BONNEVILLE POWER ADMINISTRATION

Commercial & Industrial SEM M&V Reference Guide

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Commercial & Industrial Strategic Energy Management

Measurement & Verification Reference Guide

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Bonneville Power Administration

Prepared by

Facility Energy Solutions

Energy 350

Stillwater Energy

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The Facility Energy Solutions' team is comprised of:

Lia Webster	Facility Energy Solutions
Josh Weissert	Energy 350
Kevin Campbell	Energy 350
Anne Joiner	Stillwater Energy

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Steve Martin	Cascade Energy
Megan McElfresh	Cascade Energy
Steve Mulqueen	Cascade Energy
James Roe	Cascade Energy
Jacob Schroeder	Cascade Energy
Sara York	Cascade Energy

Introduction

Purpose

BPA's Strategic Energy Management (SEM) program is founded on a Monitoring, Targeting, and Reporting (MT&R) methodology to estimate and report energy savings for SEM projects. BPA has supported SEM measures since 2009. SEM's core intent is to help end-users reduce the energy intensity of their facility or key subsystems, while establishing a system that allows them to track energy performance and savings over a multi-year program period. SEM programs emphasize behavioral, low-cost operational and maintenance improvements, and can be coordinated with any capital improvement projects including those incentivized by other programs.

This document outlines recommended methodologies to:

1. establish baseline energy models at a whole-facility or subsystem level,
2. quantify and track energy savings associated with the implementation of multiple energy efficiency measures (EEMs) over a defined reporting period, and
3. report energy savings from SEM projects appropriately to BPA.

In the context of whole-facility or subsystem energy management, the default M&V approach is a top-down, whole-facility, forecasting-based regression model as described by the International Performance Measurement and Verification Protocol (IPMVP).[1] Unless otherwise noted, these Guidelines are intended to align with the best practices outlined by IPMVP for Option C – Whole Facility approach.

Developing a linear regression model to monitor and report energy savings for SEM projects while maintaining consistency with IPMVP is an iterative process. This process requires the practitioner to work with large data sets, to understand the major energy drivers in a facility, and to have a working knowledge of statistics. The predictive ability of the model depends largely upon the stability of the operations at the site and the practitioner's ability to navigate this process in a sequential manner.

Sections 1–3 of this document focus on the model development process. Sections 4–6 of this document focus on the quantification of energy savings attributable to SEM. Specific focus is given to addressing the separation of operations and maintenance savings from concurrent capital projects and adjusting the baseline energy model for non-routine events within the SEM measurement boundary. Appendices include additional technical detail.

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1 *International Performance Measurement and Verification Protocol.* Efficiency Evaluation Organization. 10000-1:2016. *www.evo-world.org.*

User Notes

- These Guidelines are intended to provide BPA and BPA's partner utilities with consistent site-specific M&V guidance in implementing Commercial and Industrial (C&I) SEM Programs. Intended users include SEM program administrators, program implementers, BPA Engineers, and program evaluators.
- The technical approaches included in these Guidelines are applicable to both C&I sectors at small, medium, and large sites. BPA encourages partner utilities to customize SEM program offerings to engage targeted customers, and to build in flexibility so smaller customers may participate.
- Ultimately, BPA will review savings results submitted for all SEM projects from partner utilities for technical accuracy. Analyses and decision-making rationales should be documented, where possible.

Table 1: Overview of M&V Reference Guide

Section	Focus	Key M&V Action
1	Model Development Process	Characterizing the Facility
2		Establishing a Baseline Data Set
3		Developing a Baseline Energy Model
4	Quantification of Energy Savings	Making Adjustments for Non-Routine Events
5		Calculating Energy Savings for the Reporting Period
6		Adjusting for Data Gaps, if Needed
7	Reporting Energy Savings	Reporting Verified Incremental Savings
Appendices A – F	Additional Technical Details	Calculations and Examples

1. Characterizing the Facility

1.1. Identify Measurement Boundary

- Strategic Energy Management (SEM) projects are typically based on a whole-facility M&V approach (IPMVP Option C) using energy data from utility meters along with independent variables (such as outdoor air temperature) to develop a regression model. In some instances, retrofit-isolation approaches using measure-level engineering calculations with verification may be used.
- For whole-facility energy models, the measurement boundary consists of all the systems and equipment served by one or more utility meters, as shown in Figure 1. While energy sources may include natural gas, steam, or in some cases compressed air, the examples in this document assume utility provided electrical energy is the relevant energy source.
- When other energy sources such as natural gas may be impacted either directly by projects or through significant interactive effects, the energy data should also be collected and analyzed periodically.
- All electrical energy crossing the measurement boundary must be accounted for and documented. This is critical where more than one meter serves a facility.
- Where significant electrical energy-consuming equipment within the measurement boundary inconsistently supplies areas outside of the measurement boundary, this consumption should be accounted for and documented. In such cases, effective sub-metering strategies need to be deployed to measure the energy usage crossing the measurement boundary for reporting purposes.
    - → One example is where hot-water or steam is supplied to an adjacent building outside of the measurement boundary only under peak heating-load conditions when on-site boilers cannot meet loads.
    - → Another example is an air compressor within the measurement boundary that supplies variable amounts of compressed air to equipment both within the measurement boundary and to other areas.
- 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 sources for reporting purposes.
    - → One example is a hospital that adds a new natural gas boiler in addition to their existing electric boilers, or a facility that adds a solar photo-voltaic system that generates electricity which is used on site.

→ Another example is an industrial drying process that can use a fan, a steam heater, or a combination of both.

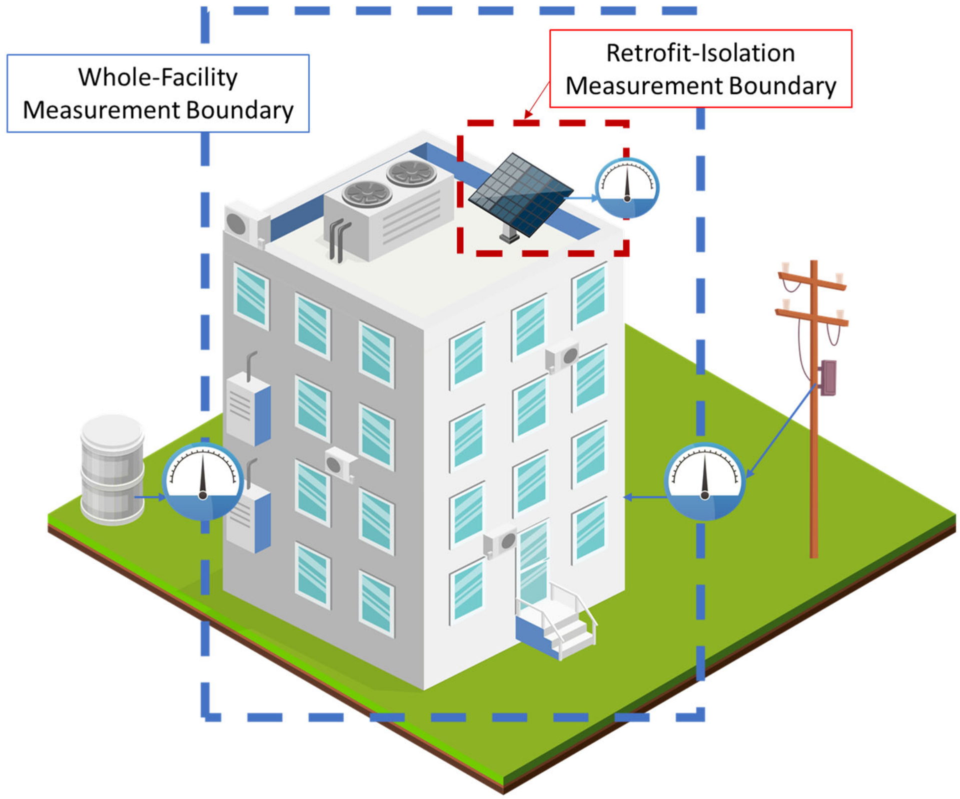

Figure 1: Measurement Boundary for Whole Facility M&V with Electric and Gas Meters and Measurement Boundary for Retrofit Isolation M&V of Photovoltaic Energy System

1.2. Identify Utility Meters or Submeters

- Identify and document which areas of the facility are served by specific utility meters or submeters. This step will be important in determining whether to create a single model for a facility or to create discrete models for individual meters that collectively represent the entire facility's energy use.
- Documentation may include system schematics which identify energy using equipment within the measurement boundary as well as one-line electrical drawings showing the relative locations of all energy meters. Meter serial numbers, utility account numbers, or other unique identifiers must be recorded in the baseline report.

- If an existing 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 sub-meter's measurement boundary does not align with a utility meter, then meter calibration should be confirmed by a certified electrician. The electrician shall use NIST-traceable calibration equipment, as recommended by ASHRAE Guideline 14.[2]
- If meters are not present or are insufficient to isolate targeted areas or systems, installing additional meters should be considered. New meters should be installed as early in the SEM engagement as possible so baseline energy data may be established. Trade-offs between proceeding using monthly utility data and waiting for more granular baseline data may need to be considered.[3]

1.3. Identify Energy Drivers

- Whole-facility energy use can vary substantially over time in a single facility or a selected portion of a facility. It is critical to identify the key energy drivers for each facility or specific meter included in the assessment. These energy drivers will include both independent variables and static factors.
- Based on an inventory of the energy-using systems and the operational characteristics of the facility, form a hypothesis of the primary and secondary energy drivers.
- Common energy drivers for industrial facilities are ambient conditions (dry-bulb and wet-bulb temperatures) and production volume but can include other variables such as operational modes (e.g., weekend/weekday), and raw material or product properties.
- The most common energy drivers in commercial buildings are ambient conditions, operational modes, and occupancy levels.
    - → School facilities are similarly impacted by ambient conditions, operational modes, and occupancy levels. Operational modes may include other periods such as summer/winter/spring breaks.
- Energy drivers must be tested for statistical significance (see Section 3.1).

Model development is an iterative process which relies upon properly identifying and validating independent variables. The model developer should identify and validate all energy drivers. In more complex facilities, there may be multiple energy drivers to consider.

[2] See Section 6.4.2 in *ASHRAE Guideline 14–Measurement of Energy, Demand, and Water Savings,* American Society of Heating, Refrigerating and Air Conditioning Engineers, 2014.

[3] *Common Considerations in Defining Baselines for Industrial Strategic Energy Management Projects*, NW Industrial Strategic Energy Management (SEM) Collaborative. 2014.

1.3.1. Continuous and Categorical Variables

- Energy drivers used as independent variables in regressions may be continuous or categorical, and both may be used in regression models.
- Continuous variables are the independent variables which provide physically meaningful numeric values, such as temperatures or number of security badge swipes. These data are recorded throughout the baseline and reporting periods, usually at the same or greater frequency as the energy data is recorded.
- Categorical variables, also called indicator variables, are commonly used to indicate the presence or absence of a condition. These binary (0, 1) values can be used to manage different modes of operation, allowing unique regression models to be applied to different operational modes (e.g., weekend, weekday).
- Effective use of these categorical variables often requires a reliable proxy variable that is recorded as frequently as the energy data used in the model. This proxy may be the primary independent variable (e.g., specific ranges of outdoor air temperatures) or other recorded operating data (e.g., system temperature). In cases where operational modes are distinct and energy consumption values do not overlap, the dependent variable can be used to indicate mode.

1.3.2. Weather Data

- Acceptable sources of weather data include the NOAA's National Center for Environmental Information (NCEI), Weather Underground, and the ASOS via Iowa State Environmental Mesonet. Use of weather data from Energy Management and Information Systems (EMIS) that agree with these sources is also acceptable, but a back-up weather data source may be required in case of missing data.
- Temperature data may need to be periodically checked to ensure it remains consistent over time. Significant deviation in calibration may be identified by comparing day-level plots of the data to nearby weather stations, and if identified can warrant adjustments. Similarly, the impact of a permanent change in the weather data source during the reporting period should be evaluated to determine if a model update is needed.
- Dry-bulb temperature data should be collected and evaluated for significance as an independent variable in all whole-facility models, although other weather variables may also be evaluated (e.g., solar irradiance, humidity). Ambient temperature must always be tested for statistical significance. If temperature is omitted from the model, the rationale must be documented.

1.3.3. Schedules and Operating Modes

- Facility and equipment operating schedules are often a key element in the variation in whole-facility energy use. Schedules often reflect unique modes of operation for a facility. Where equipment and/or occupancy follow schedules, interviews with staff and analysis of energy use data should be used to evaluate their impact on energy use.
- When facilities have multiple modes of operation, a reliable proxy should be identified. In many cases, individual models are developed for different modes of operation. Figure 2 shows an example of distinct differences between Weekday and Weekend/Holiday energy use patterns.

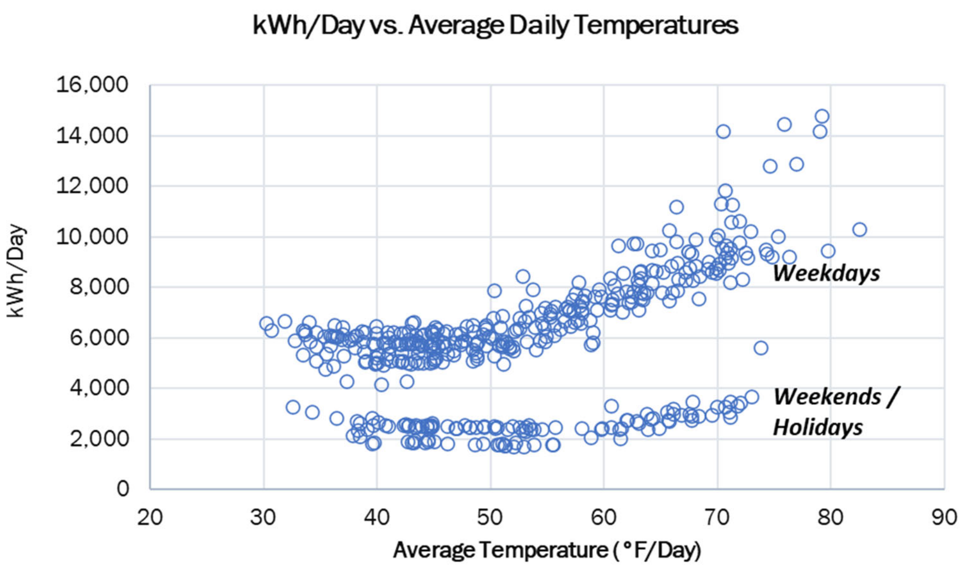

Figure 2: Operating Modes Based on Day of Week Schedules

1.3.4. Occupancy

- For many commercial facilities, including a variable related to occupancy levels can substantially improve a model. This is especially useful if the level of occupancy fluctuates over the baseline period (e.g., COVID-19) or may change during the reporting period.
- There are various continuous variables which can indicate the level of occupancy in a commercial facility. These metrics are useful to consider as a proxy for the number of facility occupants.

