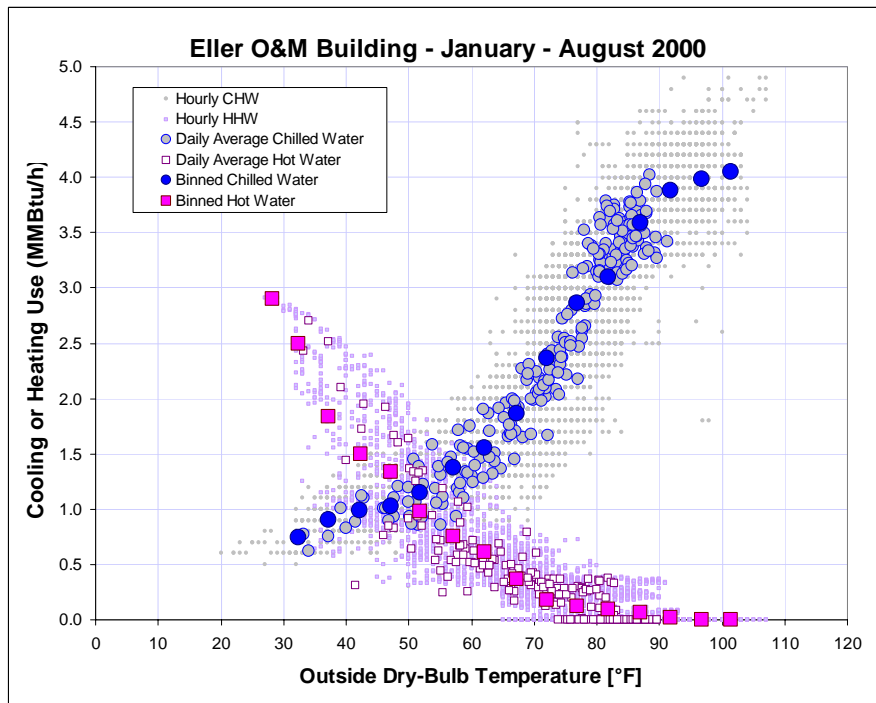
Figure 5.7 Average daily, hourly and binned chilled and hot water consumption values measured for the Eller O&M Building as a function of their corresponding outside dry-bulb temperature for the period of January though August 2000.

The chilled water and hot water consumption data for the first eight months of the year 2000 are presented in Figure 5.6. The time series was used just until August due to a hot water use trouble pattern found starting in October of that year. In Figure 5.7, the same energy use patterns are plotted as a function of outside temperature for hourly, average daily, and the equivalent hourly binned data set.

To implement the potential savings methodology for any building, it is required to have at hand some values that are not going to be optimized, such as the UA, the equivalent interior and exterior area temperatures, the approximate fraction of exterior area with respect to the total, the equivalent number of occupants and the design flow rate. As has been established in the aim of this study, limited information is sometimes available, so a calibration procedure is necessary. The calibration can be very well done with the methodology proposed in Chapter III. The need for this calibration is clear because is not practical to optimize all those variables because the building is already built, and the purpose of this study is not, at least directly, to propose retrofit measures. On the other hand, it is not convenient to optimize occupancy for obvious reasons, and the design flow rate is specified according to the capacity of a particular system. Once the calibration is done, the methodology described above is applied.

Figure 5.8 shows the partial performance of the methodology to determine the optimum cost for a particular bin and a single variable – bin number seven and for the cold deck temperature variable. The optimized cost point is clearly identified and it is observed that the energy use patterns, as the search continues, become asymptotical.
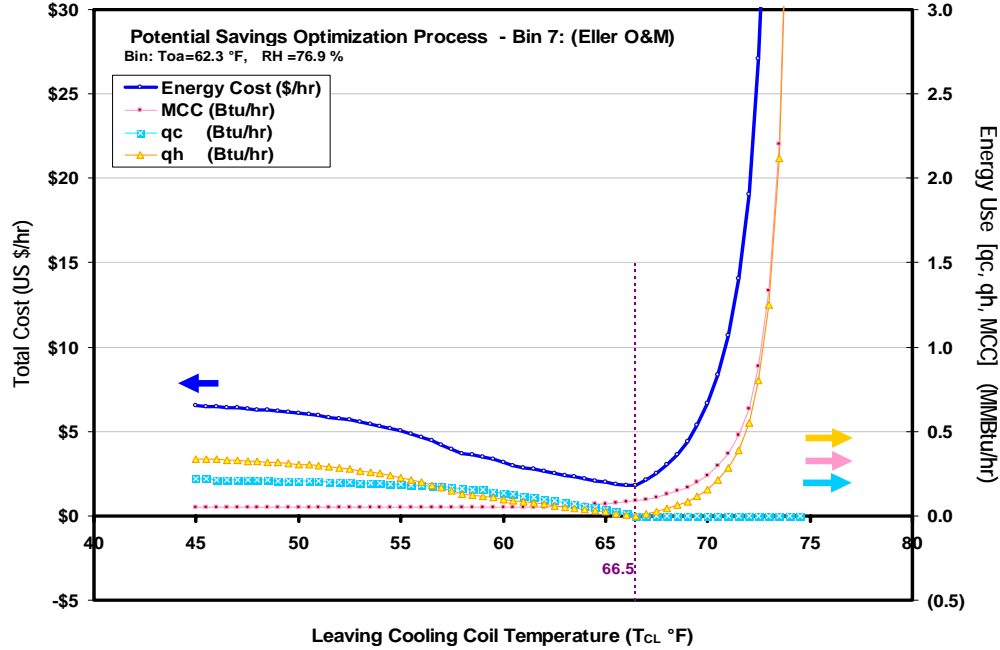
Figure 5.8   Performance of the potential energy savings methodology for the number seven bin of the Eller O&M Building energy use and ambient conditions data.

5.5.1 Potential energy and cost savings for Eller O&M Building

The application of the methodology gives optimized patterns for the heating and for the cooling as a function of the weather conditions at the location of the building. Thus, for the Eller O&M Building these patterns are presented in Figure 5.9.   The zone bounded by the "actual" energy use of the year 2000 and the optimized energy use patterns represents the potential energy savings.   These potential savings come from changes in the operation of the HVAC system's energy use which changes the heating and cooling as presented in Figure 5.10. The economic quantification is made with the help of the weather bin distribution of the building location and the difference between the "actual" and optimized heating and cooling patterns, and is tabulated as in Table 5.1.
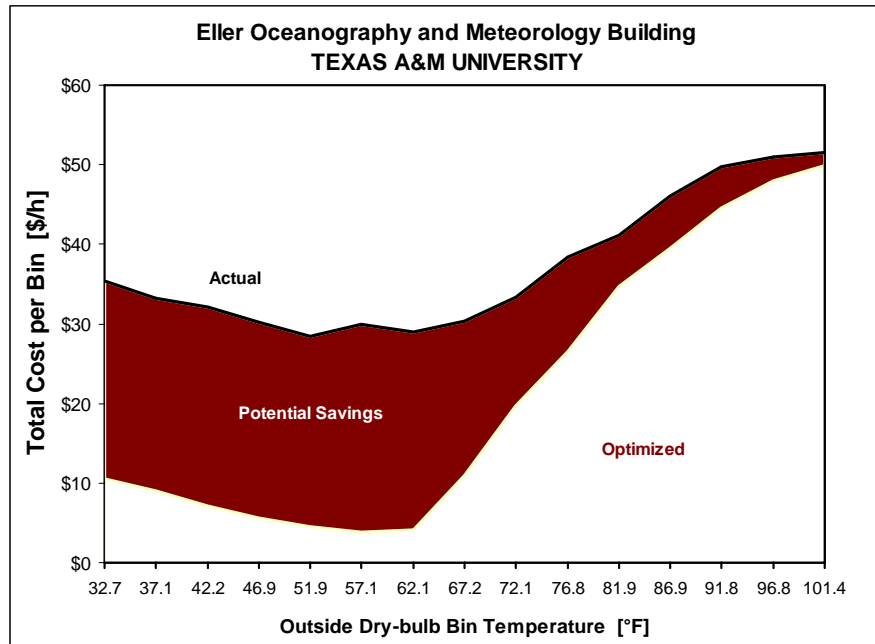
Figure 5.9   Potential dollar savings for the Eller Oceanography and Meteorology Building of Texas A&M University based on recorded energy use of the year 2000.
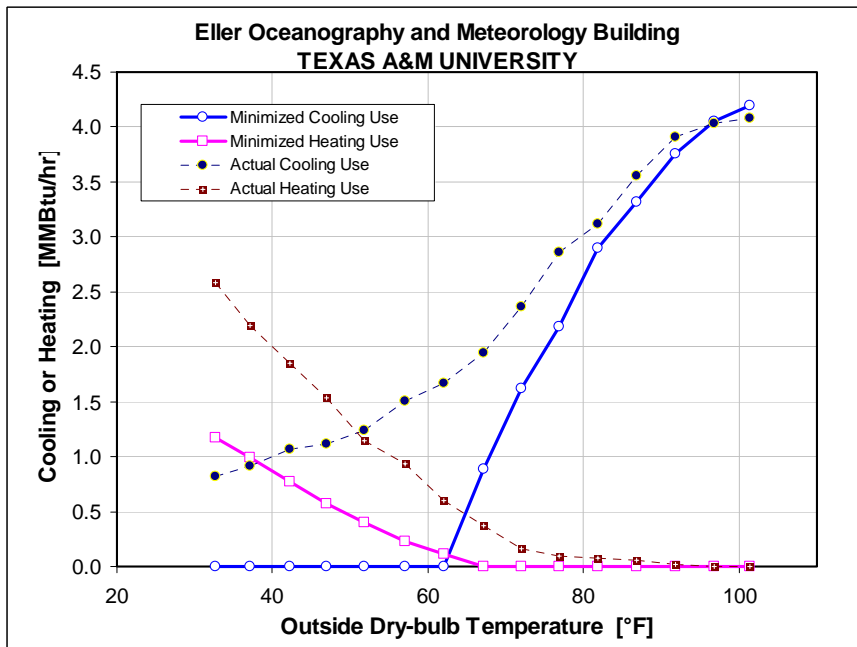
Figure 5.10 Actual and minimized cooling and heating patterns as a function of temperature for the Eller Oceanography and Meteorology Building at Texas A&M University, based on recorded energy use for the year 2000.

Table 5.1 Summary of the actual and optimized bin data and the potential savings for the Eller Oceanography and Meteorology Building of Texas A&M University, based on recorded energy use for the year 2000.

Cqc =11.293$/MMBtu; Cqh =7.9465$/MMBtu; CkWh =0.069$/KWh

Bin		Toa	Actual Use		Optimized		Costs		College Station, TX (Yr1996)		Savings
			CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Tdb Avge	Total
15	20								8	17.9	
20	25								40	22.5	
25	30								93	27.4	
30	35	32.7	0.82	2.58	0.00	1.18	$10.58	$35.43	196	32.2	$4,870
35	40	37.1	0.92	2.20	0.00	0.99	$8.95	$33.25	259	37.3	$6,292
40	45	42.2	1.06	1.85	0.00	0.77	$7.06	$32.11	317	42.2	$7,940
45	50	46.9	1.12	1.54	0.00	0.58	$5.60	$30.25	350	47.1	$8,630
50	55	51.9	1.24	1.15	0.00	0.40	$4.53	$28.47	419	52.1	$10,033
55	60	57.1	1.51	0.94	0.00	0.22	$3.83	$29.91	577	57.2	$15,053
60	65	62.1	1.66	0.60	0.00	0.12	$4.09	$29.00	662	62.0	$16,490
65	70	67.2	1.95	0.38	0.89	0.00	$10.97	$30.37	761	67.2	$14,765
70	75	72.1	2.36	0.16	1.62	0.00	$19.68	$33.40	1130	72.3	$15,505
75	80	76.8	2.86	0.10	2.19	0.00	$26.53	$38.47	1466	76.9	$17,514
80	85	81.9	3.12	0.07	2.90	0.00	$34.68	$41.18	950	81.8	$6,176
85	90	86.9	3.56	0.06	3.31	0.00	$39.49	$46.03	679	86.9	$4,446
90	95	91.8	3.91	0.02	3.76	0.00	$44.52	$49.72	481	91.9	$2,498
95	100	96.8	4.03	0.00	4.05	0.00	$47.94	$50.91	298	96.8	$887
100	105	101.41	4.08	0.00	4.20	0.00	$49.87	$51.47	74	100.7	$119
									8619		$131,216
									8760		**$133,362**

5.5.2 Effect of building occupation schedules

As is well known, changing the building operation conditions according to its occupancy may provide a source of savings. Thus, it should be possible to find extra savings by using the corresponding ambient conditions dataset in conjunction with the occupancy schedule and applying the potential energy savings methodology. The bin frequency distribution of the ambient conditions and the energy use patterns for occupied and un-occupied conditions are presented in Figure 5.11. These distributions were obtained using the scheduling definition assumed for Eller O&M Building as shown in Figure 5.12.

8 Months: January - August 2000

Frequency	TEMPS		Tdb	RH	WBELE	CHW	HHW
1	52	30 35	32.42	82.89	419.40	0.74	2.45
2	90	35 40	37.12	84.51	386.34	0.91	1.64
3	149	40 45	42.20	69.00	386.65	0.99	1.22
4	227	45 50	47.10	73.60	392.49	1.03	1.02
5	264	50 55	51.86	71.85	405.54	1.14	0.82
6	272	55 60	57.15	74.19	400.62	1.37	0.63
7	372	60 65	62.09	77.90	404.62	1.56	0.50
8	533	65 70	67.24	79.16	408.35	1.87	0.37
9	815	70 75	72.11	79.91	407.06	2.36	0.18
10	907	75 80	76.84	77.78	416.81	2.86	0.12
11	620	80 85	81.90	64.95	449.88	3.10	0.09
12	448	85 90	86.92	55.89	496.63	3.59	0.07
13	290	90 95	91.76	45.64	523.68	3.88	0.02
14	244	95 100	96.83	34.24	541.36	3.98	0.00
15	94	100 105	101.34	26.67	559.46	4.05	0.00
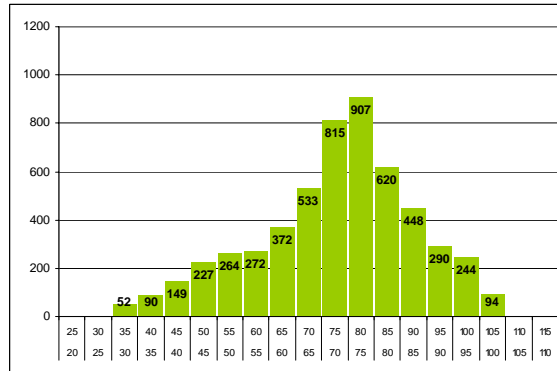
8 Months: Un-Occupied Periods

Frequency	TEMPS		Tdb	RH	WBELE	CHW	HHW
1	46	30 35	32.37	82.30	416.41	0.73	2.52
2	58	35 40	37.21	85.08	371.91	0.91	1.74
3	108	40 45	42.20	70.93	365.55	0.99	1.11
4	153	45 50	47.18	75.94	367.41	1.03	0.96
5	186	50 55	51.77	74.93	387.08	1.13	0.78
6	166	55 60	57.10	77.17	371.90	1.39	0.55
7	213	60 65	61.98	79.17	386.23	1.60	0.47
8	321	65 70	67.27	83.33	378.28	1.93	0.35
9	523	70 75	72.09	85.26	376.32	2.47	0.14
10	559	75 80	76.78	82.09	385.40	3.01	0.09
11	279	80 85	81.87	66.07	409.93	3.19	0.06
12	145	85 90	86.76	54.73	439.52	3.55	0.04
13	83	90 95	91.51	46.01	480.38	3.78	0.03
14	72	95 100	96.86	34.05	496.76	3.89	0.00
15	31	100 105	101.65	26.94	506.09	3.95	0.00
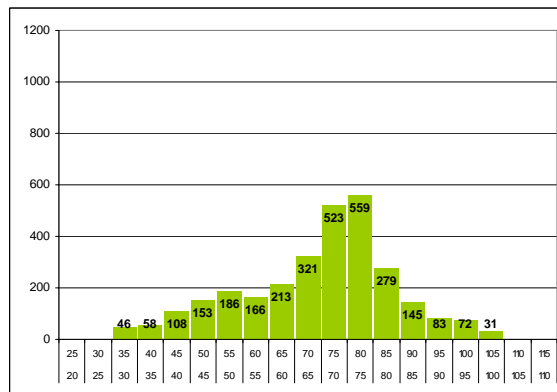
8 Months: Occupied Space Period

Frequency	TEMPS		Tdb	RH	WBELE	CHW	HHW
1	6	30 35					
2	32	35 40	36.97	83.49	412.49	0.90	1.45
3	41	40 45	42.20	63.89	442.24	0.99	1.51
4	74	45 50	46.92	68.77	444.34	1.03	1.16
5	78	50 55	52.08	64.51	449.58	1.18	0.94
6	106	55 60	57.24	69.52	445.61	1.34	0.75
7	159	60 65	62.23	76.20	429.26	1.51	0.53
8	212	65 70	67.20	72.87	453.88	1.78	0.39
9	292	70 75	72.14	70.32	462.14	2.18	0.24
10	348	75 80	76.93	70.86	467.25	2.62	0.16
11	341	80 85	81.93	64.03	482.57	3.03	0.12
12	303	85 90	87.00	56.45	523.96	3.60	0.08
13	207	90 95	91.86	45.50	541.05	3.92	0.02
14	172	95 100	96.81	34.31	560.03	4.02	0.00
15	63	100 105	101.19	26.54	585.72	4.10	0.00
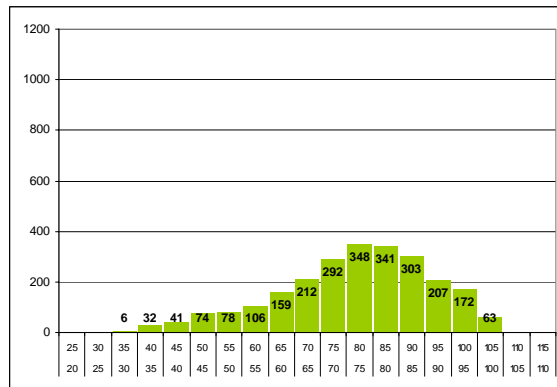
Figure 5.11 Bin frequency distribution, ambient conditions and energy use for the Eller O&M Building data sets for the whole year 2000, the first eight months of 2000 and separated into unoccupied and occupied periods.

Hour

| | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 |
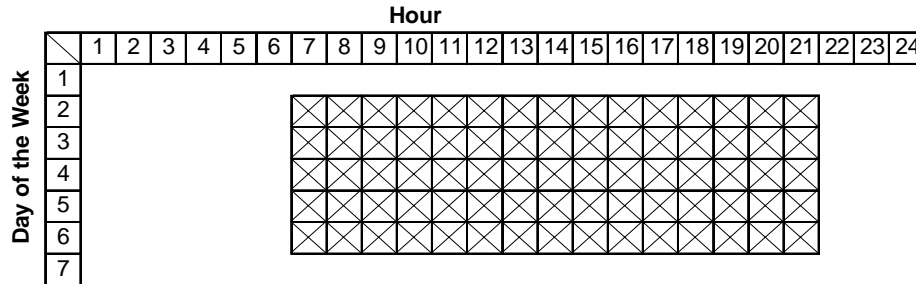
Figure 5.12 Assumed schedules for occupied and unoccupied periods for Eller O&M Building on the Texas A&M University Campus.

The patterns corresponding to the occupancy bin frequency distributions of Figure 5.11 are graphically presented in Figure 5.13. After the methodology is applied to the occupied and unoccupied periods, considering the recommendation of the new ASHRAE standard for indoor quality, the patterns for the potential savings are depicted in Figure 5.14. This figure shows that there is still opportunity to save additional energy and dollars from a change of operation conditions based on scheduling. The "extra" potential savings quantification is presented in Table 5.2. The possible savings seem to come from the high temperature range.

Figure 5.15 presents the cost of the energy used for fans for the different schedules. In this case, there is not a significant variation in cost, even though there is clearly a difference in the patterns that is attributed to the change of ambient conditions and the different load ratios in each period.
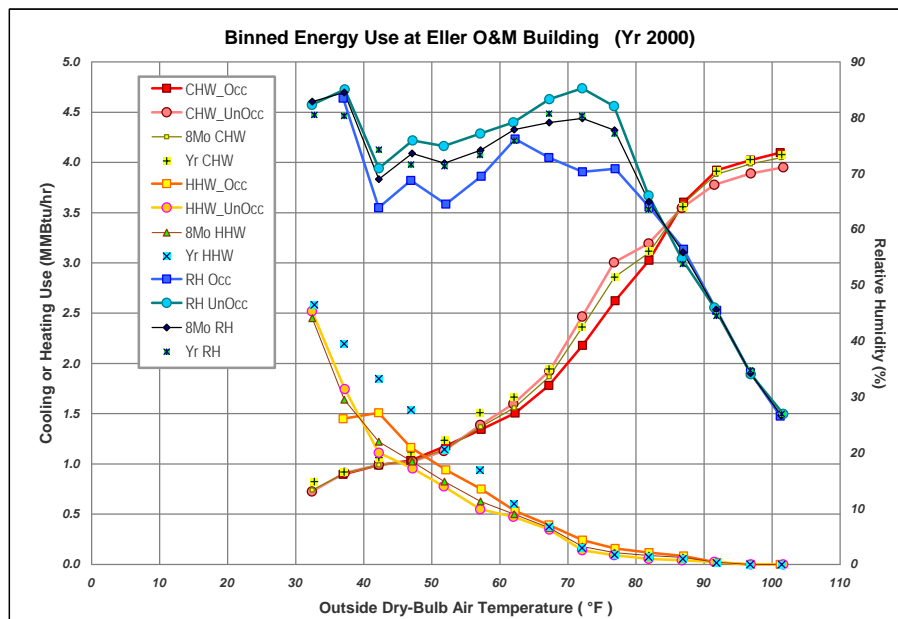
Figure 5.13 Binned hot and chilled water use for the Eller O&M Building and relative humidity of College Station, TX for the period of January to August 2000. The plot includes the separation of data for occupied and unoccupied periods.
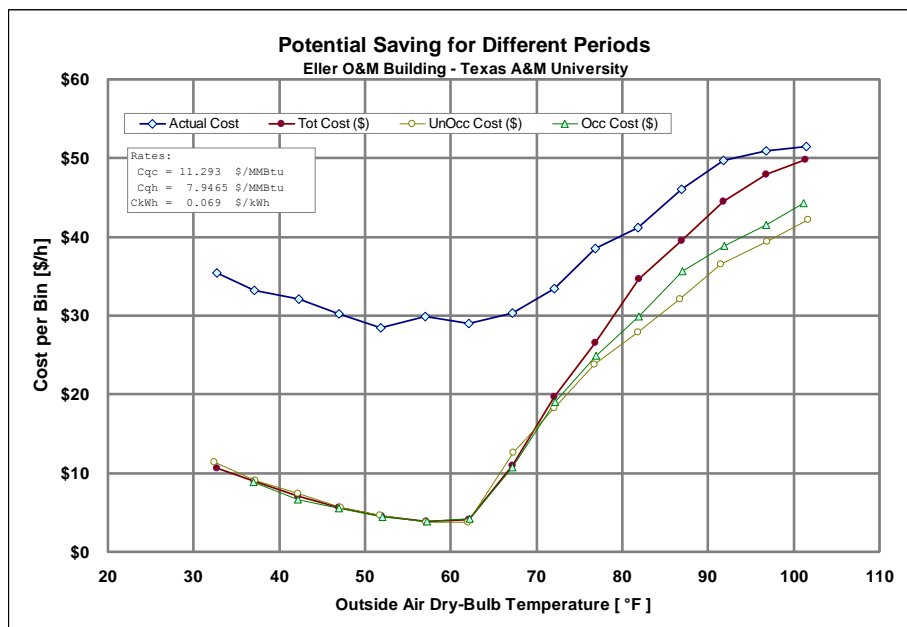
Figure 5.14 Potential dollar savings for the Eller O&M Building utilizing data of the first eight months of 2000, for the whole data set, and for the occupied and the unoccupied periods.

Table 5.2   Potential dollar savings from the occupied and unoccupied schedule for the Eller O&M Building (data from 8 months — January through August 2000).

Bin	T_{db} (°F)	Original ($/h)	Whole Period hrs/Bin	Optimized ($/h)	Savings ($)	Un-Occupied Periods hrs/Bin	Optimized ($/h)	Savings ($)	Occupied Period hrs/Bin	Optimized ($/h)	Savings ($)
1	32.7	$ 35.4	52	$ 10.6	$ 1,292	46	$ 11.3	$ 1,108	6		$ -
2	37.1	$ 33.3	90	$ 9.0	$ 2,187	58	$ 9.1	$ 1,400	32	$ 8.8	$ 782
3	42.2	$ 32.1	149	$ 7.1	$ 3,732	108	$ 7.4	$ 2,671	41	$ 6.6	$ 1,045
4	46.9	$ 30.3	227	$ 5.6	$ 5,596	153	$ 5.7	$ 3,759	74	$ 5.5	$ 1,831
5	51.9	$ 28.5	264	$ 4.5	$ 6,321	186	$ 4.6	$ 4,439	78	$ 4.5	$ 1,873
6	57.1	$ 29.9	272	$ 3.8	$ 7,094	166	$ 3.7	$ 4,343	106	$ 3.8	$ 2,764
7	62.1	$ 29.0	372	$ 4.1	$ 9,266	213	$ 3.8	$ 5,369	159	$ 4.2	$ 3,947
8	67.2	$ 30.4	533	$ 11.0	$ 10,341	321	$ 12.6	$ 5,713	212	$ 10.8	$ 4,156
9	72.1	$ 33.4	815	$ 19.7	$ 11,181	523	$ 18.2	$ 7,927	292	$ 19.1	$ 4,179
10	76.8	$ 38.5	907	$ 26.5	$ 10,833	559	$ 23.8	$ 8,193	348	$ 24.9	$ 4,736
11	81.9	$ 41.2	620	$ 34.7	$ 4,032	279	$ 27.9	$ 3,715	341	$ 29.9	$ 3,837
12	86.9	$ 46.0	448	$ 39.5	$ 2,931	145	$ 32.1	$ 2,020	303	$ 35.6	$ 3,159
13	91.8	$ 49.7	290	$ 44.5	$ 1,507	83	$ 36.6	$ 1,090	207	$ 38.9	$ 2,242
14	96.8	$ 50.9	244	$ 47.9	$ 725	72	$ 39.4	$ 826	172	$ 41.5	$ 1,619
15	101.4	$ 51.5	94	$ 49.9	$ 150	31	$ 42.2	$ 289	63	$ 44.3	$ 453
			5,377		$ 77,190	2,943		$ 52,859	2,434		$ 36,625
									Total Savings		**$ 89,484**
									Equivalent Savings Increase		**15.9%**
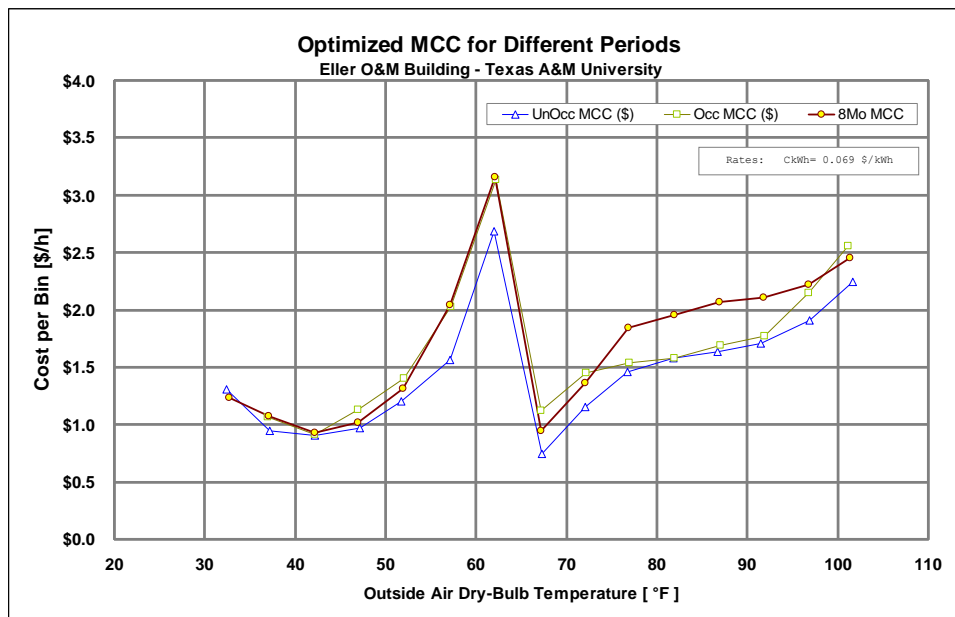
Figure 5.15 Optimized MCC cost patterns for the Eller O&M Building based on ambient conditions data of the first eight months of 2000.

5.6 Potential Savings Methodology: Analysis of Selected Cases

In the same way as applied to the Eller O&M Building, the potential savings methodology developed has been applied to eleven other buildings, whose physical characteristics, location and HVAC systems description can be found in Appendix I. This appendix also includes the potential energy savings analysis and plots for each building. In addition to having different locations and different construction characteristics, the buildings have different uses.

Table 5.3 presents savings for four of those buildings that were commissioned by the Energy Systems Laboratory of Texas A&M University in different periods. This table includes the audit-expected savings, which for Zachry Engineering Center are the estimated savings for the measures proposed in an audit assessment conducted as part of the Texas Energy Cost Containment Program report (TECCP 1986), and the savings that occurred after some of the measures were applied. Also presented in the table are the estimated potential savings and the ratio between the actual measured savings and the audit-expected. Also included in the table is the ratio between the audit-expected and the estimated potential savings.

Table 5.3 Summary of the audit-expected savings and the determined potential for selected building.

| Building Name | City | Area (ft^2) | #Data | Savings CHW+HHW+ELE | | | % Meas/ Expected | % Exp./ Pot. Sav. |
				Expected‡	Measured†	Potential		
Zachry Engineering Center, TAMU	College Station, TX	324,400	6,367	$232,900	$144,229 $191,185	$224,284	61.9% 82.1%	103.8%
Biology, TTU	Lubbock, TX	156,219	3,736	$31,734	$41,273	$117,958	130.1%	26.9%
Chemistry South, TTU	Lubbock, TX	128,600	4,791	$20,824	$32,714	$154,579	157.1%	13.5%
Law School, TTU	Lubbock, TX	129,043	6,263	$20,994	$33,268	$75,641	158.5%	27.8%

† Measured savings are detailed in the 2001 Annual LoanSTAR Energy Consumption Report for the sites of the Texas Tech University (TTU) and represent the weather normalized saving. Similarly, Zachry Engineering Center savings come from the 1996 and 1997 annual reports, respectively. ‡ Expected cost savings are the audit estimated saving.

The Texas Tech University (TTU) buildings were commissioned between March 2000 and August 2001. The major commissioning measures applied were: performed sensor calibration for key operating parameters, identification of control devices malfunctioning, upgrade several existing pneumatic controllers to DDC controllers with enhanced control sequences; optimizing variable frequency drive (VFD) chiller water pump and supply air fan speed control, set up optimal air handling unit cold deck, hot deck, and duct static pressure reset schedules and supply air temperature reset schedules. As can be observed in Table 5.3, the potential energy savings in dollars vary from building to building because of the differences in their characteristics in terms of construction, operation and conditioned area. At first glance, it seems that the expected savings were in most cases underestimated; because of the relationship between the audit-expected savings and the calculated potential savings do not have a good agreement. It could also indicate that still there exist a great potential to be explored in most of the buildings; this is partially corroborated with the actual savings reported for all the building of TTU, the measured savings were at least 30% greater than the audit-expected savings, although it is likely due to intentional understatement of expected savings in the audit.

Analyzing the TTU Law School Building in more detail, which is a building that houses mostly offices, still presents opportunity to reduce the total energy use as depicted in Figure 5.16. The cooling use is reduced considerably, but the heating remains high at low temperatures. The optimized thermal patterns do not go to temperatures as low as the actual usage, because the methodology did not find any parameters set that could satisfy the comfort zone since the HVAC simplified modeling does not include humidification equipment. Even though the cooling and heating are not in the optimum levels, the data shows that for regular operation the energy use is higher than the minimized patterns, which gives a certain level of confidence in the methodology.

For the Law School building, from July 16, 2001 through July 15, 2002, the thermal energy use was 10,034 MMBtu for cooling and 3,258 MMBtu for heating

which are respectively equivalent to $35,118 and $8,145 (using rates of 3.5 $/MMBtu of cooling and 2.5 $/MMBtu of heating). The thermal savings for that period, without strict weather normalization, total $25,988 while the potential savings are $46,843, so on the whole the savings are 55.5% of the potential savings, 5,496 MMBtu for cooling, and for heating, 1,268 MMBtu. Although the percentage of savings, without the electricity part, is considerable, the amount that is not found of the potential saving is also significant. Two reasons seem to justify the differences, the high level of heating needed at low temperatures, due to problems in the operation control, in all of the TTU buildings, when the temperatures fall lower than 40 °F; and that the economizer was shut down when the outside air is very dusty (Wei et al. 2001).
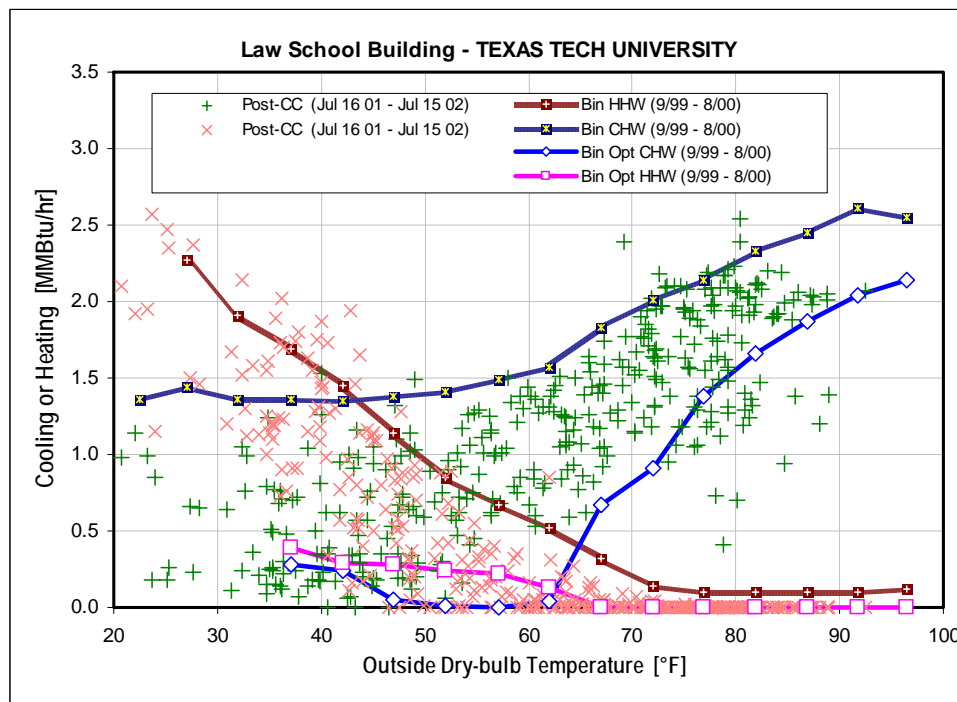
Figure 5.16 Energy use between 1999 and 2000, optimized and post-CC at TTU Law School Building.

Another interesting case is the Zachry Engineering Center at Texas A&M University (TAMU), which has been commissioned and retrofitted and has served as the basis of many energy analysis studies. The building houses offices, laboratories, and classrooms, and was retrofitted during late 1990 and early 1991. The retrofits converted the dual-duct constant volume air handler and terminal boxes to variable volume systems and upgraded the control system. The expected audit savings, as pointed out by Claridge et al. (2001), were overestimated because the total cost of the fan electricity use and heating and cooling energy use were erroneously assumed by the energy auditors to be about 50% larger than actual use. The optimized and pre-retrofit energy use patterns and daily energy-use data for the year 1996 and 1997 are presented in Figure 5.17. The data shows how the optimized patterns bound the energy use data, and in this case the heating closely follows the minimized pattern, while the cooling has the same trend at high temperatures; but for mild temperatures, where the optimized values suggest the use of economizers, the difference is substantial. Factors to consider in the optimized patterns are that they are obtained with the coincident mean conditions for humidity so just one point represents the bin conditions. For lower humidity conditions, the average of the energy use will be decreased proportionally to latent load cut corresponding to that humidity. In Figure 5.17 is included a lower band in the optimized pattern that corresponds to the potential energy use when it is subtracted the effect of one standard deviation of the humidity data. This may explain why some points fell below the optimized curve, i.e. the optimized values used an average humidity, while the measured data covered some days with lower humidity. In this case, the results support the validation of the proposed potential savings methodology.

In general, the parameter that has been found to be of substantial importance is the amount of outside air used in the building, which is related directly with the type/usage of the building. If the building houses laboratories, the amount of outside air required in the optimization procedure used here is the ASHRAE Standard 62, minimum amount of air for human occupancy. This does not consider the amount of air that has to be supplied due to the fume hoods and generally higher ventilation rates required in design

and operation of laboratories. This may be the main reason that the potential savings in the Chemistry and Biology buildings with a large number of laboratories are significantly larger than the savings achieved. In these cases, the potential savings numbers tend to be misleading.
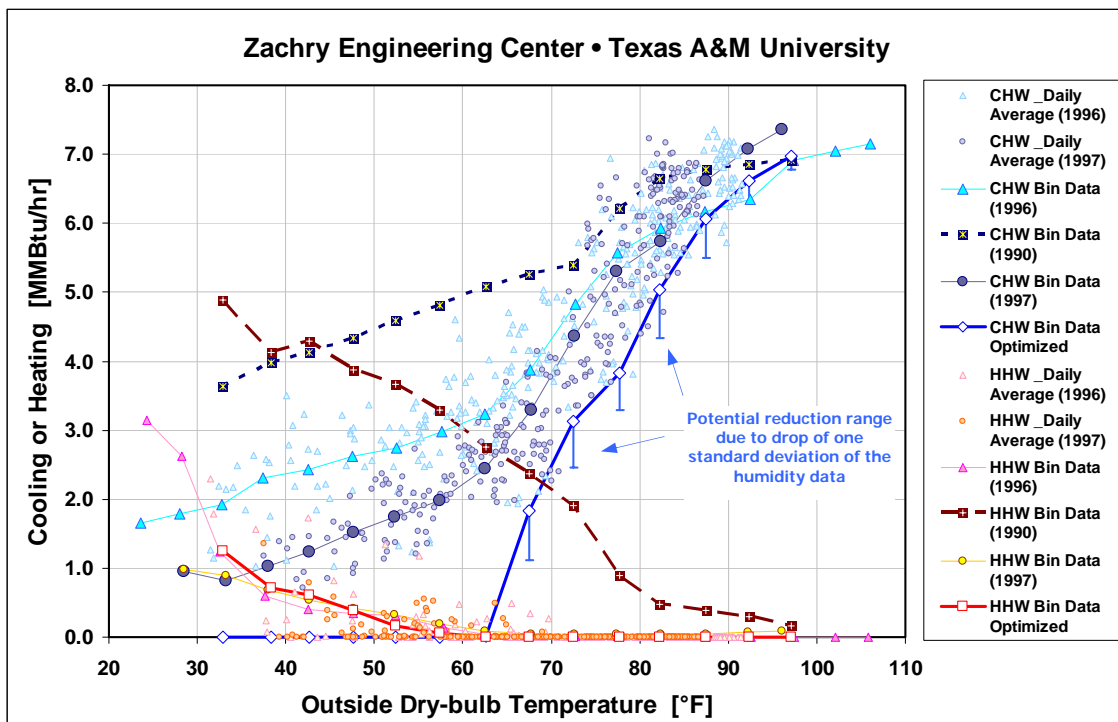
Figure 5.17 Energy use in the year 1990, optimized and post-CC$^®$ at Zachry Engineering Center at Texas A&M University.

5.7 Summary

The potential energy savings methodology presented in this study is based on the minimization of the energy use over the span of the ambient conditions at the building location. Because of the building energy use dependency on the ambient conditions and its cyclic variability over a calendar year, the methodology was applied for each representative bin obtained from the location's weather data.

The methodology was used to evaluate potential energy savings in buildings that were monitored by the Energy Systems Laboratory, some of which participated in the LoanSTAR energy program. The cases considered were buildings that house offices, classrooms and laboratories. The audit-expected savings compared with the results obtained from the methodology developed were generally low, mostly because the audit-expected savings, in all the cases, were not based on important operational changes, but mostly related to retrofits. From the buildings studied, just four were commissioned; the ratios of the audit-expected to the computed potential savings still were low, except for Zachry Engineering Center building, where the audit savings were overestimated.

Based on the cases studied herein, the potential savings methodology, for the cooling energy use part, seems to predict potential savings better at higher outside air temperatures than for mild or lower ambient temperatures, because many buildings do not have an economizer, which thermodynamically always gives important savings, as the methodology indicates. This suggests that the consumption data should be analyzed for the presence or absence of an economizer in the building before applying the methodology to estimate potential savings.

The results of the proposed methodology could be used for a commissioning team, to predict the potential energy savings and additionally to have a starting point for the changes that need to be done on the HVAC operation conditions to reach a minimum energy use.

The methodology for the determination of the potential energy savings, to the contrary to the calibration process, can not absolutely be verified, because there are no known buildings that work under comfort conditions with a proved minimal energy use. As with any new methodology, the methodology proposed in this study, for the evaluation of potential energy savings, needs to be applied to other buildings where deeper operational changes have been carried out – similar to the Zachry Engineering Center Building.

CHAPTER VI

CONCLUSIONS

A potential energy savings methodology (PESM) that requires limited building information has been presented. The methodology is based on simplified energy analysis modeling of HVAC systems, the comfort conditions and the indoor quality air requirements. The methodology requires a calibrated simulation — an automated calibration has also been developed, tested and presented in this study.

The PESM gives an indicator that, in a quantitative way, can help to anticipate the probable energy savings in a building and to improve operational practice. The best approximation of the methodology to real data was in the Zachry building where the relation between the total cost associated with the measured energy use savings and the equivalent cost of the potential energy savings is 85.2%. The difference is attributed to the fact that the original audit overestimated total building energy use, the building does not use an economizer and the potential savings methodology suggests the use of an economizer. Therefore, careful application of the methodology may give useful indicators of the achievable energy savings in a building.

Although the methodology seems promising, considering the simplified modeling from which it was developed, it produces overestimates of savings for buildings with a large number of laboratories because in those buildings the needs of fresh air are not based on indoor ventilation needed to meet minimum requirements imposed by occupants, but on safety reasons. Some of the discrepancies found on less energy intensive buildings, such as office and/or classroom buildings, could be ascribed to problems with the system operation or specific needs that the HVAC simplified modeling does not account for.

Refinements of various aspects of the proposed automated calibration methodologies could be worthwhile research topics in the future, since the methodology's accuracy for real cases deserves a review. It could be relevant to look for techniques that eliminate noise from any data sample so the calibration increases the

accuracy of the output parameters. The scope of the methodology tested, specifically the limitation to working with simplified energy analysis procedure modules and a limited number of systems, which were coded by the author, has been fulfilled but the methodology can be applied to more robust programs that include more variables that could be of interest for any user.

REFERENCES

Andersen, K.K., Madsen, H., and Hansen, L.H., 2000, "Modelling the Dynamics of a Building Using Stochastic Differential Equations", *Energy and Buildings*, Vol. 31, pp. 13-24.

ASHRAE, 1992, *ANSI/ASHRAE Standard 55-1992 Thermal Environmental Conditions for Human Occupancy*, American Society of Heating and Air Conditioning Engineers, Inc., Atlanta, GA.

ASHRAE, 1995, *Addendum to Thermal Environmental Conditions for Human Occupancy*. ANSI/ASHRAE Standard 55a-1992, American Society of Heating, Refrigerating and Air-Conditioning Engineers, Atlanta, GA.

ASHRAE, 2001, *ASHRAE Handbook: Fundamentals*, American Society of Heating and Air Conditioning Engineers, Inc., Atlanta, GA.

ASHRAE, 2002, *ASHRAE Guideline 14-2002, Measurement of Energy and Demand Savings*, American Society of Heating and Air Conditioning Engineers, Inc., Atlanta, GA.

ASHRAE, 2004, *ANSI/ASHRAE Standard 62.1-2004 Ventilation for Acceptable Indoor Air Quality*, American Society of Heating and Air Conditioning Engineers, Inc., Atlanta, GA.

Asia Pacific Energy Research Center (APERC), 2002, *Energy Efficiency Indicators and Potential Energy Savings in APEC Economies: A Study of Energy Efficiency and Savings in APEC Economies*, APEC# 202-RE-01.6, Institute of Energy Economics, Minato-ku Tokyo, Japan.

Ayres J.M. and Stamber E., 1995, "History Development of Building Energy Calculations", *ASHRAE Transactions*, 101, Pt. 1, pp. 841–849.

Balcomb, J.D., Burch, J.D., Westy, R.D., Subbarao, K., and Hancock, C.E., 1994, "Short-term Energy Monitoring for Commercial Buildings", *Proceedings of the 1994 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, pp. 5.1–5.11.

Beranek, D.A., Lawrie, L.K., 1989, "Promising (& not so Promising) Developments in Energy Analysis Software", *Proceedings of Building Simulation '89*, Vancouver, BC, Canada, June 23-24, pp. 5–10.

Bou-Saada T.E. and Haberl, J.S., 1995a, "A Weather-Daytyping Procedure for Disaggregating Hourly End-Use Load in an Electrically Heated and Cooled Building from Whole-Building Hourly Data", *IECEC paper No. 95–197*.

Bou-Saada, T.E., 1994, "An Improved Procedure for Developing a Calibrated Hourly Simulation Model of an Electrically Heated and Cooled commercial Building", *M.S. Thesis*, Mechanical Engineering Department, Texas A&M University, College Station, TX, December.

Bou-Saada, T.E. and Haberl, J.S., 1995b, "An Improved Procedure for Developing Calibrated Hourly Simulation Models", *International Building Performance Simulation Association, 4th International Conference*, Madison, WI, August 14-16, pp. 475–484.

Bronson, D., Hinchey, S., Haberl, J.S., O'Neal, D.L., Claridge, D.E. 1991, "A Toolkit to Help Calibrate the DOE-2 Simulation Program to Non-Weather Dependent Measured Loads, *IBPSA Newsletter*, December, Vol.4, No. 3, pp. 5–10.

Bronson, D.J., Hinchey, S.B., Haberl, J.S., O'Neal, D.L., 1992, "A Procedure for Calibrating the DOE-2 Simulation Program to Non-Weather Dependent Measured Loads", *ASHRAE Transactions: Symposia*, pp. 636–652.

Building Technology Center, "Benchmarking Building Energy Performance", Available Internet: http://eber.ed.ornl.gov/benchmark/homepage.htm, Oak Ridge National Laboratory, (accessed June 2005).

Carabott, M., 1989, "Building Simulation Reconciliation Using Empirical Data*", Proceedings of Building Simulation* '89, Vancouver, BC, Canada, June 23-24, pp. 27–30.

Carlson, S., 1997, "Algorithm of the Gods", *Scientific American*, March, pp. 38–38.

Carroll, W.L., and Hitchcock, 1993, "Tuning Simulated Building Descriptions to Match Actual Utility Data: Methods and Implementation", *ASHRAE Transactions*, Vol. 99, Pt. 2, pp. 928–934.

Chen, S. and Demster S., 1996, *Variable Air Volume Systems for Environmental Quality*, McGraw-Hill, Inc., New York, NY, USA.

Claridge, D. E., Liu, M., Turner, W.D., Zhu, Y., Abbas, M., and Haberl, J. S., 1998, "Energy and Comfort Benefits of Continuous Commissioning in Buildings, *Proceedings of the International Conference Improving Electricity Efficiency in Commercial Buildings*, Amsterdam, The Netherlands, September, pp. 21–23.

Claridge, D.E., 1998, "A Perspective on Methods for Analysis of Measured Energy Data from Commercial Buildings", *ASME Journal of Solar Energy Engineering*, Vol. 120, August, pp. 150–155.

Claridge, D.E., Haberl, J.S., Liu, M., Houcek, M., Athar, A., 1994, "Can You Achieve 150% of Estimated Retrofit Savings? Is it Time for Recommissioning?", *Proceedings of the 1994 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, pp. 5.73–5.87.

Claridge, D.E., Liu, M., Deng, S., Turner, W.D., Haberl, J.S., Lee, S.U., Abbas, M., Bruner, H., and Veteto, B., 2001, "Cutting Heating and Cooling Use Almost in Half Without Capital Expenditure in a Previously Retrofit Building," *Proc. of 2001 ECEEE Summer Study*, Mandeliu, France, June 11-16, 2001, Vol. 2, pp. 74–85.

Claridge, D.E., Liu, M., and Turner, W.D., 1999, "Whole Building Diagnostic", *Proceedings of the Workshop on Diagnostics for Commercial Buildings: Research to Practice*, San Francisco, CA, June 16-17, pp. 3.2.1–3.2.17.

Claridge, D.E., Liu, M., Wei, G., Lee, S. U., and Bensouda, N., 2001, *Manual of Procedures for Calibrating Simplified Simulations of Building Systems*, Energy Systems Laboratory, Texas A&M University, College Station, TX, July.

Claridge, D.E., Liu, M., Zhu, Y., Abbas, M., Athar, A., and Haberl, J.S., 1996, "Implementation of Continuous Commissioning in the Texas LoanSTAR Program: "Can You Achieve 150% of Estimated Retrofit Savings"" Revisited, *Proceedings of the 1996 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, pp. 4.59–4.67.

Claridge, D.E., Turner, W.D., Haberl, J.S., Culp, C.H., and Liu, M., 2000, "Monitoring Building for Performance Assurance and Accounting", Proceedings of the *ABST 2000: Advanced Building Systems Technology Conference and Exposition*, Washington, DC, June 6-8, pp. 1.4.1–1.4.10.

Clarke, J.A., Strachan, P.A., and Pernot, C., 1993, "An Approach to the Calibration of Building Energy Simulation Models", *ASHRAE Transactions*, Vol. 99, Pt. 2, pp. 917–927.

Cohen, D.A. and Bailey, P., 1998, "An Approach to Calibrating DOE-2 Simulation Models Using Hourly End-Use Data and Data Visualization Software", *Proceedings of the 1998 ACEEE Summer Study on Energy Efficiency in Buildings,* American Council for an Energy-Efficient Economy, Washington, DC, pp. 3.73–3.87.

Cohen, B.M. and Kosar, D.R., 2000, "Humidity Issues in Building Energy Analysis", *Heating/Piping/Air Conditioning Engineering: HPAC*, January, pp. 65-78.

Corana, A., Marchesi, M., Martini, C., and Ridella, S., 1987, "Minimizing Multimodal Functions of Continuous Variables with the Simulated Annealing Algorithm", *ACM Transactions on Mathematical Software*, Vol. 13, No. 3, September, pp. 262–280.

De Wit, M.S., 1995, "Uncertainty Analysis In Thermal Building Modeling*", Proceedings of Building Simulation '95*, Madison, WI, August 14-16, pp. 324–330.

Dhar, A., Reddy, T. A., and Claridge, D. E., 1999a, "Generalization of the Fourier Series Approach to Model Hourly Energy Use in Commercial Buildings", *ASME Journal of Solar Energy Engineering*, Vol. 121, February, pp. 54–62.

Dhar, A., Reddy, T. A., and Claridge, D. E., 1999b, "A Fourier Series Model to Predict Hourly Heating and Cooling Energy Use in Commercial Buildings with Outdoor Temperature as the only Weather Variable*", ASME Journal of Solar Energy Engineering*, Vol. 121, February, pp. 47–53.

Dhar, A., Reddy, T.A., and Claridge and D.E., 1998, "Modeling Hourly Energy Use in Commercial Buildings with Fourier Series Functional Forms", *ASME Journal of Solar Energy Engineering*, Vol. 120, pp. 217–223.

Diamond, S., and Hunn, B., 1981, "Comparison of DOE-2 Computer Program Simulations to Metered Data for Seven Commercial Buildings", *ASHRAE Transactions*, Vol. 87, Pt 1, pp. 1222-1231.

Energy Information Administration (EIA), 2005, Annual Energy Review 2004, Report DOE/EIA-0384(2004), U.S. Department of Energy, Washington, DC, August.

Federspiel, C., Zhang, Q., and Arens, E., 2002, "Model-Based Benchmarking with Application to Laboratory Buildings", *Energy and Buildings*, Vol. 34, No. 3, pp. 203–214.

Goffe, W.L., Ferrier, G.D., and Rogers, J., 1994, "Global Optimization of Statistical Functions with Simulated Annealing", *Journal of Econometrics*, Vol. 60, pp. 65–99.

Griffith, D.M. and Anderson, K.J., 1994, "Commercial Building/System Characteristics Sensitivity Analysis", *Proceedings of the 1994 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, Vol. 5, pp. 5.105–5.112.

Haberl, J. and Bou-Saada, T., 1998c, "Procedures for Calibrating Hourly Simulation Models to Measured Building Energy and Environmental Data", *ASME Journal of Solar Energy Engineering*, Vol. 120, August, pp. 193–204.

Haberl, J.S, Saman, N., and Bou-Saada, T., 2002, "Air-Side Energy Use Calculations for Four HVAC Systems: Dual Duct Constant Volume(DDCAV), Dual Duct Variable Volume (DDVAV), Constant Volume with Reheat (CAVRH), Variable Volume with Reheat (VAVRH), Four Pipe Fan Coil Unit (FC), Four Pipe Induction Unit (FI), and Single Zone (SZ) Systems", Revised June 2002, Energy Systems Laboratory, Texas A&M University, ESL-TR-01-02-02, 78 pages.

Haberl, J.S. and Komor, P.S., 1990c, "Investigating an Analytical Framework for Improving Commercial Energy Audit: Results from a New Jersey Mall", PU/CEES Report No. 234, Princeton University, Princeton, New Jersey.

Haberl, J.S., Bronson, D., Hinchey, S., O'Neal, D.L., Claridge, D.E., 1992, "Graphical Tools to Help Calibrate the DOE-2 Simulation Program to Measured Loads", *The DOE-2 User News*, Vol. 13, No. 1, pp. 5–14.

Haberl, J.S., Bronson, J.D., Hinchey, S.B., O'Neal, D.L, 1993, "Graphical Tools to Help Calibrate the DOE-2 Simulation Program", *ASHRAE Journal*, January, pp. 27–32.

Haberl, J.S.; Bou-Saada, T.; Soebarto, V., Reddy, A., 1998, "Use of Calibrated Simulation for the Evaluation of Residential Energy Conservation Options of Two Habitat for Humanity Houses in Houston, Texas", *The Eleventh Symposium on Improving Building Systems in Hot and Humid Climates*, Fort Worth, TX, June 1–2, pp. 1–5.

Hadley, D. L. and Halverson, M. A., 1993, "Energy Conservation Potential of the U.S. Department of Energy Interim Commercial Building Standards", Pacific Northwest Laboratory, PNL–7967, UC-350, Richland, Washington, December.

Harris, J. and Johnson, F., 2000, "Potential Energy, Cost, and CO2 Savings from Energy-Efficient Government Purchasing", *Proceedings of the 2000 ACEEE Summer Study on Energy-Efficient Buildings*, Panel 4 - Commercial Buildings: Program Design, Implementation, and Evaluation , pp. 4.147–4.165, Asilomar, CA, August.

Hicks, T. and Clough, D., 1998, The Energy Star[®] Building Label: Building Performance through Benchmarking and Recognition, Proceedings of the 1998 ACEEE Summer Study on Energy Efficiency in Buildings. Panel 4 - Commercial Buildings: Program Design, Implementation, and Evaluation, pp. 4.205–4.210 See Energy Star Buildings label www.epa.gov/buildings.

Hsieh, E. S., 1988, "Calibrated Computer Models of Commercial Buildings and their role in Building Design and Operation", PU/CEES Report No. 230, *M. S. Thesis*, Princeton University, Princeton, NJ

Ingber, A.L., 1989, "Very Fast Simulated Re-Annealing", *J. Mathl. Comput. Modelling*, Vol. 12, No. 8, pp. 967–973.

Ingber, A.L., 1993, "Simulated Annealing: Practice versus Theory", *J. Mathl. Comput. Modelling*, Vol. 18, No. 11, pp. 29–57.

IPMVP, 2001, International Performance Measurement and Verification Protocol Volume I: Concepts and Options for Determining Energy and Water Savings, Department of Energy, DOE/GO-102001-1187, Washington, D.C., January.

Kaplan, M., Mcferran, J., Jansen, J., and Pratt, R., 1990a, "Reconciliation of a DOE2.1c Model with Monitored End-use Data from a Small Office Building", *ASHRAE Transactions*, Vol. 96, Pt 1, pp. 981–993.

Kaplan, M.B., Caner, P., and Vincent, G.W., 1992, "Guidelines for Energy Simulation of Commercial Buildings", *Proceedings of the 1992 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, Vol. 1, pp. 1.137-1.147.

Kaplan, M.B., Jones, B., and Jansen, J., 1990b, "DOE-2.1C Model Calibration with Monitored End-Use Data", *Proceedings of the 1990 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, Vol. 10, pp. 10.115–10.125.

