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End-Use Load and Consumer Assessment Program

Characterizing Residential Thermal Performance from High Resolution End-Use Data

Volume I - Methodology

N. E. Miller
E. W. Pearson
G. M. Stokes
R. G. Pratt
M. A. Williamson

December 1990

Prepared for
the Bonneville Power Administration
under a Related Services Agreement
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Pacific Northwest Laboratory
Richland, Washington 99352

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PREFACE

This document is part of a two-volume set describing a series of thermal analyses of the residential buildings monitored under the End-Use Load and Consumer Assessment Program. Volume I describes in detail the thermal analysis methodology employed. Volume II presents the results of applying the methodology in a series of four distinct analyses: 1) an analysis of the first monitored heating season, 1985-1986, 2) an analysis of the second monitored heating season, 3) a comparison of first- and second-year analyses showing changes in residential consumption with changes in weather and evaluating the ability of the analytical technique to discriminate those changes, and 4) an extension of the previous analyses evaluating the effects of foundation type and heating system type on the results.

SUMMARY

The Bonneville Power Administration (Bonneville) began the End-Use Load and Consumer Assessment Program (ELCAP) in 1983. Prior to beginning the ELCAP, there was an abundance of information regarding total power consumption for residential structures in the Pacific Northwest (such as that found on billing records) and limited information regarding power consumption by various end uses (such as hot water, heating, and cooling). The purpose of ELCAP is to collect actual end-use load data from both residential and commercial buildings in the region.

This report presents the methodology used in several statistical modeling studies carried out on the ELCAP data between 1986 and 1989. These studies involve the thermal characterization of homes and comparisons of building techniques and conservation measures by residential and commercial consumers within the Bonneville service area of the Pacific Northwest. Each data gathering technique was successful in extracting a specific set of consumer-related energy use information. The analytical techniques used in these studies are compiled in this methodology report and are to be used in conjunction with the companion report *Characterizing Residential Thermal Performance From High Resolution End-Use Data - Volume II - Analysis*. This should facilitate ease of reference use during future analyses.

It is anticipated that the data gathered on participating consumers could potentially be used to aid in decisions regarding the management of the Northwest's electrical energy resources.

CONTENTS

ACKNOWLEDGMENTS iii

PREFACE v

SUMMARY vii

1.0 INTRODUCTION 1.1

1.1 SITE CHARACTERIZATION 1.2

1.2 SITE LOCATION 1.2

1.3 DATA DESCRIPTION 1.3

1.4 PREPARATION OF DATA SETS 1.5

2.0 ANALYTICAL TECHNIQUES 2.1

2.1 THE LINEAR-FIT COMPUTATION OF SLOPE AND BALANCE POINT . . 2.2

2.2 ESTIMATED ANNUAL SPACE HEATING - LOWESS CURVE FIT 2.5

2.2.1 Outside Air Temperature as a Predictor Variable . . 2.7

2.2.2 Inclusion and Exclusion of Zero-Heater Days for the LOWESS Fits 2.7

2.3 FIRST-YEAR/SECOND-YEAR COMPARISONS 2.8

2.4 TWO-WAY ANALYSIS 2.10

2.4.1 Simple Two-Way Analysis 2.11

2.4.2 Two-Way Analysis of Variance 2.12

2.5 PHYSICAL MODELS 2.13

2.5.1 A Simplified Interactive Model 2.15

2.6 JACKKNIFE ANALYSIS 2.16

2.7 RESIDUAL ANALYSIS 2.18

2.7.1 Examination of LOWESS Residuals 2.21

2.7.2 Relative Importance of the Variables 2.22

3.0 REFERENCES 3.1

FIGURES

1.1 Geographic Climate Zone Boundaries 1.3

2.1 Scatter Plot of Area Normalized Space Heating Energy Consumption Versus Indoor-Outdoor Temperature Difference . . . 2.2

2.2 Robust Linear Regression 2.4

2.3 Robust Linear and LOWESS Regression 2.6

2.4 Comparison of Radius of Uncertainty to Jackknife Analysis Estimate 2.17

2.5 LOWESS Residuals and Their Relation with Global Horizontal Radiation 2.19

TABLE

1.1 Climate Zone Distribution for the ELCAP-Base, Model Conservation Standards, Control, and Post-78 Sites 1.3

2.1 Single Partition 2.15

1.0 INTRODUCTION

The End-Use Load and Consumer Assessment Program (ELCAP), managed by the Pacific Northwest Laboratory (PNL)[a] under the sponsorship of the Bonneville Power Administration (Bonneville), is a study of how electricity is used by residential and commercial consumers within the Bonneville service area of the Pacific Northwest. A variety of information is being gathered on participating consumers, including metered loads for specific electrical end-uses, local weather data, physical data on the residence or place of business, as well as attitudinal and demographic data describing the consumers themselves. It is anticipated that the data gathered on participating consumers could potentially be used to aid in decisions regarding the management of the Northwest's electrical energy resources.

Between 1986 and 1989, several statistical modeling studies were carried out on ELCAP data. These studies primarily involved thermal characterization of homes and comparisons of building techniques and conservation measures. Analytical techniques used in these studies are compiled in this methodology document and will serve as a reference for future analyses. The basic thermal characterization has been previously discussed in Drost et al. 1987.

This report also includes a summary of the data sets and analysis techniques used in the companion report *Characterizing Residential Thermal Performance From High Resolution End-Use Data - Volume II - Analysis.* Brief descriptions of the sites and their geographic distributions are discussed in Sections 1.1 and 1.2. Section 2.0 discusses various analytical techniques including linear fits to space heating and temperature data (Section 2.1), LOWESS curve fits to the same data (Section 2.2), derived thermal parameters from the first- and second-year comparisons (Section 2.3), two-way analysis - simple and analysis of variance (Section 2.4), thermal performance of physical models (Section 2.5), jackknife analysis for assessing model stability (Section 2.6), and residual analysis (Section 2.7).

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1.1 SITE CHARACTERIZATION

The ELCAP residential studies incorporate an analysis of 440 homes. About 280 of these are detached, single-family homes with permanent electrical space heating equipment. And, about 50 homes are case study homes differing from the bulk of the sample by being renter occupied, attached, or not having electrical space heat. The entire category of these homes is referred to as the base sample. The remaining 110 homes were constructed under the Residential Standards Demonstration Program (RSDP), a demonstration program for a set of aggressive building codes, the Model Conservation Standards (MCS), adapted by the state of Washington.

Bonneville initiated the RSDP in 1983 to determine costs and thermal performance improvements associated with increased levels of thermal integrity in new residences as proposed by the Northwest Power Planning Council under the MCS. It was originally intended that the RSDP would provide a very detailed analysis of 100 matched pairs of homes; that is, 100 homes built according to the MCS (MCS homes) and 100 homes with like design, location, and orientation built according to the current code or construction practice. However, only 34 matched pairs were built, so the sample consisted of a combination of these matched pairs, other available MCS homes (i.e., unmatched), and recently constructed homes from the ELCAP sample (post-78 homes).

