B O N N E V I L L E   P O W E R   A D M I N I S T R A T I O N

Verification by Energy Modeling Protocol

September 2011

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Version 1.0

September 2011

Prepared for

Bonneville Power Administration

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Contract Number 00044680

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1. Introduction

1.1. Purpose

This document presents a *Verification by Energy Modeling Protocol*[1] as a complement to the Measurement and Verification (M&V) protocols used by the Bonneville Power Administration (BPA). This *Energy Modeling Protocol* is intended for measures involving equipment whose energy use is impacted by the measure(s) and also by multiple independent variables that are not affected by the measure. Modeling here refers to empirical models – that is, data-driven statistical or regression-based models – rather than engineering models of physical systems. The savings can be large or small. The protocol is appropriate for interactions between measures, but the ability to distinguish between savings for each measure is dependent upon the level of sub-metering and the types of measures. *Energy Modeling Protocol* is adherent with *IPMVP Options B* and *C*.

The protocol describes procedures for collecting and preparing necessary baseline and post-implementation data, and for developing appropriate empirical models that are used to calculate energy savings.

This document is one of many produced by BPA to direct M&V activities. The *Measurement & Verification (M&V) Protocol Selection Guide and Example M&V Plan* provides the region with an overview of all of BPA's M&V protocols, application guides, and reference guides, and gives direction as to the appropriate document for a given energy efficiency project. The document *Glossary for M&V: Reference Guide* defines terms used in the collection of BPA M&V protocols and guides.

Chapter 9 of this protocol provides full citations (and web locations, where applicable) of documents referenced.

1.2. Background

In 2009, BPA contracted with a team led by Research Into Action, Inc. to assist the organization in revising the M&V protocols it uses to assure energy savings for the custom projects it accepts from its customer utilities. The team has conducted two phases of research and protocol development under the contract, Number 00044680.

In the first phase, Research Into Action directed a team comprised of:

- Quantum Energy Services & Technologies, Inc. (QuEST), led by David Jump, Ph.D., PE and assisted by William E. Koran, PE;
- Left Fork Energy, Inc., the firm of Dakers Gowans, PE;

[1] Hereinafter, *Energy Modeling Protocol*.

- Warren Energy Engineering, LLC, the firm of Kevin Warren, PE;
- Schiller Consulting, Inc., the firm of Steven Schiller, PE; and
- Stetz Consulting, LLC, the firm of Mark Stetz, PE.

In the second phase, Research Into Action directed a team comprised of:

- David Jump, Ph.D., PE, William E. Koran, PE, and David Zankowsky of QuEST;
- Mark Stetz, PE, CMVP, of Stetz Consulting;
- Erik Kolderup, PE, LEED AP, of Kolderup Consulting; and
- Kevin Warren, PE, of Warren Energy Engineering.

The Research Into Action team was led by Jane S. Peters, Ph.D., and Marjorie McRae, Ph.D. Assisting Drs. Peters and McRae were Robert Scholl, Joe Van Clock, Mersiha Spahic, Anna Kim, Alexandra Dunn, Ph.D., and Kathleen Gygi, Ph.D.

For BPA, Todd Amundson, PE, directed the M&V protocol research and development activities. Mr. Amundson was working under the direction of Ryan Fedie, PE, and was assisted by BPA engineers. Mr. Amundson coordinated this work with protocol development work undertaken by the Regional Technical Forum. In addition, Mr. Amundson obtained feedback from regional stakeholders.

William Koran is the primary author of this *Verification by Energy Modeling Protocol*; team members reviewed and provided guidance.

2. Overview of Method

2.1. Description

This *Energy Modeling Protocol* provides guidance to verify energy savings for energy conservation measures (ECMs) implemented in commercial buildings, industrial facilities, or their subsystems. This protocol is appropriate to verify savings for ECMs that deliver large savings through high impact single ECMs or multiple smaller impact ECMs distributed throughout a building or facility. Verifying savings from individual ECMs applied to single end uses or equipment is not a good application of this protocol.

These methods are based on and extend the descriptions of the whole building method found in the *International Performance Measurement and Verification Protocol* (IPMVP) under *Option C* and in *ASHRAE Guideline 14-2002*, as well as a large volume of applied research extending back to the early 1970s. This protocol extends the application of whole building energy modeling to smaller measurement boundaries around facility subsystems, such as chilled water systems, air handling systems, or industrial processes. Such applications are considered retrofit isolation methods under *IPMVP Option B (All Parameter Measurement)* or *ASHRAE Guideline 14-2002*.

This protocol describes procedures for collecting and preparing necessary baseline and post-installation data, and for developing appropriate empirical (i.e., statistical or regression-based) models for use in calculating a project's energy savings. The methods described here are useful when the expected savings are large in comparison with the uncertainty of the empirical energy model. This protocol expands on the guidelines for performing regression analysis provided in BPA's *Regression for M&V: Reference Guide*[2], with a focus on developing and validating energy models.

The effect of selected independent variables on a building or subsystem's energy use is modeled using statistical regression techniques. This enables the baseline energy use to be projected into or adjusted to conditions occurring in the post-installation period. Savings are then determined by subtraction of the adjusted baseline and measured post-installation energy usages. The savings may also be determined for conditions other than the post-installation period, such as to typical meteorological year (TMY) weather conditions. This requires a post-installation period energy model.

With the advent of short-time interval metering[3] for many facilities above approximately 200 kW in peak demand, as well as significantly more energy monitoring capability within facilities, more data are available to explain the variation in a facility's energy use throughout the days, weeks, and seasons of the year. The short time intervals allow a broad range of data to be

2 Hereinafter, *Regression Reference Guide.*

3 Short-time interval data, hereafter referred to as *short-interval* data, refers to data collected in monitoring intervals much less than one month, typically an hour or less, although daily data could also be considered short-interval data. Short-interval does not refer to the total time period over which data are collected, but the interval between data records.

collected in a limited amount of time. Regression models built from the broadest range of data introduce the least bias error to the results, have the lowest uncertainty, and provide the best extrapolation to annual savings.

2.2. Applicability

This protocol is applicable to whole buildings, facilities, or their subsystems that meet the following criteria:

- ➡ **There is up to one year of data available from whole buildings, facilities, or their subsystems for development of baseline models prior to ECM installation**. The data includes energy use or demand, and relevant independent variables such as ambient temperature, operation schedule, or building occupancy. The data can be measured in short intervals such as 5 or 15 minutes to a day.
- ➡ **The selected independent variables explain most of the variation in energy use within the measurement boundary** (whole building, relevant meter, or subsystem).
- ➡ **Expected savings are large in comparison with energy model uncertainty**.
- ➡ **Program or project requirements allow verification of all ECMs within a measurement boundary**, whether it is a whole building or building subsystem.

For the purposes of analysis, sub-hourly data should typically be aggregated to the hourly or daily level. Selection of the appropriate time interval (also referred to in this protocol as *time granularity*[4]) depends on a number of factors. The choice to use hourly or daily aggregations is based upon ease of use, which typically favors daily data. The need for a wider range of the independent variable may favor hourly data. The calculated statistics for the hourly or daily model, such as the *correlation coefficient* and the *coefficient of variation of the root-mean squared* [CV(RMSE)] may also affect the choice of time interval, as discussed later in this document.

The following sections discuss the advantages and disadvantages of using this protocol when these criteria are met.

2.3. Advantages of this Protocol

Use of this protocol has several advantages because it:

- ➡ Uses measured energy and independent variable data to account for savings
- ➡ Verifies the impact of all ECMs implemented within the selected measurement boundary

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4 Although *time interval* is used throughout this document, the data could be collected at non-uniform intervals, such as *change-of-value* (COV) data from an energy management system, or at different intervals for different variables. *Time granularity* refers to the *general quantity* of data in the monitored period. For use in regression, data recorded at non-uniform intervals should be converted to a common time interval, or a weighed regression used to compensate for the different interval lengths.

- Leverages large volumes of research on degree-day methods, change-point models, and non-linear and multiple regressions
- Is supported by public and commercially-available data preparation and analysis tools
- Estimates savings uncertainty
- Tracks savings over long periods

2.4. Disadvantages of this Protocol

This protocol is usually not appropriate when sponsoring parties require the calculation of savings from individual ECMs amongst multiple ECMS within a measurement boundary. It cannot be applied when the monitoring systems are not in place and hence there is no available data. Its methods require a familiarity with statistical regressions, a skill not always available among service providers.

The useful tools that are available require time to become familiar with them. Furthermore, at present there is no single tool that provides all the capabilities needed, as discussed in Chapter 7 of this protocol. In most circumstances, users must leverage multiple tools to follow the guidance in this protocol.

3. Algorithm

3.1. Basic Procedure

The IPMVP outlines procedures for determining two types of energy savings: *avoided energy use* and *normalized savings*. *Avoided energy* use is the reduction in energy use that occurs in the reporting period relative to what would have occurred if the facility had been equipped and operated as it was in the baseline period, but under *reporting-period operating conditions*. *Normalized savings* are based on the reduction in energy use that occurred in the reporting period relative to what would have occurred if the facility had been equipped and operated as it was in the baseline period, but under *a predetermined and accepted, normal set of conditions*.

The typical avoided energy use approach is a subset of the normalized savings approach, as shown in the procedural steps below. The normalized savings approach adjusts both baseline and post to a fixed set of conditions. The avoided energy use approach uses the set of post conditions as the fixed set of conditions.

An M&V project using the avoided energy approach includes these general steps:

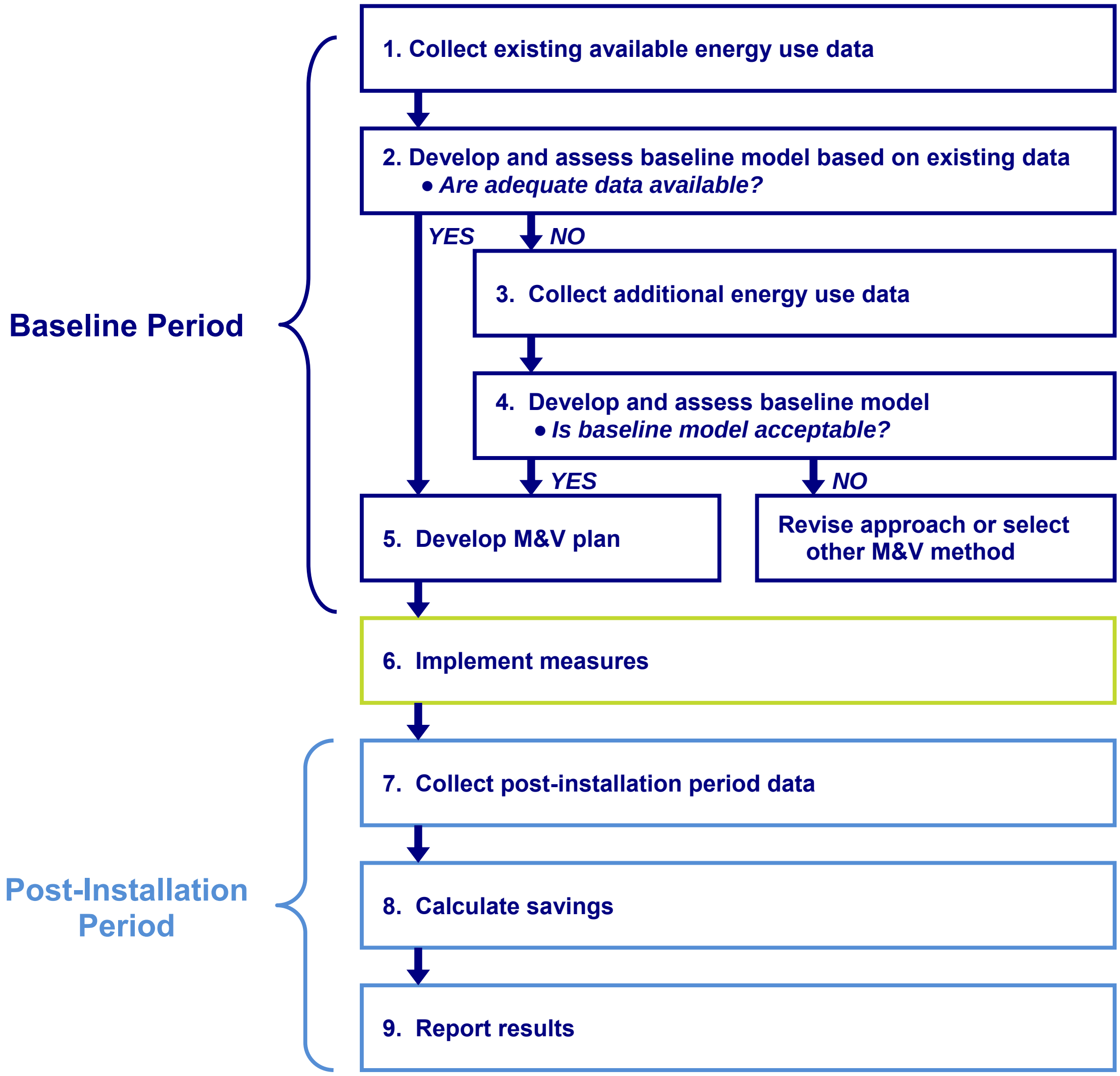
1. Collect baseline data.
2. Develop a model for the baseline period.
3. Adjust the baseline model to the post-installation period conditions.
4. Calculate savings by subtracting the measured post-installation period energy use from the *adjusted baseline* energy use.

In the normalized savings approach both baseline and post are adjusted to the fixed conditions as follows:

1. Collect baseline data.
2. Develop a model for the baseline period.
3. Adjust the baseline model to the fixed conditions.
4. Collect post-period data.
5. Develop a model for the post-period energy use.
6. Adjust the post model to the fixed conditions.
7. Calculate savings by subtracting the *adjusted post-period* energy use from the *adjusted baseline* energy use.

The overall process for a project is shown in Figure 3-1. The adjustment of the baseline model to the post conditions – or the adjustment of both the baseline and the post models to the fixed conditions – occurs as part of the *Calculate Savings* step.

Figure 3-1: Process Flowchart



In most cases, the baseline and post models will be of the same type, using the same independent variables and the same number of parameters. However, this will not always be the case, as discussed in Section 3.2 of this protocol.

Also, in most cases, the independent variable will be ambient temperature. There are important considerations in checking site weather data and in choosing site weather data or data from the nearest weather station. These considerations are discussed in Chapter 4, *Measurements and Monitoring*.

When normalized savings are used, the fixed conditions basis will commonly be annual typical meteorological year weather, but may be other agreed-upon fixed conditions for the independent variables. The most recent Version 3 (TMY3) data sets from the National Renewable Energy Laboratory's (NREL) *National Solar Radiation Data Base* are used in this protocol.

The general steps for choosing a model are an extension of the process for regression, since this is a regression-based protocol. As described in the companion document, BPA's *Regression for M&V: Reference Guide,*[5] the following steps should be used to develop models:

1. Identify all independent variables.
2. Collect datasets.
3. Synchronize the data (if necessary).
4. Chart the data.
5. Select and develop a model.
6. Validate the model.

Much of this *Energy Modeling Protocol* emphasizes development of good energy models, which comprises Steps 4, 5, and 6 above. The discussion here will expand upon the coverage in the *Regression Reference Guide*.

3.1.1. Using Charts as an Aid to Choosing a Model

Developing an energy model is an iterative process involving Steps 4, 5, and 6, above. The first step involves identifying the important variables by charting the data:

➡ **Chart the data**. Use the chart to confirm the relationship with the assumed independent variable.

➡ **Observe the scatter in the data**, especially looking for multiple groups. Use this information to determine the need for categorical variables or, in rare cases, a different or additional continuous variable. (Continuous and categorical variables are described in the *Regression Reference Guide*.)

➡ If there appears to be a need for one or more categorical variables, **filter the data used in the chart for each value of the likely categorical variable or variables to confirm they significantly reduce the scatter**.

The next steps involve choosing the best-fit regression model and validating the energy model by comparing the model uncertainty with the expected savings:

➡ **Observe the form of the data**. Use the form to select the appropriate type of regression model.

➡ **Develop the model**.

➡ **Validate the model**. Compare model uncertainty with expected savings.

5 Hereinafter, *Regression Reference Guide.*

➡ **If the model is not satisfactory, return to Step 4 and re-chart the data** changing one or more of the following: measurement boundary, time interval, or the independent variable(s).

The first step in choosing a model is to chart the data using a scatterplot. In most cases, there will be a single continuous independent variable, such as ambient temperature. However, there may be multiple categorical variables, such as daytype, occupancy status, and/or equipment status. After charting the data, the user should pick an appropriate model form, based on the shape of the data in the scatterplot. If there is not a clear form to the data, then data filtering and re-charting are used to determine relevant categorical variables.

Categorical variables are discussed in the next section. Note that model selection may be an iterative process. However, the data should always be charted first, and then the chart is used to qualitatively determine the value of incorporating various categorical variables.

For energy models, the savings must be significantly greater than the uncertainty in data and the resulting model. *ASHRAE Guideline 14* refers to this as the fractional savings uncertainty. This is accomplished by choosing the appropriate granularity for the model, with regard to both the measurement boundary and the time interval. In general, uncertainty will be decreased as model approaches change in the following order:

1. Measurement boundary around the whole building using longer-interval data
2. Measurement boundary around the whole building with short-interval data
3. Measurement boundary around the affected system with longer-interval data
4. Measurement boundary around the affected system with short-interval data

There may be multiple satisfactory solutions. For example, the two middle options above could provide very similar uncertainty, depending on the specific measurement boundaries and time intervals. Because there may be multiple satisfactory solutions, to minimize cost it is usually best to see what can be done with existing available data, rather than acquiring new data. This is reflected in Figure 3-1, above.

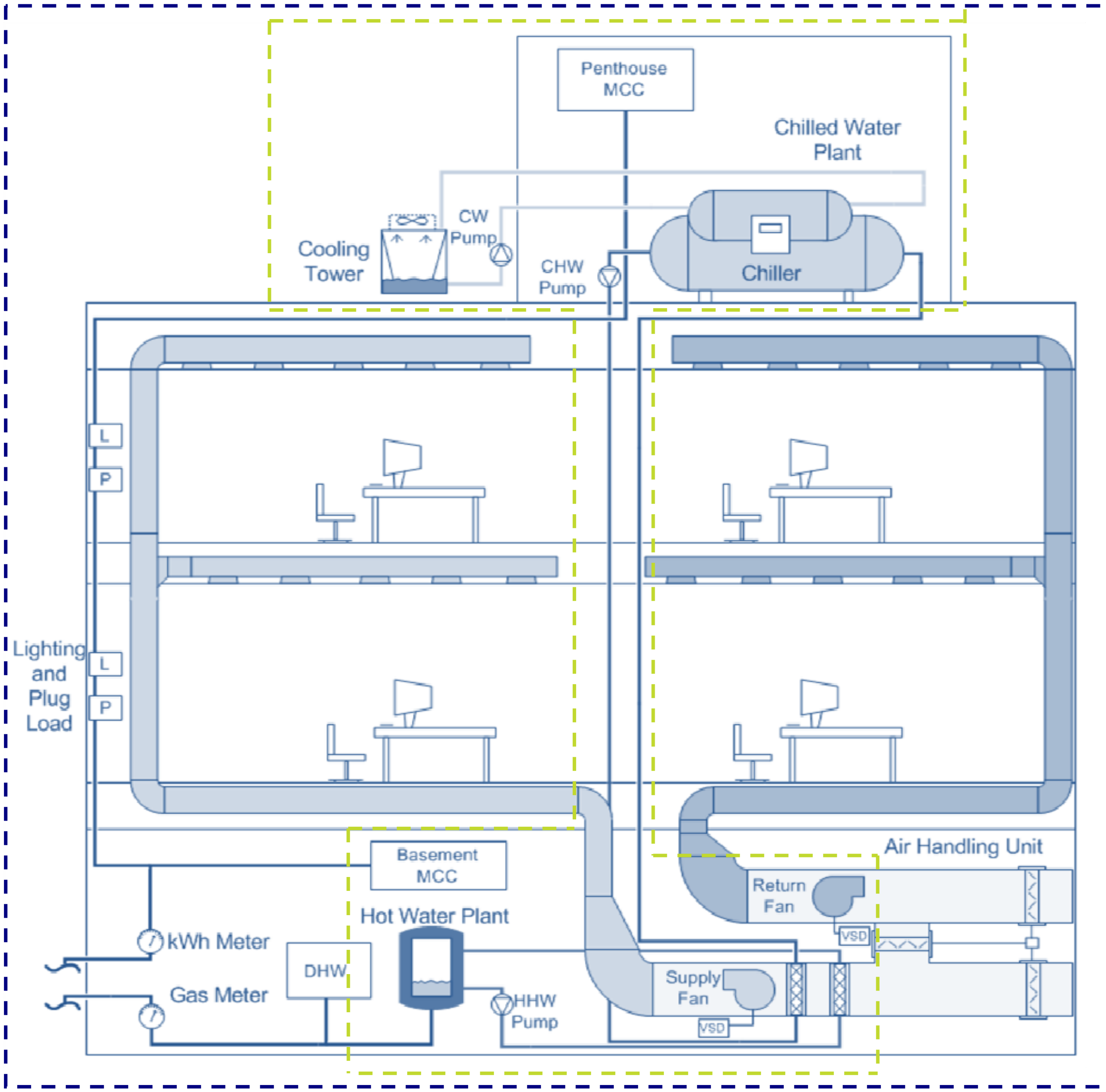
3.1.2. Identifying Measurement Boundaries

There are many choices possible for the measurement boundary. It can be drawn around a single piece of equipment, a complete system, the collection of equipment and systems served by a meter, or the whole building. In general, the *whole building* approach uses data from the utility revenue meters. A *systems or equipment* approach uses data from available sources, such as the energy management system or data loggers.

