# Verification by Energy Modeling Protocol
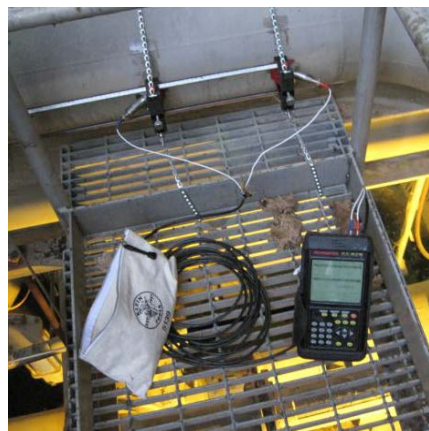
October 2018

# Verification by Energy Modeling Protocol

**Version 2.0**

**October 2018**

**Prepared for**

**Bonneville Power Administration**

**Prepared by**

**kW Engineering, Inc.**

**Research Into Action, Inc.**

**Demand Side Analytics, LLC**

**Contract Number 00077045**

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# 1.  Introduction

## 1.1.  Purpose

*Verification by Energy Modeling Protocol (Energy Modeling Protocol)* is one of the Measurement and Verification (M&V) protocols used by the Bonneville Power Administration (BPA). It 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.*[1]

Originally developed in 2012, this *Energy Modeling Protocol* is one of ten documents produced by BPA to direct M&V activities; an overview of the ten documents is given in the *Measurement and Verification (M&V) Protocol Selection Guide and Example M&V Plan (Selection Guide).*

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.

Chapter 9 of this protocol provides full citations (and web locations, where applicable) of documents referenced. The document *Glossary for M&V: Reference Guide* defines terms used in the collection of BPA M&V protocols and guides.

## 1.2.  Protocols Version 2.0

BPA revised the protocols described in this guide in 2018. BPA published the original documents in 2012 as Version 1.0. The current documents are Version 2.0.

## 1.3.  How is M&V Defined?

BPA's *Implementation Manual* (the IM) defines measurement and verification as "the process for quantifying savings delivered by an energy conservation measure (ECM) to demonstrate how much energy use was avoided. It enables the savings to be isolated and fairly evaluated."[2] The

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[1]  *International Performance Measurement and Verification Protocol.*

[2]  2017-2019 Implementation Manual, BPA, October 1, 2017.
    *https://www.bpa.gov/EE/Policy/IManual/Documents/IM_2017_10-11-17.pdf*

IM describes how M&V fits into the various activities it undertakes to "ensure the reliability of its energy savings achievements." The IM also states:

> *The Power Act specifically calls on BPA to pursue cost-effective energy efficiency that is "reliable and available at the time it is needed."[3] [...] Reliability varies by savings type: UES, custom projects and calculators.[4,5] Custom projects require site-specific Measurement and Verification (M&V) to support reliable estimates of savings. BPA M&V Protocols direct M&V activities and are the reference documents for reliable M&V. For UES measures and Savings Calculators, measure specification and savings estimates must be RTF approved or BPA-Qualified.[6]*

The *Selection Guide* includes a flow chart providing a decision tree for selecting the M&V protocol appropriate to a given custom project and addressing prescriptive projects using UES estimates and Savings Calculators.

M&V is site-specific and required for stand-alone custom projects. BPA's customers submit bundled custom projects (projects of similar measures conducted at multiple facilities) as either an M&V Custom Program or as an Evaluation Custom Program; the latter requires evaluation rather than the site-specific M&V that these protocols address.

## 1.4. Background

BPA contracted with a team led by kW Engineering, Inc. to assist the organization in revising the M&V protocols that were published in 2012 and used to assure reliable energy savings for the custom projects it accepts from its utility customers. The team conducted a detailed review and user assessment of the 2012 M&V Protocols and developed the revised version 2.0 under Contract Number 00077045.

The kW Engineering team is comprised of:

- kW Engineering, Inc. (kW), led by David Jump, Ph.D., PE, CMVP

- Research into Action (RIA), led by Marjorie McRae, Ph.D.

- Demand Side Analytics (DSA), led by Jesse Smith

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[3] Power Act language summarized by BPA.

[4] UES stands for Unit Energy Savings and is discussed subsequently. In brief, it is a stipulated savings value that region's program administrators have agreed to use for measures whose savings do not vary by site (for sites within a defined population). More specifically UES are specified by either the Regional Technical Forum – RTF (referred to as "RTF approved") or unilaterally by BPA (referred to as BPA-Qualified). Similarly, Savings Calculators are RTF approved or BPA-Qualified.

[5] Calculators estimate savings that are a simple function of a single parameter, such as operating hours or run time.

[6] https://www.bpa.gov/EE/Policy/IManual/Documents/IM_2017_10-11-17.pdf, page 1.

BPA's Todd Amundson, PE and CMVP, was project manager for the M&V protocol update work. The kW Engineering team compiled feedback from BPA and regional stakeholders, and the team's own review to revise and update this 2018 *Energy Modeling Protocol*.[7] The kW Engineering team would also like to thank Gregory Brown of Brolte, LLC and Josh Rushton of Rushton Analytics for their input.

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[7] William Koran, formerly of QuEST, was the primary author of Version 1.0 of the Energy Modeling Protocol, under Todd Amundson's direction and supported by other members of the protocol development team.

# 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 American Society of Heating, Refrigerating and Air-Conditioning Engineers (*ASHRAE) Guideline 14-2014*, 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 14-2014*.

This protocol describes procedures for collecting and preparing necessary baseline and post-installation data, and for developing appropriate empirical (that is, 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*,[8] with a focu*s* 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 proliferation of short-time interval metering[9] for many facilities and 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. With short interval

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[8]     Hereinafter, *Regression Reference Guide.*

[9]     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.

monitoring, the practitioner can more quickly obtain data representative of a broad range of conditions. 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 at least one year of data (in most situations)[10] 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 monthly bills or in short intervals such as 15 minutes, an hour, or 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 – such as whether to use hourly or daily aggregations (also referred to in this protocol as *time granularity*)[11] – depends on several factors, including ease of use (which typically favors daily data), need for a heightened variability in the independent variable (which favors hourly data), and a need to estimate peak demand impacts (which also favors 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.

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[10]  Baseline models can be constructed with less than one year of data if the available data provides coverage of a full range of operating conditions

[11]  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.

## 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

➡ 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. This protocol implicitly assumes an existing condition baseline. A different protocol is needed for ECMs where a current practice baseline is appropriate because of program guidelines or because the existing equipment had reached mechanical failure and no longer represents a viable baseline.

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.

While not necessarily a disadvantage of this protocol, it should be noted that the *Energy Modeling Protocol* may need to be supplemented by a different protocol to quantify energy usage impacts due to identified Non-Routine Events occurring within the measurement boundary. This is discussed in detail in sections 3.1.7 and 3.1.8 of 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. Use the baseline model to predict energy consumption for the post-installation period conditions.

4. Calculate savings by subtracting the measured post-installation period energy use from the predicted baseline energy consumption for the post-installation period (as calculated in Step 3).

In the normalized savings approach, both a baseline and a post-period model are developed and used to predict consumption for a common set of fixed conditions as follows:

1. Collect baseline data.

2. Develop a model for the baseline period.

3. Use the baseline model to predict energy consumption under fixed conditions.

4. Collect post-period data.

5. Develop a model for the post-period energy use.

6. Use the post-period model to predict energy consumption under fixed conditions.

7. Calculate savings by subtracting the *adjusted post-period* energy use (as calculated in Step 6) from the *adjusted baseline* energy use (as calculated in Step 3).

Selection of an avoided energy use or normalized savings approach should be guided by utility program guidelines and documented in the M&V plan. For projects with a long useful life, a normalized savings approach may be more useful for system planners. For short-lived ECMs, normalization to long-run weather averages may be less useful. When the reporting period is less than one year, a normalized savings approach is needed to estimate annual savings. When a normalized savings approach is the desired approach, practitioners should estimate both avoided energy use and normalized savings and compare the differences to the differences in post-period and fixed conditions to confirm that the differences make sense directionally (e.g. a post-period with abnormally warm weather should generate more savings using an avoided energy use approach than a normalized savings approach for cooling system measures).

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**



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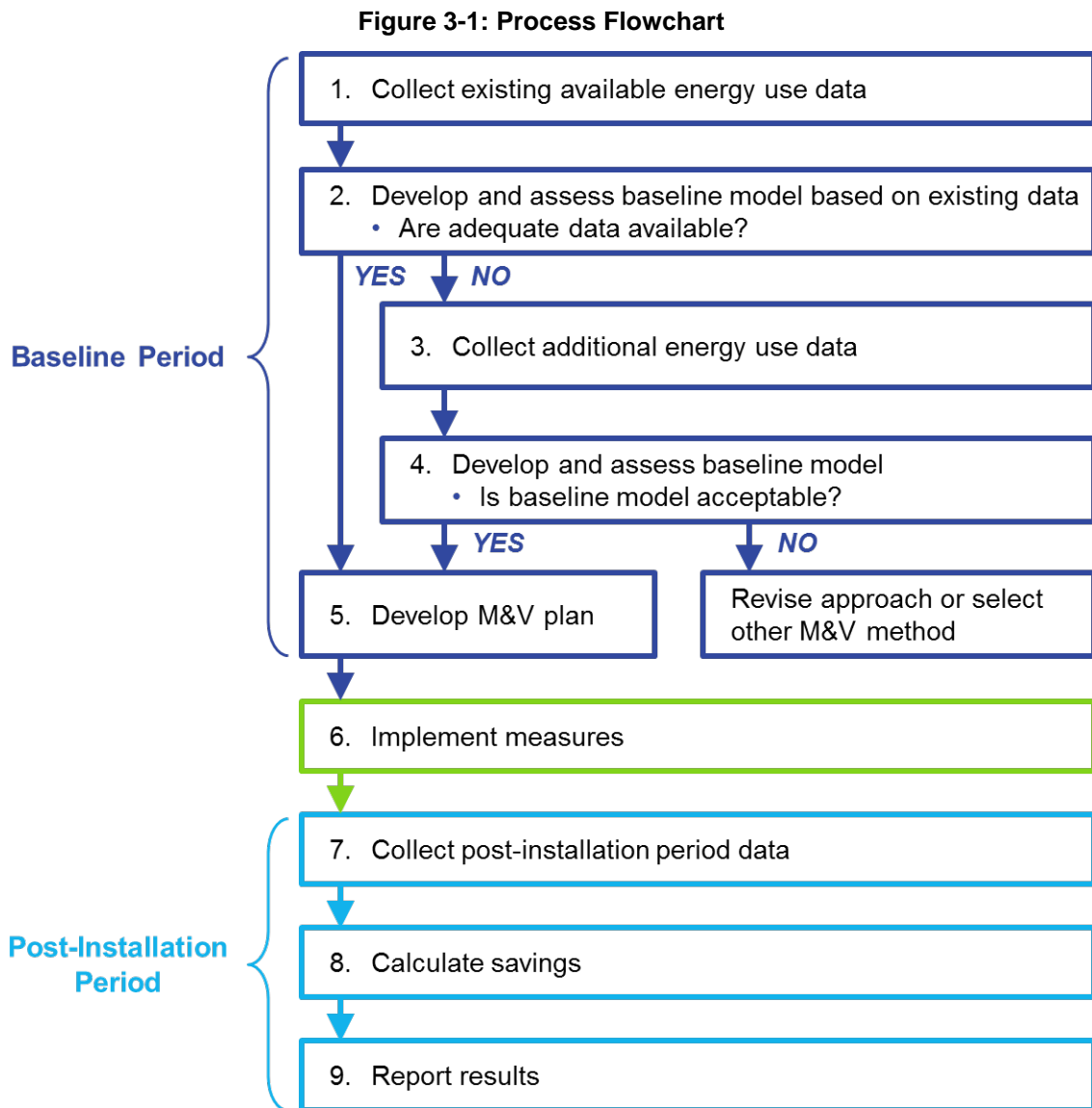
In most cases, the baseline and post models will be of the same type, using the same independent variables and the same number of parameters. However, this will not always be the case, as discussed in Section 3.2 of this protocol.

Also, in most cases, ambient temperature will be an independent variable. 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*,[12] the following steps should be used to develop models:

1. Identify all independent variables

2. Collect datasets

3. Clean the data

4. Graph the data

5. Select and develop a model

6. Validate the model

7. Perform an analysis of residuals

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 charts to confirm the relationship with the assumed independent variables. Scan the data for outlier points that do not conform to the expected relationship. Investigate suspected outliers.

➡ **Observe the scatter in the data**, especially looking for multiple groups. Use this information to determine the need for categorical variables or different or additional

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[12] Hereinafter, *Regression Reference Guide.*

continuous variables. (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**. This protocol assumes the use of ordinary least squares (OLS) regression.[13] This is the most common form of regression modeling and the default procedure in most software packages.

➡ **Validate the model**. Compare model uncertainty with expected savings. Check the goodness of fit statistics such as CV(RMSE), Net Determination Bias Error (NDBE), and R-squared.

➡ **Analyze the residuals**. Chart the model's residuals to confirm there are no violations to the underlying assumptions of OLS regression.[14]

➡ **Apply judgement.** Do the direction and magnitude of the regression coefficients make sense? Solicit feedback from relevant parties (facility energy team members and utility EE engineers) and apply judgement to assess model validity.

➡ **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 many cases, there will be a single continuous independent variable, such as ambient temperature or production. However, there may be multiple categorical variables, such as daytype (perhaps weekday, weekend, and holiday), 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.

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[13] OLS regression is a procedure that solves for the set of coefficients that minimizes the sum of the squared differences between the raw data and the fitted linear trend.

[14] The assumptions required for OLS regression: (1) Model residuals must follow an approximate Normal distribution with a mean of zero. (2) Residuals must have a constant variance (homoscedastic). (3) Residuals must not be correlated with any of the independent variables or the predicted values of the dependent variable. (4) Residuals must be independent of each other.

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 the ratio of uncertainty to savings as the fractional savings uncertainty (FSU), or relative precision. 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)**
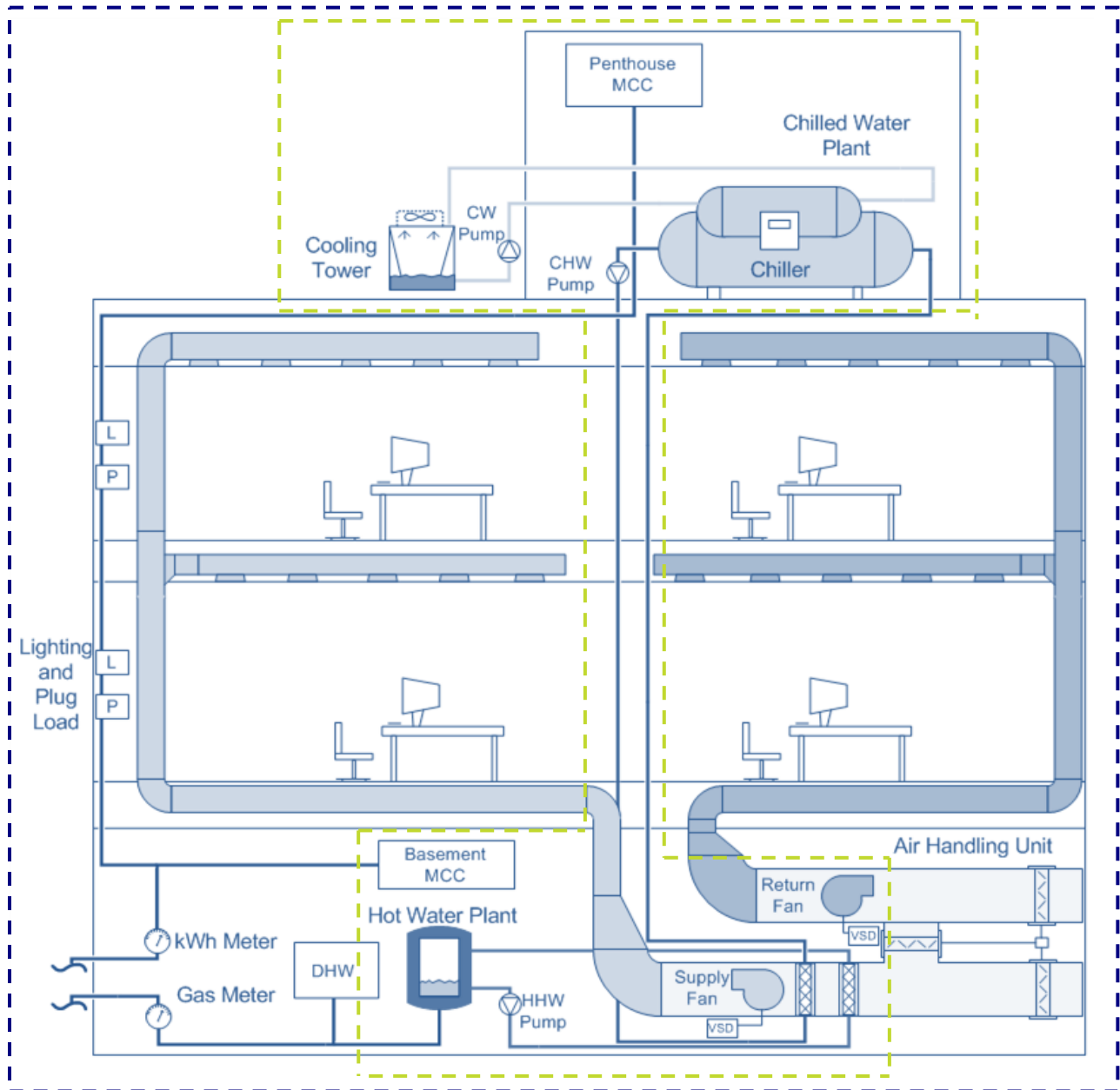


## 3.1.3. Selecting Time Intervals and Assessing Coverage

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. Whether monthly, daily, or hourly data are available, an assessment must be made as to whether it is adequate for verifying the expected amount of savings.

In most cases, the important factors influencing commercial whole-building energy use typically analyzed for energy modeling 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 (such as 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. For related details, please see sections 3.1.7 and 3.1.8.

The collected data should cover the full range of operating conditions of the building. Good empirical modeling requires that models be developed from data encompassing as much of the range of possible dependent and independent variable values as possible. Out-of-sample predictions, or extrapolation, refer to cases when the model is used to estimate the dependent variable for levels of the independent variable outside the range used to develop the model. The uncertainty formulas in Chapter 5 of this protocol deal with the uncertainty *within* the range of independent variables used to develop the model. Out-of-sample predictions lead to extrapolation errors that cause the fractional savings uncertainty calculations to under-estimate the true uncertainty.

ASHRAE Guideline 14 allows 10% extrapolation above, and 10% below, the baseline period ambient temperature range when estimating energy use for models that use ambient temperature as the independent variable. Analysts have no control over the weather so prescriptive rules are challenging and some professional judgement is needed. However, the intent of the guideline is sound. When considering use of the *Energy Modeling Protocol* with less than one year of baseline and one year of post-period data, the M&V plan should include a discussion of the "coverage" of independent variables in the baseline model. If the M&V plan calls for a normalized savings approach, the expected coverage in the post-period should be addressed because a separate post-period model is developed to predict energy consumption under fixed conditions.

For a weather model, a simple coverage factor can be computed by comparing the range of temperature conditions in the baseline period to the range of the temperature conditions in TMY3 weather for the facility location. A more robust coverage factor calculation that takes into account the distribution of weather conditions over the year might involve binning intervals, or even expected energy consumption, and looking at the proportion that is within-sample versus the proportion that is out-of-sample. Consider the following example where daily energy usage is modeled as a function of average daily weather.

➡ Baseline Period:

  ■ Minimum average daily temperature = 28 degrees (F)

- ■ Maximum average daily temperature = 74 degrees (F)

→ Typical Meteorological Year:

- ■ Minimum average daily temperature = 29 degrees (F)

- ■ Maximum average daily temperature = 83 degrees (F)

In this example, there is no coverage issue for cold weather conditions. The baseline period actually has slightly colder weather than would be encountered predicting energy consumption for fixed condition TMY weather. The issue for this example occurs with warm weather. When the baseline model is used to predict energy consumption (and savings) above 74 degrees (F), the estimates will be subject to extrapolation error. How many days per year will the model be asked to predict out-of-sample? If there are 25 such days in the TMY data file, the coverage factor could be defined as:

→ Coverage Factor = (365 – 25)/365 = 93.2%

Coverage concerns increase as the expected volume (number of days) and distance (temperature differential) of out-of-sample predictions grow. There are also ECM-specific considerations to weigh. For a gas heating project, the lack of warm weather coverage may be of little concern. For a chilled water system ECM, the lack of warm weather coverage should be clearly identified in the M&V plan as a threat to validity. Every effort should be made to gather additional summer operating data if possible.