1.2 SITE LOCATION

The ELCAP sites are located in three climate zones geographically distributed over the states of Washington, Oregon, Idaho, Wyoming, and Montana. The geographic boundaries of the three climate zones are illustrated in Figure 1.1.

Table 1.1 illustrates climate zone 1 as being the mild climate zone with between 4000 and 6000 heating-degree days per year to base 65°F. Climate zone 2 is defined as having between 6000 and 8000 heating-degree days per year, and climate zone 3, the most severe climate, is defined as having more

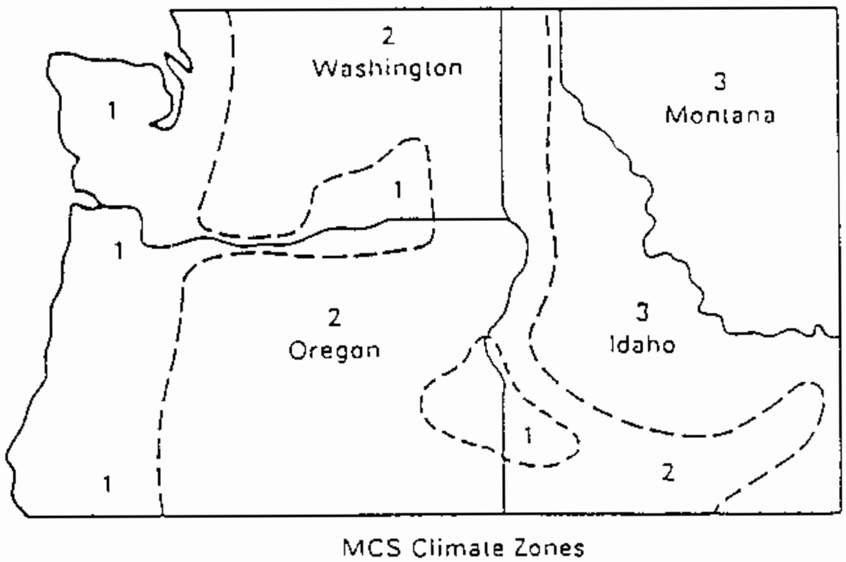


FIGURE 1.1. Geographic Climate Zone Boundaries

TABLE 1.1. Climate Zone Distribution for the ELCAP-Base, Model Conservation Standards, Control, and Post-78 Sites

Heating-Degree Days	Zone 1 4000-6000	Zone 2 6000-8000	Zone 3 > 8000	Total
ELCAP Base	203	94	31	328
MCS	38	22	11	71
Control	17	8	6	31
Post-78	6	4	-	10
Combined Total	264	128	48	440

than 8000 heating-degree days per year to base 65°F. Zone 1 contains 60% of the total sample sites. Zones 2 and 3 represent 29% and 12% of the sample sites, respectively.

1.3 DATA DESCRIPTION

All ELCAP sites were equipped with metering equipment that monitored several variables. The subset of these variables used in this analysis included the following parameters:

Space Heating Electricity Consumption - This quantity was evaluated for all sites and was a gauge of the electricity used by the space heating equipment present in each home.

Indoor Air Temperature - All ELCAP sites were equipped with an indoor air temperature sensor in the main living quarters. The RSDP sites were monitored by additional sensors located throughout the building. A mean indoor temperature was used in the analyses of buildings having more than one sensor.

Outdoor Air Temperature - This quantity was measured at some ELCAP Base and case study sites with meteorological stations and most RSDP sites. For the sites that were not equipped with outdoor temperature sensors, a nearby site equipped with a sensor was typically selected to be the substitute outside temperature source. Most sites were also matched with a substitute site for ambient temperature measurement typically at the National Weather Service station.

Wood-Stove Sensor - This sensor monitored the use of wood-burning equipment. All ELCAP sites with wood-burning equipment were equipped with this sensor except for the RSDP homes, in which residents were paid to refrain from burning wood.

Miscellaneous Parameters - Included in this category were internal gains and weather-related variables such as insolation, wind speed, humidity, and wind direction. The analysis of residuals that remained after statistical models were applied to the data were also placed in this category. These data were used as secondary explanatory variables after primary thermal analyses were carried out using the indoor and outdoor temperature data.

In addition to the metered data, survey data were collected for the bulk of the ELCAP sites. This survey reported the structural characteristics of the homes, occupants' habits and attitudes, as well as other demographic information.

1.4 PREPARATION OF DATA SETS

All the metered data used in the residential base thermal analysis characterizations were subjected to a detailed data quality review (Crowder and Miller 1990). This included checking for equipment malfunction and communication errors. The data were also filtered to include only those values representing typical occupant behavior, and not use of nonelectrical space heating. Days of diagnosed wood use (as identified by the wood-use sensor) were removed from the data sets, as were vacancy periods of 3 or more consecutive days (as evident from the usage patterns for end-uses other than space heating).

After the removal of wood-burning days, for sites with sensors, and vacation days from the data, the sites were evaluated for their suitability for analysis. The characteristics that were common to the sites appropriate for analysis included the following:

- The sites did not use gas or oil as a primary space-heating energy source.
- The sites had ample metered data during the heating season to attempt a thermal characterization of the structure.
- The metered data for the sites passed the initial data quality checks at PNL.
- A satisfactory outside temperature substitute was available if an outside temperature sensor was not installed at the site.

Some sites were deemed unsuitable for analysis. The bulk of these rejections, two-fifths of the sites, were attributed to

- poor thermal characterizations where the heater load could not adequately be predicted from indoor-outdoor temperature differences
- wood use that either totally displaced space-heating electrical consumption or supplemented electrical consumption such that when wood-use days were removed, insufficient data remained to characterize the site.

2.0 ANALYTICAL TECHNIQUES

The thermal performance characterization was based on an analysis of hourly outdoor temperatures, interior temperatures, and electrical space heat consumption data aggregated to the daily level. Specifically, this analysis was based on fitting a statistical model to a scatter plot of space-heating energy consumption versus temperature.

The space heating energy consumption (Q) may be presented as it stands, or it may be scaled per unit floor area (Q/A). The value of temperature could also be one of several measures. Typically, the difference between the mean daily indoor and outdoor temperatures is used, but the difference between a standard indoor temperature (typically 65°F, the traditional degree-day assumption for a balanced temperature) and an outside temperature or the outdoor temperature alone is also helpful. The temperature value against which Q/A is plotted depends on the characteristics of the site.

The best temperature value against which Q/A is plotted depends on the goal of the analysis and the characteristics of the site. The temperature difference between the inside of the structure and the outside air temperature is the fundamental driving force for the heating consumption. However, certain persistent occupant behaviors correlated with changes in the weather can cause a higher correlation between outside air temperature and heating load when only a single inside air temperature sensor is available in the main living area. As a result of this correlation, zoning or cracking windows in a bedroom can be a problem during the winter. Generally, however, the predictor variable of choice is the inside-outside temperature difference.

