LBNL Guidance on Requirements for Meter-Based IPMVP Option C Savings Claims

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Purpose and scope

Through collaboration with industry stakeholders and review of published standards/guidance LBNL has established general guidance for the documentation of whole-building level savings analyses. This guidance document is a 'living document' that will be updated as LBNL continues engaging with industry stakeholders and tracking progress of whole building M&V pilots.

Specifically, this guidance document applies to savings quantified in accordance with the IPMVP[1] Option C (avoided energy use method). It is intended to help practitioners develop rigorous, transparent savings claims, so that they may be reviewed by third parties. Acceptability criteria may vary based on regulatory requirements, program design, individual project conditions, etc. This document may be used or adapted for program RFPs or guidance documents.

Gray highlighted text provides additional explanatory notes. Appendix 1 provides examples and further detail for selected concepts in the guidance.

Guidance

For each meter-based savings calculation, M&V results should include:

1. A list and description of measures implemented;
2. A narrative of the model that was used to quantify savings;
3. A description of the independent variables' coverage factor;
4. An assessment of model fitness and time-series plot of the baseline period;
5. A time-series plot of the post-measure reporting period (the period of time during which meter and weather data is gathered following a project to calculate the energy savings[2]);
6. [Optional] Additional plots as needed;
7. Meter-based gross savings, and [optional]uncertainty due to model error;
8. A description of non-routine events and accounting of non-routine adjustments; and
9. [Optional] Alternative calculation method & results.

[1] Efficiency Valuation Organization (EVO). International Performance Measurement and Verification Protocol: Concepts and options for determining energy and water savings, Volume I. January 2012. EVO 10000-1:2012.

[2] Energy Market Methods Consortium (EM2). CalTRACK Methods, Version 2.0. 2018. http://docs.caltrack.org/en/latest/methods.html

Each of these reporting elements is described in more detail below, and is followed by [Optional] aggregate reporting requirements.

1. **A list and description of measures implemented.** Include implementation dates, and attach any additional evidence of implementation such as trend data from a building automation system, equipment spot measurements, invoices, etc. Also include estimated savings for each measure, if applicable, and attach savings calculations.

2. **A narrative of the model that was used to quantify savings**, including a description of:
   - The mathematical form of the model, e.g. piece-wise linear regression, or artificial neural network;
   - The dependent variables (e.g., therms, kWh, whole building combined Btu), and the independent variables used to predict consumption;
   - Independent variables (e.g. source and location of weather station data, and distance from project site);
   - The time resolution (hourly, daily, etc.) of input data and output predictions;
     - Note that buildings that are production or process driven, e.g. restaurants, may need additional variables to characterize the processes; the frequency of those data may be a limiting factor in model type and resolution.
   - How measure implementation dates were tracked and documented to establish a clear baseline and reporting period for avoided energy use calculations, and documentation of savings. Note whether a 'blackout period' was applied before and/or after the reported implementation date, to allow for discrepancies between reported and actual measure implementation date[3];
   - How missing, erroneous, or outlier data was handled, including references that support the methods of treatment. Where applicable, describe any steps taken to align data points for analysis (e.g. aligning weather data time-stamps with energy data time stamps);
   - How sites were tracked to identify site/customer participation in multiple concurrent programs;
   - How the model was implemented, e.g., in a packaged tool (provide the tool name and provider name, version number), coded in R or SAS, or other implementation;
     - Note whether the tool or method has undergone any validation tests;
     - List any fixed versus user-defined model parameters;
   - How the meters used in the savings analysis were mapped to accounts, premises, project measurement boundaries, and loads served in the building, as well as how any on-site generation (if applicable) was treated;

[3] In some cases the documented measure implementation date may correspond to a post-implementation inspection, submission of incentive claim, completion of a measure that was installed over a period of time, etc. In such cases a data 'blackout period' can be helpful in keeping the baseline and reporting periods distinct.

- Additional building characteristics and information on monitoring infrastructure that may be collected to inform M&V activities.
- In cases where utility meters were not used to collect data for savings claims, describe the meters used, and the calibration process that was used to ensure data accuracy;

[Narrative authors may find value in the modeling concepts and best practices that are presented in references such as *Applied Regression Analysis*, *Applied Statistics and Probability for Engineers,* and more domain-specific examples such as the *BPA Energy Smart Industrial Monitoring, Targeting and Reporting (MT&R) Reference Guide*.]