Coverage considerations apply equally to the baseline and reporting period when a normalized savings approach is used. If the coverage factor in the reporting period is poor, estimates of *adjusted post-period* energy use will be subject to extrapolation errors.

One year of pre and post data is not a coverage panacea, but does ensure a full range of seasons are observed. When the independent variable in the model is an operational parameter (widgets produced, tons of raw material processed, gallons pumped, etc.), 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 also 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. 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.

## 3.1.4. Adjusting Baseline to Post Conditions

When calculating the avoided-energy-use type of savings, the model's equation is used to predict what the baseline energy use would have been under 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

For avoided energy-use, 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
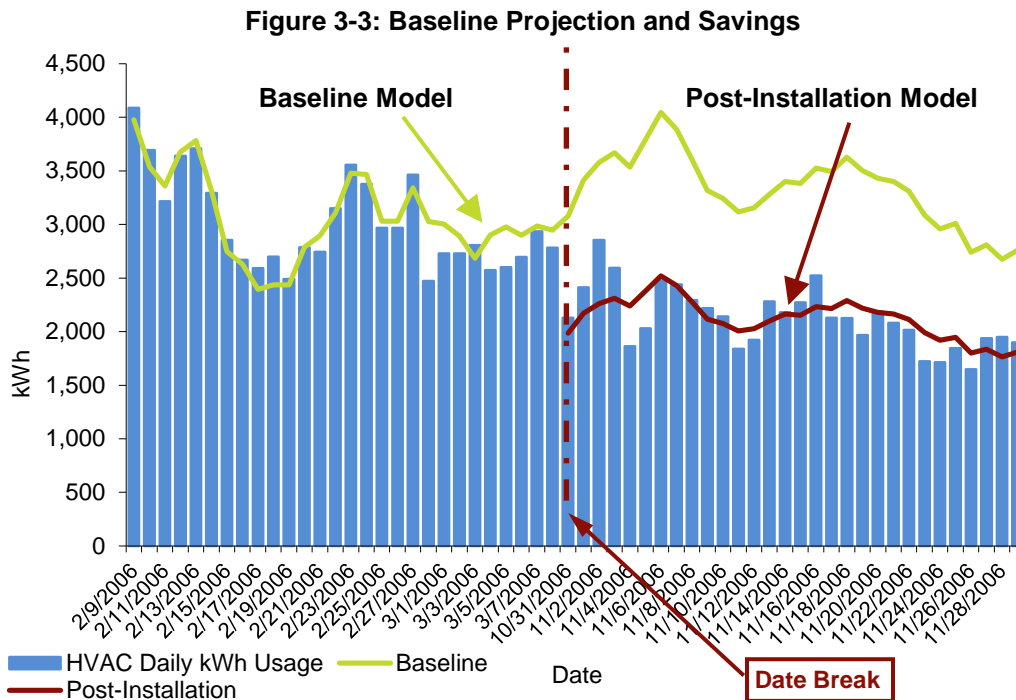
If savings are to be stated for conditions other than the post-installation period – a *fixed conditions basis* type of savings – a post-installation energy model that relates the energy use with variables describing those fixed conditions must be developed. Usually the conditions are TMY weather. Both 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 using the ambient temperature data from a TMY weather file or normalized values of the independent variable if weather is not the independent variable

➡ Assessing the coverage factor. If the coverage of the range of the independent variable(s) in the fixed conditions is poor, extend the reporting period.

➡ Developing 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 (that is, creating baseline and post-installation 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**
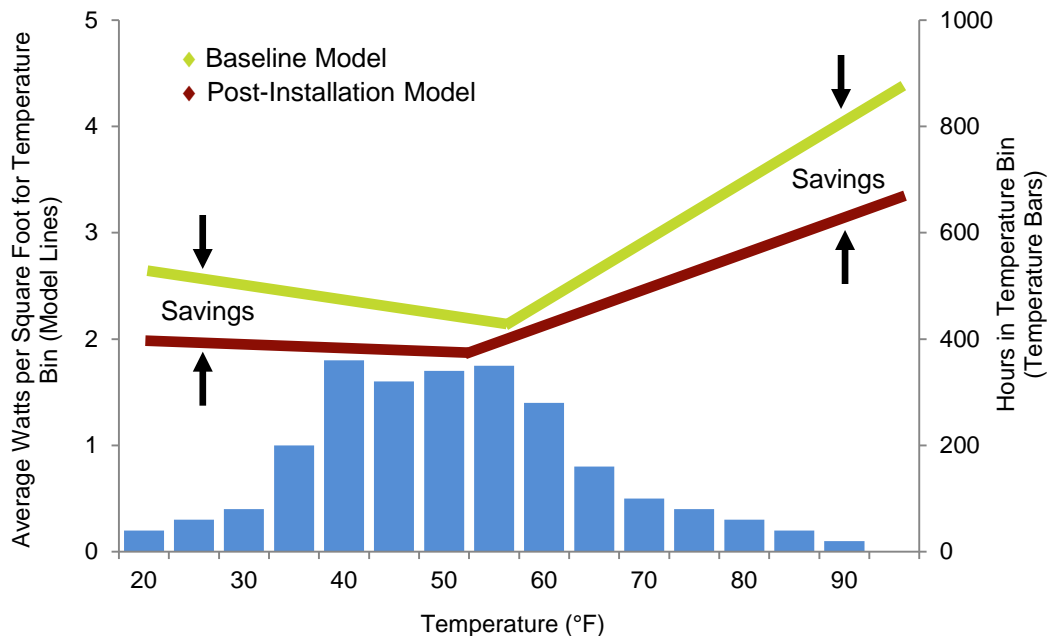


## 3.1.7. Non-Routine Events

An underlying assumption of the *Energy Modeling Protocol* is that the only change in facility operation during the baseline and reporting periods is the ECM being analyzed. Sometimes this assumption is violated and a significant one-time change unrelated to the ECM occurs within the measurement boundary. A change to static factors that affects energy use is a "non-routine event," or NRE. When a non-routine event occurs, the savings must be adjusted to isolate savings due to installed measures, and not due to measures plus changes caused by non-routine events. Non-routine events can include adjustments in facility equipment or operations, including (but not limited to) renovations, facility expansion, equipment addition or removal, and changes to occupancy type or schedule.

Non-routine events can:

➡ Add or remove load;

➡ Be permanent or temporary;

➡ Be another ECM incented under other programs, or non-incented;

➡ Occur in the baseline period, the reporting period, or during the ECM installation period.

■ Understanding the timing is important to developing an appropriate adjustment

■ When NREs occur in the baseline period, the NRE and proposed adjustment should be documented in the M&V Plan. The M&V plan should also describe in general terms how NREs in the reporting period will be flagged for consideration and treated.

- When NREs occur in the installation or reporting periods, the Savings Report should document how they were identified and the approach used to account for the effects in the savings estimate.

➡ Be independent of the ECM or have interactions with the ECM.

- An example of an ECM that is independent of an NRE is a process motor upgrade in a manufacturing facility that also installs LED lighting throughout the plant. If a whole-building energy model is being used, the reduction in lighting load will influence the model, but it is unrelated to the improved efficiency of the process motors. Even though the ECM and NRE are independent of one another, because the NRE lies within the measurement boundary, an adjustment is needed.

- An example of an interaction between an ECM and NRE is an HVAC upgrade in a facility that undergoes an expansion. If the expanded footprint would have been served by the existing system absent the ECM, the expansion can be expected to increase the savings attributable to the ECM. Whether or not the ECM is credited with this increase (or decrease) in savings is governed by program policy and procedures.

The distinction between an NRE and an outlier is not always clear and requires professional judgment based on an understanding of facility operation. A temporary NRE – such as a labor strike or equipment failure – can be handled similarly to an outlier. With justification, data from the affected period can be removed from the model provided it does not lead to excessive data gaps or poor coverage of operating conditions. A permanent NRE can be thought of as "the new normal." In the case of a permanent NRE, data from the affected period should not be removed. Instead, the effect of the NRE should be removed from the model-based savings estimate.

In addition to re-baselining (next section), there are two categories of methods that may be used to adjust for the impacts of NREs.

## 1. Net Out the NRE Using Engineering Calculations

This approach involves estimating the effects of the NRE independently and using the estimates to adjust either the input data or results of regression-based model. Consider the following example:

### *NRE Scenario A*

A large office building implements an upgrade to its chilled water system in October 2017 and applies for program support. The chiller upgrade is the ECM being analyzed using a whole-building energy model with daily kWh consumption data. In March 2018 the facility migrates its on-site data center servers to a cloud solution. The server migration may be considered an NRE. Engineering calculations for the server migration include interactive effects on the new cooling system and estimate savings of 250 MWh/year.

➡ Baseline period = October 2016 to September 2017

➡ Reporting period = November 2017 to October 2018

The server migration is within the whole-facility measurement boundary and confounds measurement of savings from the ECM of interest. A savings estimate using the whole-building model will include the reduced consumption from the server migration from March 2018 to October 2018. Two potential approaches to adjust for this NRE are to:

1. For each day in the reporting period after the server migration is complete, add back the assumed server loads to the metered consumption. This could be the same value for each day (250,000/365.25 = 684.5 kWh) or differentiated by weekday/weekend if appropriate. Use the baseline model to predict an adjusted baseline and calculate avoided energy use as the difference between the adjusted baseline and the reconstituted reporting period consumption values.

2. Calculate the total savings in the reporting reported using the actual metered data for the reporting period. This savings estimate will be inclusive of the reduced server load from March 2017 to October 2018. For the portion of the reporting period following the server migration, subtract the estimated daily server load from the aggregate savings at the meter to isolate the effect of the chiller ECM.

## 2. Explicitly Controlling for the NRE in the Regression Model

This approach involves including the presence of the NRE as an independent variable in the model. Consider the following example:

### NRE Scenario B

A large office building implements an upgrade to its chilled water system in October 2017 and applies for program support. The chiller upgrade is the ECM being analyzed using a whole-building energy model with daily kWh consumption data. In March 2017 the facility migrates its on-site data center servers to a cloud solution. The server migration is an NRE. Engineering calculations for the server migration include interactive effects on the new cooling system and estimate savings of 250 MWh/year.

➡ Baseline period = October 2016 to September 2017

➡ Reporting period = November 2017 to October 2018

In this example, the NRE occurs in the baseline period. An alternative to netting out the effect of the server migration is to directly control for it in the baseline model. To implement this approach, an indicator variable named "Server" is included in the model. It is equal to 1 on days following the server migration and zero otherwise. The coefficient of the "Server" term in the model represents the change in daily energy consumption when Server = 1. It should have a negative coefficient approximately equal to the engineering savings of 684.5 kWh per day.[15]
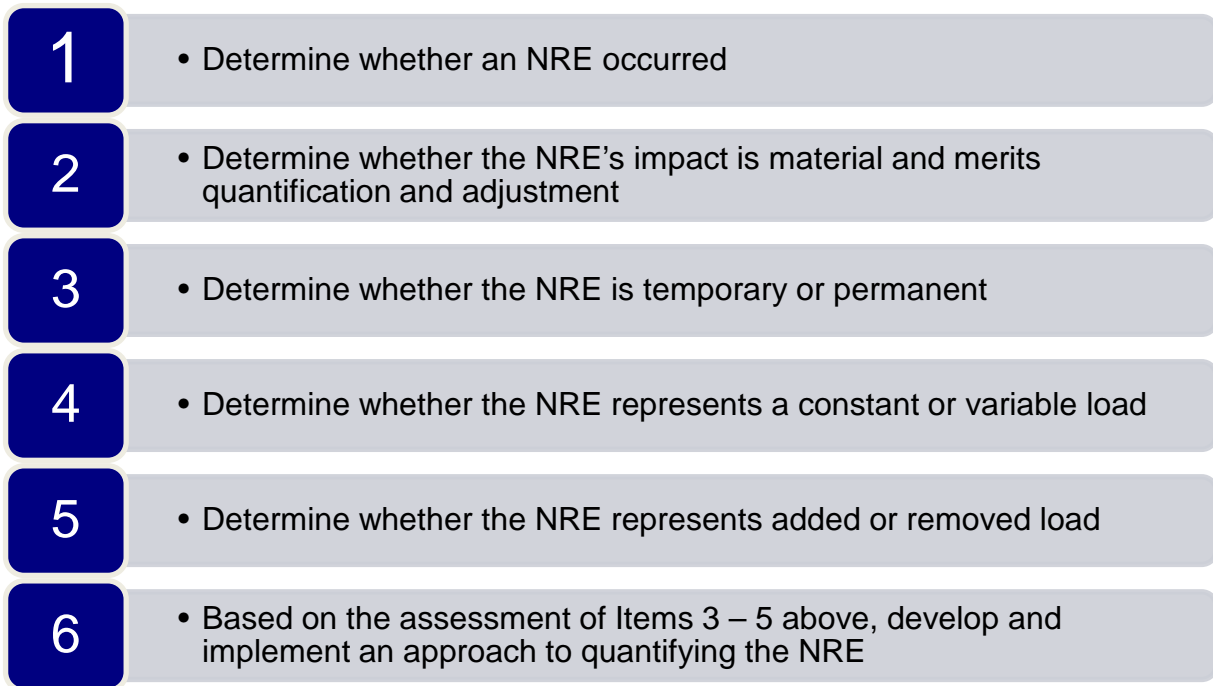
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[15] The NRE indicator variable could also be interacted with the independent variable if the magnitude of the NRE is expected to be a function of the independent variable(s). An interaction is created by multiplying two

Because the server migration is in place during the reporting period, the "Server" variable is set to 1 for each day in the reporting period and the adjusted baseline is predicted using the value of this model coefficient.

An explicit approach is useful when no engineering estimate of the NRE is available or developing one would be challenging or cost-prohibitive. This approach is also useful for temporary NREs that span a long period of time that would be problematic to drop from the analysis. Savings can be calculated with the NRE indicator variable set to "On" or "Off" (1 or zero) as appropriate based on an understanding of the ECM, facility operation, and program guidelines.

Figure 3-5 provides a general framework for addressing NREs within the *Energy Modeling Protocol*.

**Figure 3-5: Framework for Addressing NREs**

| | |
|---|---|
| 1 | • Determine whether an NRE occurred |
| 2 | • Determine whether the NRE's impact is material and merits quantification and adjustment |
| 3 | • Determine whether the NRE is temporary or permanent |
| 4 | • Determine whether the NRE represents a constant or variable load |
| 5 | • Determine whether the NRE represents added or removed load |
| 6 | • Based on the assessment of Items 3 – 5 above, develop and implement an approach to quantifying the NRE |

## 3.1.8. Re-Baselining

The discussion of NREs in Section 3.1.7 focuses on making adjustments to an existing energy model to reflect changes in the equipment or operating characteristics that affect energy consumption within the measurement boundary. In some cases, the changes within a facility are so fundamental that a new energy model is needed. The development of a new energy model is

---

independent variables to create a new variable. An interaction between an NRE indicator variable and a temperature variable would capture the change in the NRE effect on load per 1-degree change in temperature – or the slope of the NRE effect.

referred to as "re-baselining." The clearest example of this would be a significant new ECM. Generally, it is advisable to develop a new energy model to estimate savings from a new ECM if adequate time has passed since the installation of a previous ECM. Typically, adequate time would be one year so that the baseline model for the new ECM is constructed with exclusively post-period data from the prior ECM. When the implementation dates of ECMs are close together, additional care is needed to isolate the effect of the ECM of interest.

For initiatives like Strategic Energy Management (SEM) where ECMs tend to be a series of smaller adjustments rather than large capital upgrades, reporting periods can occur year after year for several years. The BPA ESI MT&R Reference Guide provides a useful taxonomy of non-programmatic effects and recommendations for adjustments, which is adapted below:

→ **Static Change** – a static change in energy use within a well-defined boundary and with minimal interactive effects.

- Net out the NRE approach using sub-metering or engineering calculations – unless the NRE is a new ECM whose savings should be captured by the model

→ **Minor Process Change** – a distinct change in operations without fundamentally changing the process itself.

- Control for the NRE via regression approach, and when a regression approach is not suitable, then apply engineering calculations.

→ **Major Process Change** – affects the fundamental energy consumption characteristics of the facility rending the original model specification invalid.

- Re-baseline and create a new regression model of the facility or process

This guidance is intended to help staff decide if and how to adjust an existing energy model to account for an NRE, or whether the NRE is significant enough to trigger re-baselining. Like many aspects of the *Energy Modeling Protocol,* professional judgement based on understanding of the utility program, facility operation, and the ECM(s) of interest is critical when determining how to handle non-programmatic changes.

## 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.[16] 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 requires the use of interaction terms that can be tedious to create and manage depending on the software package utilized for modeling.

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 assessing whether one independent variable is correlated with another.

An alternative approach to detecting multicollinearity is to calculate the variance inflation factor (VIF) statistic for each variable in the multiple regression model. Section 5.1.8 of the Regression Guide discusses VIF statistics in detail and suggests that if any independent variable in the model has a VIF statistic greater than 10, multicollinearity is a problem and a term should be removed from the model specification (consider removing high VIF variables first).

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

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

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,[17] 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 model 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[18] 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 3-6 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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[17] This variance is defined as the *coefficient of variation of the standard deviation:* CV(STD). It is calculated by $CV(STD) = \sigma / \dot{x}$, where $\sigma$ = *standard deviation about the mean value of all measurements*, and $\dot{x}$ = *mean of the measured values.*

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

**Figure 3-6: A 2P Energy Model of Electricity Use (kWh) in a University Laboratory Building, Using Daily Data**
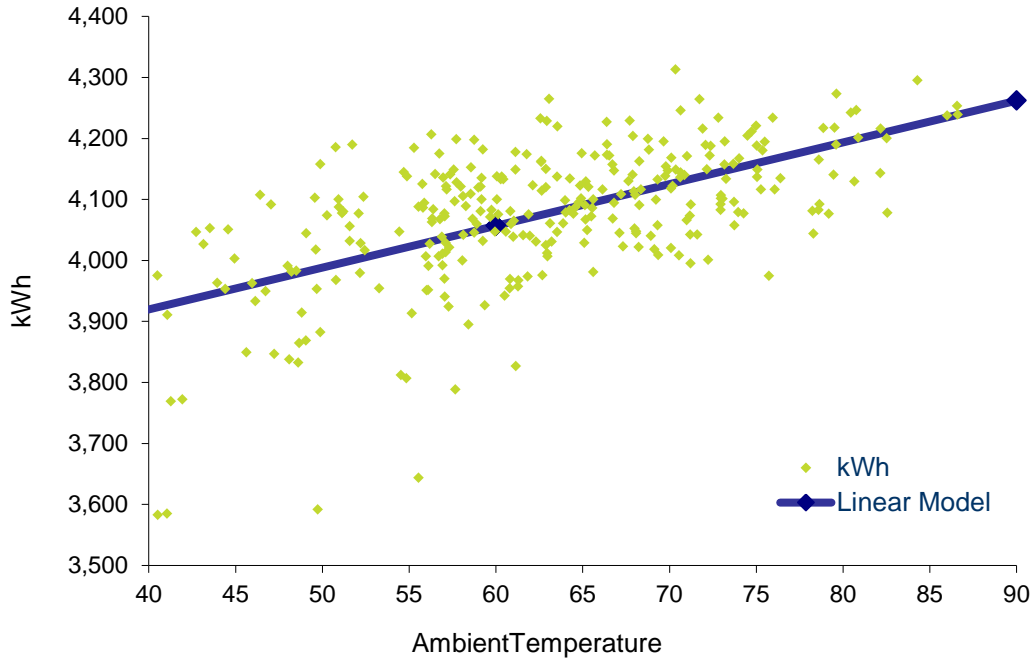


