Revision 5.0

MT&R Guidelines

Monitoring, Targeting and Reporting (MT&R) Reference Guide

Prepared by: ESI Energy Performance Tracking (EPT) Team

2/20/15

Contents

Document Objective

The Monitoring, Targeting and Reporting (MT&R) methodology, in conjunction with a process to track specific activities, is used to verify, quantify, and validate energy savings on the Track and Tune (T&T) and High Performance Energy Management (HPEM) features of ESI's Energy Management components. This document outlines recommended methodologies to establish the baseline energy models at a whole-facility or subsystem level, and ultimately quantify energy savings associated with the implementation of multiple energy efficiency measures (EEMs) over a defined performance period. Specific focus is given to the methodologies for addressing special circumstances such as separating operations and maintenance (O&M) savings from concurrent capital projects, and addressing changes in business operations that necessitate adjustments to the baseline model.

In the context of ESI whole-facility or subsystem energy management, the standard approach is a top-down, regression model at the meter level, as described by the International Performance Measurement and Verification Protocol (IPMVP)[1]. Unless otherwise noted, the ESI MT&R Process Outline is intended to align to the current best practices outlined by IPMVP for "Option C" models.

The Energy Performance Tracking (EPT) team is in place to manage and approve the MT&R strategies and methodologies that are utilized for HPEM and T&T projects, and will be responsible for the contents of this document.

[1] *International Performance Measurement and Verification Protocol*. Efficiency Evaluation Organization. 10000-1.2012. www.evo-world.org

1. Characterization of the Facility or Process

1.1 Identify Measurement Boundary

- In the application of whole-facility energy models, the measurement boundary consists of all the systems and processes served by one or more utility meters. While energy sources may include natural gas, steam, or compressed air, the examples in this document assume electrical energy as the targeted response variable.
- Care must be taken to ensure that:
    - All electrical energy crossing the measurement boundary has been documented and accounted for. Documentation may include one-line electrical drawings, energy maps, and system schematics which identify equipment and processes within the measurement boundary.
    - Significant electrical energy-consuming equipment within the measurement boundary which is inconsistently used in other areas of the plant is documented and accounted for. An example would be an air compressor within the measurement boundary that supplies variable amounts of compressed air to both the measurement boundary and other areas throughout the plant. Effective sub-metering strategies need to be deployed to measure the energy usage crossing the measurement boundary for reporting purposes.
    - If other energy sources are used to offset electrical energy use within the measurement boundary, then effective sub-metering strategies must be deployed to measure the changing energy usages for reporting purposes. One such an example would be a drying process that can be done with a fan, a steam heater, or a combination of both.

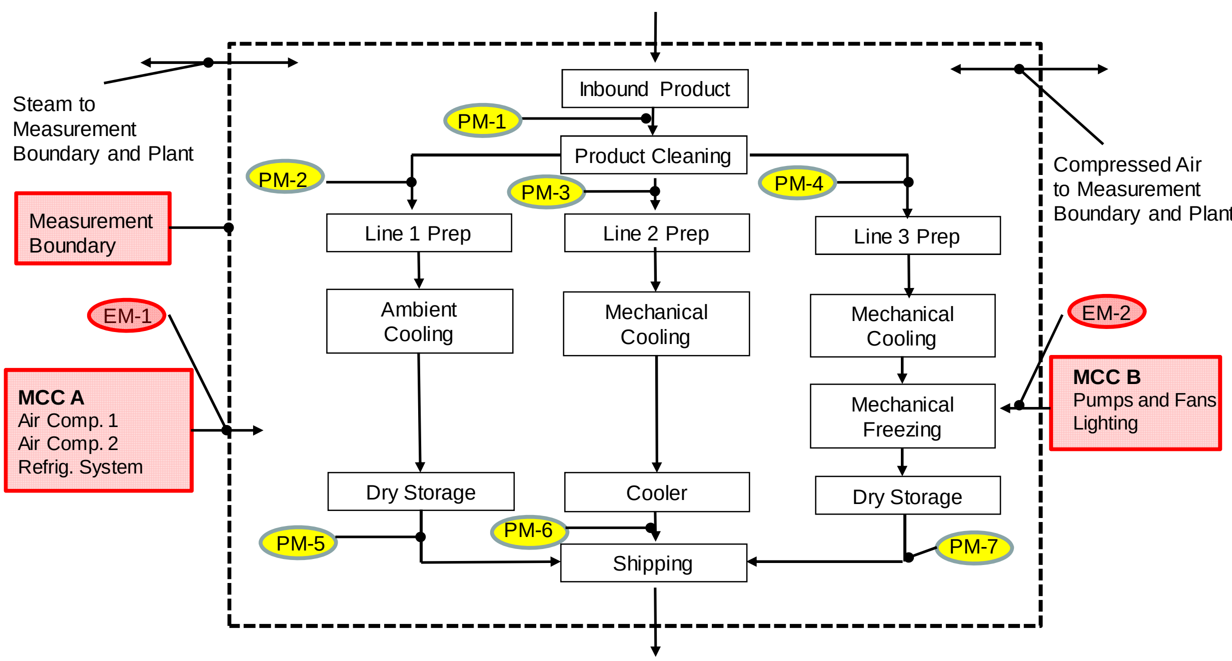

Figure 1. Illustration of measurement boundary, including where product, energy, steam and compressed air cross the measurement boundary.

1.2 Identify Production Energy Drivers - Hypothesis Stage

- Through conversations with the site's energy champion, and/or application of the Energy Mapping and MT&R Data Collection sheet, develop an energy map which organizes the major electrical loads within the facility or system boundary relative to process flow.
- The primary energy driver is typically production. At this stage, it is important to understand how many product types are manufactured in the facility, and whether there is likely to be a difference in energy intensity based on lead time, process flow, batch size, etc. Raw material, work in progress, and finished product metrics each has merits and demerits for selection as the primary energy driver variable. An informed decision will take in to account factors such as lead time, the desire to account for yield effects, and the prevalence of inventory fluctuations in-process or at the finished product stage.

Table 1. Consideration for Selection of Production Variable

MEASUREMENT GATE	MERIT	DEMERIT
Raw material input	**Provides a mechanism to capture the effects of different raw material types.**	**Will not produce a signal for energy impact of yield or productivity improvements.**
Work in progress	**Allows selection of production variable at energy-intensive process, thereby minimizing time series shift.**	**Availability of data fails to provide mechanism for incentivizing energy impact of yield/productivity improvement downstream from point of measurement.**
End of line metric	**Provides mechanism for incentivizing energy impact of yield/productivity improvements.**	**May induce a time-series shift for long lead-time processes.**
Finished product shipped	**Data can be captured from accounting systems.**	**May not correspond with production if finished product inventory fluctuates.**

- Assess where production data is available, relative to the energy-intensive process steps. If a significant offset exists between the energy-intensive process step and the production measurement gate, compensating time-series shift may be applied that corresponds to the magnitude of the time offset (see Section 2.3).
- Process flow diagrams, piping and instrumentation diagrams, and value stream maps can be helpful at this stage.
- Consider dialoguing with key contractors or trade allies if the end user relies on them for operations or other influential activities.

1.3 Identify Other Energy Drivers - Hypothesis Stage

- Based on the mechanical system inventory and process characteristics, form a hypothesis of other energy drivers. The most common example is ambient conditions (dry-bulb and wet-bulb temperatures), but could include variables such as raw material properties, operational modes (weekend/weekday), occupancy, etc.
- Energy drivers must be tested for statistical significance. A suitable explanation must be provided when an energy driver(s) is used in the model, but the energy driver(s) was not found to be statistically significant.
- Ambient temperature (wet bulb or dry bulb) should generally be tested for statistical significance, although in many industrial settings it may not be a primary driver of energy intensity.

- In the process of variable selection, the model developer will face competing objectives of capturing the full subset of statistically significant variables, while aiming to provide the customer with a model that is simple and easy to maintain. No single analytical technique will provide the perfect solution, so the modeler must rely on his or her experience and engineering judgment.
- Including process parameter variables in the energy model has the potential to add to the explanatory power of the model, but limits the ability to achieve savings by including the variable in the model. For instance, if a process variable such as "Variable A" is included in the model, and a key energy efficiency measure is to reduce Variable A, then reducing Variable A is likely to result in no energy savings because this variable is in the model. While sometimes necessary for model fitness, including variables that can be influenced in the energy model is not a preferred option.

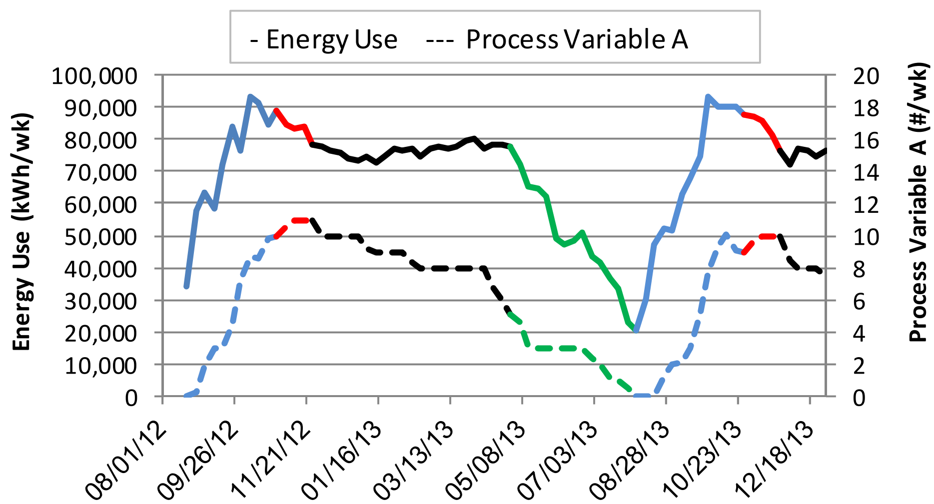

Figure 2. Energy use tracks closely with the number of average rooms in holding. Average rooms in holding could be influenced through energy efficiency measures.

1.3.1 Weather Data

- Acceptable sources of weather data include local airport weather stations, the National Climate Data Center (NCDC) database, or the Washington State University Agricultural Weather Network. A change in the weather data source during the treatment period should trigger an update to the original model, followed by EPT review.

1.4 Identify Utility Meters or Submeters

- Document which processes are served by specific meters. This step will be important in determining whether to create a single model for a facility or to create discrete models for functional units that collectively represent the entire facility's energy use.
- Meter serial number, utility account number, or other unique identifier should be recorded in the baseline report.
- If an end user-owned submeter will be used in place of the utility meter, the submeter data should be appropriately aggregated and compared to a utility bill. If the submetered measurement boundary does not align to a utility meter, then the submeter calibration should be confirmed by a certified electrician. The electrician shall strive to use no less than third order NIST-traceable calibration equipment, as recommended by ASHRAE Guide 14-2002, Section 7.5.

2. The Baseline Data Set and Hypothesis Model

2.1 Determining the Baseline Period

- In principle, the baseline period should encompass the cycles and ranges of the hypothesized primary and secondary energy drivers, and should extend as close to the start of the treatment period as possible. Ideally, the baseline period should capture two or more cycles of operation.
- The minimum standard for the number of baseline data points is: (min data points = 6 · number of coefficients in the model). If the data set falls below this guideline, the model will likely be "over-fitted," and the model's comparative performance will likely deteriorate during the treatment period. Since the number of coefficients is not known at this point, it can be assumed that there will be one coefficient for each hypothesized variable, plus the intercept.
- Models that are weather dependent should use complete years (12, 24, or 36 months) of continuous data during the baseline period, to ensure balanced representation of all operating modes. Models that use other intervals of baseline data can create statistical bias by under- or over-representing normal modes of operation.[2]
- Daily or weekly time interval data typically provide better insight into the process being modeled, and thus more accurate models are typically created when compared to data of longer durations such as monthly data. Process lead time should be considered in selecting the modeling interval, both for determining the modeling interval, and applying time-series offsets with the corresponding energy data.
- The NW Strategic Energy Management Collaborative white paper provides additional guidance and case studies on the selection of an appropriate baseline period, and the treatment of non-production periods in a daily model[3].

2.1.1 Addressing Incentivized or non-Incentivized Energy Projects

- Utility records should be reviewed to confirm whether incentivized energy projects occurred within the measurement boundary during the proposed baseline period. If so, project records should be obtained to accurately capture implementation dates and magnitude of verified savings.
    - In determining the effective date for an incentivized EEM, apply the earlier of the project M&V start date, or the date that an inflection is observed in the energy data (see Appendix A).
- Interviews should be conducted to determine if other non-incentivized energy projects occurred during the proposed baseline period.
- If either case is identified, one of the options in Appendix A can be applied to guard against double-counting of savings.