For the remainder of this report, analyses will be discussed as they are performed on Q/A versus the mean indoor-outdoor temperature difference, although the analysis techniques would also apply to any of the above mentioned variables.

Figure 2.1 displays a typical scatter plot of Q/A versus the indoor-outdoor temperature difference. For each structure, three quantities were derived from models fit to the Q/A versus delta temperature (ΔT) scatter plot:

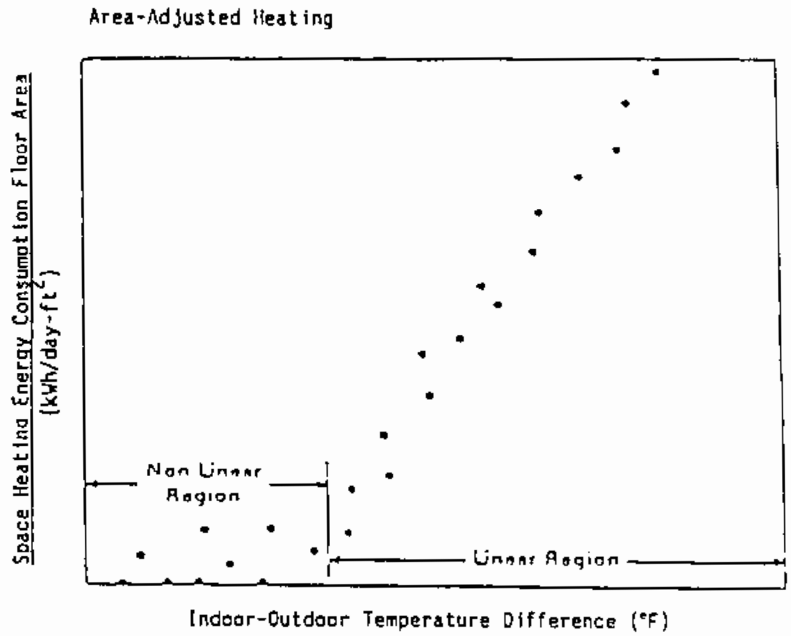


FIGURE 2.1. Scatter Plot of Area Normalized Space Heating Energy Consumption Versus Indoor-Outdoor Temperature Difference (example data)

- two parameters from a fit of a linear model to the data
- an estimated annual space-heating energy requirement under certain standard conditions based on a smooth-curve fit of the data
  - a slope giving the resistance of the envelope-to-heat transfer (apparent UA[a] [structural thermal resistance] per unit floor space)
  - an intercept giving the inside-outside temperature difference that, with some caution, may be interpreted as the structure that could support without the use of space-heating equipment (balance temperature difference).

The derivation of each of these quantities will be discussed in detail in the following sections.

(a) In this report it will be called the as-operated UA to include thermal conductance, internal and solar gains, and represent impact of occupant activities on overall heat loss.

2.1 THE LINEAR-FIT COMPUTATION OF SLOPE AND BALANCE POINT

As displayed in Figure 2.1, it is common for the plot of Q/A versus ΔT to have a linear region at intermediate and high values of ΔT and a nonlinear region at low values of ΔT. This suggests three possible approaches for fitting a linear model to the data:

- use of robust-cutoff techniques that automatically downweight or exclude certain points or regions exhibiting departures from linearity (i.e., at low ΔT values)
- use of a standard least squares fit to all data with positive electrical space heating energy consumption
- use of a standard least squares fit to the centermost range of values for all data with positive electrical space heating energy consumption.

The use of these three fits allows stepwise exploration of deviations in slope from the centermost typically linear region. These deviations usually occur in the extreme high and low regions of the model. A predominately linear heating characterization curve would lead to all three methods deriving similar parameters. If the data followed a nonlinear tendency at low consumption or a predominance of outlier data points, the modified robust-cutoff method and the standard fit would yield different fits.

All three of these models map the correlation between Q/A and ΔT by applying a linear regression (either standard or robust) to the data. The resulting line has an intercept with the horizontal axis (balance ΔT) and a slope of UA/(floor area • coefficient of performance [COP]). (See Figure 2.2 for a graphical depiction of balance ΔT and slope.) The balance ΔT of a structure is the value of ΔT at which the solar and internal gains will offset heat loss from the building under steady temperature conditions. The slope is a measure of the structure's resistance to heat transfer through the building shell (UA) divided by the heating system COP and the floor area.

The robust-cutoff technique is appropriate for the analysis of typical cases of space heating electrical consumption. It allows for the downweighting of outlier data points to reduce their influence and improve stability of the resulting correlation.

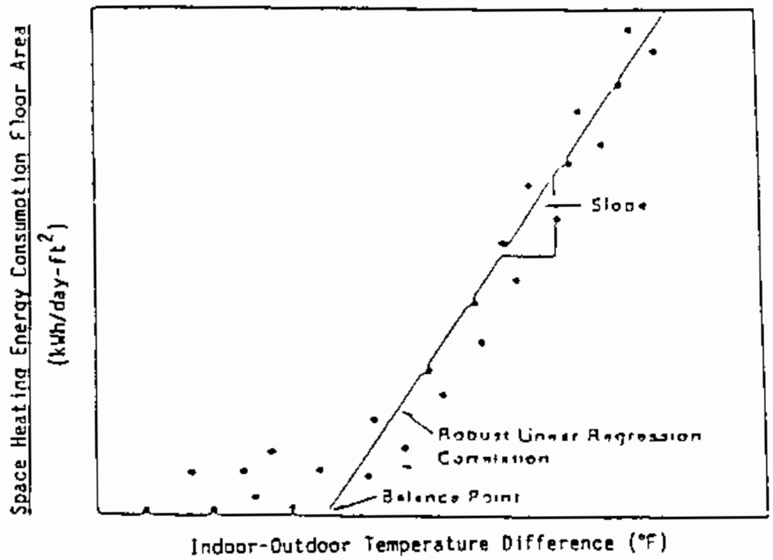


FIGURE 2.2. Robust Linear Regression (example data)

The robust-cutoff technique yields an accurate model for the linear region of the Q/A versus ΔT data; however, it is inappropriate for the nonlinear region. Figure 2.2 displays the robust-cutoff model applied to Q/A versus ΔT data. The model fit to the linear region predicts no space heating load whenever ΔT is less than the balance ΔT, although there are data points indicating that some space heating is required. Some type of procedure for defining this nonlinear region is required. Failing to exclude these points tends to lower both the balance temperature difference and the slope from the linear fit.

The nonlinear region, excluded from the linear regression, is defined as the data having ΔT values below a specific minimum cutoff point. The selection of this cutoff point is an iterative procedure. Initially, a high cutoff is selected, and the slope of the linear fit and the y axis intercept are determined. This is repeated for progressively smaller linear cutoffs. If the data can be modeled as being linear, the slope and the y intercept should not vary with changing cutoff limits. When a small enough value of ΔT is used to cause the slope or y intercept to vary outside a specified tolerance, this value is established as the minimum ΔT for the slope.

