AN INVERSE BIN METHODOLOGY TO MEASURE THE SAVINGS FROM ENERGY CONSERVATION RETROFITS IN COMMERCIAL BUILDINGS

A Dissertation

by

SABARATNAM THAMILSERAN

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

May 1999

Major Subject: Mechanical Engineering

UMI Number: 9934501

AN INVERSE BIN METHODOLOGY TO MEASURE

THE SAVINGS FROM ENERGY CONSERVATION

RETROFITS IN COMMERCIAL BUILDINGS

A Dissertation

by

SABARATNAM THAMILSERAN

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

DOCTOR OF PHILOSOPHY

Approved as to style and content by:

Jeff S. Haberl
(Co-Chair of committee)

D. E. Claridge
(Co-Chair of committee)

W. D. Turner
(Member)

W. B. Smith
(Member)

S. Jayasuriya
(Head of Department)

May 1999

Major Subject: Mechanical Engineering

ABSTRACT

An Inverse Bin Methodology to Measure the Savings from Energy Conservation Retrofits in Commercial Buildings. (May 1999)

Sabaratnam Thamilseran,

BS (Eng), University of Peradeniya, Sri Lanka;

M.Eng., Asian Institute of Technology, Bangkok, Thailand

Co-Chairs of Advisory Committee: Dr. Jeff S. Haberl
Dr. David. E. Claridge

This dissertation provides a simple yet powerful approach, the fully layered inverse bin method, to baseline hourly energy use in commercial buildings and illustrates the application through carefully selected case study buildings. The eleven step inverse bin procedure for baselining hourly energy use mainly comprises a simple inverse bin procedure (steps one through seven) and two improvements through the use of thermal lag and humidity sub-binning (steps eight through eleven).

Temperature-based binning for baselining or modeling weather dependent energy use (e.g., heating and cooling energy) and an Hour-of-the-Day binning for weather independent energy use (e.g., electrical energy use) have been developed. This procedure addresses the problem areas suggested by the previous research in the analysis community while keeping the method simple enough to be usable by an HVAC engineer. The inclusion of multiple change points (i.e., bins) through the use of 5°F (~3°C) bins enables fitting the non-linear variation of the energy use and hence improves the model's fit significantly over the existing linear and change-point methods. The additional use of humidity sub-binning and lagged temperature as independent variables for sub-binning improves the predictions for latent load dominated building loads or buildings with high thermal mass construction, respectively.

DEDICATION

To my mother, late father,

my brothers and sisters,

my wife, and to all my friends.

ACKNOWLEDGMENTS

I am indebted to my advisor, Dr. Jeff S. Haberl, for his continual encouragement, guidance, patience and readiness to help as well as his constant support in keeping me abreast of the new developments in conducting the study. Sincere thanks and appreciation are also given for the countless hours and his unlimited library resources he has given throughout this study. Much appreciation is also given for the opportunity he has provided toward my technical and professional development.

I am also grateful to my co-chair, Dr. David E. Claridge for his constant support, encouragement and helpful suggestions. His help was instrumental in improving the ideas and content of this work.

It is also with much gratitude that I acknowledge and thank Dr. W. D. Turner for his help, advice, and support, all influential in shaping my academic career at Texas A&M University.

I would like also to thank Dr. W. B. Smith for serving on my committee and Dr. Robert H. Stewart for being my graduate council representative. I am also thankful to my committee members for their time and patience in correcting and improving the content of this dissertation.

I would like to thank the Energy Systems Laboratory Monitoring and Analysis Program staff for their commitment to making the monitored data from the LoanSTAR Program available. Without their effort this study would not have been possible. I appreciate the help of Robert Sparks, Jean Mahoney, Ron Chambers, John Bryant, Rob Lopez, and other technical and office support staff at the Energy Systems Laboratory. Computer and technical support were expertly provided by Dean Willis, Chris Cunningham, Jeff Rife, John Steele, and Mike Johnson.

I would also like to thank Dr. T. Agami Reddy for his help and encouragement. Amitava Dhar also helped me to improve my language and professional skills. It has been a great pleasure to work with him. I would also like thank Mustafa Abbas and Anna Baranowski for their help in SAS graphics programming. I cannot overlook the discussions with Kelly Kissock, Srinivas Katipamula, Minsheng Liu, Jingrong Wang, Namir Saman, and Aamer Athar. I would also like to acknowledge several of my fellow students and colleagues who provided help, support, friendship and humor. Their support and encouragement helped me steer through the hard times.

I am forever grateful to my mother and father, Parameswary and the late Sabaratnam, for the inspiration and dedication they instilled in me during their tenure as parents and for their unsparing love and support. I am also grateful to my brothers and sisters who encouraged me to create my own dreams and gave me the love, confidence and support to pursue those dreams. I gratefully acknowledge all my success as the result of the guidance, teachings and inspirations of my parents, brothers, and sisters. I am also thankful for my wife for her constant support, encouragement, and patience.

Last, but foremost, I gratefully acknowledge the financial support for this work provided by the Texas State Energy Conservation Office of the General Services Commission (State Agencies program) as part of the Texas LoanSTAR Monitoring and Analysis Program.

TABLE OF CONTENTS

LIST OF FIGURES

FIGURE Page

FIGURE Page

LIST OF TABLES

TABLE Page

NOMENCLATURE

a	Type I error
A	Considered area in square feet
A	Dataset A - Engineering Center building
AHU	Air Handler Unit
alpha	a in words
Btu	British thermal Unit
BUS	Business building
C	Dataset C from Engineering Center building
CV	Coefficient of variation
cwe	Whole-building cooling
D	Degradation coefficient of the equipment
D	Dataset D from the Business building
df	Degrees of freedom
DF1	Degrees of freedom of the model
DF2	Degrees of freedom of the error
DOE	Department of Energy
DTE	Daytype identifier
DTP	Daytype identifier
DTW	Daytype identifier
EC	Engineering center building
ETP	Equivalent thermal parameter
F	Tabulated F test parameter for the given DF1 and DF2 values
GJ	Giga Joule or 0.9479 MMBtu
h	Hour
hp	Horse power
hr	Hour
hwe	Whole-building heating
IQR	Inter-quartile range
k	Outlier boundary description constant

k	Number of steps for comparison in Duncan's procedure
k	Number of sample data groups or daytypes
Kratio	Waller-Duncan test error weight ratio, nominal k=100
kWh	killo-watt-hour
LSD	Least significant difference
MMBtu	million Btu, or 1.055 GJ
MSE	Mean square error
n	Number of data points
NEP	National Energy policy
NWS	National Weather Service
oc	Outlier identifier for cooling
OFF	Unoccupied period-schedule
oh	Outlier identifier for heating
ON	Occupied perdiod -schedule
ow	Outlier identifier for wbele
p	Number of parameters in a model equation including intercept
p	Fractile point
PCA	Principal component analysis
PCL	Perry Castaneda Library building
PLF	Part-load factor
PS	Predictor Shootout Competition
q	Tabulated percentage points of the Duncans Multiple range test
Q1	First quartile (25 percentile)
Q3	Third quartile (75 percentile)
Quads	10^{15} Btu
r	Pearson's linear correlation coefficient
RAS	Russell .A. Steindham building
RMSE	Root mean square error
s	Standard deviation of the data
S	Standard deviation
sq.ft.	Squate feet of area

Sxx	Least squares estimate coefficient for xx or sums of squares of xx
Sxy	Least squares estimate coefficient for xy or sums of squares of xy
Syy	Least squares estimate coefficient for yy or sums of squares of yy
T	Outdoor dry-bulb temperature
U	Energy loss coefficient Btu/sq.ft.-hr-F
v	Degrees of dreedom in Duncan's procedure
w	Within a sample
W	Watt
WBCOOL	Whole-Building Cooling
WBELE	Whole-Building Electric
WBHEAT	Whole-Building Heating
wd	Weekday
WDD	Weather dependent data
we	Weekend
WEL	Welch hall
WID	Weather independent data
x	The x value of the datapoint
y	The y value of the datapoint
ydata	Actual or measured value of the y datapoint
ypred	Predicted value of the y datapoint
ZEC	Zachry Engineering Center or Engineering Center building

Subscripts

a	a, alpha
df	degrees of freedo
n	number of datapoints
r	number of steps the samples are apart
w	within sample data group
y	y data in the dataset

Greek Letters

α	alpha, Type I error, taken as 5% in this study
σ	standard deviation, S
Σ	summation over the given range

CHAPTER I
INTRODUCTION

This chapter describes the motivation and objectives of the work presented in this dissertation and gives a brief description of the contents of the chapters that are to follow. This section begins by reviewing the current energy use statistics and establishes the need for energy conservation in the U.S. as the motivation for this work. First, a discussion of global energy consumption is presented, followed by a discussion of U.S. energy use and finally a discussion of U.S. building sector energy use (specifically the commercial building sector).

Motivation

Energy is a key component of any economic development strategy (Levine et al., 1991). World energy consumption has risen by 24% within the last decade from 280.21 Quads in 1983 to 346.33 Quads in 1992 (Brown et al., 1994) while world population has risen by 11.1% from 4,946 million to 5,497 million (WRI, 1997). Clearly, the increasing energy use trend is fueled by the world-wide population increase, and by a continuous economic expansion of the world's nations. The majority of the energy resources that are currently being used are limited in supply or non-renewable (Bartlett, 1981; 1990). Because of this limited supply and increasing demand, the world will eventually have to face an era of increasingly scarce non-renewable energy resources. This scarcity of energy supply and the environmental pollution and degradation that accompanies un-checked energy use will establish an increased need for conservation (Goldemberg et al., 1988).

The United States plays an important role in the world energy scene since it is the single largest user consuming about 24% of world energy production (EIA, 1992a). Moreover, the energy consumption in the U.S. has been on the rise, after dropping for a few years in the early 1980s. The increasing demand and a decreasing domestic supply of energy should be a national concern in the U.S. since energy imports can be affected by disruptions in world energy markets (DOE, 1995).

Journal model is *ASME Journal of Solar Energy Engineering.*

Besides the concern over the increasing reliance on energy imports, the fiscal impact of an increasing national energy consumption is of interest to the National Energy Policy (NEP). In 1993, energy expenditures in the U.S. were \$505 billion, or 8% of the Gross Domestic Product - GDP (DOE, 1995). This was equivalent to about 323 million Btu/person (EIA, 1992b) increasing about 7.3% within the last decade alone. This increasing trend must be reversed for the U.S. economy to remain competitive (DOE, 1995). In contrast, other modern industrialized countries, such as Japan, France and Italy require only one-half as much energy to generate a dollar of GDP as does the U.S.A. (Goldemberg et al., 1988; Brown et al., 1994). Clearly, these lower levels of energy consumption indicate that there is much room for improvement if the U.S. is to achieve a sustainable energy future.

In 1991, the building sector (commercial and residential) consumed about 29.56 Quads (or about 36%) of the total U.S. national energy consumption of 81.51 Quads. Commercial buildings, which amount to about 65 billion square feet of floor area, consumed about 13 Quads, or 16% of the U.S. national energy consumption (EIA, 1992a; EIA, 1992c).

Several factors have contributed to the growth of energy use in buildings. First, the population across most of the U.S. has increased by 13% over the last two decades (EIA, 1992b). Second, building comfort levels have improved which means more buildings are being conditioned now than ever before. Third, more energy using devices such as personal computers (PCs) are now in the buildings, especially office buildings. Despite these factors, the energy consumption per unit floor area has been improving since its peak in the 1970's (Kreider and Rabl, 1994).

New buildings can be designed to consume as little as 20% of the energy consumption of a traditional building of the same size (Goldemberg et al., 1988). When one considers that these savings can accrue for 50 to 100 years over the life of the building, the true potential for savings begins to comes into focus. Unfortunately, a significant proportion of the commercial buildings that are currently in use were built before the oil crisis and are therefore, not as efficient as they could be. The installed equipment in these buildings was often oversized or much less energy efficient than the current technology. Hence, the majority of the potential savings can easily be achieved by either replacing or retrofitting the installed equipment in such commercial buildings.

Though the enormous potential of energy savings in the commercial buildings has already been identified, only a small portion of it is actually being achieved. Several studies (Ross and Whalen, 1983; Claridge et al., 1994; Greely et al., 1990) have shown that energy retrofits in buildings have resulted in savings of at least 18% of the total building energy usage. Ross and Whalen (1983) measured 23% of the before-retrofit energy consumption as savings. Claridge et al. (1994) reported a measured savings of 27% of the pre-retrofit energy use. However, even these savings fall far short of the true economic potential (Goldemberg et al. 1988; Claridge et al. 1996). Therefore, it is estimated that the potential for energy savings by means of retrofits in the U.S. commercial sector by the year 2000 could be as high as 50% to 75% of the baseline energy use from the last decade (SERI, 1981; Bevington and Rosenfeld, 1990).

Despite these encouraging projections about the potential for energy savings, there still remains some disagreement about the effectiveness of energy conservation retrofits. One study, by Claridge et al. (1996), has shown that savings as high as 149% of the traditional audit estimated savings are possible when buildings are retrofitted and the savings are continuously monitored to identify and fix Operation and Maintenance (O&M) problems. On the other hand, other studies that have focused on the reliability of the measurement methodologies for the prediction of energy savings have shown that the uncertainity associated with the energy savings estimates can be very high. A study (Greely et al., 1990) of 1700 buildings in the U.S. indicated that the estimated savings in fewer than 16% of the case study buildings, came within 20% of the measured savings. Another study by Jamieson and Qualmann (1990) showed an even larger difference (165%) between the predicted and measured energy savings in 16 commercial retrofits. These large discrepancies create a concern regarding the reliability of the predictions by computer simulation models (Jamieson and Qualmann, 1990). Hirst et al. (1986) reported similar conclusions regarding the efficiency investments in the U.S. A common theme in all these studies is the need for better measurement methodologies which would restore faith in the prospective efficiency investments. This fact points to the need for this work, which attempts to develop a simple, yet accurate methodology that could satisfy this need.

In the past savings methodologies have ranged from simple unadjusted utility bill comparison of similar periods to highly sophisticated hourly simulation methods and neural network models (Greely et al., 1990; Kreider and Haberl, 1994). Current efforts by ASHRAE (GPC 14-P: ASHRAE, 1997a) and DOE (International Performance Monitoring and Verification Protocol - IPMVP: DOE, 1997) are underway to classify the available methodologies into a few categories. The ASHRAE and DOE efforts represent a major step in the energy analysis area to consolidate and standardize future energy monitoring and analysis efforts. These standardized measurement and verification protocols will help to establish a consensus and will serve as guidelines for energy and water efficiency programs. The methods described in this study are closely related to those described in both the DOE and ASHRAE protocols.

Besides developing guidelines and establishing a consensus of measurement protocols, two other important areas are identified for the success of energy efficiency investment programs: (i) the need for repeatable analysis methods to relate the building energy use to physical building characteristics or physical significance, and (ii) the need to simplify the new analysis methods to be usable by the average analyst (McDonald and Wasserman, 1989). In this context, this research aims at developing an inverse bin approach that is simple to use and that can handle the effect of several variables, such as ambient temperature, humidity and thermal mass. The inverse approach used in this study is based on the familiar and simple ASHRAE bin design method (Sauer and Howell, 1990) that is widely used by the ASHRAE engineering design community, is a new method that can be adapted to calculate energy savings from weather dependent and weather independent retrofits.

Purpose and Objectives

The purpose of this study is to promote energy conservation retrofits in commercial buildings by developing standardized methods to measure the savings from energy conservation retrofits.

The objectives of the dissertation are to: i) develop a steady-state inverse bin method for baselining weather-dependent or weather-independent building energy consumption, ii) demonstrate the use of such a method with measured hourly before-after building energy use data from several case study sites in the Texas LoanSTAR program, and iii) compare the results of the bin method to other base-lining methods applied to the same data sets.

Description of the Following Chapters

This dissertation is presented in seven chapters, references, four appendices and a vita. In this chapter the topic has been introduced and the background and need for this work have been presented. In Chapter II a detailed literature review and an overview of the ASHRAE forward bin method are provided. The detailed procedure of an inverse bin methodology (also referred to as Fully Layered Inverse Bin Method) for modeling energy use in commercial building is explained in Chapter III. The inverse bin methodology is then described and illustrated on data from the case study buildings in Chapter IV. Detailed descriptions of the Forward Bin Method and Inverse Bin Method are presented for a case study building in Chapter V. Results from the comparisons between the inverse bin method and other well known methodologies in terms of the prediction accuracy are presented in Chapter VI. A summary of the present work, conclusions and future directions are presented in Chapter VII. The references are presented in Chapter VIII. The definitions and detailed descriptions of the statistical terms used in this study are provided in Appendix A. Description, data plots, and photographs of the case study buildings are presented in Appendix B. A brief discussion of the selection of a bin description parameter is outlined in Appendix C, and source codes of the processing routines for the inverse bin analysis method are given in Appendix D.

CHAPTER II
LITERATURE REVIEW

This literature review covers the previous efforts: (i) to classify building energy analysis procedures, (ii) to develop protocols or methodologies for measuring the impact of energy efficiency investments, and (iii) the ASHRAE and the DOE efforts to introduce standard measurement methodologies by establishing consensus guidelines. The traditional ASHRAE bin method is also reviewed to establish a basis for the inverse bin method.

General Overview

Classification of Methodologies

At present, there are many different methods for analyzing metered energy use in existing buildings. These methods are usually driven by the motivation or purpose behind the investigation of a building's energy use. These include: energy conservation retrofit savings analysis, component efficiency testing, demand side management (DSM) evaluation, diagnostics and the determination of repayment schedules (MacDonald and Wasserman, 1989; Haberl and Komor, 1990b; ASHRAE, 1994). Because of the broad nature of this topical area, this review is presented according to the classification scheme proposed by Rabl (Rabl et al., 1986; Rabl, 1988). Rabl's scheme divides building energy analysis into forward, inverse modeling, and hybrid modeling schemes (Rabl et al., 1986; Rabl, 1988; Rabl and Rialhe, 1992).

Rabl's first group, forward modeling, is most often employed for design purposes, such as to calculate the energy performance of a prospective building or to size the equipment to be installed in a new building. In the second group, inverse models, the analysis method is conducted empirically which means the energy use is statistically examined against one or more driving forces which affect the building. This is known as inverse or data-driven modeling because the calculation scheme is performed in a backward or inverse fashion (i.e. the measured energy data are statistically analyzed to determine the parameters that describe the building's performance). The third group, hybrid models, contains characteristics of both the forward and inverse models. One example of this would be the use of engineering equations which use measured energy consumption data to determine various coefficients (i.e., to calibrate the simulation parameters) to simulate an existing building's energy consumption. A variety of building energy use analysis methodologies have been classified and reported by Rabl (1988). This study focuses mainly on the inverse methods. The next section discusses classification schemes.

Rabl (1986) has suggested that no single analysis method or model is appropriate for the analysis of energy use in all buildings. According to Rabl (1988), the choice of a suitable model depends on the desired purpose of the analysis, the available input data, and the type of calculation scheme. MacDonald and Wasserman (1989) have also grouped building energy analysis methodologies into five types: (1) annual total energy and energy intensity comparisons, (2) linear regression and component models, (3) multiple linear regression models, (4) building simulation models and (5) dynamic thermal performance models. McDonald and Wasserman's first group, which uses the least amount of data, can use either hourly metered data or utility billing data for the analysis. The second and third groups are essentially similar, except in the number of independent parameters used in the regression scheme. Both the simple linear and multiple linear regression analyses can be performed using monthly, daily or hourly monitored data or the monthly utility billing data along with climatic data from a local National Weather Service (NWS) station. The fifth group, dynamic thermal performance models, requires either hourly or sub-hourly monitored data and weather data for the analysis and is capable of analyzing the transient effects in the building.

A slightly different classification scheme used in the LoanSTAR program categorizes the measurement methodologies into two groups. This classification is based on the mathematical and procedural requirements that are performed during the model development (Reddy et al., 1994a). Thus regressions (simple, multiple, and complex regression) are grouped together as empirical models, while simulations (both DOE-2 simulations and simplified engineering models) are grouped together as the second group. Simulations are most often used when no 'pre' data are available. In such cases the savings measurements are based on post-retrofit measurements and the predicted pre-retrofit energy use characteristics from a calibrated engineering model.

Another important source of information about energy monitoring protocols and design methods is the ASHRAE handbook, which discusses building energy monitoring and estimation methods in several chapters. Chapter 28 in the 1997 Fundamentals Handbook describes the methods used to estimate the energy use for buildings that are either under construction or are being designed. This chapter was written by Technical Committee 4.7 (ASHRAE, 1997a). The majority of the energy estimation techniques presented in the chapter are not readily applied to energy monitoring and analysis, with the exception of the Modified Bin Method, which is reviewed later in this section.

Chapters 32, 33, 36 and 37 in the ASHRAE Applications Handbook cover important elements relevant to this work (ASHRAE, 1991). The material in these four chapters is routinely cited by the Heating, Ventilating and Air-conditioning (HVAC) industry as standard reference material. Chapter 32 on Energy Management describes the importance of the facility management organization and the activities needed to maintain ongoing energy reduction in the facilities. Chapter 33 covers Owning and Operating Costs and discusses the economic aspects of energy accounting and energy costs for financial objectives which may utilize the result of a retrofit savings procedure. Chapter 36 on Computer Applications offers some advice about the software and hardware requirements for retrofit performance monitoring projects. Chapter 36 also describes the available analysis programs such as simulation programs (DOE-2, BLAST and TRNSYS) and mathematical modeling software (Artificial Neural Networks-ANN and statistical packages) and Knowledge Based Systems (KBS). Chapter 37 on Building Energy Monitoring is the primary chapter on energy monitoring. Chapter 37 covers the types of projects, relevant monitoring issues, elements of an effective monitoring project design, and presents measurement protocols for retrofit performance monitoring. The next section covers the evolution of the various methodologies, which is followed by a review of the ASHRAE GPC-14P and DOE IPMVP protocols.

Review of Analysis Methodologies

The simplest method used to measure energy savings is the direct comparison of the unadjusted pre-retrofit and post-retrofit energy use, usually on a monthly basis. This method usually includes an adjustment for the varying number of days in the billing period. This adjusted comparison can be useful in buildings that are operated 24 hours per day and have large predictable internal loads. However, varying weather conditions between the pre-retrofit and post-retrofit periods can influence energy use and obscure the measurement of the change in the energy use caused by the retrofit. Weather corrected savings can differ by up to 12% from un-corrected savings (Greely et al., 1990). This would indicate that savings calculations based on direct comparisons should only be used for retrofits that are estimated to save substantially more than 12% of the annual energy use. Greely et al. (1990) also concluded that there was no generally accepted methodology for adjusting commercial building energy use for year-to-year changes in weather.

When the energy use data are weather normalized the weather effect is usually analyzed using one or more weather parameters as independent variable(s) for the analysis. This is the primary idea behind simple and multiple linear regression models. Some recent methodologies improved upon linear regression by adding a change-point non-linearity to the regression. The change-point methodology includes the three parameter and five-parameter change-point methods used in the Princeton Scorekeeping Method - PRISM (Fels, 1986; Fels et al., 1995). A four-parameter change-point method has also been developed by Ruch and Claridge (1992). Figure 2.1 shows the applicable parameters such as slope and/or consumption at the change points for the cooling and the heating energy consumption. In these change-point models a known physical building phenomena (such as the thermostat set-point or balance point) is used to improve the statistical analysis and, thus, differs from the simple-linear, two-parameter regression models. Another improvement, proposed by Ruch et al. (1993), handles collinearity in multiple regression using the principal component regression models.

The regression coefficients can sometimes be interpreted as parameters with physical meaning (Fels, 1986; Rabl, 1988; Griffith et al., 1994; Minehart and Meier, 1990; Reddy et al., 1994; Deng et al., 1997). For example, changes in building heat transfer coefficients or heating-cooling system efficiencies are often reflected in the changes in the slope of the regression model, while the reference temperature is usually the indicator of the point at which heating or cooling commences. The base-level energy use represents the weather- independent energy use, and can yield insight into the behavior of such systems as lights, receptacle loads and air-handling units.

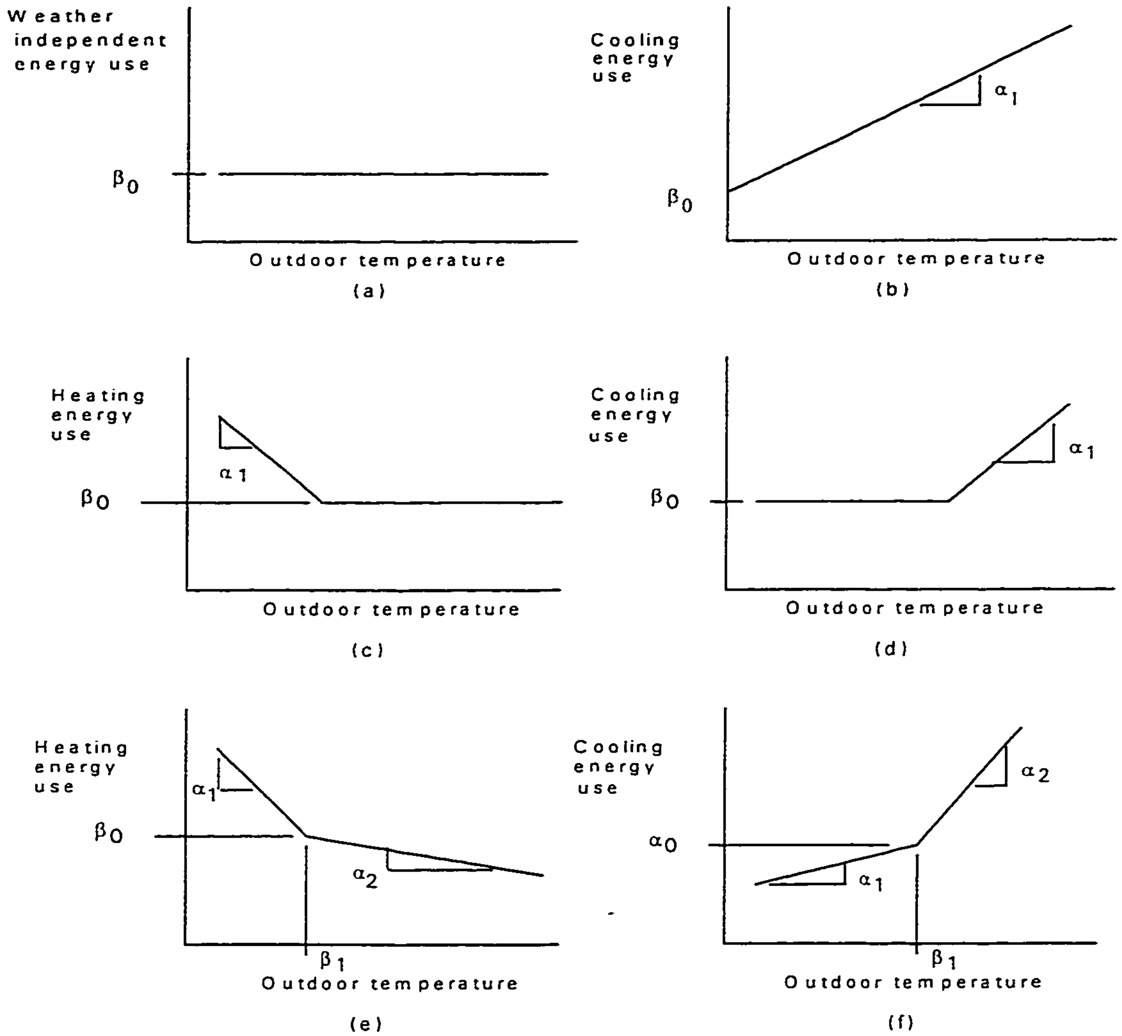


Figure 2.1 : The change-point and slope parameters that define the 1-P, 2-P, 3-P and 4-P change-point models. The illustration shows the applicable parameters for both the cooling and heating energy consumption models.

Regression models are easier to develop than mechanistic models because of their simplicity, and repeatability. Regression models also benefit from a well-defined statistical theory and possess the ability to calculate the associated uncertainty (Neter et al., 1989). However, only one of the previous regression models, the five-parameter PRISM model (Fels et al., 1995) attempts the consideration of multiple change-points. The five-parameter change-point was added only recently to the publicly available PRISM software because of the complexity of the algorithms needed to pinpoint the second change point.

The current work will combine the benefits of the inverse regression models with a variation of the ASHRAE bin method for design to develop a fully layered inverse bin method approach to determine savings from energy conservation retrofits. This new approach will be an improvement over three- and four- parameter change-point models because of its ability to handle multiple change-points (i.e., more than four change-points).

All of the methods discussed so far are steady state methods, which assume that the building responds instantly to the space heating or cooling load requirements. In reality, buildings have thermal mass which can delay the response of heating or cooling. To observe this phenomena one needs a dynamic model. Dynamic models can be used in both an inverse (to determine the model parameters from the measured data) and a hybrid fashion (first to calibrate or adjust the empirical coefficients and then to determine the model parameters) to measure the retrofit energy savings (Rabl, 1988; MacDonald and Wasserman, 1989).

Previously investigated dynamic methods include thermal networks by Sonderegger (1978), modal analyses by Bacot et al. (1984), and different forms of Fourier analyses, including a combined Auto Regressive Moving Average (ARMA) and Fourier series method in the Building Element Vector Analysis method (BEVA) by Subbarao (1986), Fourier series with response function by Shurcliff (1984), Fourier series coefficients using linear regression by Dhar (1995) and combined regressions and equivalent thermal parameters (ETP) by Taylor and Pratt (1988) on commercial buildings, singular value decomposition (SVD) in an inverse method by Reddy (1989) on residential buildings and singular value decomposition for multiple regression modeling on commercial buildings by Wang and Kreider (1990).

Unfortunately, dynamic methods are often ignored by HVAC engineers because of their complexity and the length of time to develop a model. In this context, the current method aims to develop a simple yet reasonably accurate procedure that will evaluate thermal mass dynamics by incorporating time-lagged variables. This will be possible by using a daytyping technique for weather independent loads combined with a lagged inverse bin analysis to capture the building's thermal response.

Review of ASHRAE GPC 14P and DOE IPMVP

Many of the previous studies have discussed various data collection techniques used by monitoring projects for performance evaluations (Fels, 1978; Haberl and Vajda, 1988; Diamond et al., 1990; Claridge et al., 1991; Jacobs et al., 1992; O'Brien and Crawley, 1994; Eto et al., 1990; Griffiths and Anderson, 1994; Waterbury et al., 1994; NAESCO, 1994; ASHRAE, 1994). A closer look at two of these protocols provides some instruction for the current work. For example, although the NAESCO protocol (NAESCO, 1994) suggests three levels of measurement which range from monthly utility bill analysis to detailed before-after monitoring of individual end-use loads, there is no specific advice given as to how to analyze the data (i.e., single linear regression versus change-point regression). This is in contrast to the proprietary Johnson Controls Inc. (JCI) protocol (ASHRAE, 1994) which gives explicit steps for adjusting for weather, occupancy, calendar month and degree day for the measurement of energy savings. In the JCI method, the identified baseline monthly energy consumption from the 12-month data is adjusted to match the calendar days of the later period through adjustment factors for: i) occupancy, ii) daily proration, iii) base-load and weather-sensitive load corrections, iv) weather correction for weather-sensitive loads, and v) any other factors required by agreement for bill compliance. Unfortunately, the JCI method cites no studies, published papers, or proof that the "adjustments" are statistically valid. In general, one is forced to conclude that there has been no agreement in the building community when it comes to selecting consensus methods for measuring energy savings. This is one of the motivations behind the recent efforts by the ASHRAE and DOE to provide some standard guidelines.

The ASHRAE GPC 14P is the first ASHRAE guideline for the measurement of energy and demand savings from DSM retrofits (ASHRAE, 1997b). The ASHRAE effort is meant to provide guidelines and technical expertise concerning the quantification of the measurement of energy and demand savings for residential, commercial, and industrial energy conservation retrofits. The guideline provides three approaches that can be used to measure retrofit savings. The three approaches are: (i) the whole-building before-after approach that relies on previous efforts such as PRISM (Fels, 1986) and LoanSTAR (Turner et al., 1990), (ii) the retrofit isolation approach that relies on the results of methods such as the ASHRAE RP 827 in-situ testing of fans, pumps, and chillers (Brandemuhel,

1995) and (iii) the calibrated simulation approach (Bou-Saada, 1994). The whole-building before-after approach is a procedure for projects that have adequate before-after data at the whole-building level. The retrofit isolation approach uses data from 'on-the-spot' (snap shot) before-after measurements or short-term metering for the specific equipment to be retrofitted. The third approach, the calibrated simulation approach, is meant to be used in projects where reliable calibrated simulation models can be developed and used to measure savings by adjusting the input parameters in the models.

In the calibrated simulation approach, a thermodynamically representative hourly simulation model of a building's energy use is developed from engineering principles. Model predictions are calibrated against measured data from the building being modeled. Examples include: calibrated DOE-2 analysis (Haberl and Bou-Saada, 1993; Bou-Saada, 1994; Bou-Saada and Haberl, 1994; Haberl and Bou-Saada, 1995); calibrated simplified HVAC systems models (Knebel, 1983; Katipamula and Claridge, 1993; Reddy and Claridge, 1994, Liu et al., 1995). Calibrated modeling has also been used to identify operational improvements in buildings (Claridge et al., 1994; Liu and Claridge, 1995).

A second national effort, which originated about the same time as the ASHRAE GPC14P effort, was initiated by the United States Department of Energy (DOE) and is aimed at providing general guidelines for retrofits performed under performance contracts (DOE, 1997). This effort (formerly called NEMVP) has become known as the International Performance Measurement and Verification Protocol (IPMVP). The IPMVP is different from the ASHRAE GPC 14P in two respects. First, the IPMVP includes recommendations for contractual repayment plans based on representative measurements from one of the four approaches outlined in the IPMVP. Second, the IPMVP uses slightly different methods and references from the ASHRAE GPC 14P as its technical support document.

The four methods included in the IPMVP (DOE, 1997) are: i) measured capacity and stipulated use, ii) measured capacity and measured use, iii) whole-building before-after methods, and iv) calibrated simulation. In the measured capacity and stipulated use method the energy use capacity (i.e., instantaneous use) is determined and the 24-hour usage profiles fixed or stipulated. In the second method snap-shot or short-term measurements are used to characterize the baseline energy use and short-term or continuous measurements are used to characterize the post-retrofit use. This second method can be used on whole-building data or end-use (i.e., retrofit isolation) data. The third method is essentially the same as the before-after method described in the ASHRAE GPC 14P guidelines and can use monthly, daily, or hourly before-after data. The fourth method is the same as the calibrated simulation approach in ASHRAE GPC 14P. Both GPC 14P and the IPMVP recommend only 1, 2, 3, 4 or 5 parameter change-point models for regressing against energy use. The IPMVP was updated in 1997 to include calibrated simulation for new construction and water conservation. It was also renamed to reflect (from North American Energy Measurement and Verification Protocol-NEMVP) international participation in its development.

Other Issues

Resolution and Length of the Data: The analysis schemes discussed so far have used different levels of monitored data (i.e., hourly, daily and monthly data) and have used different lengths or periods of the data for the analyses. Unfortunately, the decision to use one type of data over another is often based on the availability of data and not on statistical principles. Only four references are available on these issues and an even smaller number of studies discuss the effect of these two issues on the analysis results. Studies by Kissock (1993) and Katipamula et al. (1994, 1995) have reported that monthly or daily analysis time steps are usually best for determining retrofit savings for data that have no significant seasonal variation or data with significant seasonal variations respectively. One exception to this is when the data are used for building systems diagnosis purposes. Such studies require a higher time resolution of monitored data (Haberl and Komor, 1990a; Katipamula et al., 1994; Liu et al., 1995; Subbarao et al., 1990; Akbari et al., 1988; Burch et al., 1994).

The second issue in building energy analysis is the length of the monitoring period or available data set for analysis. If any conclusion can be drawn from the reported studies on the required monitoring period it would be that a minimum of at-least six months (Katipamula et al., 1994) of hourly or daily monitored data are needed. The recommended length for monthly analysis varies from a minimum of nine months for residential analysis (Stram and Fels, 1986) to a minimum of one year (Katipamula and Claridge, 1993; Kissock, 1993) for commercial building energy use.

Daytyping: The other important aspect of an analysis methodology is daytyping. Energy use in commercial buildings is affected by the systematic scheduling of the building systems; hence separating the data into similar operational periods (i.e., daytyping) is an important requirement for an efficient model development. The daytyping of the energy use data may involve simple calendar-based (i.e., weekday-weekend-holiday) sorting or complex mathematical algorithms using statistical methods. Katipamula and Haberl (1991) used a simple statistical test to identify diurnal load shapes using monitored end-use data. Their daytypes used a univariate statistical procedure with set limit of 10% (i.e., setting the coefficient of variation CV-STD to less than 10% for any final day-type) to effectively identify the load shapes which were used in a DOE-2 calibration (Bronson, 1992). The use of the standard deviation (STD) of the data at each individual hour (i.e., 24 individual hour-of-the-day distributions) for daytyping was later improved by Dhar (1995) with the consideration of daily mean energy use and overall diurnal load shape to identify the final daytypes. The daytyping technique proposed in this study is essentially similar to the daytyping technique used by Dhar (1995) which used the Duncan's multiple range test for primary daytyping and univariate analysis of each primary daytype for distribution. The key difference between the proposed technique and the above procedure is the use of the non-weather dependent hourly monitored data (i.e., whole-building electric energy use - WBELE) directly in the three statistical tests (Duncan's multiple range test, Waller-Duncan k-ratio test, and Scheffe's test) instead of using sample mean distribution (i.e., daily mean values of the monitored hourly data).

Forward Bin Methodology

The steady state ASHRAE bin method or forward bin method is a commonly used tabular design method for estimating the annual energy consumption of a building. In the standard ASHRAE bin method, the building energy consumption is calculated for a series of outdoor temperatures and multiplied by the number of hours of occurrence that the ambient temperature falls into a specific 5°F bin (ASHRAE, 1997b).

The ASHRAE standard (or forward) bin method, shown schematically in Figure 2.2, is a computationally intensive procedure and is based on the concept that a building's energy use is similar for a particular energy bin. With the use of the weather data in the form of 5°F bins combined with available mean coincident wet bulb temperature and the number of hours of occurrence for each bin, the binned energy consumption can be calculated for each bin for the relevant bin hours with the equipment operating under the particular operating conditions. Therefore, a detailed calculation procedure requires information such as: construction information about the building, load profile and schedule of the building loads, building occupancy schedule, equipment operating characteristics and weather information. The forward bin analysis will be illustrated for a case study building in Chapter V.

The bin method can be as simplified or as complex as the situation may require and is applicable for both the heating and the cooling energy consumption. In spite of the ease with which the bin method can be used, the method has traditionally been used only at the design stages of the building to estimate the annual energy consumption. With this in mind, this research is aimed at developing an inverse bin approach that is also simple to use and can handle the effect of scheduling and climatic variables; ambient temperature, and the effect of the humidity and the thermal mass. This inverse approach, which is similar to the simple forward bin method described above, is new and can perform energy saving calculations for weather dependent and weather independent loads.

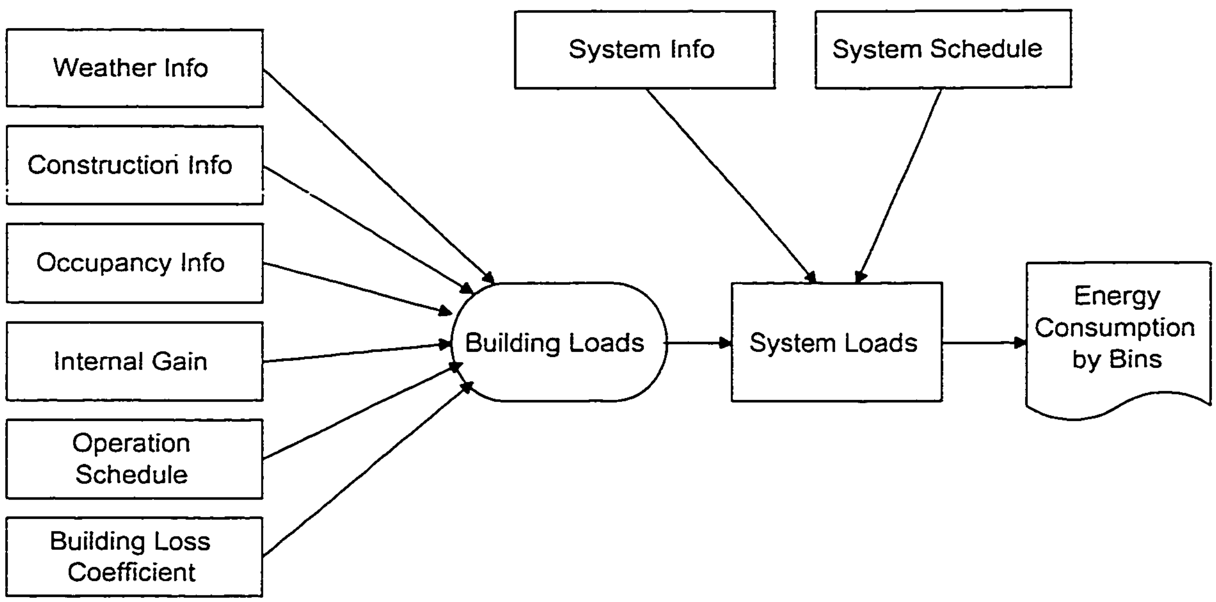


Figure 2.2 : Schematic diagram of the forward (or classical) bin method.

Summary

In this chapter, a literature review has been presented on various measurement and analysis protocols and methodologies. This review has identified the following important points:

- Previous studies have identified one, two, three, four and five parameter regression models as useful tools for the evaluation of energy conservation retrofits in commercial buildings.
- Monthly data was considered to be a sufficient indicator for buildings with no significant seasonal variation and/or constant loads.
- Daily data was found to be a better choice for the majority of commercial buildings.
- Hourly data analysis is useful for diagnosis and in buildings with significant on/off control.
- Hourly models can improve the model performance especially when additional parameters such as outside air humidity and building thermal lag are employed.
- Performance Measurement and Verification Protocols such as DOE's IPMVP and ASHRAE's GPC-14P have chosen standardized 1, 2, 3, 4, and 5 parameter models as one of the preferred analysis methods due to their repeatability.

An overview of the forward bin methodology was also presented here. The advantages and disadvantages of the standard forward bin method and development and application of the fully layered inverse bin methodology will be presented in the following chapters. A detailed methodology of the fully layered inverse bin method is given in Chapter III, application of the methodology in Chapter IV, and comparison of the forward and inverse binned energy values in Chapter V. An evaluation scheme is given in Chapter VI to test the validity and performance of the developed models against the other widely used methods.

CHAPTER III
METHODOLOGY

This chapter presents a detailed description of the inverse bin methodology to calculate baseline energy use in commercial buildings when hourly metered energy data and environmental variables are available. Individual sections of this chapter describe the added improvements in baseline models, an overview of the fully layered inverse bin methodology, and a detailed description of the eleven step fully layered inverse bin methodology.

Introduction

The baseline models reviewed in the previous chapter showed that multiple-parameter linear regression models provided sufficient accuracy when they included weather variations and certain building characteristics as input parameters. However, there is a need for new methods that include the effects of occupancy schedules and complex system operations. In this context, the fully layered inverse bin method detailed in this chapter proposes the following modeling improvements, namely: i) the use of parameters with physical significance for the analysis, ii) use of bin models to accommodate multiple change points, and iii) simplifying the methods so they can be used by practicing building professionals. Like any other multi-variable models the effect of collinearity has to be studied and resolved on a model by model basis. The effect of collinearity between ambient temperature and specific humidity was detected and resolved in Dataset C under Chapter IV.

In the inverse bin method, complex models are generated by separating data into different operational types such as daytypes. The inverse bin method provides an analysis method for data types that are not easily modeled with multiple regression methods, and when coupled with basic statistical tests, can provide accurate and reproducible results.

A second feature of the proposed bin method is inclusion of multiple change points in the baseline models to accommodate the complex nature of operation of modern HVAC systems and controls. Modern HVAC systems in commercial buildings often have outdoor temperature-based hot-deck and/or cold-deck set-points, different room thermostat set-points to accommodate the varied building usage, and different (e.g., dehumidifying, humidifying) modes of operation which are dependent upon ambient temperature. Furthermore, some buildings have seasonal changes that affect the operational mode of the buildings as well as large amounts of thermal mass that tend to dampen and delay the building response to ambient temperature.

In order to obtain a general idea of the need for an inverse bin method, data from buildings in the LoanSTAR program were inspected to determine what types of models were used and how many of these models could be improved with the use of an inverse bin model. Three sets of inspection plots were developed from the daily data from different buildings participating in LoanSTAR program. The three sets include whole-building energy consumption for cooling, heating and electricity use. Forty buildings were selected from the available list of more than two hundred buildings participating in the LoanSTAR program by limiting the selection to buildings which have been metered for the above three energy uses (i.e., whole-building cooling -WBCOOL, whole-building heating- WBHEAT, and whole-building electric -WBELE) for a period of at least one year (i.e., January 1 to December 31, 1995). Energy use data from these buildings were plotted using a comparative index normalized to conditioned area (i.e., Btu/ft^2-hr or W/ft^2). These plots are shown in Figures 3.1a through 3.3b and the building and model descriptions are given in Tables 3.1a and 3.1b. Energy consumption during the weekdays is shown using *plus* (+) symbols while energy consumption during the weekends is shown using *square* (□) symbols.

In general, the daily data are well represented by two, three, or four parameter linear models which were regressed against the outdoor dry-bulb temperature to describe the weather dependent energy use (WBCOOL and WBHEAT). In a few cases, a second variable (e.g., whole-building electricity or air-handler unit electricity) was used to account for internal heat gains in those buildings where this variable was statistically significant. Many of the models used a weekday-weekend separation of the data to account for the occupancy schedules. Nineteen of the forty buildings in Table 3.1a have retrofits that improved the whole-building cooling energy use, of which 11% were modeled with two parameter models, 11% were modeled with three parameter models, 67% were modeled with four-parameter models, and 11% by simplified system models. Similarly of the 26 buildings that have whole-building heating energy retrofits 4% of the buildings was modeled with a one-parameter model, 30% of the models used a two parameter model, 12% used a three parameter model, 39% used a four parameter model, 8% used a simplified system simulation

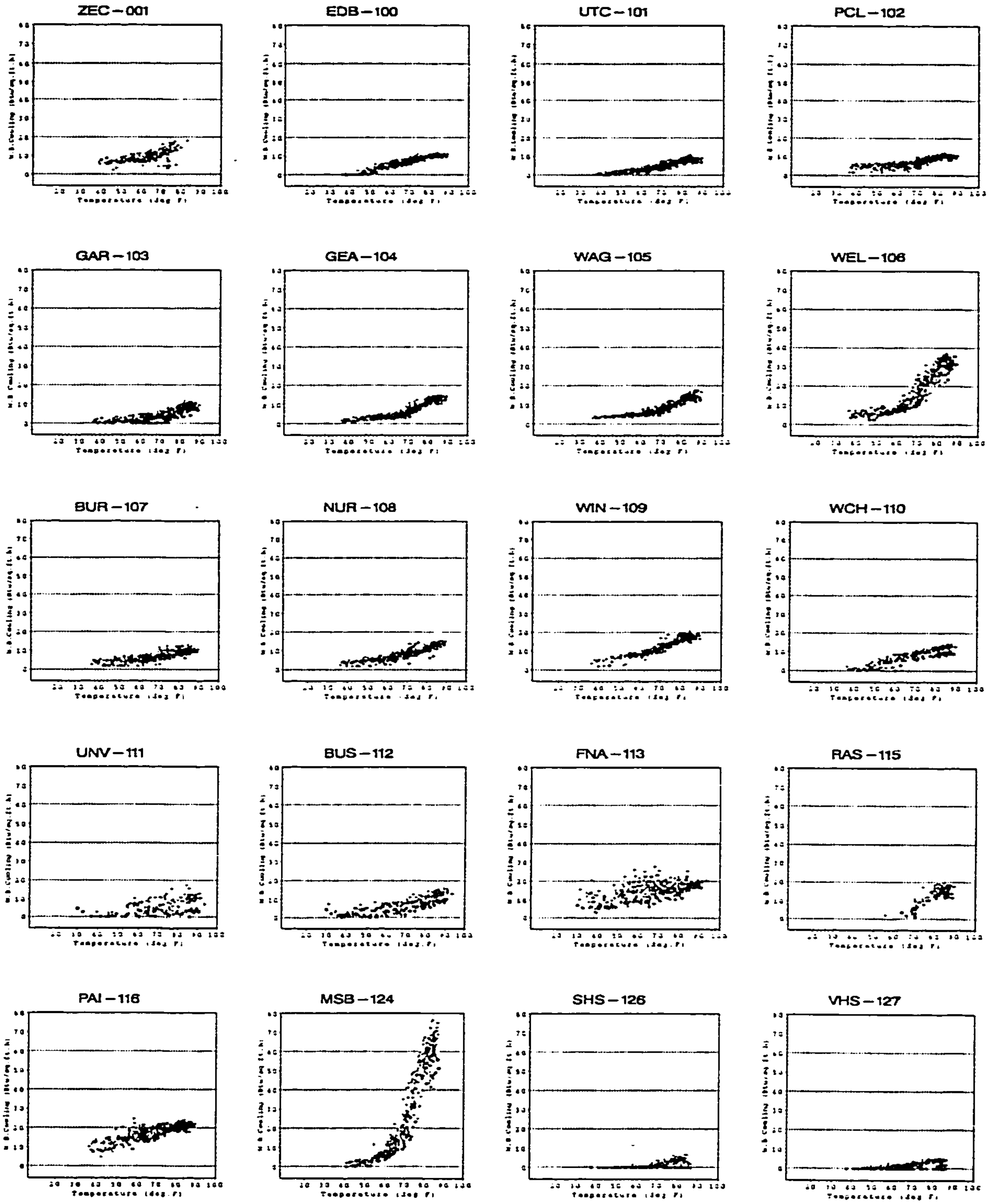


Figure 3.1a: The daily whole-building cooling (WBCOOL) energy consumption of selected buildings participating in the LoanSTAR program. The data are for the period January 1 through December 31, 1995. The uniform scales used for the axes are: vertical 0 - 80 Btu/sq.ft.-hr and horizontal 0 - 100 °F.

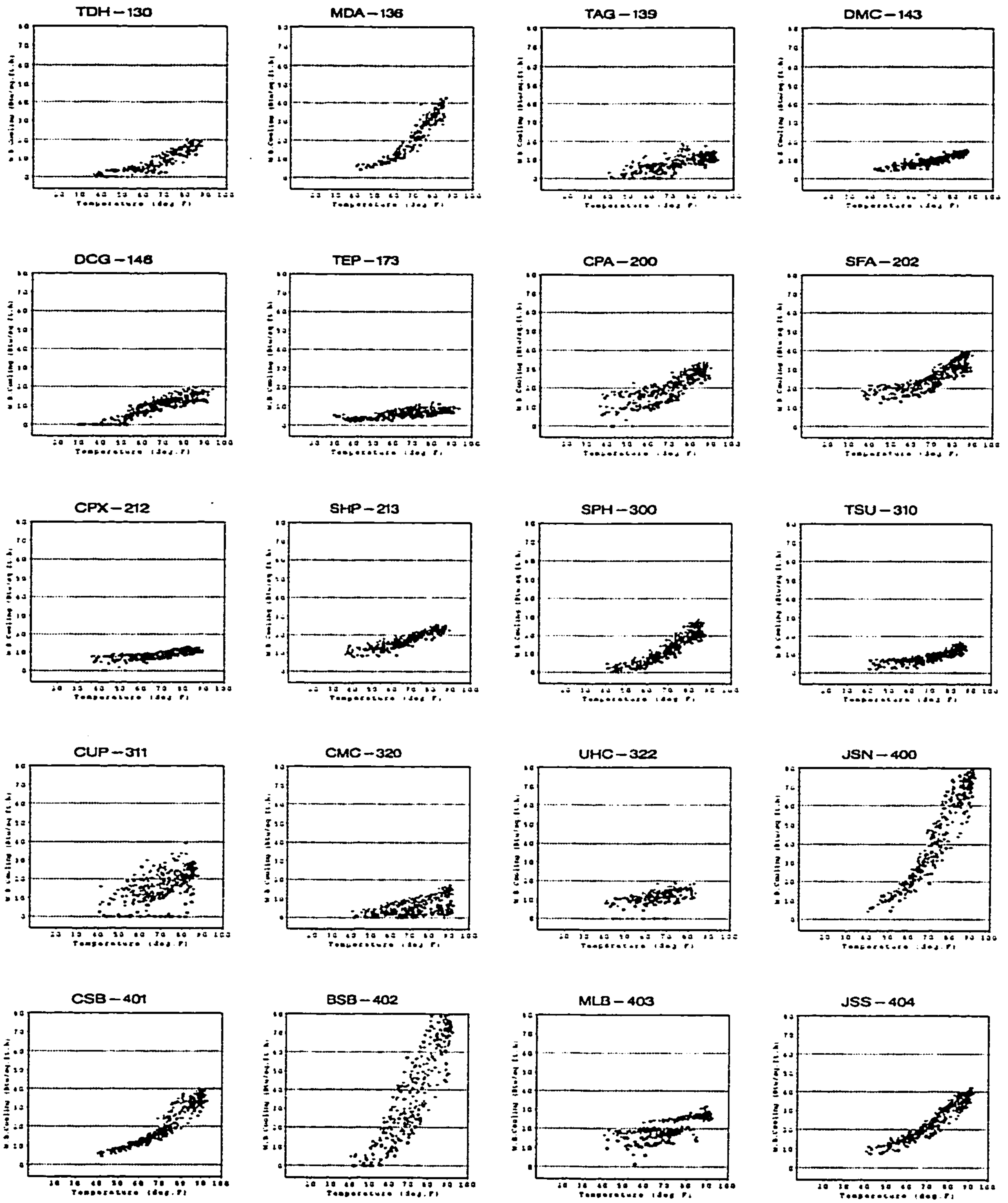


Figure 3.1b: The daily whole-building cooling (WBCOOL) energy consumption of selected buildings participating in the LoanSTAR program. The data are for the period January 1 through December 31, 1995. The uniform scales used for the axes are: vertical 0 - 80 Btu/sq.ft.-hr and horizontal 0 - 100 °F.

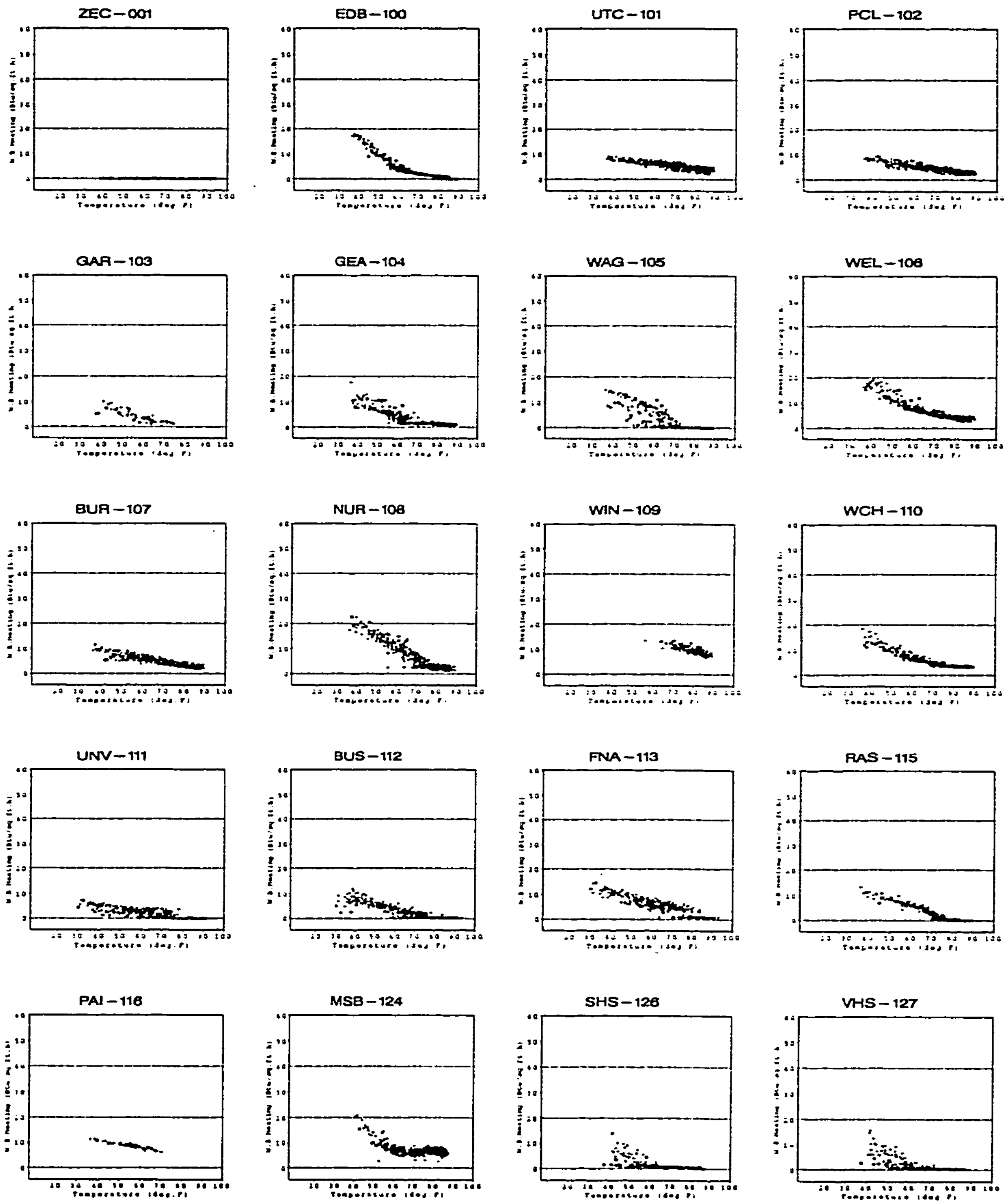


Figure 3.2a : The daily whole-building heating (WBHEAT) energy consumption of selected buildings participating in the LoanSTAR program. The data are for the period January 1 through December 31, 1995. Data for the ZEC building were missing in 1995 due to metering problems. The uniform scales used for the axes are: vertical 0 - 60 Btu/sq.ft.-hr and horizontal 0 - 100 °F.

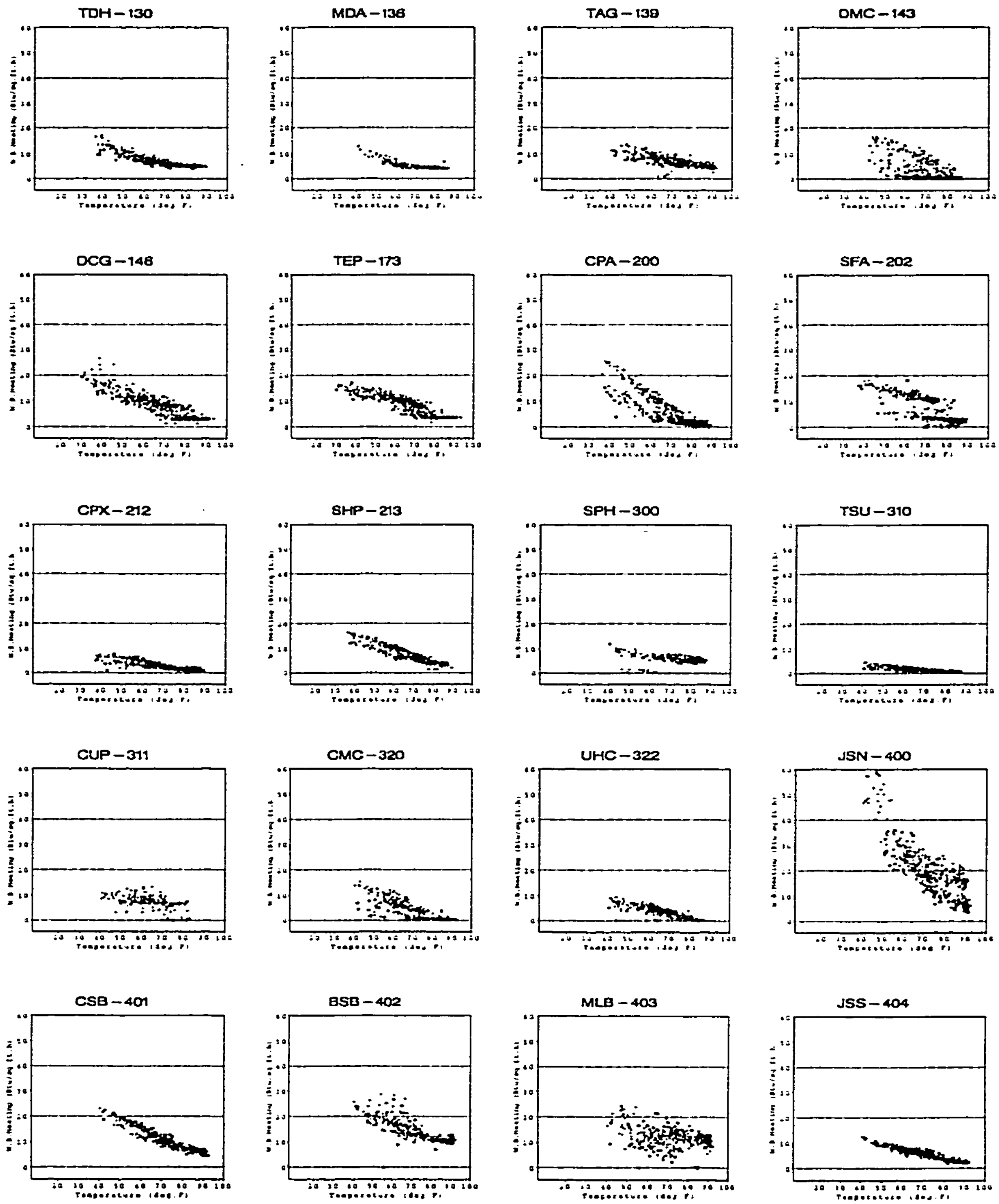


Figure 3.2b : The daily whole-building heating (WBHEAT) energy consumption of selected buildings participating in the LoanSTAR program. The data are for the period January 1 through December 31, 1995. The uniform scales used for the axes are: vertical 0 - 60 Btu/sq.ft.-hr and horizontal 0 - 100 °F.

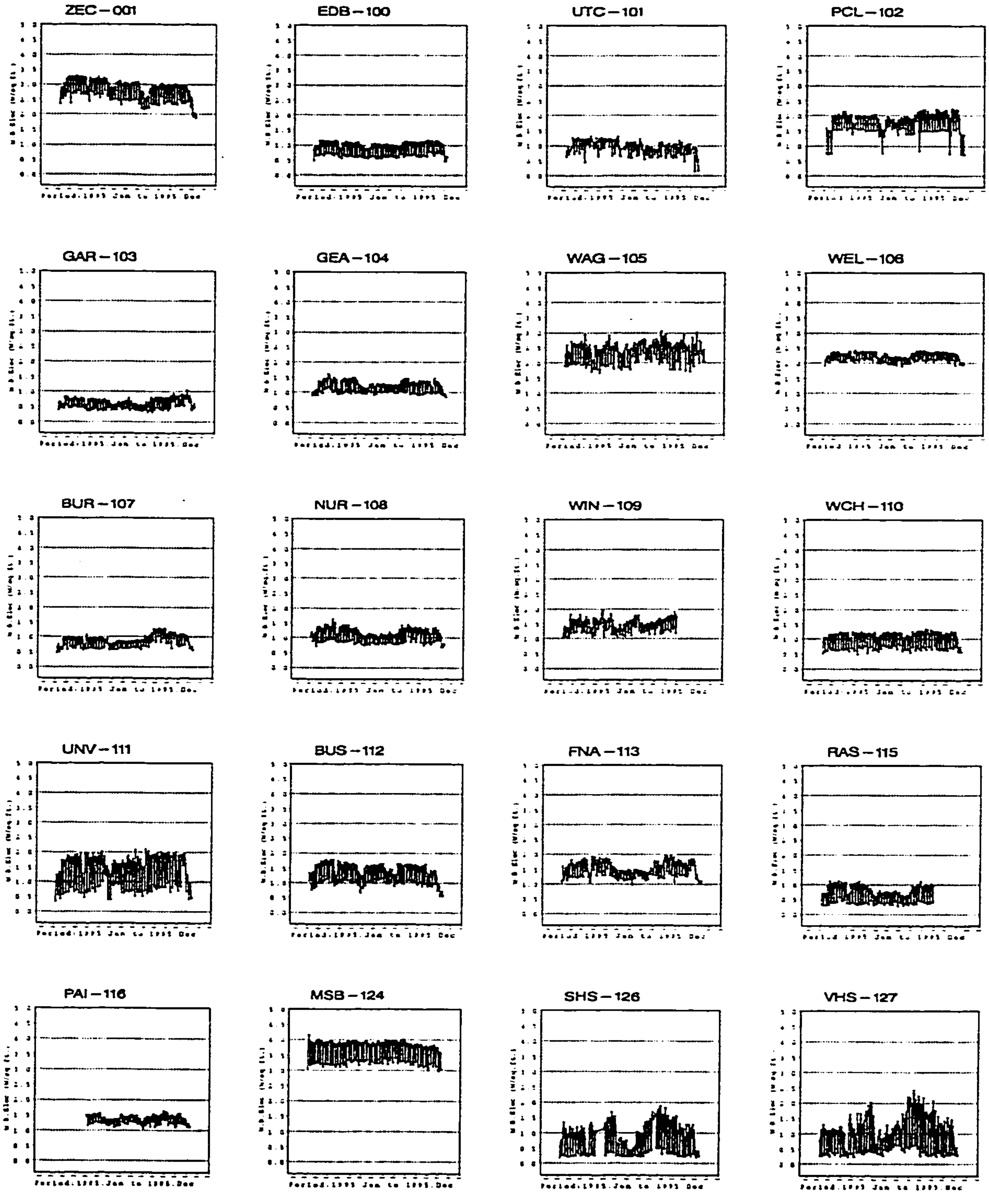


Figure 3.3a : The daily whole-building electric (WBELE) energy consumption of selected buildings participating in the LoanSTAR program. The data are for the period January 1 through December 31, 1995. The uniform scales used for the axes are: vertical 0 - 5 W/sq.ft. and horizontal Jan.1 - Dec.31, 95.

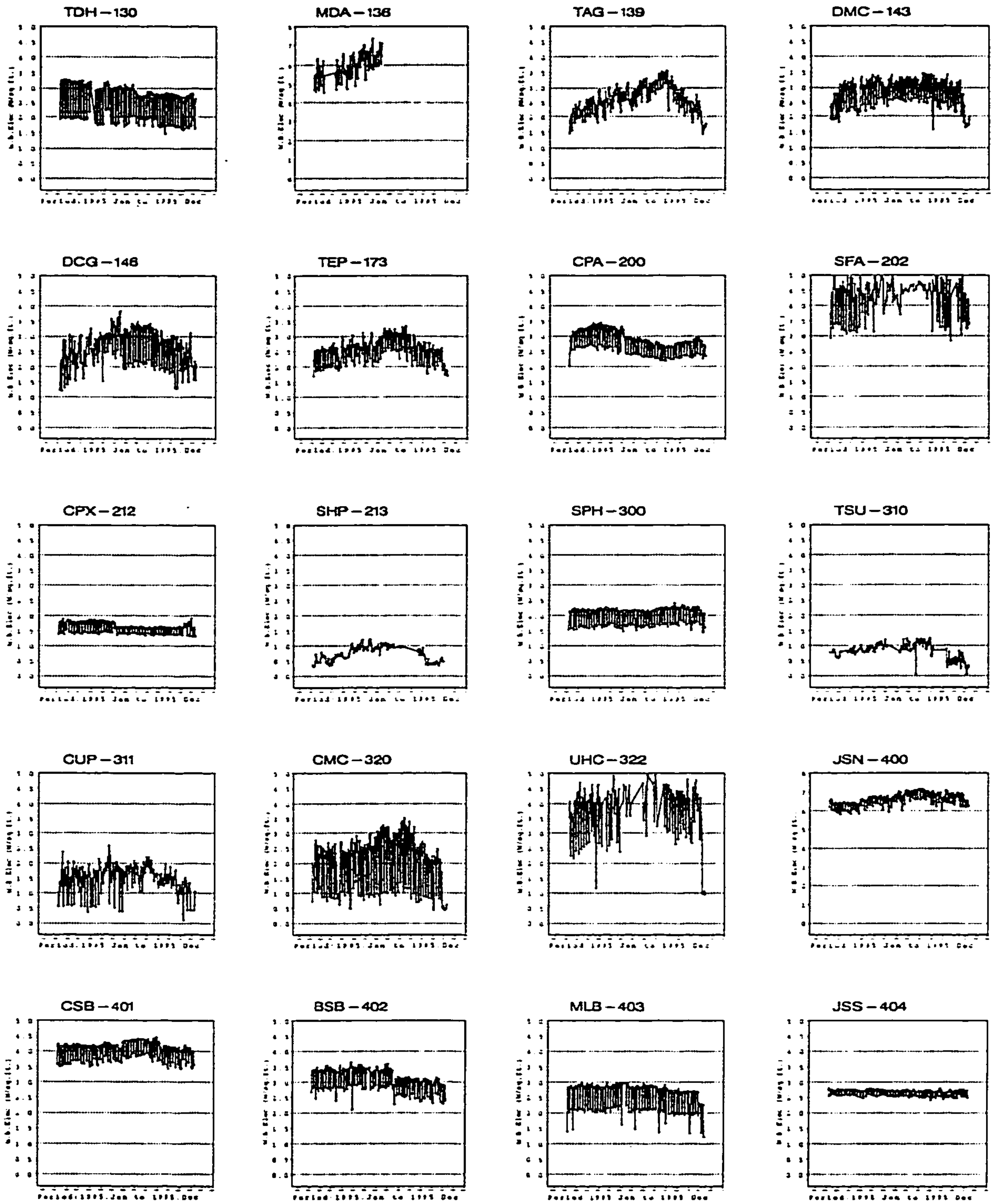


Figure 3.3b: The daily whole-building electric (WBELE) energy consumption of selected buildings participating in the LoanSTAR program. The data are for the period January 1 through December 31, 1995. The uniform scales used for the axes are: vertical 0 - 5 W/sq.ft. and horizontal Jan.1 - Dec.31, 95.

Table 3.1a : Summary of the selected buildings monitored under the LoanSTAR program with the pre-retrofit model types for the three energy types (WBCOOL, WBHEAT and WBELE).

Site	Code	Building Name	Retrofit Completion Date	Conditioned floor area (sq.ft.)	Type of Pre - retrofit Model			
					WBELE	WBCOOL	WBHEAT	other (MCC/ahu)
001	ZEC	Zachry Engineering Center	3/91	324400	*	4-P	MLR	1-P
100	EDB	Education Building	5/91	251161	*	3-P	4-P	1-P
101	UTC	University Teaching Center	11/90	152690	1-P	SSM	SSM	SSM
102	PCL	Perry Castaneda Library	11/90	483895	1-P	SSM	SSM	SSM
103	GAR	Garrison Hall	5/91	54069	*	4-P	2-P	1-P
104	GEA	Gearing Hall	5/91	61041	*	4-P	2-P	1-P
105	WAG	Waggener Hall	5/91	57598	*	4-P	2-P	1-P
106	WEL	Welch Hall	2/92	439540	1-P	4-P	4-P	1-P
107	BUR	Burdine Hall	5/91	103441	1-P	3-P	4-P	1-P
108	NUR	Nursing Building	4/91	94815	1-P	4-P	4-P	1-P
109	WCH	W.C. Hogg Hall	5/91	48905	1-P	4-P	2-P	1-P
110	PAI	Painter Hall	2/92	128409	1-P	4-P	4-P	*
111	UNV	University Hall	8/91	123450	*	4-P	2-P	1-P
112	BUS	Business Building	8/91	149900	*	2-P	3-P	1-P
113	FNA	Fine Arts Building	8/91	223000	1-P	4-P	4-P	1-P
114	WIN	Winship Hall	5/91	109064	1-P	4-P	2-P	*
115	RAS	Steindham Hall	5/91	56849	1-P	4-P	4-P	*
124	MSB	Medical School Building	7/91	887187	4-P	*	*	*
126	SHS	Stroman High School	8/91	210500	CP/sch	*	L-0	*
127	VHS	Victoria High School	8/91	257000	CP/sch	*	L-0	*
130	TDH	Texas Dept. of Health	8/92	298700	2-P	2-P	4-P	*
136	MDA	U.T.M.D. Anderson Cancer Center	8/93	239535	1-P	*	*	*
139	TAG	Texas A&M University Galveston	3/92	420868	*	*	*	*
143	DMC	Del Mar College	6/93	681592	1-P	*	2-P	*
146	DCG	Dallas County Gvmt. Center	3/94	473800	3-P	*	2-P,1-P	*
173	TEP	Thermal Energy Plant	9/95	2878537	3-P	*	3-P	*
200	CPB	Capitol Building.	construction	282599	*	*	*	*
202	SFA	S. F. Austin Building Central Plant	10/94	470000	1-P	*	3-P	*
212	CPX	Capitol Extension	N/A	592781	*	*	*	*
213	SHP	Sam Houston Central Plant	12/91	1791943	*	*	4-P	*
300	SPH	School of Public Health	3/92	233738	*	*	*	1-P
310	TSM	TSU Main Central Utility Plant	n/a	1147500	*	*	*	*
311	TSS	TSU Satellite Central Utility Plant	n/a	212500	*	*	*	*
320	CMC	College of Mainland	7/94	339167	2-P	*	4-P	*
322	UHC	Unv.Houston-Clear Lake (Boyou)	12/95	460576	*	*	*	*
400	JSN	John Sealy North	8/92	68512	*	*	*	4-P
401	CSB	Clinical Sciences	8/92	124870	*	*	*	1-P
402	BSB	Basic Sciences	4/92	137856	*	4-P	4-P	1-P
403	MLB	Moody Memorial	8/92	67380	*	*	*	1-P
404	JSS	John Sealy South	8/92	373085	*	*	*	1-P

* - model information is not available or not needed for this energy type.

#-P - # parameter regression model (#-1,2,3 & 4) sch. - regression model with different schedules

CP - Change-point model (either 3 or 4-P model)

Table 3.1b : Summary of the selected buildings monitored under the LoanSTAR program with the coefficient of variation for the three energy types (WBCOOL, WBHEAT and WBELE).

Site	Code	Building Name	Retrofit Completion Date	Conditioned floor area (sq.ft.)	CV of the Existing Model			
					WBELE	WBCOOL	WBHEAT	other (MCC/ahu)
001	ZEC	Zachry Engineering Center	3/91	324400	*	10.3	21.3	2.5
100	EDB	Education Building	5/91	251161	*	8.9	13.2	5.1
101	UTC	University Teaching Center	11/90	152690	*	SSM	SSM	SSM
102	PCL	Perry Castaneda Library	11/90	483895	*	SSM	SSM	SSM
103	GAR	Garrison Hall	5/91	54069	*	11.6	8.2	3.0
104	GEA	Gearing Hall	5/91	61041	*	12.6	11.8	1.7
105	WAG	Waggener Hall	5/91	57598	*	14.3	23.3	2.2
106	WEL	Welch Hall	2/92	439540	*	19.0	19.4	6.1
107	BUR	Burdine Hall	5/91	103441	*	12.2	11.9	3.0
108	NUR	Nursing Building	4/91	94815	*	15.3	18.8	20.1
109	WCH	W.C. Hogg Hall	5/91	48905	4.9	9.9	11.7	*
110	PAI	Painter Hall	2/92	128409	2.7	13.1	10.0	*
111	UNV	University Hall	8/91	123450	*	19.8	113.6	21.2
112	BUS	Business Building	8/91	149900	*	18.5	12.8	n/a
113	FNA	Fine Arts Building	8/91	223000	*	16.0	25.6	n/a
114	WIN	Winship Hall	5/91	109064	3.5	10.1	9.7	*
115	RAS	Steindham Hall	5/91	56849	n/a	26.1	23.8	*
124	MSB	Medical School Building	7/91	887187	3.4	*	*	*
126	SHS	Stroman High School	8/91	210500	n/a	*	*	*
127	VHS	Victoria High School	8/91	257000	n/a	*	*	*
130	TDH	Texas Dept. of Health	8/92	298700	7.9	9.6	12.7	*
136	MDA	U.T.M.D. Anderson Cancer Center	8/93	239535	n/a	*	*	n/a
139	TAG	Texas A&M University Galveston	3/92	420868	n/a	*	*	*
143	DMC	Del Mar College	6/93	681592	n/a	9.7	*	*
146	DCG	Dallas County Gvmt. Center	3/94	473800	9.3	*	11.1	*
173	TEP	Thermal Energy Plant	9/95	2878537	*	*	*	*
200	CPB	Capitol Building.	construction	282599	DOE2	DOE2	DOE2	n/a
202	SFA	S. F. Austin Building Central Plant	10/94	470000	*	*	15.1	*
212	CPX	Capitol Extension	N/A	592781	DOE2	DOE2	DOE2	*
213	SHP	Sam Houston Central Plant	12/91	1791943	*	n/a	10.2	*
300	SPH	School of Public Health	3/92	233738	*	n/a	n/a	2.1
310	TSM	TSU Main Central Utility Plant	n/a	1147500	nc	nc	nc	nc
311	TSS	TSU Satellite Central Utility Plant	n/a	212500	nc	nc	nc	nc
320	CMC	College of Mainland	7/94	339167	3.2	*	6.7	*
322	UHC	Unv.Houston-Clear Lake (Bayou)	12/95	460576	*	*	*	*
400	JSN	John Sealy North	8/92	68512	*	*	*	4.1
401	CSB	Clinical Sciences	8/92	124870	*	*	*	5.6
402	BSB	Basic Sciences	4/92	137856	*	SSM	SSM	9.9
403	MLB	Moody Memorial	8/92	67380	*	*	*	12.3
404	JSS	John Sealy South	8/92	373085	*	*	*	9.9

* - no relevant retrofit installed

nc - retrofit is not yet completed

n/a - no information available about the model

SSM - synthetic baseline data generated by simplified system models

DOE2 - synthetic baseline data generated by DOE2 simulations and 8% used special purpose models. Majority (80%) of the MCC electricity use were modeled with a one-parameter model while a small fraction (5% by a two-parameter and 5% by other) were other models. In the plots shown, the buildings 100 (WBCOOL & WBHEAT), 104 (WBCOOL), 105 (WBHEAT), 111 (WBCOOL & WBHEAT), 112 (WBCOOL & WBHEAT), 124 (WBCOOL & WBHEAT), 126 (WBHEAT), 127 (WBHEAT), 143 (WBHEAT), 146 (WBHEAT), 173 (WBCOOL & WBHEAT), 320 (WBHEAT) and 322 (WBHEAT) all indicate some schedule-based operation and/or more than one change-point. Since the effect of the varied number of hours of shut-off is only seen as scatter in daily data, it difficult to model these energy types with methodologies that use the daily data. Therefore, newer methodologies are needed that can use the multiple change-points and schedule-based daytypes. Consequently the fully layered inverse bin method, outlined in this study, is an excellent choice for these cases.