Katipamula, S. and Claridge, D.E., 1992, "Monitored Air Handler Performance and Comparison with a Simplified System Model", *ASHRAE Transactions*, Vol. 98, Pt. 1, pp. 341–351.

Katipamula, S. and Claridge, D.E., 1993, "Use of Simplified Models to Measure Retrofit Energy Savings", *ASME Journal of Solar Energy Engineering*, Vol. 115, pp. 53–68.

Katipamula, S. and Haberl, J., 1991, "A Methodology to Identify Diurnal Load Shapes for Non-Weather Dependent Electric End-Uses", *Solar Engineering 1991, Proceedings from the Second ASME-JSES-JSME International Solar Energy Conference*, Reno, NV, March, pp. 457–467.

Katipamula, S., Reddy, T. A., and Claridge, D. E., 1998, "Multivariate Regression Modeling", *Journal of Solar Engineering*, Vol. 120, pp. 177–184.

Kirkpatrick, S., Gelatt, C.D., and Vecchi, M.P., 1983, "Optimization by Simulated Annealing", *Science*, Vol., 220, No. 4598, pp. 671–680.

Kissock J.K., Reddy T.A. and Claridge D.E., 1998, "Ambient-Temperature Regression Analysis for Estimating Retrofit Savings in Commercial Buildings", *Journal of Solar Energy Engineering*, Vol. 120, August, pp. 168–176.

Knebel, D.E., 1983, *Simplified Energy Analysis Using the Modified Bin Method*. American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Atlanta, GA.

Kreider, J. F., and Rabl, A., 1994, *Heating and Cooling of Buildings: Design for Efficiency*, McGraw-Hill, Inc., USA.

Kreider, J.F. and Wang, X.A., 1991, "Artificial Neural Networks Demonstration for Automated Generation of Energy Use Predictors for Commercial Buildings", *ASHRAE Transactions*, 97, Pt. 1, pp.775-79.

Kusuda, T., 1999, "Early History and Future Prospects of Building System Simulation", *Proceedings of Building Simulation '99*, Vol. 1, pp. 3-16, Kyoto, Japan.

Kusuda, T., 2001, "Building Environment Simulation before Desktop Computers in the USA through a Personal Memory", *Energy and Buildings*, Vol. 33, pp.291–302.

Laarhoven, P.J.M. van, and Aarts, E.H.L., 1987, *Simulated Annealing: Theory and Applications*, D. Reidel Publishing Company, Dordrecht, Holland.

Lee, S.U. and Claridge, D.E., 2002, "Automatic Calibration of a Building Energy Simulation Model Using a Global Optimization Program", *Proceedings of the International Conference for Enhanced Building Operations ICEBO*, Richardson, TX, pp. 159–164.

Liu, M. 1997, "User's Manual for Air-Side Simulation Program (AirModel)", Energy Systems Laboratory, Texas A&M University

Liu, M. and Claridge, D.E., 1998a, "Use of Calibrated HVAC System Models to Optimize System Operation", *ASME Journal of Solar Energy Engineering*, Vol. 120, No. 2, May, pp. 131–138.

Liu, M. and Claridge, D.E., 1998b, "Impacts of Optimized Cold & Hot Deck Reset Schedules on Dual Duct VAV Systems – Theory and Model Simulation", *Proceedings of the Eleventh Symposium on Improving Building Systems in Hot and Humid Climates*, Fort Worth, TX, June 1-2, pp. 146–152.

Liu, M., Abbas, M., Veteto, B., Claridge, D.E., and Bruner, H., 1998, "Impacts of Optimized Cold & Hot Deck Reset Schedules on Dual Duct VAV Systems – Application and Results", *Proceedings of the Eleventh Symposium on Improving Building Systems in Hot and Humid Climates*, Fort Worth, TX, June 1-2, pp. 153-160.

Liu, M., and Claridge, D.E., 1995, "Application of Calibrated HVAC System Models to Identify Component Malfunctions and to Optimize the Operation and Control Schedules", *Solar Engineering 1995, The 1995 ASME/JMSE/JSES International Solar Energy Conference*, Maui, HI, March 19-24, pp. 209–217.

Liu, M., and Claridge, D.E., 1999, "Converting Dual-Duct Constant-Volume Systems to Variable-Volume Systems without Retrofitting the Terminal Boxes", *ASHRAE Transactions*, Vol. 105, Pt. 1, pp. 66–70

Liu, M., Athar, A., Reddy, A., Claridge, D.E., Haberl, J., and White E., 1994a, "Reducing Building Energy Costs Using Optimized Operation Strategies for Constant Volume Air Handling Systems", *Proceedings of the Ninth Symposium on Improving Building Systems in Hot and Humid Climates*, Arlington, TX, May 19-20, pp. 192–204.

Liu, M., Houcek, J., Athar, A., Reddy, A., Claridge, D., and Haberl, J., 1994b, "Identifying and Implementing Improved Operation and Maintenance measures in Texas LoanSTAR Buildings", *Proceedings of the 1994 ACEEE Summer Study Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, pp. 5.153–5.165.

Liu, M., Wei, G., and Claridge, D.E., 1998, "Calibrating AHU Models Using Whole Building Cooling and Heating Energy Consumption Data", *Proceedings of the 1998 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, pp. 3.229–3.241.

Liu, M., Zhu, Y., and Claridge, D.E, 1996a, "Use of EMCS Recorded Data to Identify Potential Savings Due to Improved HVAC Operations & Maintenance (O&M)", *Proceedings of the Tenth Symposium on Improving Building Systems in Hot and Humid Climates*, Fort Worth, TX, May 13-14, pp. 28–37.

Liu, M., Zhu, Y., Claridge, D.E, and White E., 1996b, "Impacts of Static Pressure Set Level on the HVAC Energy Consumption and Indoor Condition", *Proceedings of the Tenth Symposium on Improving Building Systems in Hot and Humid Climates*, Fort Worth, TX, May 13-14, pp. 11–18.

Mailhot, A, Gaume, E., and Villeneuve, J.P., 1997, "Uncertainty Analysis of Calibrated Parameter Values of an Urban Storm Water Quality Model Using Metropolis Monte Carlo Algorithm," *Wat. Sci. Tech.*, Vol. 36, No. 5, pp. 141–148.

Manke, J.M., Hittle, D.C., and Hancock, C.E., 1996, "Calibrate Building Energy Analysis Models Using Short Term Test Data"*, Solar Engineering ASME 1996*, pp. 369–378.

McCray, J.A., Bailey, P.L., Parker, J.L., 1995a, "Visualize-IT™ Model Calibration Tool Kit", *Proceedings of Building Simulation '95*, Madison, WI, August 14-16, pp. 709–713.

McCray, J.A., Bailey, P.L., Parker, J.L., Gillman, R., 1995b, "Using Data Visualization Tools for the Calibration of Hourly DOE-2,1 Simulations", *Proceedings of Building Simulation '95*, Madison, WI, August 14-16, pp. 461–466.

Metropolis, N., Rosenbluth, A.W., Rosenbluth, M.N., Teller, A.H., and Teller, E., 1953, "Equation of State Calculations by Fast Computing Machines", *The Journal of Chemical Physics*, Vol. 21, No. 5, June, pp. 1087–1092.

Neymark, J., Judkoff, R., Knabe, G., Le, H.T., Durig, M., Glass, A., Zweifel, G., 2001, "HVAC BESTEST: A Procedure for Testing the Ability of Whole-Building energy Simulation Programs to Model Space Conditioning Equipment", *Proceedings of the Seventh International IBPSA Conference*, Rio de Janeiro, Brazil, August 13-15, pp. 369–376.

Norford, L.K., 1984, "An Analysis of Energy Use in Office Buildings. The Case of ENERPLEX", *Ph.D. Dissertation*, Princeton University, Princeton, NJ.

Palomo, E. and Lefebvre, G., 1995, "Stochastic Simulations against Deterministic Ones, Advantages and Drawbacks", *Proceedings of Building Simulation '95*, Madison, WI, August 14-16, pp. 611–619.

Palomo, E., Marco, J., Madsen, H., 1991, "Methods to Compare Measurements and Simulations", *Proceedings of Building Simulation '91*, Nice, France, August 20-22, pp. 570–577.

Press, W.H., Flannery, B.P., Teukolsky, S.A., Vetterling, W. T., 1992, *Numerical Recipes in C: The Art of Scientific Computing*, Cambridge University Press.

Rabl, A., 1988, "Parameter Estimation in Buildings: Methods for Dynamic Analysis of Measured Energy Use", *ASME Journal of Solar Energy Engineering,* Vol. 110, pp. 52–66.

Reddy, T.A., 2006, "Literature Review on Calibration of Building Energy Simulation Programs: Uses, Problems, Procedures, Uncertainty, and Tools", *ASHRAE Transactions*, Vol. 112, Pt. 1, pp. 226-240.

Reddy, T.A., Claridge, D.E., 1994, "Using Synthetic Data to Evaluate Multiple Regression and Principal Component Analyses for Statistical Modeling of Daily Building Energy Consumption", *Energy and Buildings*, Vol. 21, pp. 35–44.

Reddy, T.A., Deng, S., and Claridge, D.E., 1999, "Development of an Inverse Method to Estimate Overall Building and Ventilation Parameters of Large Commercial Buildings", *ASME Journal of Solar Energy Engineering*, Vol. 121, February, pp. 40–46.

Reddy, T.A., Katipamula, S., Kissock, J.K. and Claridge, D.E., 1995, "The Functional Basis of Thermal Energy Use in Air-Side HVAC Equipment", *ASME Journal of Solar Energy Engineering*, Vol. 117, February, pp. 31–39.

Reddy, T.A., Saman, N.F., Claridge, D.E., Haberl, J.S., Turner, W.D. and Chalifoux, A., 1997b, "Baseline Methodology for Facility-Level Monthly Energy Use - Part 2: Application to Eight Army Installations", *ASHRAE Transactions*, Vol. 103, Pt. 2, pp. 348–359.

Reddy, T.A., Saman, N.F., Claridge, D.E., Haberl, J.S., Turner, W.D. and Chalifoux, A., 1997a, "Baseline Methodology for Facility-Level Monthly Energy Use—Part 1: Theoretical Aspects", *ASHRAE Transactions*, Vol. 103, Pt. 2, pp. 336–347.

Richalet, V. and Neirac, F., 1991, "On Site Identification of Building Energy Performance", *Proceedings of Building Simulation '91*, Nice, France, August 20-22. pp. 578–583.

Ruch, D. and D. Claridge. 1991. A Four Parameter Change-Point Model for Predicting Energy Consumption in Commercial Buildings. *Proceedings of ASME International Solar Energy Conference*, 433-40.

Salsbury, T. and Diamond, R., 2000, "Performance Validation and Energy Analysis of HVAC Systems Using Simulation", *Energy and Buildings*, Vol. 32, pp. 5–17.

Sartor, D., Piette, M. A., Tschudi, W., and Fok, F., 2000, "Strategies for Energy Benchmarking in Cleanrooms and Laboratory-Type Facilities", *Proceedings of the 2000 ACEEE Summer Study on Energy Efficiency in Buildings,* Panel 10 - Building Industry Trends, pp. 10.498-10.510, August 20–25.

Sekhar, S. C., 1997, "A Critical Evaluation of Variable Air Volume System in Hot and Humid Climates", *Energy and Buildings*, Vol. 26, pp. 223–232.

Sharp, T. 1996, "Energy Benchmarking in Commercial Office Buildings," *Proceedings of the ACEEE 1996 Summer Study on Energy Efficiency in Buildings*, 4.321–4.329.

Siarry, P., Berthiau, G., Durbin, F., and Haussy, J., 1997, "Enhanced Simulated Annealing for Globally Minimizing Functions of Many-Continuous Variables", *ACM Transactions on Mathematical Software*, Vol. 23, No. 2, June, pp. 209–228.

Soebarto, V.I., 1996a, "Development of A Calibration Methodology for Hourly Building Energy Simulation Models Using Disaggregated Energy Use Data From Existing Buildings", *Ph.D. Dissertation*, Department of Architecture, Texas A&M University, August.

Soebarto, V.I., 1997, "Calibration Of Hourly Energy Simulations Using Hourly Monitored Data and Monthly Utility Records for Two Case Study Buildings", *Proceedings of Building Simulation '97*, Prague, Czech Republic, September 8-10, Vol. 2, pp. 411–419.

Subbarao, K., 1988, "PSTAR-Primary and Secondary Term Analysis and Renormalization", SERI/TR-254-3175, Solar Energy Research Institute, Golden, CO.

Subbarao, K., 2000, "Method and Apparatus for Improving Building Energy Simulations", Patent Number 6134511, United States Patent, October.

Subbarao, K., Burch, J.D., Hancock, C.E., 1989, "Building Energy Simulations for Design, Evaluation, Commissioning, Control & Diagnostics", *Proceedings of Building Simulation '89*, Vancouver, BC, Canada, June 23-24, pp. 181–186.

Subbarao, K., Burch, J.D., Hancock, C.E., Lekov, A., and Balcomb, J. D., 1990, "Measuring the Energy Performance of Building through Short-term Tests", *Proceedings of the 1990 ACEEE Summer Study on Energy Efficiency in Buildings*, American Council for an Energy-Efficient Economy, Washington, DC, pp. 10.245–10.252.

Sun, J., and Reddy, T. A., 2006, "Calibration of Building Energy System Simulation Programs Using the Analytic Optimization Approach (RP-1051)", *International Journal of Heating Ventilating, Air Conditioning, and Refrigerating Research,* Vol.12, No. 1, pp. 177-196.

Texas Energy Cost Containment Program, 1986, "Energy Cost Reduction Analysis of Texas A&M University (7110)": Oceanography and Meteorology Bldg, Soil & Crop Sciences Bldg. (Including Entomology), Zachry Engineering Center", Texas Energy Engineers, Inc., 164 pp.

Thamilseran, S. 1999, "An Inverse Bin Methodology to Measure the Savings from Energy Conservation Retrofits in Commercial Buildings", *PhD Dissertation*, Mechanical Engineering Department, Texas A&M University, May.

Thamilseran, S., and Haberl, J.S., 1994, "A Bin Method for Calculating Energy Conservation Retrofit Savings in Commercial Buildings", *Proceedings of the Ninth Symposium on Improving Building Systems in Hot and Humid Climates*, Arlington, TX, May 19-20, pp. 142–152.

Vadon, M., Kreider, J.F., and Norford, L.K., 1991, "Improvement of the Solar Calculations in the Modified Bin Method", *ASHRAE Transactions*, Vol. 97, Pt. 2, pp. 204–211.

Vanderbilt, D., and Louie, S.G., 1984, "A Monte Carlo Simulated Annealing Approach to Optimization over Continuous Variables", *Journal of Computational Physics*, Vol. 56, pp.259–271.

Wei, G. Baltazar, J. C., Zhu, Y., Truner, D., and Claridge, D., 2001, "Continuous Commissioning® of Texas Tech University: Final Report, Energy Systems Laboratory, ESL-TR-01-09-02, September, 73 pages.

Wei, G., Liu, M., and Claridge, D.E., 1998, "Signatures of Heating and Cooling Energy Consumption for Typical AHUs", *Proceedings of the Eleventh Symposium on Improving Building Systems in Hot and Humid Climates*, Fort Worth, TX, June 1-2, pp. 387–402.

Wendes, H., 1991, *Variable Air Volume Manual*, The Fairmont Press, Inc., Lilburn, GA, USA.

Williamson, T.J., 1995, "A Confirmation Technique For Thermal Performance Simulation Models", *Proceedings of Building Simulation '95 Fourth International Conference, International Building Performance Simulation Association (IBPSA),* Madison, WI, August 14-16, pp. 268–275.

Yoon, J.H. and Lee, E.J., 1999, "Calibration Procedure of Energy Performance Simulation for a Commercial Building", *Proceedings of Building Simulation '99*, Kyoto, Japan, Vol. 3, pp.1439–1446.

Yoon, J.H., Lee, E.J. and Claridge, D. E., 2003, "Calibration Procedure for Energy Performance Simulation of a Commercial Building", *Journal of Solar Energy Engineering*, Vol. 125, pp.251–257.

Yuill, G.K., Haberl, J.S., and Caldwell, J.S., 2005, "Accuracy Tests for Simulations of Constant Volume, Dual Duct, and Variable Volume Air-Handling Systems", *ASHRAE Transactions: Research*, Vol. 111, Pt, 2, pp. 137-153.

APPENDIX A

SIMULATED ANNEALING - THEORY

Traditional search techniques are often incapable of optimizing non-linear multimodal functions, and in such cases a random search method might be required. However, undirected search techniques are extremely inefficient for large domains. For this reason, new approaches for optimization were developed in the past two decades. Some of these techniques are loosely classified as "intelligent" due to the fact that they are seen as a meld of human cleverness and natural efficiency. The Tabu Search, Genetic Algorithms, Neural Networks, and the Annealing Simulation are, perhaps, the best known techniques belonging to this approach since they mimic nature to solve complex optimization systems.

A.1   Classical Optimization

An optimization problem is one in which parameter values must be determined under certain constraints. Typically, an optimization problem is described in terms of an objective function to be minimized while conforming to a set of restrictions, called constraints. These constraints are expressed in terms of the decision parameters and they may include inequalities and/or equalities. A classical optimization methodology schema is shown in Figure A.1.

Optimization problems can be classified according to the mathematical features of the problem, i.e. linear or non-linear. On the other hand, the optimization techniques may be grouped into two categories, according to the approach used to find the solution to the optimization problem: direct search and gradient-based methods. This grouping is based on whether or not derivatives are needed in the performance of the search. Direct search methods that do not use derivatives, contrary to the gradient methods, require only the computation of objective function values to select suitable search directions.
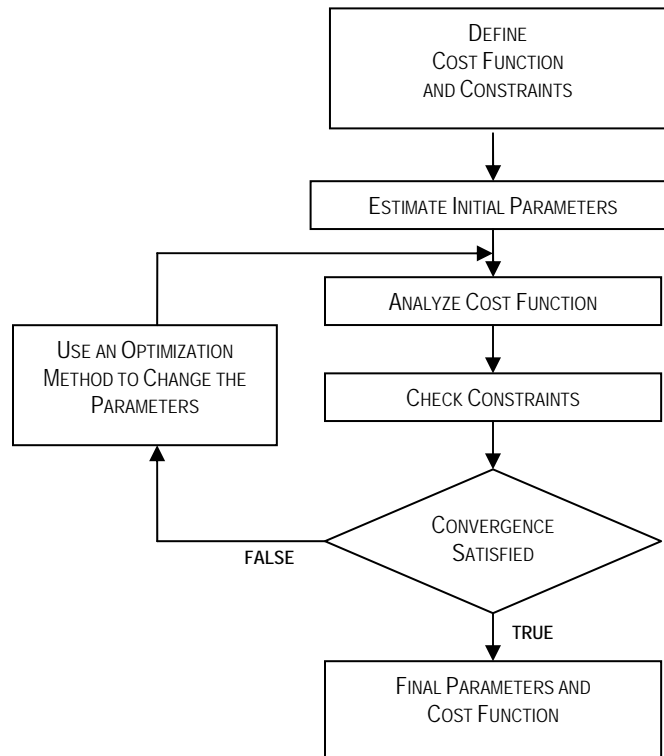
Figure A.1 Classical optimization methodology schema.

In general, the optimization processes are carried out in two phases: the search direction is determined followed by determination of the step length of the next step(s) as a one-dimensional minimization problem. Unfortunately, not all optimization problems have a clearly defined minimum (or maximum). Some problems have several local minima or a shallow valley where the minimum is not easily detected. In practice, these cases cause the search for the optimum to require prohibitive amounts of computation time or to stop in a local minimum instead of the global minimum. To avoid this inconvenience, it is necessary to use approximation algorithms or heuristics for which the solution found by the algorithm is not guaranteed to be optimal.

Approximation algorithms can be divided into two groups: algorithms tailored to a specific problem and general algorithms applicable to a wide variety of optimization problems. The simulated annealing algorithm can be included in the latter group; it is a general optimization technique mainly used for solving combinatorial optimization problems. This algorithm is based on randomization techniques; however, it also incorporates a number of aspects related to iterative improvement algorithms.

Iterative improvement is also known as neighborhood search or local search. The application of an iterative improvement algorithm presupposes the definition of a configuration, a cost function, and a generation mechanism, i.e. a simple way to generate a transition from one configuration to another by a small perturbation.

Typically, the algorithm can be formulated as follows. Starting at a given configuration, a sequence of iterations is generated, each iteration consisting of a possible transition from the current configuration to a configuration selected from the neighborhood of the current configuration. If this neighborhood configuration has a lower cost, this neighbor replaces the current configuration; otherwise, another neighbor is selected and compared to its cost value. The algorithm terminates when a configuration is obtained whose cost is no worse than that of any of its neighbors.

Some disadvantages of iterative improvement algorithms include the following (Laarhoven and Aarts 1987):

- By definition, iterative improvement algorithms terminate in a local minimum and there is generally no information as to the amount by which this local minimum deviates from a global minimum.

- The local minimum obtained depends on the initial configuration, for the choice of which, generally no guidelines are available.

- In general, it is not possible to give an upper bound for the computation time.

However, it is clear that iterative improvement does have the advantage of being generally applicable.

To avoid some of the disadvantages, one alternative that keeps the general applicability is the limited acceptance of transitions that correspond to an increase in the

cost function. This is a main variation from an iterative improvement algorithm where just transitions corresponding to a decrease in cost are accepted.

A.2   Simulated Annealing Optimization Methodology

The method of simulated annealing is a technique that has attracted significant attention as suitable for optimization problems of large scale, especially ones in which a desired global *extremum* is hidden among many local *extrema*.

Simulated annealing can be viewed as a probabilistic version of a classical local search with the additional ability to move out of local optima. Classical local search starts with an initial solution. It then searches for a better solution in the neighborhood of the current solution. This process is continued until no better solution is found, which terminates the search process. As explained above, an obvious shortcoming of the classical local search is that it terminates at the very first local optimum. Another deficiency is that the final solution strongly depends on the selection of the initial solution.

Simulated annealing is also based on the idea of exploring the solution space of a problem by moving around in the neighborhood structure. However, there are several pronounced distinctions between classical local search and simulated annealing. First, simulated annealing randomly generates a solution in the neighborhood of the current solution instead of searching for a better one. Second, whether the generated solution will be approved is decided by an acceptance criterion that allows both improvements and, in a probabilistic way, deteriorations in the cost function. Initially, due to the nature of the algorithm, deteriorations are accepted with a large probability. The probability slowly decreases to become zero at the end. Allowing deteriorations enables simulated annealing to escape from local optima. This makes the final solution relatively independent of the choice of the initial solution.

The simulated annealing (SA) algorithm was originally proposed by Kirkpatrick et al. (1983) to solve complex combinatorial optimization problems. The methodology was called "simulated annealing" by analogy to the physical annealing process of solids

used as the basis for its formulation. Thermodynamically the process is derived from statistical mechanics through the Metropolis algorithm (1953).

The method of simulated annealing is an analogy to thermodynamics: specifically with the way that liquids freeze and crystallize, or metals cool and anneal. At high temperatures, the molecules of a liquid move freely with respect to one another. If the liquid is cooled slowly, thermal mobility is lost. The atoms are often able to line themselves up and form a pure crystal that is completely ordered over a distance up to billions of times the size of an individual atom in all directions. This crystal is the state of minimum energy for this system. The amazing fact is that, for slowly cooled systems, nature is able to find this minimum energy state. In fact, if a liquid metal is cooled quickly, or "quenched", it does not reach this state but rather ends up in a polycrystalline or amorphous state having somewhat higher energy (Press et al. 2000).

Therefore, the essence of the process is slow cooling: allowing plenty of time for redistribution of the atoms as they lose mobility. If an analogy were possible, most of the classical minimization algorithms would correspond to rapid cooling, or quenching. In all those cases, the idea is to try to obtain the solution as quickly as possible, which leads to a local, but not necessarily a global, minimum.

Starting at the maximum value for the temperature, the cooling phase of the annealing process can be described as follows (Laarhoven and Aarts 1987). At each temperature value T, the solid is allowed to reach thermal equilibrium characterized by a probability of being in a state with energy E given by the Boltzmann distribution:

$$P(E) \propto \exp(-\frac{E}{k_B T}) \tag{A.1}$$

Even at a low temperature, there is a chance, although very small, of a system being in a high-energy state. Therefore, there is a corresponding chance for a system to get out of a local energy minimum in favor of finding a better, more global, one. As the temperature decreases, the Boltzmann distribution concentrates on the states with lowest energy, and finally, when the temperature approaches zero, only the minimum

energy states have a non-zero probability of occurrence. However, if the cooling is too rapid and, as mentioned above, the solid is not allowed to reach thermal equilibrium for each temperature value, defects can be 'frozen' into the solid and metastable amorphous structures can be reached rather than the low energy crystalline structure. Thus, a simulated thermodynamic system is assumed to change its configuration from energy E_1 to energy E_2 with probability $p=exp \ [-(E_2-E_1)/k_BT]$. Notice that if $E_2<E_1$, this probability is greater than unity; in such cases the change is arbitrarily assigned a probability of one. This general scheme of always taking a downhill step while sometimes taking an uphill step has come to be known as the Metropolis algorithm (see Figure A.2). Application of this algorithm to an optimization problem requires that the following items be specified:

- A description of possible system solutions.
- An objective function E, analog of energy, whose minimization is the goal of the procedure.
- The definition of a generation mechanism of random changes on the neighborhood; these changes are the "options" presented to the system.
- A control parameter T, analog of temperature, and an annealing schedule that tells how it is lowered from high to low values.

The most obvious representation of control variables is usually appropriate, but generating new solutions needs some planning. These solutions should be generated by small random changes.

In general, is recommend that the new trial should be generated according to the formula (Vanderbilt and Louise 1984)

$$x_{i+1} = x_i + \mathbf{V}\mathbf{r} \tag{A.2}$$

where $\mathbf{r}$ is now a vector of random numbers in the range [-1,1] and $\mathbf{V}$ is a diagonal matrix which defines the maximum change allowed in each variable. After an accepted change in the solution, $\mathbf{V}$ is updated by

$$\mathbf{V}_{i+1} = (1-\alpha)\mathbf{V}_i + \alpha\omega\mathbf{S} \qquad\qquad (A.3)$$

where α is a damping constant that controls the rate at which information from $\mathbf{S}$ is folded into $\mathbf{V}$ with weighting ω. $\mathbf{S}$ is a diagonal matrix whose elements consist of the magnitudes of the successful changes made to each variable. This tunes up the maximum step size associated with each variable to provide acceptable changes. Corana et al. (1987) suggest some expressions to determine the variations in step length, at a given temperature, that maintain the average percentage of accepted moves at about 50% of the total number of moves. Thus for each direction, h, the step vector is decided by

$$v_h = \begin{cases} v_h^o(1+c(n/N_k-0.4)/0.4) & n > 0.6N_k \\ v_h^o/(1+c(0.4-n/N_k)/0.4) & n < 0.4N_k \\ v_h^o & \text{Otherwise} \end{cases} \qquad (A.4)$$

where c is a constant parameter, and n/N_k, is the ratio of the number of accepted moves to the total number of evaluated moves at a given temperature.

A.3 Annealing Schedule

The annealing schedule determines the degree of uphill movement permitted during the search and is critical to the algorithm's performance. In the design of the cooling schedule four parameters must be specified: an initial temperature, a final temperature or a stopping criterion for the search, a temperature update rule, and the number of iterations to be performed at each temperature step. The initial temperature, T_o, depends on the scaling of the objective function and is always problem-specific. The final temperature, T_f, which represents the "freezing temperature", can be determined in several ways, by fixing the number of temperature values to be used, or the total number of solutions to be generated. The search can be stopped when the function ceases to make progress; i.e. no improvement is found at one temperature and the acceptance ratio decreases.
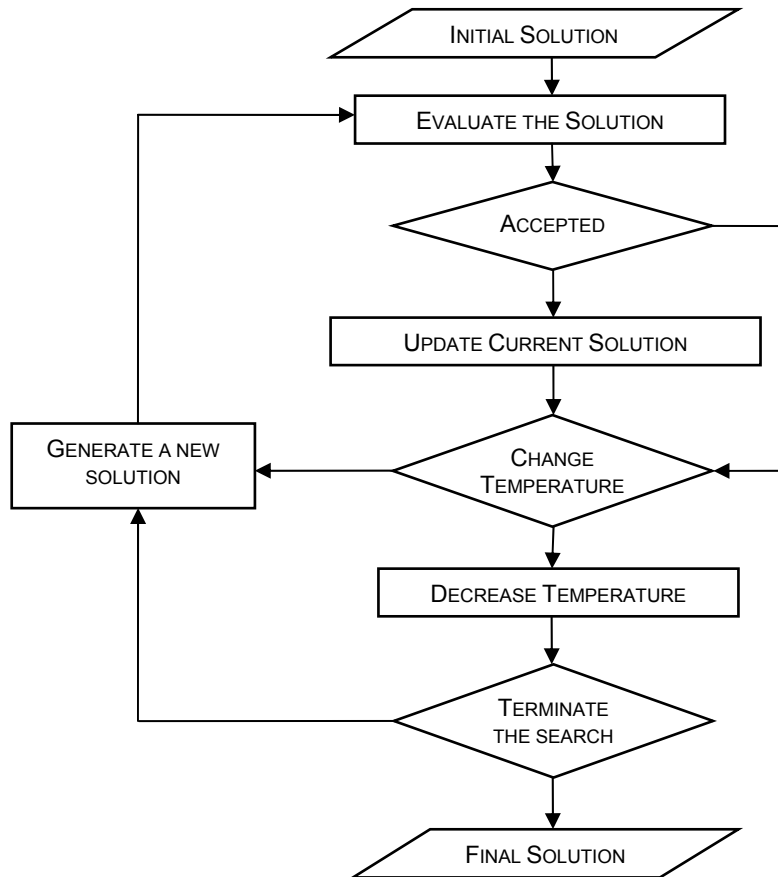
Figure A.2 Flowchart of a standard simulated annealing algorithm.

The schemes to update, or decrement the temperature, used most widely are the stepwise, the continuous, and the non-monotonic temperature reduction schemes. Stepwise reduction schemes include very simple cooling strategies; one example is the geometric cooling rule. This rule is the simplest and most common temperature decrement, which was suggested by Kirkpatrick et al. (1983) and updates the temperature by the following expression

$$T_{i+1} = c_T T_i \qquad\qquad i = 0,1... \qquad\qquad\qquad (A.5)$$

where c_T is a temperature factor, which commonly is a constant smaller than, but close to, one. Other authors have proposed more elaborate annealing schedules which were reviewed by van Laarhoven and Aarts (1987).

A.4   Simulated Annealing Algorithm Performance

In general, any optimization algorithm needs to be tested before applying it to a new problem. A basic requisite of a global optimization algorithm is the capability to find the minimum of unimodal functions, even in ill-conditioned cases. There is a large number of functions that can be used for benchmarking any optimization numerical algorithm. For testing the performance of an optimization algorithm upon a minimization search, one of the most suitable functions is the Rosenbrock function, which is a multivariable function and is more utilized in two and four dimensions (its representation in two-dimensions is shown in Figure A.3).
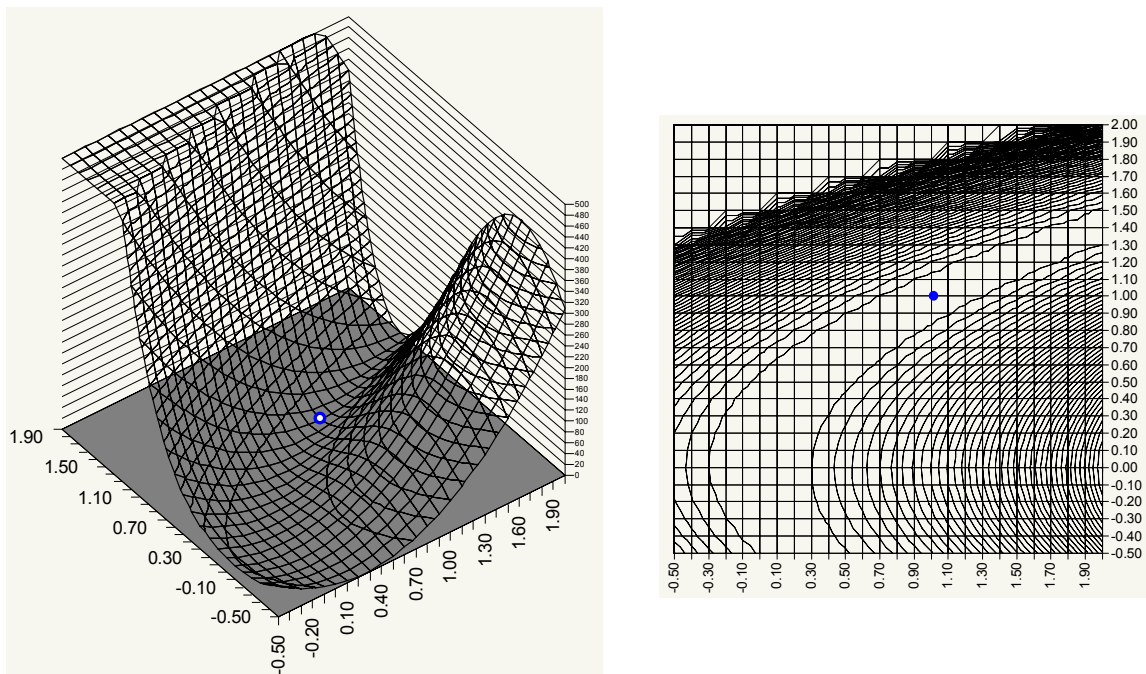
Figure A.3   Illustration of the two-dimensional Rosenbrock function with the location of its minimum.

These functions are characterized by having a curved valley path close to the minimum, and for more than two dimensional cases, canonical optimization methodologies fail (Corana et al. 1987). The mathematical representation of the Rosenbrock function is as follows

$$f(x_1 \ldots x_d) = \sum_{k=1}^{d-1} 100(x_{k+1} - x_k^2)^2 + (1 - x_k)^2 \qquad (A.6)$$

These curved valley functions are indeed a hard test for every minimization algorithm.

The SA algorithm always obtains the minimum in any of the cases tested (two and four dimensions). A summary of the results obtained for the application of the SA method to the Rosenbrock functions, for two and four variables, is presented in Tables A.1 and A.2, respectively.

Table A.1 Simulated Annealing optimization progress of the Rosenbrock function in two dimensions.

Evaluation	x1	x2	f (x1,x2)
1	-35.43013334274	0.806608796120	1.573753E+08
801	-3.9851612448692	15.8774072783334	3.008649E+01
1601	-3.9551609025924	15.6447713594047	2.500330E+01
2401	-3.8157769914424	14.5666488662058	2.733705E+01
3201	-3.3676250996249	11.3272696062010	2.123414E+01
⋮	⋮	⋮	⋮
164001	1.0000003515705	1.0000007326944	2.521129E-09
164801	1.0000003515705	1.0000007326944	9.582120E-10
165601	0.9999997815571	0.9999995881042	3.724443E-10
166401	0.9999997815571	0.9999995881042	1.345539E-10
167201	0.9999997815571	0.9999995881042	1.551742E-10

The search is wide-ranging only in the earlier stages of the algorithm when some large increases in the function are accepted and some areas far from the optimum are explored. As execution continues and the temperature is decreased, fewer uphill

excursions are tolerated and their magnitudes are smaller. Due to the accuracy sought in this numerical exercise, 1.0 E-9 and 1.0 E-13 for the function with two and four variables, respectively, more than 50% of the total algorithm run is spent searching around the optimum (see Figure A.4). This fact is expected and is typical of the SA algorithms.

The results of the SA are stable and always located the minimum of the function for both two and four variables. However, the computational effort is significant, the required number of evaluations of the function is considerable, but application of this algorithm is recommended to assure finding the global minimum.

Table A.2 Simulated Annealing optimization progress of the Rosenbrock function in four dimensions.

Evaluation	x1	x2	x3	x4	F (x1,x2,x3,x4)
1	86.3191872835159	-42.6975786685944	48.8113373517990	-23.4662652015686	6.509259E+09
1601	1.5380172133446	2.2900614632501	5.2266357358171	27.3584750200863	2.779635E+01
3201	1.4917949938026	2.1919211878208	4.8305256949978	23.2968445608825	2.348261E+01
4801	1.4887752027975	2.1625026079657	4.6908358055881	22.0475050184110	1.673296E+01
6401	1.4602162666017	2.1625026079657	4.6908358055881	22.0475050184110	2.664948E+01
8001	1.4723292107670	2.1433451459160	4.5821373110213	20.9963605773852	3.443396E+01
.	.	.	.	.	.
.	.	.	.	.	.
.	.	.	.	.	.
529601	0.9999999987646	0.9999999977066	0.9999999954564	0.9999999907813	4.567161E-15
531201	0.9999999987646	0.9999999977066	0.9999999954564	0.9999999907813	6.740740E-15
532801	0.9999999987646	0.9999999977066	0.9999999954564	0.9999999907813	6.111852E-15
534401	0.9999999987646	0.9999999977066	0.9999999954564	0.9999999907813	2.940563E-15

A.5 Closure

The simulated annealing methodology has several extremely attractive features and is rather unique when compared with other optimization techniques. It does not require or deduce derivative information; it merely needs to be supplied with an objective function for each trial solution it generates. The evaluation of the problem functions is essentially a "Black-box" operation as far as the optimization algorithm is concerned. From the point of view of computational performance, it is important that the problem function should be evaluated efficiently.
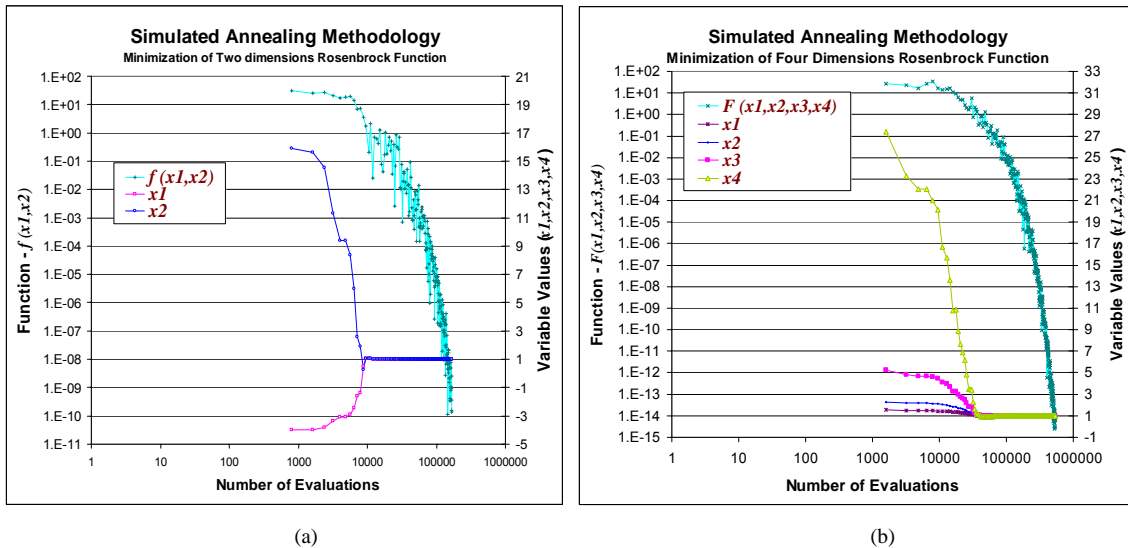
Figure A.4 Simulated Annealing algorithm progress for the Rosenbrock functions for a) two dimensions and b) four dimensions.

The simulated annealing algorithm is not easily fooled by the quick payoff achieved by falling into unfavorable local minima. Configuration decisions tend to proceed in a logical order – it is intrinsically a sequential algorithm. Provided sufficiently general reconfigurations, it wanders freely among local minima. Changes that cause the greatest differences are sifted over when the control parameter T is large. As T is lowered, these decisions become more permanent and the number of such minima qualifying for frequent visits is gradually reduced.

As the procedures controlling the generation and acceptance of new solutions are so simple, the computational cost of implementing the algorithm is almost invariably dominated by that associated with the evaluation of the problem functions. It is essential that these evaluations should be performed as efficiently as possible.

A significant component of the simulated annealing codification is the random generator, which is used for the random changes in the variables and for the temperature dependent increase acceptance test. Therefore, it is important that the random number generator used have good spectral properties.

APPENDIX B

STATISTICAL INDICATORS OF ACCURACY

One of the central problems of statistics is inferring the properties of a function $f(x)$ based on observations $x_1,...,x_n$. A function of observed measurements $x_1,...,x_n$ that contains no unknown parameters is called a statistic. In particular, a statistic used to estimate some property of a probability density function is called an estimator (e.g. its mean, variance, or other parameter). The estimator for a quantity θ is usually written with a hat $\hat{\theta}$ to distinguish it from the true value θ whose exact value commonly is unknown. If $\hat{\theta}$ converges to θ in the limit of large n, the estimator is said to be consistent. Consistency is usually a minimum requirement for a useful estimator.

The bias of an estimator $\hat{\theta}$ may be defined as:

$$b = E[\hat{\theta}] - \theta \tag{B.1}$$

where the operator $E[x]$ stands for the expected value of the variable x.

Note that bias does not depend on the measured values of the sample, but rather on the sample size, the functional form of the estimator, and the true properties of the probability density function, including the true value of θ. A parameter for which the bias is zero, independent of the sample size n, is said to be unbiased; if the bias vanishes in the limit as $n \rightarrow \infty$, then it is said to be asymptotically unbiased. Note also that an estimator $\hat{\theta}$ can be biased even if it is consistent.

In most practical cases, the bias is small compared to the statistical error (i.e. the standard deviation), and one does not usually reject the use of an estimator with a small bias if there are other characteristics, like simplicity, in its favor.

All of the above can be considered a test of the goodness-of-fit, which may be understood as a measure of how well a given null hypothesis Ho is compatible with the observed data without specific reference to any alternative hypothesis. This assessment

can be done by constructing a statistic test whose value itself reflects the level of agreement between the observed measurements and the predictions of *Ho*.

Another measure of the quality of an estimator is the mean squared error (*MSE*), defined as:

$$MSE = E\left[(\hat{\theta} - \theta)^2\right] = V\left[\hat{\theta}\right] + b^2 \tag{B.2}$$

The *MSE* is the sum of the variance and the bias squared, and thus it can be interpreted as the sum of squares of statistical and systematic errors.

It should be emphasized that classical statistics provide no unique method for constructing estimators. Given an estimator, however, one can say to what extent it has desirable properties such as small (or zero) bias, small variance, small *MSE*, etc. Often an estimator is deemed 'optimal' if it has zero bias and the minimum variance, although other measures of rightness, such as the root of the mean square error (*RMSE*), may well be considered.

B.1 Definitions of Accuracy

A function of observed measurements $y_1,...,y_n$ produces an average value equal to

$$\bar{y} = \frac{\sum_{i=1}^{n} y_i}{n} \tag{B.3}$$

and a standard deviation whose expression is

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \bar{y})^2}{n-1}} \tag{B.4}$$

The mean bias error (MBE) for a predicted time series with the same observed measurements y_i may be expressed analytically by

$$MBE = \frac{1}{n} \sum_{i=1}^{n} (\hat{y}_i - y_i) \tag{B.5}$$

where $\hat{y}_i$ is the ith predicted value, y_i represents the ith actual measured data value, and n is the total number of elements in the data set.

The root mean square error (*RMSE*) of an estimated time series is a statistical index that assesses the deviation of the actual data from the estimate; it is also called the standard error of the estimate and is defined by the following expression:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n - p}} \tag{B.6}$$

where p is the number of parameters that the model uses to make the estimates.

The coefficient of variation of the root mean square error (*CV-RMSE*) is a normalized (non-dimensional) measure that is found by dividing the *RMSE* by the mean value of the observations. The *CV-RMSE* is computed through the expression:

$$CV - RMSE = \frac{1}{\bar{y}}\sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n - p}} \tag{B.7}$$

where all the variables in this expression hold the definitions of the previous equations. The same coefficient of variation concept can be applied to standard deviation.

Another statistic that might be used to test the goodness-of-fit is the inequality of Theil, which is expressed as

$$U = \frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}}{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{y}_i)^2} + \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i)^2}} \tag{B.8}$$

This coefficient describes the inequality in time series due to three sources: unequal tendency (mean), unequal variation (variance), and imperfect covariation (covariance). When $\hat{y}_i = y_i$ at all times, U is equal to zero (Williamson 1995).

On the other hand, a non-parametric statistical test may also be utilized to test some aspects of the goodness-of-fit. It is possible to determine whether there are differences between the distributions of the predicted and measured data series through the F^2 test and the Kolmogorov-Smirnov two sample test. The first tests for differences between predicted and observed frequencies of binned data while the second test compares the cumulative frequency distribution of continuous data set.

The Time-series analysis field also provides several methods of testing the correspondence between two time series. Palomo (1991) suggested the use of the cross-correlation function and the coherency function as the first methods to this end. Cross correlation examines the relationship of the time series in the time domain. The linear correlation of the series at different frequencies is measured by the coherency function.

APPENDIX C

PERFORMANCE OF THE AUTOMATED CALIBRATION PROCEDURE USING
MULTIVARIABLE MINIMIZATION WITH ONE-DIMENSIONAL GOLDEN
SECTION SEARCH

The assessment of any multivariable optimization methodology is based on how well it performs the search to find its objective. Thus, it is desirable to track any changes of each variable and determine which one, and maybe why, any changes behave in a troublesome pattern. This appendix shows one example of the tracking of seven variables using the Golden Section search technique in the *RMSE* minimization procedure in a dual-duct variable air volume system (DDVAV).

Figure C.1 shows the *RMSE* minimization pattern for a typical DDVAV system as a function of the number of iterations. The search performance of each variable by iteration is illustrated in Figure C.2 in terms of the relative change. In this case, the procedure is stopped manually, because of its length at iteration 22603. This was approximately equivalent to 13,561,800 evaluations of the compound function, and it took 41 hours and 47 minutes to get the values shown in Table C.1 (run with *Microsoft Visual Basic for Applications*® programming language in a PC *Intel*® *Pentium*® 4 CPU at 1.60 GHz and 512 MB of RAM).

Table C.1 Results of the autocalibrated methodology for a typical DDVAV system using one-dimensional Golden search. (a) Initial, (b) final, and (c) expected values.

	Ti | Te	Tc	DTh	Minimum Air	Outside Air	People	UA	RMSE
	°F	°F	°F				Btu/hr-sq ft-°F	MMBtu/hr
(a)	70.00	62.00	1.500	33.00%	20.00%	4,000	60,000	5.414E -03
(b)	**74.83**	**55.10**	**0.875**	**45.06%**	**14.99%**	**2,965**	**40,014**	**6.882E-08**
(c)	75.00	55.15	1.000	45.00%	15.00%	3,000	40,000	0.000E 00

Although the procedure seems to work satisfactorily in finding the expected values for this case, as seen in Table C.1, the time that is spent in the minimization process makes it impractical. The methodology around iteration 3000 is near to a local minimum, but for unknown reasons the methodology jumped to another more favorable zone. That jump causes some variables to modify their values in a path that is apparently going to reach the global minimum. Unfortunately, the number of evaluations of the compound function to obtain this global minimum tends to be enormous.

In each of the Figures C.3 through C.15, the performance of each variable is shown at a particular iteration, from iteration 10 to 22600. Each of the seven plots in every figure illustrates the variation of the compound function (total *RMSE*) as the Golden search performs in each dimension (variables) to obtain a one-dimensional minimum. The plots include the minimum value of each variable in each particular iteration (light solid line), the expected variable value (dark solid line), and the initial variable value (dotted line).

These plots are very helpful to understand the needs and the kind of procedures or artifices that should be implemented to reach the global *RMSE* minimum in a more efficient and reliable methodology.
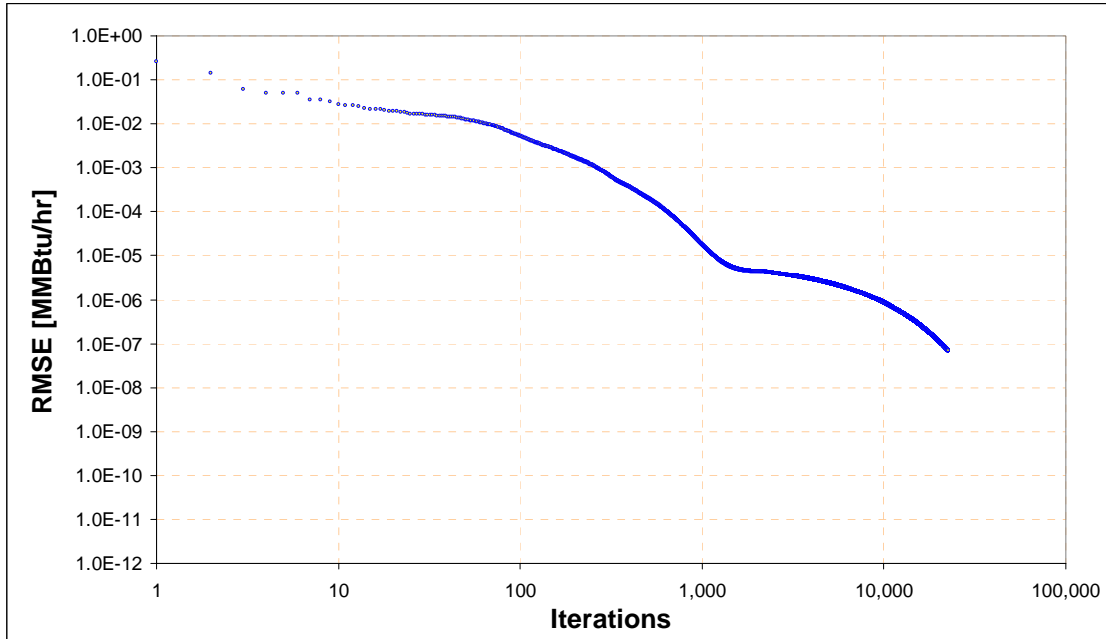
Figure C.1   *RMSE* minimization pattern for a typical DDVAV system.
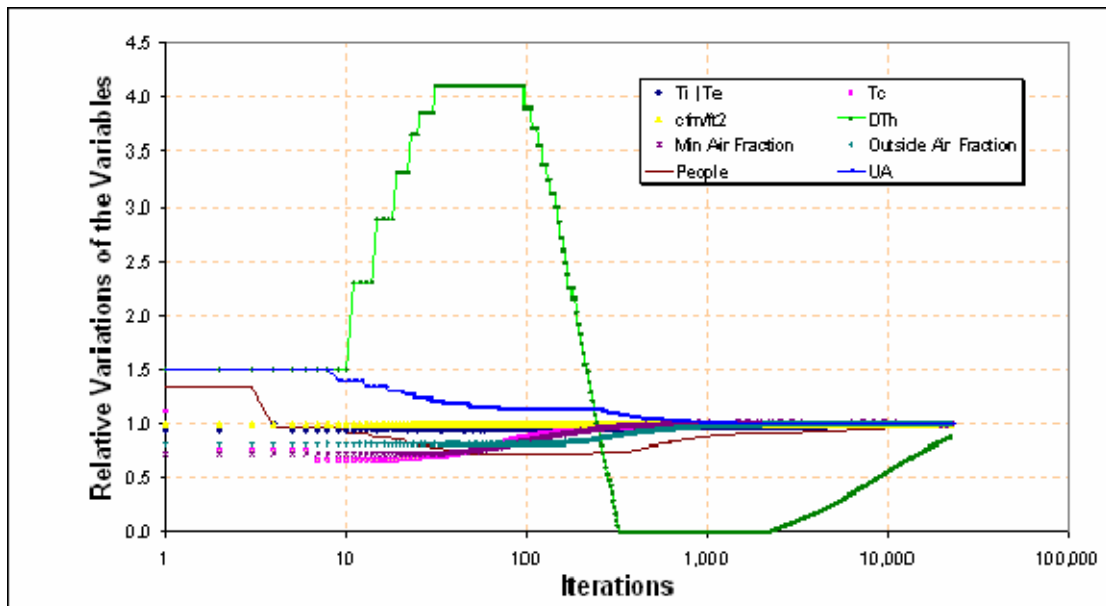
Figure C.2   Variable behavior corresponding to the minimization pattern presented above.
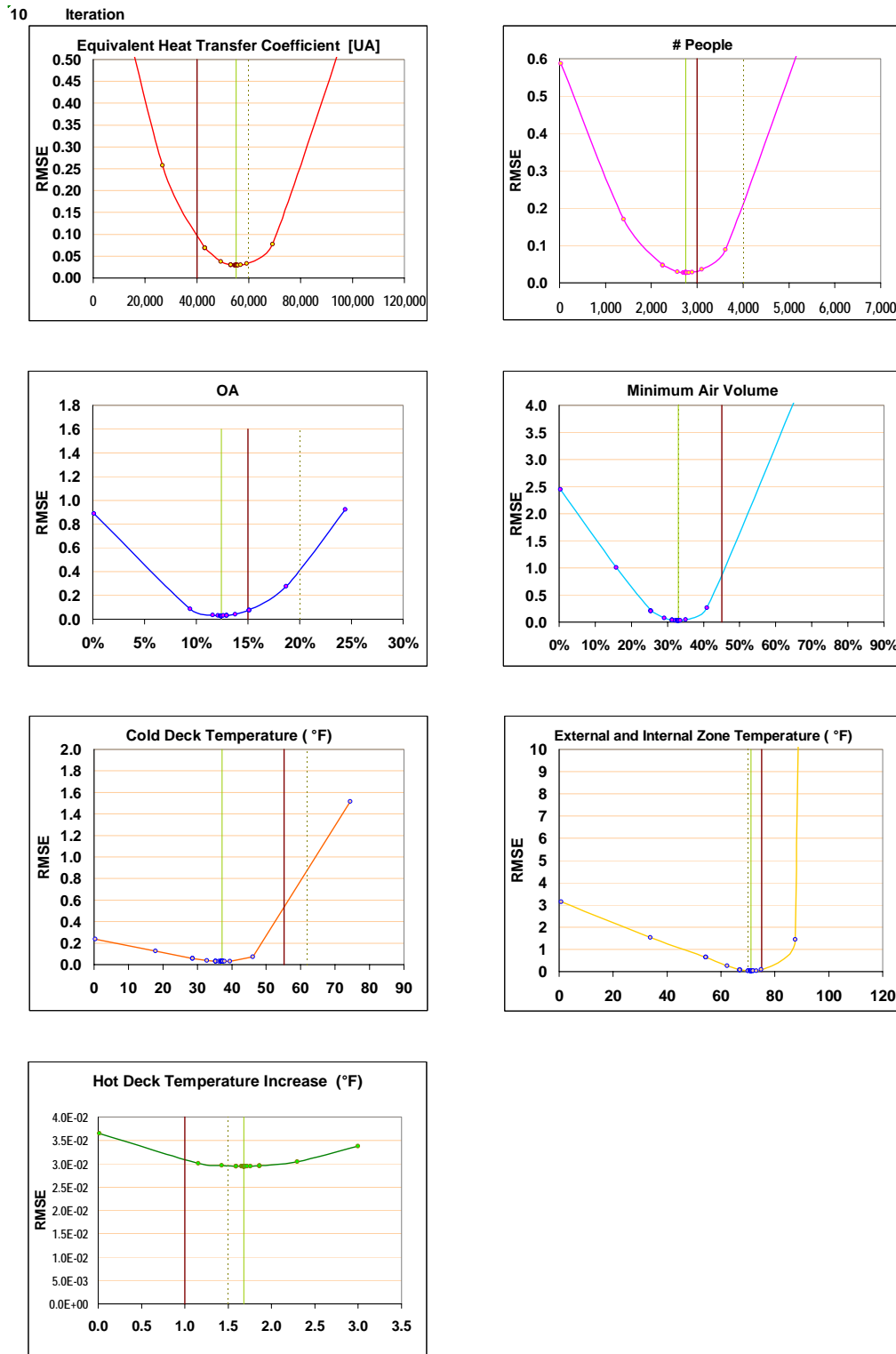
´10   Iteration

Figure C.3 Performance of the Golden search on the *RMSE* minimization in the 10th iteration.
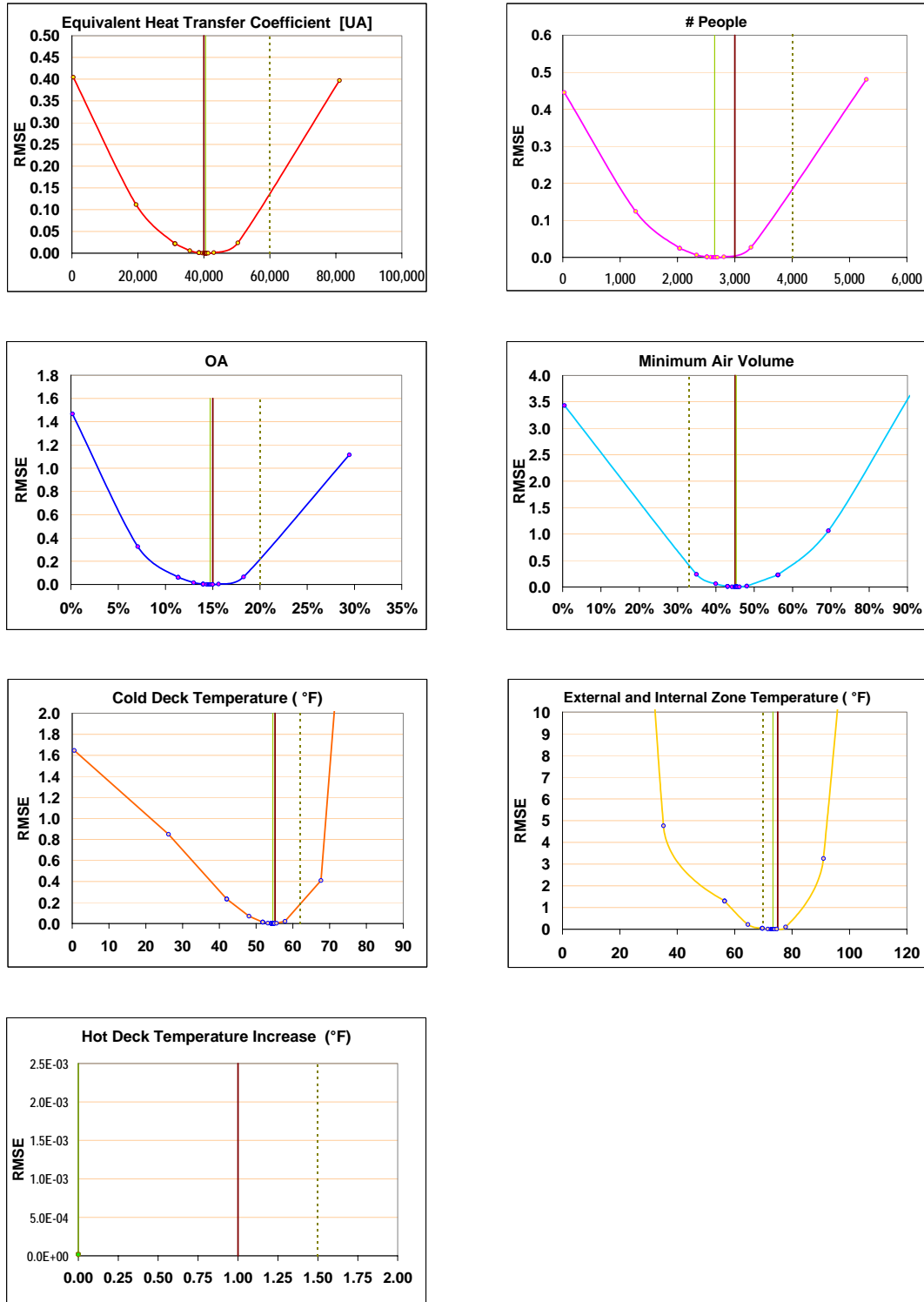
Figure C.4 Performance of the Golden search on the *RMSE* minimization in the 1010th iteration.