- The occupancy data must be available for both the baseline and reporting periods. Data at the same measurement interval as the energy data is best, although the practitioner may consider changing the frequency of the data used in the model to accommodate the available data when needed.

Table 2: Examples of Possible Occupancy Variables

Possible Data Source	Examples of Potential Metrics
Control System Trends	A weighted average speed of significant motors; Average speed of the primary ventilation fan
Security Data	Number of scanned security badges; Total number of cars parked/day
Computer System Records	Number of computer user log-ins
Sub-Metered Data	Daily ton-hours of cooling and/or therms for heating; Tenant energy consumption
Management Data	Number of meals served; Number of classes on-site; Daily sales totals or number of transactions

1.3.5. Production Energy Drivers

- For many industrial facilities, the primary energy driver is production-related, and the measurement boundary is often set around the production process. With complex systems, process flow diagrams, piping and instrumentation diagrams, and value stream maps can be helpful at this stage.
- It is important to quantify variables such as how many product types are manufactured in the facility and understand whether there is likely to be a difference in energy intensity based on lead time, process flow, batch size, and other relevant parameters.
- The availability and consistency of production data should be considered. Preference should be given for production data that can be readily accessed by site staff and can be easily understood.

- Raw material, work in progress, and finished product metrics each have advantages and drawbacks for selection as the primary independent variable(s), discussed in

- Table 3. Developing a schematic of the process and measurement points available, such as shown in Figure 3, can be helpful. An informed decision will consider 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.
- The details of production data must be understood to assess how it physically relates to the energy intensive processes. If a significant time delay exists between the energy-intensive process step and the production variable measured, a compensating time-series shift that corresponds to the magnitude of the time offset may be applied (see Section 2.3).

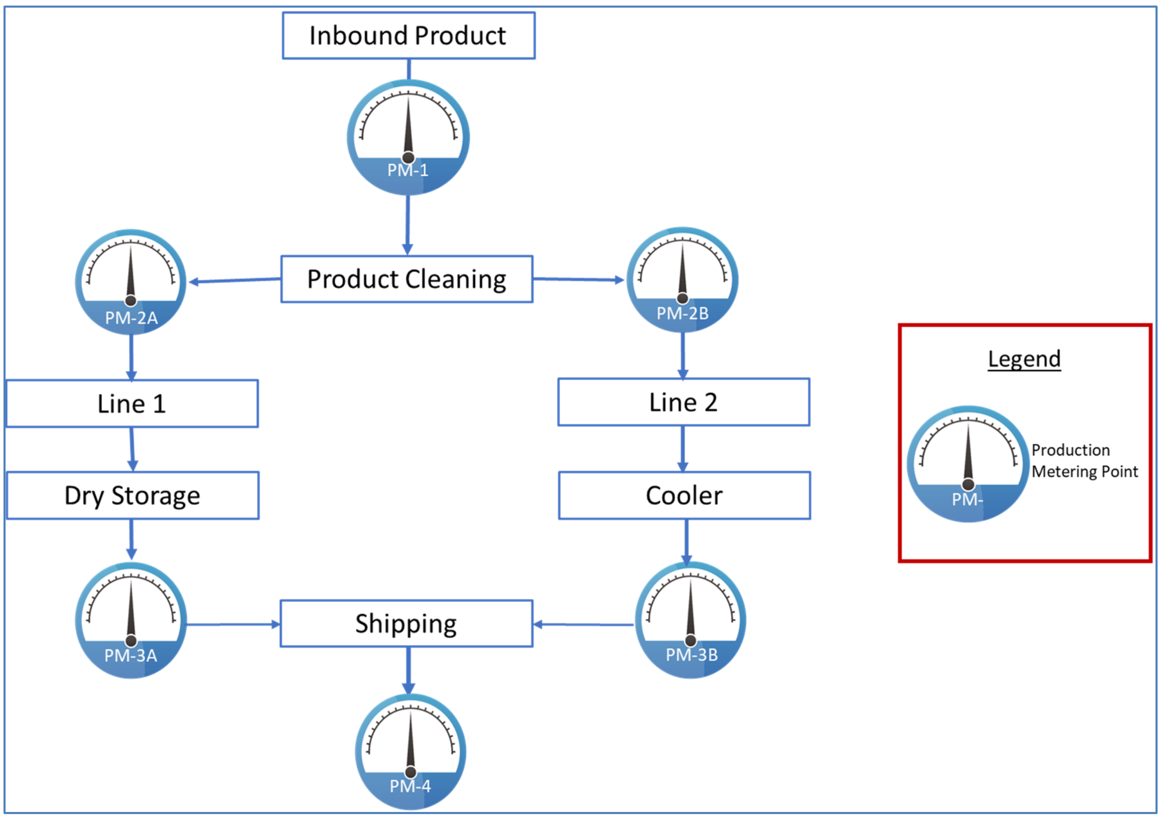

Figure 3. Example Production Schematic with Metering Points

Table 3. Considerations for Selection of Metered Production Variable

Measurement Location	Advantage	Example (above)	Drawback
Raw material input	Provides a mechanism to capture the effects of different raw material types.	PM-1	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 step, thereby minimizing time series shift.	PM-2A, PM-2B	Availability of data may be limited. Does not 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.	PM-3A, PM-3B	May induce a time-series shift for long lead-time processes.
Finished product shipped	Reliable data is typically available from business systems.	PM-4	May not correspond with production if finished product inventory fluctuates.

1.3.6. Static Factors

- In addition to independent variables, the other conditions at the facility which drive energy use but are not expected to change must be documented. These "static factors" include conditions present at a facility which impact energy use within the measurement boundary but are not expected to change over the course of the SEM engagement. Static factors are not included in energy savings calculations and are often related to facility design, equipment and systems installed, and the operational details of those systems.
    - → For example, one manufacturing site's static factors included the number, capacity, and usage patterns of all compressed-air-driven equipment, production-line speed, and vehicle models being produced.
    - → At an office facility, the static factors included the specifications of the installed HVAC and lighting systems along with their operating setpoints and schedules for each tenant.

- When changes in these factors significantly impact energy use within the measurement boundary, non-routine adjustments to energy savings are required to accurately report savings from the targeted measures.
- A procedure is needed to initially document and then track the static factors for changes so that non-routine events can be reported and any needed adjustments to baseline energy validated. Generally, data required to validate any significant non-routine events includes the actual dates and detailed description of static factor changes.
- Any energy projects such as equipment upgrades or other capital projects implemented outside of the SEM effort during the baseline or reporting periods also need to be tracked.
- Detailed site data can also act as a back-up if problems are encountered in executing whole building M&V methods and engineering calculations are required to adjust for data gaps during the reporting period (described in Section 6).

2. Establishing a Baseline Data Set

2.1. Determine the Baseline Period

- Determine the baseline period that best represents current and expected operating conditions for which sufficient data is available. Standard practice is to pick a baseline period without capital projects which occurs immediately prior to the reporting period.
- Evaluate the baseline period for the implementation of energy projects and for the occurrence of non-routine events.
- If an energy project is identified, the appropriate option from Appendix A should be used to ensure savings are not double counted. In these cases, a different baseline period may be preferred.
- If any non-routine event such as facility upgrades or an operational change is identified, the need for a non-routine adjustment should be evaluated as described in Section 4.
- The baseline period should encompass the cycles and ranges of the hypothesized primary and secondary energy drivers and extend as close to the start of the reporting period as possible. Ideally, the baseline period captures at least one to two cycles of normal operations, usually a recent continuous 12-month period.
- Energy use that exhibits seasonal dependence should use one complete year of continuous data during the baseline period to ensure balanced representation of all operating modes. If a longer time-period is needed, data from full years (i.e., 24, or 36 months) should be used. Models that use other lengths of baseline data can create statistical bias by under- or over-representing normal modes of operation.[4]
- Monthly utility data may be the most granular available from the utility and is often viable for determining savings from SEM engagements. Data with daily or weekly time resolutions, when available, will typically provide better insights about energy use and result in more accurate models when compared to data of longer durations such as monthly data.
- When using monthly data, ensure there are sufficient data points.
    - → The guideline for the minimum number of baseline data points is: 6 × number of coefficients in the model. If the data set falls below this guideline, the model will

4 *International Performance Measurement and Verification Protocol (IPMVP) Core Concepts.* Efficiency Evaluation Organization. 10000-1:2016.

likely be "over-fitted," and the model's comparative performance will likely deteriorate during the reporting 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. Monthly models with one independent variable require a full year of data (two coefficients requiring 2 × 6 = 12 points). Monthly models with two independent variables (three coefficients requiring 3 × 6 = 18 points) then require a minimum of 18 monthly data points with a preference for 24 or 36 months.

- The NW Strategic Energy Management Collaborative's focused white paper[5] 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.

2.1.1. Adjusting for Baseline 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 incentivized savings.
- To determine the effective date for an incentivized EEM, apply the earlier of the project installation or measurement and verification (M&V) start date, or the date that an inflection is observed in the energy savings data (i.e., CUSUM chart described in Appendix A).
- Where incentivized EEMs are larger (>200,000 kWh/yr.), the performance of the EEM should be operationally verified prior to adjusting for the EEM's savings. If possible, review the assumptions used in the M&V of the EEM to ensure they are valid and represent current operations. This can identify underperforming EEMs and help ensure savings from the SEM efforts are accurately reported. Any issues identified should be reviewed with the program stakeholders.

[5] *Common Considerations in Defining Baselines for Industrial Strategic Energy Management Projects*. NW Industrial Strategic Energy Management (SEM) Collaborative. 2014.

2.2. Collect and Review Data

2.2.1. Establish Data Sources and Maintain Records

- When collecting data for energy or energy drivers, ensure that accurate records are established and maintained regarding the details of the data sources (e.g., utility meter number, sub-meter specifications, meter location and coverage, control system parameter identifier, weather station, etc.).
- Repeatable procedures should be established for collection of data that will be used in the model (e.g., daily energy consumption and outdoor air temperature).
- Similarly, procedures are needed to track changes in static factors. Utilize any existing surveillance and reporting procedures in place, as well as any maintenance management or energy management systems, and consider establishing regular reports from site staff.

2.2.2. Review and Adjust Data

- Once data is collected, a process for ensuring data quality must be implemented. This generally includes graphing, assessing, cleaning and/or adjusting the data, as needed, and documenting any changes. Systematic reviews of data are needed to ensure data are valid, timestamps are correct, intervals are aligned, and missing or erroneous data are identified.
- Level of effort and procedures required for data reviews and adjustments will depend on the time-interval(s) at which data are recorded, clock settings, and the level of erroneous or missing data for each data source. The quality of data will vary by source, some of which require a higher level of scrutiny. In some cases, systematic adjustments may be needed. This data is often hourly or sub-hourly and frequently includes the following types of “bad data”:
    - → Erroneous values: a value such as “Control System Error”
    - → Null values: no data for the given variable and observation
    - → Anomalous values: data that appear out of range expected for normal operations. For example, this may include values that remain constant when equipment is off, in data from sources such an industrial control system.
- Visual review of data using graphing strategies can be an effective way to detect erroneous and anomalous data. Time-series charts and histograms can be effective.
- Perform an initial review of data for missing data and outliers by plotting each variable independently in a time series format. Evaluate data (maximum, minimum, mean, standard deviation, number of entries) and identify and flag any erroneous entries by

establishing limits. For variables, applying control limits of three standard deviations (±3σ) from the mean are often useful for identifying outliers as shown in Figure 4.

- Simply being an outlier is typically not sufficient grounds for removing a data point, but outliers often merit special scrutiny because they sometimes reveal data errors or unexpected events, but they can also represent important extreme conditions. Other criteria may be applied to data evaluation when appropriate.

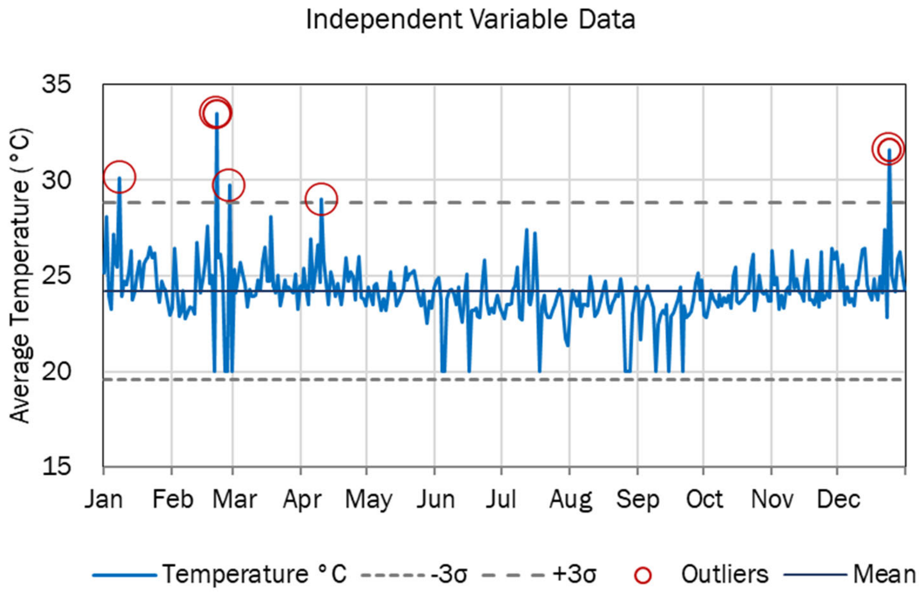

Figure 4. Example Time Series Graph to Identify Anomalies

- Any outliers that are ultimately removed from the baseline data set should be annotated with assignable cause. Understanding and assigning cause will likely require communication with the end user's Energy or Data Champion.
- Missing data points or data entry errors should be investigated and corrected by the facility, if possible. Generally, avoid replacing missing or outlier data with estimated values. Exceptions are permissible when data is provided at a much finer interval than the model (e.g., if time interval of data is 15 minutes or hourly for a daily model). For energy data, best practice requires values in aggregate match a known reference such as utility billing history.
- When billing data is used, verify no estimated values are used in utility readings. Where they are present, they must be replaced with actual data once available.