Overview of the Fully Layered Inverse Bin Methodology

In the forward (standard) bin method annual energy consumption for a building is estimated from the building description (i.e., building construction, load schedules and profiles, and occupancy schedule and profile), systems data (i.e., type and size of distribution equipment, schedule and operational performance plant data), and weather characteristics. The inverse bin method is similar to the standard bin method because it extends the idea of binning for temperatures to include binning for different building and system modes of operation. However, the new method uses the monitored data to derive the different modes of operations and hence is referred to as the *inverse bin method.* This method provides four areas where improvements are needed in the existing inverse modeling scheme, namely: i) the use of bins to accommodate non-linear behavior, ii) the consideration of different operational modes (i.e., ON and OFF) of building operation, iii) the inclusion of thermal mass and latent load effects, and iv) the simplification of the procedure so that it can be used by HVAC system designers. The use of thermal mass and latent loads in this method were conceptually different from other earlier studies (Wu et al., 1992; Katipamula et al., 1994).

In this section the basic procedure of the inverse bin method and the general data requirement are described. The basic procedure is illustrated in Figure 3.4 as a flowchart

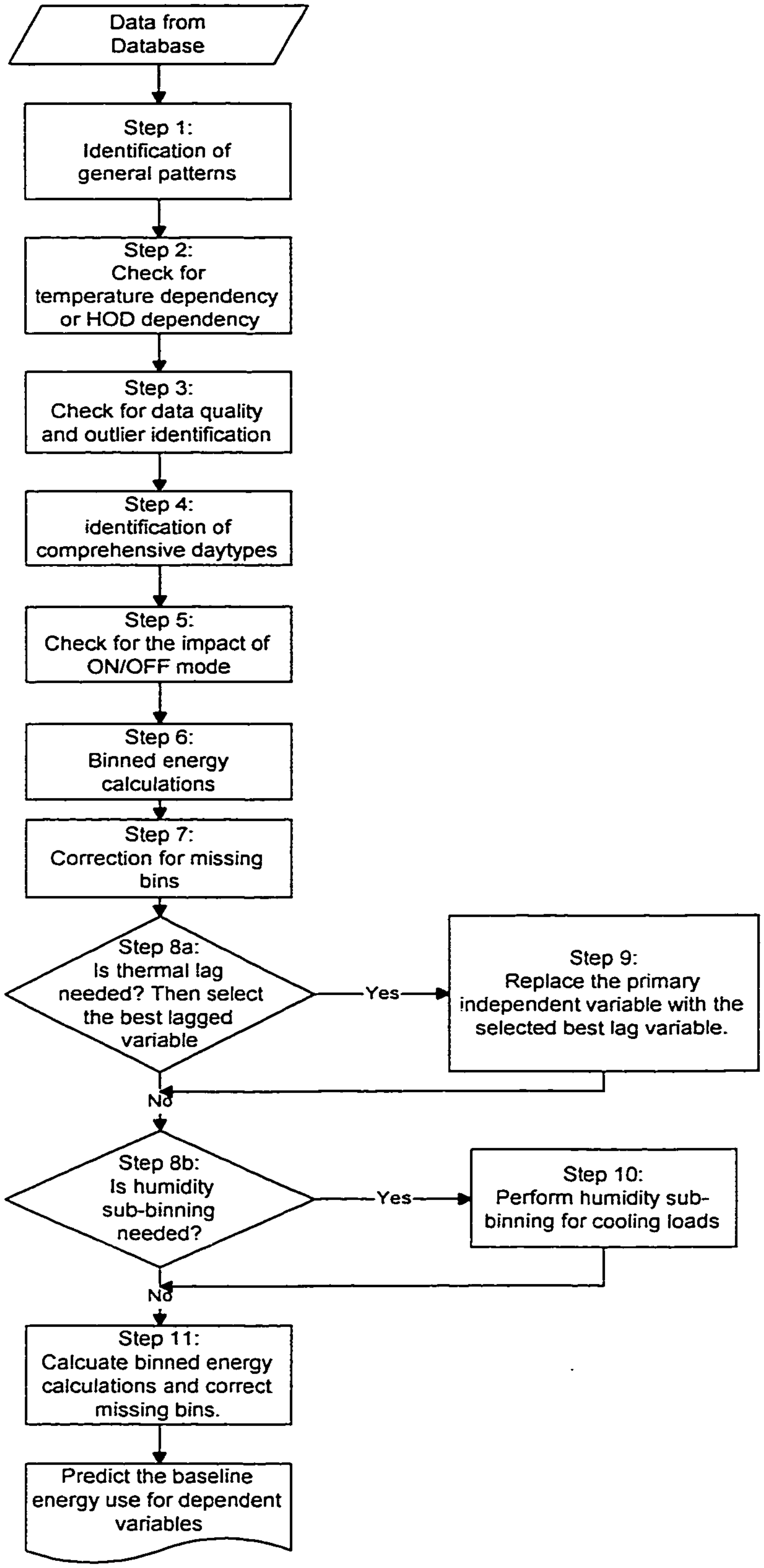


Figure 3.4 : Overview of the fully layered inverse bin method data analysis procedure

format. The improvements used in this analysis procedure include: i) a procedure for testing and grouping the data as temperature dependent energy use or Hour-of-the-Day (HOD) energy use (also known as weather independent energy use), ii) testing to identify and remove any bad or unusual data periods, iii) dividing the data into groups (or day-types) to separate the different data sets by the different operating schedules and modes of the building systems, iv) describing the data through a set of representative binned energy values, and v) correcting the binned energy use to fill in missing bins, if any. Though the ideas i, ii, and iii were used in one or more earlier studies (Akbari et al., 1988; Katipamula and Claridge, 1993; Katipamula et al., 1994; Kissock, 1993; Dhar, 1995; Abbas, 1993) none of these studies have shown any formal procedure to achieve these objectives. The idea of resolving the issue of missing data was used for in the LoanSTAR program in a different form (Kissock, 1993).

In addition to the primary steps, there are additional steps in the fully layered inverse bin method to better describe weather dependent energy use (mainly whole-building cooling). These elements, also termed "sub-binning", were developed to improve the prediction in the higher temperature cooling region where humidity effects can become more pronounced as reported by Katipamula et al. (1994). In these regions the cooling energy use data exhibits heteroscedastic characteristics, namely the energy use during the higher temperature occurrence has a larger variation than the variation of the data at low temperature regions. The sub-binning scheme was devised to account for the part of these variations that are due to latent load changes. A second procedure was also developed to account for the thermal mass effect. Therefore, by using these procedures the temperature dependent data can be further tested and sub-binned into additional sub-groups to improve the prediction of the combined model.

In general, an inverse hourly bin analysis works best with at least nine months of pre-retrofit (baseline) energy consumption data. In addition, the prediction accuracy of the inverse bin method improves considerably with the availability of certain additional data channels that capture the relevant system operations. For example, availability of motor control center (MCC) and/or whole building electric (WBELE) data enables a schedule-based (On/Off) daytyping for improved predictions. The Air-Handler Unit (AHU) energy consumption data can also be used as an alternative in schedule-based daytyping procedure.

Description of the Modeling Procedure

The following is a detailed description of the eleven steps involved in the inverse bin method. The individual steps are illustrated through a series of plots that are generated from a sample data that used dataset A from the ASHRAE Predictor Shootout I competition that was held in 1993 (Kreider and Haberl, 1994). The dataset contains energy consumption (cooling, heating and electric) and weather variables (temperature, humidity, solar radiation and wind speed) for a case study building (The Zachry Engineering Center at Texas A&M University - ZEC) located in central Texas. Selected plots using the energy consumption from a second building (i.e., the Education building of the University of Texas at Austin - EDB) from the Texas LoanSTAR dataset are also shown to illustrate certain steps of the inverse bin procedure because dataset A does not exhibit a schedule-dependent operation.

<u>Identification of General Patterns (Step 1)</u>

The role of this step is to reveal the basic features of the data set under study and to identify the type of model that is appropriate or to suggest areas where the proposed model may become inadequate for certain features. Failure to explore the data before embarking on a formal analysis may cause much time, effort and resources to be wasted. Three different types of graphical techniques (univariate, bivariate and time-series plots) were utilized to explore the features of a dataset: linear relationships, time trends, periodicity or seasonality, boundary points, outliers, and clumps or clusters of data.

In Step 1 graphical techniques are recommended because formal numerical statistics yield only narrowly defined answers to specific questions. Graphical techniques do not suffer from this rigidity and consequently are a useful tool for the data analysis at this stage. Furthermore, graphical representation of the data often yields quick and easy identification of these general patterns and features. Though there exists various methods of plotting data that will help one gain an insight into the structure of the data in hand (Tukey, 1977; Cleveland, 1985; Abbas, 1993), we limit our graphical exploration of the data to univariate plots, time series (hourly time series) plots and response plots (i.e., x-y scatter plots of the dependent variable). When the size of the dataset is large enough individual variables on similar scales can be used to compare the distributions over the range of the periods (e.g., three time-series plots of four-month periods covering January-April, May-August and

September - December periods may enhance the distribution than a single time-series plot covering the same twelve-month period). Furthermore, all graphs should be drawn so as to exhibit the data in as clear a manner as possible.

The univariate plots are useful for finding clumps, outliers and hard boundaries that occur in individual variables. We can also observe the general distribution of points within each variable and spot any unusual features. Generally used plots in this type (single variable plots) are histograms, bar charts, stem and leaf plots, and box and whisker plots.

A further study of the energy use pattern can be performed by inspecting a histogram or frequency plot. In this case, a frequency plot was generated for both weekday and weekend data sets of whole-building electric energy use because of the large difference between the weekday and weekend consumption. A closer look at the frequency plot of WBELE consumption (Figure 3.5) (weekday-weekend) shows the existence of more than one daytype within the distribution for weekday consumption. In general, a distribution is expected to be of normal distribution with one peak and tails on either side. However, in the distribution shown, the existence of two peaks indicates that there are two predominant modes of operation (i.e., daytime and night-time modes). This is confirmed later when one inspects the data using Step 3. For the weekend mode, only one dominant operational mode exists (under Step 3).

The second and third group of plots (time series and response plots) can be generally termed as bivariate plots because these plots are generated to investigate the relationships between two variables. In the time series plots, the relationship/response of the variable is studied against time, while in the x-y scatter plots (i.e., response plots), the plots are generated to show the dependency of one variable (i.e., the y-axis) upon another variable (i.e., the x-axis). To illustrate the use of bivariate (time series) plots, whole-building electric (WBELE) data are shown as a time-series plot in Figure 3.6. In general, the time-trends and seasonality or periodicity can be studied in the time-series plots. The effect of weekday-weekend, holidays and breaks, and the periodicity of peak consumption over the time period are visible in this plot.

The cooling and heating energy consumptions are generally weather dependent. Hence, scatter plots (Figure 3.7) of cooling or heating energy consumption against the

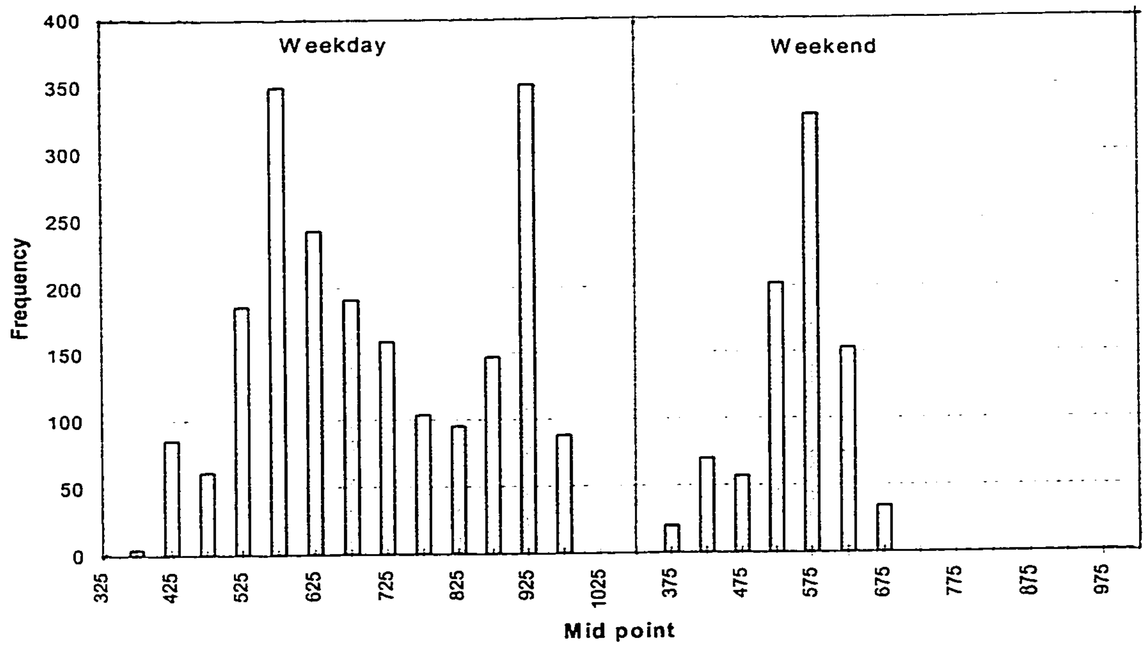


Figure 3.5 : Frequency distribution of the whole-building electric (WBELE) energy use data for calendar daytypes (weekday-weekend). The frequency values are calculated for 50 kWh WBELE data intervals and plotted against the mid point of data interval.

weather variable can yield more information about the variation than a time series plot (Figure 3.8). However, certain types of abnormal data may be visible when both plots were studied together, while variations between weekday and weekend in weather-dependent consumption may be more easily identified in a scatter plot.

In general, ventilation and infiltration in a building causes outdoor air to be drawn into the building. When ambient conditions are outside the comfort range this outdoor air has to be conditioned before being supplied to the rooms. During the cooling season, the latent cooling load is the energy necessary to remove the moisture from this air-stream. The magnitude of this latent load effect can be visualized by plotting each data point according to its accompanying outdoor dry-bulb temperature and specific humidity conditions (Figure 3.9). This plot is essentially a psychometric chart with the x-axis representing the dry-bulb temperature, the curvilinear boundary of the data points representing the dew-point line, and the y-axis (i.e., vertical axis) representing the specific humidity. When the amount of moisture in the outdoor region is higher than the amount present at a typical coil dew-point temperature of 54°F (12.2°C) (marked as the influential area in the figure) it increases the

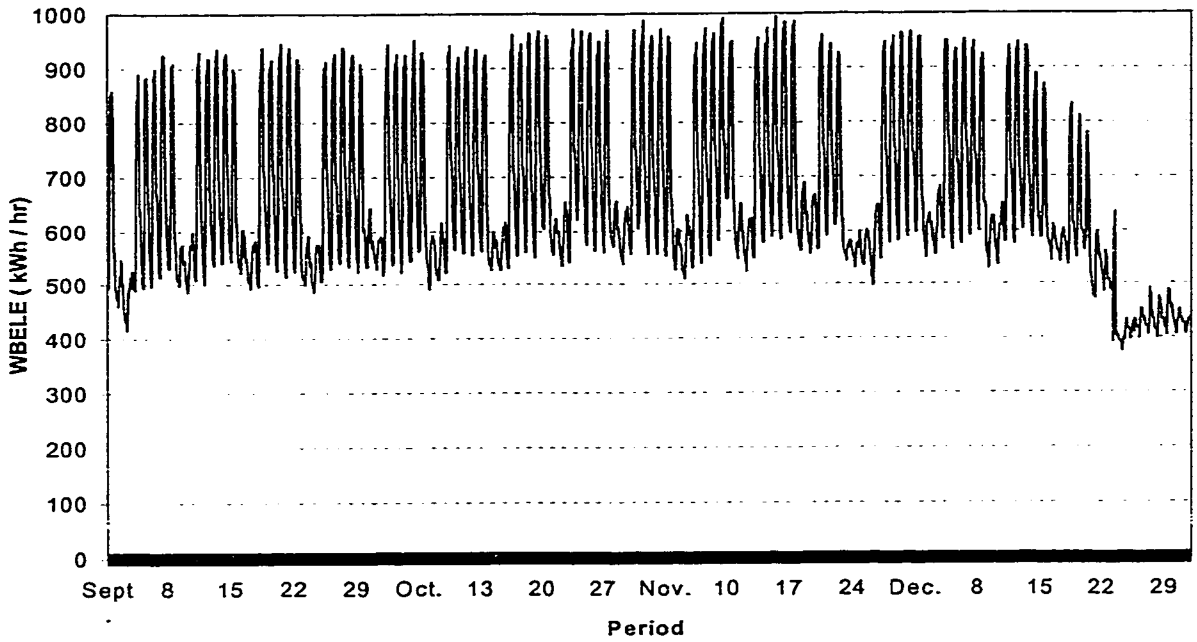


Figure 3.6: Time series plot of the whole-building electric (WBELE) energy consumption of the Engineering Center for the 09/01/89 - 12/31/89 period.

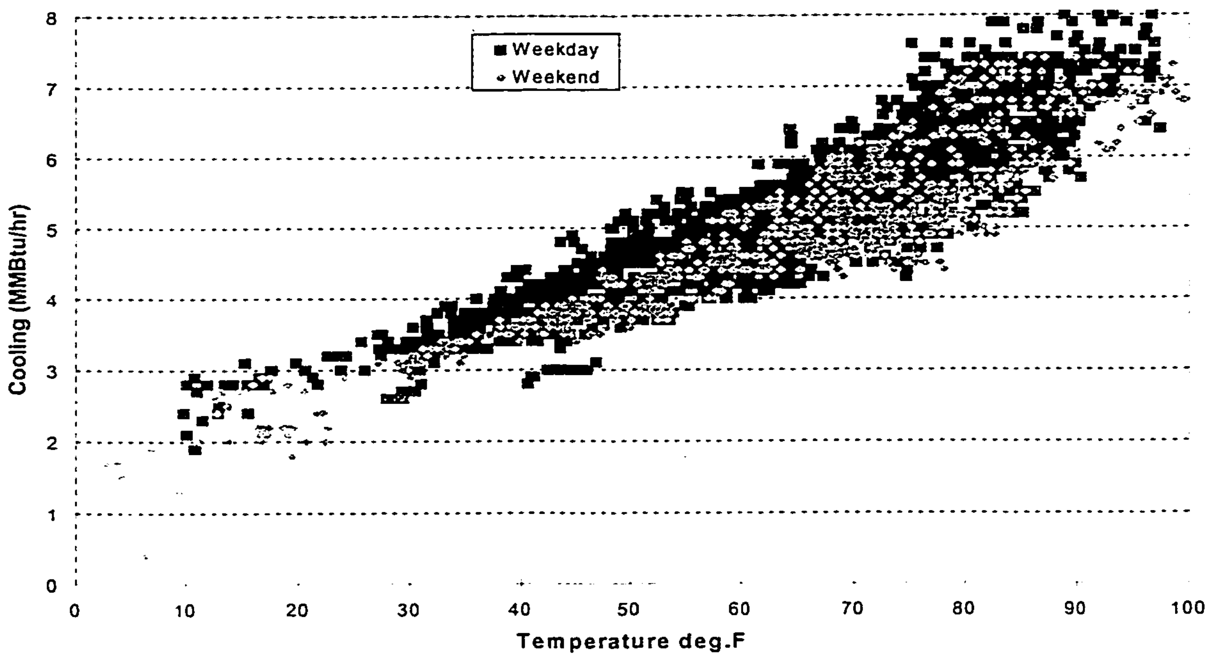


Figure 3.7 : Scatter plot of the whole-building cooling energy consumption vs outdoor dry-bulb temperature for the Engineering Center. Separate symbols for weekday and weekend are indicated as shown.

cooling load by adding a dehumidification load which is proportional to the distance of the data point above the 0.01 specific humidity line.

The cooling energy variation at the high temperature range is larger than the variation at the low temperature range. One known cause for this variation the latent load effect. Figure 3.9 also shows that the highest temperatures do not correspond to the highest specific humidities. This inherent feature is clearly seen in the diurnal variation of specific humidity plots shown in Figure 3.10. Specifically, for specific humidities above 0.006 lbm/lba there is a very clear inverse relationship between specific humidity and air temperature which roughly follows a constant enthalpy line when plotted on a psychometric chart. This would seem to indicate that as heat energy is added to the air mass during the day the temperature response is affected by the amount of moisture in the air. During days when the moisture content is high the increase in temperature is dampened because the process behaves as a constant enthalpy process moving roughly down the isoenthalpy line. On dryer days at the same temperature the temperature increase is higher.

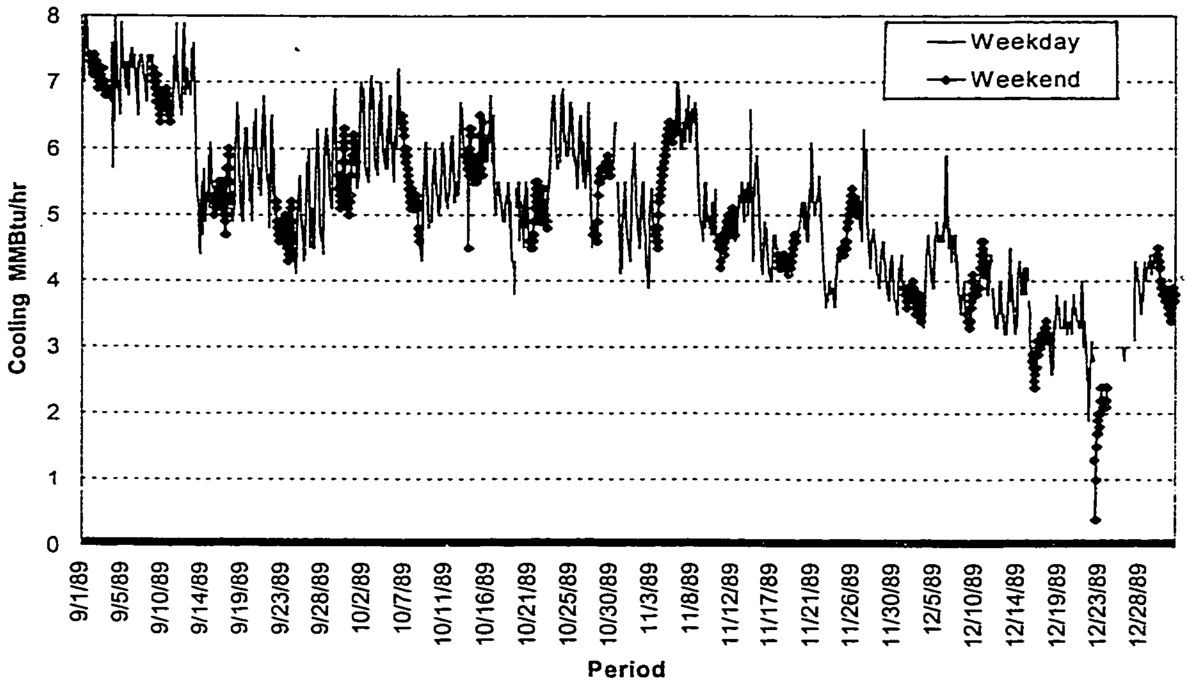


Figure 3.8 : Time series trend of the whole-building cooling energy consumption for the Engineering Center for the 09/01/89 - 12/31/89 period.

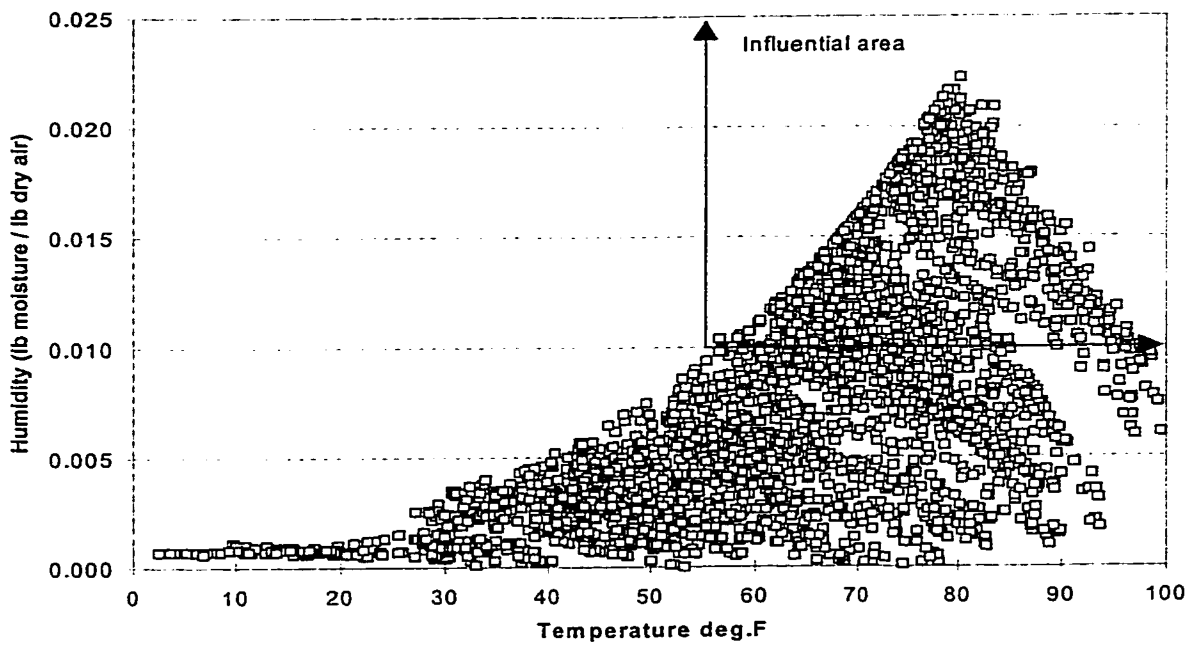
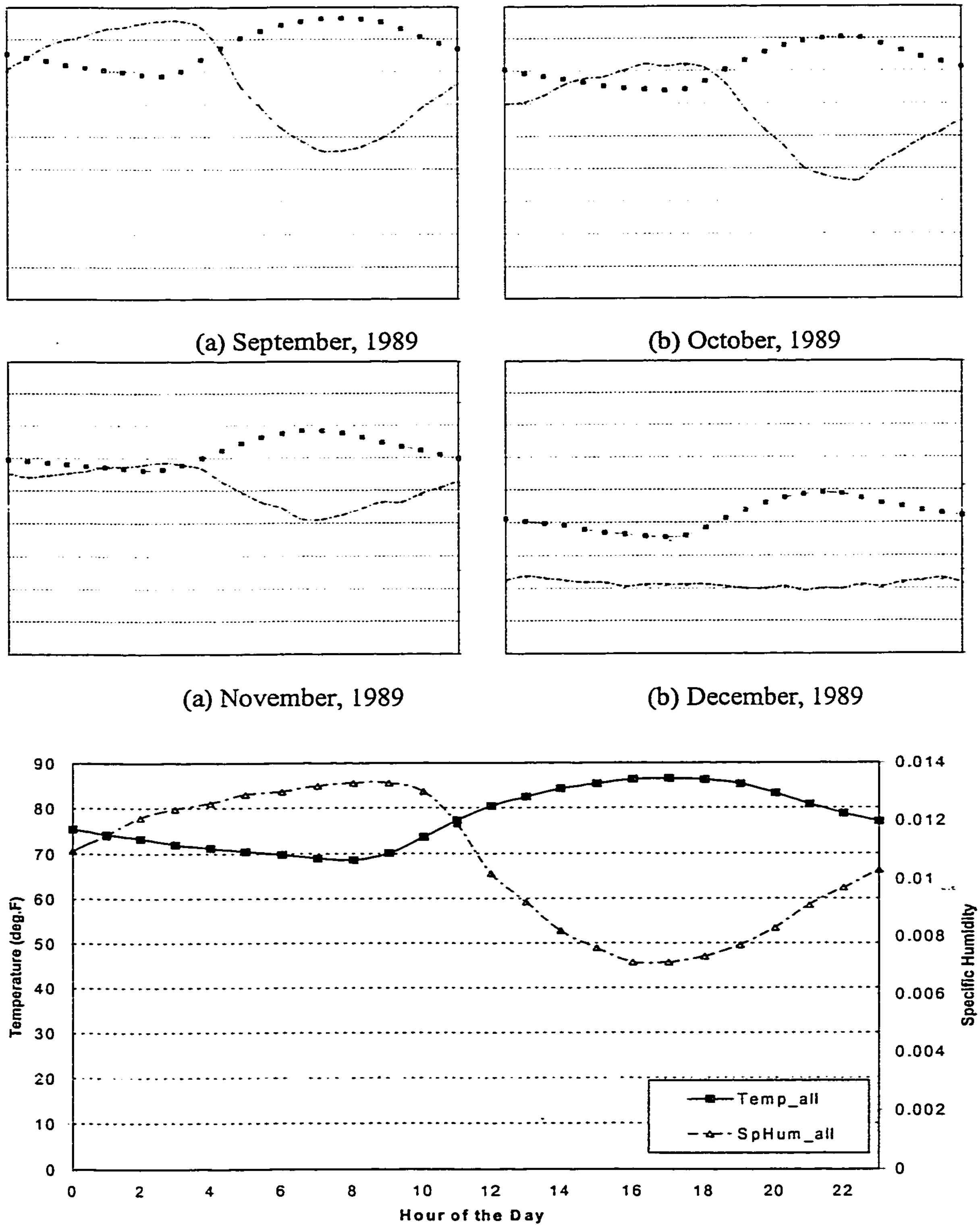


Figure 3.9 : Scatter plot of outdoor specific humidity vs outdoor dry-bulb temperature to visualize the latent load effect in building cooling energy consumption.

The following plots can also be visually examined for identifying given features: existence of outliers (Figure 3.7 for cooling), existence of multi-modal operation (Figure 3.5 weekday-weekend WBELE frequency plot), existence of on/off modes (not for this dataset), and latent load as a function of specific humidity and temperature (Figure 3.9).

Check for Temperature Dependency or HOD Dependency (Step 2)

The goal of this modeling process is to characterize baseline building energy use using a few readily available and highly reliable input (independent) variables or binning variables. The purpose of this step in the procedure is to group the criterion (dependent) variables into two categories, weather dependent data (WDD) and weather independent data (WID), using the correlation between the dependent variables and the independent variables. The independent variable that has the most significant correlation with the dependent variable will be chosen as the bin variable. This bin variable will then be used to group the energy consumption data into several bins of equal intervals and help to characterize energy consumption use for prediction. In addition, each independent variable must be unaffected



(e) Complete data: Sept.1 - Dec.31, 1989

Figure 3.10: Relationship between outdoor dry bulb temperature and outdoor specific humidity for dataset A (Engineering Center : 9/01/89 - 12/31/89). The uniform scales used for the plots are:Hour-of-the-day 0 to 23; Temp. 0 to 90°F; and SpHum 0 to 0.014 lbm/lbda.

by the retrofit so that the model can accurately predict the energy use that would have occurred if the retrofit had not taken place. Independent variables which meet the above criteria include outside air dry-bulb temperature, solar radiation, specific humidity, and time-of-the-day or hour-of-the-day (HOD).

There are also practical incentives for identifying the simplest model possible. Models which depend on multiple independent variables become useless if any of the independent variables become unavailable due to sensor failure. Furthermore, models that require multiple independent variables, although they may be quite accurate, cannot be used by practitioners who do not have access to those variables. For these reasons, this analysis will focus on correlating empirical thermal energy use with the most relevant independent variable that is also the most robust and readily available: outdoor air dry-bulb temperature.

Alternatively, for those cases where the outdoor air temperature was not the appropriate predictor variable, the hour-of-the-day (HOD) variable was chosen as the bin variable. Furthermore, where the accuracy of temperature-based models is not sufficient, an improvement was added to this analysis in the form of sub-binning. This sub-binning scheme will use specific humidity and lagged outdoor air temperature (to account for the thermal lag effect of the building's thermal mass) as additional variables. In such cases, the outdoor air dry-bulb temperature is the basic independent variable, while lagged outdoor air temperature, and specific humidity are the additional (sub-binning) set of independent variables for those cases where better accuracy is required. Hereafter, these variables will be referred to as temperature (Temp), lagged temperature (lagTemp), humidity (SpH), and hour-of-the-day (HOD), respectively.

The predictor variable identification procedure has been shown in flowchart format in Figure 3.11. In general this temperature dependency check is based on the following assumptions: 1) a random sample of data for each pair of variables, 2) a linear relationship between the dependent and predictor variable, and 3) a bivariate normal association between the dependent and predictor variables. Fortunately, the Pearson's correlation coefficient is robust against the violation of the third assumption (normal relationship) because the size of the available data is often more than 25 data points. In certain cases the correlation between the dependent and predictor variable is not linear (i.e., second order variation or non-linear). Therefore, care must be taken in interpreting the test results (i.e., a non-linear variation may require second correlation coefficient with modified form of the independent variable or a bivariate plot of the two relevant variables would provide necessary information).

As stated in the previous step, we will use dataset A from the ASHRAE Predictor Shootout I to illustrate this check and resultant data types. The given dependent or criterion

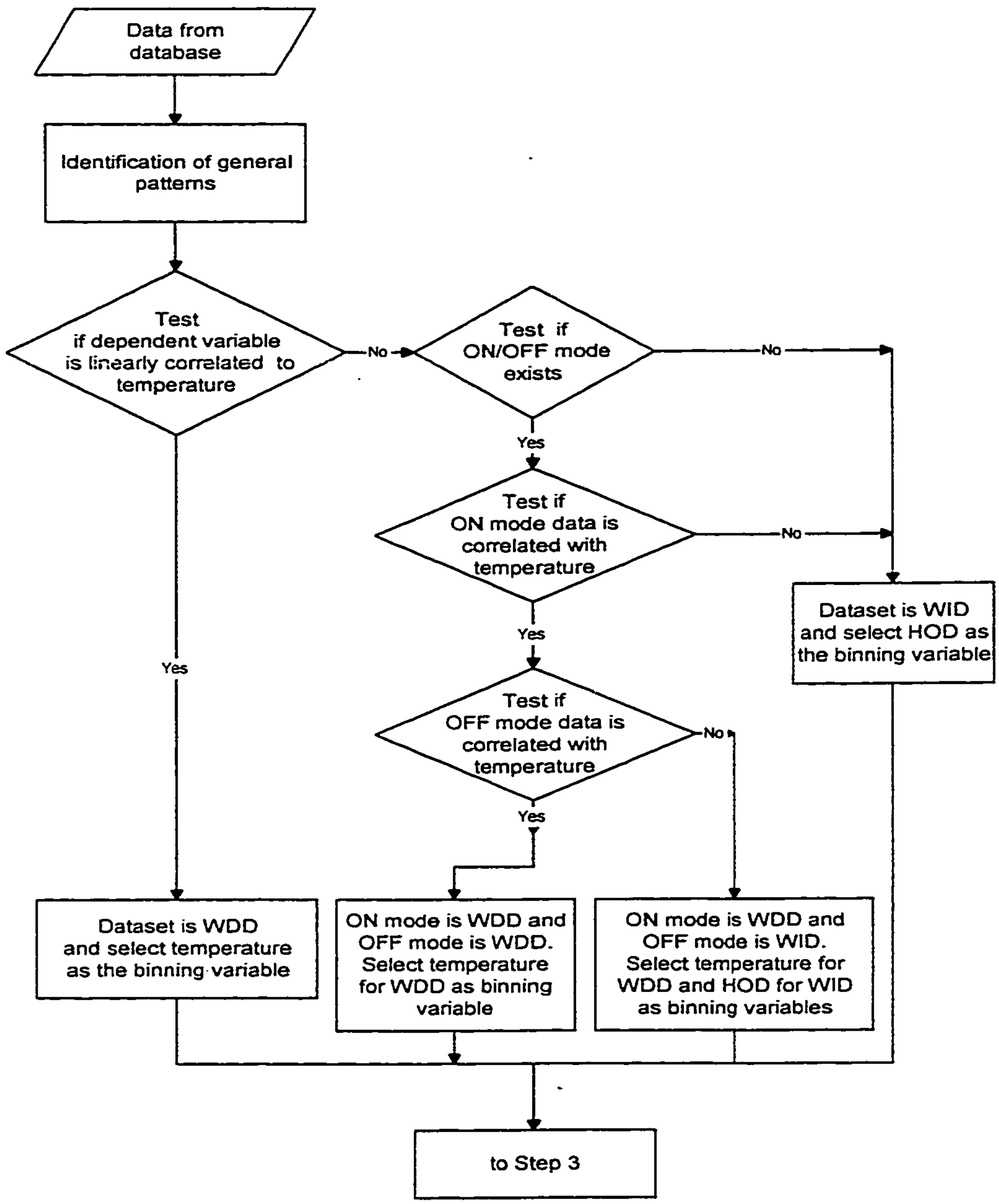


Figure 3.11: Flowchart illustrating Step 1 (identification of general patterns) and Step 2 (selection of the binning variable). After the selection of the binning variable the process is transferred to the outlier identification and data quality control procedure (Step 3).

variables are whole-building cooling energy (WBCOOL), whole-building heating energy (WBHEAT), and whole-building electric (WBELE), while the predictor variables are outdoor air temperature (Temp), outdoor air specific humidity (SpH), horizontal solar radiation and average wind speed. In this check, each criterion or dependent variable is tested against the identified predictor or independent variables (ambient temperature, specific humidity) and a time period variable (hour-of-the-day-HOD) to check the temperature (weather) dependency. The results are tabulated in a standard format as shown in Table 3.2. A description of the Pearson's linear correlation coefficient and properties are given in Appendix A. The number in each cell describes the linear correlation between the column variable and the row variable. A higher value indicates a higher linear correlation and hence the predictor variable with the highest correlation coefficient with the dependent variable will be chosen as the 'bin variable'.

Table 3.2 Pearson's linear correlation coefficients between the dependent variables and the independent variables

	WBELE	WBCOOL	WBHEAT
Temp	0.2310	0.8926 #1	-0.9284 #1
HOD	0.2901 #1	0.1019	-0.1052
Humid	-0.0672	0.7040 #2	-0.6198 #2

The correlation coefficients between the dependent variables WBELE, WBCOOL and WBHEAT and independent variables Temp, HOD, and Humid are shown in Table 3.2 above. The results show that WBCOOL and WBHEAT variables have the highest correlation (arithmetic sign is not relevant) with outdoor temperature (Temp). Therefore, this variable (Temp) is taken as the bin variable for these two energy types and hence these two energy types can also be described as temperature (weather) dependent energy types. The third energy type, WBELE has the highest correlation with HOD although this is much weaker than the previous correlation. Therefore, the WBELE data will be binned using the bin variable HOD. For further usage the temperature or weather dependent data will be identified as Weather Dependent Data (WDD), while the remaining dependent variables (or data) will be identified as Weather Independent Data (WID). It is interesting to note that each dependent variable also has significant secondary variables. For WBELE this variable is temperature and for WBCOOL and WBHEAT the variable is Humidity.

After grouping the dependent variables into WDD and WID groups, we can further ensure the remaining variables are properly grouped, by testing these variables for temperature or weather dependency through another refined check. This check will be possible only if schedule-dependent data are available, such as the Motor Control Center energy use (MCC) or Air Handler Unit energy use (AHU). This energy use often closely follows the schedule-based operation of the building: for example, a normal level of energy use when the building is occupied and a minimal level of energy consumption when the building is in the shutdown mode. Because of this feature the hourly MCC or AHU energy consumption can be used to identify the mode of operation as occupied or unoccupied. We will use the ON mode of operation to identify the occupied periods and the OFF mode of operation to identify the shutdown periods.

Figure 3.12 shows data from a building which can benefit from an hourly schedule-based ON/OFF mode daytyping, while Figure 3.7 shows the data of a building which can be best described by a simple linear two-parameter model with daytyping. Therefore, a test for the existence of schedule-based daytypes is included in the inverse bin method to identify the data that would benefit by the schedule-based daytyping.

Test for existence of schedule-based daytypes: In this test the dependent variable will be tested against the previously identified predictor variable to test the existence of ON/OFF modes of operation. This energy use can also be studied graphically using a UNIVARIATE statistical procedure (SAS, 1990) or by testing the confidence limit of derived or modified dependent variable of the data.

This test cannot be performed for the given data in dataset A because the given data did not include MCC or AHU energy use data. Therefore, we have used a sample dataset from a different building (Education Building, The University of Texas at Austin) to illustrate this procedure (Figure 3.13). The description of the dataset was provided in an earlier study (Thamilseran and Haberl, 1994) and in Appendix B. The main purpose of this test is to see whether the data in a bin contains a shutdown mode by testing the mean value of the bin against zero (0). This hypothesis can be tested statistically by calculating a normalized value for each bin (i.e., score) with a 95% confidence limit. If the calculated score shows a value not significantly higher than the value from the standard normal distribution tables, then the mean value of the bin is close to zero. If the mean value of the data is not significantly different from zero, the bin data can be assumed to have energy use data from a shutdown mode of operation. Hence, this dataset is a suitable candidate for schedule-based daytyping. For datasets with sample sizes greater than 100, 95% of the data points are expected to be within $\bar{y} \pm 1.96\sigma_{\bar{y}}$. Hence if the score, defined as (Ott, 1988):

$$\text{score} = \frac{\bar{y} - 0}{\sigma_{\bar{y}}}$$

has a value less than 1.96, it is plausible or likely that the sample contains values y » 0. For example, for Hour-of the-Day of 6 (i.e., 0600 hrs) the binned data is described by a mean value of $\bar{y}$ =7.701, standard deviation, $\sigma_{\bar{y}}$ = 7.755. This will result in a score (0.99) less than the critical score of 1.96. Therefore, the 06:00 hourly bin is likely to have data with y=0

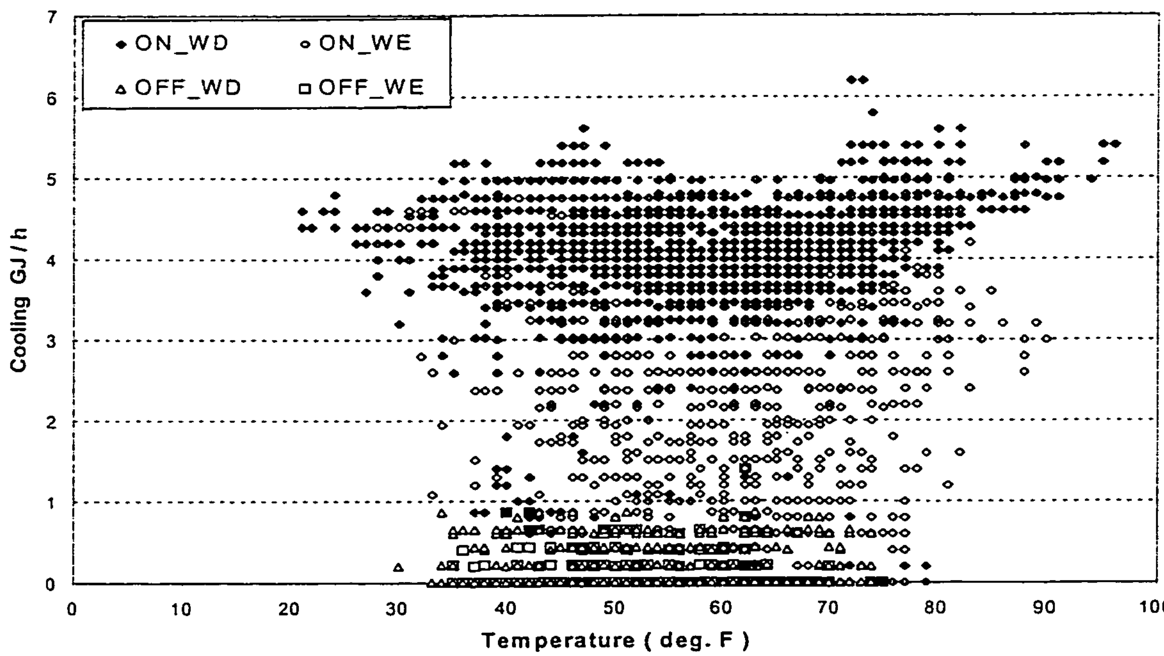


Figure 3.12: Cooling energy consumption against outdoor air dry bulb temperature for the Education building at the University of Texas at Austin. This data is an illustration where hourly schedule-based daytyping is required.

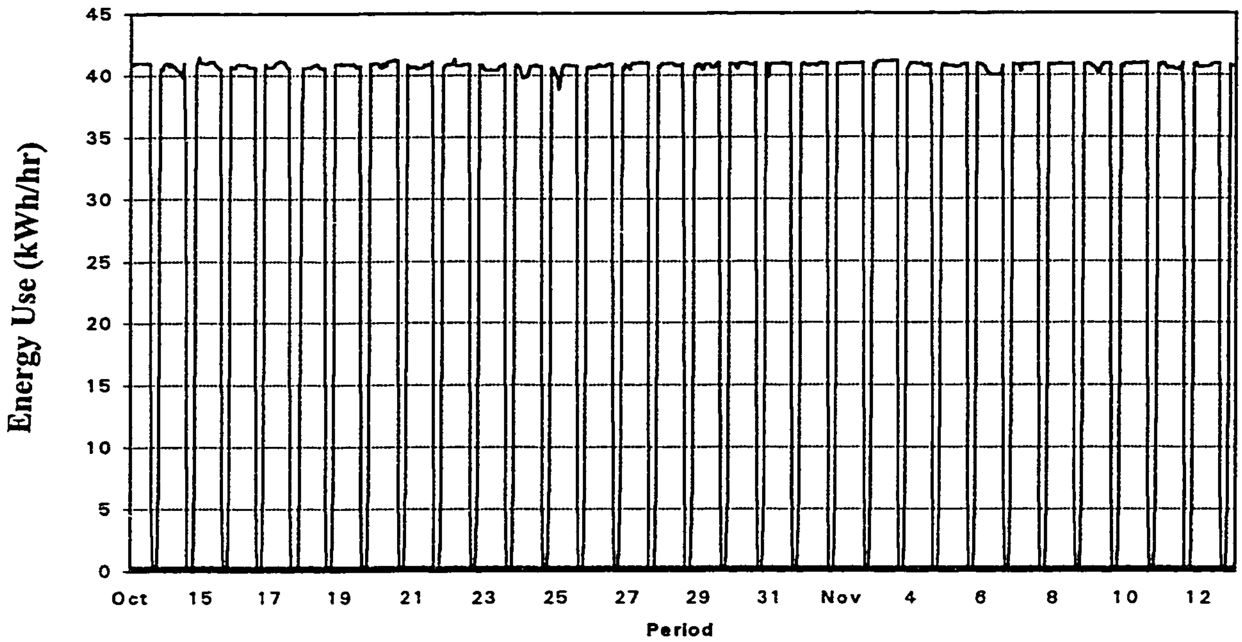
which corresponds to a shutdown mode. In other words, 95% of the MCC energy use data are expected to fall between 22.901 and -7.499, inclusive of 0 energy use (i.e., shut down mode of operation).

The energy consumption data monitored for the Education building (Site #100 - LoanSTAR program) exhibits the existence of early morning shut-off of air-handling equipment as shown in Figure 3.13. Hence the check for the existence of schedule-based operation was applied to this dataset, and the results are illustrated graphically in Figure 3.13(b) and tabulated in Table 3.3. The boxplot for the hours 2 through 5 was not visible because the inter-quartile range is so small that it appears as a line on the x- axis of the box-and-whisker plot. The calculated scores for hours 1 through 6 were significantly lower than the limiting score of 1.96. This means that the corresponding bin data contain energy use data from the shutdown operation period (i.e., during these hours the HVAC equipment was shut off resulting in OFF mode operation). Hence, the data are separated into two types of operations: the ON mode of operation when the HVAC equipment was operating and the OFF mode of operation when the HVAC equipment was not operating. When the equipment was not operating the consumption was measured to be approximately zero. Therefore, further testing of the data for temperature dependence is not necessary for the shutdown or OFF mode. Consequently the temperature dependency test can be repeated for this data by rechecking the correlation coefficients between the ON data and the relevant weather variable (i.e., temp). This refinement will avoid any data that might have been falsely identified as weather independent data (WID).

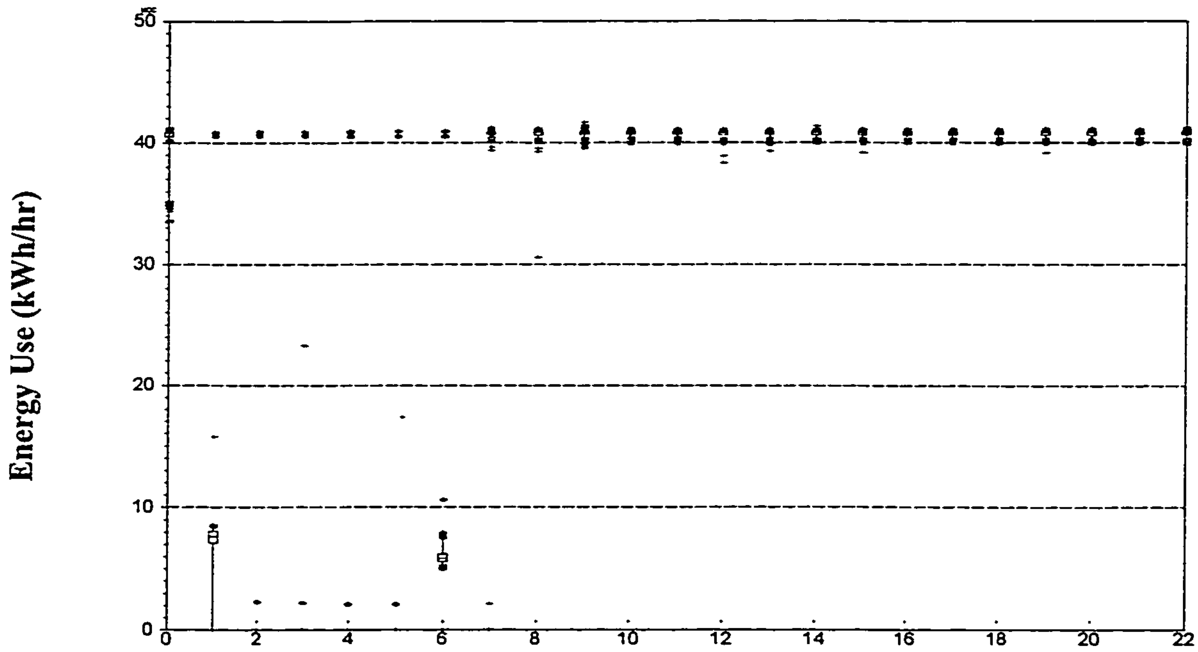
Once the identification of data types is complete the next step, assigning a bin variable, can be performed. Since weather dependent data usually have the highest correlation with temperature, temperature is assigned as the binning variable. Subsequently, weather independent data will have Hour-of-Day (HOD) as the binning variable.

Data Quality and Outlier Identification (Step 3)

The reliability of a model is no better than the data that were used for the model development process. Therefore, data quality control should be the next step prior to the model development. The monitored energy use data may be spurious (or abnormal) for any



(a) Time series plot of one-month MCC data to show the shut-down mode



(b) Box and whisker plot of the baseline period MCC data (10/13/90 - 03/31/91)

Figure 3.13: Illustration of the existence of schedule based operation for a sample dataset (Education Building for the period 10/13/90 - 03/31/91).

Table 3.3 : Parameters used for testing the existence of schedule-based operation

HOD	Mean	Standard Deviation	Calculated score	On/Off mode Exists
0	40.177	3.443	11.67	No
1	8.452	8.391	*1.01*	*Yes*
2	2.329	9.439	*0.25*	*Yes*
3	2.226	9.119	*0.24*	*Yes*
4	2.108	8.999	*0.23*	*Yes*
5	2.109	9.003	*0.23*	*Yes*
6	7.701	7.755	*0.99*	*Yes*
7	40.729	5.557	7.33	No
8	41.08	3.895	10.55	No
9	41.168	3.831	10.75	No
10	41.147	3.824	10.76	No
11	41.089	3.284	12.51	No
12	40.924	2.73	14.99	No
13	40.941	2.731	14.99	No
14	40.936	2.722	15.04	No
15	40.932	2.719	15.05	No
16	40.928	2.713	15.09	No
17	40.929	2.704	15.14	No
18	40.947	2.721	15.05	No
19	40.941	2.743	14.93	No
20	40.947	2.748	14.90	No
21	40.961	2.728	15.02	No
22	40.953	2.721	15.05	No
23	41.012	2.713	15.12	No

one of several reasons associated with the monitoring process: power loss to the data loggers, interfering noise signals from surrounding equipment, partial failure of the instrumentation, or physical degradation of the sensor (due to dirt, moisture, etc.).

In some cases, the abnormality in the monitored data may be due to unusual operation of the building. Therefore, care must be taken in identifying and rejecting outlier data so that valid outlier data that represent actual operation is not rejected. One way to account for this unusual operation is to take known changes in building operation into consideration during the data grouping (or daytyping) process. A subsequent outlier identification scheme within each daytype will be needed to detect spurious data. In this step, an outlier identification scheme for the weather dependent and weather independent data are presented and illustrated with examples using data set A. The entire procedure for the outlier identification scheme is shown in Figure 3.14.

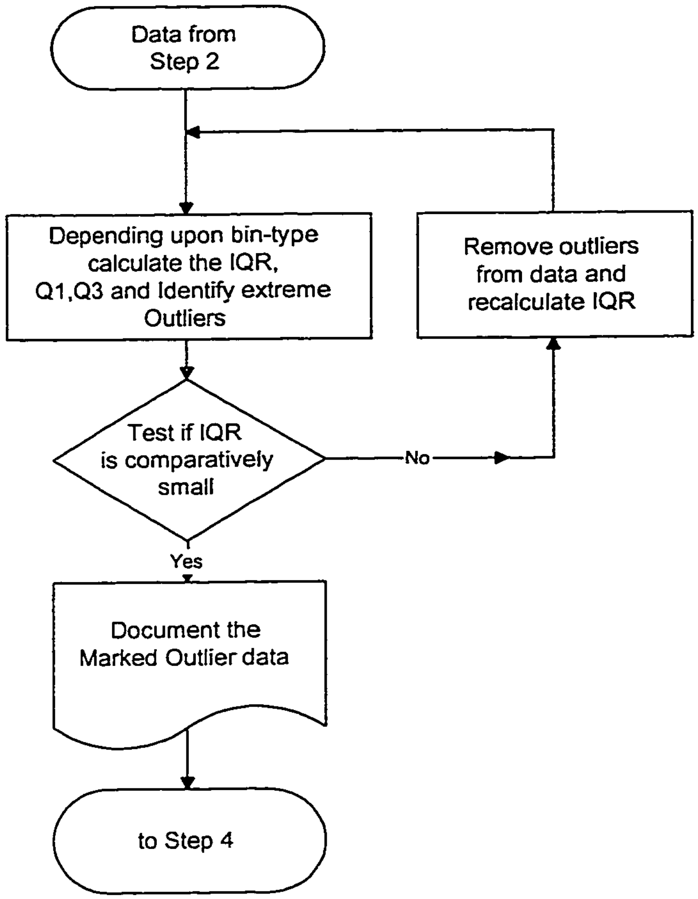
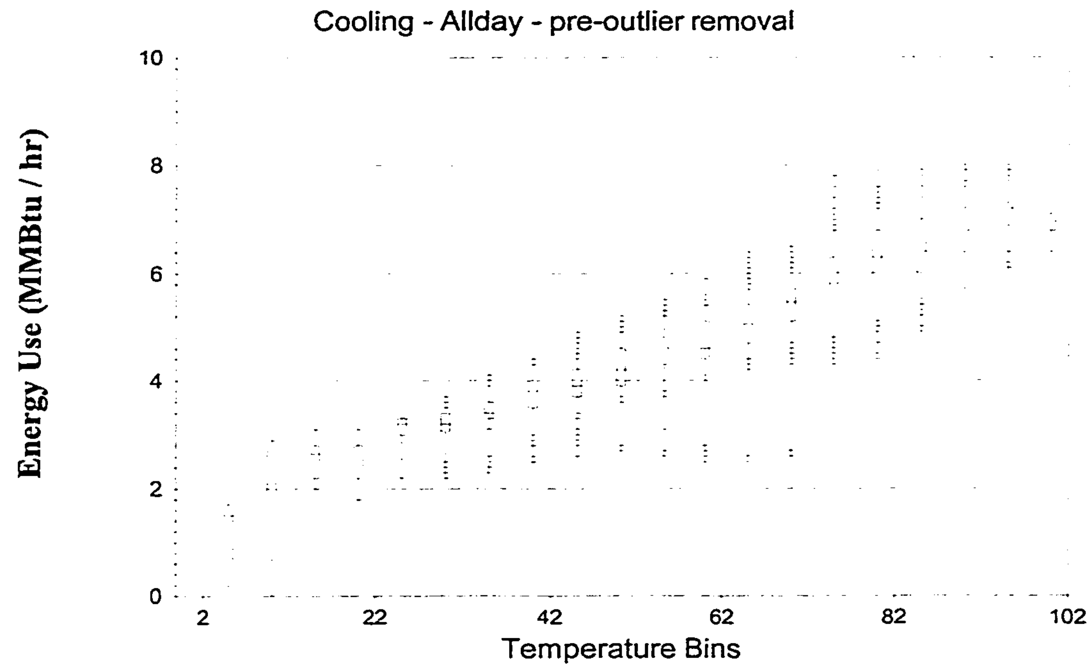


Figure 3.14: Flowchart illustrating the Step 3(outlier identification and data quality control).

In this step, the popular graphical outlier labeling rule (Iglewicz and Hoaglin, 1993) is used for the identification of the outliers which are identified using box plots. The primary calculations for a box plot are the median, the lower quartile (Q1), and the upper quartile (Q3). In a large sample one quarter of the data lie below Q1 and three quarters of the data lie below Q3 (hence one quarter lie above Q3). Also it should be noted that care must be taken when the sample size is small or moderate. Cutoff points, also known as fences, can be determined at the point k*(Q3-Q1) above the upper quartile or below the lower quartile. Tukey suggested a scheme to identify mild (k=1.5) and extreme (k=3.0) outliers (Iglewicz and Hoaglin, 1993; Tukey, 1977). When the calculated inter-quartile range (IQR) is comparatively small (when the IQR for the post-outlier removed data is more than 95% of the IQR of the pre-outlier removed data), no further outlier identification is needed and the resultant data will be passed on to the next step.

In general the box plot outlier identification scheme provides only an exploratory tool. Observations flagged as outlier require further study to determine their causes. Once all the outliers are flagged, the flagged data should be checked to see whether or not they are the result of an unusual operation. This process may require additional information about the building operation to justify whether the abnormal data resulted from operational changes, data processing, or is simply bad data. Once this process is complete the marked outliers that are not due to a known change in building operational practice will be removed from the original data set. This clean data set will then be transferred to the next step for further processing. A mild outlier scheme (i.e., k=1.5) will be assumed to be appropriate for the fully layered inverse bin method.

The data before and after the mild outliers were removed were then compared as shown in Figure 3.15 for the cooling and heating energy use. The mild outliers (outside the $1.5 \times$ IQR boundaries) were identified for the cooling and heating energy consumption in dataset A by considering all the data in one ALLDAY group. The identified outliers were then checked for any abnormal operation or equipment failure. For example, the outliers removed from the dataset A as shown in Figure 3.15 (i.e., the datapoints that are located below the dominant cluster scattered between 67°F and 72°F) were part of a known abnormal operation. A similar analysis of the WBELE data shows that the mild outliers that were identified in the weekday and weekend data effectively identified the holiday and breaks (Figure 3.16). Since these holidays and breaks actually represent a third daytype the marked outliers for the WBELE data were identified for further processing, since the data for these holiday and breaks can be another daytype by itself. The daytyping procedure that describes how these daytypes can be separated into different groups to signify the different modes of building operation is analyzed in the following section.



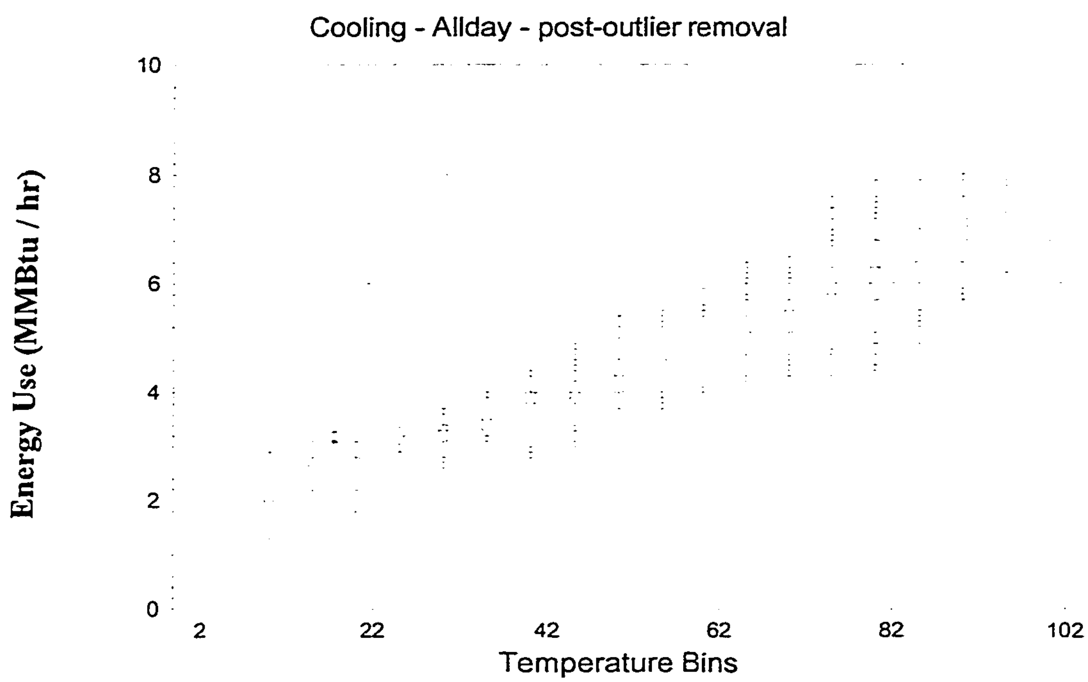
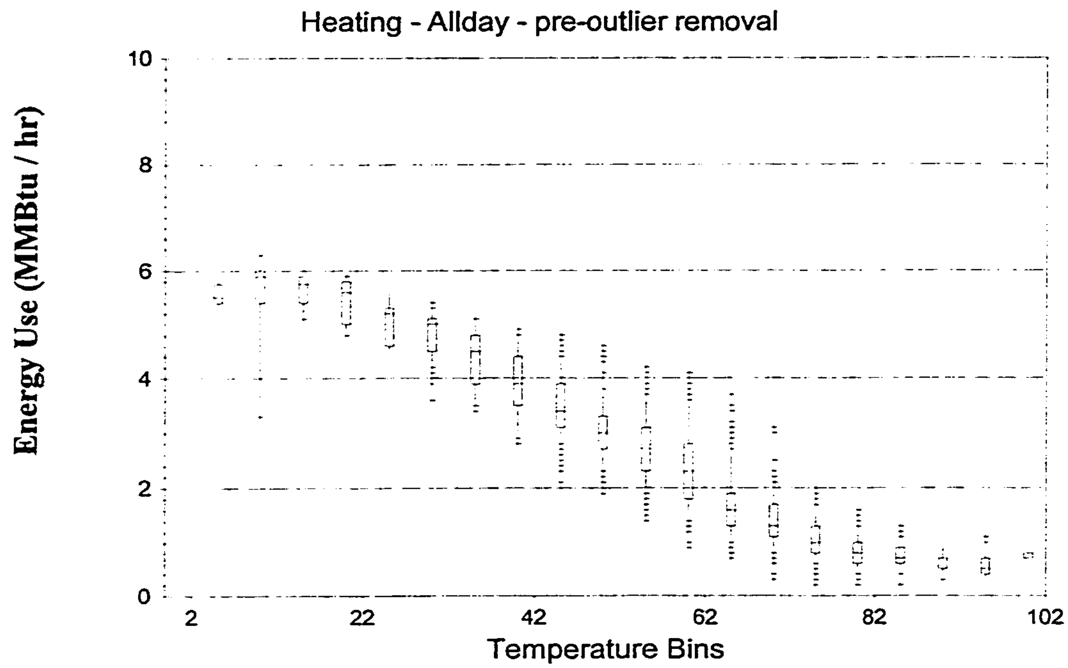


Figure 3.15: Comparison of the cooling and heating data before and after outlier removal using the mild outlier identification scheme (i.e., k=1.5). Dataset A (09/01/89 - 12/31/89) was used for this testing.



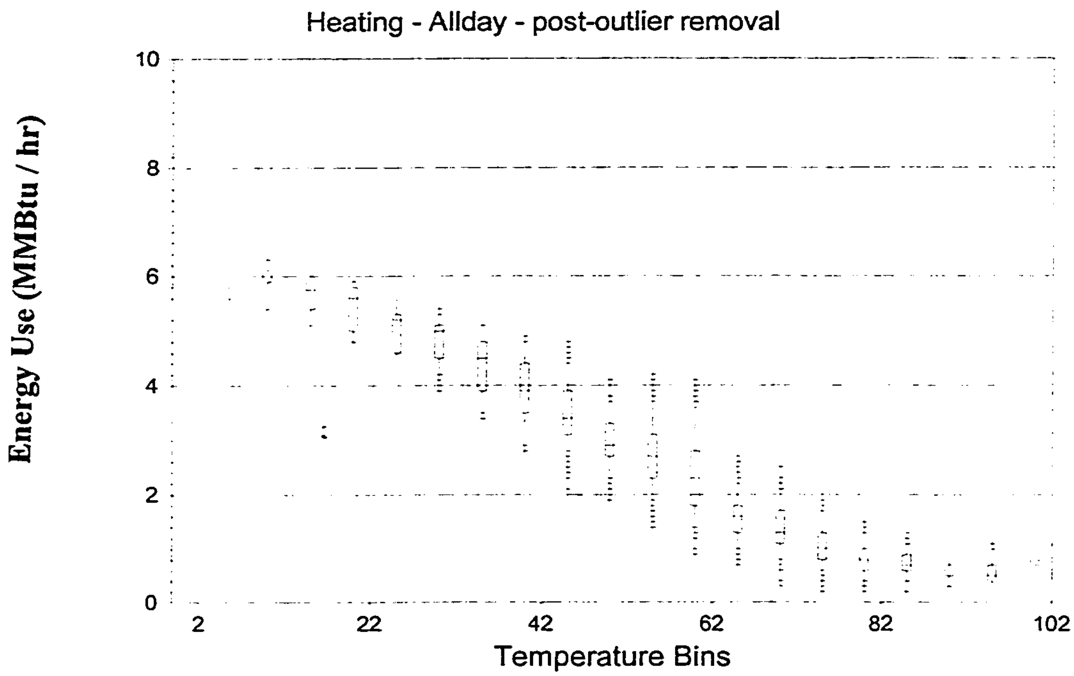


Figure 3.15: Continued ....

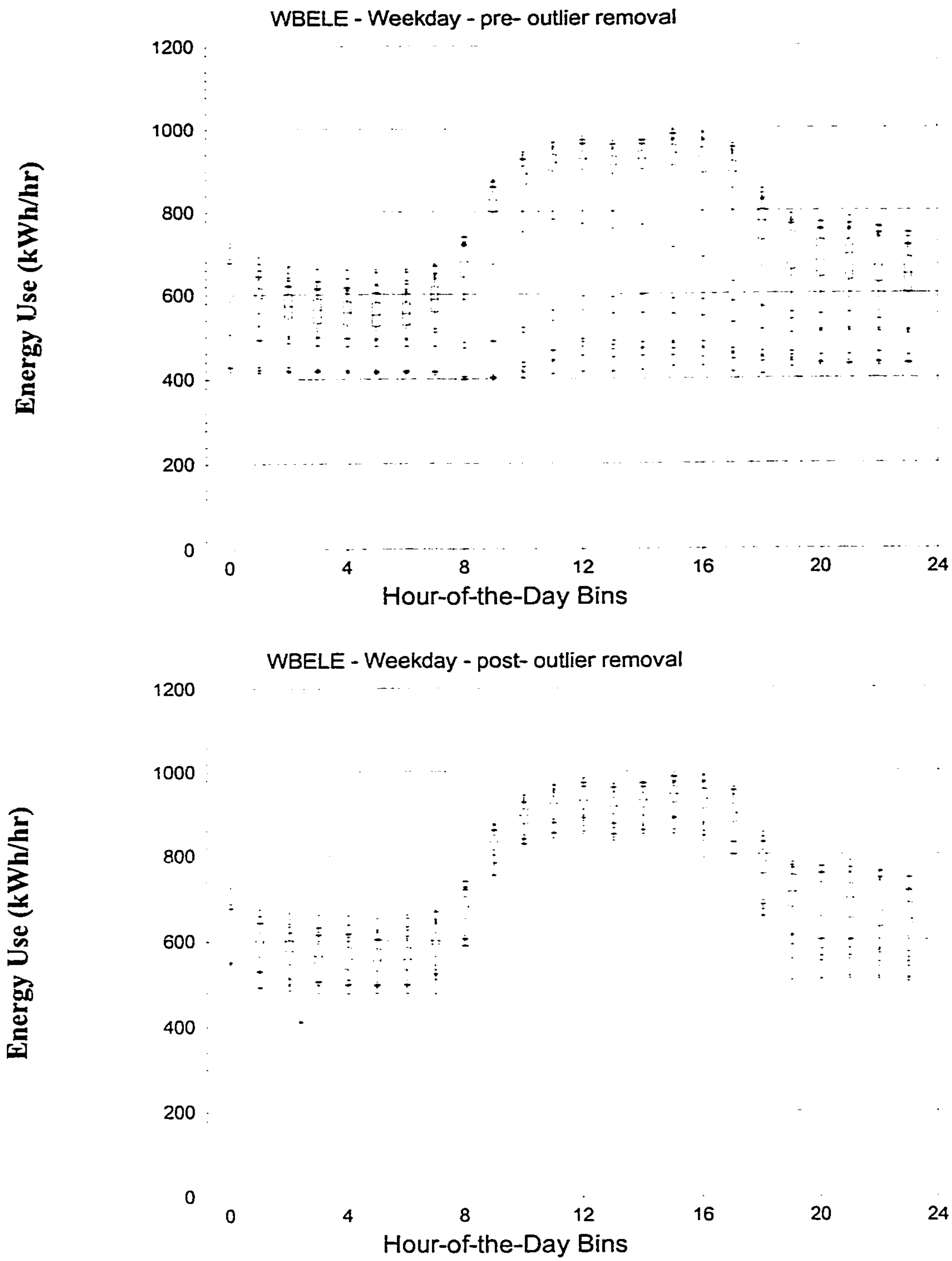
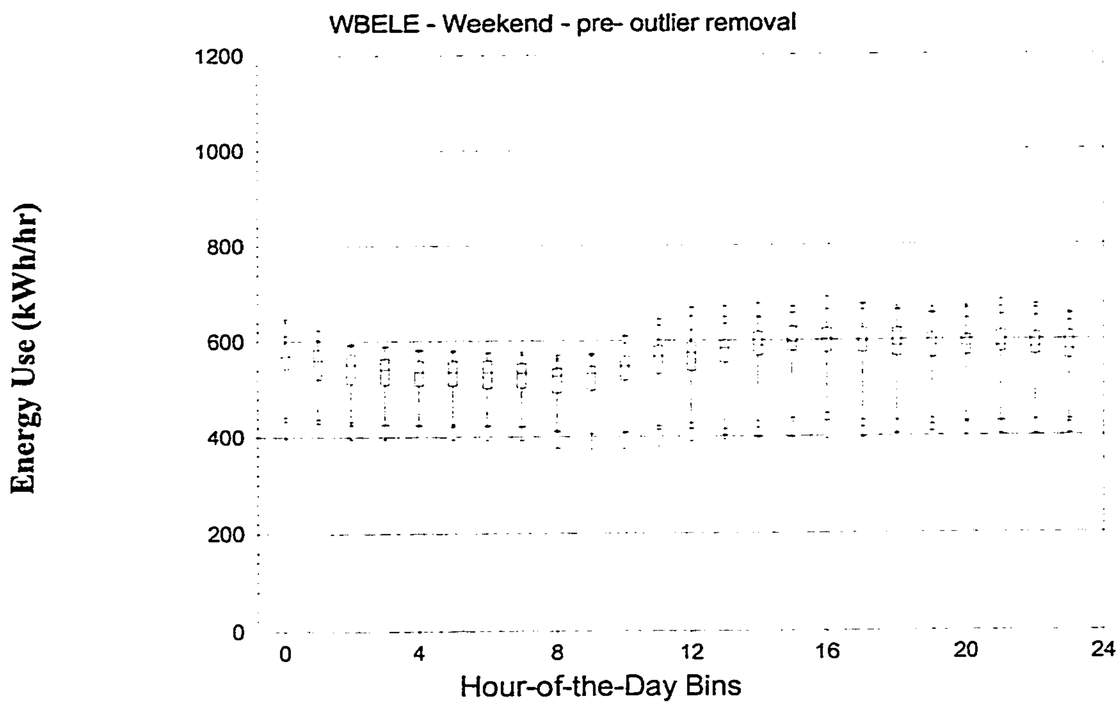


Figure 3.16: Comparison of the WBELE data before and after outlier removal by the mild outlier identification scheme. Dataset A (09/01/89 - 12/31/89) was used for this testing.



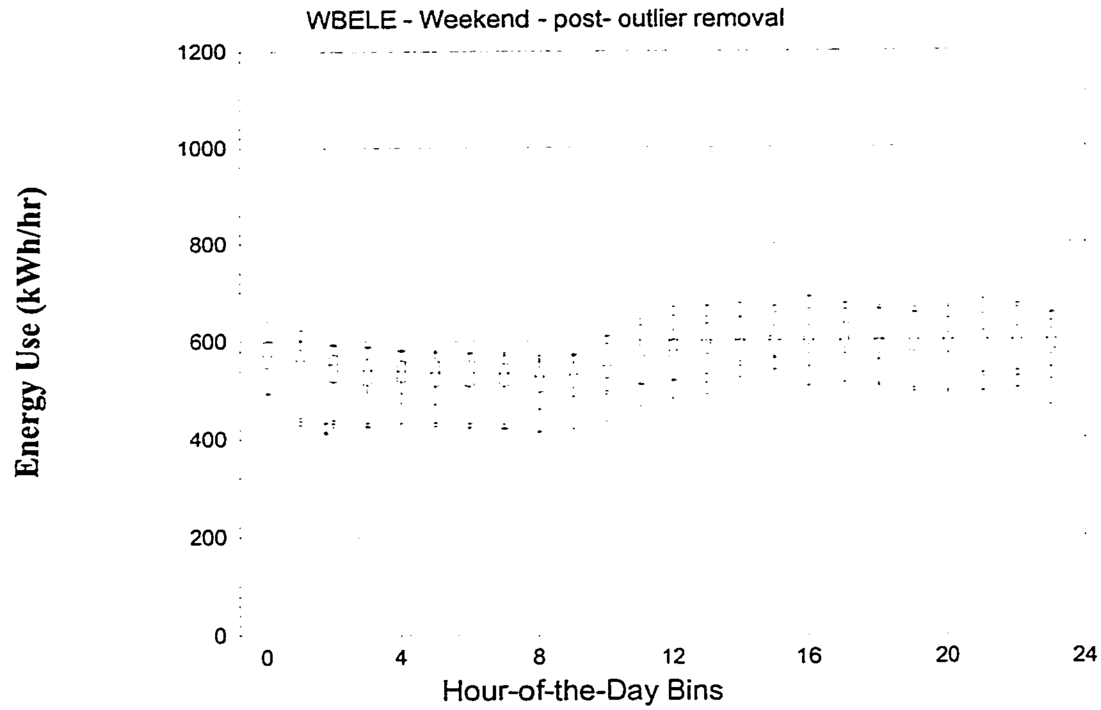


Figure 3.16: Continued .....

Identification of Comprehensive Daytypes (Step 4)

In general, weather independent energy use (such as lighting and equipment electrical energy use) in a building depends on the level of occupancy and the number of hours of use. These two parameters vary significantly between the regular days and holidays or weekends. Since the level of occupancy or usage of the building is not generally monitored or available, the weather independent energy use data may be chosen as an alternative to identify the different levels of building operation. In the analysis presented here the daytype information derived from the lighting and equipment electric consumption or whole-building electric consumption data is used to group the days with similar building occupancy levels as one daytype.

Although elaborate day-typing can be performed using the weather independent data, a simple separation of weekday and weekend groups is adequate for most cases. A third daytype, holidays, can be formed by separating any known holidays. The holiday daytype can also be identified by performing an outlier identification scheme on the separated data and separating the days with data significantly different from the respective group, (e.g., weekday or weekend). In certain buildings (e.g., university buildings) the Christmas vacation period can be grouped as the third group (holidays).