2010   Iteration

Equivalent Heat Transfer Coefficient [UA]

 # People

OA

Minimum Air Volume

Cold Deck Temperature (°F)

External and Internal Zone Temperature (°F)

Hot Deck Temperature Increase (°F)
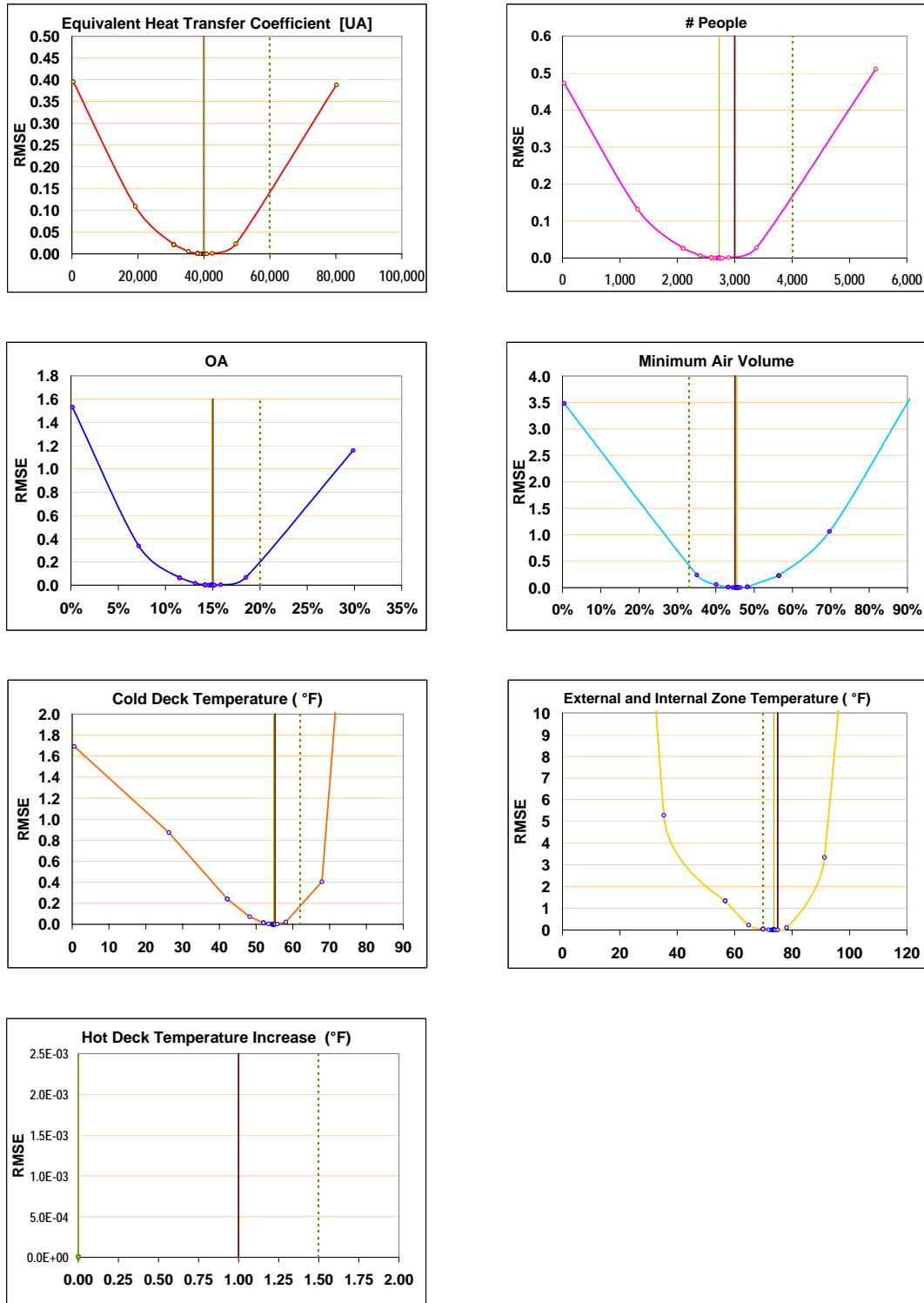
Figure C.5 Performance of the Golden search on the *RMSE* minimization in the 2010th iteration.

3010   Iteration
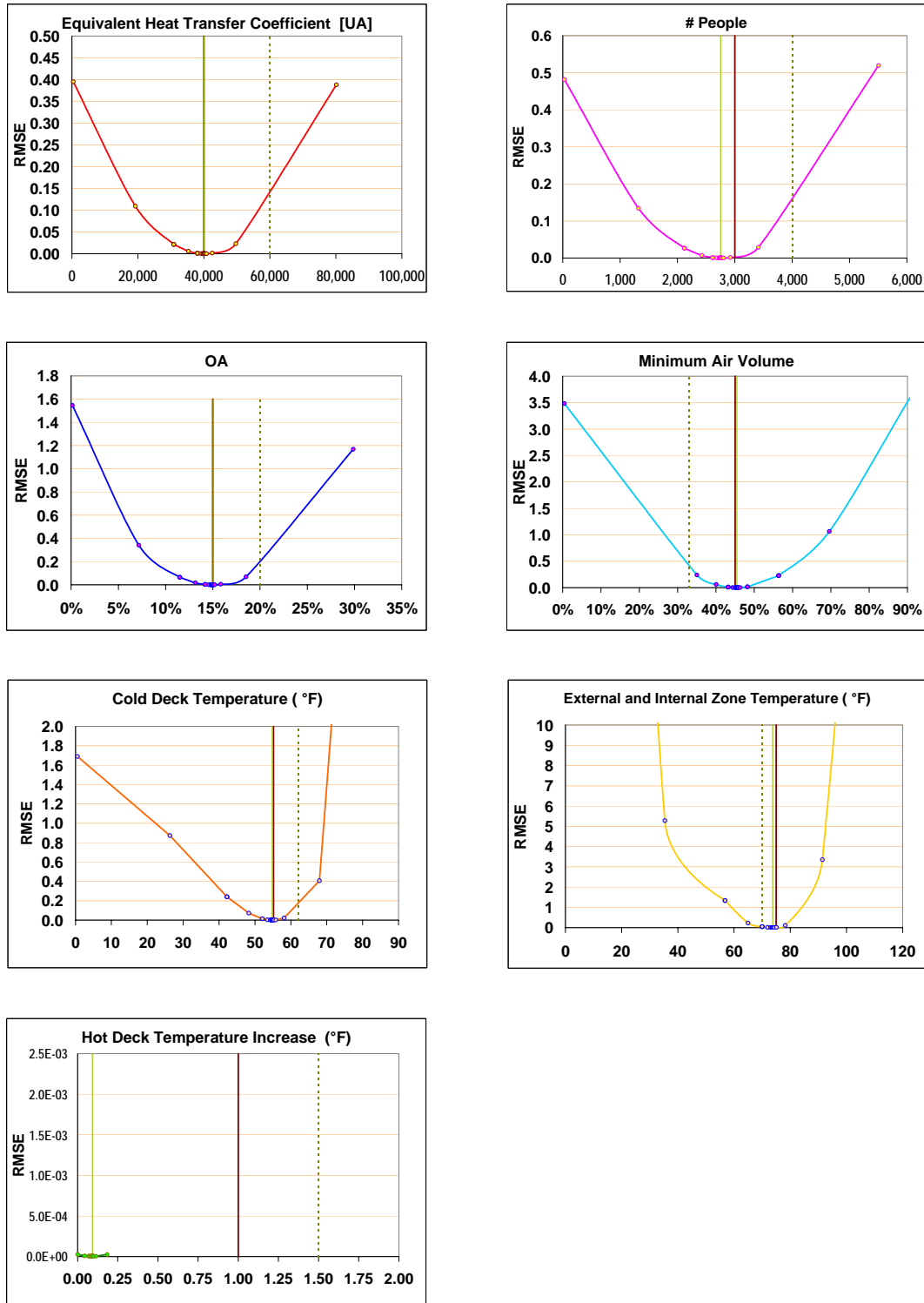
Figure C.6 Performance of the Golden search on the *RMSE* minimization in the 3010 iteration.
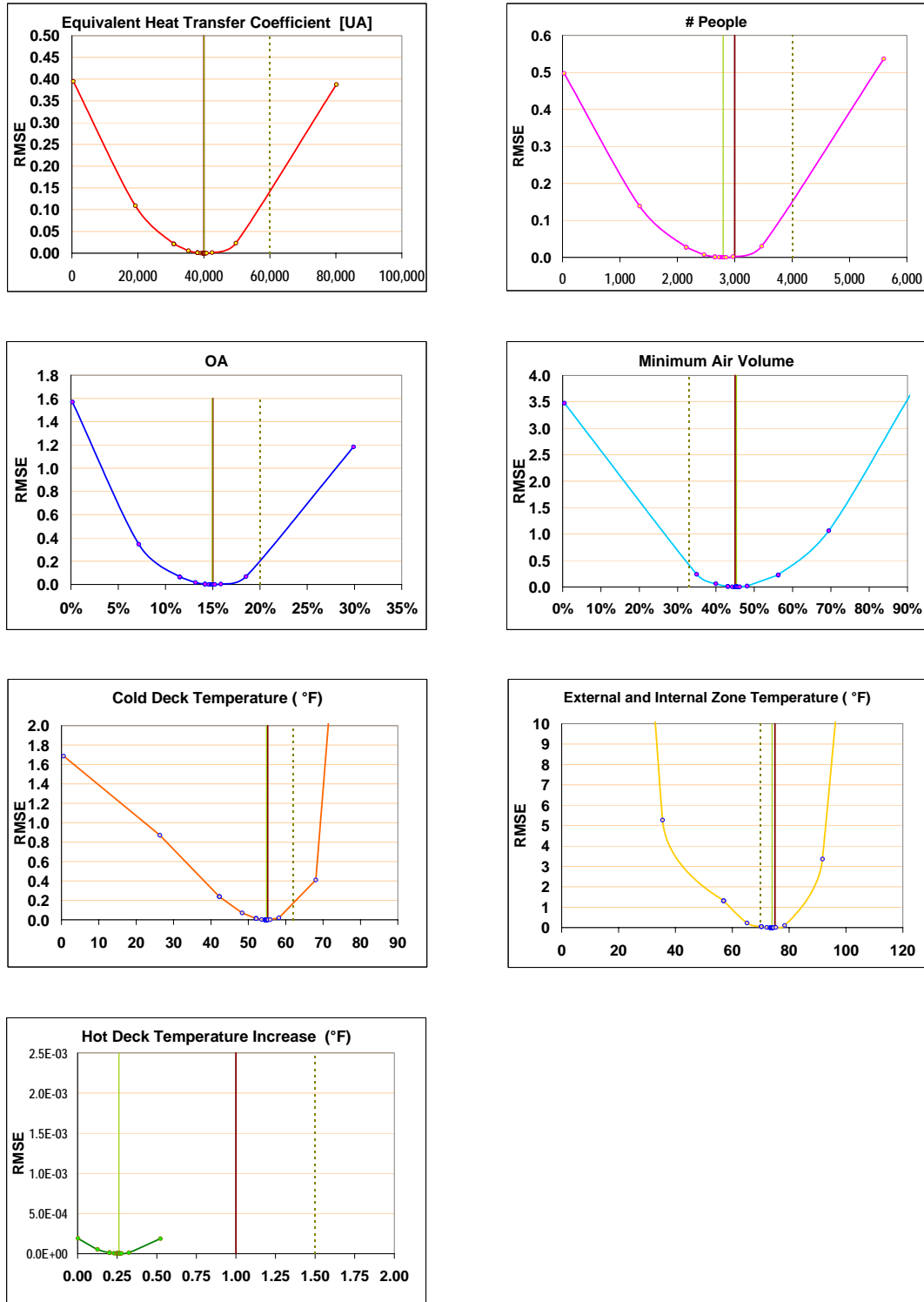
Figure C.7 Performance of the Golden search on the *RMSE* minimization in the 5010 iteration.

7010   Iteration
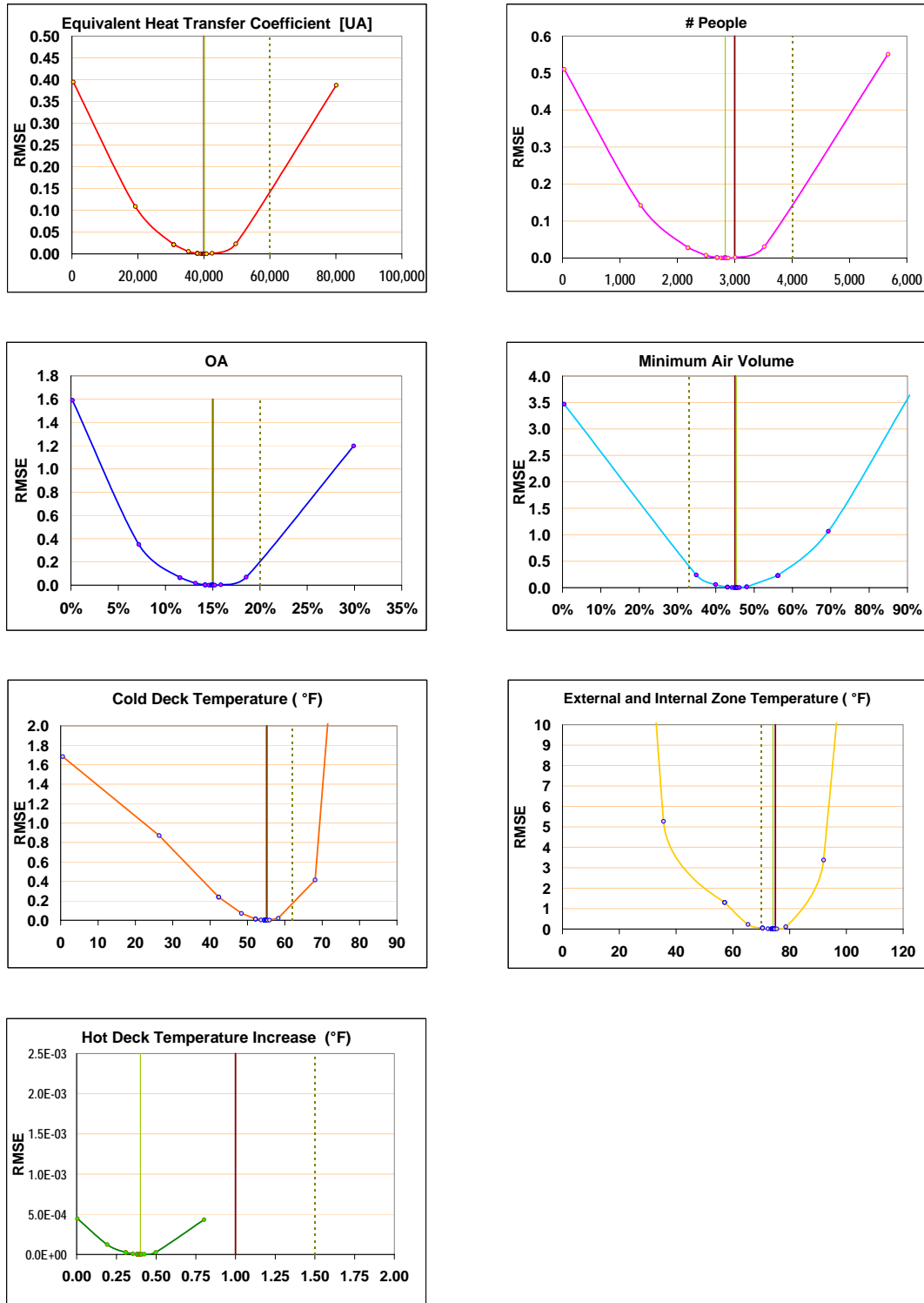
Figure C.8 Performance of the Golden search on the *RMSE* minimization in the 7010th iteration.

9010 Iteration
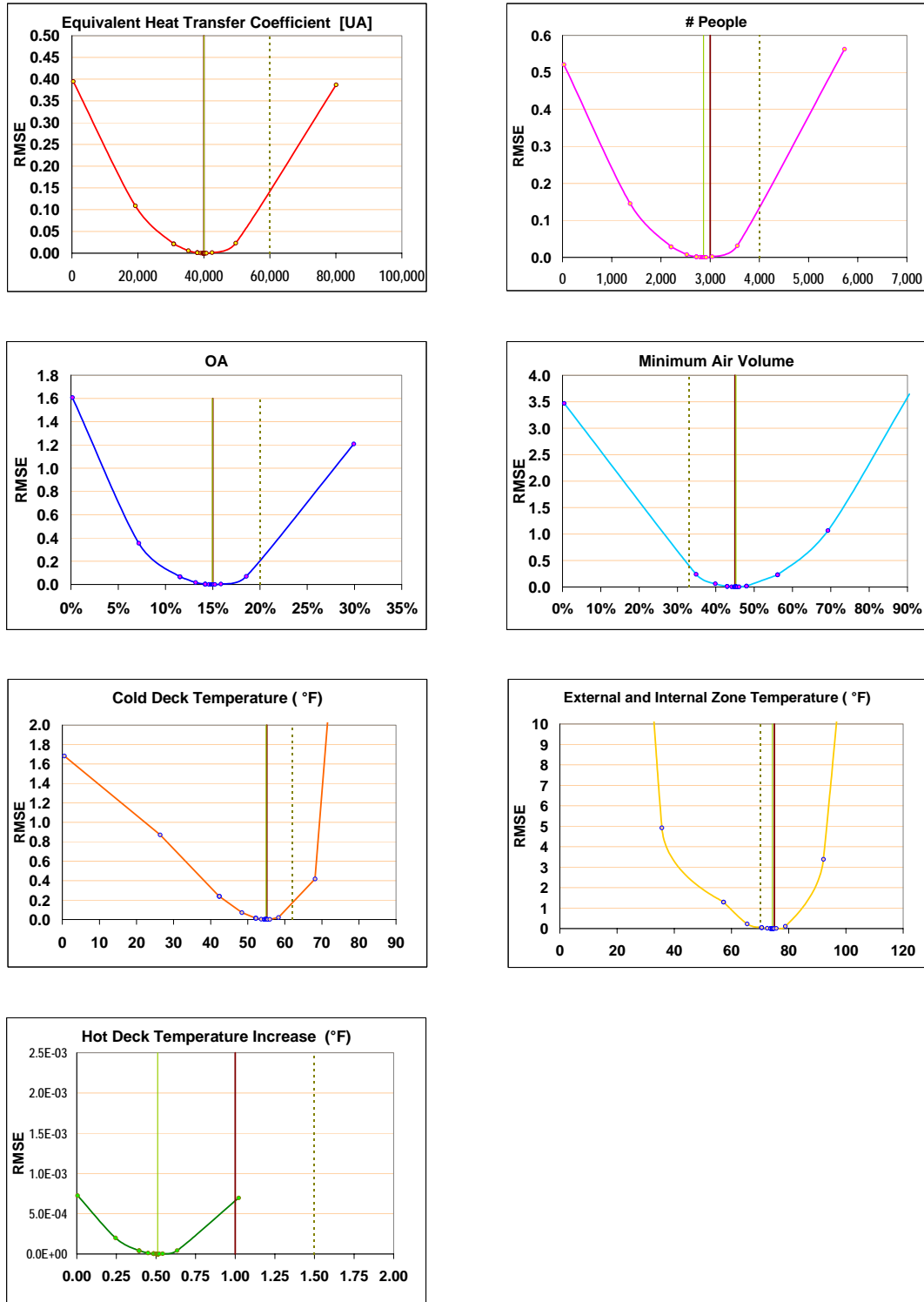
Figure C.9 Performance of the Golden search on the *RMSE* minimization in the 9010th iteration.

10010 Iteration
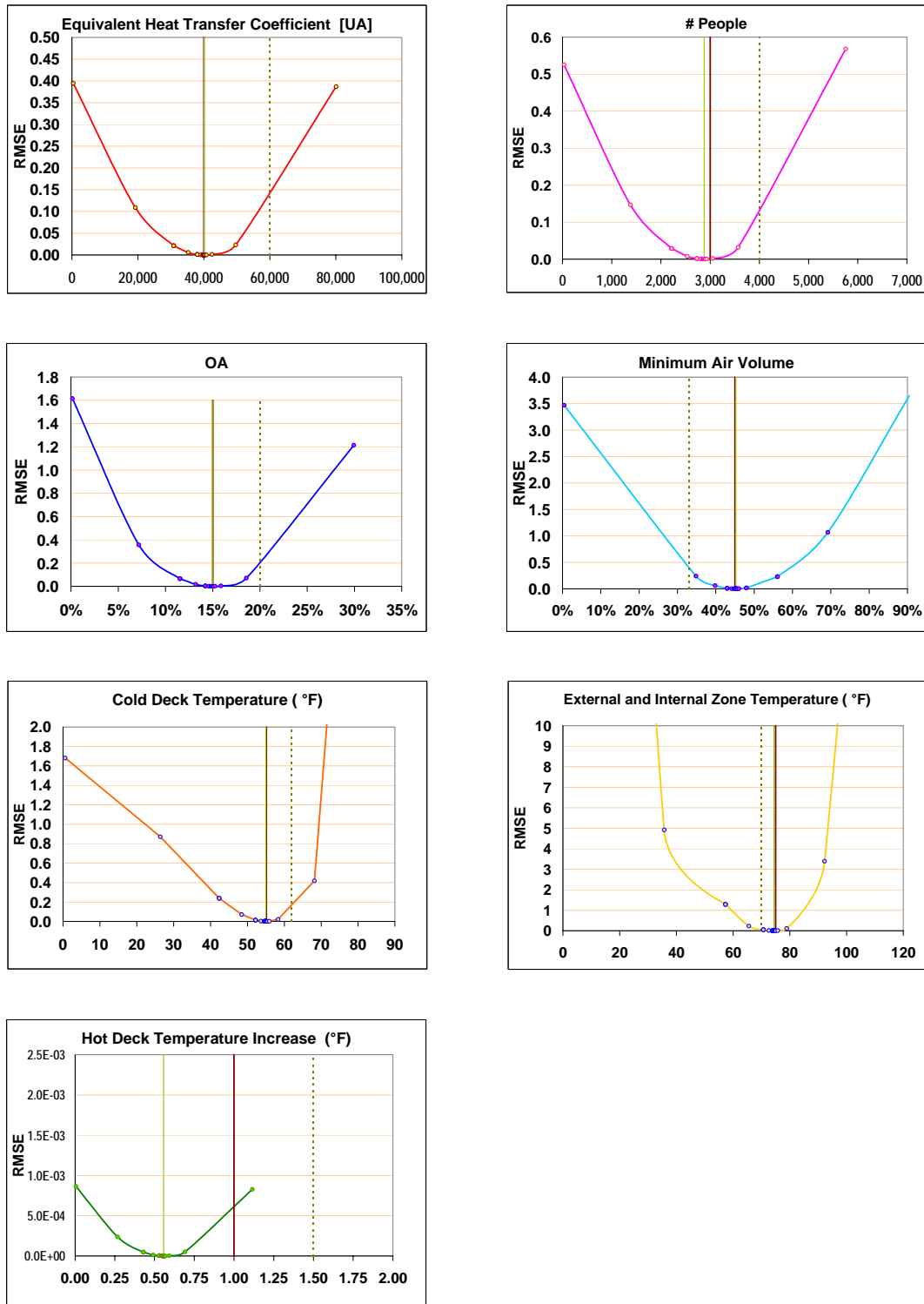
Figure C.10 Performance of the Golden search on the *RMSE* minimization in the 10010th iteration.
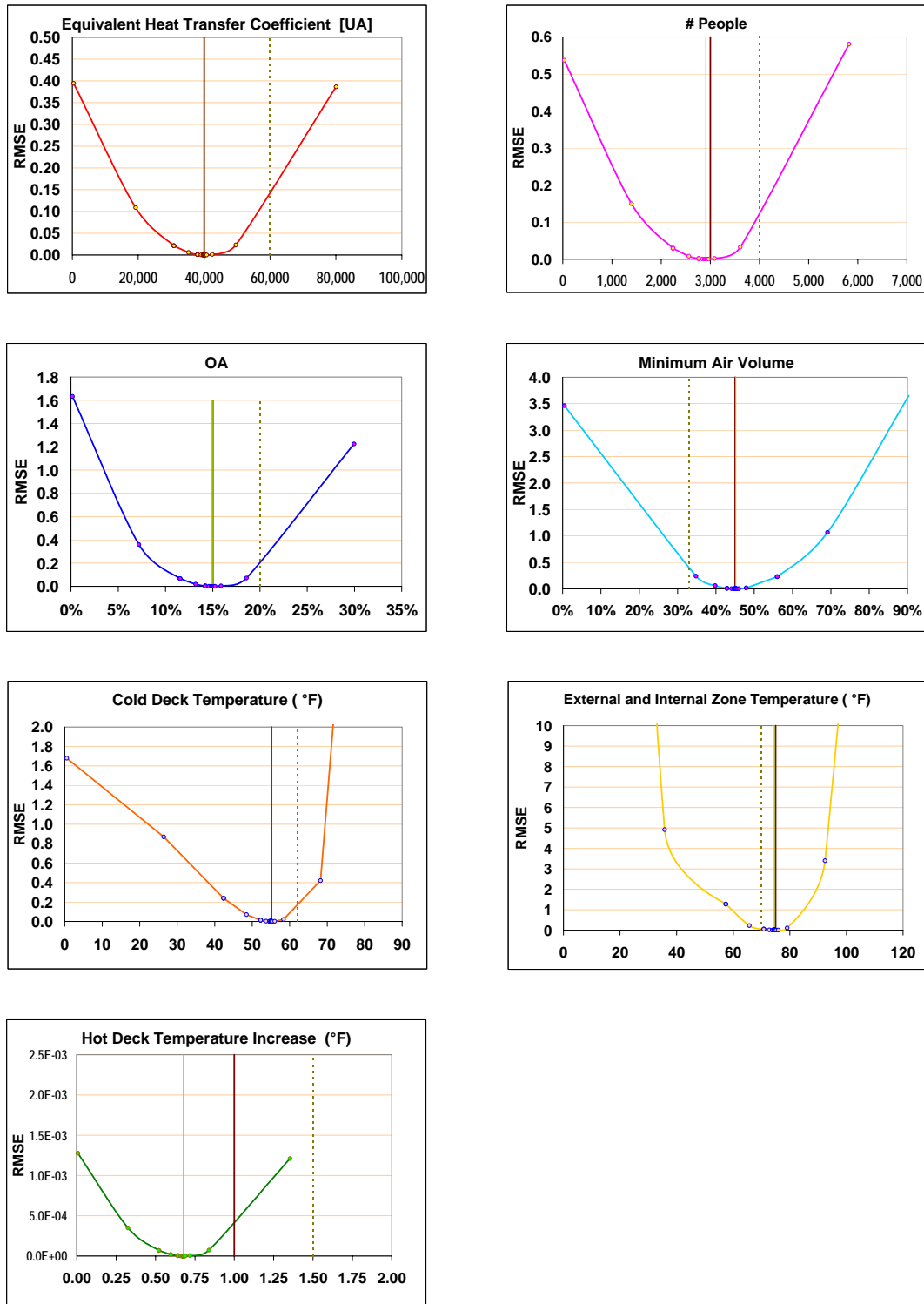
Figure C.11 Performance of the Golden search on the *RMSE* minimization in the 13110th iteration.

16210   Iteration
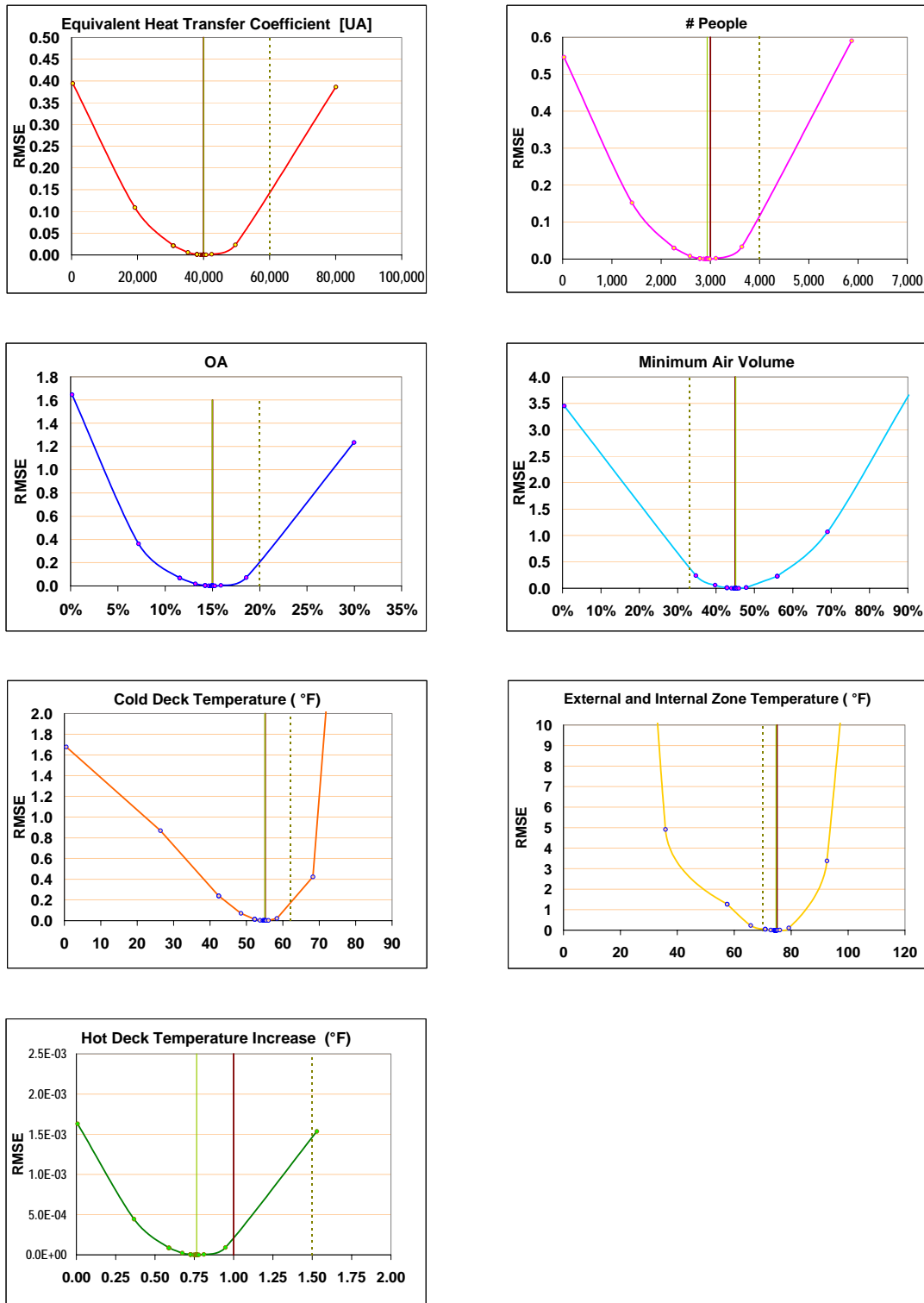
Figure C.12 Performance of the Golden search on the *RMSE* minimization in the 16210th iteration.

17610   Iteration
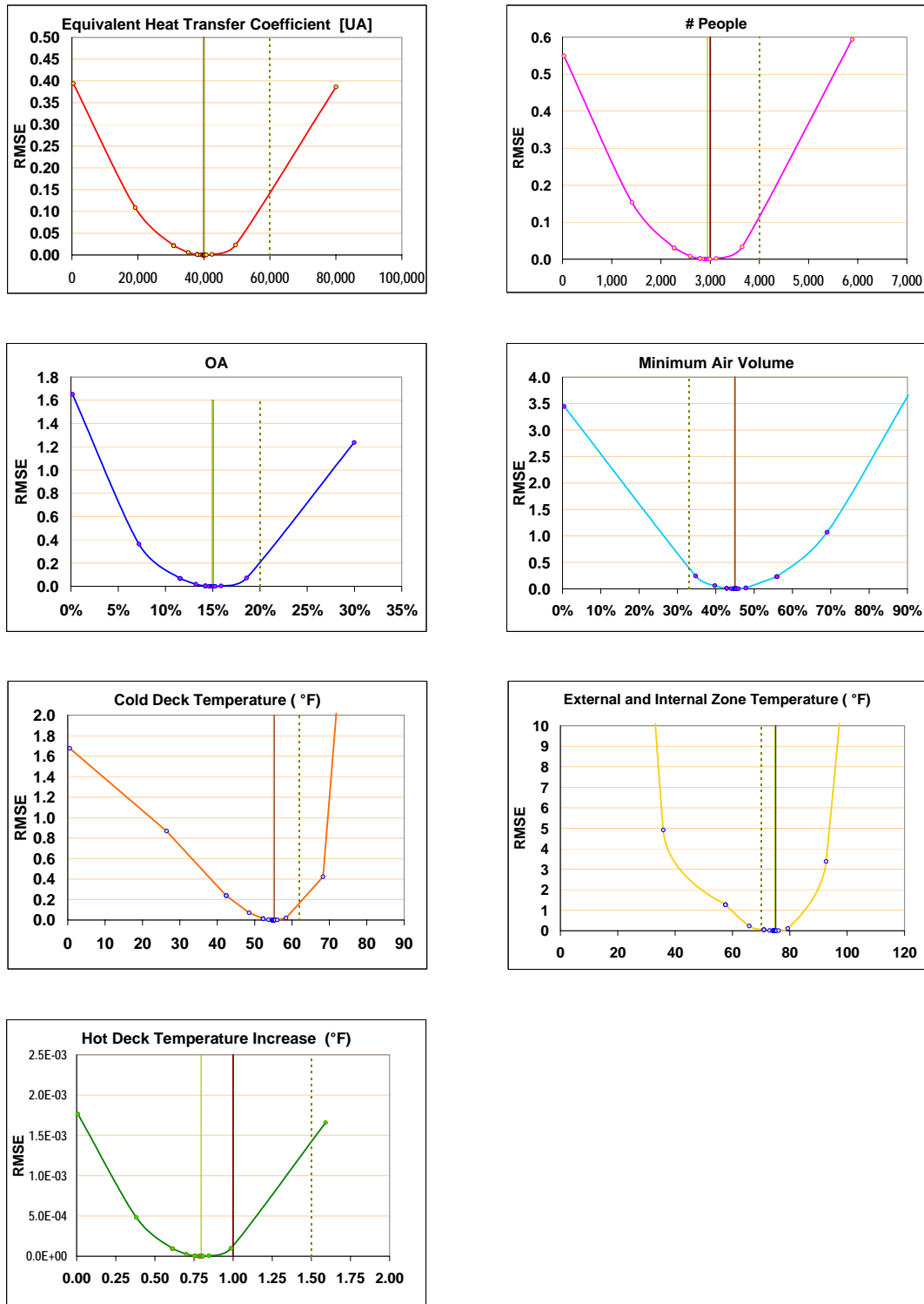
Figure C.13 Performance of the Golden search on the *RMSE* minimization in the 17610th iteration.
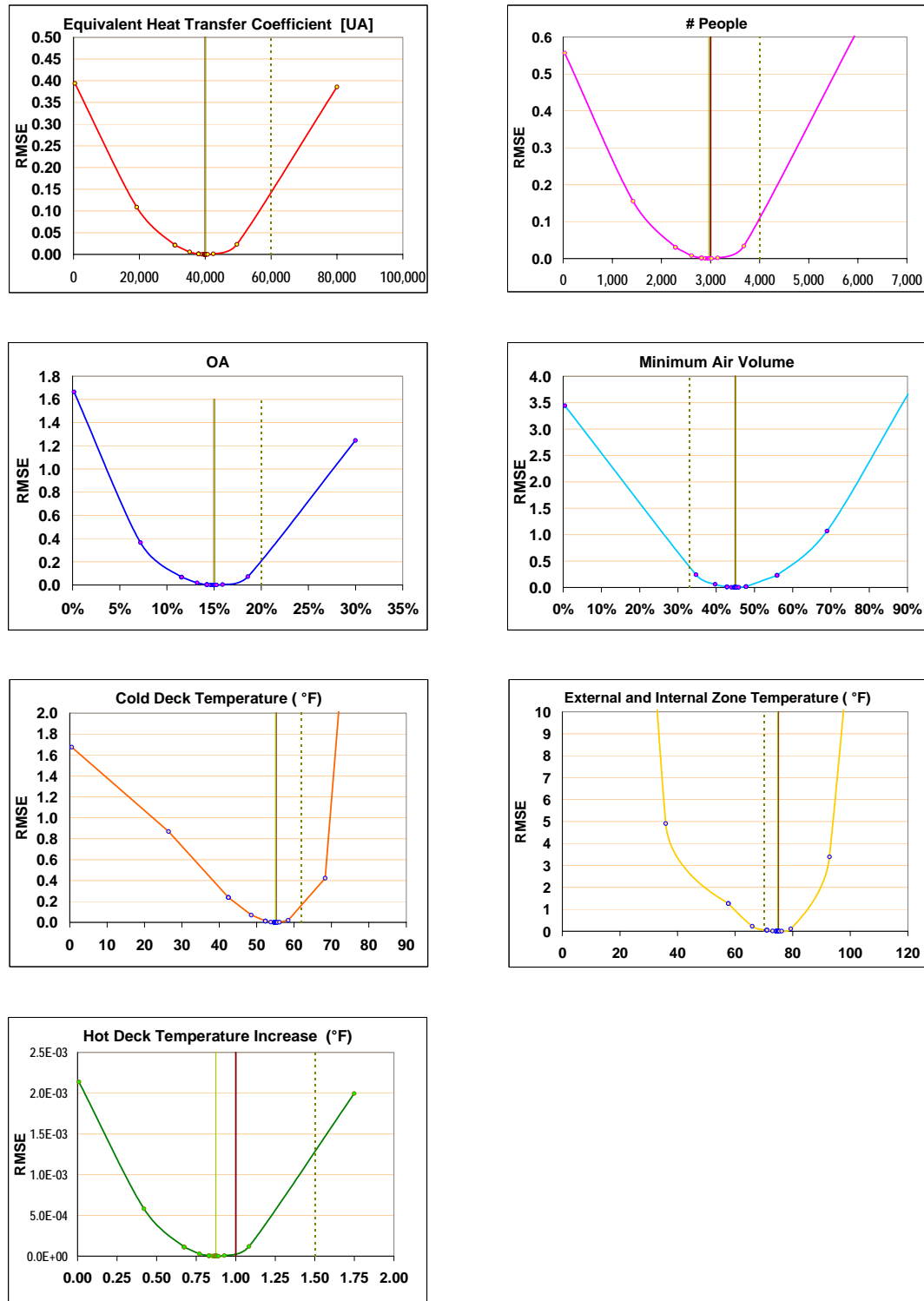
Figure C.14 Performance of the Golden search on the *RMSE* minimization in the 22600th iteration.

APPENDIX D

SIMPLIFIED AIR-SIDE ENERGY ANALYSIS OF HVAC SYSTEMS

Simplified energy analysis is a procedure based on a time averaging technique and, as such, has limited capability in accurately dealing with highly time-dependent problems. The time average technique is based on the premise that the net time dependent energy rate, added to or removed from the space during a given interval, is equivalent to the average energy rate added to or removed from the space and multiplied by the duration of the interval. The weakness in this idea is the approximation used in developing the average rates of the energy gains or losses from the space. The thermal capacitance of the space induces a time lag before the thermal load to the space actually becomes a load on the HVAC system. Thus, the load computed by averaging may not become the actual load on the HVAC system. Furthermore, variations of space temperatures characteristic of any control system that causes heat storage and release are not accurately represented. The strengths of the method lie in the nature of the energy analysis problem to be solved, and it is generally useful when the building mass, or thermal capacitance, is not a primary issue in the analysis. In buildings dominated by internal loads or in low mass structures, the method provides reasonable results. However, the method should be used with prudence when the primary analysis deals with a thermal capacitance dominated problem such as wide dead band thermostats, set up and setback, or massive envelopes. This issue may also be argued in hourly simulation programs since the space temperature variations may occur within the hourly time step. Large space temperature variations associated with dead band controls and night set back and set up conditions may show significant variation with hourly simulators (Knebel 1983). The method described in this appendix and used in the analysis contained in this dissertation was developed by ASHRAE TC4.7 and described in detail in Knebel (1983). The equations used in this appendix

largely come from that treatment. The notation follows that generally used within the Energy Systems Laboratory.

This appendix includes the simplified analysis of air-side cooling and heating thermal energy use for four of the most widespread HVAC system types, namely terminal reheat and dual duct, both under constant air volume and under variable air volume operation.

D.1   Constant Volume Terminal Reheat System

The constant-volume reheat system is considered an energy-inefficient constant-volume system. The constant volume terminal reheat system is a single path air system consisting of a central air handling unit with a fan, a cooling coil, a preheat coil, and a mixing box. The air leaving the cooling coil may be controlled as a fixed set point, an outside air reset, or a zone controlled reset. The air leaving the unit is delivered to the zone reheat coil at a single temperature (Knebel 1983). This system operates with a fixed-volume flow rate and a fixed cold deck temperature, typically 55°F (13°C), selected to meet the peak sensible and latent cooling load. Variations of load within a zone or among zones below the peak are accounted for by adding heat to the air at each zone with a reheat coil, be it from electricity, steam, or hot water (Kreider and Rabl 1994). Outside air may be set at a fixed amount, or economy cycles may be used to increase the outside air quantity to reduce the cooling load. If the mixed air temperature is lower than the desired cooling coil leaving air temperature, a preheat coil may be used to heat the mixed air to the desired cooling coil leaving air temperature. The source of energy waste is obvious – cooled air is reheated prior to release to the zone(s). To minimize energy waste, the cold air temperature should be reset to the highest possible temperature that will just meet the cooling load.

The use of a CVRH system is now restricted by energy codes except for special circumstances where accurate zone temperature or humidity control is needed.

D.2   Single Duct Variable Air Volume System

The fundamental VAV system is a cooling-only system that modulates system airflow in response to cooling loads as sensed by a dry-bulb thermostat. The variable air volume system is a single path air system consisting of a central air handling unit with a fan, a cooling coil, a preheat coil, and a mixing box. The air leaving the cooling coil may be controlled as a fixed point, an outside air reset, or a zone controlled reset. The air supply is cool and at a fixed temperature. Therefore, a separate system is needed for zones with heating loads. Reset options result in increased air flow rates and may have a negative impact on fan energy reduction. The basic concept of a VAV system is to reduce system air flow from full-load levels whenever loads are less than peak. The air leaving the unit is delivered to the zone's volume control box, which modulates the zone air flow in response to the zone thermostat. In the simple VAV system, if the heating is needed in a perimeter zone, this is supplied by a separate subsystem, such as a baseboard radiation or reheat coil. Thus, the system only provides ventilation air, which may itself require some heating.

Since flow is reduced, energy transfer at the air handler coils is reduced and fan power is reduced markedly. The reduction of energy transfer is essentially proportional to the airflow reduction. The reduction in fan energy is dependent on the type of fan and the control method. Control of outside air quantity and preheating is the same as for the reheat system.

Under peak conditions, the VAV system operates identically to a fixed-volume system with the air handler operating at maximum flow and maximum coil capacity. However, at a reduced cooling load, the system airflow is reduced by the combined action of the closing of zonal VAV box dampers and the closing of the fan speed controller.

D.3   Dual Duct Constant Volume System (DDCV)

The dual-duct constant-volume system has an air handling unit with a single supply fan and two sets of ducts – one for cold air and the other for hot air. The two sets of

ducts terminate at a mixing box at each zone. The cold deck and the hot deck each may be controlled as a fixed point, an outside air reset, or a zone-controlled reset. The DDCV system supplies cold air and warm air through two separate ducts: a cold deck and a hot deck. A constant total air flow rate is maintained in this system, and the cooling or heating loads are met in each zone by mixing the right proportions of cold air and warm air to produce the required supply temperature. The relative amounts of hot and cold air passed to each zone are controlled by reverse-acting dampers operated by the thermostat in each zone. The air flow is maintained constant to each zone by the action of these dampers.

Control of the fixed-volume system should ensure that heating and cooling coils do not operate simultaneously to avoid energy waste; when both coils operate, they are said to "fight" or "buck" each other (Kreider and Rabl 1994). Air leaving a zone's mixing box is controlled by a zone thermostat to get the desired zone's supply air temperature by mixing air from hot and cold decks. If the mixed air temperature is lower than the desired cooling coil leaving air temperature, a preheat coil may be used to heat the mixed air to the desired cooling coil leaving air temperature. The quantity of outside air may be increased to reduce the cooling coil load. Control of outside quantity and preheating is the same as for the reheat system. Comfort control is poor in this system with its single pair of coils when used in a building with several thermally distinct zones.

D.3.1 Advantages and disadvantages of the dual duct constant air volume systems

Based on the usual operation of a dual-duct system several of its advantages can be identified:

☑ All space conditioning needs are taken care of at a central plant – no HVAC primary heating or cooling equipment is located in the zones.

☑ Since warm air is available year round, temperature control of highly loaded zones is good during the cooling season. Control response to load changes is rapid.

☑ Duct sizing calculations are not that critical since the dampers at each zone absorb any pressure imbalance caused by design inaccuracy or part load operation.

☑ If humidity control is needed, this system is a good candidate.

However, there are a number of disadvantages related to the use of a dual-duct system; some of which include:

☒ Frequent duct leaks.

☒ Zone damper leakage requires oversizing both the heating plant (to account for cold air damper leakage during peak heating) and the cooling plant (inverse case).

☒ The space required for two full-sized ducts and the requirement that each zone have two duct connections makes duct design more difficult. Duct velocities and pressures are higher because two ducts must fit into the space of one.

☒ An economizer should not be applied to the basic dual-duct system because the heating coil inlet air will be at the cold deck set point, not at the mixed-air temperature. Heating energy requirements will be much higher and can exceed the cooling energy savings. Hence, the benefits of an economizer are not available to dual-duct (Kreider and Rabl 1994).

D.4 Dual Duct Variable Air Volume System (DDVAV)

The dual-duct variable air volume (DDVAV) system is a single path air system consisting of a central air-handling unit with a fan, a cooling coil, a heating coil, and a mixing box. This DDVAV system supplies cold air and warm air through two separate ducts, a cold deck and a hot deck, which may be controlled as a fixed set-point, an outside air reset, or a zone controlled reset strategy. The central air handling unit in the dual duct single fan variable air volume system has two supply decks, a hot deck below with a heating coil and a large cold deck on top with a cooling coil. A single supply fan blows the supply air through both coils and the total flow is controlled with a fan-flow modulation device.

In general, a variable air volume (VAV) system maintains the air supply at a constant temperature while, through the response to individual zone thermostats, the mixing boxes modulate the zone air flow rates to each space, maintaining the desired zone temperature. In contrast, the constant air volume (CAV) system maintains a constant volume of airflow to the space, but varies the temperature of the air stream in response to space temperature changes.

A typical VAV system delivers a mixture of outdoor and re-circulated return air to multiple spaces via local terminal units that control the flow rate. Hot and cold ducts branch-off from the main ducts and feed into the hot and cold intakes of the VAV terminal boxes. While the amount of supply air delivered to each space varies with the thermal load, the amount of outdoor air remains constant. Since the air flow is modulated to meet the zone load, fan power consumption will also be adjusted. As the air volume is reduced, fan power consumption will be reduced. The reduction in fan energy is dependent on the type of fan and the control method. The specific amount of air volume required to maintain a particular zone temperature set point is dictated by the size of the space and the internal and external heat loads. Typically, the VAV boxes may be oversized to allow for quiet operation or to reserve cooling capacity. The outside air may be set at a fixed amount, or an economy cycle may be used to increase the outside air quantity in order to reduce the cooling coil load. The system first uses return air in the heating duct, and if additional heat is needed, the hot deck heating coil turns on. The reset option results in increased airflow rates and may have a negative impact on fan energy reduction.

D.4.1 Advantages and disadvantages of the dual duct variable air volume systems

According to the typical operation of the VAV systems, the following advantages can be identified:

☑ A properly designed VAV system can be one of the most energy-efficient and comfortable systems for the space occupants.

☑ The flexibility and adaptability of the system to changing load conditions is a key feature.

☑ Because the systems are generally capable of moving large volumes of air, many problems such as interior painting, smoke, and other sources of air contamination can be removed more effectively than with any other system.

☑ VAV technology has the primary advantaged of flexibility and adaptability that no other system can offer. It is also able to manage changes as the building changes, and it is successful in a wide range of building types and in all climates.

Nevertheless, some disadvantages can be identified, including the following:

☒ The required accuracy and complexity of the control system is often a problem when the control system is not properly designed or installed.

☒ Fan-powered terminals and diffusers that are subjected to wide variances in air flow often produce a change in the room background sound level which is noticed by the occupants.

☒ Occupants' complaints of being too cold or too warm are often the result of inadequate or limited zoning that places the control thermostats in locations that cannot allow the system to respond to occupant comfort.

☒ If the ceiling plenum is used for return air, the fans can pull contaminated air from adjacent zones, causing an IAQ problem.

D.5   Air-side HVAC Simplified Engineering Modeling

The simplified engineering models are based on the air-side HVAC systems analysis and indoor building conditions using fundamental steady-state engineering equations (Knebel 1983, Haberl et al. 2002). The following assumptions are made in all four systems unless otherwise specified:

- Though actual commercial buildings may have a number of zones, a two-zone treatment with one exterior, or perimeter, zone and one interior, or core, zone is

a good compromise between accuracy and simplification (Knebel 1983, Katipamula and Claridge 1993, Reddy et al. 1995, Liu et al. 1998).

- Both zones have identical thermostat set point temperatures and no night set-back is assumed.

- Infiltration loads are negligible or considered part of the ventilation loads.

- Ducts are perfectly insulated and no air leakage occurs.

- Solar and transmission loads affect the perimeter zone only.

- No air stream reheating is provided by the circulation fans or by the ducts.

- The heating and cooling coils have an infinite capacity, i.e., the coils can heat or cool (and dehumidify) the airflow to the required deck control settings at all times.

- Heat gains from lights are assumed to appear as zone loads rather than being carried off directly by return air (as in vented recessed lights). Also, internal loads are shared between both zones in proportion to their conditioned floor areas.

- Dynamic effects of building heat flows are neglected in order to keep the equations simple without losing clarity.

- The response times of various HVAC system components and their controls are neglected. This assumption can be justified by the fact that these response times are much shorter than an hour, which is the smallest time scale assumed both in this study and by most other studies and simulation programs.

D.6   Load Calculations

The building is commonly divided into interior and exterior zones. Envelope loads including solar gain, infiltration loads, and internal gains must be determined for each zone.

Envelope. The envelope loads include conduction losses/gains and solar radiation. Solar radiation gain is treated as a constant. Consequently, envelope loads can be calculated by the next equation

$$q_{env} = UA(T_z - T_{OA}) + q_{sol}$$

The envelope global heat transfer coefficient (UA) is the sum of the heat transfer coefficients for the windows, the walls and the roof, as determined from as-built plans. The solar heat gain (q_{sol}) can be determined using the annual average solar radiation data and building envelope information. The room temperature may be measured during a walk through.

Internal gain. The lighting and receptacle heat gain is determined as the product of the gain per unit area (q_i) and the floor area of each zone. The internal gain per unit area is based on the measured whole building electricity consumption as well as the types of electricity-using equipment.

The heat gain (q_{pe}) and moisture (M_w) production from people also affect the total sensible loads in the buildings, thus

$$q = q_{env} + q_i + q_{inf,s} + q_{pe,s}$$

and the moisture production can be evaluated as

$$M_w = q_{pe,l} / h_{fg}$$

The nomenclature for these equations and those that will be presented in the following simplified analysis of each HVAC system is found in Table D.1.