2.2 ESTIMATED ANNUAL SPACE HEATING - LOWESS CURVE FIT

The empirical measure considered most powerful for comparing groups of structures is the annual estimated electrical space heating consumption (AEC). This quantity is derived by fitting a smooth curve to the scatter plot of daily space heating energy consumption against the daily inside-outside temperature difference, outside temperature, or assumed inside-outside temperature difference. This curve, along with the observed average inside temperature (or assumed inside temperature), is then used to estimate the space heating requirement given a standard set of outside temperature data. The standard set of outside temperature data used by the ELCAP analyses is the National Weather Service's typical meteorological year (TMY) weather data for Seattle, Washington; Spokane, Washington; and Missoula, Montana for homes in climate zones 1, 2, and 3, respectively. For more discussion on this approach, see *Thermal Characterization Based on High Time Resolution End-Use Metering Data* by Pearson, Miller, and Stokes (1988).

The first step in the computation of the estimated annual space heating consumption is the selection of the internal temperature of the structure. Although most homes in the study have a single indoor temperature sensor located in the main living area, some homes have multiple sensors. For those homes with more than one sensor, the readings from all sensors were averaged to obtain the indoor temperature data. With the internal temperature determined, a reference outside temperature is selected, and the inside-outside temperature difference, ΔT, is calculated. If ΔT is less than or equal to zero, space heating energy consumption is negligible. A smooth or LOWESS correlation is then used to make a statistical model of the data.

The *Robust Locally Weighted Regression and Smoothing Scatterplots* (LOWESS) (Cleveland 1979) algorithm is an iteratively reweighted regression scheme applied to a moving window of the data sample. The procedure for calculating the coordinates of one point of the smooth curve will be discussed. First, the scatter plot of Q/A versus ΔT is divided into vertical strips, and the independent variable coordinate x1 of the point of interest is selected so that the point is centered in the strip. In each strip, a weighting function is used to assign weights to all data points in the strip. The weighting function assigns the maximum weight to any data point at coordinate xl and will decrease in weight as x moves away from coordinate xl. With the weights assigned, a line is fitted to the data points using a weighted least squares procedure. The y coordinate of the smoothed points is given by the y value of the fitted line at coordinate xl. After computation of the initial fit, the residuals from the fits are calculated for all data points. In second and subsequent iterations, each point is weighted not only inversely with distance from the center of the current data window, but also inversely with residuals from the fit obtained in the previous iterations. This inverse weighting with residuals reduces the influence of outliers on the fits. Figure 2.3 displays an example of a LOWESS fit in addition to the linear regression.

To estimate the total annual space heating energy consumption from the LOWESS curve, typically the annual temperature distribution is divided into approximately 30 bins resulting in a temperature resolution of 1°F to 2°F per bin. The total annual space heating energy consumption is then calculated by summing over the number of temperature bins the product of the number of days

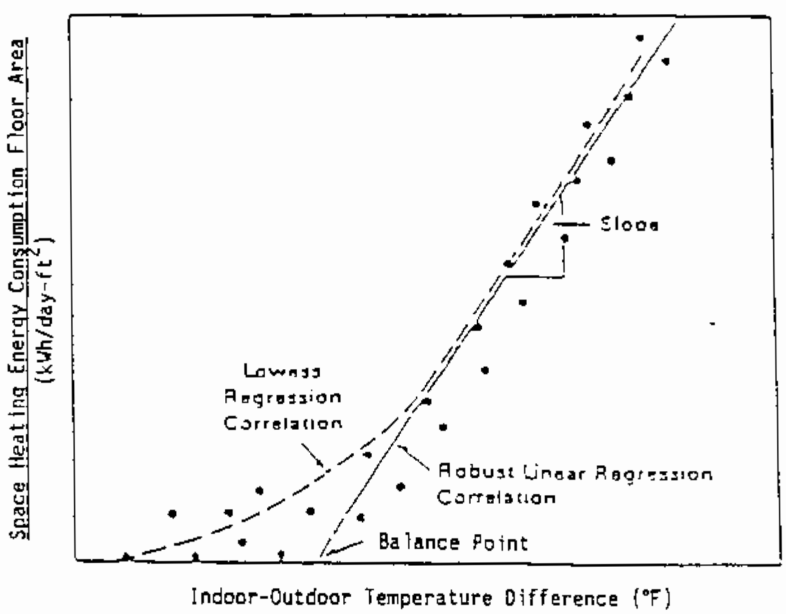


FIGURE 2.3. Robust Linear and LOWESS Regression

during the heating season at a particular outside temperature, T_i, and the LOWESS estimate for energy used for the particular ΔT, that is $T_{indoor} - T_i$.

The LOWESS fit more accurately models the energy consumption associated with small values of ΔT than does the linear fit. If a nonlinear region exists at high ΔT, then the LOWESS fit would also model this region more accurately than would the linear model. In some cases, the LOWESS curve must be extrapolated into regions without data to estimate energy consumption at extreme values of ΔT (or values having no collected data). If this occurs at the high ΔT end of the curve, a linear extrapolation based on the last few points of the LOWESS curve is used. If extrapolation is required at the low ΔT end of the curve, the assumption is made that the energy consumption will be zero for any ΔT less than the smallest ΔT associated with a data point. All data points with zero-energy consumption were excluded from the LOWESS curve fit for the first-year characterizations. This was modified for the second year characterizations.

2.2.1 Outside Air Temperature as a Predictor Variable

In some residences, there can be a high degree of correlation between the daily inside air temperature and outside air temperature over the heating season. Such correlations may be a result of factors such as occupant resistance to operating the heater at the beginning of the heating season. For these homes, an AEC based on a LOWESS fit of space heat to outside temperature alone produces a more reliable AEC estimate. Additionally, the residuals from the LOWESS fit of space heat to outside temperature can help quantify the impact of including the inside air temperature in a residual analysis, especially where thermostat setbacks can be identified. Comparison of AECs and as-operated UAs derived from the two types of independent variables, inside-outside temperature difference and outside air temperature, will further clarify the role of inside air temperature control strategy in the apparent thermal performance of the residual envelope.

2.2.2 Inclusion and Exclusion of Zero-Heater Days for the LOWESS Fits

Excluding all spring and autumn month days with zero-heating load from the LOWESS fit can result in overestimation of the heating requirements, because it will artificially raise the estimated mean consumption for days with similar mean inside-outside temperature differences (or with similar mean outside temperatures). Conversely, because the heating season is defined very broadly in these analyses, the inclusion of days of zero-heater usage for those temperatures when the heat is never on would produce a LOWESS curve that was artificially low. Consequently, if there are some days which do exhibit a positive heating load for the same ΔT values, the LOWESS enhancements include computation of a cutoff point above which zero-heater-load days are included in the analysis. The zero-heater days actually included in the various LOWESS fits would be of special interest to an analysis of residuals.