For the Engineering Center data, illustrated in Figure 3.5, separation of the data into three daytypes (weekday, weekend, and holiday) was adequate. Subsequently, Duncan's, Duncan-Waller's, or Scheffe's multiple comparison tests can then be performed to aggregate any daytypes which have means with statistically insignificant differences. The Duncan, Waller or Scheffe procedures (described in Appendix A with an explanation of a sample output) can be performed as options within the standard analysis procedures available in SAS software (see sample routines provided in Appendix C). The resultant daytypes (preliminary daytypes) can then be checked statistically for unimodal distributions by generating a statistical output from a SAS UNIVARIATE procedure. If the distribution is multi-modal and no explanation can be given for the multiple modes, then the daytypes should be further investigated for sub-groups or sub-daytypes. After each daytype is analyzed for sub-daytypes, the multiple comparison test (Duncan's or Waller or Scheffe) can be repeated until the final daytypes have statistically insignificant differences in mean values. The final daytypes are then plotted to check for unimodal distribution. A sample output (for the 57°F temperature bin) from the SAS UNIVARIATE procedure is shown in Figure 3.17. This Figure illustrates the frequency distribution, moments, quantiles, stem-leaf plot, and box-plot for the 57°F bin. The stem - leaf plot is used for verifying the unimodal distribution of the daytype, and only selected (number of data points and mean) data under the moments section are the necessary statistical parameters that are used for the outlier removal and bin-prediction procedures. The stem-leaf plot is a graphical illustration of the frequency distribution of the temperature bins, or grouped data. This plot mainly show the number and the repetition (i.e., frequency) of data points within the defined data group (i.e., temperature bin). The data in each bin is grouped under 'class' which is bounded by the two adjacent numbers printed on the left of the stem-leaf plot multiplied by the multiplier printed at the bottom of the stem-leaf plot. For example, the class bounded by the numbers 30, 32 and multiplier 10^{-1} means the class 3.0 - 3.1 contains one data point within the class. The box plot which marks the borders of 10, 25, 75, and 90 percentile points is also shown in this Figure. The daytyping procedure described above is illustrated in Figure 3.18 in a flowchart format.

Impact of Schedule-based Operation on the Dependent Variable (Step 5)

In some buildings, the air-conditioning equipment is shut-off during the unoccupied hours. This information was tested as part of an earlier procedure (Step 2: Check for Temperature Dependency), and can help to identify further sub-groups in the daytypes. The results from Step 2 are used in step 5 to separate ON mode data from OFF mode data for each of the identified daytypes (e.g., weekdays, weekends and holidays). As suggested in Step 2, MCC or AHU equipment use data are often an appropriate tool for this purpose. However, in some buildings the dependent variable itself can provide this information. The whole- building cooling (WBCOOL) energy consumption was plotted against the MCC energy use for the Education building (EDB) to illustrate the three different data clusters resulting from the schedule-based operation (Figures 3.19 and 3.20). Three different clusters were identified from the hourly data shown in Figure 3.19. These clusters are relevant to the three operational modes with data values below 20 kWh/hr ("OFF"), normal ON mode operation with consumption approximately 40 kWh/hr and an unusual mode with energy

```
Statistics by hr for each daytype 23:15 Sunday,January14,1996
------------------------------- TA1=57 -------------------------------------
                          Univariate Procedure
Variable=CWE
Moments                                            Quantiles(Def=5)
N             192      Sum Wgts        192       100% Max       5.9        99%        5.9
Mean     4.521875      Sum           868.2        75% Q3        4.8        95%        5.3
StdDev    .565816      Variance   0.320147        50% Med       4.6        90%        5.2
Skewness -0.91742      Kurtosis   2.374054        25% Q1        4.3        10%        3.9
USS       3987.04      CSS        61.14813         0% Min       2.6         5%        3.7
CV       12.51285      Std Mean   0.040834                                  1%        2.6

T:Mean=0   110.7374   Pr>|T|       0.0001      Range          3.3
Num ^= 0        192   Num > 0         192      Q3-Q1          0.5
M(Sign)          96   Pr>=|M|      0.0001      Mode           4.7
Sgn Rank       9264   Pr>=|S|      0.0001
W:Normal   0.929612   Pr<W         0.0001

   Stem Leaf                                            #       Boxplot
     58 000                                             3          0
     56
     54 000000                                          6          |
     52 00000000000                                    11          |
     50 00000000000000000                              17          |
     48 0000000000000000000000000                      25       +-----+
     46 00000000000000000000000000000000000000000      41       *-----*
     44 00000000000000000000000000000                  29       |  +  |
     42 0000000000000000000000                         22       +-----+
     40 0000000000000                                  13          |
     38 0000000000000                                  13          |
     36 00000                                           5          |
     34
     32
     30 0                                               1          0
     28
     26 000000                                          6          *
        ----+----+----+----+----+----+----+----+-
    Multiply Stem.Leaf by 10**-1
```

Figure 3.17 : Sample SAS UNIVARIATE procedure output for 57°F bin. The stem-leaf plot was inspected to check the existence of multi-modal distribution of each bin within each daytype.

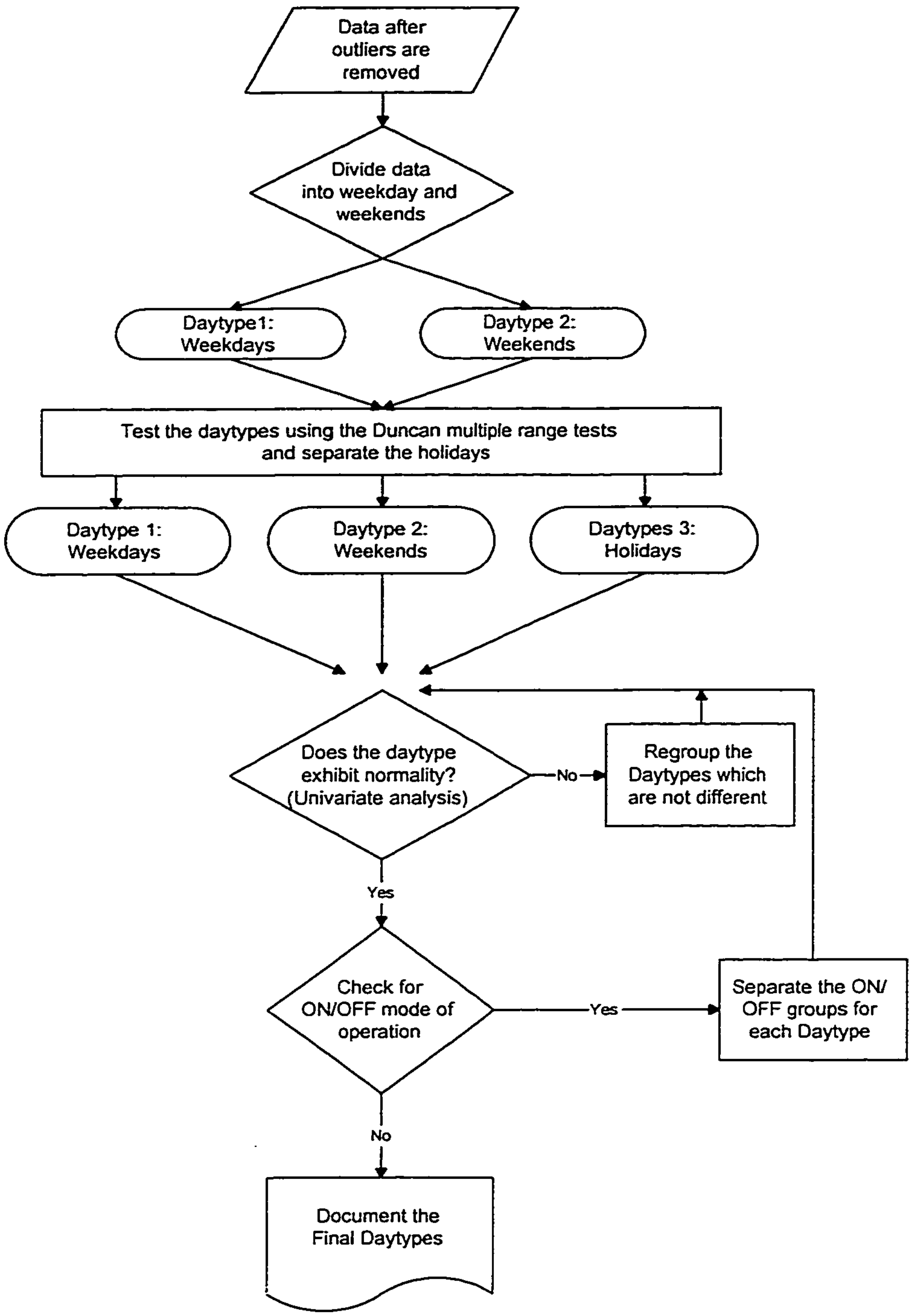


Figure 3.18 : Schematic illustration of the daytyping procedure. The cleaned data from Step 3 (outlier identification and cleaning) is daytyped and the resultant final daytypes are documented for binned energy calculations in the next step.

consumption approximately 79 kWh/hr. Figure 3.20 also shows the unusual operation (in which two pump motors were operating simultaneuosly) which resulted as the third cluster of data. The main and alternate pumps were accidentally left ON two days during the spring break period before the mistake was corrected. Therefore, this period was not counted as a new daytype. Since the WBCOOL energy data were comparable to the normal ON mode of operation this data period was grouped with the normal operation daytype.

Once the impact of the schedule-based operation on the daytypes is assessed, the final daytypes for weather-dependent and weather-independent data can be determined and the next step, binned energy calculation, can be performed.

Binned Energy Calculations (Step 6)

Once the final daytypes are identified, the outdoor temperature data are used to separate the dependent variable into bins. The weather dependent energy consumption is binned within standard 5°F (~3°C) temperature bins (i.e., the energy use that falls within 94.5°F and 99.49°F are grouped as one bin) and tabulated against the mid-point (i.e., 97 °F) of the bin. The weather-independent data was binned according to the Hour-of-the-day (i.e., bin variable) in which it was recorded. Therefore, the data are grouped for the hour

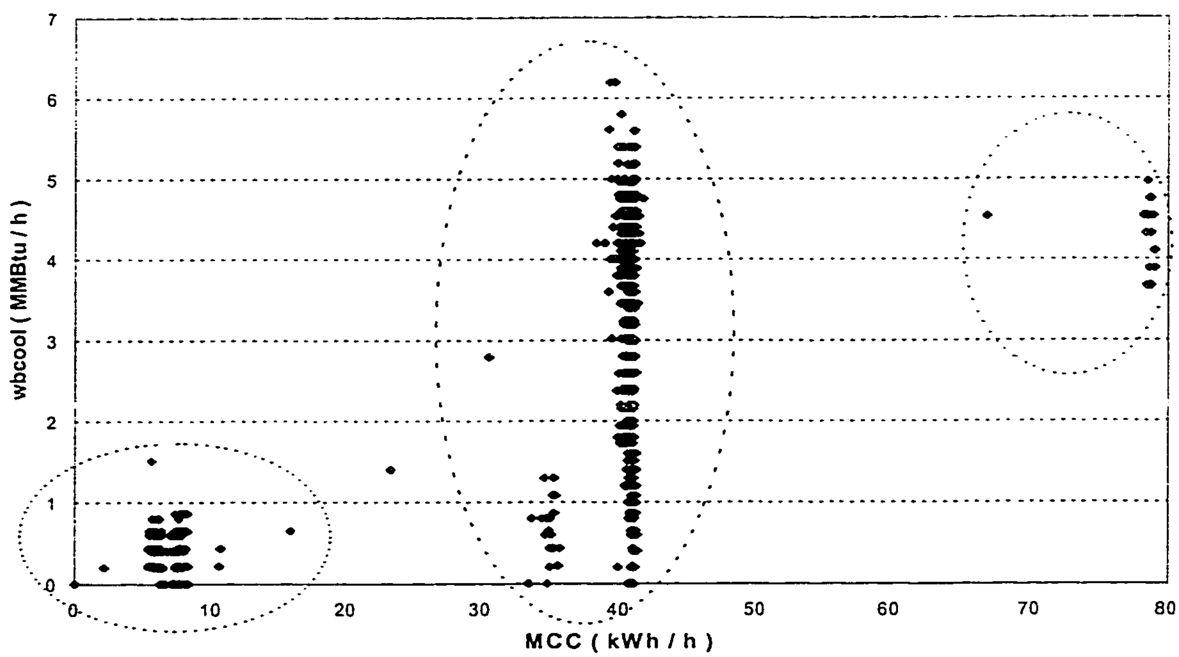


Figure 3.19 : Effect of the schedule-based (ON/OFF modes) operation on the hourly whole-building cooling (WBCOOL) energy use for the EDB building. The three clusters are for the partial shutdown, normal operation and unusual operation of the MCC between 10/13/90 and 4/29/91.

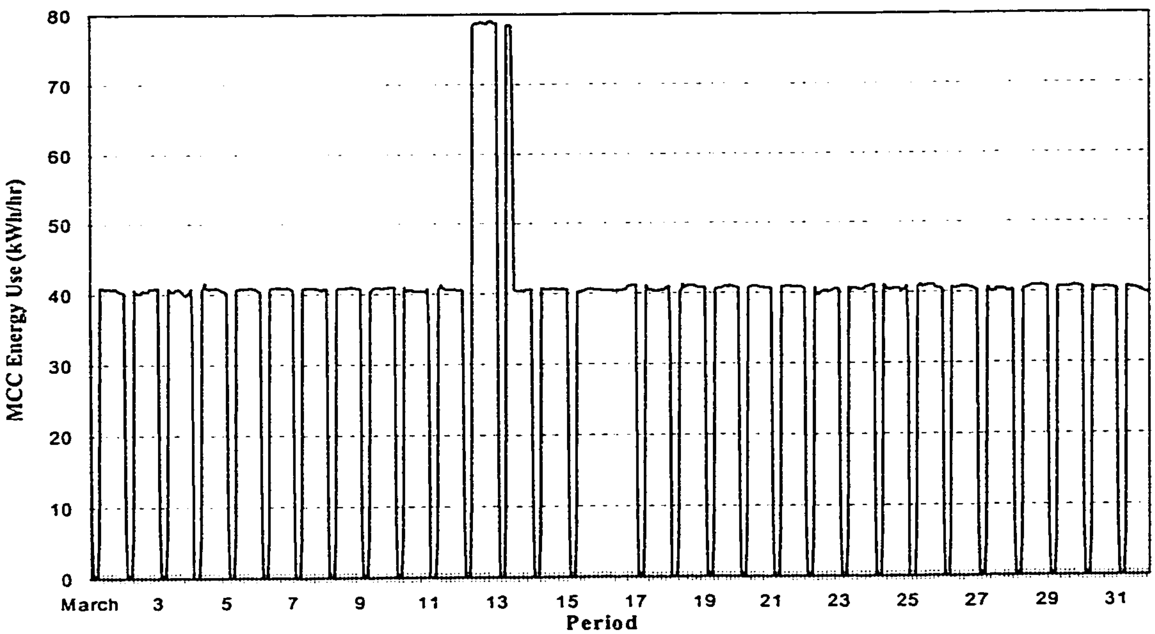


Figure 3.20 : Time series plot of the MCC energy use for the selected period between 3/01/91 and 3/31/91. During the early part of the spring break, equipment was accidentally left ON resulting in the peak MCC electricity use of 79 kWh/hr.

against which it is tabulated. Then a mean value of the dependent variable is calculated for each bin. This value will define the energy consumption for the specific bin of the particular daytype. A brief discussion which explains why a mean value is chosen (over other central tendency parameters) as the binned energy consumption is provided in Appendix D. The schematic diagram of the calculation methodology is shown in Figure 3.21 for a single daytype. Binned energy calculations for each of the different energy daytypes complete the baseline models for that specific energy type.

The resultant binned energy distributions of the weather dependent and weather independent data are illustrated in Figures 3.22 for WBCOOL and 3.23 for WBELE data respectively. The two binned energy values marked by arrows for the weather dependent energy type (i.e., WBCOOL) have abnormal values caused by the small number of data points within those bins. These binned energy values are checked and corrected in the following section entitled Correction of Missing Bins.

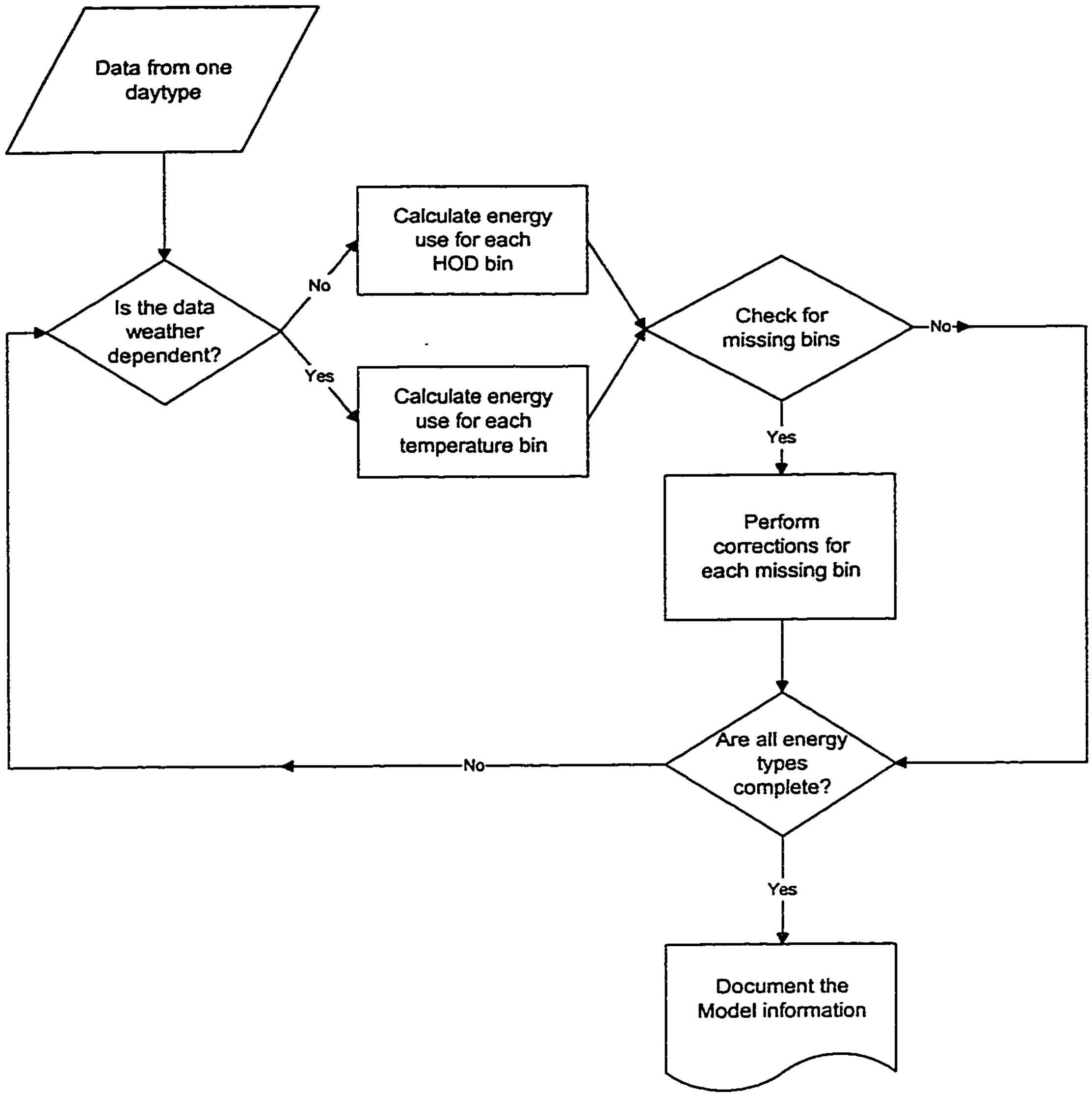


Figure 3.21: Calculation scheme for the binned energy calculation for a single daytype.

Correction for Missing Bins (Step 7)

The binned values calculated for the daytypes may still contain some abnormal values due to one or more reasons. One such reason, insufficient data within the bin, was clearly visible in the weather-dependent data (WBCOOL) shown in Figure 3.22 in the 5°F (-15°C) bin for Daytype 1 and the 100°F (38°C) bin for Daytype 2. When the number of data points in a bin is too small the existing data may misrepresent the energy use of the bin. Consequently, minimum number of data points are required for the calculation of a representative energy use for each bin. After inspecting several sites from the LoanSTAR program, the minimum criterion for labeling the bin as missing data bin was set as 1% of the data for each daytype. For the Engineering Center data from ASHRAE Predictor Shootout I (Kreider and Haberl, 1994), 1% of the smaller daytype (excluding holiday daytype which contains only breaks and holidays) represents a minimum number of 9 data points per bin. Therefore, the 5°F bin (i.e., -15°C) of the daytype 1 and 100°F (37.7°C) bin of the daytype 2 do not have enough data points. Consequently, these two bins are considered as missing bins and a procedure is then used to fill-in the missing bin. It should also be noted that the holiday daytype (i.e., daytype 3) have data that spans only 11°F to 75°F.

The missing bins were generally of two types; (1) the missing bin is at either end of the data range, or (2) the bins are near the end points of the data range. For the data presented in Figure 3.22, the missing bins are at the ends of the data range of each daytype. This is the most common type of occurrence of missing bins resulting from short-term monitored data. These missing bins may occur when the baseline or pre-retrofit data is less

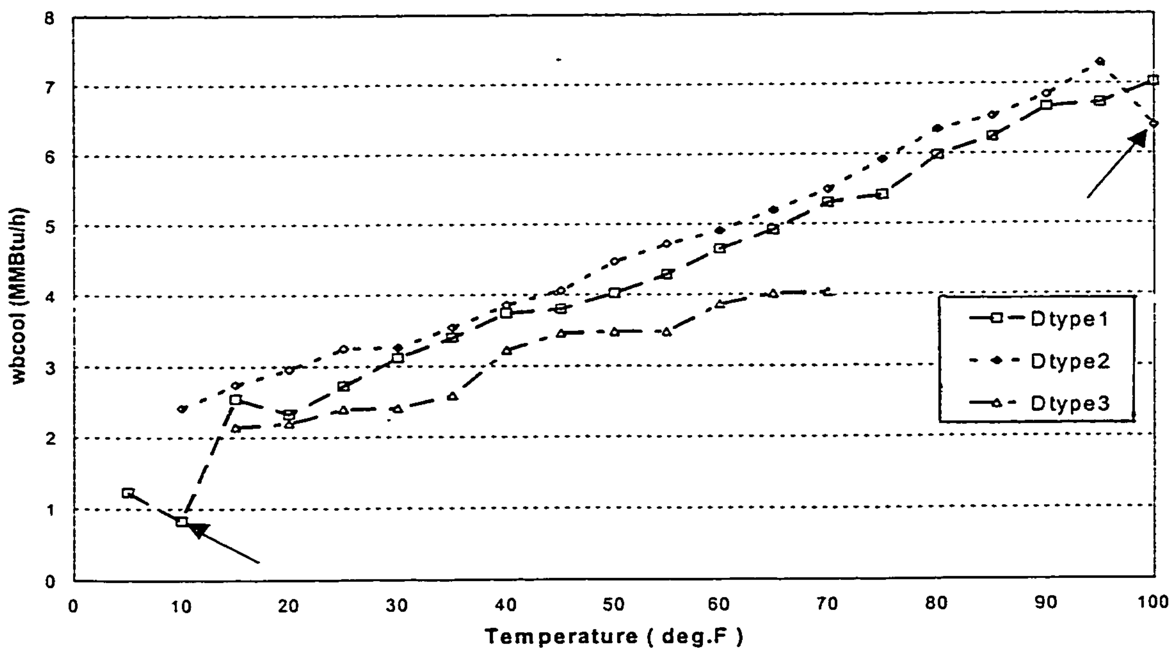


Figure 3.22: Binned values of the whole-building cooling energy consumption (WBCOOL) for the three identified daytypes.

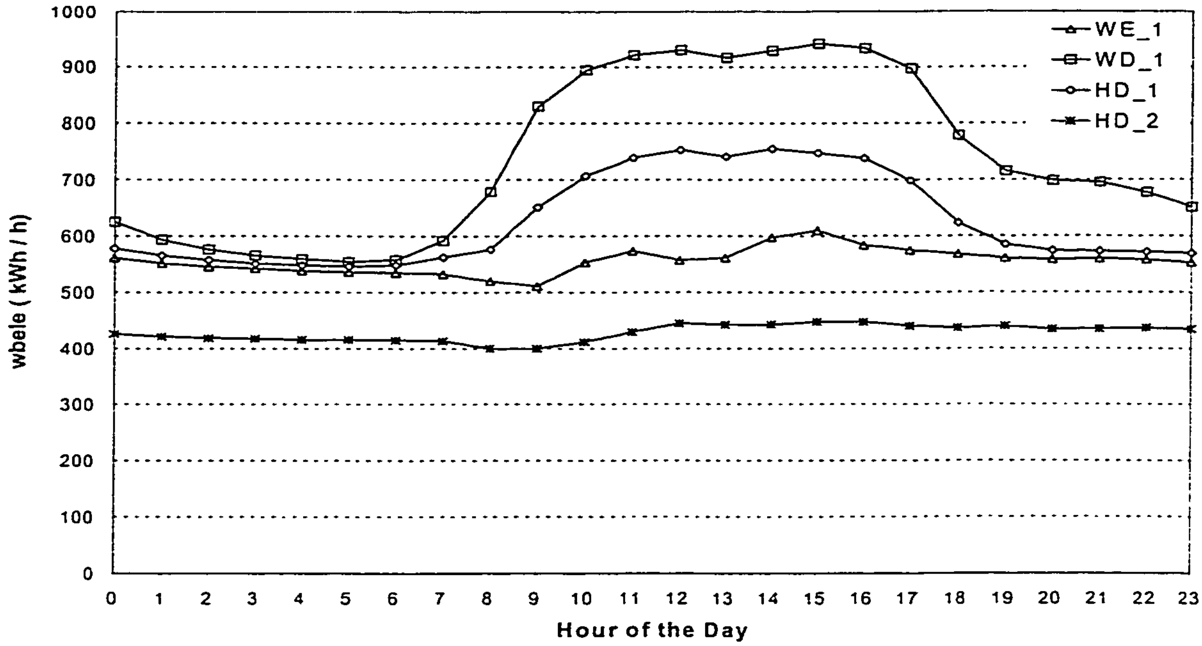


Figure 3.23: Binned values of the whole-building electric energy use (WBELE) for all the identified daytypes.

than one year or does not contain one of the seasons (heating or cooling) or when the monitored weather data is not representative data for the weather year. In some cases a metering failure or sensor drift can result in missing data. This may result in missing bins of both types as stated above.

In the inverse bin method, a simple linear interpolation algorithm is used when the missing bins are inside the end points of the data range. This procedure will calculate the missing bin energy use as the mid point of the two adjacent bin values. A linear extrapolation scheme with limiting values is used when the missing bin is at either end of the data range. In this scheme, the missing bin values are calculated using a linear extrapolation that uses the average difference between the last four bins. This value is then checked against the limiting value (i.e., the applicable maximum or minimum recorded value of the energy type within the data or other known limits such as the manufacturer's maximum hourly level consumption rate) to minimize any possible abnormalities. The second method was applied to the Engineering Center data shown in Figure 3.22 and the corrected energy data is shown in Figure 3.24 for cooling energy use and Figure 3.25 for the heating energy use data. The applicable minimum limiting value is 0 GJ/h (0 MMBtu/h) energy use for the missing bins at the low temperature region. The maximum energy use of 8.44 GJ/hr (8.0 MMBtu/h) is used as the limiting value of the extrapolation for the bin from daytype 1 at the high end of the temperature region.

Improved Bin Prediction with Additional Variables (Step 8)

The first seven steps described above can be considered to constitute a complete method. However, further improvements are possible for weather dependent predictions that utilize adjustments for latent load and thermal lag effects. In general, hourly whole-building cooling energy data for a large building in a hot and humid climate usually contains latent and thermal mass effects. In the event that these effects are significant the cooling energy use model benefits from the inclusion of these two variables. Therefore, in the fully layered inverse bin method or improved inverse bin method, a methodology has been devised to test the significance of the inclusion of these variables in a model.

This testing consists of two sequential procedures to determine the influence of the latent load and thermal lag effect on cooling energy use. Depending on the outcome of the tests, either or both of these variables can improve the inverse bin model. The first step is to test the significance of the latent load by checking the linear correlation coefficient between the cooling energy use and the specific humidity. If the correlation coefficient is found to be high as shown in Table 3.2 and as explained for the identification of the primary independent variable in Step 2, the addition of specific humidity as a second variable may improve the developed model. However, the existence of multi-collinearity often negate or reduce the improvement achieved by the second variable. Consequently, diurnal variation of specific humidity and temperature plots can provide some insights into the effect of multi-collinearity on the improved model. The humidity sub-binning scheme is given in Step 10. An alternative method is to calculate the standard deviation or variance of the cooling energy use for individual temperature bins. A latent effect can also be observed as additional scatter in the higher temperature region of the cooling energy data when plotted against ambient temperature. A high secondary correlation coefficient (i.e., numerical value higher than 0.5) or more than twice the level of scatter in high temperature bins than the bins below 52°F suggests better model predictions with the humidity sub-binning.

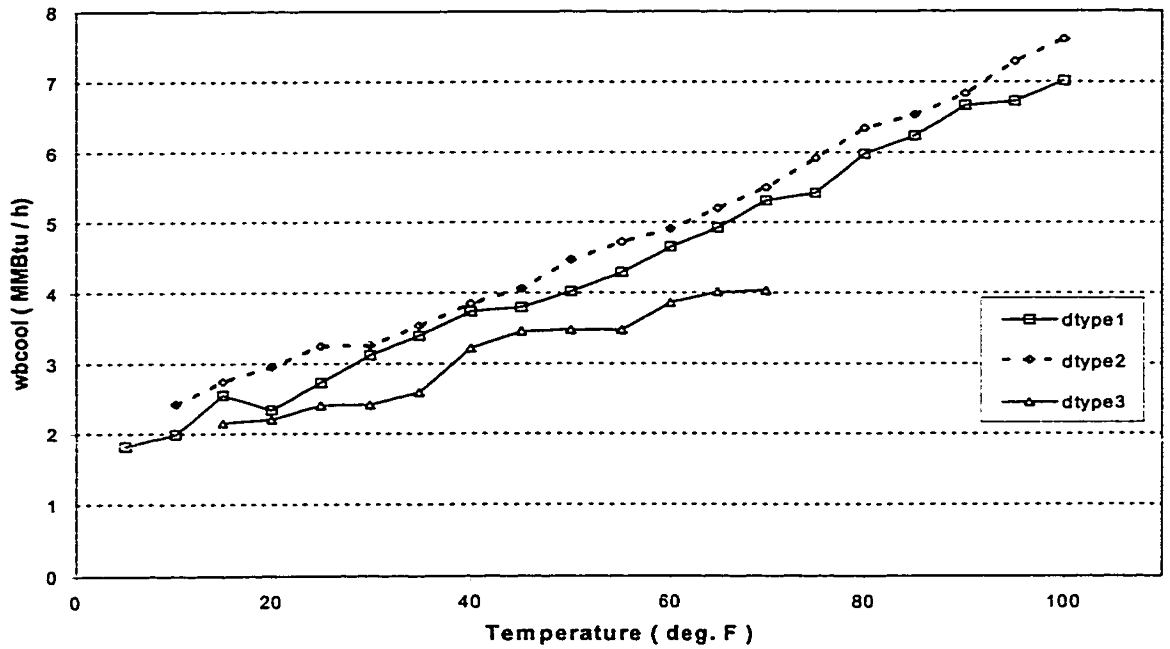


Figure 3.24 : Corrected, binned energy consumption for missing bins for the WBCOOL binned data (dataset A) shown in Figure 3.21.

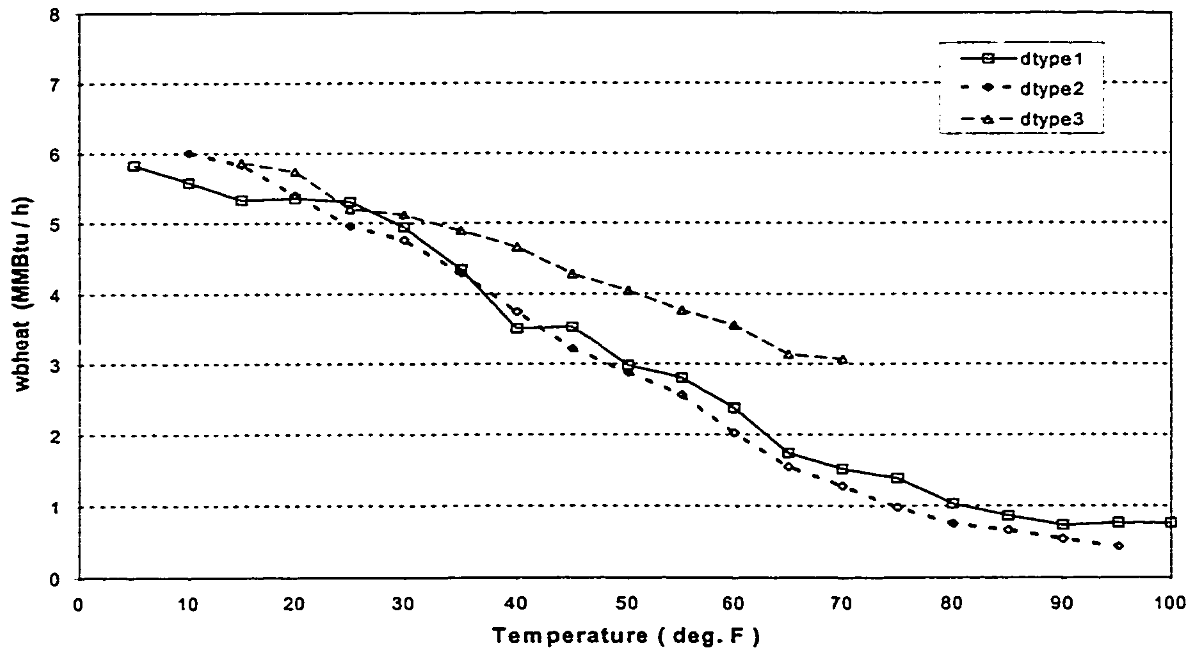


Figure 3.25: Corrected, binned energy consumption for the WBHEAT data from dataset A. Dataset A (i.e., Engineering Center) is from the period 09/01/89 - 12/31/89.

The second step is to introduce a time lag in the independent temperature variable (i.e., temperature) and check the coefficient of variation (CV-RMSE) between the lagged bin model and measured data until the best lag time is determined. The time lag can be introduced by shifting the temperature data back one hour, recalculating the bin model with 1 hour lagged temperature and calculating the CV (RMSE) to determine if the model has improved. The hourly lag or stagger introduced in this manner is called time lagging (i.e., temperature data that is matched with cooling energy use that occurred four hours later is called a 4 hour temperature lag and is noted by the variable name "lag4temp"). In general, a lower CV-RMSE value for any lag temperature variable will indicate the existence of thermal lag. On the other hand, if the lowest CV-RMSE is observed for the coincident temperature data (i.e., zero time lag), the effect of the time lag in the cooling energy consumption is minimal.

Once the above two variables have been investigated the following sequence can be summarized into five cases: a) cooling energy use that is influenced by latent effects and thermal lag effects, b) cooling energy use that is influenced by latent load effect and is not influenced by thermal lag effects, c) cooling energy use that is influenced by thermal lag effects and is not influenced by latent load effect, d) cooling energy use that is neither influenced by thermal lag effects nor by latent load effect, and e) cooling energy use that is not influenced by temperature and thermal lag effects but is influenced by latent load effect. Therefore, for the cooling energy data that falls under case (a), both Steps 9 and 10 will be skipped because this case is the same as the simple inverse bin method that consists of the first six steps. Since case (e) is probably only applicable to buildings with an interior water source (e.g., a swimming pool) this case is not considered for this study.

For the cooling energy data that falls under cases (c) and (d), an appropriate lag (determined by the variable with the lowest CV-RMSE) will be introduced to the temperature variable, and this lag variable will be used as the bin variable instead of the unlagged temperature which was previously used. In this case the procedure follows steps 9 and 11 only. Likewise for cases (b) and (d), a sub-binning of the cooling energy data should be performed based on the specific humidity and temperature and therefore follows Steps 10 and 11 only. If both the humidity and latent load effects are present (for case d), the procedure involves the determination of an appropriate lag temperature as the first step (followed by the sub-binning based on the non-lagged specific humidity coincident with energy use data) before the binned energy calculation. Therefore, the sequence for case (d) will be steps 9, 10 and 11 in that order. Results from different cases are illustrated in a flowchart format in Figure 3.26.

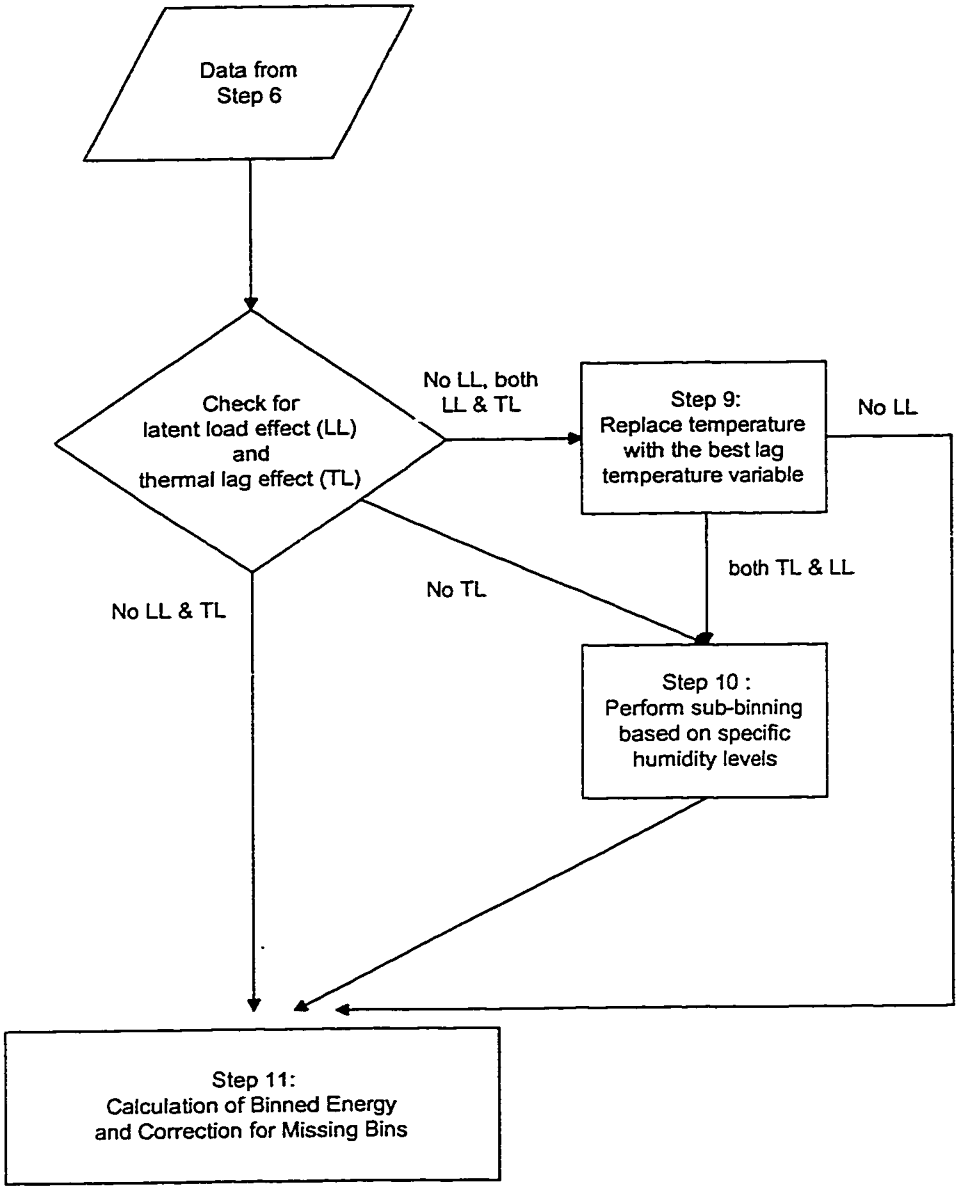


Figure 3.26 : Illustration of the sequencing of the Steps 8, 9, 10 and 11. The two checks in Step 8 determine the next step in the sequence. The four possible cases a:(No LL & TL), b:(No TL), c:(No LL), and d:(both TL & LL) follows the sequence indicated by the arrow.

Lagged Temperature for Prediction Improvement (Step 9)

If the cooling energy data has a thermal lag effect, a lagged temperature variable will be introduced to replace the coincident temperature as the bin variable. The lag is introduced by shifting the temperature data back one or more hours against the cooling energy data. If no lag is introduced the data will represent a zero hour lag and therefore will have the dependent variable (i.e., WBCOOL) matched with coincident temperature. If a one hour lag is introduced the temperature variable, the cooling energy use will be matched against a temperature data recorded one hour earlier and noted as one hour lag (lag1temp). Consequently, a new data set will be generated with the cooling energy use matched against temperature data with 0 to 32, and 168 hours of time lag to the temperature variable. The use of 0-32 hours of lag was for finding the best possible lag variable, while the 168 hour lag was used for testing the suitability of the data from similar day in the previous week. Then a CV-RMSE value based on a linear model between the cooling energy use and the independent (appropriate lag temperature) variable for each dataset will be calculated and tabulated. The calculated CV-RMSE values in Figure 3.27 are plotted against the lagged temperature data for two case study buildings. The figure shows the variation of CV- RMSE

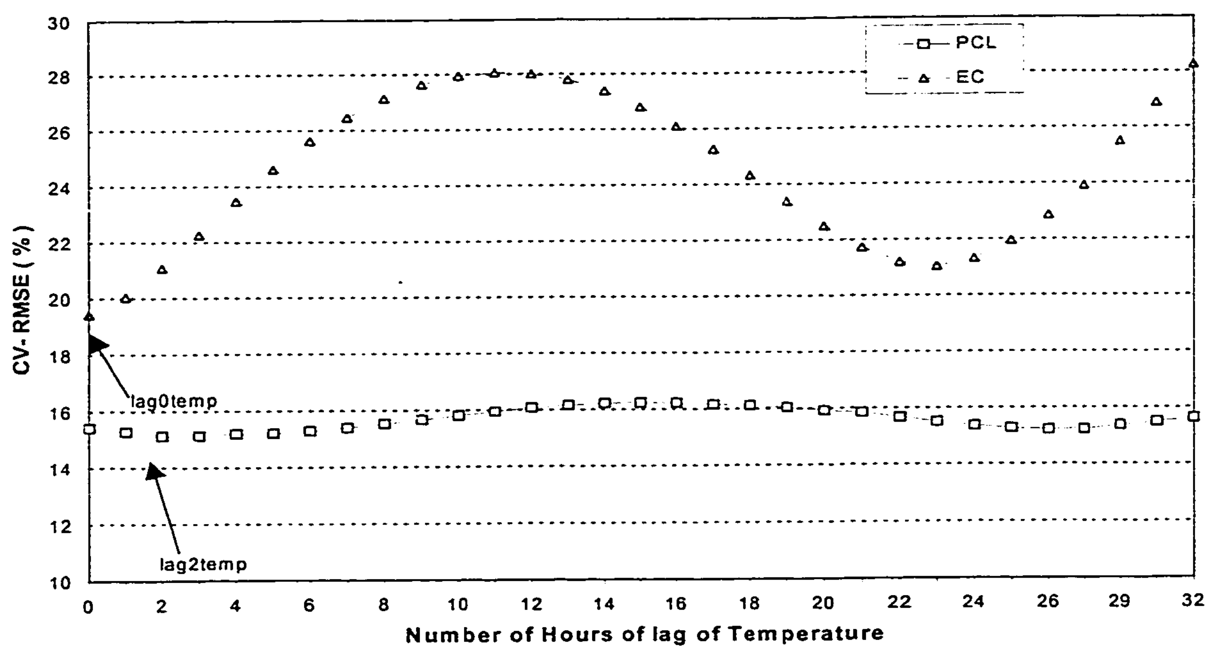


Figure 3.27: Selection of the best lagged variable for bin prediction from various levels of lag temperature data.

for a building with minimal or no thermal lag effect (EC building with lag0temp as the variable with the lowest CV-RMSE) and a building with 2 hour thermal lag (PCL building with lag2temp as the variable with the lowest CV-RMSE).

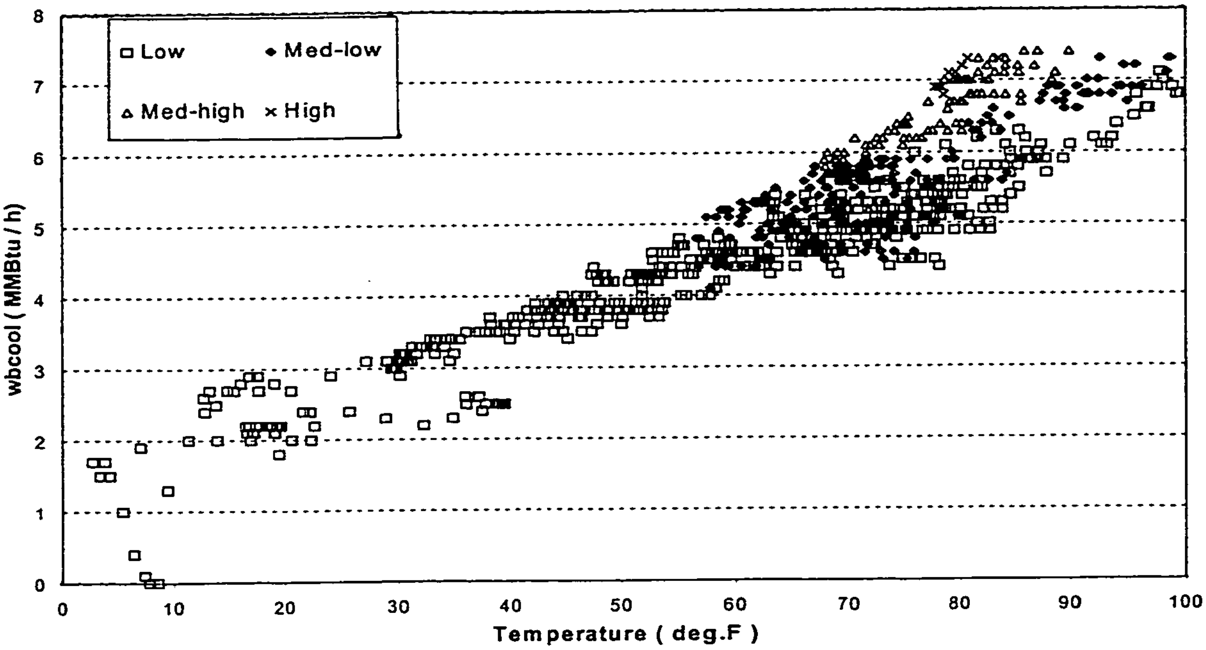
In general, a lower CV-RMSE value for any lag temperature variable, other than lag=0, will indicate the existence of thermal lag. If the zero lag variable is not the variable with the lowest CV-RMSE, then select the variable with the lowest CV-RMSE as the bin (independent) variable and proceed to the next sequential suggested in Step 8. The next step (step 10) is to check and reduce the dispersion possibly caused by the humidity.

Humidity Sub-binning (Step 10)

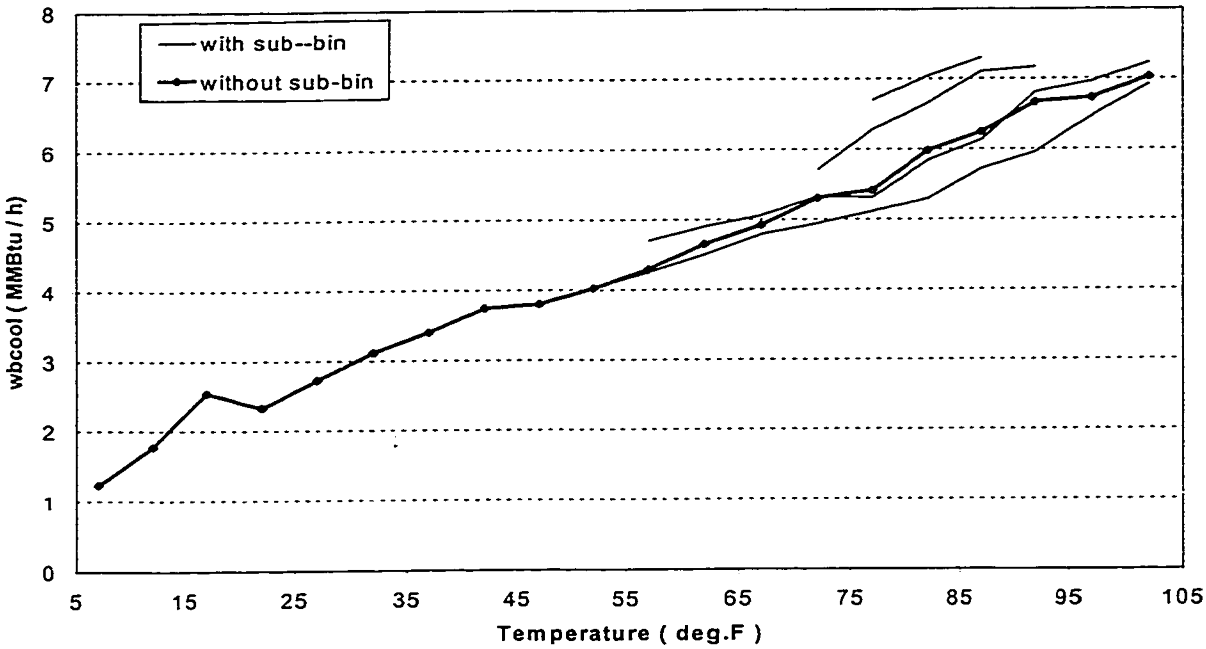
In this step the data from Step 8 (case b) or Step 9 (case d) are separated into humidity groups before being separated into temperature bins. The humidity groups are defined according to the level of moisture content in pound of moisture per pound of dry air (lbm/lbda) in the outside ventilation air to separate the effect of the latent load that create the dispersion of the cooling energy use. These four groups are high humidity (specific humidity is above 0.02 lbm/lbda), medium-high humidity (specific humidity between 0.015 - 0.02 lbm/lbda), medium-low humidity (specific humidity between 0.01- 0.015 lbm/lbda) and low humidity (specific humidity 0.01 lbm/lbda and below) groups. If a lag temperature has also been identified, then the appropriate lag temperature variable will be used for binning the data of each sub-humidity group.

Improved Binned Energy Predictions (Step 11)

Once the sequence of the appropriate combination of lag temperature variable selection and/or humidity sub-binning is completed, the mean value of the binned energy data can be calculated for each bin or sub-bin within each daytype. This is a repetition of steps 6 and 7 for the data with revised bins. Dataset A (Engineering Center building), which does not have a significant thermal lag effect (i.e., the zero-hour lag variable has the minimum CV-RMSE as shown in Figure 3.27) shows the existence of a latent load effect (Table 3.2). Detailed application and sample results for another dataset (Dataset C also for the same building) are provided in the next chapter entitled Application of the Methodology.



(a) Scatter plot of the cooling energy within humidity sub-bins



(b) Binned energy prediction with and without the humidity sub-binning

Figure 3.28 : Improved binned energy prediction by the humidity sub-binning scheme for the Engineering Center data - dataset A.

In Table 4.6, identification of zero-hour lagged temperature as the variable with the smallest CV-RMSE verifies this effect (the thermal mass effect is minimal or not significant).

The sample dataset A was processed by steps 8, 10 and 11 as illustrated in the flowchart. This sub-binning effect has moved the binned energy prediction closer to the actual data distribution as illustrated in Figure 3.28. Figure 3.28a shows the scatter plot of the cooling energy data categorized into four sub-binned humidity groups. Figure 3.28b shows the binned energy predictions for a single daytype with and without the humidity sub-binning. It is also evident from this plot (Figure 3.28b) that the humidity sub-binning produces binned predictions that are much closer to the spread of the actual data

Summary

A detailed description of the fully layered inverse bin methodology has been presented in this chapter. This section also addressed general areas of improvements needed in the inverse modeling in commercial buildings using metered data as suggested in the previous literature. How these needs were addressed within the inverse bin methodology were also provided. The eleven steps of the improved inverse bin methodology have been described and illustrated with selected data, flowcharts and data plots. In the next chapter, application of the inverse bin method to case study buildings and selected datasets will be presented.

CHAPTER IV

APPLICATION OF THE INVERSE BIN METHOD

The previous chapter discussed the theory and basis of an fully layered inverse bin method for modeling building energy consumption data. This chapter presents the application of the inverse bin method in detail to selected case study buildings. The simple inverse bin analysis is illustrated using dataset A from the ASHRAE Building Energy Predictor Shootout I (Kreider and Haberl, 1994) competition. The inverse bin analysis is further demonstrated when combined with daytypes and humidity sub-binning through the use of dataset C from the Predictor Shootout II (Haberl and Thamilseran, 1996) (comprehensive daytyping and humidity sub-binning) and dataset D from Predictor Shootout II (schedule-based daytyping and humidity sub-binning).

Introduction

The prediction of energy usage by HVAC systems is important for purposes of HVAC diagnostics, system control, optimization and energy management. In this regard, the ASHRAE predictor shootout competitions were developed to compare how well different empirical models predict building energy data. In order to facilitate the comparison, the first competition was tested on a controlled format where only building energy and environmental data were made available for the training period (09/18/1990 to 12/31/1990). The contestants were then asked to predict energy use during a testing period without knowing the actual energy use in the testing period (Kreider and Haberl, 1994). The data selection for the second competition used a common sampling standard in which uniform intervals of data were extracted from the original dataset and withheld for testing while the remaining data was used by the contestants for the training or developing of their models. In this selection scheme the training data set was compared against the testing dataset for the predictability of the evaluation data, and the contestant's answers were tested for their model's ability to predict the evaluation data. The datasets were selected using a four point criteria: i) five types of energy use data (WBELE, MCC, LTEQ, WBCOOL and WBHEAT), ii) reasonable period of baseline data, iii) installed retrofits to alter the energy types, and iv) a reasonable period of post-retrofit data (Haberl and Thamilseran, 1995). The predictability of the extracted sample (evaluation data) was compared against the training data to verify the appropriateness of the training dataset for its ability to predict the evaluation dataset.

Description of the Case Study Data

The two shootout competitions were organized by ASHRAE to help verify the various modeling techniques and evaluate their ability to predict the building energy data and to foster contact among the energy analysts (Kreider and Haberl, 1994). Furthermore, the intent of the competition was to establish a format in which rigorous evaluations of modeling techniques can be made. Therefore, four carefully selected datasets were provided in each competition. In the first competition (Kreider and Haberl, 1994), the first two datasets, which contain energy consumption and relevant independent variables, were intended to be used by the contestants to 'train' their models, while the second group of two datasets, which contain only the independent variables, were used for testing the predictions by various contestants. In the second competition (Haberl and Thamilseran, 1996), the first two datasets were used for the training and testing of the modeling procedure and the second two datasets were used to compare how well the modeling techniques calculate energy savings. Therefore, the goal of both competitions is to collect, analyze, and publish quantitative results in order to understand similarities and differences among the approaches.

The datasets in the Predictor Shootout I and II competitions therefore represent some of the best case studies for testing the performance of various modeling techniques and thus were considered as the most appropriate datasets for applying the inverse bin method. These datasets (except dataset B which does not involve building energy consumption) were used in this study as case study datasets. The following are brief descriptions of the two competitions and the selected case study datasets for demonstrating the inverse bin method. A detailed description of the case study buildings (that were provided for the competition participants) is provided in Appendix C.

The ASHRAE Predictor Shootout I

In this competition two distinct data sets were provided for testing the prediction capability of the inverse models. These datasets were obtained from two areas: Building energy consumption and solar radiation measurements. Dataset A, which contains building energy consumption data was chosen for the demonstration of this study.

This competition was held with a split sample from a continuous dataset. In this competition six months of continuous hourly data was split into two datasets, the first one containing the first four months of the data (a.trn) and the second one containing the remaining two months of the data (a.tst). The complete four month dataset of the first set was made available to help with the training of the models and hence was called the 'train' dataset (a.trn), while only the independent variables of the second data set were made available and used for testing the predictions against the withheld measured energy consumption (i.e., the dependent variables) and hence was called 'test' data (a.tst).

In the test dataset, contestants were given a set of independent variables with the corresponding values of dependent variables (e.g., energy usage in dataset *a.trn*) and a set of independent variables only in the test dataset (e.g., environmental variables in the test dataset *a.tst*). The dependent variable values (i.e., energy usage) in the dataset *a.tst* were withheld from the participants in order to test the 'blind' forecasting ability of their models. The accuracy of predictions was judged by comparing the predicted building energy use with the withheld data. This contest provided a common platform for the various techniques to be compared and ranked. The predictions submitted by each contestant were compared and published (Kreider and Haberl, 1994). The complete description of the competition can also be found in the published literature (Kreider and Haberl, 1994; Feuston and Thurtell, 1994; Iijima et al., 1994; Kawashima, 1994; Mackay, 1994; Ohlsson et al., 1994; Stevenson, 1994). A brief description of the data that are relevant to the case study are provided in Appendix B.

The ASHRAE Predictor Shootout II

In keeping with this philosophy, the second competition was developed with a slightly different purpose and testing philosophy in which two continuous datasets were selected from several qualified buildings. This time, however, the sampling was performed in a slightly different manner from the first competition. In each of the training datasets dependent variables were extracted from each baseline period at uniform intervals to form 'evaluation' datasets on which the performance of the models were evaluated. The remaining data (that contained only independent variables for the extracted periods and both independent variables and dependent variables for the non-extracted periods) were made available as the 'training' datasets (C.trn and D.trn). In this way the prediction capability of the model was tested. Furthermore, this competition was also different from the first competition in the following ways: (i) both datasets contained building energy usage and environment data, and (ii) in the Shootout II competition the baseline models were then used to measure retrofit savings in each building by forecasting the baseline into the post-retrofit period (i.e., each building actually had an energy conservation retrofit).

These two datasets were carefully selected from about 100 monitored buildings that are part of the Texas LoanSTAR program. The first dataset (dataset C) was selected from energy consumption data for the Engineering Center (EC) located at Texas A&M University, College Station, Texas. The second dataset (dataset D) was from energy consumption data from the Business building (BUS) located at the University of Texas at Arlington, Texas.

The descriptive information of the case-study buildings and sample data are provided in Appendix B as made available for the predictor shootout participants. Hence these datasets were used as case studies for the application of the bin method. This has the following advantages: a) use of a well-compiled dataset for the application of the methods, b) the ability to compare the performance of the inverse bin model prediction against the other modeling techniques, and c) the ability to study the impact of different modeling techniques on the retrofit savings calculations.

Application of the Methodology

The inverse bin approach has been applied to the above case study buildings. Dataset A from the Predictor Shootout I (PS-I) competition was chosen for the demonstration of the simple inverse bin method (i.e., steps 1 through 6 were demonstrated with minimal daytyping). Datasets C and D from the Predictor Shootout II (PS-II) were selected for the illustration of the inverse bin method with comprehensive daytyping and humidity sub-binning techniques. A detailed discussion of these three datasets are presented below where the simple bin method is demonstrated with dataset A from Predictor Shootout I, and the improved inverse bin method with thermal mass and humidity sub-binning is demonstrated with datasets C and D under Predictor Shootout II.

The ASHRAE Predictor Shootout I

Dataset A was extracted from the monitored data from the Zachry Engineering Center on the Texas A&M University campus. The building contains classrooms, labs, offices and computer facilities. Electricity, cooling, and heating energy are supplied by the central plant. The dataset was first analyzed using graphical techniques as described in Chapter III under Step 1 and shown in Figures 3.5 through 3.9. The changes in operational pattern between weekdays, weekends and holidays were observed in Figures 3.5. The potential modes of operation for weekdays were observed in the WBELE weekday-weekend frequency distribution plots in Figure 3.6. The variations between weekday and weekend operations were noted in Figures 3.7 and 3.8. The potential of the latent load effect in building's cooling energy consumption was visually shown in Figure 3.9. Then the independent variable (or bin variable) was identified using the Pearson's linear correlation coefficient (Table 3.2 in Chapter 3: Methodology). The outdoor dry-bulb temperature (Temp) was identified as the bin variable for the weather dependent energy consumption (WBCOOL and WBHEAT) and Hour-of-the-day (HOD) was identified as the bin variable for weather independent energy consumption (WBELE, MCC and LTEQ).

Dataset A was then tested for outliers and four consecutive days (Dec. 23 -Dec. 26) of cooling and heating energy data were identified as outliers. The WBELE data were then grouped by using the calendar days as follows: i) regular days, ii) low days (Dec.13 - Dec.23) and iii) breaks and holidays (Christmas holidays: Dec.24 - Dec.31). Then the data in the regular days and low days were separated into weekday-weekend daytypes which resulted in five daytypes (regular-weekday, regular-weekend, low days-weekday, low days-weekend, breaks and holidays). These daytypes were then tested for significant differences between groups by using the multiple comparisons tests (i.e., Duncan's multiple range, Duncan-Waller k-ratio test, and Scheffe's procedure. These tests are explained in Appendix A). The sample output from a Statistical Analysis System (SAS) software is provided for the initial daytypes in Tables 4.1. In these procedures the mean values of the data groups are first arranged according to the order (i.e., size) and then each mean is compared against others to compare the between-group variation against the within group variation. If the within group variation is smaller than the between group variation, then the daytypes are identified as significantly different. Otherwise, the daytypes are identified as not significantly different. This information is generally provided at the bottom of the summary tabulation for each test. For example, this summary is provided in the last six lines of the Duncan's procedure output, where the last five lines (data groups or daytypes) were marked by letters A, B, C, D, and E. These correspond to the initial daytypes, 2 (regular weekdays), 4 (low weekdays), 1 (regular weekends), 3 (low weekends), and 5 (holidays or Christmas period). Since the daytypes were marked with different letters, these daytypes were identified as significantly different daytypes (as noted in the ninth line) The daytypes that are identified with the same letter are not significantly different.

In the output from the Duncan's multiple range test procedure, the description, as shown in the third and fourth lines, shows the type of error that was controlled by the specific test procedure. In this test (with α = 0.05 for 95% confidence level) the type I comparison-wise error is determined by the number of levels the comparison of means are apart, r, and the distribution of the data within the groups. This error rate is equivalent to $\{1-(1-\alpha)^{r-1}\}$. These values were calculated for all the possible comparisons and presented in the eighth and ninth lines of the output. The data are used further as follows for determining whether the selected daytyping is significantly different. When the sample means are compared (e.g., when comparing daytypes which are three steps apart, r=3, for the daytypes DTP=2 and DTP=1, the critical range (explained in Appendix A under Duncan's multiple comparison's procedure) is calculated as 26.03 from the tabulated value of $q_{\alpha,(r,df)}$=2.92 for the given df=2897 and $\sqrt{S_w^2/n}$ is $\sqrt{15062.64/189.5877}$=8.913, resulting in 26.03 (=8.913*2.92). The difference between the DTP=2 and DTP=1 of 738.07 - 568.97 = 169.1 is higher than the calculated value of 26.03. Therefore, the two considered daytypes are significantly different.

Table 4.1: Results of tests performed to identify the initial daytypes for whole-building electric (WBELE) data for the dataset A.

(a) Duncan's multiple range test

Analysis of Variance Procedure
Duncan's Multiple Range Test for variable: WBELE
NOTE: This test controls the type I comparison-wise
error rate, not the experimentwise error rate
Alpha= 0.05 df= 2897 MSE= 15062.64
Harmonic Mean of cell sizes= 189.5877

Number of Means	2	3	4	5
Critical Range	24.72	26.03	26.90	27.55

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	DTP	
A	738.07	1726	2	regular weekdays
B	614.65	144	4	low weekdays
C	568.97	672	1	regular weekends
D	542.38	72	3	low weekends
E	475.25	288	5	Christmas

(b) Scheffe's procedure

Analysis of Variance Procedure
Scheffe's test for variable: WBELE
NOTE: This test controls the type I experimentwise error rate but generally
has a higher type II error rate than REGWF for all pairwise comparisons

Alpha= 0.05 df= 2897 MSE= 15062.
Critical Value of F= 2.37500
Minimum Significant Difference= 38.85
Harmonic Mean of cell sizes= 189.5877
Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	DTP	
A	738.07	1726	2	regular weekdays
B	614.65	144	4	low weekdays
C	568.97	672	1	regular weekends
C				
C	542.38	72	3	low weekends
D	475.25	288	5	Christmas

The comparison continued for all the possible combinations, and the final daytypes are given by the same letter to groups which are not significantly different. However, in this data grouping different letters were given to the daytypes indicating that all the daytypes are significantly different. These results are given in the output of the Duncan's procedure shown in Table 4.1a where the daytypes were marked with different letters to show the significant difference between daytypes. However, the output from the Scheffe's procedure (a sample output and interpretation are provided in Appendix A) indicated the existence of insignificant difference between the regular days-weekends and low days-weekends, by marking these daytypes with the same letter C. The calculated difference between the sample means is 26.59 (=568.97 - 542.38), which is significantly lower than the critical range of 38.85, thus resulting in these two daytypes being marked by the same letter C to show the insignificant difference between daytypes. Therefore, both of these initial daytypes were aggregated together to form a single daytype and thus four final daytypes were obtained.

Histogram plots for each daytype were then generated and inspected for the presence of multi-modal distributions. The data for the 19^{th} hour through the 23^{rd} hour distributions show the existence of a multi-modal distribution. A sample distribution for the 20th hour is shown in Figure 4.1. The histograms for other hourly distributions from the remaining three daytypes did not show any clear presence of multi-modal distributions (e.g., Figure 4.2). This may be the reason that Duncan's multiple range test, a less conservative procedure, identified the two periods of the weekend data (regular days and low days) as significantly different daytypes. However, Scheffe's procedure, a more conservative procedure, identified these two daytypes as not significantly different daytypes. Thus accepting the more conservative approach, the above four daytypes were accepted as the final daytypes and the Duncan's and Scheffe's procedures were repeated. The results are summarized in Table 4.2. Using the test results the four final daytypes were accepted and used as separate daytypes for the remaining steps of the inverse bin method.

Once the final daytypes were identified, the general procedure was used to check for the existence of a schedule-based operation. However, this step should be bypassed for this dataset because of the unavailability of schedule-based information. Therefore, the additional schedule-based daytypes are taken as zero because of the non-availability of any

```
Stem Leaf                    #              Boxplot
  77 12                      2                 |
  76                                           |
  75 224568                  6                 |
  74 14557777                8                 |
  73 03489                   5              +-----+
  72 2558                    4              |     |
  71 2235556                 7              |     |
  70 01112468                8              *-----*
  69 2224667                 7              |  +  |
  68 3668                    4              |     |
  67 579                     3              +-----+
  66 5799                    4                 |
  65 248                     3                 |
  64 22                      2                 |
  63 15                      2                 |
  62                                           |
  61 3569                    4                 |
  60 1                       1                 |
  59                                           |
  58                                           |
  57 8                       1                 |
  56 2                       1                 0
     ----+----+----+----+
  Multiply Stem.Leaf by 10**+1
```

Figure 4.1 : Frequency distribution and the box-and-whisker plot of the 20th hour whole-building electric energy use for weekends for dataset A using SAS software.

```
Stem Leaf                    #              Boxplot
  97 0                       1                 |
  96 12                      2                 |
  95 05                      2                 |
  94 122446666               9                 |
  93 0123466888             10              +-----+
  92 011266899               9              |     |
  91 00022344667789         14              *--+--*
  90 011233559               9              +-----+
  89 12233567                8                 |
  88 29                      2                 |
  87 578                     3                 |
  86 6                       1                 |
  85 0                       1                 |
  84
  83 5                       1                 0
     ----+----+----+----+
  Multiply Stem.Leaf by 10**+1
```

Figure 4.2 : Frequency distribution and the box-and-whisker plot of the 13th hour whole-building electric energy use for weekends for dataset A using SAS software.

Table 4.2: Results of tests performed to identify the final daytypes for whole-building electric (WBELE) data for the dataset A.

(a) Duncan's multiple range test

Analysis of Variance Procedure
Duncan's Multiple Range Test for variable: WBELE
NOTE: This test controls the type I comparison-wise error rate, not the experimentwise error rate

Alpha= 0.05 df= 2875 MSE= 6072.941
WARNING: Cell sizes are not equal.
Harmonic Mean of cell sizes= 324.1458

Number of Means	2	3	4
Critical Range	12.00	12.64	13.06

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	DTE	
A	738.073	1726	2	regular weekdays
B	614.646	144	3	low weekdays
C	566.399	744	1	weekends
D	475.247	288	4	Christmas

(b) Scheffe's procedure

Analysis of Variance Procedure
Scheffe's test for variable: WBELE
NOTE: This test controls the type I experimentwise error rate but generally has a higher type II error rate than REGWF for all pairwise comparisons
Alpha= 0.05 df= 2875 MSE= 6072.941
Critical Value of F= 2.60800
Minimum Significant Difference= 17.122
Harmonic Mean of cell sizes= 324.1458

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	DTE	
A	738.073	1726	2	regular weekdays
B	614.646	144	3	low weekdays
C	566.399	744	1	weekends
D	475.247	288	4	Christmas

relevant weather independent data other than WBELE data. Consequently, the same four daytypes will be passed onto the next step as the final daytypes.

The data in each daytype was then binned according to the identified bin variable. The weather independent energy data were binned into hour-of-the-day bins, and the weather dependent energy use was binned within standard 5°F (~3°C) temperature bins.

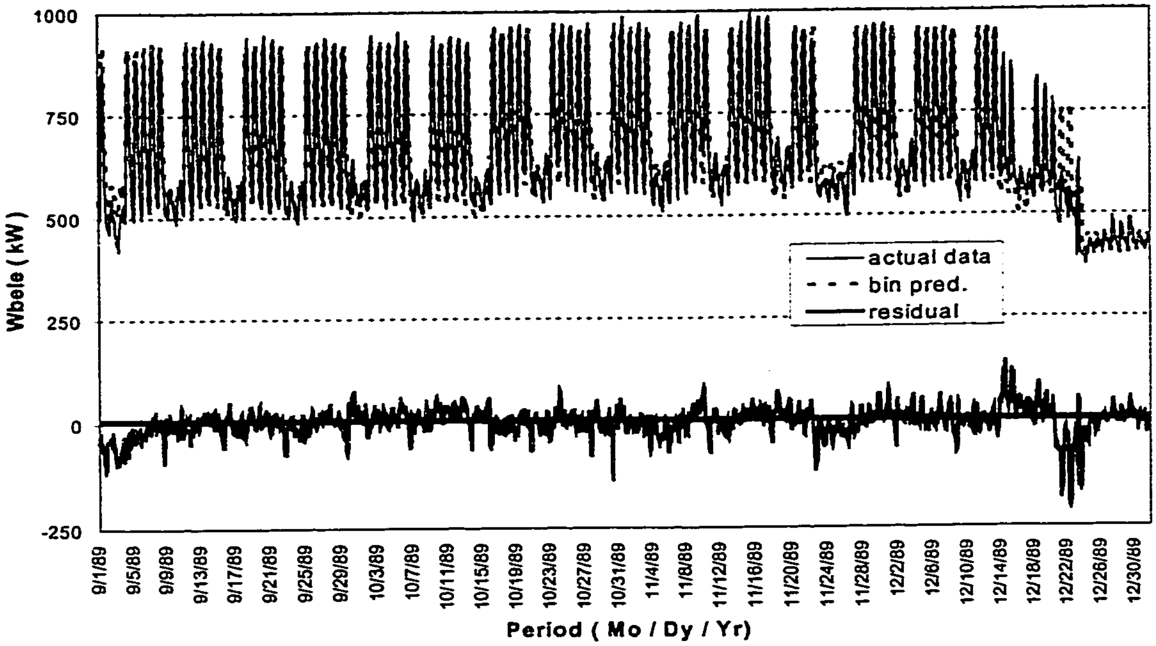
Then the mean value of the data within each bin was calculated and used as the energy use for that particular bin. This process is repeated until all the energy use values are calculated for all the daytypes. The binned whole-building electric energy consumption is shown in Figure 4.3 in a time series format and compared against the actual data in scatter plot (Figure 4.36). Since the differences between these data are not clearly visible, the difference between the inverse bin fit and the actual data are plotted at the bottom of Figure 4.3 (a). This plot is labeled as the residual plot.

Likewise the comparison of whole-building cooling and whole-building heating energy consumption is shown in scatter plots (Figures 4.4 and 4.5). The points shown on the vertical axes in Figure 4.4 (b) and 4.5 (b) indicate the original dataset has some energy use marked as zero. However, these points, when calculated by bin analysis, had values other than zero for the relevant temperature bin. Hence the inverse bin fit value has a non-zero number while the actual data has zero resulting in the points marked on the axes. Both WBCOOL and WBHEAT energy use matches well with the binned WBCOOL and WBHEAT energy values (Figures 4.4 and 4.5.). The inverse bin fit was then compared against the actual data to calculate the model statistics (i.e., performance parameters) to evaluate the model's ability to predict the actual data. These results are summarized in the following chapter.

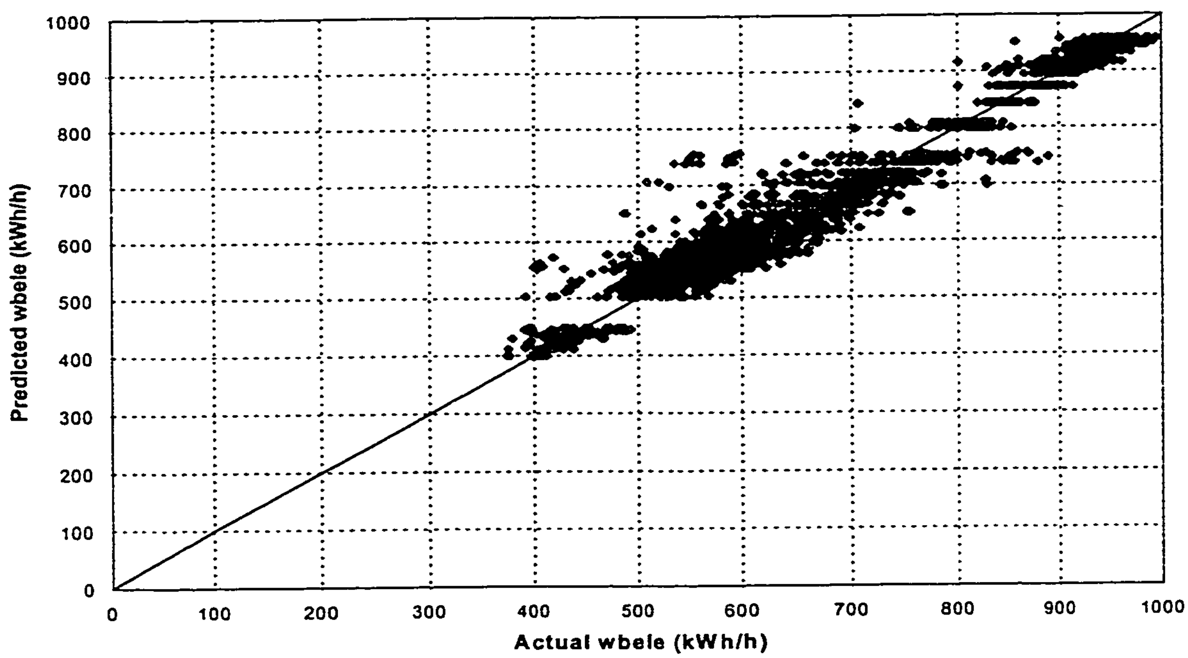
<u>The ASHRAE Predictor Shootout II</u>

The bin methodology with comprehensive daytyping and humidity sub-binning added was illustrated through the datasets from this competition. Dataset C (the Engineering Center building) and dataset D (the Business building) from the Predictor Shootout - II competition contain energy use information from two significantly different types of buildings. Detailed daytyping and humidity sub-binning were illustrated using dataset C while the schedule-based daytyping was illustrated using dataset D.