All energy from a certain utility type (electricity, gas) crossing the measurement boundary should be measured. If multiple meters for the same utility provide services within the measurement boundary, data from each meter may be combined. The measurement boundary should be drawn so that measurements and modeling are as simplified as possible.

Measurement boundaries may be drawn around the whole building, as shown in Figure 3-2 (blue boundary) or a complete HVAC system (green boundary), or it may be drawn to define specific systems, such as the chilled water plant, boiler plant, or air handlers.

Figure 3-2: Measurement Boundaries for Whole Building (blue) and Sub-Systems (green)



3.1.3. Selecting Time Intervals

At the start of the energy efficiency project, energy use data should be collected. Monthly bills and short-interval data should be included as available, as should weather data from the site and a local weather station. An initial energy baseline model should be quickly developed and evaluated for its suitability. This evaluation will support a decision on whether to go forward with the initial model or whether another approach – using different data or a different measurement boundary – will be necessary.

Models built from short-interval data are generally more accurate than those built from monthly data, as there are more data covering a greater range of conditions. When only monthly billing data are available, an assessment can be made as to whether it is adequate for verifying the expected amount of savings. There are several references on the monthly baseline model development procedure.[6] In addition to far fewer data points, monthly models have another disadvantage: collection of post-installation data takes much longer. Monthly models are not described explicitly in this protocol, but they may be used when no other method is viable.[7]

The important factors influencing whole-building energy use typically analyzed using energy models are ambient temperature and building schedules. The data for these factors must be collected for the same time period, and processed into the same time intervals, as the energy data.

Any time periods with unusual loads or operation (i.e., a period with major equipment failures or renovations) must be identified. The effects of such anomalous operations must be measured and accounted for, or the affected time period may be removed from the data set used for the model.

The collected interval data should cover the full range of operating conditions of the building. This is typically assumed to be one year, but often a shorter period can provide the needed range, if it covers times of both heating and cooling. *Chapter 5, Uncertainty*, of this protocol provides more insight on the issues associated with not covering the full range of data.

The data quality must be evaluated. The data should not have lengthy periods of missing values and should not have any clearly erroneous values. The energy and independent variable data need to be normalized to a common time interval. An analysis time interval of one day or one hour is recommended for energy models. In most cases, shorter time intervals are not appropriate. Determine the total energy use (or average demand) during the interval and the average ambient temperature.[8]

Time intervals shorter than one hour are seldom appropriate because they capture shorter-term equipment behavior, which increases the scatter in the data, but does not increase the information content in the model, since the shorter-term behavior is not related to the independent variables. For example, hourly intervals may capture behavior due to scheduling or occupancy, but shorter intervals capture behavior due to equipment controls. Therefore, time intervals shorter than one hour are only appropriate for system-level or equipment-level models where the control or status is one of the independent variables.

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6 R. Sonderegger, "A Baseline Model for Utility Bill Analysis Using Both Weather and Non-Weather Related Variables"; and D. Landman and J. Haberl, *Monthly Variable-Based Degree Day Template: A Spreadsheet Procedure for Calculating 3 Parameter Change-Point Model for Residential and Small Commercial Buildings*.

7 A tool designed for M&V of web-enabled thermostats in school portable classrooms was developed for BPA in 2010 and is being updated for greater flexibility at the time this protocol was prepared. That tool provides *IPMVP Option C* analysis and could be used for other measures using monthly billing analysis.

8 The California Commissioning Collaborative provides a useful spreadsheet tool: *Energy Charting and Metrics* (ECAM) *Tool* that develops occupancy and operation schedule data; it is described in *Appendix C.* Note that other representations of ambient temperature may be used, including the minimum temperature for the time interval, or the maximum. When the interval is daily, a heating or cooling degree-day or degree-hour variable may be used.

3.1.4. Adjusting Baseline to Post Conditions

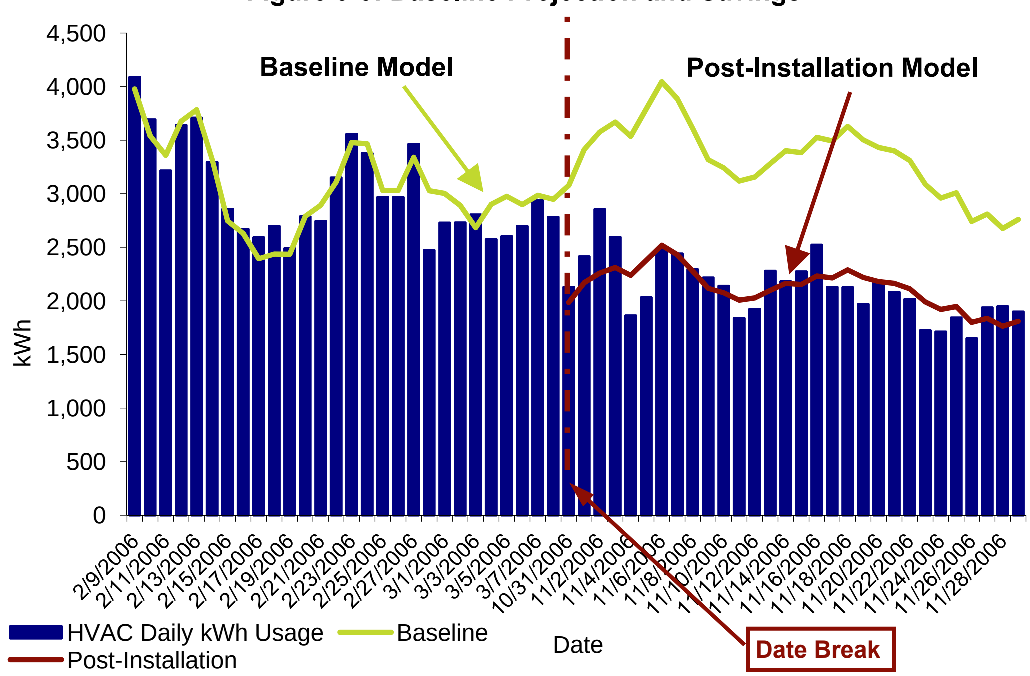
When calculating the avoided-energy-use type of savings, the model's equation is used to adjust the baseline to the post conditions. For each post point, the post energy use and the associated value(s) of the independent variable(s) needed for use in the baseline model should be available. The value(s) of the independent variable(s) are plugged into the baseline model's equation and the resulting estimated energy use represents the baseline projected to the post conditions.

3.1.5. Calculating Savings

The actual post-period energy use, totaled for all the post points in the reporting period, is subtracted from the projected baseline energy use to get the estimated savings for the reporting period.

In some cases (such as for very long reporting periods), only the actual accrued savings in the period must be determined. In these cases, the measured post-installation energy use may be subtracted from the adjusted baseline energy use as determined by the baseline model. This approach is illustrated in Figure 3-3.

Figure 3-3: Baseline Projection and Savings



If savings are to be stated for conditions other than the post-installation period – a *fixed conditions basis* type of savings – a post-installation energy model that relates the energy use with variables describing those fixed conditions must be developed. Usually the conditions are TMY weather. Both baseline and post-installation energy use must then be estimated using TMY data, providing normalized energy use. Savings are estimated by subtracting the normalized post-energy from the normalized baseline energy. The estimated savings are termed *normalized savings*.

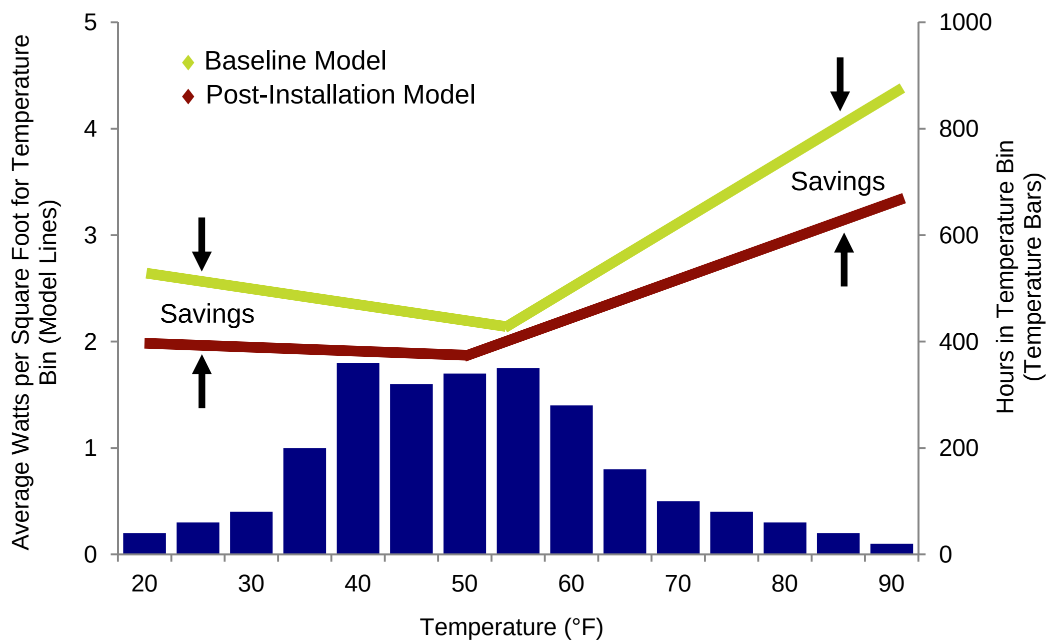
3.1.6. Extrapolating Annual Models Based on Less Than a Year of Data

Unless the reporting period is a full year or more, the collected datasets will be for a shorter time period. In these cases, the energy use from the measured reporting period must be extrapolated to an entire year. This is done by:

- ➡ Creating a post-installation model from the collected data in the same way the baseline model was created
- ➡ Developing annual fixed-conditions models using the ambient temperature data from a TMY weather file, and the baseline and post-installation models based on partial-year data, to estimate baseline and post-installation annual energy use
- ➡ Subtracting the estimated annual post-installation energy from the baseline energy to estimate the annualized savings

Figure 3-4 illustrates the process. Regression models are created by plotting energy use per hour versus temperature before and after changes are made to the building (i.e., the baseline and post models). The baseline model is green; the post model is red. The two models are used to get the savings at each temperature bin. The savings at each temperature bin are multiplied times the number of hours in each temperature bin, which are shown by the bars. Then, the savings for each bin are added together to get the total annual savings. Note, this is not an IPMVP-adherent procedure, since the savings in this case will not be based on actual measurements in the post-installation period for the entire year.

Figure 3-4: Annual Extrapolation and Normalized Savings



3.2. Equations and Model Applications

This protocol recommends that linear and simple polynomial model types be used to develop the baseline and post-installation period models for use in M&V analysis. The linear models, which include simple linear regressions, change-point models, and multiple regression models are discussed at depth in the BPA *Regression Reference Guide*. The model equations and physical significance are briefly described again here for convenience, but equation coefficients are not. This protocol describes additional model types not included in the *Regression Reference Guide* that may be useful for certain types of buildings or systems. Examples of actual applications are also provided to illustrate concepts.

3.2.1. Model Types

The model types described in this protocol include the following: *linear, change-point linear*, and *polynomial*. Change-point models often have a better fit than a simple regression when modeling energy usage for a facility.[9] Because of the physical characteristics of buildings, the data points have a natural two-line angled pattern to them. Sometimes it is even appropriate to use multiple change points. Multi-variable change-point linear models derived from multiple regression are usually not appropriate, for reasons discussed in Section 3.2.2, *Multiple Models*.[10]

As discussed in the following sections, there are a variety of considerations in developing an appropriate energy model. For example, some energy analysts and M&V practitioners believe that models based on weather conditions should include a measure of ambient humidity, as well as ambient temperature. While this can be true in certain circumstances, it is usually not necessary. Commonly used measures of humidity are collinear with temperature and hence add little to a model, and can lead to incorrect inferences and uncertainty.

When using empirical models, care should be taken to gather as much data over the entire range of conditions as possible and to avoid extrapolating energy use to conditions outside the data range. While some higher parameter models have bounds at least at the lower end, many models are unbounded and can easily yield erroneous results not far outside their data limits.

In most cases, the analyst will know the appropriate independent variable. For multivariate models, use as few independent variables as possible to obtain a reasonable model and have a good understanding of the variables you are using. Creating a good multivariate model needs to begin with a strong understanding of what drives energy use. You can avoid *multicollinearity* – where two independent variables are highly correlated – by creating a model that you think best describes your dependent variable and then check via scatter plots to see that the relationships between each independent variable and the dependent variable are viable. This will give you a sense of the impact that each independent variable has on the dependent variable. Additional scatter plots of the independent variables together can assist in visually seeing whether one independent variable is correlated with another.

9 See the BPA *Regression Reference Guide* for a detailed description of change-point linear regression.

10 For information on multi-variable change-point models, refer to the BPA *Regression Reference Guide*, *ASHRAE Guideline 14*, or the *Inverse Modeling Toolkit* (ASHRAE 1050-RP), developed for ASHRAE by Kissock, Haberl, and Claridge.

Understanding the theoretical impact that an independent variable has on the dependent variable can help you to avoid using two independent variables that are correlated. Finally, after running the whole multivariate model, if you are still concerned about multicollinearity, you can add independent variables one at a time. This is commonly known as *step-wise regression*. Then evaluate the *t-statistic* or *p-value* for each variable as it is added, to make sure it is significant. (See the section on *Multicollinearity* in the BPA *Regression Reference Guide*.)

One-Parameter Model (Mean Model)

The simplest model is the one-parameter (1P) model, in which the energy use does not vary with any independent variable. The energy use is a constant when the equipment or system is in use, or it has less than a 5% variation,[11] in which case, an average is used. This can apply to constant speed pumps and fans, and lighting circuits and similar equipment. One-parameter models have a simple equation:

- **One Parameter Equation:** $E = \beta_1$

Two-Parameter Model (Ordinary Linear Regression)

Two-parameter (2P) models are equivalent to simple linear regressions with one independent variable. These models types are appropriate for buildings that require cooling or heating for the entire year, such as in extremely cold or warm climates. Selected building systems can be modeled with 2P models: Haberl and Culp[12] cite dual-duct, single-fan, constant volume systems without economizers. Two-parameter models have equations in the form:

- **Two Parameter Equation:** $E = \beta_1 + \beta_2 T$

Figure 3-5 provides an example of a 2P cooling model. It is based on 2½ months of daily (analysis time interval) data of the electricity use at a university laboratory building. This data is for weekdays only; the weekend days had lower energy use and had a separate model.

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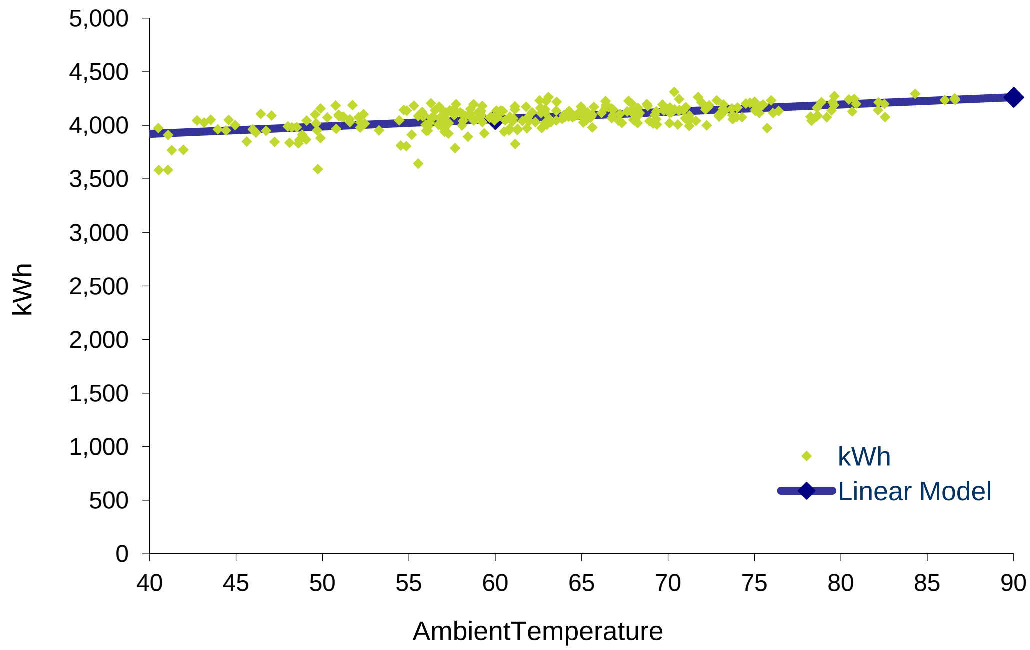
11 This variance is defined as the *coefficient of variation of the standard deviation:* CV(STD). It is calculated by *CV(STD)* = $\sigma / \bar{x}$, where σ = *standard deviation about the mean value of all measurements*, and $\bar{x}$ = *mean of the measured values*.

12 *Review of Methods for Measuring and Verifying Savings from Energy Conservation Retrofits to Existing Buildings*.

Figure 3-5: A 2P Energy Model of Electricity Use (kWh) in a University Laboratory Building, Using Daily Data



Three-Parameter Change-Point Models

Three-parameter (3P) linear change-point heating and cooling models are applicable to many types of buildings and systems. The change point indicates a change in the dependence of energy use on the independent variable.

Three-Parameter Heating Model

In the heating mode, the energy use (e.g., natural gas, etc.) has a decreasing dependence on ambient temperature as it increases until the change point is reached. As the ambient temperature increases beyond the change point, the heating energy use remains constant. This is typical of most buildings. Three-parameter change-point heating models have equations in the form:

- **Three-Parameter Change-Point Heating Model:** $E = \beta_1 + \beta_2(T - \beta_3)^+$

The superscript + after the parenthetical term means that only positive values of the term will be used, otherwise it should be evaluated as zero. In pseudo-code, it is equivalent to:

- *IF* $(\beta_3 - T) > 0$, $(\beta_3 - T)$, *else* 0

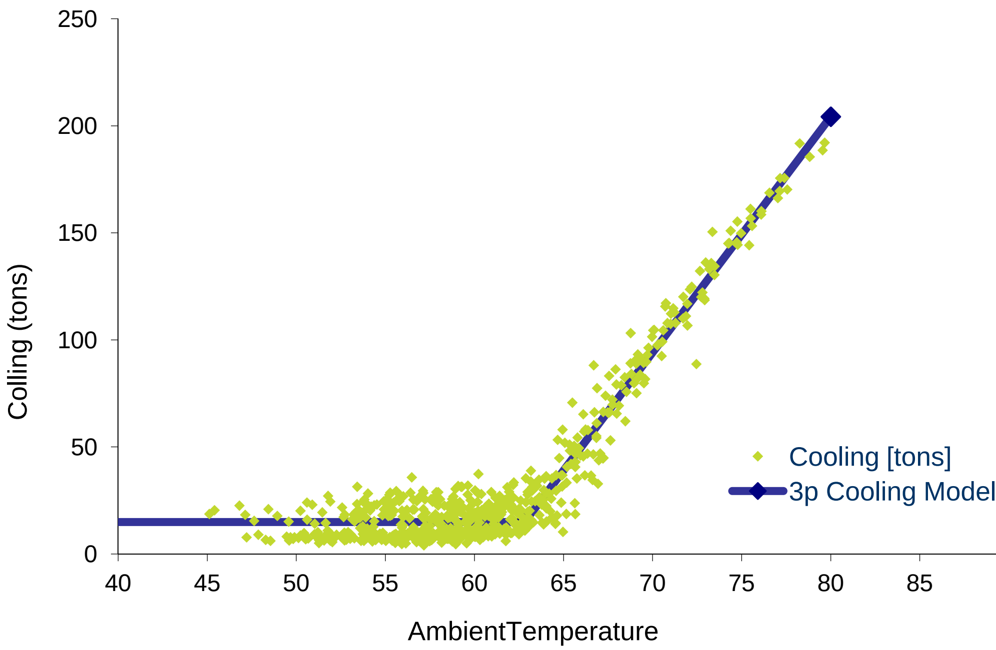
Three-Parameter Cooling Model

For the three-parameter cooling model, the cooling energy use is constant below the change-point temperature and increases linearly as temperature rises above it. Three-parameter change-point cooling models have equations in the form:

- **Three-Parameter Change-Point Cooling Model**: $E = \beta_1 + \beta_2(T - \beta_3)^+$

Figure 3-6 provides an example of a 3P cooling model. It is based on a month of hourly data for chilled water energy use in a university building.

Figure 3-6: A 3P Energy Model of Chilled Water Use (tons) in a University Laboratory Building, Using Hourly Data



Four-Parameter Change-Point Models

Four-parameter (4P) linear change-point heating and cooling models are applicable to buildings and systems that display different linear dependence of energy use with the independent variable in different ranges. For example, a building with a chilled water plant and variable volume air distribution systems equipped with economizers will display different electric energy dependence on ambient temperature when the air handling unit is economizing at mild temperatures than displayed in warmer temperatures, when the building will rely exclusively on mechanical cooling.