- Observations that appear anomalous should be reviewed with facility personnel to better understand the operation of the system. Periods with actual anomalous operations may reflect non-routine events.
- If any data point within the observation is deemed invalid as described above, the observation should be removed. Details, including justification should be documented in the Energy Model Report. If the number of observations per period vary due to removal of invalid data, a weighted regression should be considered as outlined in Appendix E.
- Use scatter diagrams to understand the relationship between energy use and energy drivers. Non-linear and interactive terms should be evaluated when suggested by the data.
- For example, a plant's energy intensity often becomes progressively more efficient at higher production volumes. This implies a non-linear relationship between energy use and production, as illustrated in Figure 5.

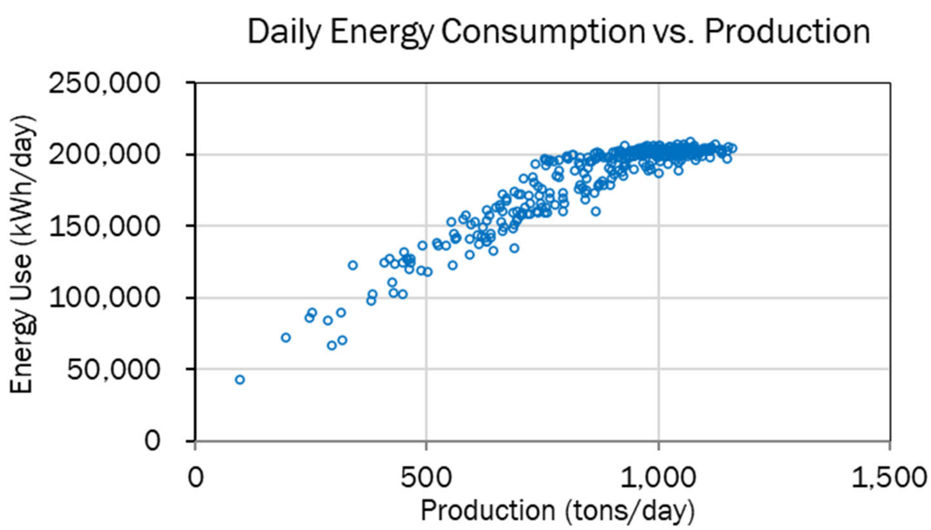

Figure 5. Example Scatter Plot (Energy vs. Production)

- The energy profiles of facilities with large space conditioning or refrigeration loads often exhibit a "change-point" characteristic. 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.
- The presence of one or more change-points can be identified by plotting energy use versus ambient temperature, as illustrated in Figure 6. The energy profiles of facilities with both space conditioning and heating may have multiple change-points based on outdoor air temperature.

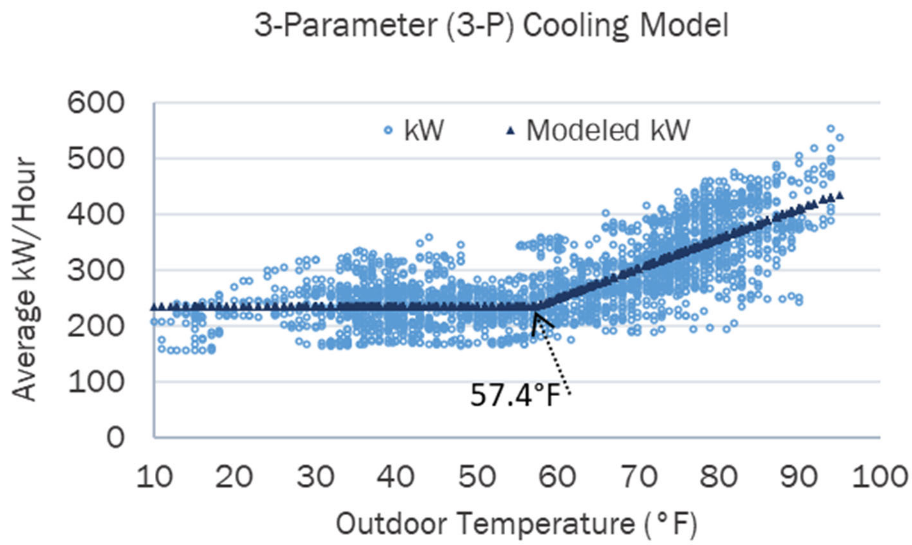

Figure 6: Three-Parameter (3-P) Cooling Model

2.3. Time-Series Offsets

- Time delays between a measured independent variable and the corresponding energy use can occur. In these cases, an offset may be needed in the data when constructing and using the model. Use time-series plots to identify offsets between energy use and independent variables.
- The example in shown in Figure 7 indicates a consistent time offset. The energy-intensive manufacturing process is two days' lead time from the production measurement point, a consistent two-day time series adjustment may need to be applied to the production variable.
- In many cases, however, a required offset may not be consistent over time and the offset needed will vary depending on conditions. For example, the energy used by a chiller plant at a corporate office that charges an ice storage system at night may not align with energy drivers.
- In these cases, using a model interval longer than the offset needed (e.g., weekly versus daily model) can avoid using an offset.

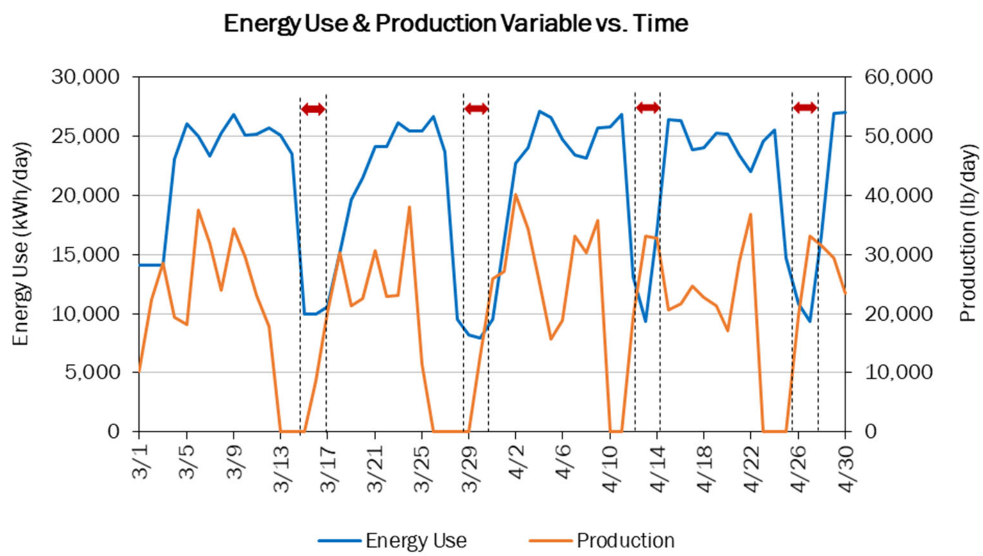

Figure 7. Example of Data Needing a Time-Series Offset

- 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. The data processing procedures used must be documented and used when applying the model during the reporting period.

2.4. Model Interval Considerations

- Baseline energy models can use various data intervals, depending on the frequency of the data available. Both energy and independent variable data used in a model must be in the same measurement interval.
- The availability of historic and ongoing data can largely determine the data intervals considered in developing a model.
- Process lead time should be considered when selecting the modeling interval, both for determining the modeling interval and applying any time-series offsets with the corresponding energy data.

2.4.1. Models Using Monthly Billing Data

- Models using utility billing data must account for irregular time intervals (e.g., billing days). In these cases, a weighted regression accounting for these differences is needed.

- Detailed strategies for dealing with irregular time intervals are provided in Appendix E.

2.4.2. Models Using Hourly, Daily, or Weekly Data

- Energy data from MV-90 and newer utility meters and sub-meters are often available in increments of 15-minutes or less. In these cases, the frequency of the independent variable data may limit the data increment used in the model, although hourly, daily, and weekly models are most common.
- For models with daily time resolution, there is no loss in information when using a change-point model based on outdoor air temperature over a degree-day model. For models based on weekly or longer time periods, the differences between the two approaches are generally slight. Degree-day models may sometimes improve results in mild climates with many outdoor temperatures near the facility's heating and cooling balance-point (changepoint).

3. Developing a Baseline Energy Model

3.1. Assess 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.
- When selecting variables, there may be competing objectives where no single selection criterion will provide the perfect solution, so the modeler must rely on his or her experience and engineering judgment.
- The general guidelines in Table 4 provides two options that can be used to test for the significance of each independent variable, depending on the preference of the modeler. The evaluation of both metrics is not required.
  - → The t-statistic is measure of the significance for each coefficient (and, therefore, of each independent variable) and is equal to the estimated parameter, normalized by its estimated standard error. The larger the t-statistic, the more significant the coefficient is for estimating the dependent variable, while the closer T is to 0 the more its impact is not significant. The suggested criterion for a two-sided t-test of greater than |1.3| is based on an 80% level of confidence.
  - → Related to the t-statistic, a p-value conveys the probability that the variable is not impactful. Small p-values, therefore, indicate that the coefficient for each independent variable is a significant predictor of the dependent variable. To include an independent variable, a p-value approaching zero is desired. For an 80% level of confidence, the variable's p-value should be less than 0.20.
- Appendix C shows where these values can be found in typical regression output tables.
- Independent variables that do not pass the criteria in Table 4 should generally not be included, although exceptions may be permissible in cases where a variable shows moderate statistical significance (e.g., p-value ~ 0.2) and is generally understood to impact energy use for the target system (e.g., in addition to outdoor temperatures, building demand is impacted by high humidity levels for a limited number of hours per year). The rationale for including these variables must be aligned with a physical understanding of the energy use of the facility.

Table 4. Options for Validating Independent Variables[6]

Statistic	Guideline
T-statistic	Absolute value > 1.3
p-value	<0.20

3.2. Statistical Criteria for Model Fitness

- The fitness of the overall model can be assessed against several guidelines for forecast regression models. These metrics assume an 80% confidence level is used in the analyses.

Table 5. Model Fitness Guidelines

Statistic	Guideline
Net Determination Bias Error (NDBE)	< 0.5%
Coefficient of Variation (C_V RMSE)[7]	< 20% for daily models < 10% for weekly models < 5% for monthly models
Coefficient of Determination (R^2)	> 0.5
Fractional Savings Uncertainty (FSU)	< 65%

- For models using intervals less than monthly, test for autocorrelation as described in Section 3.3.2 using the Durbin-Watson test or the autocorrelation coefficient.
- In addition to the statistical criteria above the implementer should consider also documenting additional statistics such as the standard error of the regression, adjusted R^2, and F-statistic for overall regression significance.

[6] See *BPA's Regression for M&V: Reference Guide* for additional information on statistical tests and metrics for models.

[7] See *ASHRAE Guideline 14-2104* for discussion. The level of noise in an energy model is reflected by the Cv(RMSE) and generally varies from 5% to 30%.

- → The standard error of the estimate is useful in addition to FSU in evaluating the suitability of a model. Standard error is in the units of model and can easily indicate if a model is precise enough to use for prediction.
- → The details on calculating FSU are provided in Section 5.5.1. Note the level of confidence for the FSU threshold specified is 80%. (FSU is a percentage with the savings estimate in the denominator, so a low FSU can be obtained with either a smaller standard error or a larger savings estimate.)

- Evaluating these statistics requires an estimate of the energy savings expected. Since savings are unknown at this time, a conservative estimate of savings expected the first year should be used.
- The model quality cannot be judged solely based on meeting the recommended guidelines, or conversely the weakness of a model on the failure of a statistical guideline. The strength of a model is highly dependent on context and relies on the experience and knowledge of the modeler to make the final assessment of model fitness. Exceptions may be permissible in some cases at the discretion of the modeler. These exceptions should be well documented to support the model justification.

3.3. Form Initial Forecast Model(s)

- Generally, one or more models are created (e.g., for different day-types) and then combined into a final model. A variety of statistical analysis and modeling tools can be used to create forecasting models. The model development procedures should be sufficiently documented so that similar results can be produced by others.
- In some instances, M&V-specific analysis tools[8] (e.g., ECAM, NMECR, etc.) may be used. Use of specialized modeling tools may be allowable if the data is provided, analysis is clear and aligns with this SEM M&V Reference Guide, and statistical results are well documented. In most cases, detailed procedures should be included so results can be verified.
- The initial model or models should be driven by an informed understanding of the physical and operational characteristics of the facilities and the primary energy driver(s). The model form selected should align to the physical characteristics of the system.
- For example, a 3- or 4-parameter (3-P or 4-P) model based on outdoor air temperatures for an office served by a central heating and cooling plant should align with facility HVAC system types and operations. In this case, a linear relationship with changepoints

[8] For more information on M&V specific analysis tools see *IPMVP's Snapshot on Advanced Measurement &Verification*, January 2020.

based on the HVAC systems installed is expected, and the slope of the segments reflect system efficiency. A manufacturing facility with large variable speed motors operating continuously, on the other hand, may have a non-linear correlation.

- Plot the actual versus predicted energy use on a scatter diagram to review the accuracy of the initial model. Check that the point pattern is narrowly clustered and uniformly distributed along the diagonal as illustrated in Figure 8.

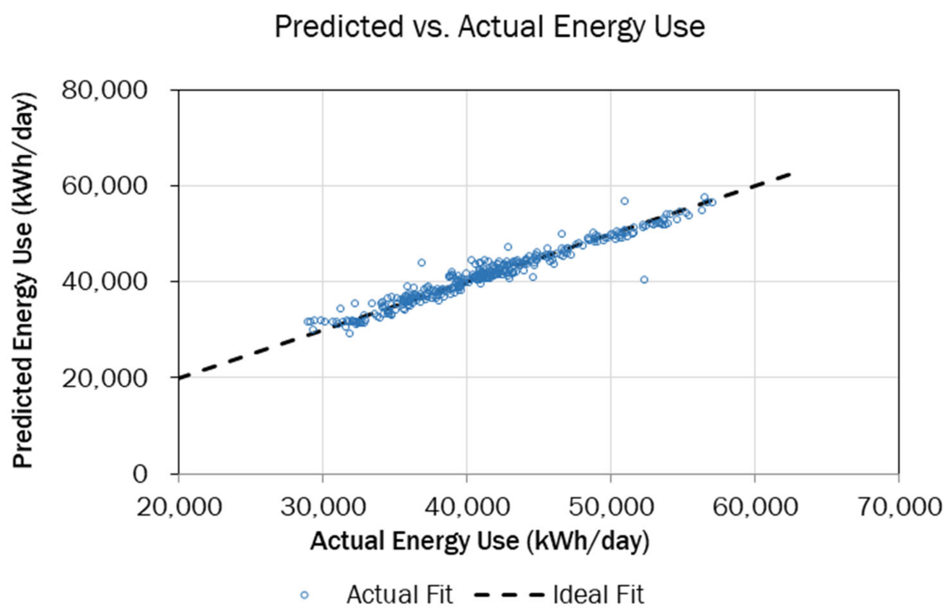

Figure 8. Example of Predicted vs. Actual Scatter Plot.