3. **A description of the independent variables' coverage factor (see example in Appendix 1).** Coverage factor refers to the range in observed values of independent variables during the baseline period, compared with the range in values during the period for which savings are being claimed. Baseline model projections for values of independent variables that are beyond those observed in the baseline period may under- or over-estimate the counterfactual and associated savings estimates. For example, if a baseline model is constructed with baseline data that spans 50-75°F, it may not prove reliable in predicting consumption for 90°F conditions in the reporting period. Analogous considerations apply to other potential independent variables such as those related to production.

   Savings claims shall be in line with ASHRAE Guideline 14[4], which advises: *"Apply the algorithm for savings determination for all periods where independent variables are no more than 110% of the maximum and no less than 90% of the minimum values of the independent variables used in deriving the baseline model."* Submitted savings claim shall confirm adherence to this requirement; alternative or enhanced assessments of coverage factor may be presented, but must include documentation sufficient to justify the approach.

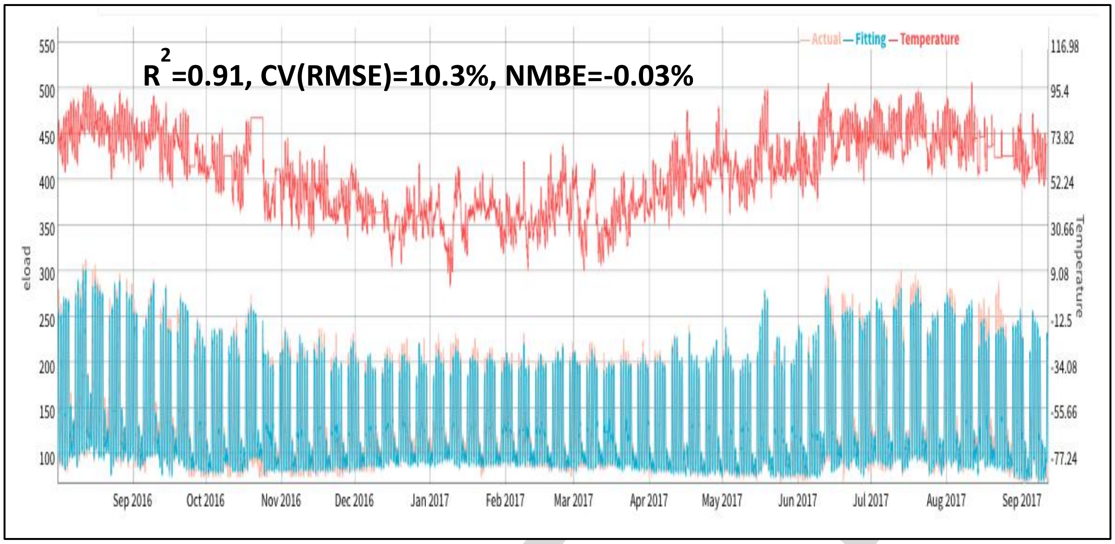
4. **Assessment of model fitness and time-series plot of the baseline period** (example below) that shows:
   - Metered baseline data;
   - The fitted baseline model;
   - The independent variables; and
   - The model CV(RMSE), NMBE, and R^2.

   Suggested requirement: The following general criteria shall apply for baseline model fitness:
   - $R^2 > 0.7$;
   - CV(RMSE) <25%; and

[4] ASHRAE Guideline 14 (2014). ASHRAE Guideline 14-2014 for Measurement of Energy and Demand Savings, American Society of Heating, Refrigeration and Air Conditioning Engineers, Atlanta, GA.