This 'training' dataset contained the data between January 1, 1990 and November 27, 1990 from the Engineering Center (EC) in dataset C and December 22, 1990 through March 7, 1991 from the Business building (BUS) in dataset D. In these 'training' periods the data values of the dependent variable for one week out of every four weeks was withheld (i.e., not provided to the competition participants). This was later used as the

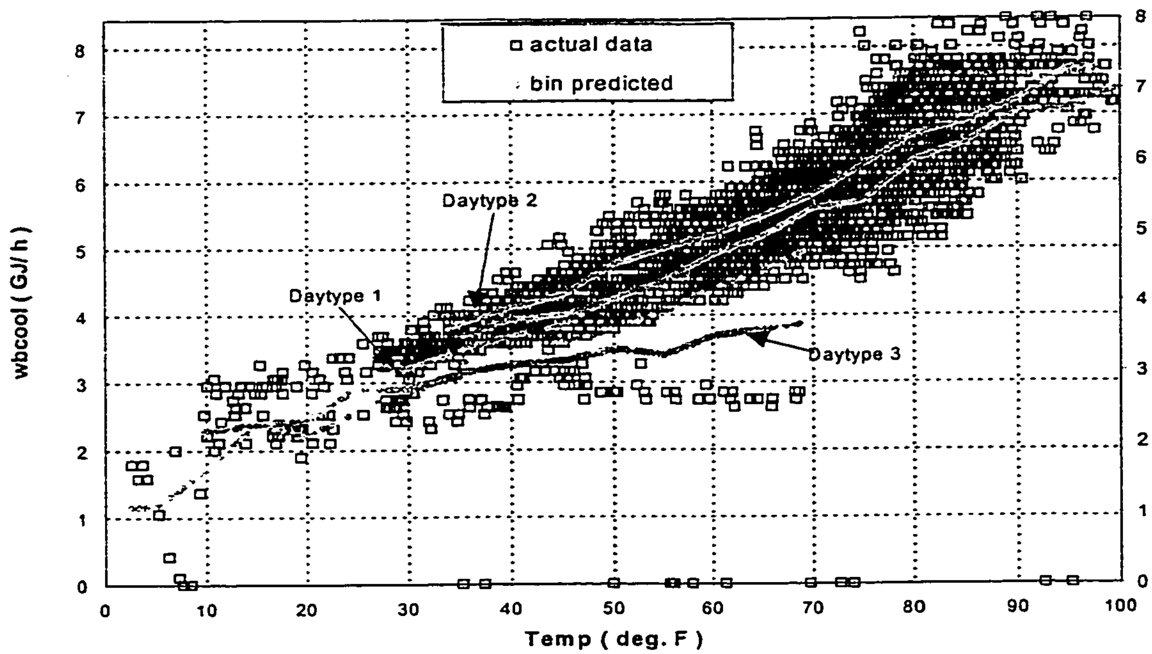


(a) Time series plot

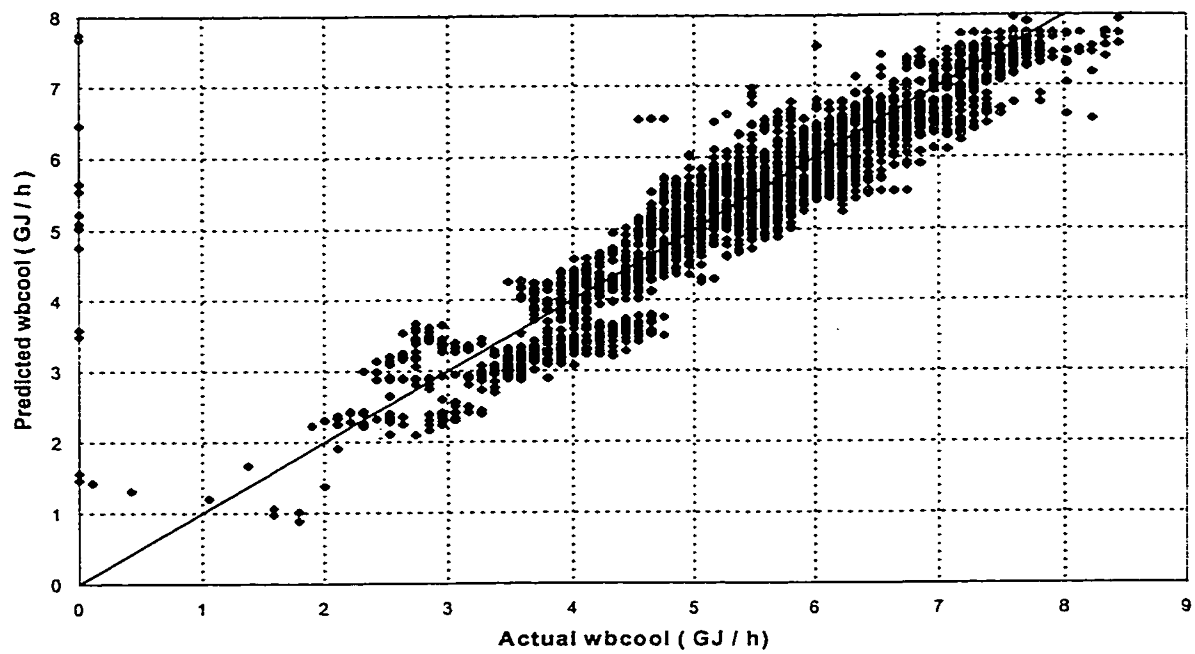


(b) Comparison plot

Figure 4.3 : Comparison of the inverse bin model fit and the actual whole-building electric (WBELE) energy use data for the dataset A. (a) Time series plot of the data (b) Comparison of the inverse bin model fit data against the actual data

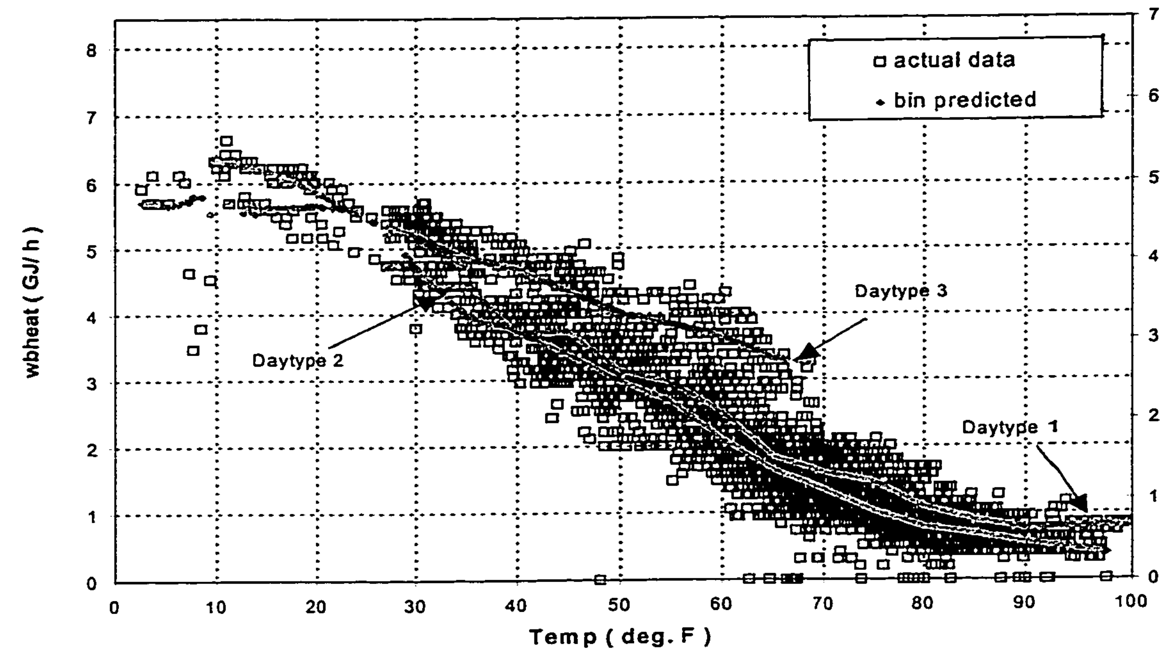


(a) Scatter plot

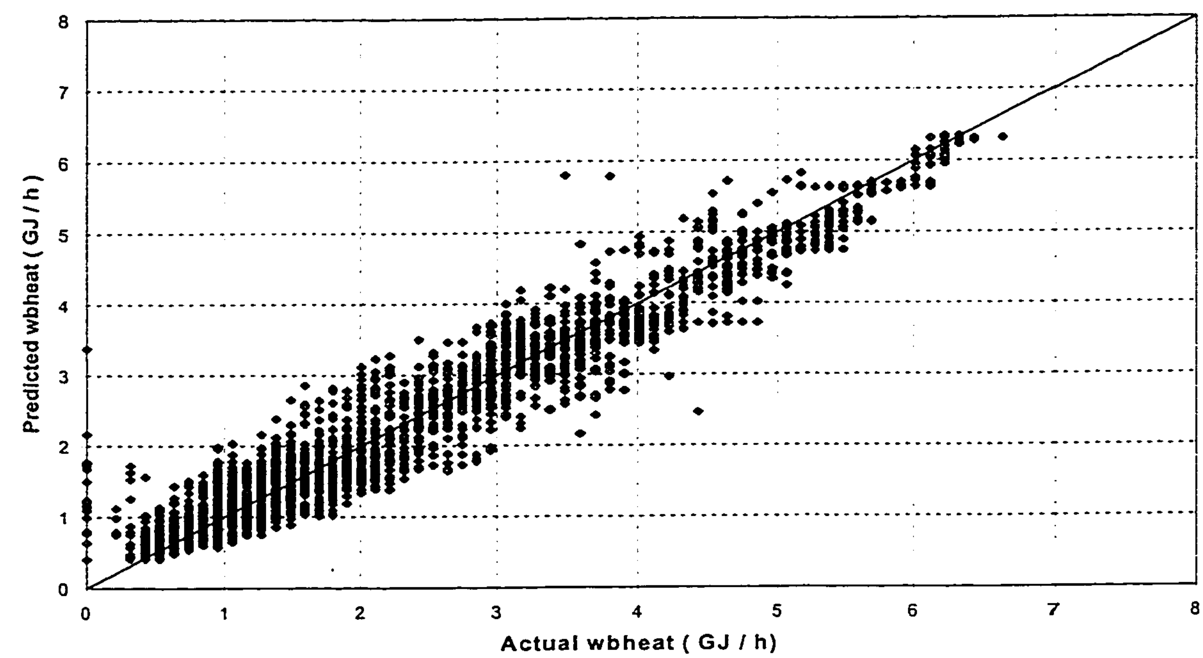


(b) Comparison plot

Figure 4.4 : Comparison of the inverse bin model fit data and the actual whole building cooling (WBCOOL) energy use data for the dataset A. (a) Scatter plot of the inverse bin model fit (b) Comparison of the inverse bin fit data against the actual data



(a) Scatter plot



(b) Comparison plot

Figure 4.5 : Comparison of the inverse bin prediction and the actual whole-building heating (WBHEAT) energy use data for the dataset A. (a) Scatter plot of the inverse bin fit data (b) Comparison of the inverse bin fit against the actual data

'evaluation' dataset. Each participant was expected to complete a prediction of the data values of the dependent variable that was withheld using the environment variables provided in the training data. These predictions were then compared against the withheld data (or evaluation data) for evaluating the performance of the predictions by the participants. The details of the competition format and description of the data are available in the published literature (Haberl and Thamilseran, 1996). A brief description of the buildings, operational schedules and a description of the data are provided in Appendix B.

Dataset C (c.trn): This dataset was first visually analyzed using the time series and the scatter plots for each dependent variable. The data were then cleaned using the outlier identification scheme described under methodology (Step 3). The Hour-of-the-Day was identified as the variable for predicting the whole-building electric (WBELE), Motor Control Center (MCC), and lights and equipment (LTEQ) energy consumption, while the outdoor dry bulb temperature (Temp) was identified as the bin variable for the whole-building cooling (WBCOOL) and whole-building heating (WBHEAT) energy variables using the Pearson's linear correlation coefficient. This procedure is very similar to the analysis described as the example for Dataset A in Table 3.2 (Step 2).

The data were then grouped into six daytypes based on the calendar days and operational schedules provided, using the information extracted from visual inspection of the plots. The initial six daytypes are: 1) fall semester, 2) spring semester, 3) summer semester, 4) spring break period, 5) days between semesters, and 6) holidays and other breaks. These daytypes were then separated into weekdays and weekends, resulting in 12 daytypes. Duncan's, Duncan-Waller's k-ratio and Scheffe's multiple comparison procedures were then performed on these daytypes to test the following: (i) whether there is significant difference between the three types of holidays: 1) spring break days, 2) holiday and breaks, and 3) days between semester periods, and (ii) whether any of these daytypes can be aggregated together to form a smaller number of daytypes.

The results from the first comparisons (testing the significance between the three holidays) are shown in Table 4.3. Waller, Duncan and Scheffe's procedures indicated that these daytypes are significantly different (i.e., the daytypes were marked with different letters A, B, and C). Daytype 5 (days between semesters) has the highest mean

Table 4.3: Results of the multiple-comparison tests performed to identify the difference between three holiday daytypes for WBELE data for the dataset C.

(a) Waller's test

```
Waller-Duncan K-ratio T test for variable: WBELE
NOTE: This test minimizes the Bayes risk under additive
loss and certain other assumptions.
Kratio= 100  df= 1146  MSE= 9613.233  F= 46.46078
Critical Value of T= 1.75331
Minimum Significant Difference= 32.432
Means with the same letter are not significantly different.

Waller Grouping   Mean      N  DT
      A         1059.16   1032  5
      B         1010.50     93  4
      C          883.61     24  6
```

(b) Duncan's test

```
Duncan's Multiple Range Test for variable: WBELE
NOTE: This test controls the type I comparison-wise error rate,
not the experimentwise error rate
Alpha= 0.05  df= 1146  MSE= 9613.233
Number of Means    2     3
Critical Range  36.29 38.21
Means with the same letter are not significantly different.

Duncan Grouping   Mean      N  DT
      A         1059.16   1032  5
      B         1010.50     93  4
      C          883.61     24  6
```

(c) Scheffe's test

```
Scheffe's test for variable: WBELE
NOTE: This test controls the type I experimentwise error rate but generally has a
higher type II error rate than REGWF for all pairwise comparisons
Alpha= 0.05  df= 1146  MSE= 9613.233
Critical Value of F= 3.00358
Minimum Significant Difference= 45.336
Means with the same letter are not significantly different.

Scheffe Grouping   Mean      N  DT
      A          1059.16   1032  5
      B          1010.50     93  4
      C           883.61     24  6
```

among these holidays. The second highest mean is for daytype 4 (spring break period) with daytype 6 (holidays and other breaks) having the smallest mean value.

In the second comparison all twelve (12) daytypes were tested with the multiple comparison procedures. The comparison indicated that some of these daytypes were not significantly different (i.e., indicated by the same letter against the daytypes in the output). Therefore, the daytypes that were not significantly different were then regrouped to form six final daytypes: (i) Fall-weekdays, (ii) Spring and Summer-weekdays, (iii) semester-breaks-weekdays, (iv) Spring- break weekdays and Fall, Spring and Summer weekends, (v) Spring-break and semester-break weekends, and (vi) holidays. These daytypes were tested again for the WBELE and LTEQ variables and the results are summarized in Tables 4.4 and 4.5 respectively. The results of Duncan's and Waller's procedures showed that these daytypes are significantly different. Only Scheffe's test showed that there is no significant difference between the daytypes (iv) and (v) for WBELE variable. This is indicated by the same letter, C, in the output (Table 4.4c) against the daytypes 4 and 5. However, all three comparisons (including Scheffe's test) showed that these daytypes are significantly different for LTEQ variable as shown in Table 4.5 (i.e., different letters against the daytypes in output shown in Table 4.5). In this output, the sixth daytype for LTEQ is empty because the LTEQ data was not available for holiday periods. Therefore, these six daytypes were accepted as the final daytypes.

After checking the frequency distribution for each hour for each daytype for the above revised daytypes, it was decided that no significant additional daytypes were required because all the frequency distributions are acceptable uni-modal distributions. This process is similar to the process described for dataset A (under The ASHRAE Predictor Shootout I) and illustrated in Figure 4.2. Therefore, the final daytypes remain the same as the above revised daytypes. This resulted in the following final daytypes for the WBELE data: (i) Fall -weekdays, (ii) Spring and Summer -weekdays, (iii) breaks-weekdays, (iv) Fall, Spring and Summer weekends and spring break-weekdays, (v) breaks and spring breaks-weekends, and (vi) holidays. Likewise, the final daytypes for LTEQ were also tested and the same daytypes were determined for LTEQ. Since the sixth daytype is an empty group (i.e., all the LTEQ data in this daytype were missing), the energy use was assumed to be the same as the other holidays daytypes (breaks and spring breaks).

Similarly the daytypes were also tested for the Motor Control Center (MCC) energy use data to obtain the final daytypes. The final daytypes for the MCC energy use data were

Table 4.4: Results of the multiple-comparison tests performed for revised daytypes for whole-building electric (WBELE) data for the dataset C.

(a) Waller's test

Waller-Duncan K-ratio T test for variable: WBELE

NOTE: This test minimizes the Bayes risk under additive loss and certain other assumptions.

Kratio= 100 df= 5749 MSE= 12983.15 F= 458.1824

Critical Value of T= 1.73569 Minimum Significant Difference= 24.94

Means with the same letter are not significantly different.

Waller Grouping	Mean	N	DTE
A	1193.04	1221	1
B	1151.44	2137	2
C	1091.90	741	3
D	1019.94	1248	4
E	984.18	384	5
F	883.61	24	6

(b) Duncan's test

Duncan's Multiple Range Test for variable: WBELE

NOTE: This test controls the type I comparison-wise error rate, not the experimentwise error rate

Alpha= 0.05 df= 5749 MSE= 12983.15

Number of Means	2	3	4	5	6
Critical Range	28.17	29.66	30.66	31.40	31.98

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	DTE
A	1193.04	1221	1
B	1151.44	2137	2
C	1091.90	741	3
D	1019.94	1248	4
E	984.18	384	5
F	883.61	24	6

(c) Scheffe's test

Scheffe's test for variable: WBELE

NOTE: This test controls the type I experimentwise error rate but generally has a higher type II error rate than REGWF for all pairwise comparisons

Alpha= 0.05 df= 5749 MSE= 12983.15

Critical Value of F= 2.21565 Minimum Significant Difference= 47.826

Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	DTE
A	1193.04	1221	1
A	1151.44	2137	2
B	1091.90	741	3
C	1019.94	1248	4
C	984.18	384	5
D	883.61	24	6

Table 4.5: Results of the multiple-comparison tests performed for revised daytypes for lights and equipment (LTEQ) data for the dataset C.

(a) Waller's test

Waller-Duncan K-ratio T test for variable: LTEQ
NOTE: This test minimizes the Bayes risk under additive loss and certain other assumptions.
Kratio= 100 df= 4519 MSE= 12933.31 F= 426.0042
Critical Value of T= 1.73584 Minimum Significant Difference= 11.071
Means with the same letter are not significantly different.

Waller Grouping	Mean	N	DTE
A	702.994	1221	1
B	663.583	1482	2
C	614.005	525	3
D	535.353	1008	4
E	502.278	288	5

(b) Duncan's test

Duncan's Multiple Range Test for variable: LTEQ
NOTE: This test controls the type I comparison-wise error rate, not the experimentwise error rate
Alpha= 0.05 df= 4519 MSE= 12933.31

Number of Means	2	3	4	5
Critical Range	12.50	13.17	13.61	13.94

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	DTE
A	702.994	1221	1
B	663.583	1482	2
C	614.005	525	3
D	535.353	1008	4
E	502.278	288	5

(c) Scheffe's test

Scheffe's test for variable: LTEQ
NOTE: This test controls the type I experimentwise error rate but generally has a higher type II error rate than REGWF for all pairwise comparisons
Alpha= 0.05 df= 4519 MSE= 12933.31
Critical Value of F= 2.37390 Minimum Significant Difference= 19.653
Means with the same letter are not significantly different.

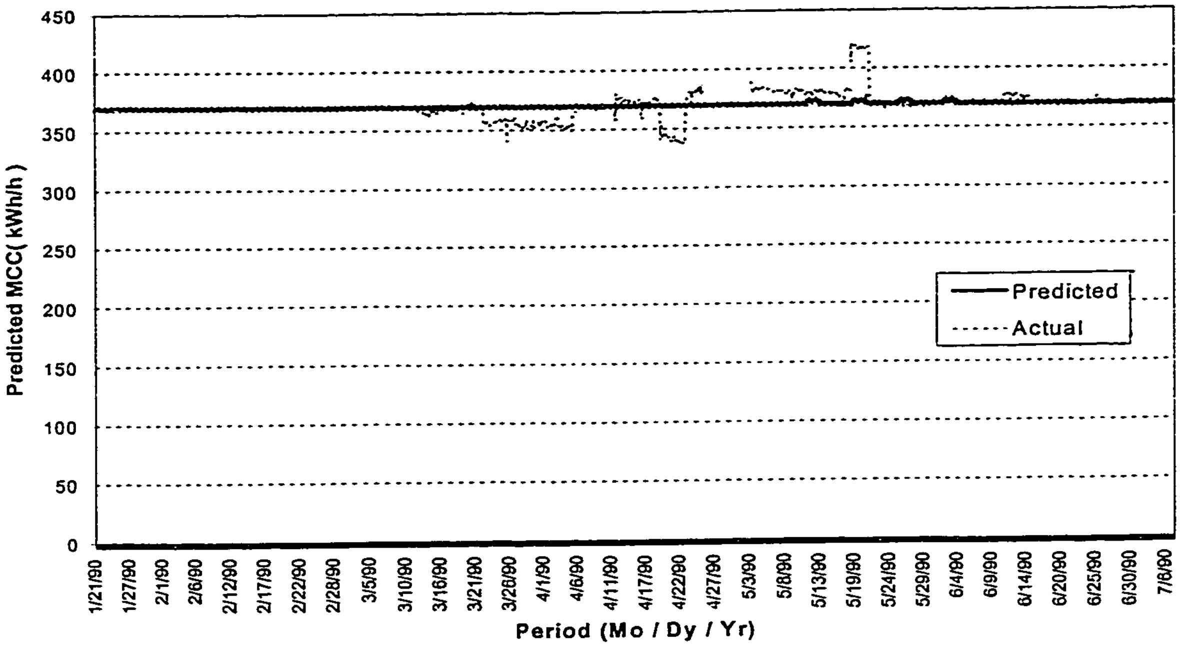
Scheffe Grouping	Mean	N	DTE
A	702.994	1221	1
B	663.583	1482	2
C	614.005	525	3
D	535.353	1008	4
E	502.278	288	5

(i) Fall - weekdays and weekends, (ii) between semester-weekdays, and (iii) the remainder of the days. Once the final daytypes were determined the data were then separated into the final daytypes. Subsequently each daytype was then binned (i.e., weather dependent data into temperature bins and weather independent data into HOD bins) and a representative mean value was calculated for each bin.

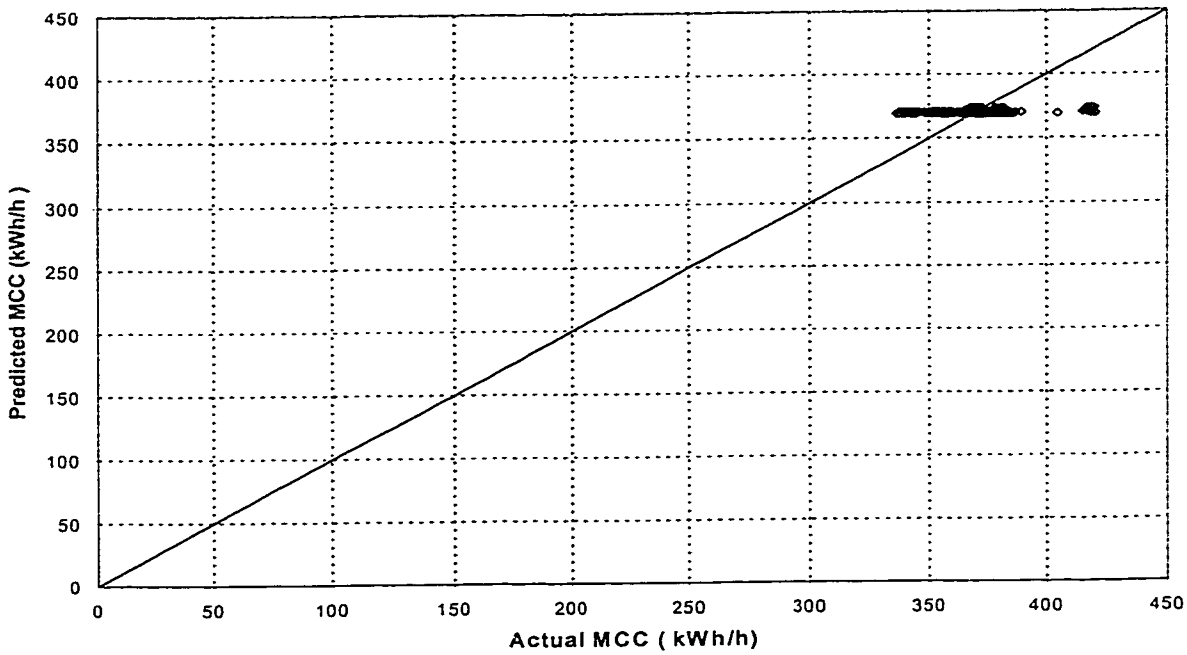
The binned energy consumption for whole-building electric (WBELE) , MCC, and lights and equipment (LTEQ) were plotted and compared against the actual data. The comparison for the WBELE data for dataset C is similar to the comparison shown in Figure 4.3 for dataset A. Only new energy types are illustrated for this dataset. The MCC energy use is shown as a time series in Figure 4.6a and compared against the actual data as shown in Figure 4.6b. These plots show that the actual data has minimal variation between the binned groups, resulting in very similar predictions. Similarly the inverse bin fit was also compared against the actual data for LTEQ energy use as shown in Figure 4.7. The identified daytypes may have a few days of data from other daytypes resulting in some predicted data points straying from the main line.

This dataset was then analyzed for the improved bin predictions by performing steps 8, 9, 10 and 11 of the inverse bin method. The results (Figure 3.26 for the EC building) showed that the thermal mass effect is less significant and the use of a lagged temperature variable does not improve the predictions. The CV-RMSE value for the linear regression model, with the lagTemp as the independent variable was calculated for various levels of lag. The results are shown in Table 4.6.

The dataset was also tested for the existence of latent load effect on whole-building cooling energy (WBCOOL). This was performed both visually from the scatter plots (similar to the plots shown in Figures 3.9 - specific humidity against outdoor dry-bulb temperature and Figure 3.7 - WBCOOL against temperature) and statistically by checking the standard deviation and inter-quartile range (IQR = Q3-Q1) of the data within each temperature bin. The visual comparison of the IQR can also be performed using a plot similar to the one described in Figure 3.15 for dataset A. For example, the data that falls between 59.5°F and 64.49°F were grouped together in one bin and tabulated against the mid-point of the bin 62°F. Then the descriptive parameters (number of observations in the

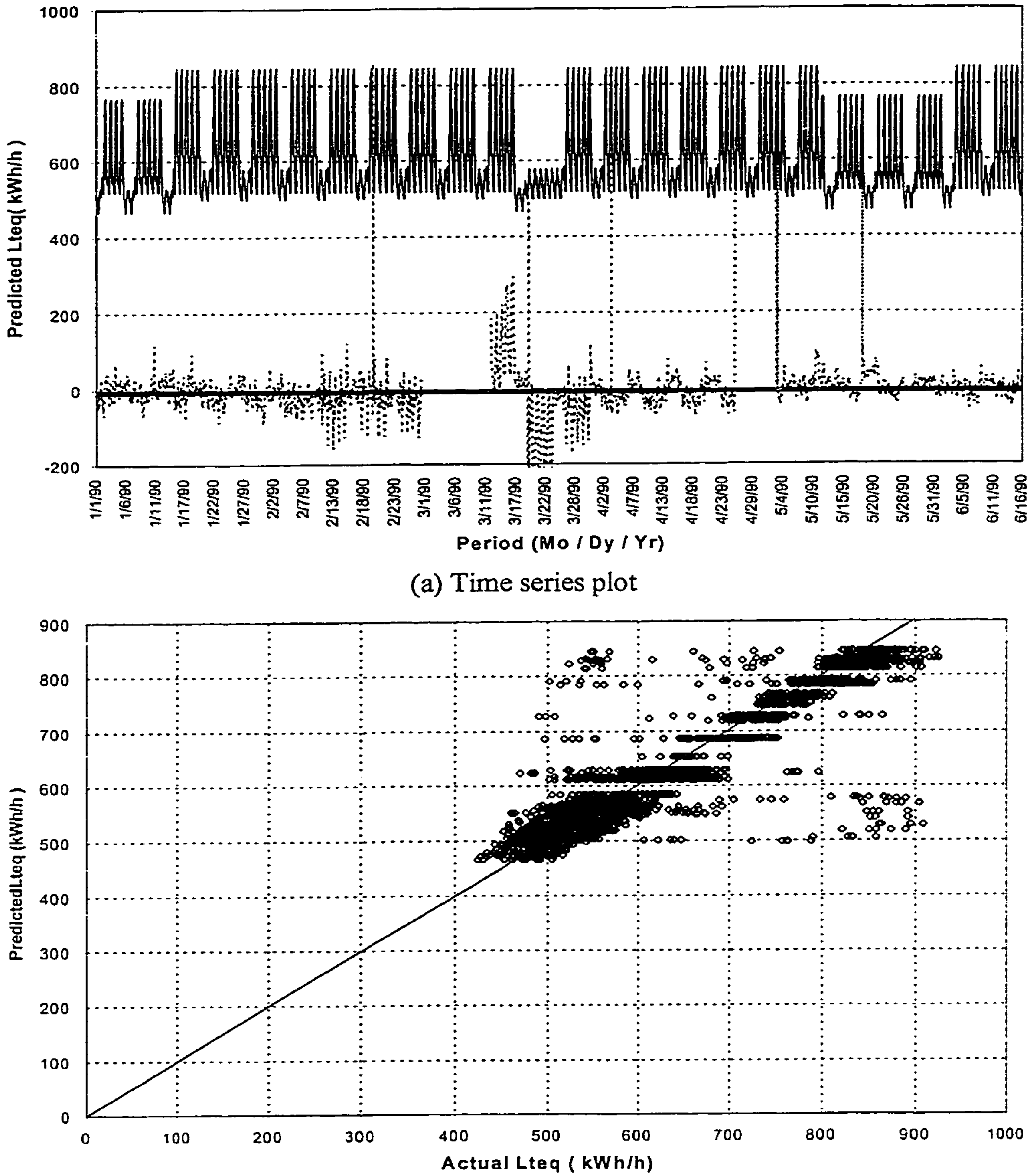


(a) Time series plot



(b) Comparison plot

Figure 4.6 : Comparison of the simple inverse bin model fit data and the actual MCC energy use data for the dataset C. (a) Time series plot of the inverse bin fit data and actual use, (b) Comparison of the inverse bin model fit data against the actual data



(a) Time series plot

(b) comparison plot

Figure 4.7 : Comparison of the simple inverse bin prediction and the actual lights and equipment energy use data for the dataset C. (a) Time series plot of the bin prediction (b) Comparison of the bin prediction against the actual data.

Table 4.6 : Selection of the suitable LagTemp variable for dataset C

Number of Hours of lag	CV-RMSE for linear regression model
0	11.39 ... minimum
1	11.40
2	11.50
3	11.66
4	11.85
5	12.05
6	12.25
7	12.45
8	12.61
9	12.76
10	12.87
11	12.94
12	12.97
13	12.98
14	12.95
15	12.89
16	12.81
17	12.69
18	12.55
19	12.41
20	12.27
21	12.15
22	12.08
23	12.05
24	12.10

bin - N, standard deviation of the binned data - σ, mean value of the binned data, bottom 25% quartile - Q1, bottom 75% quartile - Q3, and IQR) were calculated and the three parameters needed for the inspection tabulated. The data description parameters (standard deviation and inter-quartile range) are provided in Table 4.7 for Dataset C (Engineering Center data).

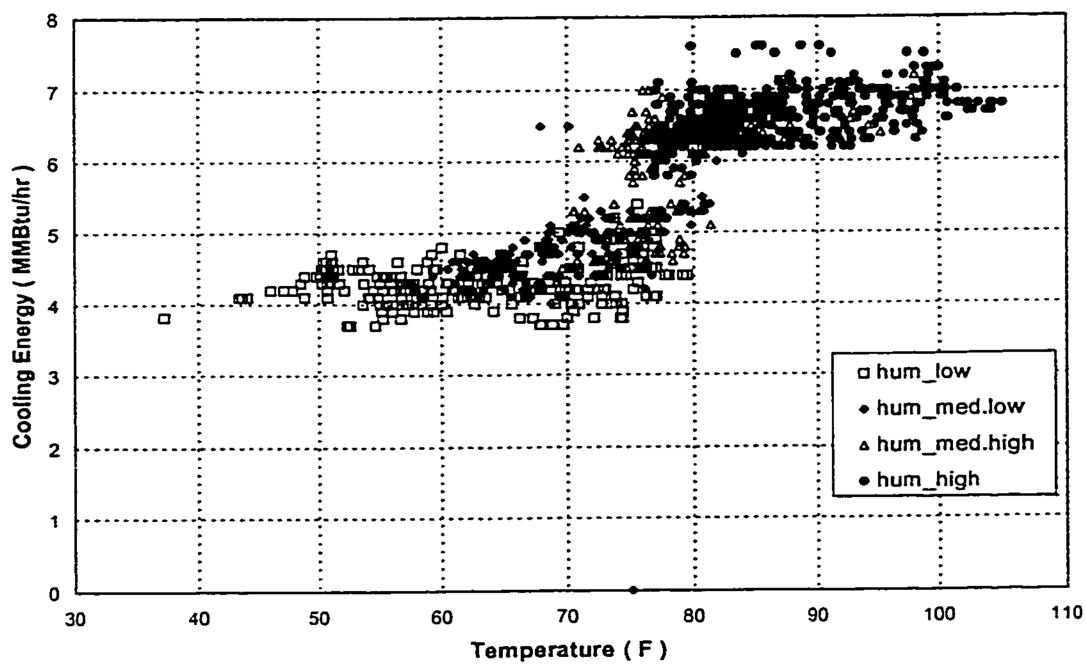
The inspections and the significant secondary correlation of humidity suggested that the latent effect on cooling energy may be significant and the humidity sub-binning procedure may improve the predictions. A spread in the binned data can be seen for the 57°F to 77°F bins from the tabulated IQR (i.e., 0.8 MMBtu/hr or greater as shown in Table

4.7). However, only twice the level of spread as the spreads of the bins below 57°F may be an indication of the multi-collinearity between weather variables. The actual improvement is compared and tabulated in Chapter VI for with and without sub-binned predictions. The resulted binned values for the cooling energy consumption for one of the daytypes (e.g., Fall semester weekday) and the actual data are shown in Figure 4.8. The top plot shows the humidity sub-binned actual data and the bottom plot is a comparison of the bin prediction without humidity sub-binning and the bin prediction with humidity sub-binning.

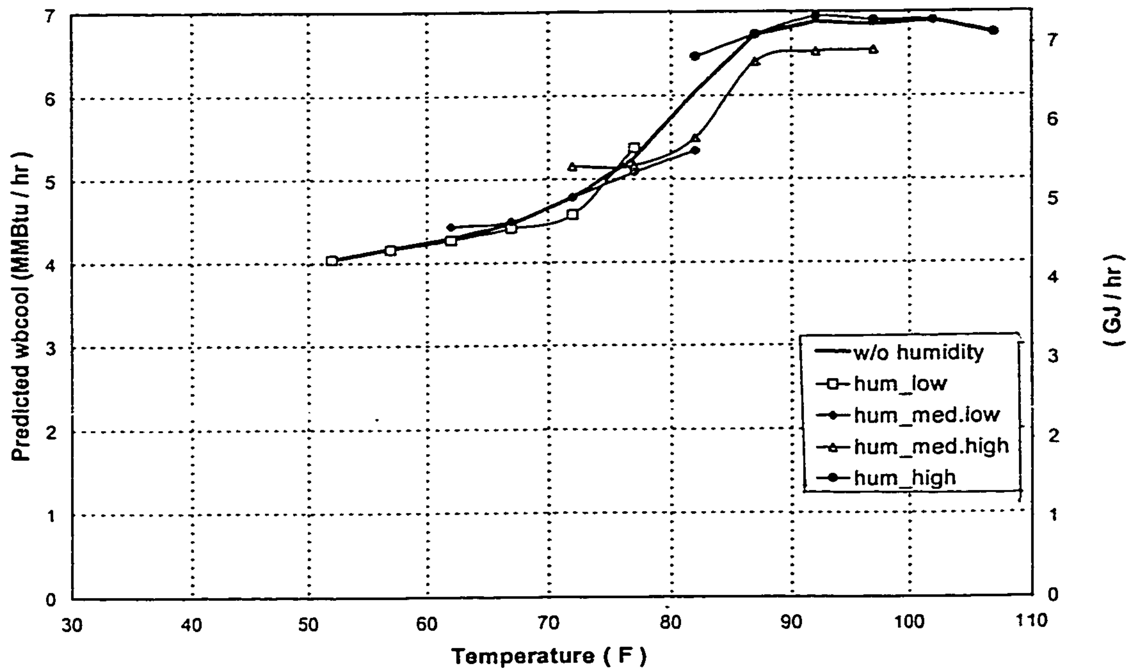
Summary: Dataset C was graphically and statistically analyzed and twelve preliminary daytypes were identified. These preliminary daytypes were tested to determine if significant difference exists, and resulted in six final daytypes. These final daytypes were then used for the calculation of binned energy consumption for the five energy types (WBELE, LTEQ, MCC, WBHEAT and WBCOOL). In addition, the WBCOOL data were also tested for the influence of thermal mass effect and latent load effects, and only the latent load effect was found to influential (small but significant) to this dataset and hence the data were sub-binned into four specific humidity groups and revised binned data were calculated. The resultant predictions were then compared against the actual data. The comparison plots for data that are not similar to dataset A (MCC and LTEQ) and WBCOOL data with humidity sub-binning are shown in Figures 4.6, 4.7 and 4.8.

Table 4.7 : Description of the WBCOOL data for checking the existence of latent-effects

Bin mid-point (F)	Number of observations	Standard deviation	Inter-quartile range
37	8	1.392	0.1
42	76	0.301	0.3
47	188	0.492	0.4
52	264	0.786	0.5
57	314	0.692	0.8
62	300	0.605	0.8
67	388	0.805	1.0
72	361	1.006	1.2
77	391	0.845	1.3
82	685	0.481	0.5
87	516	0.359	0.5
92	32	0.371	0.5
97	350	0.515	0.7
102	150	0.456	0.6



(a) Actual data for the daytype 1 - Fall weekdays



(b) Bin predicted data for daytype 1 - Fall weekdays

Figure 4.8 : Comparison of the bin predicted cooling energy use data. The continuous line represents the prediction without humidity sub-binning. The four symbols represent the four humidity sub-groups.

<u>Dataset D (d.trn)</u>: The analysis of dataset D was similar to dataset C except for the variation in daytyping. This dataset was tested for the existence of schedule-based operation in addition to the daytypes analyzed for dataset C. The testing for the existence of schedule- based operation was illustrated in steps 2 and 5 in Chapter 3. In dataset D, the MCC data shows that the building schedules can be separated into two modes: ON mode when the MCC use was greater than 61 kW, and OFF mode when the MCC use was less than 61 kW.

The initial daytypes were tested and revised using the multiple comparison procedures as shown in Chapter 3 and illustrated for dataset C. The revised daytypes are as follows: i) holidays and weekends (Christmas, New Year, federal holidays, and all weekends), ii) semester weekdays, and iii) Spring-break and semester breaks. These daytypes were then separated and tested for difference between daytypes. The resultant final daytypes are: i) semester weekday periods with MCC use greater than 61 kW, ii) Spring-break and semester break weekday periods with MCC use greater than 61 kW, iii) holidays and weekend periods with MCC use greater than 61 kW, and iv) all other periods with MCC use less than 61 kW. These daytypes were then retested and the results are summarized as shown in Table 4.8. All three comparisons show that the final daytypes are significantly different by marking the daytypes with different letters (A, B, C, and D) against the daytypes. The mean values of the WBELE energy data for each of the four final daytypes are 401.079 kW (semester weekday periods with MCC use greater than 61 kW), 306.233 kW (spring-break and semester-break weekday periods with MCC greater than 61 kW), 293.318 kW (holidays and weekend periods with MCC greater than 61 kW) and 205.955 kWh (all the periods for which MCC use was less than 61 kW).

The data were then grouped into these final daytypes and the binned energy consumption was calculated for weather dependent energy usage (WBCOOL and WBHEAT). Since the schedule effect is already included within the HOD variable binning, the primary daytypes were kept the same for the weather independent data. The binned energy consumption was then calculated for the final daytypes for the cooling (WBCOOL) and heating (WBHEAT) energy consumption data. Since the OFF mode of separation occurred during the early morning hours (02:00 a.m. to 05:00 a.m.) no separation

Table 4.8: Results of the multiple-comparison tests performed for revised daytypes for WBELE data for the dataset D.

(a) Waller's test

Waller-Duncan K-ratio T test for variable: WBELE
NOTE: This test minimizes the Bayes risk under additive loss and certain other assumptions.
Kratio= 100 df= 2264 MSE= 3558.99 F= 1519.743
Critical Value of T= 1.73434
Minimum Significant Difference= 7.1307
Means with the same letter are not significantly different.

Waller Grouping	Mean	N	DTK
A	401.079	919	1
B	306.233	292	2
C	293.318	269	3
D	205.955	788	4

(b) Duncan's test

Duncan's Multiple Range Test for variable: WBELE
NOTE: This test controls the type I comparison-wise error rate, not the experimentwise error rate
Alpha= 0.05 df= 2264 MSE= 3558.99

Number of Means	2	3	4
Critical Range	8.063	8.489	8.775

Means with the same letter are not significantly different.

Duncan Grouping	Mean	N	DTK
A	401.079	919	1
B	306.233	292	2
C	293.318	269	3
D	205.955	788	4

(c) Scheffe's test

Scheffe's test for variable: WBELE
NOTE: This test controls the type I experimentwise error rate but generally has a higher type II error rate than REGWF for all pairwise comparisons
Alpha= 0.05 df= 2264 MSE= 3558.99
Critical Value of F= 2.60883
Minimum Significant Difference= 11.502
Means with the same letter are not significantly different.

Scheffe Grouping	Mean	N	DTK
A	401.079	919	1
B	306.233	292	2
C	293.318	269	3
D	205.955	788	4

was needed for the weather independent data which were already binned against the Hour-of-the-Day (HOD). Therefore, the initial daytypes were used without change for weather independent data (WBELE, MCC and LTEQ).

The bin predicted and actual data were then compared for the WBELE, WBCOOL and WBHEAT data. The bin predicted WBELE data were compared against the actual data as shown in Figure 4.9. The predictions compared very well against the actual data as shown in the figure. Similarly the WBCOOL and WBHEAT were compared against the actual data as shown Figures 4.10 and 4.11. In this energy type (i.e., WBCOOL), the actual energy use has a wide variation for the temperature bins above 42°F (5.6°C). The inverse bin prediction is the representative mean value of the data in each bin and therefore follows the same pattern as the actual data. However, these predicted values tend to reach only up to 2.5 MMBtu/hr (2.64 GJ/hr) while the actual data varied up to 4.5 MMBtu/hr (4.75 GJ/hr). This feature may be the result of the short data set that does not include any peak cooling season (summer period). The data for this building were mainly from the winter and spring periods (10/13/90 - 04/30/91). A longer dataset might have improved the predictions.

For the WBHEAT energy use the predicted data was comparable to the actual data as shown in Figure 4.11. The identified daytyping also helped to improve the predictability of the actual data. However, care should taken when interpreting the model statistics for this data because the range of the data is very small (0.0 - 1.95 MMBtu/hr). The data were tested for the existence of thermal mass effect and latent load effect and verified to have the influence of the latent load effect only (results are similar to the output for Dataset C as shown in Tables 4.6 and 4.7). The data were then sub-binned for humidity and binned energy values were calculated. The predicted data (WBCOOL) with and without humidity sub-binning were then compared as shown in Figure 4.12. The predictions with humidity sub-binning are shown by the narrow line with *diamond* symbols while the without humidity sub-binning was plotted as wide lines formed by *square* symbols. For the bins between 42°F and 77°F the inverse bin predictions with humidity sub-binning tend to reach higher and dip lower than the predictions without humidity sub-binning (Figure 4.12).

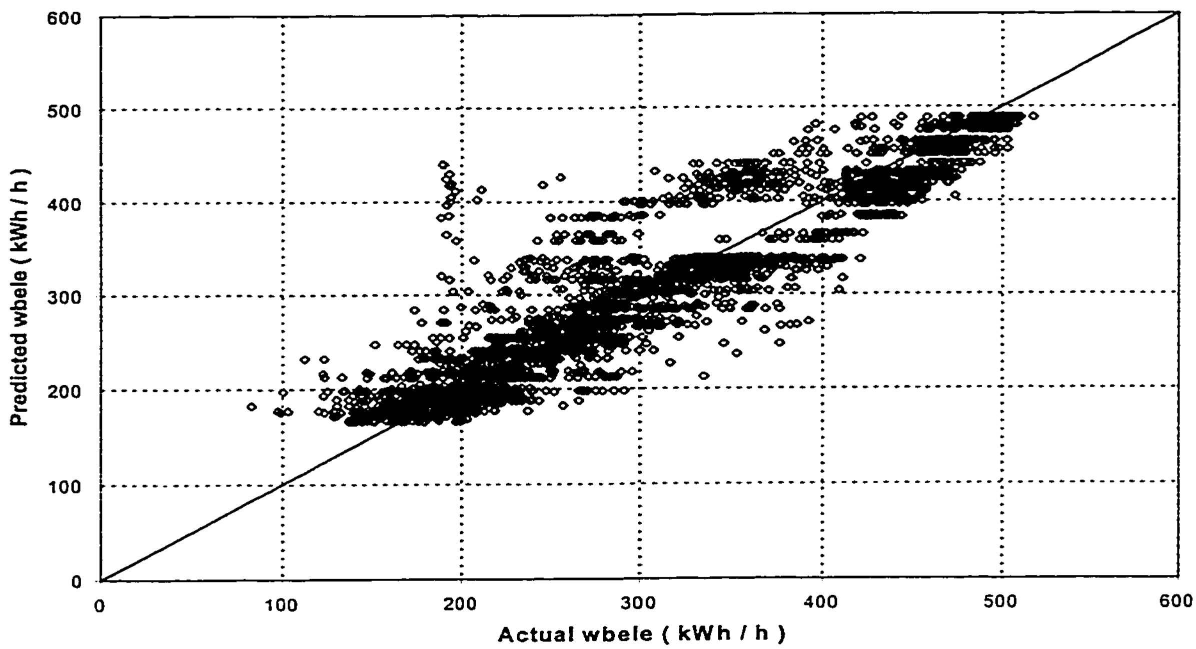


Figure 4.9 : Comparison of the bin predicted and actual data of the WBELE for the dataset D (Business building : 10/13/90 - 04/30/91).

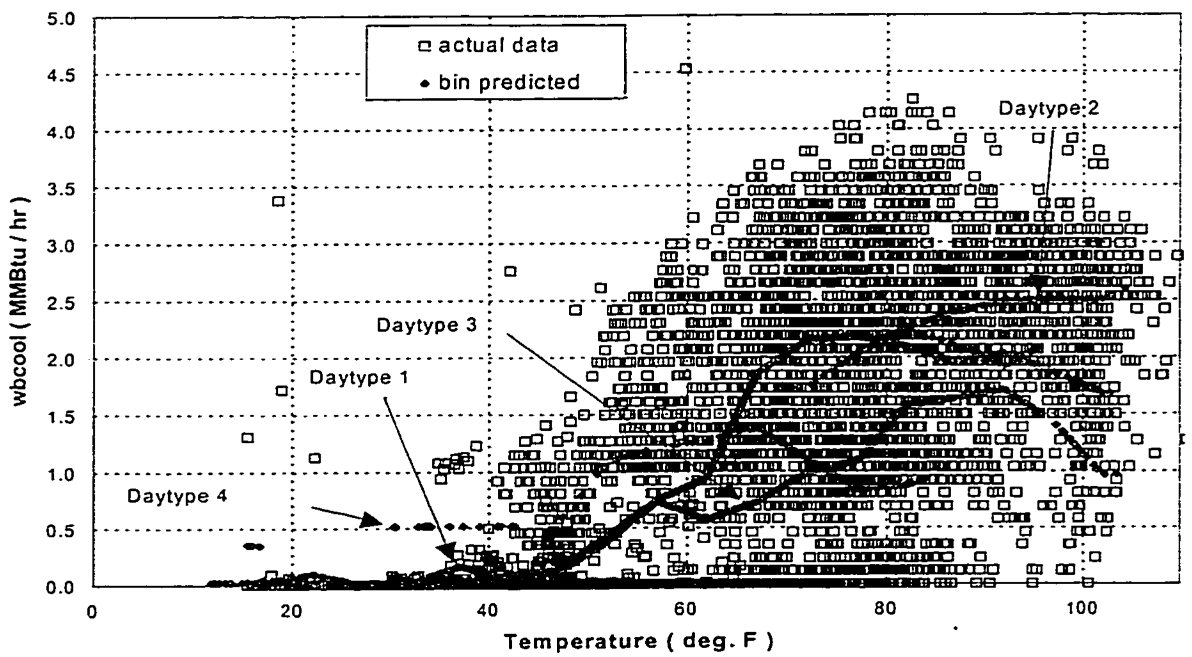


Figure 4.10: Comparison of the bin predicted and actual data of the WBCOOL for the dataset D (Business building : 10/13/90 - 04/30/91).

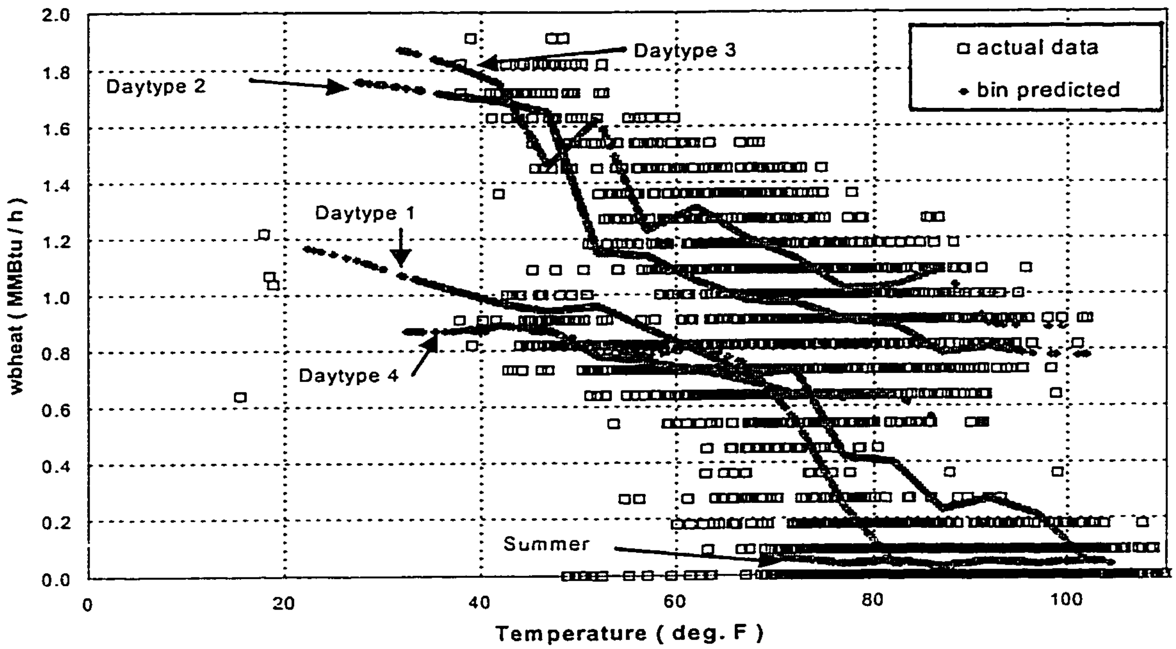


Figure 4.11: Comparison of the bin predicted and actual data of the whole-building heating energy (WBHEAT) for the dataset D.

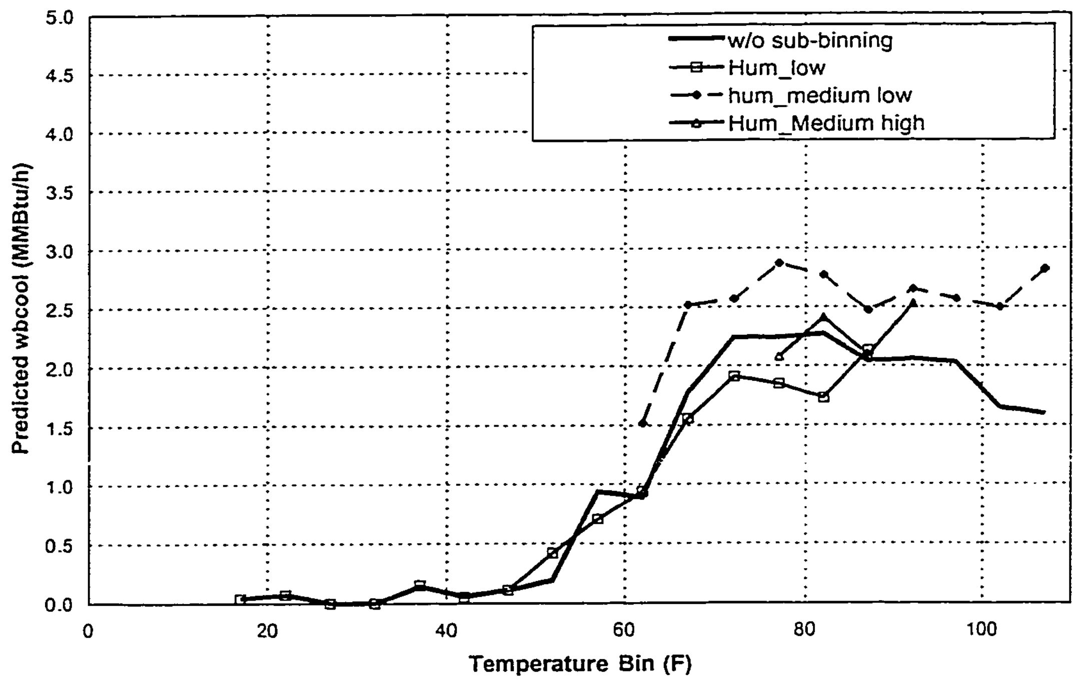


Figure 4.12: Comparison of the bin predicted WBCOOL data with and without humidity sub-binning for a single daytype (semester period ON group) in the dataset D.

Summary: Dataset D was analyzed graphically and tested statistically to remove extreme outliers. The resultant data were analyzed and four preliminary daytypes were identified. The daytypes were then further separated using the schedules (ON / OFF) identified from the MCC energy use data. The resultant daytypes were then tested and revised to form four final daytypes. These final daytypes were then used for the weather-dependent energy data (WBCOOL and WBHEAT), while the initial daytypes were found to be the best daytypes for the weather independent data. The WBCOOL data were further tested for the influence of thermal mass effect and latent load effects for the improved predictions. Since only latent load effects were present in the dataset, the WBCOOL data were further sub-binned into humidity groups, and improved binned energy data were calculated for this energy type. The resultant predictions were then compared against the actual data as shown in Figures 4.9, 4.10, and 4.11.

Summary

The inverse bin methodology was illustrated using three datasets (Dataset A, C and D). The simple inverse bin method was illustrated using dataset A from the ASHRAE Predictor Shootout I competition. Datasets C and D from the second competition (the ASHRAE Predictor Shootout II) were used for the demonstration of detailed daytyping with humidity sub-binning and detailed daytyping with schedule-based daytyping, respectively. In the next chapter, a comparison of energy data from forward and inverse bin analysis methods will be presented.

CHAPTER V
COMPARISON OF FORWARD AND INVERSE BIN METHODS

Introduction

In general, the operation of commercial buildings is complex because of the existence of multiple zones, a variety of installed equipment, changes in occupancy, and different modes of operation. One of the reasons for creating an inverse bin method was the idea that it could be directly compared with the results from a forward bin method for the same building. Such a comparison yields some useful insights into the building's performance. In order to make a successful comparison of the results from the forward and the inverse bin methods a building should be selected with the following criteria in mind:. i) The building should be small enough to be analyzed and described within this study. ii) The building should have minimal or no simultaneous cooling and heating, and iii) The building should be monitored and have a reasonable period of necessary WBELE, WBCOOL and WBHEAT data available for an inverse bin analysis. With these factors in mind, after a careful review of the available site information, the Russell A. Steindham (RAS) building at the University of Texas at Austin was chosen for the demonstration of the comparison. This section of the thesis presents a comparison of the inverse bin and forward bin methods using the RAS building as a case study building.

Description of the Building

The RAS building was constructed in 1956 and has a floor area of 56,800 square feet. This four story building was constructed with a reinforced concrete frame and floors, concrete blocks and face brick walls, three inch lightweight fill and insulation for the roof, and single-pane, clear, operable glass windows. Each floor is 12 feet in height and the drop-ceiling is about 10 feet above the floor. The glazing covers approximately 5,292 square feet surface and has no shading. Further description of the building is given in the Appendix B. A front view of the case study building and time series plots of the measured data are provided in Appendix B.

The building is used for ROTC classes and offices. The classrooms are primarily occupied between 7:30 a.m. to 6:30 p.m. during the weekdays. The offices are occupied between 7:30 a.m. and 5:30 p.m. during weekdays. The laboratory spaces are available from 7:30 a.m. to 9:30 p.m. on weekdays. The heating and cooling energy for this building is supplied by the campus cogeneration plant. There were two constant air volume dual duct (CAVDD) air-handler units (AHU) serving the building. These were retrofitted to variable air volume dual duct (VAVDD) units in April 1991. Hot water is generated in a steam-fed heat exchanger and supplied to the AHU by a 2 hp (1.492 kW) pump. AHU1, which is located in the east wing mechanical room, serves the east wing of the building. Likewise AHU2 (located in the west wing) serves the west half of the building. Lighting is provided by 4 foot fluorescent fixtures with 40 watt lamps. The AHUs are controlled by a central energy management system and operated 18 hours per day during the weekdays. The building space is maintained at approximately 75°F. The lighting is controlled by individual room switches. The CAVDD AHUs were reported as having a wasteful blending of hot and cold air and lower than necessary coil set point temperatures. There was no partial operational mode of the equipment during the partial load or occupancy periods.

The building was first analyzed by the ASHRAE standard bin method (i.e., forward bin method) and binned energy consumption for the two periods (occupied and unoccupied) was calculated. During the calculation phase, some factors (diversity factors and load factors) were assumed from the known building and operating information. Then the building was also analyzed using the fully layered inverse bin method using the given building description and operating schedule information. The inverse bin energy values were then compared with the values calculated from the forward bin method to see what sort of useful information was provided.

Forward Bin Analysis

The standard or forward bin method, shown schematically in Figure 2.2, is an ASHRAE design methodology used for sizing the equipment and calculating the energy consumption of a building. Since this exercise is an illustration of the forward bin analysis for hourly and annual energy calculations, only a simple analysis was performed for the building. The variations of operating schedules and indoor loads are accounted for by performing separate calculations for different time periods. However, the equipment was assumed to be operating under two conditions: 1) ideal conditions (i.e., systems were assumed to operate at 100% or without any losses), and 2) actual design condition where the air-side performance was simulated with a simplified system model.

A simple forward bin analysis uses building data, climatic data, indoor load data and system and equipment data and involves the following calculation steps: Envelope loss coefficient, ground loss coefficient, internal loads for occupied and unoccupied periods, balance point temperatures, binned energy calculations, and annual energy calculations. The building construction, envelope, occupancy, internal loads information and operating schedules are used for the calculation of building loss coefficients and balance point temperatures for various modes of operation. The system, equipment and schedules are also used with weather information for the binned energy calculations.

Envelope Loss Coefficient (UA_{elc})

The building loss coefficient is an equivalent loss or gain from the envelope and infiltration loads. This is calculated by sequential calculation of the loss coefficients for the walls, roof/ceiling, doors, windows, and infiltration. The loss coefficient is the inverse of the equivalent resistance multiplied by the wall area. The equivalent resistance is calculated by analogy to electrical resistance. Therefore, the units for resistance and loss coefficients are F-hr-sq.ft./Btu and Btu/hr-F-sq.ft. respectively. The individual resistance values for construction material and air are available in Cooling and Heating Load Calculation Manual (McQuiston and Spitler, 1992). The building-construction description is given in Appendix B.

Walls: The equivalent resistance is the combination of internal and external air film resistance and the wall resistance. The total wall area is 16,983 sq.ft. Therefore, the total R-values values for the given construction are equal to 5.29 F-hr-sq.ft./Btu for winter and 5.37 F-hr-sq.ft./Btu for summer. Therefore, the loss coefficients are 3,208 Btu/hr-F and 3,160 Btu/hr-F for Winter and Summer respectively.

Roof/Ceiling: This calculation is similar to the wall calculations except the construction materials are different. The total roof area is 13,500 sq.ft. Therefore, the equivalent resistance and the loss coefficient are 7.569 F-hr-sq.ft./Btu and 1,782 Btu/hr-F for Winter and 7.649 F-hr-sq.ft./Btu and 1,765 Btu/hr-F for Summer respectively.

Doors: This calculation is similar to the wall calculations except the construction materials of doors are used. The total door surface area is 144 sq.ft. and, therefore, the loss coefficients are 53 and 52 Btu/hr-F for Winter and Summer respectively.

Windows: This calculation is similar to the wall calculations except for the construction materials. The total (windows) surface area is 5,249 sq.ft. and, therefore, the loss coefficients are 635 and 630 Btu/hr-F for Winter and Summer respectively.

Infiltration: The infiltration is calculated by the volume of air gain (or loss) and expressed in cubic feet per minute (CFM) or air changes per hour (ACH). The infiltration is calculated using the crack length method for this study. This is performed by estimating air volume loss/gain for the given construction and for an estimated crack length. The calculated values for the walls, windows, and doors are 375 CFM, 4,816 CFM and 480 CFM, resulting in a total infiltration of 5,671 CFM or approximately 0.63 ACH. Therefore, the loss coefficients for Winter and Summer seasons are 6, 615 and 6,737 Btu/hr-F.

The envelope loss coefficient is the summation of all the envelope loss coefficients. Therefore the total envelope loss coefficients for Winter and Summer are 12,293 and 12,344 Btu/hr-F, respectively.

Ground Loss Coefficient (UA_{glc})

The equivalent ground loss coefficient is a combined loss coefficient value from 13,465 sq.ft. basement floor (0.036 Btu/hr-F-sq.ft.) and 9050 sq.ft. of basement wall (0.085 Btu/hr-F-sq.ft.). Therefore, the values are calculated for the given construction as 1,258 Btu/hr-F.

Heat Gains (q_{gain})

Occupied: The occupied period (7:30 a.m. - 6:30 p.m.) total internal gain is the combination of the heat load generated by solar radiation, people, and lights and equipment. A nominal peak occupancy of 250 with a diversity factor of 0.75 for classrooms and 245 occupants with a diversity factor 0.5 for offices was assumed for the calculation. Therefore, total heat gain from occupants (seated light work) is 139,500 Btu/h. The total equipment and lighting loads were calculated to be 28,400 and 21,300 Btu/hr (from a peak 1.0 W/sq.ft lighting and 0.75 W/sq.ft. from equipment with a diversity factor of 0.5). Therefore, the total occupied period heat gain is approximately 189,200 Btu/hr.

Unoccupied: The internal heat gains during the unoccupied period is similar except for the reduced occupancy levels and the absence of some loads (i.e., solar radiation heat gain). The majority of the unoccupied hours falls in the night-time during which solar heat gains and heat gains from occupants are nearly zero. The lights and equipment usage is at 40% of the nominal values after time averaged for weekends and nights (with 80% day time, 40% evenings and 20% otherwise). Therefore, the unoccupied period heat gains are 47,780 Btu/hr.

Building Loss Coefficient (UA_{blc})

The building loss coefficient is the equivalent total of the envelope and ground loss coefficients. The ground temperature (T_G) varies during the seasons and it is related to the average outdoor temperature (T_{out}) of the year. In general this can be assumed to be approximately 10°F below the average outdoor temperature for Summer and about 10°F above the average outdoor temperature for the Winter. The envelope temperature difference is approximately the difference between the room thermostat set-point and the envelope bin mid-point.

Balance Point Temperature (T_{bpt})

The balance point temperature is the temperature at which the building needs neither heating nor cooling. This is calculated by balancing the heat losses to the heat gains of the building. Therefore, the balance point can be calculated for occupied and unoccupied periods for cooling and heating separately. The generalized equation (with positive for heat loss and negative for heat gain) is

$$q_{building\ loss} + q_{ground\ loss} - q_{gain} = q_{system\ input}$$

At the balance point no heating or cooling is needed to maintain the comfort of the space and hence the system input is zero. Therefore, the equation will be simplified as

$$UA_{blc}(75 - T_{out}) + UA_{glc}(75 - T_G) = q_{gain}$$

With the substitution of $T_G = (T_{out} + 10)$ for Winter and $T_G = (T_{out} - 10)$ for Summer, the balance points can be calculated. These are:

$T_{bal,occ} = 46$ F and $T_{bal,unocc} = 65$ F for heating

$T_{bal,occ} = 47$ F and $T_{bal,unocc} = 65$ F for cooling

System Performance Factor

The building system (secondary system) is the delivery mechanism by which conditioned air is introduced into the space to provide comfortable room temperatures and humidity levels. These systems must be sized for the most extreme conditions expected. However, those conditions are usually present only a small fraction of time in a year. Thus the majority of time, the secondary systems must operate at part-load conditions. In this state energy is used inefficiently. The dual duct constant air volume (DDCAV) system installed in the case study building provides necessary comfort by mixing the constant volume cold and hot air streams to satisfy requirements of the zone. During this process, the system encounters inefficiencies due to heat transfer in the hot and cold deck, during mixing in the zone mixing boxes, and due to leakage and other losses (Knebel, 1983). Due to the changing occupancy and operational pattern in the building and because of the fluctuating or changing weather conditions, the DDCAV system incurs inefficient operation resulting in performance loss.

The system loss factor which is often available for a building designer would help estimate the energy consumption at various conditions. However, in the above case study such parameters were not available. Therefore, the calculated energy use at various temperature bins should be termed as forward binned energy for the ideal conditions. The binned energy use for the actual conditions were therefore obtained from the ASHRAE simplified energy analysis procedure as detailed in the ASHRAE RP 865 report (Haberl et al., 1997). These simulations are often nearly as accurate as the detailed DOE-2 simulations for majority of the buildings (Brotherton et al., 1987; Haberl et al., 1997). Therefore, the actual binned energy use was calculated using the simplified system simulation of the building conditions for two zones (interior and exterior) and for two modes (occupied and unoccupied period) of operation. This energy use is termed as actual binned energy consumption because of its inclusion of the system loss effects in the simulation. A sample input parameters used for actual energy use is given in Appendix D.

Binned Energy Calculations

The binned energy consumption can then be calculated using the expression below.

Heating Energy Use $q_{h,bin} = (T_{bal} - T_{out})^{+}\ UA_{blc}$,

where '+' the energy use will be calculated only when the value within the parenthesis is positive. Likewise the cooling energy use is calculated with $(T_{out} - T_{bal})^{+}$ instead of $(T_{bal} - T_{out})^{+}$ in the above expression.

Annual Energy Calculations

The annual energy use is the summation of the binned energy use times the number of hours of the occurrence of the specific bin. Therefore, this is expressed as

Annual heating energy use $= \Sigma\ q_{h,bin}\ NH_{bin}$,

where NH is the number of hours of occurrence.

The binned and annual energy values from the forward bin analysis of the RAS building are summarized in Table 5.1. The binned and annual energy calculation for each bin was calculated as shown in the above expressions. For example, the cooling and heating energy calculations for the 77°F bin during the occupied period is calculated as follows: The frequency of 77°F bin is the number of hours when the ambient temperature (i.e., outdoor dry-bulb temperature) falls within 74.49°F and 79.5°F. For the given dataset the frequency of the bin is 288 hours out of 2623 total hours or approximately 10.98%. Then the cooling energy for this bin is the difference between the balance-point temperature and the bin mid-point times the loss coefficient. Hence the cooling at this bin mid-point is equal to temperature difference times the building loss coefficient or (77- 47) *12,344 /1,000,000 MMBtu = 0.370 MMBtu.. Likewise, the heating energy for this bin is calculated as =$(46 - 77)^{+}$ * 12,293 / 1,000,000 = 0 MMBtu because the value within the parenthesis is below zero (i.e., the heating will be zero when the temperature is above the heating balance-point temperature).

Table 5.1 : Forward (Classical) bin analysis of the Russell A. Steindham building, University of Texas at Austin.

1= occupied 2=unoccupied	Bin Mid Point	Bin Frequency	Frequency as Percent of total hours	cooling energy (w/o losses)	heating energy (w/o losses)	cooling energy actual	heating energy actual
1	42	6	0.23	0.000	0.049	0.000	0.799
1	47	36	1.37	0.000	0.000	0.000	0.797
1	52	63	2.40	0.062	0.000	0.000	0.794
1	57	64	2.44	0.123	0.000	0.095	0.708
1	62	113	4.31	0.185	0.000	0.215	0.595
1	67	138	5.26	0.247	0.000	0.465	0.483
1	72	274	10.45	0.309	0.000	0.563	0.371
1	77	288	10.98	0.370	0.000	0.645	0.321
1	82	181	6.90	0.432	0.000	0.656	0.260
1	87	118	4.50	0.494	0.000	0.650	0.010
1	92	19	0.72	0.555	0.000	0.665	0.008
2	42	10	0.38	0.000	0.283	0.000	0.887
2	47	58	2.21	0.000	0.221	0.000	0.886
2	52	72	2.74	0.000	0.160	0.000	0.885
2	57	106	4.04	0.000	0.098	0.084	0.787
2	62	161	6.14	0.000	0.037	0.191	0.661
2	67	214	8.16	0.025	0.000	0.414	0.537
2	72	296	11.28	0.086	0.000	0.486	0.412
2	77	266	10.14	0.148	0.000	0.547	0.357
2	82	91	3.47	0.210	0.000	0.557	0.290
2	87	40	1.52	0.272	0.000	0.550	0.013
2	92	9	0.34	0.333	0.000	0.564	0.010
Total		2623	100	3.85	0.85	7.35	10.87

The actual cooling and heating can generally be calculated by multiplying the calculated values by a factor to account for the effect system inefficiencies. In this study the actual binned energy use was obtained by the simplified system simulations with the ASHRAE RP865 calculation algorithm. The sample input and calculation scheme from the ASHRAE RP 865 that was used for the derivation of the actual energy use is given in Appendix D. These values are shown in the seventh and eighth columns, while the ideal forward binned energy values are shown in the fifth and sixth columns in Table 5.1. The percentage of annual energy use for any bin can be calculated as follows: The percentage hours of occurrence of the relevant bins times the bin energy use. This value multiplied by the total number of cooling hours would provide the total annual cooling energy consumption. For example, if we take the occupied period bin for 77°F. This occurs 288 hours or 10.98% of the time. Therefore, the annual energy for the 77°F bin is equal to the percentage of times the bin occurs times the bin energy use time the total cooling hours for the period or (10.98/100) * 0.645 * 2623 hours = 185.8 MMBtu. Once the energy consumption in each bin is calculated, the total annual energy consumption is the sum of the energy use for all the bins for both the occupied and unoccupied periods. The calculated annual cooling energy consumption for the period is 1138 MMBtu.

Inverse Bin Analysis

To perform the inverse bin analysis on the RAS building the whole-building heating and the cooling energy use were visually inspected by plotting the hourly whole-building cooling and heating energy use against outdoor dry-bulb temperatures as shown in Figures 5.1 and 5.2. In Figure 5.2, there are two different clusters of heating energy values for temperatures below 65°F. The heating energy consumption of 0.4 - 1.0 MMBtu/hr results from a normal operation while the shut-down mode of operation results in heating energy values between 0.0 - 0.2 MMBtu/hr. The data points falling in the range below 65°F that were in between the points that were equal to zero and the primary sloped cluster around 0.6 MMBtu/hr represents points that were recorded during hours that included a partial shut-down.. This feature is an indication of a schedule-based operation. This may be the result of the late-night and weekend shut-off as given in the building description. This can be seen by the low and zero energy values for the same temperature bins where the building also shows a consumption in the range of 0.6 - 1.0 MMBtu/hr in the WBHEAT plot (Figure 5.2). Therefore, the data were further studied by plotting the WBHEAT and WBCOOL data against Hour-of-the-Day (HOD) as shown in Figure 5.3 and 5.4. The HVAC equipment shut-off was observed within the hours from 23:00 hr. to 05:00 hr, and consequently these data are grouped as an unoccupied data set. Using this behaviou the data were separated into two groups forming occupied (ON) and unoccupied (OFF) groups.

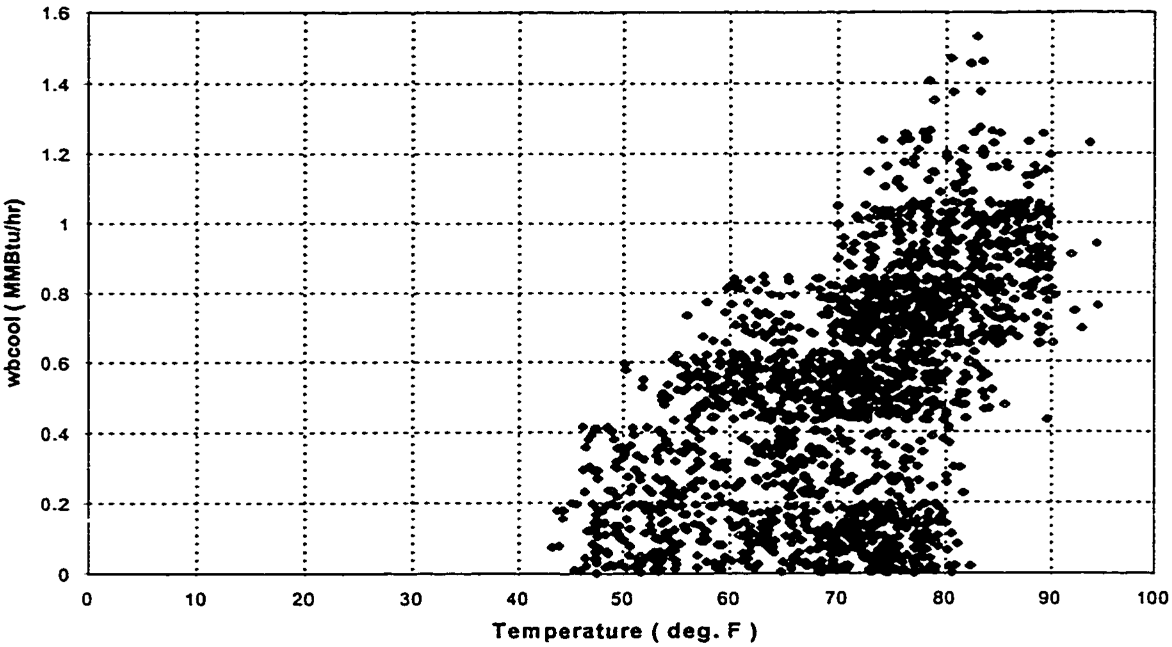


Figure 5.1 : Whole-building cooling (WBCOOL) energy consumption for RAS building for the baseline period between 10/13/90 - 03/31/91.

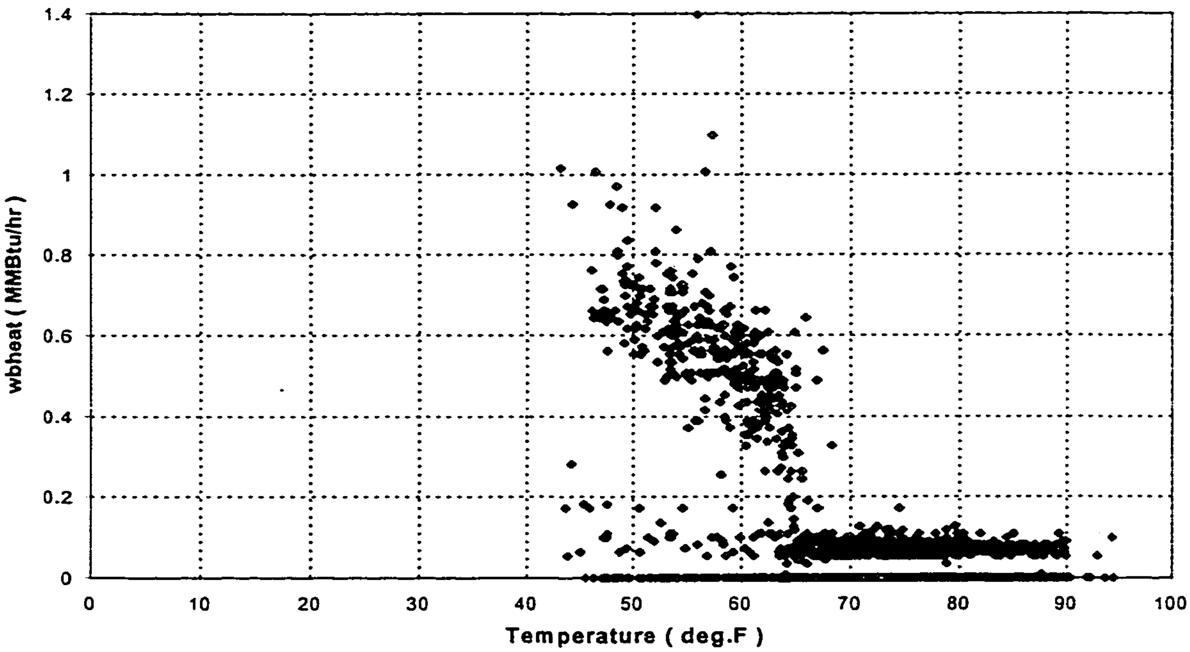


Figure 5.2 : Whole-building heating (WBHEAT) energy consumption for RAS building for the baseline period between 10/13/90 - 03/31/91.

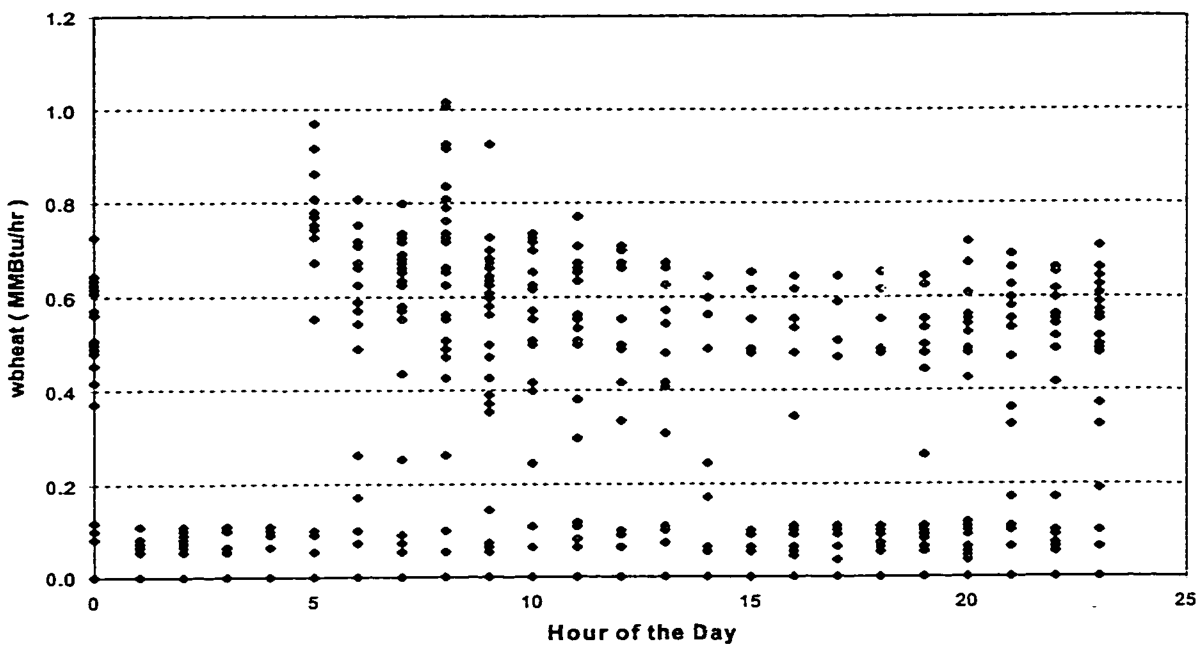


Figure 5.3 : WBHEAT scatter plot versus Hour-of-the-day to illustrate the early-morning hour shut-off of the equipment.