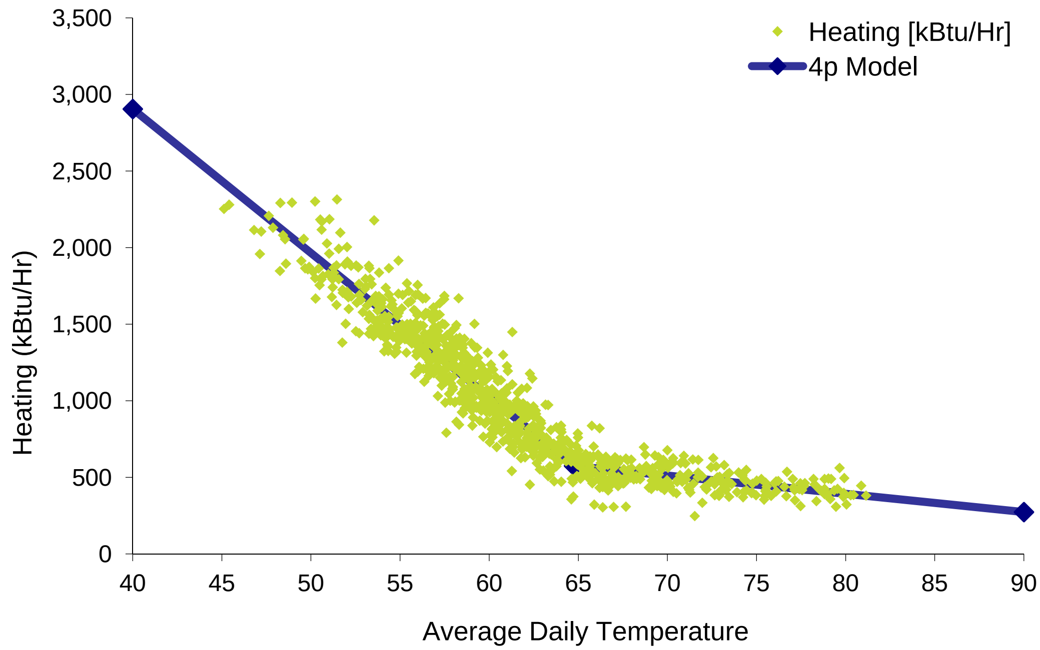
Four-Parameter Heating Model

Four-parameter change-point heating models have equations in the form:

- **Four-Parameter Change-Point Heating Model:** $E = \beta_1 + \beta_2(\beta_4 - T)^+ - \beta_3(T - \beta_4)^+$

Figure 3-7 provides an example of a 4P heating model. It is based on a month of hourly data for heating hot water energy use in a university building.

Figure 3-7: A 4P Energy Model of Hot Water Use in a University Laboratory Building, Using Hourly Data



Four-Parameter Cooling Model

Four-parameter change-point cooling models have equations in the form below:

- **Four-Parameter Change-Point Cooling Model:** $E = \beta_1 - \beta_2(\beta_4 - T)^+ + \beta_3(T - \beta_4)^+$

Five-Parameter Change-Point Model

Five-parameter (5P) linear change-point models are useful for modeling building energy use when the same energy source provides both heating and cooling, such as a building with air conditioning and electric heating. Five-parameter models can also be useful for modeling the weather dependence of energy use in variable volume air distribution systems. Five-parameter models display a linear dependence of energy use on ambient temperature below the heating change point and above the cooling change point, and constant energy use between the heating and cooling change-points. Five-parameter change-point heating models have equations in the form:

- **Five-Parameter Change-Point Heating Model**: $E = \beta_1 + \beta_2(\beta_4 - T)^+ + \beta_3(T - \beta_5)^+$

Future Model Types

One weakness of the change-point models developed by *ASHRAE RP-1050* is that they typically assume that the slope is constant above the cooling change point. An exception could be the use of a 4P model covering only the range of temperatures associated with cooling. Additional change-point model types have been proposed and are being developed in software by Quantum

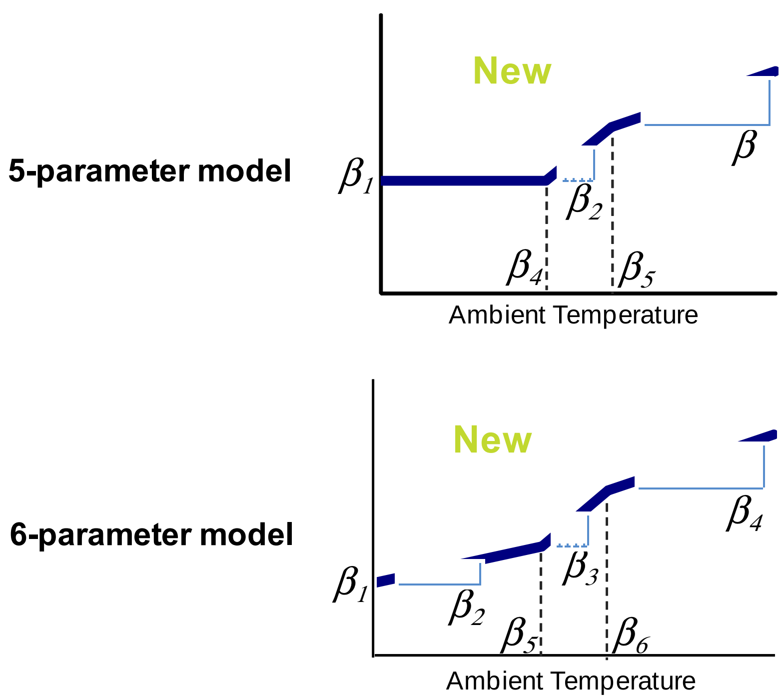
Energy Services and Technologies and Lawrence Berkeley National Laboratory through a California Public Interest Energy Research project funded by the California Energy Commission. These new model types have been presented by the author of this protocol at ASHRAE conferences and were enthusiastically received by some of the authors of *RP-1050*. There are two or more building behaviors that warrant considering that the cooling slope may not be constant. First, normal air-side economizer operation will result in a steeper slope at the lower temperatures of the cooling range. Second, if the cooling equipment is too small for the peak load, the slope may flatten near the high temperatures. Another consideration is variable-speed auxiliaries – pumps and fans – which may result in a curve to the cooling slope.

Whether any of these are an important consideration depends upon the types of measures in the project, the measurement boundary, and the time interval. A change in slope due to the economizer can often be seen with hourly data, even at the whole-building level; it is rarely seen with daily data. Since equipment undersizing is rare, the flattening of slope at the upper end is not seen often, but it does occur on occasion. In whole-building data, a notable curve to the cooling slope associated with variable speed auxiliaries is rarely evident, but it can occur with system-level data. When it occurs, a polynomial model may be appropriate as described below.

Models with Improved Economizer Characterization

To better account for economizer operation, two additional types of change-point models may be considered. Accounting for the economizer operation may be particularly valuable in Northwest climates. These additional model types are shown in Figure 3-8, below.

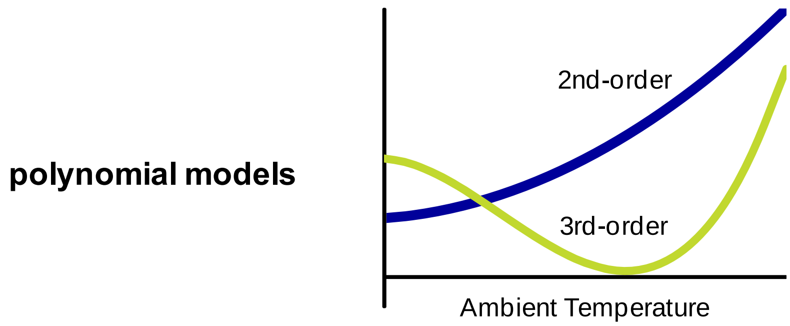
Figure 3-8: Additional 5P and 6P Model Shapes



Polynomial Models

Polynomial models will most often be 2nd-order, and they should almost always be limited to 2nd- and 3rd-order. Even 3rd-order polynomial models must be used with extreme caution, as they can significantly misestimate energy use when extrapolating beyond the data range upon which the model was developed. Figure 3-9 shows 2nd and 3rd order polynomial model shapes.

Figure 3-9: Polynomial Model Shapes



Polynomial models can be useful for system-level models (e.g., estimating energy use as a function of flow and, in some cases, as a function of ambient or other temperatures). Flow is often a function of temperature, and energy use is a function of flow. For a fixed system, the affinity laws state that the power is proportional to the cube of the flow. Thus, some practitioners believe that 3rd-order polynomials are the best for modeling variable-flow systems. However, this is seldom the case in practice, at least in commercial buildings.

First, most variable flow systems are not fixed systems. Part of the system often has a controlled pressure and there are valves or dampers that modulate the flow and maintain the pressure. Second, the efficiencies are not constant if the flow is changed significantly. Third, a significant portion of these systems do not have pressure drops that are proportional to the square of the flow – filters and coil pressure-drop exponents are something less than two. Therefore, most variable-flow systems can be well modeled with a 1st- or 2nd-order equation.

Simulation of variable flow systems also confirms that variable flow systems can be modeled with a 2nd-order equation with the same accuracy as a 3rd-order equation, even without taking into account the superior extrapolation capability of the 2nd-order model. Variable-speed cooling tower fans may be the exceptional case that is better modeled with a 3rd-order polynomial, since those fans are truly operating against a fixed system.

Polynomial models have equations of the following form:

- **2nd-Order Polynomial Model**: $E = \beta_1 + \beta_2 X + \beta_3 X^2$
- **3rd-Order Polynomial Model:** $E = \beta_1 + \beta_2 X + \beta_3 X^2 + \beta_4 X^3$

3.2.2. Multiple Regression vs. Multiple Models

Multiple Regression Models

This section and the next include information from the BPA *Regression Reference Guide* section on *Categorical Variables*. In this document, the information is expanded with examples. For an explanation of the statistics included in the examples, refer to the *Regression Reference Guide,* except for *fractional savings uncertainty,* which is discussed in Chapter 5 of this document.

Variables can be divided into two general types: *continuous* and *categorical*. Continuous variables are numeric and can have any value within the range encountered in the data. Continuous variables are measured things, such as energy use or ambient temperature. Categorical variables include things like daytype (weekday or weekend, or day of week), occupancy (occupied or unoccupied), and equipment status (on or off). (Though *occupancy* might be stated as a categorical variable, *number of occupants* would be a continuous variable.) Most energy models for M&V will have only one continuous variable, but may also incorporate categorical variables. Because of this, few M&V projects will require the use of multiple regression with change points, as described in the prior section.

Categorical variables are commonly used in multiple regression models for M&V. Applying a constant term to a categorical variable in the model will result in a model with the same slope for all categories. This often results in an inaccurate model. For example, a category of *occupancy status* will usually have a different slope for the model of the occupied period than for the unoccupied period. A *daytype* category also will often have different slopes for weekday and weekend models.

A weakness of the multiple regression models in *ASHRAE RP-1050* is that they suffer from this issue, and can create a model with the same slope for all categories, even when the slopes should be different.

Multiple Models

As an alternative to using a multiple regression model, the analyst can create separate models for each category or combination of categories and then combine these individual models into a complete model. The basic process is similar to using *IF* statements to determine, for each data point, the category of the categorical independent variable, and then using the intercept and slope that are appropriate for that category.

To determine which categorical variables are important, the analyst should use a procedure such as the following to explore the data:

- ➡ Create a scatter plot using all the data (i.e., without any category filters).
- ➡ If there is a very good fit, as observed in the chart and quantified by the *R-squared* and *CV(RMSE)* statistics, then categories are unimportant.
- ➡ If the scatter shows a bi-modal or multi-modal distribution (i.e., there are distinct groupings of the scatter), then there is at least one important categorical variable.

If the scatter is wide, then one of the following is true:

- One or more categorical variables are important.
- The relationship is simply weak.
- There may be a better independent (continuous) variable or a second important independent variable.

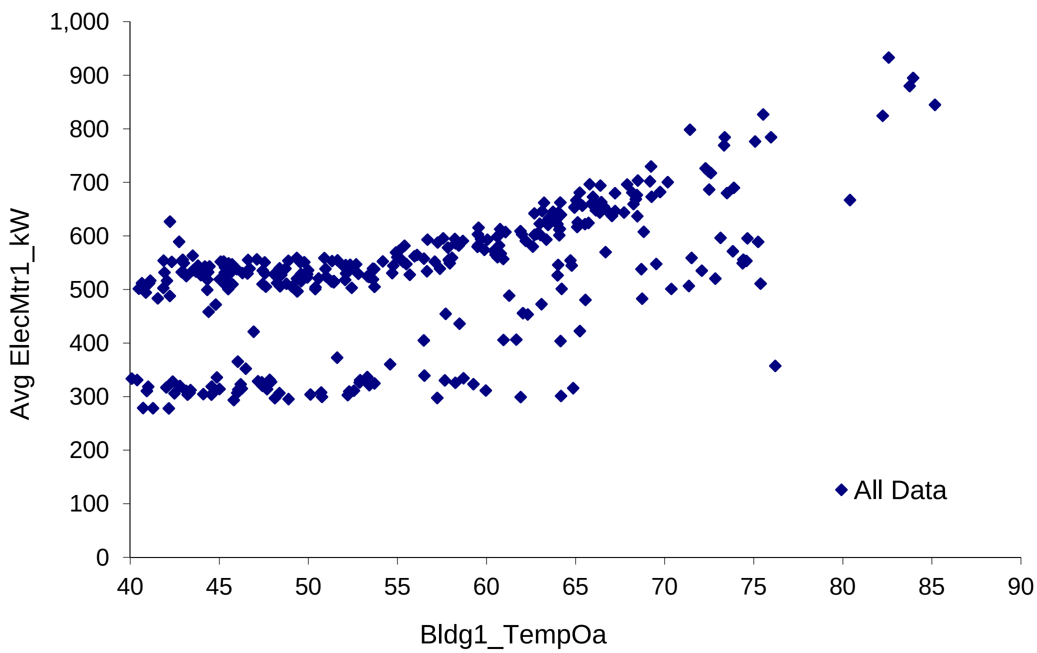
For most models, the appropriate conclusion may be found in the first bullet above. To evaluate which categorical variables are important, the analyst should explore the data, filtering the chart data for different categories. The most common category will be *daytype*, and for sub-daily data, *occupancy* or *time-of-day*.

Daytyping

The following charts show how daily data may be disaggregated by daytype.

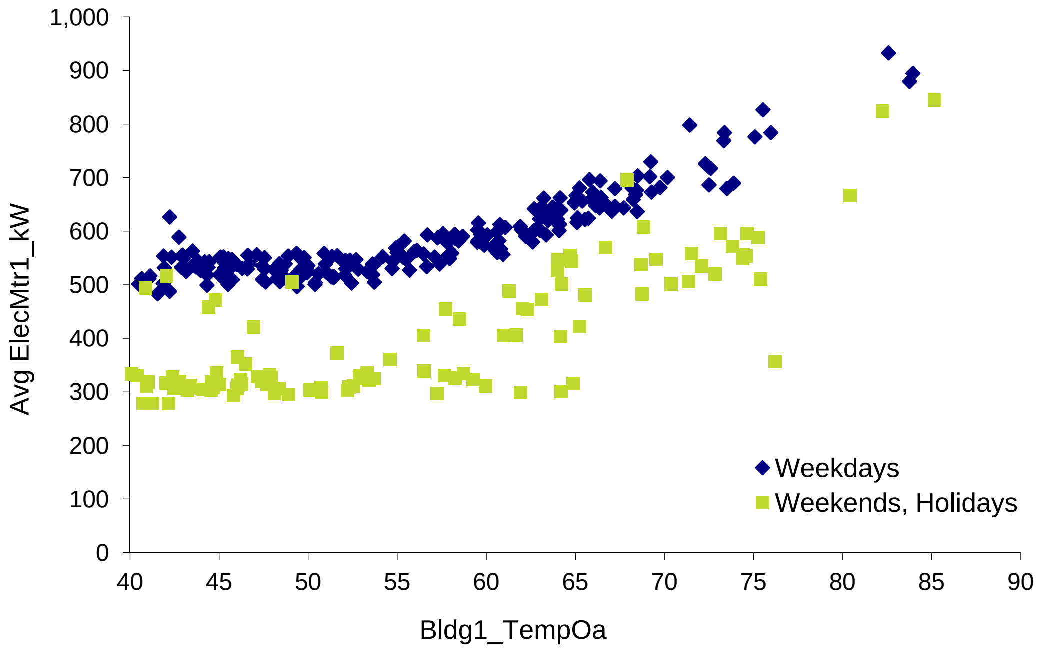
First, all the data is plotted. Figure 3-10 shows a year of meter data with demand averaged for each day. The individual data points could be totaled to give kWh as well; if the math is done properly, the approaches are equivalent.

Figure 3-10: Sample Electricity Meter Data (kW), Using Daily Data



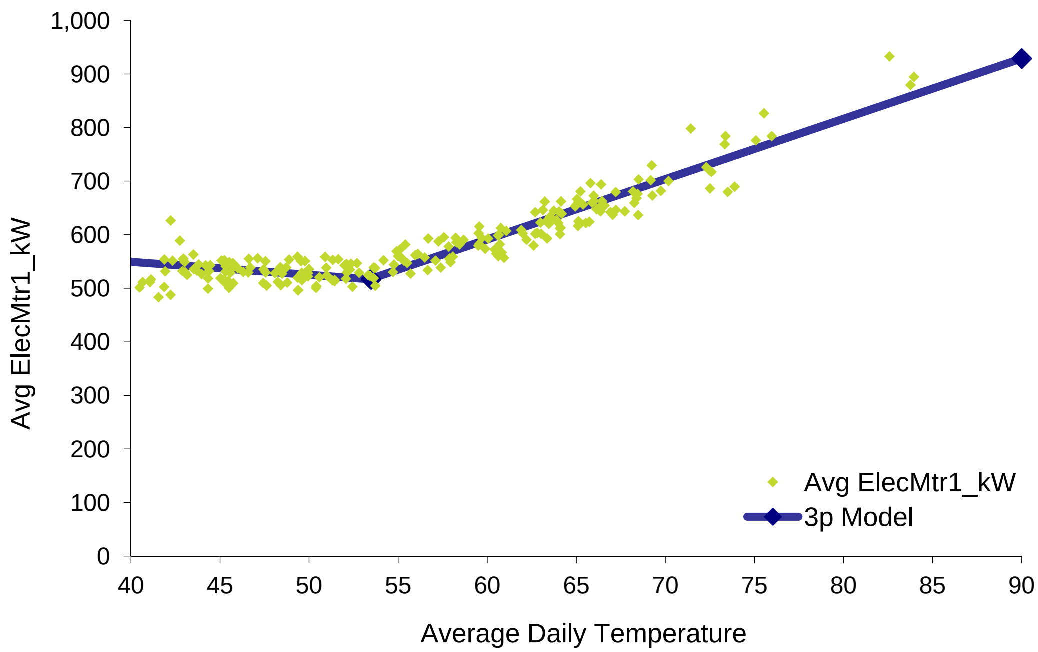
Note the two distinct data clusters. This is an indication of two modes of operation. In this case, the two modes represent two daytypes, as shown in Figure 3-11.

Figure 3-11: Sample Electricity Meter Data (kW) Showing Daytypes, Using Daily Data



In this situation, separate regression models should be created for weekdays and weekends. After the models have been created and validated, they can be combined into a single model to simplify the calculations. Figure 3-12 is an example model for weekdays. From the form of the scatter chart, it appears that a 3P model might be appropriate.

Figure 3-12: Sample 3P Model of Electricity Meter Data (kW) for Weekdays, Using Daily Data



The equation for this model in spreadsheet function form is:

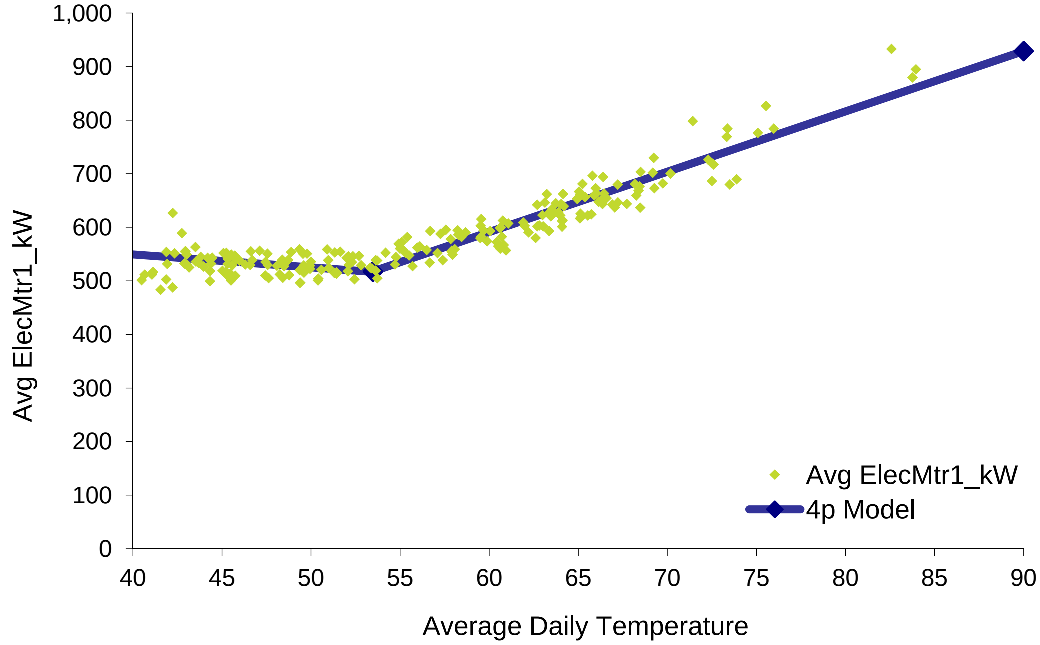
- *=IF(T<56.09, 538.2, 133.5 + 11.983*T))*

The statistics for the regression are:

R-squared:	0.86
CV-RMSE:	4.8%
Fractional Savings Uncertainty:	20.2%
Savings Range:	5.0% ±0.5%
Net Determination Bias:	0.000%

A 4P model could also be appropriate, as shown in Figure 3-13.