D.7 Simplified Analysis of a Dual Duct Variable Air Volume System
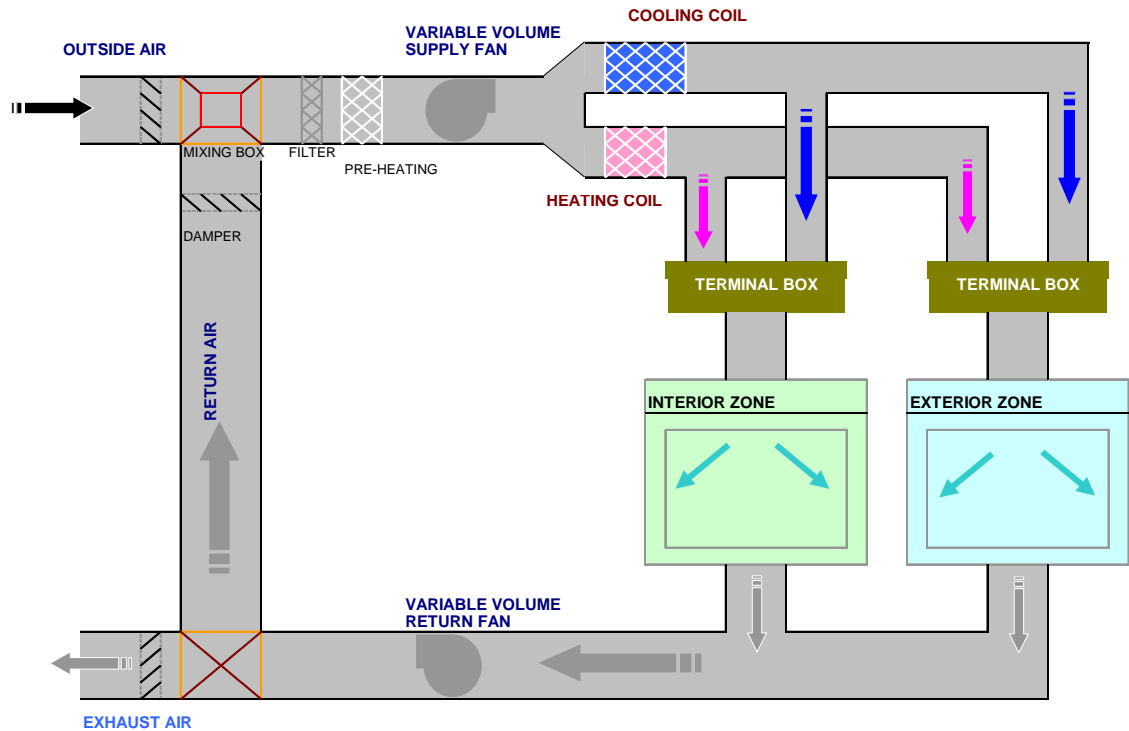
Figure D.1 Schematic Diagram of a Dual Duct Variable Air Volume System.

$$T_{HL} = \begin{cases} 85 & T_{OA} > 75 \\ 85 + (75 - T_{OA}) & 35 \le T_{OA} \le 75 \\ 125 & T_{OA} < 35 \end{cases}$$

Hot deck temperature schedule [$°F$]

$$if \quad q_{is} > 0 \qquad else \quad q_{is} \le 0$$

$$\begin{cases} T_{is} = T_{CL} \\ \dot{V}_{iC} = \dfrac{q_{is}}{1.08(T_i - T_{is})} \\ \dot{V}_{iH} = 0 \end{cases} \qquad \begin{cases} T_{is} = T_{HL} \\ \dot{V}_{iH} = \dfrac{q_{is}}{1.08(T_i - T_{is})} \\ \dot{V}_{iC} = 0 \end{cases}$$

Interior zone supply air dry bulb temperature [$°F$]

Interior zone cold and hot air volume flow rates [ft^3/min]

$$if \quad q_{es} > 0 \qquad\qquad else \quad q_{es} \leq 0$$

$$\begin{cases} T_{es} = T_{CL} \\ \dot{V}_{eC} = \dfrac{q_{es}}{1.08(T_e - T_{es})} \\ \dot{V}_{eH} = 0 \end{cases} \qquad \begin{cases} T_{es} = T_{HL} \\ \dot{V}_{eH} = \dfrac{q_{is}}{1.08(T_e - T_{es})} \\ \dot{V}_{eC} = 0 \end{cases}$$

Exterior zone supply air dry bulb temperature [$°F$]

Exterior zone cold and hot air volume flow rates [ft^3/min]

$$if \quad \dot{V}_{i,\min} > \left(\dot{V}_{iC} + \dot{V}_{iH} \right)$$

$$\begin{cases} T_{is} = T_i - \dfrac{q_{is}}{1.08 V_{i,\min}} \\ \dot{V}_{iC} = V_{i,\min}\left(\dfrac{T_{is} - T_{HL}}{T_{CL} - T_{HL}} \right) \\ \dot{V}_{iH} = V_{i,\min}\left(\dfrac{T_{is} - T_{CL}}{T_{HL} - T_{CL}} \right) \end{cases}$$

Test for minimum comfort requirements in interior zone and correction of volume flow rates

$$\dot{V}_i = \dot{V}_{iC} + \dot{V}_{iH}$$

Interior zone total supply air volume flow rate [ft^3/min]

$$if \quad \dot{V}_{e,\min} > \left(\dot{V}_{eC} + \dot{V}_{eH} \right)$$

$$\begin{cases} T_{es} = T_e - \dfrac{q_{es}}{1.08 V_{e,\min}} \\ \dot{V}_{eC} = V_{e,\min}\left(\dfrac{T_{es} - T_{HL}}{T_{CL} - T_{HL}} \right) \\ \dot{V}_{eH} = V_{e,\min}\left(\dfrac{T_{es} - T_{CL}}{T_{HL} - T_{CL}} \right) \end{cases}$$

Test for minimum comfort requirements in exterior zone and correction of volume flow rates

$$\dot{V}_e = \dot{V}_{eC} + \dot{V}_{eH}$$

Exterior zone total supply air volume flow rate [ft^3/min]

$$T_{iR} = T_i + \frac{q_{iR}}{1.08\dot{V}_i} \qquad\qquad T_{eR} = T_e + \frac{q_{eR}}{1.08\dot{V}_e}$$

Interior and exterior zone return air dry bulb temperatures [$°F$]

$$T_R = \frac{\dot{V}_e T_{eR} + \dot{V}_i T_{iR}}{\dot{V}_i + \dot{V}_e}$$

Zone return air dry bulb temperature [$°F$]

$$X_{OA} = \frac{\dot{V}_{OA}}{\dot{V}_i + \dot{V}_e}$$

Outside air volume ratio

$$T_{ma} = T_R + X_{OA}(T_{OA} - T_R)$$

Mixed air dry bulb temperature [$\degree F$]

$$PLR = \frac{\dot{V}_i + \dot{V}_e}{\dot{V}_{TD}}$$

Part Load Ratio

$$\frac{P_{fan}}{P_{fan-rated}} = \begin{cases} \text{Variable Speed Drive} \\ 0.00153 \ + \ 0.0052\,PLR + 1.1086PLR^2 - 0.1164PLR^3 \\ \text{Inlet Vanes Control} \\ 0.351 + 0.308PLR - 0.541PLR^2 + 0.872PLR^3 \\ \text{Outlet Dampers} \\ 0.371 + 0.973PLR - 0.342PLR^2 \end{cases}$$

Power use due to different possibilities of Variable Speed Mechanism

$$\Delta T_{SF} = \frac{P_{fan}}{1.08(\dot{V}_i + \dot{V}_e)}$$

Supply air fan temperature rise [$\degree F$]

If $\quad T_{ma} < T_{CL} - \Delta T_{SF}$	*Otherwise*
$T_{PH} = T_{CL} - \Delta T_{SF}$	$T_{PH} = T_{ma}$
$q_{PH} = 1.08(\dot{V}_i + \dot{V}_e)(T_{CL} - T_{PH})$	$q_{PH} = 0$

Preheat coil leaving air dry bulb temperature [$\degree F$]

Preheat coil load [*Btu/hr*]

$$T_{CE} = T_{PH} + \Delta T_{SF}$$

Cooling coil entering air dry bulb temperature [$\degree F$]

$$T_{HE} = T_{PH} + \Delta T_{SF}$$

Heating coil entering air dry bulb temperature [$\degree F$]

$$\dot{V}_C = \dot{V}_{iC} + \dot{V}_{eC}$$

Cold deck air volume flow rate [*ft³/min*]

$$\dot{V}_H = \dot{V}_{iH} + \dot{V}_{eH}$$

Hot deck air volume flow rate [*ft³/min*]

$$X_C = \frac{\dot{V}_C}{\dot{V}_i + \dot{V}_e} \qquad X_{iC} = \frac{\dot{V}_{iC}}{\dot{V}_C} \qquad X_{eC} = \frac{\dot{V}_{eC}}{\dot{V}_C}$$

Cold deck Air Flow Fraction Interior and exterior cooling coil air fractions

$$X_H = \frac{\dot{V}_H}{\dot{V}_i + \dot{V}_e} \qquad X_{iH} = \frac{\dot{V}_{iH}}{\dot{V}_H} \qquad X_{eH} = \frac{\dot{V}_{eH}}{\dot{V}_H}$$

Cold deck Air Flow Fraction
Interior and exterior cooling coil air
fractions

$$X_R = 1 - X_{OA}$$

Return air volumetric flow fraction

$$w'_R = \frac{X_C w_{CL} + X_H X_{OA} w_{OA} + \dfrac{q_{il} + q_{el}}{4840(\dot{V}_i + \dot{V}_e)}}{1 - X_H X_R}$$

"Wet coil" Return air humidity
ratio [lb_w/lb_a]

$$w'_{iR} = \frac{X_C w_{CL} + X_{iH} X_{OA} w_{OA} + \dfrac{q_{il}}{4840(\dot{V}_i)}}{1 - X_{iH} X_R}$$

"Wet coil" interior zone return air
humidity ratio [lb_w/lb_a]

$$w'_{eR} = \frac{X_C w_{CL} + X_{eH} X_{OA} w_{OA} + \dfrac{q_{el}}{4840(\dot{V}_e)}}{1 - X_{eH} X_R}$$

"Wet coil" exterior zone return air
humidity ratio [lb_w/lb_a]

$$w'_{ma} = X_R w'_R + X_{OA} w_{OA}$$

"Wet coil" mixed air humidity ratio
[lb_w/lb_a]

$$w''_R = w_{OA} + \frac{q_{il} + q_{el}}{4840 X_{OA}(\dot{V}_i + \dot{V}_e)}$$

"Dry coil" return air humidity ratio
[lb_w/lb_a]

$$w''_{ma} = X_R w''_R + X_{OA} w_{OA}$$

"Dry coil" mixed air humidity ratio
[lb_w/lb_a]

$$
\begin{aligned}
&if \ w'_{ma} < w_{CL} \qquad Otherwise \\
&w_R = w''_R \qquad\qquad w_R = w'_R \\
&w_{ma} = w''_{ma} \qquad\quad w_{ma} = w'_{ma}
\end{aligned}
$$

Actual return and actual mixed air
humidity ratios [lb_w/lb_a]

$$w_{CE} = w_{ma}$$

Cold deck entering air humidity
ratio [lb_w/lb_a]

$$q_{Cs} = 1.08 \dot{V}_C (T_{CE} - T_{CL})$$

Cooling coil sensible load [*Btu/hr*]

$$q_{Cl} = \begin{cases} 4840 \dot{V}_C (w_{CE} - w_{CL}) & w_{CE} > w_{CL} \\ 0 & \text{Otherwise} \end{cases}$$

Cooling coil latent load [*Btu/hr*]

$$q_{CT} = q_{Cs} + q_{Cl} \qquad \text{Cooling coil total load } [\,Btu/hr\,]$$

$$q_{HT} = 1.08\dot{V}_H(T_{HE} - T_{HL}) + q_{PH} \qquad \text{Heating coil total load } [\,Btu/hr\,]$$
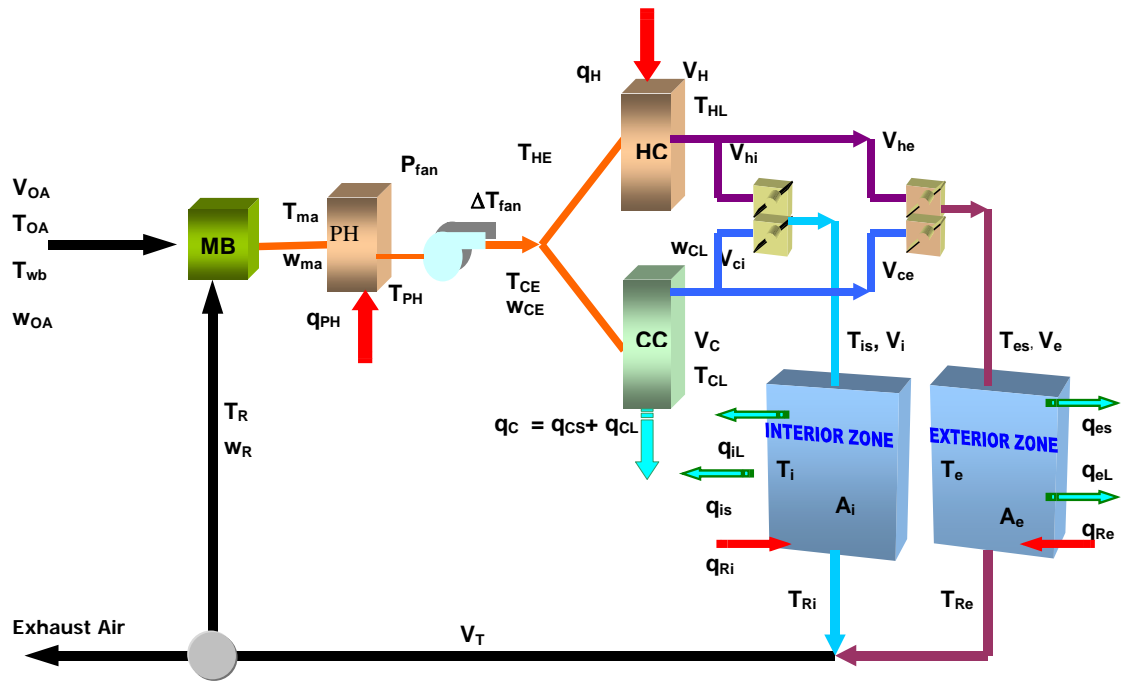
Figure D.2 Variable identification in a dual duct variable air volume system.

D.8   Simplified Analysis of a Dual Duct Constant Air Volume System
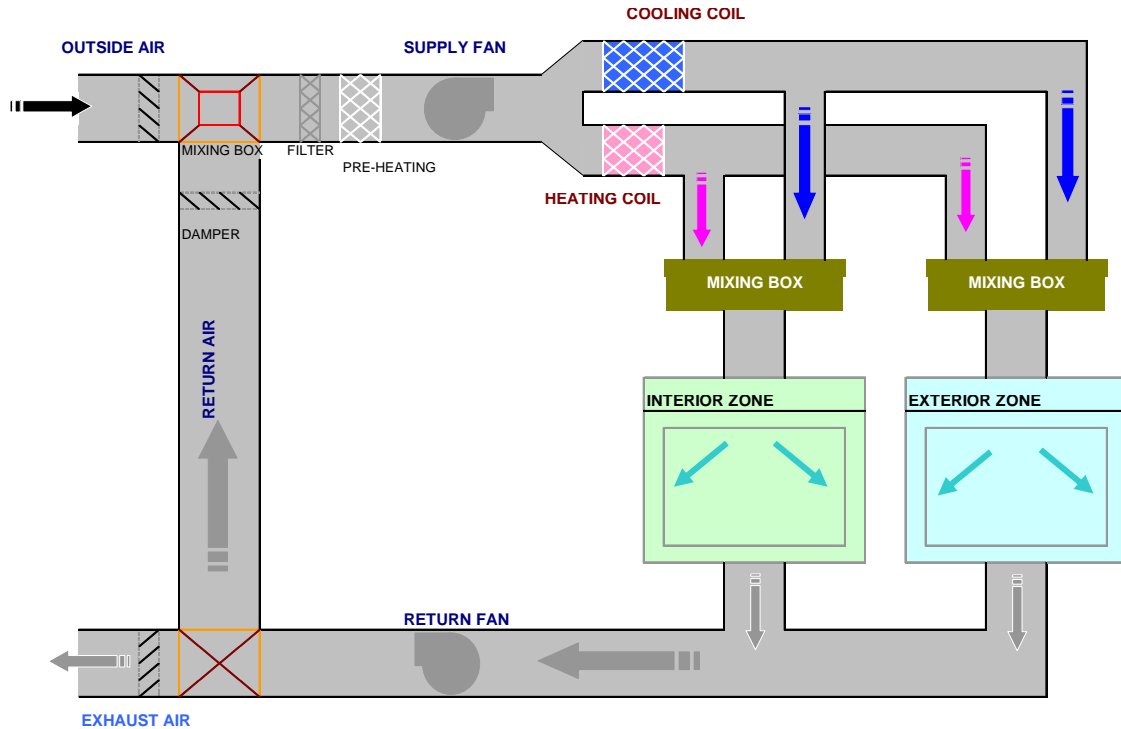
Figure D.3   Schematic Diagram of a Dual Duct Constant Air Volume System.

$$T_{is} = T_i - \frac{q_{is}}{1.08\dot{V}_i} \qquad T_{es} = T_e - \frac{q_{es}}{1.08\dot{V}_e}$$

Interior and exterior supply air temperatures [$°F$]

$$T_{iR} = T_i + \frac{q_{iR}}{1.08\dot{V}_i} \qquad T_{eR} = T_e + \frac{q_{eR}}{1.08\dot{V}_e}$$

Interior and exterior return air temperatures [$°F$]

$$T_R = \frac{\dot{V}_e T_{eR} + \dot{V}_i T_{iR}}{\dot{V}_i + \dot{V}_e}$$

Average return air temperature [$°F$]

$$X_{OA} = \frac{\dot{V}_{OA}}{\dot{V}_i + \dot{V}_e}$$

Outside air volume ratio

$$T_{ma} = T_R + X_{OA}(T_{OA} - T_R)$$

Mixed air temperature [$°F$]

$$If \quad T_{ma} < T_{CL} - \Delta T_{SF} \qquad Otherwise$$
$$T_{PH} = T_{CL} - T_{ma} \qquad T_{PH} = T_{ma}$$
$$q_{PH} = 1.08\dot{V}_{TD}(T_{CL} - T_{PH}) \qquad q_{PH} = 0$$

Preheat coil leaving air dry bulb temperature [$°F$]

Preheat coil load [Btu/hr]

$$T_{CE} = T_{PH} + \Delta T_{fan} \qquad T_{HE} = T_{PH} + \Delta T_{fan}$$

Cold and Hot deck entering temperatures [$°F$]

$$T_{HL} = \begin{cases} 85 & T_{OA} > 75 \\ 85 + (75 - T_{OA}) & 35 \le T_{OA} \le 75 \\ 125 & T_{OA} < 35 \end{cases}$$

Heating coil leaving air temperature

$$\dot{V}_{iC} = \dot{V}_i \left(\frac{T_{is} - T_{HL}}{T_{CL} - T_{HL}} \right)$$

Interior cold air volume flow rate [ft^3/min]

$$\dot{V}_{iH} = \dot{V}_i \left(\frac{T_{is} - T_{CL}}{T_{HL} - T_{CL}} \right)$$

Interior hot air volume flow rate [ft^3/min]

$$\dot{V}_{eC} = \dot{V}_e \left(\frac{T_{es} - T_{HL}}{T_{CL} - T_{HL}} \right)$$

Exterior cold air volume flow rate [ft^3/min]

$$\dot{V}_{eH} = \dot{V}_e \left(\frac{T_{es} - T_{CL}}{T_{HL} - T_{CL}} \right)$$

Exterior hot air volume flow rate [ft^3/min]

$$\dot{V}_C = \dot{V}_{iC} + \dot{V}_{eC}$$

Total flow through the cooling coil
$[ft^3/min]$

$$\dot{V}_H = \dot{V}_{iH} + \dot{V}_{eH}$$

Total flow through the heating coil
$[ft^3/min]$

$$X_R = 1 - X_{OA} \qquad X_C = \frac{\dot{V}_C}{\dot{V}_{TD}} \qquad X_H = \frac{\dot{V}_H}{\dot{V}_{TD}}$$

Return, Cold and Hot deck air volumetric flow fractions

$$w'_R = \frac{X_C w_{CL} + X_H X_{OA} w_{OA} + \dfrac{q_{il} + q_{el}}{4840(\dot{V}_i + \dot{V}_e)}}{1 - X_H X_R}$$

"Wet coil" Return air humidity ratio $[\ lb_w/lb_a\ ]$

$$w'_{ma} = X_R w'_R + X_{OA} w_{OA}$$

"Wet coil" mixed air humidity ratio $[\ lb_w/lb_a]$

$$w''_R = w_{OA} + \frac{q_{il} + q_{el}}{4840 X_{OA}(\dot{V}_i + \dot{V}_e)}$$

"Dry coil" return air humidity ratio $[\ lb_w/lb_a\ ]$

$$w''_{ma} = X_R w''_R + X_{OA} w_{OA}$$

"Dry coil" mixed air humidity ratio $[\ lb_w/lb_a]$

$$
\begin{array}{ll}
if \ \ w'_{ma} < w_{CL} & Otherwise \\
w_R = w''_R & w_R = w'_R \\
w_{ma} = w''_{ma} & w_{ma} = w'_{ma}
\end{array}
$$

Actual return and actual mixed air humidity ratios $[\ lb_w/lb_a\ ]$

$$w_{CE} = w_{ma}$$

Cold deck entering air humidity ratio $[\ lb_w/lb_a]$

$$q_{Cs} = 1.08 \dot{V}_C (T_{CE} - T_{CL})$$

Cooling coil sensible load $[\ Btu/hr\ ]$

$$q_{Cl} = \begin{cases} 4840\dot{V}_C(w_{CE} - w_{CL}) & w_{CE} > w_{CL} \\ 0 & \text{Otherwise} \end{cases}$$

Cooling coil latent load [*Btu/hr*]

$$q_{CT} = q_{Cs} + q_{Cl}$$

Cooling coil total load [*Btu/hr*]

$$q_H = 1.08\dot{V}_H(T_{HE} - T_{HL})$$

Heating coil load [*Btu/hr*]

D.9 Simplified Analysis of a Constant Volume Terminal Reheat System
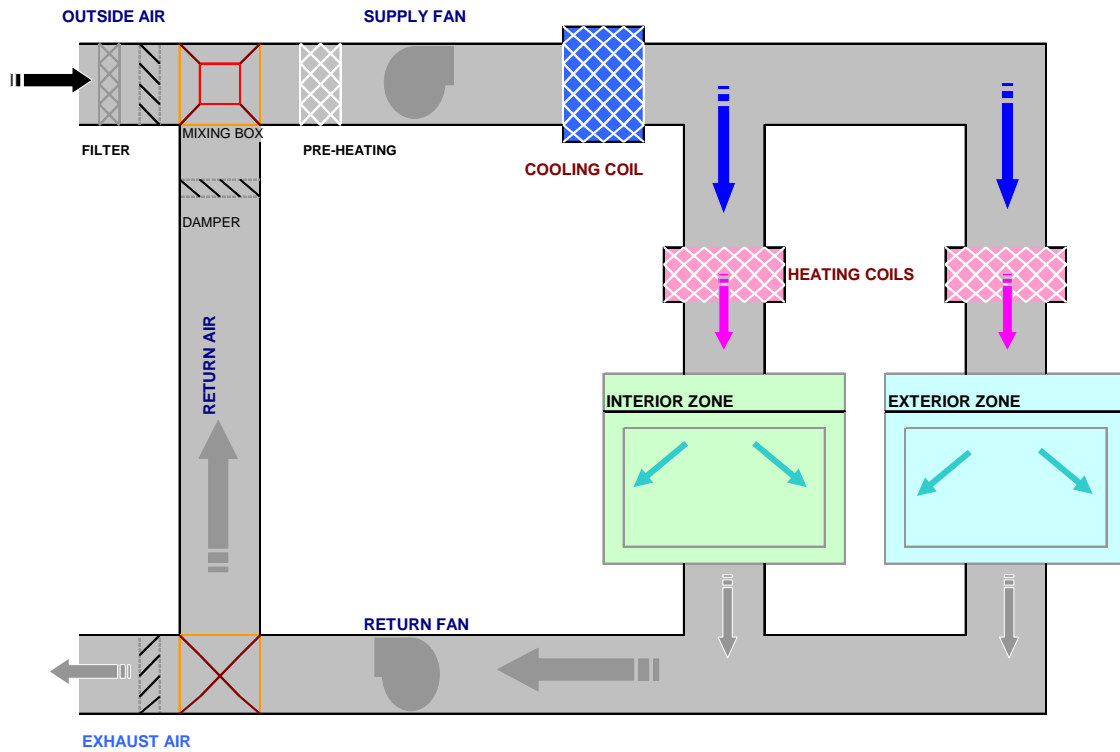
Figure D.4 Schematic Diagram of a Constant Volume Terminal Reheat System.

$$T_{CL} = T_{SA} - \Delta T_{SF}$$

Cooling coil leaving air dry bulb.
Assuming T_{SA} as if downstream of the fan

$$T_{is} = T_i - \frac{q_{is}}{1.08\dot{V_i}} \qquad T_{es} = T_e - \frac{q_{es}}{1.08\dot{V_e}}$$

Interior and exterior supply air
temperatures [$°F$]

$$q_{e,RH} = \max\left(0, \ 1.08V_e(T_{es} - T_{CL})\right)$$

Exterior zone reheat coil load [Btu/hr]

$$q_{i,RH} = \max\left(0,\ 1.08 V_i (T_{is} - T_{CL})\right)$$

Interior zone reheat coil load [*Btu/hr*]

$$T_{eR} = T_e + \frac{q_{eR}}{1.08\dot{V}_e} \qquad T_{iR} = T_i + \frac{q_{iR}}{1.08\dot{V}_i}$$

Zones return air temperatures [°F]

$$T_R = \frac{T_{iR}\dot{V}_i + T_{eR}\dot{V}_e + \dots}{\dot{V}_i + \dot{V}_e + \dots}$$

Average return air temperature [°F]

$$T_{ma} = T_R - X_{OA}(T_{OA} - T_R)$$

sans economizer
$$X_{OA} = X_{OA\min} \quad \text{—\textit{Minimum required}}$$
$$\textit{outside air fraction}$$
and
with economizer
$$X_{OA} = \max\left(X_{OA\min},\ \frac{T_{CL} - T_R}{T_{OA} - T_R} \right)$$

If $X_{OA} > 1$ then $X_{OA} = 1$

Mixed air temperature [°F]

if $\quad T_{ma} < T_{CL}$
$$q_{PH} = 1.08 V_{TD}(T_{CL} - T_{ma})$$
$$T_{PH} = T_{CL}$$
Otherwise
$$q_{PH} = 0$$
$$T_{PH} = T_{ma}$$

Preheat coil load [*Btu/hr*] and its temperature [°F]

$$T_{CE} = T_{PH}$$

Cooling coil entering temperature [°F]

$$q_{Cs} = 1.08 V_{TD}(T_{CE} - T_{CL})$$

Cooling coil sensible load [*Btu/hr*]

$$w'_R = w_{CL} + \frac{q_{il} + q_{el}}{4840 V_{TD}}$$

"Wet coil" return air humidity ratio
[lb_w/lb_a]

$$w'_{ma} = w'_R + X_{OA}(w_{OA} - w'_R)$$

"Wet coil" mixed air humidity ratio
[lb_w/lb_a]

$$w''_R = w_{OA} + \frac{q_{il} + q_{el}}{4840 X_{OA} V_{TD}}$$

"Dry bulb" return air humidity ratio
[lb_w/lb_a]

$$w''_{ma} = w''_R + X_{OA}(w_{OA} - w''_R)$$

"Dry bulb" mixed air humidity ratio
[lb_w/lb_a]

$$
\begin{array}{ll}
if \ w'_{ma} < w_{CL} & Otherwise \\
w_R = w''_R & w_R = w'_R \\
w_{ma} = w''_{ma} & w_{ma} = w'_{ma}
\end{array}
$$

Actual return and mixed air humidity
ratio [lb_w/lb_a]

$$w_{CE} = w_{ma}$$

Cold deck entering air humidity ratio
[lb_w/lb_a]

$$q_{Cl} = \begin{cases} 4840 V_{TD}(w_{CE} - w_{CL}) & w_{CE} > w_{CL} \\ 0 & \text{Otherwise} \end{cases}$$

Cooling coil latent load [*Btu/hr*]

$$q_H = q_{e,RH} + q_{i,RH}$$

Total heating load [*Btu/hr*]

$$q_C = q_{Cs} + q_{Cl}$$

Cooling total load [*Btu/hr*]

D.10 Simplified Analysis of a Single Duct Variable Air Volume System
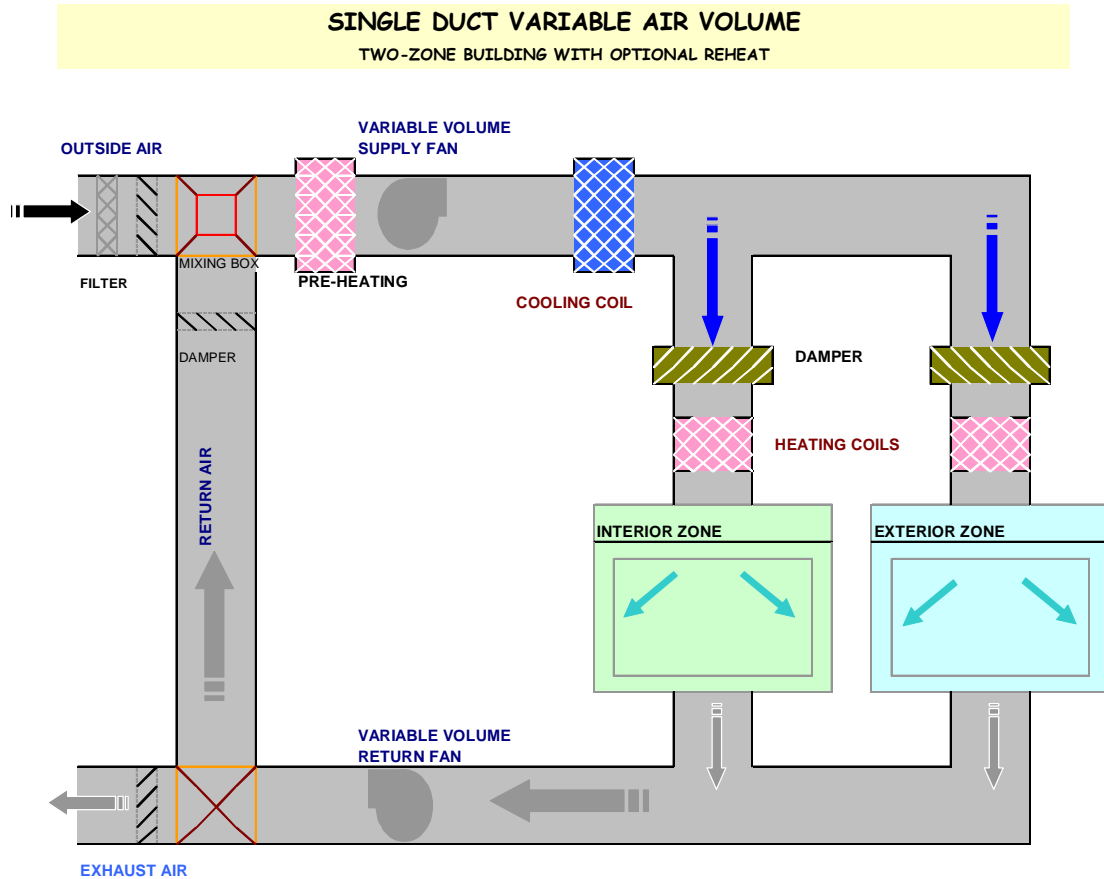
Figure D.5 Schematic Diagram of a Single Duct Variable Air Volume System.

$$T_{is} = T_{CL}$$

$$\dot{V}_i = \max\left\{\frac{q_{is}}{1.08(T_i - T_{is})}, \dot{V}_{i,\min}\right\}$$

Interior zone supply air dry bulb temperature [$°F$]

Interior zone air volume flow rates [ft^3/min]

$$T_{es} = T_{CL}$$

$$\dot{V}_e = \max\left\{\frac{q_{is}}{1.08(T_e - T_{es})}, \dot{V}_{e,\min}\right\}$$

Exterior zone supply air dry bulb temperature [$°F$]

Exterior zone air volume flow rates [ft^3/min]

$$\dot{V}_T = \dot{V}_i + \dot{V}_e \qquad \qquad \text{Supply total air volume flow rate } [ft^3/min]$$

$$T_{eR} = T_e + \frac{q_{eR}}{1.08\dot{V}_e} \qquad T_{iR} = T_i + \frac{q_{iR}}{1.08\dot{V}_i} \qquad \qquad \text{Zone return air temperatures } [\,^\circ F\,]$$

$$T_R = \frac{T_{iR}\dot{V}_i + T_{eR}\dot{V}_e + \cdots}{\dot{V}_i + \dot{V}_e + \cdots} \qquad \qquad \text{Average return air temperature } [\,^\circ F\,]$$

$$T_{ma} = T_R - X_{OA}(T_{OA} - T_R)$$

sans economizer

$$X_{OA} = X_{OA\min}$$

  Minimum required outside air fraction

$$\qquad = V_{OA\min}/V_T \qquad \qquad \text{Mixed air temperature } [\,^\circ F\,]$$

and

with economizer

$$X_{OA} = \max\left(X_{OA\min}, \frac{T_{CL} - T_R}{T_{OA} - T_R} \right)$$

$$PLR = \frac{\dot{V}_i + \dot{V}_e}{\dot{V}_{TD}} \qquad \qquad \text{Part Load Ratio}$$

$$\frac{P_{fan}}{P_{fan-rated}} = \begin{cases} \text{Variable Speed Drive} \\ 0.00153 + 0.0052 PLR + 1.1086 PLR^2 - 0.1164 PLR^3 \\ \text{Inlet Vanes Control} \\ 0.351 + 0.308 PLR - 0.541 PLR^2 + 0.872 PLR^3 \\ \text{Outlet Dampers} \\ 0.371 + 0.973 PLR - 0.342 PLR^2 \end{cases} \qquad \begin{array}{c} \text{Power use due to} \\ \text{different possibilities of} \\ \text{Variable Speed} \\ \text{Mechanism} \end{array}$$

$$\Delta T_{SF} = \frac{P_{fan}}{1.08(\dot{V}_i + \dot{V}_e)}$$

Supply air fan temperature rise [$°F$]

If $T_{ma} < T_{CL} - \Delta T_{SF}$ *Otherwise*

$T_{PH} = T_{CL} - \Delta T_{SF}$ $T_{PH} = T_{ma}$

$q_{PH} = 1.08(\dot{V}_i + \dot{V}_e)(T_{CL} - T_{PH})$ $q_{PH} = 0$

Preheat coil leaving air dry bulb temperature [$°F$]

Preheat coil load [Btu/hr]

$$T_{CE} = T_{PH} + \Delta T_{SF}$$

Cooling coil entering air dry bulb temperature [$°F$]

$$q_{Cs} = 1.08\dot{V}_T(T_{CE} - T_{CL})$$

Cooling coil total sensible load [Btu/hr]

$$q_{iH} = \max\{1.08V_i(T_{is} - T_{SA}),0\}$$

Interior sensible heating load [Btu/hr]

$$q_{eH} = \max\{1.08V_e(T_{es} - T_{SA}),0\}$$

Exterior sensible heating load [Btu/hr]

$$w'_R = w_{CL} + \frac{q_{il} + q_{el}}{4840\dot{V}_T}$$

"Wet coil" return air humidity ratio [lb_w/lb_a]

$$w'_{ma} = w'_R + X_{OA}(w_{OA} - w'_R)$$

"Wet coil" mixed air humidity ratio [lb_w/lb_a]

$$w_R'' = w_{OA} + \frac{q_{il} + q_{el}}{4840 X_{OA} \dot{V}_{TD}}$$

"Dry bulb" return air humidity ratio $[lb_w/lb_a\ ]$

$$w_{ma}'' = w_R'' + X_{OA}(w_{OA} - w_R'')$$

"Dry bulb" mixed air humidity ratio $[lb_w/lb_a\ ]$

$$\begin{array}{ll} if\ \ w_{ma}' < w_{CL} & Otherwise \\ w_R = w_R'' & w_R = w_R' \\ w_{ma} = w_{ma}'' & w_{ma} = w_{ma}' \end{array}$$

Actual return and mixed air humidity ratio $[lb_w/lb_a\ ]$

$$w_{CE} = w_{ma}$$

Cold deck entering air humidity ratio $[lb_w/lb_a]$

$$q_{Cl} = \begin{cases} 4840 \dot{V}_T (w_{CE} - w_{CL}) & w_{CE} > w_{CL} \\ 0 & \text{Otherwise} \end{cases}$$

Cooling coil latent load $[Btu/hr]$

$$q_H = q_{eH} + q_{iH}$$

Total heating load $[Btu/hr]$

$$q_C = q_{Cs} + q_{Cl}$$

Total cooling load $[Btu/hr]$

D.11 Thermodynamic Properties of Moist Air

To determine the saturation humidity ratio of moist air it is necessary to know the water vapor saturation pressure. The most commonly used relations were developed by Hyland and Wexler (ASHRAE 2001), and are based on the thermodynamic temperature scale. This ideal scale differs slightly from practical temperature scales used for physical measurements. The saturation pressure over ice and over liquid water is given by

$$\ln(p_{ws}) = \begin{cases} C_1/T + C_2 + C_3T + C_4T^2 + C_5T^3 + C_6T^4 + C_7\ln T & -148°F < T < 32°F \\[2ex] C_8/T + C_9 + C_{10}T + C_{11}T^2 + C_{12}T^3 + C_{13}\ln T & 32°F < T < 392°F \end{cases}$$

where

$$C_1 = -1.0214165 \ \text{E}+04 \qquad C_8 = -1.0440397 \ \text{E}+04$$
$$C_2 = -4.8932428 \ \text{E}+00 \qquad C_9 = -1.1294650 \ \text{E}+01$$
$$C_3 = -5.3765794 \ \text{E}-03 \qquad C_{10} = -2.7022355 \ \text{E}-02$$
$$C_4 = 1.9202377 \ \text{E}-07 \qquad C_{11} = 1.2890360 \ \text{E}-05$$
$$C_5 = 3.5575832 \ \text{E}-10 \qquad C_{12} = -2.4780681 \ \text{E}-09$$
$$C_6 = -9.0344688 \ \text{E}-14 \qquad C_{13} = 6.5459673 \ \text{E}+00$$
$$C_7 = 4.1635019 \ \text{E}+00$$

In addition, p_{ws} is the saturation pressure (in psia) and T represents the absolute temperature, (in °R, which is equivalent to °F + 459.67).

Humidity ratio w of a given moist air sample is defined as the ratio of the mass of water vapor to the mass of dry air contained in the sample. Its expression for the outside air, based on the approximate perfect gas relation, is

$$w_{oa} = \frac{(1093 - 0.556t_{wb})w_s^* - 0.24(t_{db} - t_{wb})}{1093 + 0.444t_{db} - t_{wb}}$$

where the outside air dry-bulb (t_{db}) and wet-bulb (t_{wb}) temperatures are in °F.

The term $w_s{}^*$ is the humidity ratio corresponding to the saturation at temperature t*, so when moist air is considered a mixture of independent perfect gases (i.e., dry air and water vapor), each is assumed to obey the law of perfect gasses, and in a constant pressure process it can be expressed as:

$$w_s^* = \frac{0.62198\,p_{ws}}{p - p_{ws}}$$

where the term p_{ws} represents the saturation pressure of water vapor in the absence of air at the given temperature t. This pressure p_{ws} is a function only of temperature and differs slightly from the vapor pressure of water in saturated moist air.

D.12   Simulation Methodology of the HVAC Systems

As shown above, the solution of the air-side analysis of HVAC systems is primarily an exercise in mass and energy balances on moist air. The psychrometric relationships are well known and a general approach to system analysis follows these steps:

a. Obtain zone loads and temperatures.
b. Compute cooling coil leaving air dry bulb temperature based on control strategy implemented.
c. Compute heating coil leaving air dry bulb temperature based on control strategy implemented.
d. For constant volume systems, determine the zone's supply air temperature.
e. For variable volume systems, determine the zone's supply air volumetric rate.
   - If zone sensible load is positive, then compute air volume for cooling coil, each zone. Else, compute air volume for heating coil, each zone.
   - If air volume is lower than the specified "minimum" air flow rate, set the air volume to that minimum value.
f. Total zone air volumetric flow: air volume through the cooling and heating coil.
g. Compute air entering and leaving conditions of each zone. Return and mixed temperatures and humidity ratios.

h. Compute heating and cooling loads, both sensible and latent.

Table D.1 Nomenclature for Simplified Engineering Energy Analysis of the HVAC Systems.

Symbols	Variable	Unit
ΔT_{SF}	Supply air fan temperature rise	$°F$
q_{Cl}	Cooling coil latent load	Btu/hr
q_{Cs}	Cooling coil sensible load	Btu/hr
q_{CT}	Cooling coil total load	Btu/hr
q_{el}	Exterior zone latent load	Btu/hr
q_{eR}	Exterior zone return air heat gain	Btu/hr
q_{es}	Exterior zone sensible load	Btu/hr
q_{HT}	Heating coil total load	Btu/hr
q_{il}	Interior zone latent load	Btu/hr
q_{iR}	Interior zone return air heat gain	Btu/hr
q_{is}	Interior zone sensible load	Btu/hr
q_{PH}	Preheat coil load	Btu/hr
T_{CE}	Cooling coil entering air dry bulb temperature	$°F$
T_{CL}	Cooling coil leaving air dry bulb temperature	$°F$
T_e	Exterior zone design air dry bulb temperature	$°F$
T_{eR}	Exterior zone return air dry bulb temperature	$°F$
T_{es}	Exterior zone supply air dry bulb temperature	$°F$
T_{HE}	Heating coil entering air dry bulb temperature	$°F$
T_{HL}	Heating coil leaving air dry bulb temperature	$°F$
T_i	Interior zone design air dry bulb temperature	$°F$
T_{iR}	Interior zone return air dry bulb temperature	$°F$
T_{is}	Interior zone supply air dry bulb temperature	$°F$
T_{ma}	Mixed air dry bulb temperature	$°F$
T_{OA}	Outside air dry bulb temperature	$°F$
T_{PH}	Preheat coil leaving air dry bulb temperature	$°F$
T_R	Return air dry bulb temperature	$°F$
$\dot{V}_C$	Cold deck air volume	ft^3/min
$\dot{V}_e$	Exterior zone supply air volume	ft^3/min
$\dot{V}_{eC}$	Exterior zone cold air volume	ft^3/min
$\dot{V}_{eH}$	Exterior zone hot air volume	ft^3/min
$\dot{V}_H$	Hot deck air volume	ft^3/min
$\dot{V}_i$	Interior zone supply air volume	ft^3/min
$\dot{V}_{iC}$	Interior zone cold air volume	ft^3/min
$\dot{V}_{iH}$	Interior zone hot air volume	ft^3/min

Symbols	Variable	Unit
$\dot{V}_{OA}$	Outside air volume	ft^3/min
$\dot{V}_{R}$	Return air volume	ft^3/min
$\dot{V}_{T}$	Total air volume	ft^3/min
w_{CE}	Cooling coil entering air humidity ratio	lb_w/lb_a
w_{CL}	Cooling coil leaving air humidity ratio	lb_w/lb_a
w_{eR}	Exterior zone return air humidity ratio	lb_w/lb_a
w_{es}	Exterior zone supply air humidity ratio	lb_w/lb_a
w_{HE}	Heating coil entering air humidity ratio	lb_w/lb_a
w_{HL}	Heating coil leaving air humidity ratio	lb_w/lb_a
w_{iR}	Interior zone return air humidity ratio	lb_w/lb_a
w_{is}	Interior zone supply air humidity ratio	lb_w/lb_a
w_{ma}	Mixed air humidity ratio	lb_w/lb_a
w_{OA}	Outside air humidity ratio	lb_w/lb_a
w_{R}	Return air humidity ratio	lb_w/lb_a
X_{C}	Cold deck air volume ratio = V_C / V_T	Dimensionless
X_{eC}	Exterior zone cold air volume ratio = V_{eC} / V_e	Dimensionless
X_{eH}	Exterior zone hot air volume ratio = V_{eH} / V_e	Dimensionless
X_{H}	Hot Deck air volume ratio = V_H/V_T	Dimensionless
X_{iC}	Interior zone cold air volume ratio = V_{iC} / V_i	Dimensionless
X_{iH}	Interior zone hot air volume ratio = V_{iH} / V_i	Dimensionless
X_{OA}	Outside air volume ratio = V_{OA} / V_T	Dimensionless
X_{OAmin}	Minimum required outside air volume ratio = $V_{OA\,min} / V_{TD}$	Dimensionless
X_{R}	Return air volume ratio = V_R / V_T	Dimensionless

APPENDIX E

SUBROUTINES TO SIMULATE THE HVAC SYSTEMS AND TO PERFORM
THE AUTOMATED CALIBRATION AND DETERMINATE POTENTIAL
SAVINGS

This appendix includes the main subroutines used for the simulation of each of the HVAC systems being analyzed in this thesis. The appendix also contains subroutines that are utilized for the minimization methodology of the RMSE applied to fulfill a calibration process – Simulated Annealing Minimization. The same methodology is employed to determine potential savings in a facility, so the functions developed for this end are also listed. Specific functions were developed to evaluate the comfort zone and the thermodynamic properties of air, which are fundamental for the evaluation of thermodynamic states of different HVAC systems.

The subroutines are written in *Microsoft$^®$ Visual Basic for Applications* which is used through *Microsoft Excel$^®$* as an interface. The advantages of using this language and interface are the flexibility to promptly observe the results in a friendly manner and graphically analyze the variables performance, though some penalty in speed might exist.

The subroutines are integrated according to their end. Thus, there are auxiliary subroutines, which were used for evaluation of properties, to delimit the comfort zone, and others just for purposes of tracking variables or providing preliminary results such as the printing subroutines. Important subroutines are those related to the performance of the HVAC systems; there is one subroutine per system. Other important subroutines are the Simulated Annealing routine that presents the optimization procedure for the autocalibration and for the determination of the potential savings (see Table E.1).

The required input datasets, for different synthetic data with/without white noise (WN), have been managed through arrays; their format is indicated in the subroutines that have been implemented as shown in the last subroutines of this appendix. Some of the samples are presented graphically in the appendix F.

Table E.1 Subroutines and functions for the minimization procedure and for the potential savings determination.