2.3 FIRST-YEAR/SECOND-YEAR COMPARISONS

In previous sections of this report, the core ELCAP thermal analysis methodology has been described. In the first-year/second-year comparison work, two sets of derived thermal parameters are compared. The first set of parameters are calculated using metered data from the 1985-1986 heating season, while the latter set uses data from the 1986-1987 heating season. Each structure is compared to itself. For example, the change in AECs between the first and second heating season is compared within the base case study. Thus, this work can be viewed as a stability study. A different type of comparison, a pairwise comparison, is also performed. In the pairwise comparisons, differences between heating seasons for a particular class of homes are compared to observed differences for a different class. An example of this would be to compare the changes observed in AECs across heating seasons between the base and MCS samples. Thus, this work may also be viewed as a sensitivity study.

Characterization analyses based on metered data are becoming an informational tool for regional load forecasters. Understanding the stability of these characterizations over time is a crucial step in legitimizing empirical approaches such as those used by Drost et al. (1987). Characterization analyses begin with metered data--inherently biased by resident behaviors and actual weather conditions interacting with the physics of the residential thermal envelope. The current work addresses the question of how stable the ELCAP characterizations are for the set of analyzed homes.

Effectively, the AEC is the estimated space heat consumption of the home as it is actually operated, but as if exposed to annual patterns of outdoor temperature for the standard weather year. The AEC includes no standardization for solar differences or levels of internal gains. Thus the AEC reflects solar and internal gains implicit in the metered data for the given heating season. A comparison of AECs across years can help delimit the impact of omitting such factors.

In the discussions that follow, several simple statistical measures are used to determine how significant the observed mean differences are for the various quantities of interest from one heating season to the next. These quantities include the three types of AEC estimates, two parameters (slope and intercept) from the various linear fits, and other metered quantities such as mean heating season inside air temperatures. For testing purposes, the combined sample of homes is divided into four subsamples: all homes, Base, MCS, and Control homes. For each site, a difference is calculated as a second year value minus the corresponding first year value. Relative comparisons are used for the pairwise population means where a systematic difference in magnitude can be expected for the various case studies, such as in AEC comparisons for Base and RSDP homes. The scaling used is to divide each observation by the overall sample mean for the first year. Several questions are then posed for each quantity of interest:

- Given a specific subsample, how significant are the estimated mean differences across years?
- Given a specific subsample, how does the within-year variation (across sites) for each of the two heating seasons compare to the variation of site-by-site differences across years?
- How significantly different are the estimated mean differences for each pair of subsamples?

One method for quantifying the significance of these comparisons is to compute the minimum level alpha (α) for which the hypothesis of no difference is rejected. For an alpha level test, the probability of rejecting a true hypothesis (of no difference) is no larger than α. Under this definition, a small significance level represents strong sample evidence of a real difference in the underlying population, while a large significance level denotes weak evidence of any such difference. In the interpretation of results for this report, significance levels less than .01 are deemed highly significant, levels between .05 and .01 are deemed significant, levels between .10 and .05 are considered marginally significant, and those greater than .10 are reported as nonsignificant. As in all hypothesis testing, there may be a difference between a statistically significant result and one that is practically significant. For example, given a large sample, very small changes may prove to be highly significant in a statistical sense, yet the magnitude of change may be so small as to be negligible from a practical standpoint.

An example of the first type of question would be to determine the significance of the average first year-second year difference in AEC_{iats} across the Base case home common to both years. Answering the second question provides a measure of spread for the 1985-1986 and 1986-1987 AEC_{iat} distributions, as well as for the distribution of differences across the years. The latter quantities can be used to determine how well the first year estimates correlate with the second year estimates. If AEC_{iat} is a property of the structure, as desired, a fairly high positive correlation should result. The last test determines whether the estimated average first year-second year differences for two different subsamples of home types are significantly different. For example, what is the minimum alpha level at which the mean estimated difference of AEC_{oat} for the Base homes can be judged as significantly different from the mean estimated difference for the MCS homes? Absolute or relative comparisons are made depending on the quantity analyzed.

2.4 TWO-WAY ANALYSIS

In this section, a short discussion is presented on the additive model associated with empirical modeling using two-way tables. Also, there is a short discussion of the technique of two-way analysis of variance.

2.4.1 Simple Two-Way Analysis

In the two-way model, the variability in the dependant variable is partitioned between two independent variables. Observations of the dependent variable are placed in bins based on values of the independent variables associated with each observation. A summary table is created that contains the summarized values from the observations falling into each cell. Each value in the table is identified by a row and a column. The values in the summary table are modeled using the following simple additive model:

$$X(i,j) = G + R(i) + C(j) + E(i,j) \tag{2.1}$$

where $X(i,j)$ = the actual value for the row i, column j element in the table

G = the grand median of the full set of bin values

$R(i)$ = the row effect associated with the ith row

$C(j)$ = the column effect associated with the jth column

$E(i,j)$ = the difference between the actual cell value in the ith row and jth column and $G + R(i) + C(j)$.

$E(i,j)$ is, therefore, the residual of the fit. A study of the distribution of the residuals can be used as a measure of goodness of the overall fit. For a detailed example of a two-way fit by iterative extraction of medians, see Tukey (1977).

If the summary table has m rows and n columns, the parameters of the two-way fit are G, R(i), where i = 1,2,3,...,m, and C(j), where j = 1,2,3,...,n. There will be a total of nm residuals, E(i,j), where j = 1,2,3,...,mn.

As an example, energy consumption estimates from residential base, MCS, and control homes are binned by heating system type and by effective U value for the home. Each binned observation is the estimated annual electrical space heat consumption per ft^2 of surface area. These energy consumption estimates assume an average inside operating temperature over the heating season of 65°F. The units are kWh/ft^2. For the simple two-way modeling and two-way analysis of variance tests, the median cell values were used.

2.4.2 Two-Way Analysis of Variance

In a two-way analysis of variance, a summary table of observation values is constructed just as in the two-way model. The two independent variables are commonly called the factors of the analysis. The total variation in the summary table is partitioned into three components. The three components are associated with the row effect or row factor, a column effect or column factor, and that effect which cannot be explained by either the row or column effects. The total variation in the data set is defined as the sum of squared differences between the overall mean of the cell values and the individual cell values. The significance of each factor depends on the amount of variance explained by that factor's effect relative to that portion of the variance which is unexplained. All variance apportioning is scaled for the degrees of freedom allowed. (Degrees of freedom are determined by summary table size.)

The ratio of two independent unbiased estimates of a common variance follows an F distribution. If no difference is noted between the levels of the dependent variable for a given factor, say heating system type, then the ratio of variance that can be attributed to that factor compared to the unexplained variance (each scaled appropriately for the degrees of freedom allowed) will follow such an F distribution. If the ratio of factor-explained variance to that of unexplained variance exceeds the value of the F distribution for the appropriate degrees of freedom, then the Null hypothesis is rejected, the Null hypothesis being that there are no differences among the mean effects of the levels of the factor under investigation.