Figure 3-13: Sample 4P Model of Electricity Meter Data (kW) for Weekdays, Using Daily Data



The equation for this model is:

- *=IF(T<53.47, 645.99 +-2.416*T, -84.44+11.260*T))*

Note that the change point for best fit changed slightly from the 3P model, from 56.09 to 53.47. The following statistics for the regression indicate a slight improvement relative to the 3P model:

R-squared:	0.876
CV-RMSE:	4.6%
Fractional Savings Uncertainty:	18.2%
Savings Range:	5.0% ±0.5%
Net Determination Bias:	0.000%

Combining Multiple Time Categories into a Single Category

The benefit of using daily averages is that information regarding facility occupancy and equipment schedules may not be required to build the model. However, when interval data is available, more accurate and robust models may be possible using schedule and occupancy information. This is more evident when less than a year of data is available to build the model and is dependent on the time of year the data is collected.

When using daily models, similar days are typically combined into a single model by daytype. With hourly models, it can be informative to create separate models for each hour in the day. However, when creating the best model for M&V, similar hours should be grouped, just as similar days are grouped when using daily models. The individual hourly models can be one of the best ways to determine which hours are similar. The goal is to create as few models as possible, with the greatest number of data points in each model. This approach has the potential to reduce uncertainty, especially when developing models using less than a year's worth of data.

By clustering hours into groups of similar data, robust models can be created more quickly for two reasons:

1. The models can be populated with data over a wide range of temperatures more quickly (see Figure 3-14).
2. More data will be included within each model or bin (see Figure 3-15).

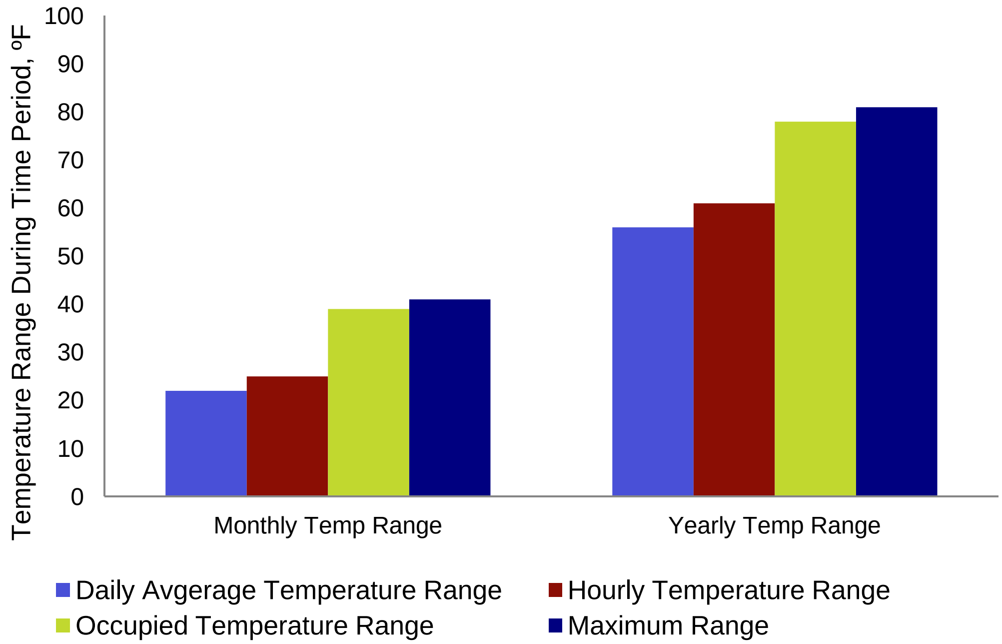
By appropriately using the data, it is possible to shorten the time period needed to cover a wide range of operating conditions.

One caution when using occupancy as a category*: occupancy is generally somewhat collinear with ambient temperature*. Therefore, analysts need to be careful as to whether the relationship seen is due to temperature or occupancy.

Figure 3-14 shows the temperature range, by month and by year, for the following types of temperature aggregations. Data shown is for Portland, Oregon. Here are the definitions of the temperature ranges:

- ➡ **Daily Average Temperature:** The range is the maximum daily average minus the minimum daily average for the month.
- ➡ **Actual Hourly Temperatures:** The range is the maximum average temperature in a particular hour of the month minus the minimum average temperature in the same hour of the month.
- ➡ **Occupied/Unoccupied Temperatures:** The range is the maximum temperature when the building is occupied minus the minimum temperature when the building is occupied, for the same month.
- ➡ **Maximum Temperature Range:** The maximum temperature in the month minus the minimum temperature in the same month.

Figure 3-14: Typical Monthly and Annual Range in Outdoor Temperatures by Aggregation Method



From Figure 3-14, we can deduce the following:

- The daily average temperature typically varies by about 22º F over a month and 56º F over a year.
- The temperature at a given hour typically varies by about 25º F over a month and 61º F over a year.
- The range of temperatures during the typically occupied hours varies by 39º F over the month and by 78ºF over a year.
- The maximum temperature minus the minimum temperature is typically 41º F over a month and 81º F over a year.

So, by using hourly rather than daily average temperatures and combining time periods with similar operating conditions (such as grouping all occupied hours), we can increase the range of operating temperatures in the model.

Note that using average daily temperatures provides only about 58% (22÷41) of the full monthly temperature range using a month of data, and only about 69% (56÷81) of the full annual temperature range using a year of data. Grouping hourly data for similar conditions raises these values to 95% for both monthly and annual comparisons. Of course, the monthly data varies slightly month-to-month, but these are typical values.

Grouping data at similar operating conditions has an additional benefit: it increases the number of data points in the model. Since uncertainty is a function of the number of data points, uncertainty will be further reduced by this grouping.

Figure 3-15 illustrates that clustering all occupied hours together into a single model and all unoccupied hours together in another model will permit the use of fewer models or bins. It will also result in many more data points per model than either the daily average model (approximately 30 data points per month) or the hourly model (a model for every hour in the week).

Figure 3-15: Number of Data Points per Month by Model Type

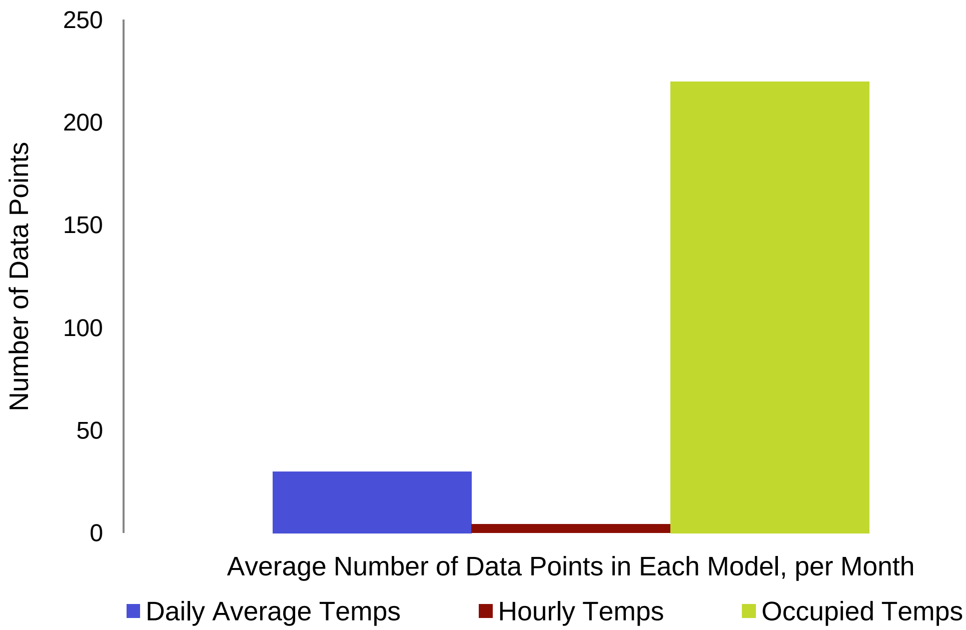


Figure 3-15 shows that a model using daily average temperatures will have approximately 30 data points per month, since there are typically about 30 days in a month. A bin-based model using a separate bin for every hour in the week will have only about four data points per bin per month, since there are about 4 weeks per month. Grouping data for times with similar operating conditions into a single model, such as a model for occupied hours, will have upwards of 220 points in the model per month, depending upon the operating schedule.

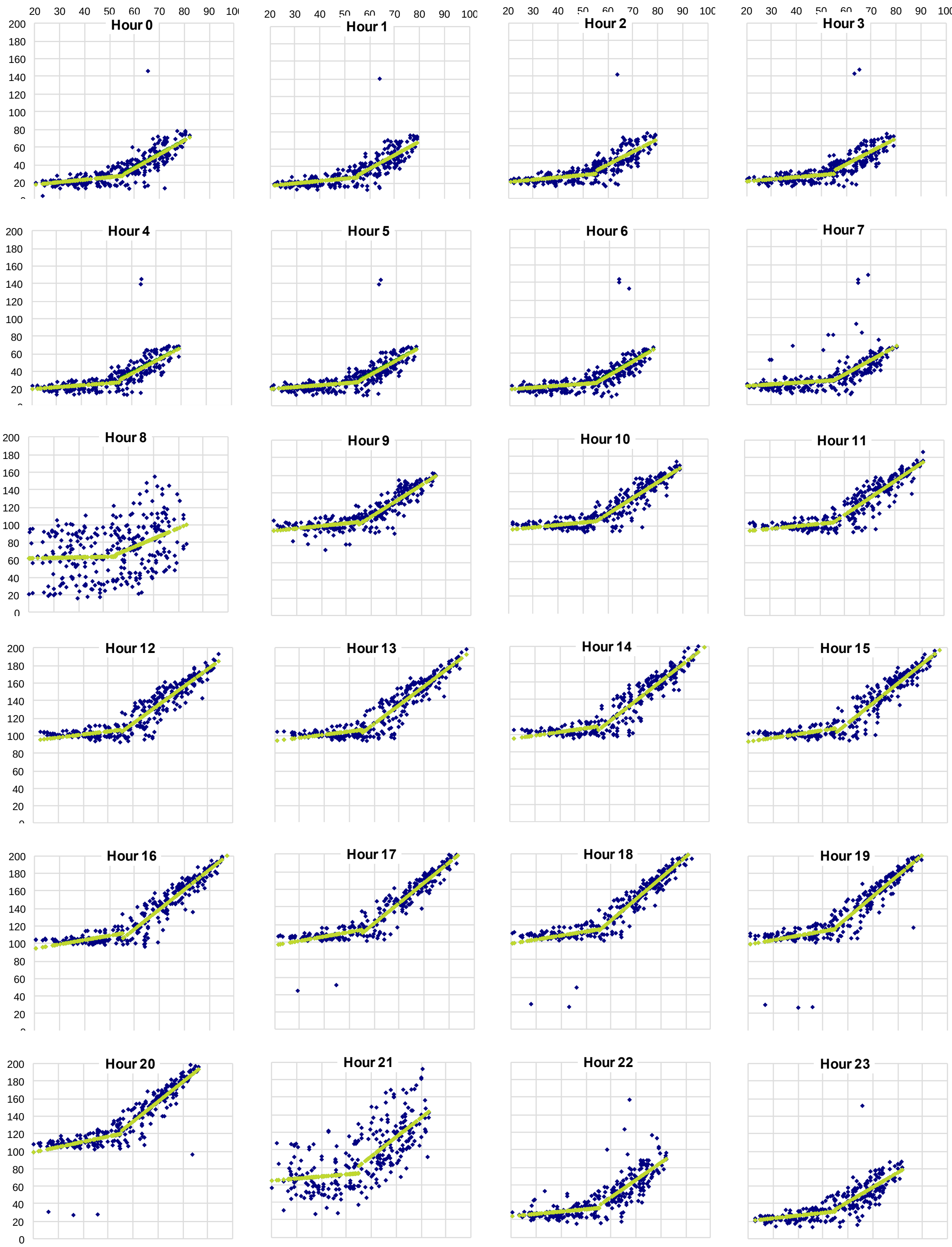
Therefore, using short-time-interval data, and grouping it appropriately, can reduce the metering time period necessary for sufficient data, improving the ability to separate the impact of an energy project from other building changes.

Hourtyping and Occupancy

There are several approaches to determining which hours are similar and could be combined. It usually is not sufficient to accept the occupancy or HVAC plant operating hours provided by the site. One of the best approaches is to create models for each hour of the day, as mentioned in the prior section, as shown in Figure 3-16.

Figure 3-16: Electricity Models Showing Demand (kWh) for Each Hour of the Day, Using Hourly Data

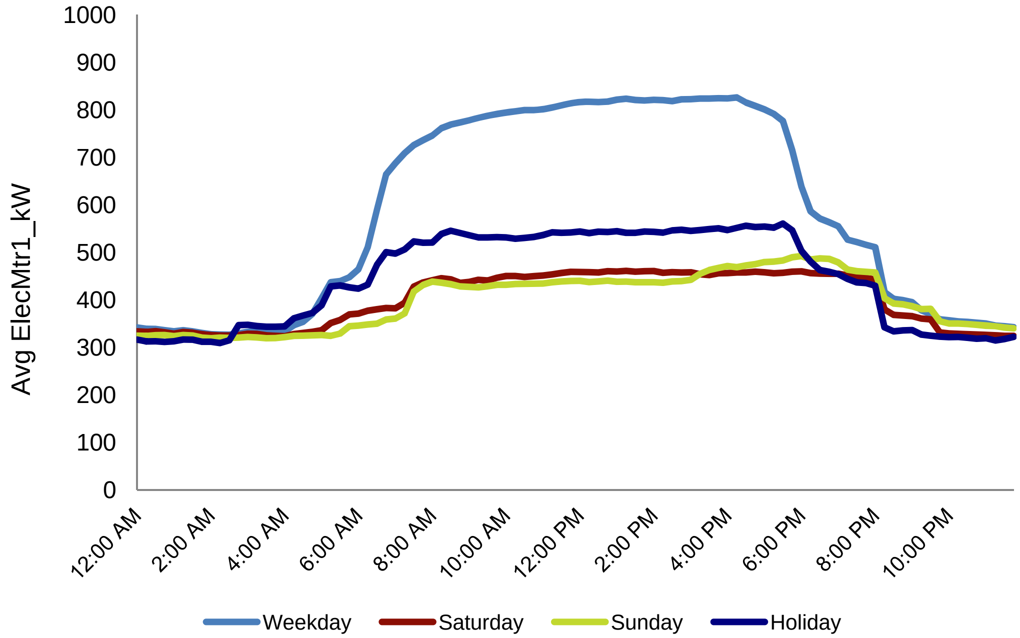
Weekdays and Saturdays



From these models, it can be concluded that hours 0 through 7 and hours 22 and 23 are similar hours, representing unoccupied operation. Hour 8 can be considered startup. Hours 9 through 20 are similar, representing occupancy. Hour 21 represents shutdown. So, there are four groups of hours, with all hours in a group showing pretty similar operation.

Creating models for each hour of the day may be more complex than needed to determine similar hours. Another approach is to plot the average load profiles, filtered by daytype, to confirm the times when the load changes as shown in Figure 3-17.

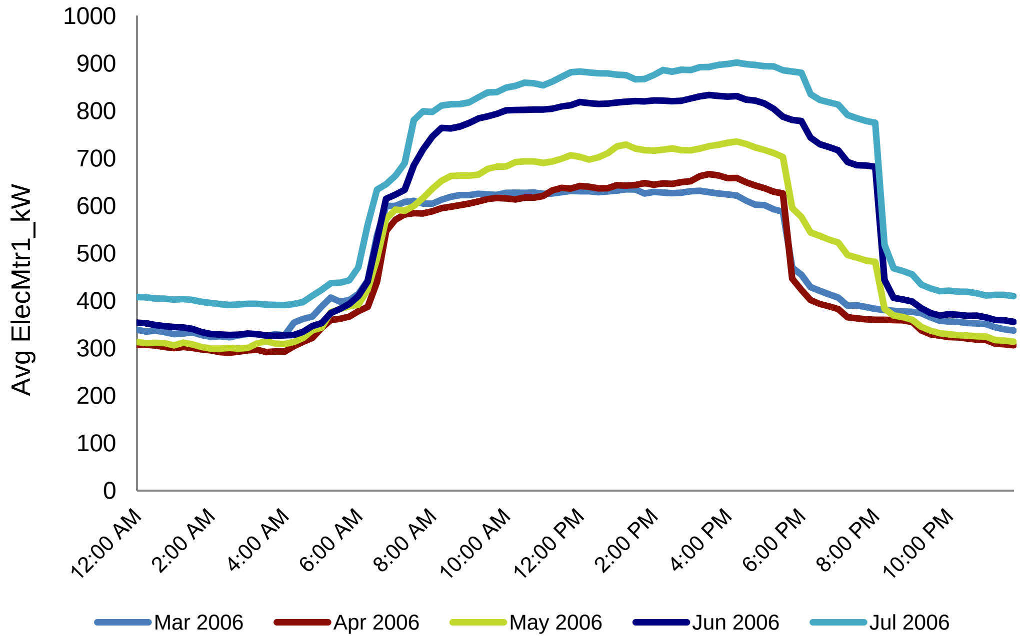
Figure 3-17: Average Electricity Load Profiles (kW) by Daytype, Using 15-Minute Data



If this is done, the data should be checked to confirm that the daily operating times are consistent over the time period of the data. In this case, they were not. Figure 3-18 shows the average load profiles for March through July.

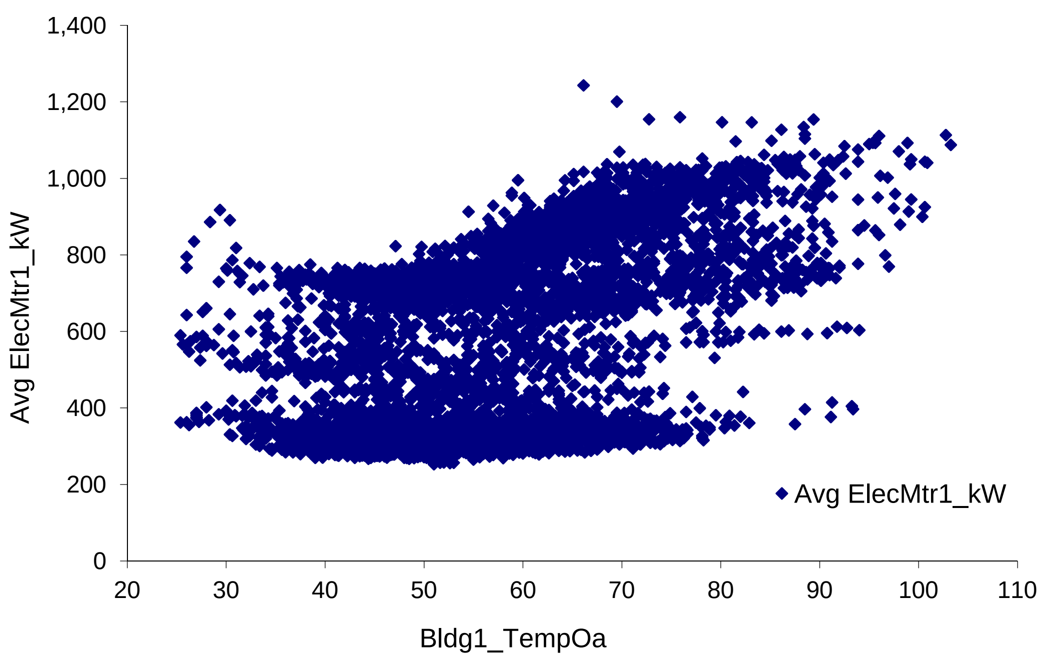
Note how the operating hours, particularly at the end of the day, changed starting in May. When evaluating how to combine similar hours, changes in schedule must be considered.