2.2 Collecting Data and Correcting for Outliers

- When collecting data for energy or energy drivers, ensure that accurate records are maintained regarding the data source (e.g., end user database, production gate, weather station identification).
- Perform an initial review for outliers by plotting each variable independently in a time series format. Identify and flag erroneous entries. Missing data points or data entry errors should be investigated and corrected by the facility, if possible.

[2] *International Performance Measurement and Verification Protocol*. Efficiency Evaluation Organization. 10000-1.2012. Section 4.8.4.
[3] *Common Considerations in Defining Baselines for Industrial Strategic Energy Management Projects*. NW Industrial Strategic Energy Management (SEM) Collaborative, 2014.

- Outliers can be flagged for review by applying a common rule of thumb for identifying data that lie outside the range of four or more standard deviations from zero.[4]

  Control Limit = mean +/- 4 standard deviations

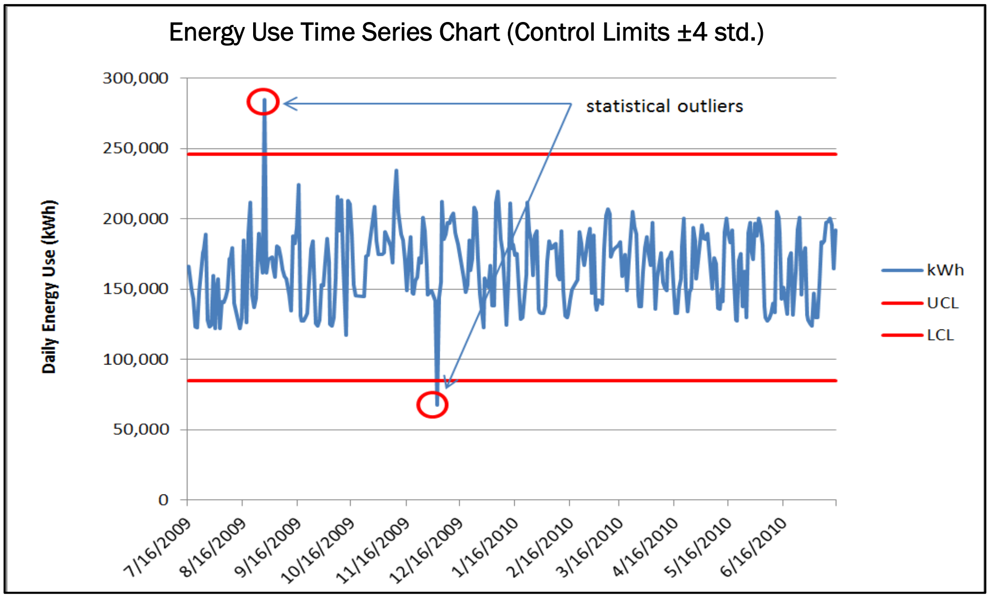

Figure 3. Example of Graphical Methods to Identify Outliers

- Any outliers that are ultimately removed from the baseline data set should be annotated with the assignable cause. Understanding assignable cause will likely require communication with the end user's energy champion.
- Correct for missing or extracted outlier data by closing the gap in the data set. Avoid replacing missing or outlier data by calculated interpolation.
- Data must be examined with a higher level of scrutiny when obtained from industrial control systems. Data obtained from control systems is often on an hourly or sub-hourly basis. This data frequently has erroneous and null values and anomalous operations and the modeler should review the data set for these types of bad data.

  - Erroneous values: A value such as "Control System Error"
  - Null values: No data for the given variable and observation
  - Anomalous operations: Values that appear out of range of normal operations.

- Graphing the data can be an effective way to detect erroneous and anomalous data. As shown in Figure 4, power data within the dashed box is considerably lower than power above the dashed box for similar machine speeds. The operation of this machine needs to be fully understood prior to performing calculations.

[4] Neter, J., W. Wasserman, *Applied Linear Statistical Models*, 1974, Irwin Publishers, Homewood, Illinois, p 106.

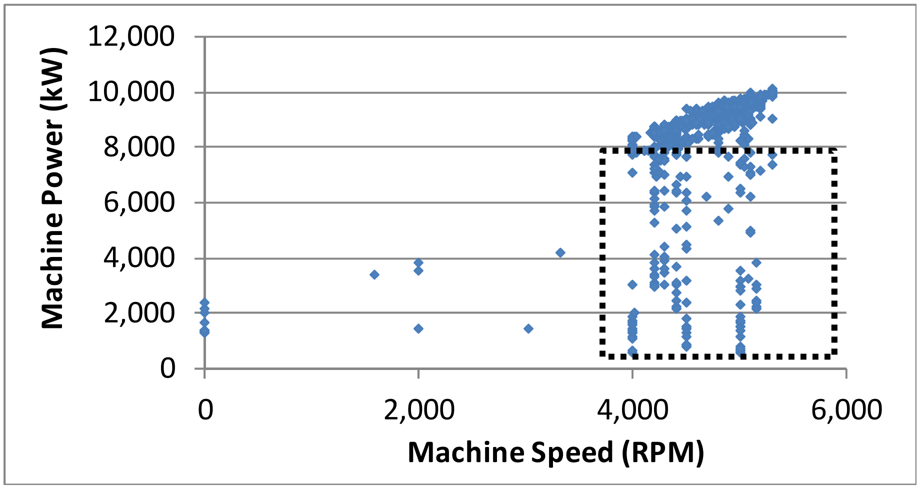

Figure 4. Illustration of control system data showing machine power vs. machine speed.

- Observations that appear to be anomalies should be reviewed with plant personnel to better understand the operation of the system.
- If any data point within the observation is deemed erroneous, null, or anomalous, the observation should be removed from the analysis. Documentation should be provided for observations removed from the analysis. To account for irregular observations per time period when observations are removed from the analysis, a weighted regression can be applied as outline in Appendix E.

2.3 Adjusting for Time-Series Offsets

- Use time-series plots to identify consistent offsets between the energy use and an independent variable. For example, if the energy-intensive process is two days' lead time from the production measurement point, a two-day time series adjustment may need to be applied to the production variable. However, this approach may be unnecessary if a longer model interval is selected (e.g., instead of a daily model, select a weekly model). Figure 5 shows an Example of a Time-Series Plot (Energy and Production vs. Time).

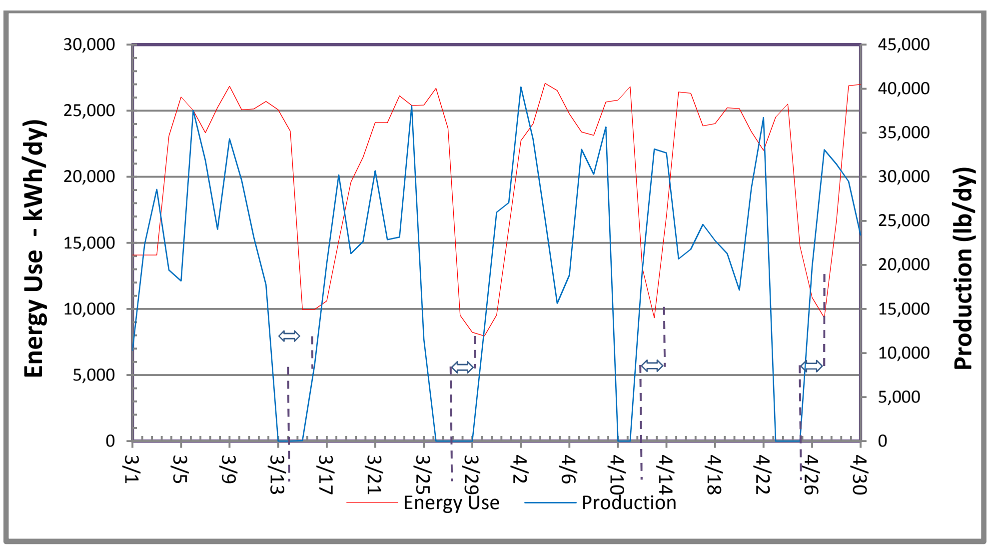

Figure 5. Example of a Time-Series Plot (Energy and Production vs. Time)

- If necessary, apply the time-series offset to the relevant independent variable(s), maintaining the original source data in a separate file.
- At this point, the baseline data set is ready for the regression modeling process.

2.4 Forming a Hypothesis Model

Key Point: The hypothesis model should be driven by an informed understanding of the physical characteristics of the process.

- Use scatter diagrams to confirm whether significant relationships are linear or non-linear in nature. For example, a plant's energy intensity often becomes progressively more efficient at higher production volumes. This phenomenon implies a non-linear relationship, and is illustrated in Figure 6.

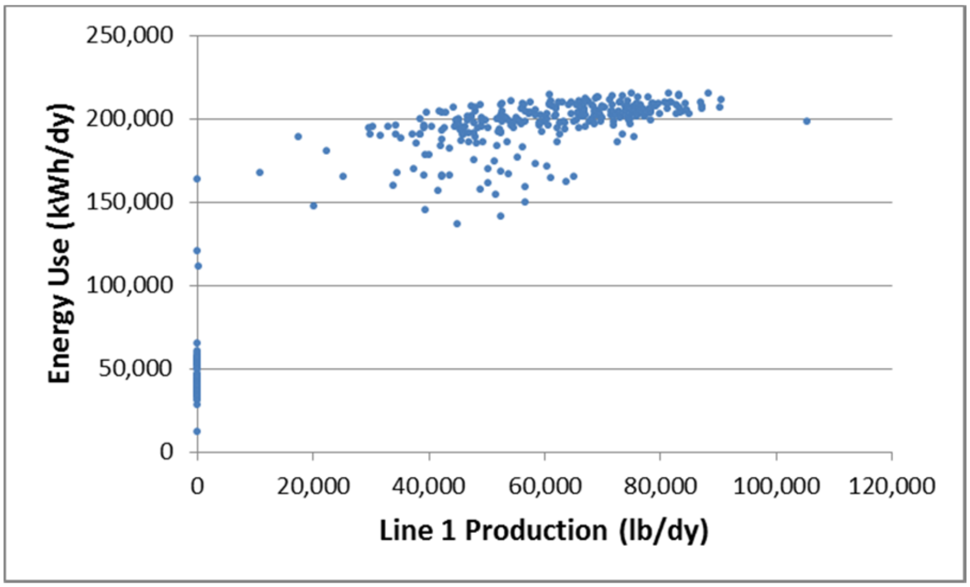

Figure 6. Example of a scatter plot (energy vs. production).

- Facilities that have an ambient-dependent energy profile will often exhibit a "change-point" characteristic. The presence of a "change-point" can be determined by plotting an independent variable versus a dependent variable, for example ambient temperature versus energy. Modeling a facility that exhibits a change-point with a single linear model would introduce unnecessary error. Instead, this system should be modeled with a change-point model, as illustrated in Figure 7. For additional details on regression change-point models, see Section 4 of BPA Regression for M&V: Regression Guide[5].

[5] *Regression for M&V: Reference Guide*, Version 1.1, May 2012. Bonneville Power Administration.

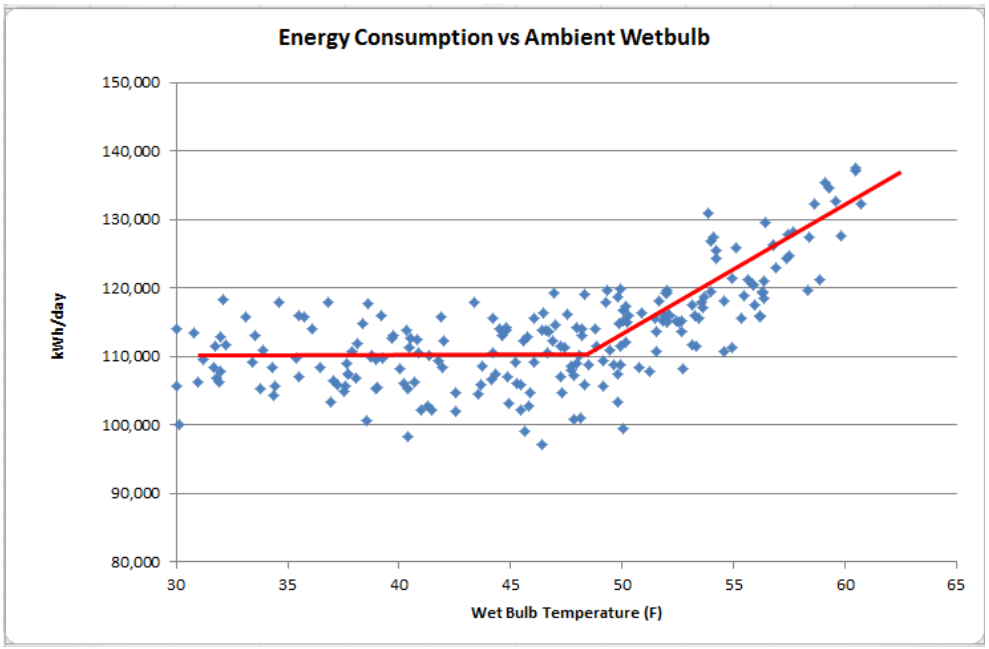

Figure 7. Example of a 3-parameter cooling change-point model.