- Determine and evaluate the residuals from the model, as described below. The residual from each data point is actual energy minus predicted energy from the model.
- Residual plots that may be of value include:
  → Residuals versus the independent variables (e.g., Figure 9) can confirm the variance in residuals is consistent throughout the observations (i.e., homoscedastic).
  → Residuals versus time (e.g., Figure 10) shows goodness of fit of the model over the baseline period.
  → Histogram of residuals can support identification of Net Determination Bias Error.

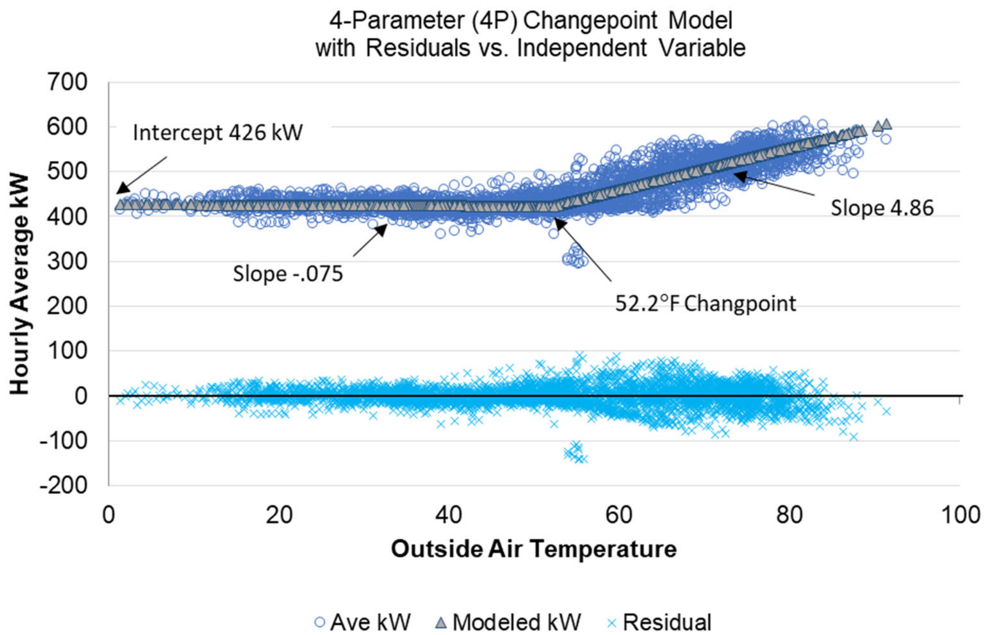

Figure 9. 4-Parameter Model with Evenly Distributed Residuals

3.3.1. Screening for Residual Outliers

- Residuals from the model should be plotted in a time-series graph and reviewed to assess the goodness of fit over the baseline period and to identify outliers in the data. Outliers from the residual analysis should be flagged for additional review.
- One approach for reviewing outliers is applying a common rule of thumb for identifying data that lie outside the range of $\pm 3\sigma$, as illustrated in Figure 10.[9] For normally distributed residuals, the probability that a residual will exceed $\pm 3\sigma$ due to random chance is only 99.73%, or 1 in 370.

[9] Sometimes referred to as the Empirical Rule.

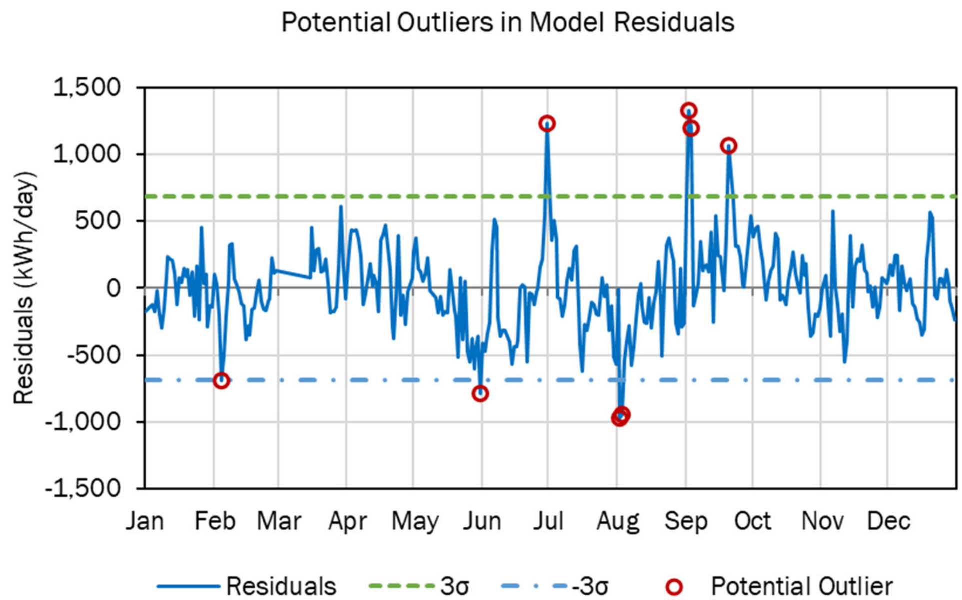

Figure 10. Identification of Potential Outliers in Residuals

- The modeler should review any outlier in the residuals flagged with the Energy Champion to understand the cause of the anomaly. The modeler must provide a supporting explanation when removing or modifying any baseline data.
- When residuals contain substantial outliers, consider changing the proposed model. This may be needed for changes such as:
  - → Accounting for additional operating modes (include as additional indicator variables and identify data sources),
  - → Adding continuous variables,
  - → Using a different form of the model,
  - → Considering a non-routine adjustment to the baseline data,
  - → Using a longer data increment, or
  - → Removing outliers from baseline data (< 25%).

3.3.2. Autocorrelation

- Autocorrelation is an issue in models using frequent energy data, e.g., hourly models, which can become a consideration in the uncertainty analysis. Autocorrelation is not a concern for data in monthly intervals.

- Autocorrelation is characterized by a correlation in the residuals and is present with the error term in a period *t* is related to the error term in period *t*-1. Typically, regression-based energy models exhibit positive autocorrelation. Positive autocorrelation occurs when the sign change of the residuals is infrequent. Conversely, frequent sign changes in the residual values results in negative autocorrelation.

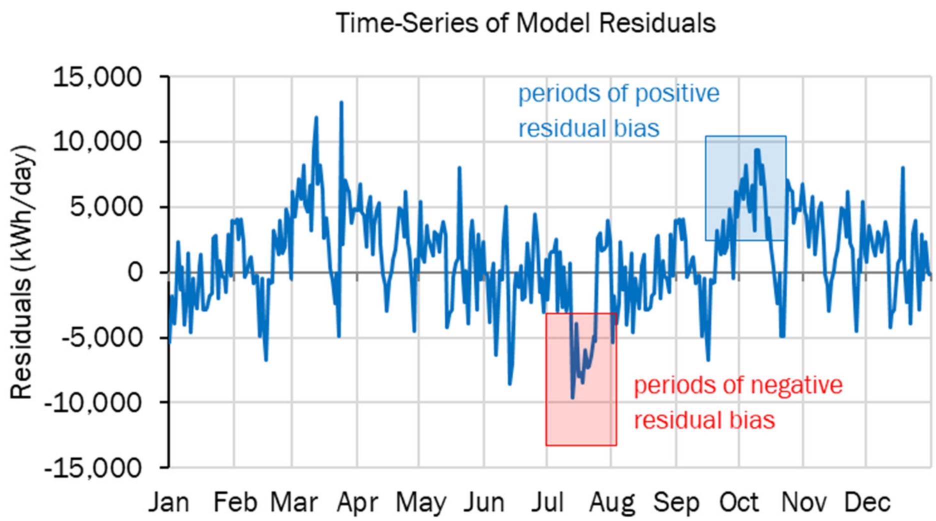

Figure 11: Example of Autocorrelation in a Time-Series Graph

- High autocorrelation may occur with hourly and daily data and can require a correction.[10] In other cases, it may indicate the omission of a key variable, or the occurrence of an event that changed energy consumption characteristics during the baseline.
- If autocorrelation is present, the number of independent data points is effectively reduced and error statistics may become unreliable.
- There is not a defined threshold for the autocorrelation coefficient in the model development phase. Models with daily baseline intervals, moderate autocorrelation may not be a significant concern. However, values of ρ over 0.5 may be considered significant.
- Another measure of autocorrelation is the Durbin-Watson test, which is another option to determine if autocorrelation is statistically significant. The Durbin-Watson test statistic, *d*, ranges from 0-4, where a value diverging from 2 indicates autocorrelation:
  - → d = 2, residuals are not correlated
  - → d ≪ 2, residuals are positively autocorrelated
  - → d ≫ 2, residuals are negatively autocorrelated

[10] Approaches for managing autocorrelation are detailed in *Uncertainty Assessment for IPMVP*, EVO 10100 – 1:2018.

- The lower and upper bounds for the Durbin-Watson test statistic are a function of sample size, number of predictor variables, and the desired confidence level. The Northwest Industrial SEM Collaborative has provided a paper pertaining to autocorrelation in regression-based energy models for industrial facilities.[11]
- Where autocorrelation is present, it is important to evaluate FSU using Equation 5. The terms of this equation include an autocorrelation coefficient to help correct for level of independent data.

3.3.3. Multicollinearity

- When two or more independent variables exhibit significant correlation, multicollinearity is present within the model. This should be evident if the coefficients have high standard errors and will be reflected in their p-values and in their t-statistics.
- Multicollinearity can be identified using XY scatter plots, a correlation matrix, or by regressing each independent variables against the other hypothesis variables to assess the relationship between energy drivers. As a rule of thumb, any R^2 that exceeds 0.7 between any two independent variables generally indicates the need to address multicollinearity.[12]
- Although in some cases multicollinearity is unavoidable, the presence of collinear variables can affect the precision of individual coefficients and can understate the statistical significance of individual variables, making it difficult to differentiate their impacts.
- Some ways to address multicollinearity include:
  - → Re-specify or simplify the model. Consider excluding the variable that provides the least improvement to the model.
  - → If submeters are available, split the facility into two or more measurement boundaries and split variables by measurement boundary as appropriate.
- When multicollinearity is present, the modeler should clearly explain the rationale for both the inclusion and exclusion of variables in the energy model. While multicollinearity does not affect the model's predictive capacity, it has the potential to add unnecessary complexity. The modeler should exercise caution when excluding variables that might be significant energy drivers as this can bias the model.

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

[12] Ibid.

3.3.4. Simplifying the Model

- For models that include three or more independent variables, the modeler should consider options to simplify the model. A simple model has many benefits including easier data collection, reduced likelihood of outliers and errors, and may be easier to understand. On the other hand, a model that's too simple and lacks sufficient energy drivers can suffer from a poor fit. The modeler must weigh the pros and cons of each combination of variables to determine the best overall model.
- When simplifying a model, the adjusted R^2 can help determine when the addition of a variable improves the model. If adjusted R^2 decreases as variables are added, the model is likely to be over-fit. Also consider that removing (and adding) variables will affect the significance of other variables and multicollinearity. While multicollinearity does not affect the model's predictive capacity, it has the potential to add unnecessary complexity.

3.4. Considering Competing Models

3.4.1. Selection of One or Multiple Models

- Some facilities have distinct operating modes or processes that vary throughout the year. These may be high and low production periods such as maintenance shutdowns and seasonal production, or multiple production processes that independently influence energy consumption. The resultant variation in energy use is often difficult to capture with energy drivers and indicator variables alone in a single regression model.
- When the facility has one dominant mode of operation, and the energy use and expected savings during other times are small, a model that includes only the dominant mode is the preferred option. If a model is required for more than one significant mode of operation, separate models for each mode are recommended to reduce model bias.
  - → For example, a two-pipe heating and cooling system will have distinct modes of operation which includes different equipment and will need to be modeled separately.
- Utility and end-user feedback should be solicited in the process. Judgment is required to balance accuracy versus simplicity.

Table 6. Consideration for Selection of One or Multiple Models

Model Selection	Merit	Drawback
Single Model – all operational modes	Simple to explain and use for tracking purposes. Uses all data in the baseline period, increasing the number of observations. Includes full range of each variable.	Models often tend to over predict during low or no production. R^2 values may be inflated due to extended range. Collinear variables cannot be separated to their appropriate energy meter contribution.
Single Model – one operational mode	Model provides better prediction during production. Eliminates the complexity of maintaining multiple models.	Unable to estimate savings for mode(s) not modeled. Model may not include full range of each variable.
Multiple Models	Each model provides better prediction for all modes of operation. Often necessary to meet goodness of fit guidelines. Estimates savings for each mode modeled. When applicable, separates collinear variables based on engineering judgment of system.	Increases complexity of the tracking and measuring of energy savings. Reduces the number of data points for each model, respectively.

3.4.2. Evaluate Competing Models

- A table of competing models should be used to consolidate and compare the statistical results of the most likely hypothesis model variations. The table of potential hypothesis models should be used along with the qualitative assessments to identify the final hypothesis model.
- The table should include key model criteria for each model variation including data interval, independent variables and the corresponding p-values, R^2, NDB, Cv(RMSE), autocorrelation coefficient, projected fractional savings uncertainty (FSU), comments about the models, etc. An example summary of competing models is shown in Table 7.

Table 7. Example of Competing Model Summary Table

No.	Freq.	Period	Days in Baseline Period	R^2	Adj. R^2	CV-RMSE (%)	Auto-corr. Coeff.	FSU (5.0% savings, 80% CL)	Net Det. Bias	Variables	Coefficients	T-value	Comments
1	Daily	9/1/2014 to 8/31/2016	365	0.771	0.765	12.2%	0.280	37.4%	1.08E-14	Constant	37,340	10.3	Linear model with both production variables and temperature.
										Temp	560	7.5	
										Variable 1	1,103	0.8	
										Variable 2	1,200	8.1	
2	Daily	9/1/2014 to 8/31/2016	365	0.882	0.876	8.4%	0.270	25.0%	-1.01E-14	Constant	33,288	9.6	Simplified model including temperature and the most significant production variable.
										Temp	1,997	8.8	
										Variable 2	1,178	8.5	
3	Daily	9/1/2014 to 8/31/2016	365	0.912	0.901	5.1%	0.260	15.0%	3.98E-14	Constant	27,643	9.5	This model includes temperature, the most significant production variable, and a non-production day indicator variable. This model provided the best fit and accounts for the effects of the days the production is offline. **Final Model**
										Temp	1,875	9.2	
										Variable 2	1,009	8.3	
										Non-Production Day Indicator Variable	-15,321	2.9	

3.5. Modifying the Hypothesis

- If the statistical metrics outlined in Sections 3.1 and 3.2 indicate insufficient model fitness, modify the model hypothesis. This process might include modifications to the assumed energy drivers, including categorical variables such as modes of operation, changing the time intervals used, adjusting number of change points, or the changing the order of relationships (second order, square root, etc.) used.
- If the measurement boundary is supplied by multiple meters, disaggregating the meters and creating one model for each may result in better model resolution.
- When modifying a hypothesis, confirm that the characteristics of the equation remain aligned with the mechanics of the process, and that the baseline data set meets the standards outlined in Section 2. This information should be documented in a competing model summary. An example of a competing model summary is provided in Appendix C.