Figure 3-18: Average Electricity Load Profiles (kW) for Specific Months by Daytype, Using 15-Minute Interval Data



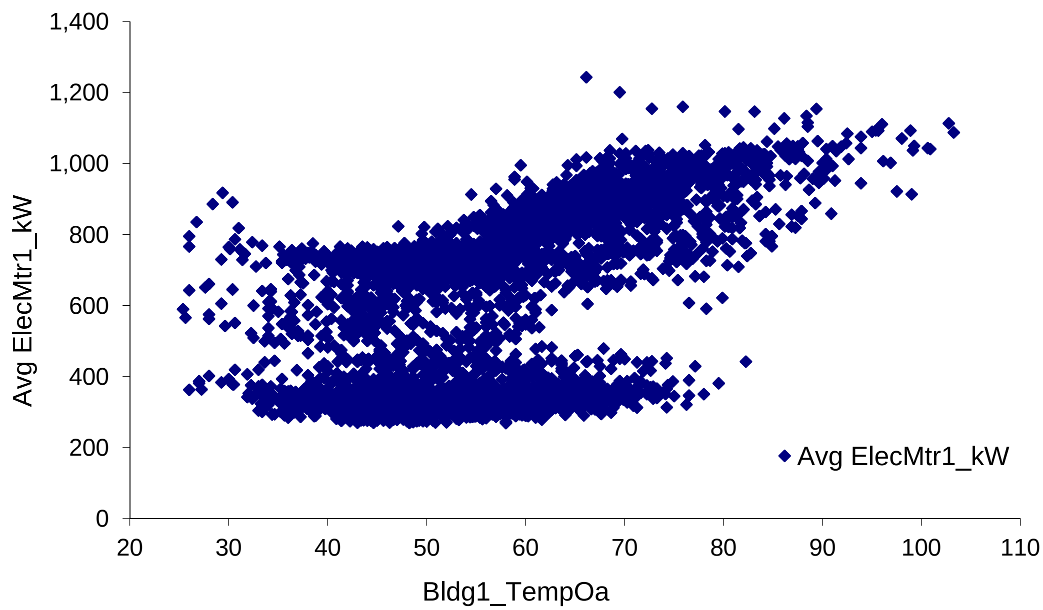
Another approach is to plot all the data in a scatter chart, filter the data for daytype and occupancy or other possible categories, and see if the scatter is reasonably tight. Figure 3-19 shows the same data in a scatter chart. This data is similar to the data shown in Figure 3-10, but it uses hourly data rather than daily averages.

Figure 3-19: Scatter Chart of Electrical Demand (kW) vs. Ambient Temperature, Using Hourly Data



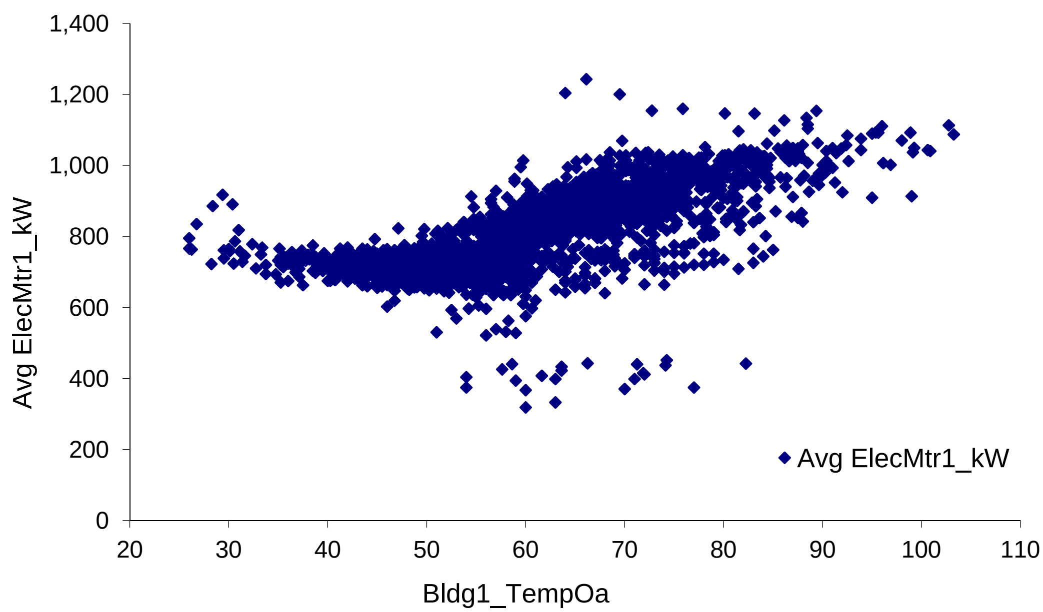
In Figure 3-19, we see two general "clouds" of data, although they are not as distinct here as for the daily average data. So, the first thing is to evaluate what categories explain the individual clouds. Figure 3-20 shows the data filtered so it is only showing weekdays.

Figure 3-20: Scatter Chart of Weekday Electrical Demand vs. Ambient Temperature, Using Hourly Data



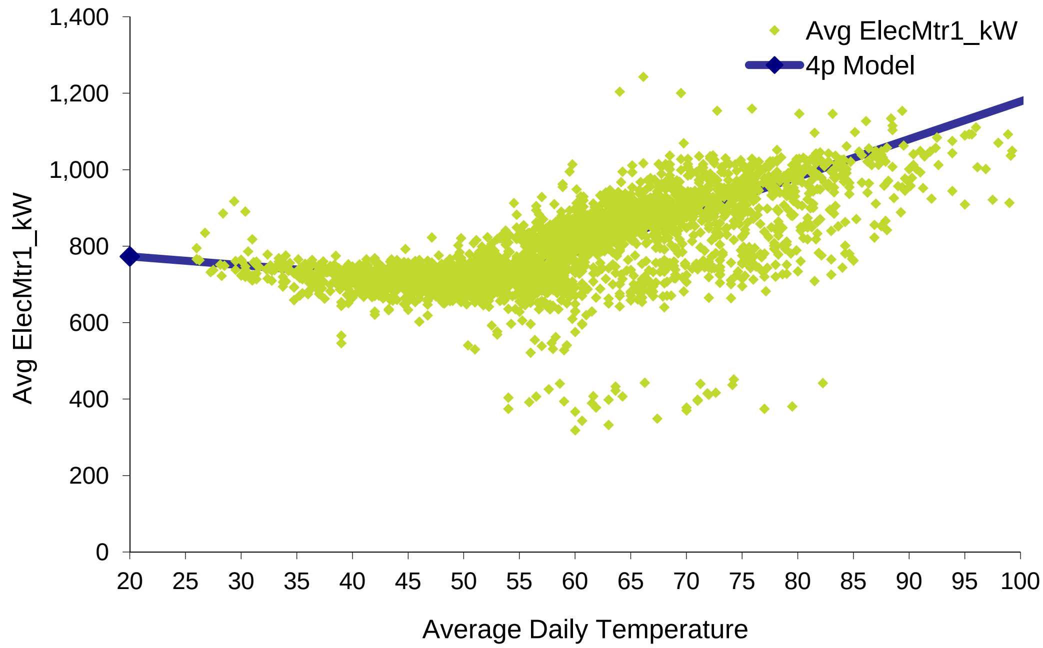
The clouds are still present, albeit a bit more distinct. Since that didn't explain things, we'll try plotting only the occupied hours, as shown in Figure 3-21.

Figure 3-21: Scatter Chart of Weekday Electrical Demand (kW) During Occupancy vs. Ambient Temperature, Using Hourly Data



The data still shows a lot of scatter. Figure 3-22 shows a 4P model based on the hourly data for the occupied period.

Figure 3-22: Scatter Chart of Weekday Electrical Demand (kW) During Occupancy vs. Ambient Temperature, Using Hourly Data



Here is the resulting equation:

- *=IF(T<51.48, 819.15+-2.294*T, 193.09+9.855*T)*

Here are the statistics for the regression:

R-squared:	0.47
CV-RMSE:	5.6%
Fractional Savings Uncertainty:	35.1%
Savings Range:	5.0% ±0.9%
Net Determination Bias:	0.000%

Note that the fractional savings uncertainty is higher than for the daily model. So, in this case, the daily model would provide a better estimate of baseline energy use for calculating savings.

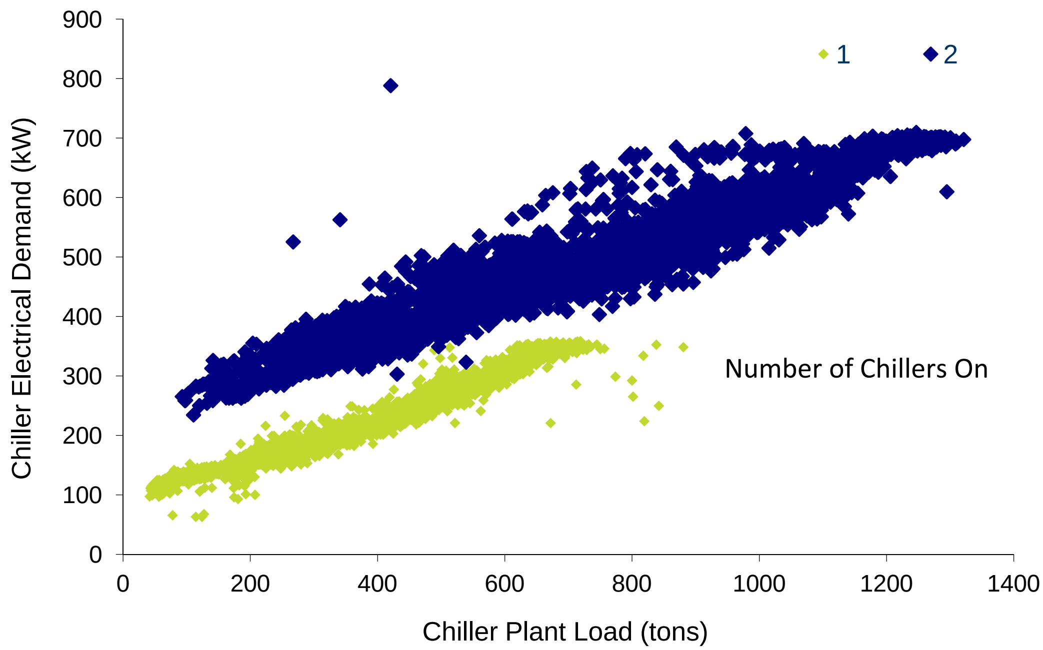
This is not surprising in this case: the models all included nearly a year of data. Therefore, there was a sufficient range of ambient temperatures to clearly define the change point and slopes for the daily model. If the data had been collected for a shorter time period, it is possible that the daily model might include points on only one side of the change point, but the hourly model has sufficient data to cover both sides of the change point. These are the types of considerations that go into determining whether a daily or hourly model should be used.

Other Categorical Variables

Practitioners should be aware that other categorical variables can be useful. Equipment status is obviously an important consideration. Related to this is the need to create separate models, depending upon which piece of equipment is on or how many pieces of equipment are on.

Figure 3-23 shows the chiller plant electrical demand versus load. There are two scatter clouds. Recall that separate clouds are an indicator that categorical variables should be considered. In this case, one cloud is for a single chiller operating and the second cloud is for two chillers running. Note the overlap in tonnage served by one or two chillers. There was an opportunity to change the chiller staging at this plant for improved efficiency.

Figure 3-23: Scatter Chart of Chiller Plant Electrical Demand (kW) vs. Plant Load (tons), Using Hourly Data



Combining Multiple Models into One Model

It may seem tedious to have all these separate models by category. However, they can be combined using *IF* statements, just as the change-point models use *IF* statements. For example, the *IF* statement could check for whether the time of day represents the occupied period; if so, it uses the equation created for the occupied model. If the time of day is part of the unoccupied period, another model is used. Note that the uncertainty is calculated for the individual category models.

4. Measurements and Monitoring

Application of these methods under an *IPMVP Option C (Whole Building)* or *Option B (Retrofit Isolation – All Parameter Measurement)* approach requires collection of extensive data sets. While energy models may be developed from monthly whole-building meter data, the utility of this methodology is derived from much shorter interval data, such as hourly or daily data. Short-interval data provides the opportunity to understand what the key independent variables are and how they influence energy use in a building. This chapter provides background information on the type and potential sources of energy and independent variable data that may be used to develop energy models.

4.1. Whole Building Energy Data

Most utilities have high-demand rate categories for their large commercial and industrial customers. Typically, these customers have over 200 kW in peak electric demand. For these customers, the utility provides a time-of-use meter and records the electric energy use or demand in 15-minute intervals, and provides the data back to the customer through a website. Buildings and facilities with high demand are generally large and have complicated HVAC, lighting, and control systems. These facilities have the most savings potential in large retrofit or retro-commissioning projects.

Many of these buildings have multiple electric meters. The data from these meters may be used to develop energy models if all the ECMs are downstream of one of the meters. Note that interactions between meters or impacts of the ECMs should be checked to assure that energy use on systems connected to other meters is not affected.

A building may be connected to a central or district plant that operates multiple electric chillers. Btu meters are commonly installed at the service entrance to a building. The Btu meters calculate instantaneous thermal energy use from measured flow, and entering and leaving chilled-water temperature difference. This data may be recorded by the Energy Management Control System (EMCS) or an alternate energy monitoring system. The amount of data varies, based on each building's particular system and storage capacity. A well-written document on metering technologies, communications, and data storage, is available.[13]

4.2. System Energy Data (Option B)

For large, multi-component systems, such as an industrial process, a chilled water system, or an air distribution system, multiple ECMs may be implemented and the total energy savings resulting from those improvements must be verified. Measurements of energy use for the entire

13 *Metering Best Practices, A Guide to Achieving Utility Resource Efficiency*, by Sullivan et al. for the Federal Energy Management Program (FEMP).

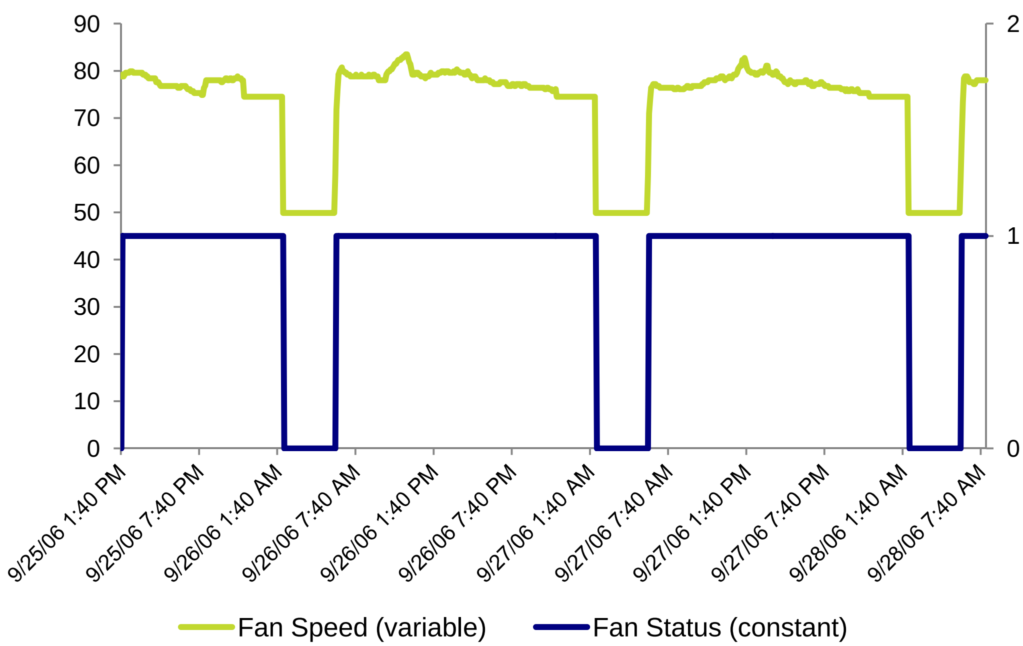
system may be required. However, energy-use meters that directly monitor the energy use of each component are limited. Some common equipment level data sources include:

- **Chiller electric energy**. Many chiller control panels are equipped to provide analog output signals of chiller demand or amps. These output signals may be recorded by the building's EMCS or independently installed data loggers.
- **Variable frequency drives (VFD) that modulate motor speed**. Analog output signals of motor and inverter wattage or amperage from the VFD can be monitored in an EMCS. The desired output can often be selected by dip switches or programming on the VFD. The VFD output signal readings should be checked against readings from a reliable watt or amperage meter.

Probably the most common sources of energy data are indirect. Equipment feedback status signals in a building's EMCS indicate whether equipment is on or at what percent load it is operating. Generally, constant-load equipment is monitored with digital or binary on/off status signals, while variable-load equipment is monitored by its variable speed, position, or load signal. These signals can be converted to energy use data with the aid of simultaneous power measurements from instruments and independently installed power loggers.

An example of a feedback signal for variable load equipment is the actual speed or output frequency of a VFD on a pump or fan motor, or the position of an inlet guide vane on an air handler fan. Figure 4-1 provides examples of both constant and variable speed feedback signals. These signals may serve as proxy variables for energy use if a relationship between the feedback signal and the equipment's energy use can be determined.

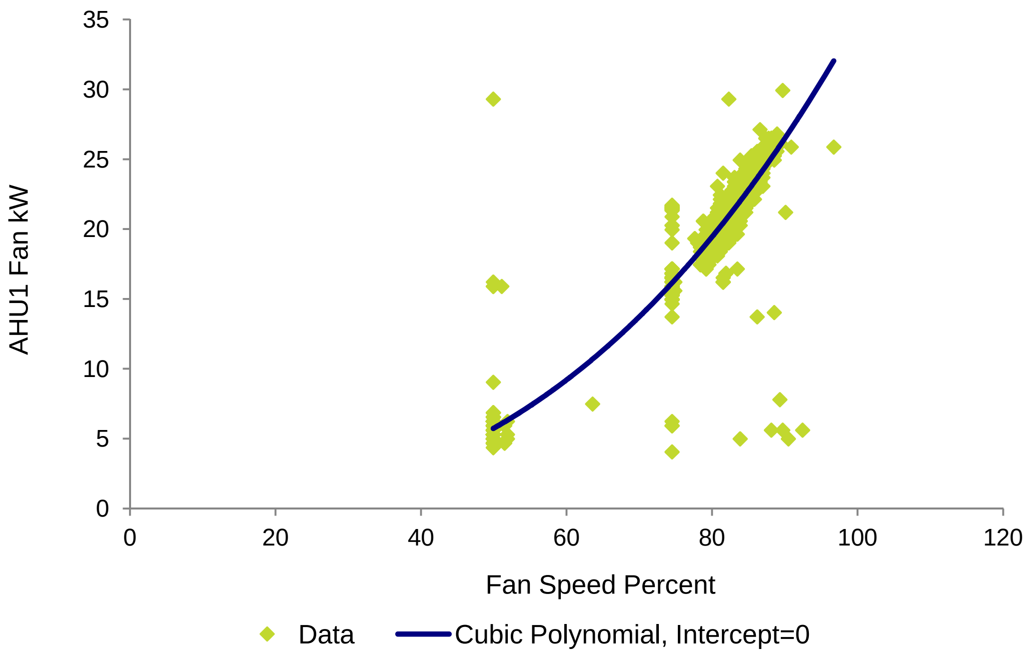
Figure 4-1: Fan Speed and Status of a Return Air Fan vs. Time



Constant load equipment feedback signals may be made into proxy energy variables by assigning the equipment power to it when it is operating. The equipment power may be determined from the average of multiple measurements of the equipment's power when operating.

Variable load equipment feedback signals may be made into proxy energy variables by developing a relationship between the feedback signal and the power at various loads, obtained by measurements. Multiple measurements may be made as the equipment is forced through its range of operation, or the feedback signal and power may be logged over a period of time to obtain the data. A regression technique may be used to develop the proxy energy variable relationship between the power and feedback signal. Figure 4-2 shows such a relationship between the VFD speed feedback signal and the fan power.

Figure 4-2: Variable Load Proxy Energy Variable Example



For a complete discussion of end-use monitoring associated with constant load and variable load equipment, refer to the BPA *Verification by Equipment or End-Use Metering Protocol*.[14]

4.3. Required Independent Variables and Sources

The primary independent variable data used to explain the variation in a building or system's energy use are the ambient conditions (usually dry-bulb temperature), building operation schedule, and building occupancy. Sometimes a building's internal heat and cooling loads are used when data is available. Some sources of this data are described in this section.

14 Hereinafter, *End-Use Metering Protocol.*

There are many sources of weather data available. Weather data from most airports around the United States is collected by the National Oceanographic and Atmospheric Administration (NOAA).[15] This data can be obtained through a subscription service at NOAA's website. Other websites provide weather data as well; an extensive directory can be found in the websites listed below. Some services require a subscription; others offer the data for free. Most of the information needed for energy models, such as ambient conditions (including dry-bulb temperatures and wet-bulb temperatures or relative humidity) is provided by these sources. Data intervals are usually hourly, but can be as frequent as five minutes. Generally over a year's worth of data is available, up to a few weeks behind the current date.

Weather data sources can be found at these websites:

- NOAA Satellite and Information Service: *National Climatic Data Center*
- GARD Analytics, Inc.: *Building Simulation Weather Data Resources*
- Weather Underground, Inc.: *WunderSearch*®

The building EMCS is a rich data source for independent variables. Often, ambient temperatures are trended and recorded in short time intervals. Equipment feedback status signals can verify the actual daily equipment operating schedule. Care should be taken to validate the data from the building EMCS. Poor sensor placement or poor calibration often plague EMCS ambient temperature sensor and relative humidity data.

Time series data come with date and time stamps, which may be used to establish building operation schedules. Using calendar functions, weekdays, weekends, and holidays may be identified. Flag variables may be set up to identify different hours of the day or days of the week. These flags may be used to separate the energy data into operating and non-operating periods for separate energy modeling analysis. A useful spreadsheet add-in tool that helps develop these variables is described in Chapter 7, *Software Tools to Assist with Energy Modeling*.