# Three-Parameter Change-Point Models

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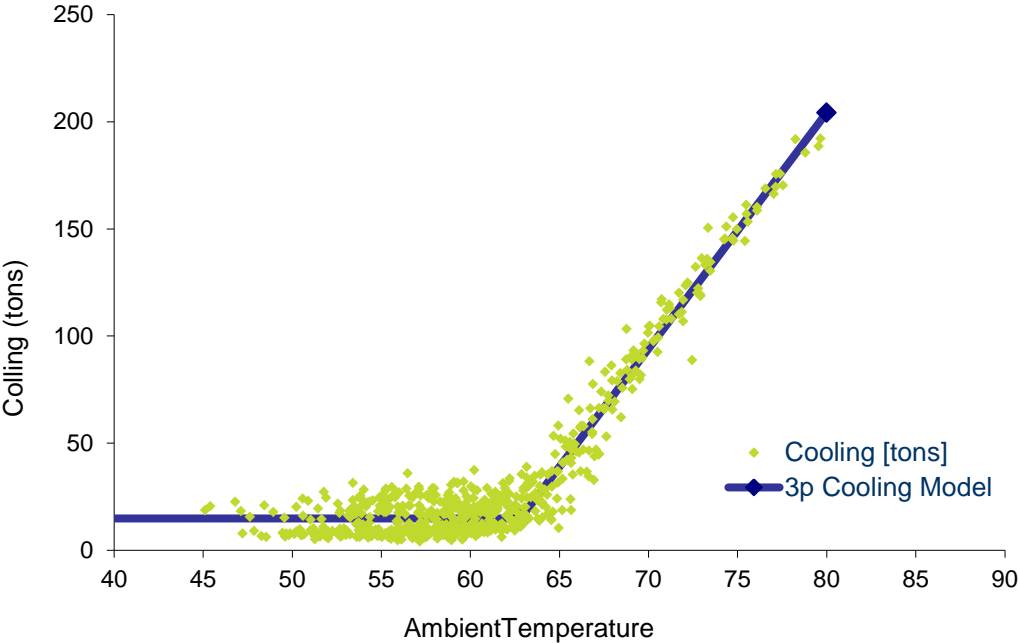
➡ **Three-Parameter Change-Point Cooling Model:** $E = \beta_1 + \beta_2 (T - \beta_3)^+$

Figure 3-7 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 3-7: 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 3-8 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 3-8: A 4P Energy Model of Hot Water Use in a University Laboratory Building, Using Hourly Data**



### Four-Parameter Cooling Model

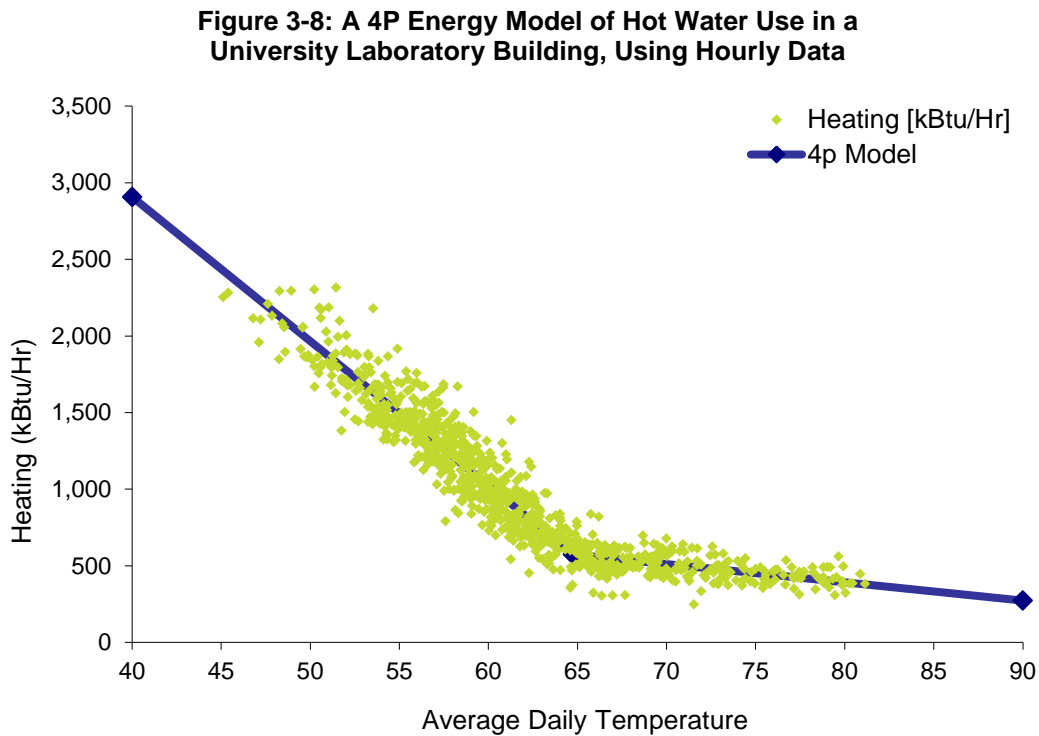Four-parameter change-point cooling models have equations in the form below:

➡ **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 that are extensions of the *ASHRAE RP-1050* models have been presented by the author of the 2012 Energy Modeling 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 under-sizing 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 3-9, below.

**Figure 3-9: Additional 5P and 6P Model Shapes**
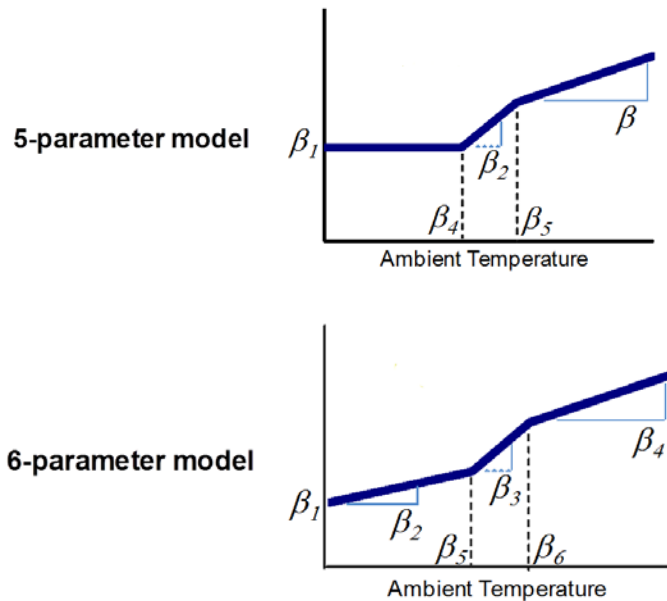


**Polynomial Models**

Polynomial models will most often be $2^{nd}$-order, and they should almost always be limited to $2^{nd}$- and $3^{rd}$-order. Even $3^{rd}$-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 3-10 shows $2^{nd}$ and $3^{rd}$ order polynomial model shapes.

**Figure 3-10: Polynomial Model Shapes**
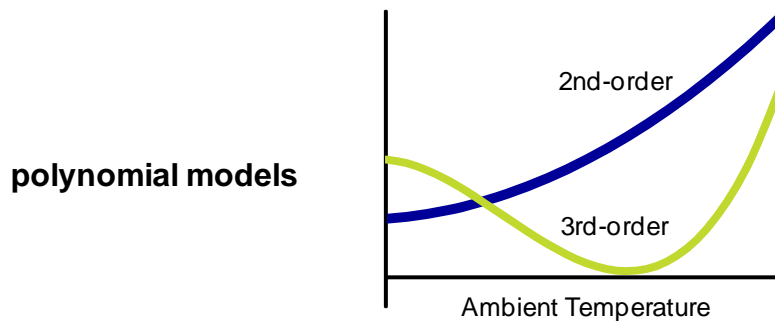


Polynomial models can be useful for system-level models (that is, for estimating energy use as a function of flow and, in some cases, as a function of ambient or other temperatures). Flow is often a function of temperature, and energy use is a function of flow. For a fixed system, the affinity laws state that the power is proportional to the cube of the flow. Thus, some practitioners believe that $3^{rd}$-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 $1^{st}$- or $2^{nd}$-order equation.

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

Polynomial models have equations of the following form:

➡ **$2^{nd}$-Order Polynomial Model:** $E = \beta_1 + \beta_2 X + \beta_3 X^2$

➡ **$3^{rd}$-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, unless the categorical variable is interacted with the continuous variable. An interaction term is when two independent variables are multiplied together to create a new independent variable. A binary indicator variable will create a change the model intercept according to the level of indicator variable. If the indicator variable is interacted with a continuous the model will also a different slope for the levels of the indicator variable. 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.

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, 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 (that is, 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*.

A weakness of the multiple regression models in *ASHRAE RP-1050* is that they can create a model with the same slope for all categories, even when the slopes should be different. This weakness can be overcome, though, via creating an interaction term that is the product of a categorical indicator variable (0, 1) and a continuous variable. When differing slopes are needed by category, interaction terms (discussed below) or multiple models (discussed in the following section) are needed.

Figure 3-11 is a scatter plot of daily gas consumption (therms) against heating degree days base 55 degrees (F) for a hypothetical facility over the course of a heating season. Charting of the data and an understanding of facility operations have revealed that gas usage on the weekends is much lower than on weekdays. It is clear from Figure 3-11 that two different slopes are needed to capture the relationship between weather and gas consumption.

**Figure 3-11: Daily Gas Consumption (Therms) vs. HDD, by Day Type**
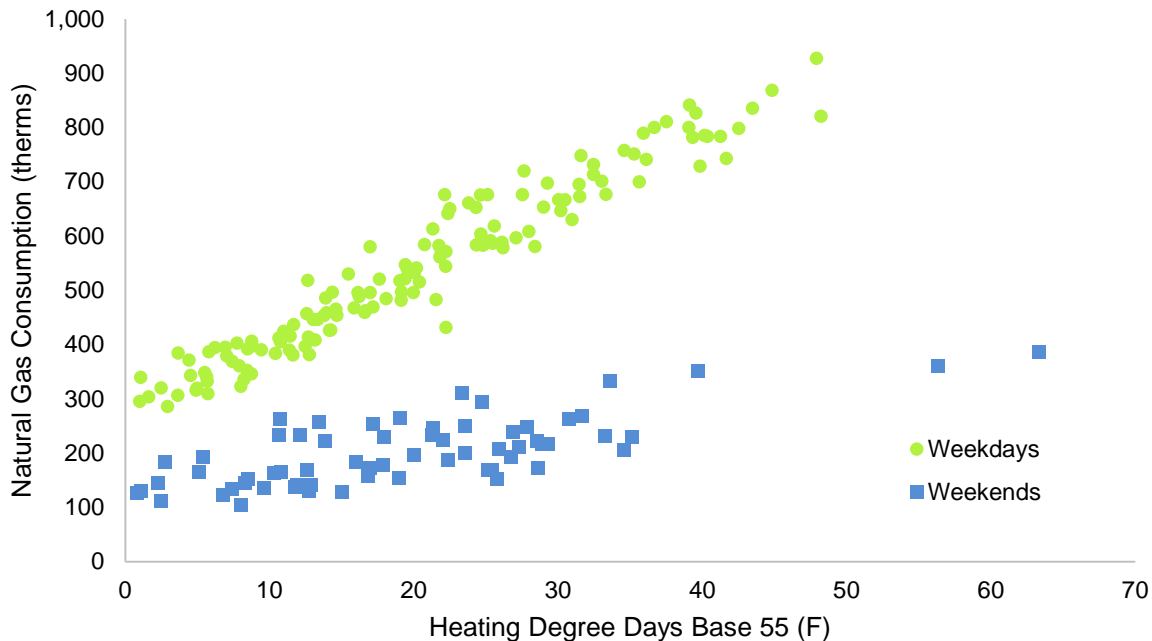


To estimate separate slopes in one regression model, an interaction term is needed between the categorical variable for day type and the continuous weather variable (HDD55). For this example, we create a Boolean indicator variable named "Weekend" that is equal to 1 on Saturday and Sunday and equal to 0 Monday through Friday. An interaction term is also created by multiplying the continuous HDD55 variable by the "Weekend" indicator variable. On weekends, the 'HDD55*Weekend' variable is equal to the HDD55 variable. On weekdays it is equal to zero. Figure 3-12 shows the regression output as analyzed by the Microsoft Excel Regression function[19].

---

[19]   The regression function in Excel is one of the tools in the Data Analysis Add-In

**Figure 3-12: Regression Output with Day Type Indicator Variable**

SUMMARY OUTPUT

| Regression Statistics | |
|---|---|
| Multiple R | 0.9814 |
| R Square | 0.9632 |
| Adjusted R Square | 0.9627 |
| Standard Error | 39.7568 |
| Observations | 205 |

ANOVA

| | df | SS | MS | F | Significance F |
|---|---|---|---|---|---|
| Regression | 3 | 8,324,023 | 2,774,674 | 1755.5 | 0.000 |
| Residual | 201 | 317,701 | 1,581 | | |
| Total | 204 | 8,641,724 | | | |

| | Coefficients | Standard Error | t Stat | P-value | Lower 95% | Upper 95% |
|---|---|---|---|---|---|---|
| Intercept | 275.41 | 6.827 | 40.339 | 0.000 | 261.95 | 288.87 |
| HDD55 | 13.03 | 0.291 | 44.694 | 0.000 | 12.45 | 13.60 |
| Weekend | -147.88 | 11.741 | -12.595 | 0.000 | -171.03 | -124.73 |
| Weekend*Therms | -9.17 | 0.508 | -18.053 | 0.000 | -10.17 | -8.17 |

The coefficients of this model are interpreted as follows:

➡ **Intercept (275.41)**: is the model intercept when 'Weekend' = 0 (that is, on weekdays)

➡ **HDD55 (13.03)**: the model slope when 'Weekend' = 0. The change in expected daily therms for a one-unit change in HDD.

➡ **Weekend (-147.88)**: the *difference* in the intercept when 'Weekend' = 1. By calculating (275.41 – 147.88), we determine that the model intercept on weekends is 127.53 therms.

➡ **Weekend*Therms (-9.17)**: the *difference* in the slope between weekdays and weekdays. By calculating (13.03 – 9.17), we determine that the model slope on weekends is 3.86 therms/HDD55.

This approach is mathematically identical to estimating two separate regression models and using them to predict the consumption for the post-period. It does become more complex to execute in Microsoft Excel as the number of categories increases because the number of indicator variables is a function of the number of categories. If the number of categories is equal to c, the number of indicator variables required is equal to c-1.

## 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.

## Daytyping

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

First, all the data is plotted. Figure 3-13 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 3-13: Sample Electricity Meter Data (kW), Using Daily Data**
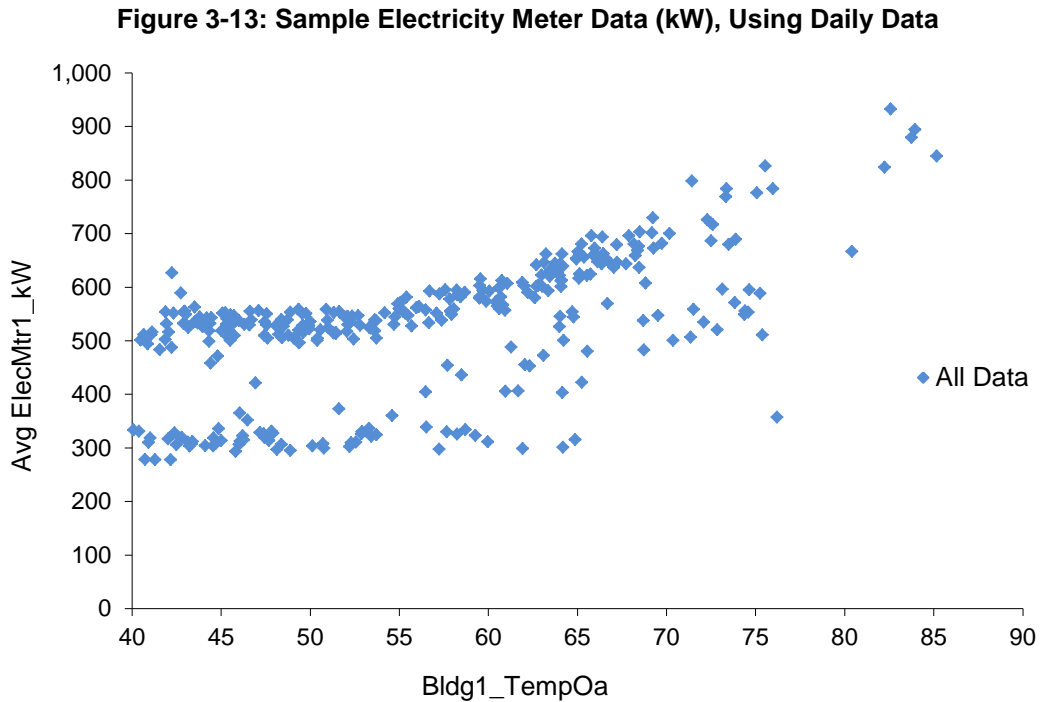


Note the two distinct data clusters. This is an indication of two modes of operation. In this case, the two modes represent two daytypes, as shown in Figure 3-14.

**Figure 3-14: Sample Electricity Meter Data (kW) Showing Daytypes, Using Daily Data**
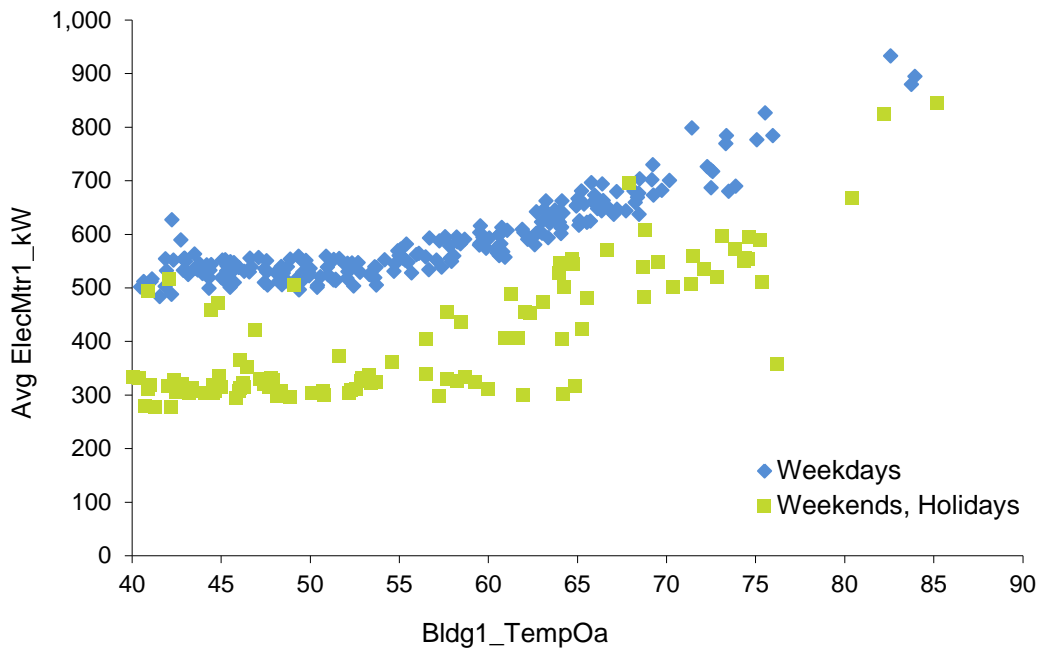


In this situation, separate regression models should be created for weekdays and weekends. After the models have been created and validated, they can be combined into a single model to simplify the calculations. Figure 3-15 is an example model for weekdays. From the form of the scatter chart, it appears that a 3P model might be appropriate.

**Figure 3-15: Sample 3P Model of Electricity Meter Data (kW) for Weekdays, Using Daily Data**



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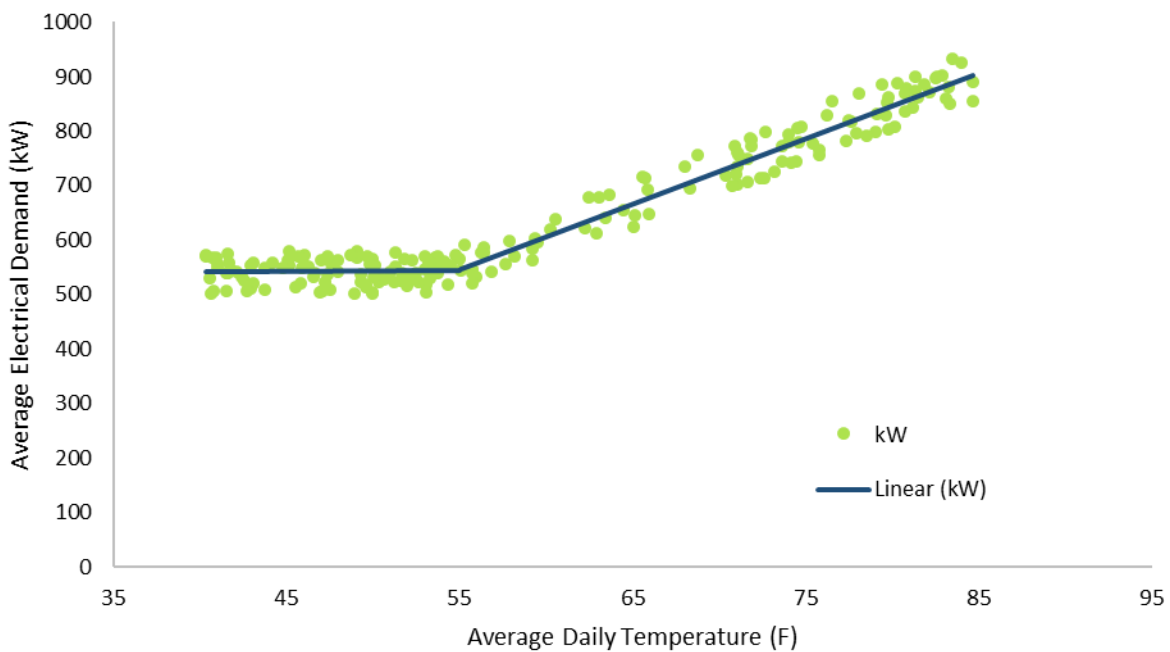
The equation for this model in spreadsheet function form is:

➡ = 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 3-16.