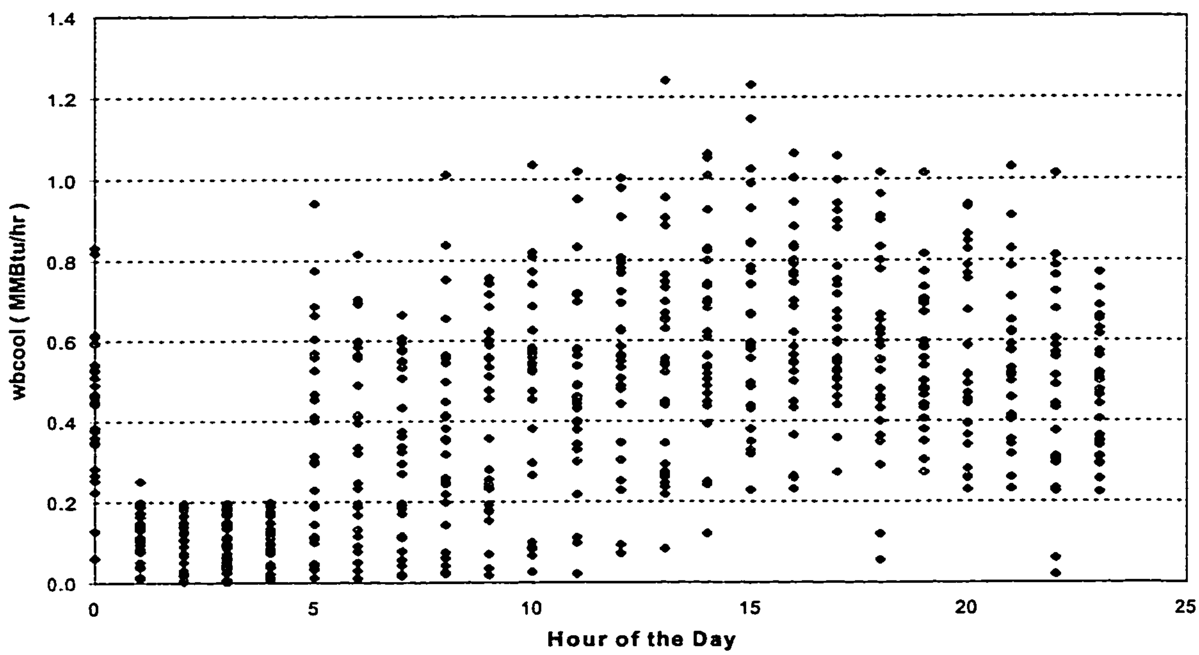


Figure 5.4 : WBCOOL scatter plot versus Hour-of-the-day to illustrate the early-morning hour shut-off of the equipment.

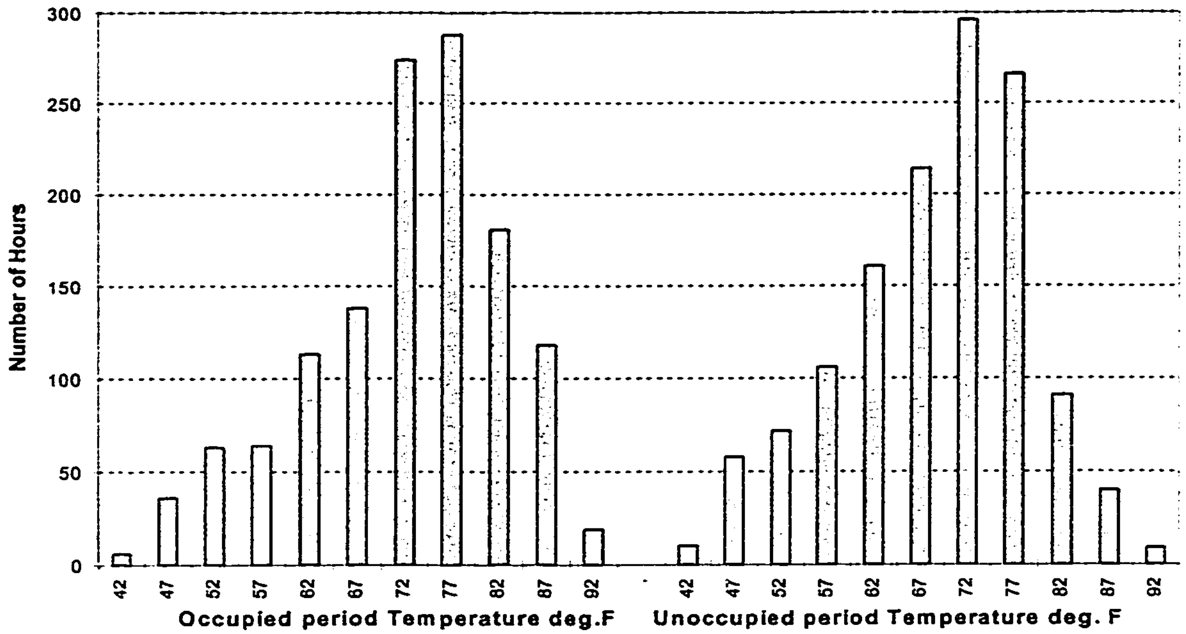


Figure 5.5 : Frequency distribution of the occupied and unoccupied groups used in the inverse bin analysis of the RAS building

The frequency distribution of the data that is provided in Table 5.1, column #3 is also shown graphically in Figure 5.5. The frequency distribution shows the number of hours of occurrences in each temperature bin. For example, the 72°F bin has occurred 274 times during the occupied period as shown in the left plot. It also occurred 296 times during the unoccupied period as shown on the right plot. The grouped data were also checked by multiple comparison procedures and verified to determine whether they are from significantly different groups. These data were then binned in the ASHRAE standard 5°F bins and the energy values for the cooling and heating data were then calculated. The resultant energy values from the inverse bin analysis are shown in Table 5.2. The SAS processing routine used for the inverse bin analysis is given in Appendix D.

Comparison of the Binned Energy Values

The binned values for the cooling energy consumption (WBCOOL) and heating energy consumption (WBHEAT) for the forward bin analysis (Table 5.1) and inverse bin analysis (Table 5.2) are compared in Figures 5.6 and 5.7. These values are plotted for the occupied and unoccupied periods and for the three calculation schemes separately for the WBCOOL in Figure 5.6. Similarly the WBHEAT energy use is compared in Figure 5.7. The forward bin energy consumption without the system losses is labeled as Forward_ideal. The values were calculated as UA overall * (Tbpt-Tout). The second line shows the values for the forward bin analysis with the inclusion of system losses, and is labeled as the Forward_actual trace. The inverse bin energy values are the average of all the energy consumption for the specific bin and thus account for the actual measured system losses.

In these plots the cooling energy values for the occupied period (Figure 5.6 left plot) using the inverse analysis are higher than the values calculated by the forward bin analysis for all the bins except the 67°F and 72°F bins. The probable cause of the difference between these two bin analyses may be the higher than expected system losses in the

Table 5.2: Binned energy values by the inverse bin analysis of the Russell A. Steindham building, University of Texas at Austin for the baseline period 10/13/90 - 3/31/91.

1= occupied 2=unoccupied	Bin Mid Point	Bin Frequency	Frequency as Percent of total hours	Cooling energy by inverse bin	Heating energy by inverse bin
1	42	6	0.23	0.16	0.87
1	47	36	1.37	0.19	0.72
1	52	63	2.40	0.19	0.64
1	57	64	2.44	0.36	0.58
1	62	113	4.31	0.45	0.32
1	67	138	5.26	0.46	0.04
1	72	274	10.45	0.56	0.02
1	77	288	10.98	0.71	0.02
1	82	181	6.90	0.86	0.03
1	87	118	4.50	0.87	0.02
1	92	19	0.72	0.83	0.03
2	42	10	0.38	0.02	0.47
2	47	58	2.21	0.06	0.38
2	52	72	2.74	0.08	0.38
2	57	106	4.04	0.21	0.38
2	62	161	6.14	0.22	0.23
2	67	214	8.16	0.24	0.05
2	72	296	11.28	0.32	0.03
2	77	266	10.14	0.38	0.02
2	82	91	3.47	0.59	0.03
2	87	40	1.52	0.75	0.02
2	92	9	0.34	0.67	0.03
Total		2623	100	9.18	5.30

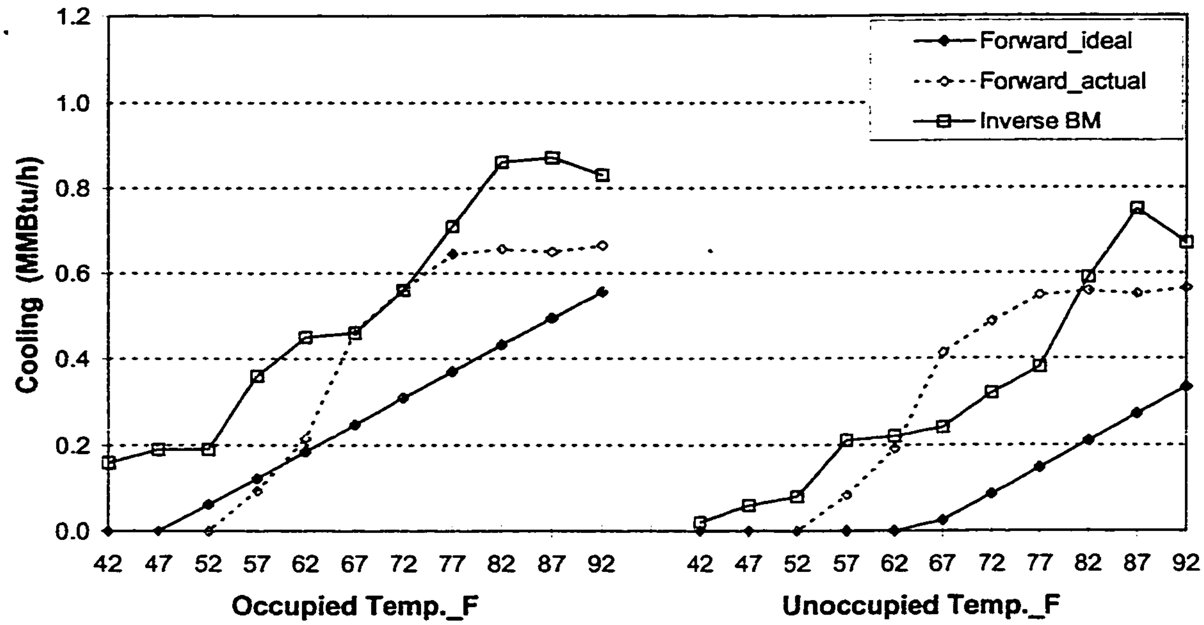


Figure 5.6 : Comparison of the binned cooling (WBCOOL) energy use for the baseline period 10/13/90 - 3/31/91.

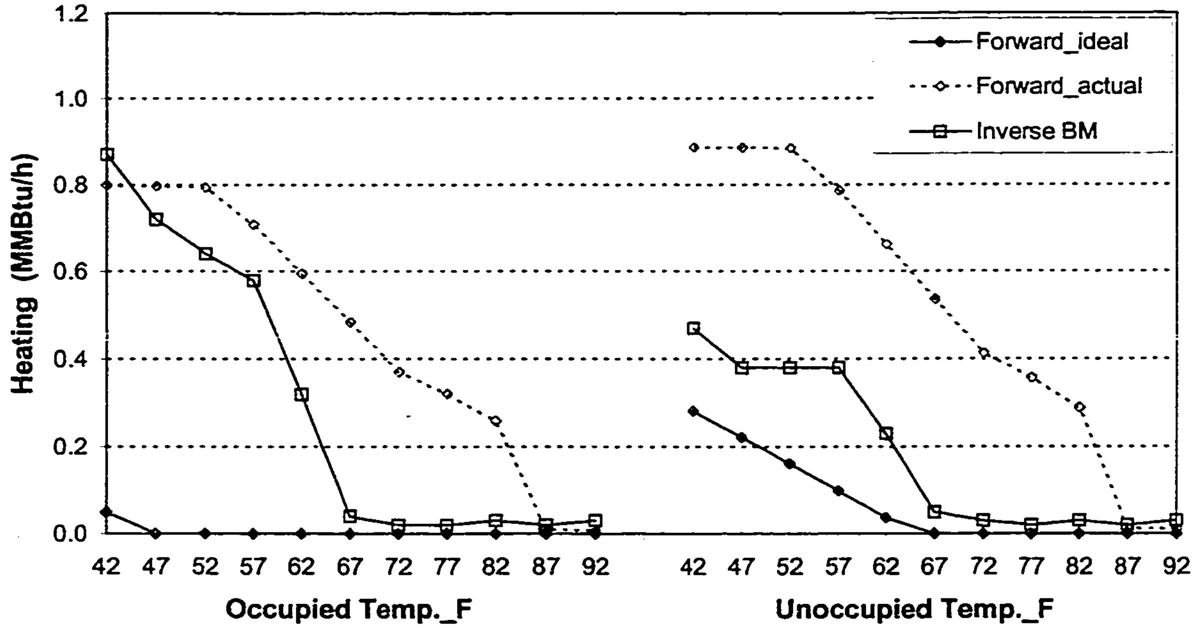


Figure 5.7 : Comparison of the binned heating (WBHEAT) energy use for the RAS building for the baseline period 10/13/90 - 3/31/91.

existing DDCAV system. The difference for the bins below 62°F may be the system efficiency losses due to mixing of the hot and cold deck air streams. The higher occupied period cooling energy consumption in the bins above 72°F may be due to the operation beyond its normal operation. The drop in consumption below the trend (for both inverse and Forward_actual analyses) observed in the 87°F and 92°F degree bins may be due to a smaller proportion of the latent load at higher temperatures. This reason and its effect were discussed in Chapter III and illustrated graphically in Figure 3.10 using dataset A. This feature was also observed in energy values plotted for the unoccupied period. Furthermore, similar differences between the Forward_actual and the inverse analyses for both WBCOOL and WBHEAT for 47°F through 67°F bins may be the result of the unnecessary mixing losses associated with the DDCAV systems.

The comparison shows that the inverse bin cooling values were higher than the forward-actual values except the 67°F and 72°F occupied bins and were actually lower than the 67°F, 72°F and 77°F for the unoccupied period bins. This can be indicating the following: 1) Except for the five bins indicated above, the existing system is not as efficient as a DDCAV system. 2) higher internal electric load estimates may be driving the cooling high during the 67°F, 72°F and 77°F bins during the occupied period. 3) Except for the 42°F occupied period bin the existing system is much more efficient than a DDCAV system simulation.

The comparison of the forward binned energy values (ideal and actual) against the inverse binned energy values has pointed out the operational deviations due to system inefficiencies or changes in design conditions associated with the system. Therefore, this comparison can also serve as a commissioning tool.

Summary

A brief summary of the forward and inverse bin analyses for the Russell A. Steindham building have been presented in this chapter. The results from these two analyses were also presented and compared. The usefulness of these types of analyses as diagnostic tools was also outlined.

In the next chapter, a discussion of the results from the application of the fully layered inverse bin method are presented to the case studies shown in the previous chapter. The chapter on conclusions, and future directions will follow the next chapter.

CHAPTER VI
RESULTS AND DISCUSSION

In the previous chapters, the fully layered inverse bin methodology was applied to three different case study buildings and the inverse bin method was compared to the forward bin method. The results for those case studies are summarized and presented in this chapter along with the results from several other monitored buildings. The detailed results presented in this section cover the following case studies: 1) Simple inverse bin method with basic daytyping applied to Dataset A, 2) an inverse bin method with detailed daytyping and sub-binning applied to Dataset C, and 3) an inverse bin method with schedule-based daytyping and sub-binning applied to Dataset D. Furthermore, the results from selected case study buildings participating in the LoanSTAR program are also presented and compared with the existing LoanSTAR models that are used to calculate savings.

Simple Inverse Bin Method

In the Predictor Shootout I only the description of dataset A was provided for the analysis by the organizers and did not contain information about the building type or operation (Kreider and Haberl, 1994). Therefore, only the basic features of the inverse bin method were used for developing the baseline model from dataset A. The detailed daytyping was also not possible for this case study because of the absence of the information about the building operation in the contest. Consequently only the simple inverse bin method (when the first six steps of the fully layered inverse bin method was applied to a dataset) was applied to the dataset A and the generated model was then compared against the answers given by the Shootout I organizers.

The comparison of the bin predicted energy values against the training data set presented in the previous chapter (Figures 4.3, 4.4 and 4.5) shows that the inverse bin method represented the ('training') data very well. The generated inverse bin model was then applied to the test data set (i.e., a.tst) and the prediction was then compared against the answers for evaluating the performance of the inverse bin model. The model statistics (i.e., performance parameters) were then calculated and tabulated with the competition winners as shown in Table 6.1. The detailed description of these parameters is given in Appendix A.

Table 6.1 : Comparison of the inverse bin method prediction against the competition winners (Kreider and Haberl, 1994: © ASHRAE, Inc. from ASHRAE Transactions. Used by permission *)

Predictions		Winner1	Winner2	Winner3	Winner4	Winner5	Winner6	Bin Method
Wbele	CV	10.36	11.78	11.89	16.95	16.1	12.79	12.3
	MBE	8.06	10.5	8.01	6.2	12.56	7.33	9.72
Wbcool	CV	13.02	12.97	13.69	14.32	18.06	12.78	13.18
	MBE	-6.37	-5.95	-6.67	-8.25	-9.79	-5.31	-6.2
Wbheat	CV	15.24	30.63	31.65	29.75	28.08	30.98	32.97
	MBE	-5.84	-27.33	-27.55	-26.19	-21.26	-27.1	-29.16
Average	CV	12.87	18.46	19.08	20.34	20.75	18.85	19.48
	MBE	6.75	14.59	14.08	13.55	14.54	13.24	15.02
Global	CV	10.46	14.53	16.35	16.48	16.55	16.58	--
	MBE	5.15	10.99	10.59	10.17	10.95	10.01	--

Note: CV and MBE values in percent as defined. The Global values are combined for the prediction of dataset A and dataset B.

The winning entries show remarkable accuracy in predicting the dependent variables for the testing data set. Furthermore, all the winning entries used some form of connectionist approach (Mackay, 1994; Ohlsson et al., 1994; Feuston and Thurtell, 1994; Stevenson, 1994; Iijima and Takeuchi, 1994; Kawashima, 1994). Neural networks of various designs and training methods received the top honors while the predictions by traditional methods (as used by the entrants) were found less accurate (Kreider and Haberl, 1994). The average hourly electricity use in the testing data set was roughly 100 kW less than the training dataset. This is because of several academic departments (computer science and aerospace engineering) having moved out of their offices in the Zachry

* Reprinted with permission from "Predicting Hourly Building Energy Use: The Great Energy Predictor Shootout – Overview and Discussion of results," by Kreider, J. and Haberl, J.S., 1994, ASHRAE Transactions, ASHRAE, Vol. 100, Pt. 2, pp. 1038 - 1052. Copyright 1994 by the American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc. A copy of the letter of permission is included in Appendix E.

Engineering Center (ZEC) and into newly constructed facilities in another building. The vacant offices were then filled by faculty and staff from other departments that existed within the building (Kreider and Haberl, 1994). This had the effect of reducing both the electricity and the chilled water use, while slightly increasing the hot water use to make up for the lower internal heat gain. Conversation with the building operators also indicated that the outside air dampers were shut in mid December during the extreme cold conditions and were not reopened until later in the Spring which would help explain why the contestants under predicted the heating. The faculty move information was not provided to the contestants. Therefore, the accuracy levels achieved by the top six winning entrants were within the range of experimental errors. In this outset, the results from the inverse bin method are tabulated in Table 6.1 with the competition winners for the comparison. This comparison would also provide a benchmark to rank the performance of the inverse bin method.

The energy values for the three energy types (WBELE, WBCOOL, and WBHEAT) for the training data (i.e., a.trn) and testing data (i.e., a_ans.dat) were compared in Figures 6.1, 6.2 and 6.3 respectively. This comparison shows the predictability of the withheld testing data set using the given training data set. The comparison of the inverse bin predicted and the actual data are also shown graphically in Figures 6.4, 6.5 and 6.6 for electrical energy use (WBELE), cooling energy use (WBCOOL) and heating energy use (WBHEAT) use respectively. These comparison plots reiterate the features observed in the performance parameters compared in Table 6.1 and the energy predictions in Table 6.2. All the predictions have shown considerable bias error: WBELE data shows positive bias error (Table 6.1) indicating the predictions are higher than the actual measured energy use (Table 6.2). The thermal energy predictions have shown negative bias error (Table 6.1) or predicted values are lower than the actual data (Table 6.2). The reason for this bias is that the change occurred in the building at the end of the training period described earlier in this section. This has resulted in a drop of about 100 kW in the testing data period which immediately followed (Figure 6.1), resulting in the predictions having a positive bias error. The changes in occupancy and internal load have also caused a slightly higher WBHEAT energy use to compensate for the loss of internal heat gain (Figure 6.3). One cause for the increase in the WBCOOL was due to outside air dampers being closed to avoid freezing of the chilled water supply system as documented in published literature (Bronson, 1992; Kreider and Haberl, 1994). This may be the reason that the thermal energy predictions have a negative bias. The size of the bias is a representation of the predominant operational mode and the type of HVAC system involved.

Furthermore, a comparison of the predictions by the competition winners to the bin method prediction also shows the following features:

1. The heating models have the highest average error (mean bias error-MBE) and unbiased error (i.e., CV-RMSE) of the three predicted variables. The reason for the mean bias error was outlined earlier. The reason for the higher CV-RMSE is due to the smaller magnitude of the heating energy values. This also points to the fact that a slightly different model statistics would be a better choice for comparison across the different predictions (i.e., use of normalized values instead of the actual energy values).

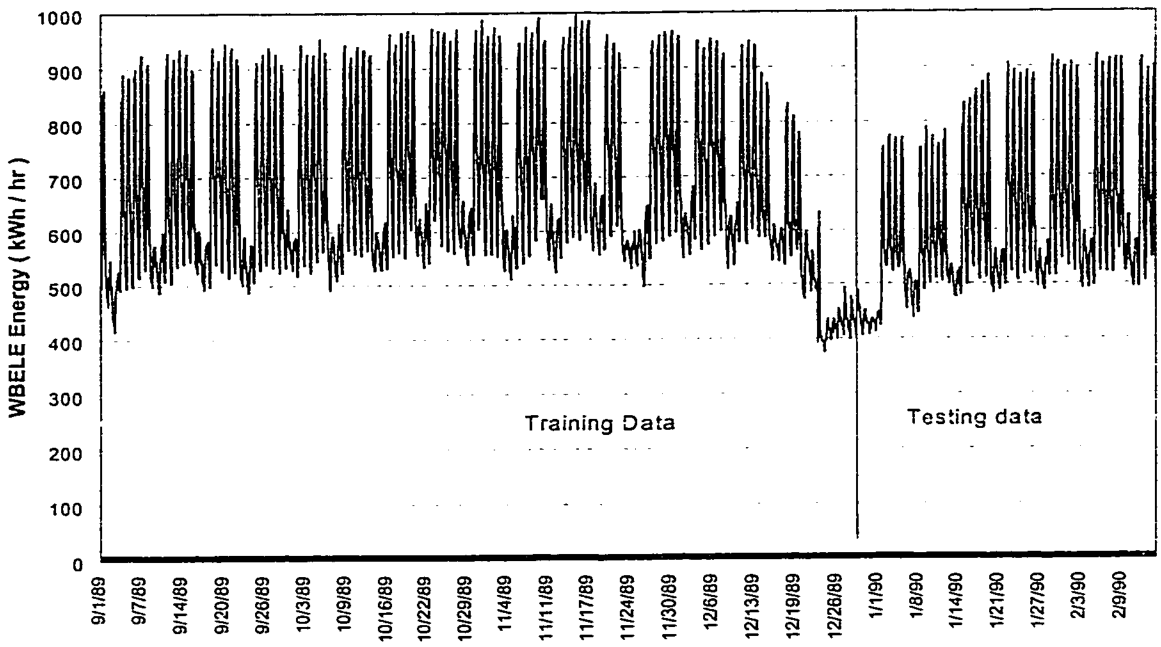


Figure 6.1: Comparison of the WBELE data for the training (a.trn) and testing (a.ans) datasets. The time series is marked by a vertical line to separate the datasets.

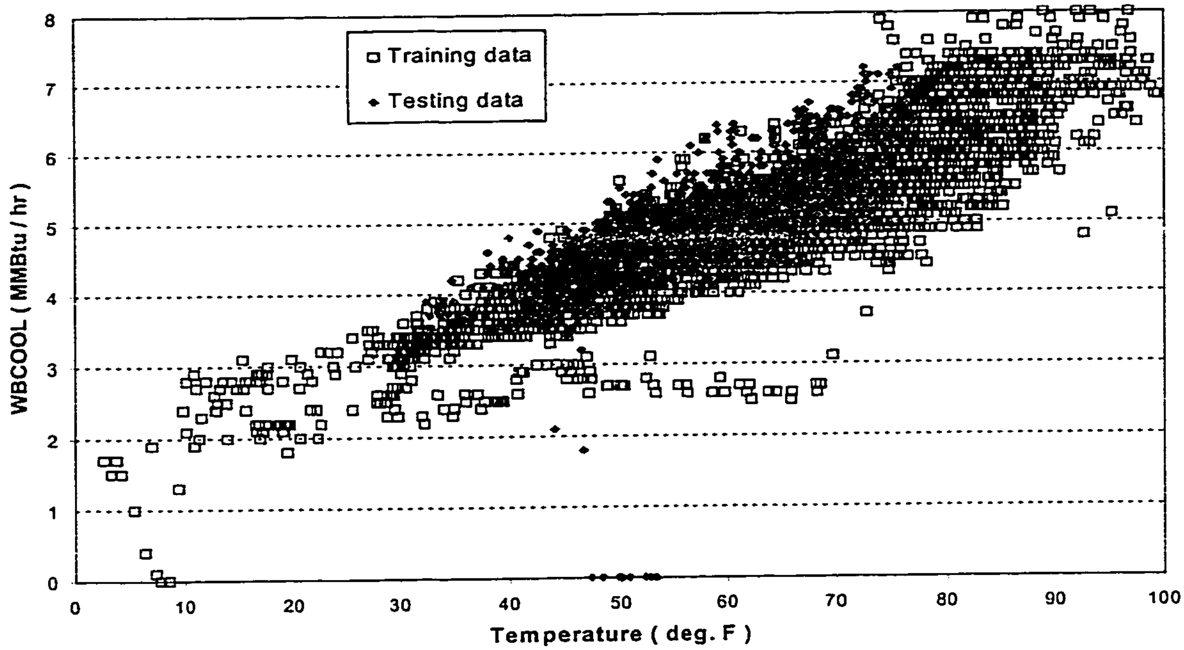


Figure 6.2: Comparison of the WBCOOL data for the training (a.trn) and testing (a.ans) datasets. Separate symbols were used to show the difference between the two datasets.

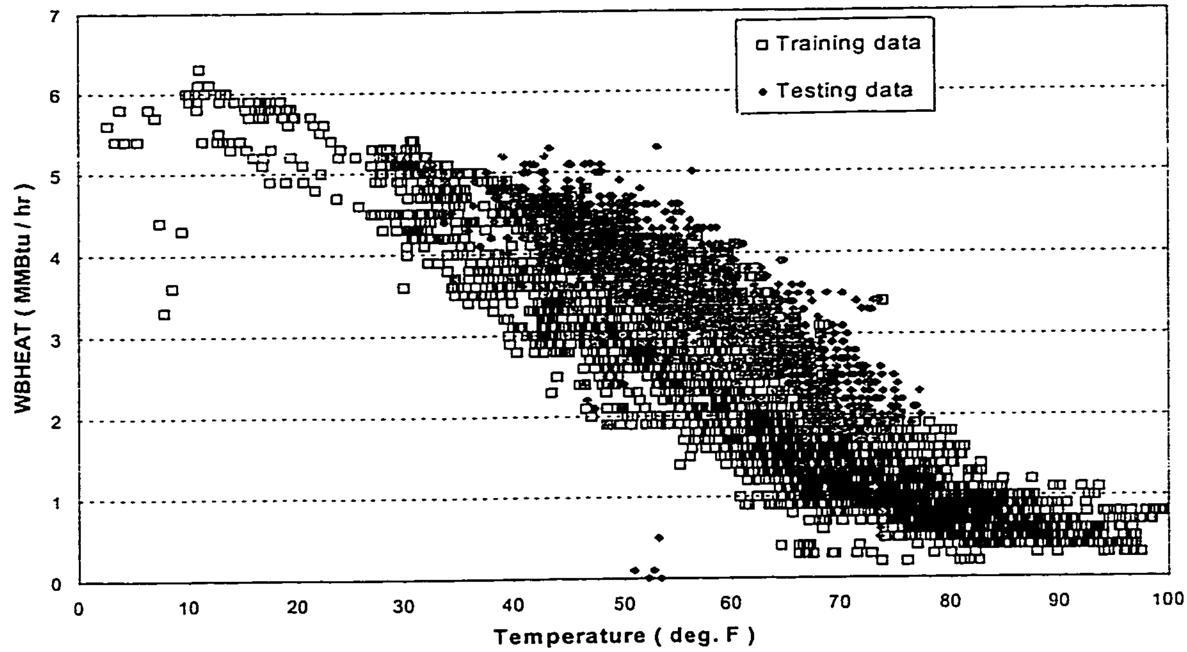


Figure 6.3: Comparison of the WBHEAT data for the training (a.trn) and testing (a.ans) datasets. Separate symbols were used to show the difference between the two datasets.

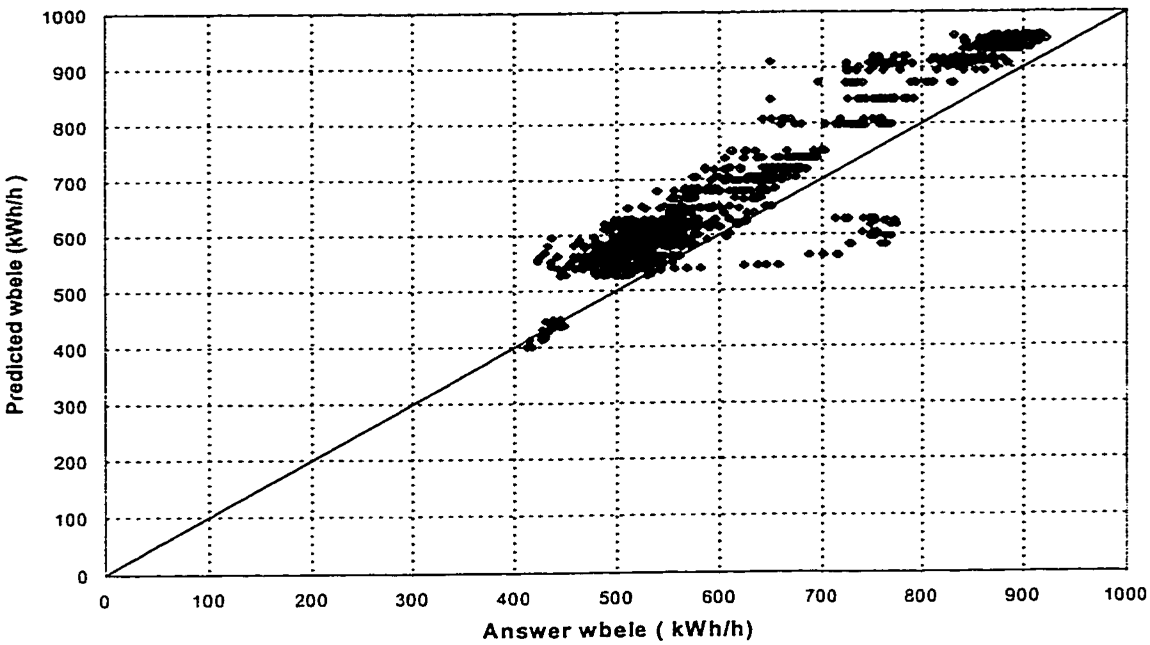


Figure 6.4 : Comparison of the inverse bin prediction and the actual whole-building electric (WBELE) energy use data from the dataset A.

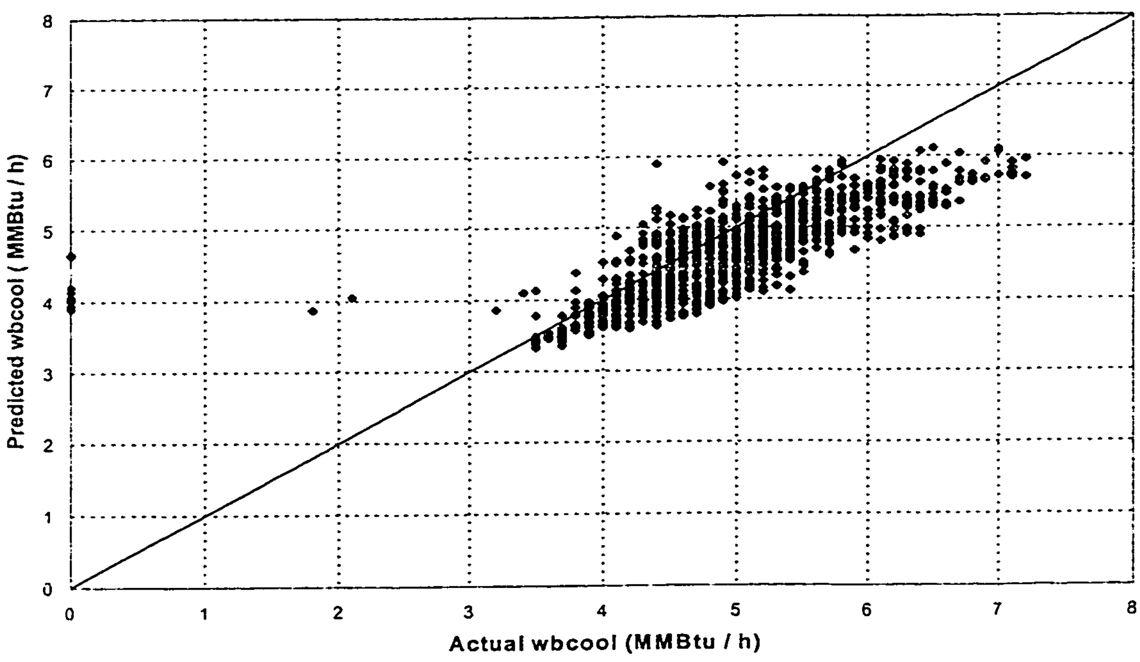


Figure 6.5 : Comparison of the inverse bin prediction and the actual whole-building cooling (WBCOOL) energy use data from the dataset A.

2. The bin method predictions were comparable with the predictions by the winners in this competition. The bin method predictions would have ranked in the middle (i.e., fourth) among the predictions as shown (i.e., average CV) in Table 6.1. This is a remarkably good showing for the bin method since the winning entries used various artificial neural network models with different pre-processing calculation schemes and calculation/hidden layers (see Table 6.3). Table 6.1 shows the model statistics (MBE and CV-RMSE) for each of the energy types and an overall parameter for the dataset (i.e., all three energy variables). The comparisons of the overall CV-RMSE values show that the inverse bin method predictions are as equally impressive as other artificial neural network or other connectionist methods (Tables 6.1 and 6.2).

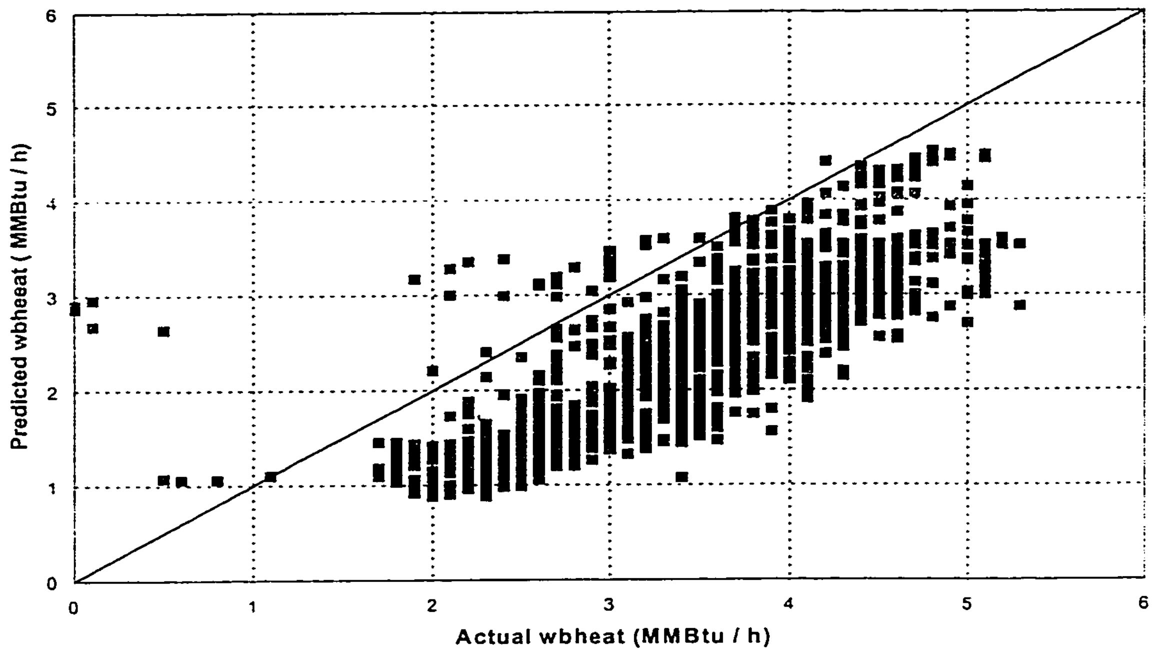


Figure 6.6 : Comparison of the inverse bin prediction and the actual whole-building heating (WBHEAT) energy use data for the dataset A.

Furthermore, the inverse bin prediction was also compared against other generally used methods that were made available as part of the ASHRAE competition (Kreider and Haberl, 1994). The comparison is summarized in Table 6.4. Some of these methods (2-P, 4-P, MLR, Principal Component Analysis-PCA and Fourier Series Equivalent Thermal

Parameters - FSETP) are generally applied for weather dependent data and Fourier Series-FS is only applied for weather independent data. Therefore, only the applicable model statistics are provided in Table 6.4. The comparison shows that the bin prediction performed well against the other methods. On the other hand, some of these methods (i.e., 2-P, 4-P) have comparable model statistics and are very simple to develop. Therefore, in an energy conservation program where the program cost is a factor the preferred model selection for a specific application should consider the following information: i) the performance, ii) the relative complexity, iii) the data requirements, and iv) the model development time. A sample comparison of the model development time for the various statistical techniques used for the LoanSTAR program and the inverse bin method is given in the Appendix D.

Table 6.2 : Comparison of the inverse bin method prediction and the competition winners against the actual energy use data

	Actual Data	Winner1	Winner2	Winner3	Winner4	Winner5	Winner6	Bin Method
Wbele	800,956	865,470	885,031	865,080	850,626	901,537	859,623	878,801
Wbcool	6,324	5,921	5,941	5,902	5,802	5,705	5,988	5,932
Wbheat	4,481	4,220	3,256	3,246	3,308	3,528	3,267	3,175

Table 6.3 : The methodologies used by the winning predictions

Predictions	Analysis Method
Winner #1	ANN with Bayesian non-linear modeling scheme
Winner #2	ANN by Feed-forward multi-layer perception network
Winner #3	ANN with pre and post processing schemes
Winner #4	ANN with Conjugate gradient scheme
Winner #5	Piecewise linear regression
Winner #6	ANN – standard neural network

ANN- Artificial neural Network calculation scheme

Inverse Bin Method with Detailed Daytyping

The inverse bin method with detailed daytyping was also applied to Dataset C from the Predictor Shootout II (Haberl and Thamilseran, 1996). The whole-building cooling (WBCOOL) was modeled with and without humidity sub-binning. The prediction was then compared against the measured data for the training and testing periods. Details of the application of the inverse bin methodology to this dataset were described in Chapter IV. The comparison of the inverse bin fit and actual data was similar to dataset A (comparison of WBELE, WBHEAT and WBCOOL variables of dataset A were shown in detail under Chapter IV). Consequently, only the new energy variables (MCC and LTEQ) were compared for the training dataset as shown in Figures 4.6 and 4.7. The baseline prediction was then performed to fill-in the missing or 'removed' data in the provided training data set (i.e., c.trn) with detailed daytyping and with humidity sub-binning. This sub-dataset was then extracted and compared against the provided answers. The model statistics were then calculated for all the energy types and shown in Table 6.5.

Table 6.4 : Comparison of the performance of the predictions by some widely used methods (Kreider and Haberl, 1994: © ASHRAE, Inc. from ASHRAE Transactions. Used by permission *)

Predictions		2-P linear regression	4-P linear regression	Multi-linear regression-MLR	Principal Component Analysis	Fourier Series Model	Fourier Series with ETP	Inverse Bin Method
WBELE	CV	-	-	-	-	11.86	-	12.3
	MBE	-	-	-	-	8	-	9.72
WBCOOL	CV	13.52	13.56	13.92	14.09	13.4	12.88	13.18
	MBE	-6.43	-5.55	-6.2	-7.17	-5.63	-5.22	-6.20
WBHEAT	CV	29.96	30.72	31.34	28.68	47.72	31.16	32.97
	MBE	-26.44	-27.2	-27.84	-24.98	-37.94	-28.12	-29.16
Average	CV	-	-	-				19.48
	MBE	-	-	-				15.02

Note: The CV and MBE values were extracted from Kreider and Haberl (1994). The average was calculated where applicable.

* Reprinted with permission from "Predicting Hourly Building Energy Use: The Great Energy Predictor Shootout – Overview and Discussion of results," by Kreider, J. and Haberl, J.S., 1994, ASHRAE Transactions, ASHRAE, Vol. 100, Pt. 2, pp. 1038 - 1052. Copyright 1994 by the American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc. A copy of the letter of permission is included in Appendix E.

Table 6.5 : Comparison of the model statistics for the inverse bin method and the predictions by the winners for the dataset C (i.e., c.trn from Engineering Center) (Haberl and Thamilseran, 1995).

Energy Type	Parameter	Winner1	Winner2	Winner3	Winner4	Bin Method
WBELE	CV	2.9032	8.6475	3.1205	13.2116	3.1647
	MBE	-0.0907	-6.5555	0.2722	-1.8049	-0.1237
MCC	CV	3.5751	3.2811	3.2803	3.4728	3.1796
	MBE	0.3613	0.4871	0.4817	0.5929	0.2165
LTEQ	CV	4.2476	3.4384	4.4560	25.6786	4.2927
	MBE	-0.7068	0.3971	0.5106	-2.6949	-0.4096
WBCOOL	CV	7.0312	8.8770	7.1312	8.2585	9.4499
	MBE	-1.3372	-3.4214	-0.8917	-3.0309	-1.6890
WBCOOL	CV	*	*	*	*	9.3143
...w/ sub-bin	MBE	*	*	*	*	-1.8390
WBHEAT	CV	16.591	35.372	21.276	39.202	24.654
	MBE	-2.143	-10.978	-3.099	-15.310	-2.874
Overall	CV	6.8707	11.923	7.853	17.965	8.961
	MBE	*	*	*	*	*

* - not available or not calculated.

In this competition three of the four top entrants used some form of neural network method. In contrast to other winners, the second best performance came from a method that utilized judicious input variable selection and processing. In this method a net-based daytyping routine for weather independent channels and calendar-based daytyping with individual hour multiple regressions for the weather dependent channels were used. The performance of this model and that of the fully layered inverse bin method show that a careful choice of daytyping or statistical regression performs just as well as a neural network. The methods used by the four winning entries are described in detail in published literature (Dodier and Henze, 1996; Katipamula, 1996; Chonan et al., 1996; Jang et al., 1996) and summarized in Table 6.6.

This comparison also shows that bin prediction performs very well and are comparable in performance to the winning predictions. The predictions by the inverse bin method perform remarkably well and could be ranked in the middle (i.e., third best). The MCC energy predictions were found to be the best among entrants while the WBCOOL predictions were the poorest. This may be due to the fact that the use of internal load as one independent parameter was not possible in the inverse bin analysis unlike the other methods. Like dataset A (discussed earlier), the higher unbiased errors observed for the weather dependent energy variables may be because the mean energy consumption values are small when compared to the similar values of the weather independent energy variables. In addition, some of the WBHEAT energy values are approximately zero during the summer period, resulting in are even smaller mean value for WBHEAT data. The effect of a small mean value for the WBHEAT variable has in turn affected the predictions by all the competition participants resulting in relatively high CV values. This is evident from the good fit observed in the comparison plot (Figure 6.7). The plot also shows significant number of data points with values under to 1 MMBtu/hr (1.055 GJ/hr) which occurred mainly during the summer period. The data was aggregated for the entire period for the actual data and compared against the inverse bin predictions as shown in Table 6.7.

Table 6.6 : The description of the methodologies used by the four top predictions (Haberl and Thamilseran, 1995)

Identification	Analysis method used
Winner #1 (E4)	10 neural networks, 2 hidden layers of 25 units, then activation, single output layer with linear activation. Input variable selection using Wald's test
Winner #2 (E3)	Statistical daytyping for weather independent variable, weekday-weekend MLR models for each hour of the day for weather dependent variable.
Winner #3 (E1)	Bayesian nonlinear regression with multiple hyper-parameters. Manual outlier removal.
Winner #4 (E2)	Auto associative feed forward neural networks with Hyperbolic tangent transfer function.

The model statistics were also calculated for the WBCOOL energy prediction with the humidity sub-binning as described in Chapter IV. The CV-RMSE and MBE values, shown in Table 6.5 in the row below WBCOOL and marked by "*w/ sub-bin*", were 9.3143 and -1.839 respectively. The CV value show a slight improvement over the similar predictions without the humidity sub-binning, but the MBE value is 0.15% larger suggesting that the model without sub-binning would be preferred for savings determination. This was also observed in the binned energy values (Fall weekday daytype) shown in Figure 4.8 in Chapter IV, where the with humidity sub-binning energy values showed only a small improvement over the without humidity sub-binning predictions.

Table 6.7 : Comparison of the total energy consumption and the inverse bin predictions for the dataset C for the baseline period 11/90 - 11/27/90.

Energy Type	Actual Data	Bin Method
Wbele (kWh)	1,008,607	1,009,716
MCC (kWh)	224,493	224,979
Lteq (kWh)	397,652	396,003
Wbcool (MMBtu)	5,407	5,315
Wbcool w/ sub-bin (MMBtu)	5,407	5,307
Wbheat (MMBtu)	1,427	1,386

Inverse Bin Method with Schedule-based Daytyping

In the previous case studies, the dataset does not show any evidence of schedule based operation and hence was not daytyped for schedule-based operation. However, the MCC data in dataset D show clear evidence of the schedule-based operation as shown in Figure 3.18. Therefore, this dataset (Dataset D) was daytyped using the schedules observed in MCC energy use data. The daytyping technique employed in the inverse bin method includes procedures for standard calendar-based daytyping, and a schedule-based daytyping. The application of the resultant daytypes was shown in Chapter IV for dataset D. The resultant final daytypes were tested as shown in Table 4.8.

The three multiple-comparison procedures, used for the daytyping step, show that the selected daytypes were significantly different. Therefore, the identified daytypes were taken as final daytypes. The binned energy values were then calculated and used to fill-in the evaluation data that was marked as -99 in the provided training data set (i.e., c.trn). This dataset was extracted from the training data to create the evaluation data set. The inverse bin prediction with schedule-based daytyping and with humidity sub-binning was then compared using these evaluation data.

The binned energy predictions for the WBELE, MCC, LTEQ, WBCOOL, and WBHEAT data were compared against the given answers (i.e., the *d0.dat* data file in the Predictor Shootout II dataset). The comparisons for the WBELE, WBCOOL and WBHEAT are similar to Figures 4.9, 4.10 and 4.11 respectively. The comparison of the MCC and LTEQ are similar to the results from dataset C shown in Figures 4.6 and 4.7 in both time series and scatter plots. The comparison of the model statistics for the predictions by the winners and the inverse bin method are shown in Table 6.8. The aggregated total energy values are compared for the actual data and inverse bin predictions in Table 6.9. The comparison (Table 6.8) shows that the inverse bin method is capable of providing a prediction as accurate as several of the winners'. The individual energy type ranked within the top three predictions and the overall value provided the third best performance as shown in Table 6.8. The predictions were further improved by the use of humidity sub-binning in the cooling energy variable (WBCOOL). The statistics for the predictions with humidity sub-binning were 44.21 (CV-RMSE) and -12.34 (MBE). Therefore, the overall values for CV(RMSE) and MBE are 26.70 and -3.420 respectively.

Table 6.8 : Comparison of the model statistics for the inverse bin method and the predictions by the winners for evaluation data for the dataset D (i.e., d.trn from Business building) (Haberl and Thamilseran,, 1995).

Energy Type		Winner1	Winner2	Winner3	Winner4	Bin Method
WBELE	CV	16.54	20.87	17.05	26.84	14.99
	MBE	2.289	-1.609	2.79	4.222	1.194
MCC	CV	22.29	17.76	17.54	41.05	23.52
	MBE	0.321	4.145	4.405	-0.135	0.446
LTEQ	CV	17.05	21.16	21.32	43.96	17.06
	MBE	0.683	-3.487	-3.481	14.637	0.251
WBCOOL	CV	42.05	40.98	55.95	53.02	51.81
	MBE	-11.463	-8.773	-3.672	-16.522	-19.253
WBHEAT	CV	36.85	24.74	46.05	47.35	33.71
	MBE	-12.252	-4.861	-11.131	-8.31	-6.653
Overall	CV	26.96	25.1	31.58	42.45	28.22
	MBE	-4.085	-2.917	-2.218	-1.222	-2.889

Table 6.9`: Comparison of the total energy consumption and the inverse bin predictions for the dataset D.

Energy Type	Actual Data	Bin Method
Wbele (kWh)	265,647	268,819
MCC (kWh)	107,214	107,692
Lteq (kWh)	68,367	68,539
Wbcool (MMBtu)	1,642	1,326
Wbheat (MMBtu)	508	474

Consequently the overall performance of the inverse bin predictions with humidity sub-binning improved to the second best model statistics. The retrofit savings are the difference between the baseline energy prediction and the post-retrofit energy consumption (Claridge et al., 1991). Therefore, the aggregated energy values are compared in Table 6.9 for dataset D.

The comparisons indicate that the bin method predictions with detailed daytyping, which includes a scheduled-based daytyping compared favorably against the winning predictions that often use complex neural nets. The addition of humidity sub-binning enhanced the predictability and in turn improved the rank of the inverse bin predictions (winner #2 has the best prediction for the dataset). The comparison of the prediction on the type of predictor variable (weather dependent or weather independent) provides further insights into the comparisons. The weather independent energy predictions (WBELE, MCC, and LTEQ) have shown that the overall model statistics of the inverse bin prediction are better than all the winning predictions. However, the overall value of the

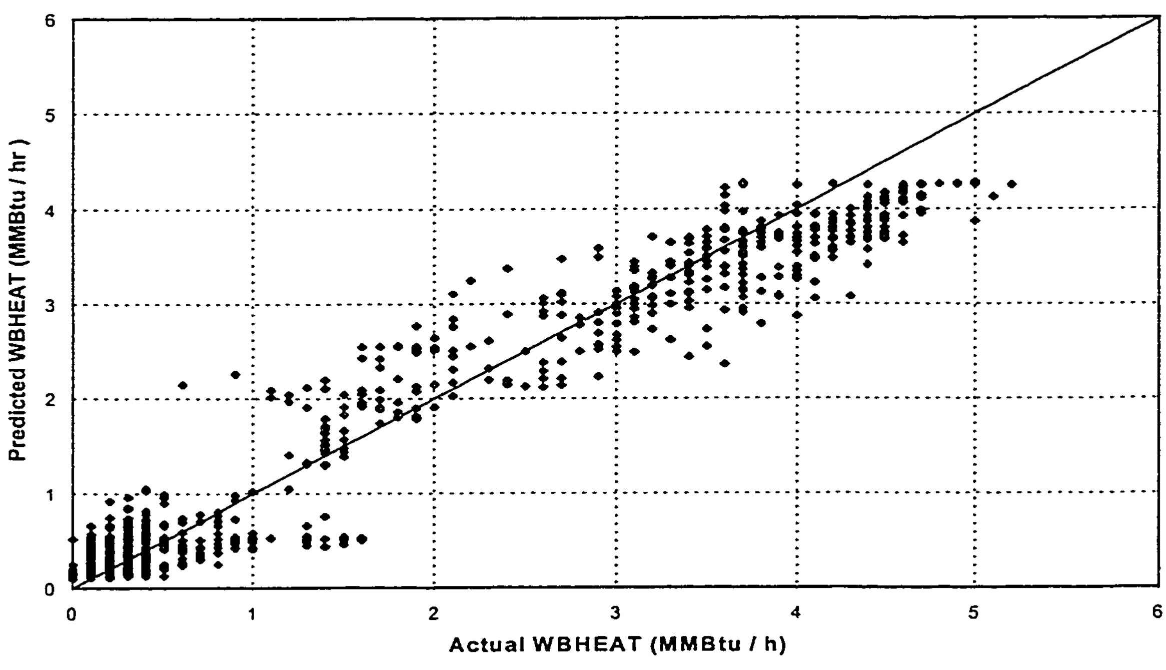


Figure 6.7 : Comparison of the inverse bin prediction and the actual whole building heating (WBHEAT) energy use data for the dataset C. The plot was generated from the extracted sub-set (evaluation data) from the dataset C.

value of the weather dependent energy prediction, particularly the WBCOOL data, has the worst CV value. Fortunately, the global/overall CV value falls close to middle of the winning entries. The humidity sub-binning improved the WBCOOL energy prediction considerably to bring it on par with other winning entries. One of the shortcomings of the inverse bin prediction is that this method cannot take direct advantage of the occupancy level information indirectly available through the WBELE and LTEQ data, unlike other winning entries that use this information as one of the predictor variables.

Comparison with Models Used in the LoanSTAR Program

In addition to the above three detailed case studies, the inverse bin method was also applied to a few selected case study buildings to provide an additional check of the performance against the existing methodologies used in the LoanSTAR program for the retrofit savings calculations. Since the existing models are based on daily data and using the independent variables identified from the daily data, predictions that are not based on the daily data would not be compatible. Therefore, the best possible comparison would be to perform both the evaluations at the same time scale (hourly data) on a previously tested and cleaned dataset. Moreover, the different type of modeling may be needed for different types of buildings and circumstances. Consequently both the modeling schemes (existing modeling procedure and inverse bin method) were applied to the same clean data with the same features (i.e., daytypes, humidity potential, thermal lag, and seasonal pattern).

The following case study building were analyzed for the comparison: 1) ZEC building with change-point and humidity potential for existing model-EM and humidity sub-binned prediction for inverse bin method-BM, 2) RAS building with only ON-OFF mode separation for both methods, 3) PCL building with thermal lag variable and no daytyping for both methods, and 4) WEL building with and without humidity sub-binning for BM and with and without humidity potential as the second variable for EM. In each case, the outliers were identified and daytyping were completed prior to the application or a single daytype was chosen for the demonstration to enable a fair comparison of the performance.

The statistical parameter CV-RMSE that is often used to evaluate the performance of these models is compared in Table 6.10. Description of the selected dataset and any additional evaluation parameters are given in Appendix D. The bin predictions showed a comparable performance as the existing method or a considerable improvement in goodness-of-fit for all the buildings as shown in Table 6.10. In the above buildings and in the case study buildings presented in earlier sections, the results show that the bin method is capable of providing a more accurate baseline model in complex buildings where energy use is weather and/or schedule dependent. Moreover, in certain cases the bin method may have the edge in capturing the non-linear variations in the data that cannot be described by the hourly or daily linear or change-point regression models. This feature was also present in the datasets that were used for the comparison of the inverse bin predictions to predictions by connectionist (Artificial neural networks, Fourier series, and wavelet) methods.

Table 6.10 : Summary of results from the existing models and inverse bin method predictions for four selected sites in Texas

Site	Energy Type	Daytype	CV-RMSE (%)		Existing Model
			Bin method	Existing method	
ZEC	Cooling	Allday	6.80	6.79	4P
	Heating	Calendar	58.7	57.4	MLR
RAS	Cooling	Schedule	42.23	42.52	4P
	Heating	Schedule	54.40	62.44	4P
Wel	Cooling	Allday	18.90	26.74	4P
	Cooling+h-bins	Allday	12.11	12.49	4P+H-potential
PCL	Cooling	Thermal lag	12.96	13.03	4P with lag temperature
	Heating	Calendar	17.36	17.45	4P with calendar daytype

Calendar - calendar dates based daytype
4P - Four parameter change-point model
H- Specific humidity groups or potential
Allday - All the data in one single daytype
Schedule – Schedule-based On -Off groups

If the only criteria for the model selection were to maximize the goodness-of-fit, then a detailed daytyping would be beneficial because this combination of models has the highest number of degrees of freedom to fit the given data (e.g., most of the connectionist models). However, in applications where the model development has cost constraints, ease of use of the model, and the time required to produce the baseline predictions are important and therefore the simplest model would be the most suitable for use. These reasons (ease of use and time to generate baseline predictions) often point toward the use of simple- and multiple-linear regression modes. Therefore, a model selection process should also include the proper optimization of the relevant factors (associated costs as opposed to prediction accuracy). Furthermore, the complex models may not be reproducible except by the original analyst because of the inherent complexity in the way the original model was built and trained or developed. This often precludes the use of such a model by another analyst.

The daytyping has shown that the identification of different daytypes has helped to improve the predictions. However, when predicting the data from a baseline model into a different period the same daytypes have to be identified and delineated into the post-retrofit period to keep the Mean Bias Error (MBE) to a minimum. Therefore, all building operational information is required for properly identifying the daytypes - any missing information would make the use of the model invalid. Because of this reason, it is recommended to keep the daytyping to the minimum necessary levels that provide adequate performance. In the case studies discussed in the previous chapters, the accepted daytypes used include three daytypes (weekday-weekend-holidays) or four daytypes (weekday-weekend-summer-holidays) with any schedule-based separation.

The hourly data actually represent energy use within the specified 60 minute period. Whenever equipment shuts-off between the hour, the resulting hourly data cannot be easily identified as ON or OFF mode. Therefore, a cut-off point for the ON-OFF modes was determined by marking off one-third of the difference from the OFF mode consumption. For example, if the MCC energy use is 100 kW in the ON mode and 42 kW when operating under partial or shut down mode, the cut-off for ON-OFF mode was decided as 61 kW (i.e., 42 plus one-third of the difference 58). In general, this creates a cleaner grouping of the stray points that result from the staggered shut down times. Therefore, care must be taken to revise the new cut-off points for schedule based daytyping when a baseline model is to be used for predicting data for a different time period.

Summary

In this chapter, the results from the application of the fully layered inverse bin method to three case studies were presented and illustrated. These case studies also showed the effect of different daytyping schemes, humidity sub-binning, and use of thermal lag effect. These different approaches were only limited by the available information. In general, the use of the simple inverse bin method is recommended for buildings where partial or no information is available. However, the use of the inverse bin method with detailed daytyping, humidity sub-binning and thermal lag variable was recommended when detailed information and building operation data are available.

In the following chapter, conclusions based on the work described in this study and future directions are presented.

CHAPTER VII
CONCLUSION AND FUTURE DIRECTIONS

General

A fully layered inverse bin methodology has been developed to model weather dependent and weather independent building energy use data. The method has been demonstrated through several carefully selected case studies to show the model's ability to analyze separate daytypes, capture the non-linear variations, and include latent and thermal mass effects. The inverse bin method was also applied to the ASHRAE Predictor Shootout I and II datasets and showed results that were comparable to more complex methods, such as neural network methods. The bin method was also applied in case study buildings monitored as part of the LoanSTAR program with good results. The fully layered inverse bin method (including comprehensive daytyping, humidity sub-binning, and thermal mass effects) has also emphasized the importance of the data preview, outlier identification and removal, separation of daytypes and schedules, humidity sub-binning and lagged temperature.

Outlier Identification

In general, any monitored data may contain bad data due to various reasons such as meter failures or software errors. Therefore, an outlier identification scheme or quality control of the data is a must. In this study, a simple scheme was presented where the outlier boundaries are set by the data distribution within each bin. This procedure worked adequately on weather-dependent data (e.g., cooling and heating energy use). This procedure also helped to identify holidays when applied to weather-independent data (e.g., electrical energy use). Both mild and extreme outlier schemes should be tested on more buildings from other climates to decide which scheme would be more suited across North America. The outlier identification scheme presented in the current work is an improvement over other schemes because of its simplicity and use of a single variable.

Daytyping

The modeling of the energy use data that contains economizer cycle operation causes difficulty for the inverse bin method because the current daytyping scheme only separates schedule-based operation using the identifiable differences in data plots and prior knowledge of the building operation. In modern HVAC systems where the fresh air intake is controlled by Energy Management Control Systems (EMCS), the separation of data with and without the economizer cycle operation is very difficult if not impossible without a calibrated engineering model. However, when a dataset is not well-fit by the inverse bin method chances are it may contain an economizer.

The other limitation of the daytyping scheme used in the current inverse bin methodology is the extension of the daytypes into a period other than the training (or modeling) period. Even though these baseline data can be modeled with good accuracy, the extension of these baseline models into data outside the modeling period has shown to be error prone if critical information is missing. This was evident in one case study (dataset A from Predictor shootout I) where the dataset contained training and testing data sets from adjacent periods that included a large reduction in plug loads. Similar problems could arise when schedule or other operational changes that were included in the training period which are not explicitly available for use on the data outside the training periods. Care should be taken to identify these modes and to assign these daytypes for prediction periods because mismatched daytypes may cause more error than the error associated with the measured energy use or a regression model predicted energy use.

Humidity Sub-binning

Humidity sub-binning has been shown to improve the inverse bin predictions over the prediction without the humidity sub-binning in selected buildings with large ventilation loads in a hot and humid climate. In general, whether or not the sub-binning should be performed is currently decided based on Pearson's linear correlation coefficients and the test for existence of latent load effect. However, the selection of a modeling scheme for retrofit savings procedure should be based to a larger extent on MBE and to a lesser extent on CV-RMSE. A higher MBE often indicate larger deviation from the baseline data and hence may not accurately measure the retrofit savings. It is also interesting to note that higher number of missing datapoints that is common problem in multi-parameter or sub-binned models may hinder the use due to the possible increase in MBE.

In one case study building, where ventilation loads were not detectable (i.e., the Engineering center; dataset A and C) the improvement observed by the inclusion of humidity sub-binning was small. Despite the fact that dataset A showed a very good correlation between the specific humidity and cooling energy (Table 3.2), the results from the test for existence of latent effect (Table 4.7) indicated the effect as significant but small in the influential range (bins 57°F and 77°F). The lower bounds may probably be the result of the building cold deck set-point temperature (12.2°C or 54°F) while the higher bound may be the result of the onset of the inverse relationship between the temperature and specific humidity which results is minimal increase of the building's total cooling load.

The case study results also showed that Pearson's linear correlation coefficients are less effective in quantifying the effect of the specific humidity sub-binning. This may also be the result of collinearity between the weather variables (i.e., temperature and humidity). Further analysis of the results showed that the test for the existence of the latent effect and the use of scatter plots of cooling energy use versus temperature and humidity such as those predicted in this thesis are more appropriate.

Lag Temperature Variable

The effect of thermal mass on the cooling energy consumption was modeled using a lag temperature variable. Only one of the case study buildings (i.e., the Perry Castenada Library-PCL) showed any improvement with the use of a lag temperature variable. However, in other buildings where a lag temperature variable was not appropriate as a bin variable, the use of more than one lag temperature variable positively contributed to the model's ability as reported earlier (Mackay, 1994). The current fully layered inverse bin method also has a limitation on this aspect because it is incapable of incorporating more than one lag temperature variable as bin variable.

Comparison of the Forward and Inverse Bin Methods

A comparison of the binned energy values calculated by the ASHRAE forward bin method and the inverse bin method was also presented. The two cases of binned energy values for the forward bin method (i.e., forward_ideal with no associated losses, and for forward_actual with secondary system losses) were compared with the inverse bin energy values. The results from these comparisons indicated the following: 1) their usefulness for seeing how efficient the secondary HVAC system is with the comparison of forward_ideal and forward_actual with inverse bin values, 2) as an additional tool for identifying the operational problems or changes, and 3) their possible use as a commissioning tool.

Results from Case Studies

The inverse bin method predictions for the three case studies demonstrated the model's ability to predict energy use using three well described datasets. The results also showed that the performance of the inverse bin prediction consistently ranked among the top half of the winning entries. These case studies also brought out the following:

- the inverse bin predictions (as well as other winning entries with the exception of the top winner) can have a high MBE when an unknown change has affected the building's energy consumption (Dataset A).
- reasonably good predictions can be made for a fairly long dataset with available building operation (Dataset C).
- short dataset and multiple operational schedules adversely effect the model's ability to predict a given dataset that includes data that are outside of the range of the short dataset (Dataset D).

Verification of Retrofit Savings

Studies have indicated the potential for cost-effective efficiency improvements in the building sector. Savings measurement methodologies can help to verify and evaluate the effectiveness of these retrofits. However, the verification and evaluation of the effectiveness of the improvements are greatly affected by the selection of verification methodology. Therefore, this study attempts to provide a savings verification methodology in this respect.

In general, the selection of a methodology for the verification of savings should depend on several contributing factors: (i) simplicity, (ii) ease of development, (iii) ease of use (or repeatability), (iv) required and monitored independent variables, (v) adaptability to different situations, (vi) prediction accuracy, and (vii) associated monitoring costs. In general, the methods with high accuracy and methods that are simple are often placed at the opposite end of the spectrum of available methodologies. The model simplicity, ease of development and ease of use are the factors that determine how widely a method is used in the field. The required and monitored variables and adaptability to situations can restrict the use of some models. Furthermore, the final selection of a method often depends on the associated cost of the retrofit. In other words, major retrofits often call for accurate methods which may have high monitoring costs while minor retrofits or general operational and maintenance improvements are verified by a simple comparison of utility bills (i.e., no additional monitoring or costs). Therefore, the simplest, repeatable, and most accurate methodology should be recommended for the verification of any retrofit savings and, most importantly, the method should have a calculated uncertainity which is less than the anticipated savings from the retrofit.

Future Directions

The development and application of this methodology has also increased understanding in other areas as well. In another study (Dhar, 1995), it was shown that mathematical modeling of the simple inverse bin method using a temperature-based Fourier series improved the accuracy of the procedure and made the procedure a less time intensive process. A similar extension to the inverse bin method such as a Fourier series to include the outdoor dry-bulb temperature and outdoor humidity as base variables (i.e., x-y variables) would also simplify the prediction scheme by allowing a single mathematical expression for each daytype instead of a series of binned energy values or expressions.

Finally, modern air conditioning systems have very complex operational strategies, and the resultant energy consumption patterns are often non-linear and discontinuous. This development has necessitated: the model's ability to capture the non-linear variation with ambient temperature. In this study an inverse bin method was developed to model this feature. It is also recognized that a polynomial-based model with orthogonal independent variables should be able to provide equally good predictions utilizing the inverse bin method's main feature (ability to capture the non-linear variation). There are several mathematical methodologies available for the generation of orthogonal polynomials. Despite the fact that the derivation of orthogonal polynomials itself is a tedious task, the advantages (i.e., ease of use and repeatability of the model for baseline prediction) would outweigh the disadvantage (i.e., time intensive process).

REFERENCES

Abbas, M., 1993, "Development of Graphical Indices for Building Energy Data," M.S. Thesis, Mechanical Engineering Department, Texas A&M University, College Station, TX.

Akbari, H., Heinemeier, K.E., Flora, D., and LeConiac, L., 1988 "Analysis of Commercial Whole-Building 15-minute-interval Electric Load Data," *ASHRAE Transactions*, ASHRAE, Vol.94. Pt.2, pp. 432-449.

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers, 1991, *ASHRAE Handbook: Applications*, ASHRAE, Atlanta, GA.

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers, 1994, "Minutes for GPC 14P Measurement of Energy and Demand Savings," *ASHRAE GPC-14P*, Orlando, FL., June.

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers, 1997a, "ASHRAE GPC 14Protocol - Measurement of Energy and Demand Savings," *ASHRAE GPC-14P*, Chicago, IL, January.

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers, 1997b, *ASHRAE Handbook: Fundamentals*, ASHRAE, Atlanta, GA.

Bacot, P., Neveu, A., and Sicard, J., 1984, "Analyse Modale des Phenomenes Thermiques en Regime Variable dans le Batiment," *Revue Generale de Thermique*, No. 267, p.189.

Bartlett, A. A., 1981, "Forgotten Fundamentals of the Energy Crisis," *Journal of Geological Education*, Vol. 28, Pt. 4, pp. 35-81.

Bartlett, A. A., 1990, "A World Full of Oil: The Exponential Function," *The Physics Teacher*, Vol. 28, New York, NY, November, pp. 540-541.

Bevington, R. and Rosenfeld, A. H., 1990, "Energy for Buildings and Homes," *Scientific American*, September, Vol. 102, pp. 76-86.

Bou-Saada, T., 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.

Bou-Saada, T. and Haberl, J. S., 1993, "Analysis of Energy Conservation Options for USDOE Child Development Center," Energy Systems Laboratory Technical Report ESL-TR-93/12-04, Texas A&M University, College Station, TX.

Bou-Saada, T. and Haberl, J. S., 1994, "Analysis of Energy Conservation Options for USDOE Child Development Center : Final Summary Report," Energy Systems Laboratory Technical Report ESL-TR-94/12-08, Texas A&M University, College Station, TX.

Bou-Saada, T. E., Bronson, J. D., Cox, R. L., Dhar, A., Katipamula, S., Kissock, K., Thamilseran, S., Reddy, T. A., Haberl, J. S., and Claridge, D. E., 1994, "Summary of Shootout Modeling Techniques," Energy Systems Laboratory Technical Report ESL-PA-94/04-01, Texas A&M University, College Station, TX.

Box, G., Hunter, W. and Hunter, J., 1978, *Statistics For Experimenters*, John Wiley and Sons, New York, NY.

Brandemuhel, M., Krarti, M., and Phelan, J., 1995, "Methodology Development to Measure In-Situ Chiller, Fan, and Pump Performance (ASHRAE 827-P)," Technical Report JCEM/ TR/ 94-2, University of Colorado, Boulder, CO.

Bronson, J. D., 1992, "Calibrating DOE-2 to Weather and Non-weather Dependent Loads for a Commercial Building," M.S. Thesis, Mechanical Engineering Department, Texas A&M University, College Station, TX.

Brotherton, T. M., Kreider, J.F., Claridge, D.E., and Norford, L.K., 1987, "A Multiclimate Comparison of the Simplified ASHRAE Building Consumption Model with DOE-2 Results," *ASHRAE Transactions*, ASHRAE, Vol. 93, Pt. 2, pp. 600-620.

Brown, L. R., Kane, H., and Roodman, D. M., 1994, *Vital Signs 1994: The Trends that are Shaping Our Future*, Worldwatch Institute, New York, NY.

Burch, J. D., Balcomb, J. D., Westby, R. D., Subbarao, K. and Hancock C. E., 1994, "Short-Term Energy Monitoring for Commercial Buildings," *Proceedings of the ACEEE 1994 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 5, pp. 5.1-5.11.

Chonan, Y., Nishida, K., and Matsumoto, T.., 1996, "Great Energy Predictor Shootout II: A Bayesian Nonlinear Regression with Multiple Hyperparameters," *ASHRAE Transactions*, ASHRAE, Vol. 102, Pt. 2, pp. 405-411.

Claridge, D., Haberl, J., Turner, W., O'Neal, D., Heffington, W., Tombari, C., Roberts, M. and Jaeger, S., 1991, "Improving Energy Conservation Retrofits With Measured Savings," *ASHRAE Journal*, October, pp. 14-22.

Claridge, D. E, Haberl, J. S., Liu, M., Houcek, J., and Athar, A., 1994, "Can You Achieve 150% of Predicted Retrofit Savings? Is it Time for Recommissioning," *Proceedings of the ACEEE 1994 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 5, pp. 5.73-5.87.

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 ACEEE 1996 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 4, pp. 4.59-4.67.

Cleveland, W. S., 1985, *The Elements of Graphing Data*, Wadsworth and Brooks/Cole, Pacific Grove, CA.

Deng, S., Reddy, T. A., and Claridge, D. E, 1997, "Development of an Inverse Method to Estimate Building and Ventilation Parameters of Large Commercial Buildings," *Proceedings of the ASME/JSME/JSES Solar Energy Conference*, Washington, DC, April, pp. 463-472.

Dhar, A. 1995. "Development of Fourier Series and Artificial Neural Network Approaches to Model Hourly Energy Use in Commercial Buildings," Ph.D. Dissertation, Mechanical Engineering Department, Texas A&M University, College Station, TX.

Diamond, R., Harris., J., de Buen, O., Norman, B., and Cody, B., 1990, "Evaluating Actual Performance of New Commercial Buildings: The Energy Edge Demonstration Program," *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 3, pp. 3.77-3.89.

Dodier, R. H., and Henze, G. P., 1996, "Statistical Analysis of Neural Networks as Applied to Building Energy Prediction," *Journal of Solar Energy Engineering, ASME Transactions*, 1996, pp. 495 - 505.

DOE, 1995, "Sustainable Energy Strategy: Clean and Secure Energy for a Competitive Economy," *National Energy Policy Plan*, Washington, DC, July.

DOE, 1997, *IPMVP - International Performance Measurement and Verification Protocol*, Department of Energy, Washington, DC, November.

EIA Energy Information Administration, 1992a, *Annual Energy Review*, EIA publication No. DOE/EIA-0389 (91), Washington, DC.

EIA Energy Information Administration, 1992b, *Energy Facts 1991*, EIA publication No. DOE/EIA-0469(91), Washington, DC.

EIA Energy Information Administration, 1992c, *Monthly Energy Review: Commercial and Residential Buildings*, EIA publication No. DOE/EIA-0384 (91), Washington, DC, June.

Eto, J. H., Akbari, H., Pratt, R. G., and Braithwait, S. D., 1990, "End-use Load Shape Data Application, Estimation, and Collection," *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 10, pp. 10.39-10.55.

Fels, M., 1978, *"Data Specifications Document for the New Jersey Energy Data System,"* Princeton Technical Report PU/CEES 72, Princeton University, Princeton, NJ.

Fels., M., 1986, "Special Issue Devoted to Measured Energy Savings, The Princeton Score Keeping Method (PRISM)," *Energy and Buildings*, Vol. 9, Nos. 1 and 2.

Fels., M., Kissock, J. K., Marean, M. A. and Reynolds, C., 1995, "Advancing the Art of PRISM Analysis," *Home Energy*, July/August, pp. 19-23.

Feuston, B., and Thurtell, J., 1994, "Generalized Non-linear Regression with Ensemble of Neural Nets: The Great Energy Predictor Shootout *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp.1075-1080.

Freund, R. J., and Wilson, W. J., 1993, *Statistical Methods*, Academic Press, San Diego, CA.

Goldemberg, J., Johansson, T B., Reddy, A. K. N., and Williams, R. H., 1988, *Energy for a Sustainable World*, Wiley Eastern Limited, New Delhi, pp. 2-183.

Greely, K. M., Harris, J. P., and Hatcher, A. M., 1990, "Measured Energy Savings and Cost-Effectiveness of Conservation Retrofits in Commercial Buildings," *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 3, pp. 3.95-3.108.

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

Griffith, L., Reddy, T. A., and Claridge, D. E, 1994, "Cooling-only PRISM Analysis of Eleven College Station Homes and Interpretation of Building Physical Parameters," *Proceedings of the Ninth Symposium on Improving Building Systems in Hot and Humid Climates*, Arlington, TX, pp. 182-191.

Haberl, J. S. and Vajda, E. J., 1988, "Use of Metered Data Analysis to Improve Building Operation and Maintenance: Early Results from Two Federal Complexes," *Proceedings of the ACEEE 1988 Summer Study on Energy Efficient Buildings*, Washington, DC, Vol. 3, pp. 3.98-3.111.

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

Haberl, J. S. and Komor, P. S., 1990b, "Improving Energy Audits: How Annual and Monthly Consumption Data Can Help," *ASHRAE Journal*, August, pp. 26-33.

Haberl, J. S. and Thamilseran, S., 1994, "Instructions- The Great Energy Predictor Shootout II : Measuring Retrofit Savings," Energy Systems Laboratory Technical Report ESL-TR-94/07-01, Texas A&M University, College Station, TX.

Haberl, J. S. and Bou Saada, T. E., 1995, "The USDOE Forrestal Building Lighting Project: Preliminary Analysis of Electricity Savings," *Proceedings of the ASME/JSME/JSES International Solar Energy Conference*, Maui, Hawaii, pp. 295-304.

Haberl, J. S., and Thamilseran, S., 1995, "The Great Building Energy Predictor Shootout II: Measuring Retrofit Energy Savings," Energy Systems Laboratory Technical Report ESL-TR-95/09-02, Texas A&M University, College Station, TX.

Haberl, J. S. and Thamilseran, S., 1996, "The Great Energy Predictor Shootout II: Measuring Retrofit Savings - Overview and Discussion of Results," *ASHRAE Transactions*, ASHRAE, Vol. 102, Pt.2, pp. 419-435.

Haberl, J. S., Saman, N., Bou-Saada, T. and Soeborto, V., 1997, "Development of Accuracy Tests for Mechanical System Simulation 865 TRP - Research Report," Energy Systems Laboratory Technical Report ESL-TR-97/06-01, Texas A&M University, College Station, TX.

Hirst, E., Clinton, J., Geller, H. and Kroner, W., 1986, *Energy Efficiency in Buildings: Progress and Promise*, ACEEE, Washington, DC.

Iglewicz, B., and Hoaglin, D. C., 1993, *How to Detect and Handle Outliers*, The ASQC Basic References in Quality Control - Volume 16, American Society for Quality Control-Statistics Division, Milwaukee, WI.

Iijima, M., Takagi, K., Tekeuchi, R., and Matsumoto, T., 1994, "A Piece-wise Linear Regression on the ASHRAE Time Series Data," *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp. 1088-1095.

Jacobs, P. C., Waterbury, S. S., Frey, D. J., Johnson, K. F. 1990, "Short-term Measurements to Support Impact Evaluations of Commercial Lighting Programs," *Proceeding of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 5, pp. 5.113-5.121.

Jamieson., D. and Qualmann, R., 1990, "Computer Simulation Energy Use Metering or Can We Count on Energy Savings Estimates in Designing Demand Side Programs," *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 10, pp. 10.105-10.114.

Jang, K. J., Bartlett, E. B., and Nelson, R. M., 1996, "Measuring retrofit Energy Savings Using Autoassociative Neural Networks," *ASHRAE Transactions*, ASHRAE, Vol. 102, Pt. 2, pp. 412-418.

Katipamula S. and Haberl, J. S., 1991, "A Methodology to Identify Diurnal Shapes for Non-weather Dependent Electric End-uses," *Proceedings of the ASME/JSME/JSES International Solar Energy Conference*, Reno, NV, March, pp. 457-468.