Modules	Description or Comment
Subroutines	
SimAnn()	Simulated Annealing minimization procedure
dataDDCVwn1_2()	Data sets of the original or modified data sets
SA05()	Control subroutine to generate the tests
bin_sort()	Generate the bins from the daily (or even hourly) data to be utilized in the potential savings evaluation
BINDATA()	Bin data used for the evaluation of the potential savings
cntrl_0()	Mesh generator to evaluate the HVAC system function on all points that belong to a mesh with equidistant spacing between each variable that belongs to the multidimensional mesh points
Auxiliary Subroutines	
Print_0(), Print_0f(), Print_Ff(), Print_F(), Print_1f(), PrintVec_f(), PrintVec2_f()	Partial or final printing subroutines
Functions	
RMSE_ddvav(), RMSE_sdvav(), RMSE_cvrh(), RMSE_ddcv()	Compound function for the evaluation of the RMSE through the simplified energy analysis for a HVAC system (DDVAV, CVRH, or DDCV) and actual data sets
C_ddvav(), C_cvrh(), C_ddcv()	Function employed to evaluate the total energy use (cooling and heating) in a HVAC system (DDVAV, CVRH, or DDCV) inside the comfort zone utilized for the potential savings determination
ww(), wsat()	Actual and saturated air humidity ratio function
cz(), cz60()	Comfort zone definition from ASHRAE and other as a function just of the air temperature and limited to a RH of 60%
Auxiliary Functions	
FNC()	Generic objective function in the Simulated Annealing minimization procedure
MaxJC(A, B), MinJC(A, B)	Maximum and Minimum auxiliary in the minimization procedure
gt()	Conditional function "greater than" with two outputs
FP()	Positive function: positive when parameter >0,Otherwise =0
ExpJC()	Exponential function used in the Simulate Annealing minimization procedure

```
Option Explicit
Dim Tamb(200), RH_(200), Qc_(200), Qh_(200), MCC_(200), WBE_(200) As Double
Dim x(100), xL(100), xU(100), c(100), yL(100), yU(100)
Dim xOPT(100), VM(100), FSTAR(100), zN, nCASE, cj, ll$, Cp_ddvav, p_ddvav
Dim Q, Min_OPT As Boolean
Dim contar


Sub SimAnn(x(), N, Min_OPT, Neps, Ns, Nt, MaxEvl, T, eps, RT)
Dim F
Dim NACC, NOBDS, NFCNEV, IER, i, NUP, NREJ, NNEW, NDOWN, LNOBDS, m, j, h, estm, KK As
Integer
Dim NACP(100), FOPT, xp(100), FP, P, PP, RAT
Randomize
    Print_0f x(), N, "Variables", FNC(x()), "Function=", 6
NACC = 0          'Number of Accepted function evaluations
NOBDS = 0         'Total Number of Trial Function Evaluations out of bounds of LB and UB
NFCNEV = 0        'Total Number of Function Evaluations
IER = 99
For i = 1 To N
    xOPT(i) = x(i)
    NACP(i) = 0
Next i
For i = 1 To Neps
    FSTAR(i) = 1E+20
Next i
F = FNC(x())
If (Min_OPT) Then F = -F
NFCNEV = NFCNEV + 1
FOPT = F
START:
    NUP = 0
    NREJ = 0
    NNEW = 0
    NDOWN = 0
    LNOBDS = 0
    For m = 1 To Nt
        For j = 1 To Ns
            For h = 1 To N
                For i = 1 To N
                    If (i = h) Then
                        xp(i) = x(i) + (Rnd() * 2 - 1) * VM(i)
                    Else
                        xp(i) = x(i)
                    End If
                    If ((xp(i) < xL(i)) Or (xp(i) > xU(i))) Then
                        xp(i) = xL(i) + (xU(i) - xL(i)) * Rnd()
                        LNOBDS = LNOBDS + 1
                        NOBDS = NOBDS + 1
                    End If
                Next i
                FP = FNC(xp())
                If (Min_OPT) Then FP = -FP
                NFCNEV = NFCNEV + 1
                If (NFCNEV > MaxEvl) Then
                    If (Min_OPT) Then FOPT = -FOPT
                    IER = 1
                    Print_1f xp(), N, 6
                    Exit Sub
                End If
                If (FP > F) Then
                    For i = 1 To N
                        x(i) = xp(i)
                    Next i
                    F = FP
                    NACC = NACC + 1
                    NACP(h) = NACP(h) + 1
```

```
                                NUP = NUP + 1
                        If (FP > FOPT) Then
                            For i = 1 To N
                                xOPT(i) = xp(i)
                            Next i
                            FOPT = FP
                            NNEW = NNEW + 1
                        End If
                    Else
                        P = ExpJC((FP - F) / T)
                        PP = Rnd()
                        If (PP < P) Then
                            For i = 1 To N
                                x(i) = xp(i)
                            Next i
                            F = FP
                            NACC = NACC + 1
                            NACP(h) = NACP(h) + 1
                            NDOWN = NDOWN + 1
                        Else
                            NREJ = NREJ + 1
                        End If
                    End If
                    If (Int((NFCNEV - 1) / 5000) = (NFCNEV - 1) / 5000) Then
                    End If
            Next h
        Next j
        For i = 1 To N
            RAT = ((NACP(i)) / ((Ns)))
            If (RAT > 0.6) Then
                VM(i) = VM(i) * (1 + c(i) * (RAT - 0.6) / 0.4)
            ElseIf (RAT < 0.4) Then
                    VM(i) = VM(i) / (1 + c(i) * (0.4 - RAT) / 0.4)
            End If
            If (VM(i) > (xU(i) - xL(i))) Then
                VM(i) = (xU(i) - xL(i))
            End If
        Next i
        For i = 1 To N
            NACP(i) = 0
        Next i
Next m
Print #6, NFCNEV, F, FSTAR(1), Format(Time(), "HH:MM:SS")
PrintVec2_f xOPT(), N, "Partial Solution", 6
FSTAR(1) = F
Q = False
If ((FOPT - FSTAR(1)) < eps) Then Q = True

For i = 1 To Neps
    If (Abs(F - FSTAR(i)) > eps) Then Q = False
Next i

If (Q) Then
    For i = 1 To N
        x(i) = xOPT(i)
    Next i
    IER = 0
    If (Min_OPT) Then FOPT = -FOPT
    Print_Ff x(), N, F, FOPT, 6
    Exit Sub
End If

T = RT * T
For i = Neps To 2 Step -1
    FSTAR(i) = FSTAR(i - 1)
Next i
F = FOPT
```

```vb
    For i = 1 To N
        x(i) = xOPT(i)
    Next i
estm = estm + 1
GoTo START
End Sub


Sub SA05()
Dim NV, Ns_, Neps_, Nt_, MaxEvl_, i As Integer
Dim eps_, RT_, T_ As Double
Dim time1, A, sss$
Dim y(100), y0(100) As Variant
Randomize
nCASE = nCASE + 1
sss$ = "ANN_" + Format(nCASE) + ll$ + "_VAV"
Open sss$ For Output As 6
time1 = Time()
    Min_OPT = True
    NV = 5
    Ns_ = 20
    eps_ = 0.000000001
    RT_ = 0.8
    Nt_ = 100
    MaxEvl_ = 100000000
    Neps_ = 4
    For i = 1 To NV
            xL(i) = -1
            xU(i) = 1
            c(i) = 2#
            VM(i) = 1#
    Next i
yL(1) = 65#:    yU(1) = 85#:    y(1) = yL(1) + Rnd * (yU(1) - yL(1)):    y0(1) = 75#
yL(2) = 45:     yU(2) = 80:     y(2) = yL(2) + Rnd * (yU(2) - yL(2)):    y0(2) = 55.15
yL(3) = -3:     yU(3) = 3:      y(3) = yL(3) + Rnd * (yU(3) - yL(3)):    y0(3) = 1#
yL(4) = 0.01:   yU(4) = 1:      y(4) = yL(4) + Rnd * (yU(4) - yL(4)):    y0(4) = 0.45
yL(5) = 0.01:   yU(5) = 1:      y(5) = yL(5) + Rnd * (yU(5) - yL(5)):    y0(5) = 0.15
yL(6) = 500:    yU(6) = 10000:  y(6) = yL(6) + Rnd * (yU(6) - yL(6)):    y0(6) = 3000
yL(7) = 1000:   yU(7) = 100000: y(7) = yL(7) + Rnd * (yU(7) - yL(7)):    y0(7) = 40000
    For i = 1 To NV                          'Normalization of the Variables
            y(i) = (2 * y(i) - yU(i) - yL(i)) / (yU(i) - yL(i))
    Next i
    Print_0 y(), NV, "Variables", FNC(y()), "Function="
    PrintVec_f yL(), NV, "Lower Boundaries", 6
    PrintVec_f yU(), NV, "Upper Boundaries", 6
    PrintVec_f c(), NV, "Controls", 6
    PrintVec_f VM(), NV, "Initial Step Length", 6
    If FNC(y()) <= eps_ Then
        Print_F y(), NV, FNC(y()), FNC(y())
        Exit Sub
    End If
    T_ = 5
    zN = 0
    SimAnn y(), NV, Min_OPT, Neps_, Ns_, Nt_, MaxEvl_, T_, eps_, RT_
    Print #6, Format(Time() - time1, "HH:MM:SS")
    PrintVec_f xOPT(), NV, "Solution", 6
    PrintVec_f VM(), NV, "Final Step Lenght", 6
    PrintVec2_f xOPT(), NV, "Solution", 6
Close 6
End Sub


Function RMSE_ddvav(y(), Optional z)
  Dim RHb, Pt, TCLb As Double
  Dim Ti, Te, TCL, CFM_FT2, DTH, SA, OA, NuPer, UA, At, Ae, Ai As Double
  Dim VTD, Voa, Vemin, Vimin As Double
  Dim sum0, sum0_1, sum1, sum2, sum1_1, sum2_2 As Double
```

```
   Dim fel, WCL, Toa, RH, Pfan_MCC, WBE, Woa As Double
   Dim THL, qes, qis, qel, qil, Tis, Tes, Vci, Vce, Vhi, Vhe, Ve, Vi, Vc, Vh As Double
   Dim Tis1, Tes1, Vci1, Vce1, Vhi1, Vhe1, RVe, RVi As Double
   Dim qlights, TR, TRi, TRe, Tma, DTfan, TPH, qPH, TCE, THE As Double
   Dim Xoa, Xc, Xh, XR As Double
   Dim WR, Wma, WCE  As Double
   Dim qcs, qcl, qc, qh As Double
   Dim i, j, j0, j2, h0, h9 As Integer
   Dim Mean_qc, Mean_qh, MBE_qc, MBE_qh, NMBE_qc, NMBE_qh, RMSE_qc, RMSE_qh, CV_RMSE_qc,
CV_RMSE_qh

         If IsMissing(z) Then z = 2
         If z = 1 Then data5
'--------------------------------------------------------------------------------
         'x(1)    x(2)    x(3)          x(4)    x(5)    x(6)    x(7)
         '75.00   55.15   1.00    1.00   0.45    0.15    3,000   40,000
'--------------------------------------------------------------------------------
         Ti = y(1): Te = y(1):                       TCL = y(2)
         DTH = y(3):
         CFM_FT2 = 1#
         SA = y(4):                                  OA = y(5)
         UA = y(6)
'--------------------------------------------------------------------------------
         RHb = 90:            Pt = 14.696:            TCLb = 55.15
         At = 230000:         Ae = At * (0.34):       Ai = At * (0.66)
         VTD = CFM_FT2 * At:            Voa = OA * VTD
         qil = (105) * NuPer * (0.66):   qel = (105) * NuPer * (0.34)
         Vemin = SA * Ae:              Vimin = SA * Ai
         sum0 = 0:     sum0_1 = 0:     sum1 = 0
         sum2 = 0:     sum1_1 = 0:     sum2_2 = 0
         fel = 3.4129 * 1000
         WCL = ww(TCL, RHb, Pt)
                For j = 1 To 187
                  j0 = j0 + 1
                  Toa = Tamb(j):                      RH = RH_(j)
                  Pfan_MCC = MCC_(j) / 24 * fel:     WBE = WBE_(j) / 24 * fel
                  Woa = ww(Toa, RH, Pt)
                  If Toa < 35 Then
                      THL = 125
                  ElseIf Toa > 75 Then
                      THL = 85
                  Else
                      THL = 85 + (75 - Toa) '+ DTH
                  End If
                  qes = UA * (Toa - Te) + 245 * NuPer * 0.34
                  qis = 245 * NuPer * 0.66
                  If qis > 0 Then
                      Tis = TCL
                  Else
                      Tis = THL
                  End If
                  If qes > 0 Then
                      Tes = TCL
                  Else
                      Tes = THL
                  End If
                  If qis > 0 Then
                      Vci = qis / (1.08 * (Ti - Tis))
                  Else
                      Vci = 0
                  End If
                  If qis <= 0 Then
                      Vhi = qis / (1.08 * (Ti - Tis))
                  Else
                      Vhi = 0
                  End If
                  If qes > 0 Then
```

```
    Vce = qes / (1.08 * (Te - Tes))
Else
    Vce = 0
End If
If qes <= 0 Then
    Vhe = qes / (1.08 * (Te - Tes))
Else
    Vhe = 0
End If
If Vimin >= (Vci + Vhi) Then
    Vi = Vimin
Else
    Vi = Vci + Vhi
End If
Tis1 = Ti - qis / (1.08 * Vimin)

If Vemin >= (Vce + Vhe) Then
    Ve = Vemin
Else
    Ve = Vce + Vhe
End If
Tes1 = Te - qes / (1.08 * Vemin)
Vci1 = Vimin * (Tis1 - THL) / (TCL - THL)
Vhi1 = Vimin * (Tis1 - TCL) / (THL - TCL)
Vce1 = Vemin * (Tes1 - THL) / (TCL - THL)
Vhe1 = Vemin * (Tes1 - TCL) / (THL - TCL)
If Vimin < (Vci + Vhi) Then
    RVi = 0
Else
    RVi = 1
End If
If Vemin < (Vce + Vhe) Then
    RVe = 0
Else
    RVe = 1
End If
If RVi = 0 Then
    Tis = Tis
Else
    Tis = Tis1
End If
If RVe = 0 Then
    Tes = Tes
Else
    Tes = Tes1
End If
If RVi = 0 Then
    Vci = Vci
Else
    Vci = Vci1
End If
If RVi = 0 Then
    Vhi = Vhi
Else
    Vhi = Vhi1
End If
If RVe = 0 Then
    Vce = Vce
Else
    Vce = Vce1
End If
If RVe = 0 Then
    Vhe = Vhe
Else
    Vhe = Vhe1
End If
Vi = Vci + Vhi
```

```
                            Ve = Vce + Vhe
                            qlights = WBE - Pfan_MCC
                            TRi = Ti + qlights * 0.66 / (1.08 * Vi)
                            TRe = Te + qlights * 0.34 / (1.08 * Ve)
                            TR = (TRe * Ve + TRi * Vi) / (Ve + Vi)
                            Xoa = Voa / (Ve + Vi)
                            Tma = TR + Xoa * (Toa - TR)
                            DTfan = Pfan_MCC / (1.08 * (Ve + Vi))
                            If (Tma < (TCL - DTfan)) Then
                                TPH = TCL - Tma
                                qPH = 1.08 * (Ve + Vi) * (TCL - TPH)
                            Else
                                TPH = Tma
                                qPH = 0
                            End If
                            TCE = DTfan + TPH
                            THE = TCE
                            Vc = Vci + Vce
                            Vh = Vhi + Vhe
                            Xc = Vc / (Ve + Vi)
                            Xh = Vh / (Ve + Vi)
                            XR = 1 - Xoa
                            WR = ((Xc * WCL) + (Xoa * Xh * Woa)
                            + ((qil + qel) / (4840 * (Ve + Vi)))) / (1 - (Xh * XR))
                            Wma = (XR * WR) + (Xoa * Woa)
                            WCE = Wma
                            qcs = 1.08 * Vc * (TCE - TCL)
                            If WCE <= WCL Then
                                qcl = 0
                            Else
                                qcl = 4840 * Vc * (WCE - WCL)
                            End If
                            qc = (qcs + qcl) / 1000000
                            qh = Abs(-1.08 * Vh * (THE - THL) / 1000000)
                            If z = 1 Then
                                    Qc_(j) = qc
                                    Qh_(j) = qh
                            Else
                                    sum0 = sum0 + Qc_(j)
                                    sum0_1 = sum0_1 + Qh_(j)
                                    sum1 = -(qc - Qc_(j)) + sum1
                                    sum2 = ((qc - Qc_(j)) ^ 2) + sum2
                                    sum1_1 = -(qh - Qh_(j)) + sum1_1
                                    sum2_2 = ((qh - Qh_(j)) ^ 2) + sum2_2
                            End If
                        Next j
                        If z = 1 Then Exit Function
                    j2 = j0
                    If j0 > 1 Then j2 = j0 - 1
                    Mean_qc = sum0 / j0
                    Mean_qh = sum0_1 / j0
                    MBE_qc = sum1 / j2
                    MBE_qh = sum1_1 / j2
                    NMBE_qc = MBE_qc / Mean_qc
                    NMBE_qh = MBE_qh / Mean_qh
                    RMSE_qc = Sqr(sum2 / j2)
                    RMSE_qh = Sqr(sum2_2 / j2)
                    CV_RMSE_qc = RMSE_qc / Mean_qc
                    CV_RMSE_qh = RMSE_qh / Mean_qh
                    RMSE_ddvav = RMSE_qh + RMSE_qc
End Function


Function RMSE_cvrh(y(), Optional z)
  Dim k0(500), k1(500)
  Dim j, j0, j2 As Integer
  Dim RHb, Pt, Yi, Ye As Double
```

```
    Dim CFM_FT2, Ti, Te, TCL, OA, Xoa, NuPer, UA, At, Ae, Ai    As Double
    Dim VTD, Voa, Ve, Vi As Double
    Dim sum0, sum0_1, sum1, sum2, sum1_1, sum2_2 As Double
    Dim fel, Toa, RH, RHi  As Double
    Dim qel, qil, qes, qis  As Double
    Dim Ts, Tis, Tes, Tma As Double
    Dim WCL, Woa, WRp, WRbp, Wmap, Wmabp, WR, Wma, WCE   As Double
    Dim qCLs, qCLl, qRH, qeRH, qiRH, qCLtot, qtot, qtc, qth, qc, qh  As Double
    Dim Mean_qc, Mean_qh, MBE_qc, MBE_qh, NMBE_qc, NMBE_qh As Double
    Dim RMSE_qc, RMSE_qh, CV_RMSE_qc, CV_RMSE_qh As Double
      If IsMissing(z) Then z = 2
      If z = 1 Then dataCVRHwn1
    '----------------------------------------------------------------------------
     RHb = 90:              Pt = 14.696
     Yi = (2 / 3):          Ye = (1 / 3):       CFM_FT2 = 1#
     Ti = y(1):             Te = y(1)
     TCL = y(2):            Xoa = y(3)
     NuPer = y(4):          UA = y(5)
     At = 230000:           Ai = At * Yi:       Ae = At * Ye
     VTD = CFM_FT2 * At:    Voa = Xoa * VTD
     Ve = CFM_FT2 * Ae:     Vi = CFM_FT2 * Ai
     qil = (105) * NuPer * Yi:                  qel = (105) * NuPer * Ye
     qis = 245 * NuPer * Yi
     fel = 3.4129 * 1000
     WCL = ww(TCL, RHb, Pt)
For j = 1 To 187
     j0 = j0 + 1
     Toa = Tamb(j):        RH = RH_(j)
     Woa = ww(Toa, RH, Pt)
     qes = UA * (Toa - Te) + 245 * NuPer * Ye
     Ts = TCL
     Tis = Ti - qis / (1.08 * Vi)
     Tes = Te - qes / (1.08 * Ve)
     qeRH = MaxJC(0, 1.08 * Ve * (Tes - Ts))
     qiRH = MaxJC(0, 1.08 * Vi * (Tis - Ts))
     Tma = Te + Xoa * (Toa - Te)
     qCLs = 1.08 * VTD * (Tma - TCL)
     WRp = WCL + (qel + qil) / (4840 * VTD)
     Wmap = WRp + Xoa * (Woa - WRp)
     WRbp = Woa + (qel + qil) / (Xoa * 4840 * VTD)
     Wmabp = WRbp + Xoa * (Woa - WRbp)
     WR = MinJC(WRbp, WRp)
     Wma = MinJC(Wmap, Wmabp)
     WCE = Wma
     If (WCE > WCL) Then
         qCLl = 4840 * VTD * (WCE - WCL)
     Else
         qCLl = 0
     End If
     qRH = (qiRH + qeRH) / 1000000
     qCLtot = (qCLl + qCLs) / 1000000
     qtot = qRH + qCLtot
     RHi = WR / ww(Ti, 100, Pt)
     If (qes < 0) Then
         qtc = qis
     Else
         qtc = qis + qes
     End If
     If (qes < 0) Then
         qth = -qes
     Else
         qth = 0
     End If
     qc = qCLtot
     qh = qRH
       If z = 1 Then
               Qc_(j) = qc
```

```
                Qh_(j) = qh
        Else
                sum0 = sum0 + Qc_(j)
                sum0_1 = sum0_1 + Qh_(j)
                sum1 = -(qc - Qc_(j)) + sum1
                sum2 = ((qc - Qc_(j)) ^ 2) + sum2
                sum1_1 = -(qh - Qh_(j)) + sum1_1
                sum2_2 = ((qh - Qh_(j)) ^ 2) + sum2_2
        End If
Next j
  If z = 1 Then Exit Function
        j2 = j0 - 1
        Mean_qc = sum0 / j0
        Mean_qh = sum0_1 / j0
        MBE_qc = sum1 / j2
        MBE_qh = sum1_1 / j2
        NMBE_qc = MBE_qc / Mean_qc
        NMBE_qh = MBE_qh / Mean_qh
        RMSE_qc = Sqr(sum2 / j2)
        RMSE_qh = Sqr(sum2_2 / j2)
        CV_RMSE_qc = RMSE_qc / Mean_qc
        CV_RMSE_qh = RMSE_qh / Mean_qh
        RMSE_cvrh = RMSE_qc + RMSE_qh
End Function


Function RMSE_ddcv(y(), Optional z)
  Dim RHb, Pt, TCLb As Double
  Dim Ti, Te, TCL, CFM_FT2, DTH, OA, NuPer, UA, At, Ae, Ai, Yi, Ye As Double
  Dim sum0, sum0_1, sum1, sum2, sum1_1, sum2_2 As Double
  Dim fel, WCL, Toa, RH, Pfan_MCC, WBE, qLight_i, qLight_e  As Double
  Dim qel, qil, Ve, Vi, qes, qis, Tis, Tes, Vci, Vce, Vhi, Vhe, Vc, Vh, VTD, Voa, VT As
Double
  Dim Tir, Ter, TR, Tma, DTfan, TPH, qPH, TCE, THE, THL As Double
  Dim Xoa, Xc, Xh, XR, Woa, WR, Wma, WCE As Double
  Dim qcs, qcl, qc, qh As Double
  Dim i, j, j0, j2, i0 As Integer
  Dim Mean_qc, Mean_qh, MBE_qc, MBE_qh, NMBE_qc, NMBE_qh, RMSE_qc, RMSE_qh, CV_RMSE_qc,
CV_RMSE_qh
    If IsMissing(z) Then z = 2
    If z = 1 Then data
      Ti = y(1): Te = y(1):                          TCL = y(2)
      DTH = y(3):                                    OA = y(4)
      NuPer = y(5):                                  UA = y(6)
      CFM_FT2 = 1#:            Yi = 2# / 3#:              Ye = 1# / 3#
      RHb = 90:               Pt = 14.696:          TCLb = 55.15
      At = 230000:            Ae = At * (Ye):       Ai = At * (Yi)
      VTD = CFM_FT2 * At:     Voa = OA * VTD
      qil = (105) * NuPer * Yi:     qel = (105) * NuPer * Ye
      Ve = CFM_FT2 * Ae:      Vi = CFM_FT2 * Ai
      fel = 3.4129 * 1000
      WCL = ww(TCL, RHb, Pt)
      For j = 1 To 187
        j0 = j0 + 1
        Toa = Tamb(j):                     RH = RH_(j)
        Pfan_MCC = MCC_(j) / 24 * fel:     WBE = WBE_(j) / 24 * fel
    qLight_i = Int((WBE - Pfan_MCC) * Yi + 0.5):    qLight_e = Int((WBE - Pfan_MCC) *
Ye + 0.5)
        Woa = ww(Toa, RH, Pt)
        qes = UA * (Toa - Te) + 245 * NuPer * Ye
        qis = 245 * NuPer * Yi
        Tis = Ti - qis / (1.08 * Vi)
        Tes = Te - qes / (1.08 * Ve)
        Tir = Ti + qLight_i / (1.08 * Vi)
        Ter = Te + qLight_e / (1.08 * Ve)
        TR = (Tir * Vi + Ter * Ve) / (Vi + Ve)
        Xoa = OA
```

```
        Tma = Xoa * Toa + (1 - Xoa) * TR
        DTfan = Pfan_MCC / (1.08 * VTD)
        If Tma < (TCL - DTfan) Then
            qPH = 1.08 * VTD * DTfan
            TPH = TCL + DTfan
        Else
            qPH = 0
            TPH = Tma
        End If
        TCE = Tma + DTfan
        THE = TCE
        If Toa < 35 Then          'Hot Deck Schedule ~~~~~~~~~~~~~~~~~
            THL = 125 + DTH
        ElseIf Toa > 75 Then
            THL = 85 + DTH
        Else
            THL = 85 + (75 - Toa) + DTH
        End If
        Vhi = Vi * (Tis - TCL) / (THL - TCL)
        Vci = Vi - Vhi
        Vhe = Ve * (Tes - TCL) / (THL - TCL)
        Vce = Ve - Vhe
        Vh = Vhi + Vhe
        Vc = Vci + Vce
        VT = Vh + Vc
        qcs = 1.08 * Vc * (TCE - TCL)
        Xc = Vc / VTD
        Xh = Vh / VTD
        XR = 1 - Xoa
        WR = ((Xc * WCL) + (Xoa * Xh * Woa) + ((qil + qel) / (4840 * (VTD)))) / (1 - (Xh
* XR))
        Wma = (XR * WR) + (Xoa * Woa)
        WCE = Wma
        If WCE <= WCL Then
            qcl = 0
        Else
            qcl = 4840 * Vc * (WCE - WCL)
        End If
        qc = (qcs + qcl) / 1000000
        qh = Abs(-1.08 * Vh * (THE - THL) / 1000000)
      If z = 1 Then
              Qc_(j) = qc
              Qh_(j) = qh
        Else
              sum0 = sum0 + Qc_(j)
              sum0_1 = sum0_1 + Qh_(j)
              sum1 = -(qc - Qc_(j)) + sum1
              sum2 = ((qc - Qc_(j)) ^ 2) + sum2
              sum1_1 = -(qh - Qh_(j)) + sum1_1
              sum2_2 = ((qh - Qh_(j)) ^ 2) + sum2_2
        End If
    Next j
    If z = 1 Then Exit Function
    j2 = j0
    If j0 > 1 Then j2 = j0 - 1
    Mean_qc = sum0 / j0
    Mean_qh = sum0_1 / j0
    MBE_qc = sum1 / j2
    MBE_qh = sum1_1 / j2
    NMBE_qc = MBE_qc / Mean_qc
    NMBE_qh = MBE_qh / Mean_qh
    RMSE_qc = Sqr(sum2 / j2)
    RMSE_qh = Sqr(sum2_2 / j2)
    CV_RMSE_qc = RMSE_qc / Mean_qc
    CV_RMSE_qh = RMSE_qh / Mean_qh
    RMSE_ddcv = RMSE_qh + RMSE_qc
End Function
```

```
Function RMSE_ sdvav(y(), Optional z)
  Dim RHb, Pt, TCLb As Double
  Dim Ti, Te, TCL, CFM_FT2, DTH, OA, NuPer, UA, At, Ae, Ai, Yi, Ye As Double
  Dim fel, WCL, Toa, RH, Pfan_MCC, WBE, qLight_i, qLight_e  As Double
  Dim qel, qil, Ve, Vi, qes, qis, Tis, Tes, Vci, Vce, Vhi, Vhe, Vc, Vh, VTD, Voa, Vt As
Double
  Dim Tir, Ter, TR, Tma, DTfan, TPH, qPH, TCE, THE, THL As Double
  Dim Xoa, Xc, Xh, XR, Woa, WR, Wma, WCE As Double
  Dim qcs, qcl, qc, qh As Double
  Dim i, j, j0, j2, i0 As Integer
  Dim sum0, sum0_1, sum1, sum2, sum1_1, sum2_2 As Double
  Dim Mean_qc, Mean_qh, MBE_qc, MBE_qh, NMBE_qc, NMBE_qh, RMSE_qc, RMSE_qh, CV_RMSE_qc,
CV_RMSE_qh
  Dim VFD, fe, fi, SA, Yoa, Pe, Pi, Vemin, Vimin, fc, qLights, veo, vio, vip, vep, vtot
  Dim TPHL, TPHE, qCLtot, qRHTOT As Double
  Dim qCLs, qCLl, qiRH, qeRH, f As Double
  Dim WRp, WRpp, Wmap, Wmapp, RMSE_sdvav_ As Double
    If IsMissing(z) Then z = 2
    If z = 1 Then data
  '-----------------------------------------------------------------------------------
    Ti = y(1): Te = y(1):                           TCL = y(2)
    OA = y(3):                                        SA = y(4)
    NuPer = y(5):                                     UA = y(6)
  '-----------------------------------------------------------------------------------
At = 230000                                                              '[sf]
Total Area
VFD = 1                               '[cfm/sf]
fi = 0.66:   fe = 0.34                            'Interior and exterior area fractions
Pi = 0.66:   Pe = 0.34                            'Interior and exterior area fractions
Yoa = 0.15
        RHb = 90:        Pt = 14.696
        Ae = At * Pe
        Ai = At * Pi
        VTD = CFM_FT2 * At:     Vemin = SA * Ae:    Vimin = SA * Ai:    Voa = Yoa * VTD
        qil = (105) * NuPer * Pi
        qel = (105) * NuPer * Pe
        fel = 3.4129 * 1000
        'qlights = 2.5 * 230 * fel
         sum0 = 0:    sum0_1 = 0:    sum1 = 0
         sum2 = 0:    sum1_1 = 0:    sum2_2 = 0
For j = 1 To 187
j0 = j0 + 1
Toa = Tamb(j):                        RH = RH_(j)
Pfan_MCC = MCC_(j) / 24 * fel:       WBE = WBE_(j) / 24 * fel
qLights = (WBE - Pfan_MCC) '* fc
qLight_i = Int((WBE - Pfan_MCC) * fi + 0.5):    qLight_e = Int((WBE - Pfan_MCC) * fe +
0.5)
Woa = ww(Toa, RH, Pt)
fc = 3.4129 * 1000
Woa = ww(Toa, RH, Pt)
WCL = ww(TCL, RHb, Pt)                            'Wet Coil Humidity Ratio (90%)
Ai = At * fi                              '[sf]
Ae = At * fe                              '[sf]
vio = Ai * VFD                            '[cfm]
veo = Ae * VFD                            '[cfm]
VTD = At * VFD                            '[cfm]          Supply air (1   cfm/sf)
'VTD = CFM_FT2 * At:      Vemin = SA * Ae:     Vimin = SA * Ai:    Voa = OA * VTD
qis = (245 * NuPer * fi) '+ (qLights * fi) '* 0.5
qil = ((105) * NuPer * fi)
qes = (UA * (Toa - Te)) + (245 * NuPer * fe) '+ qLights * fe '* 0.5
qel = ((105) * NuPer * fe)
vip = FP(qis) / (1.08 * (Ti - TCL))     'Air Flow from Cooling Coil for Interior Zone
Vi = MaxJC(vip, (SA * vio))                                       'Air Flow from
Cooling Coil for Interior Zone vep = FP(qes) / (1.08 * (Te - TCL))            'Air
Flow from Cooling Coil for Exterior Zone
```

```
Ve = MaxJC(vep, (SA * veo))                'Air Flow from Cooling Coil for Exterior Zone
vtot = Vi + Ve
'Actual Total Air Flow
Xoa = VTD * Yoa / vtot                           'Ventilation air fraction
Tis = Ti – qis / (1.08 * Vi)                     'Interior Zone Supply Temperature
Tes = Te – qes / (1.08 * Ve)                     'Exterior Zone Supply Temperature
Tir = Ti + qLight_i / (1.08 * Vi)
Ter = Te + qLight_e / (1.08 * Ve)
TR = (Tir * Vi + Ter * Ve) / (Vi + Ve)
Tma = TR + Xoa * (Toa – TR)                      'Mixed Air Temperature
TPHE = Tma                                       'Cooling Coil Entering Air Temperature
DTfan = Pfan_MCC / 24 / (1.08 * vtot)            'Increment Air Temperature by Fan
TPHL = gt((TCL – DTfan), TPHE, (TCL – DTfan), TPHE)     'Preheater Temperature
TCE = TPHL                                       'Cooling Coil Entering Air Temperature
qCLs = 1.08 * vtot * (TCE – (TCL – DTfan))       'Cooling Coil Sensible Load
qiRH = MaxJC(0, 1.08 * Vi * (Tis – (TCL – DTfan)))     'Interior Zone Reheat Coil Load
qeRH = MaxJC(0, 1.08 * Ve * (Tes – (TCL – DTfan)))     'Exterior Zone Reheat Coil Load
WRp = WCL + (qel + qil) / (4840 * vtot)          'Wet Coil Return Air Humidity Ratio
Wmap = WRp + Xoa * (Woa – WRp)                   'Wet Coil Mixed Air Humidity Ratio
'WRpp = Woa + (qel + qil) / (Xoa * 4840 * vtot)  '"Dry Coil" Return Air Humidity Ratio
'Wmapp = WRpp + Xoa * (Woa – WRpp)               '"Dry Coil" Mixed Air Humidity Ratio
'WR = gt(Wmap, WCL, WRp, WRpp)                   'Actual Return Air Humidity Ratio
[if(wma < wCL, wR', wR)]
'Wma = gt(Wmap, WCL, Wmap, Wmapp)                'Actual Mixed Air Humidity Ratio
[if(wma < wCL, wma', wma)]
WCE = Wmap                                       'Cooling Coil Entering Air Humidity Ratio
qCLl = 4840 * vtot * FP(WCE – WCL)               'Cooling Coil Latent Load
IF(wCE>wwet coil, 4840Vc(wCE – WCL),0)
qCLtot = qCLs + qCLl                             'Total Cooling Coil
qRHTOT = qeRH + qiRH + qPH                       'Total Reheat Coil Load
f = WR / Wsat(Te, Pt) * 100                      'Relative Humidity of Zones
qc = qCLs + qCLl                                 'Total Cooling Coil Load    –
qh = qeRH + qiRH + qPH                           'Total Reheat Coil Load
qc = qc / 1000000
qh = qh / 1000000
  If z = 1 Then
      Qc_(j) = qc
      Qh_(j) = qh
  Else
        sum0 = sum0 + Qc_(j)
        sum0_1 = sum0_1 + Qh_(j)
        sum1 = –(qc – Qc_(j)) + sum1
        sum2 = ((qc – Qc_(j)) ^ 2) + sum2
        sum1_1 = –(qh – Qh_(j)) + sum1_1
        sum2_2 = ((qh – Qh_(j)) ^ 2) + sum2_2
  End If
Next j
If z = 1 Then Exit Sub
        j2 = j0
        If j0 > 1 Then j2 = j0 – 1
        Mean_qc = sum0 / j0
        Mean_qh = sum0_1 / j0
        MBE_qc = sum1 / j2
        MBE_qh = sum1_1 / j2
        NMBE_qc = MBE_qc / Mean_qc
        NMBE_qh = MBE_qh / Mean_qh
        RMSE_qc = Sqr(sum2 / j2)
        RMSE_qh = Sqr(sum2_2 / j2)
        CV_RMSE_qc = RMSE_qc / Mean_qc
        CV_RMSE_qh = RMSE_qh / Mean_qh
        RMSE_sdvav_ = RMSE_qh + RMSE_qc
End Function
```

```
Function ww(Toa, RH, Pt) As Double
Dim c(20), Pw, T, Pwh, Wsat As Double
c(1) = -10214.165:          c(8) = -10440.39:
c(2) = -4.8932428:          c(9) = -11.29465:
c(3) = -0.0053765794:       c(10) = -0.027022355:
c(4) = 0.00000019202377:    c(11) = 0.00001289036:
c(5) = 3.5575832E-10:       c(12) = -0.000000002478068:
c(6) = -9.0344688E-14:      c(13) = 6.5459673
c(7) = 4.1635019

    T = Toa + 459.67
    If (Toa < 32) Then
        Pw = c(1) / T + c(2) + c(3) * T + c(4) * T ^ 2 + c(5) * T ^ 3 _
        + c(6) * T ^ 4 + c(7) * Log(T)
    Else
        Pw = c(8) / T + c(9) + c(10) * T + c(11) * T ^ 2 + c(12) * T ^ 3 _
        + c(13) * Log(T)
    End If
    Pw = Exp(Pw)
    Pwh = RH * Pw / 100
    Wsat = 0.62198 * Pw / (Pt - Pw)
    ww = 0.62198 * Pwh / (Pt - Pwh)
End Function


Function C_ddvav(y(), Optional z)
  Dim RHb, Pt, TCLb As Double
  Dim Ti, Te, TCL, CFM_FT2, DTH, SA, OA, NuPer, UA, At, Ae, Ai As Double
  Dim VTD, Voa, Vemin, Vimin As Double
  Dim sum0, sum0_1, sum1, sum2, sum1_1, sum2_2 As Double
  Dim fel, WCL, Toa, RH, Pfan_MCC, WBE, Woa As Double
  Dim THL, qes, qis, qel, qil, Tis, Tes, Vci, Vce, Vhi, Vhe, Ve, Vi, Vc, Vh As Double
  Dim Tis1, Tes1, Vci1, Vce1, Vhi1, Vhe1, RVe, RVi As Double
  Dim qlights, TR, TRi, TRe, Tma, DTfan, TPH, qPH, TCE, THE As Double
  Dim Xoa, Xc, Xh, XR As Double
  Dim WR, Wma, WCE  As Double
  Dim qcs, qcl, qc, qh As Double
  Dim i, j, j0, j2, h0, h9 As Integer
  Dim Mean_qc, Mean_qh, MBE_qc, MBE_qh, NMBE_qc, NMBE_qh, RMSE_qc, RMSE_qh, CV_RMSE_qc,
CV_RMSE_qh
  Dim cfzn, f_ddvav
        If IsMissing(z) Then z = 2
'--------------------------------------------------------------------------------
        'x(1)    x(2)    x(3)            x(4)    x(5)    x(6)    x(7)
        '75.00   55.15   1.00    1.00    0.45    0.15    3,000   40,000
'--------------------------------------------------------------------------------
            y(6) = 3000:  y(7) = 40000
            Ti = y(1): Te = y(1):                    TCL = y(2)
            DTH = y(3):
            CFM_FT2 = 1#
            SA = y(4):                               OA = y(5)
            NuPer = y(6):
            UA = y(7)
'--------------------------------------------------------------------------------
            RHb = 90:            Pt = 14.696:             TCLb = 55.15
            At = 230000:         Ae = At * (0.34):        Ai = At * (0.66)
            VTD = CFM_FT2 * At:           Voa = OA * VTD
            qil = (105) * NuPer * (0.66): qel = (105) * NuPer * (0.34)
            Vemin = SA * Ae:             Vimin = SA * Ai
            sum0 = 0:    sum0_1 = 0:    sum1 = 0
            sum2 = 0:    sum1_1 = 0:    sum2_2 = 0
            fel = 3.4129 * 1000
            WCL = ww(TCL, RHb, Pt)
                    j = cj
                    j0 = j0 + 1
                    Toa = Tamb(j):                   RH = RH_(j)
                    Pfan_MCC = MCC_(j) / 24 * fel:     WBE = WBE_(j) / 24 * fel
```

```
Woa = ww(Toa, RH, Pt)
If Toa < 35 Then
    THL = 125 + DTH
ElseIf Toa > 75 Then
    THL = 85 + DTH
Else
    THL = 85 + (75 - Toa) + DTH
End If
qes = UA * (Toa - Te) + 245 * NuPer * 0.34
qis = 245 * NuPer * 0.66
If qis > 0 Then
    Tis = TCL
Else
    Tis = THL
End If
If qes > 0 Then
    Tes = TCL
Else
    Tes = THL
End If
If qis > 0 Then
    Vci = qis / (1.08 * (Ti - Tis))
Else
    Vci = 0
End If
If qis <= 0 Then
    Vhi = qis / (1.08 * (Ti - Tis))
Else
    Vhi = 0
End If
If qes > 0 Then
    Vce = qes / (1.08 * (Te - Tes))
Else
    Vce = 0
End If
If qes <= 0 Then
    Vhe = qes / (1.08 * (Te - Tes))
Else
    Vhe = 0
End If
If Vimin >= (Vci + Vhi) Then
    Vi = Vimin
Else
    Vi = Vci + Vhi
End If
Tis1 = Ti - qis / (1.08 * Vimin)
If Vemin >= (Vce + Vhe) Then
    Ve = Vemin
Else
    Ve = Vce + Vhe
End If
Tes1 = Te - qes / (1.08 * Vemin)
Vci1 = Vimin * (Tis1 - THL) / (TCL - THL)
Vhi1 = Vimin * (Tis1 - TCL) / (THL - TCL)
Vce1 = Vemin * (Tes1 - THL) / (TCL - THL)
Vhe1 = Vemin * (Tes1 - TCL) / (THL - TCL)
If Vimin < (Vci + Vhi) Then
    RVi = 0
Else
    RVi = 1
End If
If Vemin < (Vce + Vhe) Then
    RVe = 0
Else
    RVe = 1
End If
If RVi = 0 Then
```

```
                                    Tis = Tis
                                Else
                                    Tis = Tis1
                                End If
                                If RVe = 0 Then
                                    Tes = Tes
                                Else
                                    Tes = Tes1
                                End If
                                If RVi = 0 Then
                                    Vci = Vci
                                Else
                                    Vci = Vci1
                                End If
                                If RVi = 0 Then
                                    Vhi = Vhi
                                Else
                                    Vhi = Vhi1
                                End If
                                If RVe = 0 Then
                                    Vce = Vce
                                Else
                                    Vce = Vce1
                                End If
                                If RVe = 0 Then
                                    Vhe = Vhe
                                Else
                                    Vhe = Vhe1
                                End If
                                Vi = Vci + Vhi
                                Ve = Vce + Vhe
                                qlights = WBE - Pfan_MCC
                                TRi = Ti + qlights * 0.66 / (1.08 * Vi)
                                TRe = Te + qlights * 0.34 / (1.08 * Ve)
                                TR = (TRe * Ve + TRi * Vi) / (Ve + Vi)
                                Xoa = Voa / (Ve + Vi)
                                Tma = TR + Xoa * (Toa - TR)
                                DTfan = Pfan_MCC / (1.08 * (Ve + Vi))
                                If (Tma < (TCL - DTfan)) Then
                                    TPH = TCL - DTfan
                                    qPH = 1.08 * (Ve + Vi) * (TCL - TPH)
                                Else
                                    TPH = Tma
                                    qPH = 0
                                End If
                                TCE = DTfan + TPH
                                THE = TCE
                                Vc = Vci + Vce
                                Vh = Vhi + Vhe
                                Xc = Vc / (Ve + Vi)
                                Xh = Vh / (Ve + Vi)
                                XR = 1 - Xoa
            WR = ((Xc * WCL) + (Xoa * Xh * Woa) + ((qil + qel) / (4840 * (Ve + Vi)))) / (1
- (Xh * XR))
                                Wma = (XR * WR) + (Xoa * Woa)
                                WCE = Wma
                                qcs = 1.08 * Vc * (TCE - TCL)
                                If WCE <= WCL Then
                                    qcl = 0
                                Else
                                    qcl = 4840 * Vc * (WCE - WCL)
                                End If
                                qc = (qcs + qcl) / 1000000
                                qh = Abs(-1.08 * Vh * (THE - THL) / 1000000)
                                  sum0 = sum0 + qc
                                  sum0_1 = sum0_1 + qh
                        Mean_qc = sum0 / j0
```

```
                    Mean_qh = sum0_1 / j0
                    cfzn = cz(Ti, WR)
                    f_ddvav = qc + qh
                    If cfzn = 1 And f_ddvav > 0 _
                        And Vci >= 0 And Vce >= 0 _
                        And Vhi >= 0 And Vhe >= 0 _
                        And Ve >= 0 And Vi >= 0 _
                        And Vc >= 0 And Vh >= 0 _
                        And Vci1 >= 0 And Vce1 >= 0 _
                        And Vhi1 >= 0 And Vhe1 >= 0 _
                        And RVe >= 0 And RVi >= 0 _
                        And Xoa >= 0 And Xc >= 0 And Xh >= 0 And XR >= 0 _
                        And Xoa <= 1 And Xc <= 1 And Xh <= 1 And XR <= 1 _
                        Then
                        C_ddvav = f_ddvav
                        contar = contar + 1
                    Else
                        C_ddvav = Abs(f_ddvav + 10) * 1000000
                    End If
End Function


Function cz(x, y)
    Dim u1, u2, u3, u4, v1, v2, v3, v4
    cz = 0
    If x < 68 Or x > 81 Then
        cz = 0
        Exit Function
    End If
    If y < 0.0045 Or y > 0.0136 Then
        cz = 0
        Exit Function
    End If
    u1 = 0# * x + 0.0045:            v1 = 0# * x + 0.0045
    u2 = -0.003 * x + 0.2325:        v2 = -0.003813829787234 * x + 0.313420212765957
    u3 = -0.00022695035461 * x + 0.027294326241135:     v3 = -0.000248226950355 * x +
0.031737588652482
    u4 = -0.00736170212766 * x + 0.512457446808511:     v4 = -0.009117021276596 * x +
0.679159574468085
    If (y >= u1 And y <= u2 And y <= u3 And y >= u4) Then
        cz = 1
        Exit Function
    End If
    If (y >= v1 And y <= v2 And y <= v3 And y >= v4) Then
        cz = 1
        Exit Function
    End If
End Function


Function cz60(x)
    cz60 = 0
    If x >= 0.0045 And x <= 1.11165877729753E-02 Then cz60 = 1
End Function


Function MaxJC(A, B)
    If A < B Then
        MaxJC = B
    Else
        MaxJC = A
    End If
End Function
```

```vb
Function MinJC(A, B)
    If A < B Then
        MinJC = A
    Else
        MinJC = B
    End If
End Function


Function ExpJC(R)
    If R > 174 Then
        ExpJC = 3.69E+75
    ElseIf R < -180 Then
        ExpJC = 0
    Else
        ExpJC = Exp(R)
    End If
End Function


Function FNC(z())
Dim i, NV, rz(100)
NV = 7
    For i = 1 To NV
            rz(i) = (z(i) * (yU(i) - yL(i)) + yU(i) + yL(i)) / 2
    Next i
    FNC = C_ddvav(rz())
End Function


Sub Print_0(z(), N, A$, F2, B$)
    Dim k, rz(100)
    Debug.Print A$
    For k = 1 To N
        rz(k) = (z(k) * (yU(k) - yL(k)) + yU(k) + yL(k)) / 2
        Debug.Print k, z(k), rz(k)
    Next k
    Debug.Print B$; F2
End Sub


Sub Print_0f(z(), N, A$, F2, B$, F1)
    Dim k, rz(100)
    Print #F1, A$
    For k = 1 To N
        rz(k) = (z(k) * (yU(k) - yL(k)) + yU(k) + yL(k)) / 2
        Print #F1, z(k), rz(k)
    Next k
    Print #F1, B$, F2
End Sub


Sub Print_Ff(z(), N, F1, F2, f3)
    Dim k
    Debug.Print "The Optimum was Found"
    For k = 1 To N
        Print #f3, k, z(k)
    Next k
    Print #f3, "Optimum Function= "; F1, F2
End Sub


Sub Print_F(z(), N, F1, F2)
    Dim k
    Debug.Print "The Optimum was Found"
    For k = 1 To N
        Debug.Print k, z(k)
```

```
    Next k
    Debug.Print "The funciton is "; F1, F2
End Sub


Sub Print_1f(z(), N, F1)
    Dim k
    Debug.Print "The Maximum Number of Function Evaluations was Reached"
    For k = 1 To N
        Print #F1, k, z(k)
    Next k
End Sub


Sub PrintVec_f(z(), N, A$, F1)
    Dim k
    Print #F1, A$
    For k = 1 To N
        Print #F1, k, z(k)
    Next k
End Sub


Sub PrintVec2_f(z(), N, A$, F1)
    Dim k, rz(100)
    Print #F1, A$
    For k = 1 To N
        rz(k) = (z(k) * (yU(k) - yL(k)) + yU(k) + yL(k)) / 2
        Print #F1, rz(k);
    Next k
    Print #F1,
End Sub


Function Wsat(Toa, Pt) As Double
'Dim c(20), pw, T, Pwh, Wsat As Double
Dim c(20), pw, T As Double
c(1) = -10214.165:         c(8) = -10440.39:
c(2) = -4.8932428:         c(9) = -11.29465:
c(3) = -0.0053765794:      c(10) = -0.027022355:
c(4) = 0.00000019202377:   c(11) = 0.00001289036:
c(5) = 3.5575832E-10:      c(12) = -0.000000002478068:
c(6) = -9.0344688E-14:     c(13) = 6.5459673
c(7) = 4.1635019

    T = Toa + 459.67
    If (Toa < 32) Then
        pw = c(1) / T + c(2) + c(3) * T + c(4) * T ^ 2 + c(5) * T ^ 3 _
        + c(6) * T ^ 4 + c(7) * Log(T)
    Else
        pw = c(8) / T + c(9) + c(10) * T + c(11) * T ^ 2 + c(12) * T ^ 3 _
        + c(13) * Log(T)
    End If
    pw = Exp(pw)
    Wsat = 0.62198 * pw / (Pt - pw)
End Function


Function gt(x, y, zp, zpp)
    If x > y Then
        gt = zp
    Else
        gt = zpp
    End If
End Function
```

```vb
Function FP(x) As Double
If x > 0 Then
    FP = x
Else
    FP = 0
End If
End Function


Sub Fddvav(At, Ti, Te, NuPer, UA, TCL, SA, OA, DTH, CFM_FT2, Toa, RH, Pe, Pi, MCC, WBE)
  Dim RHb, Pt As Double
  Dim Ae, Ai As Double
  Dim VTD, Voa, Vemin, Vimin As Double
  Dim fel, WCL, Pfan_MCC, WBEbtu, Woa As Double
  Dim THL, qes, qis, qel, qil, Tis, Tes, Vci, Vce, Vhi, Vhe, Ve, Vi, Vc, Vh As Double
  Dim qlights, TR, TRi, TRe, Tma, DTfan, TPH, qPH, TCE, THE As Double
  Dim Xoa, Xc, Xh, XR, qcs, qcl, qc, qh As Double
  Dim WR, Wma, WRi, WRe, WCE As Double
    RHb = 90:        Pt = 14.696
    Ae = At * Pe
    Ai = At * Pi
    VTD = CFM_FT2 * At:      Vemin = SA * Ae:     Vimin = SA * Ai:     Voa = OA * VTD
    WCL = ww(TCL, RHb, Pt): Woa = ww(Toa, RH, Pt)
            qil = (105) * NuPer * Pi
            qel = (105) * NuPer * Pe
            fel = 3.4129 * 1000
            'Pfan_MCC = MCC / 24 * fel:     WBEbtu = WBE / 24 * fel
            qlights = 2.5 * 230 * fel 'WBEbtu - Pfan_MCC
            If Toa < 35 Then
                THL = 125 + DTH
            ElseIf Toa > 75 Then
                THL = 85 + DTH
            Else
                THL = 85 + (75 - Toa) + DTH
            End If
            qes = UA * (Toa - Te) + 245 * NuPer * Pe + qlights * Pe * 0.5
            qis = 245 * NuPer * Pi + qlights * Pi * 0.5
                If (Ti - Tis) = 0 Or (Te - Tes) = 0 Or (THL - TCL) = 0 Then
                    GoTo next9
                End If
            If qis > 0 Then
                Tis = TCL
                Vci = qis / (1.08 * (Ti - Tis))
                Vhi = 0
            Else
                Tis = THL
                Vci = 0
                Vhi = qis / (1.08 * (Ti - Tis))
            End If
            If qes > 0 Then
                Tes = TCL
                Vce = qes / (1.08 * (Te - Tes))
                Vhe = 0
            Else
                Tes = THL
                Vce = 0
                Vhe = qes / (1.08 * (Te - Tes))
            End If
            If Vimin >= (Vci + Vhi) Then
                Vi = Vimin
                Tis = Ti - qis / (1.08 * Vimin)
                Vci = Vimin * (Tis - THL) / (TCL - THL)
                Vhi = Vimin * (Tis - TCL) / (THL - TCL)
            Else
                Vi = Vci + Vhi
            End If
            If Vemin >= (Vce + Vhe) Then
```

```
                        Ve = Vemin
                        Tes = Te - qes / (1.08 * Vemin)
                        Vce = Vemin * (Tes - THL) / (TCL - THL)
                        Vhe = Vemin * (Tes - TCL) / (THL - TCL)
                    Else
                        Ve = Vce + Vhe
                    End If
                    TRi = Ti
                    TRe = Te
                    TR = (TRe * Ve + TRi * Vi) / (Ve + Vi)
                    Xoa = Voa / (Ve + Vi)
                    Vc = Vci + Vce
                    Vh = Vhi + Vhe
                    N49 = Vc + Vh
                    F12 = CFM_FT2 * At
                    N97 = N49 / F12:   N99 = 4:    N100 = 0.7
                    N96 = 0.00153 + 0.0052 * (N97) + 1.1086 * (N97) ^ 2 - 0.1164 * (N97) ^ 3
                    Pfan_MCC = 0.000157 * F12 * N99 / N100 * 0.746 * 3.4129 * 1000 * N96
                    Tma = TR + Xoa * (Toa - TR)
                    DTfan = Pfan_MCC / (1.08 * (Ve + Vi))
                    If (Tma < (TCL - DTfan)) Then
                        TPH = TCL - DTfan
                        qPH = 1.08 * (Ve + Vi) * (TCL - TPH)
                    Else
                        TPH = Tma
                        qPH = 0
                    End If
                    TCE = DTfan + TPH
                    THE = TCE
                    Xc = Vc / (Ve + Vi)
                    Xh = Vh / (Ve + Vi)
                    XR = 1 - Xoa
                    Xci = Vci / (Vi)
                    Xhi = Vhi / (Vi)
                    Xce = Vce / (Ve)
                    Xhe = Vhe / (Ve)
WR = ((Xc * WCL) + (Xoa * Xh * Woa) + ((qil + qel) / (4840 * (Ve + Vi)))) / (1 - (Xh *
XR))
    WRi = ((Xci * WCL) + (Xoa * Xhi * Woa) + (Xhi * XR * WR) + ((qil) / (4840 * (Vi))))
    WRe = ((Xce * WCL) + (Xoa * Xhe * Woa) + (Xhe * XR * WR) + ((qel) / (4840 * (Ve))))
                    Wma = WR + Xoa * (Woa - WR)
                    If Wma < WCL Then
                       WR = Woa + (qil + qel) / (4840 * Xoa * (Ve + Vi))
                       WRi = WR:          WRe = WR
                       Wma = WR + Xoa * (Woa - WR)
                    End If
                    WCE = Wma
                    'icz = cz(Ti, WR): Iczi = cz(Ti, WRi): Icze = cz(Ti, WRe)
                    icz = cz60(WR): Iczi = cz60(WRi): Icze = cz60(WRe)
                    qcs = 1.08 * Vc * (TCE - TCL)
                    If WCE <= WCL Then
                        qcl = 0
                    Else
                        qcl = 4840 * Vc * (WCE - WCL)
                    End If
                    qc = (qcs + qcl) / 1000000
                    If THE < THL Then
                        qh = ((1.08 * Vh * (THL - THE)) + qPH) / 1000000
                    Else
                        qh = 0
                    End If
                  next9:
                  j2 = j2 + 1
    If icz = 1 And VFmax < (qh + qc + Pfan_MCC / 1000000) And qh >= 0 And qc >= 0
            Then VFmax = (qh + qc + Pfan_MCC / 1000000)
                  If (icz = 1) And (Vf > (qh + qc + Pfan_MCC / 1000000)) And _
                      (qh >= 0) And (qcl >= 0) And (qcs >= 0) And (qPH >= 0) And _
```

```
                           (THE >= 0) And (THL >= 0) And (THL > THE) And _
                           (Vce >= 0) And (Vci >= 0) And (Vhe >= 0) And (Vhi >= 0) _
                        Then
                           Vf = (qh + qc + Pfan_MCC / 1000000)
                           flag = flag + 1
                           TCL_ = TCL: DTH_ = DTH: SA_ = SA: OA_ = OA
                     End If
End Sub


Sub bin_sort()
'Program to evaluate the bin data for a multiple column data "nv"
  Dim c(100)
  Dim T(20000), RH(20000), WOA(20000)
  Dim Tb(100), RHb(100), WOAb(100)
  Dim Ts(100), RHs(100), WOAs(100)
  Dim V(10000, 10), VB(100, 10), VS(100, 10)
  Dim MnV(100, 20), MxV(100, 20)
     'The procedure assume that the bin is generated by the first column "pc"
        Range("G1").Select
        ActiveCell.FormulaR1C1 = "=COUNT(C[-5])"
        n = Cells(1, 7)
        Range("G1").ClearContents
        Range("A1").Select
        ActiveCell.FormulaR1C1 = "=MAX(C[1])"
        mx = Cells(1, 1)
        Range("A1").ClearContents
        Range("A1").Select
        ActiveCell.FormulaR1C1 = "=MIN(C[1])"
        mn = Cells(1, 1)
        Range("A1").ClearContents
     Li = Int(Int(mn) / 10) * 10           'Min Toa value
     Lf = (Int(Int(mx) / 10) + 1) * 10     'Max Toa Value
     m = 3                                  'bin interval
     nv = 6                                 'Number of Variables
     p = 3                                  'start row data
     pc = 2                                 'start column data
     For i = 1 To n
         For z = pc To nv + pc - 1
             V(i, z) = Cells(i + p - 1, z)
         Next z
     Next i
     k = 0
     For j = Li To Lf Step m
             k = k + 1
             For z = pc To nv + pc - 1
                   MxV(k, z) = -1E+20
                   MnV(k, z) = 1E+20
             Next z
             Ts(k) = 0
             For i = 1 To n
                 If V(i, pc) >= j And V(i, pc) < j + m Then
                         c(k) = c(k) + 1
                         Cells(k, nv + pc + 1) = c(k)
                         For z = pc To nv + pc - 1
                             VS(k, z) = V(i, z) + VS(k, z)
                             If V(i, z) > MxV(k, z) Then MxV(k, z) = V(i, z)
                             If V(i, z) < MnV(k, z) Then MnV(k, z) = V(i, z)
                         Next z
                 End If
             Next i
     Next j
     For u = 1 To Int((Lf - Li) / m)
         cs = c(u) + cs
         If c(u) = 0 Then c(u) = 1
         Cells(u, nv + pc + 2) = Li + m * (u - 1)
         Cells(u, nv + pc + 3) = Li + m * (u)
```

```
        For z = pc To nv + pc - 1
            VB(u, z) = VS(u, z) / c(u)
            Cells(u, nv + pc + z + 2) = VB(u, z)
        Next z
    Next u
    Cells(u + 1, nv + pc + 1) = cs
    pc1 = pc + 4                      'Varible whose minimum and maximum values  will be
printed
    For u = 1 To Int((Lf - Li) / m)
            Cells(u, nv + pc + z + 3) = MxV(u, pc1)
            If MxV(u, pc1) = -1E+20 Then Cells(u, nv + pc + z + 3) = "-"
            Cells(u, nv + pc + z + 4) = MnV(u, pc1)
            If MnV(u, pc1) = 1E+20 Then Cells(u, nv + pc + z + 4) = "-"
    Next u
End Sub


Dim flag As Integer
Dim TCL_, SA_, OA_, DTH_ As Double
Dim Tamb(20), RH_(20), MCC_(20), WBE_(20) As Double
Dim Vf, VFmax, j2 As Double

Sub cntrl_0()
    At = 230000
    Ti = 75
    Te = 75
    NuPer = 3000
    UA = 40000
    CFM_FT2 = 1
    Pe = 0.34
    Pi = 0.66
    TCL = 50
    SA = 0.265
    OA = 0.265
    DTH = 1
    Fmin = 20 * NuPer / (At * CFM_FT2)
    BINDATA
    For u = 1 To Numberofbins
    'If u = 8 Then u = 9
        Cells(1, 18) = u
      Toa = Tamb(u)
      RH = RH_(u)
      MCC = MCC_(u)
      WBE = WBE_(u)
      j2 = 0
      DTH1 = -30: DTH2 = 30
      TCL1 = 50: TCL2 = 60
      SA1 = 0.265: SA2 = 1
      OA1 = 0.265: OA2 = SA1
      j2 = 0
      nt2 = 0
      nt = Time
      VFmax = 1E-300
      Vf = 1E+230
      Vf_bck = Vf
      flag = 5
      For G = 1 To 10
        For Z = 1 To 11
            DTH = (DTH2 - (DTH1)) / 10 * (Z - 1) + (DTH1)
            For j = 1 To 11
                TCL = (TCL2 - TCL1) / 10 * (j - 1) + TCL1
                For k = 1 To 11
                    SA = (SA2 - SA1) / 10 * (k - 1) + SA1
                    OA2 = SA
                    For m = 1 To 11
                        OA = (OA2 - OA1) / 10 * (m - 1) + OA1
      Cells(2, 13) = OA: Cells(2, 14) = SA: Cells(2, 15) = TCL: Cells(2, 16) = DTH
```

```
        Fddvav At, Ti, Te, NuPer, UA, TCL, SA, OA, DTH, CFM_FT2, Toa, RH, Pe, Pi, MCC, WBE
                    Next m
                Next k
            Next j
        Next Z
        If Abs(Vf_bck - Vf) < 0.000001 Then Exit For
        Vf_bck = Vf
        DDTH = (DTH2 - DTH1)
        DTCL = (TCL2 - TCL1)
        DSA = (SA2 - SA1)
        DOA = (OA2 - OA1)
        If (DTH_ - 0.125 * DDTH) >= DTH1 Then DTH1 = (DTH_ - 0.125 * DDTH)
        If (DTH_ + 0.125 * DDTH) <= DTH2 Then DTH2 = (DTH_ + 0.125 * DDTH)
        If (TCL_ - 0.125 * DTCL) >= TCL1 Then TCL1 = (TCL_ - 0.125 * DTCL)
        If (TCL_ + 0.125 * DTCL) <= TCL2 Then TCL2 = (TCL_ + 0.125 * DTCL)
        If (SA_ - 0.125 * DSA) >= SA1 Then SA1 = (SA_ - 0.125 * DSA)
        If (SA_ + 0.125 * DSA) <= SA2 Then SA2 = (SA_ + 0.125 * DSA)
        If (OA_ - 0.125 * DOA) >= OA1 Then OA1 = (OA_ - 0.125 * DOA)
        OA2 = SA2
      Next G
    Next u
End Sub
```

```
Sub dataDDCVwn1_2()

Example of input dataset used in autocalibration: this case is for second data test with 1%WN for a DDCV system

Tamb( 1) = 31.09   RH_( 1) = 38.8790   Qc_( 1) = 3.1128164056890   Qh_( 1) = 2.4197327660598   MCC_( 1) = 4072.250   WBE_( 1) = 21932.694
Tamb( 2) = 38.36   RH_( 2) = 86.0235   Qc_( 2) = 2.9806195034210   Qh_( 2) = 2.2000188923166   MCC_( 2) = 4110.822   WBE_( 2) = 19090.339
Tamb( 3) = 38.38   RH_( 3) = 67.6989   Qc_( 3) = 3.1192762689745   Qh_( 3) = 2.1469569115454   MCC_( 3) = 4232.091   WBE_( 3) = 21232.753
Tamb( 4) = 38.47   RH_( 4) = 62.7497   Qc_( 4) = 3.1177479815245   Qh_( 4) = 2.1388600607021   MCC_( 4) = 4262.357   WBE_( 4) = 20947.199
Tamb( 5) = 39.09   RH_( 5) = 73.3387   Qc_( 5) = 3.2217754050394   Qh_( 5) = 2.0666887941261   MCC_( 5) = 3827.991   WBE_( 5) = 22011.690
Tamb( 6) = 40.40   RH_( 6) = 59.8618   Qc_( 6) = 3.0248358331834   Qh_( 6) = 2.0769044538847   MCC_( 6) = 3665.188   WBE_( 6) = 18731.449
Tamb( 7) = 41.20   RH_( 7) = 63.9871   Qc_( 7) = 3.4387972021310   Qh_( 7) = 1.7887640536147   MCC_( 7) = 4252.227   WBE_( 7) = 25036.379
Tamb( 8) = 41.38   RH_( 8) = 46.2687   Qc_( 8) = 3.2012931634509   Qh_( 8) = 1.9283924628869   MCC_( 8) = 4061.816   WBE_( 8) = 21329.195
Tamb( 9) = 41.41   RH_( 9) = 96.4272   Qc_( 9) = 3.2876849238060   Qh_( 9) = 1.8800899855486   MCC_( 9) = 4303.680   WBE_( 9) = 22475.806
Tamb(10) = 42.02   RH_(10) = 88.0308   Qc_(10) = 3.1375111980725   Qh_(10) = 1.9048914270921   MCC_(10) = 4145.070   WBE_(10) = 21237.274
Tamb(11) = 42.12   RH_(11) = 47.5895   Qc_(11) = 3.2019566112623   Qh_(11) = 1.9134619124993   MCC_(11) = 4060.172   WBE_(11) = 21331.701
  .              .              .                .                 .          .
  .              .              .                .                 .          .
  .              .              .                .                 .          .
  .              .              .                .                 .          .
  .              .              .                .                 .          .
Tamb(186) = 84.40  RH_(186) = 69.4664  Qc_(186)= 4.4844872089444   Qh_(186) = 0.5019561445824   MCC_(186) = 4084.929   WBE_(186) = 20218.995
Tamb(187) = 85.21  RH_(187) = 68.2187  Qc_(187)= 4.9512659137314   Qh_(187) = 0.7307230844246   MCC_(187) = 4403.062   WBE_(187) = 24491.890
End Sub
```

```vba
Sub BINDATA()

    Tamb( 1) = 31.085600        RH_( 1) = 38.879000        MCC_( 1) = 4072.2500        WBE_( 1) = 21932.6940
    Tamb( 2) = 38.575475        RH_( 2) = 72.452700        MCC_( 2) = 4108.3153        WBE_( 2) = 20820.4953
    Tamb( 3) = 42.684633        RH_( 3) = 70.077892        MCC_( 3) = 4117.1117        WBE_( 3) = 22106.3683
    Tamb( 4) = 47.258476        RH_( 4) = 65.774742        MCC_( 4) = 4158.1072        WBE_( 4) = 21835.2206
    Tamb( 5) = 52.334255        RH_( 5) = 64.486021        MCC_( 5) = 4159.8685        WBE_( 5) = 21455.9873
    Tamb( 6) = 57.352644        RH_( 6) = 65.618853        MCC_( 6) = 4168.9038        WBE_( 6) = 22428.0971
    Tamb( 7) = 62.016162        RH_( 7) = 63.900257        MCC_( 7) = 4186.1800        WBE_( 7) = 22566.4824
    Tamb( 8) = 67.130450        RH_( 8) = 71.298775        MCC_( 8) = 4169.1938        WBE_( 8) = 22468.2901
    Tamb( 9) = 72.803913        RH_( 9) = 69.310913        MCC_( 9) = 4389.2066        WBE_( 9) = 23389.6530
    Tamb(10) = 77.721300        RH_(10) = 67.845300        MCC_(10) = 4415.0450        WBE_(10) = 21634.7556
    Tamb(11) = 82.978325        RH_(11) = 69.533038        MCC_(11) = 4358.4571        WBE_(11) = 22467.7290
    Tamb(12) = 85.209700        RH_(12) = 68.218700        MCC_(12) = 4403.0620        WBE_(12) = 24491.8900

    ...                         ...                        ...                         ...
    ...                         ...                        ...                         ...
    ...                         ...                        ...                         ...

End Sub
```

APPENDIX F

SAMPLE DATA SETS UTILIZED IN THE AUTOMATED CALIBRATION TESTS

The data samples utilized in the automated calibration methodology are included in this appendix. The data sets contained in this appendix are the outside dry-bulb temperature, the relative humidity, the cooling and heating energy use loads generated through the compound functions that simulate the performance of different HVAC systems from the weather data sets, the whole-building electricity consumption, and the characteristics of the defined building prototype. Also herein, the representation of the modified synthetic energy use data sets, due to different white noise percentages added to the samples, are included for all the HVAC systems analyzed in this work.

F.1   Building Prototype

Although the conditions to fulfill the automated calibration or potential savings methodologies are generic, it is desirable to relate them to the physical characteristics of a real case. Thus, this research makes use, for the testing of the algorithms or methodologies, of the parameters of a building similar to the Zachry Engineering Center at Texas A&M University in College Station, Texas. This facility is a five level structure, erected in 1973 that serves office, classroom, laboratory and parking garage uses. There is approximately 264,000 sq. ft. of conditioned space and 66,000 sq. ft. of unconditioned space. The unconditioned space is used for a garage and is ventilated to the roof. The total area of the building is 323,400 sq. ft. The Zachry Engineering Center was constructed of concrete block with 12% of total wall area single pane windows and a flat roof.

The building is conditioned by twelve dual duct VAV air-handling units (40 hp each) and they are located in the basement. On the second floor, three small constant volume single zone units serve the three lecture halls in the center of the building. Two pumps of 30 hp and two of 20 hp are used for supplying chilled water and hot water,

respectively, to the building from the power plant. This building has suffered many changes in its operation, and many improvements have been made in its systems.

F.2   Description of the Data Sets Utilized in the Numerical Experiments

The data sets utilized in the study, and included in this appendix, correspond to daily values; average outside air dry-bulb temperature (T_{OA}) and relative humidity (RH), see Figure F.1; whole building and motor control center electricity use (wbele and MCC), see Figure F.2; synthetic, and modified with normal white noise, whole building cooling (wbcool) and heating energy (wbheat) use for all the HVAC systems. The weather-related data are corresponding to College Station, Texas and electricity consumption data come from real measured data in the Zachry building. The cooling and heating loads were generated from HVAC systems simulations using the simplified energy analysis procedure; each systems simulation, as expected, generated different energy usage data sets.

A 187 data (days) sample size is utilized in this study. Each record in the data sets includes all the parameters mentioned above. The first two time series are sorted in an ascending way, according to the daily average outside air dry-bulb temperature.