**Figure 3-16: Sample 4P Model of Electricity Meter Data (kW) for Weekdays, Using Daily Data**
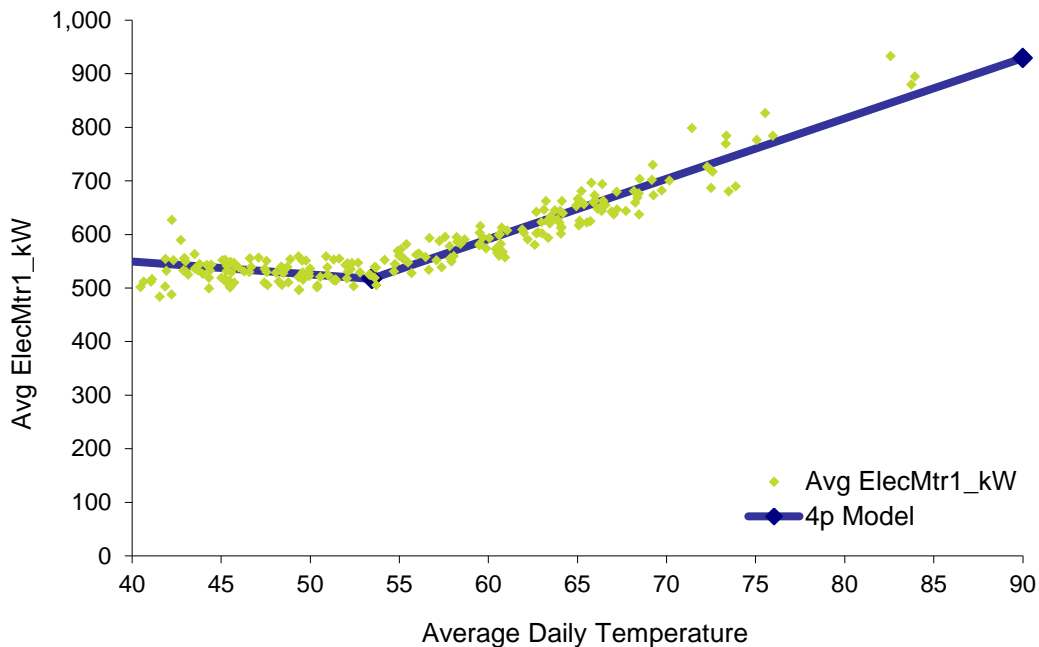


The equation for this model is:

➡ = 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 3-17).

2. More data will be included within each model or bin (see Figure 3-18).

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 3-17 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 3-17: Typical Monthly and Annual Range in Outdoor Temperatures
by Aggregation Method**
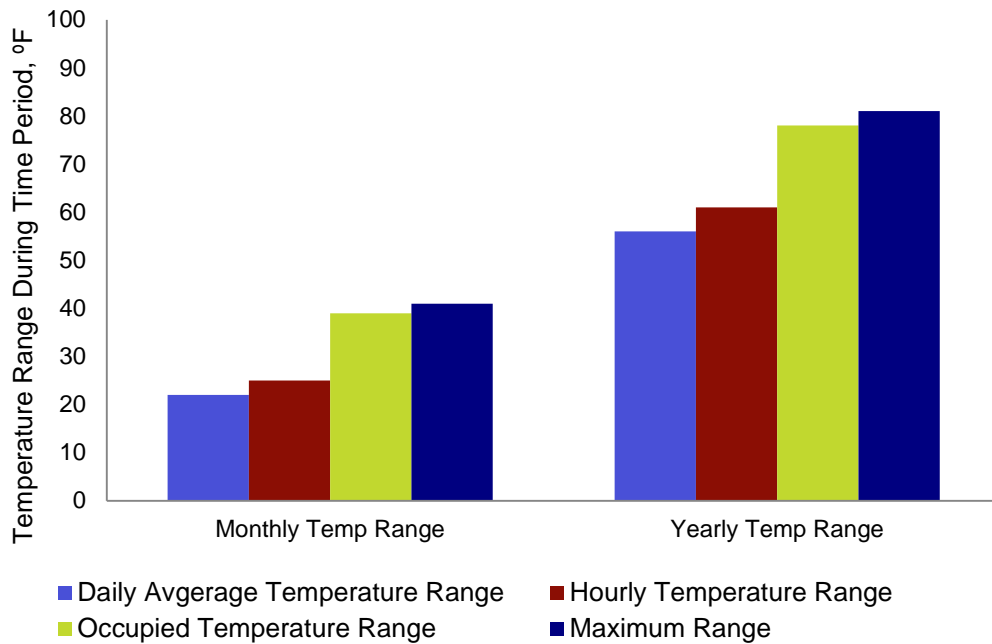


From Figure 3-17, we can deduce the following:

➡ 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 3-18 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 3-18: Number of Data Points per Month by Model Type**
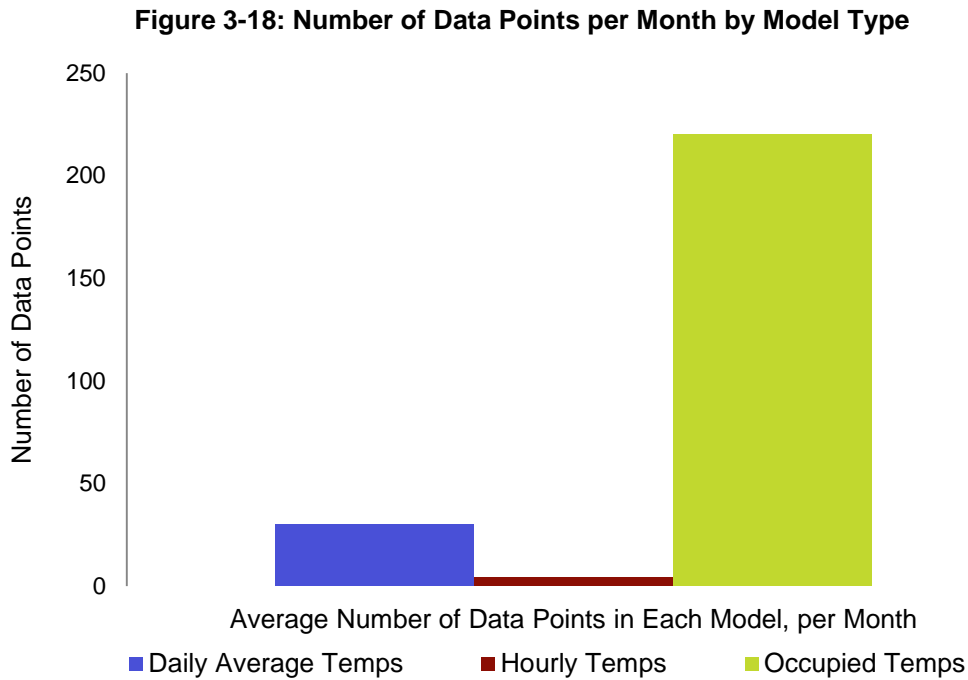


Figure 3-18 shows that a model using daily average temperatures will have approximately 30 data points per month, since there are typically about 30 days in a month. A bin-based model using a separate bin for every hour in the week will have only about four data points per bin per month, since there 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.

## Hour-typing 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 3-19.

**Figure 3-19: Electricity Models Showing Demand (kWh) for Each Hour of the Day, Using Hourly Data**

## Weekdays and Saturdays
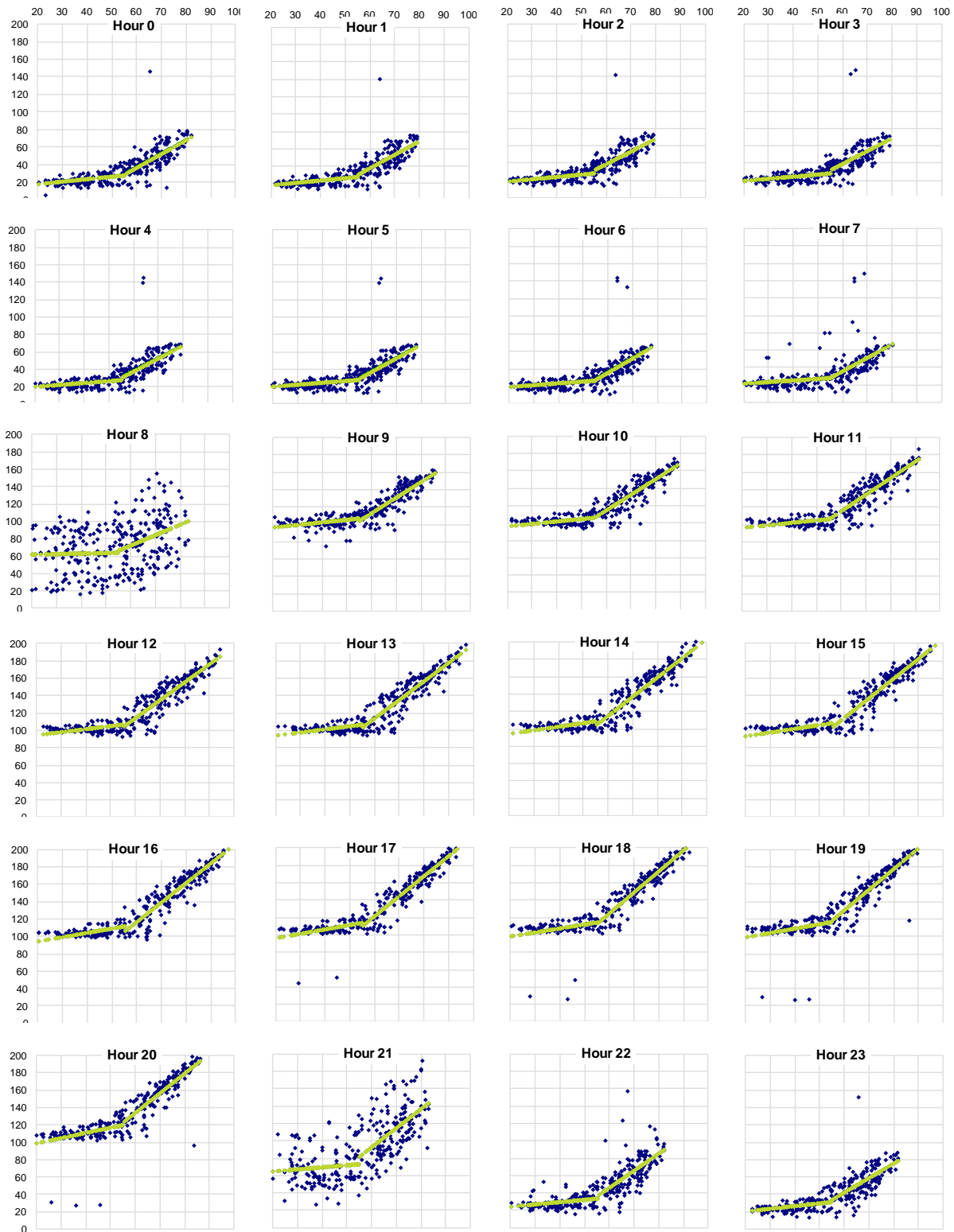
From these models, it can be concluded that hours 0 through 7 and hours 22 and 23 are similar hours, representing unoccupied operation. Hour 8 can be considered startup. Hours 9 through 20 are similar, representing occupancy. Hour 21 represents shutdown. So, there are four groups of hours, with all hours 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 3-20.

**Figure 3-20: Average Electricity Load Profiles (kW) by Daytype, Using 15-Minute Data**
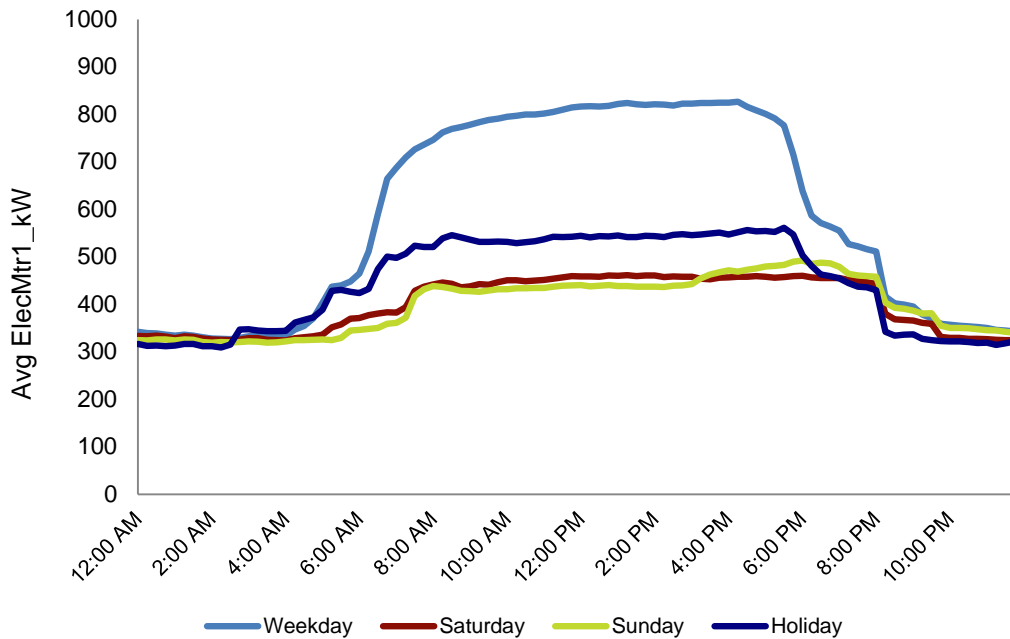


If this is done, the data should be checked to confirm that the daily operating times are consistent over the time period of the data. In this case, they were not. Figure 3-21 shows the average load profiles for March through July.

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 3-21: Average Electricity Load Profiles (kW) for Specific Months by Daytype, Using 15-Minute Interval Data**
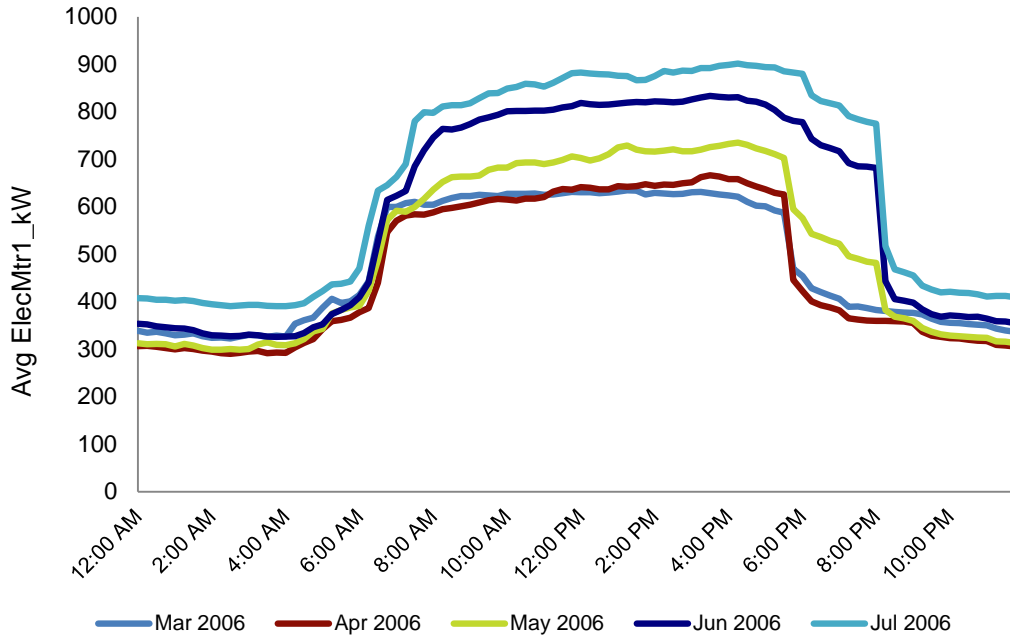


Another approach is to plot all the data in a scatter chart, filter the data for daytype and occupancy or other possible categories, and see if the scatter is reasonably tight. Figure 3-22 shows the same data in a scatter chart. This data is similar to the data shown in Figure 3-13, but it uses hourly data rather than daily averages.

**Figure 3-22: Scatter Chart of Electrical Demand (kW) vs. Ambient Temperature, Using Hourly Data**
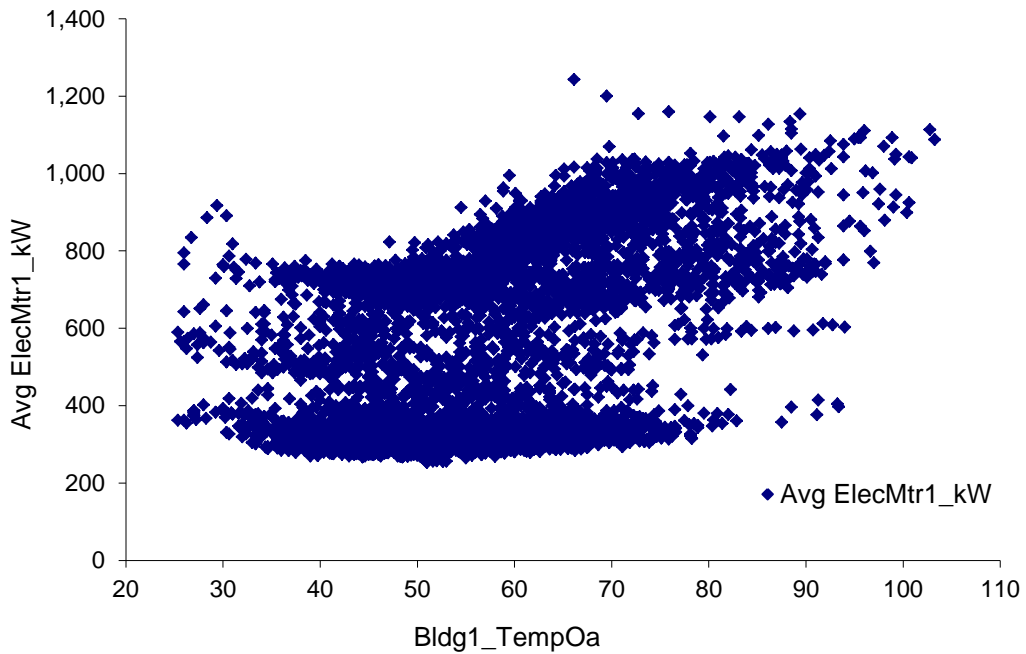
In Figure 3-22, we see two general "clouds" of data, although they are not as distinct here as for the daily average data. So, the first thing is to evaluate what categories explain the individual clouds. Figure 3-23 shows the data filtered so it is only showing weekdays.

**Figure 3-23: Scatter Chart of Weekday Electrical Demand vs. Ambient Temperature, Using Hourly Data**
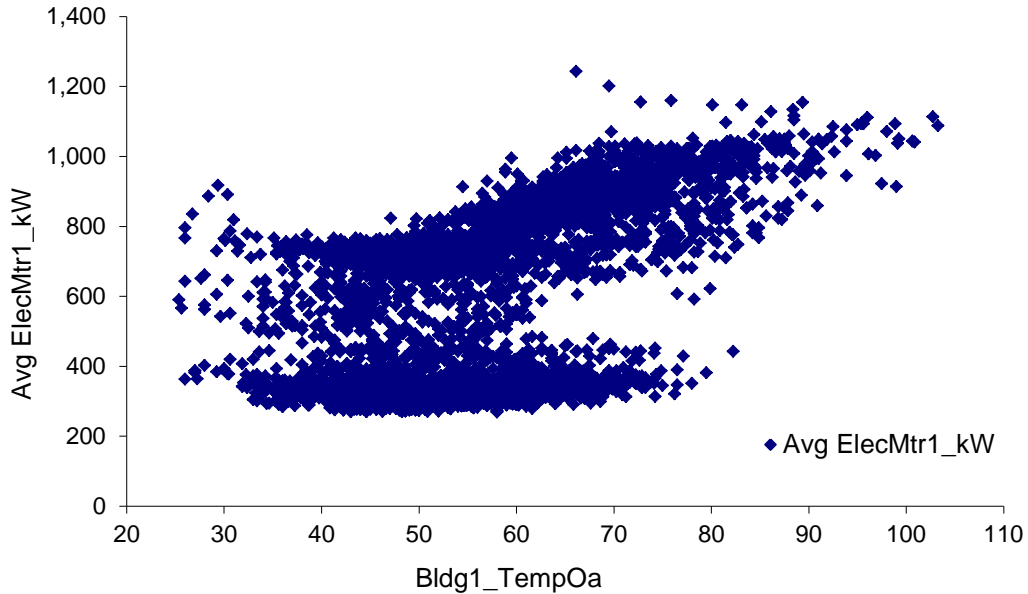


The clouds are still present, albeit a bit more distinct. Since that didn't explain things, we'll try plotting only the occupied hours, as shown in Figure 3-24.