Katipamula S. and Claridge, D. E, 1993, "Use of Simplified Systems Models to Measure Retrofit Savings," *ASME Journal of Solar Energy Engineering*, Vol. 115, pp. 57-68.

Katipamula, S., Reddy, T. A. and Claridge, D. E, 1994, "Development and Application of Regression Models to Predict Cooling Energy Consumption in Large Commercial Buildings," *Proceedings of the ASME/JSME/JSES Solar Energy Conference*, San Francisco, CA, pp. 307-322.

Katipamula, S., Reddy, T. A., and Claridge, D. E., 1995, "Effect of Time Resolution on Statistical Modeling of Cooling Energy Use in Large Commercial Buildings," *Proceedings of the ASME / JSME/ JSES International Solar Energy Conference*, Maui, HI, pp. 309-316.

Katipamula, S., 1996, "Great Energy Predictor Shootout II : Modeling Energy Use in Large Commercial Buildings," *ASHRAE Transactions*, ASHRAE, Vol. 102, Pt. 2, pp. 397-404.

Kawashima, M., 1994, "Artificial Neural Network Backpropagation Model with Three-Phase Annealing Developed for the Building Energy Predictor Shootout," *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp. 1096-1103.

Kissock, J. K., 1993, "A Methodology to Measure Retrofit Energy Savings in Commercial Buildings," Ph.D. Dissertation, Mechanical Engineering Department, Texas A&M University, College Station, TX.

Knebel, D., 1983, *Simplified Energy Analysis Using the Modified Bin Method,* ASHRAE, Atlanta, GA.

Kobayashi, A. S., Ed., 1993, *Handbook of Experimental Mechanics*, Second Edition, Society of Engineering Mechanics (US), New York, NY.

Kreider, J. and Wang, X., 1991, "Artificial Neural Networks Demonstrated for Automated Generation of Energy Use Predictors for Commercial Buildings," *ASHRAE Transactions*, ASHRAE, Vol. 97, Pt. 1, pp. 775-779.

Kreider, J. and Haberl, J. S., 1994, "Predicting Hourly Building Energy Use: The Great Energy Predictor Shootout - Overview and Discussion of Results," *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp.1038-1052.

Kreider, J. and Rabl, A., 1994, *Heating and Cooling of Buildings: Design for Efficiency*, McGraw Hill, Hightstown, NJ.

Levine, M. D., Gadgil, A., Meyers, S., Sathye, J., Strafurik, J., and Wilbanks, T., 1991, "Energy Efficiency, Developing Nations and Western Europe," *A Report to the U.S. Working Group on Global Energy Efficiency*, Ernest Orlando Lawrence Berkeley Laboratory, Berkeley, CA, pp. 1-7.

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," *Proceedings of the ASME/JSME/JSES International Solar Energy Conference*, Maui, Hawaii, pp. 209-217.

Liu, M., Athar, A., Reddy, T. A., Claridge, D. E, Haberl, J. S., and White, E., 1995, "Reducing Building Energy Costs Using Improved Operation Strategies for Constant-volume Air-handling Systems," *ASHRAE Transactions*, ASHRAE, Vol. 101, Pt. 2, pp. 209-220.

MacDonald, J. and Wasserman, D.,1989, "Investigation of Metered Data Analysis Methods for Commercial and Related Buildings," ORNL Technical Report ORNL/CON-279, Oak Ridge National Laboratory, Oak Ridge, TN.

Mackay, D. J., 1994, "Bayesian Nonlinear Modeling for the Energy Predictor Shootout Competition," *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp.1053-1062.

McQuiston, F. C. and Spitler, J. D., 1992, *Cooling and Heating Load Calculation Manual*, ASHRAE, Atlanta, GA.

Minehart, D. L. and Meier, A. K., 1990, "Using Simulations to Explore the Physical Meaning of PRISM's Parameters," *Proceedings of the ACEEE 1990 Summer Study on Energy Efficient Economy*, Washington, DC, Vol.4, pp. 4.145-4.155.

NAESCO National Association of Energy Service Companies, 1994, *Measurement and Verification Protocol*, New England Chapter of the Association of Energy Engineers, National Association of Energy Service Companies, Boston, MA.

Neter, J., Wasserman, W. and Kutner, M., 1989, *Applied Linear Regression Models*, Richard D. Irwin, Inc., Boston, MA.

O'Brien, C., and Crawley, D. B., 1994, "Advantages of Staged Implementation of Efficiency Upgrades," *Proceedings of the ACEEE 1994 Summer Study on Energy Efficiency in Buildings*, Washington, DC, Vol. 5, pp. 5.181-5.191.

Ohlsson, M., Peterson, C., Pi., H., Rognvaldsson, T., and Soderberg, B., 1994, "Predicting Utility Loads with Artificial Neural Networks - Methods and Results from Energy Predictor Shootout," *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp. 1063-1074.

Ott, L., 1988, *An Introduction to Statistical Methods and Data Analysis,* PWS-KENT Publishing Company, Boston, MA.

Rabl, A., Norford, L. K., and Spadaro, G. V., 1986, "Steady State Models for Analysis of Commercial Building Energy Use Data," *Proceedings of the ACEEE 1986 Summer Study on Energy Efficiency in Buildings,* Washington, DC, Vol. 9, pp. 9.239-9.261.

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.

Rabl, A. and Rialhe., A.,1992, "Energy Signature Models for Commercial Buildings: Test with Measured Data and Interpretation," *Energy and Buildings*, Vol.19, pp. 143 -154.

Reddy, A., 1989, "Identification of Building Parameters Using Dynamic Inverse Models: Analysis of Three Occupied Residences Monitored Non-Intrusively," *Proceedings of the ASHRAE/DOE/BTECC/CIBSE Conference: Thermal Performance of the Exterior Envelopes of Buildings IV*, ASHRAE, Atlanta, GA, pp. 654-671.

Reddy, A. and Claridge, D., 1994, "Using Synthetic Data To Evaluate Multiple Regression and Principal Component Analysis for Statistical Modeling of Daily Building Energy Consumption," Energy Systems Laboratory Report, Mechanical Engineering Department, Texas A&M University, College Station, TX.

Reddy, T. A., Katipamula, S. and Claridge, D. E, 1994a, "The Functional Basis of Thermal Energy Use in Air-side HVAC Equipment," *The ASME Journal of Solar Energy Engineering*, Vol.116, pp. 31-39.

Reddy, T. A., Kissock, J. K., Katipamula, S., Ruch. D., and Claridge, D. E, 1994b, "An Overview of Measured Energy Retrofit Savings Methodologies Developed in the LoanSTAR Program," Energy Systems Laboratory Report, Texas A&M University, College Station, TX.

Ross, H., and Whalen, S., 1983, "Building Energy Use Compilation and Analysis (BECA) Part C: Conservation and Progress in Retrofitted Commercial Buildings," *Energy and Buildings,* Vol. 5, No. 3, pp. 171-196.

Ruch, D. and Claridge, D. E, 1992, "A Four-Parameter Change Point Model for Predicting Energy Consumption in Commercial Buildings," *ASME Journal of Solar Energy Engineering*, Vol. 114, pp. 77-83.

Ruch, D., Chen, L., Haberl, J. and Claridge, D., 1993, "A Change-Point Principle-Component Analysis (CP/PCA) Method for Predicting Energy Usage in Commercial Buildings: The PCA Model," *Journal of Solar Energy Engineering*, Vol. 115. pp. 77-84.

SAS (SAS Institute), 1990, *SAS/STAT Users Guide :Version 6,* Volume 1 and 2, SAS Institute, Cary, NC.

Sauer, H. J., Jr., and Howell, R. H., 1990, *Principles of Heating, Ventilating and Air Conditioning : A Textbook Supplement to the 1989 ASHRAE Handbook - Fundamentals*, ASHRAE, Atlanta, GA.

SERI, 1981, *A New Prosperity: Building a Sustainable Energy Future*, The SERI Solar/Conservation Study, Brickhouse, Andover, MA.

Shurcliff, W. A., 1984, *Frequency Method of Analyzing a Building's Dynamic Thermal Performance*, A. Shurcliff, 19 Appleton Street, Cambridge, MA.

Sonderegger, R., 1978, "Dynamic Models of House Heating Based on Equivalent Thermal Parameters," Ph.D. Dissertation, Princeton University, Princeton, NJ.

Stevenson, W. J., 1994, "Predicting Building Energy Parameters Using Artificial Neural Nets," *ASHRAE Transactions*, ASHRAE, Vol. 100, Pt. 2, pp. 1081-1087.

Stram, D. and Fels, M., 1986, "The Applicability of PRISM to Electric Cooling and Heating," *Energy and Buildings*, Vol. 9, No.1&2, pp. 101-110.

Subbarao, K., 1986, "Thermal Parameters for Single and Multi-zone Buildings and their Determination from Performance Data," SERI Technical Report SERI/TR-253-2617, Solar Energy Research Institute report, Golden, CO.

Subbarao, K., Burch, J., Hancock, C. E., Lekov, A. and Balcomb, J.D., 1990, "Measuring the Energy Performance of Buildings Through Short-Term Tests," *Proceedings of the ACEEE 1990 Summer Study on Energy Efficiency in Buildings,* Washington, DC,Vol. 10, pp. 10.245-10.252.

Taylor, Z. T., Pratt, R. G., 1988, "The Effects of Model Simplifications on Equivalent Thermal Parameters Calculated from Hourly Building Performance Parameters," *Proceedings of the ACEEE 1988 Summer Study on Energy Efficiency in Buildings,* Washington, DC,Vol. 10, pp. 10.268-10.252.

Thamilseran, S., and Haberl, J. S., 1995, "A Bin Method for Calculating Energy Conservation Retrofit Savings in Commercial Buildings," *Proceedings of the ASME / JSME/ JSES International Solar Energy Conference*, Maui, HI, March, pp. 111 - 123.

Tukey, J. W., 1977, *Exploratory Data Analysis*, Addison-Wesley Publishing, Reading, MA.

Turner, W., 1990, "Overview of the Texas LoanSTAR Monitoring Program," *The Seventh Symposium on Improving Building Systems in Hot and Humid Climates*, Ft. Worth, TX, pp. 28-34.

Waller, R. A., and Duncan, D. B., 1969, "A Bayes Rule for the Symmetric Multiple Comparison Problem," *Journal of the American Statistical Association*, Volume 67, pp. 253 - 255.

Wang, X. A. and Krieder, J. F., 1990, "SVD Algorithm and Multiple Linear Regression," JCEM Technical Report JCEM/TR/90-5, Joint Center for Energy Management, University of Colorado, Boulder, CO.

Waterbury, S. S., Frey, D. J. and Johnson, K. F., 1994, "Commercial Building Performance Evaluation System for HVAC Diagnostic and Commissioning," *Proceedings of the ACEEE 1994 Summer Study on Energy Efficiency in Buildings,* Washington, DC,Vol. 5, pp. 5.249-5.255.

WRI (World Resources Institute), 1997, *World Resources 1996-97 : Guide to the Global Environment*, The World Resources Institute, Oxford University Press, New York, NY.

Wu, J., Reddy, T.A., and Claridge, D.E., 1992, "Statistical Modeling of Daily Energy Consumption in Commercial Buildings Using Multiple Regression and Principal Component Analysis," *Proceedings of the Eighth Symposium on Improving Building Systems in Hot and Humid Climates,* Dallas, TX, pp. 97-103.

APPENDIX A

STATISTICAL PARAMETERS AND DEFINITIONS

This section presents definition and an example interpretation of the statistical parameters used in this study. These statistical parameters include diagnostic parameters (Pearson's linear correlation coefficient), goodness-of-fit parameters or model statistics (coefficient of determination (R^2), Coefficient of Variation of the Root Mean Square Error-(CV-RMSE), and Mean Bias Error (MBE) and multiple comparison procedures (Duncan, Waller-Duncan-k-ratio and Scheffe procedures).

Pearson's Linear Correlation Coefficient (r)

Definition

This coefficient measures the strength of the linear relationship between two quantitative variables. This coefficient is the ratio of the sum of squares of the regression to the total sum of squares, and is defined (Ott, 1984) as

$$r = \frac{\sum\left(x-\bar{x}\right)\left(y-\bar{y}\right)}{\sqrt{\sum\left(x-\bar{x}\right)^2\sum\left(y-\bar{y}\right)^2}} \quad \text{...(EA1)}$$

where $\bar{x}$ and $\bar{y}$ are the $\sum x/n$ and $\sum y/n$

Properties

The calculated r value lies between -1 and 1 (inclusive) with values greater than 0 showing a positive slope or variation and the values lower than 0 showing a negative slope or variation. A zero value, however, does not necessarily indicate no correlation because the coefficient measures only the linear relationship. Therefore, a 0 value may still indicate a non-linear correlation. The r value is symmetric about the independent and dependent variable regardless of x or y as the independent variable. The value of r^2 gives the proportion of the total variability of the dependent variable that is accounted by the independent variable.

If a known non-linearity is observed in the standard scatter (y vs x) plot either x or y variable can be transformed to linearize the data. The correlation coefficient of the transformed variable would then be used for testing the strength of the linear variation between the variables. Some of the general forms of transformation for x and y are as follows:

- transformation choices for x variable are x^2, x^3, log(x), -1/x and
- transformation choices for y variable are y^2, y^3, log(y), -1/y.

Example

A sample correlation coefficient analysis using the SAS software (SAS, 1990) is provided below. In this calculation the following variables are used. The variable name used in the program is given within ( ).

- dependent variables: WBELE (wbe), WBCOOL (cwe), and WBHEAT (hwe).
- independent variables: Temperature (temp), Hour-of-the-day (hr), and humidity (humid).

```
proc corr data=newa;
      var wbe cwe hwe;
     with temp hr humid;
run;
```

A sample output from the SAS routine is given below. The output includes information on sample statistics and Pearson's linear correlation coefficient.

Simple Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
TEMP	2926	63.137457	17.968821	184740	2.60	99.500
HR	2926	11.507519	6.919743	33671	0	23.000
HUMID	2926	0.007615	0.005285	22.282	0	0.022
WBE	2926	662.210185	156.004869	1937627	374.00	995.000
CWE	2926	5.055947	1.235140	14794	0	8.000
HWE	2926	2.094190	1.402316	6127.6	0.20	6.300

Pearson Correlation Coefficients / Prob > |R| under Ho: Rho=0 / N = 2926

	WBE	CWE	HWE
TEMP	0.23100	0.89262	-0.92842
	0.0001	0.0001	0.0001
HR	0.29014	0.10190	-0.10522
	0.0001	0.0001	0.0001
HUMID	-0.06720	0.70399	-0.61983
	0.0003	0.0001	0.0001

This correlation coefficients from the above output was summarized for analysis in Table 3.2 in Chapter III. The correlation coefficient of wbe with temp can be calculated as follows.

$$r = \frac{\sum\left(x-\bar{x}\right)\left(y-\bar{y}\right)}{\sqrt{\sum\left(x-\bar{x}\right)^2 \sum\left(y-\bar{y}\right)^2}} = \frac{S_{xy}}{\sqrt{S_{xx}S_{yy}}}$$

The additional statistic for this calculation are as follows:

Simple Statistics						
Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
temp*wbe	2926	42458	17095	124230922	1219.4	87507
temp*temp	2926	4309.1067	2118.77	12608446	6.76	9900.25
wbe*wbe	2926	462852	221826	1354303577	139876	990025

Therefore, the values can be calculated as follows:

S_{xy} = Sum(xy) - Sum(x)*Sum(y)/N = 124230922 - (184740)*(1937627)/ 2926 =1894212.5

S_{xx} = Sum(xx) - Sum(x)*Sum(x)/N= 12608446 - $(184740)^2$ / 2926 = 944444.77

S_{yy} = Sum(yy) - Sum(y)*Sum(y)/N= 1354303577 - $(1937627)^2$ / 2926 = 71187243.74

r = 1894212.5/$(944444.77*71187243.74)^{0.5}$ =**0.23100**145.

The result in bold (0.2310) is the value shown as the linear correlation coefficient in the tabulation. In other words, the strength of the linear correlation between the variable WBE and variable temp is about 23.1%. A value of 0 would indicate no linear correlation between the variables. In this study, the variable that is highly correlated to the dependent variable is taken as the primary independent variable (i.e., bin variable). If there is a second variable with sufficient correlation available, that may be used as the secondary (i.e., sub-binning). In some cases, where physical principles suggest otherwise the identified secondary variable was not used. For example, the variables Temp and WBE are correlated at 0.231. However, the majority of this correlation was already accounted by the use of HR variable, which has a 29.0% linear correlation with WBE.

Coefficient of Determination (R^2)

Definition

The coefficient of determination for a single variable model can be defined using the correlation coefficient r, as r^2. Thus the value of r^2 is between 0 and 1 and is a very useful statistic in single variable regression models. However, when a model is developed with more than one variable, the coefficient of determination is denoted by R^2 (which is the ratio of the sums of squares due to regression to total the sums of squared for y variable corrected for the mean). The parameter is defined (Ott, 1984; Neter et al., 1990) as follows

$$R^2 = \left(1 - \frac{\sum_{i=1}^{n}\left(y_{pred,i} - y_{data,i}\right)^2}{\sum_{i=1}^{n}\left(\bar{y}_{data} - y_{data,i}\right)^2} \right) \quad \text{...(EA2)}$$

where

$y_{data.i}$ is i^{th} data value of the dependent variable,

$y_{pred.i}$ is i^{th} predicted dependent variable using the given set of independent variables,

$\bar{y}_{data}$ is the mean value of the dependent variable in the data set and

n is the number of data points in the data set.

For example, if the calculated R^2 value is 0.992, then it can said that 99.2% of the variable in the y variable is accounted by x variables used in the model.

Table A.1 : Sample dataset and calculation for the illustration of model statistics

N_obs	x1	x2	y	yp	yp-y	$(yp-y)^2$	$(y-y_{mean})^2$
1	1.04	2.10	9.05	9.17	0.12	0.0146	283.63
2	3.02	3.40	18.31	17.58	-0.73	0.5293	57.44
3	5.10	5.78	28.95	29.82	0.86	0.7458	9.41
4	7.01	1.74	20.32	20.20	-0.12	0.0146	30.99
5	4.06	9.82	41.58	41.22	-0.36	0.1308	246.31
6	6.01	3.63	24.57	24.48	-0.08	0.0072	1.75
7	5.32	3.07	20.44	21.19	0.75	0.5667	29.70
8	9.09	7.22	43.89	42.82	-1.06	1.1322	323.93
Mean	5.08	4.60	25.89	25.81	-0.08	0.39	122.89
Sum	40.65	36.76	207.10	206.48	-0.62	3.14	983.15

Example

Assume a sample dataset with 8 data points consisting of two independent variables x1 and x2, one dependent variable y, and model predicted value for y-variable as yp. The dataset is given in Table A.1. The labels are N_obs = observation number, x1 = independent variable 1, x2=independent variable 2, y = dependent variable, yp = predicted y, (yp - y) = prediction error, and $(yp\text{-}y)^2$ = squared error. This dataset will be used for sample calculation of the parameters described in this section.

Therefore, the value for the R^2 is calculated as = 1 - (3.14/983.15) = 0.997. In other words, 99.7% of the variability of y is accounted by the two independent variables x1 and x2 in the derived model.

Coefficient of Variation (CV)

Definition

Although several measures of a model's goodness-of-fit are available, the Coefficient of Variation (CV) is generally preferred. The calculation scheme of the CV differs depending on the type of model: The coefficient of variation of the standard deviation (CV-SD) for single-parameter models and the coefficient of variation of the root mean square error (CV-RMSE) for multiple-parameter models. The CV-RMSE is defined as (SAS, 1990; Kobayashi, 1993; Freund and Wilson, 1993) below.

$$CV(RMSE) = \frac{\sqrt{\dfrac{\sum_{i=1}^{n}\left(y_{pred,i} - y_{data,i}\right)^2}{n-p}}}{\bar{y}_{data}} \quad \text{.......................................(EA3)}$$

where

$y_{data,i}$ is i^{th} data value of the dependent variable,

$y_{pred,i}$ is i^{th} predicted dependent variable using the given set of independent variables,

$\bar{y}_{data}$ is the mean value of the dependent variable in the data set

p is number of parameters in the model and

n is the number of data points in the data set.

The parameter CV-SD, which is calculated for the predictions by a one-parameter model (i.e, mean model), can be derived from CV-RMSE by substituting p = 1 in the above expression. These parameters are hence, an indication of average unbiased error associated with the model. The values are often given in percentage. A lower variation or small CV value represents a better model fit.

Note

Care should be taken in interpreting the comparison of the CV-RMSE values across different parameters because of the dependence of this parameter on the sample mean. Therefore, a comparison of CV across different variables of similar measurements should not be used unless all variables have a uniform scale and mean value.

Example

The CV-RMSE can be calculated for the sample data shown in Table A.1 as follows. If a model ($\hat{y} = 2.05 * x1 + 3.35x2$) was used for the prediction, then the predicted values of the y are yp as given in the Table A.1. The remaining columns (yp-y), $(yp-y)^2$, $(yp-y_{mean})^2$ were calculated for the expression. These are then used for the sample calculation of R^2, CV(RMSE), and MBE. The CV (RMSE) is calculated using the expression and the sum or mean values tabulated in Table A.1. Therefore, the CV(RMSE) for the given model is,

$$CV(RMSE) = \frac{\sqrt{\dfrac{3.14}{8-2}}}{25.89} = 0.0279.$$

The value for CV(RMSE) is often expressed as a percentage and hence it is 2.79%.

Mean Bias Error (MBE)

Definition

The second parameter that is often used for evaluating a model is termed as Mean Biased Error (MBE). This parameter expresses the bias between the model and the data and is defined (SAS, 1990) as

$$MBE = \frac{\dfrac{\sum_{i=1}^{n}\left(y_{pred,i} - y_{data,i}\right)}{n-p}}{\bar{y}_{data}} \times 100 \qquad \text{...(EA4)}$$

where

$y_{data,i}$ and $y_{pred,i}$ are the actual and predicted data of (i^{th}) value of the dependent variable corresponding to a particular set of the independent variables and

$\bar{y}_{data}$ is the mean value of the dependent variable of the selected data set.

n and p are the number of data points and the number of regression parameters in the model respectively.

Since these parameters are given as ratios of the mean value of the dependent variable, these are non-dimensional measures and are often given as a percentage. A small value (i.e., zero) is expected if all the given data points are considered for the development of the model. However, an analyst often removes data that were considered outliers prior to model development. Therefore, this number is usually a small non-zero value.

<u>Example</u>

The MBE value is the ratio of arithmetic average of the error values for a specific model divided by the mean value of the data, expressed in percentage. For the model used in the sample data shown in Table A.1 (i.e., the model $\hat{y} = 2.05 * x1 + 3.35x2$) , the average error is 0.08 (i.e., 0.062/8), and the mean value of the y-variable is 25.89. Therefore, the MBE value is calculated as,

$$MBE = \frac{\frac{0.062}{8}}{25.89} * 100 = 0.0299.$$

Multiple Comparison Procedures

In this study we have used comparison procedures mainly to identify the difference between an a number of data groups (daytypes) of a dependent variable. The daytypes are nominal variable with more than two values while the criterion variable is measured on an interval scale. This type of comparison is known as one-way analysis of the variance

(ANOVA). In the SAS software system these can be calculated using the GLM or ANOVA procedures with "model" and "mean" options. The sub-option under mean may be one of the several available comparison procedures (Duncan, student-t, SNK, Waller, Scheffe). Though essentially the comparison is similar, these procedures differ according to which type of error is controlled and how restrictive the error control algorithm should be. Therefore, the critical difference value is calculated using one of several algorithms and the type of controlled error that is relevant for the procedure in use.

For example, Scheffe's procedure which is the most conservative of all the above procedures, controls the experiment-wise error rate (Ott, 1984; Box et al., 1978; Freund, 1993). Thus the probability of observing an experiment getting rejected falsely after all the possible comparisons is defined as α. For example if a value of α=0.05 (5% error) was used, the probability is still 5%. On the other hand, the Duncan's multiple range test, which uses a less conservative approach and controls the error rate by a protection level based on the number of steps the samples are apart (Ott, 1984; Freund, 1993). With the designated value for α=0.05 (5% error), the Duncan's procedure controls the error 0.05 (or 5%) if the samples are 2 steps apart. When the samples are more than two steps apart, the error rate will not linearly propagate with additional steps (i.e., the error rate for 3, and 4 steps apart are calculated as 0.097 and 0.143). Because of this reason, Duncan's procedure is considered less conservative. However, studies suggest that this inherent feature makes the procedure more powerful and more popular among researchers (Ott, 1984).

Duncan's Multiple Range Test

This test was developed for obtaining all pairwise comparisons among k sample (i.e., daytype) means. This procedure makes use of the studentized t range and the error rate has neither on an experiment-wise basis nor on a per-comparison basis (Ott, 1984). The defined protection level when two sample means that are r steps apart, is defined as $(1-\alpha)^{(r-1)}$. The error rate (probability of falsely rejecting the equality) of two population means when sample means are r steps apart is then defined as $1-(1-\alpha)^{r-1}$. The steps for the test can be summarized for pairwise comparison of k population means is as follows (Ott, 1984):

- Rank the k sample means
- The two population means are then declared significantly different if the absolute value of their sample differences exceeds $q'_{\alpha}(k,v)*\sqrt{\frac{S_w^2}{n}}$, where n is the number of observation in each sample mean, S_w^2 is the mean square within sample obtained from the analysis of variance table, v is the number of degrees of freedom for S_w^2, and $C'_{\alpha}(k,v)$ is the critical value of the studentized range calculated by Duncan's procedure when means being compared are r apart. This value is given in tabular format in standard statistics texts by Ott (1984), Freund (1993), and Neter et al. (1990).

Duncan's procedure can also be adapted to test unequal sample sizes by replacing the sample size n with $\frac{k}{{}^1/_{n_q} + {}^1/_{n_2} + \ldots\ldots + {}^1/_{n_k}}$, where $n_1,\ldots n_k$ denote sample sizes of the daytypes 1,..,k.

Example

This procedure can be performed as an option to GLM or ANOVA procedures available in the SAS software. A sample section of the routine is given below.

```
/*checking daytypes for wbe separation*/
proc anova data=newa;
class dtw;
model wbe =dtw;
means dtw / duncan;
run;
```

A sample output (for the given routine) is given in Table A.2 for the *proc ANOVA* statement with the *dtw* class option. This output is generally used for checking whether the five identified daytypes are considered as data from a single daytype or from significantly different daytypes. This output is the same as output obtainable by either using the *proc ANOVA* or *proc GLM* procedure within SAS software. A sample result for the above analysis applied to dataset A is given in Table A.2.

The ANOVA output (also referred to as ANOVA table) is given in Table A.2 was based on the following:

Daytypes : Initial daytypes:

1 (regular weekends),
2 (regular weekdays),
3 (low weekends),
4 (low weekdays),
5 (holidays or Christmas period).

Null hypothesis:

Symbolic expression:

$dtw_1=dtw_2=dtw_3=dtw_4=dtw_5$

Statement:

In the given dataset (energy use data), there is no difference between the five daytypes (detail below) with respect to the mean energy use.

Alternate hypothesis:

Symbolic expression:

$dtw_1 \neq dtw_2 \neq dtw_3 \neq dtw_4 \neq dtw_5$

Statement:

In the given dataset (energy use data), there is a significant difference between the five daytypes (detail below) with respect to the mean energy use.

where dtw_1, dtw_2, dtw_3, dtw_4, and dtw_5 are the mean values of the five daytypes identified above. An illustration of the data and how these were separated based on calendar periods was given in Chapter IV. The source variable is the number for the identified daytypes, dtw. The degrees of freedom (DF) is the degrees of freedom associated with the predictor variable dtw (i.e., (5) - 1 = 4). The values given under the *sums of square* are the sums of the data squared (i.e., *Model=dtw*, and *Error*). The values under *corrected total* is the total sum corrected for degree of freedom, and is equal to the total of the two sums of squares: *Model* and *Error*. The *mean square* is calculated by dividing the *sums of squares* by *degrees of freedom (DF)*. Then the F value (486.71) is calculated by dividing the Model sums of square value (7117845.2274) by Error sums of square value (14624.3751). This value is compared against a F-statistics to decide whether to accept or reject the null hypothesis. For the work presented here, we have used an alpha (α) = 0.05, DF = 4,2897 and therefore, the tabulated F value is 2.37. The calculated value is higher than the tabulated value. Therefore, the null hypothesis is rejected. In other words, there is a significant difference between the daytypes in the given dataset with respect to the mean energy use.

Table A.2 : Sample SAS output for the ANOVA analysis procedure.

```
                       Analysis of Variance Procedure
                          Class Level Information
                         Class     Levels     Values
                         DTW          5     1 2 3 4 5
                  Number of observations in data set = 2926
        NOTE: Due to missing values, only 2902 observations were used.
                      Analysis of Variance Procedure
                       Dependent Variable: WBE
Source    DF      Sum of Squares      Mean Square     F Value      Pr > F
Model     4       28471380.9097     7117845.22742    486.71       0.0001
Error 2897        42366814.6716       14624.37510
Corrected Total
      2901        70838195.5813
       R-Square      C.V.         Root MSE          WBE Mean
       0.401921    18.27165     120.93128         661.85217
Source      DF       Anova SS        Mean Square     F Value      Pr > F
DTW          4    28471380.9097     7117845.2274    486.71       0.0001
```

This ANOVA analysis table is the same for a given daytype grouping (i.e., five daytypes as given in dtw) regardless of the multiple comparison procedure. Therefore, the Duncan-Waller-k-ratio procedure and Scheffe's procedure use the same table.

Results from Duncan's Procedure

This comparison procedure is performed in SAS software by adding a line (means dtw / Duncan) to the previous routine. This line will perform Duncan's multiple comparisons procedure in addition to the ANOVA analysis.

A sample output is given in Table A.3 for wbe (WBELE) variable with the five identified initial daytypes. The decision is summarized at the bottom of the tabulation for the test. For example, this summary is provided though the last six lines of the output, the last five lines (i.e., data groups or daytypes) were marked by letters A, B, C, D, and E. These correspond to the initial daytypes: 2 (regular weekdays), 4 (low weekdays), 1 (regular weekends), 3 (low weekends), and 5 (holidays or Christmas period). Since the daytypes were marked with different letters, these daytypes were identified as significantly different daytypes (as noted in the twelfth line).

```
/*checking daytypes for wbe separation*/
proc anova data=newa;
class dtw;
model wbe =dtw;
means dtw / Duncan ;
run;
```

Table A.3 : Sample SAS output for the Duncan's multiple comparison procedure.

```
               The SAS system
               Analysis of Variance Procedure
        Duncan's Multiple Range Test for variable: WBE
NOTE: This test controls the type I comparisonwise error rate, not the
experiment wise error rate
               Alpha= 0.05  df= 2897  MSE= 14624.38
              Harmonic Mean of cell sizes= 179.0631

             Number of Means     2     3     4     5
              Critical Range  25.06 26.39 27.27 27.93

Means with the same letter are not significantly different.

      Duncan Grouping      Mean       N  DTW

             A            738.07   1726  2
             B            614.65    144  4
             C            568.99    768  1
             D            542.38     72  3
             E            428.30    192  5
```

In the output from Duncan's multiple range test procedure, the description, as shown in the third and fourth lines, shows the type of error that was controlled by the specific test procedure. In this test, the designated error is $\alpha = 0.05$, or 5%. In Duncan's procedure the type I, comparison-wise error, is determined by the number of levels the comparison of means are apart, r, and the designated error. This error rate is equivalent to $\{1-(1-\alpha)^{r-1}\}$. These values were calculated for all the possible comparisons and presented in the ninth and the tenth lines of the output. The following is a sample calculation of the given output. First the means are arranged according to the size. Then the number of steps are determined as follows. The steps will be 2 when the means are next to each other and 3 when the means have one another mean between them (e.g., the daytypes DTP=2 and DTP=1 with DTP=4 in between them). Likewise the step is increased when the means are further apart. For comparing the means for daytypes 2 and 1 (3 steps apart), the percentage value is taken from the tables using the DF=2897, r=3 which is $C_{\alpha,(r,df)}$=2.92. Then the mean square sample within samples was taken from the $\sqrt{S_w^2/n}$ is $\sqrt{14624.38/179.0631}$ = 9.0372. Therefore, the critical range is calculated as 2.92 * 9.0372 = 26.38. The observed difference between the DTP=2 and DTP=1 is the difference between the means (738.07 - 568.99) which is equal to 169.08. This calculated value is higher than the critical range of 26.03. Therefore, the two daytypes are considered as significantly different.

This comparison continued for all the possible combinations of the five daytypes shown in Table A3 in the last six lines. The results and the relevant parameters are also summarized in Table A.3. For this dataset (dataset A) the initial daytypes are given with different letters to show the existing difference between the daytypes. If there is no significant difference between some daytypes then those daytypes would be marked with same letter. Then these daytypes would be aggregated together to form a single daytype and the resultant daytypes will be tested again until all the daytypes are identified as significantly different daytypes.

Waller-Duncan-K-Ratio Procedure

This procedure is referred to as the Waller procedure in the SAS software system (SAS, 1990). This procedure was suggested to eliminate some identified circumstances where the daytypes could be falsely identified as different by other methods (i.e., Scheffe, Tukey's or Fisher's procedures) (Waller and Duncan, 1969; Ott, 1984). In this procedure, the critical range or the Least Significant Difference (LSD) is calculated and compared against the difference between the mean values of the daytypes. The LSD value is calculated using an expression as follows

$$\text{LSD} = t_c\sqrt{S_w^2\left(\frac{2}{n}\right)} \qquad \text{.........(EA5)}$$

where t_c is taken from a tabulated values based on a designated error weight ratio k, DF for model, DF for error, S_w^2 is the mean square error from ANOVA tables and n is the number of observation in each population. The two daytypes are declared different when the absolute difference between the daytypes is larger than the calculated LSD. The tabulation is available for values of k=50, to 500 with a nominal value 100 often taken.

Example

The analysis is similar to the Duncan's procedure in defining the null hypothesis and alternate hypothesis.

Identified daytypes:

1 (regular weekends),
2 (regular weekdays),
3 (low weekends),
4 (low weekdays),
5 (holidays or Christmas period).

Null hypothesis:

Symbolic expression:

$dtw_1=dtw_2=dtw_3=dtw_4=dtw_5$

Statement: In the given dataset (energy use data), there is no difference between the five daytypes (detail below) with respect to the mean energy use.

Alternate hypothesis:

Symbolic expression:

$dtw_1 \neq dtw_2 \neq dtw_3 \neq dtw_4 \neq dtw_5$

Statement: In the given dataset (energy use data), there is a significant difference between the five daytypes (detail below) with respect to the mean energy use.

Sample Results from Waller-Duncan-k-ratio Test

The nominal k-ratio of 100 was taken for this study. The other relevant values from the ANOVA table are: DF1=4 ; DF2= 2897 ; MSE= 14624.38 ; F= 486.7111. Therefore, the critical value t_c is taken from the statistics tables (Box et al., 1978) as 1.7356. Accordingly, the LSD is calculated as $1.736*\sqrt{14624.38\left(2/179.0631\right)}$ = 22.1817. If the difference between the two successive means are higher than this value (22.182), the daytypes will be decided as significantly different. The summarized values are given in the sample output from the SAS routine as given in Table A.4.

Table A.4:Sample SAS output for the Waller-Duncan- k- ratio procedure.

```
                    Analysis of Variance Procedure
             Waller-Duncan K-ratio T test for variable: WBE
              Kratio= 100  df= 2897  MSE= 14624.38  F= 486.7111
                   Critical Value of T= 1.73558
                   Minimum Significant Difference= 22.182

   Means with the same letter are not significantly different.

                         Waller Grouping    Mean      N    DTW
                                A          738.07   1726   2
                                B          614.65    144   4
                                C          568.99    768   1
                                D          542.38     72   3
                                E          428.30    192   5
```

Scheffe's Procedure

This is the most general procedure, proposed by Scheffe, that can be used to make all possible comparisons among the k population means (Ott, 1984; Freund and Wilson, 1993). It is less sensitive than other multiple comparison procedures for detecting significant differences among pairs of population means (Ott, 1989; Freund and Wilson, 1993). In this test the experiment-wise error rate is controlled so that the experiment-wise level of significance is at most α (designated error rate, 0.05 for this study). In Scheffe's procedure the difference is compared against a critical value, S, which is defined (Ott, 1984) as

$$S = \sqrt{(k-1)F_\alpha \sum S_w^2\left(\frac{a_i^2}{n}\right)} \quad \text{.......(EA6)}$$

where F_α is the F distribution value defined by F with corresponding degrees of freedom of the ANOVA test, which is [(k-1), n-1-(k-1)]. S_w^2 is sum of squares of within variation, a=alpha, and k=the number of daytypes. If a value is larger than the calculated critical value, S, the null hypothesis will be rejected and the alternate hypothesis will be accepted. The null and alternate hypothesis are described below. If the difference between any mean value of the daytype is smaller than the minimum calculated significance difference for Scheffe's expression then the daytypes are not significantly different and hence will be marked by the same letter.

Null hypothesis: $L = 0$

Alternate hypothesis: $L \neq 0$

where $L = \Sigma(a_i\mu_i)$ and μ_i is the i^{th} treatment. The contrast is calculated as $\hat{L} = \Sigma(a_i y_i)$

y_i is the mean of the i^{th} contrast. For comparing two daytypes this will be calculated as

$L = \mu_1 - \mu_2$. $a_1=1$, $a_2= -1$.

Example

For the given dataset (dataset A) the relevant values from the ANOVA table are Alpha= 0.05 ; DF1=4, DF2= 2897; and MSE= 14624.38. Therefore, the F_α is from tabulation is 2.37. Therefore, the minimum significance difference is calculated as

$$\sqrt{4*2.37*(\frac{1}{179.0631}+\frac{1}{179.0631})*14624.38} = \sqrt{4*2.37*12.078^2} = 39.39.$$

Table A.5 : Sample output from the Scheffe's procedure using the SAS software

```
                    Analysis of Variance Procedure
                   Scheffe's test for variable: WBE
Alpha= 0.05  df= 2897  MSE= 14624.38       Critical Value of F= 2.37500
                  Minimum Significant Difference= 39.392
    Means with the same letter are not significantly different.
        Scheffe Grouping     Mean      N  DTW
               A           738.07    1726  2
               B           614.65     144  4
               C           568.99     768  1
               C
               C           542.38      72  3
               D           428.30     192  5
```

Therefore, if any of the contrasts (i.e., $\mu_1 - \mu_2$, difference between two means of daytypes) is larger than 39.39, then the null hypothesis is rejected. The sample output from SAS software for the procedure is given in Table A.5. In the given output, only the dtw=3 and dtw=1 has shown that the contrast is smaller than S. Hence these daytypes were marked with the same letter C. The calculated difference between the sample means is 26.59 (=568.97 - 542.38) which is significantly lower than the critical range of 39.39, thus resulting in these two daytypes being marked by the same letter C to show the insignificant difference between these two daytypes. Therefore, both of these initial daytypes were aggregated together to form a single daytype and thus four final daytypes were obtained.

Summary

In this section, the definitions and sample results of the diagnostic and goodness-of-fit parameters that are widely used for model development process were presented. Three multiple comparison procedures were also outlined along with sample output and guideline for interpreting the sample results.

APPENDIX B

DESCRIPTION OF THE CASE STUDY BUILDINGS

Introduction

In order to provide a complete demonstration of the inverse bin analysis, the case study buildings have chosen carefully to enable the method to be tested on buildings that can represent typical buildings. After a careful consideration, we have found that the monitored data from a single building did not provide a complete demonstration of method. Therefore, several case study sites were selected from available monitored data in the LoanSTAR program from buildings to provide the demonstration of the inherent features of this inverse bin method. The selected buildings represent typical buildings which are: a) internal load dominated buildings (Engineering Center-ZEC), b) schedule-effect and ventilation dominated buildings (Business building-BUS), c) thermal mass dominated buildings (Perry Castenada Library-PCL), and d) small commercial building (Russell A. Steindham building-RAS). Table B1 shows the selected datasets for the application of the inverse bin method.

Table B.1 : Selected Datasets for the Application of the Inverse Bin Method

Dataset	Building / Data origin	Type of demonstration
A	EC building, Predictor shootout I	simple inverse bin method
C	EC building, Predictor Shootout II	simple inverse bin method, improved inverse bin method, and humidity sub-binning
D	BUS building, Predictor Shootout II	simple inverse bin method, improved inverse bin method, and humidity sub-binning
RAS	LoanSTAR program	small institutional building
WEL	LoanSTAR program	lagged temperature variable
PCL	LoanSTAR program	improved bin method with lagged temperature variable

Description of the Case Study Buildings

Dataset A from Predictor Shootout I Competition

In this dataset the monitored energy use and environmental data represent data from a real building that was used to test hourly empirical models in the ASHRAE Predictor Shootout I competition (Kreider and Haberl, 1994). During the competition no additional information other than the independent variables (or environmental data) was made available to the participants. Participants were given these independent variables with the corresponding values of the dependent variables (e.g., energy usage for the training period). A second data set was also given with only the independent (or environmental) variables. The data set from which the independent variables have been withheld were called the "testing set" whereas the data that include both independent and dependent variable values were called the "training set.". The independent variable values in the testing set were used by each participant to make their best predictions of the corresponding dependent variables in the testing data set. The organizers compared these predictions by each contestant with the true (data) values of the dependent variables that were known only to the organizers. The accuracy of predictions of the dependent variables from values of independent variables from this data set was the criteria for judging the competition. This accuracy was calculated using the two parameters (Coefficient of Variation -CV-RMSE and Mean Bias Error -MBE) defined under Appendix A-Parameters for the Evaluation of Model Performance. The following are the descriptions provided with the dataset for assistance and identification (Kredier and Haberl, 1994).

A.dat (approximately 3,000 points): This is a time series record of hourly chilled water, hot water and whole-building electricity usage for a four-month period in an institutional building. Weather data and a time stamp are also included. The hourly values of usage of these three energy forms is to be predicted for the two following months. The testing set consists of the two months following the four-month period. The withheld testing data used for evaluating the predictions after the close of the competition will not be available to any of the entrants. For data set A submit predictions (i.e., forecasts) for chilled water, hot water and whole building electricity use for the two months following the four-month training set. The testing set will include values of the same independent variables (weather, date and time) as the training set. Submit your predictions of the three energy end uses in serial order by appending three columns containing your predictions to the right of the testing set columns provided on the disk data file. A sample of how you are to submit your data will be supplied with the data diskette.

Data Format and Units: The formats and units of the data in the data sets are given below. The training data set has both dependent and independent variables. In the testing sets the dependent variables are missing. Here are the formats for the data files. The numbers are shown below in a column for convenience but in the data files each of the sets of data given below represents the first ROW of data in that file.

ATRAIN.DAT

Month	9
Day of month	1
Year	89
Hour	200 (military numbering)
DB Temperature	81.9 (deg F)
Humidity ratio	0.0184 (lb water/lb dry air)
Solar flux	0 (W/sq meter)
Wind speed	7.62 (mi/hr)
Whole bldg electric	496.07 (kWh/hr)
Whole bldg chil'd water	7.2 (millions of Btu/hr)
Whole bldg hot water	0.4 (millions of Btu/hr)

(the last three entries are the dependent variables)

ATEST.DAT

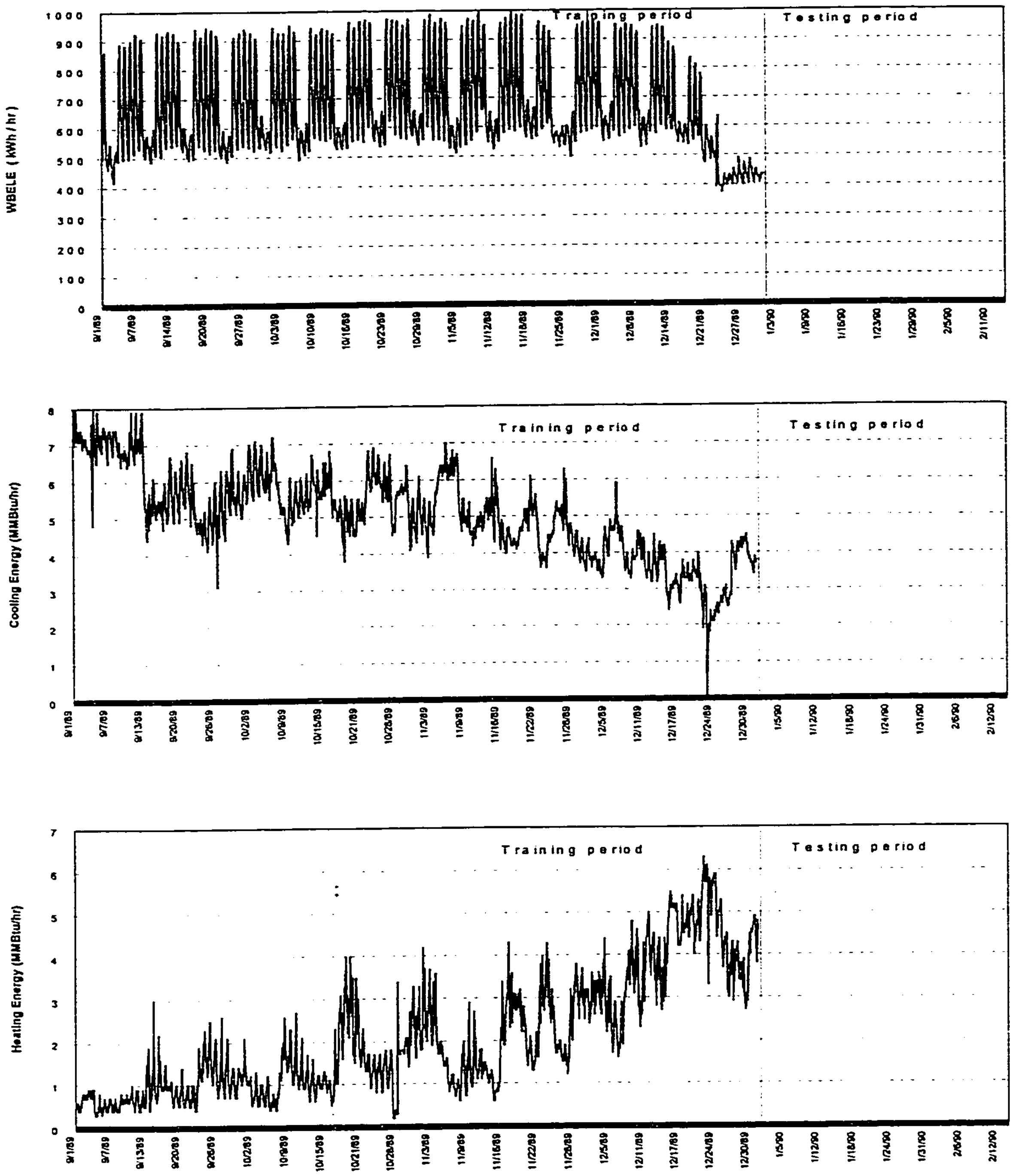
Month	1
Day of month	1
Year	90
Hour	0 (military numbering)
DB Temperature	43 (deg F)
Humidity ratio	0.0031 (lb water/lb dry air)
Solar flux	2 (W/sq meter)
Wind speed	4.88 (mi/hr)

(the three dependent variables are not in the testing set)

DATA SET A

You will submit file ATEST.DAT supplied to you with three new columns added to the right for each hour. The first column will contain predictions of whole building electric usage. The second and third columns will contain

Figure B1: Daily time series plots of the dataset A (a.trn). In the upper figure daily whole-building electricity is shown followed by chilled water and hot water use. Data for the testing period is left blank.



predicted whole building chilled water and whole building hot water, respectively. For example, the first row of your file ATEST.DAT that you submit might look like this (the last three predicted values are just examples and will not necessarily bear any resemblance to your predictions for the first hour of the testing data set for data set A)

Month	1
Day of month	1
Year	90
Hour	0 (military numbering)
DB Temperature	43 (deg F)
Humidity ratio	0.0031 (lb water/lb dry air)
Solar flux	2 (W/sq meter)
Wind speed	4.88 (mi/hr)
Predicted WBE	450 (kWh/hr, the prediction)
Predicted WBCW	6 (millions of Btu/hr, the prediction)
Predicted WBHW	4 (millions of Btu/hr, the prediction)

Dataset C and dataset D from Predictor Shootout II Competition

These data sets, from the ASHRAE sponsored Predictor Shootout II competition (Haberl and Thamilseran, 1996), were selected from the monitored data for two buildings in the LoanSTAR program. In this competition, unlike the previous competition, all the building information including description, schedules, holidays, and location were provided to help enhance the predictability.

The following descriptions are extracted from the details provided by the organizers for the competition (Haberl and Thamilseran, 1994).

Two data sets are provided from two different buildings in four files. The "*.trn, and *.tst" files contain independent variables (i.e., weather data and time stamp) and the corresponding dependent variables (i.e., whole-building energy use) for the training (*.trn) and testing (*.tst) periods respectively. These data sets are to be used by the contestants to build their models. Portions of the dependent variables (i.e., the whole-building energy use) have been removed from the *.trn files and replaced with "-99." The independent variables that correspond to the removed data remain in the *.trn file and should be used by the contestants to predict energy use for the removed periods. The predictions of energy use for the removal period will then be compared to actual removal data (known only by the contest organizers) to test the accuracy of the contestant's model.

The two "*.tst" files contain independent and dependent variables from the post retrofit period for each building. The contestants are be required to use their baseline models to predict energy use for every hour contained in the "*.tst" file and submit their predictions in the required format. Predictions in the post retrofit period will be compared against other contestants predictions to see how large the differences are in the savings calculations from one model to the next.

Dataset C

c.trn and c.tst data set These data sets represent data from the Zachry Engineering Center on the Texas A&M University campus. The Zachry Engineering Center (ZEC), located at Texas A&M University, contains 324,000 square foot (30,000 m^2) of classroom, office, computer center and laboratory facilities comprising four stories with an underground parking garage. It was constructed in the early 1970s. The building is a heavy structure with 6-inch (0.15 m) concrete floors and insulated exterior walls made of pre-cast concrete and porcelain-plated steel. About 12% of the exterior wall area is covered with single pane, bronze-tinted glazing. The windows are recessed approximately 2 ft. (0.61 m) from the exterior walls, providing some shading. Approximately 3100 ft^2 (288 m^2) of northeast-facing celestory windows admit daylight into the core of the building.

The building is served by 12 dual-duct air-handling units located in the parking garage. Chilled and hot water for the cooling and heating coils are supplied to the building by the campus physical plant. Two multi-zone units and a dedicated centrifugal chiller serve a super-computing facility located within the building. Manual operation of the secondary chilled and hot water pumps also affects the systems cooling and heating capacity. Outside air dampers are permanently set to supply about 10% to 20% outdoor air (Katipamula 1992) and do not operate on an economizer cycle.

The primary retrofit to the building was to replace the existing Constant Air Volume (CAV) air distribution systems with a variable frequency, Variable Air Volume (VAV) air distribution system. During the retrofit the energy management and control system was also upgraded. Additional information about the building can be found in Bronson (1992), Bronson et. al. (1992), and Haberl et. al. (1993, 1995).

The ZEC was the first building instrumented under the LoanSTAR program. About 50 channels of hourly data have been recorded and collected each week since May, 1989. Additional information concerning the building can be found in Table 1. Figure 1 displays the data for the pre+post periods. The ZEC data are provided in the "c.trn" and "c.tst" files on the FTP server. These files have the following format:

C.TRN (1/1/90 0:00 to 11/27/90 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe	temp	rh	sol	wspeed
1	1	1	90	0	883.00	-99.00	-99.00	3.70	4.70	42.99	53.32	2.00	4.88
1	1	1	90	1	877.30	-99.00	-99.00	3.70	4.70	41.80	55.48	2.10	4.86
1	1	1	90	2	878.00	-99.00	-99.00	3.60	4.70	41.49	54.02	2.20	4.61
1	1	1	90	3	880.80	-99.00	-99.00	3.70	4.70	41.36	53.22	2.20	4.88
1	1	1	90	4	879.80	-99.00	-99.00	3.60	4.80	40.99	53.17	2.10	4.34

C.TST (11/28/90 0:00 to 12/31/92 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe	temp	rh	sol	wspeed
1	11	28	90	0	1126.40	375.83	632.08	5.20	1.60	68.36	72.95	5.91	4.87
1	11	28	90	1	1100.03	376.42	606.78	4.90	1.70	66.36	68.95	6.53	7.08
1	11	28	90	2	1081.44	376.33	586.52	4.70	2.30	59.63	80.06	6.84	8.35
1	11	28	90	3	1064.36	374.57	571.73	4.50	2.70	56.10	66.54	6.53	9.41
1	11	28	90	4	1061.10	375.09	568.40	4.40	2.80	53.70	67.70	6.53	5.65

where

site = an arbitrary site number,
mo = month,
dy = day,
yr = year,
hr = hour,
wbe = whole-building electricity (kWh/h),
mcc = motor control center electricity (kWh/h),
lteq = lights and equipment electricity (kWh/h),
cwe = whole-building chilled water (MBtu/h),
hwe = whole-building hot water (MBtu/h),
temp = ambient temperature (F),
rh = ambient relative humidity (%),
sol = global horizontal solar (W/m2, ignore negative values),
wspeed = wind speed (MPH).

-99 has been used to replace the removal data in the "*.trn" training set. Your energy predictions should be provided in the following formats, where your predictions are inserted into the "nnn.nn" values are shown:

C.TRN (1/1/90 0:00 to 11/27/90 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe
1	1	1	90	0	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	1	1	90	1	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	1	1	90	2	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	1	1	90	3	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	1	1	90	4	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn

C.TST (11/28/90 0:00 to 12/31/92 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe
1	11	28	90	0	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	11	28	90	1	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	11	28	90	2	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	11	28	90	3	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
1	11	28	90	4	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn

Data are missing during the following periods: for lights and equipment and motor control center electricity use during January and February of 1990, for chilled water from April 1991 to November 1991 and for a few weeks in July of 1992, and for hot water during April 1991, and from June through November of 1991. The calculation of retrofit savings during these periods requires the use of both pre-retrofit and post-retrofit models.

The prediction for the "c.trn" data set will be tested against the removed data to evaluate your models accuracy. The prediction for the "c.tst" data set will be used to calculate the energy savings from the conservation retrofit. Place only the ASCII numeric information in your files to be named "c.trn", "c.tst", etc. Do not include alphanumeric headers in the file. It will be assumed that the columns represent the data specified.

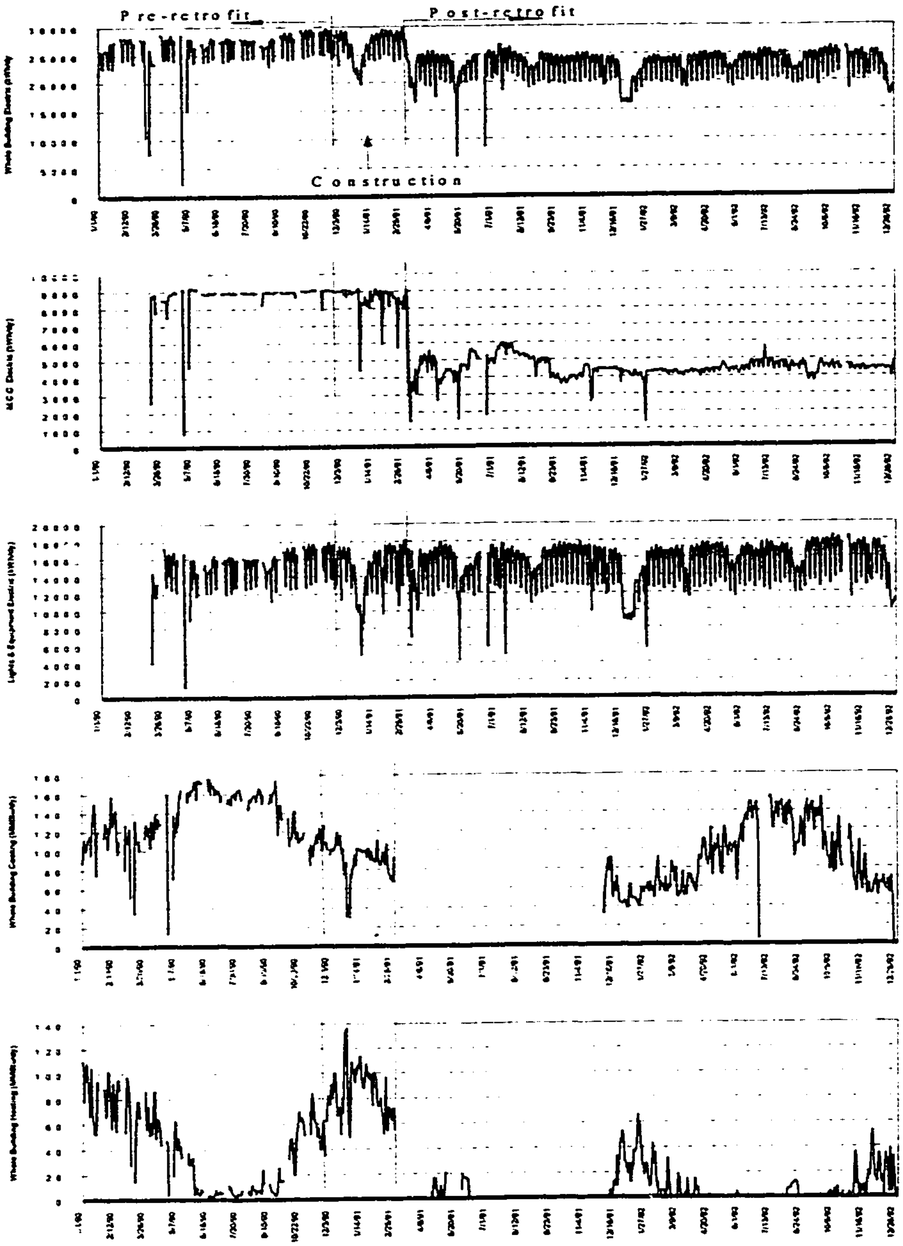
Dataset D

d.trn and d.tst data set These data sets represent data from the Business building at the University of Texas in Arlington, Texas. The 149,900 square foot (13,926 m^2) Business buildings houses classrooms and lecture halls. It was constructed in 1976. The building is

Table B2: General Information about the Zachry Engineering Center, Texas A & M University..

TEXAS A & M UNIVERSITY: Zachry Engineering Center
Building Envelope: 324,400 sq.ft. 3-1/2 floors and a ground floor level, erected in 1973, classes, offices, labs, computer facility, and clean rooms for solid Electronics Walls: cement block Windows: 22% of total wall area single pane with built-in-place vertical blinds roof: flat
Building Schedule: classrooms and labs: 7:30 am to 6:30 pm weekdays offices: 7:30 am to 5:30 pm weekdays computer facility: 24 hrs/day
Building HVAC: 12 variable volume dual duct AHUs (12-40 hp) 3 constant volume multizone AHU (1-1hp, 1-7hp,1-10hp) 4 constant volume single zone AHU (4-3hp) 10 fan coils (10-0.5 hp) 2 constant volume chilled water pump (2-30hp) 2 constant hot water pump (2-20 hp) 7 misc. pumps (total of 5.8hp) 50 exhaust fans (50-0.5hp)
HVAC schedule: 24 hrs/day
Lighting: fluorescent
Retrofits Implemented: control modifications to the dual duct systems variable volume dual duct systems
Other Information: EMCS system to control HVAC was also installed along with the retrofits
Date of retrofits: date of completion for VAV and control modifications to the dual duct system: 3/30/91

Figure B2: Daily time series plots of the ZEC. In the upper figure daily whole-building electricity is shown followed by motor control center, lights and equipment electric, chilled water and hot water use. Data are for the training, construction and post-retrofit periods. Lights and equipment data are derived by subtracting motor control center electricity from the whole-building electricity. Data have been removed from the training period for testing purposes. Missing data occur for some period within the data as noted in the instructions.



heavy structure with face brick on concrete block walls. The windows are tinted, single pane and represent 4% of the wall area. The building is served by 3 dual duct air-handling units located in the basement. Chilled water and steam are provided by the central physical plant. AHUs operate 24 hrs/day, 7 days/week.

The primary retrofit to the building was a VAV conversion for the AHUs and lighting control which utilizes motion sensors. The retrofits were completed in July of 1991. Additional information concerning the building can be found in Table 2. Figure 2 displays the data for both the pre+post periods.

The Business data are provided in the "d.trn" and "d.tst" files on the LoanSTAR FTP server. These files have the following format:

D.TRN (12/22/90 0:00 to 7/12/91 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe	temp	rh	sol	wspeed
112	12	22	90	0	-99.00	-99.00	-99.00	-99.00	-99.00	15.48	81.97	-1.20	8.68
112	12	22	90	1	-99.00	-99.00	-99.00	-99.00	-99.00	15.08	83.77	-1.20	9.69
112	12	22	90	2	-99.00	-99.00	-99.00	-99.00	-99.00	14.24	85.67	-1.14	11.56
112	12	22	90	3	-99.00	-99.00	-99.00	-99.00	-99.00	14.20	86.17	-1.07	11.45
112	12	22	90	4	-99.00	-99.00	-99.00	-99.00	-99.00	13.88	86.88	-1.07	10.88

D.TST (7/13/91 0:00 to 12/31/92 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe	temp	rh	sol	wspeed
112	7	13	91	0	179.68	27.69	34.34	0.81	0.09	84.87	49.52	-0.13	0.00
112	7	13	91	1	177.27	27.62	32.94	0.92	0.00	83.34	54.27	-0.13	0.02
112	7	13	91	2	161.04	27.69	30.28	0.69	0.09	82.22	58.08	-0.13	0.14
112	7	13	91	3	152.61	27.71	29.52	0.81	0.00	81.50	60.53	0.01	0.34
112	7	13	91	4	151.34	27.70	29.24	0.81	0.09	80.46	64.24	0.08	0.04

Your energy predictions should be provided in the following formats, where your predictions are inserted into the "nnn.nn" values are shown:

D.TRN (12/22/90 0:00 to 7/12/91 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe
112	12	22	90	0	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	12	22	90	1	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	12	22	90	2	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	12	22	90	3	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	12	22	90	4	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn

D.TST (7/13/91 0:00 to 12/31/92 23:00):

site	mo	dy	yr	hr	wbe	mcc	lteq	cwe	hwe
112	7	13	91	0	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	7	13	91	1	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	7	13	91	2	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	7	13	91	3	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn
112	7	13	91	4	nnn.nn	nnn.nn	nnn.nn	nnn.nn	nnn.nn

Data are missing during the following periods: December 1990 through March 1991 (chilled water and heating energy use), and for a few weeks in December of 1992.

Table B3: General Information about the UT Arlington Business Building.

UNIVERSITY OF TEXAS AT ARLINGTON: Business Building

Building Envelope:
- 149,900 sq.ft.
- 2 sections (A & B); 3 floors in A section and 6 floors in B section.
- classrooms and lecture halls; built in 1976.
- Walls: face brick.
- Windows: brown tinted, single pane, fixed, 4% of wall area
- roof: N/A

Building Schedule:
- offices: 8 am to 6 pm (M-F)

Building HVAC:
- 3 variable volume dual duct AHUs (1-100 hp, 1-50hp, 1-40 hp)
- 13 exhaust fans (total of 4 hp)
- 1 constant volume chilled water pump (1-30 hp)
- 1 hot water pump (N/A)
- 3 return air fans (RF1-10 hp, RF2&3-7.5 hp each)

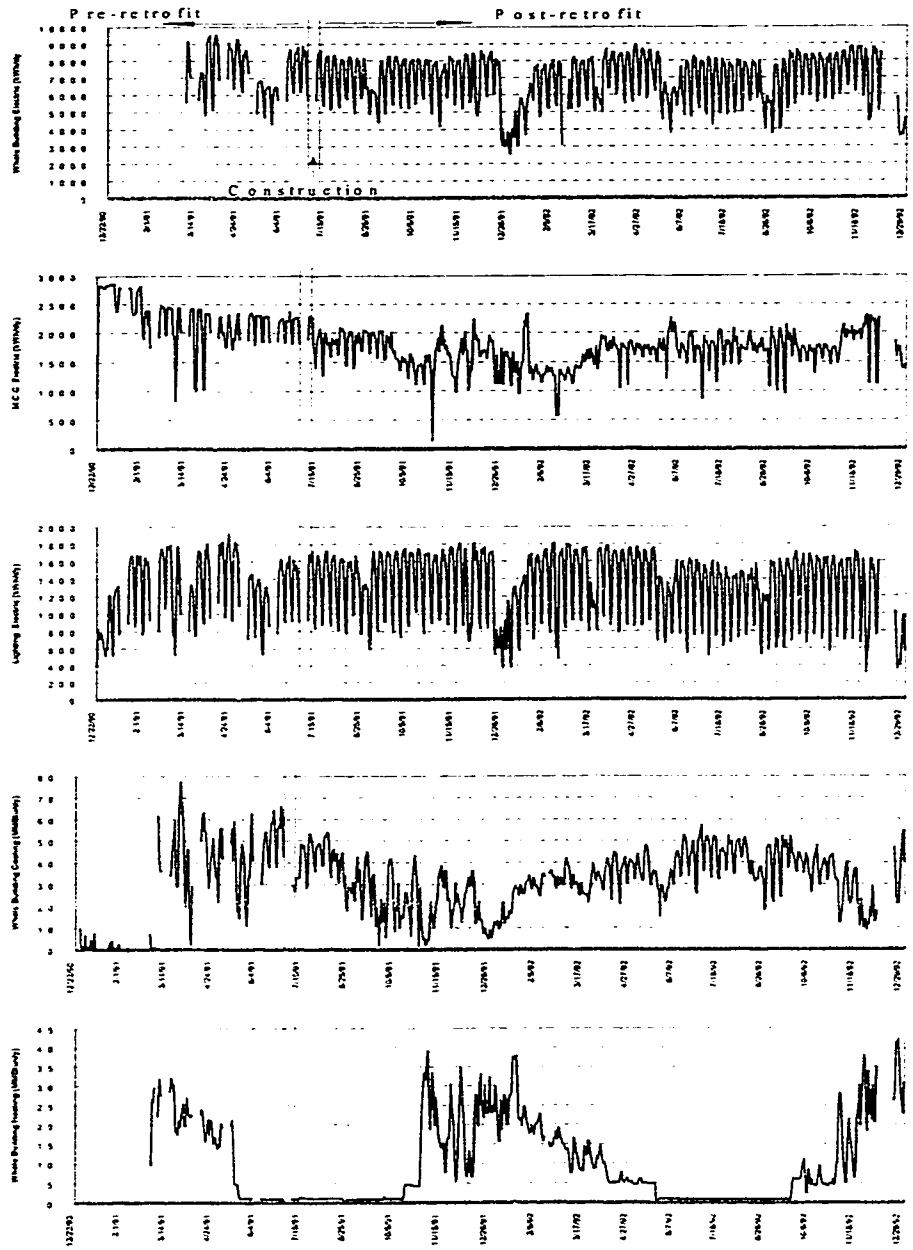
HVAC schedule:
- 24 hrs/day, 7 days/week (AHU-1 & RF-1)
- 6 am tp 11 pm, 7 days a week (AHU2&3, RF2&3)

Lighting:
- fluorescent 34 W

Retrofits Implemented:
- VAV conversion for the AHUs
- lighting control

Date of retrofits:
- VAV conversion and lighting modifications were completed in July 1991.

Figure B3: Daily time series plots of the Business building. Beginning with the upper figure daily whole-building electricity, motor control center, lighting electric, chilled water and heating energy use is shown for the training, construction and post-retrofit periods. Lighting electric is a derived channel that is obtained by subtracting motor control center electricity use from the whole-building electricity. Data have been removed from the training period for testing purposes.



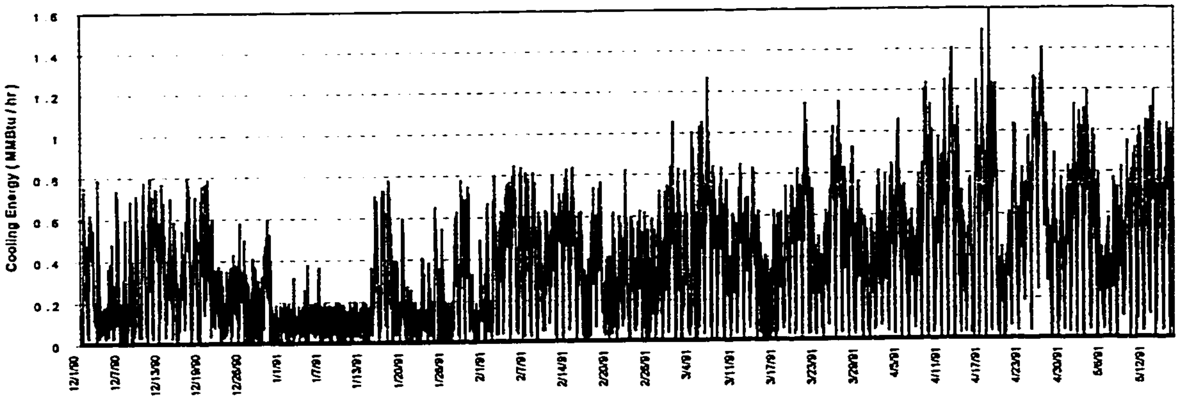
Russell A. Steindham Building (RAS)

This 56,800 square foot four-story building building was constructed in 1956 with reinforced concrete frame and floors. Its walls are constructed of concrete blocks with face brick. The windows which cover about 28% of the wall area are single-pane clear glass operable units. The is built-up on a three-inch lightweight fill with one-inch of insulation supported by structural concrete. The building mainly houses classrooms, laboratories and offices with classrooms primarily occupied from 7:30 a.m. to 6:30 p.m. weekdays.

The cooling and heating are provided by the steam and chilled water received from the campus central plant. Two DDCAV units serve the building: AHU-1 serves the east-half of the building, and AHU-2 serves the west-half of the building. A hot water heat exchanger located in the west mechanical room produce hot water by converting the high pressure steam. This hot water is then served by a 2 hp pump for the AHUs. Chilled water coils have no valves and are allowed to run wild.

The space temperatures are well maintained at 75F. The AHUs are controlled (start and stop) by the campus EMCS. The building was retrofitted in May 1991. The retrofits were conversion of DDCAV systems into DDVAV systems, hot and cold deck resets, and lighting improvements. The systems were operated 18 hours per day, five days per week plus school holidays. The EMCS control capability has been lost since April 1992. Additional information concerning the building is given in Table B4.

Figure B4: Hourly time series plots of the RAS building. Beginning with the upper figure hourly whole-building electricity, chilled water and heating energy use is shown for the baseline period analyzed in this study. Missing data occur within the selected data period. The entire WBELE data for baseline period was missing. The baseline and construction periods are 10/13/90 - 03/31/91 and 04/01/91 - 06/01/91.



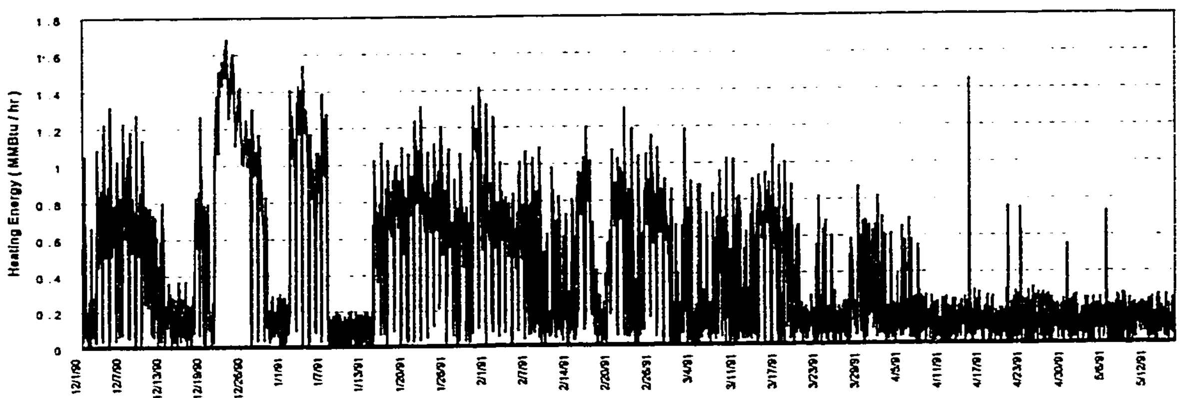


Table B4: General Information about the R.A. Steindham Building at the University of Texas, Austin.

UNIVERSITY OF TEXAS AT AUSTIN : Russell A Steindham Building
Building Envelope: 56,800 sq.ft.; 4floors, erected 1956, classes, offices, and lab. walls: concrete block with face brick,windows: 28% of total area, single pane clear roof: 3"lightweight fill and 1" insulation
Building Schedule: classrooms: 7:30 - 18:30 (M-F); offices: 8:00 to 18:00 (M-F); labs 7:30 to 21:30 (M-F)
Building HVAC: 2 constant volume dual duct AHUs (1-50 hp, 1-40hp); 2 return fans (1-10hp,1-71/2hp) 1 const. volume chilled water pump (1-7.5 hp); 1 constant volume hot water pump (1-2 hp)
HVAC schedule: 18 hrs/day weekdays and school holidays
Lighting: fluorescent 34 W

Table B5: General Information about the Welch Hall at the University of Texas, Austin.

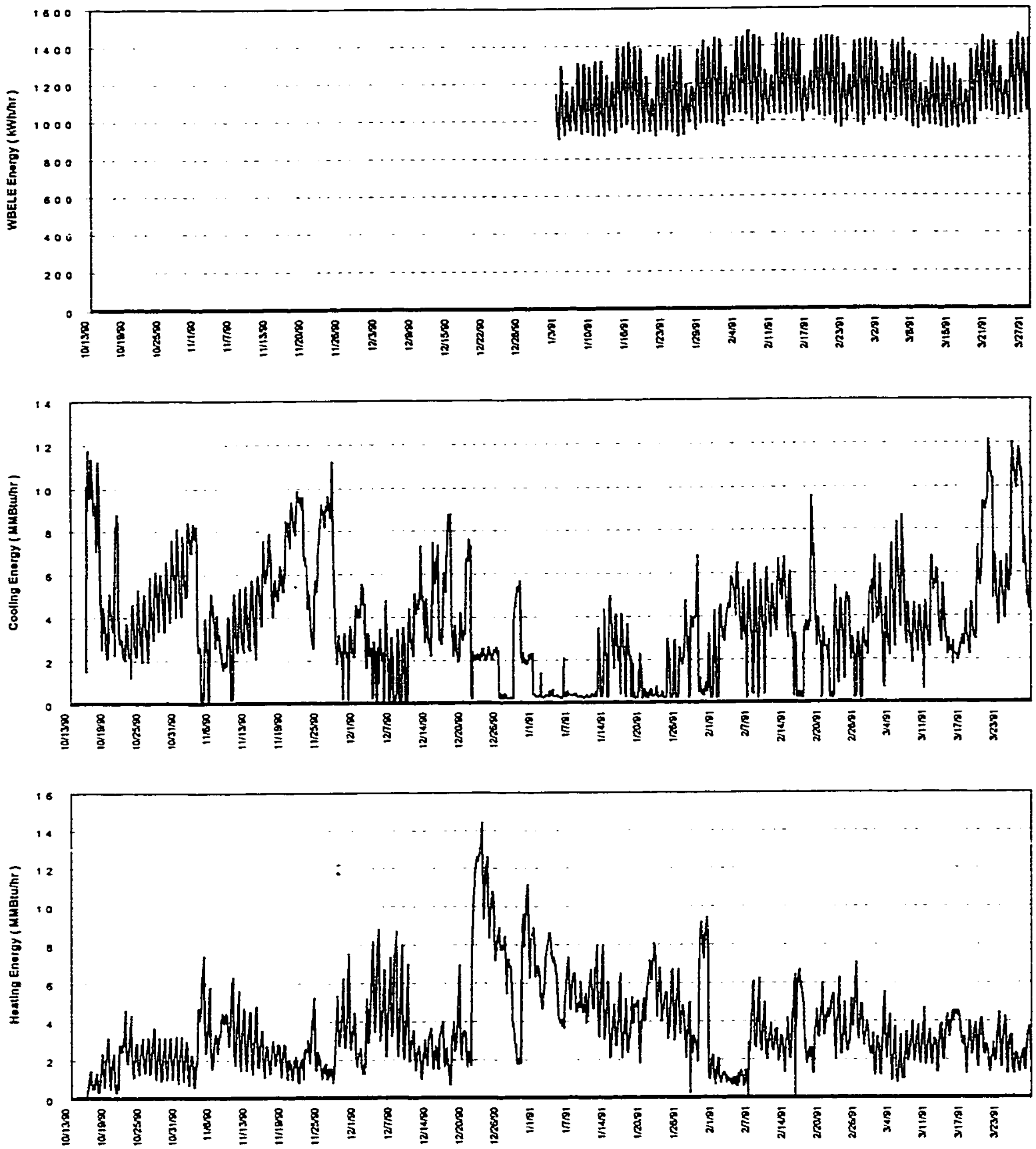
UNIVERSITY OF TEXAS AT AUSTIN : Welch Building
Building Envelope: 439,540 sq.ft.; 6floors, erected 1974, classes, offices, and labs. walls: red face brick on block,windows: 20% of total area, single pane tinted roof: built-up with 4.5" insulation
Building Schedule: 18 hrs/day (7:30 to 22:30 all week long
Building HVAC: 4 constant volume dual duct AHUs (4-100 hp); 2 variable air volume dual duct AHUs (2-100 hp) 1 variable speed return air fan for AC3 (1-50hp) 1 variable speed hot deck fan AC3 (1-60 hp) 3 return air fans (2-30 hp, 1-60 hp)
HVAC schedule: 24 hrs/day
Lighting: fluorescent 34 W

Welch Hall (WEL)

This building is a six story, 243000 square foot building which houses laboratories, classrooms of the Department of Chemistry, University of Texas at Austin. The building which was originally constructed in 1929 and was later added with five floors in 1969 and extended with a south wing in 1974, is mainly consists of several laboratories, plant growth chambers and a green house complex. The building sparsely occupied in the night, though opens 24 hours per day.