Figures F.3 to F.10 present the synthetic and the modified samples generated by simulation of each of the HVAC systems, included in this research, as a function of the outside temperature. The right section of these figures is the scatter plot of the synthetic and the modified energy use sample, which helps to illustrate the added white noise percentage to the synthetic data. The left hand plots contain the data of the energy use; for cooling in the upper section and for heating in the lower segment. These figures, besides showing the thermal behavior of the energy use patterns, illustrate the distribution of the normal white noise applied in the samples.
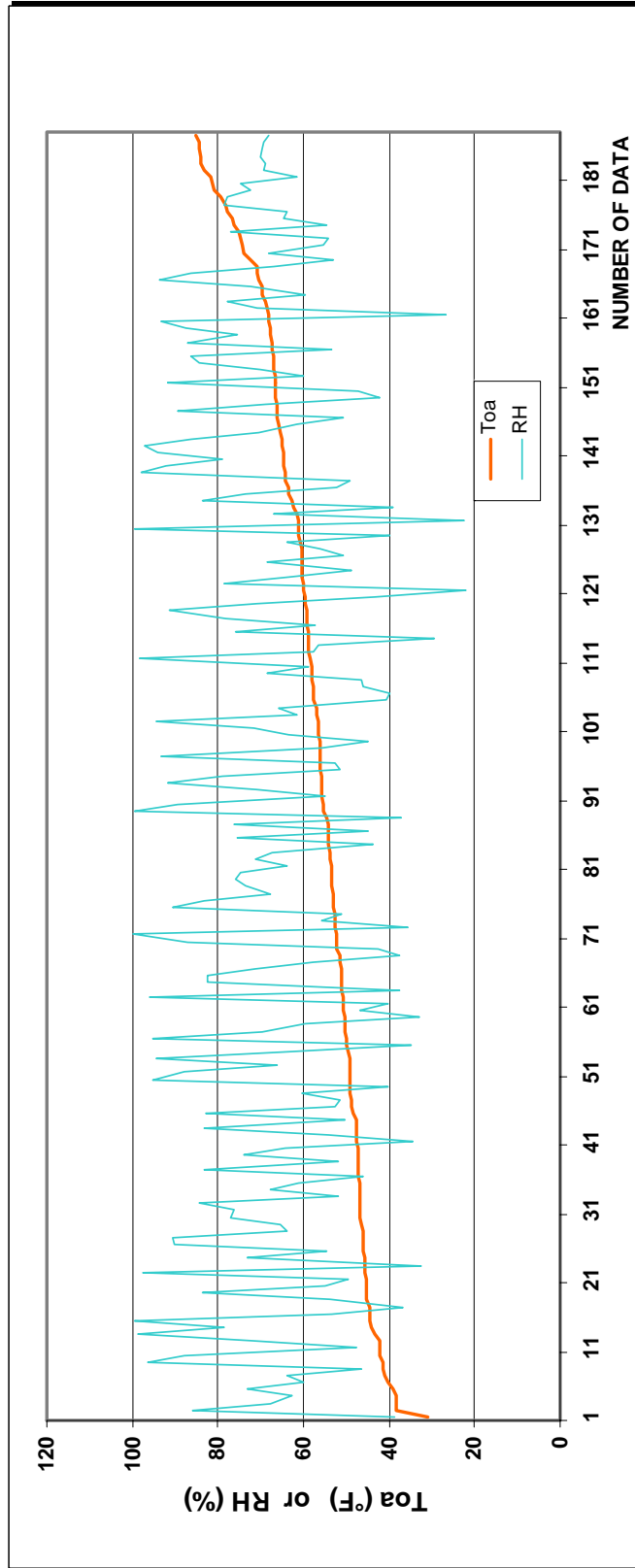
Figure F.1 Daily outside dry-bulb temperature and relative humidity data sets.
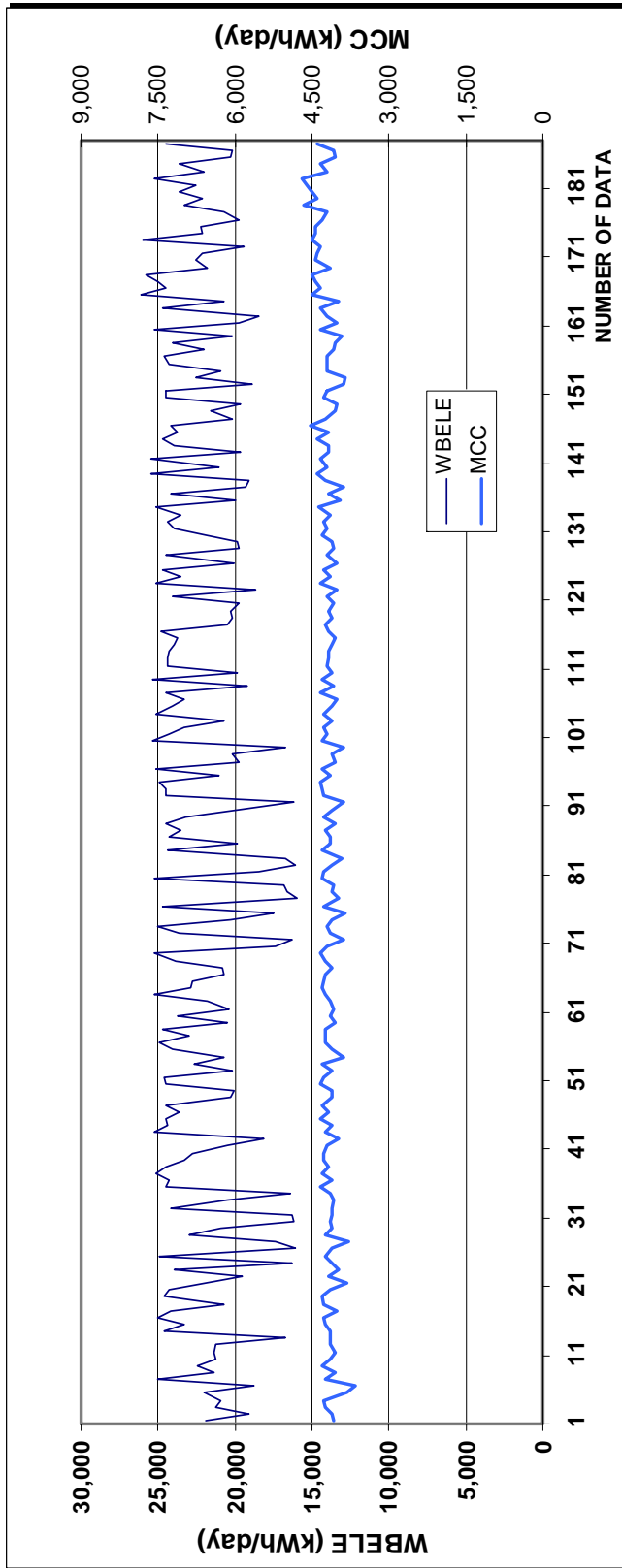
Figure F.2 Whole building and motor control center electricity use data set.
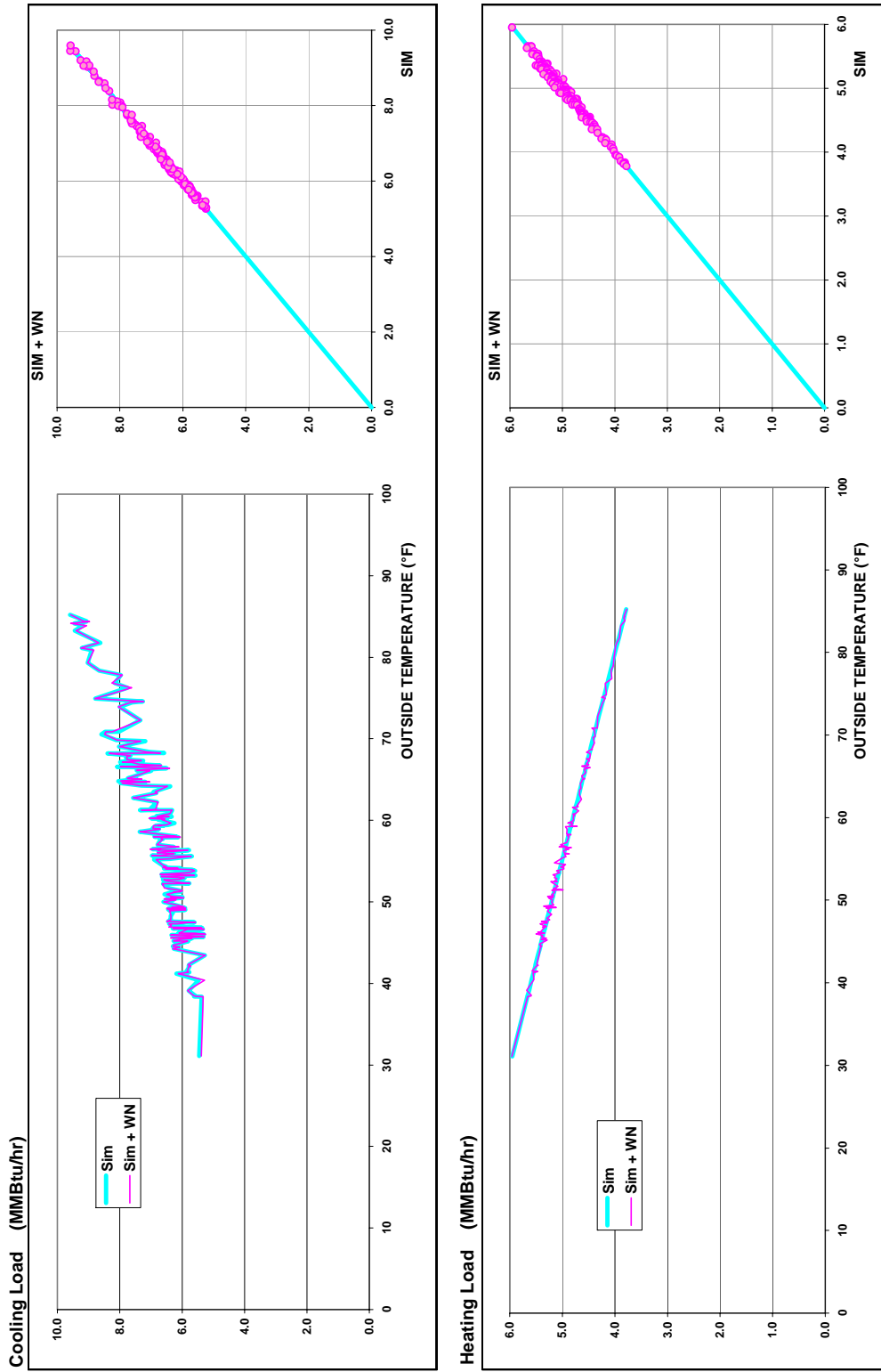
Figure F.3 Synthetic daily whole building cooling and heating energy use dataset of a CVRH system modified with white noise of 1% standard deviation.
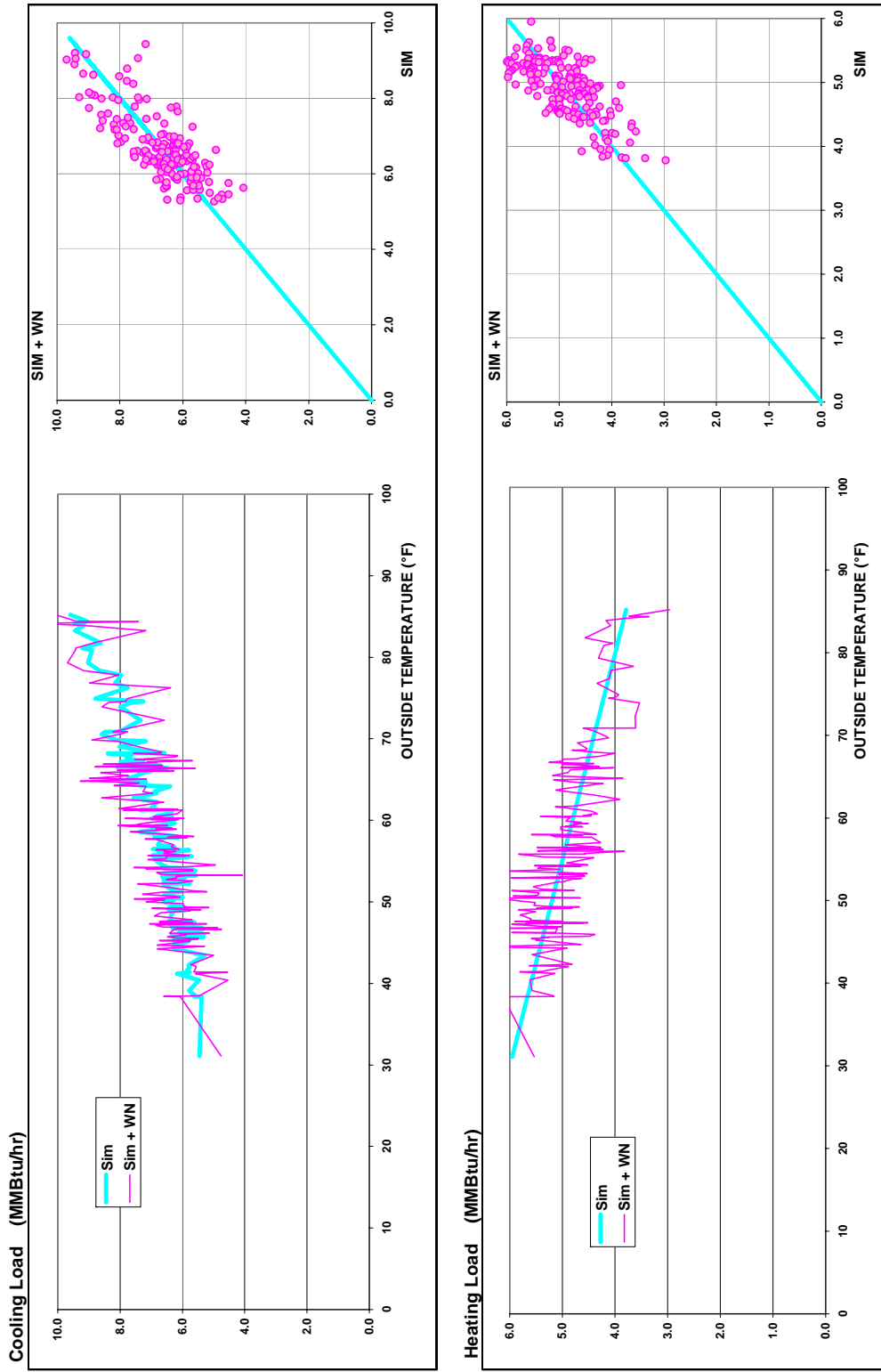
Figure F.4 Synthetic daily whole building cooling and heating energy use dataset of a CVRH system modified with white noise of 10% standard deviation.
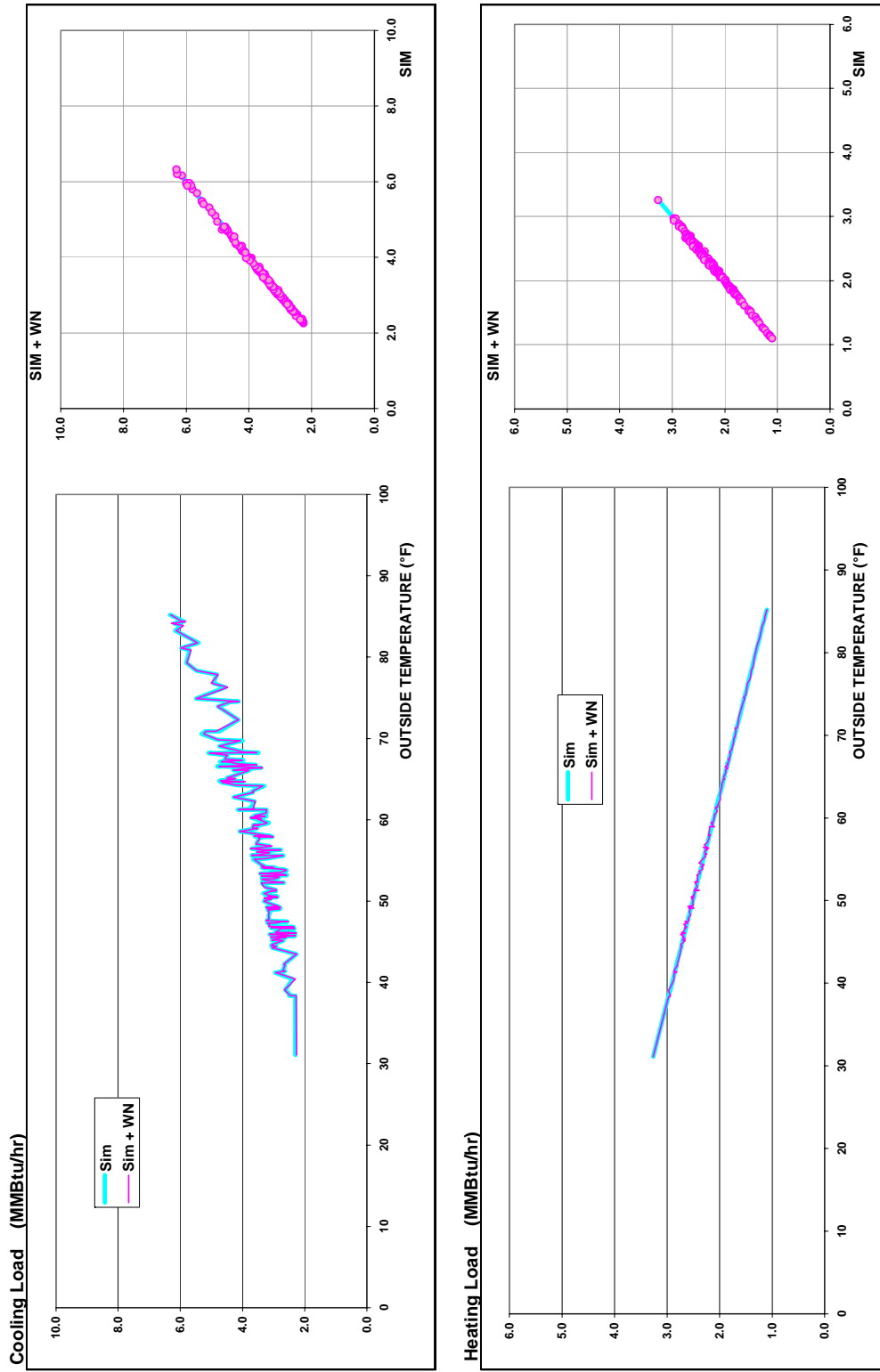
Figure F.5 Synthetic daily whole building cooling and heating energy use dataset of a SDVAV system modified with white noise of 1% standard deviation.
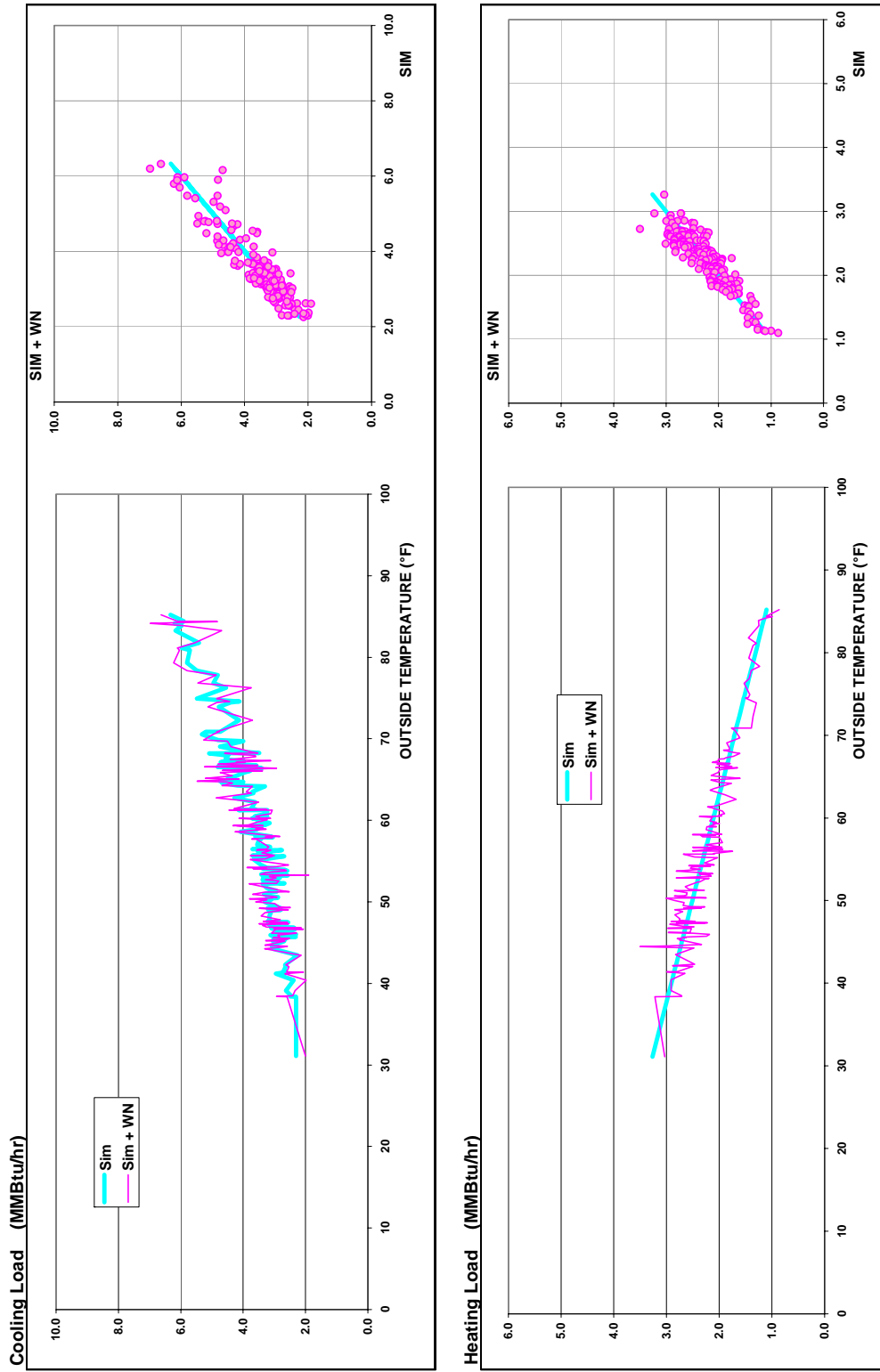
Figure F.6 Synthetic daily whole building cooling and heating energy use dataset of a SDVAV system modified with white noise of 10% standard deviation.
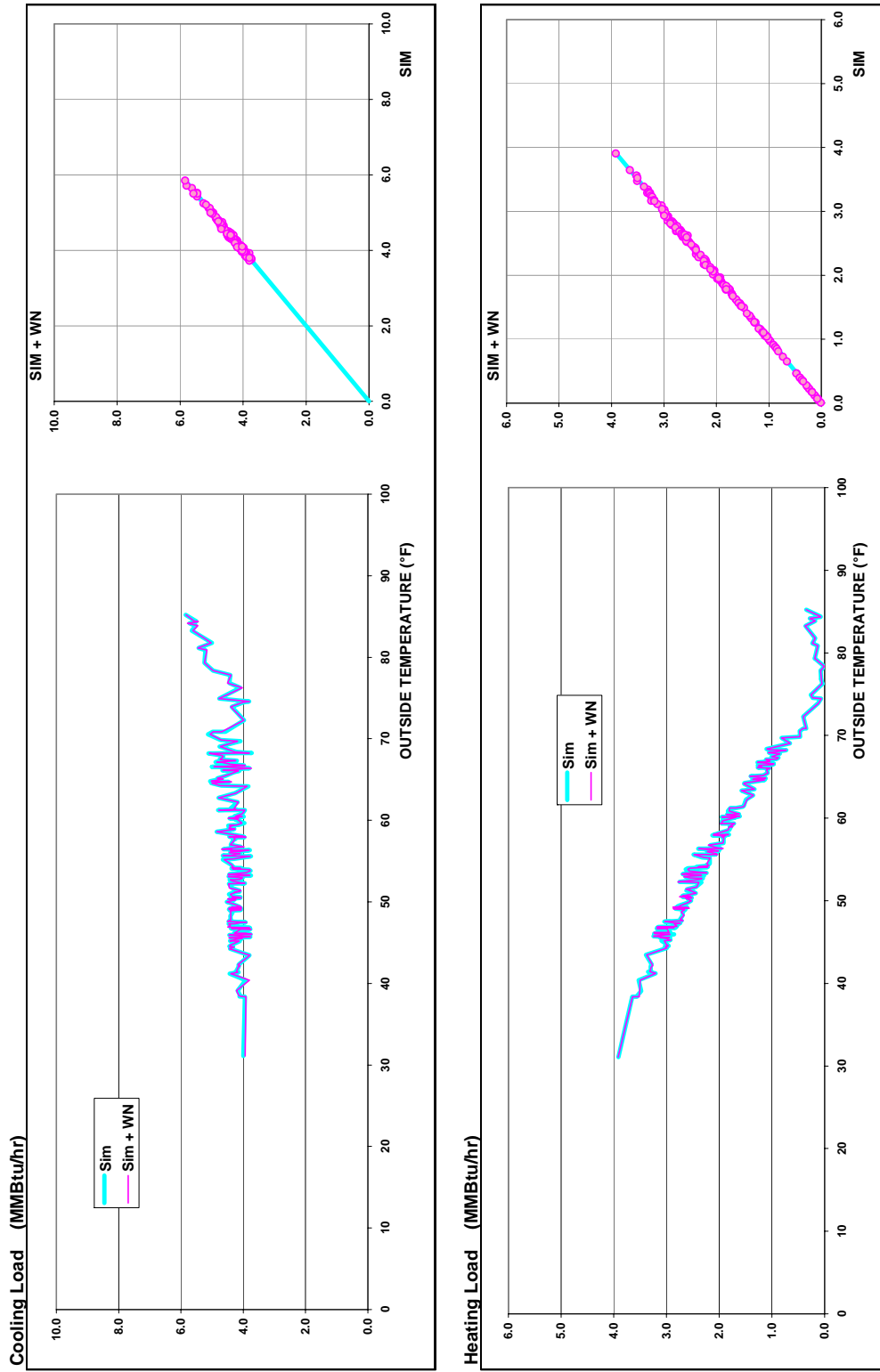
Figure F.7 Synthetic daily whole building cooling and heating energy use dataset of a DDCV system modified with white noise of 1% standard deviation.

Cooling Load   (MMBtu/hr)

Heating Load   (MMBtu/hr)
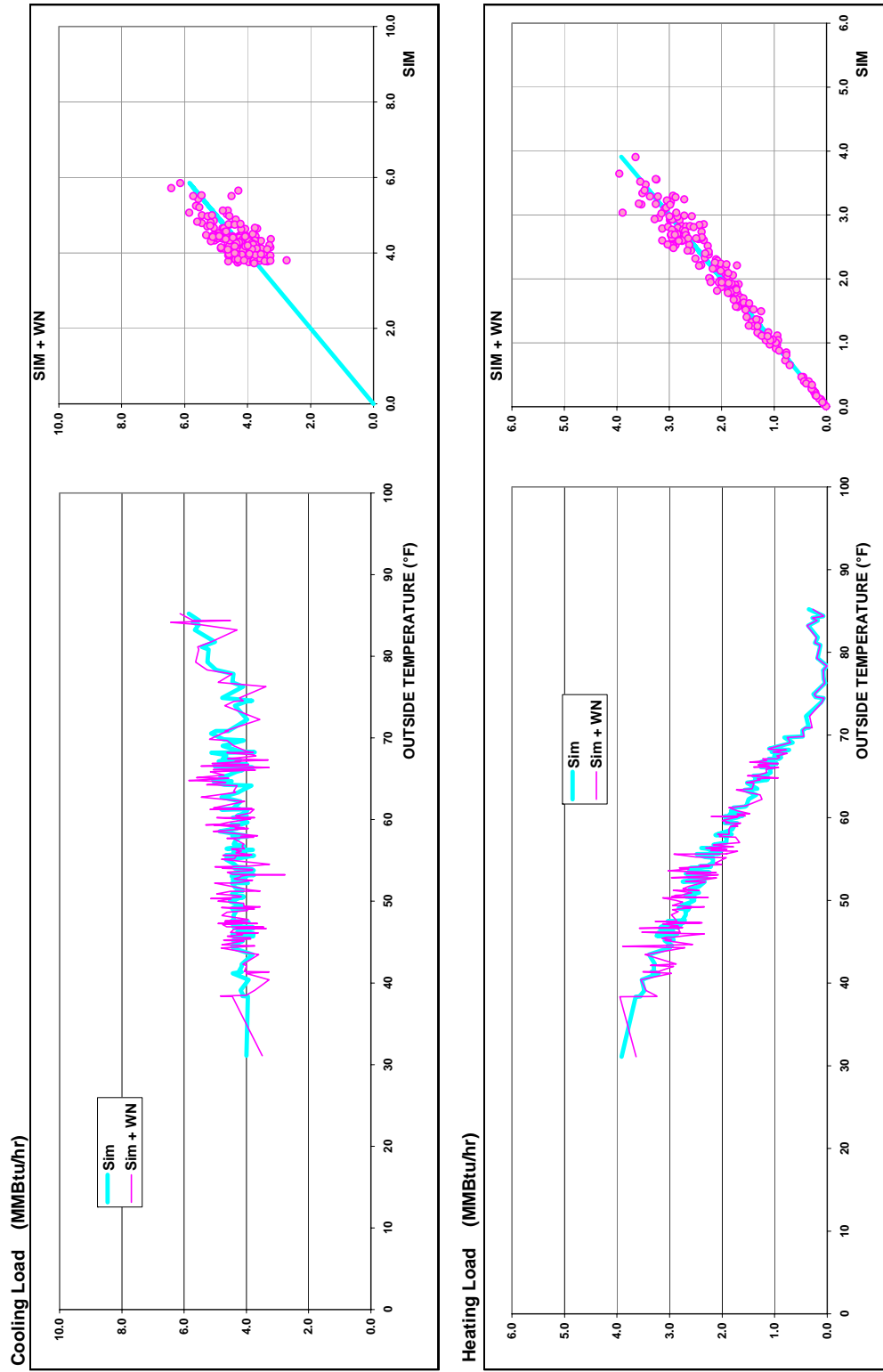
Figure F.8 Synthetic daily whole building cooling and heating energy use dataset of a DDCV system modified with white noise of 10% standard deviation.
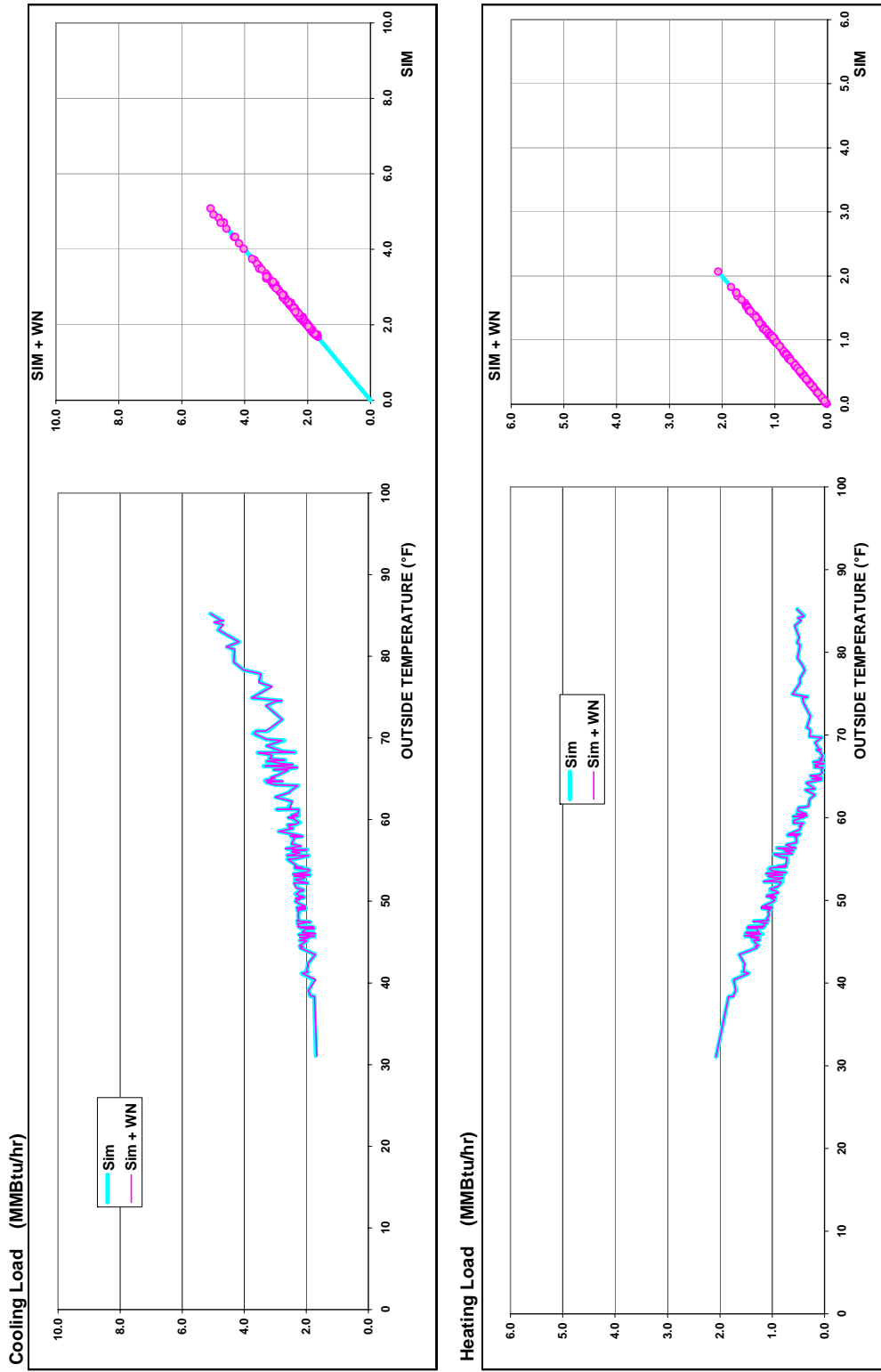
Figure F.9 Synthetic daily whole building cooling and heating energy use dataset of a DDVAV system modified with white noise of 1% standard deviation.

Cooling Load (MMBtu/hr)

Heating Load (MMBtu/hr)
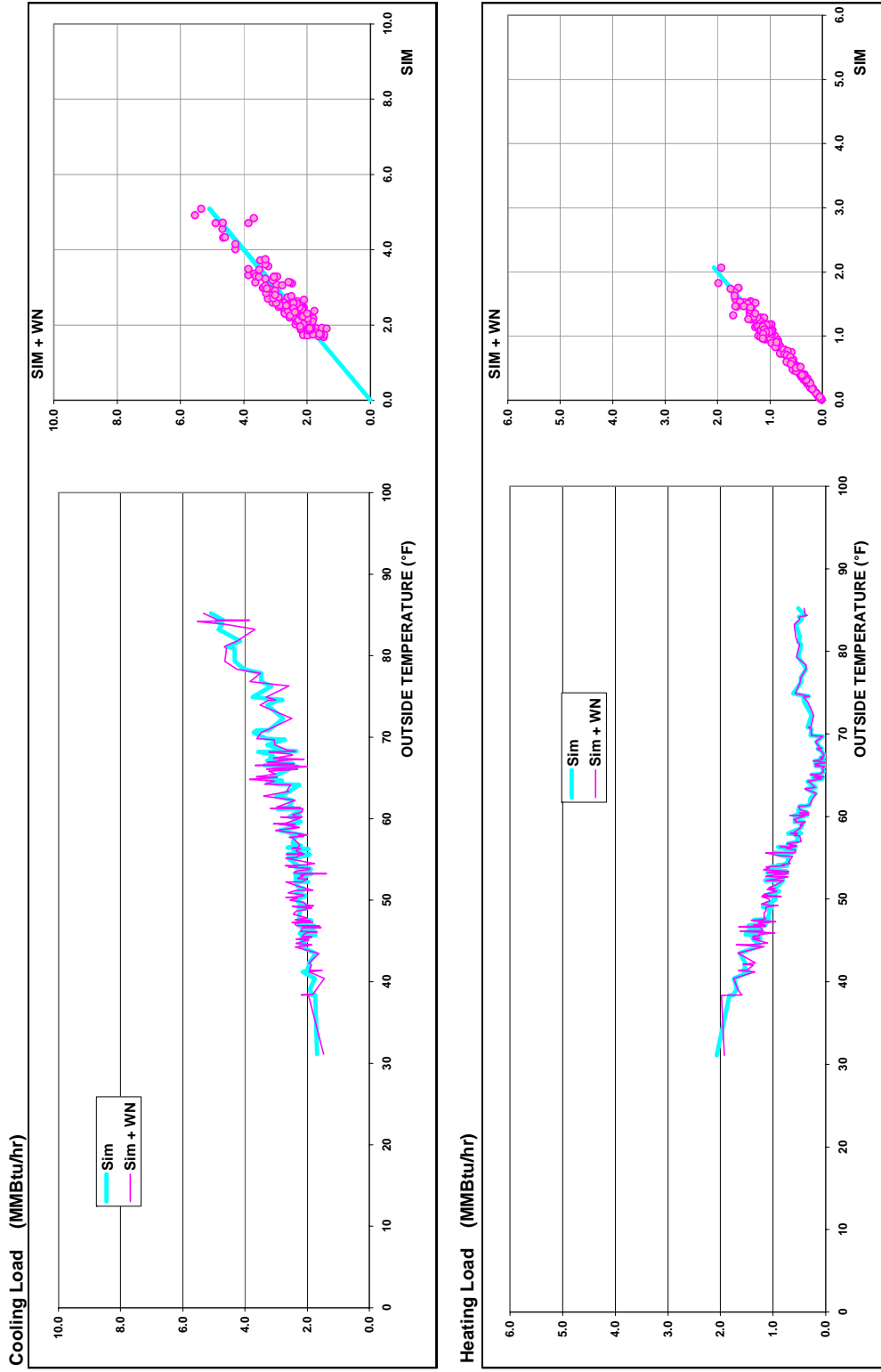
Figure F.10   Synthetic daily whole building cooling and heating energy use dataset of a DDVAV system modified with white noise of 10% standard deviation.

APPENDIX G

RESULT TABLES OF THE AUTOMATED CALIBRATION TESTS

This appendix contains the whole set of results obtained from the tests of the automated calibration methodology through Simulated Annealing (SA). The dual-duct variable and constant air volume, and the single duct variable and constant air with reheat HVAC systems were evaluated under the same ambient conditions. The daily thermal loads obtained from these simulations, which are called "synthetic data", are used as the base data set samples for testing the performance of the *RMSE* minimization methodology.

Two categories of tests were carried out, the accuracy and the consistency tests. Any technique, algorithm, or methodology should always show accuracy in the results that are generated. In addition, procedures also have to be reliable and consistent; that is to say, the methodology has to provide the same reliable results regardless of the initial variable values that are entered.

The accuracy and consistency tests were performed with the synthetic data sets and with the same synthetic data modified with different percentages of white noise. The white noise that was used was statistically normal and added in different quantities. Thus, synthetic data sets were combined with samples of white noise with standard deviations of 1%, 3%, 5%, and 10%, for each system. Some of the generated samples of data were presented in Appendix F.

The tables presented in this appendix are classified by system and by test type. The results of the synthetic data are presented first, followed by the results from the samples with white noise. Additionally, this appendix includes the statistical description of each of the samples modified with white noise for all the HVAC systems.

Table G.1 (a) Performance of the accuracy and stability tests of the automated calibration methodology with Simulated Annealing for a dual-duct variable air volume system carried out with synthetic data. (b) Statistical parameters for each variable for the whole test samples.

(a)

	Test	1	2	3	4	5	6
Initial Guess	Te | Ti	71.5330	97.5766	76.4219	60.4510	61.2662	61.7515
	Tc	49.3299	52.4831	78.4381	68.9983	75.8803	74.1692
	DTh	0.0707	0.9503	0.8507	1.1839	1.8498	1.5857
	Xmin	0.3896	0.5723	0.1272	0.5298	0.7793	0.2388
	Xoa	0.3551	0.3036	0.7710	0.8922	0.3248	0.7424
	#Persons	6,679	2,172	5,395	9,360	3,266	4,527
	UA	34,668	3,969	37,677	33,360	77,380	92,922
Optimized	Te | Ti	75.0014	75.0065	74.9838	74.9974	74.9676	75.0001
	Tc	55.1506	55.1530	55.1424	55.1488	55.1349	55.1501
	DTh	1.0009	1.0045	0.9887	0.9982	0.9774	1.0001
	Xmin	0.4500	0.4500	0.4500	0.4500	0.4501	0.4500
	Xoa	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
	#Persons	3,000	3,002	2,995	2,999	2,989	3,000
	UA	40,000	40,000	40,000	40,000	40,001	40,000
	RMSE	1.2896E-06	6.1806E-06	1.5330E-05	2.4605E-06	3.0709E-05	1.3045E-07
	Run Time	5:18:03	3:57:27	3:53:37	3:56:27	3:56:22	3:51:21
	Annealings	160	163	160	162	162	158

(b)

		Base	Average	Std Dev	CV-StDev	MBE	NMBE
Initial Guess	Te | Ti	°F	71.1559	12.8886	18.11%	-3.844144	-5.40%
	Tc	°F	62.7094	11.5212	18.37%	7.559432	12.05%
	DTh	°F	0.3662	1.0756	293.71%	-0.633797	-173.07%
	Xmin		0.5272	0.2861	54.26%	0.077210	14.64%
	Xoa		0.6496	0.2429	37.40%	0.499622	76.91%
	#Persons		5,146	1,969	38.25%	2,146	41.71%
	UA	Btu/hr-ft^2-°F	51,066	29,436	57.64%	11,066	21.67%
Optimized	Te | Ti	75.00	74.9959	0.011611	0.0155%	-0.004147	-0.0055%
	Tc	55.15	55.1481	0.005421	0.0098%	-0.001937	-0.0035%
	DTh	1.00	0.9971	0.008087	0.8110%	-0.002889	-0.2897%
	Xmin	0.45	0.4500	0.000022	0.0049%	0.000008	0.0018%
	Xoa	0.15	0.1500	0.000003	0.0019%	-0.000001	-0.0007%
	#Persons	3,000	2,999	3.9462	0.1316%	-1.409530	-0.0470%
	UA	40,000	40,000	0.3279	0.0008%	0.117223	0.0003%
	RMSE		6.22E-06				
	Run Time		3:47:13				
	Annealings		151				

Table.G.2 (a) Performance of the accuracy and stability tests of the automated calibration methodology with Simulated Annealing for a dual-duct constant air volume system carried out with synthetic data. (b) Statistical parameters for each variable for the whole test samples.

(a)

	Test	1	2	3	4	5	6
Initial Guess	Te | Ti	62.7142	69.3596	58.7633	93.6954	50.6239	55.7165
	Tc	55.2713	67.1899	66.6871	68.8795	65.4658	63.1412
	DTh	-2.5161	2.0477	-2.4911	1.7771	2.6805	-1.1784
	Xoa	0.4480	0.8157	0.7346	0.7772	0.3187	0.1521
	#Persons	8,809	8,104	3,826	1,115	8,108	5,004
	UA	96,337	7,492	75,701	95,531	77,114	62,273
Optimized	Te | Ti	75.0000	74.9977	74.9982	75.0000	75.0000	75.0000
	Tc	55.1500	55.1481	55.1485	55.1500	55.1500	55.1500
	DTh	0.0000	-0.0020	-0.0015	0.0000	0.0000	0.0000
	Xoa	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
	#Persons	3,000	2,999	3,000	3,000	3,000	3,000
	UA	40,000	40,000	40,000	40,000	40,000	40,000
	RMSE	1.0192E-09	3.2529E-06	2.5042E-06	4.6011E-11	5.5876E-10	4.5649E-11
	Run Time	1:57:12	2:45:01	2:47:50	1:58:04	1:55:55	1:59:07
	Annealings	110	155	156	111	109	112

(b)

		Base	Average	Std Dev	CV-StDev	MBE	NMBE
Initial Guess	Te | Ti	°F	65.1016	13.1069	20.13%	-9.898449	-15.20%
	Tc	°F	63.4095	9.0362	14.25%	8.259528	13.03%
	DTh	°F	0.2223	2.0835	937.42%	0.222255	100.00%
	Xoa		0.5224	0.2835	54.27%	0.372431	71.29%
	#Persons		4,986	3,086	61.90%	1,986	39.83%
	UA	Btu/hr-ft²-°F	61,092	34,927	57.17%	21,092	34.53%
Optimized	Te | Ti	75.00	74.9995	0.000964	0.0013%	-0.000514	-0.0007%
	Tc	55.15	55.1496	0.000799	0.0014%	-0.000427	-0.0008%
	DTh	0.00	-0.0004	0.000814		-0.000434	
	Xoa	0.15	0.1500	0.000000	0.0001%	0.000000	-0.0001%
	#Persons	3,000	3,000	0.2649	0.0088%	-0.141433	-0.0047%
	UA	40,000	40,000	0.0052	0.0000%	-0.002777	0.0000%
	RMSE		7.20E-07				
	Run Time		2:09:22				
	Annealings		121				

Table G.3 (a) Performance of the accuracy and stability tests of the automated calibration methodology with Simulated Annealing for a constant air volume with re-heat system carried out with synthetic data. (b) Statistical parameters for each variable for the whole test samples.

(a)

	Test	1	2	3	4	5	6
Initial Guess	**Te | Ti**	81.0499	77.7824	76.2224	56.8085	56.7519	92.5737
	Tc	78.5631	79.7127	48.5889	70.8904	70.4710	51.9792
	Xoa	0.7895	0.0629	0.2399	0.5952	0.9240	0.5251
	#Persons	2,524	7,111	9,419	9,889	3,859	9,060
	UA	89,207	47,930	47,486	13,880	20,749	42,172
Optimized	**Te | Ti**	74.9995	75.0034	75.0000	75.0000	74.9995	75.0000
	Tc	55.1496	55.1528	55.1500	55.1500	55.1496	55.1500
	Xoa	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
	#Persons	3,000	3,001	3,000	3,000	3,000	3,000
	UA	40,000	40,000	40,000	40,000	40,000	40,000
	RMSE	8.2927E-07	5.2516E-06	1.2294E-10	1.2271E-10	7.3946E-07	5.1495E-11
	Run Time	1:55:25	1:52:10	1:54:15	1:54:36	1:57:13	1:57:12
	Annealings	109	106	108	108	110	110

(b)

		Base	Average	Std Dev	CV-StDev	MBE	NMBE
Initial Guess	**Te | Ti**	°F	75.8019	14.2722	18.83%	0.801920	1.06%
	Tc	°F	64.6578	13.3034	20.58%	9.507774	14.70%
	Xoa		0.5665	0.3187	56.25%	0.416547	73.52%
	#Persons		6,746	2,904	43.05%	3,746	55.53%
	UA	Btu/hr-ft^2-°F	41,721	24,715	59.24%	1,721	4.12%
Optimized	**Te | Ti**	75.00	75.0003	0.001359	0.0018%	0.000338	0.0005%
	Tc	55.15	55.1503	0.001131	0.0021%	0.000281	0.0005%
	Xoa	0.15	0.1500	0.000000	0.0002%	0.000000	0.0001%
	#Persons	3,000	3,000	0.3721	0.0124%	0.092500	0.0031%
	UA	40,000	40,000	0.0000	0.0000%	0.000000	0.0000%
	RMSE		9.74E-07				
	Run Time		1:55:25				
	Annealings		109				

Table G.4 (a) Performance of the accuracy and stability tests of the automated calibration methodology with Simulated Annealing for a single duct variable air volume system carried out with synthetic data. (b) Statistical parameters for each variable for the whole test samples.

(a)

	Test	1	2	3	4	5	6
Initial Guess	Te | Ti	63.1711	72.8655	82.6063	82.7693	73.5733	58.9186
	Tc	74.9628	57.2854	70.9197	61.5112	65.2155	73.4382
	min	0.8121	0.5378	0.8193	0.1595	0.5508	0.9624
	Xoa	0.4446	0.3413	0.9976	0.1740	0.7194	0.5497
	#Persons	660	1,204	9,167	6,694	2,059	1,812
	UA	8,772	86,249	74,302	54,431	38,980	2,916
Optimized	Te | Ti	75.0000	75.0000	74.9315	75.0000	75.0000	75.0000
	Tc	55.1500	55.1500	55.1180	55.1500	55.1500	55.1500
	Xmin	0.4500	0.4500	0.4502	0.4500	0.4500	0.4500
	Xoa	0.1500	0.1500	0.1500	0.1500	0.1500	0.1500
	#Persons	3,000	3,000	2,977	3,000	3,000	3,000
	UA	40,000	40,000	40,000	40,000	40,000	40,000
	RMSE	1.3766E-10	1.8701E-10	6.3239E-05	3.0838E-10	9.8069E-11	7.2496E-11
	Run Time	4:23:18	4:25:49	4:27:35	4:22:45	4:29:58	4:30:46
	Annealings	223	225	230	226	232	233

(b)

		Base	Average	Std Dev	CV-StDev	MBE	NMBE
Initial Guess	Te | Ti	°F	72.3174	9.7996	13.5509%	-2.68263	-3.71%
	Tc	°F	67.2221	7.0372	10.4685%	12.07211	17.96%
	Xmin		0.6403	0.2881	44.9916%	0.190325	29.72%
	Xoa		0.5378	0.2913	54.1656%	0.387751	72.11%
	#Persons		3,600	3,479	96.6533%	599.58	16.66%
	UA	Btu/hr-ft^2-°F	44,275	33,958	76.6973%	4275.01	9.66%
Optimized	Te | Ti	75.00	74.9886	0.027961	0.0373%	-0.011415	-0.0152%
	Tc	55.15	55.1447	0.013080	0.0237%	-0.005340	-0.0097%
	Xmin	0.45	0.4500	0.000088	0.0196%	0.000036	0.0080%
	Xoa	0.15	0.1500	0.000001	0.0010%	-0.000001	-0.0004%
	#Persons	3,000	2,996	9.5857	0.3199%	-3.913374	-0.1306%
	UA	40,000	40,000	0.0000	0.0000%	-0.000001	0.0000%
	RMSE		1.05E-05				
	Run Time		4:26:42				
	Annealings		229				

Table G.5 Performance of the accuracy test of the automated calibration methodology with Simulated Annealing for a dual-duct variable air volume system carried out on synthetic data modified with WN (1%).

Sample			DDVAV-1-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	56.5362	75.2685	82.1104	75.2695
Tc	55.15	°F	63.6457	55.3328	79.5062	55.3332
DTh	1.00	°F	-1.8326	1.2282	-1.8914	1.2289
Xmin	0.45		0.3001	0.4498	0.3425	0.4498
Xoa	0.15		0.6866	0.1495	0.3335	0.1495
#Persons	3,000		6,603	3,076	9,608	3,076
UA	40,000	Btu/ft^2 °F	81,383	40,097	44,207	40,097
RMSE				3.3833E-02		3.3833E-02
Run Time				2:26:08		2:24:40
Annealings				108		107

Sample			DDVAV-2-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	84.6730	75.4246	51.6638	75.4262
Tc	55.15	°F	65.6461	55.5136	67.5396	55.5144
DTh	1.00	°F	-2.7779	1.1657	2.7994	1.1668
Xmin	0.45		0.9741	0.4518	0.9724	0.4518
Xoa	0.15		0.2733	0.1510	0.7257	0.1510
#Persons	3,000	Persons	3,055	3,179	1,502	3,179
UA	40,000	Btu/ft^2 °F	6,893	40,046	24,802	40,046
RMSE				3.5816E-02		3.5816E-02
Run Time				2:27:44		2:23:29
Annealings				107		105

Sample			DDVAV-3-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	68.6598	77.5997	65.0028	77.6030
Tc	55.15	°F	78.3324	56.5808	75.2498	56.5822
DTh	1.00	°F	-2.6574	2.6528	-0.7871	2.6551
Xmin	0.45		0.6571	0.4483	0.2091	0.4483
Xoa	0.15		0.8208	0.1509	0.8556	0.1509
#Persons	3,000	Persons	4,258	3,912	8,889	3,913
UA	40,000	Btu/ft^2 °F	63,953	40,277	52,450	40,277
RMSE				3.4585E-02		3.4585E-02
Run Time				2:40:14		2:37:31
Annealings				113		107

Table G.6 Performance of the accuracy test of the automated calibration methodology with Simulated Annealing for a dual-duct variable air volume system carried out on synthetic data modified with WN (5%).

Sample			DDVAV-1-WN5%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	82.3341	79.2534	96.0077	79.2533
Tc	55.15	°F	56.1980	58.5987	59.3945	58.5985
DTh	1.00	°F	2.7161	3.0000	0.4108	3.0000
Xmin	0.45		0.2915	0.4636	0.8938	0.4636
Xoa	0.15		0.0467	0.1540	0.4753	0.1540
#Persons	3,000		2,621	4,630	3,119	4,630
UA	40,000	Btu/ft^2 °F	27,658	41,436	68,661	41,436
RMSE				1.7265E-01		1.7265E-01
Run Time				3:03:29		3:05:06
Annealings				109		110

Sample			DDVAV-2-WN5%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	63.7838	68.8224	77.6086	68.8222
Tc	55.15	°F	67.2438	51.5041	71.8381	51.5040
DTh	1.00	°F	2.0141	-3.0000	-0.7673	-3.0000
Xmin	0.45		0.8352	0.4526	0.9961	0.4526
Xoa	0.15		0.7351	0.1465	0.2497	0.1465
#Persons	3,000	Persons	3,310	910	8,460	910
UA	40,000	Btu/ft^2 °F	2,321	40,732	98,648	40,732
RMSE				1.8298E-01		1.8298E-01
Run Time				2:33:29		2:33:12
Annealings				109		109

Sample			DDVAV-3-WN5%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	70.1206	78.0117	52.5817	78.0118
Tc	55.15	°F	62.4261	57.2104	72.0421	57.2104
DTh	1.00	°F	2.3758	3.0000	-2.0730	3.0000
Xmin	0.45		0.5898	0.4524	0.3187	0.4524
Xoa	0.15		0.0616	0.1506	0.1275	0.1506
#Persons	3,000	Persons	5,095	3,841	3,344	3,841
UA	40,000	Btu/ft^2 °F	39,038	38,145	64,459	38,145
RMSE				1.7061E-01		1.7061E-01
Run Time				2:28:00		2:26:39
Annealings				110		109

Table G.7　Performance of the accuracy test of the automated calibration methodology with Simulated Annealing for a dual-duct variable air volume system carried out on synthetic data modified with WN (10%).

Sample			DDVAV-1-WN10%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	61.0523	69.4849	95.2734	69.4851
Tc	55.15	°F	62.5978	52.4874	50.3344	52.4875
DTh	1.00	°F	-0.7572	-2.9999	-2.6022	-3.0000
Xmin	0.45		0.0591	0.4623	0.8000	0.4623
Xoa	0.15		0.8451	0.1486	0.8718	0.1487
#Persons	3,000		9,386	1,172	7,984	1,172
UA	40,000	Btu/ft^2 °F	43,158	41,006	82,049	41,005
RMSE				3.7004E-01		3.7004E-01
Run Time				2:19:13		2:23:54
Annealings				103		106

Sample			DDVAV-2-WN10%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	69.9292	77.8082	63.5641	77.8082
Tc	55.15	°F	50.3864	55.3232	50.2052	55.3232
DTh	1.00	°F	2.9661	3.0000	1.7768	3.0000
Xmin	0.45		0.1004	0.4347	0.4577	0.4347
Xoa	0.15		0.1415	0.1555	0.3827	0.1555
#Persons	3,000	Persons	4,761	3,943	8,705	3,943
UA	40,000	Btu/ft^2 °F	86,972	36,914	81,164	36,914
RMSE				3.5118E-01		3.5118E-01
Run Time				3:18:34		3:23:00
Annealings				108		110

Sample			DDVAV-3-WN10%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	54.7019	68.1725	79.5025	68.1725
Tc	55.15	°F	73.9791	50.7180	47.7975	50.7182
DTh	1.00	°F	-0.7302	-3.0000	-2.0852	-3.0000
Xmin	0.45		0.6618	0.4469	0.5009	0.4469
Xoa	0.15		0.4677	0.1433	0.2281	0.1433
#Persons	3,000	Persons	8,151	624	4,971	624
UA	40,000	Btu/ft^2 °F	45,474	40,227	39,199	40,226
RMSE				3.6590E-01		3.6590E-01
Run Time				3:15:56		3:22:17
Annealings				107		110

Table G.8 Statistical description of the three samples of synthetic data modified with WN (1%) used in the tests of the automated calibration of a dual-duct variable air volume system.

Sample DDVAV-1-WN1%	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0000030134	1.0000122449	
MEAN w/wn	2.5266024246	0.7687960433	
RMSE	0.0246073390	0.0093358007	0.0339431397
CV-RMSE	0.97%	1.21%	
MBE	0.0002637875	-0.0002965670	-0.0000327796
NMBE	0.01%	-0.04%	

Sample DDVAV-2-WN1%	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0007180588	1.0002098492	
MEAN w/wn	2.5291743928	0.7685314641	
RMSE	0.0271060809	0.0091984209	0.0363045017
CV-RMSE	1.07%	1.20%	
MBE	-0.0023081807	-0.0000319879	-0.0023401686
NMBE	-0.09%	0.00%	

Sample DDVAV-3-WN1%	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0001435692	1.0001411961	
MEAN w/wn	2.5273563811	0.7688112533	
RMSE	0.0267376709	0.0084199722	0.0351576431
CV-RMSE	1.06%	1.10%	
MBE	-0.0004901690	-0.0003117770	-0.0008019460
NMBE	-0.02%	-0.04%	

Table G.9   Statistical description of the three samples of synthetic data modified with WN (5%) used in the tests of the automated calibration of a dual-duct variable air volume system.