**Figure 3-24: Scatter Chart of Weekday Electrical Demand (kW) During Occupancy vs. Ambient Temperature, Using Hourly Data**
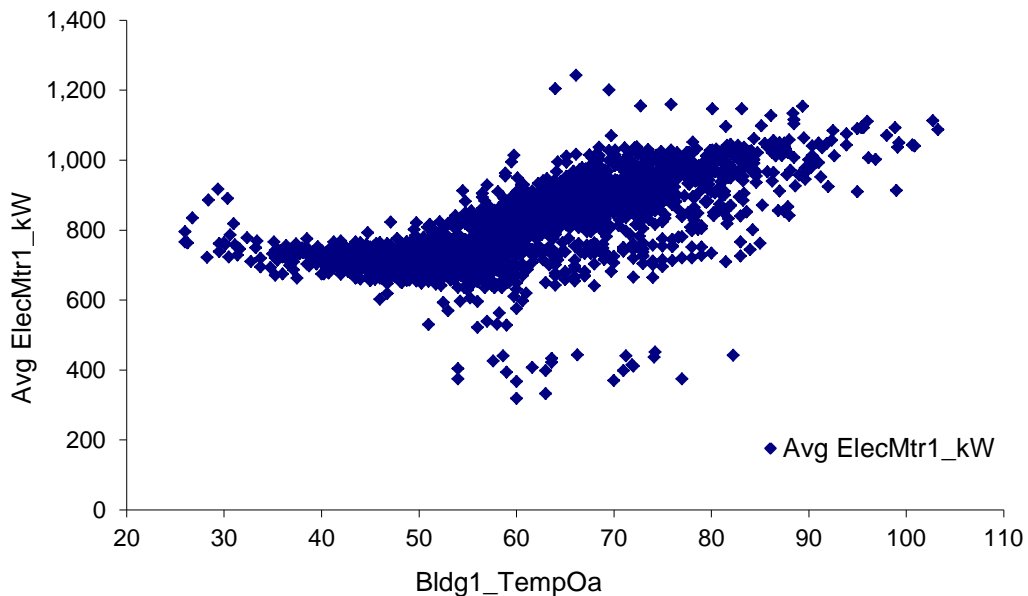
The data still shows a lot of scatter. Figure 3-25 shows a 4P model based on the hourly data for the occupied period.

**Figure 3-25: Scatter Chart of Weekday Electrical Demand (kW) During Occupancy vs. Ambient Temperature, Using Hourly Data**
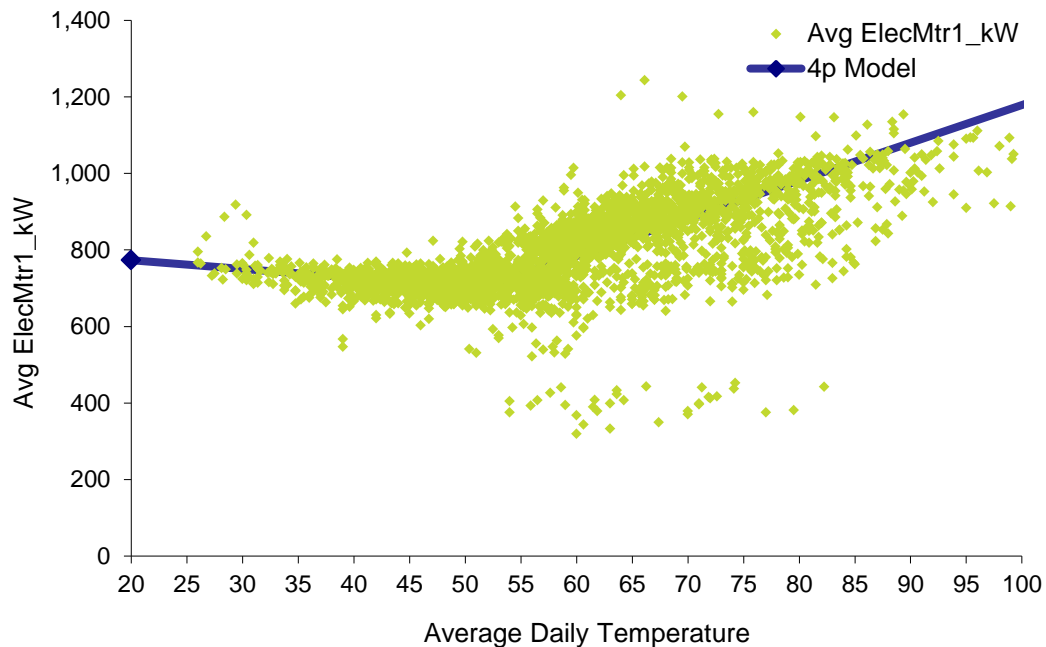


Here is the resulting equation:

➡ = 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 3-26 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 3-26: Scatter Chart of Chiller Plant Electrical Demand (kW) vs. Plant Load (tons), Using Hourly Data**
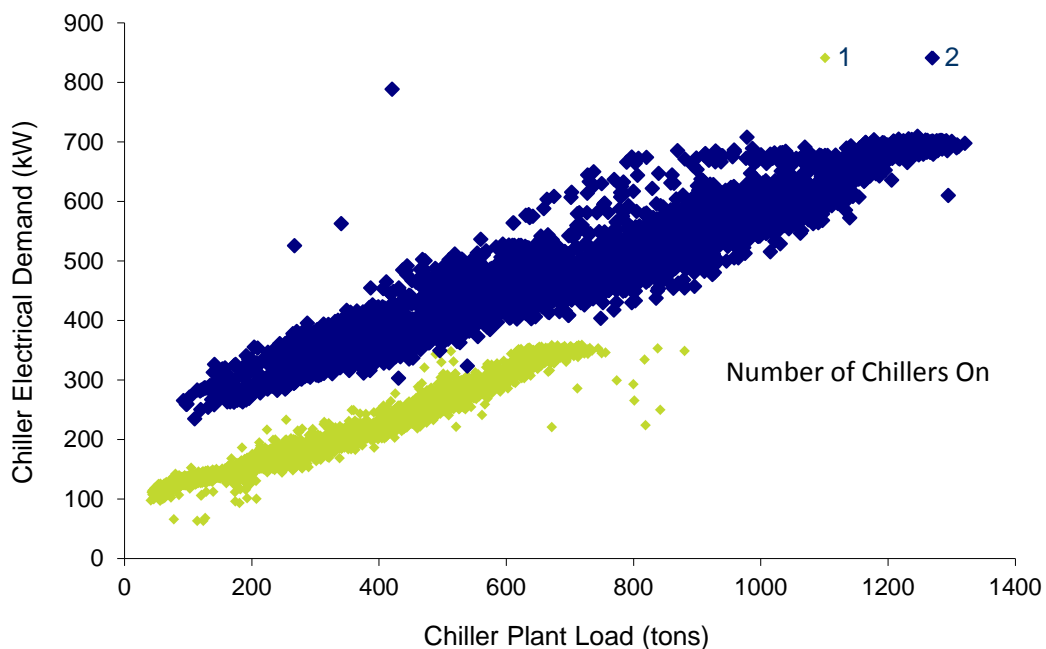


## Combining Multiple Models into One Model

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.[20]

## 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

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[20]   *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**
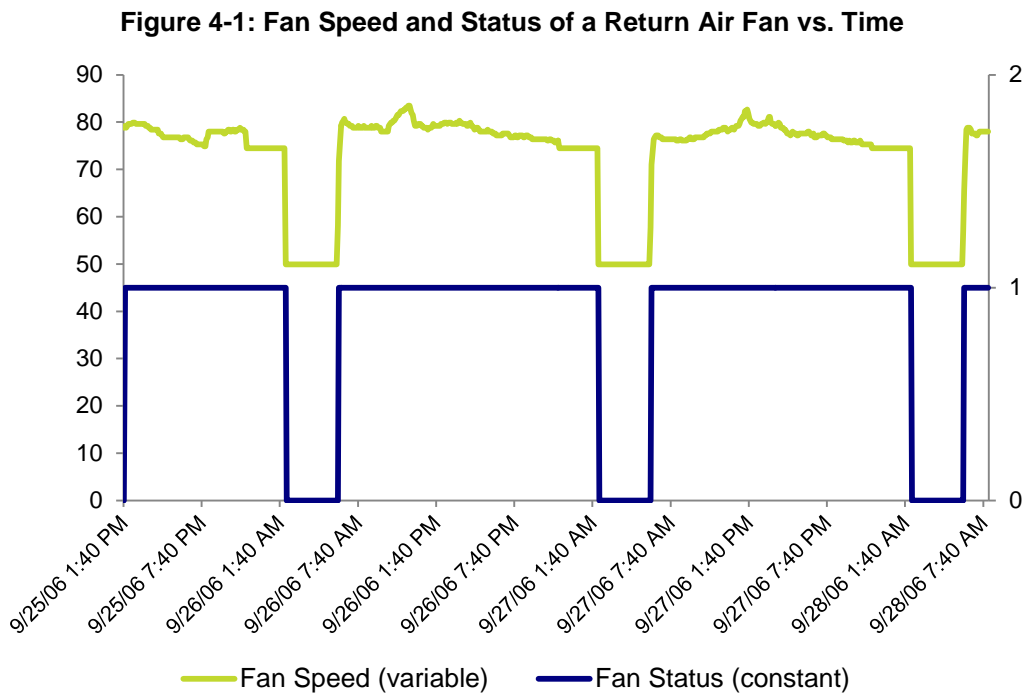
Constant load equipment feedback signals may be made into proxy energy variables by assigning the equipment power to it when it is operating. The equipment power may be determined from the average of multiple measurements of the equipment's power when operating.

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**
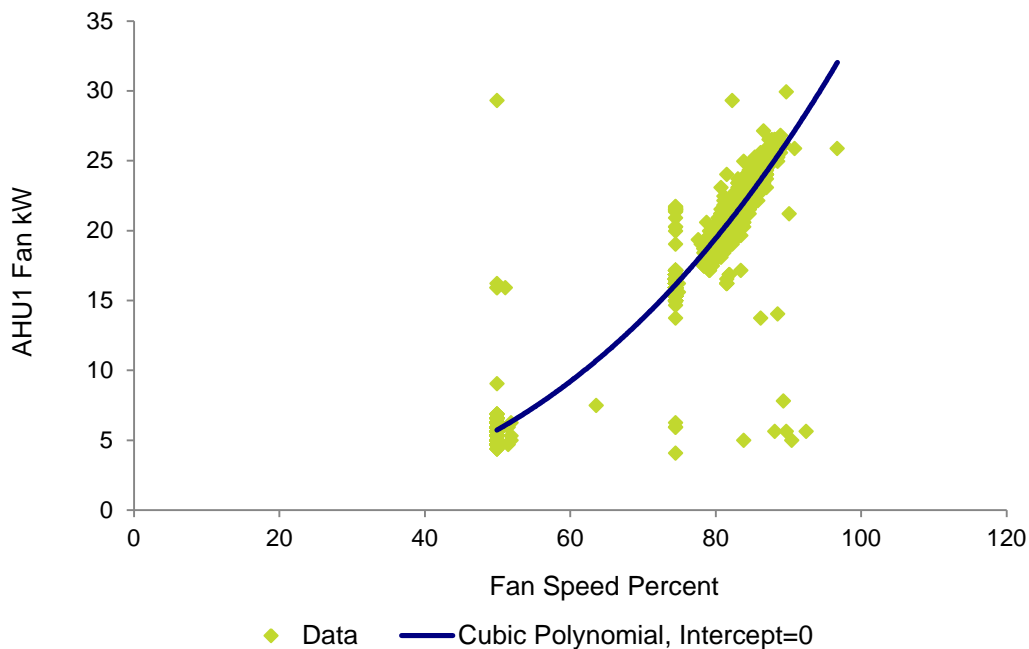


For a complete discussion of end-use monitoring associated with constant load and variable load equipment, refer to the BPA *Verification by Equipment or End-Use Metering Protocol*.[21]

# 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.

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[21] 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).[22] 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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[22]   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 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

Energy usage modeling relying on regression analysis yields estimates, or predictions, that will not be 100% accurate. Thus, modelers speak of the uncertainty of the estimates, that is, uncertainty in the predicted *y-value*. Uncertainty in regression analysis results from three principal sources:

➡ Measurement uncertainty or measurement error,

➡ Coverage error, and

➡ Regression uncertainty or model uncertainty.

Some sources of uncertainty, such as regression model uncertainty within the range of independent variables, can be estimated using accepted formulas. Other sources of uncertainty, such as model misspecification or extrapolation due to poor coverage are difficult to quantify.

## 5.1.  Measurement Uncertainty

Measurement uncertainty has two principal components: *measurement bias* and *measurement precision*. *Bias* relates to issues of calibration and accuracy; *precision* relates to the magnitude of random variation that occurs when multiple measurements are made. (See BPA's reference guides *Sampling for M&V* and *Regression for M&V* for fuller discussion of these concepts.) The concept of measurement uncertainty as it relates to regression analysis pertains to the independent variables, as any measurement error in the dependent variable contributes to model uncertainty, with the error contributing to the model residual.

Instruments for acquiring measurements should be of sufficient resolution and precision that the uncertainties in measurements are small relative to the regression uncertainty. Measurement bias due to measuring equipment error should be eliminated through calibration, and careful instrumentation design and installation should be used to minimize other measurement bias errors. Installation criteria for accurate measurement, such as the need for a straight duct of a specific number of equivalent duct diameters for a flow measurement, may be important.

Note that, even though an installation limitation may introduce the same bias to the pre and post periods, the fact that the bias is the same may not mean that the savings estimate is not biased. Whether or not there is a savings bias is dependent upon the type of bias (that is, additive or multiplicative) and how the measurement is mathematically used.

As applicable, when possible, utility meters should be used for energy-use measurements. By M&V convention, utility meter data is considered to have zero uncertainty for savings estimates. Similarly, data from a nearby National Oceanic and Atmospheric Administration (NOAA) weather station should be used for weather measurements, but such measurements should be verified to be representative of the conditions at the treated building. NOAA sites are far less likely to have biases or inaccuracies due to solar effects and sensor calibration errors than site measurements.

For a thorough discussion of measurements, refer to *Section 6, Instrumentation*, and *Annex A, Physical Measurements*, within *ASHRAE Guideline 14, Measurement of Energy, Demand, and Water Savings*.

## 5.2. Coverage Error

Coverage error occurs when an M&V data set does not fully "cover" the range of conditions that drive energy use, that is the full range of building or system operating conditions. Measurements should be conducted for a sufficient period to capture a significant range of the independent variable. Beyond that, no definitive criteria can be provided regarding the sufficiency of shorter-term data for annual extrapolation. *ASHRAE Research Project 1404*, *Measurement, Modeling, Analysis and Reporting Protocols for Short-term M&V of Whole Building Energy Performance* provides some guidance.

In a production environment, the consistency of production will determine this length of time. When weather is the independent variable, the season and climate will determine the length of time necessary. If seasonal variations in weather are minor, a relatively short time may be possible and still cover a wide range of conditions. If seasonal variations are significant, longer periods (up to a year) may be advisable.

Measurements of the dependent and independent variables must cover the same time periods.

## 5.3. Regression Uncertainty

Regression uncertainty (also referred to as savings uncertainty) results both from modeling errors – explanatory variables are omitted from the model or an incorrect functional form is specified – and because people's unpredictable behaviors affect energy use. Uncertainty in regression typically refers to the uncertainty in the output from a regression; uncertainty in the regression coefficients is typically referred to in a more explicit manner as the *uncertainty of the slope*.

A goal of any M&V plan should be to minimize uncertainty in the savings estimate (regression uncertainty). More specifically, the goal should be to make the uncertainty small relative to the savings. *ASHRAE Guideline 14-2014, Annex B* refers to this as the *fractional savings uncertainty (FSU)*.[23]

Generally, factors that affect regression modeling uncertainty include:

➡ Number of points used in the baseline regression

➡ Number of points in the post-installation period

➡ Number of significant independent variables included in the regression

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[23] Refer to *ASHRAE Guideline 14-2014, Annex B: Determination of Savings Uncertainty* for a more detailed discussion of savings uncertainty than is provided here.

One way to reduce the fractional savings uncertainty is to use more data. Gathering data over a longer period, and/or at more frequent intervals, will generally reduce the uncertainty. Note, though, that as data is gathered at more frequent intervals, this will increase serial autocorrelation – each reading becomes more significantly related to the prior reading. Uncertainty estimates must account for this autocorrelation. Costs may be affected by increasing the length of time required to collect data or monitoring additional variables.

Another way to reduce the fractional savings uncertainty is to include more relevant independent variables. The *t-statistic* and *p-value* should be used to check for the relevance of additional independent variables. If multiple continuous independent variables are significant, the practitioner should not use the *Indexing Protocol.* However, the uncertainty in an index model can sometimes be reduced by including one or two categorical variables (discussed more subsequently). Note that the categorical variables may be different in the baseline and post scenarios, and care should be taken to check their significance.

As with all M&V protocols, the emphasis on accuracy needs to be balanced against the level of savings and cost. Parametric analyses may be exercised on the M&V methodology, or if measurement uncertainty is a minimum, then factors affecting regression uncertainty may be assessed to determine the amount of effort and cost needed to increase accuracy.

## 5.4.  Current Status of Uncertainty Calculations

The best treatment of uncertainty in energy regressions is probably in *ASHRAE Guideline 14-2014, 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 14-2014*.

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).

➡ IPMVP. 2018. International Performance Measurement and Verification Protocol: Uncertainty Assessment for IPMVP. EVO 10100-1:2018. Washington, D.C.: Efficiency Valuation Organization. Available at: *https://evo-world.org/en/products-services-mainmenu-en/protocols/ipmvp*

# 5.5.  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 (FSU):** $\Delta E_{save,m} / E_{save,m}$

> where:    $E_{save,m}$    =   total savings over *m* periods
>
>          $\Delta E_{save,m}$   =   the calculated 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.

## 5.5.1. Models with Uncorrelated Residuals

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:

➡ $$\mathrm{FSU} = \frac{\Delta E_{save,m}}{E_{save,m}} = t * \frac{1.26 * CV * \sqrt{\left(1+\frac{2}{n}\right) * \frac{1}{m}}}{F}$$

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

➡ $$CV(RMSE) = 100 * \frac{\sqrt{\sum_i (E_i - \hat{E}_i)^2 / (n-p)}}{\bar{E}}$$

> where:    $F$        =   Savings fraction = $E_{save}/E_{baseline}$
>
>          $E_{baseline}$   =   Adjusted baseline energy predicted for the reporting period or fixed conditions
>
>          $t$         =   Student's t-statistic
>
>          $(\ )_i$      =   measured value

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

$$(\_)_i \quad = \quad \text{average value}$$

$$n \quad = \quad \text{number of points in the baseline period}$$

$$m \quad = \quad \text{number of points in the post period}$$

$$p \quad = \quad \text{the number of model parameters}$$

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)*.

Advanced practitioners should note that the constant factor 1.26 in the FSU equation above can be replaced with a calculated value "Y" using the number of measurements in the post period (m) assuming the data are monthly or daily. (IPMVP, 2018) Equations for Y are shown below.

➡ Polynomial Correction Factor for Monthly Data

$$Y = (-0.00022 * m^2) + (0.03306 * m) + 0.94054$$

➡ Polynomial Correction Factor for Daily Data

$$Y = (-0.00024 * m^2) + (0.03535 * m) + 1.00286$$

## 5.5.2. Models with Correlated Residuals

*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 avoided energy use models with correlated residuals, the equation is just slightly different:

$$\quad \Rightarrow \quad \frac{\Delta E_{save,m}}{E_{save,m}} = t * \frac{1.26*CV*\sqrt{\frac{n}{n'}*\left(1+\frac{2}{n'}\right)*\frac{1}{m}}}{F}$$

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

$$\Rightarrow \quad n' = n * \frac{1-\rho}{1+\rho}$$

where: $\rho$ = 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

The reason that uncertainty formulas are different for models with correlated residuals is because one of the four key conditions of OLS regression is violated. As discussed in Section 3 of the *Regression Guide*, OLS regression requires that the errors (residuals) of the regression model be independent, so the residual at time t must not be correlated with the residual at time t-1 or at any other time period. It is important to note that the regression coefficient estimates remain unbiased in the presence of autocorrelation, but the uncertainty calculations may not. Thus, any uncertainty inferences drawn may be incorrect. Specifically, the uncertainty estimates will be understated in the presence of autocorrelation because each data point does not contain additional information about the relationship between the dependent and independent variable(s). The purpose of the *n'* adjustment is to discount the number of observations used in the uncertainty calculations by the extent of the first-order autocorrelation.