- When two or more independent variables exhibit correlation, multicollinearity is present within the model. The presence of collinear variables can affect the precision of individual coefficients and can understate the statistical significance of individual predicator variables.
- The modeler should exercise caution when excluding variables that might be significant energy drivers as this can bias the model. When multicollinearity is present, the modeler should clearly explain the rationale for both the inclusion and exclusion of variables in the energy model.
- Further work has been done to address the effects of multicollinearity in baseline regression models by the NW Industrial Strategic Energy Management (SEM) Collaborative[6].

3. The Baseline Model

3.1 Assessing Statistical Significance of Independent Variables

- Screening variables for statistical significance is a critical step in the model review process, as the inclusion of erroneous variables will introduce error in the model. Likewise, the omission of critical energy driver variables will negatively affect the ability of the model to accurately characterize variation in energy use. The following guidelines can be used to test for the significance of each independent variable:
  - IPMVP EVO 10000-1.2012: Rule of Thumb: T-statistic > 2.0, or reference t-table
  - SEP: At least one variable with a p-value < 0.10[7]

[6] *Tools and Methods for Addressing Multicollinearity in Energy Modeling*. NW Industrial Strategic Energy Management (SEM) Collaborative. 2013.
[7] *Superior Energy Performance Measurement and Verification Protocol for Industry*. Written under contract by The Regents of the University of California for the United States Department of Energy. Nov. 19, 2012. Section 3.4.5, p. 10.

- For the purpose of ESI Energy Management projects, the IPMVP will serve as the official guideline.
- Appendix C shows where these values can be obtained from typical regression output tables.
- Independent variables that do not pass the above test should not be included. Exceptions may be permissible in cases where a variable shows moderate statistical significance, and is generally understood to impact energy use for the target system. The rationale for such exceptions must be documented.

3.2 Statistical Criteria for Model Fitness

- The fitness of the overall model can be judged against several guidelines:
    - International Performance Measurement and Verification Protocol (IPMVP[8]): R-sqr: >0.75
    - Superior Energy Performance (SEP) M&V Protocol[9]: F-test for overall model p-value<0.1
    - ASHRAE Guideline 14-2002[10]: R-sqr: >0.80; Net Determination Bias (NDB): <0.005%
- For the purpose of ESI Energy Management projects, the IPMVP will serve as the official guideline. However, the following parameters shall be reported in the MT&R document for the overall model:
    - R-Square, Adjusted R-Square, Coefficient of Variation, Net Determination Bias, Auto-correlation coefficient.
- Appendix C shows where the basic regression parameters can be obtained from typical regression output tables.
- Plot the actual versus predicted values for the dependent variables on a scatter diagram. Check to see that the point pattern is narrowly clustered and uniformly distributed along the diagonal as illustrated in Figure 8.

[8] *International Performance Measurement and Verification Protocol*. Efficiency Evaluation Organization. 10000-1.2012. www.evo-world.org. Appendix B, page 95.
[9] The Regents of the University of California, Section 3.4.5, p. 10.
[10] *ASHRAE Guideline 14-2002. Measurement of Energy and Demand Savings*. American Society of Heating, Refrigerating, and Air-Conditioning Engineers, Inc. 2002. www.ashrae.org

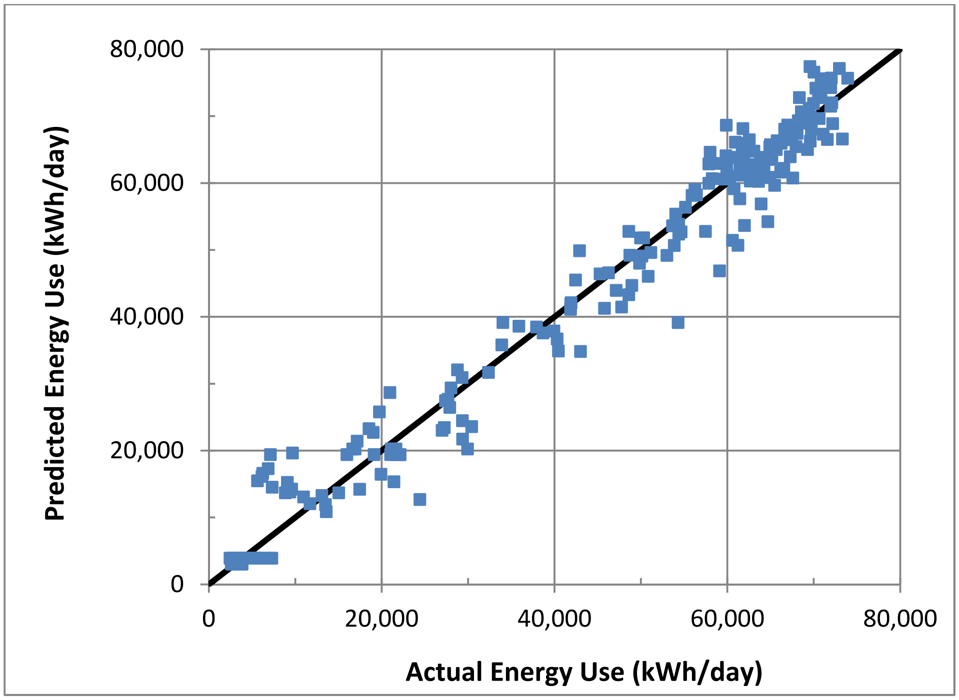

Figure 8. Example of actual vs. predicted scatter plot.

- Calculate the autocorrelation coefficient (see Appendix D), and plot the model residuals over the baseline period. If autocorrelation is detected, the number of independent data points is effectively reduced. The typical remedy involves increasing the sample size, or selecting a different data interval.
- Typically, regression-based energy models exhibit positive auto-correlation. Positive auto-correlation occurs when the sign change of the residuals is infrequent. Conversely, frequent sign changes in the residual values results in negative auto-correlation.
- There is not a defined threshold for the autocorrelation coefficient in the model development phase. However, a review of literature finds references to "light autocorrelation" for levels in the ρ=0.3 range[11]. This becomes a factor in the uncertainty analysis, discussed in Section 4.5.1.

An example of autocorrelation in a time series graph is shown in Figure 9.

[11] *Guidelines for Verifying Existing Building Commissioning Project Savings – Using Interval Data Energy Models: IPMVP Options B and C*. Revision Date: November 12, 2008. California Commissioning Collaborative. Appendix B, Page 70.

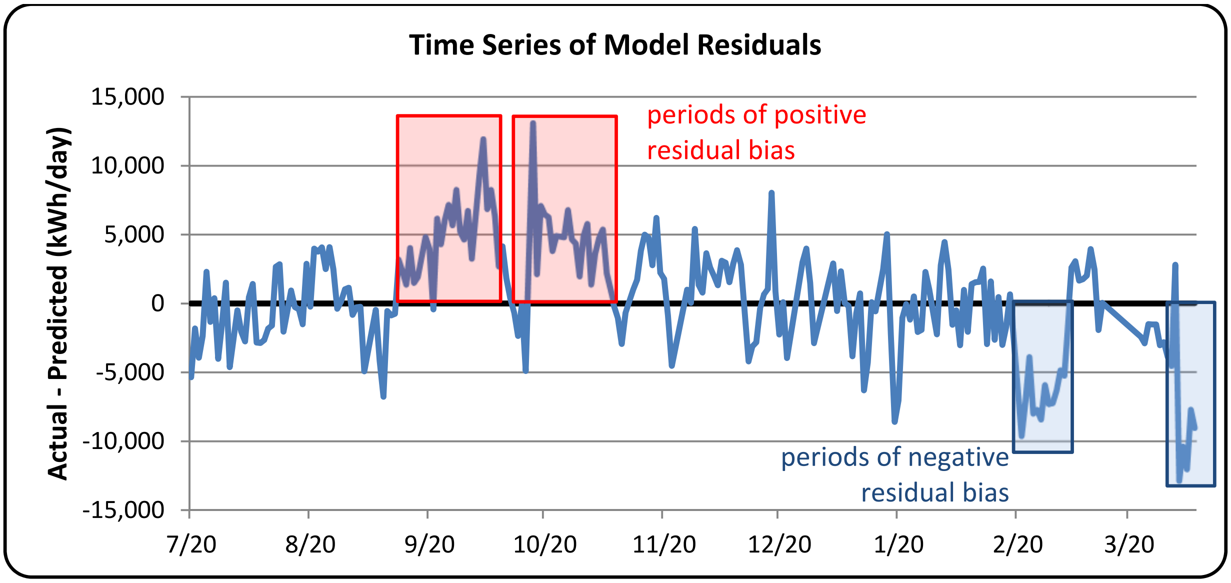

Figure 9. An example of autocorrelation in a time series graph.

- The Durbin-Watson test can be used to determine if auto-correlation is statistically significant. The Durbin-Watson test statistic, d, ranges from 0-4, where:

  d = 2, residuals are not correlated

  d << 2, residuals are positively auto-correlated

  d>> 2, residuals are negatively auto-correlated

- The lower and upper bounds for the Durbin-Watson test statistic will be a function of sample size, number of predictor variables, and the desired confidence level.
- The Northwest Industrial Strategic Energy Management (SEM) Collaborative has provided a paper pertaining to autocorrelation in regression-based energy models for industrial facilities[12].
- Residual plots that may be of value:
  - Residuals versus time (e.g. Figure 9)
  - Residuals versus the independent variables (confirmation of homoscedastic or heteroscedastic residuals)
  - Histogram of residuals (supports Net Determination Bias)

[12] *Tools and Methods for Addressing Autocorrelation in Energy Modeling*. NW Industrial Strategic Energy Management (SEM) Collaborative. 2013

3.3 Modifying the Hypothesis

- If the statistical tests outlined in 3.1 and 3.2 indicate insufficient fitness of the model, modify the model hypothesis.
- This process might include modifications to the assumed energy drivers, time intervals, or the order of relationships (second order, square root, etc.).
- If the measurement boundary is supplied by multiple meters, disaggregating the meters may result in better model resolution.
- In forming an alternative hypothesis, confirm that the characteristic of the equation remains aligned with the mechanics of the process, and that the baseline data set meets the standards outlined in Section 2.1. This information should be documented in a competing model summary. An example of a competing model summary is provided in Appendix G.

3.4 Screening for Residual Outliers

- Outliers from the residual analysis should be flagged for review. One approach to reviewing outliers is by applying a common rule of thumb for identifying data that lie outside the range of +/- 4 standard deviations [13].
- Before removing outliers, the modeler should review any residuals outside the control limits of +/- 4 standard deviations with the Energy Champion to understand the cause of the anomaly.
- The modeler must provide a supporting explanation when removing statistical outliers.

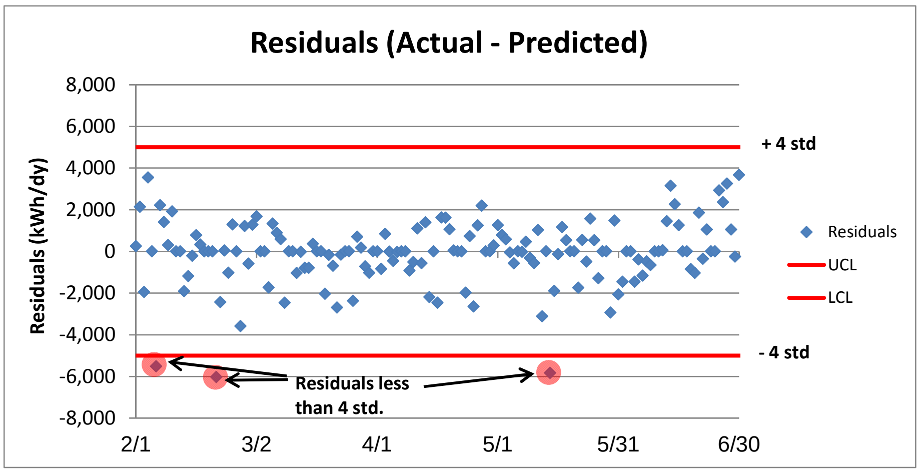

Figure 10. Inspection of residual outliers.