The alpha (α) associated with an analysis of variance test for a given factor is the probability that random causes alone have accounted for the portion of the unexplained variance that one is attributing to the given factor. Consequently, the smaller the alpha the more significant the result that the analysis of variance testing provides. However, considerations such as the number of observations falling into each cell are quite important. The degree to which the basic assumptions of the model are followed should also be considered. Each cell is assumed to represent a normally distributed population with equal variance.

2.5 PHYSICAL MODELS

This section describes the methodology used to assess the impact of heating system and foundation type on the thermal performance of residential structures. The analyses are based on a widely used model which expresses electrical energy usage for space heating as a function of heating degree days, the heat loss coefficient for the structure, and the efficiency of the heating system. In theory, the influence of foundation type is accounted for by the heat loss coefficient for calculated UA[a]; hence, in its usual formulation, the model mentioned above does not explicitly include terms for foundation effects. Heating system efficiency, on the other hand, is an explicit component of the model.

Our analyses have shown a marked tendency for as-operated UAs to be lower than nameplate UAs (Conner et al. 1990) (indicating that actual heat loss tends to be less than predicted by nameplate UAs), even before correcting the nameplate UAs for infiltration. It has been postulated that these differences may be from differences in heating system types or foundation types. Preliminary analyses suggested that such differences do exist and indicated a need for further study.

The analyses described below are motivated by the following relation which is derived from the fundamental heat balance equation:

$$AEC = \frac{C \cdot UA(np) \cdot HDD(Tb)}{COP(hs)} \tag{2.2}$$

Here, AEC is the annualized estimate of electrical consumption for space heating, UA(np) is the nameplate envelope heat loss coefficient (including an

(a) In this report it will be referred to as the "nameplate" UA as determined from engineering calculations.

assumed infiltration proportional to floor area), HDD(Tb) is the annual number of heating degree days, based on the structure's balance temperature difference, COP(hs) is the coefficient of performance for the building's heating system, and C is a constant which is the product of a units conversion factor (.007) and an adjustment of UA(np) to reflect actual average performance. Of these quantities, AEC, UA(np), and HDD(Tb) have been estimated in prior analyses. Model (1) is the same as that used by Bonneville for analyses involving heat loss methodology.

For a given residence, the AEC may be interpreted as an estimate of the annual heating load under standardized weather and operating conditions with no nonelectric supplemental space heat. While a first-order setback adjustment has been incorporated into the AEC, no correction has been attempted for any zoning. Internal and solar gains are not explicitly treated, even though they are reflected in the measured load data. As described by Drost, et al. 1987, computation of the AEC for a given residence is based on an empirical, nonparametric (LOWESS) fit of the daily metered space heating loads to corresponding daily inside-outside temperature differences. Applying the results to temperature differences generated by a TMY and an average measured inside air temperature over the heating season yields the AEC. Heating degree days are based on the nonnegative differences between an empirically derived balance temperature difference, Tb, and temperatures observed in a TMY. The building balance point is estimated by subtracting the temperature difference intercept of a least squares line fit to the metered load/temperature difference intercept of a least squares line fit to the metered load/temperature difference data from the average heating season inside air temperature.

As defined above, Model (1) presupposes the separability of foundation and heating system effects; that is, the improvement or degradation in thermal performance associated with a particular heating system is assumed to be constant across foundation types. Conversely, the improvement or degradation in thermal performance associated with a particular foundation type is assumed to be constant across heating systems. To test these assumptions, an expanded model was employed:

$$AEC = \frac{C \cdot UA(np) \cdot HDD(Tb)}{COP(hs) \cdot EFF(fd) \cdot EFF(hs,fd)} \quad (2.3)$$

Here Eff(fd) is the effect of foundation type, fd, and EFF(hs,fd) is the interactive effect of heating system, hs, and foundation type, fd. Note that Model (1) is obtained by setting the additional parameters equal to 1. Dividing through by UA(np) and HDD(Tb) and taking the natural logarithm of both sides yields the following linear (mean) model:

$$\ln[AEC/UA(np)/HDD(Tb)] = \ln(C) - \ln[COP(hs)] - \ln[EFF(fd)] - \ln[EFF(hs,fd)]. \quad (2.4)$$

Upon choosing a heating system and foundation as a standard for comparison, the latter model has the form of a two-way analysis of variance (ANOVA), including interaction terms. This allows testing of whether the heating system and foundation effects are separable (i.e., additive in the linear model), in which case EFF(hs,fd) = 1 for all heating systems and foundation types. In the present application, the standardizations are

$$COP(FA) = EFF(CS) = EFF(FA,fd) = EFF(hs,CS) = 1 \quad (2.5)$$

where FA denotes forced air and CS denotes crawl space. When referring to Table 2.1, it is clear that the EFF(HP,fd) interactions are not estimable because of the absence of sites in three of the four heat pump cells. A test of the estimable interactions was significant at the .0007 level, indicating that the interactions cannot be ignored, hence heating system and foundation effects are not separable.

TABLE 2.1. Sample Partition

	Forced Air	Baseboard	Radiant	Heat Pump
Crawl Space	14	31	6	10
Heated Basement	6	18	1	0
Unheated Basement	3	3	1	0
Slab	3	10	1	0

2.5.1 A Simplified Interactive Model

Because of the difficulty of interpreting the results of a standard ANOVA with significant interactions, a simpler (but equivalent) analysis was performed in which a denominator

$$COP(hs) \cdot EFF(fd) \cdot EFF(hs,fd) \tag{2.6}$$

of equation 2.3 was replaced by a single parameter, COP(hs,fd). In this approach, simple estimating of the joint efficiency of each heating system/foundation combination without attempting to separate the heating system and foundation contributions is accomplished. This model is constrained by COP(FA,CS) = 1; that is, forced air homes with crawlspace foundations are taken as the basis for comparison, and are arbitrarily assigned an efficiency rating of 1.

2.6 JACKKNIFE ANALYSIS

To assess the stability of the annualized space heating estimate, a statistical procedure called the jackknife analysis was applied to AEC estimates. The jackknife analysis offers a way to set sensible confidence limits in the face of complex calculations by assessing the sensitivity of the calculation to a random omission of subsets of data points. Hence, this procedure measures the stability of the fit under study. In this section, the details of the mathematics are presented for the jackknife analysis.