Table 5-1 shows the maximum allowable *CV\*F/FSU* to meet the ± 50% FSU guideline at the 68% confidence level for monthly 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 |

There are other methods for dealing with autocorrelation that are outside the scope of this protocol. The *Uncertainty Guide for IPMVP* includes a discussion of the Newey-West method to adjust OLS regression calculations to address autocorrelation. There are also techniques such as ARMA (autoregressive moving average) and ARIMA (autoregressive integrated moving average) that incorporate the time-series nature of the data into the functional form of the model.

# 5.6. Issues with Current Status of Uncertainty Calculations

## 5.6.1. 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 out-of-sample, 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 adequate coverage of the range of 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.

## 5.6.2. 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**
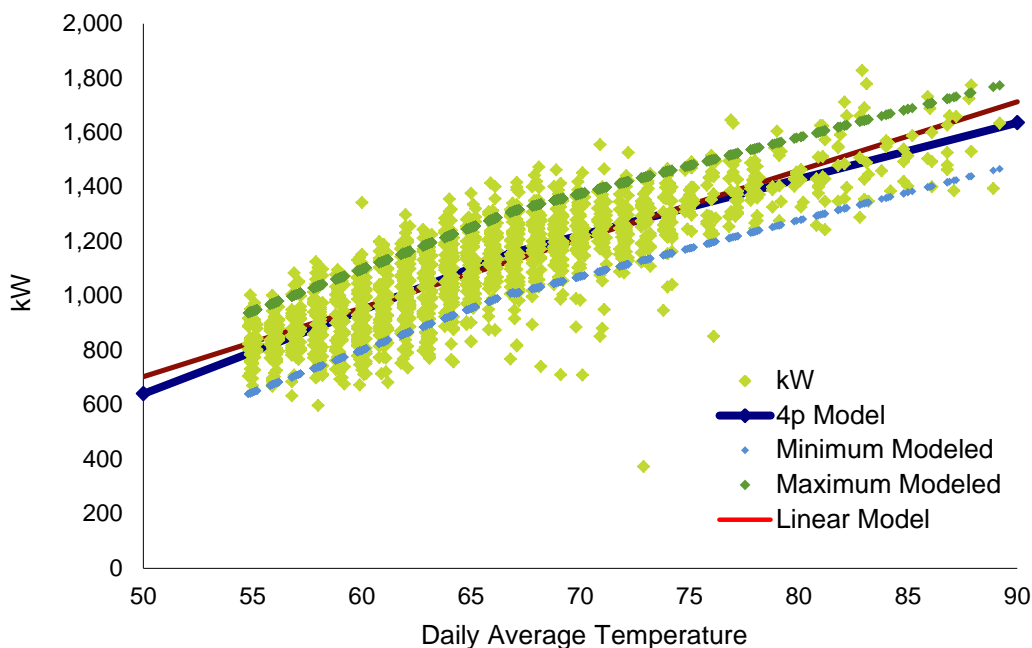


Figure 5-2 shows what happens without the full range of data. In this case, the data above 78º F have been taken out of the data set. The change point was calculated to be the same value, 67º F, but there is a difference in expected electrical demand at 90º F between the 2P and 4P models.

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**
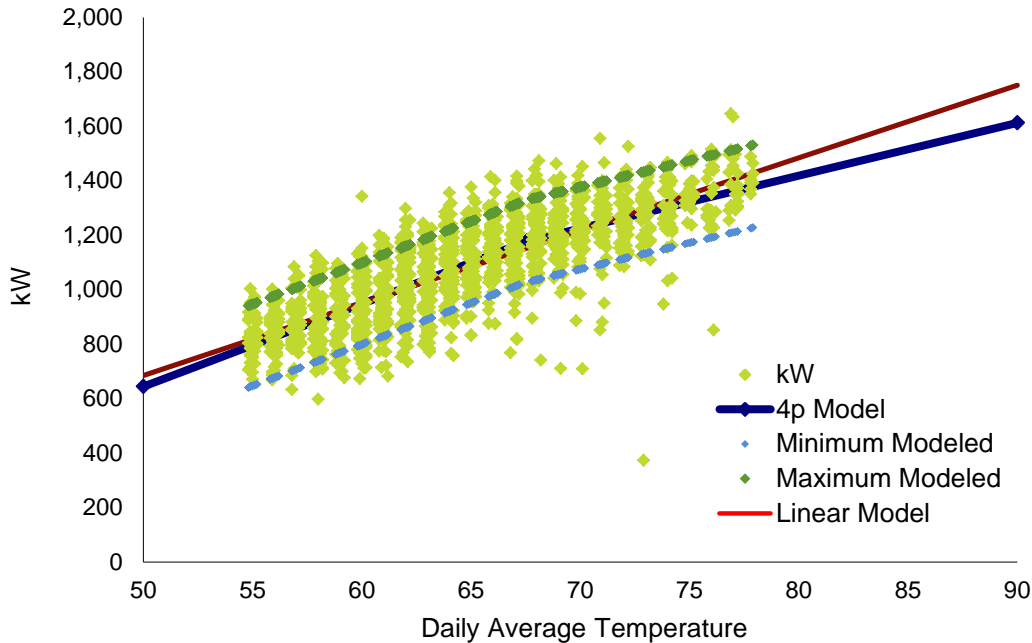


In this case, there was only a minor difference in slope between the economizer regime and the regime with only mechanical cooling. This effect would be more significant where the slope change is greater.

# 5.7. 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:

➡ $E_{save,m} \pm \Delta E_{save,m} \div 2$

Since $\Delta E_{save,m}$ 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 = $E_{save,m} \pm \Delta E_{save,m} \div 2$, at the 90% confidence level

## 5.8.  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.

## 5.9.  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:

➡️ $(\Delta E_{save})^2 = ((\Delta E_{base})^2 + (\Delta E_{post})^2)$

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

➡️ Annual Savings = $E_{save} \pm \text{sqrt}((\Delta E_{base})^2 + (\Delta E_{post})^2)$

# 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.[24] The previous sections in this *Energy Modeling Protocol* describe methods to verify savings in equipment and end uses. This protocol describes planning requirements 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 (such as air handling or chilled water system). In industrial applications, systems may also be defined by their process.

➡ **Baseline Equipment and Conditions:** Document the end-use baseline systems affected by the ECMs. Document equipment configurations, operational characteristics (operating practices or operation schedules that characterizes its hours of use), and equipment inventories, sizes, types, and conditions.

➡ **Energy and Independent Variable Data:** Include all energy data from spot measurements and short- or long-term monitoring from each source. Describe:

■ The parameters needed to characterize equipment load,

■ The sources of the energy and independent variable data and the time interval at which they are monitored,

■ The start and duration of monitoring for both the baseline and post-installation periods, and

■ Any needed corrections to the data.

➡ **Reporting Period:** Describe the length of the reporting period and the activities that will be conducted, including data collection and sources.

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[24] *Chapter 7, IPMVP Core Concepts. 2016*

→ **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 methods for identifying and energy usage adjustments for Non-Routine Events, Describe any extrapolations of energy use or savings beyond the reporting period. Describe how savings uncertainty (if required) will be estimated. Document all assumptions.

→ **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 (such as meters and instruments, and associated safety equipment) 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 reporting database*:*

→ 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 Core Concepts Chapter 7.4, M&V Reports*, 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

Determine the relationships between load and continuous variables such as temperature, air or water flow, pressure, and so on. This includes the relationships of indicator variables such as daytypes and seasons to energy consumption. 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.

### Savings Verification Report Information

The report should include the following information in most cases. 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 program or project.

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 Core Concepts Section 5.5* suggests that, "Operational verification serves as a low cost initial step for assessing savings potential or verifying performance over time and should be included in the M&V Plan and precede other post-installation saving verification activities." 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. Clean the data.

4. Graph the data.

5. Select and develop a model.

6. Validate the model.

7. Perform an analysis of residuals.

Software tools can assist with Steps 3 through 7.

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, 2010, and 2016. It's latest version is distributed by SBW Consulting through its website *www.sbwconsulting.com/ecam*. At the time of the revision of this protocol, the website had Version 5.0 revision 8 of ECAM. AS its name implies, ECAM is a flexible tool designed for 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). It also includes energy modeling based M&V capability based on change-point modeling originally developed under ASHRAE RP-1050.

## 7.2.1. Significant Features for Energy Modeling & M&V

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.

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.

ECAM supports energy modeling M&V approaches for sub-hourly, hourly, daily or monthly energy use data. It enables the user to develop and assess baseline energy use models using goodness of fit metrics and estimates of savings uncertainty. When post-installation data is

available, it supports estimation of avoided energy use and normalized savings, also providing estimates of savings uncertainty.

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.

**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, Version 3

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. It has recently been updated to version 3 (UT3) to allow users to develop analysis modules. Through a California Energy Commission funded project, an M&V analysis module has been added. This M&V analysis module uses a temperature-and-time-of-week (TTOW) energy modeling algorithm developed by Lawrence Berkeley National Laboratory (LBNL).

## 7.3.1. Significant Features for Energy Modeling and M&V

UT3 is a premier tool for resampling data to synchronize time stamps, and merging and synchronizing multiple data streams. 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, UT3 makes it painless.

UT3 also facilitates charting, creating standard time-series and scatter charts. There is an excellent capability to zoom into time series charts. UT3 also makes it easy to add and subtract points from a chart. Users can create data filters and schedules, and can create calculated points. UT3 also provides linear and polynomial regression capability. UT3 has many other useful

features and is extremely flexible, making it possible to handle most needed data manipulation tasks.

Once data is prepared within UT3, its M&V analysis module is available to estimate savings using an energy modeling approach. The M&V analysis module accepts sub-weekly time interval data, such as daily or hourly intervals, but not monthly energy use data. The M&V analysis module enables users to access the prepared data files, develop and assess baseline and post-installation period models, estimate avoided energy use for the post-installation period, and estimate normalized savings.

The M&V analysis module enables users to select from a menu of different modeling approaches, including models with both a time-of-week and temperature dependence, a time-only dependence, and a temperature-only dependence. It enables users to characterize the temperature relationship in different ways as well. It provides diagnostic charts, including time-series charts, and scatter plots of residuals. It enables users to set up scheduling filters to account for different building operation schedules. It runs sub-models for each filtered bin, and assembles each sub-model into complete baseline or post-installation models. As models are developed, it displays the charts and the goodness of fit metrics CV(RMSE) and $R^2$, so that users may determine whether the model meets their criteria.

# 7.4. 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.

## 7.4.1. 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 RP-1050* change-point models. (Dr. Kissock was the primary investigator for ASHRAE RP-1050.) 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.

# 7.5. M&V 2.0

Automated M&V, or M&V 2.0, is a popular discussion topic among M&V practitioners. There are many possible definitions, but in general M&V 2.0 refers to using software and advanced modeling techniques to largely automate Whole Building Energy Modeling – typically with high-frequency reads from the utility revenue meter (daily, hourly, or sub-hourly). M&V 2.0 also

often refers to frequent reporting of savings – perhaps on a weekly or monthly basis throughout the reporting period.

Most of the same principles that apply to analysis of a single ECM apply to these advanced platforms. The accuracy and precision of the model estimates are still predominantly a function of the signal-to-noise ratio and the coverage of the range of independent variables in the baseline period. Advanced methods offer significant opportunities to automate and codify many of the data exploration and management steps, which can lead to improved efficiency and reduce reliance on individual judgement. Improved computing power has enabled powerful estimation approaches that are not closed-form solutions like OLS, and instead iterate to convergence.

An advanced modeling process is no substitution for an understanding of the energy drivers within a facility. The most important factor in a quality energy model is obtaining the right independent variables that explain the variation in energy consumption. When weather is not the primary independent variable, the automation advantage is often lost because it is necessary for an analyst to interact with a facility contact to gather the key operating parameters. In facilities with Energy Management Systems that trend key non-weather parameters, it may be possible to still largely automate the data exchange and analysis once the key independent variables are established. Automated M&V can also overlook NREs, especially if NREs occur in the baseline period.

# 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.

One additional programs that overlap with UT and ECAM:

➡ **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.

Data management, charting, and modeling for M&V can also be conducted in statistical software packages like SAS, Stata, Python, and R. R and Python are open-source packages that are free for download. SAS and Stata are available for purchase. These statistical packages offer many powerful tools that can applied to M&V, but the learning curve can be steep, especially for practitioners who don't use the *Energy Modeling Protocol* frequently. There are also R and Python packages containing energy modeling algorithms free for download such as Open EE Meter's CalTRACK package on Github.

# 8. Examples

## 8.1. Verification by Energy Modeling Example #1: Whole-Building Approach

The following example illustrates how to apply the *Energy Modeling Protocol* using a whole building approach to determine avoided energy use and normalized energy savings. Since it is a whole-building approach, it would be considered *IPMVP Option C*. The project analysis models electricity consumption as a function of ambient dry bulb temperature (F) using a four-parameter '4P' linear change point model.

### 8.1.1. Introduction

The HVAC controls upgrade project was implemented in a five-story 125,000 square foot medical office building located outside of Eugene, Oregon. The facility operates Monday to Friday from approximately 6am to 9pm and is unoccupied on weekends and holidays. The HVAC system consists of five rooftop units (RTUs) and air handler units (AHUs) – each dedicated to a floor of the building. There were variable air volume (VAV) boxes serving each zone and a Trane building management system monitors temperature, pressure setpoints, and other operating parameters.

In fall 2016, a controls upgrade project was implemented including the following measures:

➡ Employ a seasonal outside air temperature reset of the AHU discharge air temperature setpoints from 55° to 65°

➡ Employ a duct static pressure reset upon VAV load demand to reduce fan speed at low loading conditions

➡ Create occupied/unoccupied schedules for each tenant area and implement unoccupied setback schedules of 65° (winter) and 82° (summer)

➡ Retro commissioning of rooftop HVAC equipment

  ▪ Review and correct issues with dampers, actuators, and sensors

The controls upgrades were implemented from September 2016 to February 2017. In the 12 billing periods (366 days) prior to project implantation, the facility used 4,478,900 kWh. The identified upgrades were projected to save at least 15% of the whole-building electric consumption.

### 8.1.2. Baseline Period

The measurement boundary for the project is the entire facility served by the electric meter. The baseline period was defined as the twelve most recent electric billing cycles prior to the implementation of the controls upgrade project. Figure 8-1 shows the average daily electric

consumption and average outdoor temperature for each of the twelve billing periods. Electric consumption is highest during the winter months when average outdoor temperatures are lowest and during the summer when temperatures are warm.

**Figure 8-1: Baseline Period Electric Consumption and Outdoor Temperature**
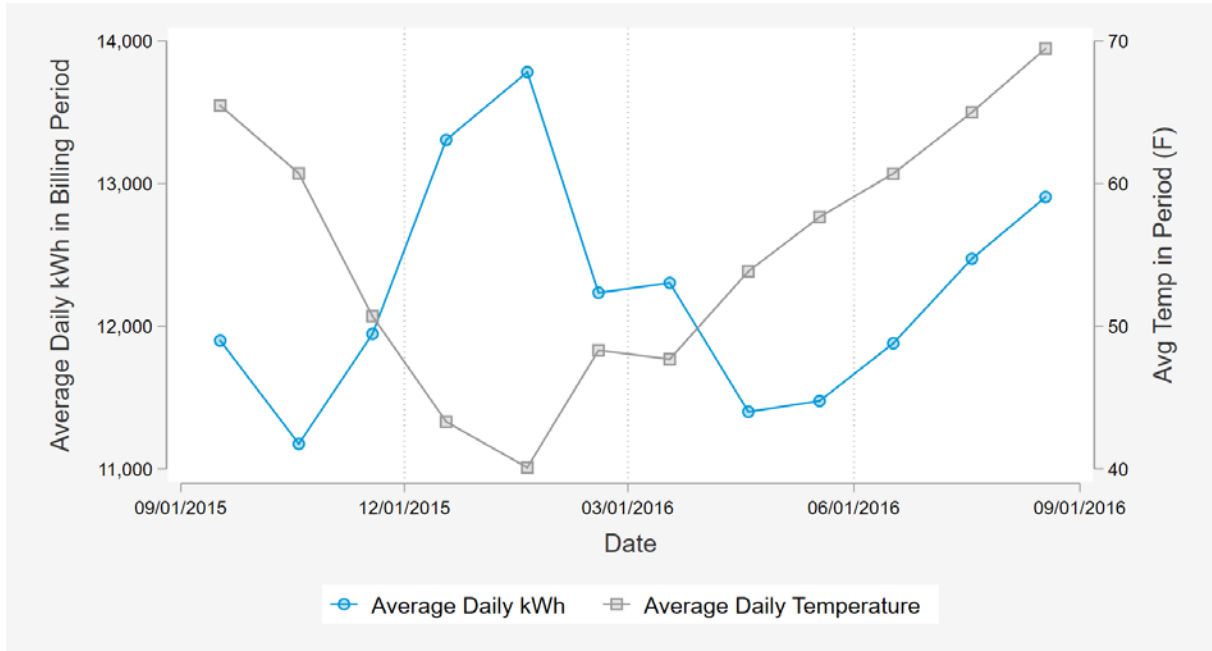


The Verification by Energy Modeling protocol was selected from the project for several reasons:

1. Pre-existing building conditions were the appropriate baseline for the savings calculation.

2. The project included multiple ECMs which interact with one another, making standalone engineering calculations challenging and cost-prohibitive.

3. The signal-to-noise ratio is good. The observed variation in historic electric consumption in the facility is largely explained by weather conditions and the project was expected to achieve a large reduction in the overall building consumption.

4. Good coverage of normal weather conditions. Figure 8-2 plots the baseline period average daily energy consumption against ambient weather conditions and includes two vertical green lines for the most extreme weather months in the TMY3 weather file for Eugene, Oregon[25]. The baseline period includes observations that provide coverage of both ends of the range of normal weather conditions expected for the facility. This means the regression model will not be required to extrapolate estimates of consumption outside of the range of weather conditions it was fitted upon.