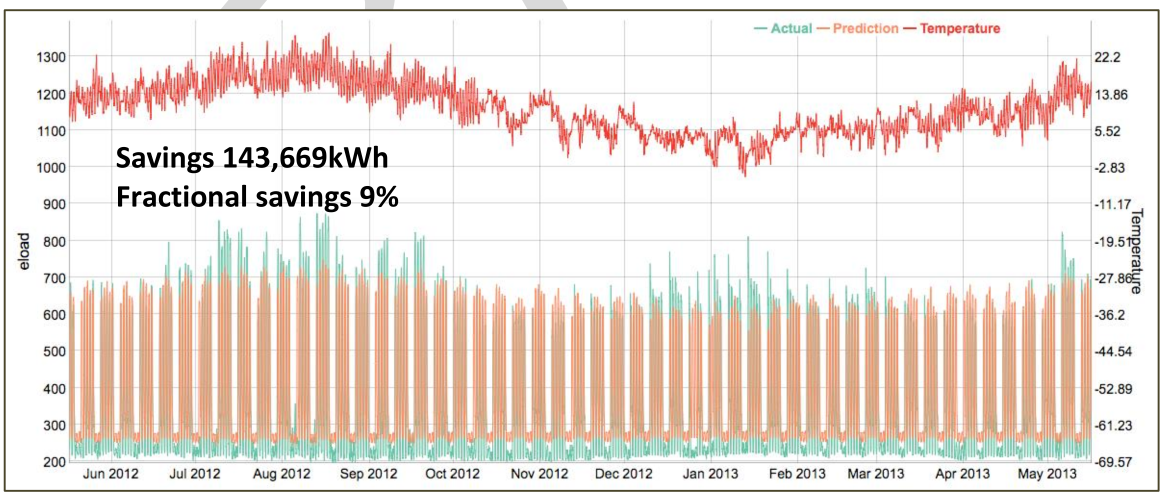
- NMBE <0.5%.

If savings claim is submitted with baseline model fit that doesn't meet one or more of the above thresholds, justification should be given for its inclusion. [LBNL suggests these model fit metrics and guidance values, but others may be considered depending on the situation]



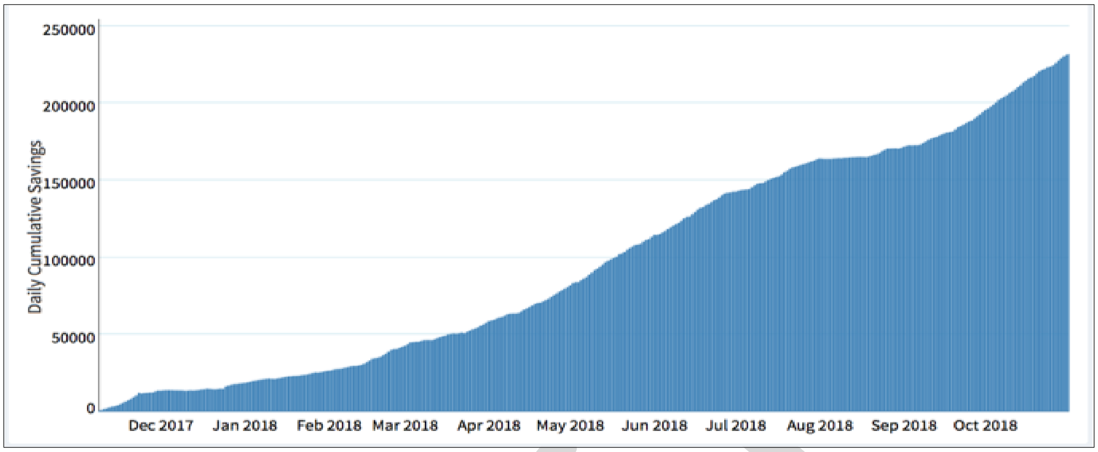
Above: Example of a plot showing metered baseline data, a fitted baseline model, the independent variable (temperature), and the baseline model goodness of fit metrics R^2, CV(RMSE), and NMBE.

5. **A time-series plot of the post-measure reporting period** (example below) that shows:
    - The projected baseline model and the metered data, and/or the residual, i.e., the difference between the projected baseline and the metered data; and
    - The independent variables.



Above: Example of a plot for post-measure reporting period showing metered data, the projected baseline model, the independent variable (temperature), and the fractional savings.

6. **[Optional] Additional plots** such as plots of residuals or scatter plots of consumption vs. independent variables is recommended to supplement fitness statistics, and modeling narratives and to facilitate review and evaluation (See Appendix 2 for examples). A CUSUM chart of a project's reporting period may also be helpful in illustrating the savings profile (example below).



Above: Example CUSUM plot for project reporting period showing the cumulative sum of savings over time. This type of chart can be useful for checking the savings profile, and identifying possible non-routine events in in a timely manner if they occur.