3.6. Alternatives to Forecasting

- Adopting a methodology that does not use a standard regression-based forecasting energy model may be necessary under certain conditions. The NW SEM Collaborative, published a technical reference that provides additional details on method selection.[13]

[13] *SEM Energy Modeling Method Selection Guide*, Northwest Strategic Energy Management Collaborative, 6/14/2019. Available at https://semhub.com/assets/resources/SEM-Energy-Modeling-Method-Selection-Guide.pdf.

- Note not all methods provide energy performance feedback in a timely manner like a forecast regression model. Specifically, a backcast and pre-post model are limited in that they only reflect on historical performance and require a post-implementation dataset to operate.

3.6.1. Backcasting Approach

- For the backcasting approach, the regression energy model is developed from the data obtained during the reporting period. This method is applicable in instances where the resolution of the energy data for the original baseline was relatively poor (e.g., monthly) and the resolution of the energy data during the reporting period has significantly improved.

3.6.2. Mean Model

- The mean model represents the simplest form of forecasting, and may be necessary when:
  - → There is insufficient variation in the independent energy drivers (e.g., production is constant) such that it cannot account for the variation in energy use.
  - → There is insufficient correlation between suspected energy drivers and energy.
- For an 80% level of confidence, a p-value less than 0.20 is required to reject the null hypothesis for a coefficient. If no independent variable produces a coefficient that meets this criterion, a mean model may be considered. A mean model may also be preferred when the only statistically significant coefficients contradict known system behavior (e.g., a negative coefficient for production).
- 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 reporting period can be properly assigned to EEMs directed at energy efficiency versus other changes in plant operation.
- This approach is valid for saving determination provided the relevant operational parameters remain within a defined range. A generally acceptable guideline for this tolerance is ± 10% of values recorded in the baseline period.

3.6.3. Pre-Post Model

- When using a pre-post model, a regression model is constructed using data from both the baseline and reporting period data. Generally, a single indicator variable is used to estimate the difference in energy use between the two time periods, though interactive effects between energy drivers can be modeled. For more details, see the SEM Energy Modeling Method Selection Guide.[14]

3.6.4. Engineering Calculations

- An alternative approach may be necessary when an acceptable top-down, whole-facility energy model cannot be developed for a participating facility, or the accuracy of the model may be insufficient for expected levels of savings. In these instances, using a retrofit-isolation approach with measure-level engineering calculations with implementer justification and program approval are acceptable.
- Sufficient justification should include documentation of the attempted energy models and a plan to reassess the suitability of top-down, whole-facility energy models again in the future. Level of analytical rigor and documentation for engineering calculations is expected to scale with complexity and magnitude of savings for completed opportunities. Further discussion of specific guidance pertaining to engineering calculations is provided in Section 5.5.5.
- To attain consistency with a top-down modeled savings approach, BPA requests that all savings claims made with support from engineering calculations only consider those savings that are observed within a reporting period. This is to say, engineering calculations should be pro-rated from the date of implementation (as documented in the opportunity register) through the end of the reporting period. In subsequent performance periods, incremental measure-level savings can be claimed if savings verification supports persistence of the measures.

3.7. Energy Model Report and Review

The model and supporting statistics and graphics should be documented in the Energy Model Report. BPA will provide final approval after a review by the utility and end user.

[14] Ibid.

4. Making Adjustments for Non-Routine Events

- Non-routine events (NREs) are events unrelated to the energy projects that impact the calculated energy savings (e.g., facility changes, process changes or other contributing factors).
- Without a non-routine adjustment (NRA), energy savings can be skewed and misrepresent the impacts of energy efficiency efforts. NRAs introduce risk to the savings results and require documentation, justification, and adequate determination.
- When a non-routine event requires an adjustment, a description of static factor changes is required and should include the actual dates and relevant details.
- For a fuller treatment of non-routine events and adjustments, see *IPMVP Application Guide on Non-routine Events & Adjustments*.[15]

4.1. Scenarios for Model Reassessment

- During the reporting period, 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 consistent with baseline operation throughout the reporting periods. BPA validates the acceptable range of energy models if the independent variables are within the control limits set for the baseline data as established in Section 3 (i.e., either three standard deviations ($\pm 3\sigma$) from the mean of the baseline data or within 110% of the baseline data range.
- Non-routine events may occur during the reporting period. Such scenarios would trigger a reassessment of the energy model. These scenarios can be characterized into three different categories of increasing complexity: static, minor, and major changes.

4.1.1. Static Change Assessment

- A static change is a change in electric load within a well-defined boundary and with minimal interactive effects. Examples of static non-routine changes are:
  - → Installation of new or removal of old equipment

[15] *IPMVP Application Guide on Non-Routine Events and Adjustments*, EVO 10400 – 1:2020

→ Added section of the facility in which the energy flows can be easily isolated

4.1.2. Minor Facility Operations Change Assessment

- A minor facility or operational change is a distinct change in operations that does not fundamentally change the facility or production process itself. These non-routine changes generally impact one or just a few static factors. Examples of minor non-routine changes are:
  - → Change in business operations that requires a new independent variable (e.g., new product type)
  - → Change in the control setpoints of a sub-system within the facility, not attributable to energy efficiency
  - → Change in the ventilation rate for health and safety
  - → A school that closes for an inclement weather day
  - → A commercial office building that gains or loses a minor tenant

4.1.3. Major Facility Operations Change Assessment

- A major facility or operational change affects the fundamental energy consumption characteristics of the facility, rendering the original model specification invalid. These non-routine events may impact many systems within the facility or process. Examples of a major change are:
  - → A sustained increase or decrease in the observed level of an independent variable outside the range for which the baseline energy model was established.
  - → A change in manufacturing operations from batch-type to continuous
  - → A change to facility operating schedules
  - → A commercial office building that gains or loses a major tenant
  - → Major construction or renovation projects that affect multiple systems, space use type, impacting energy use patterns or signature.

4.2. Options for Non-Routine Baseline Adjustments

Baseline adjustments due to non-routine events should reflect the scenario encountered, as described above. Corresponding adjustment scenarios are described below for static, minor, and major changes.

4.2.1. Static Change Adjustment

The change in electrical load can be accounted for based on engineering estimates or sub-metered data and accompanying analysis. The level of rigor to determine adjustments should be aligned with measure-level engineering calculations, see Table 8 in Section 5.5.5.

- For constant loads, annual energy use can often be extrapolated using short-term (e.g., two weeks') data logging. If necessary, empirical models can be developed to correlate energy use from these loads to weather, production, and/or process variables.
- For variable loads, long-term or permanent submetering is preferred. Where long-term submetering is not feasible or variation is predictable, empirical models can be developed to correlate energy use from these loads to weather, production, and/or process variables.
- For relatively small static changes, engineering calculations supported with equipment specifications and operational information may be acceptable.

4.2.2. Minor Facility Operational Change Adjustment

To account for a minor process change, a non-routine adjustment based on a regression approach is generally preferred. The model must include sufficient data before and after, if temporary, the change to accurately estimate the impact of the change. Production or process data is required to document when the change occurred.

- When the change is an added product, a regression model, including the added product, can be used to estimate the change in energy use for this product. Generally, the other variables are the same variables used in the energy model. The estimated coefficient of the new variable can then be added to the energy model.
- When a change in sub-system operation occurs, a regression model with an indicator variable can be evaluated. Again, the other variables are the same variables used in the energy model and the indicator variable is set to one when the change occurs. The estimated coefficient of the indicator variable can then be added to the energy model. This approach is only suited for static load changes, those that are variable are not fitting for treatment as an indicator variable.
- Options for regression-based non-routine adjustments are detailed in IPMVP's Application Guide on Non-Routine Events and Adjustments.[16]

[16] Ibid.

- When the regression model is not a suitable approach, estimates of the change may be made based on engineering calculations or published data. When loads are variable, weather or production normalization may be required.

4.2.3. Major Facility or Operational Change Adjustment

Like minor process changes, a regression approach is preferred when making non-routine adjustments for major process changes.

- When the process itself has fundamentally changed, creating a new regression model or re-baselining may be necessary. The implementation dates of the EEMs need to be considered when changing the time period of the model.
- When independent variables are frequently outside the acceptable limits of the model, a new regression model may be required. The SEP Protocol[17] provides a "chaining adjustment" methodology to model these situations.
- Other options for dealing with a major process change include a pre-post or engineering calculation approach.

4.3. Modification of Regression Models

- When a new baseline energy model is necessary, the revised baseline period must adequately capture the new range of operating conditions, including seasonal cycles (if applicable). For major facility or operational change adjustments, SEM participation payments are typically put on hold until a new model can be established. Any energy savings that preceded the change would be considered based on the previous energy model or other BPA-approved M&V method such as engineering calculations with verification.
- Baseline energy models may continue to be used for multiple performance periods so long as the criteria listed in Section 4.1 are met. Re-enrollment in an SEM engagement does not necessarily trigger a revision of the baseline energy model. However, the following items may provide a sufficient basis for re-evaluating the model:
    - → Utilities or end users may request re-evaluation of the model at set intervals (e.g., every four years). If re-baselining is requested/required for participants re-enrolling in SEM, the last reporting period of the previous engagement is typically used for the new baseline period. For SEM participants wishing to

[17] Guidance for the SEP 50001™ Program Measurement & Verification Protocol: 2019, section 6.2.4, page 35.

maintain the original baseline model, a review of current and baseline operating practices must be made to ensure they are aligned.

→ Re-enrollees from other types of energy management programs may require re-modelling due to savings accounting needs.

→ The accumulation of changes and non-routine adjustments may warrant a model revision.

→ Though not strictly required, the model may need to be revised when a long period of time intervenes between performance periods. Factors such as utility preference, the range of data, and process changes should be considered. Changes between these periods should be evaluated in accordance with the adjustments described in Section 5.2.

→ A revised model could simplify or improve the performance tracking process.

- If a baseline energy model is revised, the new model may be considered for a chaining adjustment. In this case the revised model would be chained to the previous model in order to continue estimating savings relative to energy intensity in the original baseline period.

4.4. Approvals for Non-Routine Adjustments

- When a baseline energy model must be adjusted, the proposed adjustment should be reviewed and approved by BPA in advance of any modeling work.
- When implemented, the details of non-routine adjustments to a baseline energy model should be documented in appendices of a SEM annual completion report and/or in an updated baseline energy model report.

5. Calculating Energy Savings During the Reporting Period

5.1. Reviewing Records of Events and Changes

- The savings calculated using whole-facility energy models represent the total (gross) energy savings for the site. To properly attribute savings to SEM efforts, it is critical that the Energy Champion maintain accurate records of key operations and maintenance (O&M) actions, behavior-based improvements, and other changes.
- Records of changes in facility operations and other static factors that influence energy use, established in Section 2.2.1 should also be reviewed. When impacts to savings are significant, a non-routine adjustment should be considered.
- Any effects from fuel switching must be accounted for and excluded from the gross energy savings. If fuel switching is a possibility, it is advisable to maintain records of alternate fuel sources crossing the measurement boundary beginning with the baseline period. These records can be used to document that fuel switching did not occur during the reporting period.

5.2. Adjusting for Concurrent Incentivized Projects

- If the end user is participating in other program offerings, gross energy savings adjustments will likely be needed to net out savings from EEMs incentivized by other programs. 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 M&V start date to the end of the reporting period.
- Appendix B outlines the options for determining the value of the adjustment and identifying a suitable date of application.

5.3. Calculation of Savings Using Regression Model

5.3.1. Review Data

- As data is collected during the reporting period, it should be methodically reviewed to detect anomalous values for the range of measured energy consumption or independent variable values to ensure that the independent variables fall within the ranges specified for the model. Generally, variable values are acceptable when they fall within an allowable range:

- → A range of ±3 σ or the range specified in the model, for variables that are normally distributed.
- → For variables that are not normally distributed (e.g., variables that include multiple modes of operation), ±10% of the actual range is generally a more appropriate method.

- All variables should also be tracked and reviewed for completeness and quality at the interval of the raw data. For weekly or monthly models, daily data (if available) may be helpful to identify data errors or anomalous performance. It may also prove useful if it becomes necessary to apply chaining or backcasting.
- To identify non-routine events, it may be appropriate to collect and analyze variables not included in the baseline energy model (i.e., static factors) to ensure that they continue to fall within an acceptable range. This could mean:
  1. tracking individual parts of a whole (e.g., tracking production from individual lines even though the model only uses total production), or
  2. tracking variables not included in the baseline energy model (e.g., tracking production for a mean model, or monitoring occupancy levels for a temperature-based model).

5.3.2. Calculate Savings

Once data has been reviewed as described above, energy savings can be calculated by applying the following equation:

Equation 1

$$\begin{aligned} \mathit{Energy\ Savings} &= \mathit{Predicted\ Energy\ Use} - \mathit{Actual\ Energy\ Use} \\ &\pm \mathit{Non\text{–}Routine\ Event\ Adjustments} \end{aligned}$$

- For periods with infrequent occurrences of out-of-range variables, the magnitude of energy savings should be reviewed. Generally, no further adjustments are needed if energy savings are reasonable and similar to the other observations, and otherwise data falls within the ranges specified by the baseline model.
- Variable values that fall outside of the acceptable range specified for the model should be closely analyzed to determine how the out-of-range values should be treated. This determination will be dependent on the specified acceptable range and the specific context of facility operation related to the variable in question. The decision to include,

cap, or exclude a data point based on an out-of-range value should be justified and documented accordingly.

- When variables exceed the valid range of the model, capping variables may be necessary to avoid overestimating/underestimating energy savings. If capping is applied, all values must be capped consistently.
- If an acceptable capping limit cannot be determined, an expected value of energy savings may be provided. If an expected value cannot be determined, then energy savings for these occurrences should be excluded.