The walls were constructed with red-brick on block and fitted with tinted single-pane glass windows. The building has flat built-up roof with 4.5 inch all weather deck. The mechanical equipment are located in the first and sixth floor of the building. The systems located in the first floor (three DDCAV AHUs and two 30 hp return air fans) supply conditioned air through the building except the green house chambers which are supplied by one DDCAV AHU. The systems operate nearly 100 outside air because of the large volumes of air expelled from the building by exhaust fans. These fans operate 24 hours per day because of the various experiments taking place in the building which may release harmful or obnoxious odor and/or fumes. The mechanical systems are monitored by a EMCS though none of the equipment are turned off according to regular schedule. Additional information concerning the building is given in Table B5.

Figure B5: Hourly time series plots of the WEL building. Beginning with the upper figure hourly whole-building electricity, chilled water and heating energy use is shown for the selected period (01/01/92 - 07/31/92 for cooling and 07/01/92 - 12/31/92 for heating) analyzed in this study. Missing data occur within the selected data period.



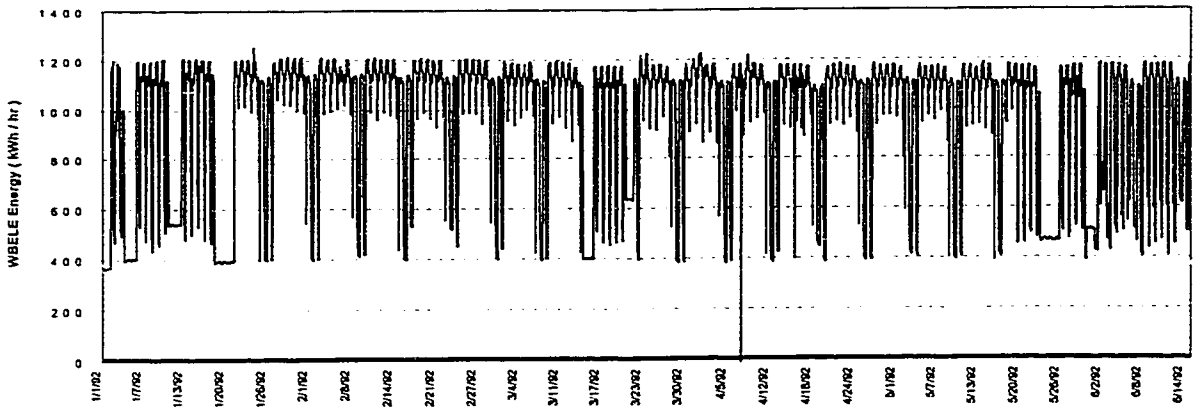
Perry Castaneda Library (PCL)

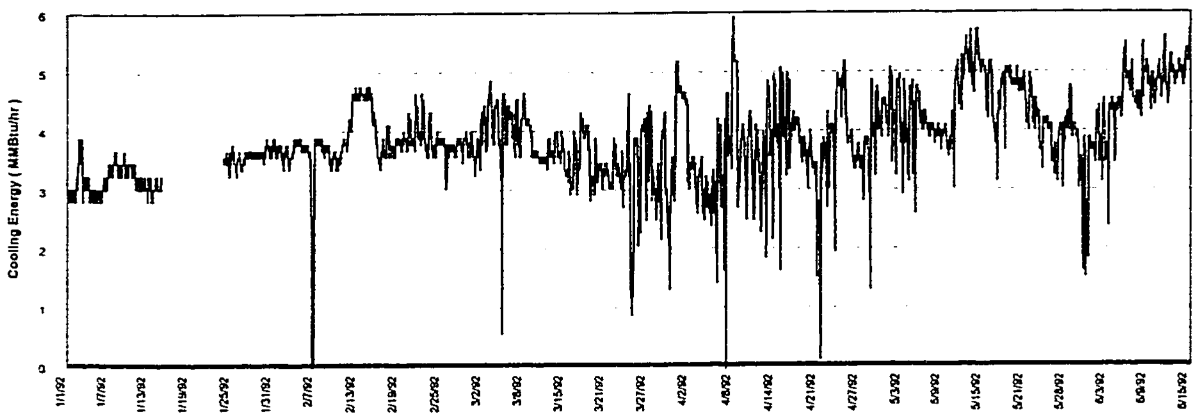
The Perry Castaneda Library (PCL) is a six-story, 483,895 square foot building located in the University of Texas, Austin. The building which was constructed in 1977, houses an open-stack library, offices, and computer facilities. The library area bookshelves and study tables, while the remaining space consists of miscellaneous offices and work rooms. The building walls are constructed on limestone panels on concrete blocks. The windows consist of 0.25 inch single-pane tinted glass and cover approximately 30% of the exterior wall.

The building is open seven days per week, Monday through Friday from 8:00 am to 12:00 am, Saturday from 8:00 am to 5:00 p.m. and noon to 10:00 p.m. on Sundays. The HVAC systems operates 24 hours a day. The building is conditioned by 12 AHUs in four groups (each with two single-duct CAV and one DDCAV) that serve west side, northwest, northeast and south sections of the building. These units were converted to variable air volume (VAV) units in November, 1990 as part of the major retrofit which also include variable speed pumping and lighting improvements. In normal operating conditions one 60 hp pump (1500 GPM) provide the required chilled water flow to this building. However, a second pump of equal capacity operates to double the flow rate when the internal humidity rise above a preset limit. Steam supplied from the main utility plant at 165 psi and reduced to 10 psi at entry to the building to provide necessary heating and domestic hot water production. The preheat is cut-off when the outdoor temperatures are above 40F. The economizer cycle operation was also added as part of the retrofit in 1990.

This building was chosen as one to test building to verify the inverse bin method (with thermal lag effect) analysis. As suspected this building has shown favorable energy use variation with lag temperature variables. In addition to being affected by the massive internal thermal mass the building was also dominated by ventilation latent loads to keep humidity levels to reduce deterioration of books and journals. Additional information concerning the building is given in Table B6.

<u>Figure B6: Hourly time series plots of the PCL building.</u> Beginning with the upper figure hourly whole-building electricity, chilled water and heating energy use is shown for the selected period analyzed in this study. Missing data occur within the selected data period..





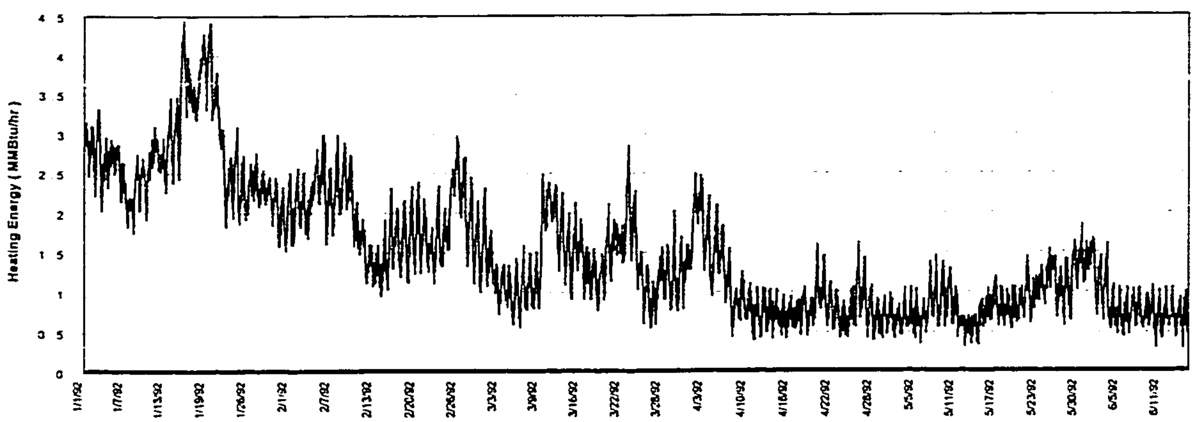


Table B6: General Information about the PCL Building at the University of Texas, Austin.

UNIVERSITY OF TEXAS AT AUSTIN : P.C. Library Building
Building Envelope: 483,895 sq.ft.; 6floors, erected 1977, book shelves, open stack library, offices and computer labs. walls: limestone panels on block,windows: 12% of total area, single pane tinted roof: built-up with light weight insulation fill
Building Schedule: 08:00 - 24:00 (Monday-Friday); 08:00 - 17:00 (Saturday), and 12:00 - 22:00 (Sunday)
Building HVAC: 8 variable volume single duct AHUs (8-75 hp); 4 variable volume dual duct AHUs (4-100 hp) 12 variable speed return fan (12-25 hp); 4 variable speed hot deck fans (4-50 hp)
HVAC schedule: 24 hrs/day
Lighting: fluorescent 34 W

Education Building (EDB)

The Education Building (EDB), located at the University of Texas at Austin contains 250,000 ft^2 (23,300 m^2) of gross conditioned space of five stories and consists of classrooms, office and administration offices. It was constructed in 1976. The building is face brick on block wall construction. About 30% of the exterior wall area is covered with single pane, tinted glazing, which is shaded. The building has a flat built-up roof, and is occupied from 8 a.m. to 5 p.m. Monday through Friday.

The building is served by 11 dual-duct air-handling units, three constant air volume units and eight variable air volume units. Chilled and hot water for the cooling and heating coils are supplied to the building by the campus central energy plant. During the pre-retrofit period the air-handling units were operated during the occupied periods (i.e., about 18 hours per day, Monday through Friday). In the post-retrofit period the HVAC system operated 24 hours per day. The building has an economizer cycle that was not used during the pre-retrofit period. The primary retrofits were to replace the existing Constant Air Volume (CAV) air distribution systems with a variable frequency, Variable Air Volume

(VAV) air distribution system and the incandescent lighting in the corridors with compact fluorescent lamps.

The EDB at the University of Texas at Austin campus was monitored under the LoanSTAR program. About 18 channels of hourly data were metered, including whole-building electricity, MCC, whole-building heating and cooling energy use, and a derived channel which represents the lights and equipment. The lights and equipment channel is derived by subtracting MCC energy use from the whole-building electric energy use. The monitored pre-retrofit period was from October 14, 1990 to April 29, 1991.

Photograph of the Case Study Buildings

Engineering Center (EC, Dataset A and Dataset C)

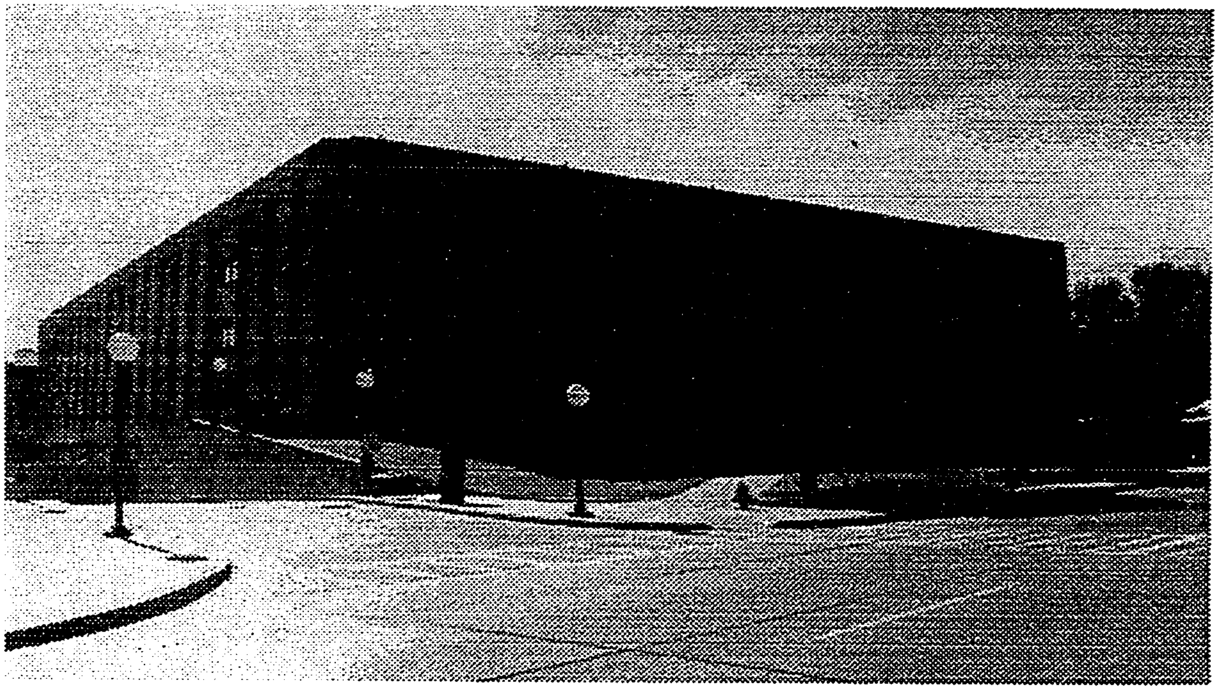


Figure B.7 : The Engineering Center at Texas A&M University, College Station, Texas. Monitored data from this building (Dataset A and Dataset C) were used for the inverse bin analysis.

Business Building (BUS, Dataset D)

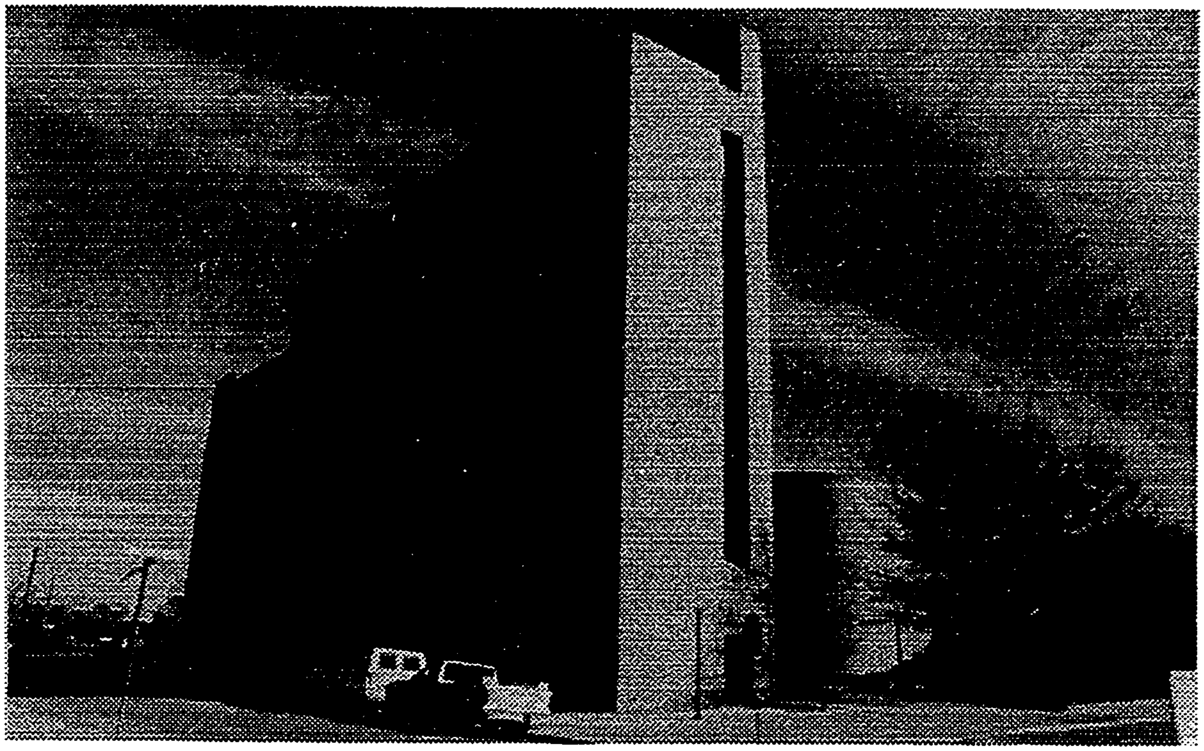


Figure B.8 : The Business building at the University of Texas at Arlington, Arlington, Texas. Monitored data from this building (Dataset D) was used for the inverse bin analysis.

Russell A. Steindham Building (RAS)

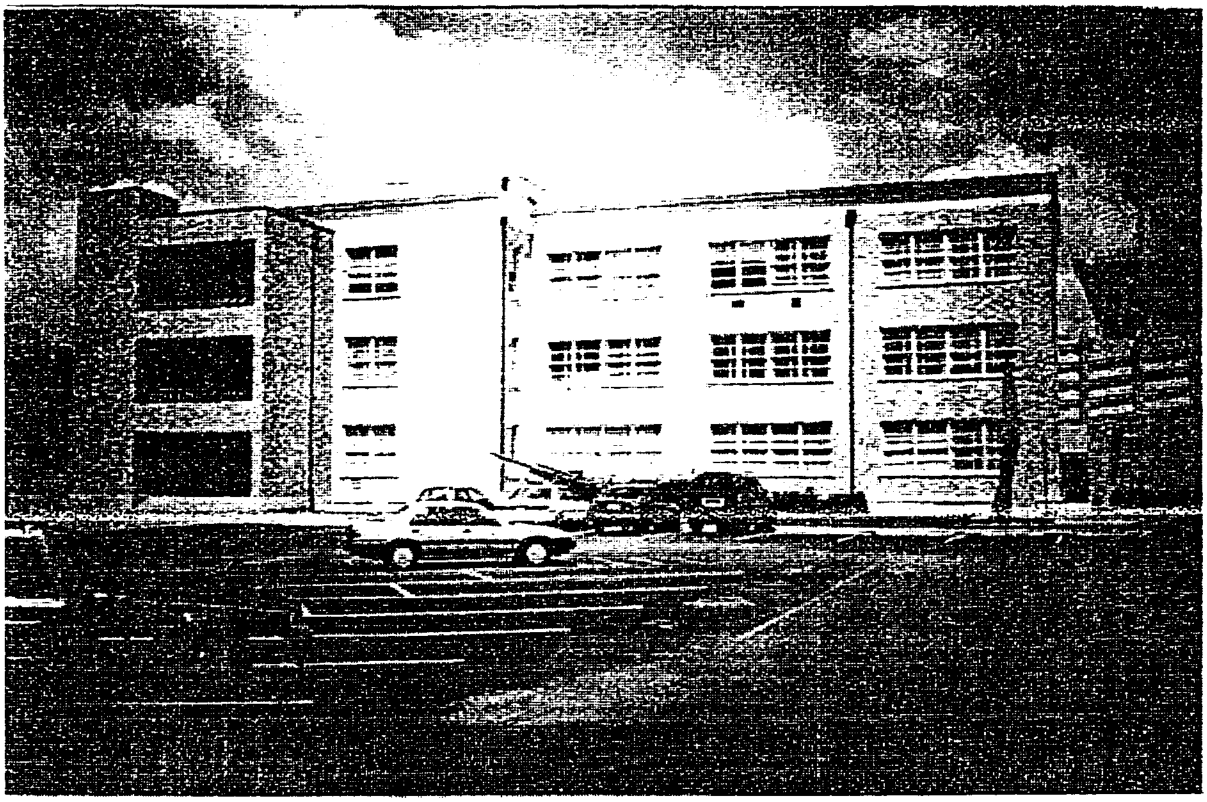


Figure B.9 : The Russell A. Steindham building at the University of Texas at Austin, Austin, Texas. This building is monitored as part of the LoanSTAR program. The baseline data from this building was used for the comparison of forward and inverse bin analyses.

Welch Hall (WEL)

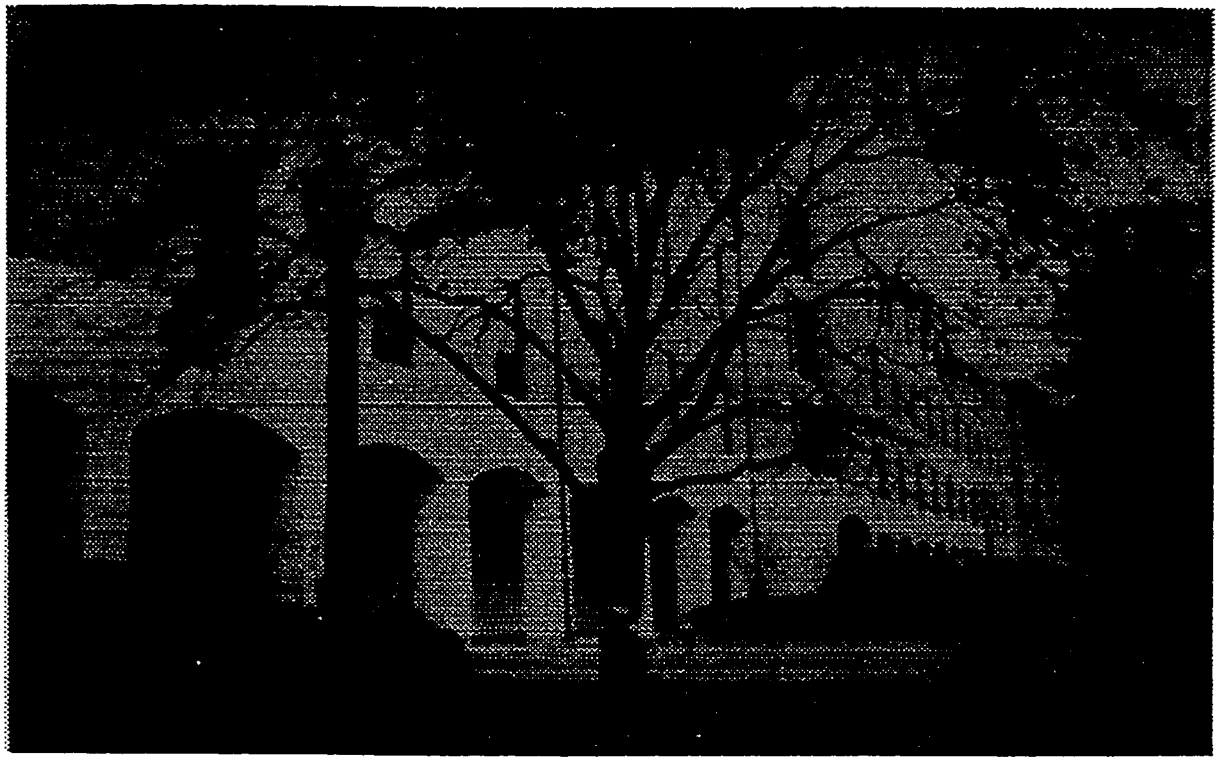


Figure B.10 : The Welch Hall at the University of Texas at Austin, Austin, Texas. This building is monitored as part of the LoanSTAR program. The baseline data from this building was used for the demonstration of the inverse bin method.

Perry Castaneda Library (PCL)

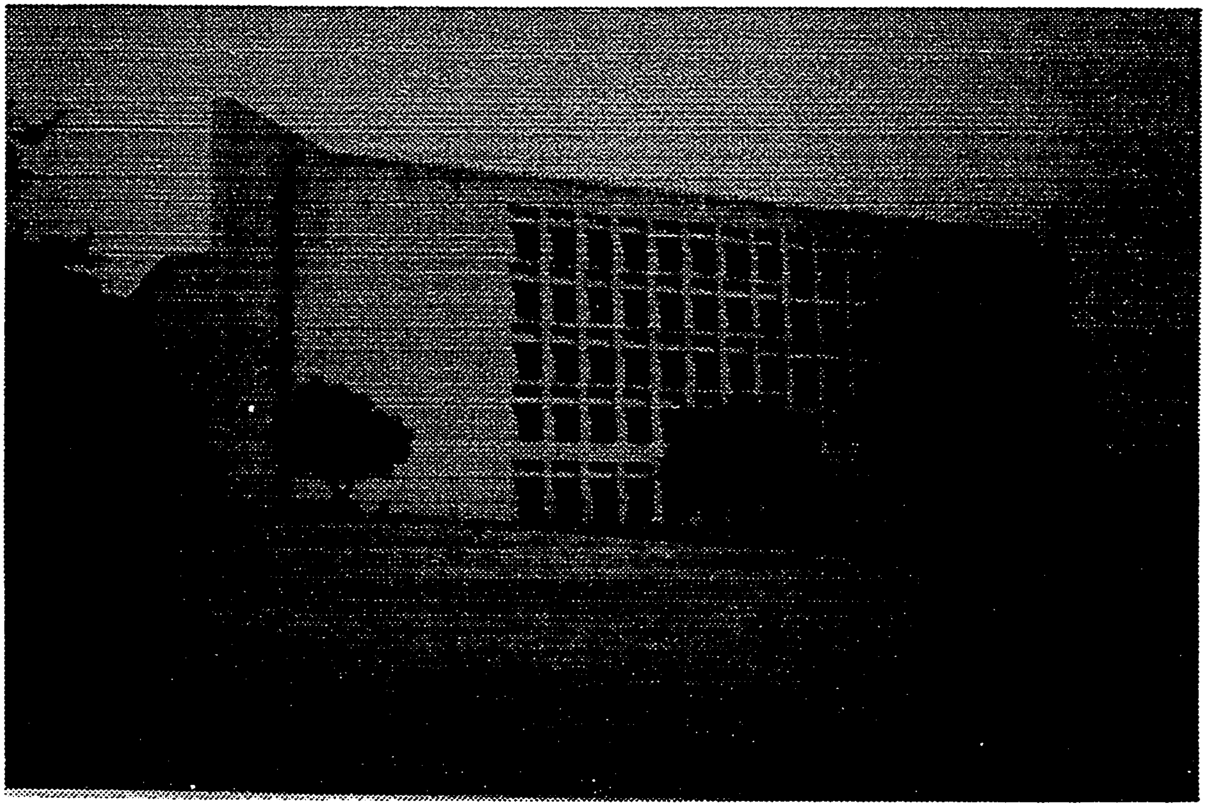


Figure B.11 : The Perry Castaneda Library building at the University of Texas at Austin, Austin, Texas. This building is monitored as part of the LoanSTAR program. The post-retrofit period data from this building was used for the demonstration of the inverse bin method (specifically to the thermal mass effect section).

APPENDIX C

SELECTION OF BIN PARAMETER

Introduction

In the inverse bin method, the bin value is expected to be the best representative value for the bin. Therefore, this value should be calculated based on parameters that represent a bin or closely grouped data. The three most common measures of central tendency parameters are the arithmetic mean, the median, and the mode. Of these three, the mean (or arithmetic mean) is the most frequently used parameter. For a normal distribution (without any skewness), calculated value of all three parameters would almost the same. However, in actual data which is frequently skewed, these parameters often takes different values.

Central Tendency Parameters

Mean

This is the arithmetic average of the represented data group (i.e., bin) and often represented by a overbar. The mathematical description of the mean is as follows: for a data set that contains measurements $y_1, y_2, y_3, \ldots y_n$, the mean, $\bar{y} = \sum_{i=1}^{n} y_i \Big/ n$. For a geometric distribution or a highly skewed distribution a geometric mean is recommended. However, in this work only the usefulness of an arithmetic mean is studied.

Median

This is middle point of the dataset when the observations data are arranged in ascending or descending order. Median is the middle-most value in an odd number of observations and the smaller of the two middle values when the number of observations is even. In mathematical term it is defined as follows. For a given number p, $0 < p < 1$, the fractile $\tilde{x}(p)$ is defined as the smallest number x for which the cumulative frequency distribution function $F(x) > p$, then median is given by $\tilde{x}(0.5)$.

Mode

The observation which has the maximum frequency is called the mode. Mathematically it is defined for a continuous variate as the value of x for which the density function f(x) is maximum.

Selection of a Bin Description Parameter

In normal distributions all the above three parameters are equally useful as central tendency parameters. The experimental or measured data can often be assumed to be normally distributed. However, at times there may have some skewness and the effect of the skewness on these parameters are to verified. Therefore, the above three parameters were calculated for the dataset A and compared. Then we have plotted these parameters for the

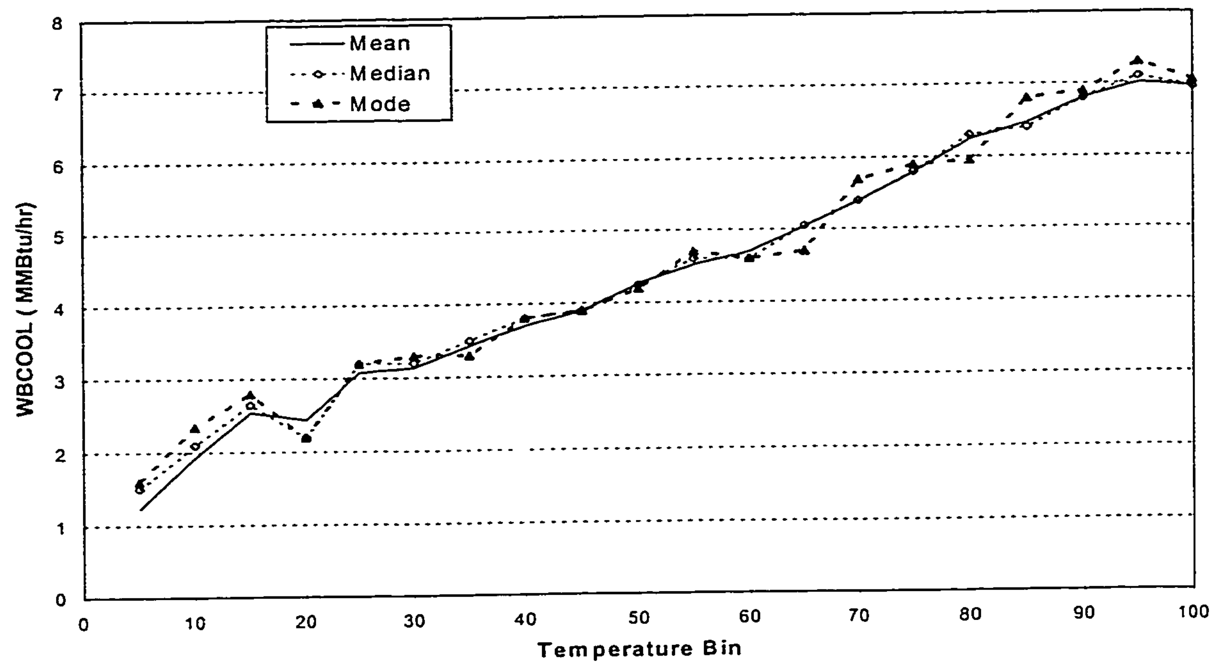


Figure C1: Comparison of the three bin description parameters for weekday daytypes of Dataset A (Engineering Center 09/01/89 - 12/31/89).

important daytypes (Figure C1 for weekdays of Dataset A) and chose the parameter that was minimally affected by the data distribution in the bins within a daytype. Figure C1 is the comparison of the parameters for the whole-building cooling (WBCOOL) energy use for Dataset A. The mean was noticeably stable over the range of the temperature bins. Moreover, it was the most stable parameter for the bins at extreme ends of the temperature range.

These bin description parameters were then calculated for the another building (Perry Castaneda Library-PCL, University of Texas at Austin) for the whole-building cooling and whole-building heating energy consumption. Figures C2 and C3 show the comparison for the PCL building for non-holiday daytype. In addition to the selected daytypes, the comparisons were also performed for the whole dataset represented as one daytype. This comparison has helped to identify the susceptibility of these parameters to the skewness observed within some temperature bins in the dataset (Welch Hall, University of Texas, Austin). The comparisons for the whole-building cooling and whole-building heating energy use are illustrated in Figure C4 and C5.

The following typical buildings were selected for the demonstration of the bin description parameters: 1) internal load dominated buildings (dataset A), 2) buildings with high internal thermal mass (PCL building), and 3) buildings with high ventilation loads (i.e., nearly 100% outside air intake) (WEL building). The following characteristics were studied for the selection of a bin description parameter in the comparisons shown in Figures C1 through C5: a) stability over the temperature range, b) less susceptibility to small number of data points within the temperature bins at the extreme ends of temperature range, and 3) less susceptibility to smaller skewness observed in some temperature bins. The stability and central tendency of the mean parameter over the other parameters (median and mode) helped the mean as a better description parameter for the inverse bin energy predictions. However, All the three studied parameters have some shortcomings. The mean as bin description parameter also has some shortcomings for datasets with outliers. The important limitation of the mean is its susceptibility to outliers. The size and number of outliers affect

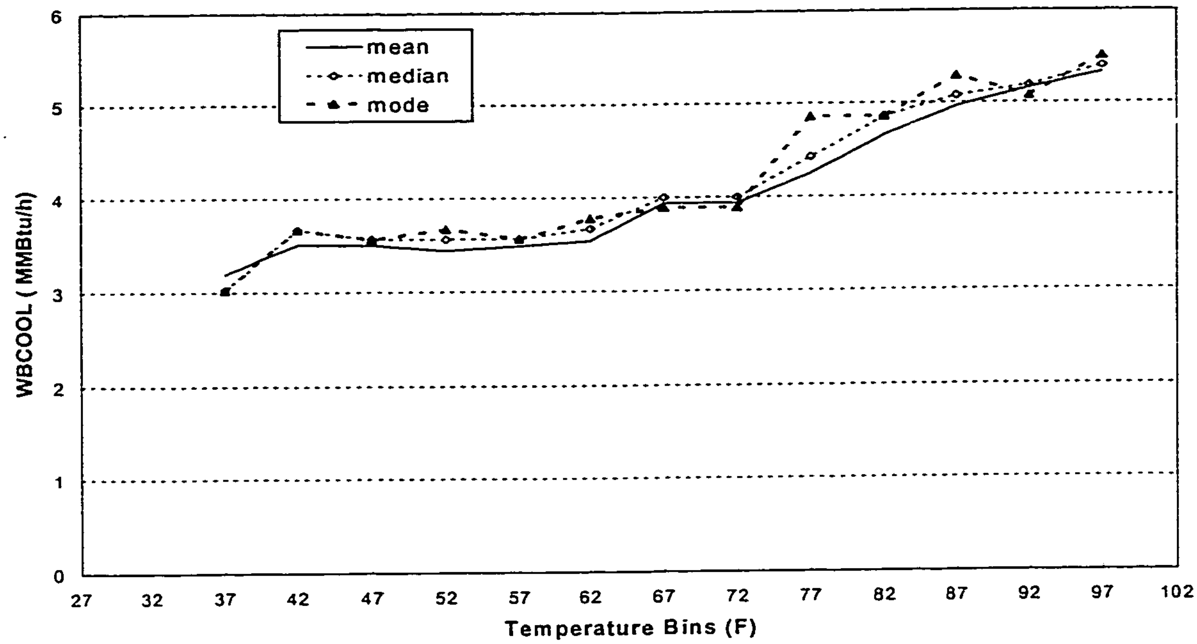


Figure C2: Comparison of the three bin description parameters for PCL building cooling energy use for the period from 01/01/92 to 07/31/92.

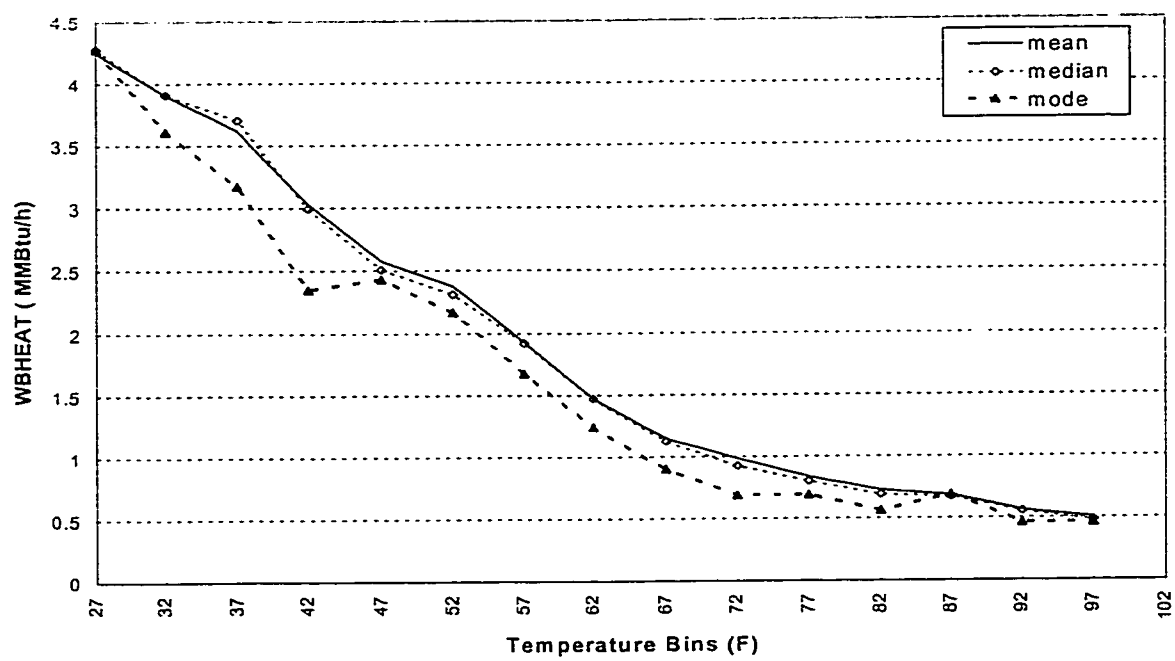


Figure C3: Comparison of the three bin description parameters for PCL building heating energy use for the period from 01/01/92 to 07/31/92.

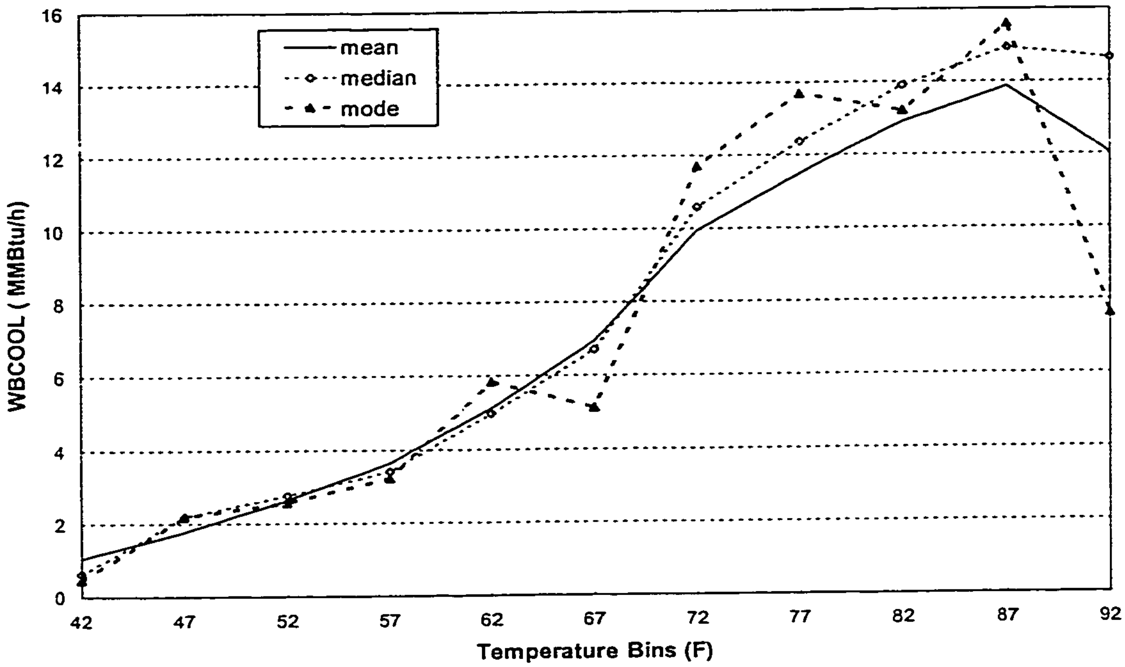


Figure C4: Comparison of the three bin description parameters for WEL building cooling energy use for the baseline period from 10/13/90 to 05/31/91.

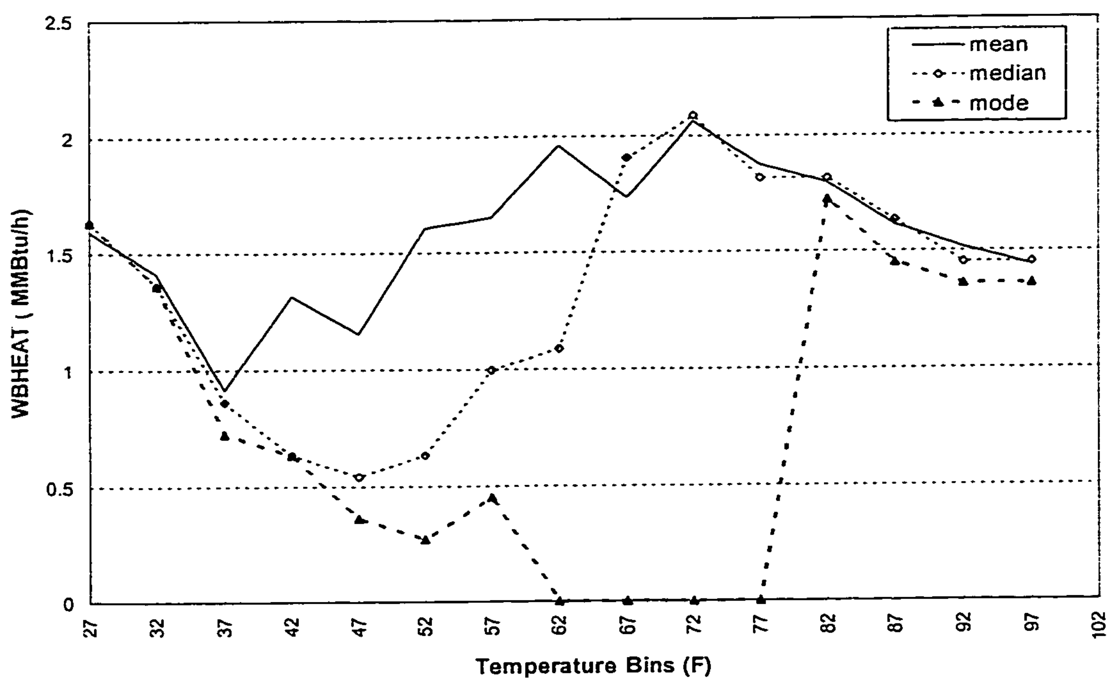


Figure C5: Comparison of the three bin description parameters for WEL building heating energy use for the baseline period from 10/13/90 to 05/31/91.

the calculated mean value. However, the decision to include or remove an outlier from the dataset in consideration affect all these parameters.

In the case study buildings presented here, HVAC system shut down exists very often. This affects the mode more than any other parameter as shown for the WEL building data Figure C5. In Figure C1 median is affected to minor variations within a operational mode. This has negatively affected in the low temperature region of the scatter plot.

Summary

In this section the suitability of the three central tendency parameters for describing the binned energy consumption was studied. The stability and central tendency of the mean parameter over the other parameters (median and mode) for the selected datasets helped the mean as a better description parameter for the inverse bin energy predictions.

APPENDIX D
SAMPLE ANALYSIS AND PREDICTION ROUTINES

General

The processing routines that are used for the inverse bin data analysis and described in Chapters IV, V and VI are presented in this section. The preprocessing (outlier identification) program is presented below, followed by the routines for the daytyping and binned energy calculations. A sample worksheet with input information for forward bin analysis of the RAS building is also given here. The following routines are given in the order in which they were analyzed in Chapter VI : the simple inverse bin analysis, Impact of secondary variable, improved inverse bin predictions, and simple inverse bin analysis of the RAS building. A summary of the data on which the inverse bin analysis and the existing LoanSTAR program models were tested is also given.

A sample comparison of the time used by three methodologies discussed in this study is compared below in Table D1.

Table D.1 : Average Processing Time for the Analysis.

Methodology	Process	Development time
Inverse bin method	data analysis	180 minutes
	bin energy calculations	120 minutes
	predictions	10 minutes
Linear regression analysis	data analysis	60 minutes
	model parameter calculations	5 minutes
	predictions	10 minutes
Neural network methods	data training	300 minutes
	predictions	10 minutes

Sample Calculation and Input Parameters for the Forward Bin Analysis (Actual) Using the ASHRAE RP 865 Research

The following is a sample input parameters used in the ASHRAE RP 865 study (Haberl et al., 1997). The Forward Bin Analysis - actual usage in the RAS building was calculated by this methodology as noted in Chapter V - Comparison of the Forward and

Inverse Bin Methods. The results were used in this study only as a benchmark comparison for the work presented here. Figure D1 illustrates the input parameters, weekend-unoccupied period data as sample input data, and parameter notation as used in the spreadsheet calculation procedure of the RP 865 analysis framework.

sample input

ECON(y=1)	1.00	SAMPLE W calc...	
AIRCRLR(1,2,3)=	1.00		
CCLASP(F) =	54.00		
CCLABP(psia)=	14.70	Tdew(F) =	55.000
CFMMA (CFM) =		Tdew(R) =	514.670
CFMZD1 (CFM) =	22570	Tdry(F)=	75.000
CFMZD2 (CFM) =	33850	Tdry(R) =	534.670
CFMZMIN1=	2260	P(psia)=	14.696
CFMZMIN2=	3400	pws,dew(<32)=	0.242
CPAIR(Btu/lbF)=	0.24 CPair @80F	pws,dew(>32)=	0.214
CPh20(Btu/lbF)=	1.00 CPwater @55F	pws,dry(<32)=	0.540
FTP(in-H20) =	2.00	pws,dry(>32)=	0.430
FRACT(0,1)=	0.00	w(sat,dew)=	0.009
FRACTR(0,1)=	0.00		
FAN EFFICIENCY=	0.70	w(sat,dry)=	0.019
HCLASP (F) =	120.00		
HCLABP(psia)=	14.70	mu=	0.490
MOTEFF=	0.90	RH%=	0.498
MOTEFFR=	0.90		
OADB(F) =	82.00		
OAWB(F)=	70.66	C1=	-10214
PHLABP (PSIA) =	14.70	c2=	-4.893
PHLASP(F)=	40.00	c3=	-0.005
QZL1(Btuh)=	20000	c4=	0.000
QZL2(Btuh)=	20000	c5=	0.000
QZS1(Btuh)=	50000	c6=	0.000
QZS2 =	50000	c7=	4.164
RFAN EFFICIENCY=	0.70	c8=	-10440
		c9=	-11.295
R =	1545	c10=	-0.027
Ra =	53.35	c11=	0.000
RABPNF=	14.70	c12=	0.000

RABP=	14.70	c13=	6.546

NOTE:
This has been modified to
shut off the return fan by
setting RFTP=0 in H20
Normally, this is 2 "H20
NOTE:This assumes 1"H20 = 0.0361 psi

Co,C1,C2,C3 for Brandemuel's FFLP calcs:

	Co	C1	C2	C3
1=Discharge Dampers	0.35	0.31	-0.54	0.87
2=Inlet Vane	0.37	0.97	-0.34	0.00
3=Var.Speed Drive	0.00	0.01	1.11	-0.12
RFTP(in-H20)=	0.00			

ZDB1(F)=	75.00
QRA1(F)=	0.00
ZDB2(F)=	75.00
QRA2(F)=	0.00
ZSABP1(Psia)=	14.696
ZSABP2(Psia)=	14.696
ZBP1(Psia)	14.70
ZBP2(Psia)	14.70

Sample Output

Total_cool	Total_heat	Iteration
1.1096	0.7543	4th
1.1096	0.7543	fifth

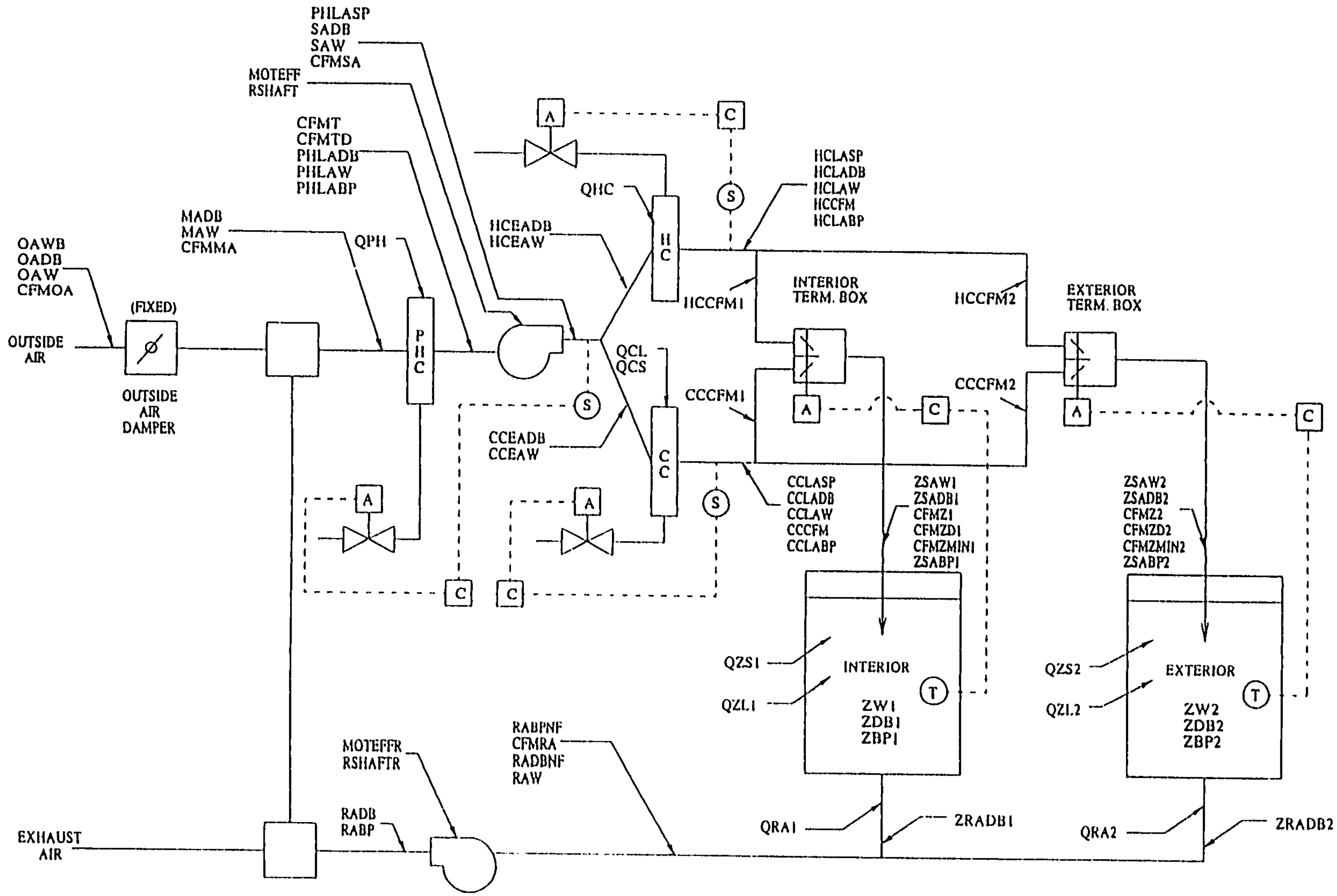


Figure D.1: Schematic diagram of the ASHRAE RP 865 analysis procedure for the CAVDD system without economizer.

Sample SAS Programs for the Inverse Bin Analysis

Outlier Identification Scheme

```
/*                          COPYRIGHT NOTICE                              */
/*  This program bears a copyright notice to prevent rights from being claimed*/
/*  by any other party.  The Texas Engineering Experiment Station intends that*/
/*  the program be placed in the public domain and grants permission for its  */
/*  unrestricted use and distribution, provided that:                         */
/*        1) the source code is distributed without changes,                  */
/*        2) the copyright notice is retained in all copies of the code, and  */
/*        3) the program is distributed from the Texas Experiment Station(TEES)*/
/*  The program is distributed "as is". TEES DOES NOT WARRANT THAT THE        */
/*  OPERATION OF THE PROGRAM WILL BE UNINTERRUPTED OR ERROR-FREE, AND MAKES NO*/
/*  REPRESENTATIONS OR OTHER WARRANTIES, EXPRESS OR IMPLIED, INCLUDING NOT    */
/*  LIMITED TO THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A    */
/*  PARTICULAR PURPOSE. No support service will be provided unless special    */
/*  arrangements have been made to do so.Certain manufacturers and trade names*/
/*  are mentioned in this code for the purpose of describing their            */
/*  communications protocol. Such references does not constitute an endorsement*/
/*  or recommendation of such equipment, but is provided for information      */
/* purposes only.                                                              */


/* This program was written by S. THAMILSERAN for the analysis work performed */
/* towards his dissertation in the Dept. of Mechanical Engineering.           */
/* This program was written to run on a UNIX machine with SAS system SOFTWARE */
/* VERSION 6 or later.                                                        */
/* The input file is trna.dat (dataset A - training data).                    */
/* The output was written to trnaf.dat file - a outlier marked training data. */

   /* reading data from a file dataset A */

   data newa;
   infile 'trna.dat';
   input mo dy yr hrm temp humid solar wind wbe cwe hwe;
   date=mdy(mo,dy,yr);
   format date date7.;
   dow=weekday(date);

   /* marking any missing data as unusable for work */

   if wbe < 0 then wbe= ".";
   if cwe < 0 then cwe =".";
   if hwe < 0 then hwe =".";
   if temp <-20 then temp=".";
   if humid <0 then humid=.;

   /*marking a weekday weekend daytype */

   if dow=1 or dow=7 then grp=1;
   if dow>1 and dow <7 then grp=2;

   /*military to normal hour conversion */
   hr=hrm/100;run;
   /* print the correlation coefficients for the */
   /* required variables and independent variables */
```

```
proc corr data=newa;
var wbe cwe hwe;
with temp hr humid;run;
proc print data=corrout;run;

/* temperature bins by 5 deg f: The addition of 2F for the */
/* analysi to take the same bin info as ASHRAE */

data newb;
set newa;
temp=temp-2;
tempgrpa = round(temp,5);
ta = tempgrpa;
ta1=ta+2;run;

/* outlier statistics by various methods */

proc reg data=newb Noprint;
model cwe=temp humid;
output out=outl1 cookd=cookd1 h=h1 press=press1 rstudent=rs1
       student=s1 p=p1 dffits=dffits1 r=r1;
title1 'outlier check by various mtds';run;

/* testing the influence for collinearity etc. */

title1 'this influence testing';
proc reg data=newb Noprint;
model cwe=temp humid/vif influence;
output out=outl2 cookd=cookd1 press=press1
       student=s1 ;
run;

/* generating univariate infor for visual inspection */
/* univariate statistics by each bins for weekday/end */

proc univariate data=newb freq plot normal;
by ta1;
var cwe hwe;
id grp;
output out=stat1
        mean=mcwe mhwe ;
title1 'Statistics by hr for each daytype';
        run;

/* sorting the data by temp & hr for univariate procedure*/
/* by temp for cwe & hwe, by hr for wbe analysis */

proc sort data=newb out=newf;
by temp;run;
proc sort data=newb out=newff;
by hr;run;

/* univariate statistics by each bins for after sorting */
/* also aloows the IQR, outlier boundary set up for cwe & hwe */

proc univariate data=newf freq plot normal;
by ta1;
var cwe hwe;
id grp;
```

```
output out=univ1
        mean=mcwe mhwe
        median=mdcwe mdhwe
        q3=qcu qhu
        q1=qcl qhl;
title1 'Statistics by T-Bins for each daytype';
        run;

/* also aloows the IQR, outlier boundary set up for wbe */

proc univariate data=newff freq plot normal;
by nr;
var wbe;
id grp;
output out=univ2
        mean=mwbe
        median=mdwbe
        q3=qwu
        q1=qwl;
title1 'Statistics by hr for each daytype';
        run;

/* merging cwe, hwe, and wbe data together */

data rev1;
merge newf
      univ1;
by ta1; run;
proc sort data=rev1 out=rev2;
by hr;run;
data rev3;
merge rev2
      univ2;
by hr;run;

/* resorting to bring the original order for printing the data */
proc sort data=rev3 out=rev4;
by yr mo dy hrm;run;

/* the data now has original data and a outlier information */
/* with last charater as u & l for upper 7 lower boundaries */

data rev5;
set rev4;
iqrc=qcu-qcl;
iqrh=qhu-qhl;
iqrw=qwu-qwl;
cwl=qcl-1.5*iqrc;
cwu=qcu+1.5*iqrc;
hwl=qhl-1.5*iqrh;
hwu=qhu+1.5*iqrh;
wwl=qwl-1.5*iqrw;
wwu=qwu+1.5*iqrw;
if cwe < cwl or cwe > cwu then dtc=2;
if cwe > cwl and cwe < cwu then dtc=1;
if hwe < hwl or hwe > hwu then dth=2;
if hwe > hwl and hwe < hwu then dth=1;
if wbe < wwl or wbe > wwu then dtw=2;
if wbe > wwl and wbe < wwu then dtw=1;run;
```

```
data test;
set rev5;
if dtc=2 or dth=2 ;run;

/* Printed data for remaining steps, with included outlier info*/
data print;
set rev5;
if temp =. then temp=-99;
if humid=. then humid=-99;
if cwe=. then cwe=-99;
if hwe=. then hwe=-99;
if wbe=. then wbe=-99;
file 'trnaf.dat';
put (mo dy yr hr cwe hwe wbe temp humid dtc dth dtw)(4*5.0 2*6.2 5.0 6.2 6.3
3*3.0); run;
```

Sample Input File

The outlier identification scheme was performed by running the above routine on a sample dataset trna.dat (a.trn from dataset A of Predictor Shootout I was renamed as trna.dat) as input file. The first five lines of the input data file is provided here.

trna.dat (a.trn 09/01/89 0:00 to 12/31/89 23:00):

mo	dy	yr	hr	temp	sphum	solar	wspeed	wbe	cwe	hwe
9	1	89	200	81.9	0.0184	0	7.62	496.07	7.2	0.4
9	1	89	300	80.7	0.0187	0	7.94	497.06	7.1	0.5
9	1	89	400	79.7	0.0194	0	7.72	496.67	7.1	0.5
9	1	89	500	79	0.0197	0.1	6.08	494.54	7.1	0.6
9	1	89	600	78.9	0.0199	0.1	5.68	498.09	7	0.6

The notation used for the variables are given below with the description

mo	calendar month
dy	calendar date
yr	calendar year in shortened two digit format
hr	time of the day in military format
temp	outdoor dry-bulb temperature in degrees F
sphum	outdoor air specific humidity in lb.moisture/lb.dry air
wspeed	average wind speed in miles per hour
wbe	whole-building electric energy use in kWh
cwe	whole-building cooling energy use in MMBtu/hr
hwe	whole-building heating energy use in MMBtu/hr

Sample Output File

The first five lines of the output written by the program is given below.

trnaf.dat (a.trn 09/01/89 0:00 to 12/31/89 23:00 with outlier groups):

mo	dy	yr	hr	cwe	hwe	wbe	temp	sphum	oc	oh	ow
9	1	89	2	7.20	0.40	496	81.90	0.018	1	1	1

9	1	89	3	7.10	0.50	497	80.70	0.019	1	1	1
9	1	89	4	7.10	0.50	497	79.70	0.019	1	1	1
9	1	89	5	7.10	0.60	495	79.00	0.020	1	1	1
9	1	89	6	7.00	0.60	498	78.90	0.020	1	1	1

The notation of the additional variables used by the program are:

ow identified index variable for outlier in wbe data: ow=1 - usable data, ow=2 - outlier
oc identified index variable for outlier in cwe data: oc=1 - usable data, oc=2 - outlier
oh identified index variable for outlier in hwe data: oh=1 - usable data, oh=2 - outlier

Daytype Testing and Inverse Bin Energy calculations

```
/*                           COPYRIGHT NOTICE                              */
/*  This program bears a copyright notice to prevent rights from being claimed*/
/*  by any other party.  The Texas Engineering Experiment Station intends that*/
/*  the program be placed in the public domain and grants permission for its  */
/*  unrestricted use and distribution, provided that:                         */
/*       1) the source code is distributed without changes,                   */
/*       2) the copyright notice is retained in all copies of the code, and   */
/*       3) the program is distributed from the Texas Experiment Station(TEES)*/
/*  The program is distributed "as is". TEES DOES NOT WARRANT THAT THE         */
/*  OPERATION OF THE PROGRAM WILL BE UNINTERRUPTED OR ERROR-FREE, AND MAKES NO*/
/*  REPRESENTATIONS OR OTHER WARRANTIES, EXPRESS OR IMPLIED, INCLUDING NOT     */
/*  LIMITED TO THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A     */
/*  PARTICULAR PURPOSE. No support service will be provided unless special     */
/*  arrangements have been made to do so.Certain manufacturers and trade names*/
/*  are mentioned in this code for the purpose of describing their            */
/*  communications protocol. Such references does not constitute an endorsement*/
/*  or recommendation of such equipment, but is provided for information      */
/* purposes only.                                                              */

/* This program was written by S. THAMILSERAN for the analysis work performed */
/* towards his dissertation in the Dept. of Mechanical Engineering.          */
/* This program was written to run on a UNIX machine with SAS system SOFTWARE */
/* VERSION 6 or later.                                                        */
/* The input file is trnaf.dat (outlier identified - training data).         */
/* The necessary information is in the SAS compiled file trna.lst            */

/* This program takes the previously marked dataset with outlier information  */
/* and then disaggregate according the previously known daytype information   */
/* Then performs the Duncan's and  other multiple comparison procedures and   */
/* generate a univariate output for further visual checking. Finally produces a*/
/* output with binned energy consumption.                                      */


   data newa;
   infile 'trnaf.dat';
   input mo dy yr hr cwe hwe wbe temp humid dtc dth dtw;
   date=mdy(mo,dy,yr);
   format date date7.;
   dow=weekday(date);

   if temp <-20 then temp=".";
   if humid < 0 then humid=".";
```

```
if wbe < 0 then wbe= ".";
if cwe < 0 then cwe =".";
if hwe < 0 then hwe =".";

/* selecting daytype from prevue/prior knowledge */

if (date>='01sep89'd and date<='13dec89'd) then dtw=1;
if (date>='14dec89'd and date <='23dec89'd) then dtw=2;
if  date>='24dec89'd                        then dtw=3;
if (date>='23nov89'd and date<='26nov89'd) or (date>='24dec89'd)
then dow=1;

/* separate daytypes for testing */

if dtw=1 or dtw=2 then dt=1;
if dtw=3 then dt=2;

/*dt=1 for regular,dt=2 for holidays */
/* also removing outliers from usable data */

if (date>='01sep89'd and date<='14dec89'd) and dtc=2  then cwe=.;
if (date>='01sep89'd and date<='14dec89'd) and dth=2  then hwe=.;
if (date>='01sep89'd and date<='14dec89'd) and dtw=2  then wbe=.;

/* separation of weekday and weekends */

if dt=1 and (dow=1 or dow=7) then dtp=1;
if dt=1 and (dow>1 and dow<7) then dtp=2;
if dt=2 and (dow=1 or dow=7) then dtp=3;
if dt=2 and (dow>1 and dow<7) then dtp=4;

/* also wbe daytypes */

if dtw=1 and (dow=1 or dow=7) then dwt=1;
if dtw=1 and (dow>1 and dow<7) then dwt=2;
if dtw=2 and (dow=1 or dow=7) then dwt=3;
if dtw=2 and (dow>1 and dow<7) then dwt=4;
if dtw=3 and (dow=1 or dow=7) then dwt=5;
if dtw=3 and (dow>1 and dow<7) then dwt=6;

/*regrouping we/wd types */

if dow=1 or dow = 7 then dtd=2;
if dow>1 and dow <7 then dtd=1;
run;

/*checking for we/wd separation*/

proc anova data=newa;
class dtd;
model wbe =dtd;
means dtd/duncan waller scheffe;
run;

/*checking for significantly different groups */

proc anova data=newa;
class dtw;
model wbe =dtw;
```

```
means dtw/duncan waller scheffe;
run;

/*checking for daytypes and we/wd separation*/

proc anova data=newa;
class dtp;
model wbe =dtp;
means dtp/duncan waller scheffe;
run;

/*checking for daytypes for wbe separation*/

proc anova data=newa;
class dwt;
model wbe =dwt;
means dwt/duncan waller scheffe;
run;


/* rearranged daytypes here for further analysis */
/* newa with dtp daytypes was chosen as the final daytypes */
/*temperature bins by 5 deg f*/

data newb;
set newa;
temp=temp-2;
tempgrpa = round(temp,5);
ta=tempgrpa;
ta1 = ta+2;
run;


/* final format of the daytypes for univariate statistics visual inspection */
/* by temp for cwe & hwe, by hr for wbe analysis */

proc sort data=newb out=newf;
by temp;
run;
proc sort data=newb out=newff;
by hr;
run;

/* univariate statistics by each bins for after sorting */
/* also aloows the IQR, outlier boundary set up for cwe & hwe */

proc univariate data=newf freq plot normal;
by ta1;
var cwe hwe;
id grp;
output out=univi
        mean=mcwe mhwe
        median=mdcwe mdhwe
        q3=qcu qhu
        q1=qcl qhl;
title1 'Statistics by T-Bins for each daytype';
```

```
        run;

/* also aloows the IQR, outlier boundary set up for wbe */

proc univariate data=newff freq plot normal;
by hr;
var wbe;
id grp;
output out=univ2
        mean=mwbe
        median=mdwbe
        q3=qwu
        q1=qwl;
title1 'Statistics by hr for each daytype';
        run;


/* calculate the hourly mean of wbe for each daytype */

proc means data=newa;
class dtp hr;
var wbe ;
output out=nne
        mean=mwbe;
        title 'Statistics of wbe by hr for each daytype';
        run;

proc means data=newb;
class dtp tal;
var cwe ;
output out=tnc
       mean=mcwe;
        title 'Statistics of cwe by bin  for each daytype';
       run;

proc means data=newb;
class dtp tal;
var hwe ;
output out=tnh
       mean=mhwe;
        title 'Statistics of hwe by bin for each daytype';
       run;

/* ========= Printing the bin-mean out files ========= */
data ttn1;
set tnc;
file 'zcool.dat';
put (dtp tal mcwe) (2*5.0 9.2);
run;

data ttn2;
set tnh;
file 'zheat.dat';
put (dtp tal mhwe) (2*5.0 9.2);
run;

data ttn3;
```

```
set nne;
file 'zwbe.dat';
put (dtp hr mwbe) (2*5.0 9.2);
run;
```

Sample Input File

This program uses the output file written by the previous outlier identification program. The knoweldge gained from the time series and scatter plots of the dependent variable was incorporated into the preliminary daytypes.

trnaf.dat (a.trn 09/01/89 0:00 to 12/31/89 23:00 with outlier groups):

mo	dy	yr	hr	cwe	hwe	wbe	temp	sphum	oc	oh	ow
9	1	89	2	7.20	0.40	496	81.90	0.018	1	1	1
9	1	89	3	7.10	0.50	497	80.70	0.019	1	1	1
9	1	89	4	7.10	0.50	497	79.70	0.019	1	1	1
9	1	89	5	7.10	0.60	495	79.00	0.020	1	1	1
9	1	89	6	7.00	0.60	498	78.90	0.020	1	1	1

Sample Output File

The relevant sections of the output file written by the program are given below.

Output1: The Analysis of Variance (ANOVA)

```
                              The SAS System
                        Analysis of Variance Procedure
                        Class Level Information
                        Class     Levels    Values
                         DWT          5      1 2 3 4 5

                    Number of observations in data set = 2926
NOTE: Due to missing values, only 2902 observations can be used in this analysis.

                              The SAS System
                        Analysis of Variance Procedure
          Dependent Variable: WBE
Source        DF       Sum of Squares        Mean Square          F Value          Pr > F

Model          4      28471380.90967750    7117845.22741938      486.71           0.0001
Error       2897      42366814.67164560      14624.37510240
Error       2897      42366814.67164560      14624.37510240
Corrected Total 2901  70838195.58132310

              R-Square                  C.V.                 Root MSE       WBE Mean
              0.401921                18.27165             120.93128256   661.85217092

Source           DF            Anova SS         Mean Square       F Value          Pr > F
 DWT              4      28471380.90967750   7117845.22741938   486.71           0.0001
```

Output 2: The Multiple Comparison of the Means

```
                         The SAS System
                   Analysis of Variance Procedure
             Waller-Duncan K-ratio T test for variable: WBE
NOTE: This test minimizes the Bayes risk under additiveloss and certain other assumptions.

   Kratio= 100  df= 2897  MSE= 14624.38  F= 486.7111; Critical Value of T= 1.73558
   Minimum Significant Difference= 22.182   Critical Value of T= 1.73558
   Minimum Significant Difference= 22.182; Harmonic Mean of cell sizes= 179.0631

          Means with the same letter are not significantly different.
                    Waller Grouping      Mean      N  DWT
                         A             738.07   1726  2
                         B             614.65    144  4
                         C             568.99    768  1
                         D             542.38     72  3
                         E             428.30    192  5


                              The SAS System
                       Analysis of Variance Procedure
                Duncan's Multiple Range Test for variable: WBE
      NOTE: This test controls the type I comparisonwise error rate, not the
            experimentwise error rate
         Alpha= 0.05  df= 2897  MSE= 14624.38;  Harmonic Mean of cell sizes= 179.0631

                Number of Means      2     3     4     5
                  Critical Range  25.06 26.39 27.27 27.93

        Means with the same letter are not significantly different.

               Duncan Grouping       Mean      N  DWT
                     A             738.07   1726  2
                     B             614.65    144  4
                     C             568.99    768  1
                     D             542.38     72  3
                     E             428.30    192  5
                           The SAS System
                    Analysis of Variance Procedure
                    Scheffe's test for variable: WBE

      NOTE: This test controls the type I experimentwise error rate but generally has
            a higher type II error rate than REGWF for all pairwise comparisons

          Alpha= 0.05  df= 2897  MSE= 14624.38;    Critical Value of F= 2.37500
          Minimum Significant Difference= 39.392
          Harmonic Mean of cell sizes= 179.0631

        Means with the same letter are not significantly different.

              Scheffe Grouping       Mean      N  DWT
                     A             738.07   1726  2
                     B             614.65    144  4
                     C             568.99    768  1
                     C
                     C             542.38     72  3
                     D             428.30    192  5
```

Output 3 : Univariate Output of Daytypes by Temperature Bins

```
              Statistics by T-Bins for each daytype                                     1
------------------------------ TA1=5 ---------------------------------------
                                Univariate Procedure
Variable=CWE
   Moments                                  Quantiles(Def=5)
N               8   Sum Wgts        8      100% Max       1.9        99%        1.9
Mean        1.225   Sum           9.8       75% Q3        1.7        95%        1.9
Std Dev  0.660627   Variance  0.43643       50% Med       1.5        90%        1.9
Skewness -0.94688   Kurtosis  -0.6006       25% Q1        0.7        10%        0.1
USS         15.06   CSS         3.055        0% Min       0.1         5%        0.1
CV       53.92877   Std Mean  0.23356                                 1%        0.1

 T:Mean=0  5.244746  Pr>|T|      0.0012       Range          1.8
 Num ^= 0         8  Num > 0          8       Q3-Q1            1
 M(Sign)          4  Pr>=|M|     0.0078       Mode           1.5
 Sgn Rank        18  Pr>=|S|     0.0078
 W:Normal  0.862793  Pr<W        0.1306


  Stem Leaf              #         Boxplot
    18 0                 1            |
    16 00                2         +-----+
    14 00                2         *-----*
    12                             |  +  |
    10 0                 1         |     |
     8                             |     |
     6                             +-----+
     4 0                 1            |
     2                                |
     0 0                 1            |
       ----+----+----+
 Multiply Stem.Leaf by 10**-1


Normal Probability Plot
1.9+                        +++   *
   |                    *+++*
   |          *    *+++
1.3+                +++
   |       * +++
   |      +++
0.7+   +++
   |+++*
   |          +++
0.1+       +++ *
    +----+----+----+----+----+----+----+----+
    -2        -1         0        +1       +2


                                          Frequency Table
Frequency Table
          Percents                     Percents                   Percents
 Value Count  Cell    Cum     Value Count Cell   Cum     Value    Count Cell   Cum
 0.1       1  12.5   12.5        1     1  12.5  37.5       1.7     2    25.0  87.5
 0.4       1  12.5   25.0      1.5     2  25.0  62.5       1.9     1    12.5 100.0
```