[13] Neter, J., W. Wasserman, *Applied Linear Statistical Models*, 1974, Irwin Publishers, Homewood, Illinois, p 106.

3.5 Alternatives to Baseline Regression Energy Modeling

The adoption of a methodology that does not use a standard baseline regression energy model may be necessary under certain conditions.

3.5.1 Backcast Approach

For the Backcast approach, the regression energy model is developed from the data obtained during the treatment period. This method is applicable in instances where:

1) One or more independent variables has significantly increased or decreased from the baseline period through the savings period.
2) The resolution of the energy signature for the original baseline was relatively poor and the resolution of the energy signature during the treatment period has significantly improved.

For more details, reference Superior Energy Performance Measurement and Verification Protocol for Industry[14] .

3.5.2 Mean Model

The Mean Model approach may be necessary when:

1) There is insufficient variation in the independent energy drivers (e.g., production is constant) such that there is also insufficient variation in the corresponding energy variable.
2) There is insufficient correlation between suspected energy drivers and energy.

For the Mean Model approach, the estimate of baseline energy use is the average energy use.

Baseline Energy per interval = Average Annual Energy Consumption for baseline period.

This approach requires that baseline operating conditions be thoroughly documented, so that changes in energy intensity observed during the treatment period can be properly assigned to EEMs directed at energy efficiency versus other changes in plant operation.

This approach is valid given that:

- The independent variable and relevant operational parameters remain within a defined range. An acceptable guideline for this tolerance is $\pm 3\sigma$ of values recorded in the baseline period[15].

3.6 The MT&R Baseline Report and EPT Review

The baseline model and supporting statistics and graphics should be documented in the MT&R baseline report. The Energy Performance Tracking (EPT) team will provide final sign-off, after a review by the utility and end user.

[14] The Regents of the University of California, Section 3.4.12, p.12
[15] The Regents of the University of California, Section 3.4.6, p.11

4. Treatment Period – Calculation of Savings

4.1 Maintaining Records of Events and Changes

The savings calculated in Sections 4.3 and 4.4 represent the total (gross) energy savings for the site. In order to establish attribution, it is critical that the energy champion maintain accurate records of key O&M actions or behavior-based improvements. The energy champion should attempt to correlate inflections in the cumulative sum of differences (CUSUM) graph to these actions or changes.

Any effects from fuel switching must be accounted for and excluded from the gross MT&R savings. If fuel switching is a possibility, it is advisable to maintain records of other alternate fuel sources crossing the measurement boundary, beginning with the baseline period. These records can be used to show that fuel switching did not occur during the treatment period.

4.2 Adjusting for Concurrent Incentivized Projects

If the end user is participating in other ESI components, there will likely be a need to adjust the MT&R savings to net out the site savings from EEMs incentivized by other components. The typical approach is an adjustment to the gross savings by the utility-approved M&V savings value associated with the project, prorated from the in-service date to the end of the treatment period.

Appendix B outlines the options for determining the value of the adjustment and identifying a suitable date of application.

4.3 Calculation of Savings Using Regression Model

- As data is collected during the treatment period, it should be methodically reviewed to detect anomalous values and to ensure that the independent variable data fall within the range used to establish the baseline model. Section 5.0 outlines the methodology for rebaselining, if such action is necessitated by a dramatic increase or decrease in production.
- Net Energy Savings can be calculated by applying the following equation:

    Energy Savings = (Predicted Energy Use from Baseline Model – Actual Energy Use) ± Adjustments

- The CUSUM calculation is an effective means of quantifying the total energy savings benefit. In graphical form, the CUSUM provides a powerful illustration of the total savings achieved during a specified treatment period. However, the CUSUM graph should be used in conjunction with a time series plot of energy and the independent variables. Together, these graphs help establish an informed understanding of energy intensity inflections.

    An example of a CUSUM graph is shown in Figure 11.

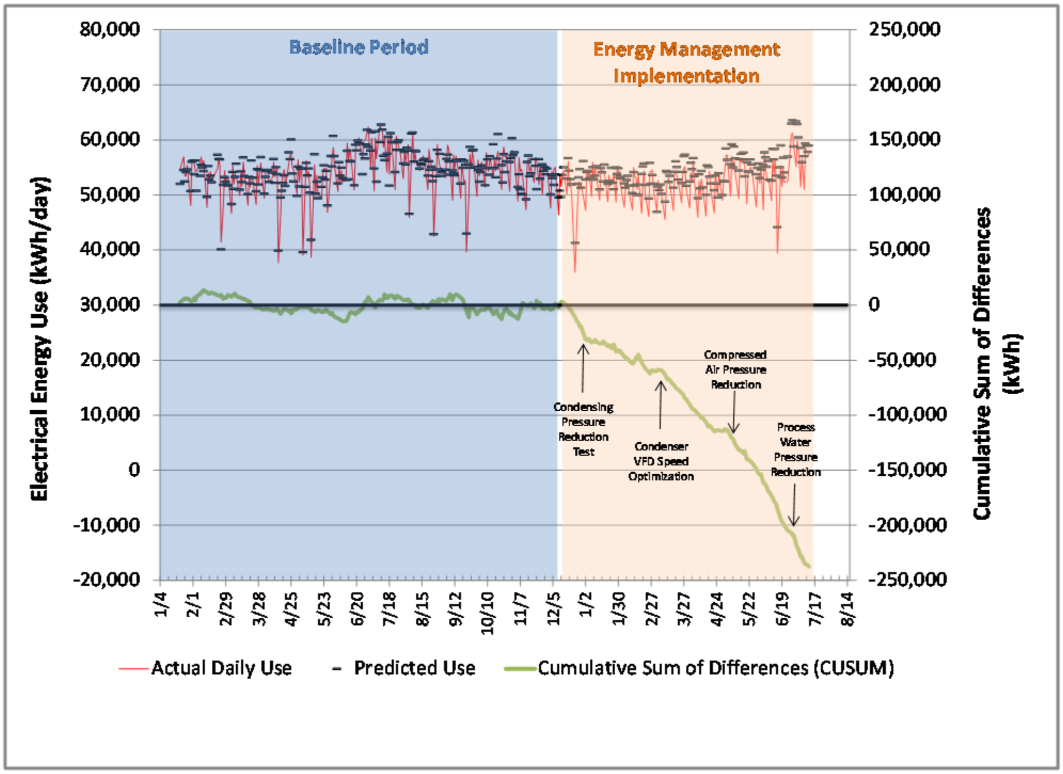

Figure 11. CUSUM graph example.

4.4 Calculation of Savings Using Alternative Approaches

4.4.1 Savings Calculation by Backcast Approach

When using the Backcast approach, the baseline model is developed with data from the treatment period. The baseline energy use is then estimated from the data obtained during the baseline period. The energy savings are then calculated as:

Energy Savings = (Actual Energy Use - Predicted Energy Use from Baseline Model) ± Adjustments

Note that, as the name would imply, the energy savings calculation is the reverse of the standard regression approach.

4.4.2 Savings Calculation by Mean Model

For a mean model, baseline energy is calculated as the mean or average energy use during the baseline period. For a given time interval, energy savings are then calculated as the difference between the mean value from the baseline period and the actual energy use for that time interval, plus or minus any adjustments.

$$\text{Energy Savings} = \text{Mean}(\text{Actual Energy Use})_{\text{Baseline}} - (\text{Actual Energy Use})_{\text{Treatment}} \pm \text{Adjustments}$$

4.4.3 Savings Calculation by Bottom-up Approach

Quantification of energy savings using the bottom-up approach consists of engineering calculations supported by short-term data logging. The application of this approach is limited to the Small Industrial High Performance Energy Management (SI HPEM) component[16]. Further information regarding the application of engineering calculations including, determination of the baseline, calculations of energy savings, and required project documentation is provided in BPA's Engineering Calculations with Verification (ECwV) Protocol[17].

4.4.4 Savings Calculation by KPI Bin Model

If the major energy driver at a site is not a continuous or ordinal variable but a nominal variable, then regression modeling of the system can prove difficult. For these reasons, the ESI EPT Team is demonstrating the use of a KPI Based Classification method. Details regarding this method are provided in Appendix F.

4.5 Options for Establishing Statistical Confidence to Savings Value

4.5.1 Uncertainty in the Regression Model

In certain instances, it may be necessary to specify a range of energy savings performance for a defined statistical confidence level.

ASHRAE Guideline 14-2002 Measurement of Energy and Demand Savings, Annex B provides a detailed description of uncertainty analysis. The following methodology provides an approach for calculating uncertainty derived from model error. It should be noted that this approach does not capture error associated with the measurement hardware. In most cases, the measurement error component should be small relative to the regression model error.

The fractional uncertainty for the majority of ESI MT&R models can be estimated by the following equation:

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

Where:

t=	t-statistic for desired confidence level
CV=	Coefficient of variation
n,m =	number of observations in the baseline and treatment period, respectively
F=	observed savings during treatment period

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[16] Bonneville Power Administration (2014). *Small Industrial High Performance Energy Management (SI HPEM) Delivery Guide* [revision 2]. Section 3.4, p. 20.

[17] Bonneville Power Administration (2012). *Engineering Calculations with Verification Protocol* [version 1.0] http://www.bpa.gov/Energy/N/pdf/6_BPA_MV_ECwV_Protocol_May2012_Final.pdf

n= number of observations in baseline
n'= number of independent baseline period observations
ρ= auto-correlation coefficient

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

While the preceding methodology is generally applied to analyze savings uncertainty in an ex-post analysis, this analysis can be used to inform the model development, particularly when the model developer is faced with multiple options related to time interval or variable selection.

4.5.2 Statistical Confidence for Backcast Method

The fractional savings uncertainty (FSU) equation can also be used to estimate savings uncertainty for the Backcast method. When using the fractional savings uncertainty equation, the model statistics and baseline observations (n) occur during the savings period of the project. Likewise, the number of observations during the treatment period (m) occurs during the baseline period of the project.

4.5.3 Statistical Confidence for Mean Model

When applying the Mean Model approach, the student T-test should be applied to establish statistical confidence that the energy use of the baseline and treatment period are truly different and the assumed energy drivers are not. This is performed by:

1. Calculating the average energy use during the baseline period.
2. Calculating the t-stat at 80% confidence for the energy use during the treatment period.

Energy savings will be achieved if:

1. $tstat \geq \frac{Mean\ Euse_{Baseline}}{Mean\ Euse_{Treatment}}$

2. Distribution of the perceived energy drivers from both baseline and treatment periods is deemed acceptable by EPT Team.

4.6 EPT Review and Approval

The savings calculation methodology and verified savings value will be documented in the HPEM or Track and Tune Completion Report. The Energy Performance Tracking (EPT) team will provide final sign-off, but BPA's Energy Management Engineering COTR (EM-ECOTR) will provide final authorization of the savings and incentive.

5. Adjustments to the Baseline Model

5.1 Scenarios for Model Reassessment

The model is considered valid for the range of the independent variables observed during the baseline period, provided the general operation and qualitative factors of the facility or system remain constant. The SEP protocol provides an additional provision that validates the model if the independent variable is within ±3 standard deviations from the mean of the baseline data set[18].

Scenarios that would trigger a reassessment of the baseline model include:

- A sustained increase or decrease in the observed level of an independent variable, outside the range for which the baseline model was established.
- A change in business operations making an independent variable obsolete (e.g., change in process flow).
- A change in business operations that requires a new independent variable (e.g., new product type).
- An uncontrollable and unforeseen change in raw material types, grades, or properties that changes the energy intensity in a positive or negative direction.
- Other changes in what the IPMVP refers to as "static factors," such as facility size, occupancy, or equipment design.

5.2 Options for Baseline Adjustment

Options for baseline adjustment include the following, in order of preference:

1. If the change involves new equipment or facility space, isolation of the electrical load through a dedicated submeter. The ensuing MT&R savings is simply the gross MT&R savings minus the submetered energy use.
2. Development of a new regression model, with the addition of a new independent variable that reflects the change, if that variable proves to be statistically significant.
3. If the energy drivers have remained the same, but have significantly increased or decreased relative to the baseline period, a new regression model can be developed from a more current data set.
4. Utilization of the existing baseline model, with the addition of an "indicator variable" placed in the data set at the time of the change. The impact of the change is thereby quantified by solving for the indicator variable coefficient using regression, following a suitable data collection period.