4.4. EMCS as a Source of Data

An EMCS' capability to trend and store data varies widely, depending on the manufacturer, vintage, and installed capabilities of the system. Users are well aware that establishing trends and recovering the data on many EMCS can be a very cumbersome process, often requiring a controls technician familiar with the system. Trends are seldom stored in a format that is accessible without use of proprietary software. There may also be data storage limits to a system's trending capability, requiring frequent downloading of data before the trend file is halted, reset, or overwritten. Establishing many trend functions may slow down the EMCS' ability to perform its prime function. While use of trended EMCS data is a rich source, these real limits often hinder the effort for M&V purposes.

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15 NOAA Satellite and Information Service *National Climatic Data Center* website.

More recently manufactured EMCS are responding to the market's need for more trending capability, more storage capability, and easier access to the data. An EMCS not only provides valuable data, it may also serve as a tracking system to help maintain good energy performance.

4.5. Temperature Data

Temperature is frequently the independent variable in energy models. When available, temperature data from the site may be used. However, site temperature data should be not be used blindly, without consideration of its accuracy and suitability. Here are some common issues and considerations in the use of site temperature data:

- Site temperature measurements may be higher than the actual air temperature at the measurement device, due to inadequate solar shielding.
- Site temperatures on roofs may be correct, but higher than ambient air temperatures around the building.
- Site temperatures may be taken inside air handler unit (AHU) outside air intakes. They may give good readings when the AHU fan is running, but when off, damper leakage may allow interior air to exit through the air intake, biasing the reading.

These situations may be able to be evaluated by inspection of the data or by comparison of the site data with data from the nearest national weather station.

In the first situation, the weather station data may be able to be substituted for the site data, or used to identify spikes in the site data due to solar effects, which may then be reduced to a more reasonable value. Alternatively, it may be possible to filter out the times or days with such spikes. Note that the effect of any of these changes on the uncertainty in the model will not be known.

In the second situation, the choice of whether to use site data or national weather station data may be dependent upon the measures being evaluated, and/or upon the measurement boundary. Upon which temperature are the building loads and resultant electrical demand most dependent? This is really just like the typical situation where the most important independent variable needs to be selected. If the measurement boundary is around the whole building, then perhaps the weather station data should be used, especially if the outside air intakes are on the sides of the building. However, if the building uses 100% outside air, and the outside air intakes are on the roof, then it might be more appropriate to use the site temperature data.

Handling the third situation involves the same considerations as the first two. If the AHU is seldom off or the M&V calculations are most important for times when the fan is on, then site data may be appropriate. However, if the off times are significant and the M&V includes times when the fan is off, then the weather station data may be more appropriate.

In nearly all cases, the site weather data should be cross-checked with the nearest weather station data to make sure it is reasonable.

5. Uncertainty

Uncertainty is associated with a given confidence level. The confidence level is the stated range that includes the true value, such as "we are 90% confident that the range 433 to 511 includes the true value." This chapter of the protocol describes the accepted methods of estimating uncertainty in energy models and savings estimates, and the limitations of those methods.

The calculation of uncertainty in the calculation of savings using energy models is complex. Assuming that the model uses the appropriate independent variables and is of the appropriate form, the two key sources of uncertainty are:

- Measurement uncertainty
- Regression uncertainty

Of these, regression uncertainty is of more consistent concern. However, there are certain types of measurements that can be challenging, even disregarding any instrumentation uncertainty. Temperature measurement was discussed in Chapter 3. Flow measurements, for when flow is used as an independent variable, can also be challenging. In general, the measurement issues are generally with the independent variables more than with the measurement of energy. Indeed, when revenue-grade meters are used for the measurement of energy, the measurement uncertainty is assumed to be zero.

There are at least two main sources of savings uncertainty associated with regressions:

- **There is uncertainty in the regression**. Associated with this are uncertainty in the coefficients and uncertainty in extrapolation beyond the range of values covered by the independent variables.
- **Regression assumes there is no uncertainty in the independent variable**. As previously discussed, this is typically not true for energy regressions. However, we believe that this is a minor consideration and it will typically be at least partially accounted for in the uncertainty of the regression.

Note that for savings estimates normalized to fixed conditions, these uncertainties occur in both the baseline and the post-period regression.

5.1. Current Status of Uncertainty Calculations

The best treatment of uncertainty in energy regressions is probably in *ASHRAE Guideline 14-2002, Annex B: Determination of Savings Uncertainty*. In *Annex B*, the basis for calculating uncertainty is provided, and its sources and treatment are described. Identifying sources of uncertainty, and quantifying and propagating them in savings calculations, is often viewed by energy engineers as a cumbersome process with little reward or justification.

In *Annex B*, a streamlined approach that enables the analyst to gain a reasonable estimate of uncertainty that can both help select an appropriate M&V approach and enable savings to be stated within confidence bounds is described. For more detailed discussion on the definition of uncertainty, description of uncertainty sources, and development of uncertainty formulae, the reader is referred to *Annex B* of *ASHRAE Guideline 14-2002*.

For a broader discussion of uncertainty concepts within the BPA M&V protocol documents, refer to the *Regression Reference Guide*. Further information on the source of some of the uncertainty formulae can be found in the documents from the following resources:

- Reddy, T., and D. Claridge. 2000. "Uncertainty of Measured Energy Savings from Statistical Baseline Models." *International Journal of HVAC&R Research*.
- Kissock, J., J. Haberl, and D. Claridge. 2004. *Inverse Modeling Toolkit: Numerical Algorithms*. (ASHRAE RP-1050).

5.2. Determining Model Sufficiency

This section focuses on the concept of *fractional savings uncertainty*, as described in *ASHRAE Guideline 14, Annex B*. The key approach to understanding whether the model is sufficient is to evaluate the fractional savings uncertainty, which is the *uncertainty divided by the savings*. During the baseline period, this is based on expected savings; during the post period, actual estimated savings can be used.

Intuitively, the smaller the fractional savings uncertainty, the better – more precise – the savings estimate. ASHRAE guidelines are that the level of uncertainty must be less than 50% of the annual reported savings, at a confidence level of 68%. This is the same as a fractional savings uncertainty less than 0.5 at the 68% confidence level. This is a pretty modest requirement, since it uses quite a low confidence level. Specific projects or programs may require different precision and confidence.

Fractional savings uncertainty is defined as:

- **Fractional Savings Uncertainty**: $\Delta Esave,m \,/\, Esave,m$

  where: $Esave,m$ = total savings over m periods

  $\Delta Esave,m$ = the uncertainty in the total savings over the same time period

Following are relationships among energy model parameters that may be used to determine the fractional savings uncertainty.

5.2.1. Weather Models with Uncorrelated Residuals

Weather models with uncorrelated residuals are models where each point does not have a relationship with the previous point, just a relationship with the independent variable. For these types of models, the equation is:

- $$\frac{\Delta E_{save,m}}{E_{save,m}} = t \cdot \frac{1.26 \cdot CV\left[\left(1+\frac{2}{n}\right)\frac{1}{m}\right]^{1/2}}{F}$$

where: CV = the coefficient of variation of the root mean squared error *CV(RMSE)*

- $$CV(RMSE) = 100 * \frac{\left[\sum_i (E_i - \hat{E}_i)^2 \Big/ (n-p)\right]^{1/2}}{\overline{E}}$$

where: F = Savings fraction=$E_{save}/E_{baseline}$

t = Student's t-statistic

$( )_i$ = measured value

$(\hat{})_i$ = predicted value

$(\_)_i$ = average value

n = number of points in the baseline period

m = number of points in the post period

p = the number of model parameters

The *t-statistic* is evaluated at the desired confidence level. The numerator of the fractional savings uncertainty is the width of the confidence interval at the confidence level for which the *t-statistic* was evaluated. See the BPA *Regression Reference Guide* for further discussion of the *t-statistic* and *CV(RMSE)*.

5.2.2. Weather Models with Correlated Residuals

*Weather models with correlated residual*s are models where each point has a relationship with the points associated with recent prior timestamps. There is the potential for correlated residuals (known as time-series autocorrelation) when the time unit is short, such as with hourly models. There can also be autocorrelation with daily models.

For models with correlated residuals, the equation is just slightly different:

- $$\frac{\Delta E_{save,m}}{E_{save,m}} = t \cdot \frac{1.26 \cdot CV\left[\frac{n}{n'}\left(1+\frac{2}{n'}\right)\frac{1}{m}\right]^{1/2}}{F}$$

where: n' = the effective number of points after accounting for autocorrelation

- $n' = n \cdot \frac{1-\rho}{1+\rho}$

where: r = the autocorrelation coefficient
(the square root of the R^2 calculated for the correlation between the residuals and the residuals for the prior time period)

Using the equations above, the CV necessary to achieve a required fractional savings uncertainty can be estimated if the required confidence level, expected savings percentage, and number of pre-and post data points are known. The following tables provide the required CV times the expected savings fraction and the required fractional savings uncertainty. These are approximate values based on the specified number of monitored data points.

In the following tables:

CV = CV(RMSE)

F = expected savings fraction

FSU = fractional savings uncertainty

rho = autocorrelation coefficient

n = number of baseline points

m = number of post-implementation points

Table 5-1 shows the maximum allowable *CV*F/FSU* to meet the required confidence level for daily data, with at least 12 months of data in the baseline period. Table 5-2 shows the maximum allowable *CV*F/FSU* for daily data, with at least 30 days of data in the baseline period. Table 5-3 shows the maximum allowable *CV*F/FSU* for hourly data, with at least 168 hours (7 days) of data in the baseline period.

Table 5-1: Maximum Acceptable CV*F/FSU vs. Confidence Level, Autocorrelation Coefficient, and Quantity of Post-Period Data, for Monthly Data

Maximum Allowed CV * F / FSU		M				
Confidence Level	rho	2	4	6	8	12
68%	0.00	0.010	0.014	0.017	0.020	0.024
80%	0.00	0.008	0.011	0.013	0.015	0.019
90%	0.00	0.006	0.008	0.010	0.011	0.014
95%	0.00	0.005	0.007	0.008	0.009	0.011

Table 5-2: Maximum Acceptable CV*F/FSU vs. Confidence Level, Autocorrelation Coefficient, and Quantity of Post-Period Data, for Daily Data

Maximum Allowed CV * F / FSU		M				
Confidence Level	rho	336	720	1440	4380	8760
68%	0.00	0.043	0.061	0.075	0.106	0.152
	0.25	0.033	0.047	0.058	0.082	0.117
	0.50	0.024	0.035	0.043	0.061	0.087
	0.75	0.015	0.022	0.027	0.039	0.056
80%	0.00	0.033	0.047	0.058	0.083	0.118
	0.25	0.025	0.036	0.045	0.064	0.091
	0.50	0.019	0.027	0.033	0.047	0.068
	0.75	0.012	0.017	0.021	0.030	0.044
90%	0.00	0.026	0.037	0.045	0.064	0.092
	0.25	0.020	0.028	0.035	0.050	0.071
	0.50	0.014	0.021	0.026	0.037	0.053
	0.75	0.009	0.013	0.016	0.024	0.034
95%	0.00	0.021	0.031	0.038	0.054	0.077
	0.25	0.017	0.024	0.029	0.042	0.059
	0.50	0.012	0.017	0.022	0.031	0.044
	0.75	0.008	0.011	0.014	0.020	0.029

Table 5-3: Maximum Acceptable CV*F/FSU vs. Confidence Level, Autocorrelation Coefficient, and Quantity of Post Period Data, for Hourly Data

Maximum Allowed CV * F / FSU		M				
Confidence Level	rho	336	720	1440	4380	8760
68%	0.00	0.113	0.166	0.234	0.409	0.578
	0.25	0.084	0.123	0.175	0.305	0.431
	0.50	0.055	0.080	0.114	0.199	0.282
	0.75	0.088	0.128	0.182	0.317	0.449
80%	0.00	0.065	0.096	0.136	0.236	0.335
	0.25	0.042	0.062	0.089	0.155	0.219
	0.50	0.068	0.100	0.142	0.247	0.350
	0.75	0.051	0.075	0.106	0.184	0.261

Continued

Maximum Allowed CV * F / FSU		M				
Confidence Level	**rho**	**336**	**720**	**1440**	**4380**	**8760**
90%	0.00	0.033	0.049	0.069	0.121	0.171
	0.25	0.057	0.084	0.119	0.207	0.293
	0.50	0.043	0.063	0.089	0.155	0.219
	0.75	0.028	0.041	0.058	0.101	0.143
95%	0.00	0.113	0.166	0.234	0.409	0.578
	0.25	0.084	0.123	0.175	0.305	0.431
	0.50	0.055	0.080	0.114	0.199	0.282
	0.75	0.088	0.128	0.182	0.317	0.449

5.3. Issues with Current Status of Uncertainty Calculations

5.3.1. Extrapolation

The most significant issue regarding uncertainty of savings using energy models is probably extrapolation. For simple linear regression, there are clear equations from classical statistics that address the regression uncertainty, including the increased uncertainty toward the extremes of the independent variables used for the regression. However, the equations used for fractional savings uncertainty are simplifications and provide a constant uncertainty over the range of independent variables. Therefore, when extrapolating, those equations can significantly underestimate the uncertainty, even if the model form is correct.

The best approach is to use fractional savings uncertainty during the baseline time period and make sure that the model includes at least some data for the full range of the independent variable(s) to minimize the need for extrapolation when projecting the baseline to the post conditions. If the baseline model does not include the full range of the independent variable(s), the uncertainty will be underestimated.

An alternate approach is to treat each segment of the change-point model as a simple regression and use the complete calculation for uncertainty using the confidence or prediction intervals associated with the desired confidence level. Then, the uncertainty will increase toward the extremes of the independent variable and beyond, allowing the uncertainty in extrapolation to increase.

5.3.2. Model Form and Extrapolation

Note that the model form must still be correct for the extrapolated region. If not, then the extrapolation will not be correct. For a model with ambient temperature as the independent variable, one case where the model form would not be correct in the extrapolated region is if the HVAC cooling runs out of capacity at high temperatures and the model did not cover those high temperatures. In this case, the slope of the model should get flatter at the high temperatures, but the model wouldn't show it, thereby overestimating energy use and demand at those conditions.

A common issue associated with extrapolation may be neglecting the change in cooling slope associated with economizer operation. In this case, if the temperature range did not cover the high temperatures and all the data above the cooling change point was at the same slope (no slope change associated with the economizer), the slope would be too high for the upper range of the data and projections of energy use at higher temperatures would be too high. Figure 5-1 illustrates what happens when extrapolating with an incomplete range of temperature data, using real data, but with the data above 80º F removed; the chart shows a 4P regression using all the data above 55º F. The results of a linear 2P regression are included on the chart as the red line. Note that the results for the two regressions are fairly close over most of the range, but deviate a bit more at the warmest temperatures. The 4P model predicts the demand at 90ºF to be 1,636 kW, and the 2P model predicts it to be 5% higher, at 1,713 kW.

Figure 5-1: Comparison of 2P and 4P Models of Electrical Demand (kW) vs. Ambient Temperature, Using a Full Year of Data

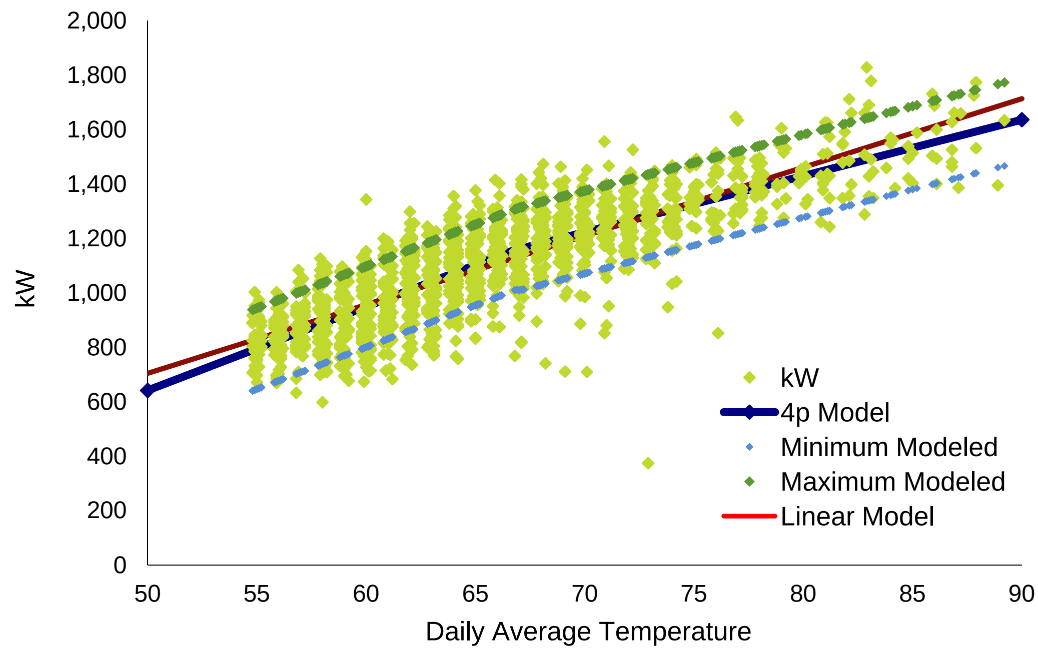
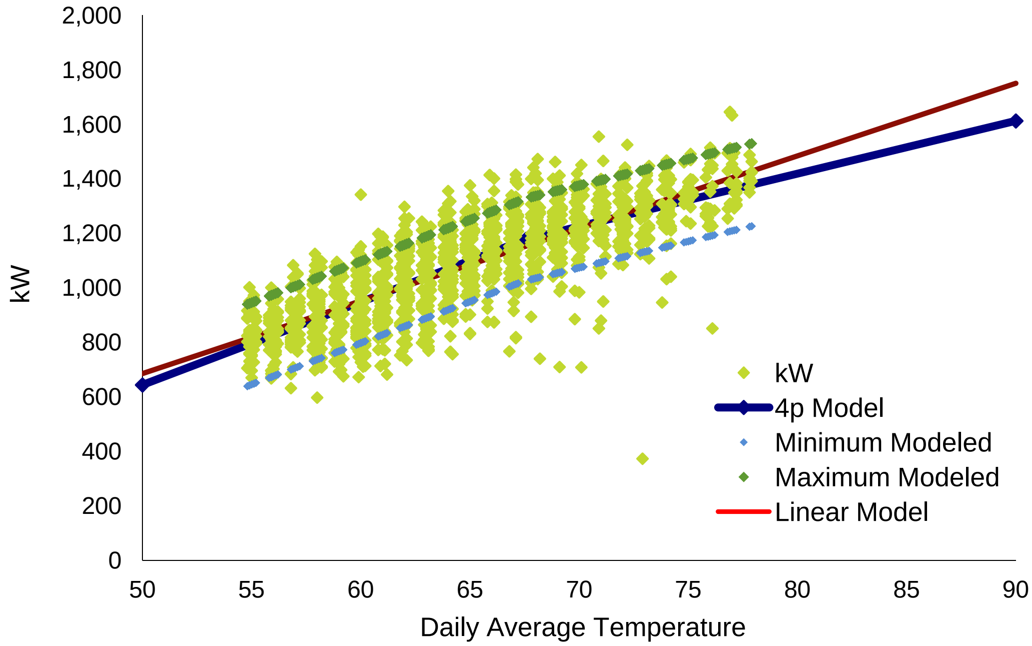


Figure 5-2 shows what happens without the full range of data. In this case, the data above 78º F have been taken out of the data set. The change point was calculated to be the same value, 67º F, but there is a difference in expected electrical demand at 90º F between the 2P and 4P models. The 4P model projects the electrical demand to be 1,613 kW, which is close (within 1.4%) to the value predicted using a 4P model with all the data, 1,636 kW. However, the 2P model now predicts the electrical demand to be 1,750 kW, 9% higher than the corresponding value for the 4P model, and 7% higher than the value obtained by a 4P model using all the data.

Figure 5-2: Comparison of 2P and 4P Models of Electrical Demand vs. Ambient Temperature, Using Less Than a Full Year of Data



In this case, there was only a minor difference in slope between the economizer regime and the regime with only mechanical cooling. This effect would be more significant where the slope change is greater.

5.4. Uncertainty in Reporting Period Savings (Avoided Energy Use type of savings)

If the baseline model includes the full range of the independent variable, the uncertainty in the reporting period savings will be the same as the uncertainty in the baseline model. This assumes there is no measurement uncertainty in the post period, such as when the energy data comes from a revenue-grade utility meter.

The savings, with uncertainty, would be expressed as:

- *Esave,m ± ΔEsave,m ÷ 2*

Since *ΔEsave,m* comes from the fractional savings uncertainty, which in turn requires an input *t-statistic*, which is based on the input confidence level, it has all the components needed for a complete statement of the precision and confidence of the savings estimate. If the *t-statistic* was evaluated at the 90% confidence level, then savings would be stated as:

- *Savings = Esave,m ± ΔEsave,m ÷ 2*, at the 90% confidence level

5.5. Uncertainty in Annual Models

As described in Section 5.3, the uncertainty in annual models, based on data that covers less than one year, will be underestimated using the fractional savings uncertainty if the full range that the independent variable would see is not covered in the dataset used for the model. A better result may be obtained by using the equations for prediction intervals described in the BPA *Regression Reference Guide*; but since this would be based on extrapolation, it is unknown how much better it would be.