Because the jackknife analysis is used predominantly for complex calculations to help set confidence limits, the set of n data points is partitioned into k disjoint subsets. The computation under investigation is then performed k times, where each iteration excludes one of the disjoint subsets. Let y_j represent the k parameter estimates where each of the k computations was performed under the "one group out" scenario. Let the computation performed with all n data points be called y_{all}. Now k pseudovalues, y^*_j, where $j = 1,2,3,\ldots,k$, are formed where

$$y^*_j = ky_{all} - (k-1)y_j, \ j = 1,2,3,\ldots,k \tag{2.7}$$

The jackknife value, y^*, which is the best estimate for the computation under investigation, is defined by the average of the pseudovalues:

$$y^* = (y^*_1 + y^*_2 + y^*_3 + \ldots + y^*_k)/k \tag{2.8}$$

An estimate of the variance in the jackknife value, $(s^*)^2$, is computed by examining the variance in the pseudovalues:

$$(s^*)^2 = (1/k) \cdot \text{variance}(y^*_j) \tag{2.9}$$

A student t distribution for some selected α with k-1 degrees of freedom (under most circumstances) is then used with s^* to build the confidence limits about the jackknife value. The $(1-\alpha)$ confidence interval is thus

$$\left(y^* - s^*|t_{k-1}|\alpha, \ y^* + s^*|t_{k-1}|\alpha\right) \tag{2.10}$$

In using the jackknife analysis on the data from a residential base sample site, the set of heating-season data actually present is partitioned into 11 randomly selected subsets. The LOWESS procedure, used to model electrical heating consumption on the basis of the inside-outside temperature difference, is then performed 11 times for each set of total data points, with one disjoint subset left out. The annualized energy consumption is then computed 11 times for each LOWESS definition. The 11 energy-consumption estimates are used with Equation (2.2) to compute the pseudovalues. The jackknife estimate is then the arithmetic mean of these values as displayed in Equation (2.3). The confidence interval used in this analysis was 95%.

To assess the stability of the fit, the radius of uncertainty, $s^*|t_{k-1}|\alpha$, may be compared to the jackknife value, y^*. The larger the ratio, the less stable the fit. Figure 2.4 displays a histogram of the ratio of the radius of uncertainty to the jackknife analysis estimate. A nonuniform distribution of data points in the initial scatter plot of space heating

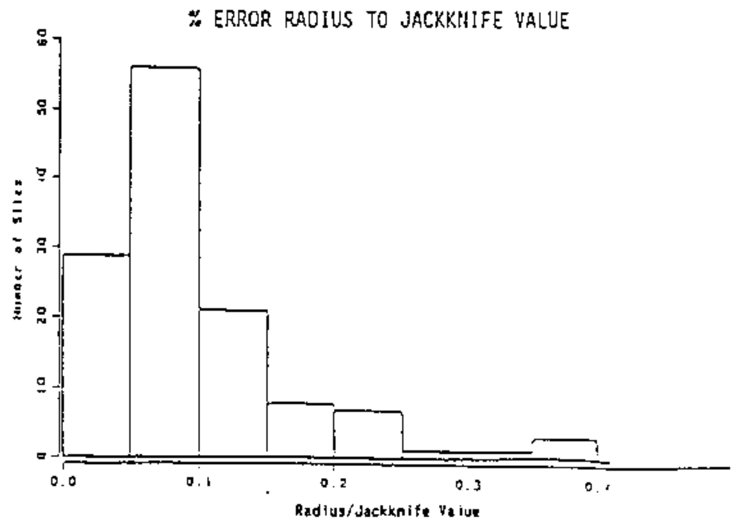


FIGURE 2.4. Comparison of Radius of Uncertainty to Jackknife Analysis Estimate

energy versus inside-outside temperature difference, with large variations in heating values at the upper end of ΔT, is more commonly associated with the less stable fits.

To assess the effect that inclusion of the dozen less stable jackknife sites may have on results, comparisons are made between derived thermal parameters for the two groups.

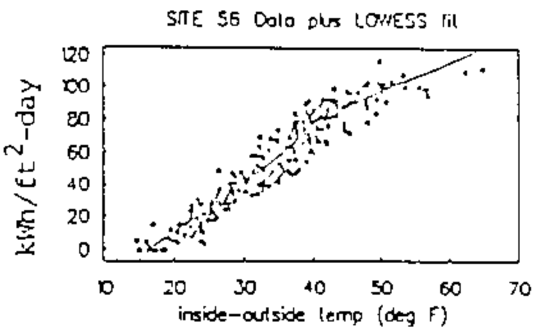
2.7 RESIDUAL ANALYSIS

The thermal analyses described in Section 2.4.1 allow the prediction of weather-normalized, annual energy use for space heat based on a LOWESS fit of daily heating-season data to measured differences between daily indoor and outdoor temperatures. While traditional physical models based on a heat-balance equation suggest that the outdoor temperature and the indoor-outdoor temperature difference are the primary predictors of a residence's energy demand for space heating, it is recognized that other variables may be significantly affect energy consumption as well.

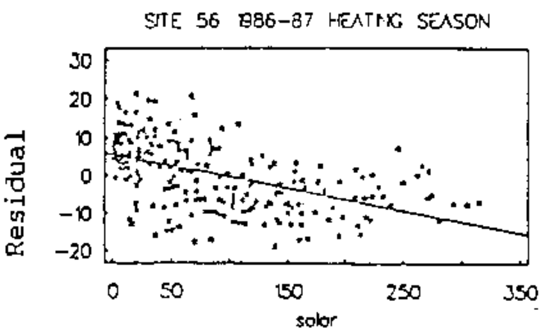
For example, Figure 2.5a displays a plot of heater load per square foot of floor area versus the inside-outside temperature difference for site 56 during the 1986-1987 heating season. The curve drawn through the scatter plot represents the LOWESS fit to the data. If the vertical distance from a particular data point to the LOWESS curve is measured, then the resulting residual represents the deviation of the data point from the model. When the residuals for the entire heating season are plotted against a measure of solar radiation, a linear (mean) relation between solar radiation and the LOWESS residuals is suggested (see Figure 2.5b). If similar plots are produced for each climatic subseason (fall, winter, and spring) of the heating season, linear relations are again suggested, but with varying slopes (see Figures 2.5c through 2.5e). The varying slopes represent the changing angle of solar declination throughout the year. Other variables potentially related to the LOWESS residuals include measured electrical loads contributing to internal gains and weather-related variables such as wind speed, humidity, and wind direction. This section summarizes the findings of an exploratory analysis, the purpose of which was to

- provide a preliminary indication of the relative usefulness of these variables in the prediction of energy use for space heating
- investigate the feasibility of incorporating the variables into the thermal analyses described above.

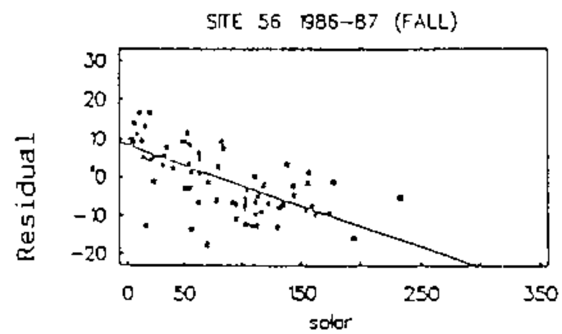
For each site, a four-stage analysis was performed. The first stage consisted of three graphical examinations of the LOWESS residuals. A plot of the corresponding residuals (vertical axis) versus the LOWESS predictions (horizontal axis) was made. These plots were used to indicate whether the dispersion of the residuals appears to be a function of the magnitude of the predicted values. When such is the case, an inadequacy of the model may be indicated. Because the original temperature and energy-consumption data were time ordered, a plot of the corresponding residuals (vertical axis) versus time (horizontal axis) was also made. These plots indicated whether the fit of the model varied in some systematic way across time. Finally, the residuals from each time period were plotted against the residuals from the next available time periods. The latter plots were used to look for a first-order serial correlation of the residuals.