Sample DDVAV-1-WN5%			
	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0007178461	1.0007059807	
MEAN w/wn	2.5293170572	0.7700583613	
RMSE	0.1336883547	0.0420998610	0.1757882156
CV-RMSE	5.29%	5.48%	
MBE	-0.0024508451	-0.0015588850	-0.0040097302
NMBE	-0.10%	-0.20%	

Sample DDVAV-2-WN5%			
	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0003583233	1.0000612246	
MEAN w/wn	2.5279283473	0.7699823114	
RMSE	0.1366683341	0.0466790036	0.1833473377
CV-RMSE	5.41%	6.07%	
MBE	-0.0010621352	-0.0014828352	-0.0025449704
NMBE	-0.04%	-0.19%	

Sample DDVAV-3-WN5%			
	COOLING	HEATING	TOTAL
MEAN orig	2.5268662121	0.7684994763	
WN mean	0.9998730346	0.9997686473	
MEAN w/wn	2.5200238449	0.7666074155	
RMSE	0.1302392230	0.0458392536	0.1760784765
CV-RMSE	5.15%	5.96%	
MBE	0.0068423672	0.0018920608	0.0087344280
NMBE	0.27%	0.25%	

Table G.10 Statistical description of the three samples of synthetic data modified with WN (10%) used in the tests of the automated calibration of a dual-duct variable air volume system.

Sample DDVAV-1-WN10%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0015056144	1.0048658562	
MEAN w/wn	2.5318430079	0.7708125907	
RMSE	0.2726429706	0.0978537294	0.3704967000
CV-RMSE	10.79%	12.73%	
MBE	-0.0049767958	-0.0023131144	-0.0072899102
NMBE	-0.20%	-0.30%	

Sample DDVAV-2-WN10%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0020984924	0.9982183412	
MEAN w/wn	2.5302915727	0.7659751103	
RMSE	0.2709865570	0.0818081151	0.3527946721
CV-RMSE	10.72%	10.65%	
MBE	-0.0034253606	0.0025243659	-0.0009009947
NMBE	-0.14%	0.33%	

Sample DDVAV-3-WN10%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	2.5268662121	0.7684994763	
WN mean	1.0006760190	0.9993107094	
MEAN w/wn	2.5284797186	0.7694421834	
RMSE	0.2804685333	0.0861787457	0.3666472790
CV-RMSE	11.10%	11.21%	
MBE	-0.0016135065	-0.0009427072	-0.0025562137
NMBE	-0.06%	-0.12%	

Table G.11 Performance of the accuracy tests of the automated calibration methodology with Simulated Annealing for a dual-duct constant air volume system carried out on synthetic data modified with WN (1%).

Sample			DDCV-1-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	59.9821	73.7586	91.9056	73.7591
Tc	55.15	°F	53.8993	54.1376	62.6833	54.1380
DTh	1.00	°F	1.8457	-1.0123	2.5834	-1.0118
Xoa	0.15		0.4390	0.1483	0.3189	0.1483
#Persons	3,000		4,168	2,648	4,138	2,648
UA	40,000	Btu/ft^2 °F	97,556	40,224	96,212	40,224
RMSE				4.4739E-02		4.4739E-02
Run Time				2:15:05		2:22:13
Annealings				104		108

Sample			DDCV-3-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	85.2815	77.4658	82.5332	77.4658
Tc	55.15	°F	75.0046	57.1596	68.3858	57.1595
DTh	1.00	°F	0.0641	2.0551	0.8401	2.0550
Xoa	0.15		0.1713	0.1520	0.5930	0.1520
#Persons	3,000	Persons	5,783	3,708	3,696	3,708
UA	40,000	Btu/ft^2 °F	76,635	39,893	75,131	39,893
RMSE				4.7415E-02		4.7415E-02
Run Time				2:20:09		2:20:08
Annealings				109		109

Sample			DDCV-2-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	51.6964	73.2644	66.5726	73.2640
Tc	55.15	°F	68.5456	53.6512	65.6705	53.6509
DTh	1.00	°F	-1.6455	-1.5242	2.4954	-1.5246
Xoa	0.15		0.8475	0.1529	0.8211	0.1529
#Persons	3,000	Persons	1,309	2,541	9,132	2,541
UA	40,000	Btu/ft^2 °F	26,313	39,277	93,025	39,277
RMSE				4.8118E-02		4.8118E-02
Run Time				2:22:38		2:25:16
Annealings				111		113

Table G.12 Performance of the accuracy tests of the automated calibration methodology with Simulated Annealing for a dual-duct constant air volume system carried out on synthetic data modified with different percentages of white noise (WN).

Sample			DDCV-1-WN3%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	50.6079	78.6225	94.5283	78.6225
Tc	55.15	°F	75.4051	58.1760	65.7205	58.1760
DTh	1.00	°F	-2.6504	3.0000	2.6268	3.0000
Xoa	0.15		0.6530	0.1572	0.4927	0.1572
#Persons	3,000		1,296	4,024	3,013	4,024
UA	40,000	Btu/ft^2 °F	10,366	38,486	10,145	38,486
RMSE				1.3099E-01		1.3099E-01
Run Time				2:22:39		2:17:32
Annealings				111		107

Sample			DDCV-1-WN5%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	83.5752	77.1013	83.0647	77.1013
Tc	55.15	°F	54.1408	65.1181	74.9494	65.1181
DTh	1.00	°F	-2.1332	-3.0000	-2.3601	-3.0000
Xoa	0.15		0.4805	0.2834	0.0484	0.2834
#Persons	3,000	Persons	7,421	4,331	6,437	4,331
UA	40,000	Btu/ft^2 °F	67,285	40,673	41,246	40,673
RMSE				2.1873E-01		2.1873E-01
Run Time				2:18:40		2:18:14
Annealings				107		110

Sample			DDCV-1-WN10%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	87.3700	71.4052	66.4427	71.4052
Tc	55.15	°F	63.1740	52.0564	55.0080	52.0564
DTh	1.00	°F	-0.8979	-3.0000	1.9779	-3.0000
Xoa	0.15		0.6085	0.1460	0.8922	0.1460
#Persons	3,000	Persons	851	2,022	8,257	2,022
UA	40,000	Btu/ft^2 °F	84,388	40,444	15,677	40,444
RMSE				4.6720E-01		4.6720E-01
Run Time				2:18:51		2:18:51
Annealings				108		108

Table G.13 Statistical description of the three samples of synthetic data modified with WN (1%) used in the tests of the automated calibration of a dual-duct constant air volume system.

Sample DDCV-1-WN1%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.4328115152	1.0107487420	
WN mean	1.0000030134	1.0000122449	
MEAN w/wn	3.4326810513	1.0111329963	
RMSE	0.0327416731	0.0121212340	0.0448629070
CV-RMSE	0.95%	1.20%	
MBE	-0.0001304638	0.0003842544	-0.0002537905
NMBE	0.00%	-0.04%	

Sample DDCV-3-WN1%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.4328115152	1.0107487420	
WN mean	1.0007180588	1.0002098492	
MEAN w/wn	3.4355309117	1.0108977051	
RMSE	0.0360946449	0.0117861749	0.0478808197
CV-RMSE	1.05%	1.17%	
MBE	-0.0027193965	-0.0001489632	-0.0028683597
NMBE	-0.08%	-0.01%	

Sample DDCV-2-WN1%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.4328115152	1.0107487420	
WN mean	1.0000107844	0.9999837364	
MEAN w/wn	3.4332855127	1.0105725953	
RMSE	0.0360481942	0.0124711542	0.0485193484
CV-RMSE	1.05%	1.23%	
MBE	-0.0004739975	0.0001761467	-0.0002978508
NMBE	-0.01%	0.02%	

Table G.14 Statistical description of the three samples of synthetic data modified with different percentages of white noise (WN) used in the tests of the automated calibration of a dual-duct constant air volume system.

Sample DDCV-1-WN3%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.4328115152	1.0107487420	
WN mean	0.9993190659	0.9993971923	
MEAN w/wn	3.4315250559	1.0085065052	
RMSE	0.0980344130	0.0345827847	0.1326171977
CV-RMSE	2.86%	3.42%	
MBE	0.0012864593	0.0022422368	0.0035286960
NMBE	0.04%	0.22%	

Sample DDCV-1-WN5%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.4328115152	1.0107487420	
WN mean	1.0007178461	1.0007059807	
MEAN w/wn	3.4355363924	1.0124025636	
RMSE	0.1736488840	0.0540810576	0.2277299416
CV-RMSE	5.06%	5.35%	
MBE	-0.0027248772	-0.0016538217	-0.0043786989
NMBE	-0.08%	-0.16%	

Sample DDCV-1-WN10%			
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.4328115152	1.0107487420	
WN mean	1.0006760190	0.9993107094	
MEAN w/wn	3.4354815674	1.0118832005	
RMSE	0.3560746511	0.1116051319	0.4676797829
CV-RMSE	10.37%	11.04%	
MBE	-0.0026700522	-0.0011344585	-0.0038045107
NMBE	-0.08%	-0.11%	

Table G.15 Performance of the accuracy tests of the automated calibration methodology with Simulated Annealing for a constant air volume with re-heat system carried out on synthetic data modified with different percentages of white noise (WN).

Sample			CVRH-1-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	58.5037	74.2758	50.1965	74.4544
Tc	55.15	°F	45.5943	54.5549	64.7869	54.7043
Xoa	0.15		0.6881	0.1492	0.0249	0.1493
#Persons	3,000	Persons	7,554	2,806	4,789	2,854
UA	40,000	Btu/ft^2 °F	32,964	40,152	23,086	40,152
RMSE				6.2803E-02		6.2803E-02
Run Time				2:18:02		2:16:14
Annealings				105		104

Sample			CVRH-1-WN3%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	99.0151	79.9841	76.1605	79.9843
Tc	55.15	°F	75.8000	59.2395	74.6441	59.2396
Xoa	0.15		0.9651	0.1536	0.2840	0.1536
#Persons	3,000	Persons	940	4,386	4,982	4,387
UA	40,000	Btu/ft^2 °F	73,423	39,705	37,757	39,705
RMSE				1.8499E-01		1.8499E-01
Run Time				2:18:48		2:20:05
Annealings				106		107

Sample			CVRH-1-WN5%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	62.4075	74.5135	79.0900	74.5131
Tc	55.15	°F	63.5716	54.7040	63.3995	54.7036
Xoa	0.15		0.7158	0.1516	0.6803	0.1516
#Persons	3,000	Persons	5,386	2,854	9,631	2,853
UA	40,000	Btu/ft^2 °F	75,523	39,475	83,352	39,475
RMSE				3.0831E-01		3.0831E-01
Run Time				2:21:36		2:22:51
Annealings				107		108

Table G.15 (Continued). Performance of the accuracy tests of the automated calibration methodology with Simulated Annealing for a constant air volume with re-heat system carried out on synthetic data modified with different percentages of white noise (WN).

Sample			CVRH-1-WN10%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	**75.00**	**°F**	69.8568	79.8576	87.3646	79.8580
Tc	**55.15**	**°F**	67.6155	59.0708	67.3594	59.0711
Xoa	**0.15**		0.6820	0.1549	0.7612	0.1549
#Persons	**3,000**		6,952	4,366	7,174	4,366
UA	**40,000**	**Btu/ft^2 °F**	7,998	40,170	89,894	40,170
RMSE				6.5721E-01		6.5721E-01
Run Time				2:22:34		2:21:18
Annealings				108		107

Table G.16 Statistical description of the four samples of synthetic data modified with different percentages of white noise (WN) used in the tests of the automated calibration of a constant air volume with re-heat system.

Sample	CVRH-1-WN1%		
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.0129817234	3.1942220814	
WN mean	1.0000107844	0.9999837364	
MEAN w/wn	3.0134203335	3.1938601530	
RMSE	0.0321060815	0.0326450238	0.0647511053
CV-RMSE	1.07%	1.02%	
MBE	-0.000438610	0.000361928	-0.000076681
NMBE	-0.01%	0.01%	

Sample	CVRH-1-WN3%		
	COOLING	**HEATING**	**TOTAL**
MEAN orig	3.0129817234	3.1942220814	
WN mean	0.9993190659	0.9993971923	
MEAN w/wn	3.0114184348	3.1921090343	
RMSE	0.0847525367	0.1010443228	0.1857968594
CV-RMSE	2.81%	3.16%	
MBE	0.0015632886	0.0021130470	0.0036763357
NMBE	0.05%	0.07%	

Table G.16 (Continued) Statistical description of the four samples of synthetic data modified with different percentages of white noise (WN) used in the tests of the automated calibration of a constant air volume with re-heat system.

Sample CVRH-1-WN5%			
	COOLING	HEATING	TOTAL
MEAN orig	3.0129817234	3.1942220814	
WN mean	1.0007178461	1.0007059807	
MEAN w/wn	3.0153857303	3.1949723088	
RMSE	0.1559710733	0.1525793725	0.3085504458
CV-RMSE	5.18%	4.78%	
MBE	-0.002404007	-0.000750227	-0.003154234
NMBE	-0.08%	-0.02%	

Sample CVRH-1-WN10%			
	COOLING	HEATING	TOTAL
MEAN orig	3.0129817234	3.1942220814	
WN mean	1.0015056144	1.0048658562	
MEAN w/wn	3.0189831727	3.2094229621	
RMSE	0.3185728006	0.3395598023	0.6581326028
CV-RMSE	10.57%	10.63%	
MBE	-0.006001449	-0.015200880	-0.021202330
NMBE	-0.20%	-0.48%	

Table G.17 Performance of the accuracy tests of the automated calibration methodology with Simulated Annealing for a single duct variable air volume system carried out on synthetic data modified with different percentages of white noise (WN).

Sample			SDVAV-1-WN1%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	87.5190	70.2090	59.8451	70.2094
Tc	55.15	°F	54.4891	52.6145	53.5055	52.6146
Xmin	0.45		0.8761	0.4606	0.9627	0.4606
Xoa	0.15		0.5082	0.1495	0.4250	0.1495
#Persons	3,000	Persons	5,123	1,376	6,599	1,376
UA	40,000	Btu/ft^2 °F	37,448	39,934	88,186	39,934
RMSE				6.05E-02		6.05E-02
Run Time				3:56:33		4:00:49
Annealings				222		226

Table G.17 (Continued) Performance of the accuracy tests of the automated calibration methodology with Simulated Annealing for a single duct variable air volume system carried out on synthetic data modified with different percentages of white noise (WN).

Sample			SDVAV -1-WN5%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	93.9279	67.5471	63.9794	67.5471
Tc	55.15	°F	67.2100	50.7208	68.1874	50.7208
Xmin	0.45		0.4833	0.4526	0.2711	0.4526
Xoa	0.15		0.8026	0.1459	0.1563	0.1459
#Persons	3,000	Persons	7,259	500	6,391	500
UA	40,000	Btu/ft^2 °F	4,020	41,116	27,460	41,116
RMSE				3.07E-01		3.07E-01
Run Time				4:28:06		4:01:24
Annealings				228		227

Sample			SDVAV -1-WN10%			
			RUN 1		RUN 2	
	Base	Units	Input	Output	Input	Output
Te | Ti	75.00	°F	68.3821	69.2101	66.7669	69.2101
Tc	55.15	°F	54.8531	49.5922	54.2374	49.5922
Xmin	0.45		0.1408	0.4031	0.2856	0.4031
Xoa	0.15		0.2487	0.1380	0.2791	0.1380
#Persons	3,000	Persons	6,381	1,079	8,752	1,079
UA	40,000	Btu/ft^2 °F	31,467	41,168	29,149	41,168
RMSE				6.18E-01		6.18E-01
Run Time				3:54:40		4:17:11
Annealings				216		219

Table G.18 Statistical description of the samples of synthetic data modified with different percentages of white noise (WN) used in the tests of the automated calibration of a single duct variable air volume system.

Sample SDVAV -1-WN1%			
	COOLING	HEATING	TOTAL
MEAN orig	2.6301545013	0.4476560830	
WN mean	1.00000301	1.00001224	
MEAN w/wn	2.6298285812	0.4478694413	
RMSE	0.026469816	0.005851671	0.0323214873
CV-RMSE	1.01%	1.31%	
MBE	0.000325920	-0.000213358	0.0001125617
NMBE	0.01%	-0.05%	

Table G.18 (Continued) Statistical description of the samples of synthetic data modified with different percentages of white noise (WN) used in the tests of the automated calibration of a single duct variable air volume system.

Sample SDVAV -1-WN5%			
	COOLING	HEATING	TOTAL
MEAN orig	1.8563823485	0.9607993741	
WN mean	1.0007178461	1.0007059807	
MEAN w/wn	1.8585188980	0.9603914323	
RMSE	0.1069760648	0.0503117927	0.1572878575
CV-RMSE	5.76%	5.24%	
MBE	-0.002136549	0.000407942	-0.001728608
NMBE	-0.12%	0.04%	

Sample SDVAV -1-WN10%			
	COOLING	HEATING	TOTAL
MEAN orig	1.8563823485	0.9607993741	
WN mean	1.0015056144	1.0048658562	
MEAN w/wn	1.8612967177	0.9647652060	
RMSE	0.2158752586	0.1165410472	0.3324163058
CV-RMSE	11.63%	12.13%	
MBE	-0.004914369	-0.003965832	-0.008880201
NMBE	-0.26%	-0.41%	

APPENDIX H

CONVEX AND CONCAVE FUNCTIONS

Optimization is the process of seeking the best solution for a system or process. The optimization techniques can be classified by the number of independent variables involved in the system. Single-variable methods are used with a function of a single variable, and multivariable methods are used for optimizing a function of several variables. A second scheme for classifying methods of optimization depends on whether the method employs derivatives. That is, there are derivative methods and numerical methods. Derivative methods seek to determine those values of the variable(s) for which the first derivative vanishes. Numerical methods typically use algorithms, and they are, therefore, well suited for implementation by a digital computer. The process may also consider unconstrained and constrained conditions. In constrained problems, the solution must satisfy special conditions. Implicitly the constrained versus unconstrained classification of optimization procedures is yet another basis for categorization – the number of dependent variables or responses. It is referred to as a single-response or multiple-response problem. In the optimization sense, they are often called single-objective and multiple-objective problems. Thus, it is clear that the knowledge of the conditions and the characteristics of the objective function are relevant to determine a suitable procedure.

As was mentioned before, certain characteristics of a function are useful in optimization. A function $y(x)$ is said to be monotonically increasing (decreasing) when, for $x_2 > x_1$, $y(x_2) > y(x_1)$ $(y(x_2) < y(x_1))$. Here x_1 and x_2 refer to successive values of a single variable x. The function $y(x)$ is monotonically non-decreasing and monotonically non-increasing if, for $x_2 > x_1$, $y(x_2) \geq y(x_1)$ and $y(x_2) \leq y(x_1)$, respectively.

The modality of a function is particularly important in the optimization of a function $y(x)$. The term "unimodal" function refers to a function having a single mode, which can be a peak (maximum) or a trough (minimum). The term multi-modal refers

to a function possessing several modes. Concave and convex functions are special cases of unimodal functions. A concave or convex function is necessarily unimodal, but unimodal functions need not be concave or convex. A concave function $y(x)$ is one in which

$$y\big((1-\theta)x_1 + \theta x_2\big) \geq (1-\theta)y(x_1) + \theta y(x_2)$$

for all $0<\theta<1$ and any two points x_1 and x_2 in n-dimensional space. A convex function has the same definition, as before, but with the direction of the inequality reversed.
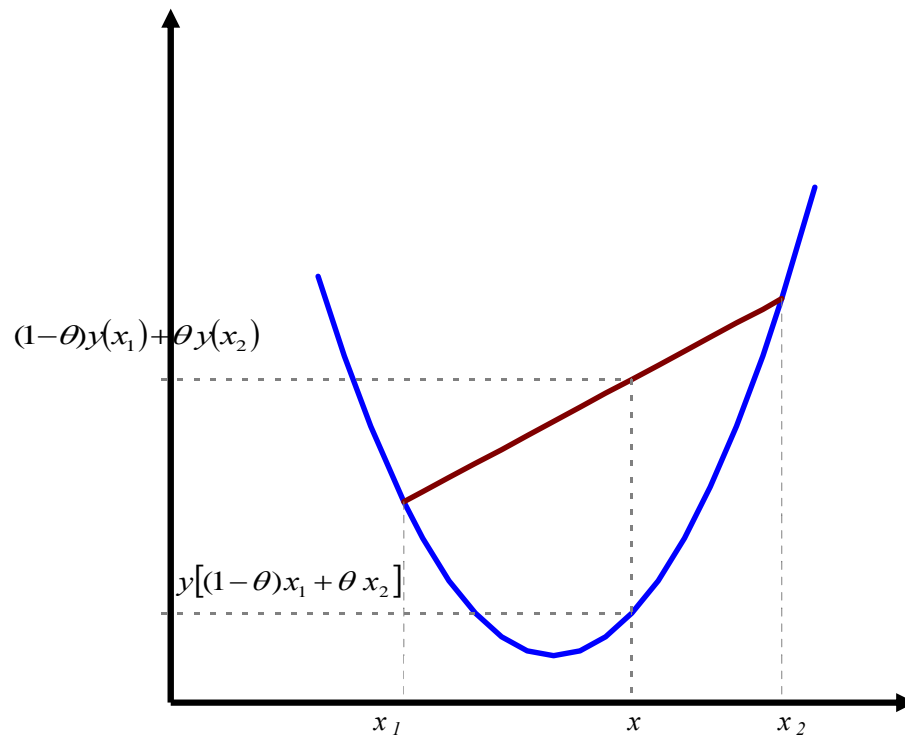
Figure H.1 Typical convex function $y(x)$.

Optimum conditions exist only at particular points within a region of the function $y(x)$. Typically, an optimum is denoted as x^*. A function $y(x)$ may have one or more maximum and minimum values within the region of interest. Either a maximum or a minimum will coincide with each mode of the function, that point is called *local maximum* or *local minimum*. If a particular maximum (or minimum) is the largest maximum (or smallest minimum), the point is termed a *global maximum* (or a *global minimum*).

APPENDIX I

RESULTS OF POTENTIAL ENERGY SAVINGS ON COMMERCIAL
BUILDINGS: CASES OF STUDY

This appendix presents the results of potential energy savings for the study cases obtained with the application of the methodology proposed in Chapter V. The sample includes 11 buildings whose data was available in the ESL database; most of them considered in the LoanSTAR program.

Table I.1 contains the characteristics of the building construction materials, HVAC systems, and major equipment of the analyzed buildings and Table I.2 includes the building operation conditions, major retrofits and audit expected savings for those buildings. Note that the utilities prices used to evaluate the potential savings correspond to the costs of the utilities at the time the building was retrofitted or commissioned. That is the reason that they seem low if they are compared to current rates.

First, the energy use simulation is calibrated to the measured building energy use – its representative operation parameters were obtained, and next the determination of potential savings was carried out. A summary of the potential dollar savings for each building is presented in the Table I.3. In this table is also presented a ratio of the audit savings with respect to the potential savings. The values of this ratio are not a fair comparison, but may serve as a reference of the audit expected dollar savings and the potential savings with optimized operation conditions.

The binned potential dollar savings of each building are presented graphically, similar to Figure I.1 for the Zachry Engineering Center. The potential dollar savings are bounded between the lines of the "actual cost" — total cost of the building energy use evaluated to the rates corresponding to the year of the data, and the optimized cost pattern obtained to the same period.

The binned cooling and heating use patterns, actual and optimized, are also included, as in Figure I.2 for Zachry Engineering Center.

The annual potential dollar savings are presented in a tabular way, as in Table I.4. These savings are annually lumped, and if required, are scaled by the number of days with available data and using the related costs.

Table I.1   Characteristics of the building construction materials, HVAC systems, and equipment of the assessed buildings.

Building, Facility, Location	Area (ft²)	ESL #	Bulding Envelope	Building HVAC and Equipment
1 Zachry Engineering Center Texas A&M University College Station, TX	324,400	1	3 1/2 floors and a ground floor level, classes, offices, labs, computer facility, and clean rooms for solidstate electronics walls: cement block; windows: 12% of total wall area, single pane with built-in-place vertical blinds; roof: flat	12 VAV AHUs (12 x 40hp); 3 MZCAV AHUs (1hp, 7hp, 10hp) 4 SZCAV (4 x 3hp); 10 fan coils (10 x 1/2hp); 2 CV chilled water pumps (2 x 30hp) 2 CV hot water pump (2 x 20hp); 7 misc. pumps (total of 5.8hp); 50 exhaust fans (20 x 1/2hp)
2 Welch Hall University of Texas Austin, TX	439,540	106	6 story erected 1974; classrooms offices, and labs; walls: red face brick on block; windows: single pane tinted glass; roof: build-up roof with 4.5" insulation	6 DDCAV AHUs (6 x 100HP); 3 return air fans (2-30 HP, 1- 60 HP); 12 exhaust fan units (6 x 7.5 HP, 6 x 15 HP);3 chilled water pumps (2x 75HP, 1 x 7.5 HP)
3 Burdine Hall University of Texas Austin, TX	103,441	107	classrooms, lecture halls, offices, and auditorium walls: concrete with face brick, windows: single pane; roof concrete	2 DDVAV AHUs (1 - 100hp, 1 - 75hp); 2 SZCAV AHUs (1 - 15hp, 1 - 1/2 hp) 2 Outside fans (2x10hp); 1VV chilled water pump (40hp); 1CV chilled water pump (40hp) 1 domestic hot water pump (3/4 hp); 10 exhaust fans (1/2 - 1.5 hp)
4 Nursing Building University of Texas Austin, TX	99,815	108	classrooms, lecture halls, and lounges walls: pre-cast concrete windows: single pane; roof: flat concrete	2 VAV AHUs (2 x 100 hp); 8 Relief fans (8 x 5 hp); 1VV chilled water pump (30hp) 1 domestic hot water pump (1/12 hp); 10 exhaust fans (1/20 - 1 hp)
5 Painter Hall University of Texas Austin, TX	128,409	116	6 floor; labs, offices, and classrooms walls: hollow clay tile, brick; windows:brown tinted, single pane clear, operable, 24% of total wall area; roof: clay tile	2 MZ AHUs (1-10hp, 1-30hp); 4 SZCAV AHUs (2 x 3hp, 1-1.5hp, 1-50hp); 2DDCAV (2-40hp) 2 chilled water pump (1-15hp, 1-20hp) 2 hot water pumps (2 x 5hp); 15 exhaust fans (0.1 - 1 hp) 4 return fans (3 x 1.5 hp, 1-0.75 hp)
6 W.C. Hogg University of Texas Austin, TX	48,905	117	4 floor and basement; auditorium, workshop, offices, and classrooms walls: hollow clay tile, brick; windows:brown tinted, single pane clear, operable, 12% of total wall area; roof: clay tile	2 DDVAV AHUs (2 x 40 hp); 2 SDCAV AHUs (2 x 5 hp); 1VV chilled water pump (25hp) 1 condensate pump (3/4hp); 6 exhaust fans (total 2hp)
7 Biology Texas Tech University Lubbock, TX	156,219	187	6 floor and basement; labs, animal rooms, offices, and classrooms An auditorium beside the building	2 chilled water pumps of 30HP each, one standby pump; 2 hot water pumps of 25 HP each, one standby pump; One hot water generator using steam; 3 SDVAV AHU's with hot water reheat for the main building; 1 SZCAV AHU for the auditorium; 13 exhaust fans
8 Chemistry South Texas Tech University Lubbock, TX	128,600	195	3 story center section, and 4 story south section, housing offices, laboratories and an auditorium	One 50HP chilled water pump; 9 DDVAV AHUs, 5 SZCAV AHUs; one makeup air AHU; Use Steam supplied from central plant for hot deck temp control; 94 exhaust fans (Chem South + Chem North) All HVAC equipment operating continuosly
9 Law School Texas Tech University Lubbock, TX	129,043	197	3 floors with a basement housing offices, a library, a forum, and a courtroo m	1 chilled water pump of 30HP each; 1 hot water pumps of 15 HP; 1 heat exchanger using steam to product hot water 4 DDVAV AHUs; 1 SZCAV AHU; and SDVAV cooling only AHU
10 E. Langford Architecture Center Texas A&M University College Station, TX	102,105	494	4 floors, consisting of clasrooms, offices, visualization lab and design studios; Walls: precast concrete; windows: fixed single pane Roof: built-up roof on concrete slabs with 2 in of rigid insulation	25 hp chilled water pump, 3hp hot water pump; 2 -30 ton chiller 10 SDVAV AHUs; 3 Liebert units; 1 split DX unit
11 Biological Sciences West Texas A&M University College Station, TX	96,038	496	4 floors and a basement; mainly laboratories and officces; Walls: suspended slab with brick veneer Roof: flat, built-up	3 AHUs; 1 air cooled chiller; Three way control valves

Table I.2   Building operation conditions, major retrofits and audit expected savings for the analyzed buildings.

Building, Facility, Location	Bldg Schedule	HVAC schedule	Retrofits Implemented	Retrofits Dates	Audit Expected Savings
1 Zachry Engineering Center Texas A&M University College Station, TX	7:30 - 18:30 7:30 - 17:30 Computer Lab 24hrs/day	24hrs/day	▪ Control modifications to the dual duct system ▪ Variable Volume dual duct system ▪ EMCS system to control HVACwas also installed along with the retrofits	Date of completion for VAV and control modifications to the dual duct system: 3/05/1991	$0.02788/kWh, $4.67/MMBtu (CHW), $4.74/MMBtu Audit Savings WBE: $41,000, CHW: $93,000, HHW: $41,000
2 Welch Hall University of Texas Austin, TX	24 hrs/day	All the HVAC equipment operate 24 hrs/day	▪ Replace incandescent lights ▪ Variable air volume (AC3 only, 30hp return air fan converted to 60hp hot deck fan. AC3 constituted of two cold deck dfans (100hp each), one hot deck fan (60hp) and one return air fan (50hp) ▪ Variable speed pumping	Work on variable air volume and variable speed started in December 1991 Retrofit Completion date: February 1992 (VAV &VSP)	$0.0455/kWh, $7.425/MMBtu (CHW), $6.2/MMBtu
3 Burdine Hall University of Texas Austin, TX	7:30 -9:30	24hrs/day	▪ Variable air volume ▪ Variable speed pumping	Completed in May 1991	$0.0455/kWh, $7.425/MMBtu (CHW), $6.2/MMBtu Audit Savings WBE: $26,600, CHW: $11,000, HHW: $5,600
4 Nursing Building University of Texas Austin, TX	6:30 - 9:30	24hrs/day	▪ Variable air volume ▪ Variable speed pumping	Completed in April 1991	$0.0455/kWh, $7.425/MMBtu (CHW), $6.2/MMBtu Audit Savings WBE: $22,500, CHW: $13,100, HHW: $7,700
5 Painter Hall University of Texas Austin, TX	WDKs 7:30 - 18:30 7:30 - 17:30 7:30 - 21:30	24hrs/day	▪ Variable air volume for AC-1,5,6 ▪ Modify (Replace) AC-3,4 ▪ New vent cycle controls on AC-1, AC-5, & AC-6 (Cold deck control) ▪ Variable speed chilled water pumping	Variable air volume conversion for AC-1,5,6 Completed in July 1991 Work on all retrofits were completed by February 1992	$0.0455/kWh, $7.425/MMBtu (CHW), $6.2/MMBtu
6 W.C. Hogg University of Texas Austin, TX	WDKs 7:30 - 18:30 7:30 - 17:30 7:30 - 21:30	24hrs/day	▪ Variable air volume ▪ Variable speed pumping ▪ Replace economizer	Variable air volume and variable speed pumping was completed in June (May) 1991	$0.0455/kWh, $7.425/MMBtu (CHW), $6.2/MMBtu Audit Savings WBE: $9,400, CHW: $3,700, HHW: $1,400
7 Biology Texas Tech University Lubbock, TX		All the HVAC equipment operate 24 hrs/day Auditorio schedule		Completed by August 2001	$0.048/kWh, $8.18/kW; $3.50/MMBtu (CHW), $2.5/MMBtu Total estimated savings: $31,734/yr
8 Chemistry South Texas Tech University Lubbock, TX	24 hrs/day	All the HVAC equipment operate 24 hrs/day		Completed by August 2001	$0.048/kWh, $8.18/kW; $3.50/MMBtu (CHW), $2.5/MMBtu Total estimated savings: $20,824/yr
9 Law School Texas Tech University Lubbock, TX		HVAC schedule varies on each AHU - check ESL-AECR 2001		Completed by August 2001	$0.048/kWh, $8.18/kW; $3.50/MMBtu (CHW), $2.5/MMBtu Total estimated savings: $20,994/yr
10 E. Langford Architecture Center Texas A&M University College Station, TX	24 hrs/day	24hrs/day	▪ SD Variable air volume ▪ Variable CHW pumping ▪ Photocell project ▪ Studio occupancy sensors	Completed by January 1997	$0.02788/kWh, $4.67/MMBtu (CHW), $4.75/MMBtu Audit Savings WBE: $17,677, CHW: $12,721, HHW: -$1,311
11 Biological Sciences West Texas A&M University College Station, TX	24hrs/day	24hrs/day	▪ Install new lighting ▪ Convert dual duct to dual duct VAV ▪ Install variable volume laboratory hoods ▪ Remove small unit from old chiller ▪ Install Variable volume pumping	Completed by January 1997	$0.02788/kWh, $4.67/MMBtu (CHW), $4.75/MMBtu Audit Savings WBE: $33,330, CHW: $12,721, HHW: $8,208

Table I.3 Summary of the audit expected savings and the determined potential energy savings for a regional group of buildings.

Building Name	Area (ft²)	#Data	Reported Yearly Audit Expected Savings				CHW+HHW	Potential Savings	% Audit/ Potential Savings
			WBE	CHW	HHW	Total			
Zachry Engineering Center, TAMU	324,400	6,367	$54,300	$124,100	$54,500	$232,900	$178,600	224,284	79.6%
Welch Hall, UT	439,540	6,672	$54,218	$38,400	$42,545	$135,164	$80,945	$557,208	14.5%
Burdine Hall, UT	103,441	1,700	$45,600	$18,857	$9,600	$74,057	$28,457	$70,527	40.3%
Nursing Building, UT	99,815	1,209	$38,600	$22,500	$13,200	$74,300	$35,700	$90,485	39.5%
Painter Hall, UT	128,409	1,553	$29,600	$49,100	$40,700	$119,400	$89,800	$177,611	50.6%
W.C. Hogg, UT	48,905	6,489	$16,114	$6,343	$2,400	$24,857	$8,743	$40,765	21.4%
Biology, TTU	156,219	3,736				$31,734	$31,734	$117,958	26.9%
Chemistry South, TTU	128,600	4,791				$20,824	$20,824	$154,579	13.5%
Law School, TTU	129,043	6,263				$20,994	$20,994	$75,641	27.8%
E. Langford Architecture C., TAMU	102,105	5,264	$17,677	$12,721	($1,311)	$29,087	$11,410	$61,589	18.5%
Biological Sciences West, TAMU	96,038	7,786	$33,330	$12,721	$8,208	$54,259	$20,929	$66,273	31.6%
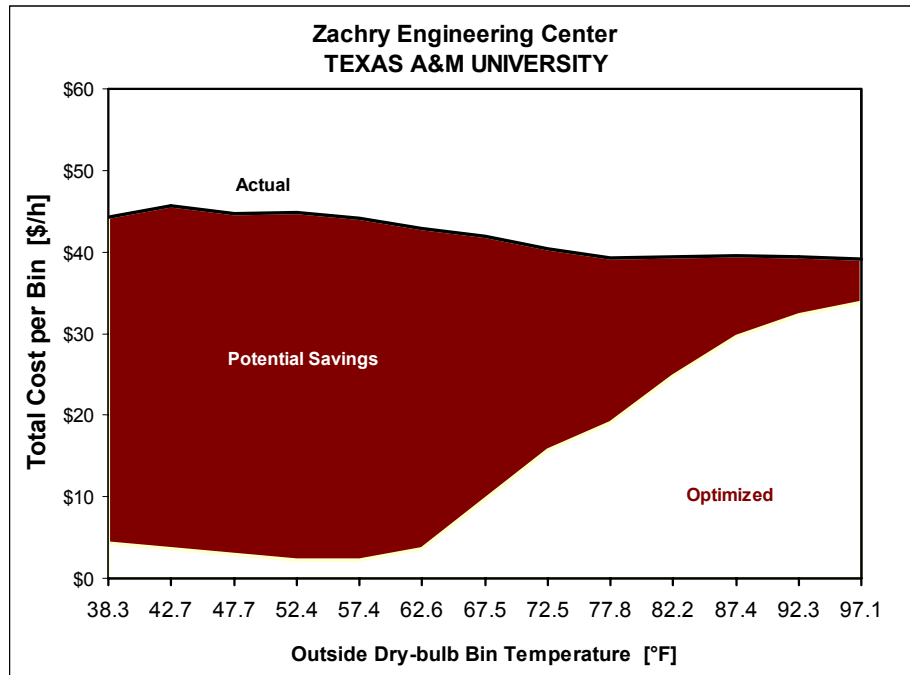
Figure I.1   Potential dollar savings for the Zachry Engineering Center of Texas A&M University based on the available data before any retrofit was implemented.
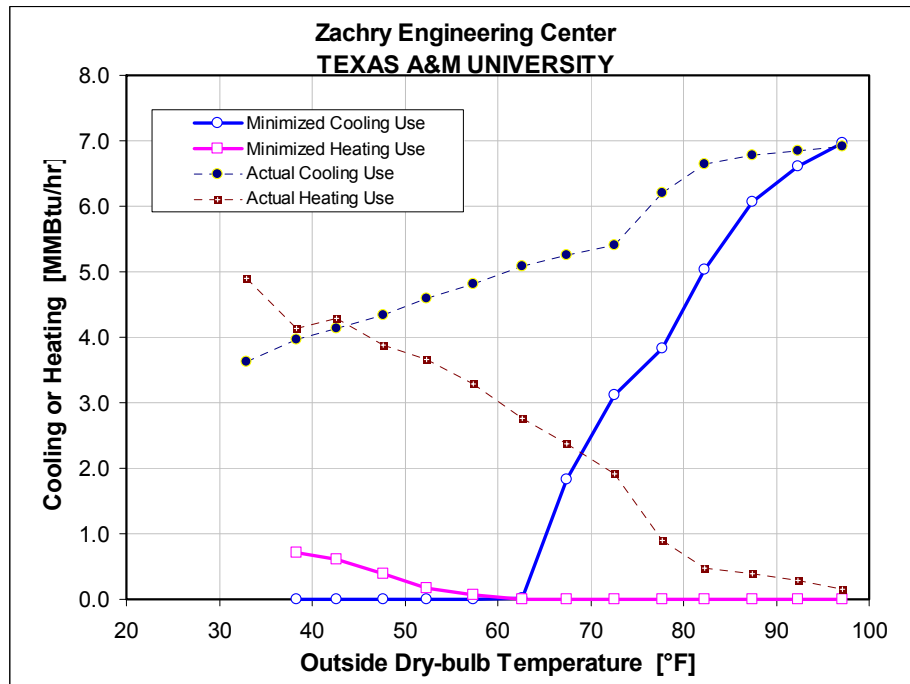
Figure I.2   Actual, and minimized, cooling and heating patterns as a function of temperature for the Zachry Engineering Center of Texas A&M University based on the available data before any retrofit was implemented.

Table I.4   Summary of the actual and optimized bin data and the potential savings for the Zachry Engineering Center of Texas A&M University based on the available data before any retrofit was implemented.

Zachry Engineering Center ▪ TEXAS A&M UNIVERSITY

Cqc =4.67$/MMBtu;   Cqh =4.75$/MMBtu;   CkWh =0.02788$/KWh

Bin			Actual Use		Optimized		Costs		College Station, TX (Yr1996	Tdb	Savings
	Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10										
10	15										
15	20								8	17.9	
20	25								40	22.5	
25	30								93	27.4	
30	35	32.9	3.63	4.89	0.00	1.25		$46.26	196	32.2	
35	40	38.3	3.97	4.13	0.01	0.72	$4.29	$44.22	259	37.3	$10,341
40	45	42.7	4.13	4.29	0.00	0.60	$3.61	$45.70	317	42.2	$13,345
45	50	47.7	4.33	3.88	0.00	0.39	$2.86	$44.71	350	47.1	$14,648
50	55	52.4	4.59	3.66	0.00	0.16	$2.27	$44.86	419	52.1	$17,844
55	60	57.4	4.81	3.29	0.00	0.06	$2.26	$44.17	577	57.2	$24,183
60	65	62.6	5.09	2.76	0.01	0.00	$3.62	$42.91	662	62.0	$26,015
65	70	67.5	5.26	2.37	1.84	0.00	$9.68	$41.87	761	67.2	$24,495
70	75	72.5	5.40	1.91	3.12	0.00	$15.78	$40.33	1130	72.3	$27,744
75	80	77.8	6.21	0.89	3.83	0.00	$19.09	$39.27	1466	76.9	$29,583
80	85	82.2	6.65	0.47	5.04	0.00	$24.79	$39.36	950	81.8	$13,836
85	90	87.4	6.78	0.39	6.07	0.00	$29.64	$39.56	679	86.9	$6,736
90	95	92.3	6.85	0.29	6.62	0.00	$32.25	$39.43	481	91.9	$3,451
95	100	97.1	6.91	0.16	6.97	0.00	$33.89	$39.06	298	96.8	$1,540
100	105								74	100.7	
							$14.16	$41.96	8349		$213,761
									8760		**$224,284**
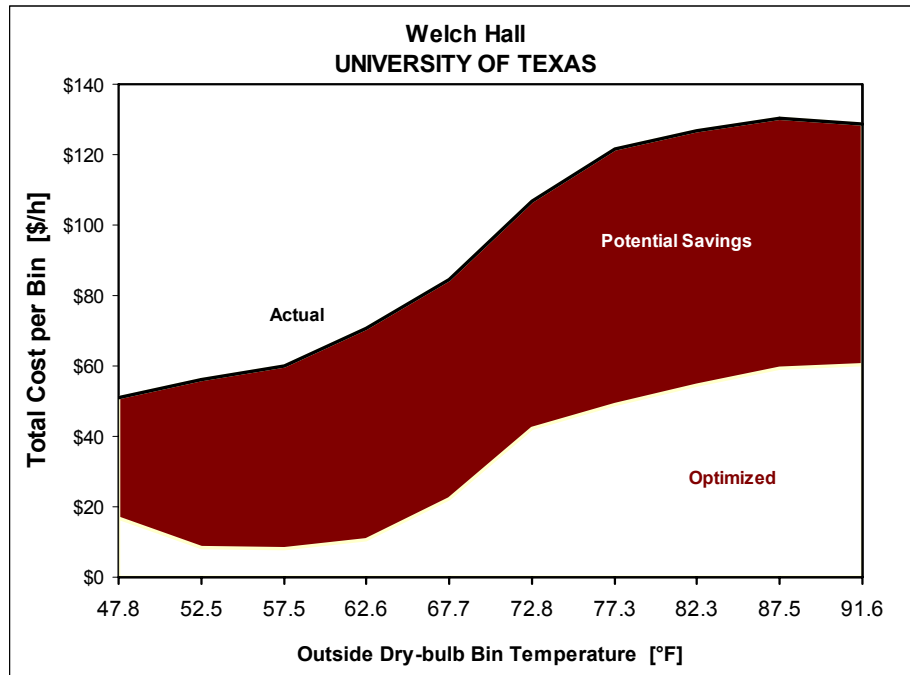
Figure I.3   Potential dollar savings for Welch Hall of the University of Texas based on the available data before any retrofit was implemented.

Figure I.4   Actual, and minimized, cooling and heating patterns as a function of temperature for Welch Hall of the University of Texas based on the available data before any retrofit was implemented.

Table I.5   Summary of the actual and optimized bin data and the potential savings for Welch Hall of the University of Texas based on the available data before any retrofit was implemented.

Welch Hall ▪ UNIVERSITY OF TEXAS

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

| Bin			Actual Use		Optimized		Costs		Austin, TX TMY2	Tdb	Savings
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10										
10	15										
15	20										
20	25										
25	30								74	28.2	
30	35	33.3	2.05	6.70				$67.79	173	32.2	
35	40	38.1	1.81	4.45				$51.98	386	37.4	
40	45	42.8	2.05	4.58				$54.65	338	43.1	
45	50	47.8	2.56	3.39	1.58	0.66	$16.91	$50.96	331	47.6	$11,272
50	55	52.5	3.42	3.19	0.09	0.73	$8.52	$56.15	518	52.1	$24,671
55	60	57.5	4.06	3.02	0.00	0.65	$8.14	$59.87	567	57.2	$29,327
60	65	62.6	5.37	3.18	0.00	0.43	$10.55	$70.55	915	62.7	$54,907
65	70	67.7	7.41	2.98	2.09	0.00	$22.32	$84.45	934	67.9	$58,027
70	75	72.8	10.63	2.73	5.30	0.00	$42.23	$106.76	945	72.7	$60,981
75	80	77.3	12.98	2.32	6.17	0.00	$48.89	$121.77	1441	76.9	$105,016
80	85	82.3	13.93	1.98	6.92	0.00	$54.47	$126.66	1053	82.1	$76,013
85	90	87.5	14.68	1.70	7.55	0.00	$59.28	$130.45	604	87.9	$42,985
90	95	91.6	14.53	1.56	7.70	0.00	$60.35	$128.57	358	92.3	$24,421
95	100								123	95.8	
100	105										
							$33.17	$86.90	7666		$487,620
									8760		**$557,208**
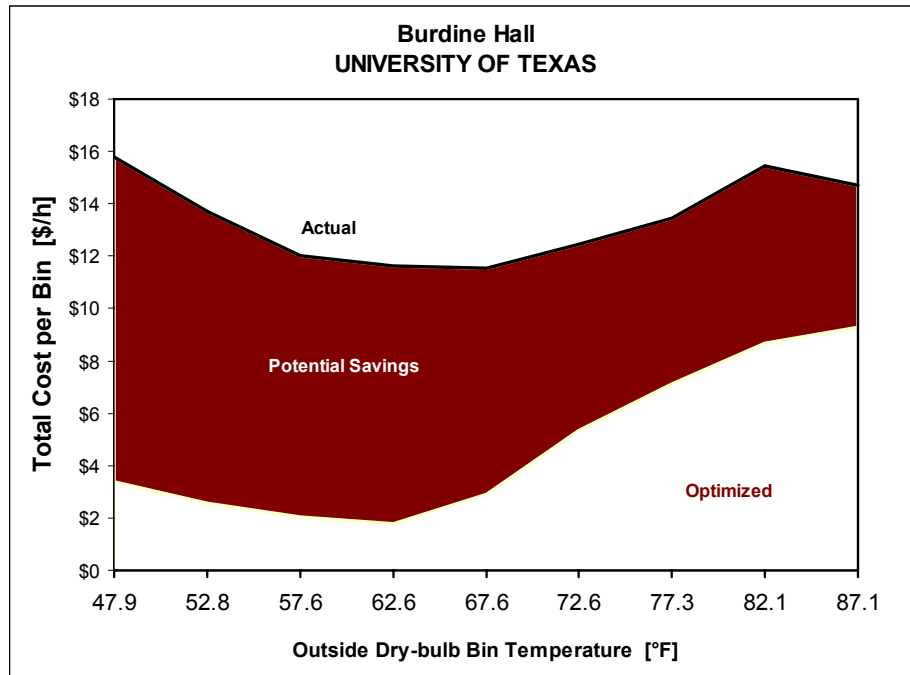
Figure I.5 Potential dollar savings for Burdine Hall of the University of Texas based on the available data before any retrofit was implemented.
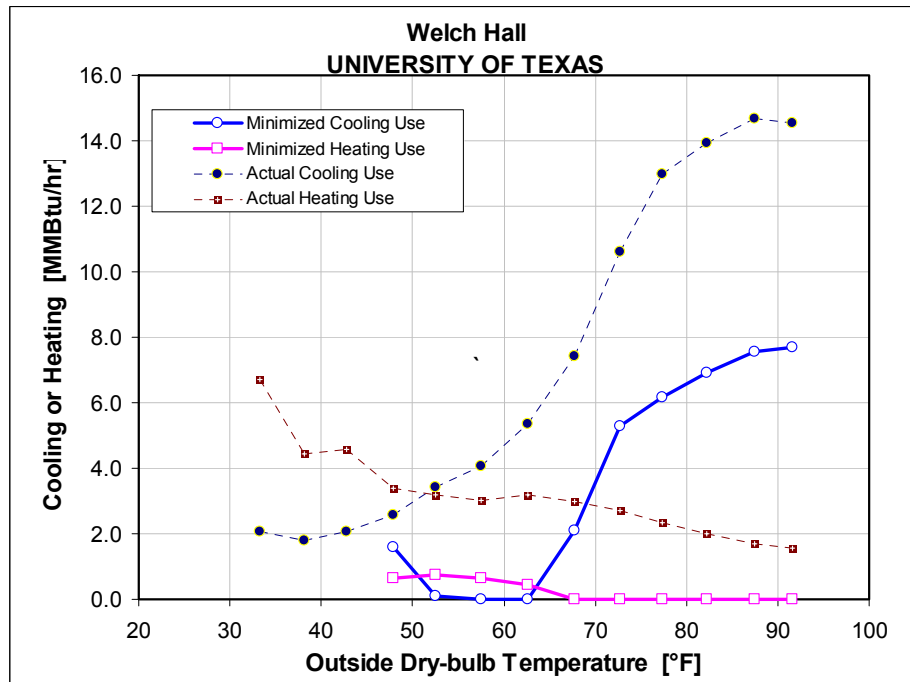

Figure I.6 Actual, and minimized, cooling and heating patterns as a function of temperature for Burdine Hall of the University of Texas based on the available data before any retrofit was implemented.

Table I.6   Summary of the actual and optimized bin data and the potential savings for Burdine Hall of the University of Texas based on the available data before any retrofit was implemented.

Burdine Hall ▪ UNIVERSITY OF TEXAS

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

Bin			Actual Use		Optimized		Costs		Austin, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10										
10	15										
15	20										
20	25										
25	30								74	28.2	
30	35								173	32.2	
35	40								386	37.4	
40	45	43.9	0.71	0.90	0.00	0.62			338	43.1	
45	50	47.9	1.05	1.14	0.00	0.49	$3.38	$15.79	331	47.6	$4,107
50	55	52.8	0.93	0.94	0.00	0.36	$2.55	$13.72	518	52.1	$5,786
55	60	57.6	0.87	0.74	0.00	0.25	$2.04	$12.02	567	57.2	$5,661
60	65	62.6	0.93	0.61	0.00	0.16	$1.80	$11.62	915	62.7	$8,990
65	70	67.6	1.03	0.47	0.37	0.00	$2.91	$11.54	934	67.9	$8,059
70	75	72.6	1.27	0.33	0.69	0.00	$5.34	$12.44	945	72.7	$6,710
75	80	77.3	1.46	0.27	0.90	0.00	$7.11	$13.45	1441	76.9	$9,137
80	85	82.1	1.73	0.26	1.09	0.00	$8.68	$15.45	1053	82.1	$7,131
85	90	87.1	1.67	0.21	1.17	0.00	$9.30	$14.70	604	87.9	$3,258
90	95	92.2	1.48	0.21	1.52	0.00			358	92.3	
95	100								123	95.8	
100	105										
							$4.79	$13.41	7308		$58,837
									8760		**$70,527**

Figure I.7   Potential dollar savings for the Nursing Building of the University of Texas based on the available data before any retrofit was implemented.

Figure I.8   Actual, and minimized, cooling and heating patterns as a function of temperature for the Nursing Building of the University of Texas based on the available data before any retrofit was implemented.

Table I.7 Summary of the actual and optimized bin data and the potential savings for the Nursing Building of the University of Texas based on the available data before any retrofit was implemented.

Nursing Building ▪ UNIVERSITY OF TEXAS

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

| Bin			Actual Use		Optimized		Costs		Austin, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10										
10	15										
15	20										
20	25										
25	30								74	28.2	
30	35								173	32.2	
35	40								386	37.4	
40	45	43.9	0.29	0.54	0.00	0.71			338	43.1	
45	50	47.9	0.82	1.10	0.00	0.48	$3.32	$14.02	331	47.6	$3,543
50	55	52.8	0.72	0.89	0.00	0.36	$2.50	$11.96	518	52.1	$4,897
55	60	57.6	0.89	0.90	0.00	0.25	$1.89	$13.31	567	57.2	$6,472
60	65	62.6	1.10	0.88	0.00	0.16	$1.60	$14.76	915	62.7	$12,042
65	70	67.4	1.21	0.73	0.27	0.00	$2.09	$14.65	934	67.9	$11,735
70	75	72.4	1.38	0.59	0.61	0.00	$4.67	$15.04	945	72.7	$9,798
75	80	77.3	1.73	0.55	0.88	0.00	$6.96	$17.36	1441	76.9	$14,991
80	85	81.8	1.70	0.42	1.10	0.00	$8.63	$16.35	1053	82.1	$8,130
85	90	87.8	1.58	0.48	1.18	0.00	$9.39	$15.81	604	87.9	$3,877
90	95	93.2	1.67	0.28	1.42	0.00			358	92.3	
95	100								123	95.8	
100	105										
							$4.56	$14.81	7308		$75,487
									8760		**$90,485**
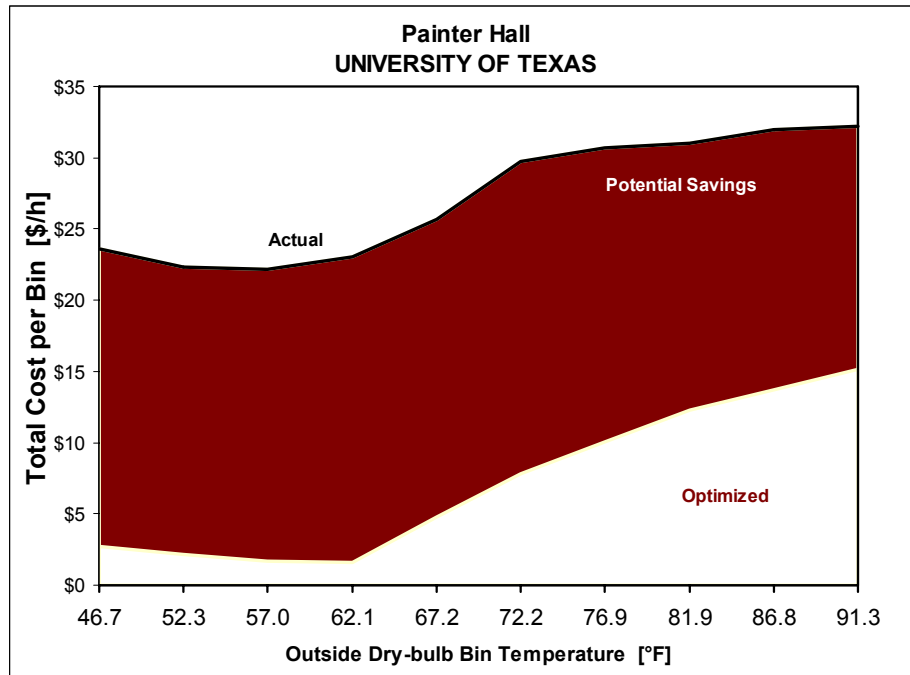
Figure I.9 Potential dollar savings for Painter Hall of the University of Texas based on the available data before any retrofit was implemented.
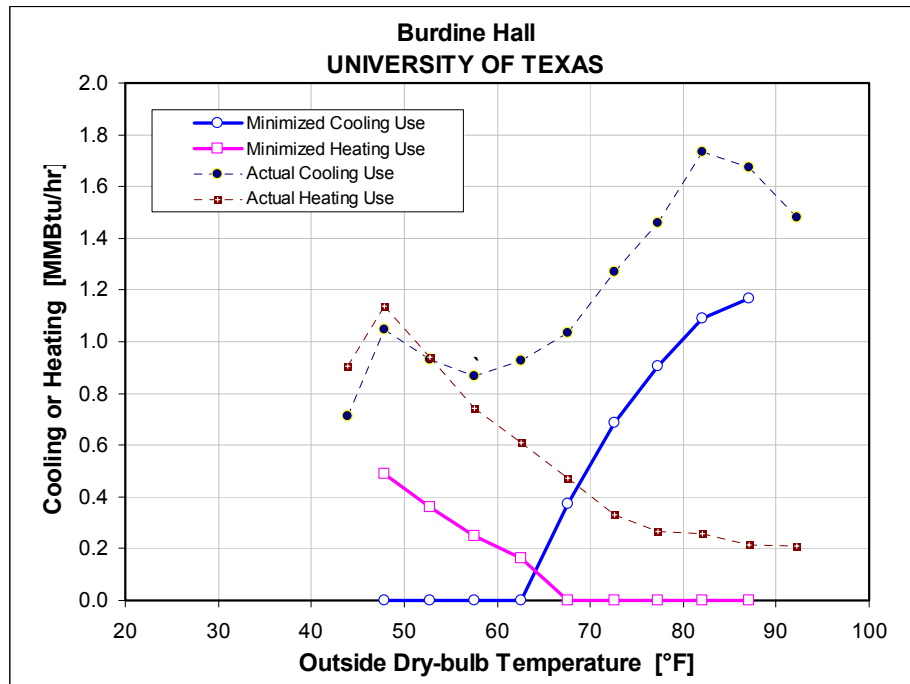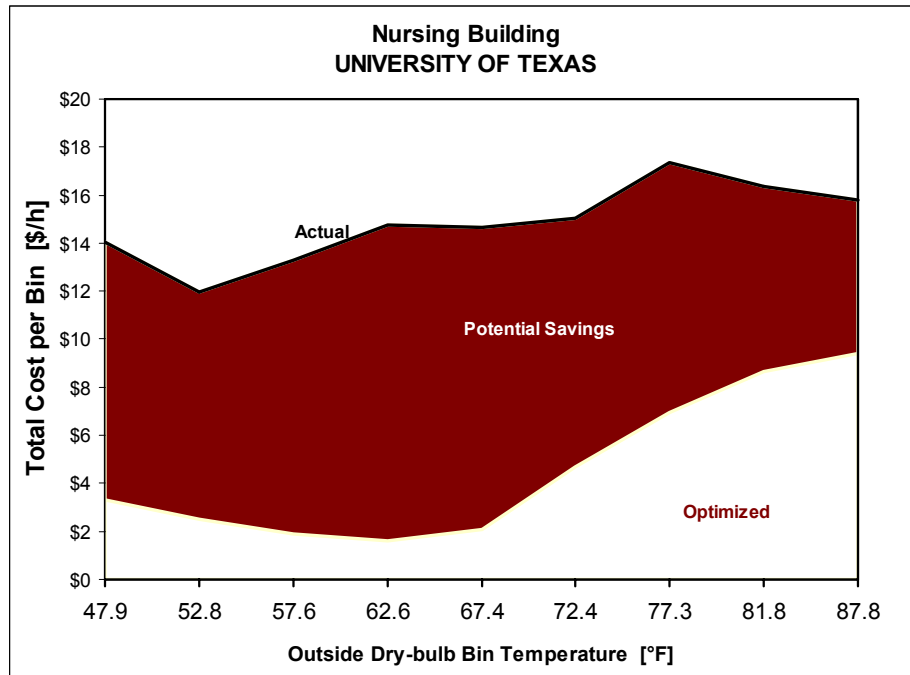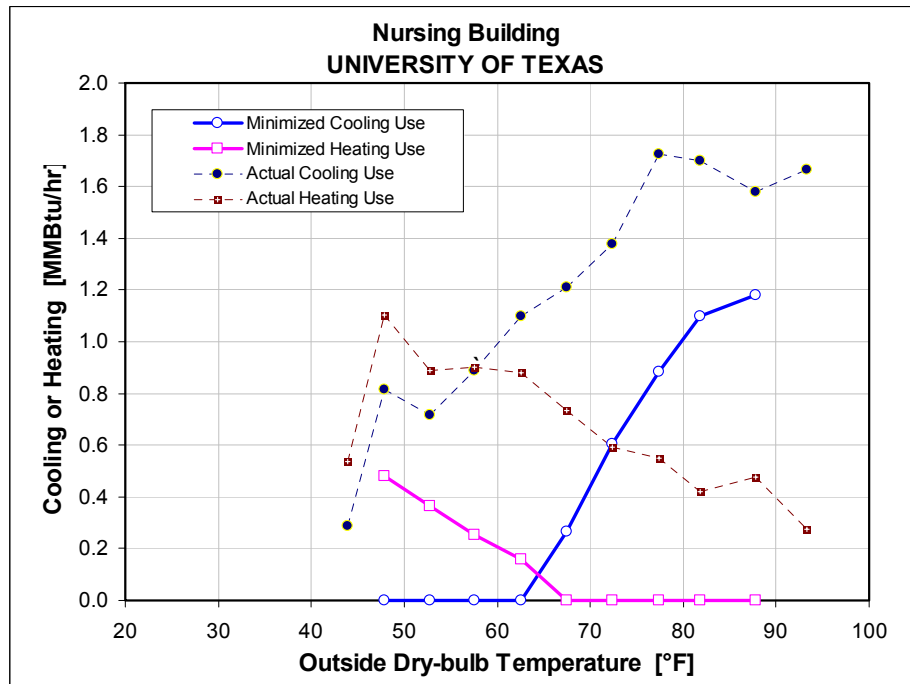

Figure I.10 Actual, and minimized, cooling and heating patterns as a function of temperature for Painter Hall of the University of Texas based on the available data before any retrofit was implemented.