5.3 Guidelines for Modification of Regression Model

When Options 2 or 3 are required, a decision must be made regarding a suitable rebaselining period that adequately captures the new range of operating conditions, including seasonal cycles (if applicable). During this period, savings incentives would typically be put on hold, but the accumulated savings that preceded the retrofit would be considered through engineering calculations with verification.

[18] The Regents of the University of California, Section 3.4.6, p.11

5.4 EPT Approval

When a need arises to adjust a baseline model, a rebaselining proposal should be reviewed and approved by the EPT team, preferably in advance of the change.

6. Projecting Year 1 Energy Savings from the Performance Period

For Track and Tune projects, incentives are based on a projection of Year 1 energy savings. The projected Year 1 energy savings are based on the achieved energy savings obtained during the performance period, which is typically 90 days. Four methods to project Year 1 energy savings are provided below. For each of these methods, it is essential that the following factors are taken into account:

1. The number of valid observations during the performance period.
2. The expected number of valid observations during the remainder of Year 1.
3. The expected distribution of the energy drivers during the remainder of Year 1 relative to the distribution of the energy drivers during the performance period.

6.1 Direct Percentage Basis

- When the distribution of the energy drivers is expected to be the same for the remainder of Year 1, Year 1 energy savings can be projected by extrapolating percent energy savings from the performance period.

6.2 Percentage Basis with Forecast of Energy Drivers

- When the distribution of energy drivers is expected to be different for the remainder of Year 1, the distribution of energy drivers must be considered when projecting Year 1 energy savings. For example, if during the performance period, energy savings were only obtained when production was low, then the expected distribution of production should be used to project Year 1 energy savings. If production is expected to be high for the majority of the Year 1, it would be incorrect to project Year 1 savings based on savings achieved during the performance period that occurred when production was low.

6.3 Normalized Annual Consumption

- This method can be used in lieu of the “Percentage Basis with Forecast of Energy Drivers” method described above. This method requires the development of a second regression model for the performance period. The total derivative of the baseline energy equation is taken to develop a governing equation. The inputs for the governing equation are the coefficients from the baseline and performance period models, as well as the projected distribution of energy drivers. TMY3 weather data is typically used for the weather dependent energy drivers and the best estimate of Year 1 production is used for the production energy drivers.
- This modeling approach provides a disaggregation of energy savings by energy drivers, which provides transparency for how energy savings were achieved.
- The weakness of this approach is that it requires additional calculation steps and that the energy signature of the baseline and performance periods must be the same.
- This method is similar to the Standard Condition Adjustment Model defined by SEP.

6.4 Intervention Step Model

- The intervention step model approach can also be used in lieu of the "Direct Percentage Basis" method described in Section 6.1. This method was used by Cadmus for the 2012 Energy Management Impact Evaluation, and follows a methodology described by Luneski's publication (2011)[19] . The intervention step model entails developing a new regression model using an indicator variable to differentiate the baseline and performance period data. The value of the indicator variable represents the energy savings.
- This modeling approach does not normalize the savings value for annual weather or production and thus it should not be used when the distribution of the energy drivers is expected to be significantly different for the remainder of Year 1.

[19]Luneski, R.D. 2011. *A Generalized Method for Estimation of Industrial Energy Savings from Capital and Behavior Programs.* Industrial Energy Analysis 2011.

Appendix A – Treatment of EEMs During the Baseline Period

OPTION*	DESCRIPTION	GUIDELINES	MERITS	DEMERITS
1	<u>Standard Approach</u> Select a baseline period without capital projects and immediately prior to the treatment period. $y\ (kWh/period) = B_0 + B_1x_1 + B_ix_i$	a. Verify absence of utility-incentivized EEMs by interviewing facility and speaking to serving utility. b. Confirm energy intensity profile is consistent over the selected period.	a. Incorporates the full data set in the baseline model. b. Requires no manipulation of data. c. Requires no adjustments during treatment period.	a. No obvious demerits, provided energy intensity profile is consistent through baseline period.
2	<u>Year-End MT&R Adjustment</u> Choose a baseline period immediately prior to the first capital project. Subtract M&V savings from the <u>year-end</u> MT&R savings. $y\ (kWh/period) = B_0 + B_1x_1 + B_ix_i + (IV=0,1)_K \cdot (M\&V)_K$	a. Maximum exclusion period = 12 months. b. Exclusion period must have a consistent energy profile, aside from the EEM(s).	a. Provides direct reconciliation with EEM M&V value. b. Requires no adjustment of baseline data set.	a. Data immediately preceding treatment period is excluded. b. M&V adjustment must be performed through treatment period.
3	<u>Pre-EEM Baseline Normalization by M&V Value</u> Adjust the pre-EEM baseline values by the EEM M&V value. $y\ (kWh/period) = B_0 + B_1x_1 + B_ix_i$	a. EEM completion report must be reviewed and included as attachment. b. Interactive effects described in project report must be factored in to baseline adjustment.	a. Provides direct reconciliation to M&V value. b. Enables use of the entire baseline data set. c. CUSUM for treatment period starts at zero.	a. Requires adjustment to baseline data set (IPMVP does not prohibit). b. Accurately incorporating interactive effects is challenging and labor intensive.
4	<u>Baseline Normalization by Factored Indicator Variable</u> Apply an indicator variable in the baseline data set, representing the implementation of an EEM. The indicator variable may or may not be factored with one or more primary independent variables to account for interactive effects. $y\ (kWh/period) = B_0 + B_1x_1 + Box_y + + B' \cdot (IV=0,1) \cdot x'$	a. Factored indicator variable will add to the number of points required in the baseline data set (n*6).	a. Allows regression model to solve for interactive effects of EEM with other energy drivers. b. Yields the highest R-square.	a. No reconciliation with EEM's M&V value. b. If backsliding occurred on the EEM, program component would pick up any recapturing of the original savings.

OPTION*	DESCRIPTION	GUIDELINES	MERITS	DEMERITS
5	<u>Indicator Variable Representation of Non-Incentivized EEM</u> To prevent incentivizing a previously implemented non-incentived EEM by program component, apply an indicator variable representing the implementation of the EEM, and solve for the coefficient. y (kWh/period) = $B_0 + B_1x_1 + B_ix_i + B'(IV=0,1) \cdot x'$	a. Non-incentivized EEMs implemented during baseline period should be accurately reflected in baseline model.	a. Prevents “free-rider” EEMs from inflating the savings associated with program component. b. Allows use of the entire baseline data set.	a. The quantification of the savings associated with the EEM is limited to the precision of the model.

*Options 1~4 are listed in a hierarchical order of preference.   Option 5 describes an independent scenario.

Appendix B – Treatment of Incentivized EEMs Installed During the Treatment Period

PROJECT INSTALLED	SAVINGS OBSERVED IN CUSUM?	M&V STATUS	PRORATING METHOD	
			Start Date	Savings Value
No, or Incomplete	n/a	n/a	n/a	n/a
Yes	No	Not started	n/a	n/a
		In progress	Use the Actual Project M&V End Date.	Wait for M&V to be completed (if an early estimate is needed, solve for value in CUSUM).
		Completed	Use the Actual Project M&V End Date.	Use site savings M&V value.
	Yes	Not started	Based on CUSUM inflection, and ideally supported by email from ESIP (e.g., equipment was commissioned on xx/xx date).	Option A. Solve for saving value using indicator variable during treatment period.
				Option B. Use estimated site savings from custom project proposal.
				Option C. If the savings value from A and B differ significantly, confer with EPT team.
		In progress	Option A. Based on CUSUM inflection, and ideally supported by email from ESIP.	Wait for M&V to complete (if an early estimate is needed, solve for value).
			Option B. At the latest, use "Actual Project M&V End Date."	
		Completed	Option A. Based on CUSUM inflection, and ideally supported by email from ESIP.	Use site savings M&V value.
			Option B. At the latest, use "Actual Project M&V End Date."	

Appendix C – Overview of Regression Output

```
Baseline relationship for Production Days Only

m(formula = Total_KWH ~ IND_early + IND_late + IND_missingkWh +
    Prod_carrots + Prod_Corn + Prod_Peas + WetBulb_KHRI, data =
Dataset)

Residuals:
   Min      1Q Median     3Q    Max
-38223   -7100    358   8095  32761

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)     2.038e+04  9.919e+03   2.054   0.0416 *
IND_early      -5.203e+04  3.998e+03 -13.012  < 2e-16 ***
IND_late        4.889e+04  3.998e+03  12.229  < 2e-16 ***
IND_missingkWh -2.515e+04  6.204e+03  -4.054 7.97e-05 ***
Prod_carrots    9.017e-02  7.928e-03  11.373  < 2e-16 ***
Prod_Corn       8.252e-02  5.217e-03  15.819  < 2e-16 ***
Prod_Peas       6.696e-02  5.122e-03  13.075  < 2e-16 ***
WetBulb_KHRI    6.573e+02  1.596e+02   4.120 6.18e-05 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 13170 on 154 degrees of freedom
Multiple R-squared: 0.8452, Adjusted R-squared: 0.8381
F-statistic: 120.1 on 7 and 154 DF,  p-value: < 2.2e-16
```

Figure 12. Regression output from “R” open source statistical software.

Regression Statistics	
Multiple R	0.965375
R Square	0.931949
Adjusted R Square	0.916827
Standard Error	590.4573
Observations	12

CV = 0.03

Note: CV must be calculated separately.

ANOVA

	df	*SS*	*MS*	*F*	*ignificance F*
Regression	2	42971374	21485687	61.627181	5.59E-06
Residual	9	3137758	348639.8		
Total	11	46109132			

	Coefficients	*tandard Err*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	24373.82	5738.171	4.247664	0.0021499	11393.18	37354.46	11393.18	37354.46
Ave Temp	-428.045	208.7444	-2.05057	0.0705487	-900.258	44.1677	-900.258	44.1677
Ave Temp^2	5.392718	1.845353	2.922323	0.0169676	1.218239	9.567196	1.218239	9.567196

Figure 13. Regression output from Microsoft Excel.

Appendix D – Glossary of Terms

The definitions included below address terms used within the body of this document, presented in the context of ESI's Monitoring, Targeting and Reporting procedure. For a more comprehensive overview of statistical terms related to measurement and verification, please refer to BPA's Glossary for M&V: Reference Guide[20].

1. Autocorrelation Coefficient: The autocorrelation coefficient is a measure of the correlation of a time series with its past and future values (also referred to as serial correlation). In a time series plot of residuals, autocorrelation is characterized by a tendency for the bias in data point "n" to be a predictor of a similar bias in data point "n+1". The autocorrelation coefficient can be calculated by performing regression on two identical data sets, offset by one unit of time. The square root of the resulting coefficient of determination is the autocorrelation coefficient (ρ) for the data set.

   Auto-correlation (p) can also be calculated from the residuals, e, from the following equation:

$$\rho = \frac{\sum_{t=2}^{n} e_t \; e_{t-1}}{\sum_{t=1}^{n} e_t^2}$$

2. Change-Point Model: A model in which the relationship of a dependent variable is discontinuous with respect to an independent variable. The change-point is the value of the independent variable at which this discontinuity occurs. In the context of industrial energy efficiency, a common scenario arises when the energy intensity of a building or system changes at a specific ambient temperature, at which the HVAC system switches from a heating mode to a cooling mode.

3. Coefficient of Determination (R-square): Statistically, the R-square represents the proportion of the total variation in the dependent variable that is explained by the regression equation. Mathematically, R=square is defined as R-square = $\frac{\sum(\hat{Y}_i - \overline{Y})^2}{\sum(Y_i - \overline{Y})^2}$, where,

   $\hat{Y}_i =$ the predicted energy value for a particular data point using the measured value of the independent variable.

   $\overline{Y} =$ mean of the n measured energy values, $\overline{Y} = \frac{\sum Y_i}{n}$.

   $Y_i =$ actual observed value of the dependent variable.

4. Coefficient of Variation (CV RMSE): The CV is calculated as the ratio of the root mean squared error (RMSE) to the mean of the dependent variable (energy). CV is a dimensionless value, and the ratio is typically multiplied by 100 and given as a percentage. The CV aims to describe the model fit in terms of the relative sizes of the squared residuals. CV evaluates the relative closeness of the predictions of the actual values (the uncertainty of the model), while R-square evaluates how much of the variability in the actual values is explained by the model.