7. **Meter-based gross savings, and [optional] fractional savings uncertainty (FSU) due to model error**:
    - Savings shall be expressed in energy units (e.g. 267,000 kWh) and as a percentage of baseline whole building energy use (e.g. 12.3% of whole building electric);
    - Savings summary shall include the start and end dates of the baseline period and reporting period used in savings calculation. If annualized savings are documented based on a reporting period of more/less than a year, the annualization method shall be documented. If savings are normalized to a typical meteorological year, document the weather data type/source and confirm that climate zone is appropriate for project location;
    - [optional] Fractional savings uncertainty (FSU) due to model error to be calculated, per ASHRAE Guideline 14, at 80-90% confidence. [Suggested confidence level 80-90%. More specific guidance may be provided, for example setting different thresholds based on magnitude of savings]
    - [In considering requirements for acceptable FSU the following general guidance is provided: ≤25% uncertainty is good. 25%-50% uncertainty may be acceptable, based on project magnitude, program design, etc.]
    - If whole building calculated savings are significantly different from the sum of measure-by-measure estimates, an explanation of possible causes shall

be provided. [Optional, as some program designs may not require measure-by-measure savings estimates]

[Note: ASHRAE formulation to estimate uncertainty was developed with monthly models in mind; it may not be appropriate for more granular models or non-linear models.]

8. **A description of non-routine events and accounting of non-routine adjustments, to include**:
   - Description to include timing (start and end date if temporary; start date if a permanent change), nature of the non-routine event, and any information collected to quantify the magnitude of the event. If non-routine event was identified using analytical means (e.g. Based on anomaly in interval data use), include data and/or annotated charts as needed (See Appendix 3 for an example);
   - Calculations or models used to quantify the necessary adjustment to savings claim, including data and assumptions used in the analysis; and
   - Adjusted gross savings, after accounting for non-routine events.

9. **[Optional] Alternative calculation method & results.** If a meter-based Option C analysis was not used to quantify savings, describe the reason (e.g., poor model fitness, insufficiency of data), and provide a full accounting of the alternative approach that was used, with associated calculations, models used, and data used in the analysis

[Optional] Project reporting at aggregate level. For the cohort of all projects, M&V results should include:

- The number of projects for which the meter-based Option C approach was used, including:
  - The sum of all meter-based gross savings results, *before* non-routine adjustments, and the uncertainty in this sum due to model error, at 90% confidence; and
  - The total savings for all meter-based savings results, *after* accounting for non-routine adjustments.
- The number of projects for which an alternative savings estimation approach was used, and the sum of all savings from alternative estimation approaches;
- All Option C models or tools, any calculations or simulation models used in alternate approaches, and all associated data. Data, calculations, models, and tools must be sufficient to enable replication of results and review by a third party.

Appendix 1. Examples of model creation, variable selection, calculation of fitness metrics, and verification of coverage factor

Model creation and variable selection

Determination of appropriate baseline model resolution and independent variables is informed by assessment of model fitness metrics, including for example, the coefficient of variation of the root mean squared error, CV(RMSE), normalized mean bias error, NMBE, and coefficient of determination, R^2.

In Example 1, whole building electric use is modeled using monthly electricity data and cooling degree days, and plotted in Figure A1. In the figure, the fit model is shown with a red line, and the metered consumption is plotted in yellow dots.