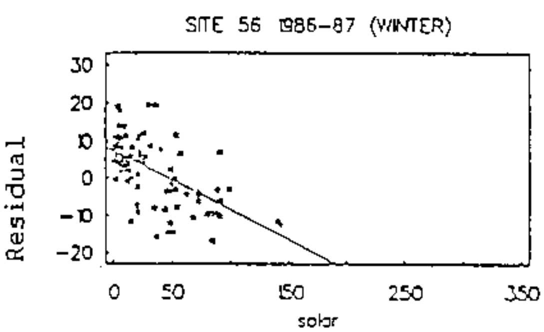
a) LOWESS data and its fit



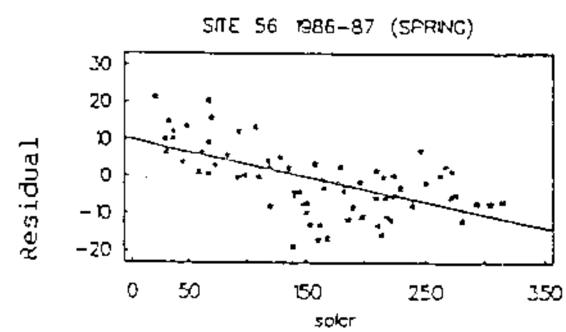
b)



c)



d)



e)

b-e) relation between LOWESS residuals and global horizontal radiation (solar) over various subsets of the 1986-1987 heating season

FIGURE 2.5. LOWESS Residuals and Their Relation with Global Horizontal Radiation (solar)

In the second stage of the analysis, the stepwise variable selection technique was employed to determine which of the additional variables best predicted the LOWESS residuals through an ordinary least squares (ols) regression. The full model was in the form

$$
\begin{aligned}
\text{resid}(i,j) = m &+ a(i) + b(i)\cdot\text{pyrometer}(j) + c(i)\cdot\text{int\_gains}(j) \\
&+ d(1)\cdot\text{wind\_speed}(j) + d(2)\cdot\text{humidity}(j) \\
&+ d(3)\cdot\text{wind\_direction}(j) + d(4)\cdot\text{inside\_air\_temp}(j) \\
&+ d(5)\cdot\text{outside\_air\_temp}(j) + e(i,j)
\end{aligned}
$$

where i denotes a time period within the heating season (1 = August through October, 2 = November through February, 3 = March through May) and j denotes a specific day during the heating season. The variables a(i) are assumed to sum to zero and thus represent subseasonal adjustments to the overall mean m. The pyrometer and int_gains variables are measures of solar radiation and the internal heat gains generated by other end-uses, respectively. The variables e(i,j) represent errors from the mean model for the ith time period and the jth observed day. Because these heat sources to space heating contributions were expected to vary by climatic subseason, the model allows for the estimation of subseason-specific slopes. The remaining variables are assumed to be less dependent on the subseason, so that a single overall slope is estimated for each.

For each site, a reduced model containing only a subset of the terms in the full model was actually fit. The reductions occurred because of the measurement unavailability and the variable selection procedure. The stepwise procedure builds a best model in a series of steps. At each step, the significant variable exhibiting the highest partial correlation with the dependent variable is added, and one or more of any resulting nonsignificant variables are dropped. The procedure terminates when no more variables can be added or dropped. The resulting model at that step is considered to be the best model.

In the third stage, the relative importance of the variables included in the model was assessed by comparing their beta weights. A beta weight is formed by multiplying the regression coefficient for a given predictor variable by the quotient of its standard deviation and the standard deviation of the dependent variable. The resulting value indicates the number of standard deviations of change that occurs in the dependent variable for a single standard deviation of change in the predictor variable (with all other predictors held constant).

The final stage of the analysis was a graphical examination of the ols residuals (i.e., the differences between the LOWESS residuals and their ols-predicted values) carried out as in stage one.

2.7.1 Examination of LOWESS Residuals

In the fitting of linear or LOWESS models, the assumption is usually made that the deviations of actual observations from the model are independently distributed with mean 0 and common variance. Often the deviations are assumed to be normally or at least symmetrically distributed as well. When these assumptions can be empirically validated through an examination of residual plots, the analyst feels some confidence that the model has captured the essential structure of the physical relation being modeled, and that any unexplained variance is truly random in nature.

When examining residuals, the most common practice is to plot the m-fitted values to detect any dependence of error variance on the level of fitted values. If the model assumptions are met (assuming a uniform density of observations across predicted values), the resulting plot should display a random scattering of points above and below the fitted axis, with the spread remaining nearly uniform across predicted values. Any trends observed in the mean residuals may reflect the omission of important variables or higher order terms in the basic model. Variation of spread, as a function of predicted values, may point to model inadequacies or simply nonhomogeneity of the error variances.

If the data can be naturally sequenced with respect to time, it is also of interest to plot the residuals chronologically according to time. Again, one hopes to find a random scattering of points above and below the time axis, with the spread remaining nearly uniform across time. Departures may suggest the introduction of time-related variables into the model. Correlation of errors across time can be detected by plotting residuals against lagged residuals. If no correlation is present, the plot should have a shotgun-scattered appearance. Presence of a positive (or negative) correlation will cause the plotted points to appear to be randomly scattered along a line with a positive (or negative) slope. While the LOWESS model is nonlinear, the assumptions regarding its deviations are similar.

2.7.2 Relative Importance of the Variables

Beta weights, as described above, provide a measure of the relative importance of the predictor variables in a multiple regression fit. Because the sign of a beta weight is the same as that of its corresponding regression coefficient, the relative importance of two variables is best measured by comparing the absolute magnitudes of their respective beta weights. In general, the larger the beta weight (in absolute magnitude, relative to the other beta weights), the more significant the variable.

Because a beta weight is meaningful only when the other predictor variables are held constant, it is best viewed as applicable to only small changes in its corresponding variable. Dramatic changes in outside air temperature, for example, are often accompanied by somewhat predictable changes in other weather variables; hence, it may be of more academic than practical interest to consider a large temperature change during which the other weather variables are held constant.

Care must be taken in interpreting beta weights for a regression coefficient because it is applicable to less than the full set of data. For example, b(i) is applicable only to the ith subseason of the heating season; hence, the scaling of b(i) to obtain its corresponding beta weight must also be based only on the ith subseason. Furthermore, the resulting beta weight can only be compared to other beta weights based on the same subseason. This requires the computation of up to four sets of beta weights for each site: one set for each of the subseasons, plus one set that covers the entire season. Clearly, beta weights restricted to a particular subseason can be derived for coefficients applicable to the entire set of data, while only a single beta weight over the appropriate subseason can be obtained for coefficients applicable to a single subseason.

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