   CV(RMSM) = $\frac{\sqrt{\left(\frac{\sum(\hat{y}_i - y_i)^2}{(n-p-1)}\right)}}{\overline{y}} \; x\; 100$

5. Energy Champion: This person, assigned by the end user, determines potential energy efficiency projects and tracking techniques.

6. Energy Management: The application of the business principles of continuous improvement to drive systematic, long-term reductions in the energy intensity of a system, facility, or organization.

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[20] *Bonneville Power Administration's Glossary for M&V: Reference Guide*, Version 1.0, September 2011

7. Fractional Savings Uncertainty: The uncertainty divided by the savings, where uncertainty is measured as the quantity of savings from the upper confidence limit to the lower confidence limit surrounding a savings estimate.

8. Heteroscedasticity: In contrast to homoscedasticity, this occurs when error (or residual) variance is not constant throughout the observations. For example, when the residual variance is shown to increase or decrease with the value of an independent variable.

9. Homoscedasticity: Homoscedasticity generally means that all data in a model have similar variance, over the modeling period. Within linear regression, this means that the variance around the regression line is similar for all values of the dependent variables.

10. Indicator Variable: Also referred to as categorical variables, a variable used to account for discrete levels of a qualitative variable. Generally, indicator variables are assigned a value of 0 or 1 to account for different modes of operations, and a qualitative variable with *r* levels can be modeled with *r-1* indicator variables.

11. International Measurement and Verification Protocol (IPMVP): The IPMVP provides an overview of current best practice techniques available for verifying results of energy efficiency, water efficiency, and renewable energy projects in commercial and industrial facilities. It may also be used by facility operators to assess and improve facility performance. The IPMVP is the leading international standard in Measurement and Verification protocols. It has been translated into ten languages and is used in more than 40 countries.

12. Measurement and Verification (M&V): The process of using measurement to reliably determine actual savings created within an individual facility by an energy management, energy conservation, or energy efficiency project or program. As savings cannot be directly measured, the savings can be determined by comparing measured use before and after implementation of a project, making appropriate adjustments for changes in conditions."[21]

13. Measurement Boundary: A notional boundary drawn around equipment and/or systems to segregate those which are relevant to savings determination from those which are not. All energy uses of equipment or systems within the measurement boundary must be measured or estimated, whether the energy uses are within the boundary or not.

14. Mean Model: (Also known as a *Single Parameter Model.*) A model that estimates the mean of the dependent variable.

15. Monitoring, Tracking and Reporting (MT&R): MT&R refers to the measurement systems, statistical tools, and business practices associated with measuring energy intensity, establishing targets for improvement, and reporting results and impacts. MT&R has many similarities to the Plan-Do-Check-Act (PDCA) methodology that is central to several widely adopted business performance standards.

16. Multicollinearity: A phenomenon in which two or more independent variables in a multiple regression model are correlated.

17. Net Determination Bias Error (NBD or NBE): A statistical metric that quantifies the tendency of a model to underestimate or overestimate savings. Typically represented as a percentage. Note that if regression is performed properly, net determination bias should be zero.

[21] *International Performance Measurement and Verification Protocol.* Efficiency Evaluation Organization. 10000-1.2010. www.evo-world.org

NTB = $\frac{\sum(Y_i - \hat{Y}_i)}{\sum Y_i}$ x 100; a positive value indicates a tendency of the model to overestimate savings.

18. Regression Model: A mathematical model based on statistical analysis where the dependent variable is regressed on the independent variables which are said to determine its value. In so doing, the relationship between the variables is estimated statistically from the source data.

19. Tune-up – The major on-site technical effort, led by the Tune-up engineer, which may result in immediate operational changes and produces a prioritized list of low-cost/no-cost action items.

Appendix E – Models with Irregular Time Intervals

When developing an energy model based on data of varying intervals, time intervals must be accounted for in the regression analysis or the model will be biased. This is accomplished by first converting the data for each observation of the independent and response variables to average values. Then all dependent and independent variables need to be weighted by the number of intervals in the billing period. This can be accomplished by using weighted regression analysis, or duplicating each observation by the number of time intervals in the billing period.

Energy models with irregular time intervals occur most often when developing energy models with monthly utility bills. Consider, for example, the case when the billing period for each utility bill is different. When developing the energy model, the model must account for this irregular time interval to eliminate bias from the varying time periods. Table 2. shows the data per billing period and the daily average values for this data. Note that because Tdb was already provided as an average value, this value is the same for both the billing period and the daily average.

Table 2. Example data set for weighted regression.

Billing Period					Daily Average		
Billing Period	**Days/Billing Period**	**Electricity Use (kWh/Billing Period)**	**Avg. Tdb (°F/Billing Period)**	**Production (lbs/Billing Period)**	**Electricity Use (kWh/dy)**	**Avg. Tdb (°F/dy)**	**Avg. Production (lbs/dy)**
Jan	27	227,772	39.0	2,649	8,436	39.0	98.1
Feb	29	246,471	39.7	2,448	8,499	39.7	84.4
Mar	28	142,072	42.1	2,335	5,074	42.1	83.4
Apr	29	172,318	48.2	1,891	5,942	48.2	65.2
May	28	123,368	52.5	1,229	4,406	52.5	43.9
Jun	39	126,945	61.3	1,685	3,255	61.3	43.2
Jul	29	101,529	66.8	1,595	3,501	66.8	55.0
Aug	29	133,429	67.4	2,042	4,601	67.4	70.4
Sep	33	150,975	63.5	2,290	4,575	63.5	69.4
Oct	30	144,720	52.7	2,112	4,824	52.7	70.4
Nov	24	140,880	47.5	1,596	5,870	47.5	66.5
Dec	38	221,502	37.4	1,661	5,829	37.4	43.7
Total/Avg.	**363**	**1,931,981**	**51.5**	**1,961**	**5,401**	**51.5**	**66.1**

After the average values per interval are obtained, in this case daily average values, the analysis can be performed by either using weighted regression or duplicating each observation by the corresponding number of time intervals for each observation. When using weighted regression, the weights, **W**, correspond to the number of time intervals per observation. For this example, Wii, which is a diagonal matrix, would be:

Wii = [27, 29, 28, 29, 28, 39, 29, 29, 33, 30, 24, 38]

When duplicating observations, each observation of average values is duplicated by the number of time intervals for the observation. In this example, the observations for January would be duplicated 27 times; the observations for February would be duplicated 29 times, and so forth. A spreadsheet can be used to facilitate duplicating the observations.

A weighted regression set was developed to demonstrate how weighted regression is performed by duplicating observations as described above. Then both the weighted regression set and the daily average, or ordinary least squares regression set, was fit to a three parameter, multivariable heating model as:

$$E\left(\frac{kWh}{dy}\right) = \beta_o + \beta_1(\beta_2 - Avg.Daily\ Temp)^+ + \beta_2(Avg.Daily\ Saw\ Dust)$$

Table 3 shows that the regression coefficients calculated using weighted regression are different from the ordinary least squares method.

Table 3. Coefficient results from weighted and ordinary regression analysis.

	Weighted (Observations = 363)	Ordinary (Observations = 12)
Bo	1,477.6960	1,518.1765
B1	124.4626	125.1822
B2	58.5320	58.5860
B3	42.1438	41.4257

Table 4 shows that the sum of the residuals for ordinary regression analysis differs from zero. This difference is caused by bias in the model coefficients. The sum of the residuals for weighted regression is nearly zero. This difference of -1 is the result of numerical errors in transferring coefficient values from the modeling program to the calculation spreadsheet and underscores the necessity of reporting and using coefficients with adequate precision.

Table 4. Comparison of residuals between weighted and ordinary regression analysis.

Actual		Weighted		Ordinary	
Billing Period	**Electricity Use (kWh/Billing Period)**	**Predicted Electricity Use (kWh/Billing Period)**	**Residual (kWh/Billing Period)**	**Predicted Electricity Use (kWh/Billing Period)**	**Residual (kWh/Billing Period)**
Jan	227,772	217,161	10,611	216,914	10,858
Feb	246,471	213,977	32,494	213,977	32,494
Mar	142,072	197,054	-54,982	197,054	-54,982
Apr	172,318	159,831	12,487	159,831	12,487
May	123,368	114,200	9,168	114,200	9,168
Jun	126,945	128,634	-1,689	128,634	-1,689
Jul	101,529	110,073	-8,544	110,073	-8,544
Aug	133,429	128,894	4,535	128,894	4,535
Sep	150,975	145,282	5,693	145,282	5,693
Oct	144,720	155,115	-10,395	155,115	-10,395
Nov	140,880	135,680	5,200	135,680	5,200
Dec	221,502	226,082	-4,580	226,082	-4,580
Total	1,931,981	1,931,982	**-1**	1,931,735	**246**

Table 5 shows that ordinary regression analysis results in a net determination bias (NDB) of more than the acceptable cut-off criterion of 0.005% given in ASHRAE Guideline 14. The weighted regression provides a net bias error that meets this criterion and could be improved by using more precise estimates of the coefficients.

Table 5. Comparison of NDB between weighted and ordinary regression analysis.

Method	NDB
Weighted	-5.8E-07
Ordinary	1.3E-04

While weighted regression is a useful tool for eliminating model bias, it should be noted that the duplication of observation results in artificially high R-square values and T-statistics for independent variables. Therefore, ordinary regression should be applied for the screening of competing models and the selection of independent variables, with weighted regression applied as a final step to dial-in the coefficient values on the selected model (for the purpose of minimizing Net Determination Bias).

Appendix F – KPI Bin Model

If the major energy driver at a site is not a continuous or ordinal variable but a nominal variable, then regression modeling of the system can prove difficult. Examples of such nominal variables are paper grade in a paper mill, color in a glass plant, or product type in a manufacturing process. If the number of different types in that nominal variable is small, then the unique energy intensity characteristic of each group can be represented by an individual variable, which then can be used in a conventional least-square regression analysis. For instance, if there are only three possible glass colors, three variables can be created with production volumes for each of the three colors and all three variables can have separate parameters in the final model. If number of types within the nominal variable is too big, however, it becomes unfeasible to create and use individual variables within a regression model.

Therefore, because nominal variables cannot be used in a regression, a different modeling technique must be chosen if that energy driver is to be considered. One modeling type that has been used in this situation is a KPI bin model using the nominal variable as one of the binning factors. A KPI bin model essentially calculates a KPI for each type within the nominal variable. If paper grade is the nominal variable, then a KPI with the units kWh/ton is created. In addition, a baseload electricity can be calculated if there are times where the production is zero by averaging all the electricity values during zero production. The benefit to this methodology is that each type within the nominal variable has its own equation, which can lend clarity to the effect the different types have on the electrical usage.

The steps to this technique are as follows:

1. Determine the threshold for minimum number of hours acceptable to create each specific KPI.
2. Determine the baseload or energy use during zero production (i.e., shutdowns).
3. Calculate the average production rate and total average power for each type within the nominal variable and acceptable production range.
4. Calculate the average power for each KPI by subtracting the baseload power from the total average power for each type within the nominal variable using the following equation:

$$Average\ KPI\ Power = Total\ average\ power - Baseload\ power$$

5. Calculate the variable KPI using the following formula:

$$\frac{Average\ KPI\ Power\ [kWh]}{(Average\ Production\ [unit])} = \frac{kWh}{Unit}$$

6. Calculate the variable energy by using the bin type and production rate, making sure the production rate is within the model range, and create a predicted energy consumption using the following formula:

$$Predicted\ energy = KPI\ \left[\frac{kWh}{unit}\right] \cdot Total\ Production[unit] + baseload\ energy\ [kWh]$$

7. Calculate residuals
8. Create a CUSUM

One drawback for this type of modeling is that it requires a lot of data to create. In order to create a KPI for each type within the nominal variable, pure data for that type is needed. For instance, if a glass plant makes multiple colors within a day then in order to calculate the KPI both production and electrical energy data need to be obtained for the hours each of the different colors were made. Therefore, data would most likely need to be hourly, unless the plant only made one color each day, in which case the model could be created using daily data.

Savings Calculation

Savings calculations for this type of modeling are really no different than for a regression model. Once the bin KPIs are created, a predicted value for electrical usage can be calculated and compared to the actual usage. If the interval of the data used to create the KPI Bin model is daily, for instance, then for every day after the baseline, the nominal type created that day and the production amount would be plugged into the KPI equation and a predicted electricity value would be calculated. That predicted electricity would be used to create a residual for that day and the residuals would be added up to create a CUSUM. The CUSUM value would be used as the savings amount.