5.3.3. Track Savings

- Occurrences of abnormal energy savings, i.e., exceeding $\pm 3\sigma$, should be reviewed. Plant operations can be reviewed with the Energy Champion if further questions persist upon reviewing the data. The expected or average value of savings can be used for these anomalous observations.
- The cumulative sum of differences (CUSUM) is an effective means of quantifying the total energy savings benefit. The CUSUM calculation sums the residuals, the differences of each actual energy consumption value from the predicted value, over the reporting period.
- In graphical form, the CUSUM provides a powerful illustration of the total savings measured and verified during a specified reporting period. However, the CUSUM graph should be used in conjunction with a time series plot of energy and the independent variables. Additionally, the Energy Champion should attempt to correlate inflections in the CUSUM graph to key actions or changes implemented and documented on the opportunity register during the program period. Together, these graphs help establish an informed understanding of energy intensity inflections.
- An example of a CUSUM graph is shown in Figure 12. The CUSUM may slope upward or downward (as illustrated below). The slope convention for the CUSUM should be clearly identified to avoid potential confusion when interpreting energy savings.
- When forecasting baseline energy using models with intervals longer than one day (e.g., monthly, weekly), the following items should be considered:
  - → Reporting periods should begin and end on billing period start and end dates, respectively. If meter billing periods do not align, care should be taken to avoid biasing the energy savings when aggregating monthly energy use.
  - → Weighted per day residuals should be interpreted with caution as they are calculated against a multi-day average of actual energy usage.

→ Special calculations may be required to average variables for each billing period. This is especially the case when a change-point has been applied to a term. In such cases, a degree-day variable or similar term may avoid this difficulty.

→ Valid ranges of model data must still be evaluated based on average values at the same intervals used for the baseline regression.

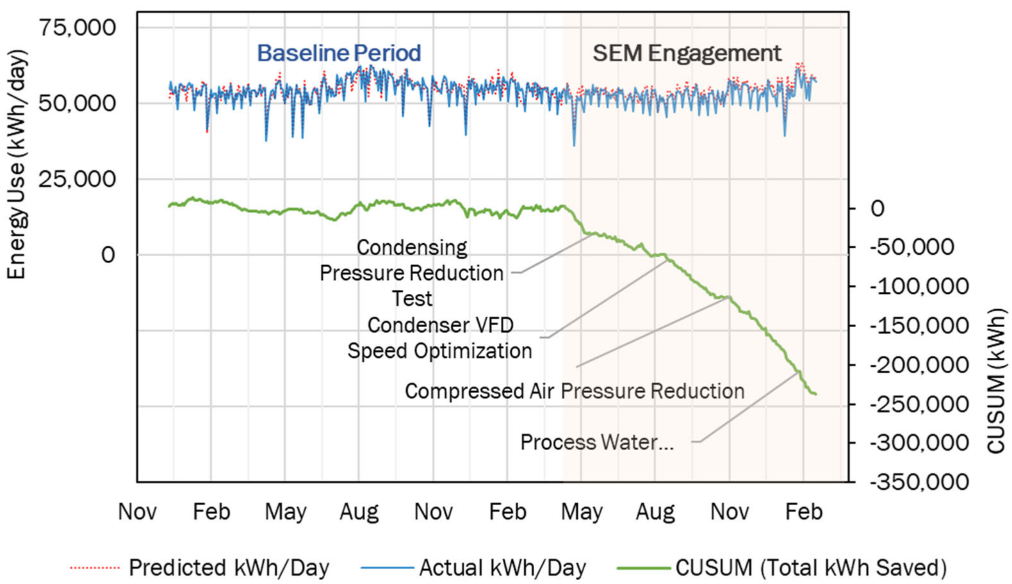

Figure 12. Example CUSUM Graph

5.4. Calculation of Savings Using Alternative Approaches

5.4.1. Savings Calculation by Backcasting Approach

- When using the backcasting approach, separate energy models are created for each reporting period. Each respective model estimates energy use during the baseline period using the weather and production observed during the baseline period. A timeline for the backcasting procedure is illustrated in Figure 13.

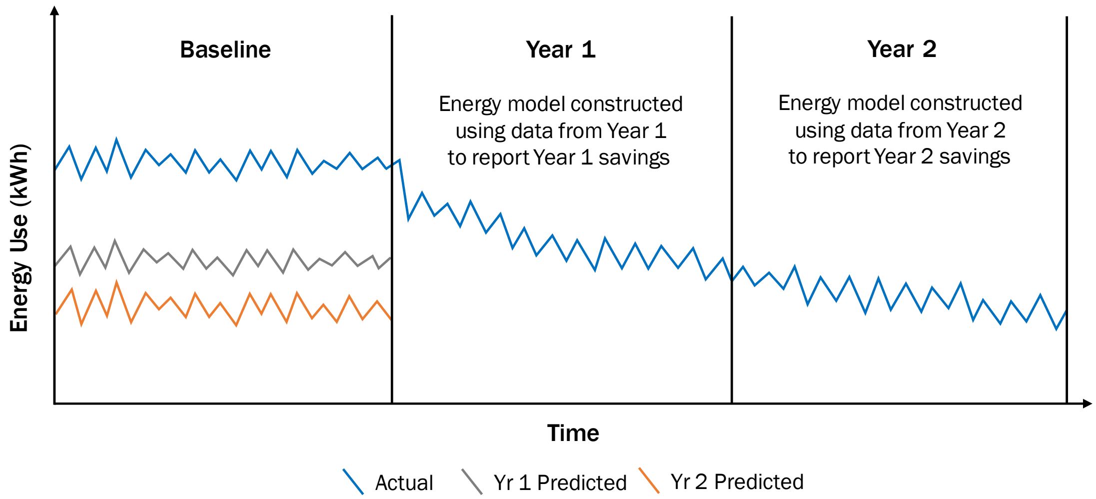

Figure 13. Backcasting Approach

- To calculate energy savings for Year 1, an energy model is created using actual energy and key independent variable data from Year 1. This model is used to predict energy use during the baseline period based on key independent variable data reported during that same baseline period. Finally, savings are calculated using the actual energy use during the baseline period and the energy use predicted for the baseline period using the Year 1 model. Thus, energy savings for the Year 1 reporting period are calculated as:

$$
\begin{aligned}
&Energy\ Savings_{Year\ 1} \\
&\quad = (Actual\ Energy\ Use)_{Baseline} \\
&\quad - (Predicted\ Energy\ Use, Year\ 1\ Model)_{Baseline} \\
&\quad \pm\ Non\text{-}Routine\ Event\ Adjustments
\end{aligned}
$$

Equation 2

- Likewise, the energy savings for the Year 2 reporting period are based on an energy model created using actual energy and key independent variable data from Year 2. This model is used to predict energy use during the baseline period based on key independent variable data reported during the same baseline period. Energy savings for the Year 2 reporting period are calculated as:

$$
\begin{aligned}
&Energy\ Savings_{Year\ 2} \\
&\quad = (Actual\ Energy\ Use)_{Baseline} \\
&\quad - (Predicted\ Energy\ Use, Year\ 2\ Model)_{Baseline} \\
&\quad \pm\ Non\text{-}Routine\ Event\ Adjustments
\end{aligned}
$$

Equation 3

5.4.2. Savings Calculation by Mean Model

- The validity of the mean model needs to be verified before it is used to calculate savings. The reporting period conditions must be the same as those in the baseline period under which the mean model was established. This requires confirming the (assumed) independent variable is within range (+- 10%) of the baseline data.

- For a mean model, baseline energy is calculated as the mean (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 non-routine adjustments.

$$Energy\ Savings = Mean\ (Actual\ Energy\ Use)_{Baseline} - (Actual\ Energy\ Use)_{Reporting} \pm Non\text{–}\ Routine\ Event\ Adjustments$$

Equation 4

5.4.3. Savings Calculation by Pre-Post Approach

- For pre-post models with a single indicator variable, the savings estimate per time interval is the estimated coefficient of the indicator variable. The Industrial Strategic Energy Management (SEM) Impact Evaluation Report[18] provides more details for calculating energy savings when the indicator variable (for the reporting period) is included as an interaction term with other model variables.

5.4.4. Savings Calculation by Engineering Calculation Approach

- Quantification of energy savings using a measure-level engineering calculation approach consists of custom calculations supported by short-term data logging, trend data acquisition or spot observations. In some cases, assumptions are sufficient, refer to Table 8 in Section 5.5.5 for more specific guidance on levels of rigor.
- The application of this approach is limited to specific cases when top-down, whole-facility energy modeling efforts are unsuccessful. This approach may also be used for comparison purposes. Further information regarding the application of engineering calculations including determination of the baseline, calculations of energy savings, and recommended project documentation is provided in Section 5.5.5 and generally aligns with BPA's Engineering Calculations with Verification (ECwV) Protocol.[19]

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[18] SBW Consulting, Inc. and The Cadmus Group, Appendix B, p. 73. https://www.bpa.gov/energy-and-services/efficiency/evaluation.

[19] *Engineering Calculations with Verification Protocol,* Version 2.0. Bonneville Power Administration, 2018. https://www.bpa.gov/energy-and-services/efficiency/measurement-and-verification

5.5. Options for Establishing Statistical Confidence of Savings Value

- During model development, it is important confirm the model is appropriate for the level of whole-facility savings expected to ensure the savings reported are valid. The statistical metrics of the regression model can be used as an initial check, but calculating the fractional savings uncertainty based on the actual energy savings is needed. In certain instances, it may be necessary to specify a range of energy savings for a defined statistical confidence level.

5.5.1. Uncertainty in the Forecasting Estimate

- The fractional savings uncertainty (FSU) methodology described in this section is generally applied to analyze the uncertainty in reported savings. the same analysis is used to inform the model development, particularly when the model developer is faced with multiple options related to time interval or variable selection.
- ASHRAE Guideline 14 provides a detailed description of uncertainty analysis.[20] The following methodology provides an approach for calculating uncertainty derived from model error. This method is a simplified version of the uncertainty analysis provided in the Industrial Strategic Energy Management (SEM) Impact Evaluation Report.[21] It should be noted that this approach does not capture error associated with measurement hardware. In most cases, the measurement error component should be small relative to the regression model error and can be assumed to be negligible.
- The fractional savings uncertainty (FSU) for the majority of SEM models can be estimated by the following equation[22]:

$$FSU = 1.26 * \ t - statistic \times \frac{CV\left[\left(\frac{n}{n'}\right)\left(1+\frac{2}{n'}\right)\left(\frac{1}{m}\right)\right]^{\frac{1}{2}}}{F}$$

Equation 5

Where:

$t - statistic$ = t-statistic for confidence level at 80%

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

[20] ASHRAE Guideline 14 - 2014, Annex B.

[21] *Industrial Strategic Energy Management (SEM) Impact Evaluation Report*, SBW Consulting, Inc. and The Cadmus Group, Feb. 2017; Appendix B, p. 75.

[22] Other forms of this equation that include corrections for autocorrelation may also be acceptable and should be documented.

n = number of observations in the baseline period (see Note 1)

m = number of observations in the reporting period

F = fractional savings (percent of total energy use saved) (see Note 2)

ρ = autocorrelation coefficient (see Note 3)

n' = effective number of observations in the baseline period after accounting for autocorrelation (see Note 4)

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

Notes about Equation 5:

→ Note 1. The coefficient of 1.26 in the FSU equation may underpredict FSU for baseline periods longer than twelve months.23

→ Note 2. F, the percent of total energy use saved, is an assumed value in the baseline evaluation (i.e., expected annual energy savings divided by baseline energy consumption). In the reporting period, F uses the actual savings (SEM Cumulative Verified Savings) divided by the predicted baseline energy consumption.

→ Note 3. If ρ is negative, n' would be greater than n, resulting in a lower FSU. In such cases, the negative value should be reported for ρ, but it is recommended to use the absolute value of ρ to calculate a conservative estimate of FSU.

→ Note 4. when calculating FSU for a monthly model, ASHRAE permits the assumption $\rho = 0$, so that n' is equal to n.[24] This is because any correlation between the residuals of consecutive months for a well-specified model would likely be coincidental. However, this assumption may not be valid if a key variable has been omitted.

5.5.2. Statistical Confidence for Backcasting Method

The FSU equation in Section 5.5.1 can also be used to estimate savings uncertainty for the backcasting method. When using the FSU equation, the model statistics and "baseline" observations (n) occur during the reporting period of the project. Likewise, the number of observations during the "reporting" period (m) occur during the baseline period of the project.

5.5.3. Statistical Confidence for Mean Model

When applying the mean model approach, two-sided t-tests are performed on energy use and assumed energy drivers prior to reporting energy savings. The t-test should demonstrate that the

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[23] *Uncertainty Approaches and Analyses for Regression Models and ECAM*. SBW Consulting, August 11, 2017.

[24] ASHRAE Guideline 14-2014, 4.2.11

energy use of the reporting period is less than the baseline period. It must be shown that changes in the assumed energy drivers did not influence energy savings. T-tests or other methods may be used to demonstrate this. All t-tests should be performed at the 80% level of confidence using methods for equal or unequal variances as appropriate for the samples under study.

5.5.4. Statistical Confidence for Pre-Post

When using a pre-post model, the indicator variable's standard error is used to determine the uncertainty of the savings estimate. For a desired level of confidence, the t-statistic or p-value can be used to determine the confidence in the savings estimates.

5.5.5. Rigor in Engineering Calculation Approach

- Measure-level engineering calculations can be carried out independently for each completed opportunity or grouped to consolidate by system. For example, if an HVAC system is tuned, a system model is an acceptable way to estimate the savings resulting from a set of actions. These calculations should be traceable from the opportunity register (see Appendix F – Opportunity Register) through the M&V supporting documents. In support of the calculations, the opportunity register should include details such as:
    - → Defines individual energy efficiency measures implemented.
    - → Documents the specific subsystem affected (i.e., elevator lighting, bldg 4 compressed air system, AHU-7, cooling tower 5a).
    - → States the existing conditions observed.
    - → States the new conditions of the measure implementation (setpoints, run-time changes, added capability).
    - → Documents the date individual energy efficiency measures were implemented that reflects when the energy savings began.
    - → Clearly documents parameters that changed.
- The details presented in the opportunity register should align with values used in energy savings calculations. The rigor applied to savings calculations should scale with the magnitude of savings. For measure-level savings analyses that span more than one program year, the level of rigor, data collection, and calculation requirements should be applied for applicable program year.
- Measure-level energy savings calculations should only quantify energy savings for the time the measure was in place during the reporting period. For example, if the opportunity was installed on day 300 of Program Year 1, the measure savings can only be

quantified for the 65 days after installation. In Year 2, if the continued performance of the measure is verified, 365 days of energy savings may be quantified.