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[25] *https://rredc.nrel.gov/solar/old_data/nsrdb/1991-2005/data/tmy3/726930TYA.CSV*

**Figure 8-2: Scatterplot of Daily Energy Use vs. Temperature with TMY3 Extremes - Baseline**
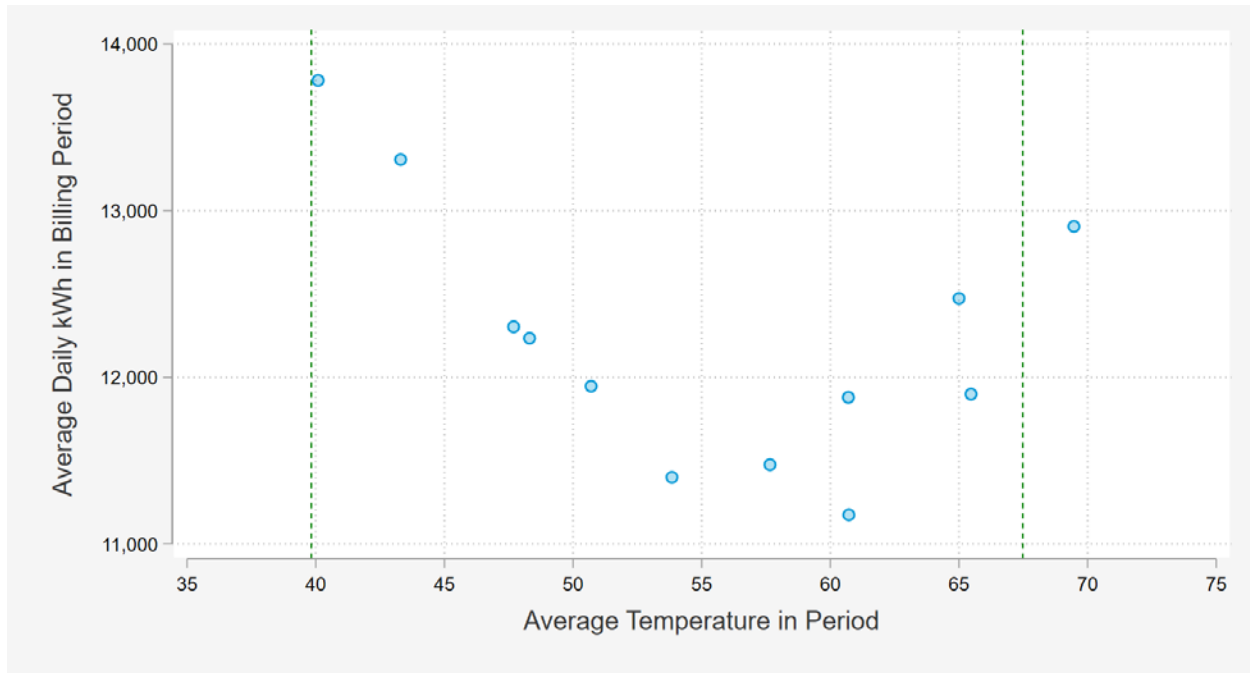


Figure 8-2 shows a clear linear trend below 55°. As weather conditions become increasingly cold, the electric consumption of the building increases. This is expected with electric heating elements used to heat the building during morning warmup. The relationship between energy use and weather is a bit noisier above 55°, but shows a clear positive correlation between temperature and energy use.
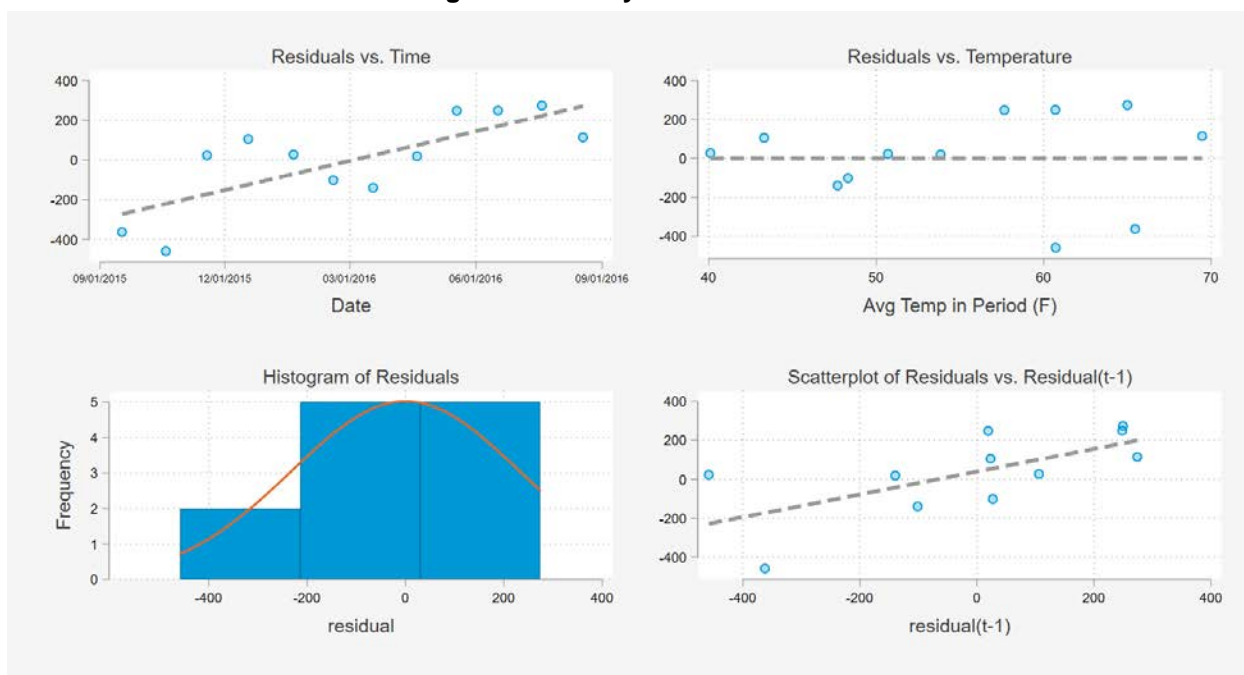
Based on visual inspection of the data in ECAM and testing of model fit for each integer change point from 50° to 60°, the BPA engineer selected a four parameter (4p) model with a change point of 56°. Figure 8-3 shows the fitted trend on top of a scatterplot of the raw data.

**Figure 8-3: 4P Model – Baseline Period**
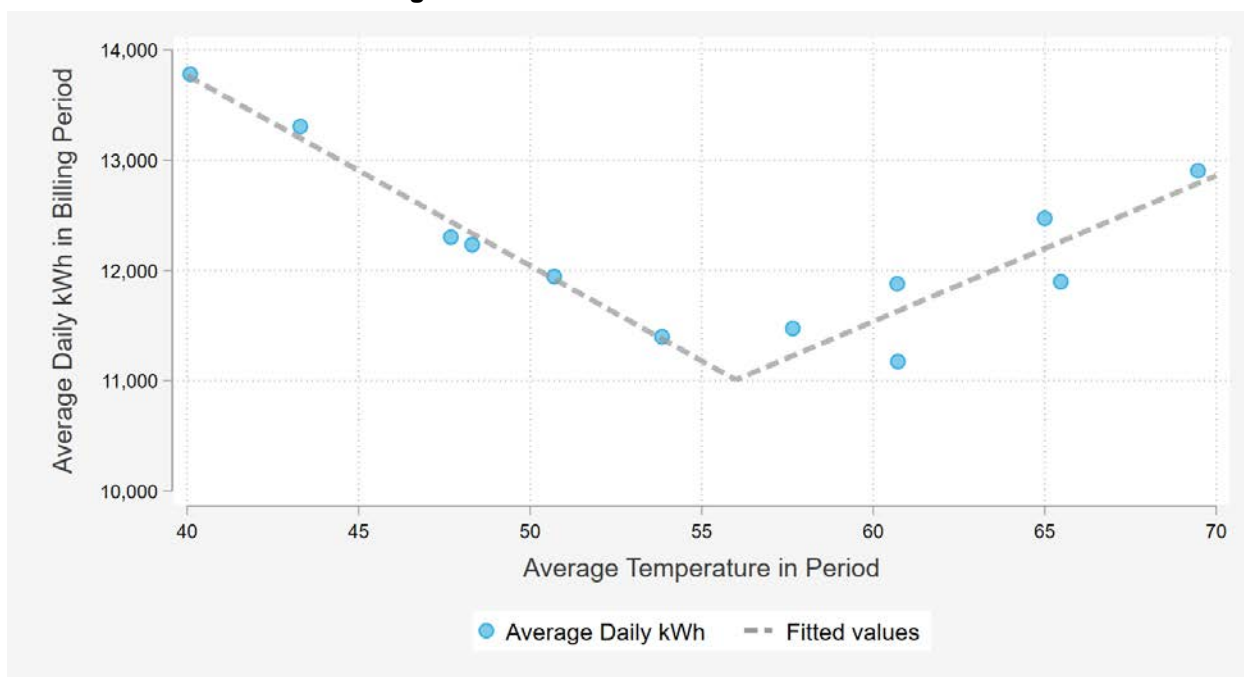


A key step in the Verification by Energy Modeling protocol is an analysis of the residuals to confirm that none of the key assumptions of OLS regression are violated. Residuals are model errors calculated as the difference between the actual value minus the predicted value. Figure 8-4 presents the output of key checks.

**Figure 8-4: Analysis of Residuals**



Verification by Energy Modeling Protocol

Based on a visual inspection of the charts in Figure 8-4, we see that:

➡ The residuals are approximately normally distributed with a mean of zero. With monthly data the limited number of observations can make histogram plots challenging.

➡ There is no distinct trend in residuals vs. the independent variable. The size of the residuals increases at warmer temperatures, but there is no directional trend. There is more noise in the data at warmer temperatures.

➡ There is a directional trend in residuals over time. The model tends to over-predict early in the baseline period and under-predict late in the baseline period. The extent of the time trend was determined to be acceptable by the BPA engineer.

➡ Autocorrelation does not appear to be a major issue. The two largest (negative) residuals occur during the first two billing periods of the baseline period, but subsequent residuals are not overly correlated with the residuals from the prior billing period.


## M&V Plan

The M&V plan for this project called for execution of the Verification by Energy Modeling Protocol by a BPA engineer with the coordination of the electric utility and the facility (if needed). The M&V plan also called for:

➡ A regression analysis, using the software Energy Charting and Metrics (ECAM) tool, of whole building utility billed energy data as a function of actual local weather data.

➡ Pre/post regression curves to be normalized using long-term average weather based on TMY3 data for Eugene, Oregon.

➡ A post-project performance period of 6-9 months, which was anticipated to provide statistical results of less than 50% fractional savings uncertainty at the 80% confidence level.

➡ The M&V plan noted that if more than 50% FSU was observed, the performance period would be extended until results showed a level of statistical significance deemed appropriate by the reviewing BPA engineer.

➡ The M&V plan discussed an understanding with the participant that no deemed measures (i.e. lighting, computer network management, etc.) would be implemented until the 6-9 months of post-project data collection is complete. If any deemed measures were installed, the M&V plan states that the deemed energy savings will be subtracted from the whole building energy savings to determine the 'net' savings specifically from the measures in this HVAC controls upgrade project.

## 8.1.3. Reporting Period

Six billing cycles were excluded from the HVAC controls upgrade project analysis. This was the period of time during which changes were being made, so the operation of the building was neither in the baseline state or the post-period. The reporting period for the HVAC controls project was ten billing periods and included weather and electric consumption from February 17, 2017 to December 19, 2017. Figure 8-5 is a scatterplot of the average daily kWh consumption of the facility against the average daily temperature for the ten billing cycles in the reporting period. The vertical green lines represent the average temperature for the most extreme calendar months in the TMY3 weather file for Eugene, Oregon. Like the baseline period, the reporting period shows good coverage of the expected range of weather conditions.

**Figure 8-5: Scatterplot of Daily Energy Use vs. Temperature with TMY3 Extremes - Reporting**
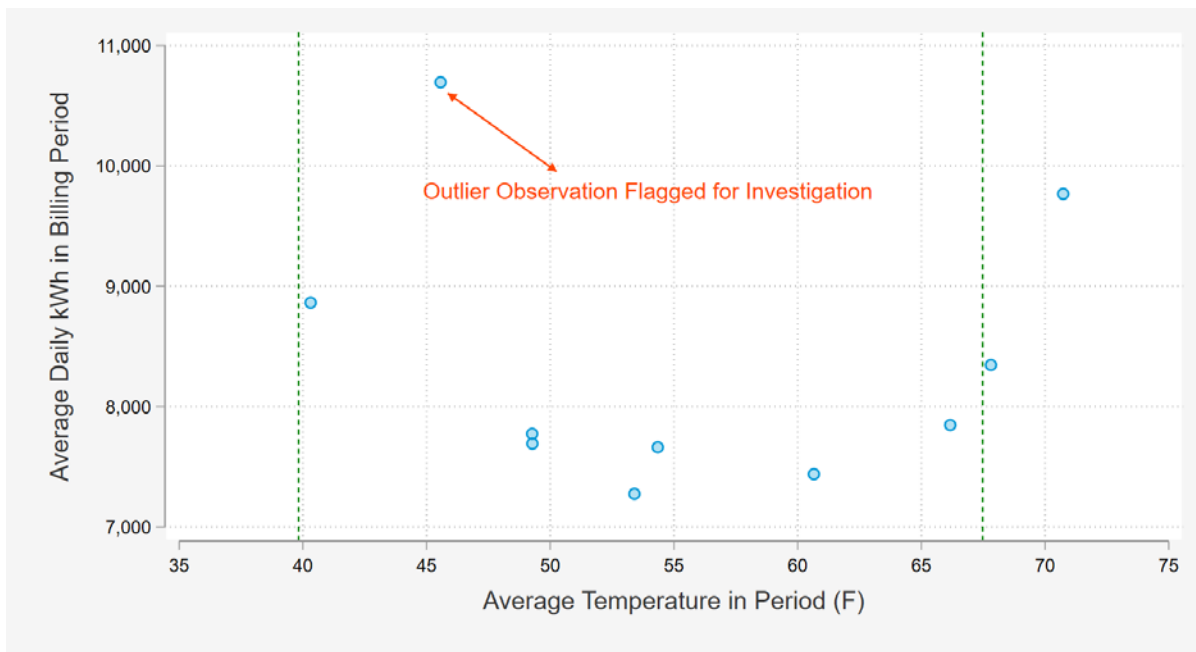


As shown in Figure 8-5, one of the billing periods in the reporting period was flagged by the BPA engineer as a potential outlier. Discussions with the site contact revealed that several mobile medical trailers were located at the facility during this period and that the electric service for those temporary units was provided through the primary facility meter used in the analysis. The BPA engineer determined that this situation was a non-routine event and excluded the billing period from the analysis. This outlier observation was the first billing cycle of the reporting period.

## Avoided Energy Use

The avoided energy use approach involves using the regression model fitted from the baseline period to predict what energy use would have been in the reporting period absent the energy conservation project. Table 8-1 illustrates the calculation. The fractional savings is the avoided energy use divided by the predicted consumption using the baseline model and is equal to 37.7%.

**Table 8-1: Avoided Energy Use Calculation**

| Meter Read Date | Average Temp in Period (F) | Billed kWh | Days in Period | Daily kWh | Predicted Daily kWh | Avoided Energy Use (kWh) |
|---|---|---|---|---|---|---|
| 4/18/2017 | 49.28 | 223,080 | 29 | 7,692.4 | 12,169.3 | 129,829 |
| 5/18/2017 | 53.40 | 218,240 | 30 | 7,274.7 | 11,457.4 | 125,481 |
| 6/19/2017 | 60.66 | 238,040 | 32 | 7,438.8 | 11,624.9 | 133,955 |
| 7/19/2017 | 66.17 | 235,400 | 30 | 7,846.7 | 12,354.2 | 135,225 |
| 8/18/2017 | 70.73 | 293,040 | 30 | 9,768.0 | 12,958.6 | 95,717 |
| 9/19/2017 | 67.81 | 267,080 | 32 | 8,346.3 | 12,572.0 | 135,224 |
| 10/18/2017 | 54.34 | 222,200 | 29 | 7,662.1 | 11,294.3 | 105,334 |
| 11/17/2017 | 49.27 | 233,200 | 30 | 7,773.3 | 12,170.9 | 131,926 |
| 12/19/2017 | 40.31 | 283,624 | 32 | 8,863.3 | 13,716.5 | 155,303 |
| **Total** | | | **274** | **2,213,904** | **3,361,899** | **1,147,995** |

Based on the analysis of the residuals shown in Figure 8-4, the uncertainty calculations for this project can utilize formulas from Section 5.5.1 (Models with Uncorrelated Residuals).

$$\text{FSU} = t * \frac{1.26 * CV * \sqrt{\left(1 + \frac{2}{n}\right) * \frac{1}{m}}}{F}$$

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

For the avoided energy use approach at the 80% confidence level, the values are shown in Table 8-2.

**Table 8-2: Uncertainty Calculations for Avoided Energy Use**

| Parameter | Definition | Value |
|---|---|---|
| t | Student's t-statistic | 1.397 |
| n | Number of points in the baseline period | 12 |
| m | Number of points in the post period | 9 |
| p | Number of parameters in the model | 4 |
| F | Savings Fraction | 0.3415 |
| CV(RMSE) | Coefficient of variation of the root mean squared error | 2.23% |

The FSU for the avoided energy use calculation is $\pm$ 4.13% at the 80% confidence level. This is comfortably below the 50% threshold identified in the M&V plan. FSU is a ratio of uncertainty to savings. Because the savings fraction (F) is in the denominator of the FSU calculation, the large savings as a percent of whole-building electric consumption leads to a small estimated FSU.

## 8.1.4. Normalized Savings

Unlike the avoided energy use approach, a normalized savings approach involves creating a second regression model to identify the mathematical relationship between energy consumption and the independent variable(s) during the reporting period. The regression models for both the baseline and reporting periods are then used to estimate the normalized annual consumption for the facility under the same conditions. In this example, the independent variable in the model is weather so the fixed conditions were TMY3 weather conditions for Eugene, Oregon.

Because a separate regression model is developed for the reporting period, the coverage of the range of independent variable(s) must be considered. Figure 8-5 showed that the coverage of temperature conditions in the reporting period was excellent (e.g. the reporting period included intervals as cold and as warm as expected in the fixed condition TMY3 assumptions).

When using a normalized savings approach, the same general model specification will typically be used for the baseline and reporting periods. The two models will typically have the same dependent and independent variable(s) unless additional explanatory variables are available for the reporting period that were not collected for the baseline period. In the case of weather change point modeling, analysts will sometimes find it beneficial to the model fit statistics to use a different change point in the baseline and reporting period models. This is especially true if the installed measures change the operating profile of the facility with respect to setpoints. That was the case for the HVAC controls upgrade project analysis. Figure 8-6 shows the temperature change point used by the BPA engineer in the baseline and reporting period model. The change point in the reporting period was 3° higher.

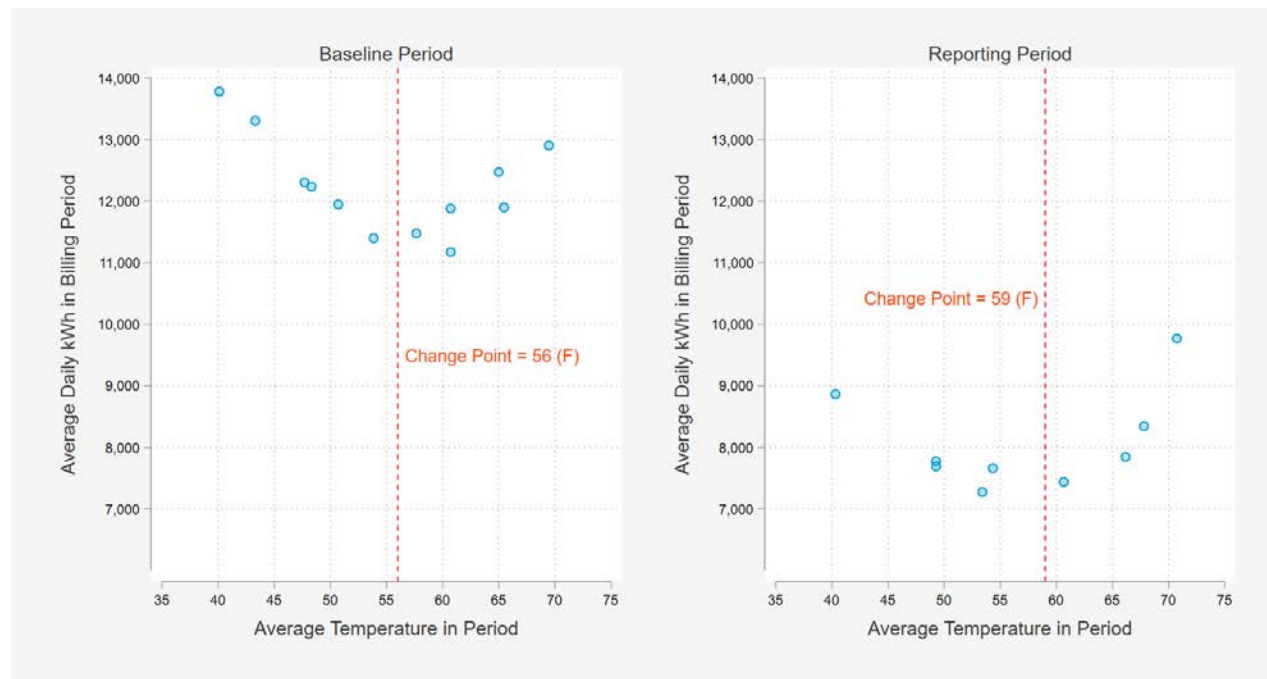**Figure 8-6: Baseline and Reporting Period Scatter Plots with Change Points**

Table 8-3 shows the calculation of weather-normalized annual savings for the project. The (4P) linear change-point models developed for the baseline and reporting periods were used to predict the daily electric consumption of the facility. The predicted daily consumption is multiplied by the number of days in the month and summed across the twelve months. The savings fraction is equal to the normalized kWh savings divided by the normalized baseline model prediction, or 35.4%.

**Table 8-3: Normalized Savings Calculation Table**

| Month | Average Temperature in TMY3 File (F) | Days In Period | kWh Use Baseline Model | kWh Use Reporting Model | kWh Savings |
|---|---|---|---|---|---|
| January | 41.82 | 31 | 417,119 | 267,398 | 149,721 |
| February | 40.70 | 28 | 382,195 | 244,807 | 137,388 |
| March | 45.85 | 31 | 395,568 | 254,386 | 141,182 |
| April | 49.88 | 30 | 361,943 | 233,582 | 128,361 |
| May | 56.15 | 31 | 341,901 | 221,099 | 120,802 |
| June | 60.50 | 30 | 348,128 | 214,421 | 133,707 |
| July | 66.40 | 31 | 383,942 | 259,560 | 124,381 |
| August | 67.48 | 31 | 388,375 | 266,518 | 121,857 |
| September | 61.46 | 30 | 351,922 | 220,375 | 131,547 |
| October | 52.83 | 31 | 358,251 | 231,854 | 126,397 |
| November | 42.90 | 30 | 398,077 | 255,399 | 142,678 |
| December | 39.83 | 31 | 427,803 | 273,850 | 153,954 |
| **Total** | | **365** | **4,555,224** | **2,943,249** | **1,611,975** |

As discussed in Section 5.9, the uncertainty of a normalized savings estimate is calculated by combining the uncertainty estimates (in kWh) of the baseline and reporting period model in quadrature. Table 8-4 shows the inputs and results of the calculation for the HVAC controls upgrade project.