Statistical Confidence

Statistical confidence in the model can be evaluated using the actual electricity values and the predicted electricity values created during the baseline period. A regression model can be created using the actual electricity value as the dependent variable and the predicted electricity value calculated using the KPI equation. That regression will give an R^2, CV, Observations, and autocorrelation coefficient which can be evaluated using the same criteria as a normal regression.

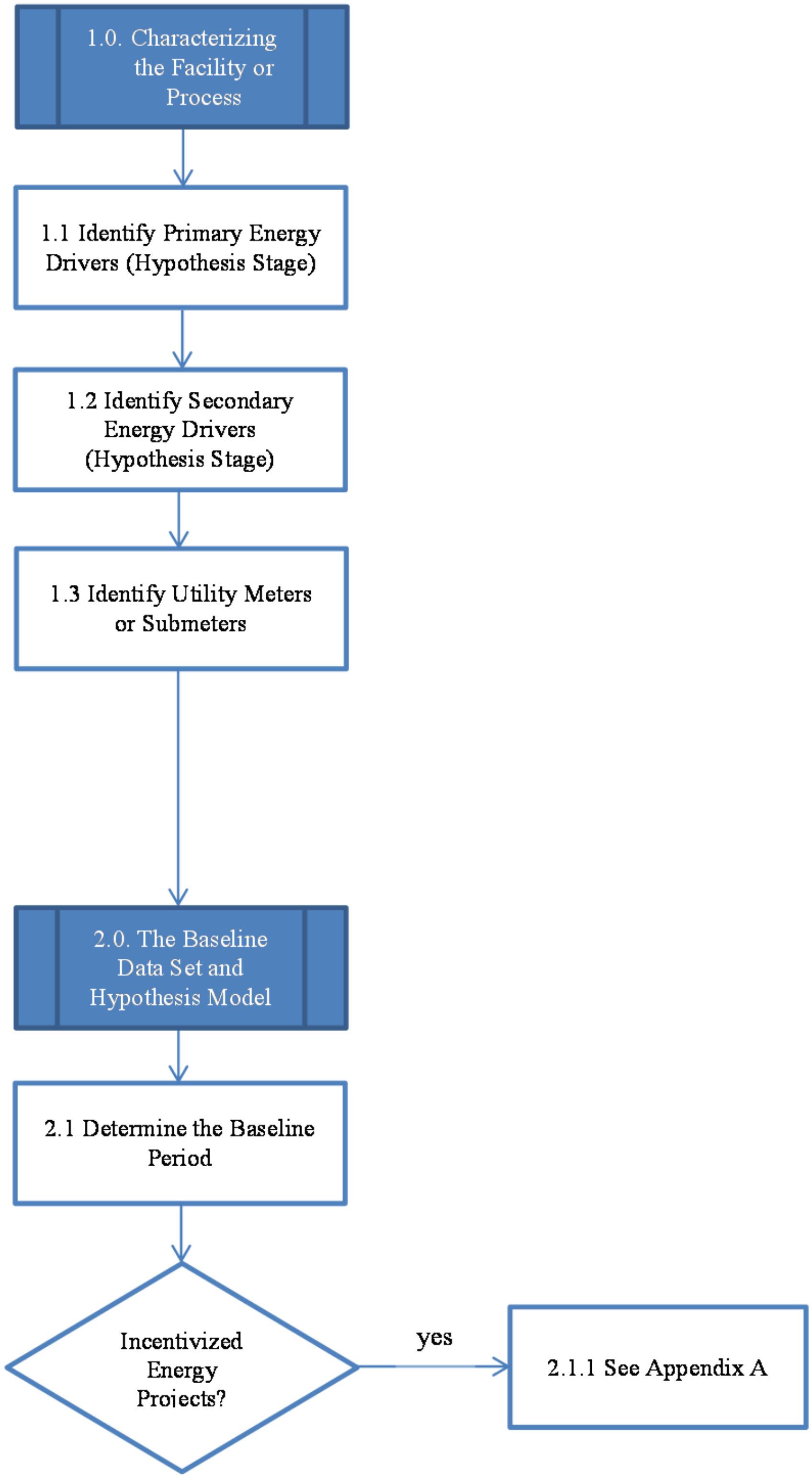
Appendix G – Summary of Competing Models

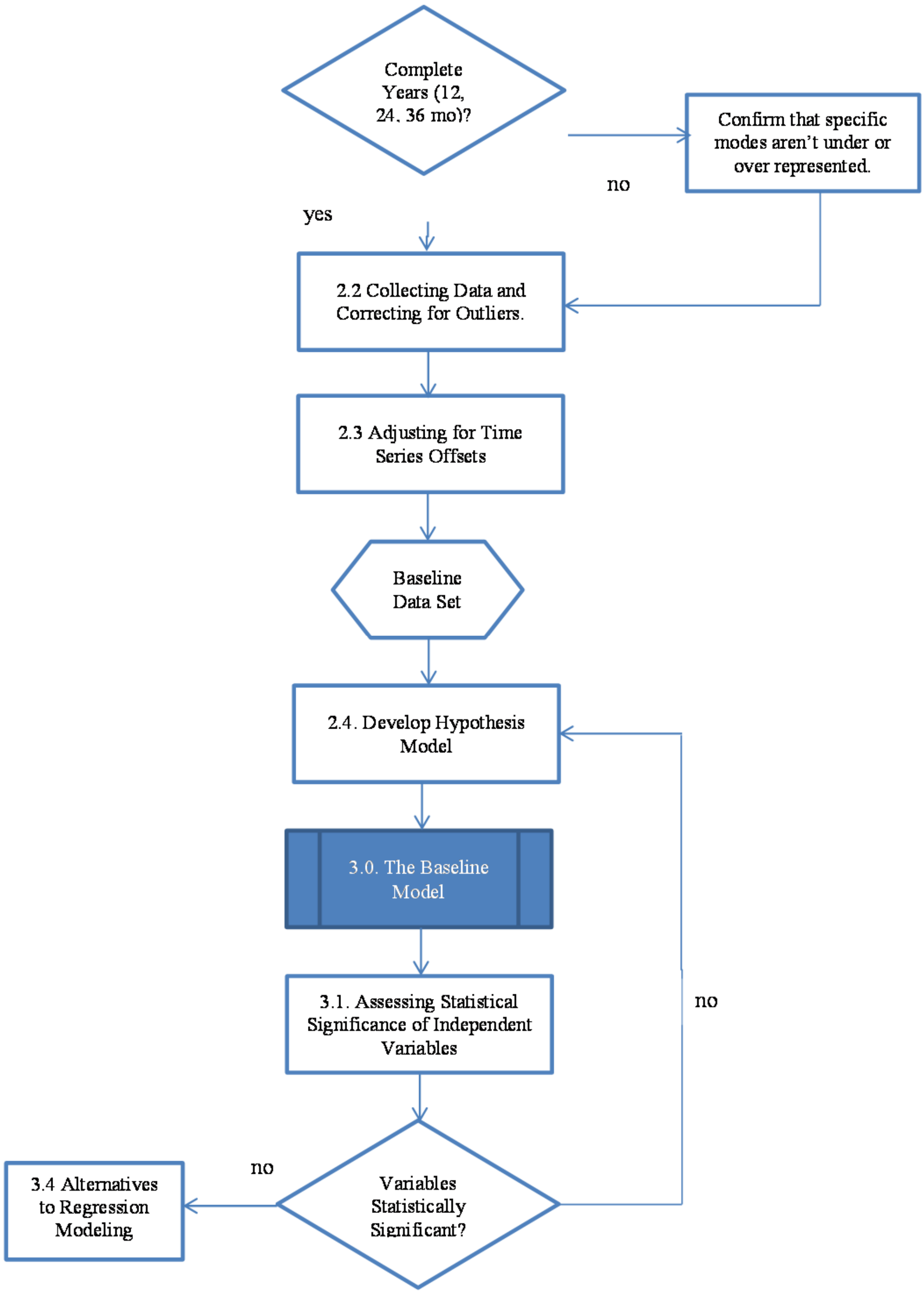
An example of a summary showing competing models is shown in Table 6.

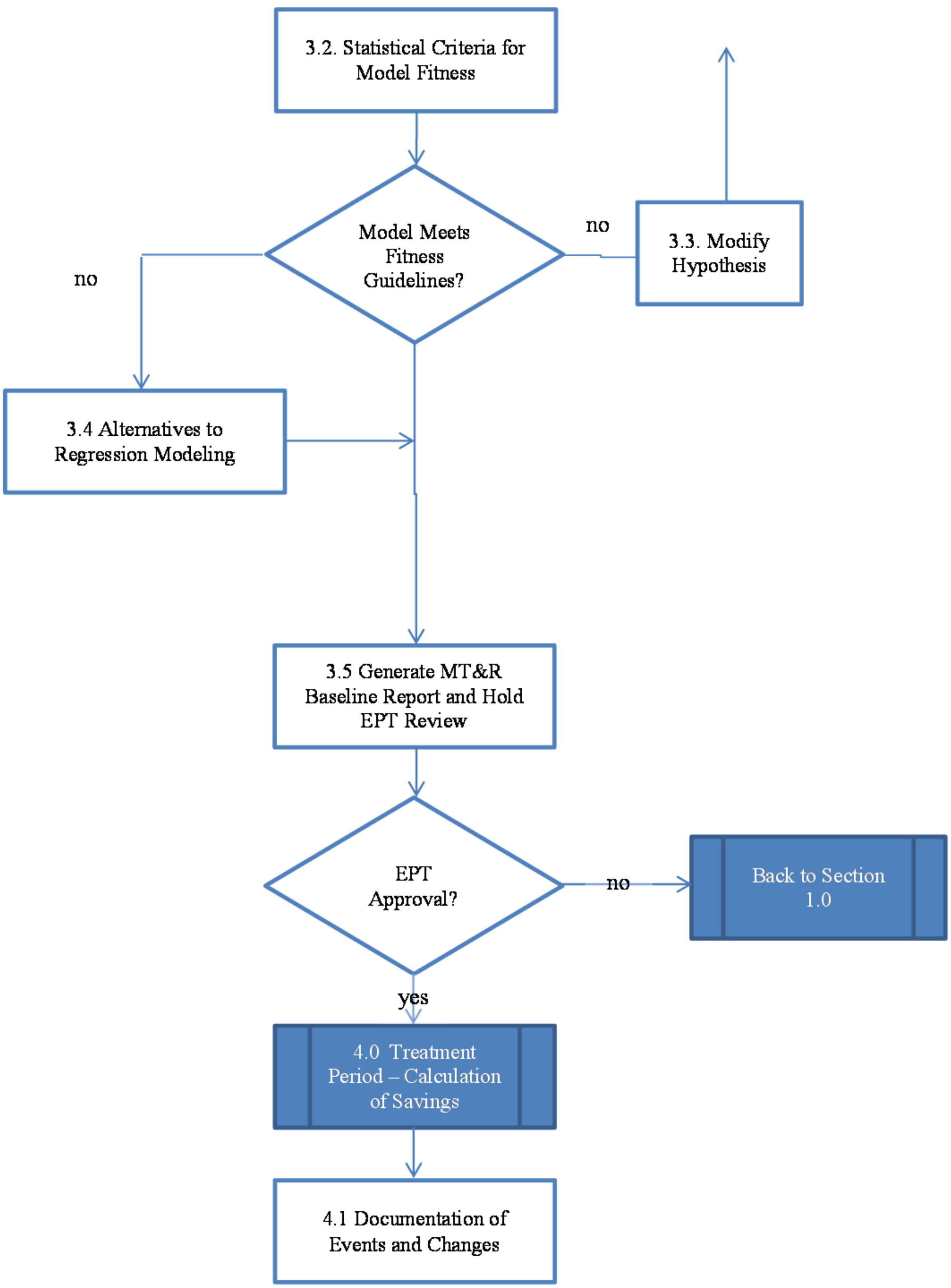
Table 6. Example of competing model summary.