Table I.8   Summary of the actual and optimized bin data and the potential savings for Painter Hall of the University of Texas based on the available data before any retrofit was implemented.

Painter Hall ▪ UNIVERSITY OF TEXAS

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

| Bin			Actual Use		Optimized		Costs		Austin, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10										
10	15										
15	20										
20	25										
25	30								74	28.2	
30	35								173	32.2	
35	40								386	37.4	
40	45	42.3	1.40	1.56	0.00	0.48			338	43.1	
45	50	46.7	1.50	1.58	0.00	0.37	$2.73	$23.56	331	47.6	$6,894
50	55	52.3	1.52	1.36	0.00	0.27	$2.13	$22.30	518	52.1	$10,452
55	60	57.0	1.56	1.29	0.00	0.17	$1.71	$22.18	567	57.2	$11,606
60	65	62.1	1.79	1.15	0.00	0.08	$1.59	$23.06	915	62.7	$19,644
65	70	67.2	2.19	1.10	0.61	0.00	$4.78	$25.67	934	67.9	$19,513
70	75	72.2	2.80	1.02	1.00	0.00	$7.85	$29.73	945	72.7	$20,681
75	80	76.9	2.99	0.95	1.27	0.00	$10.04	$30.71	1441	76.9	$29,782
80	85	81.9	3.09	0.87	1.54	0.00	$12.25	$31.01	1053	82.1	$19,750
85	90	86.8	3.29	0.79	1.73	0.00	$13.75	$31.98	604	87.9	$11,011
90	95	91.3	3.37	0.73	1.92	0.00	$15.15	$32.18	358	92.3	$6,096
95	100	95.0	3.39	0.59					123	95.8	
100	105										
							$7.20	$27.24	7666		$155,430
									8760		**$177,611**

Figure I.11 Potential dollar savings for the W.C. Hogg Building of the University of Texas based on the available data before any retrofit was implemented.
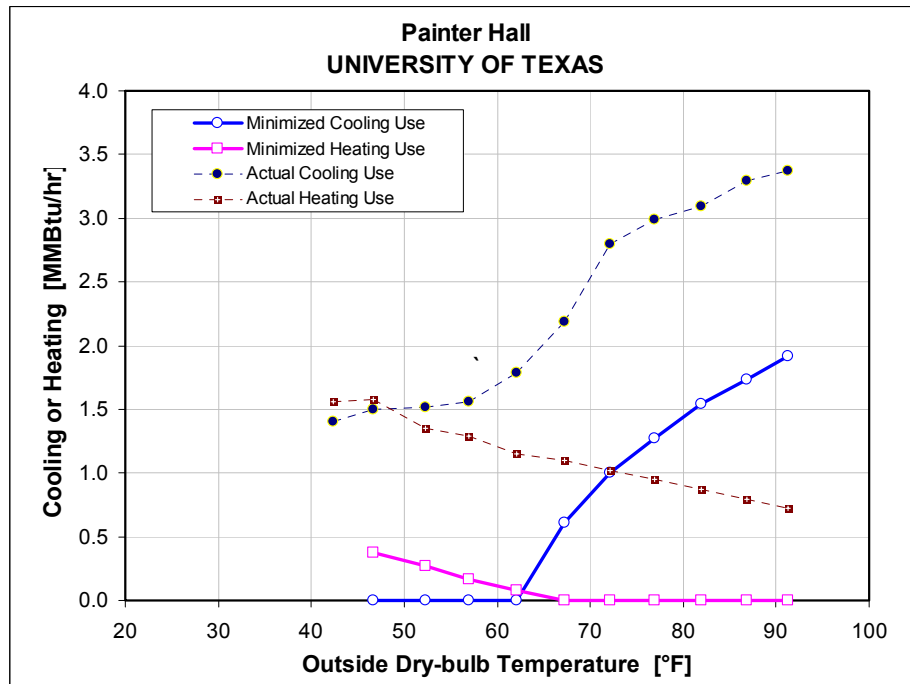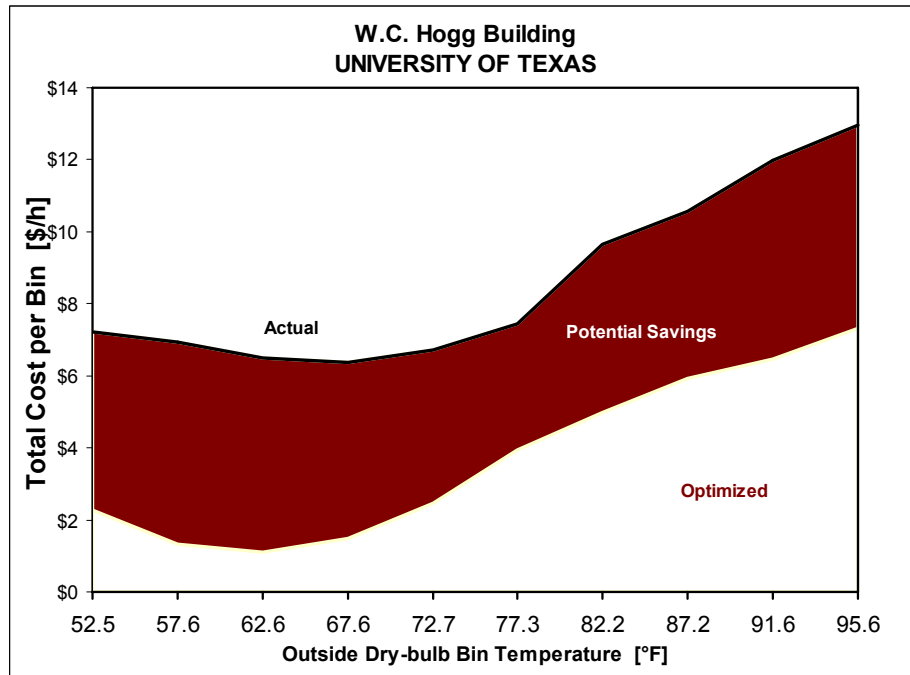

Figure I.12 Actual, and minimized, cooling and heating patterns as a function of temperature for the W.C. Hogg Building of the University of Texas University based on the available data before any retrofit was implemented.

Table I.9   Summary of the actual and optimized bin data and the potential savings for the W.C. Hogg Building of the University of Texas based on the available data before any retrofit was implemented.

W.C. Hogg Building ▪ UNIVERSITY OF TEXAS

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

Bin			Actual Use		Optimized		Costs		Austin, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10										
10	15										
15	20										
20	25										
25	30	28.7	0.31	0.69					74	28.2	
30	35	33.3	0.32	0.69					173	32.2	
35	40	38.1	0.37	0.62					386	37.4	
40	45	42.9	0.42	0.56					338	43.1	
45	50	47.9	0.43	0.49					331	47.6	
50	55	52.5	0.44	0.44	0.07	0.24	$2.27	$7.21	518	52.1	$2,560
55	60	57.6	0.45	0.37	0.00	0.17	$1.32	$6.93	567	57.2	$3,181
60	65	62.6	0.47	0.32	0.00	0.09	$1.09	$6.49	915	62.7	$4,937
65	70	67.6	0.54	0.29	0.17	0.01	$1.47	$6.38	934	67.9	$4,587
70	75	72.7	0.66	0.26	0.31	0.00	$2.47	$6.73	945	72.7	$4,021
75	80	77.3	0.95	0.26	0.49	0.00	$3.95	$7.43	1441	76.9	$5,017
80	85	82.2	1.07	0.24	0.63	0.00	$4.99	$9.65	1053	82.1	$4,913
85	90	87.2	1.24	0.24	0.75	0.00	$5.91	$10.58	604	87.9	$2,817
90	95	91.6	1.35	0.25	0.81	0.00	$6.46	$11.99	358	92.3	$1,979
95	100	95.6	1.42	0.25	0.90	0.00	$7.32	$12.96	123	95.8	$693
100	105										
							$3.72	$8.63	7458		$34,706
									8760		**$40,765**

Figure I.13 Potential dollar savings for the Biology Building of Texas Tech University based on the available data before any retrofit was implemented.
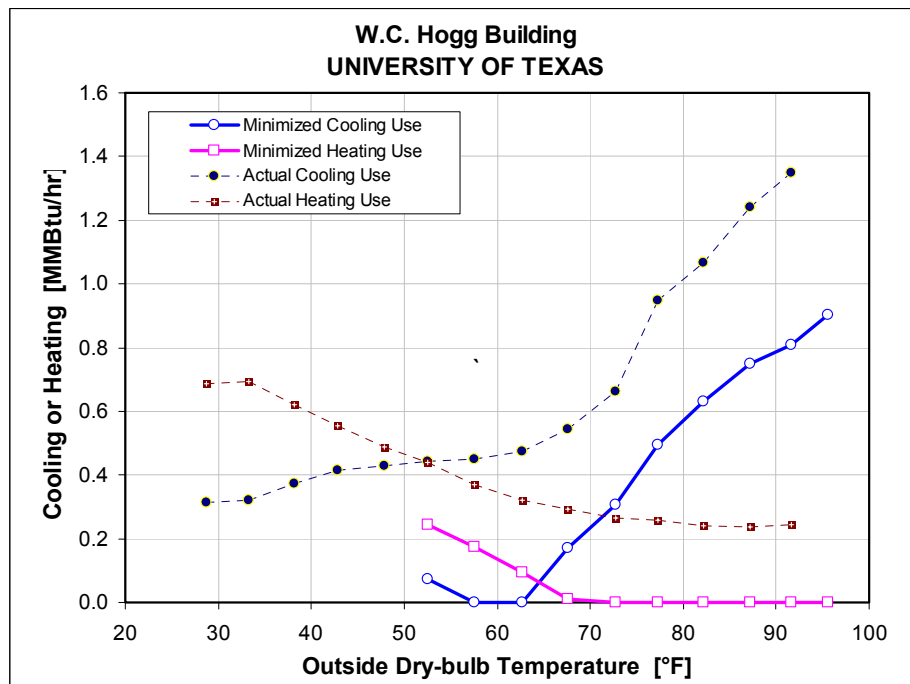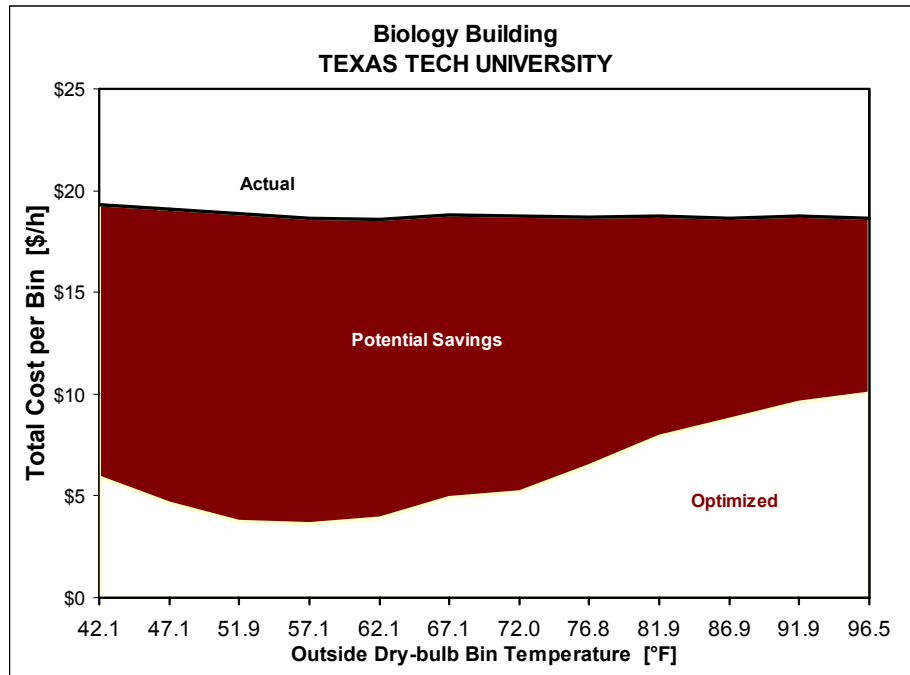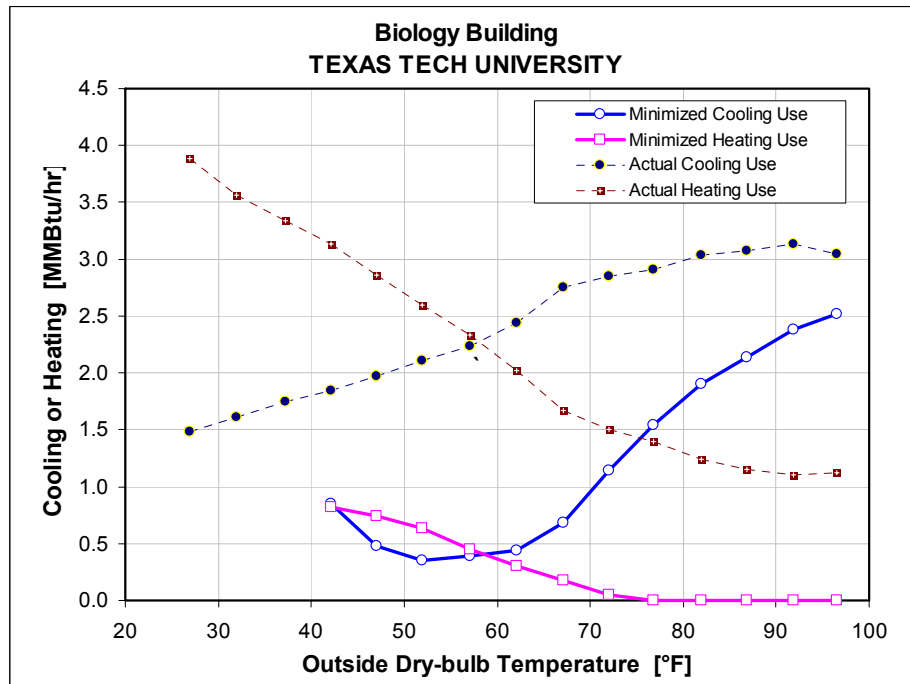

Figure I.14 Actual, and minimized, cooling and heating patterns as a function of temperature for the Biology Building of Texas Tech University based on the available data before any retrofit was implemented.

Table I.10 Summary of the actual and optimized bin data and the potential savings for the Biology Building of Texas Tech University based on the available data before any retrofit was implemented.

Biology Building ▪ TEXAS TECH UNIVERSITY

Cqc =3.5$/MMBtu; Cqh =2.5$/MMBtu; CkWh =0.048$/KWh

| Bin			Actual Use		Optimized		Costs		Lubbock, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10								23	6.6	
10	15								38	12.2	
15	20								100	18.0	
20	25								138	23.2	
25	30	27.0	1.48	3.88	0.69	1.30			208	27.7	
30	35	32.0	1.62	3.56	0.72	1.14			502	32.2	
35	40	37.2	1.74	3.34	0.81	0.97			586	37.4	
40	45	42.1	1.85	3.13	0.85	0.82	$5.89	$19.30	531	42.9	$7,116
45	50	47.1	1.97	2.86	0.47	0.74	$4.64	$19.06	585	47.4	$8,435
50	55	51.9	2.11	2.60	0.35	0.63	$3.73	$18.88	657	52.1	$9,948
55	60	57.1	2.23	2.33	0.39	0.45	$3.61	$18.66	777	57.2	$11,693
60	65	62.1	2.44	2.02	0.44	0.30	$3.90	$18.60	887	62.5	$13,041
65	70	67.1	2.75	1.67	0.69	0.18	$4.93	$18.81	1012	68.0	$14,052
70	75	72.0	2.85	1.51	1.14	0.05	$5.18	$18.74	843	72.5	$11,430
75	80	76.8	2.91	1.40	1.54	0.00	$6.49	$18.69	745	77.1	$9,084
80	85	81.9	3.04	1.23	1.90	0.00	$7.93	$18.73	555	82.3	$5,990
85	90	86.9	3.08	1.15	2.14	0.00	$8.76	$18.65	349	87.8	$3,453
90	95	91.9	3.14	1.11	2.38	0.00	$9.60	$18.76	181	92.3	$1,657
95	100	96.5	3.05	1.12	2.52	0.00	$10.07	$18.65	42	95.7	
100	105										
							$6.23	$18.79	7122		$95,901
									8760		$117,958
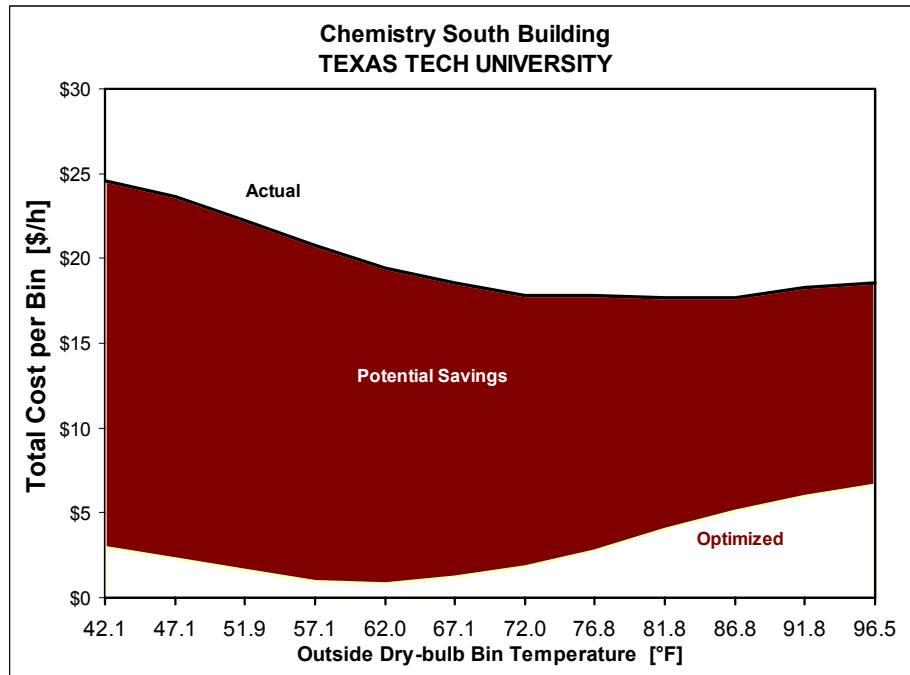
Figure I.15 Potential dollar savings for the Chemistry South Building of Texas Tech University based on the available data before any retrofit was implemented.
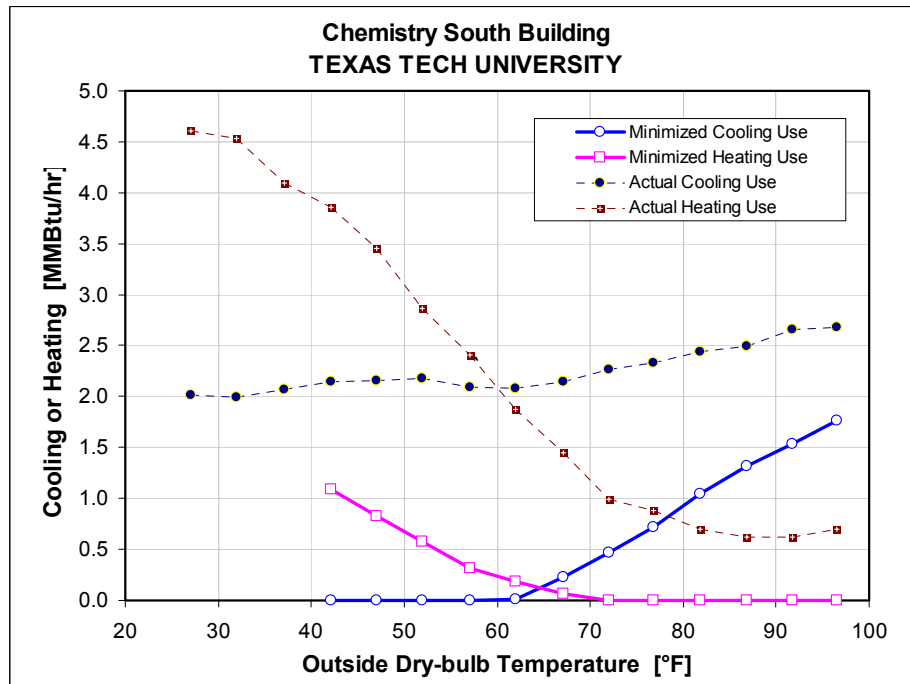

Figure I.16 Actual, and minimized, cooling and heating patterns as a function of temperature for the Chemistry South Building of Texas Tech University based on the available data before any retrofit was implemented.

Table I.11   Summary of the actual and optimized bin data and the potential savings for the Chemistry South Building of Texas Tech University based on the available data before any retrofit was implemented.

Chemistry South Building ▪ TEXAS TECH UNIVERSITY

Cqc =3.5$/MMBtu; Cqh =2.5$/MMBtu; CkWh =0.048$/KWh

| Bin			Actual Use		Optimized		Costs		Lubbock, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10								23	6.6	
10	15								38	12.2	
15	20								100	18.0	
20	25								138	23.2	
25	30								208	27.7	
30	35								502	32.2	
35	40								586	37.4	
40	45	42.1	2.15	3.85	0.00	1.08	$2.92	$24.58	531	42.9	$11,505
45	50	47.1	2.16	3.45	0.00	0.83	$2.26	$23.61	585	47.4	$12,492
50	55	51.9	2.18	2.87	0.00	0.57	$1.61	$22.21	657	52.1	$13,538
55	60	57.1	2.09	2.40	0.00	0.31	$0.95	$20.77	777	57.2	$15,397
60	65	62.0	2.09	1.87	0.01	0.19	$0.80	$19.41	887	62.5	$16,515
65	70	67.1	2.14	1.45	0.23	0.06	$1.23	$18.55	1012	68.0	$17,526
70	75	72.0	2.27	0.99	0.47	0.00	$1.80	$17.85	843	72.5	$13,527
75	80	76.8	2.33	0.88	0.72	0.00	$2.73	$17.79	745	77.1	$11,216
80	85	81.8	2.44	0.69	1.05	0.00	$4.05	$17.70	555	82.3	$7,576
85	90	86.8	2.50	0.62	1.32	0.00	$5.11	$17.70	349	87.8	$4,396
90	95	91.8	2.66	0.62	1.53	0.00	$5.98	$18.28	181	92.3	$2,227
95	100	96.5	2.68	0.70	1.77	0.00	$6.64	$18.55	42	95.7	$500
100	105										
							$3.01	$19.75	7164		$126,416
									8760		**$154,579**
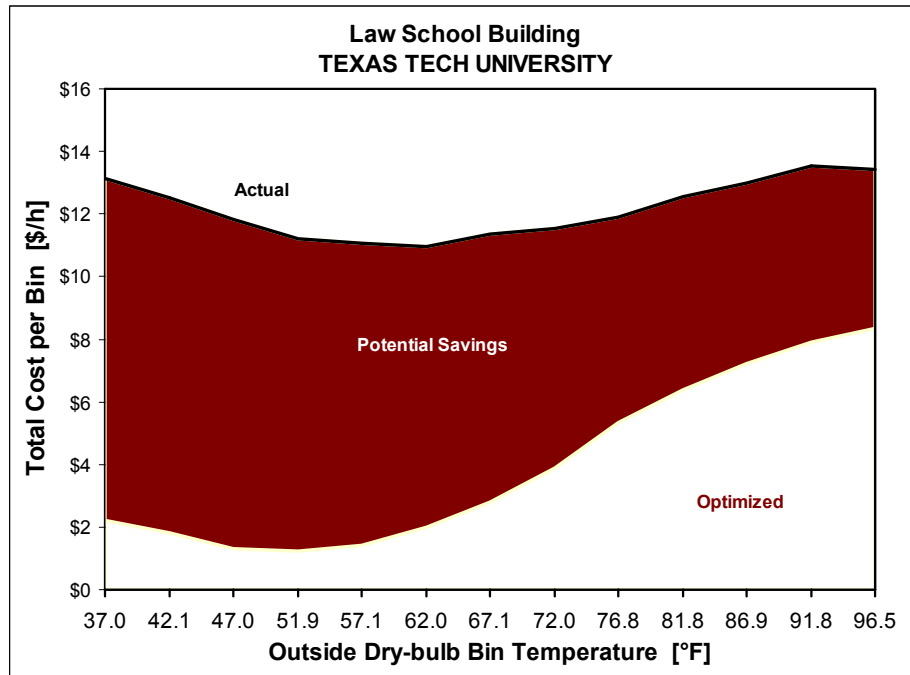
Figure I.17 Potential dollar savings for the Law school Building of Texas Tech University based on the available data before any retrofit was implemented.
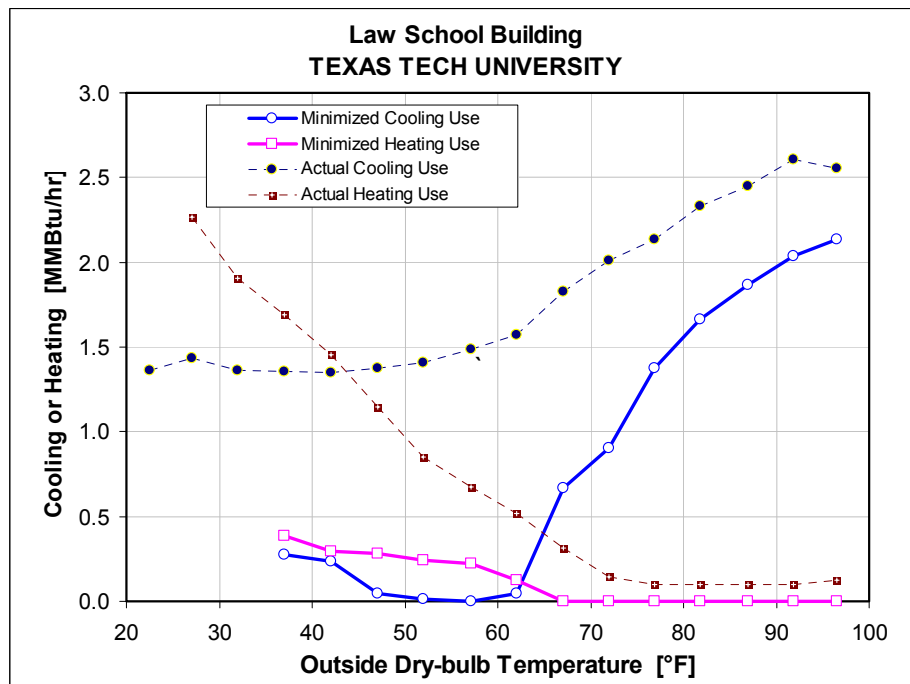

Figure I.18 Actual, and minimized, cooling and heating patterns as a function of temperature for the Law School Building of Texas Tech University based on the available data before any retrofit was implemented.

Table I.12 Summary of the actual and optimized bin data and the potential savings for the Law School Building of Texas Tech University based on the available data before any retrofit was implemented.

Law School Building ▪ TEXAS TECH UNIVERSITY

Cqc =3.5$/MMBtu;   Cqh =2.5$/MMBtu;   CkWh =0.048$/KWh

| Bin			Actual Use		Optimized		Costs		Lubbock, TX TMY2	Tdb	Tdb
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual	#Data	Avge	Total
5	10								23	6.6	
10	15								38	12.2	
15	20								100	18.0	
20	25								138	23.2	
25	30								208	27.7	
30	35								502	32.2	
35	40	37.0	1.36	1.69	0.28	0.39	$2.22	$13.12	586	37.4	$6,390
40	45	42.1	1.35	1.45	0.24	0.29	$1.82	$12.52	531	42.9	$5,682
45	50	47.0	1.38	1.14	0.05	0.28	$1.30	$11.83	585	47.4	$6,159
50	55	51.9	1.41	0.85	0.01	0.24	$1.23	$11.22	657	52.1	$6,565
55	60	57.1	1.49	0.67	0.00	0.22	$1.42	$11.05	777	57.2	$7,481
60	65	62.0	1.57	0.52	0.04	0.13	$1.99	$10.95	887	62.5	$7,954
65	70	67.1	1.83	0.32	0.67	0.00	$2.79	$11.35	1012	68.0	$8,668
70	75	72.0	2.01	0.14	0.91	0.00	$3.89	$11.54	843	72.5	$6,452
75	80	76.8	2.14	0.10	1.38	0.00	$5.32	$11.88	745	77.1	$4,889
80	85	81.8	2.33	0.10	1.66	0.00	$6.37	$12.56	555	82.3	$3,436
85	90	86.9	2.45	0.10	1.87	0.00	$7.21	$12.98	349	87.8	$2,014
90	95	91.8	2.61	0.10	2.04	0.00	$7.90	$13.52	181	92.3	$1,018
95	100	96.5	2.55	0.13	2.14	0.00	$8.35	$13.41	42	95.7	$212
100	105										
							$3.99	$12.15	7750		$66,920
									8760		**$75,641**
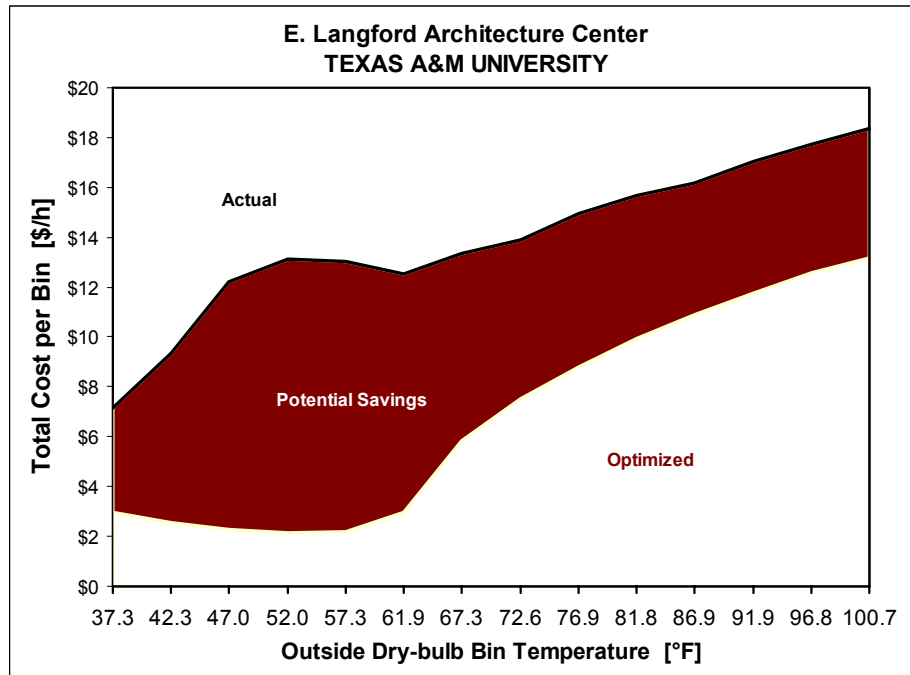
Figure I.19 Potential dollar savings for the E. Langford Architecture Center of Texas A&M University based on the available data before any retrofit was implemented.
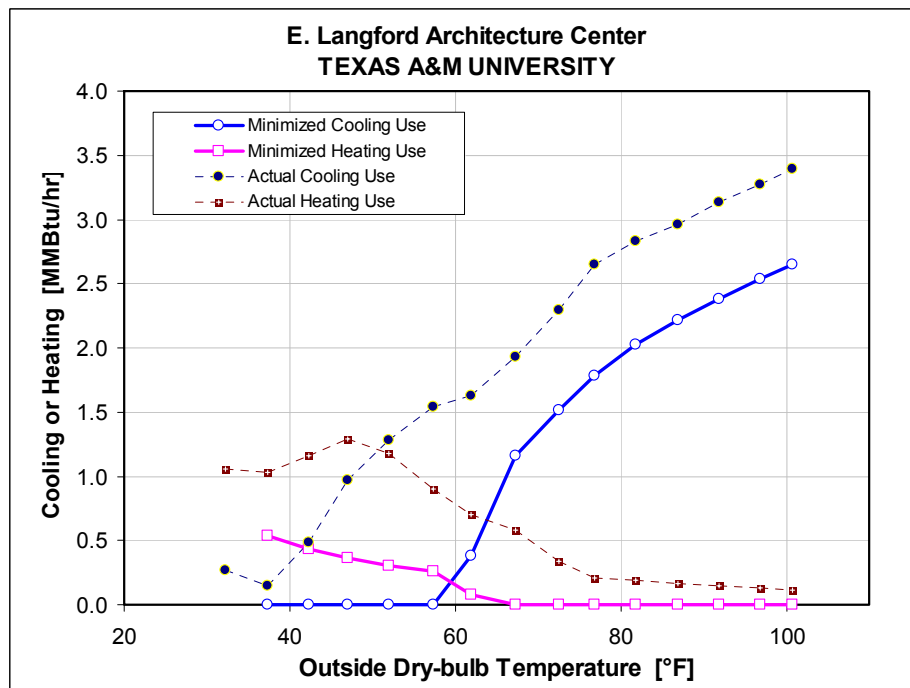

Figure I.20 Actual, and minimized, cooling and heating patterns as a function of temperature for the E. Langford Architecture Center of Texas A&M University based on the available data before any retrofit was implemented.

Table I.13 Summary of the actual and optimized bin data and the potential savings for the E. Langford Architecture Center of Texas A&M University based on the available data before any retrofit was implemented.

E. Langford Architecture Center ▪ TEXAS A&M UNIVERSITY

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

| Bin		Toa	Actual Use CHW	Actual Use HHW	Optimized CHW	Optimized HHW	Costs Optimized	Actual	College Station, TX 1996 #Data	Tdb Avge	Tdb Total
5	10										
10	15										
15	20								8	17.9	
20	25								40	22.5	
25	30								93	27.4	
30	35								196	32.2	
35	40	37.3	0.15	1.03	0.00	0.54	$2.97	$7.16	259	37.3	$1,086
40	45	42.3	0.48	1.16	0.00	0.43	$2.54	$9.34	317	42.2	$2,154
45	50	47.0	0.97	1.29	0.00	0.36	$2.29	$12.21	350	47.1	$3,470
50	55	52.0	1.28	1.18	0.00	0.30	$2.12	$13.11	419	52.1	$4,604
55	60	57.3	1.54	0.90	0.00	0.26	$2.20	$13.01	577	57.2	$6,242
60	65	61.9	1.63	0.71	0.38	0.08	$2.98	$12.51	662	62.0	$6,311
65	70	67.3	1.93	0.58	1.16	0.00	$5.83	$13.33	761	67.2	$5,709
70	75	72.6	2.30	0.33	1.52	0.00	$7.53	$13.87	1130	72.3	$7,171
75	80	76.9	2.65	0.21	1.79	0.00	$8.79	$14.93	1466	76.9	$8,996
80	85	81.8	2.83	0.19	2.02	0.00	$9.92	$15.65	950	81.8	$5,444
85	90	86.9	2.96	0.16	2.21	0.00	$10.89	$16.15	679	86.9	$3,574
90	95	91.9	3.13	0.15	2.38	0.00	$11.76	$17.04	481	91.9	$2,537
95	100	96.8	3.27	0.13	2.54	0.00	$12.57	$17.73	298	96.8	$1,537
100	105	100.73	3.39	0.11	2.65	0.00	$13.15	$18.34	74	100.7	$384
							$6.82	$13.89	8423		$59,220
									8760		**$61,589**
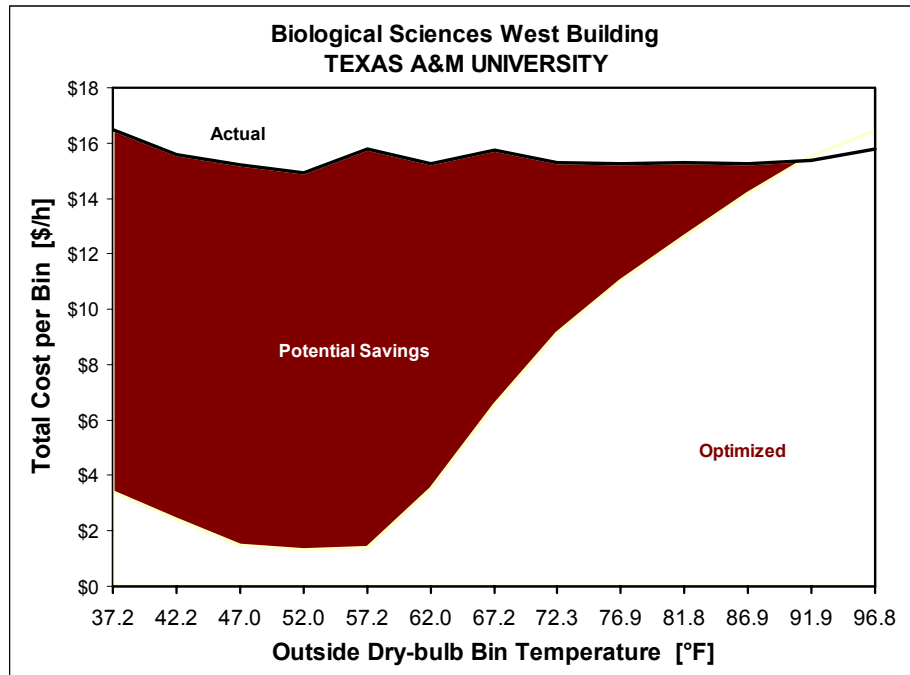
Figure I.21 Potential dollar savings for the Biological Sciences West Building of Texas A&M University based on the available data before any retrofit was implemented.
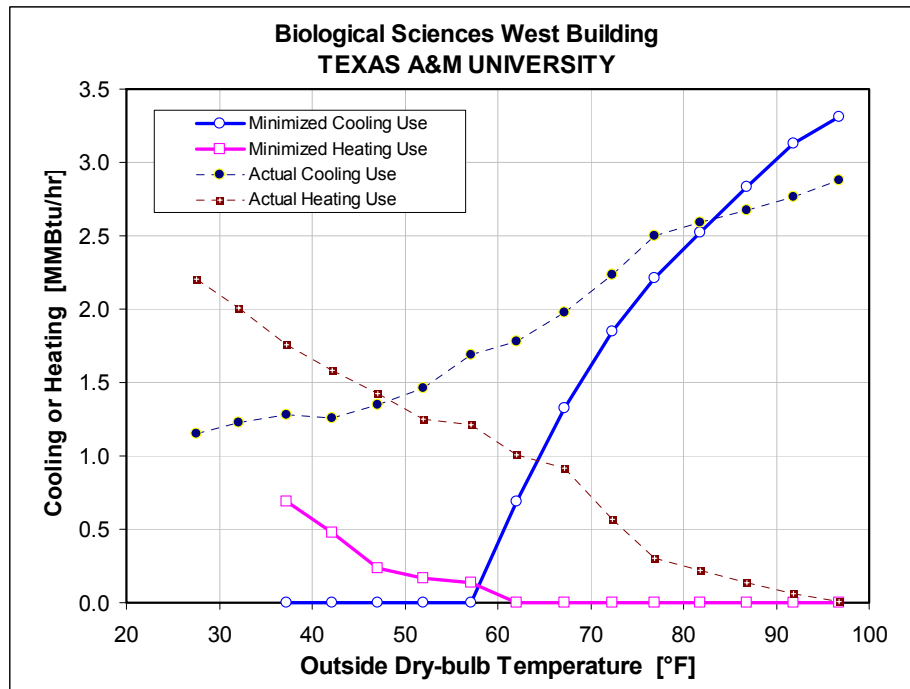

Figure I.22 Actual, and minimized, cooling and heating patterns as a function of temperature for the Biological Sciences West Building of Texas A&M University based on the available data before any retrofit was implemented.

Table I.14 Summary of the actual and optimized bin data and the potential savings for the Biological Sciences West Building of Texas A&M University based on the available data before any retrofit was implemented.

Biological Sciences West Building ▪ TEXAS A&M UNIVERSITY

Cqc =7.425$/MMBtu;   Cqh =6.2$/MMBtu;   CkWh =0.0455$/KWh

Bin			Actual Use		Optimized		Costs		College Station, TX 1996 #Data	Tdb Avge	Tdb Total
		Toa	CHW	HHW	CHW	HHW	Optimized	Actual			
5	10										
10	15										
15	20								8	17.9	
20	25								40	22.5	
25	30								93	27.4	
30	35								196	32.2	
35	40	37.2	1.28	1.76	0.00	0.69	$3.42	$16.48	259	37.3	$3,384
40	45	42.2	1.26	1.59	0.00	0.48	$2.40	$15.56	317	42.2	$4,171
45	50	47.0	1.35	1.42	0.00	0.24	$1.47	$15.20	350	47.1	$4,807
50	55	52.0	1.46	1.25	0.00	0.17	$1.31	$14.93	419	52.1	$5,704
55	60	57.2	1.69	1.22	0.00	0.13	$1.41	$15.80	577	57.2	$8,299
60	65	62.0	1.78	1.01	0.69	0.00	$3.51	$15.24	662	62.0	$7,763
65	70	67.2	1.97	0.92	1.32	0.00	$6.57	$15.72	761	67.2	$6,966
70	75	72.3	2.24	0.57	1.85	0.00	$9.15	$15.31	1130	72.3	$6,960
75	80	76.9	2.50	0.30	2.22	0.00	$11.02	$15.25	1466	76.9	$6,201
80	85	81.8	2.59	0.22	2.52	0.00	$12.61	$15.30	950	81.8	$2,550
85	90	86.9	2.67	0.14	2.83	0.00	$14.17	$15.27	679	86.9	$748
90	95	91.9	2.77	0.06	3.13	0.00	$15.55	$15.36	481	91.9	($91)
95	100	96.8	2.88	0.01	3.31	0.00	$16.44	$15.80	298	96.8	($190)
100	105								74	100.7	
							$7.62	$15.48	7570		$57,270
									8760		**$66,273**

APPENDIX J

VENTILATION FOR ACCEPTABLE INDOOR AIR QUALITY

This appendix is extracted from ANSI/ASHRAE Standard 62.1 (ASHRAE 2004) (except for the example at the end of the appendix) applies to all non-residential buildings' indoor spaces that people may occupy, except where other applicable standards and requirements dictate larger amounts of ventilation that this standard.

The purpose of the standard is to specify minimum ventilation rates and indoor air quality that will be accepted to human occupants and are intended to minimize the potential for adverse health effects. The standard also is intended for regulatory application to new buildings, additions to existing buildings, and those changes to existing buildings that are identified in the body of the standard. For existing buildings, the standard may be used as a guide for the improvement of indoor air quality.

J.1 Ventilation Rate Procedure

The design *outdoor air intake flow* (V_{ot}) for a ventilation system shall be determined in accordance with the next terms.

Outdoor air treatment. If outdoor air is judged to be unacceptable in accordance with the standard, each ventilation system that provides outdoor air through a supply fan shall comply with several specifications (Particulate Matter, Ozone, and Other Outdoor Contaminants).

Zone calculations. Zone parameters shall be determined as a total or for selected zones.

Breathing zone outdoor airflow. The design outdoor airflow required in the breathing zone of the occupiable space or spaces in a zone, i.e. the breathing zone outdoor airflow (V_{bz}), shall be determined by

$$V_{bz} = R_p P_z + R_a A_z \qquad (J.1)$$

where:

A_z = zone floor are: the net occupiable floor area of the zone

P_z = zone population: the largest number of people expected to occupy the zone during typical use. If the number fluctuates, P_z may be estimated based on averaging approaches. If the number cannot be accurately predicted during design, it shall be an estimated value based on the floor area and the default occupant density listed in Table J.1.

R_p = outdoor airflow rate required per person as determined from Table J.1.

R_a = outdoor airflow rate required per unit area as determined from Table J.1.

Equation (J.1 is the means of accounting for people-related sources and area-related sources for determining the outdoor air required at the breathing zone. The use of this equation in the context of this standard does not necessarily imply that simple addition of sources can be applied to any other aspect of indoor air quality.

Zone air distribution effectiveness (E_z), shall be determined using Table J.2

The zone outdoor airflow (V_{oz}) that must be provided to the zone by the supply air distribution system shall be determined in accordance with the following expression:

$$V_{oz} = V_{bz}/E_z \qquad (J.2)$$

Single-zone systems. When one air handler supplies a mixture of outdoor air and recirculated air to only one zone, the outdoor air intake flow (V_{ot}) shall be determined in accordance with the next equation:

$$V_{ot} = V_{oz} \qquad (J.3)$$

When one air handler supplies only outdoor air to one or more zones (100% Outdoor Air Systems), the outdoor air intake flow (V_{ot}) shall be determined in accordance with:

$$V_{ot} = \Sigma_{all\ zones}\ V_{oz} \qquad (J.4)$$

When one air handler supplies a mixture of outdoor air and recirculated return air to more than one zone, the outdoor air intake flow (V_{ot}) (Multiple-zone recirculating systems) shall be determined in accordance with the following specifications:

Primary outdoor air fraction. When Table J.3 is used to determine system ventilation efficiency, the zone primary outdoor air fraction (Z_p) shall be determined in accordance with

$$Z_p = V_{oz} / V_{pz} \qquad \text{(J.5)}$$

where V_{pz} is the zone primary airflow (for VAV systems V_{pz} is the minimum expected primary airflow for design purposes.

System ventilation efficiency. The system ventilation efficiency (E_v) shall be determined using Table J.3.

Uncorrected outdoor air intake. The design uncorrected outdoor air intake (V_{ou}) shall be determined by the next expression

$$V_{ou} = D \, \Sigma_{all\ zones} \, R_p P_z + \Sigma_{all\ zones} \, R_a A_z \qquad \text{(J.6)}$$

The occupant diversity, D, may be used to account for variations in occupancy within the zones served by the system. The occupancy diversity is defined as

$$D = P_s / \Sigma_{all\ zone} + P_z \qquad \text{(J.7)}$$

where the system population (P_s) is the total population in the area served by the system.

The uncorrected outdoor air intake is adjusted for diversity but uncorrected for ventilation efficiency.

Outdoor air intake. The design outdoor air intake flow (V_{ot}) shall be determined by

$$V_{ot} = V_{ou}/E_v \qquad \text{(J.8)}$$

Table J.1 Minimum ventilation rates in breathing zone. (Extracted from Table 6.1 of ANSI/ASHRAE Standard 62.1-2004 –This table is not valid in isolation; it must be used in conjunction with the accompanying notes.)

Occupancy Category	People Outdoor Air Rate[1] (R_p) (cfm/person)	Area Outdoor Air Rate (R_a) (cfm/ft^2)	Occupant Density[2] ($\#/1000ft^2$)	Combine Outdoor Air Rate[3] (cfm/person)	Air Class
Classroom (age 9 plus)	10	0.12	35	13	1
Lecture Classroom	7.5	0.06	65	8	1
Computer Lab	10	0.12	25	15	1
Restaurant dinning	7.5	0.18	70	10	2
Conference/meeting	5	0.06	50	6	1
Office space	5	0.06	5	17	1
Auditorium seating area	5	0.06	150	5	1
Libraries	5	0.12	10	17	1
Museums/galleries	7.5	0.12	40	11	1
Science laboratories[4]	10	0.18	25	17	
Gym, stadium (play area)	-	0.30	-		1

Table J.2 Zone air distribution effectiveness. (Extract from Table 6.2 of the standard ANSI/ASHRAE Standard 62.1-2004.)

Air Distribution Configuration	E_z
Ceiling supply of cool air	1.0
Ceiling supply of warm air and floor return	1.0
Ceiling supply of warn air 15°F or more above space temperature and ceiling return	0.8
Floor supply of cool air and ceiling return, low-velocity displacement ventilation achieves unidirectional flow and thermal stratification	1.2
Floor supply of warm air and ceiling return	0.7
Makeup supply drawn in on the opposite side of the room from the exhaust and/or return	0.8

---

[1] Air density: Volumetric airflow rates are based on an air density of 0.075lbda/ft3 (1.2 kgda/m3), which corresponds to dry air at a barometric pressure of 1 atm (101.3 kPa) and an temperature of 70°F (21°C). Rates may be adjusted for actual density but such adjustment is not required for compliance with this standard.

2 Default occupant density: The default occupant density shall be used when actual occupant density is not known.

[3] Default combined outdoor air rate (per person): this rate is based on the default occupant density.

[4] No class of air has been establish for this occupancy category.

Table J.3 System ventilation efficiency —"Max Z_p", refers to the largest value of Z_p, calculated using equation (J.5, among all the zones served by the systems. Extract from Table 6.3 of the standard ANSI/ASHRAE Standard 62.1-2004.)

Max(Z_p)	E_v
≤ 0.15	1.0
≤ 0.25	0.9
≤ 0.35	0.8
≤ 0.45	0.7
≤ 0.55	0.6
> 0.55	Use Standard's Appendix A

Example

For the Eller O&M Building

For the application of the code, the building is assumed to be an office building. Thus from Table J.1

$$R_p=5 \text{ cfm/person}, \qquad R_a=0.06 \text{ cfm/ft}^2$$

therefore the minimum outdoor air intake should be

$$V_{ou}=1,000(5)+ 180,000 (0.06)=15,800 \sim 16,000 \text{ cfm}$$

APPENDIX K

COMPARISON OF THE 865-RP DDVAV SPREADSHEET WITH THE
CORRESPONDING SUBROUTINE IN THE AUTO-CALIBRATED PROCESS
PROGRAM

Determining the accuracy of any building energy analysis computer program is an important task for obtaining accurate answers. The simulation of the air side of the air-handling systems can be verified without much trouble because it involves only first principles equations, such as the first law of thermodynamics and the law of conservation of mass. In general, this type of analysis does not consider transient states; therefore, a verification process is possible. Yuill et al. (2005) and Haberl et al. (2002), generated data sets to test the accuracy of any air-handling systems simulation under ASHRAE 865-RP. The data sets were applied to evaluate the performance of the most common types of air-handling systems – say a constant volume terminal reheat, constant volume dual duct, variable air volume system, etc., with different sets of outdoor and room conditions. These tests validated the spreadsheets for the systems previously mentioned. Therefore, it is possible to test the programs that were developed in this dissertation with the corresponding spreadsheets, which gives information about the reliability of these programs.

Table K.1 contains the parameters of two bin conditions used to test a DDVAV air-handling system simulation. The results for the spreadsheet of the 865-RP project and the subroutine developed are presented in Table K.2. The results show that there is agreement between the two programs. The small differences that were found are due to the difference in the procedures used in the two programs. The 865-RP spreadsheets use air and water properties as a function of the temperature and the subroutine developed does not. Another important difference is that the 865-RP programs use a more precise procedure to evaluate the sensible cooling load that includes the effect of a wet cooling coil in the evaporator. In general, for the purposes of the automated calibration, the subroutines were considered acceptable.

Table K.1. Input parameters for two bin conditions to be used in the subroutine and the spreadsheet for a DDVAV system.

Parameter	Bin 2	Bin 11	Parameter	Bin 2	Bin 11
UA (Btu/hr-°F)	16,560	16,560	RH (%)	73.27	70.31
People	1800	1800	V_{OA} (cfm)	36,036	36,036
%Outside Air	0.1540	0.1540	Vi_{min} (cfm)	13,860	13,860
%Min Design Vol	0.1540	0.1540	qil (Btu/hr)	94,500	94,500
ΔTh (°F)	-7.80	-5.80	Ve_{min} (cfm)	13,860	13,860
T_{CL} (°F)	63.49	61.93	qel (Btu/hr)	94,500	94,500
RH_{CL} (%)	90	90	w_{CL} (lb/lb)	0.011246	0.010635
Ti (°F)	75.00	75.00	w_{OA} (lb/lb)	0.003528	0.016797
Te (°F)	75.00	75.00	T_{HL} (°F)	114.08	79.20
WBE (W)	412	444	qes (Btu/hr)	-91,105	665,837
T_{OA} (°F)	38.13	82.46	qis (Btu/hr)	519,540	542,299

Table K.2. Comparison of outputs from the subroutine and the spreadsheet for a DDVAV air-handler system.

Outputs	Bin: 2				Bin: 11			
	RP865*	Subroutine	Diff	Err	RP865*	Subroutine	Diff	Err
q_{CL}	0.0	0.0	0.0	0.0%	928,993.5	974,230.1	-45,236.6	-4.9%
q_{CS}	8,653.8	0.0	8,653.8	100.0%	1,530,939.9	1,576,670.2	-45,730.4	-3.0%
q_{CT}	8,653.8	0.0	8,653.8	100.0%	2,459,933.4	2,550,900.3	-90,966.9	-3.7%
q_{PH}	679,243.6	652,320.5	26,923.0	4.0%	0.0	0.0	0.0	0.0%
q_H	311,770.8	315,104.7	-3,333.9	-1.1%	0.0	0.0	0.0	0.0%
$q_{H,TOT}$	991,014.4	967,425.2	23,589.2	2.4%	0.0	0.0	0.0	0.0%
FAN(HP/Btu/hr)	16.626	43,608	-1,279	-3.0%	35.246	86,884	2,853	3.2%
CFAN(HP)	0.000	0.000	0.000	0.0%	0.000	#N/A	#N/A	0.0%
HFAN(HP)	0.000	0.000	0.000	0.0%	0.000	#N/A	#N/A	0.0%
RFAN(HP)	0.000	0.000	0.000	0.0%	0.000	#N/A	#N/A	0.0%
Tma (°F)	52.939	52.782	0.157	0.3%	78.116	78.141	-0.025	0.0%
M_{AW} (lb/lb)	0.003964	0.003959	0.000005	0.1%	0.014176	0.014191	-0.000014	-0.1%
Tot Vol (cfm)	60,221.6	59,808.6	413.0	0.7%	86,265.9	85,580.5	685.4	0.8%
CCLAW (lb/lb)	0.003964	0.003959	0.000005	0.1%	0.011839	0.011839	0.000000	0.0%

* Spreadsheet provided by Professor J. Haberl (Haberl et al. 2002)

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