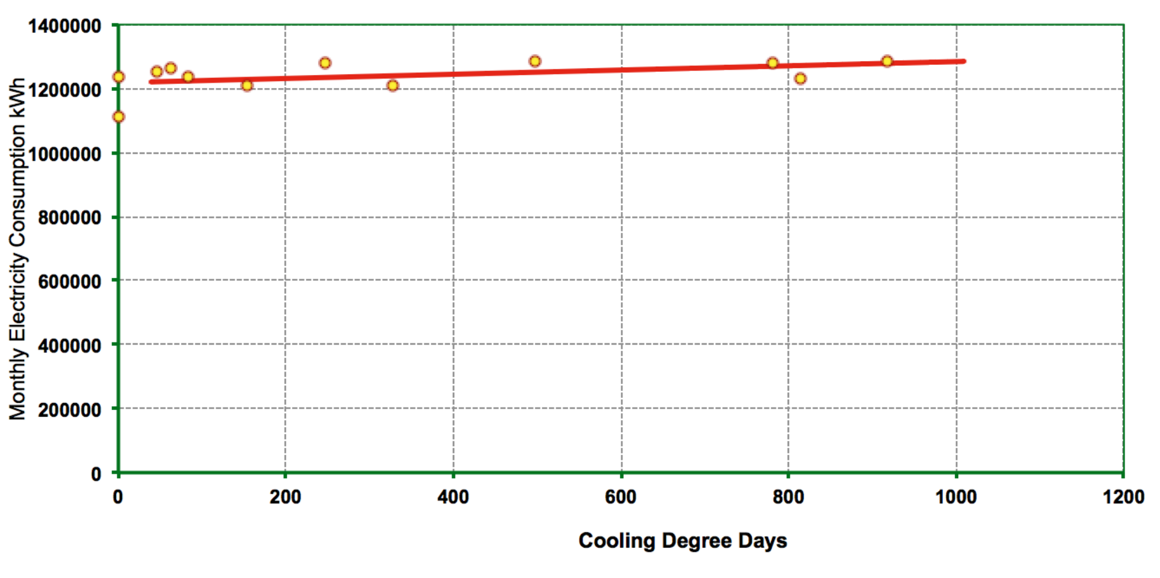


Figure A1. Monthly electricity consumption vs. cooling degree days.

As indicated in the summary of fitness metrics in Table A1, although this model exhibits low CV(RMSE) and NMBE as desired, the R^2 metric fares much worse where higher values are desired.

Table A1. Fitness metrics for the model of monthly electricity consumption vs. cooling degree days.

CV(RMSE)	3.7%
NMBE	.25%
R^2	.21

In Example 2, a second whole building electric model is tested, this time using hourly electricity consumption and outside air temperature, and plotted in Figure A2. In this model the independent variables used are time of week and outside air temperature. In the figure, the outside air temperature is plotted in red, the fit model is in blue, and the metered data is in pink.

Figure A2. Hourly electricity consumption based on time of week and outside air temperature.

As indicated in the summary of fitness metrics in Table A2, the hourly model exhibits a better fit than the monthly model, with low NMBE and CV(RMSE) as well as high R^2.

Table A2. Fitness metrics for the model of hourly electricity consumption based on time of week and outside air temperature.

CV(RMSE)	11%
NMBE	-.27%
R^2	.95

Calculation of fitness metrics

Defined in Equation A1, the CV(RMSE) is the root mean square error normalized by the mean of the measured values. In the equation y_i is the actual metered value, $\hat{y}_i$ is the predicted value from the fit model, $\bar{y}$ is the average of the y_i, and n is the total number of data points. This metric provides a quantification of the typical size of the error relative to the mean of the observations. It indicates how much variation or there is between the data and the model, and reflects the model's ability to predict the overall energy use shape that is reflected in the data. Table A3 and Equation A2 provide an example calculation of the CV(RMSE), given twelve months of load data. In the case of interval data, the calculation remains the same, although the number of points, n, becomes much larger.

Equation A1. $$CV(RMSE) = \frac{\sqrt{\frac{1}{n}\sum_i^n (y_i - \hat{y}_i)^2}}{\bar{y}} \times 100$$

Table A3. Example calculation of parameters to calculate the CV(RMSE), R^2, and NMBE fitness metrics, given twelve months of load data.

Month	Metered load (y_i)	Predicted load ($\hat{y}_i$)	Metered-Predicted ($y_i - \hat{y}_i$)	(Metered-Predicted)^2 $(y_i - \hat{y}_i)^2$
1	394383	394320	63	3969
2	355120	377089	-21969	482636961
3	400758	390158	10600	112360000
4	423004	397406	25598	655257604
5	408421	406692	1729	2989441
6	421076	412458	8618	74269924
7	433731	432736	995	990025
8	452230	432995	19235	369985225
9	406071	417556	-11485	131905225
10	411741	424201	-12460	155251600
11	385556	380632	4924	24245776
12	385027	389090	-4063	16507969
Average, $\bar{y}$	406426			
Sum			21785	2026403719
Variance (y)				69580948

Equation A2. $CV(RMSE) = \frac{\sqrt{\frac{1\times 2026403719}{12}}}{406426.5} \times 100 = 3.19$

Defined in Equation A3, R^2 is equal to one minus the mean square error divided by the variance of the actual energy use. In the equation y_i is the actual metered value, $\hat{y}_i$ is the predicted value from the fit model, var$(y)$is the variance of the y_i, and n is the total number of data points. It corresponds to the proportion of the energy use variance explained by the model. The R^2 value ranges between 0 and 1, with 0 indicating that the model explains none of the output variability, and 1 indicating that the model explains all the output variability. Using the values from Table A3, Equation A4 provides an example calculation of the R^2 given twelve months of load data.