- For guidance, the following table outlines minimum expectations for SEM measure-level savings estimates. Multiple EEMs of a similar nature may be considered as a unit rather than as individual EEMs when considering level of rigor.

Table 8: Level of Rigor for Engineering Calculations

Measure Energy Savings	Data Needed	Calculation Notes	Supporting Documentation
Level 1 < 50,000 kWh/yr.	▪ Develop supported assumptions that are evaluable in the future. ▪ Direct measurement is not required. Use equipment specifications, observations, or measurements to estimate average load (kW) for the baseline and proposed conditions. ▪ Determine hours of operation through an interview, trend data, or measurement.	▪ When possible, use simple calculations that account for the kW and hours to estimate avoided kWh/yr. ▪ Explain how each variable was determined, which were assumed, and list the source. ▪ A system or whole building simulation model is acceptable to assess measures and account for interactive effects.	▪ Minimal supporting documentation is required. ▪ Participant self-reported equipment specifications are acceptable. ▪ Photos are encouraged.

Measure Energy Savings	Data Needed	Calculation Notes	Supporting Documentation
Level 2 50,000 to 200,000 kWh/yr.	▪ A spot measurement or observation may adequately capture the load or other value when the operating conditions are constant. ▪ Users should confirm that the load is constant by observing multiple spot measurements over time and justify such an assumption. ▪ For variable operating conditions, data should be acquired over a period sufficient to observe the variation in the operational cycle. ▪ System specifications should be confirmed by direct observation (photos), as-built drawings, or equipment specifications. ▪ Annual hours of operation should be confirmed by data logging, system trend data analysis, interval data analysis, or inferred indirectly from operating schedules (HVAC system schedule, production schedule, etc.).	▪ The requirements for measures with savings in this category should closely align with BPAs ECwV Protocol.[25] The protocol recognizes two approaches, engineering calculations, and whole building simulation. ▪ Calculations should rely on data acquired from the system affected or trend data and regressions when simulating variables over time (e.g., supply air temperature vs. outside air temperature). ▪ Calculations may involve a seasonal consideration or bin hour approach. Normalization to typical conditions data is generally not required. ▪ Data from either the baseline or post-installation period is adequate when one or the other can reliably be inferred from observation or engineering assessment.	▪ Describe the engineering approach step-by-step. Separate independent measures and group like measures to consider interactive effects. ▪ Define specific equipment as named by the participant, state operating parameters, and provide supporting screen shots, photos, logged data, drawings, or equipment specifications.

Measure Energy Savings	Data Needed	Calculation Notes	Supporting Documentation
Level 3 > 200,000 kWh/yr.	→ Meet with stakeholders and consider developing a comprehensive M&V plan. Measures in this savings category require a baseline data set with supporting documentation for the conditions contributing to the energy savings. → Data logging or trend data are required for the baseline and post-implementation time periods. Time periods for data acquisition shall be long enough to support process or system load variation adequately. → If using a system or whole building simulation model, trend and logged data shall support the assumptions for any significant energy drivers. Calibration with utility data is required when feasible. → Direct measurement of power (or amps, volts, and power-factor) for the baseline and post time periods is encouraged.	→ Calculations should rely on data acquired from the system affected or trend data and regressions when simulating variables over time (i.e., supply air temperature vs. outside air temperature). → Calculations may involve a seasonal consideration or bin hour approach. Normalization to typical conditions data is generally not required.	→ Describe the engineering approach step-by-step. Separate independent measures and group like measures to consider interactive effects. → Define specific equipment as named by the participant, state operating parameters, and provide supporting screen shots, photos, logged data, drawings, or equipment specifications.

[25] Engineering Calculations with Verification Protocol Version 2, 2018.

5.5.6. Program Review and Approval

- The SEM Completion Report will document the details of energy improvement actions taken, the annual energy savings results, and the details supporting the calculation methodology.
- The Stakeholder team will provide final sign-off, but BPA will provide final authorization of the savings and SEM participation payment.

6. Adjusting for Data Gaps

- The following section outlines five methods to estimate energy savings if less than a year of data is available during the reporting period so that a full year of savings can be reported. Under the current SEM program, this method would seldom be necessary. However, in the case of meter failure or other unforeseen circumstances, these methods may be applicable to predict energy consumption for a future "projection period" for which data is not yet available.
- For each of these methods, it is essential that the following factors are considered:
  - → The number of valid observations from the reporting period available to date, compared to the number of time periods used during the projection period.
  - → Expected consistency in operations and in the distribution of energy drivers between the available reporting period data and the data expected during the projection period.
  - → Engineering and program judgment on the likelihood of savings to persist.

6.1. Direct Percentage Basis

- When the distribution of available data in the reporting period is expected to persist into the projection period, energy savings can be extrapolated based on percent energy savings.

6.2. Percentage Basis with Forecast of Energy Drivers

- When the distribution of available data is expected to change in the projection period, the distribution of energy drivers must be considered. For example, if reporting period energy savings were only obtained when production was low, then it would be incorrect to project savings when production is expected to be high. However, the percentage basis could still be used for periods when production is expected to be 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 (Section 6.2). This method requires the development of a second regression model for the reporting period. A projected distribution of energy drivers is then applied as an input to both the baseline model and the model based on available reporting period data. TMY3 weather data is typically used for weather dependent energy drivers, and the best estimate of future production is used for production energy drivers. Projected savings are calculated as the difference between the predictions of the two regression models.

→ This approach disaggregates energy savings by energy drivers, which may provide insight into how energy savings were achieved.

→ One weakness of this approach is that it requires additional calculation steps.

→ This method is similar to the Standard Condition Adjustment Model defined by SEP.[26]

6.4. Pre-Post Model

- This method can be used in lieu of the "Direct Percentage Basis" method described in Section 6.1. This method was used by Cadmus for the 2012 and 2017 Energy Management Impact Evaluations and follows a methodology described by Luneski (2011).[27] This method entails developing a new regression model using an indicator variable to differentiate the baseline and reporting period data. The value of the indicator variable represents the energy savings.
- When only an indicator is used to estimate 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.
- The model may normalize for the effects of weather/production by including cross terms of the indicator with energy drivers. If coefficient for a cross term is not statistically significant, it suggests that the original relationship between energy and that energy driver remains unaffected.

6.5. Engineering Calculations

- Engineering calculations with verification are a good alternative to regression model M&V methods when a model does not work. Requirements for these calculations are presented in Section 5.5.5.

[26] Guidance for the SEP 50001™ Program Measurement & Verification Protocol: 2019, section 6.2.3, page 34.

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

- Engineering calculations are also great for temporary use. If a model fails in the first year of engagement, pivoting to engineering calculations to estimate savings achieved during the reporting period can provide continuity to the engagement while models are attempted again in the future.
- When or if results need to be adjusted out of a baseline in the future, opportunity register details enable for data collection to provide proper adjustments.

7. Reporting Energy Savings for Multi-Year SEM Projects

7.1. Savings Reporting Elements

Energy savings achieved during multi-year SEM projects will include the following items when reported to BPA.

7.1.1. SEM Baseline

- The SEM Baseline is the energy use established prior to enrollment in a SEM program. SEM Baseline can be reestablished after a significant operational change or at customer request, as outlined in Section 4.3. Re-enrollment in additional two-year performance period resets the reference point for the purposes of calculating savings and payment but does not change the SEM Baseline.

7.1.2. SEM Cumulative Verified Savings

- SEM Cumulative Verified Savings are the verified annual energy savings measured from establishment of SEM Baseline to current performance period year. SEM Cumulative Verified Savings is not used by BPA to calculate reportable savings or any payment from BPA, but will be provided to customers for their own reporting purposes.
- The SEM Cumulative Verified Savings are represented by the unadjusted model CUSUM at the end of each reporting year.

7.1.3. SEM Annual Savings Achieved

- SEM Annual Savings Achieved are the verified incremental savings measured in each year of a two-year performance period.
- If measure-level engineering calculations are applied to quantify savings, only those savings that are observed during the performance period are eligible for savings achievement. Thus, savings for projects implemented during the performance period need to be pro-rated based on the implementation date. For future performance periods, verified incremental savings are achieved.
- In Year 1 of the first performance period, or after the re-establishment of the SEM Baseline, it is measured as all savings achieved against the SEM Baseline.

- In Year 2 of any performance period, it is measured as the savings achieved beyond the savings achieved in Year 1 of the performance period. Savings for Year 2 are incremental compared to savings achieved in Year 1.
- In Year 1 of subsequent performance periods (as a result of re-enrollment), it is measured as all savings achieved above Year 2 of the previous performance period.
- If zero or negative savings verified from the prior year, SEM Annual Savings Achieved is zero. (Note: Actual savings will be reported per Section 7.3.)
- SEM Annual Savings Achieved is used to determine the allowable Performance Payment.

7.1.4. SEM Verified Savings

- SEM Verified Savings are the verified total energy savings measured from the start of the current performance period. SEM Verified Savings are calculated at the end of Year 1 and at the end of Year 2.
- In Year 1 of the first performance period, it is measured as all savings achieved above the SEM Baseline.
- In Year 2 of any performance period, it is measured as the savings achieved in Year 1 and adjusted for any additional savings achieved in Year 2.
- In Year 1 of subsequent performance periods (as a result of re-enrollment), it is measured as all savings achieved above Year 2 of the previous performance period.
- Should there be zero or negative savings verified from the start of the performance period, SEM Verified Savings achieved is zero.
- SEM Verified savings is used to determine the energy-efficiency incentive, or participation payment.

7.1.5. SEM Participant Payment

- The SEM Participant Payment is made during each year of an SEM Performance Period. Payment is based on SEM Verified Savings.

7.2. Reporting Energy Savings Example

- The following example demonstrates the calculation and reporting of SEM Cumulative Verified Savings, SEM Annual Savings Achieved, SEM Verified Savings, and the SEM Participant Payment over a six-year engagement (three two-year enrollment periods).

Table 9. Reporting Energy Savings, Six-year Example

SEM Engagement Year	SEM Cumulative Verified Savings (kWh)	SEM Annual Savings Achieved (kWh)	SEM Verified Savings (kWh)	SEM Participation Payment*
1	200,000	200,000	200,000	$5,000
2	300,000	100,000	300,000	$7,500
3	250,000	-50,000	0	$0
4	500,000	250,000	200,000	$5,000
5	600,000	100,000	100,000	$2,500
6	550,000	-50,000	50,000	$1,250

*The example assumes an SEM incentive of $0.025/kWh. Non-BPA funding sources may still be applied as desired by utilities.

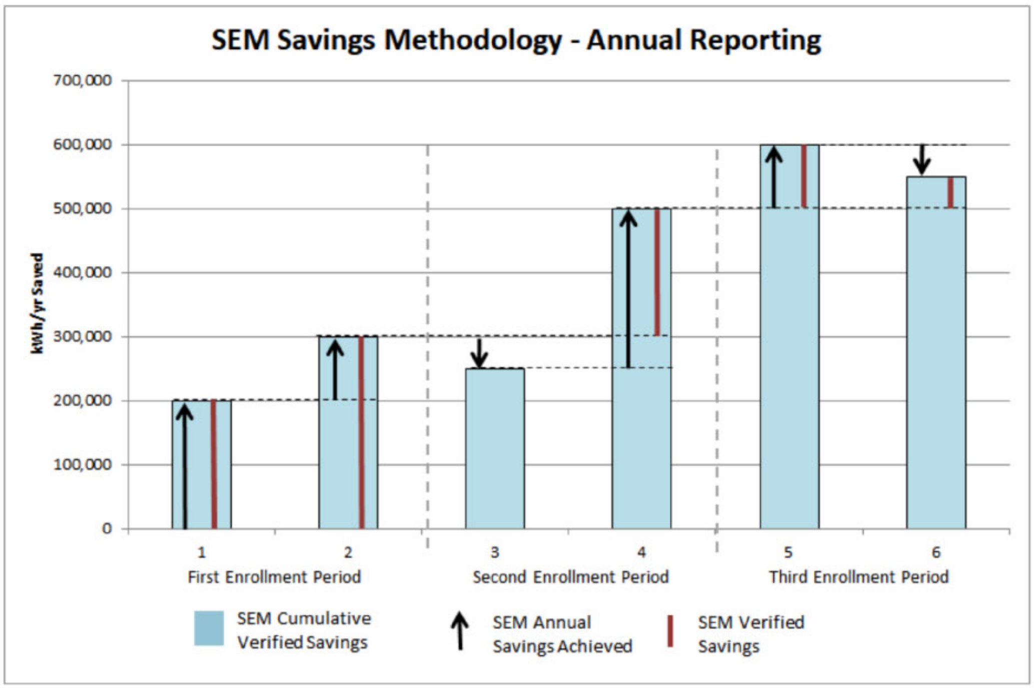

Figure 14. Reporting Energy Savings, Six-Year Example

In the example table and illustration above, note:

→ The SEM baseline energy model remains valid for all six years.

→ The SEM Cumulative Verified Savings are measured relative to the SEM Baseline.

→ The *SEM Annual Savings Achieved* are the year-to-year change in SEM savings reported to BPA

→ The *SEM Verified Savings* are the savings above the SEM savings from the final year of the previous enrollment period. These are the savings used to calculate the *SEM Participant Payment*

7.3. Handling Backsliding or Negative Savings

- Backsliding or negative energy savings could be a result of non-program-related issues beyond the control of SEM participants, such as market conditions, societal/environmental events, or a change in facility operations. In these instances, however, the efficacy of the implemented measures should be verified.
- When an SEM site demonstrates backsliding —as compared to the previous reporting period:

  → The SEM Annual Savings Achieved will be used to calculate the eligible performance payment

  → The SEM Verified Savings will be used to determine the SEM Participant Payment.
- In the case that negative savings —as compared to the SEM Baseline—are calculated, the SEM Cumulative Verified Savings will be zero.

  → SEM Annual Savings Achieved – whether negative, zero, or positive –will be reported to BPA.

7.4. Re-Baselining

- The original SEM baseline model may continue to be used through multiple two-year engagements as long as it remains valid and representative of facility operations. However, modifications to the baseline period or other changed the baseline energy model may be evaluated based on Section 4.3. Specific timing related to re-baselining the SEM Participant's baseline energy model may be specified in program-specific SEM-agreement language.