5.6. Uncertainty in Annual Savings (Normalized Savings)

Normalized savings uses two models – baseline and post – that are both adjusted to fixed conditions. If both models cover the full range of the independent variable and extrapolation uncertainty can be ignored, then the uncertainty can just be calculated by *quadrature*, which means that the uncertainty components are combined by root-sum-squares. In this case, the uncertainty components are the uncertainty in the baseline energy use projected to the fixed conditions and the uncertainty in the post-period energy use projected to the fixed conditions:

- $(\Delta Esave)^2 = (\Delta Ebase)^2 + (\Delta Epost)^2)$

Assuming, again, that the *t-statistic* was for the 90% confidence level, then:

- $Annual\ Savings = Esave \pm sqrt((\Delta Ebase)^2 + (\Delta Epost)^2))$

6. Minimum Reporting Requirements

6.1. Measurement and Verification Plan

6.1.1. Essential Elements of the Measurement and Verification Plan

Proper savings verification requires planning and preparation. The IPMVP lists several requirements for a fully adherent M&V plan.[16] The previous sections in this *Energy Modeling Protocol* describe methods to verify savings in equipment and end uses. They also describe planning requirements in the baseline period, as well as specific measurement and analysis activities in the baseline and in the post-installation periods. Documenting in an M&V Plan how these requirements will be met is important so that others who subsequently become involved in the project can get a full understanding of the project's history and progress. The following are the essential items in documenting a Savings Verification Plan:

- **Measurement Boundary:** Define the measurement boundary to encompass the building or system within which the savings will be verified. This boundary can be a whole building, all equipment connected to one of multiple meters in a building, systems connected to a building submeter, or a specific system within the building. Systems may be defined as one of the major energy-consuming systems within the building, or by their function (i.e., air handling or chilled water system). In industrial applications, systems may also be defined by their process.
- **Baseline Equipment and Conditions:** Document the baseline systems, equipment configurations, and operational characteristics of the building or facility. This includes equipment inventories, sizes, types, and condition. Describe any significant problems with the equipment.
- **Energy and Independent Variable Data:** Identify the independent variables to be used in the analysis. Describe the sources of the energy and independent variable data, and the time interval at which they are monitored. Describe any needed corrections to the data. Define the duration of monitoring for both the baseline and post-installation periods. Define what analysis time interval (i.e., hourly or daily) will be used.
- **Reporting Period:** Describe the length of the reporting period and the activities that will be conducted, including data collection and sources.
- **Analysis Procedure:** Describe how the baseline and post-installation energy use or demand will be adjusted to a common set of conditions. Describe the procedures used to prepare the data. Describe the procedures used for analyzing the data and determining savings. Describe any extrapolations of energy use or savings beyond the reporting period. Describe how savings uncertainty (if required) will be estimated. Document all assumptions.

[16] *Chapter 5, IPMVP Volume I – 2010.*

- **Option A Requirements:** For each non-key parameter, specify the basis for the estimated values used. Describe their source or sources. Describe the impact of any significant variation in the values used and what otherwise would be measured on the calculated savings.
- **Savings Verification Reports:** Describe what results will be included in the savings reports. Describe what data and calculations will be provided. Describe when savings will be reported for the project. Indicate the reporting format to be used. See the section below regarding the *Savings Verification* Report for the minimum requirements.

6.1.2. M&V Plan Additional Elements

The IPMVP describes several other elements of a good M&V plan. These items are good practice in general, but not necessary for every project. Many of them are provided here for reference and consideration for inclusion in M&V Plans written under this application guide.

- **Energy Prices:** Document the relevant energy prices to be used to value the savings. This can be a blended electric rate or a schedule of rates based on time-of-use. Note that the latter will add significant complexity to the calculations.
- **Measurement Instrument Specifications:** Document the instruments used to obtain the data used in the calculations, including their rated accuracy and range. Identify the last instrument calibration date.
- **Budget:** Estimate the budget required for the savings verification activity. Estimate labor and material (e.g., meters and instruments, associated safety equipment, etc.) costs and provide an approximate schedule for when activities will occur.
- **Quality Assurance:** Describe any quality assurance activities that will be conducted as part of this M&V project. This may include how data is validated, how *IPMVP Option A* estimates are checked, identifying other parties who will review the work, and so on.

6.1.3. Documentation for BPA Database

The documentation should also include the following information to support review and inclusion of the project and measure in the BPA *Energy Efficiency Central* database (*EE Central*):

- Utility name
- Utility program
- Sector (commercial/industrial/residential)
- Existing building or new construction
- Site address (this will be used to establish the climate zone)
- Building type (examples: office, school, hospital)
- Building size, square feet

- Affected end uses (examples: HVAC, interior lights, exterior lights, receptacle plugs, DHW)
- Affected system (examples under HVAC: cooling plant, heating plant, HVAC fans, terminal units, controls)
- Affected equipment type (examples under cooling plant: chiller, packaged unit, cooling tower, pumps)
- Measure type (broad category)
- Measure name (specific category)

6.2. Savings Verification Report

6.2.1. General Verification Report Requirements Based on IPMVP

After the M&V calculations have been completed, the savings and actual M&V process used need to be documented.

Per the IPMVP, the Savings Verification Report should follow the savings verification report requirements described in the project's M&V Plan. Any deviations from the M&V Plan must be clearly described. If the M&V method followed the M&V Plan, then the information in the M&V Plan does not need to be repeated, but can just reference the plan. However, deviations from the planned method, measurement boundary, baseline characteristics, etc. necessitate new descriptions.

IPMVP Chapter 6, M&V Reporting, generally requires the following:

- Report both energy and cost savings.
- Report the data relevant to the reporting period, including the measurement period and the associated energy data and independent variables. Any changes to the observed data must be described and justified.
- Describe any non-routine baseline adjustments, including the details of how the adjustments were calculated.
- Report the energy prices or rates used in the cost-savings calculations.

In addition, actual data for baseline and post-period energy use should both be reported.

6.2.2. Additional Savings Verification Report Requirements

Load and Schedule Relationships

In the basic procedure for the BPA *End-Use Metering Protocol*, one of the numbered items states, "Determine the relationships between load and hours-of-use terms in the energy savings equation and other parameters, such as temperature, air or water flow, pressure, and so on." This includes the relationships of daytypes and seasons to load and hours-of-use.

These relationships are important for all protocols, not just the *End-Use Metering Protocol*. In general, if the power or energy varies with respect to ambient temperature or another independent variable, then a relationship (e.g., regression) must be developed. Schedule variations require similar considerations.

The energy modeling protocol is obviously built on these relationships, and energy indexing uses the ratio between energy and some independent driving variable – another relationship. Similarly, spreadsheet-based engineering calculations should use relationships (also described as correlations) to describe the load.

The savings verification report should clearly define loads and schedules, and their relationship to other variables:

- ➡ **For a constant load**, the load value and units should be provided, as well as how the load value was obtained. If any proxies are used to define the load, the proxies should be justified and their development described.
- ➡ **For variable load**, the load frequency distribution should be provided, along with a description of how it was obtained. For loads that can be any value, they should generally be grouped into 5 to 10 bins, but this is dependent upon how much the load varies. For example, if the load varies from 0% to 100%, 10 bins might be appropriate, but if the load only varies from 80% to 100%, then 2 to 4 bins might be appropriate.
- ➡ **For a timed schedule**, report the source for the schedule and the total annual hours.
- ➡ **For a variable schedule**, report the source for the estimate of the hours during the measurement period and the total annual hours.

Variable load information, energy models, and load correlations for engineering calculations are all similar and should be shown graphically in an x-y (scatter chart), as well as an equation or table. Load frequency distributions should be shown in both a bar chart and a table.

Savings Verification Report Information

The report should include the following information. It may be organized in this order with a separate section for each of these items, or in another order or organization that makes sense for a particular program or project. However it is reported, all of this information should be included in most cases:

1. The data for the baseline period, including the time period, monitoring intervals, and data points should be described.
2. The load and schedule for the baseline period, and any relationships associated with variable loads or schedules, should be clearly defined.
3. The impact of the ECM on the load or hours-of-use in the reporting period should be described.
4. The data for the reporting period, including the time period, monitoring intervals, and data points should be described.

5. The load and schedule, and any relationships associated with variable loads or schedules, should be clearly defined for the reporting period.

6. The equations used to estimate baseline consumption, reporting period consumption, and savings should be listed and explained.

7. Report consumption (and where relevant, demand), as well as savings, since this facilitates review and reasonableness checks.

8. As required by IPMVP, report the energy prices or rates used in the cost savings calculations.

9. Also, as required by IPMVP, report both energy and cost savings.

10. Provide verification of potential to generate savings.

Post Installation Verification of Potential to Generate Savings

IPMVP Section 4.3 requires that, "After the ECM is installed, inspect the installed equipment and revised operating procedures to ensure that they conform to the design intent of the ECM." Therefore, an IPMVP-adherent process requires evidence that the efficiency measures have the potential to generate savings. BPA may require short-term monitoring, spot measurements, production data, or other forms of verification to confirm potential.

Verification includes notation of any changes to the project subsequent to the M&V plan. If the project changed, the energy and demand savings should be recalculated based on as-installed conditions. Data and analysis from metering performed before or after installation should be included with the calculations.

In general, verification of potential to generate savings can take either of two forms:

- Installation verification
- Operational verification

Installation Verification

Installation verification is the less rigorous of the two verification methods. It demonstrates the measures were installed as planned. This demonstration may vary by measure. Project developers are required to describe the evidence and documentation they plan to provide to demonstrate that the measures were installed, and this evidence and documentation belongs in the savings verification report.

Examples of installation verification include:

- Photographs of new equipment
- Photographs of new control set-points
- Screen captures from EMCS

- Invoices from service contractors (invoices should not be the sole form of evidence, but may supplement other verification documentation).

Operational Verification

Operational verification demonstrates that in the post-installation period, the system is operating (or not operating) as modeled in the calculations. It is based on visualization of *operational* data (as opposed to *energy* data) collected during one or more site visits after the measures have been installed.

Operational verification is in addition to installation verification and documentation should include the same types of evidence as for installation verification. In addition, the data logging, control system trending, or functional tests used to establish baseline shall be repeated to demonstrate that operations have been improved. Documentation of the commissioning of the new systems or equipment can be used for operational verification.

If the collected post-installation data, test results, and/or commissioning indicate less than predicted performance, or that the measures were not installed as assumed in the savings calculations (for example, due to incorrect or partial installation, or other circumstance), either:

- Take action to help the customer fully install the measure properly and then re-verify it using these procedures; or
- Use the same calculation methodology with the post-installation data to calculate a revised measure savings estimate.

Choice of Verification Method

Common, well-known measures, measures with low expected savings, and measures whose savings estimates have considerable certainty, may need only installation verification. Measures with large savings and measures with less certain savings (whose savings can vary greatly dependent upon application) typically require operational verification.

Thus, there is no hard-and-fast rule for this choice. The analyst should recommend a verification method and the evidence expected to be presented for verification when submitting calculations or simulations. The final choice of verification method and evidence will be made by the reviewer.

7. Software Tools to Assist with Energy Modeling

7.1. Introduction

This chapter reviews several common software tools for energy modeling, including freeware tools. The analyst is referred to the appropriate websites for additional information about particular features and how to obtain the application. This chapter focuses on those features that support energy model using the method presented in this protocol. It represents a professional assessment of these tools, but does not endorse any particular commercial products.

As discussed in Section 2.4, *Disadvantages of this Protocol*, a significant challenge in developing energy models from short-interval data for M&V is that there is no single tool that provides all of the needed capabilities. Fortunately, most of the work can be expedited by using several tools synergistically.

As described in Section 3.1, *Basic Procedure*, the modeling and regression process includes these steps:

1. Identify all independent variables.
2. Collect datasets.
3. Synchronize the data (if necessary).
4. Chart the data.
5. Select and develop a model.
6. Validate the model.

Software tools can assist with Steps 3 through 6.

For M&V, there are additional steps needed:

1. Combine multiple sub-models (one per category) into an overall model.
2. Project the baseline model to the post conditions or projection of baseline and post models to the fixed conditions.
3. Calculate savings.
4. Extrapolate reported period savings, when less than a year, to annual savings.
5. Estimate the uncertainty in the savings.

Software tools are also needed for these steps. The following sections discuss those tools that are useful in this process.

7.2. ECAM

The *Energy Charting and Metrics* (ECAM) *Tool* is a freeware spreadsheet tool that runs in *Excel* 2003, 2007, and 2010. It is distributed by the California Commissioning Collaborative through its website. At the time of the publishing of this protocol, the website still has Version 1.0 of ECAM. Version 2.0 is complete and should be on the website in the fall of 2011. Some of the features described below are only available in Version 2.

ECAM is a flexible tool designed for, as its name implies, charting energy data and creating metrics for performance tracking. It is particularly useful in categorizing, synchronizing, and charting the data (Steps 1, 3, and 4 in the modeling process).

7.2.1. Significant Features for Energy Modeling

ECAM has numerous features that support energy modeling. The program makes it easy to aggregate data across time to get hourly or daily energy-use totals or averages, and average temperatures or degree-days. It does require that the user start with consistent time interval data of shorter intervals that can be aggregated to hourly or daily.

One of the important modeling steps is to chart the data. ECAM makes it very easy to chart energy data in a variety of forms. The most important chart for modeling is the *x-y* or *scatter* chart. ECAM automates the creation of scatter charts, segmenting the data by occupancy or pre- and post-dates. Furthermore, since ECAM automatically recognizes different daytypes, the data can be easily segmented by daytype as well. Since the charts automatically update when filtered by these various categorical variables, or the data plotted separately by category, users can quickly ascertain which continuous and categorical variables appear important. This is a start to developing and validating the model(s).

The inclusion of the load duration charts facilitates the extrapolation of monitoring periods of less than one year to annual energy use or savings. Note that this feature is also very useful when following the BPA *End-Use Metering Protocol*.

For interval meter data, ECAM includes a very useful utility to transform the data as it often comes from utilities – a tabular format with the date down the rows and times across columns – into a list of time series data needed for further processing and charting.

Another feature is the support for proxy variables. ECAM also automatically creates the additional fields, based on available point types, shown in Table 7-1.

In addition to these points that are created automatically, users can create their own calculated point and have them available with all the other ECAM features.

Since ECAM is *Excel*-based, all of the normal *Excel* functions for regression and statistics are available. If only simple linear or polynomial models are needed, ECAM can provide most of the necessary capabilities for energy modeling.

A future version of ECAM will likely include change-point modeling capabilities and possibly additional capabilities for data resampling and synchronization, but these capabilities are not present in Version 2.

Table 7-1: Fields Created Automatically by ECAM, Based on Available Data

Field	Data Source
Equipment Status	Demand (kW) or current (amps) when status point is not available
Demand (kW)	Current (amps) as an approximate calculation when a power point is not available
Chilled water tons	A consistent set of flows and temperatures, whenever they are available
Watts per square foot	All electrical demand points that are available whenever a building square footage is entered
CFM per square foot	All airflow points that are available whenever a building square footage is entered
kW per ton	All related points
GPM per ton	All related points

7.3. Universal Translator

The *Universal Translator* (UT) is a free application designed for the management and analysis of data from loggers and trend data from building management systems. UT seamlessly handles large quantities of data since it is based on the desktop version of *Microsoft SQL Server*. The application is distributed through the UTOnline.org website.

7.3.1. Significant Features for Energy Modeling

UT is a premier tool for resampling data to synchronize time stamps. It is capable of taking multiple files, from multiple sources, with different time intervals, and synchronizing the time stamps and data through interpolation. It also provides the capability to adjust for calibration issues. If you have significant quantities of data that needs to be synchronized, UT makes it painless.

UT also facilitates charting, creating standard time-series and scatter charts. There is an excellent capability to zoom into time series charts. UT also makes it easy to add and subtract points from a chart. Users can create data filters and schedules, and can create calculated points. While the UT doesn't provide a load duration table and chart, it does provide a runtime analysis, which can provide some of the same capabilities. UT also provides linear and polynomial regression capability.

The most important feature of UT for energy modeling is its ability to synchronize multiple data streams. However, UT has many other useful features and is extremely flexible, making it possible to handle most needed data manipulation tasks.

7.4. QuEST Energy Modeling Spreadsheet

QuEST's *Energy Modeling Spreadsheet* (QuEMS) is a commercial spreadsheet application designed to assist M&V analysis. QuEMS is based on *ASHRAE Guideline 14* requirements; it includes multiple model types and important statistical information, and supports the creation of change-point models for short-interval data. The application is available through the QuEST website. The principal author of this protocol developed this tool while working at QuEST.

7.4.1. Significant Features for Energy Modeling

QuEMS's strength is its support for the creation of 2P, 3P, and 4P change-point models for short-interval data. Since it is easy to copy the regression formula, it is easy to create an annual estimate of energy use and savings. It also makes it easy to combine models for different categories, such as daytypes, into a single model.

The creation of models for different categories is made easy by the use of any columns adjacent to the data on the *Data* worksheet. These columns can be used for daytype, occupancy, or any categorical variables. Using *Excel's Autofilter* will automatically change the data used for the regressions, making it easy to change between *Weekday* and *Weekend* models, for example.

An important weakness of QuEMS is that it doesn't use the *ASHRAE 1050-RP* code for creation of the models. There is no constraint that the regressions on each side of a change point actually meet at the change point. With sufficient data, the regressions do meet and QuEMS provides identical results to *ASHRAE 1050-RP*. However, with sparse data sets, the results can be different. Therefore, the issue will not often arise with hourly data, but is more likely to arise with daily data, depending upon the number of days of data available. Also, the lack of 5P modeling capability is a limitation for certain applications.

7.5. Energy Explorer

Energy Explorer is a *Windows*-based tool for the analysis of building and facility energy use data. The application is available for purchase from J. Kelly Kissock, PhD., Professor and Chair, Department of Mechanical and Aerospace Engineering / Renewable and Clean Energy, University of Dayton through his website.

7.5.1. Significant Features for Energy Modeling

Energy Explorer provides most of the capabilities needed for creating regression models for M&V. Its greatest strength is the *ASHRAE 1050-RP* change-point models. (Dr. Kissock was the primary investigator for ASHRAE 1050-RP.) In addition, *Energy Explorer* makes it fairly easy to group data for different categories and to calculate savings, including the uncertainty of savings.

It includes animation capability, plus histograms of the *y-variable* data. The regression model equation cannot be copied, but must be manually transcribed for use in other applications, such as for annualization of energy use and savings.

7.6. Other Software Programs

Searching the web, one can find other programs that provide capabilities that may be useful for M&V. Most programs available for purchase don't provide significant capabilities beyond what are available with ECAM and UT, and there are few, if any, available applications that provide change-point modeling capability such as *Energy Explore*r and ECAM.

There are two additional programs that overlap with UT and ECAM of which the author of this guide is aware, but does not have sufficient personal experience to describe:

- **SBW LogTool**: Developed for compressed air analysis, but its capabilities to import, manage, and resample data files from loggers and other sources is similar to the UT..
- **Interval Data Analysis Toolkit (IDAT)**: A Microsoft Foxpro application developed by Richard Stroh of BPA with the ability to import, manage, and resample data files. Its resampling routine is very fast. IDAT also provides a number of ways of visualizing data, including pan and zoom capabilities.

8. Example

8.1. Example Whole-Building Approach

The following example illustrates how to apply the *Energy Modeling Protocol* using a whole building approach to determine normalized energy savings. Since it is a whole-building approach, it would be considered *IPMVP Option C*. However, since it uses short-interval data and the meters are only measuring specific systems, it is also a good example of a systems approach (*IPMVP Option B*).

8.1.1. Overview

Manfred Hall is located near the center of a large university campus. Its floor area is approximately 92,300 square feet. It has seven levels, including the basement, that are a mixture of labs, office space, and administrative uses. The building houses the anthropology department and is approximately 80% lab space.

Space conditioning at Manfred Hall is delivered by seven air handling units (AHUs); there is one unit on each floor (basement through sixth floor). The AHUs provide ventilation, heating, and cooling to the interior of the building. The AHUs have single duct fans with preheating and cooling coils that are served by the building's chilled-water and hot-water loops. There are reheat coils in the zones that are also served by the building's hot-water loop and are controlled with two-way valves. The building's hot-water loop is heated in a heat exchanger by campus steam. There are two hot-water pumps in the basement that operate lead/lag to circulate water through the loop.

The audit process led to the conclusion that many of the old hot-water valves were leaking, wasting heating energy. Cooling energy was also being wasted due to the need to overcool air from the AHUs to compensate for the leaking valves. Therefore, a retrofit project was implemented that replaced all of the old hot-water valves.

Because a full year of monitoring before and after the measures are installed was not possible, both baseline and post-installation models were developed and normalized to a TMY dataset to determine savings.

8.1.2. M&V Approach

One electric interval meter, one hot-water calculation monitor, and one chilled-water calculation monitor track the whole building energy use at Manfred Hall. An M&V Plan was developed to assist with determining the savings from the project. Baseline and post-installation models were created for the hot water and chilled water use. The targeted savings for this project was 10% of the whole-building electric energy use and 10% of the whole-building hot water and chilled water use.

M&V Option

An Option C whole building approach was used for the energy use associated with hot and chilled water.

Measurement Boundary

The measurement boundary for each affected meter measures the hot-water and chilled-water energy flowing into and out of the building. The measurements could include electricity use of the building hot-water and chilled-water pumps, but the fractional savings for the electricity use of the pumps was too low to be seen on the building electric meter. Since not including electricity use resulted in a more conservative savings estimate, this was not a concern.

Baseline Period

Baseline period data was collected to develop the baseline energy models. The baseline periods for each meter, the analysis time interval, and units are shown in Table 8-1.