Equation A3. $R^2 = 1 - \frac{\frac{1}{n}\sum_i^n (y_i - \hat{y}_i)^2}{var(y)}$

Equation A4. $R^2 = 1 - \frac{\frac{1}{12}\text{x}2026403719}{642574282} = 0.73$

Defined in Equation A5, NMBE represents the total difference between the actual metered energy use, and the energy use indicated with the fit model. In the equation y_i is the actual metered value, $\hat{y}_i$ is the predicted value from the fit model, $\bar{y}$ is the average of the y_i, and n is the total number of data points. Using the values from Table A3, Equation A6 provides an example calculation of the NMBE given 12 months of load data.

Equation A5. $NMBE = \frac{\frac{1}{n}\sum_i^n (y_i - \hat{y}_i)}{\bar{y}} \times 100$

Equation A6. $NMBE = \frac{\frac{1}{12}(21785)}{406426} \times 100 = 0.44$

Verification of coverage factor

ASHRAE Guideline 14 specifies: "apply the algorithm for savings determination for all periods where independent variables are no more than 110% of the maximum and no less than 90% of the minimum values of the independent variables used in deriving the baseline model." Table A4 provides an example of data used to verify sufficient coverage factor.

Table A4. Example of data used to verify sufficient coverage factor, given twelve months of load data, and a model that uses average outside air temperature (OAT) as the sole independent variable.

Month	Baseline Load	Average OAT	Reporting Period Baseline Prediction	Reporting Period Average OAT
1	394383	53.0	269831	54.1
2	355120	57.0	264236	57.4
3	400758	61.9	277054	58.1
4	423004	63.6	284204	61.2
5	408421	61.1	274539	59.9
6	421076	67.2	281134	67.1
7	433731	67.1	299625	69.5
8	452230	67.0	314535	70.2
9	406071	67.0	306156	69.1
10	411741	60.3	303321	66.3
11	385556	55.5	267428	53.0
12	385027	47.5	274512	50.6

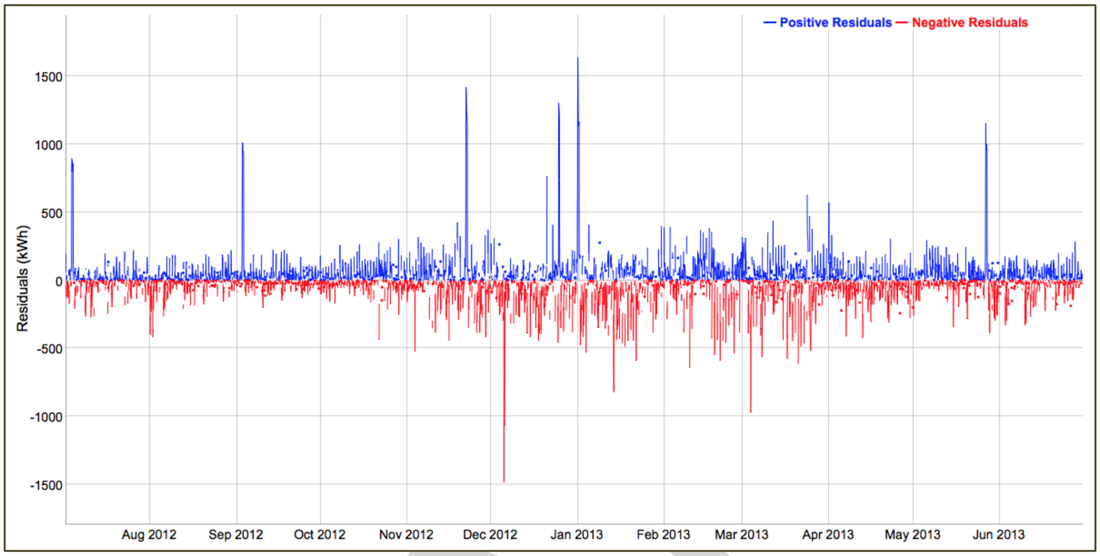
In the data set shown in Table 4 above the range of observed values of average OAT during the baseline period range from 47.5 to 67.2 degrees. Applying the 90% of minimum and 110% of maximum criteria, the model could be confidently used to predict load during the reporting period, for average outside air temperature conditions that range from 42.8 to 73.9 degrees. In the example data set, average outside air temperature ranges from 50.6 to 70.2 degrees, and therefore the coverage factor criterion is satisfied.