Sample SAS Program for the Simple Inverse Bin Prediction

```
/*                          COPYRIGHT NOTICE                                */
/*  This program bears a copyright notice to prevent rights from being claimed*/
/*  by any other party.  The Texas Engineering Experiment Station intends that*/
/*  the program be placed in the public domain and grants permission for its  */
/*  unrestricted use and distribution, provided that:                         */
/*        1) the source code is distributed without changes,                  */
/*        2) the copyright notice is retained in all copies of the code, and  */
/*        3) the program is distributed from the Texas Experiment Station(TEES)*/
/*  The program is distributed "as is". TEES DOES NOT WARRANT THAT THE        */
/*  OPERATION OF THE PROGRAM WILL BE UNINTERRUPTED OR ERROR-FREE, AND MAKES NO*/
/*  REPRESENTATIONS OR OTHER WARRANTIES, EXPRESS OR IMPLIED, INCLUDING NOT    */
/*  LIMITED TO THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A    */
/*  PARTICULAR PURPOSE. No support service will be provided unless special    */
/*  arrangements have been made to do so.Certain manufacturers and trade names*/
/*  are mentioned in this code for the purpose of describing their            */
/*  communications protocol. Such references does not constitute an endorsement*/
/*  or recommendation of such equipment, but is provided for information      */
/* purposes only.                                                             */

/* This program was written by S. THAMILSERAN for the analysis work performed */
/* towards his dissertation in the Dept. of Mechanical Engineering.           */
/* This program was written to run on a UNIX machine with SAS system SOFTWARE */
/* VERSION 6 or later.                                                        */
/* The input file is tsta.dat (given testing data set).                       */
/* The output file is the inverse bin prediction in shlprdl.dat               */

/* This program takes the original dataset, and predict energy values by the  */
/* simple inverse bin method for comparison.                                  */

   data newa;
   infile 'tsta.dat';
   input mo dy yr hr temp hum sol wspeed;
   date=mdy(mo,dy,yr);
   format date date7.;
   dow=weekday(date);
   if temp <-20 then temp=".";
   if hum < 0 then hum=".";

   /* selecting daytype from prevue/prior knowledge */
   if (date>='21jan90'd and date<='21feb90'd) then dt=1;
   if (date>='01jan90'd and date <='20jan90'd) then dt=2;

   /*dt=1 for peakday,dt=2 for low days, breaks, and xmas days */

   /* separation of weekday and weekends */

   if dt=1 and (dow=1 or dow=7) then dtp=1;
   if dt=1 and (dow>1 and dow<7) then dtp=2;
   if dt=2 and (dow=1 or dow=7) then dtp=3;
   if dt=2 and (dow>1 and dow<7) then dtp=4;

   /*wbe groups for bin calculations*/

   if dtp=1 then dte=1;
   if dtp=2 then dte=2;
```

```
if dtp=3 then dte=3;
if dtp=4 then dte=4;

/*cwe groups for bin calculations*/

if dtp=1 then dtc=1;
if dtp=2 then dtc=2;
if dtp=3 then dtc=3;
if dtp=4 then dtc=4;

/*hwe groups for bin calculations*/

if dtp=1 then dth=1;
if dtp=2 then dth=2;
if dtp=3 then dth=3;
if dtp=4 then dth=4;

/* also adding the humidity groups */

if hum < 0.01 then dh=1;
if hum >=0.01 and hum < 0.015 then dh=2;
if hum >=0.015 and hum < 0.020 then dh=3;
if hum >=0.02  then dh=4;
humid=dh;
run;


data newp;
set newa;

    if dte=. and hr=   0 then wbep=  593.31 ;
    if dte=. and hr=   1 then wbep=  570.27 ;
    if dte=. and hr=   2 then wbep=   556.6 ;
    if dte=. and hr=   3 then wbep=  548.39 ;
    if dte=. and hr=   4 then wbep=  542.93 ;
    if dte=. and hr=   5 then wbep=  540.11 ;
    if dte=. and hr=   6 then wbep=  540.87 ;
    if dte=. and hr=   7 then wbep=   561.4 ;
    if dte=. and hr=   8 then wbep=  609.11 ;
    if dte=. and hr=   9 then wbep=  702.93 ;
    if dte=. and hr=  10 then wbep=  752.38 ;
    if dte=. and hr=  11 then wbep=  777.01 ;
    if dte=. and hr=  12 then wbep=  785.43 ;
    if dte=. and hr=  13 then wbep=   779.4 ;
    if dte=. and hr=  14 then wbep=  792.08 ;
    if dte=. and hr=  15 then wbep=  801.16 ;
    if dte=. and hr=  16 then wbep=  795.77 ;
    if dte=. and hr=  17 then wbep=  770.99 ;
    if dte=. and hr=  18 then wbep=  693.57 ;
    if dte=. and hr=  19 then wbep=   653.2 ;
    if dte=. and hr=  20 then wbep=  641.48 ;
    if dte=. and hr=  21 then wbep=  641.16 ;
    if dte=. and hr=  22 then wbep=  629.84 ;
    if dte=. and hr=  23 then wbep=  612.35 ;
    if dte=          1 and hr=       0 then wbep=  596.11 ;
    if dte=          1 and hr=       1 then wbep=  581.33 ;
    if dte=          1 and hr=       2 then wbep=  569.17 ;
    if dte=          1 and hr=       3 then wbep=     562 ;
    if dte=          1 and hr=       4 then wbep=  557.06 ;
```

```
if dte=    1 and hr=    5 then wbep=  553.67 ;
if dte=    1 and hr=    6 then wbep=  551.94 ;
if dte=    1 and hr=    7 then wbep=     550 ;
if dte=    1 and hr=    8 then wbep=  539.22 ;
if dte=    1 and hr=    9 then wbep=  544.17 ;
if dte=    1 and hr=   10 then wbep=     562 ;
if dte=    1 and hr=   11 then wbep=  582.06 ;
if dte=    1 and hr=   12 then wbep=     596 ;
if dte=    1 and hr=   13 then wbep=  603.61 ;
if dte=    1 and hr=   14 then wbep=  617.83 ;
if dte=    1 and hr=   15 then wbep=     624 ;
if dte=    1 and hr=   16 then wbep=  628.56 ;
if dte=    1 and hr=   17 then wbep=  628.44 ;
if dte=    1 and hr=   18 then wbep=  620.61 ;
if dte=    1 and hr=   19 then wbep=  617.11 ;
if dte=    1 and hr=   20 then wbep=  615.61 ;
if dte=    1 and hr=   21 then wbep=  619.72 ;
if dte=    1 and hr=   22 then wbep=  618.44 ;
if dte=    1 and hr=   23 then wbep=  611.17 ;
if dte=    2 and hr=    0 then wbep=   649.1 ;
if dte=    2 and hr=    1 then wbep=  617.51 ;
if dte=    2 and hr=    2 then wbep=     600 ;
if dte=    2 and hr=    3 then wbep=  588.22 ;
if dte=    2 and hr=    4 then wbep=  580.68 ;
if dte=    2 and hr=    5 then wbep=  577.49 ;
if dte=    2 and hr=    6 then wbep=   579.9 ;
if dte=    2 and hr=    7 then wbep=  614.68 ;
if dte=    2 and hr=    8 then wbep=  698.32 ;
if dte=    2 and hr=    9 then wbep=  843.59 ;
if dte=    2 and hr=   10 then wbep=  911.12 ;
if dte=    2 and hr=   11 then wbep=  936.78 ;
if dte=    2 and hr=   12 then wbep=  945.29 ;
if dte=    2 and hr=   13 then wbep=  933.12 ;
if dte=    2 and hr=   14 then wbep=  945.07 ;
if dte=    2 and hr=   15 then wbep=  957.59 ;
if dte=    2 and hr=   16 then wbep=  951.44 ;
if dte=    2 and hr=   17 then wbep=  916.02 ;
if dte=    2 and hr=   18 then wbep=   798.8 ;
if dte=    2 and hr=   19 then wbep=  738.76 ;
if dte=    2 and hr=   20 then wbep=   721.1 ;
if dte=    2 and hr=   21 then wbep=  718.07 ;
if dte=    2 and hr=   22 then wbep=  704.51 ;
if dte=    2 and hr=   23 then wbep=  679.63 ;
if dte=    3 and hr=    0 then wbep=   591.7 ;
if dte=    3 and hr=    1 then wbep=   561.5 ;
if dte=    3 and hr=    2 then wbep=   544.9 ;
if dte=    3 and hr=    3 then wbep=  536.39 ;
if dte=    3 and hr=    4 then wbep=  530.87 ;
if dte=    3 and hr=    5 then wbep=  527.61 ;
if dte=    3 and hr=    6 then wbep=  528.94 ;
if dte=    3 and hr=    7 then wbep=  562.42 ;
if dte=    3 and hr=    8 then wbep=  651.35 ;
if dte=    3 and hr=    9 then wbep=  808.48 ;
if dte=    3 and hr=   10 then wbep=  872.87 ;
if dte=    3 and hr=   11 then wbep=  901.35 ;
if dte=    3 and hr=   12 then wbep=  907.16 ;
if dte=    3 and hr=   13 then wbep=  894.61 ;
if dte=    3 and hr=   14 then wbep=  908.39 ;
if dte=    3 and hr=   15 then wbep=  919.97 ;
```

```
if dte=          3 and hr=       16 then wbep=  909.58 ;
if dte=          3 and hr=       17 then wbep=  872.55 ;
if dte=          3 and hr=       18 then wbep=  751.03 ;
if dte=          3 and hr=       19 then wbep=  684.29 ;
if dte=          3 and hr=       20 then wbep=  667.23 ;
if dte=          3 and hr=       21 then wbep=     665 ;
if dte=          3 and hr=       22 then wbep=  639.71 ;
if dte=          3 and hr=       23 then wbep=  613.32 ;
if dte=          4 and hr=        0 then wbep=  577.71 ;
if dte=          4 and hr=        1 then wbep=  565.43 ;
if dte=          4 and hr=        2 then wbep=  557.71 ;
if dte=          4 and hr=        3 then wbep=     551 ;
if dte=          4 and hr=        4 then wbep=  548.14 ;
if dte=          4 and hr=        5 then wbep=  546.14 ;
if dte=          4 and hr=        6 then wbep=  548.71 ;
if dte=          4 and hr=        7 then wbep=  562.71 ;
if dte=          4 and hr=        8 then wbep=  576.57 ;
if dte=          4 and hr=        9 then wbep=  651.14 ;
if dte=          4 and hr=       10 then wbep=  706.71 ;
if dte=          4 and hr=       11 then wbep=  739.29 ;
if dte=          4 and hr=       12 then wbep=  753.29 ;
if dte=          4 and hr=       13 then wbep=  741.43 ;
if dte=          4 and hr=       14 then wbep=  755.43 ;
if dte=          4 and hr=       15 then wbep=  747.86 ;
if dte=          4 and hr=       16 then wbep=  738.71 ;
if dte=          4 and hr=       17 then wbep=  698.57 ;
if dte=          4 and hr=       18 then wbep=     623 ;
if dte=          4 and hr=       19 then wbep=  585.14 ;
if dte=          4 and hr=       20 then wbep=  573.86 ;
if dte=          4 and hr=       21 then wbep=  573.29 ;
if dte=          4 and hr=       22 then wbep=  571.57 ;
if dte=          4 and hr=       23 then wbep=  569.57 ;

temp=temp-2;
if temp=. and dtc=. then cwep=     5.05 ;
if dtc=. and temp< 5 then cwep=1.23;
if dtc=. and temp>= 5 and temp< 10 then cwep= 1.23 + 0.140 *(temp-    5 );
if dtc=. and temp>=10 and temp< 15 then cwep= 1.93 + 0.122 *(temp-   10 );
if dtc=. and temp>=15 and temp< 20 then cwep= 2.54 + 0.020 *(temp-   15 );
if dtc=. and temp>=20 and temp< 25 then cwep= 2.64 + 0.088 *(temp-   20 );
if dtc=. and temp>=25 and temp< 30 then cwep= 3.08 + 0.012 *(temp-   25 );
if dtc=. and temp>=30 and temp< 35 then cwep= 3.14 + 0.056 *(temp-   30 );
if dtc=. and temp>=35 and temp< 40 then cwep= 3.42 + 0.056 *(temp-   35 );
if dtc=. and temp>=40 and temp< 45 then cwep=  3.7 + 0.036 *(temp-   40 );
if dtc=. and temp>=45 and temp< 50 then cwep= 3.88 + 0.076 *(temp-   45 );
if dtc=. and temp>=50 and temp< 55 then cwep= 4.26 + 0.048 *(temp-   50 );
if dtc=. and temp>=55 and temp< 60 then cwep=  4.5 + 0.036 *(temp-   55 );
if dtc=. and temp>=60 and temp< 65 then cwep= 4.68 + 0.072 *(temp-   60 );
if dtc=. and temp>=65 and temp< 70 then cwep= 5.04 + 0.070 *(temp-   65 );
if dtc=. and temp>=70 and temp< 75 then cwep= 5.39 + 0.080 *(temp-   70 );
if dtc=. and temp>=75 and temp< 80 then cwep= 5.79 + 0.090 *(temp-   75 );
if dtc=. and temp>=80 and temp< 85 then cwep= 6.24 + 0.044 *(temp-   80 );
if dtc=. and temp>=85 and temp< 90 then cwep= 6.46 + 0.068 *(temp-   85 );
if dtc=. and temp>= 90 and temp<95 then cwep=  6.8 + 0.058 *(temp-   90 );
if dtc=. and temp>=95 and temp< 100 then cwep= 7.09+ 0.000 *(temp-   95 );
if dtc=. and temp>=100             then cwep= 7.09                     ;

if dtc=    1 and temp=.      then cwep=                    5.15 ;
if dtc=    2 and temp=.      then cwep=                    5.47 ;
```

```
if dtc=    3 and temp=.      then cwep=                    2.55 ;
if dtc=    4 and temp=.      then cwep=                    3.39 ;

if dtc= 1 and temp< 35 then cwep=       3.48 ;
if dtc= 1 and temp>=35 and temp< 40 then cwep= 3.48 +  0.052 *(temp- 35 );
if dtc= 1 and temp>=40 and temp< 45 then cwep= 3.74 +  0.012 *(temp- 40 );
if dtc= 1 and temp>=45 and temp< 50 then cwep=  3.8 +  0.044 *(temp- 45 );
if dtc= 1 and temp>=50 and temp< 55 then cwep= 4.02 +  0.054 *(temp- 50 );
if dtc= 1 and temp>=55 and temp< 60 then cwep= 4.29 +  0.072 *(temp- 55 );
if dtc= 1 and temp>=60 and temp< 65 then cwep= 4.65 +  0.054 *(temp- 60 );
if dtc= 1 and temp>=65 and temp< 70 then cwep= 4.92 +  0.078 *(temp- 65 );
if dtc= 1 and temp>=70 and temp< 75 then cwep= 5.31 +  0.022 *(temp- 70 );
if dtc= 1 and temp>=75 and temp< 80 then cwep= 5.42 +  0.112 *(temp- 75 );
if dtc= 1 and temp>=80 and temp< 85 then cwep= 5.98 +  0.052 *(temp- 80 );
if dtc= 1 and temp>=85 and temp< 90 then cwep= 6.24 +  0.086 *(temp- 85 );
if dtc= 1 and temp>=90 and temp< 95 then cwep= 6.67 +  0.012 *(temp- 90 );
if dtc= 1 and temp>=95 and temp<100 then cwep= 6.73 +  0.058 *(temp- 95 );
if dtc= 1 and temp>=100     then cwep= 7.02          ;

if dtc= 2 and temp=< 25 then cwep= 3.4;
if dtc= 2 and temp>= 25 and temp<  30 then cwep=  3.4 +  0.000 *(temp- 25 );
if dtc= 2 and temp>= 30 and temp<  35 then cwep=  3.4 +  0.056 *(temp- 30 );
if dtc= 2 and temp>= 35 and temp<  40 then cwep= 3.68 +  0.046 *(temp- 35 );
if dtc= 2 and temp>= 40 and temp<  45 then cwep= 3.91 +  0.034 *(temp- 40 );
if dtc= 2 and temp>= 45 and temp<  50 then cwep= 4.08 +  0.088 *(temp- 45 );
if dtc= 2 and temp>= 50 and temp<  55 then cwep= 4.52 +  0.046 *(temp- 50 );
if dtc= 2 and temp>= 55 and temp<  60 then cwep= 4.75 +  0.038 *(temp- 55 );
if dtc= 2 and temp>= 60 and temp<  65 then cwep= 4.94 +  0.052 *(temp- 60 );
if dtc= 2 and temp>= 65 and temp<  70 then cwep=  5.2 +  0.060 *(temp- 65 );
if dtc= 2 and temp>= 70 and temp<  75 then cwep=  5.5 +  0.084 *(temp- 70 );
if dtc= 2 and temp>= 75 and temp<  80 then cwep= 5.92 +  0.086 *(temp- 75 );
if dtc= 2 and temp>= 80 and temp<  85 then cwep= 6.35 +  0.038 *(temp- 80 );
if dtc=  2 and temp>= 85 and temp<  90 then cwep= 6.54 +  0.060 *(temp- 85 );
if dtc=  2 and temp>= 90 and temp<  95 then cwep= 6.84 +  0.090 *(temp- 90 );
if dtc=  2 and temp>= 95 and temp< 100 then cwep= 7.29 +  0.000 *(temp- 95 );
if dtc=  2 and temp>=  100 then cwep= 7.29 ;

if dtc=  3 and temp< 5 then cwep= 1.23 ;
if dtc=  3 and temp>=  5 and temp<  10 then cwep= 1.23 +  0.120 *(temp-  5 );
if dtc=  3 and temp>= 10 and temp<  15 then cwep= 1.83 +  0.144 *(temp- 10 );
if dtc=  3 and temp>= 15 and temp<  20 then cwep= 2.55  -0.044 *(temp- 15 );
if dtc=  3 and temp>= 20 and temp<  25 then cwep= 2.33 +  0.080 *(temp- 20 );
if dtc=  3 and temp>= 25 and temp<  30 then cwep= 2.73 +  0.078 *(temp- 25 );
if dtc=  3 and temp>= 30 and temp<  35 then cwep= 3.12 +  0.028 *(temp- 30 );
if dtc=  3 and temp>= 35 then cwep= 3.26 +  0.028 *(temp- 35 );

if dtc=  4 and temp<  10 then cwep= 2.42   ;
if dtc=  4 and temp>= 10 and temp<  15 then cwep= 2.42 +  0.024 *(temp- 10 );
if dtc=  4 and temp>= 15 and temp<  20 then cwep= 2.54 +  0.008 *(temp- 15 );
if dtc=  4 and temp>= 20 and temp<  25 then cwep= 2.58 +  0.102 *(temp- 20 );
if dtc=  4 and temp>= 25 and temp<  30 then cwep= 3.09  -0.010 *(temp- 25 );
if dtc=  4 and temp>= 30 and temp<  35 then cwep= 3.04 +  0.058 *(temp- 30 );
if dtc=  4 and temp>= 35 and temp<  40 then cwep= 3.33 +  0.024 *(temp- 35 );
if dtc=  4 and temp>= 40 and temp<  45 then cwep= 3.45 +  0.012 *(temp- 40 );
if dtc=  4 and temp>= 45 and temp<  50 then cwep= 3.51 +  0.038 *(temp- 45 );
if dtc=  4 and temp>= 50 and temp<  55 then cwep=  3.7 -0.020 *(temp- 50 );
if dtc=  4 and temp>= 55 and temp<  60 then cwep=  3.6 +  0.060 *(temp- 55 );
if dtc=  4 and temp>= 60 and temp<  65 then cwep=  3.9 +  0.022 *(temp- 60 );
if dtc=  4 and temp>= 65   then cwep= 4.01 +  0.022 *(temp- 65 );
```

```
if dth=. and temp< 5 then hwep=5.44;
if dth=. and temp>=  5 and temp<  10 then hwep= 5.44 +  0.000 *(temp-  5 );
if dth=. and temp>= 10 and temp<  15 then hwep= 5.44 +  0.040 *(temp- 10 );
if dth=. and temp>= 15 and temp<  20 then hwep= 5.64 -0.040 *(temp- 15 );
if dth=. and temp>= 20 and temp<  25 then hwep= 5.44 -0.078 *(temp- 20 );
if dth=. and temp>= 25 and temp<  30 then hwep= 5.05 -0.044 *(temp- 25 );
if dth=. and temp>= 30 and temp<  35 then hwep= 4.83 -0.094 *(temp- 30 );
if dth=. and temp>= 35 and temp<  40 then hwep= 4.36 -0.088 *(temp- 35 );
if dth=. and temp>= 40 and temp<  45 then hwep= 3.92 -0.082 *(temp- 40 );
if dth=. and temp>= 45 and temp<  50 then hwep= 3.51 -0.100 *(temp- 45 );
if dth=. and temp>= 50 and temp<  55 then hwep= 3.01 -0.056 *(temp- 50 );
if dth=. and temp>= 55 and temp<  60 then hwep= 2.73 -0.076 *(temp- 55 );
if dth=. and temp>= 60 and temp<  65 then hwep= 2.35 -0.128 *(temp- 60 );
if dth=. and temp>= 65 and temp<  70 then hwep= 1.71 -0.062 *(temp- 65 );
if dth=. and temp>= 70 and temp<  75 then hwep=  1.4 -0.064 *(temp- 70 );
if dth=. and temp>= 75 and temp<  80 then hwep= 1.08 -0.050 *(temp- 75 );
if dth=. and temp>= 80 and temp<  85 then hwep= 0.83 -0.024 *(temp- 80 );
if dth=. and temp>= 85 and temp<  90 then hwep= 0.71 -0.026 *(temp- 85 );
if dth=. and temp>= 90 and temp<  95 then hwep= 0.58 -0.008 *(temp- 90 );
if dth=. and temp>= 95 and temp< 100 then hwep= 0.54 -0.006 *(temp- 95 );
if dth=. and temp>=  100 then hwep= 0.51 -0.006 *(temp-  100 );

if dth=  1 and temp=.  then cwep= 1.85 ;
if dth=  2 and temp=.  then cwep= 1.61 ;
if dth=  3 and temp=.  then cwep= 5.05 ;
if dth=  4 and temp=.  then cwep= 4.36 ;

if dth=  1 and temp<  35 then cwep= 4.26 + -0.073 *(temp- 35 );
if dth=  1 and temp>= 35 and temp<  40 then hwep= 4.26 + -0.150 *(temp- 35 );
if dth=  1 and temp>= 40 and temp<  45 then hwep= 3.51 +  0.004 *(temp- 40 );
if dth=  1 and temp>= 45 and temp<  50 then hwep= 3.53 + -0.110 *(temp- 45 );
if dth=  1 and temp>= 50 and temp<  55 then hwep= 2.98 + -0.036 *(temp- 50 );
if dth=  1 and temp>= 55 and temp<  60 then hwep=  2.8 + -0.084 *(temp- 55 );
if dth=  1 and temp>= 60 and temp<  65 then hwep= 2.38 + -0.128 *(temp- 60 );
if dth=  1 and temp>= 65 and temp<  70 then hwep= 1.74 + -0.044 *(temp- 65 );
if dth=  1 and temp>= 70 and temp<  75 then hwep= 1.52 + -0.026 *(temp- 70 );
if dth=  1 and temp>= 75 and temp<  80 then hwep= 1.39 + -0.072 *(temp- 75 );
if dth=  1 and temp>= 80 and temp<  85 then hwep= 1.03 + -0.034 *(temp- 80 );
if dth=  1 and temp>= 85 and temp<  90 then hwep= 0.86 + -0.026 *(temp- 85 );
if dth=  1 and temp>= 90 and temp<  95 then hwep= 0.73 +  0.006 *(temp- 90 );
if dth=  1 and temp>= 95 and temp< 100 then hwep= 0.76 +  0.000 *(temp- 95 );
if dth=  1 and temp>=  100 then hwep= 0.76 ;

if dth=  2 and temp=< 25 then hwep=  4.5 + -0.004 *(temp- 25 );
if dth=  2 and temp>= 25 and temp<  30 then hwep=  4.5 + -0.004 *(temp- 25 );
if dth=  2 and temp>= 30 and temp<  35 then hwep= 4.48 + -0.142 *(temp- 30 );
if dth=  2 and temp>= 35 and temp<  40 then hwep= 3.77 + -0.044 *(temp- 35 );
if dth=  2 and temp>= 40 and temp<  45 then hwep= 3.55 + -0.068 *(temp- 40 );
if dth=  2 and temp>= 45 and temp<  50 then hwep= 3.21 + -0.076 *(temp- 45 );
if dth=  2 and temp>= 50 and temp<  55 then hwep= 2.83 + -0.060 *(temp- 50 );
if dth=  2 and temp>= 55 and temp<  60 then hwep= 2.53 + -0.106 *(temp- 55 );
if dth=  2 and temp>= 60 and temp<  65 then hwep=  2 + -0.090 *(temp- 60 );
if dth=  2 and temp>= 65 and temp<  70 then hwep= 1.55 + -0.054 *(temp- 65 );
if dth=  2 and temp>= 70 and temp<  75 then hwep= 1.28 + -0.060 *(temp- 70 );
if dth=  2 and temp>= 75 and temp<  80 then hwep= 0.98 + -0.046 *(temp- 75 );
if dth=  2 and temp>= 80 and temp<  85 then hwep= 0.75 + -0.018 *(temp- 80 );
if dth=  2 and temp>= 85 and temp<  90 then hwep= 0.66 + -0.024 *(temp- 85 );
if dth=  2 and temp>= 90 and temp<  95 then hwep= 0.54 + -0.022 *(temp- 90 );
if dth=  2 and temp>= 95 then hwep= 0.43 + -0.022 *(temp- 95 );
```

```
if dth=  3 and temp< 5 then hwep= 1.23 ;
if dth=  3 and temp>=  5 and temp<  10 then hwep= 5.44 + -0.258 *(temp-  5 );
if dth=  3 and temp>= 10 and temp<  15 then hwep= 4.15 +  0.236 *(temp- 10 );
if dth=  3 and temp>= 15 and temp<  20 then hwep= 5.33 +  0.004 *(temp- 15 );
if dth=  3 and temp>= 20 and temp<  25 then hwep= 5.35 + -0.010 *(temp- 20 );
if dth=  3 and temp>= 25 and temp<  30 then hwep=  5.3 + -0.166 *(temp- 25 );
if dth=  3 and temp>= 30 and temp<  35 then hwep= 4.88 + -0.082 *(temp- 30 );
if dth=  3 and temp>= 35 then hwep= 4.47 + -0.082 *(temp- 35 );

if dth=  4 and temp<  10 then hwep= 6.01 ;
if dth=  4 and temp>= 10 and temp<  15 then hwep= 6.01 + -0.032 *(temp- 10 );
if dth=  4 and temp>= 15 and temp<  20 then hwep= 5.85 + -0.056 *(temp- 15 );
if dth=  4 and temp>= 20 and temp<  25 then hwep= 5.57 + -0.082 *(temp- 20 );
if dth=  4 and temp>= 25 and temp<  30 then hwep= 5.16 + -0.044 *(temp- 25 );
if dth=  4 and temp>= 30 and temp<  35 then hwep= 4.94 + -0.066 *(temp- 30 );
if dth=  4 and temp>= 35 and temp<  40 then hwep= 4.61 + -0.030 *(temp- 35 );
if dth=  4 and temp>= 40 and temp<  45 then hwep= 4.46 + -0.066 *(temp- 40 );
if dth=  4 and temp>= 45 and temp<  50 then hwep= 4.13 + -0.066 *(temp- 45 );
if dth=  4 and temp>= 50 and temp<  55 then hwep=  3.8 + -0.032 *(temp- 50 );
if dth=  4 and temp>= 55 and temp<  60 then hwep= 3.64 + -0.034 *(temp- 55 );
if dth=  4 and temp>= 60 and temp<  65 then hwep= 3.47 + -0.066 *(temp- 60 );
if dth=  4 and temp>= 65 and temp<  70 then hwep= 3.14 + -0.014 *(temp- 65 );
if dth=  4 and temp>= 70 then hwep= 3.07 + -0.014 *(temp- 70 );
if cwep <0 then cwep=0;
if hwep < 0 then hwep=0;
run;

/* print the predicted and actual data for model statistics calculations */

data print;
set newp;
file 'sh1prd1.dat';
put (mo dy yr hr temp hum wbe cwe hwe wbep cwep hwep)
  (4*5.0 8.2 8.4 6*8.2);
  run;
```

Sample Input File

This prediction routine takes the training data file and uses only the calendar dates, temperature, and humidity to generate a inverse bin predicted wbe, cwe, and hwe data. The first five lines of the input data file is provided here.

tst.dat (a.tst 01/01/90 0:00 to 02/21/90 23:00):

```
mo dy yr       hr     temp   sphum     solar  wspeed
1     1    90      0       43   0.0031       2      4.88
1     1    90    100     41.8   0.0031     2.1      4.86
1     1    90    200     41.5    0.003     2.2      4.61
1     1    90    300     41.4   0.0029     2.2      4.88
1     1    90    400       41   0.0029     2.1      4.34
```

The notation used for the variables are the same as the training data set trna.dat

Sample Output File

The first five lines of the output file written by the program is given below.

shlprdl.dat (a.tst 01/01/90 0:00 to 02/21/90 23:00 with weather data only):

mo	dy	yr	hr	temp	sphum	wbep	cwep	hwep
9	1	89	2	81.90	0.0031	544.90	7.00	0.72
9	1	89	3	80.70	0.0031	536.39	6.94	0.74
9	1	89	4	79.70	0.0030	530.87	6.86	0.76
9	1	89	5	79.00	0.0029	527.61	7.02	0.80
9	1	89	6	78.90	0.0029	528.94	7.01	0.80

The additional notation used for the variables in this file are:

wbep inverse bin predicted wbe data for the given type of analysis

cwep inverse bin predicted cwe data for the given type of analysis

hwep inverse bin predicted hwe data for the given type of analysis

Sample SAS Program for Checking the Impact of Secondary Variables

```
/*                          COPYRIGHT NOTICE                                */
/*  This program bears a copyright notice to prevent rights from being claimed*/
/*  by any other party.  The Texas Engineering Experiment Station intends that*/
/*  the program be placed in the public domain and grants permission for its  */
/*  unrestricted use and distribution, provided that:                         */
/*        1) the source code is distributed without changes,                  */
/*        2) the copyright notice is retained in all copies of the code, and  */
/*        3) the program is distributed from the Texas Experiment Station(TEES)*/
/*  The program is distributed "as is". TEES DOES NOT WARRANT THAT THE        */
/*  OPERATION OF THE PROGRAM WILL BE UNINTERRUPTED OR ERROR-FREE, AND MAKES NO*/
/*  REPRESENTATIONS OR OTHER WARRANTIES, EXPRESS OR IMPLIED, INCLUDING NOT    */
/*  LIMITED TO THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A    */
/*  PARTICULAR PURPOSE. No support service will be provided unless special    */
/*  arrangements have been made to do so.Certain manufacturers and trade names*/
/*  are mentioned in this code for the purpose of describing their            */
/*  communications protocol. Such references does not constitute an endorsement*/
/*  or recommendation of such equipment, but is provided for information      */
/* purposes only.                                                              */

/* This program was written by S. THAMILSERAN for the analysis work performed */
/* towards his dissertation in the Dept. of Mechanical Engineering.           */
/* This program was written to run on a UNIX machine with SAS system SOFTWARE */
/* VERSION 6 or later.                                                         */
/* The input file is trnaf.dat (given training data with outlier info).       */
/* The useful information for the improved bin analysis is in the SAS compiled*/
/* output file and humidity sub-binned cwe data in zcool3.dat data file       */

/* This program takes the clean dataset, and checks the impact of various     */
/* levels of lag temperature and humidity groups on energy values for the     */
/* inverse bin method.                                                         */
   data newa;
   infile 'trnaf.dat';
   input mo dy yr hr cwe hwe wbe temp humid oc oh ow;
   date=mdy(mo,dy,yr);
   format date date7.;
   dow=weekday(date);

   if temp <-20 then temp=".";
   if humid < 0 then humid=".";
   if wbe < 0 then wbe= ".";
   if cwe < 0 then cwe =".";
   if hwe < 0 then hwe =".";

   /* selecting daytype from prevue/prior knowledge */
   if (date>='01sep89'd and date<='13dec89'd) then dtw=1;
   if (date>='14dec89'd and date <='23dec89'd) then dtw=2;
   if  date>='24dec89'd                        then dtw=3;
   if (date>='23nov89'd and date<='26nov89'd) or (date>='24dec89'd)
   then dow=1;

   /* separate daytypes for testing */

   if dtw=1 or dtw=2 then dt=1;
   if dtw=3 then dt=2;
```

```
/*dt=1 for regular,dt=2 for holidays */
/* also removing outliers from usable data */

if (date>='01sep89'd and date<='14dec89'd) and oc=2  then cwe=.;
if (date>='01sep89'd and date<='14dec89'd) and oh=2  then hwe=.;

/* separation of weekday and weekends */
if dt=1 and (dow=1 or dow=7) then dtp=1;
if dt=1 and (dow>1 and dow<7) then dtp=2;
if dt=2 and (dow=1 or dow=7) then dtp=3;
if dt=2 and (dow>1 and dow<7) then dtp=4;

/* also adding the humidity groups */
if humid < 0.01 then dh=1;
if humid >=0.01 and humid < 0.015 then dh=2;
if humid >=0.015 and humid < 0.020 then dh=3;
if humid >=0.02  then dh=4;
run;

/* adding the new lag variable by staggered temp by number of lag hours*/
/* the shortened output contains the 0 - 13 hour lag variables */

data test;
set newa;
tem1=lag1(temp);
tem2=lag2(temp);
tem3=lag3(temp);
tem4=lag4(temp);
tem5=lag5(temp);
tem6=lag6(temp);
tem7=lag7(temp);
tem8=lag8(temp);
tem9=lag9(temp);
tem10=lag10(temp);
tem11=lag11(temp);
tem12=lag12(temp);
tem13=lag13(temp);
run;

/* testing the linear regression model with various lag temps */

proc reg data=test;
model cwe=temp tem1 tem2 tem3 tem4 tem5 tem6 tem7 tem8
          tem9 tem10 tem11 tem12 tem13/selection=cp best=7;
model cwe=temp;
model cwe=tem1;
model cwe=tem2;
model cwe=tem3;
model cwe=tem4;
model cwe=tem5;
model cwe=tem6;
model cwe=tem7;
model cwe=tem8;
model cwe=tem9;
model cwe=tem10;
model cwe=tem11;
model cwe=tem12;
model cwe=tem13;
```

```
model hwe=temp;
model hwe=tem1;
model hwe=tem2;
model hwe=tem3;
model hwe=tem4;
model hwe=tem5;
model hwe=tem6;
model hwe=tem7;
model hwe=tem8;
model hwe=tem9;
model hwe=tem10;
model hwe=tem11;
model hwe=tem12;
model hwe=tem13;
run;

/* temperature bins for calculations */

data newb;
set newa;
temp=temp-2;
tempgrpa = round(temp,5);
ta = tempgrpa;
ta1=ta+2;
run;

/* hourly mean for each daytype, temp bin, & humidity group */
/* separated humidity group calculations. The std.dev. and */
/* other detail information for each bin by univariate of  */
/* individual groups that was used for visual inspections. */

proc means data=newb;
class dtp dh ta1;
var cwe ;
output out=tnc
       mean=mcwe;
       run;

/* ========= Printing the bin-mean out files ========= */
data ttn1;
set tnc;
file 'zcool3.dat';
put (dtp dh ta1 mcwe) (3*5.0 9.2);
run;
```

<u>Sample Input File</u>

This program uses the output file from the previous outlier identification program. This program creates the lagtemp variables for 0 - 13 hours of lag to given temperature variable and then test them against the cwe data to calculate a CV(RMSE) of the linear regression of lagNtemp variable against the CWE where N is the number of hours of lag introduced to the variable.

trnaf.dat (a.trn 09/01/89 0:00 to 12/31/89 23:00 with outlier groups):

mo	dy	yr	hr	cwe	hwe	wbe	temp	sphum	oc	oh	ow
9	1	89	2	7.20	0.40	496	81.90	0.018	1	1	1
9	1	89	3	7.10	0.50	497	80.70	0.019	1	1	1
9	1	89	4	7.10	0.50	497	79.70	0.019	1	1	1
9	1	89	5	7.10	0.60	495	79.00	0.020	1	1	1
9	1	89	6	7.00	0.60	498	78.90	0.020	1	1	1

Sample Output File

The lag variables used in the program have a shortened name for brevity. The lag variables are Temp1, temp2, ... for 1,2,.... hours of lag respectively. The relevant sections of the output file written by the program are given below.

Output1 : CV of the Linear Regression Model with CWE and Lag Variable

for Temp

Analysis of Variance

Source	DF	Squares	Sum of Square	Mean F Value	Prob>F
Model	1	3507.55515	3507.55515	11921.572	0.0001
Error	2874	845.58591	0.29422		
C Total	2875	4353.14107			

Root MSE	0.54242	R-square	0.8058
Dep Mean	5.04385	Adj R-sq	0.8057
C.V.	10.75409		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	1.171748	0.03687749	31.774	0.0001
TEMP	1	0.061493	0.00056319	109.186	0.0001

for temp2

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Valu	Prob>F
Model	1	3379.51795	3379.51795	9975.86	0.0001
Error	2874	973.62312	0.33877		
C Total	2875	4353.14107			

Root MSE	0.58204	R-square	0.7763
Dep Mean	5.04385	Adj R-sq	0.7763
C.V.	11.53959		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob > |T|
INTERCEP	1	1.246003	0.03954292	31.510	0.0001
TEM2	1	0.060285	0.00060358	99.879	0.0001

Output 2: The Humidity Sub-binned Energy Value with Groups

```
section 21: for no temp, no humid no daytype information available
   dtp  dh  tal    mcwe
    .    .   .      5.05
   ........
   ........

section 22: humid, daytype information not available. temp information available
    .    .   2      1.60
    .    .   7      0.67
   ........
   ........

section 23: daytype and temp information are not availablele. humid information
available
    .    1   .      4.55
    .    2   .      5.71
    .    3   .      6.43
    .    4   .      7.03
   ........
   ........

section 24: daytype information not available. humid and temp information
available

    .    1   2      1.60
    .    1   7      0.67
   ........
   ........

section 25: humid, temp information is not available. Only daytype information is
available
    1    .   .      4.93
    2    .   .      5.28
    3    .   .      3.39
   ........
   ........

section 26: humid information not available. daytype and temp information  are
available
    1    .   2      1.60
    1    .   7      0.67
   ........
   ........

section 27: all three information are available.
    1    1   2      1.60
    1    1   7      0.67
    1    1  12      2.37
    1    1  17      2.49
    1    1  22      2.34
    1    1  27      3.08
    1    1  32      3.19
    1    1  37      3.56
    1    1  42      3.77
    1    1  47      3.91
    1    1  52      4.08
    1    1  57      4.46
```

1	1	62	4.65
1	1	67	4.83
1	1	72	5.02
1	1	77	5.20
1	1	82	5.41
1	1	87	5.86
1	1	92	6.18
1	1	97	6.81
1	1	102	6.80

These binned energy information are then coded into the following program for the improved bin predictions.

Sample SAS Program for Improved Inverse Bin Method Predictions

```
/*                          COPYRIGHT NOTICE                                 */
/*  This program bears a copyright notice to prevent rights from being claimed*/
/*  by any other party.  The Texas Engineering Experiment Station intends that*/
/*  the program be placed in the public domain and grants permission for its */
/*  unrestricted use and distribution, provided that:                        */
/*       1) the source code is distributed without changes,                  */
/*       2) the copyright notice is retained in all copies of the code, and  */
/*       3) the program is distributed from the Texas Experiment Station(TEES)*/
/*  The program is distributed "as is". TEES DOES NOT WARRANT THAT THE       */
/*  OPERATION OF THE PROGRAM WILL BE UNINTERRUPTED OR ERROR-FREE, AND MAKES NO*/
/*  REPRESENTATIONS OR OTHER WARRANTIES, EXPRESS OR IMPLIED, INCLUDING NOT   */
/*  LIMITED TO THE IMPLIED WARRANTIES OF MERCHANTABILITY AND FITNESS FOR A   */
/*  PARTICULAR PURPOSE. No support service will be provided unless special   */
/*  arrangements have been made to do so.Certain manufacturers and trade names*/
/*  are mentioned in this code for the purpose of describing their           */
/*  communications protocol. Such references does not constitute an endorsement*/
/*  or recommendation of such equipment, but is provided for information     */
/* purposes only.                                                            */

/* This program was written by S. THAMILSERAN for the analysis work performed */
/* towards his dissertation in the Dept. of Mechanical Engineering.          */
/* This program was written to run on a UNIX machine with SAS system SOFTWARE */
/* VERSION 6 or later.                                                       */
/* The input file is tsta.dat (given testing data set).                      */
/* The output file is the improved inverse bin prediction with humidity sub  */
/* binning and written to shlprd3.dat data file                              */

/* This program takes the original dataset, and predict energy values by the */
/* improved inverse bin method for comparison. The prediction included here  */
/* has the humdity sub-groups                                                */


   data newa;
   infile 'tsta.dat';
   input mo dy yr hr temp hum sol wspeed;
   date=mdy(mo,dy,yr);
   format date date7.;
   dow=weekday(date);
   if temp <-20 then temp=".";
   if hum < 0 then hum=".";

   /* selecting daytype from prevue/prior knowledge */

   if (date>='21jan90'd and date<='21feb90'd) then dt=1;
   if (date>='01jan90'd and date <='20jan90'd) then dt=2;

   /*dt=1 for peakday,dt=2 for low days, breaks, xmas days */

   /* separation of weekday and weekends */
   if dt=1 and (dow=1 or dow=7) then dtp=1;
   if dt=1 and (dow>1 and dow<7) then dtp=2;
   if dt=2 and (dow=1 or dow=7) then dtp=3;
   if dt=2 and (dow>1 and dow<7) then dtp=4;
   if dt=3 and (dow=1 or dow=7) then dtp=5;
   if dt=3 and (dow>1 and dow<7) then dtp=6;
```

```
if dt=4 and (dow=1 or dow=7) then dtp=7;
if dt=4 and (dow>1 and dow<7) then dtp=8;

/*cwe groups for bin calculations*/

if dtp=1 then dtc=1;
if dtp=2 then dtc=2;
if dtp=3 then dtc=1;
if dtp=4 then dtc=2;
if dtp=5 then dtc=3;
if dtp=6 or dtp=7 or dtp=8 then dtc=4;

/*hwe groups for bin calculations*/

if dtp=1 then dth=1;
if dtp=2 then dth=2;
if dtp=3 then dth=1;
if dtp=4 then dth=2;
if dtp=5 then dth=3;
if dtp=6 or dtp=7 or dtp=8 then dth=4;


/* also adding the humidity groups */

if hum < 0.01 then dh=1;
if hum >=0.01 and hum < 0.015 then dh=2;
if hum >=0.015 and hum < 0.020 then dh=3;
if hum >=0.02 then dh=4;
humid=dh;
run;

data newp;
set newa;
temp=temp-2;
/* first the prediction for missing independent variable data */

/* here missing humidity, daytype information */

if dtc= . and humid=. and temp>=. then cwep= 5.05 ;
if dtc= . and humid=. and (temp<5 ) then cwep= 1.23 + 0.014 *(temp- 5 );
if dtc= . and humid=. and (temp>=5 and temp< 10 ) then cwep= 1.23 + 0.140
*(temp- 5 );
if dtc=. and humid=. and (temp>=10 and temp< 15 ) then cwep= 1.93 + 0.122
*(temp-10 );
if dtc=. and humid=. and (temp>=15 and temp< 20 ) then cwep= 2.54 + -0.020
*(temp-15 );
if dtc=. and humid=. and (temp>=20 and temp< 25 ) then cwep= 2.44 + 0.128
*(temp-20 );
if dtc=. and humid=. and (temp>=25 and temp< 30 ) then cwep= 3.08 + 0.012
*(temp-25 );
if dtc=. and humid=. and (temp>=30 and temp< 35 ) then cwep= 3.14 + 0.056
*(temp-30 );
if dtc=. and humid=. and (temp>=35 and temp< 40 ) then cwep= 3.42 + 0.056
*(temp-35 );
if dtc=. and humid=. and (temp>=40 and temp< 45 ) then cwep= 3.7 + 0.036
*(temp-40 );
if dtc=. and humid=. and (temp>=45 and temp< 50 ) then cwep= 3.88 + 0.076
*(temp-45 );
```

```
if dtc= . and humid=. and (temp>= 50 and temp< 55 ) then cwep= 4.26 + 0.048
*(temp- 50 );
if dtc= . and humid=. and (temp>= 55 and temp< 60 ) then cwep= 4.5 + 0.036
*(temp- 55 );
if dtc= . and humid=. and (temp>= 60 and temp< 65 ) then cwep= 4.68 + 0.072
*(temp- 60 );
if dtc= . and humid=. and (temp>= 65 and temp< 70 ) then cwep= 5.04 + 0.070
*(temp- 65 );
if dtc= . and humid=. and (temp>= 70 and temp< 75 ) then cwep= 5.39 + 0.080
*(temp- 70 );
if dtc= . and humid=. and (temp>= 75 and temp< 80 ) then cwep= 5.79 + 0.090
*(temp- 75 );
if dtc= . and humid=. and (temp>= 80 and temp< 85 ) then cwep= 6.24 + 0.044
*(temp- 80 );
if dtc= . and humid=. and (temp>= 85 and temp< 90 ) then cwep= 6.46 + 0.068
*(temp- 85 );
if dtc= . and humid=. and (temp>= 90 and temp< 95 ) then cwep= 6.8 + 0.052
*(temp- 90 );
if dtc= . and humid=. and (temp>= 95 and temp< 100 ) then cwep= 7.06 + 0.006
*(temp- 95 );
if dtc= . and humid=. and (temp>= 100 ) then cwep= 7.09 + 0.006 *(temp- 100 );


/* now for missing daytype and temperature info */

 if dtc= . and humid= 1 and (temp= . ) then cwep= 4.55 ;
 if dtc= . and humid= 2 and (temp= . ) then cwep= 5.71 ;
 if dtc= . and humid= 3 and (temp= . ) then cwep= 6.43 ;
 if dtc= . and humid= 4 and (temp= . ) then cwep= 7.03 ;


/* now for missing daytypes info */

if dtc= . and humid= 1 and (temp< 5 ) then cwep= 1.23 + 0.014 *(temp- 5 );
if dtc= . and humid= 1 and (temp>= 5 and temp< 10 ) then cwep= 1.23 + 0.140
*(temp- 5 );
if dtc= . and humid= 1 and (temp>= 10 and temp< 15 ) then cwep= 1.93 + 0.122
*(temp- 10 );
if dtc= . and humid= 1 and (temp>= 15 and temp< 20 ) then cwep= 2.54 + -0.020
*(temp- 15 );
if dtc= . and humid= 1 and (temp>= 20 and temp< 25 ) then cwep= 2.44 + 0.128
*(temp- 20 );
if dtc= . and humid= 1 and (temp>= 25 and temp< 30 ) then cwep= 3.08 + 0.012
*(temp- 25 );
if dtc= . and humid= 1 and (temp>= 30 and temp< 35 ) then cwep= 3.14 + 0.056
*(temp- 30 );
 if dtc= . and humid= 1 and (temp>= 35 and temp< 40 ) then cwep= 3.42 + 0.056
*(temp- 35 );
 if dtc= . and humid= 1 and (temp>= 40 and temp< 45 ) then cwep= 3.7 + 0.036
*(temp- 40 );
 if dtc= . and humid= 1 and (temp>= 45 and temp< 50 ) then cwep= 3.88 + 0.076
*(temp- 45 );
 if dtc= . and humid= 1 and (temp>= 50 and temp< 55 ) then cwep= 4.26 + 0.048
*(temp- 50 );
 if dtc= . and humid= 1 and (temp>= 55 and temp< 60 ) then cwep= 4.5 + 0.020
*(temp- 55 );
 if dtc= . and humid= 1 and (temp>= 60 and temp< 65 ) then cwep= 4.6 + 0.072
*(temp- 60 );
```

```
 if dtc= . and humid= 1 and (temp>= 65 and temp< 70 ) then cwep= 4.96 + 0.022
*(temp- 65 );
 if dtc= . and humid= 1 and (temp>= 70 and temp< 75 ) then cwep= 5.07 + 0.054
*(temp- 70 );
 if dtc= . and humid= 1 and (temp>= 75 and temp< 80 ) then cwep= 5.34 + 0.082
*(temp- 75 );
 if dtc= . and humid= 1 and (temp>= 80 and temp< 85 ) then cwep= 5.75 + 0.072
*(temp- 80 );
 if dtc= . and humid= 1 and (temp>= 85 and temp< 90 ) then cwep= 6.11 + 0.054
*(temp- 85 );
 if dtc= . and humid= 1 and (temp>= 90 and temp< 95 ) then cwep= 6.38 + 0.104
*(temp- 90 );
 if dtc= . and humid= 1 and (temp>= 95 and temp< 100 ) then cwep= 6.9 + 0.004
*(temp- 95 );
 if dtc= . and humid= 1 and (temp>= 100 ) then cwep= 6.92 + 0.004 *(temp- 100
);

 if dtc= . and humid= 2 and (temp< 55 ) then cwep= 4.58 + 0.090 *(temp- 55 );
 if dtc= . and humid= 2 and (temp>= 55 and temp< 60 ) then cwep= 4.58 + 0.090
*(temp- 55 );
 if dtc= . and humid= 2 and (temp>= 60 and temp< 65 ) then cwep= 5.03 + 0.018
*(temp- 60 );
 if dtc= . and humid= 2 and (temp>= 65 and temp< 70 ) then cwep= 5.12 + 0.078
*(temp- 65 );
 if dtc= . and humid= 2 and (temp>= 70 and temp< 75 ) then cwep= 5.51 + 0.042
*(temp- 70 );
 if dtc= . and humid= 2 and (temp>= 75 and temp< 80 ) then cwep= 5.72 + 0.078
*(temp- 75 );
 if dtc= . and humid= 2 and (temp>= 80 and temp< 85 ) then cwep= 6.11 + 0.072
*(temp- 80 );
 if dtc= . and humid= 2 and (temp>= 85 and temp< 90 ) then cwep= 6.47 + 0.138
*(temp- 85 );
 if dtc= . and humid= 2 and (temp>= 90 and temp< 95 ) then cwep= 7.16 + 0.010
*(temp- 90 );
 if dtc= . and humid= 2 and (temp>= 95 and temp< 100 ) then cwep= 7.21 + 0.004
*(temp- 95 );
 if dtc= . and humid= 2 and (temp>= 100 ) then cwep= 7.23 + 0.004 *(temp- 100
);

 if dtc= . and humid= 3 and (temp< 70 ) then cwep= 5.72 + 0.100 *(temp- 70 );
 if dtc= . and humid= 3 and (temp>= 70 and temp< 75 ) then cwep= 5.72 + 0.100
*(temp- 70 );
 if dtc= . and humid= 3 and (temp>= 75 and temp< 80 ) then cwep= 6.22 + 0.124
*(temp- 75 );
 if dtc= . and humid= 3 and (temp>= 80 and temp< 85 ) then cwep= 6.84 + 0.060
*(temp- 80 );
 if dtc= . and humid= 3 and (temp>= 85 and temp< 90 ) then cwep= 7.14 + 0.010
*(temp- 85 );
 if dtc= . and humid= 3 and (temp>= 90 ) then cwep= 7.19 + 0.010 *(temp- 90 );

 if dtc= . and humid= 4 and (temp< 75 ) then cwep= 6.79 + 0.054 *(temp- 75 );
 if dtc= . and humid= 4 and (temp>= 75 and temp< 80 ) then cwep= 6.79 + 0.054
*(temp- 75 );
 if dtc= . and humid= 4 and (temp>= 80 and temp< 85 ) then cwep= 7.06 + 0.078
*(temp- 80 );
 if dtc= . and humid= 4 and (temp>= 85 ) then cwep= 7.45 + 0.078 *(temp- 85 );
```

```
/* now for missing humidity and temp bin. info */

 if dtc= 1 and humid=. and (temp= . ) then cwep= 5.15 + 0.064 *(temp- . );
 if dtc= 2 and humid=. and (temp= . ) then cwep= 5.47 + -0.521 *(temp- . );
 if dtc= 3 and humid=. and (temp= . ) then cwep= 2.55 + 0.168 *(temp- . );
 if dtc= 4 and humid=. and (temp= . ) then cwep= 3.39 + 0.018 *(temp- . );


/* now prediction for missing humidity group info.*/

 if dtc= 1 and humid=. and (temp< 35 ) then cwep= 3.48 + 0.052 *(temp- 35 );
 if dtc= 1 and humid=. and (temp>= 35 and temp< 40 ) then cwep= 3.48 + 0.052
*(temp- 35 );
 if dtc= 1 and humid=. and (temp>= 40 and temp< 45 ) then cwep= 3.74 + 0.012
*(temp- 40 );
 if dtc= 1 and humid=. and (temp>= 45 and temp< 50 ) then cwep= 3.8 + 0.044
*(temp- 45 );
 if dtc= 1 and humid=. and (temp>= 50 and temp< 55 ) then cwep= 4.02 + 0.054
*(temp- 50 );
 if dtc= 1 and humid=. and (temp>= 55 and temp< 60 ) then cwep= 4.29 + 0.072
*(temp- 55 );
 if dtc= 1 and humid=. and (temp>= 60 and temp< 65 ) then cwep= 4.65 + 0.054
*(temp- 60 );
 if dtc= 1 and humid=. and (temp>= 65 and temp< 70 ) then cwep= 4.92 + 0.078
*(temp- 65 );
 if dtc= 1 and humid=. and (temp>= 70 and temp< 75 ) then cwep= 5.31 + 0.022
*(temp- 70 );
 if dtc= 1 and humid=. and (temp>= 75 and temp< 80 ) then cwep= 5.42 + 0.112
*(temp- 75 );
 if dtc= 1 and humid=. and (temp>= 80 and temp< 85 ) then cwep= 5.98 + 0.052
*(temp- 80 );
 if dtc= 1 and humid=. and (temp>= 85 and temp< 90 ) then cwep= 6.24 + 0.086
*(temp- 85 );
 if dtc= 1 and humid=. and (temp>= 90 and temp< 95 ) then cwep= 6.67 + 0.012
*(temp- 90 );
 if dtc= 1 and humid=. and (temp>= 95 and temp< 100 ) then cwep= 6.73 + 0.058
*(temp- 95 );
 if dtc=1 and humid=. and (temp>=100) then cwep= 7.02 + 0.058 *(temp- 100 );

 if dtc=2 and humid=. and (temp< 25) then cwep= 3.4 + 0.028 *(temp- 25 );
 if dtc= 2 and humid=. and (temp>= 25 and temp< 30 ) then cwep= 3.4 + 0.028
*(temp- 25 );
 if dtc= 2 and humid=. and (temp>= 30 and temp< 35 ) then cwep= 3.54 + 0.028
*(temp- 30 );
 if dtc= 2 and humid=. and (temp>= 35 and temp< 40 ) then cwep= 3.68 + 0.046
*(temp- 35 );
 if dtc= 2 and humid=. and (temp>= 40 and temp< 45 ) then cwep= 3.91 + 0.034
*(temp- 40 );
 if dtc= 2 and humid=. and (temp>= 45 and temp< 50 ) then cwep= 4.08 + 0.088
*(temp- 45 );
 if dtc= 2 and humid=. and (temp>= 50 and temp< 55 ) then cwep= 4.52 + 0.046
*(temp- 50 );
 if dtc= 2 and humid=. and (temp>= 55 and temp< 60 ) then cwep= 4.75 + 0.038
*(temp- 55 );
 if dtc= 2 and humid=. and (temp>= 60 and temp< 65 ) then cwep= 4.94 + 0.052
*(temp- 60 );
 if dtc= 2 and humid=. and (temp>= 65 and temp< 70 ) then cwep= 5.2 + 0.060
*(temp- 65 );
```

```
 if dtc= 2 and humid=. and (temp>= 70 and temp< 75 ) then cwep= 5.5 + 0.084
*(temp- 70 );
 if dtc= 2 and humid=. and (temp>= 75 and temp< 80 ) then cwep= 5.92 + 0.086
*(temp- 75 );
 if dtc= 2 and humid=. and (temp>= 80 and temp< 85 ) then cwep= 6.35 + 0.038
*(temp- 80 );
 if dtc= 2 and humid=. and (temp>= 85 and temp< 90 ) then cwep= 6.54 + 0.060
*(temp- 85 );
 if dtc= 2 and humid=. and (temp>= 90 and temp< 95 ) then cwep= 6.84 + 0.090
*(temp- 90 );
 if dtc= 2 and humid=. and (temp>= 95 and temp< 100 ) then cwep= 7.29 + -0.100
*(temp- 95 );
 if dtc=2 and humid=. and (temp>=100) then cwep= 6.79 + -0.100 *(temp- 100 );

 if dtc= 3 and humid=. and (temp< 5 ) then cwep= 1.23 + 0.120 *(temp- 5 );
 if dtc= 3 and humid=. and (temp>= 5 and temp< 10 ) then cwep= 1.23 + 0.120
*(temp- 5 );
 if dtc= 3 and humid=. and (temp>= 10 and temp< 15 ) then cwep= 1.83 + 0.144
*(temp- 10 );
 if dtc= 3 and humid=. and (temp>= 15 and temp< 20 ) then cwep= 2.55 + -0.044
*(temp- 15 );
 if dtc= 3 and humid=. and (temp>= 20 and temp< 25 ) then cwep= 2.33 + 0.080
*(temp- 20 );
 if dtc= 3 and humid=. and (temp>= 25 and temp< 30 ) then cwep= 2.73 + 0.078
*(temp- 25 );
 if dtc= 3 and humid=. and (temp>= 30 and temp< 35 ) then cwep= 3.12 + 0.028
*(temp- 30 );
 if dtc= 3 and humid=. and (temp>= 35 ) then cwep= 3.26 + 0.028 *(temp- 35 );

 if dtc= 4 and humid=. and (temp< 10 ) then cwep= 2.42 + 0.024 *(temp- 10 );
 if dtc= 4 and humid=. and (temp>= 10 and temp< 15 ) then cwep= 2.42 + 0.024
*(temp- 10 );
 if dtc= 4 and humid=. and (temp>= 15 and temp< 20 ) then cwep= 2.54 + 0.008
*(temp- 15 );
 if dtc= 4 and humid=. and (temp>= 20 and temp< 25 ) then cwep= 2.58 + 0.102
*(temp- 20 );
 if dtc= 4 and humid=. and (temp>= 25 and temp< 30 ) then cwep= 3.09 + -0.010
*(temp- 25 );
 if dtc= 4 and humid=. and (temp>= 30 and temp< 35 ) then cwep= 3.04 + 0.058
*(temp- 30 );
 if dtc= 4 and humid=. and (temp>= 35 and temp< 40 ) then cwep= 3.33 + 0.024
*(temp- 35 );
 if dtc= 4 and humid=. and (temp>= 40 and temp< 45 ) then cwep= 3.45 + 0.012
*(temp- 40 );
 if dtc= 4 and humid=. and (temp>= 45 and temp< 50 ) then cwep= 3.51 + 0.038
*(temp- 45 );
 if dtc= 4 and humid=. and (temp>= 50 and temp< 55 ) then cwep= 3.7 + -0.020
*(temp- 50 );
 if dtc= 4 and humid=. and (temp>= 55 and temp< 60 ) then cwep= 3.6 + 0.060
*(temp- 55 );
 if dtc= 4 and humid=. and (temp>= 60 and temp< 65 ) then cwep= 3.9 + 0.022
*(temp- 60 );
 if dtc= 4 and humid=. and (temp>= 65 and temp< 70 ) then cwep= 4.01 + -0.068
*(temp- 65 );
 if dtc= 4 and humid=. and (temp>=70) then cwep= 3.67 + -0.068 *(temp- 70 );

/* missing temp.bin info */

 if dtc= 1 and humid= 1 and (temp= . ) then cwep= 4.66 ;
```

```
 if dtc= 1 and humid= 2 and (temp= . ) then cwep= 5.49 ;
 if dtc= 1 and humid= 3 and (temp= . ) then cwep= 6.27 ;
 if dtc= 1 and humid= 4 and (temp= . ) then cwep= 7.04 ;
 if dtc= 2 and humid= 1 and (temp= . ) then cwep= 5.04 ;
 if dtc= 2 and humid= 2 and (temp= . ) then cwep= 5.88 ;
 if dtc= 2 and humid= 3 and (temp= . ) then cwep= 6.5 ;
 if dtc= 2 and humid= 4 and (temp= . ) then cwep= 7.02 ;
 if dtc= 3 and humid= 1 and (temp= . ) then cwep= 2.55 ;
 if dtc= 4 and humid= 1 and (temp= . ) then cwep= 3.35 ;
 if dtc= 4 and humid= 2 and (temp= . ) then cwep= 4.31 ;

/* now the prediction for all the available data in dataset */

 if dtc= 1 and humid= 1 and (temp< 35 ) then cwep= 3.48 + 0.052 *(temp- 35 );
 if dtc= 1 and humid= 1 and (temp>= 35 and temp< 40 ) then cwep= 3.48 + 0.052
*(temp- 35 );
 if dtc= 1 and humid= 1 and (temp>= 40 and temp< 45 ) then cwep= 3.74 + 0.012
*(temp- 40 );
 if dtc= 1 and humid= 1 and (temp>= 45 and temp< 50 ) then cwep= 3.8 + 0.044
*(temp- 45 );
 if dtc= 1 and humid= 1 and (temp>= 50 and temp< 55 ) then cwep= 4.02 + 0.046
*(temp- 50 );
 if dtc= 1 and humid= 1 and (temp>= 55 and temp< 60 ) then cwep= 4.25 + 0.050
*(temp- 55 );
 if dtc= 1 and humid= 1 and (temp>= 60 and temp< 65 ) then cwep= 4.5 + 0.058
*(temp- 60 );
 if dtc= 1 and humid= 1 and (temp>= 65 and temp< 70 ) then cwep= 4.79 + 0.030
*(temp- 65 );
 if dtc= 1 and humid= 1 and (temp>= 70 and temp< 75 ) then cwep= 4.94 + 0.036
*(temp- 70 );
 if dtc= 1 and humid= 1 and (temp>= 75 and temp< 80 ) then cwep= 5.12 + 0.036
*(temp- 75 );
 if dtc= 1 and humid= 1 and (temp>= 80 and temp< 85 ) then cwep= 5.3 + 0.084
*(temp- 80 );
 if dtc= 1 and humid= 1 and (temp>= 85 and temp< 90 ) then cwep= 5.72 + 0.048
*(temp- 85 );
 if dtc= 1 and humid= 1 and (temp>= 90 and temp< 95 ) then cwep= 5.96 + 0.102
*(temp- 90 );
 if dtc= 1 and humid= 1 and (temp>= 95 and temp< 100 ) then cwep= 6.47 + 0.090
*(temp- 95 );
 if dtc= 1 and humid= 1 and (temp>=100) then cwep= 6.92 + 0.090 *(temp-100 );
 if dtc= 1 and humid= 2 and (temp< 55 ) then cwep= 4.7 + 0.040 *(temp- 55 );
 if dtc= 1 and humid= 2 and (temp>= 55 and temp< 60 ) then cwep= 4.7 + 0.040
*(temp- 55 );
 if dtc= 1 and humid= 2 and (temp>= 60 and temp< 65 ) then cwep= 4.9 + 0.032
*(temp- 60 );
 if dtc= 1 and humid= 2 and (temp>= 65 and temp< 70 ) then cwep= 5.06 + 0.054
*(temp- 65 );
 if dtc= 1 and humid= 2 and (temp>= 70 and temp< 75 ) then cwep= 5.33 + -0.002
*(temp- 70 );
 if dtc= 1 and humid= 2 and (temp>= 75 and temp< 80 ) then cwep= 5.32 + 0.104
*(temp- 75 );
 if dtc= 1 and humid= 2 and (temp>= 80 and temp< 85 ) then cwep= 5.84 + 0.058
*(temp- 80 );
 if dtc= 1 and humid= 2 and (temp>= 85 and temp< 90 ) then cwep= 6.13 + 0.136
*(temp- 85 );
 if dtc= 1 and humid= 2 and (temp>= 90 and temp< 95 ) then cwep= 6.81 + 0.030
*(temp- 90 );
```

```
 if dtc= 1 and humid= 2 and (temp>= 95 and temp< 100 ) then cwep= 6.96 + 0.054
*(temp- 95 );
 if dtc= 1 and humid= 2 and (temp>=100) then cwep= 7.23 + 0.054 *(temp-100 );
 if dtc= 1 and humid= 3 and (temp< 70 ) then cwep= 5.71 + 0.114 *(temp- 70 );
 if dtc= 1 and humid= 3 and (temp>= 70 and temp< 75 ) then cwep= 5.71 + 0.114
*(temp- 70 );
 if dtc= 1 and humid= 3 and (temp>= 75 and temp< 80 ) then cwep= 6.28 + 0.076
*(temp- 75 );
 if dtc= 1 and humid= 3 and (temp>= 80 and temp< 85 ) then cwep= 6.66 + 0.088
*(temp- 80 );
 if dtc= 1 and humid= 3 and (temp>= 85 and temp< 90 ) then cwep= 7.1 + 0.014
*(temp- 85 );
 if dtc= 1 and humid= 3 and (temp>=90 ) then cwep= 7.17 + 0.014 *(temp-90 );

 if dtc= 1 and humid= 4 and (temp< 75 ) then cwep= 6.7 + 0.068 *(temp- 75 );
 if dtc= 1 and humid= 4 and (temp>= 75 and temp< 80 ) then cwep= 6.7 + 0.068
*(temp- 75 );
 if dtc= 1 and humid= 4 and (temp>= 80 and temp< 85 ) then cwep= 7.04 + 0.052
*(temp- 80 );
 if dtc= 1 and humid= 4 and (temp>= 85 and temp< 90 ) then cwep= 7.3 + -0.780
*(temp- 85 );
 if dtc= 2 and humid= 1 and (temp>= 25 and temp< 30 ) then cwep= 3.4 + 0.000
*(temp- 25 );
 if dtc= 2 and humid= 1 and (temp>= 30 and temp< 35 ) then cwep= 3.4 + 0.056
*(temp- 30 );
 if dtc= 2 and humid= 1 and (temp>= 35 and temp< 40 ) then cwep= 3.68 + 0.046
*(temp- 35 );
 if dtc= 2 and humid= 1 and (temp>= 40 and temp< 45 ) then cwep= 3.91 + 0.034
*(temp- 40 );
 if dtc= 2 and humid= 1 and (temp>= 45 and temp< 50 ) then cwep= 4.08 + 0.088
*(temp- 45 );
 if dtc= 2 and humid= 1 and (temp>= 50 and temp< 55 ) then cwep= 4.52 + 0.048
*(temp- 50 );
 if dtc= 2 and humid= 1 and (temp>= 55 and temp< 60 ) then cwep= 4.76 + 0.024
*(temp- 55 );
 if dtc= 2 and humid= 1 and (temp>= 60 and temp< 65 ) then cwep= 4.88 + 0.054
*(temp- 60 );
 if dtc= 2 and humid= 1 and (temp>= 65 and temp< 70 ) then cwep= 5.15 + 0.022
*(temp- 65 );
 if dtc= 2 and humid= 1 and (temp>= 70 and temp< 75 ) then cwep= 5.26 + 0.034
*(temp- 70 );
 if dtc= 2 and humid= 1 and (temp>= 75 and temp< 80 ) then cwep= 5.43 + 0.106
*(temp- 75 );
 if dtc= 2 and humid= 1 and (temp>= 80 and temp< 85 ) then cwep= 5.96 + 0.052
*(temp- 80 );
 if dtc= 2 and humid= 1 and (temp>= 85 and temp< 90 ) then cwep= 6.22 + 0.042
*(temp- 85 );
 if dtc= 2 and humid= 1 and (temp>= 90 and temp< 95 ) then cwep= 6.43 + 0.160
*(temp- 90 );
 if dtc= 2 and humid= 1 and (temp>=95 ) then cwep= 7.23 + 0.160 *(temp-95 );

 if dtc= 2 and humid= 2 and (temp< 55 ) then cwep= 4.1 + 0.222 *(temp- 55 );
 if dtc= 2 and humid= 2 and (temp>= 55 and temp< 60 ) then cwep= 4.1 + 0.222
*(temp- 55 );
 if dtc= 2 and humid= 2 and (temp>= 60 and temp< 65 ) then cwep= 5.21 + 0.006
*(temp- 60 );
 if dtc= 2 and humid= 2 and (temp>= 65 and temp< 70 ) then cwep= 5.24 + 0.074
*(temp- 65 );
```

```
 if dtc= 2 and humid= 2 and (temp>= 70 and temp< 75 ) then cwep= 5.61 + 0.076
*(temp- 70 );
 if dtc= 2 and humid= 2 and (temp>= 75 and temp< 80 ) then cwep= 5.99 + 0.044
*(temp- 75 );
 if dtc= 2 and humid= 2 and (temp>= 80 and temp< 85 ) then cwep= 6.21 + 0.078
*(temp- 80 );
 if dtc= 2 and humid= 2 and (temp>= 85 and temp< 90 ) then cwep= 6.6 + 0.148
*(temp- 85 );
 if dtc= 2 and humid= 2 and (temp>= 90 and temp< 95 ) then cwep= 7.34 + -0.004
*(temp- 90 );
 if dtc= 2 and humid= 2 and (temp>= 95 and temp< 100 ) then cwep= 7.32 + -
0.184 *(temp- 95 );
 if dtc= 2 and humid= 2 and (temp>=100) then cwep= 6.4 + -0.184 *(temp-100 );

 if dtc= 2 and humid= 3 and (temp< 70 ) then cwep= 5.74 + 0.096 *(temp- 70 );
 if dtc= 2 and humid= 3 and (temp>= 70 and temp< 75 ) then cwep= 5.74 + 0.096
*(temp- 70 );
 if dtc= 2 and humid= 3 and (temp>= 75 and temp< 80 ) then cwep= 6.22 + 0.136
*(temp- 75 );
 if dtc= 2 and humid= 3 and (temp>= 80 and temp< 85 ) then cwep= 6.9 + 0.052
*(temp- 80 );
 if dtc= 2 and humid= 3 and (temp>= 85 and temp< 90 ) then cwep= 7.16 + 0.008
*(temp- 85 );
 if dtc= 2 and humid= 3 and (temp>= 90 and temp< 95 ) then cwep= 7.2 + -0.080
*(temp- 90 );
 if dtc= 2 and humid= 4 and (temp>= 75 and temp< 80 ) then cwep= 6.8 + 0.054
*(temp- 75 );
 if dtc= 2 and humid= 4 and (temp>= 80 and temp< 85 ) then cwep= 7.07 + 0.086
*(temp- 80 );
 if dtc= 2 and humid= 4 and (temp>=85) then cwep= 7.5 + 0.086 *(temp- 85 );

 if dtc= 3 and humid= 1 and (temp< 5 ) then cwep= 1.23 + 0.120 *(temp- 5 );
 if dtc= 3 and humid= 1 and (temp>= 5 and temp< 10 ) then cwep= 1.23 + 0.120
*(temp- 5 );
 if dtc= 3 and humid= 1 and (temp>= 10 and temp< 15 ) then cwep= 1.83 + 0.072
*(temp- 10 );
 if dtc= 3 and humid= 1 and (temp>= 15 and temp< 20 ) then cwep= 2.19 + 0.028
*(temp- 15 );
 if dtc= 3 and humid= 1 and (temp>= 20 and temp< 25 ) then cwep= 2.33 + 0.080
*(temp- 20 );
 if dtc= 3 and humid= 1 and (temp>= 25 and temp< 30 ) then cwep= 2.73 + 0.078
*(temp- 25 );
 if dtc= 3 and humid= 1 and (temp>= 30 and temp< 35 ) then cwep= 3.12 + 0.028
*(temp- 30 );
 if dtc= 3 and humid= 1 and (temp>=35 ) then cwep= 3.26 + 0.028 *(temp-35 );

 if dtc= 4 and humid= 1 and (temp<  10) then cwep= 2.42 + 0.024 *(temp- 10 );
 if dtc= 4 and humid= 1 and (temp>= 10 and temp< 15 ) then cwep= 2.42 + 0.024
*(temp- 10 );
 if dtc= 4 and humid= 1 and (temp>= 15 and temp< 20 ) then cwep= 2.54 + 0.008
*(temp- 15 );
 if dtc= 4 and humid= 1 and (temp>= 20 and temp< 25 ) then cwep= 2.58 + 0.102
*(temp- 20 );
 if dtc= 4 and humid= 1 and (temp>= 25 and temp< 30 ) then cwep= 3.09 + -0.010
*(temp- 25 );
 if dtc= 4 and humid= 1 and (temp>= 30 and temp< 35 ) then cwep= 3.04 + 0.058
*(temp- 30 );
 if dtc= 4 and humid= 1 and (temp>= 35 and temp< 40 ) then cwep= 3.33 + 0.024
*(temp- 35 );
```

```
 if dtc= 4 and humid= 1 and (temp>= 40 and temp< 45 ) then cwep= 3.45 + 0.012
*(temp- 40 );
 if dtc= 4 and humid= 1 and (temp>= 45 and temp< 50 ) then cwep= 3.51 + 0.038
*(temp- 45 );
 if dtc= 4 and humid= 1 and (temp>= 50 and temp< 55 ) then cwep= 3.7 + -0.020
*(temp- 50 );
 if dtc= 4 and humid= 1 and (temp>= 55 and temp< 60 ) then cwep= 3.6 + 0.060
*(temp- 55 );
 if dtc= 4 and humid= 1 and (temp>= 60 and temp< 65 ) then cwep= 3.9 + -0.072
*(temp- 60 );
 if dtc= 4 and humid= 1 and (temp>= 65 and temp< 70 ) then cwep= 3.64 + 0.074
*(temp- 65 );
 if dtc= 4 and humid= 1 and (temp>= 70 and temp< 75 ) then cwep= 3.67 + 0.066
*(temp- 70 );
 if dtc= 4 and humid= 2 and (temp>= 65) then cwep= 4.31 + 0.033 *(temp- 65 );


/* now marking out any data calculated with a negative value */
if hwep < 0 then hwep=0;
if cwep <0 then cwep=0;
run;

/* now printing the predictions for model stattistics calculations */

data print;
set newp;
file 'sh1prd3.dat';
put (mo dy yr hr temp humid wbe cwe hwe wbep cwep hwep)
(4*5.0 8.2 8.3 6*8.2); run;
```

The sample input and sample output files are similar in content to the simple inverse bin prediction routine. These are provided again below.

Sample Input File

This prediction routine takes the training data file and uses only the calendar dates, temperature, and humidity to generate a inverse bin predicted wbe, cwe, and hwe data. The first five lines of the input data file is provided here.

tst.dat (a.tst 01/01/90 0:00 to 02/21/90 23:00):

mo	dy	yr	hr	temp	sphum	solar	wspeed
1	1	90	0	43	0.0031	2	4.88
1	1	90	100	41.8	0.0031	2.1	4.86
1	1	90	200	41.5	0.003	2.2	4.61
1	1	90	300	41.4	0.0029	2.2	4.88
1	1	90	400	41	0.0029	2.1	4.34

The notation used for the variables are the same as the training data set trna.dat

Sample Output File

The first five lines of the output file written by the program is given below.

shlprd3.dat (a.tst 01/01/90 0:00 to 02/21/90 23:00 with weather data only):

mo	dy	yr	hr	temp	sphum	wbep3	cwep3	hwep3
9	1	89	2	81.90	0.0031	544.90	7.00	0.72
9	1	89	3	80.70	0.0031	536.39	6.94	0.74
9	1	89	4	79.70	0.0030	530.87	6.86	0.76
9	1	89	5	79.00	0.0029	527.61	7.02	0.80
9	1	89	6	78.90	0.0029	528.94	7.01	0.80

The additional notation used for the variables in this file are:

wbep3 inverse bin predicted wbe data for the given type of analysis

cwep3 inverse bin predicted cwe data for the given type of analysis

hwep3 inverse bin predicted hwe data for the given type of analysis

Sample SAS Program for the Inverse Bin Analysis of RAS Building


```
/* This program was written by S. THAMILSERAN for the analysis work performed */
/* towards his dissertation in the Dept. of Mechanical Engineering.           */
/* This program was written to run on a UNIX machine with SAS system SOFTWARE */
/* VERSION 6 or later.                                                        */
/* The input file is ras.acs (standard LoanSTAR file with time stamp).        */
/* The output file is the inverse bin prediction for RAS building             */
/* Additional univariate, mean, mode, median infor in the SAS compiled file   */

/* This program takes the monitored data for RAS building check the difference*/
/* between daytypes, calculated the binned energy values                      */

   /* SAS routine for analyzing the RAS building binned energy use */;

   data newa;
   infile 'rasf.acs';
   input site mo dy yr doy1 doy2 hrm wbe cwe hwe temp rh sol ws tstp;
   date=mdy(mo,dy,yr);
   format date date7.;
   dow=weekday(date);
   if wbe < 0 then wbe=.;
   if cwe < 0 then cwe=.;
   if hwe < 0 then hwe=.;
   if temp < 0 then temp=.;
   hr=hrm/100;

   /*occupied and unoccupied groups */;

   if (hr <6 or hr >22) or (dow=1 or dow=7) then gr=2;
   if (hr >=6 and hr <=22) and (dow>1 and dow<7) then gr=1;
   tempa=temp-2;
   run;

   proc anova data=newa;
   class gr;
   model cwe hwe=gr;
   means gr/duncan waller scheffe;
```

```
run;

data newb;
set newa;
tmpgrp=round(tempa,5);
ta1=tmpgrp;
ta=ta1+2;
run;

/* separation of the ON and OFF groups */

data newb1;
set newb;
if gr=1;
run;

data newb2;
set newb;
if gr=2;
run;

/* frequency plots for each dataset for visual study */

proc freq data=newb1;
tables ta/missing;
run;

proc freq data=newb2;
tables ta/missing;
run;

/* calculation of the bin mean values */

proc means data=newb;
class gr ta;
var cwe hwe;
output out=tn1
       mean=mcwe mhwe;run;

/* printing out the binned values */

 data ttn1;
set tn1;
file 'bindat.dat';
put (gr ta mcwe mhwe)(2*6.0 2*9.3);run;
```

Sample Input File

This routine accepts the standard LoanSTAR timestamped data file and analyzes for defined daytypes. It also checks and prints the univariate information of the daytypes in temperature bins and finally prints the binned energy values for the final daytypes.

rasf.acs (use the rasf control file and getdatc SOFTWARE to extract the baseline data 10/16/90 0:00 to 05/31/91 23:00):

Site	mo	dy	yr	jul.dy	dec.dy	hrm	wbe	cwe	hwe	temp	sphum
0	10	13	90	90286	3938.0000	0	-99.000	-99.000	-99.000	-99.000	-99.000
0	10	13	90	90286	3938.0417	100	-99.000	-99.000	-99.000	-99.000	-99.000
0	10	13	90	90286	3938.0833	200	-99.000	-99.000	-99.000	-99.000	-99.000
0	10	13	90	90286	3938.1250	300	-99.000	-99.000	-99.000	-99.000	-99.000
0	10	13	90	90286	3938.1667	400	-99.000	-99.000	-99.000	-99.000	-99.000

The additional notation used for the variables are :

jul.dy	standard time stamp for julian day
dec.dy	standard time stamp for decimal day

Sample Output File

The output contains three sections: ANOVA and multiple comparisons for defined daytypes, Univariate information for the defined daytypes, and binned energy values for the daytype and temperature bins. These sample outputs were already given under the simple and improved bin analysis routines.

Comparison of the Existing Models Applied to the LoanSTAR Program

The existing models (EM) used in the LoanSTAR program are mainly daily models with daytyping based on the daily data. On the other hand the inverse bin method (BM) and its enhancements (outlier identification, daytyping, and sub-binning) are based on the hourly data. In order to have a fair comparison the existing models and the inverse bin method were repeated on a clean pre-grouped hourly data. A carefully selected set of four case study buildings were considered to represent the different types models used in the LoanSTAR program for calculating the retrofit energy savings.

These models were compared to the inverse bin predicted data for the four datasets: ZEC building, RAS building, PCL building, and WEL building.

ZEC Building

Period: Spring and Summer semester periods (1990/04/03-1990/07/31). Dataset has a total of 2531 data points with all the relevant variables.

Daytype: One group ALLDAY

Type of Model:

EM: Four-parameter model with humidity potential as second variable

BM: Temperature bin prediction with humidity sub-binning

Table D2: Performance Evaluation for the Fitted Models for ZEC Building.

Energy Type	Method	CV - RMSE	R^2	Average Error (RMSE)	Mean Bias Error MBE
Cooling	EM	6.79	0.9954	0.4420	-0.009
	BM	6.80	0.9954	0.4430	-0.009
Heating	EM	57.4	0.453	0.1209	-0.231
	BM	58.7	0.436	0.1212	-0.229

RAS Building

Period: Available baseline period 10/16/90 - 04/30/91. Dataset has 1606 data points.

Daytype: All data in two group based on the equipment shut off (ON/OFF group)

Type of Model:

EM: Four-parameter model on ON-OFF grouped data

BM: Inverse bin on ON-OFF grouped data

Table D3: Performance Evaluation for the Fitted Models for RAS Building.

Energy Type	Method	CV - RMSE	R^2	Average Error (RMSE)	Mean Bias Error MBE
Cooling	EM	42.52	0.873	0.1618	0.0009
	BM	42.23	0.874	0.1607	0.0012
Heating	EM	62.44	0.857	0.1113	0.0002
	BM	54.40	0.875	0.0969	0.0003

PCL Building

Period: Summer and Fall Summer semester periods (1992/07/01-1992/12/31). Dataset has 4340 datapoints.

Daytype: One group ALLDAY

Type of Model:

EM: Four-parameter model with 3 hour-lag temperature variable

BM: inverse bin with 3-hour lag temperature as binning variable

Table D4: Performance Evaluation for the Fitted Models for PCL Building.

Energy Type	Method	CV - RMSE	R^2	Average Error (RMSE)	Mean Bias Error MBE
Cooling	EM	13.03	0.9839	0.5183	0.0015
	BM	12.96	0.9840	0.5156	0.0113
Heating	EM	17.45	0.9783	0.18423	0.0002
	BM	17.36	0.9785	0.18329	0.0011

WEL Building

Period: Spring and Summer semester periods (1992/06/30-1992/12/31). Dataset has 2488 datapoints.

Daytype: One group ALLDAY

Type of Model:

EM: Four-parameter model with and without humidity potential as second variable

BM: Inverse bin prediction with and without humidity sub-binning

Table D5: Performance Evaluation for the Fitted Models for WEL Building.

Energy Type	Method	CV - RMSE	R^2	Average Error (RMSE)	Mean Bias Error MBE
Cooling	EM-1	26.74	0.9457	2.1935	-0.417
	BM-1	18.90	0.9698	1.6540	+0.133
Cooling	EM-2	12.49	0.9871	1.091	0.122
	BM-2	12.11	0.9879	1.059	0.112

APPENDIX E

LETTER OF PERMISSION

ASHRAE American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc.

1791 Tullie Circle, NE • Atlanta, Georgia 30329-2305 ☎ 404-636-8400 • Fax 404-321-5478 • http://www.ashrae.org

Melanie Brooks
Administrative Assistant
Communications and Publications
E-mail mbrooks@ashrae.org

December 8, 1997

Mr. Sabaratnam Thamilseran
Texas A&M University
Energy Systems Laboratory
College Station, TX 77843-3581

Dear Mr. Thamilseran,

You may use in your doctoral dissertation the ASHRAE content cited in your letter of December 3. The following credit should be included with each table:

"Copyright (year) by the American Society of Heating, Refrigerating and Air-Conditioning Engineers, Inc., from (name of publication). Used by permission."

This permission is granted with the understanding that (1) the material will neither imply nor state that ASHRAE endorses a commercial product or service, and (2) ASHRAE retains the exclusive copyright for the reprinted material.

Please feel free to contact me if you have any further questions.

Sincerely,

Melanie Brooks

VITA

Sabaratnam Thamilseran was born on May 19, 1962 in Karaveddy West, Karaveddy, Sri Lanka to Karthigesu Parameswary and Subramaniam Sabaratnam. He graduated from Hartley College, Point Pedro in 1980 and then joined the College of Engineering, University of Peradeniya and earned his Bachelor of Science in Engineering with Honors majoring in Mechanical Engineering in 1985. He then traveled to Thailand and earned his Master of Engineering degree in Energy Technology from the Asian Institute of Technology, Bangkok in August 1989. He first came to Ohio University, Athens, Ohio in the USA and then transferred to the Doctoral program in Mechanical Engineering at Texas A&M University.

Mr. Thamilseran can be reached through his parents' permanent address at Maili Odai, Saraswathy Vidyalaya Road, Karaveddy North, Karaveddy, Sri Lanka.

IMAGE EVALUATION TEST TARGET (QA-3)

150mm

6"

APPLIED IMAGE, Inc
1653 East Main Street
Rochester, NY 14609 USA
Phone: 716/482-0300
Fax: 716/288-5989