Appendix A – Treatment of Incentivized EEMs During the Baseline Period

- Ideally, a baseline period is selected which does not include the implementation of energy projects and occurs immediately prior to the reporting period. This scenario does not require any adjustments and is described below in the Standard Approach.
- When energy projects have been installed during the selected baseline period, the appropriate method from the table below should be applied before establishing a baseline model. Select the appropriate Method (1 through 5), below, based on the timing of the energy projects relative to the selected baseline period.
- Allocation of savings from EEMs which are implemented over time (e.g., lighting retrofits) require additional consideration.
- Symbols used:

β	Coefficient
i	Index subscript
IV	Binary indicator variable (= 1 or 0) for EEM and non-incentivized EEM adjustment
$M\&V$	EEM's measured and verified savings per period
n	number of terms in baseline (excluding EEM and non-incentivized EEM terms)
x	Independent Variable
y	Predicted energy (kWh/period)

Table 10. Savings from Incentivized EEMs Installed During Baseline Period

Method	Description	Guidelines	Merits	Drawbacks
1) Standard Approach	Select a baseline period without capital projects and immediately prior to the reporting period. $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$	Verify absence of incentivized EEMs by interviewing facility and speaking to serving utility. Confirm energy intensity profile and model residuals are consistent over the selected period.	Incorporates the full data set in the baseline energy model. Requires no manipulation of data. Requires no adjustments during reporting period.	No obvious Drawbacks, provided energy intensity profile is consistent throughout baseline period as indicated by the residuals.
2) Pre-EEM Baseline Normalization by M&V Value	Adjust the pre-EEM baseline values by the EEM M&V value. This requires granular estimates of EEM savings in the same increment $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$	EEM completion report must be reviewed and included as attachment. Interactive effects described in project report must be factored into the baseline adjustment.	Provides direct reconciliation with M&V value. Enables use of the entire baseline data set. CUSUM for reporting period starts at zero.	Requires adjustment to baseline data set (IPMVP does not prohibit). Accurately incorporating interactive effects is challenging and labor intensive.
3) Year-End Adjustment	Where granular savings over time are not available, choose a baseline period immediately prior to the first capital project. Subtract M&V savings from year-end gross savings. $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + (IV)(M\&V)$	Maximum exclusion period = 12 months. Exclusion period must have a consistent energy profile, aside from the EEM(s).	Provides direct reconciliation with EEM M&V value. Requires no adjustment of baseline data set.	Data immediately preceding reporting period is excluded. M&V adjustment must be performed throughout reporting period.

Method	Description	Guidelines	Merits	Drawbacks
4) Baseline Normalization by Factored Indicator Variable	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. $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \beta_{n+1}(IV) + \sum_{i=1}^{n} \beta_{i+n+1}(IV) x_i$	Factored indicator variable will add to the number of points required in the baseline data set ($n \times 6$).	Allows regression model to solve for interactive effects of EEM with other energy drivers. Yields the highest R^2.	No reconciliation with EEM's M&V value. If backsliding occurred on the EEM, program component would pick up any recapturing of the original savings.
5) Indicator Variable Representation of Non-Incentivized EEM	Also see Method 4. To prevent incentivizing a previously implemented, non-incentivized EEM by program component, apply an indicator variable representing implementation of the EEM*. Then solve for the coefficient. $y = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \beta_{n+1}(IV) + \sum_{i=1}^{n} \beta_{i+n+1}(IV) x_i$	Non-incentivized EEMs implemented during baseline period should be accurately reflected in baseline energy model.	Prevents "free-rider" EEMs from inflating the savings associated with program component. Allows use of the entire baseline data set.	The quantification of the savings associated with the EEM is limited to the precision of the model.

*Describes an independent scenario from SEM measures

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

When an EEM incentivized by another program is installed during the SEM Reporting Period, the energy savings from the EEM are based on the M&V for the EEM. Savings from these EEMs should allocated using the for the appropriate method from Table B-1 below.

Select the approach based on the status of the EEM's installation, the visibility of the EEM in the CUSUM tracking chart, and the status of the M&V of the incentivized EEM.

Table 11. Savings from Incentivized EEMs Installed During Reporting Period

<table>
<tr><th>Project Installed</th><th>Savings observed in CUSUM?</th><th>Status of M&V for EEM</th><th>Start Date</th><th>Savings Value Prorating Method</th></tr>
<tr><td>No or Incomplete</td><td>n/a</td><td>n/a</td><td>n/a</td><td>n/a</td></tr>
<tr><td rowspan="10">Yes</td><td rowspan="3">No</td><td>Not started</td><td>n/a</td><td>n/a</td></tr>
<tr><td>In progress</td><td>Use the actual project M&V start date.</td><td>Wait for M&V to be completed (if an early estimate is needed, solve for value in CUSUM).</td></tr>
<tr><td>Completed</td><td>Use the actual project M&V start date.</td><td>Use site savings M&V value.</td></tr>
<tr><td rowspan="7">Yes</td><td rowspan="3">Not started</td><td rowspan="3">Based on CUSUM inflection and ideally supported by email from Project (e.g., equipment was commissioned on xx/xx date).</td><td>Solve for savings value using indicator variable during reporting period.</td></tr>
<tr><td>Use estimated site savings from custom project proposal.</td></tr>
<tr><td>If the savings value from the two options (above) differs significantly, confer with Stakeholder team.</td></tr>
<tr><td rowspan="2">In progress</td><td>Based on CUSUM inflection, and ideally supported by email from Program.</td><td rowspan="2">Wait for M&V to complete (if an early estimate is needed, solve for value).</td></tr>
<tr><td>At the latest, use Actual Project M&V Start Date.</td></tr>
<tr><td rowspan="2">Completed</td><td>Based on CUSUM inflection and ideally supported by email from Program.</td><td rowspan="2">Use site savings M&V value.</td></tr>
<tr><td>At the latest, use Actual Project M&V Start Date.</td></tr>
</table>

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 15. 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 16. Example Regression output from Microsoft Excel

Appendix D – Glossary of Terms

The definitions below address terms used within the body of this document, presented in the context of BPA's SEM procedures. For a more comprehensive overview of statistical terms related to measurement and verification, please refer to BPA's Glossary for M&V: Reference Guide.[28]

Adjusted R^2	A measure of the total variation accounted for in the model that penalizes for the number of parameters used in the model.
Autocorrelation Coefficient	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 $n + 1$. Autocorrelation can be calculated from the residuals, e, from the following equation: $$\rho = \frac{\sum_{i=2}^{n} e_i \, e_{i-1}}{\sum_{i=1}^{n} e_i^2}$$
Baseline	Generally refers to the period of time selected to characterize energy consumption prior to an SEM engagement. "Baseline" is sometimes used as shorthand for the energy model or the energy use predicted by the baseline energy model.
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 heating mode to cooling mode.

28 Bonneville Power Administration's Glossary for M&V: Reference Guide, Version 1.1. Bonneville Power Administration. May 2012.

Coefficient of Determination (R^2)	Statistically, the proportion of the total variation in the dependent variable that is explained by the regression equation. Mathematically, defined as $$R^2 = \frac{\sum(\hat{y}_i - \overline{y})^2}{\sum(y_i - \overline{y})^2}$$ 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, $\overline{y} = \frac{1}{n}\sum y_i$. y_i = actual observed value of the dependent variable.
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. 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^2 evaluates how much of the variability in the actual values is explained by the model. $$CV\ (RMSE) = \frac{1}{\overline{y}}\sqrt{\frac{\sum(\hat{y}_i - y_i)^2}{n-p}} \times 100$$

Cooling Degree Days (CDD)	A measure of how many degrees the outside air temperature (T_{oa}) is above the cooling balance point (T_{cool_bal}) over the course of a day. The cooling balance point is the temperature below which the temperature has no influence on energy consumption, but above which energy increases. The units CDD are °F-days. When using average values of Toa, CDD can be calculated as[29] $$\text{CDD}(T_{bal}) = 1 \text{ day} \times \sum_{i=1}^{n \text{ days}} \left(T_{oa,i} - T_{cool\_bal}\right)$$ Once quantified at the daily level, Degree-Days may be aggregated to longer time intervals as needed for modeling. Note that hourly time intervals can be similarly used to determine degree-hours. A source for degree days is www.degreedays.net.
Cumulative Sum of Differences (CUSUM)	The sum of the differences of each actual energy consumption value from the predicted value (savings) and is often charted over time to track total savings achieved.
Data Champion	This person, assigned by the end user, is the point of contact for data review and collection. This person may be the Energy Champion or report to the Energy Champion.
Energy Champion	This person, assigned by the end user, determines potential energy efficiency projects and tracking techniques.
Energy Efficiency Measure (EEM)	Equipment and/or actions taken to reduce electrical energy use.
Fractional Savings Uncertainty (FSU)	The calculated uncertainty in the total savings over m time periods divided by the total savings over the same time period, where uncertainty is measured as the quantity of savings from the upper confidence limit to the lower confidence limit surrounding a savings estimate.

[29] Kreider, Curtiss, Rabl. 2002. *Heating and Cooling of Buildings, Second Edition.* McGraw Hill. p. 381.

Heteroscedasticity	In contrast to homoscedasticity, this undesirable condition occurs when error (or residual) variance is not constant throughout the observations (e.g., when the residual variance is shown to increase or decrease with the value of an independent variable).
Heating Degree Days (HDD)	A measure of how many degrees the outside air temperature (T_{oa}) is below the heating balance point (T_{heat_bal}) over the course of a day. The heating balance point is the temperature above which the temperature has no influence on energy consumption, but below which energy increases. The units HDD are °F-days. When using average values of Toa, HDD can be calculated as[30]: $$\text{HDD}(T_{bal}) = 1\text{ day} \times \sum_{i=1}^{n\text{ days}} \left(T_{heat\_bal} - T_{oa,i}\right)$$ Once quantified at the daily level, Degree-Days may be aggregated to longer time intervals as needed for modeling. Note that hourly time intervals can be similarly used to determine degree-hours. A source for degree days is www.degreedays.net.
Homoscedasticity	Homoscedasticity generally means that all data in a model have similar variance over the modeling period, which is preferred. Within linear regression, this means that the variance around the regression line is similar for all values of the dependent variables.
Indicator Variable	(Also referred to a categorical variable.) 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.

International Measurement and Verification Protocol (IPMVP)	The IPMVP provides an overview of current best practice techniques 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.[31]
Measurement and Verification (M&V)	The process of planning, measuring, collecting, and analyzing data for the purpose of verifying and reporting savings within an individual facility resulting from the implementation of EEMs.[32]
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.
Mean Model	(Also referred to as a single parameter model.) A model that estimates the mean of the dependent variable.
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, including SEM.
Multicollinearity	A phenomenon in which two or more independent variables in a multiple regression model are correlated.

31 Efficiency Evaluation Organization.

32 Ibid.

Net Determination Bias Error (NDBE)	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. A positive value indicates a tendency of the model to overestimate savings. NDBE is calculated as $$NDBE = \frac{\sum(y_i - \hat{y}_i)}{\sum y_i} \times 100$$
Non-Routine Adjustment	Adjustments made to energy data to compensate for the impact of non-routine events so savings are accurately calculated.
Non-Routine Event	Unrelated events or facility changes that impact energy savings and are unaccounted for in the calculations.
Performance Period	Two-year enrollment period during which SEM participants working to acquire SEM energy savings. Participants may re-enroll in additional two-year performance periods.
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.
Reporting Period	Year-long time period during which SEM energy savings are quantified. There are two reporting periods per performance period with results summarized in annual completion reports.
Retrofit-Isolation	Engineering calculations with verification
Strategic Energy Management (SEM)	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.
Static Factors	Static factors are those characteristics of a facility including installed equipment and operating parameters which are not accounted for by independent variables in the regression-based energy models.

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 minimize bias from the varying time periods. Table 12. shows the data per billing period and the daily average values for this data. Note that because T_{db} was already provided as an average value, this value is the same for both the billing period and the daily average.

Table 12. 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 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, the diagonal matrix W_{ii} would be:

$$W_{ii} = [27, 29, 28, 29, 28, 39, 29, 29, 33, 30, 24, 38]$$

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 observations.

A weighted regression set is 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, is fit to a three-parameter, multivariable heating model as:

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

Table 13. shows that the regression coefficients calculated using weighted regression are different from the ordinary least squares method.

Table 13. 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 14 shows that the sum of the residuals for ordinary regression analysis differs from zero, indicating bias in the model. This difference is caused by bias in the model coefficients. The sum of the residuals for weighted regression is nearly zero, which is expected.

Table 14. Comparison of 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	213,982	32,489
Mar	142,072	197,054	-54,982	197,031	-54,959
Apr	172,318	159,831	12,487	160,059	12,259
May	123,368	114,200	9,168	114,761	8,607
Jun	126,945	128,634	-1,689	129,003	-2,058
Jul	101,529	110,073	-8,544	110,101	-8,572
Aug	133,429	128,894	4,535	128,602	4,827
Sep	150,975	145,282	5,693	144,973	6,002
Oct	144,720	155,115	-10,395	155,141	-10,421
Nov	140,880	135,680	5,200	135,858	5,022
Dec	221,502	226,082	-4,580	227,262	-5,760
Total	1,931,981	1,931,982	**-1**	1,933,688	**-1,707**

While duplication of observations is a simple method for performing weighted regression, it should be noted that it produces artificially high R^2 values and *t*-statistics for independent variables. In these cases, 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 NDBE).

Appendix F – Opportunity Register

ID Number	Description	Subsystem	Measure Type	Identified	Completion Date	Estimated Savings (kWh/yr)	Priority (1 - 3)
1	Replace outside air damper actuators in all AHUs	HVAC	O&M	12/1/2020	3/1/2021	115,000	1
2	Adjust lighting controls to match occupied hours in office areas[33]	Lighting	O&M	12/1/2020	12/7/2021	5,000	1
3	Turn down plant air pressure, was 110 psi, now 100 psi. Monitoring stations - goal in the future is 95 psi[34]	Compressed Air	O&M	2/7/2021	2/25/2021	72,000	2
4	Install occupancy sensors in South Building's 5 conference rooms	Lighting	Capital	3/1/2021	5/5/2021	12,000	3
5	Standardize all thermostat temps to heating 70, cooling 75[35]	HVAC	O&M	4/24/2021		10,000	1
6	Shut off transfer pumps when mix chest is full. Currently the pump dead heads against a fully closed valve.	Pumping	O&M	6/1/2021		Low	1
7	Install 2-ton ductless heat pump in IT room and schedule off AHU-4 with other AHUs.	HVAC	Capital[36]	6/1/2021	8/2/2021	55,000	1
8	Replace weather stripping on front doors	Doors	O&M	7/1/2021		Low	3

[33] Occupied hours are 8 am to 6 pm on weekdays.

[34] See plant supervisor for trend data prior to making further adjustments.

[35] See running list of completed t'stats in O&M office.

[36] Note incentive provided from prescriptive program.