Appendix 2. Additional plots that may be useful when reviewing baseline models

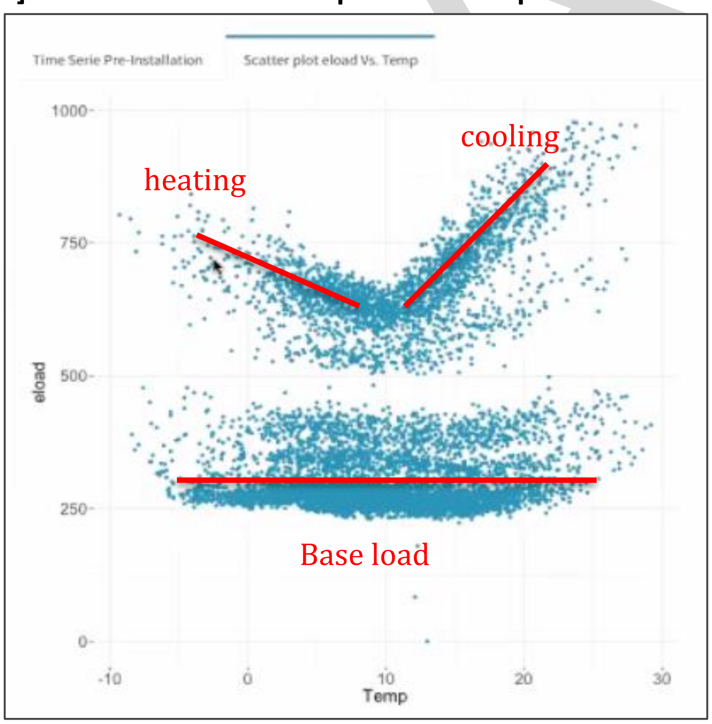
A] Time Series of Residuals Plot

Visual quality check:

- Residuals closer to zero indicate better model fit
- Large offset from zero could indicate bias
- Patterns can indicate autocorrelation, which impacts uncertainty analyses and can suggest missing independent variables



B] Scatter Plot of Consumption vs. Independent Variables



Visual quality check:

Scatter plot of load vs. temperature shows strong & consistent relationship with weather – the chosen independent variable looks appropriate

Appendix 3. Additional reference information on non-routine events and adjustments

Non-routine changes in building energy use are those that are not attributable to changes in the independent variables used in the baseline model, or to the efficiency measures that were installed. In the case of a non-routine event, the savings determined by subtracting the metered use in in the reporting period from the baseline-predicted load may have to be adjusted to accurately determine the savings due to the installed measures. Figure A5 illustrates the presence of a potential non-routine event, as indicated by the building load profile. Figure A6 provides another example of a potential non-routine event, illustrated by a profile change in a savings CUSUM chart.

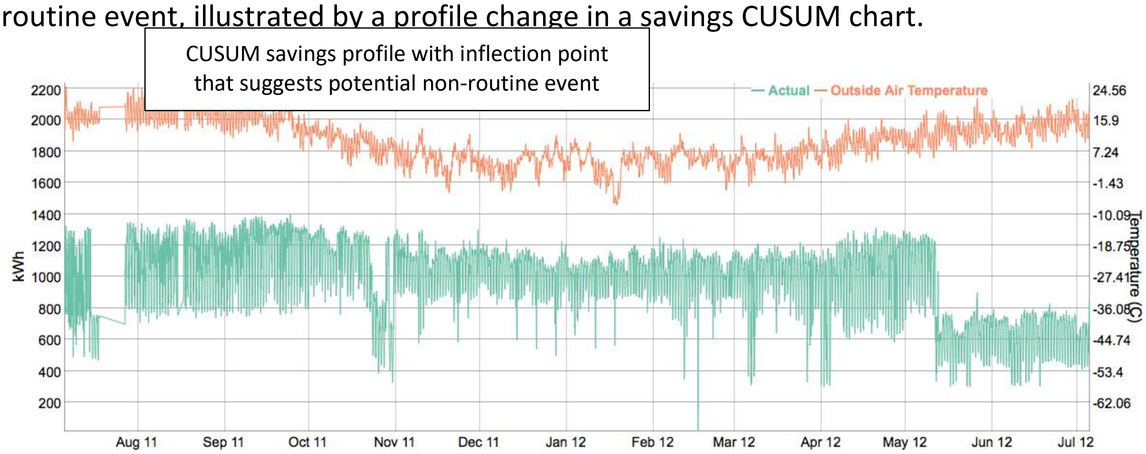


Figure A5. Approximately one year of metered electric load data(green), and outside air temperature (orange); the change in load in mid-May does not appear to be correlated with weather, and could indicate the presence of a non-routine reduction in consumption.