**Table 8-4: Uncertainty Calculations Normalized Savings**

| Parameter | $\Delta E_{base}$ | $\Delta E_{post}$ | $\Delta E_{save}$ |
|---|---|---|---|
| Annual kWh | 4,555,224 | 2,943,249 | 1,611,975 |
| t-statistic (80% confidence) | 1.397 | 1.476 | |
| n | 12 | 9 | |
| m | 12 | 12 | |
| p | 4 | 4 | |
| Sum of Squares of Residuals | 595,734 | 816,945 | |
| CV(RMSE) | 2.19 | 5.01 | |
| Uncertainty (% of Annual kWh) | 1.20 | 2.97 | 2.27% |
| Uncertainty (kWh) | 54,633 | 87,544 | 103,193 |
| Fractional Savings Uncertainty | | | 6.40% |

## 8.2. Verification by Energy Modeling Example #2: Specific Building Systems

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*).

### 8.2.1. 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.

### 8.2.2. 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 8-5.

**Table 8-5: 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 8-6 summarizes the post-installation monitoring period.

**Table 8-6: 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 |

## 8.2.3. 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 independent 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 8-7, Figure 8-8, and Figure 8-9 show the scatter plots and resulting pre- and post-installation regression models developed from the data for the chilled water. Figure 8-10, Figure 8-11, and Figure 8-12 show the scatter plots and resulting pre- and post-regression models developed from the data for the hot water.
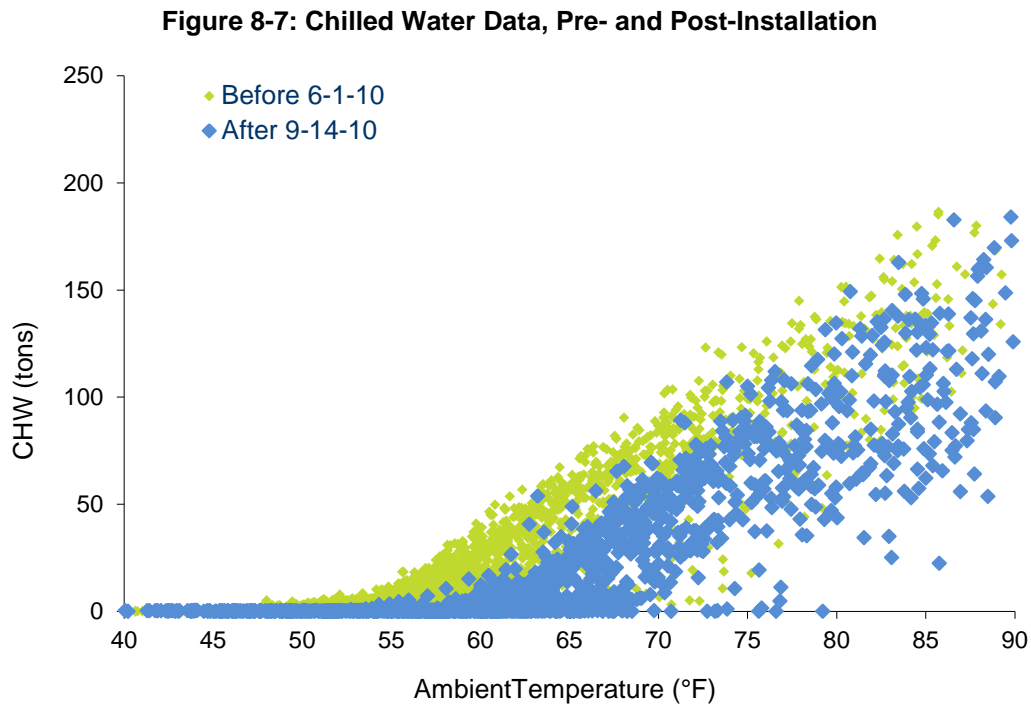
**Figure 8-7: Chilled Water Data, Pre- and Post-Installation**
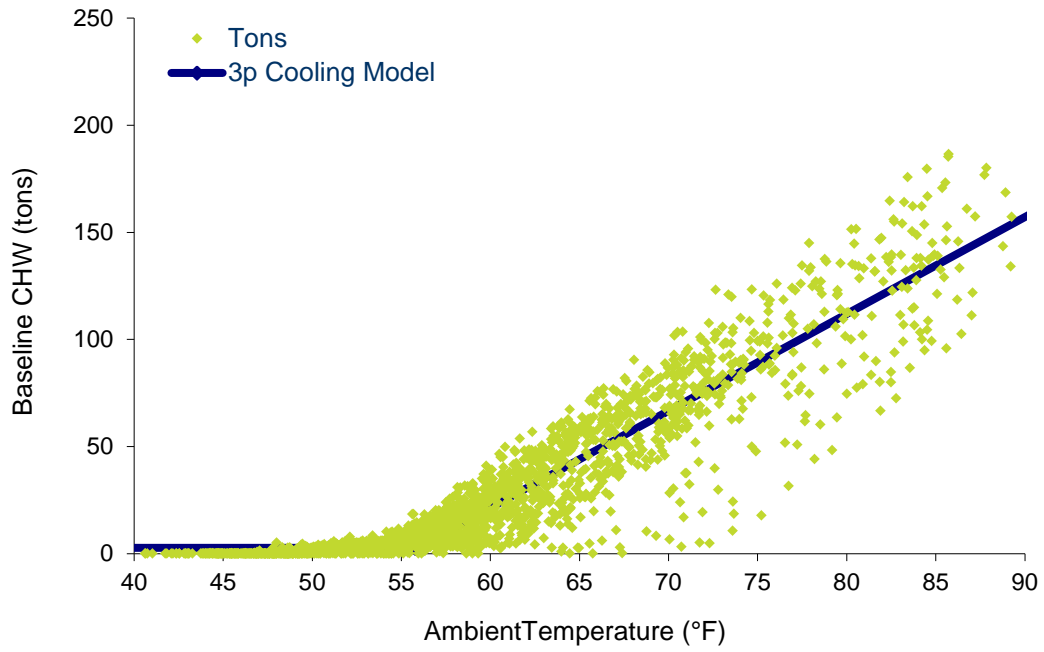
**Figure 8-8: Chilled Water Baseline Model**



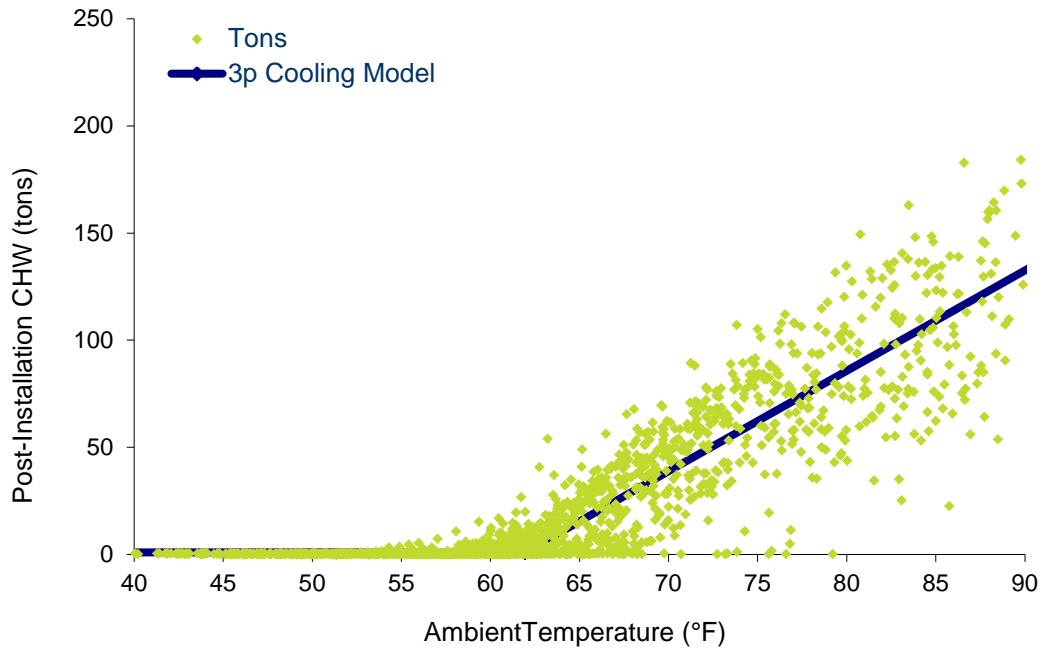**Figure 8-9: Chilled Water Post-Installation Model**

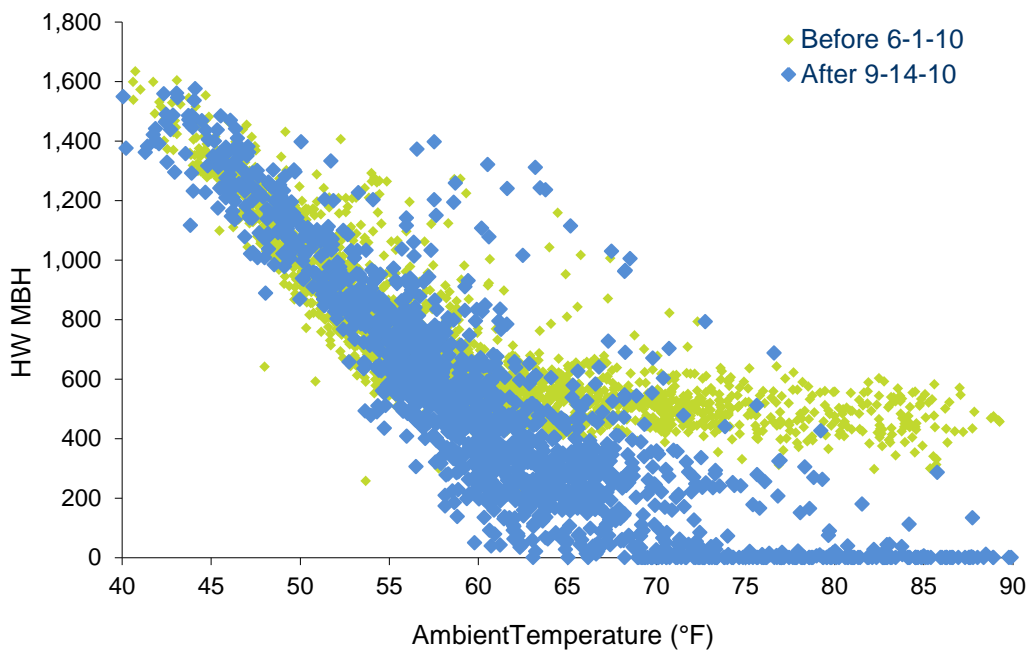**Figure 8-10: Hot Water Data, Pre- and Post-Installation**



**Figure 8-11: Hot Water Baseline Model**
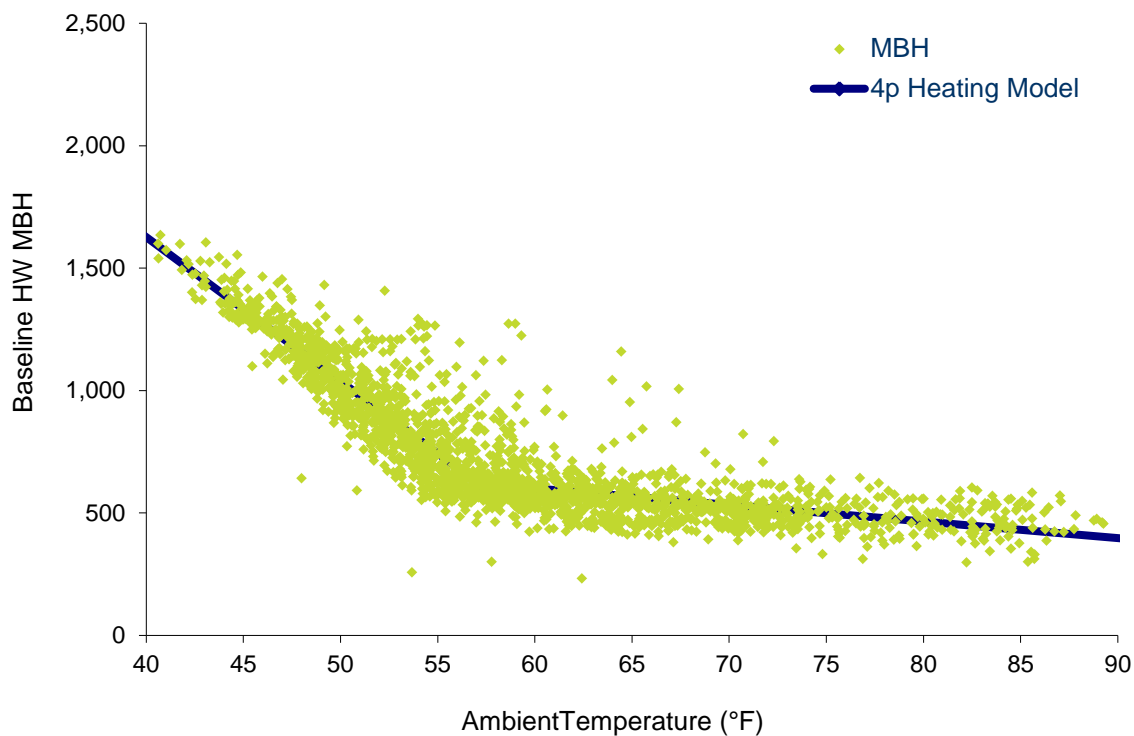


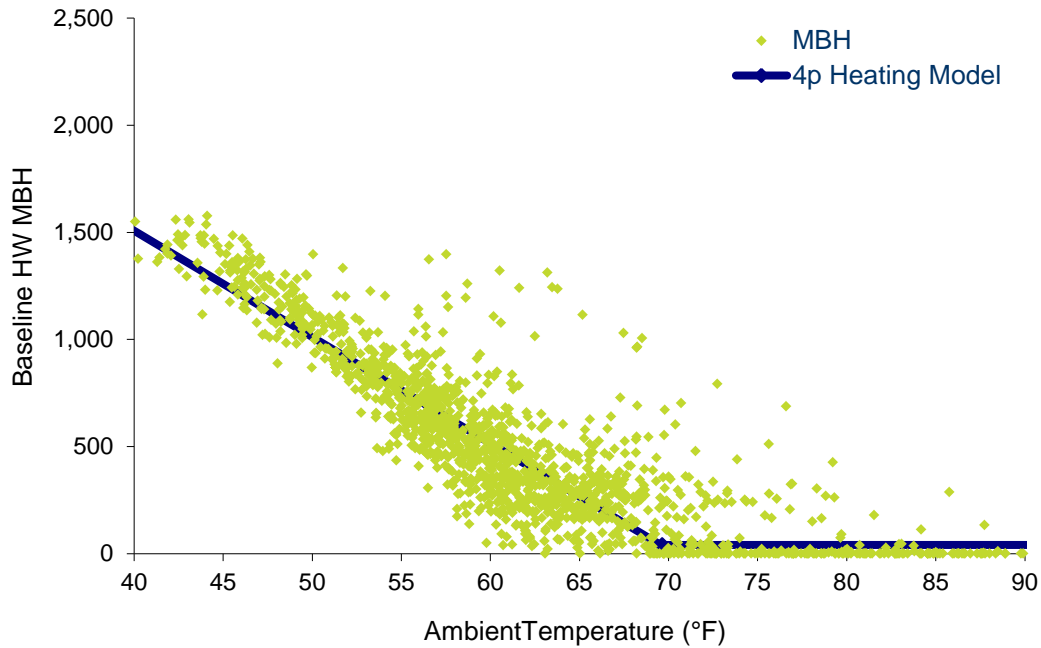Verification by Energy Modeling Protocol

**Figure 8-12: Hot Water Post-Installation Model**



## 8.2.4. 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 8-7.

**Table 8-7: 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 8-8. 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 set points.

**Table 8-8: 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 8-13 and Figure 8-14, provides conclusive evidence that the valve replacements are saving energy.

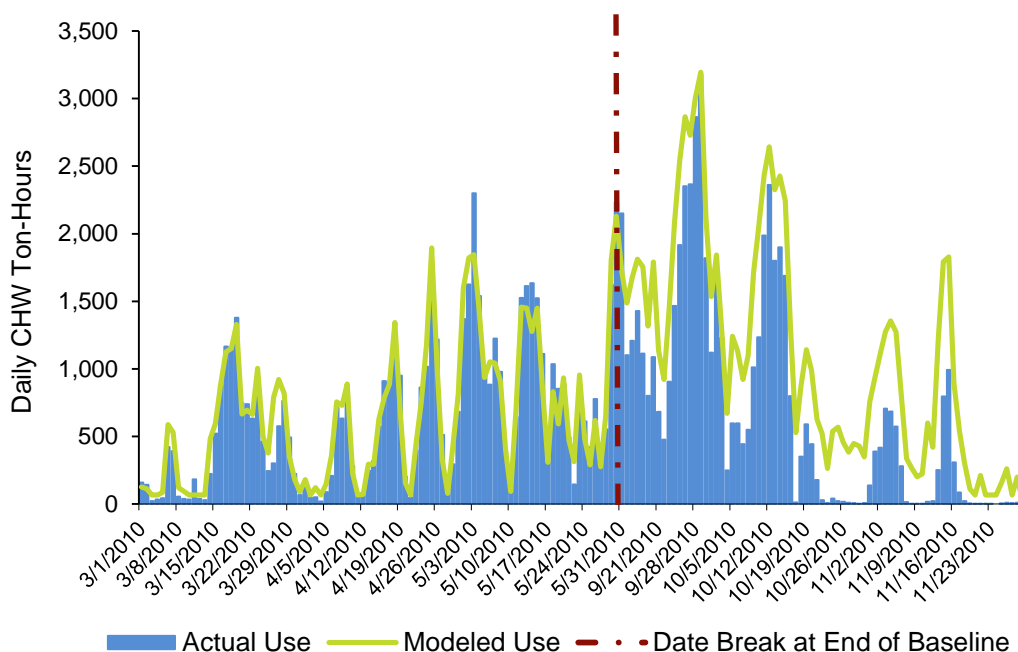**Figure 8-13: Chilled Water Savings Resulting from Valve Replacements at Manfred Hall**
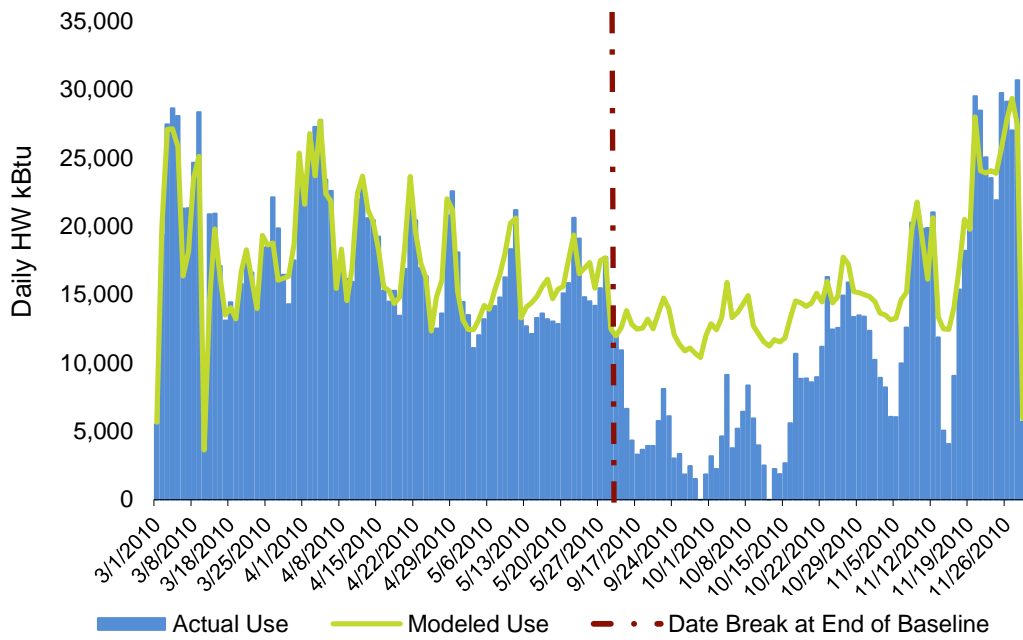
**Figure 8-14: Hot Water Savings Resulting from Valve Replacements at Manfred Hall**

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