Table 8-1: Baseline Period

Meter	Start Date	End Date	Interval	Unit
Chilled Water	Mar 1, 2010	May 31, 2010	Hours	Tons
Hot Water	Mar 1, 2010	May 31, 2010	Hours	MBH

Post-Installation Modeling Period

After the new valves were installed, post-installation energy use data was collected for the chilled- and hot-water meters. Table 8-2 summarizes the post-installation monitoring period.

Table 8-2: Post-Installation Monitoring Period

Meter	Start Date	End Date	Interval	Unit
Chilled Water	Sep 15, 2010	Nov 29, 2010	Hours	Tons
Hot Water	Sep 15, 2010	Nov 29, 2010	Hours	MBH

8.1.3. Energy Modeling

Baseline Modeling

For chilled water, an hourly analysis time interval was selected. Daily analysis time intervals did not provide enough data points that showed enough variation over the entire temperature range. In addition, the baseline period was mainly in the warmer months. An hourly analysis time interval was selected in order to obtain data in the cooler nighttime periods, thereby increasing the range of variation in the regressor variables. A categorical variable identifying weekdays from weekends and holidays was not necessary.

Similarly, the hot-water meter baseline monitoring period was short, so that an hourly analysis time interval was selected.

Post-Installation Modeling

The same analysis time interval used for the electric, chilled-water, and hot-water meters respectively was used for the post-installation models.

Figure 8-1, Figure 8-2, and Figure 8-3 show the scatter plots and resulting pre- and post-installation regression models developed from the data for the chilled water. Figure 8-4, Figure 8-5, and Figure 8-6 show the scatter plots and resulting pre- and post-regression models developed from the data for the hot water.

Figure 8-1: Chilled Water Data, Pre- and Post-Installation

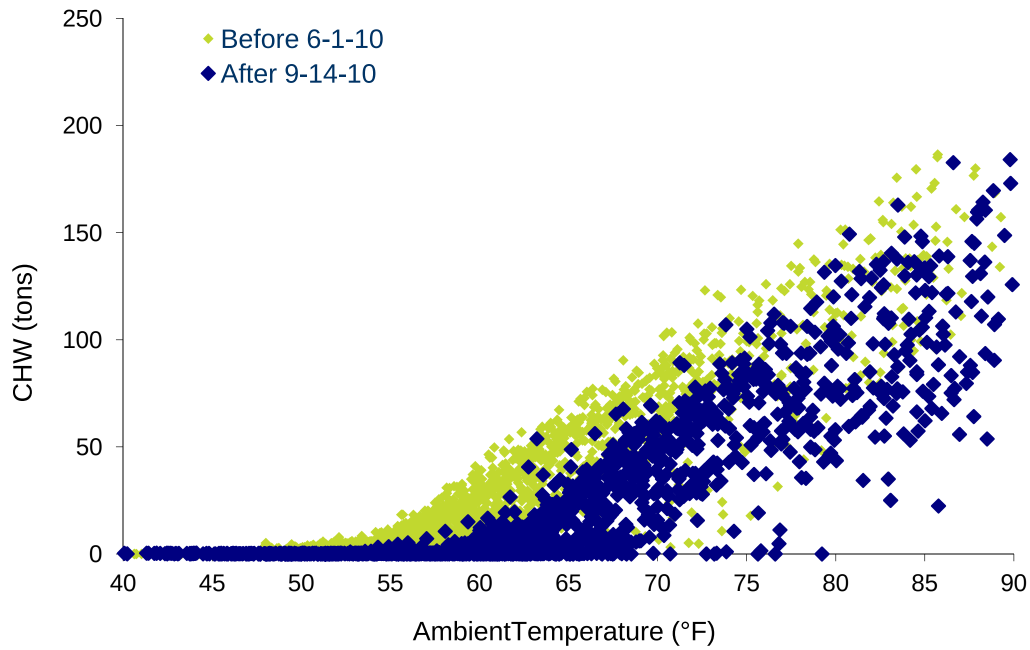


Figure 8-2: Chilled Water Baseline Model

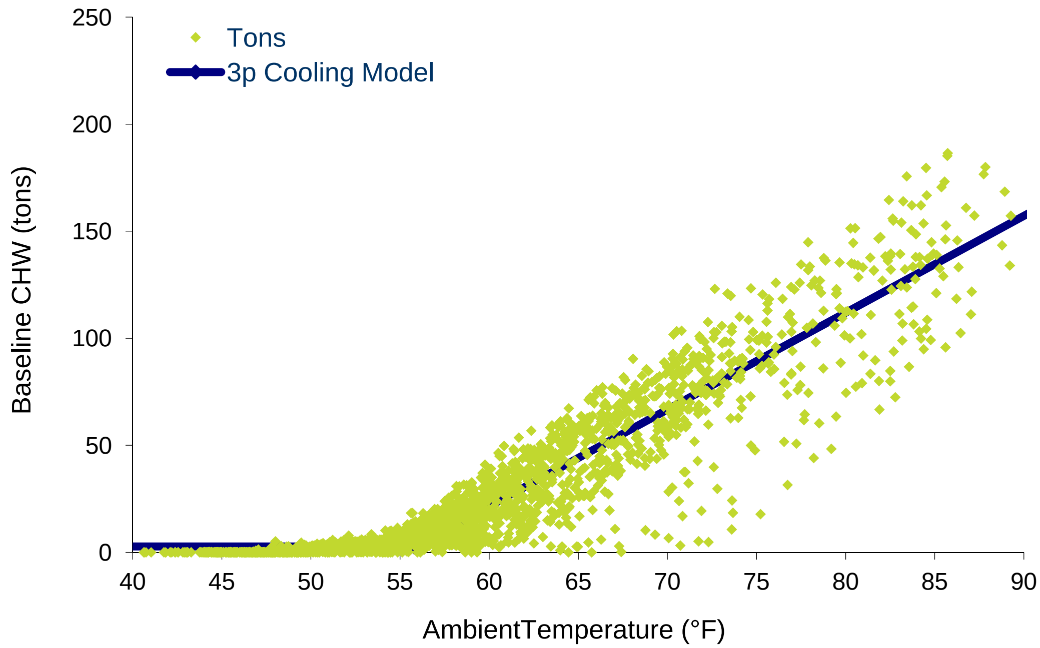


Figure 8-3: Chilled Water Post-Installation Model

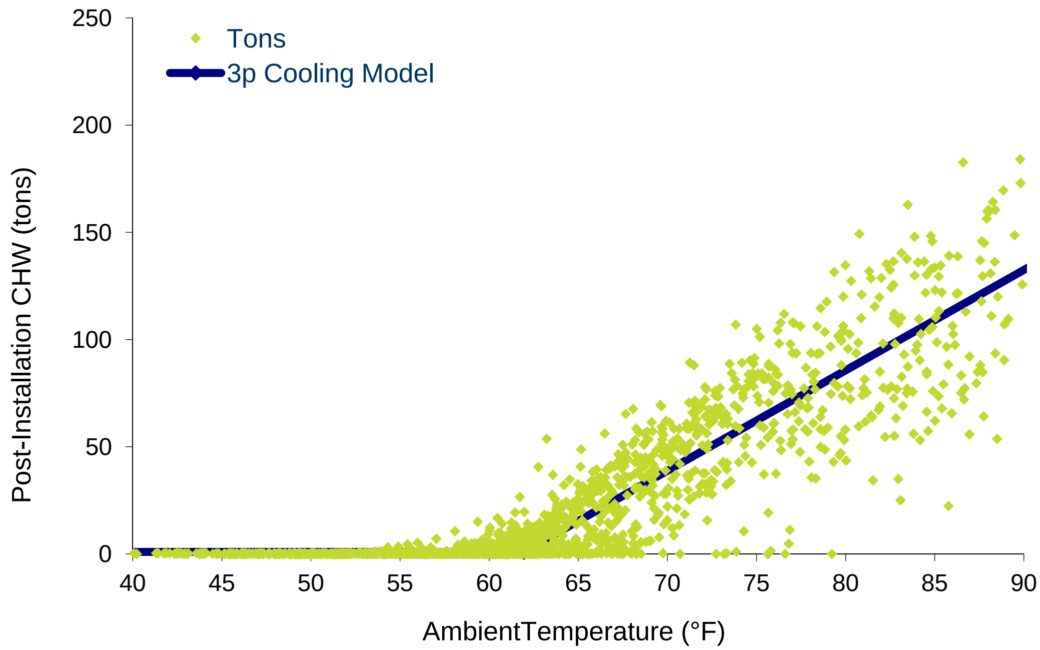


Figure 8-4: Hot Water Data, Pre- and Post-Installation

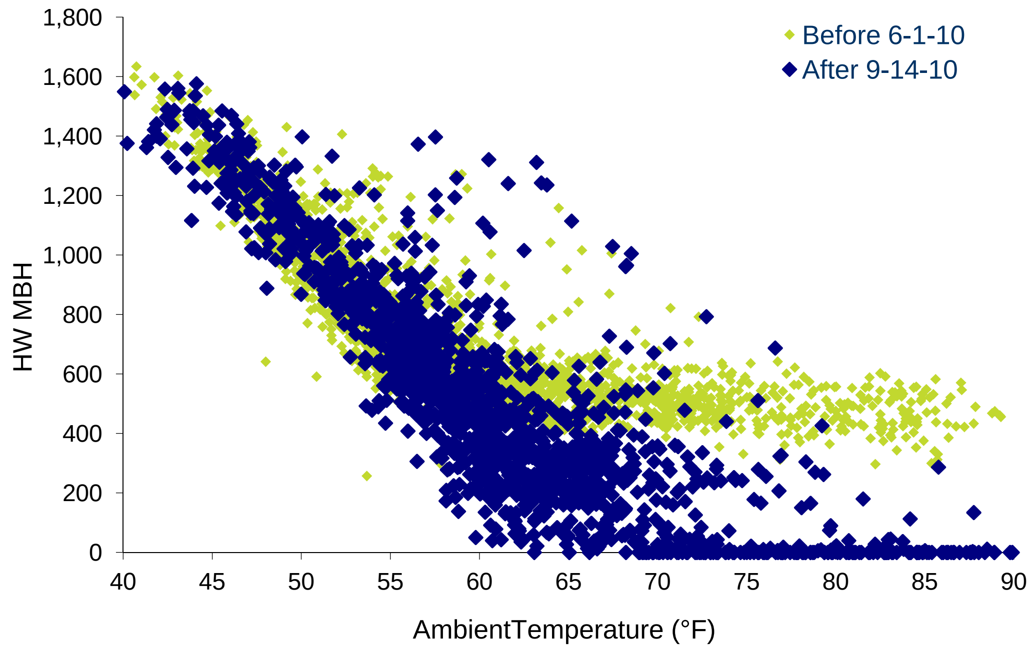


Figure 8-5: Hot Water Baseline Model

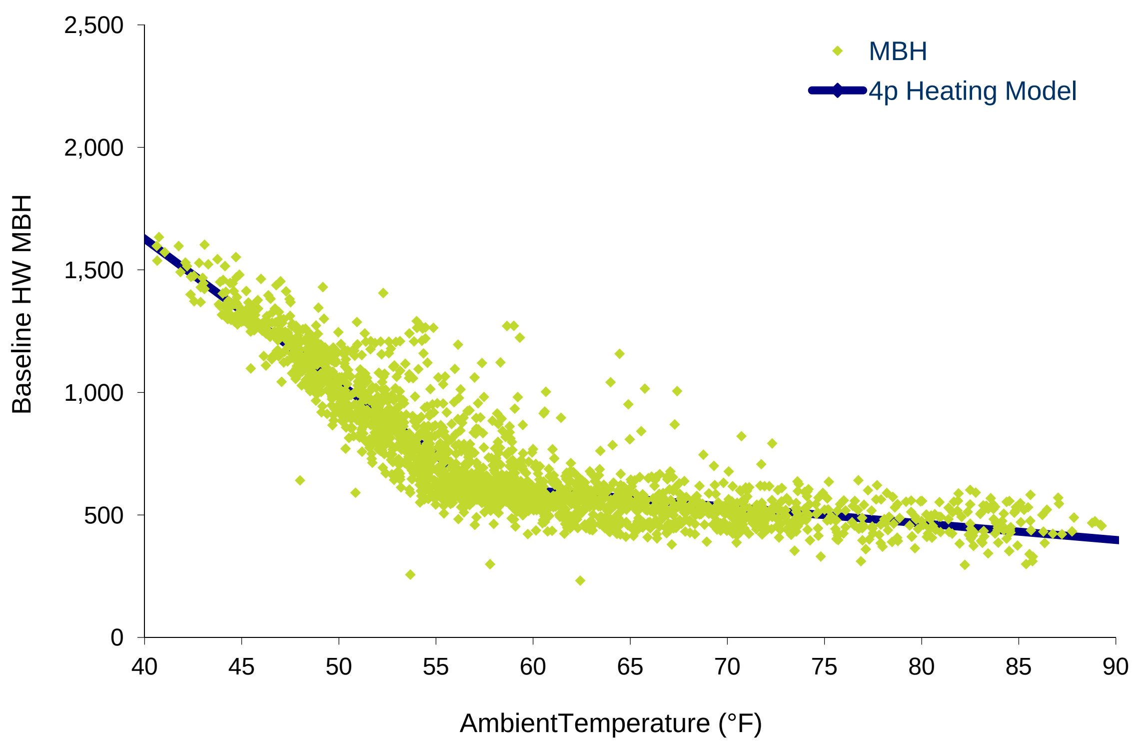
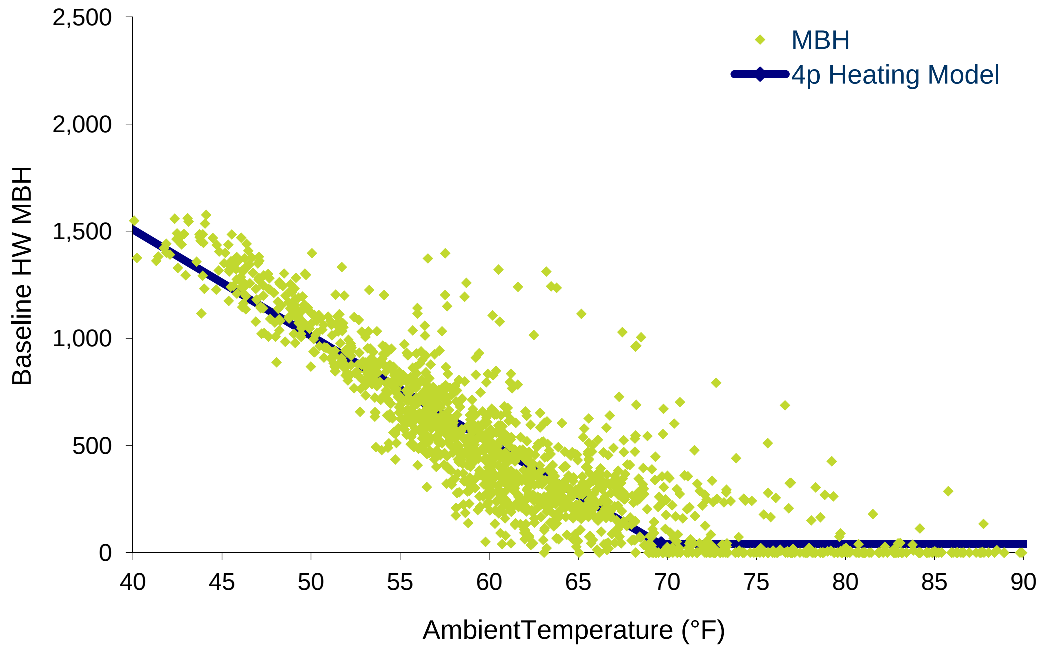


Figure 8-6: Hot Water Post-Installation Model



8.1.4. Annual Savings

Savings were estimated for each energy source by adjusting both baseline and post-installation energy use to TMY conditions. This was done simply by selecting the correct TMY weather file for the university climate zone for use in the analysis. For chilled water and hot water energy, the hourly TMY data was directly applied to the baseline and post-installation models. For each energy source, the annual baseline energy use and the annual post-installation energy use were calculated. The annual post-installation use was subtracted from the baseline use to determine savings. Results are shown in Table 8-3.

Table 8-3: Manfred Hall Energy Savings

Meter	Annual Baseline Use	Annual Post-Install Use	Savings	Units
Chilled Water	316,859	200,116	116,742	ton-hrs
Hot Water	7,294	5,815	1,478	mmBtu

Note also, that when placed on common units, the chilled water savings is almost identical to the hot water savings, as shown in Table 8-4. This makes sense, because for most of the zones in this application, reducing the hot-water valve leakage reduces the cooling needed to meet the zone setpoints.

Table 8-4: Manfred Hall Energy Savings

Meter	Annual Baseline Use	Annual Post-Install Use	Savings	Units
Chilled Water	3,802	2,401	1,401	mmBtu
Hot Water	7,294	5,815	1,478	mmBtu

Plotting the measured data with the baseline model on a chart, as in Figure 8-7 and Figure 8-8, provides conclusive evidence that the valve replacements are saving energy.

Figure 8-7: Chilled Water Savings Resulting from Valve Replacements at Manfred Hall

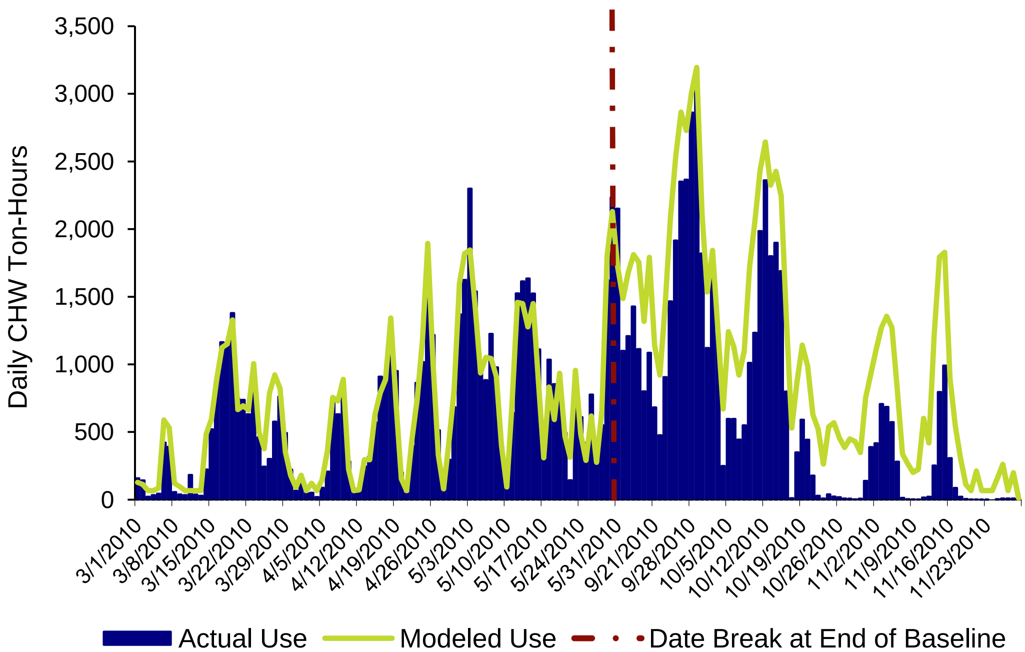
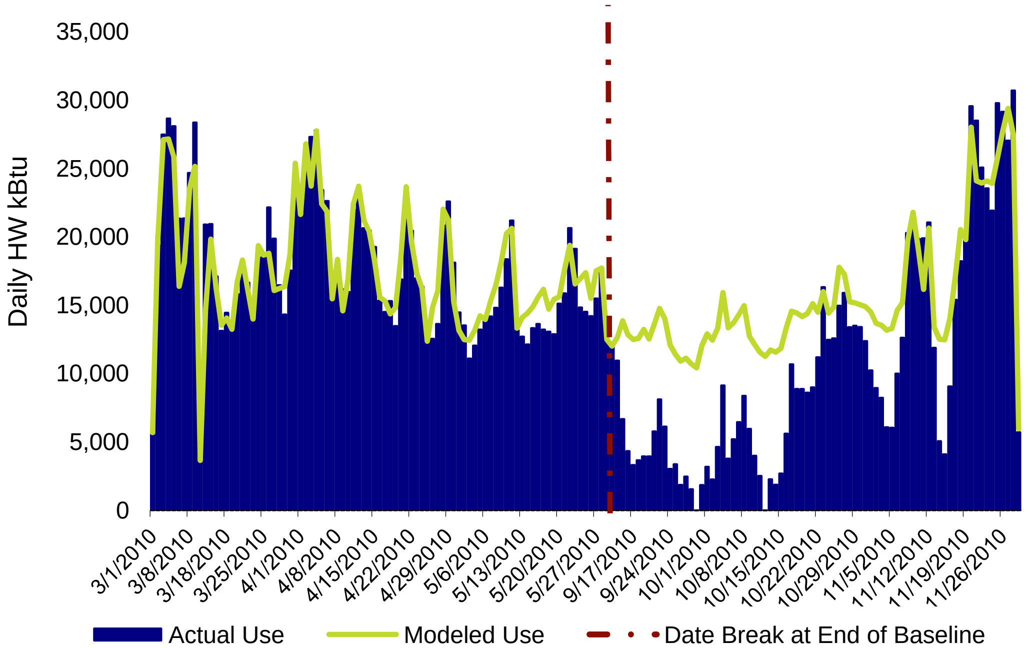


Figure 8-8: Hot Water Savings Resulting from Valve Replacements at Manfred Hall



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