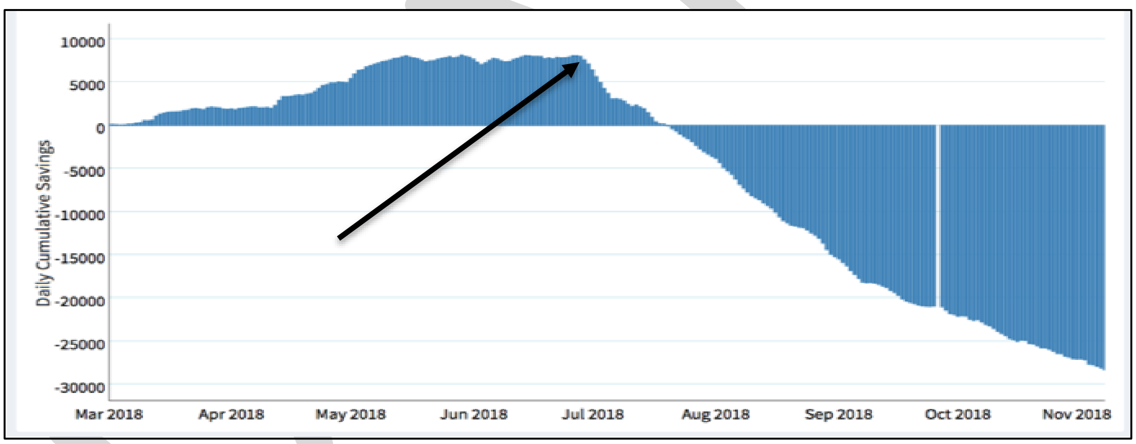


Figure A6. CUSUM chart of the reporting period for an efficiency project. The chart indicates a potential non-routine event occurred in July 2018.

Some of the more frequently encountered types of non-routine events in commercial buildings include, but are not limited to:

Services	# of rooms/beds
	food cooking/preparation
	# of registers
	#of workers

Equipment loads	# of computers
	# of walk-in or standard refrigeration units or open and closed cases
	# of MRIs
	# or capacity of HVAC units
Operations	hours of operation
	weekend operations
	heating and cooling setpoints
	system control strategies
Site characteristics	size
	% of building heated and cooled
	envelope changes

Non-routine events may be characterized as temporary or permanent, as load added or removed, and as constant or variable. A framework of assessing non-routine events may include

1. Determine whether an event is present
2. Determine whether the impact of the event is material, meriting quantification and adjustment (the threshold for what is considered 'material' should be specified in the M&V Program Plan)
3. Determine whether the event is temporary or permanent. Temporary events may be removed from the data set, however no more than 25% of the measured data should be removed, per ASHRAE Guideline 14, provided that a justifiable reason is provided.
4. Determine whether the event represents a constant or variable load
5. Determine whether the event represents added or removed load
6. Based on #3-5, the approach to measuring and quantifying the impact of the event may be determined.

General notes on non-routine events:

- Several methods may be used to determine whether an event is present. These include but are not limited to inspection of meter data, time series change detection or breakout analysis, periodic site visits and short term measurements, and site surveys.
- Determination of whether the impact of the event is material depends on engineering expertise, and the magnitude of the thresholds that are defined in the M&V Program plan.
- Permanent events are those that are expected to last through the duration of the M&V analysis period.
- Constant loads are understood to be those that do not fluctuate or change during a period of interest, such as when in the 'on' state.
- Added loads are those that increase site energy consumption, while removed loads decrease site energy consumption.

- Analogous to detecting the presence of an event, several methods may be used to quantify the impact or magnitude of the event. These include but are not limited to, engineering calculations, IPVMP Options A and B, simulation models, time series analysis of residuals, and the use of indicator variables in models fit to data before and after the event.