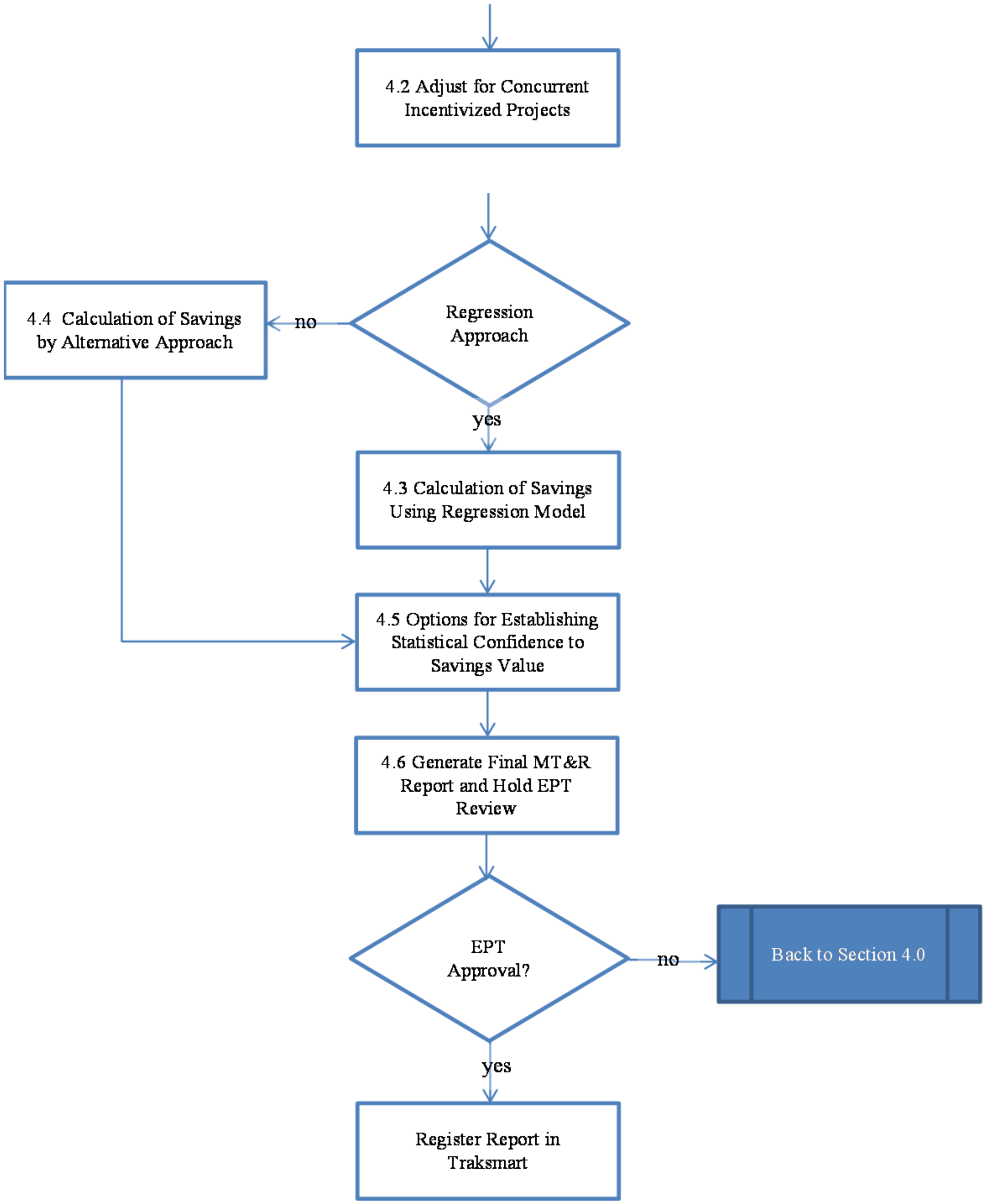
Interval	Period	Trial	n	Prod 1	Prod 2	Total Prod	Temp-Dry Bulb	R^2	SE (kWh/period)	CV-RSME (%)	FSU (5% savings at 80% confidence)	comment
Daily	5/1/2013-4/30/2014	1	364	-	-	T=25.1	T=8.9	0.66	4,734	12.2%	20.0%	excluded 3/9/2014 due to DLS change over error
		2	333	T=25.2			T=17.0	0.84	3,187	8.1%	15.5%	Eliminated December 2013 due to noisy residuals
		3	333	T=13.3	T=3.6		T=12.0	0.85	3,131	8.0%	15.9%	Note: A/C increased from 0.059--> 0.096 from Trial 7 to
		4	331	T=16.8	T=4.9		T=12.5	0.89	2,644	6.8%	11.8%	Eliminated 6/28-6/29/2013 due to high residuals
		5	329	T=21.1	T=7.1		T=15.2	0.92	2,219	5.7%	10.1%	Eliminated 10/1/2013 and 3/24/2014 - outliers
		6	360	T=22.4	T=8.2		T=16.7	0.92	2,247	5.8%	10.2%	Figured out that production data was off by one day for Dec. Added back in.
		7	360			T=15.0	T=19.6	0.94	1,882	4.8%	8.9%	Eliminate 12/25/13 outlier, return 3/24/14 (not an outlier) FINAL MODEL

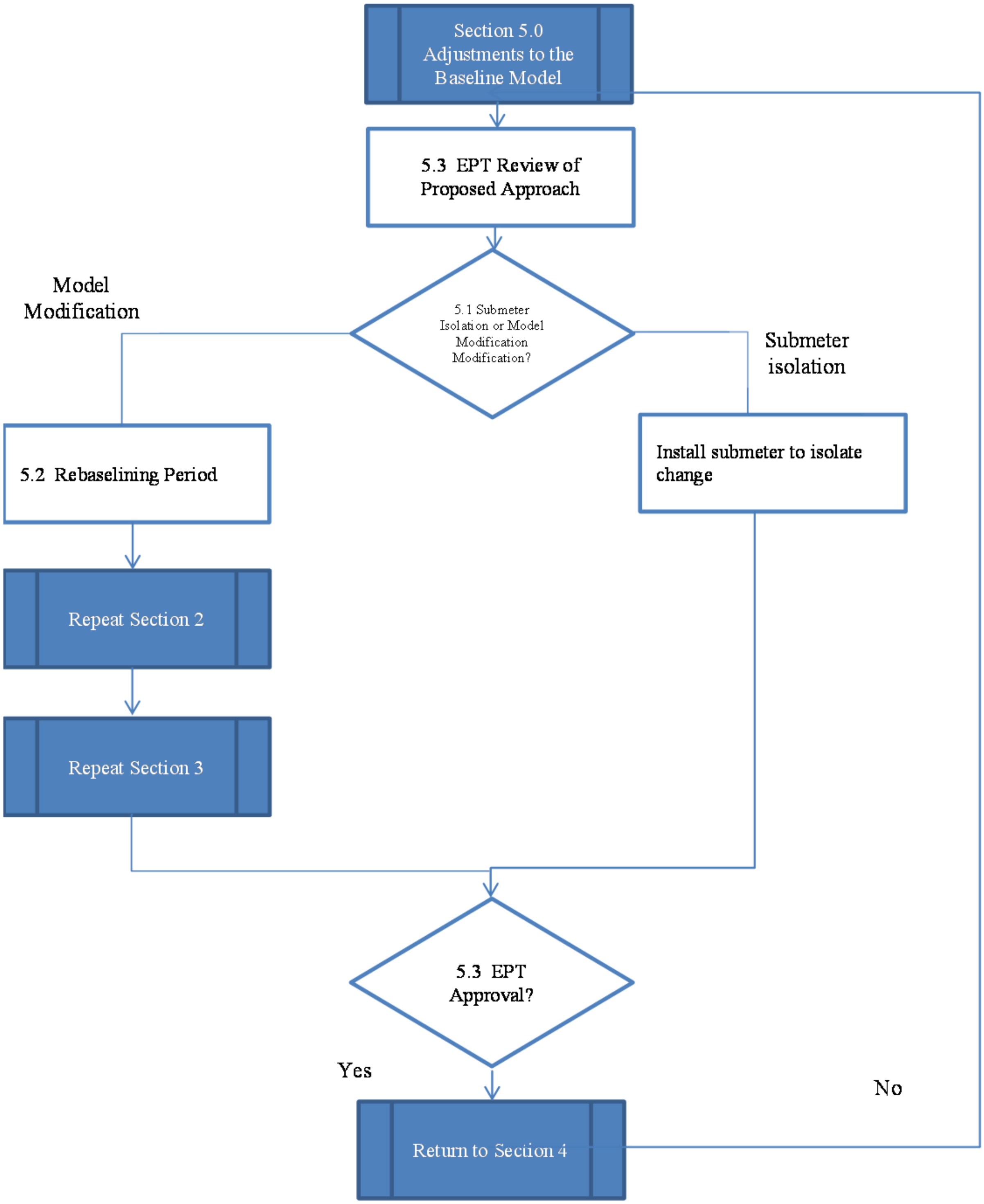
Appendix H - MT&R Decision Tree




Complete Years (12, 24, 36 mo)?
no
Confirm that specific modes aren't under or over represented.
yes
2.2 Collecting Data and Correcting for Outliers.
2.3 Adjusting for Time Series Offsets
Baseline Data Set
2.4. Develop Hypothesis Model
3.0. The Baseline Model
3.1. Assessing Statistical Significance of Independent Variables
no
no
3.4 Alternatives to Regression Modeling
Variables Statistically Significant?


3.2. Statistical Criteria for Model Fitness
Model Meets Fitness Guidelines?
no
3.3. Modify Hypothesis
no
3.4 Alternatives to Regression Modeling
3.5 Generate MT&R Baseline Report and Hold EPT Review
EPT Approval?
no
Back to Section 1.0
yes
4.0 Treatment Period – Calculation of Savings
4.1 Documentation of Events and Changes


4.2 Adjust for Concurrent Incentivized Projects
Regression Approach
no
4.4 Calculation of Savings by Alternative Approach
yes
4.3 Calculation of Savings Using Regression Model
4.5 Options for Establishing Statistical Confidence to Savings Value
4.6 Generate Final MT&R Report and Hold EPT Review
EPT Approval?
no
Back to Section 4.0
yes
Register Report in Traksmart



Section 5.0 Adjustments to the Baseline Model
5.3 EPT Review of Proposed Approach
Model Modification
5.1 Submeter Isolation or Model Modification Modification?
Submeter isolation
5.2 Rebaselining Period
Install submeter to isolate change
Repeat Section 2
Repeat Section 3
5.3 EPT Approval?
Yes
No
Return to Section 4

Appendix I – Revision History

REVISION	RELEASE DATE	CHANGES
1.0	April 12, 2010	New Document
2.0	May 14, 2010	Addressed feedback from BPA Planning and CADMUS Group (Document Dated April 15, 2010).
3.0	March 7, 2012	General • Incorporated Document Objective, clearly stating ownership by ESI EPT Team. • Added various appendixes and illustrations, including Glossary of Terms. • Added revision history. Section 1 • Added a requirement that the effect of ambient temperature should always be tested for statistical significance. • Clarified requirement for calibration of in-house submeters that don't match revenue meter boundary. Section 2 • Clarified strong preference for including even intervals of annual cycles in baseline period. • Included specific guidelines for adjusting for incentivized or non-incentivized EEMs that were installed during the baseline period. • Added additional guidance and illustration for outlier removal, and time-series adjustments. • Included discussion of change-point models. • Added a discussion of multicollinearity Section 3 • Added a requirement to assess auto-correlation of the residuals. • Added a requirement to calculate Net Determination Bias of the residuals. • Added a requirement to calculate adjusted R-sqr. • Included specific options for "Alternatives to Regression Modeling." Section 4 • Added guidance on adjustments for concurrent incentivized projects during the "treatment period." • Added discussion of model uncertainty. Section 5 • Added a section that outlines specific options for baseline adjustment.

REVISION	RELEASE DATE	CHANGES
4.0	Sept. 25, 2013	Section 2.2 • Changed data screening criteria from three standard deviations to four standard deviations. • Changed reference for data screening. • Eliminated graph in Figure 1. Section 2.4 • Adding clarifying language for multicollinearity. • Added reference for multicollinearity. Section 3.2 • Replaced Figure 6 with new figure. • Added Durbin-Watson test statistic. Section 3.4 • Added section. Section 3.5.1 • Added section. Section 3.5.2 • Terminology change from mean-shift to mean model. Section 4.3 • New figure for Figure 8. Section 4.5.2 • Added section. Section 4.5.3 • Added section. Section 6.0 • Added section.
5.0	February 20, 2015	Section 1.1 • Added content regarding the measurement boundary and accounting for all energy and mass flows crossing the boundary. Added Figure 1. Section 1.2 • Added content about the inclusion of process parameters within the energy mode. Added Figure 2. Section 2.2 • Added content regarding the handling of data from control systems. Included Figure 4 and referenced weighted regression. Section 4.4.3 • Added section: Savings Calculation by Bottom-Up Approach. Section 4.4.4 • Added section: Savings Calculation by KPI Based Classification. Appendix E • Added clarifying language about using weighted regression to determine coefficient values. Appendix F • Added Appendix F: KPI Bin Model. Appendix G • Added Appendix G: Summary of Competing Models.