

Lawrence Berkeley National Laboratory

LBL Publications

Title

Detecting the undetected: Dealing with non-routine events using advanced M&V meter-based savings approaches

Permalink

<https://escholarship.org/uc/item/58j2q193>

Authors

Fernandes, Samuel

Crowe, eliot

Touzani, samir

et al.

Publication Date

2020-08-01

Peer reviewed



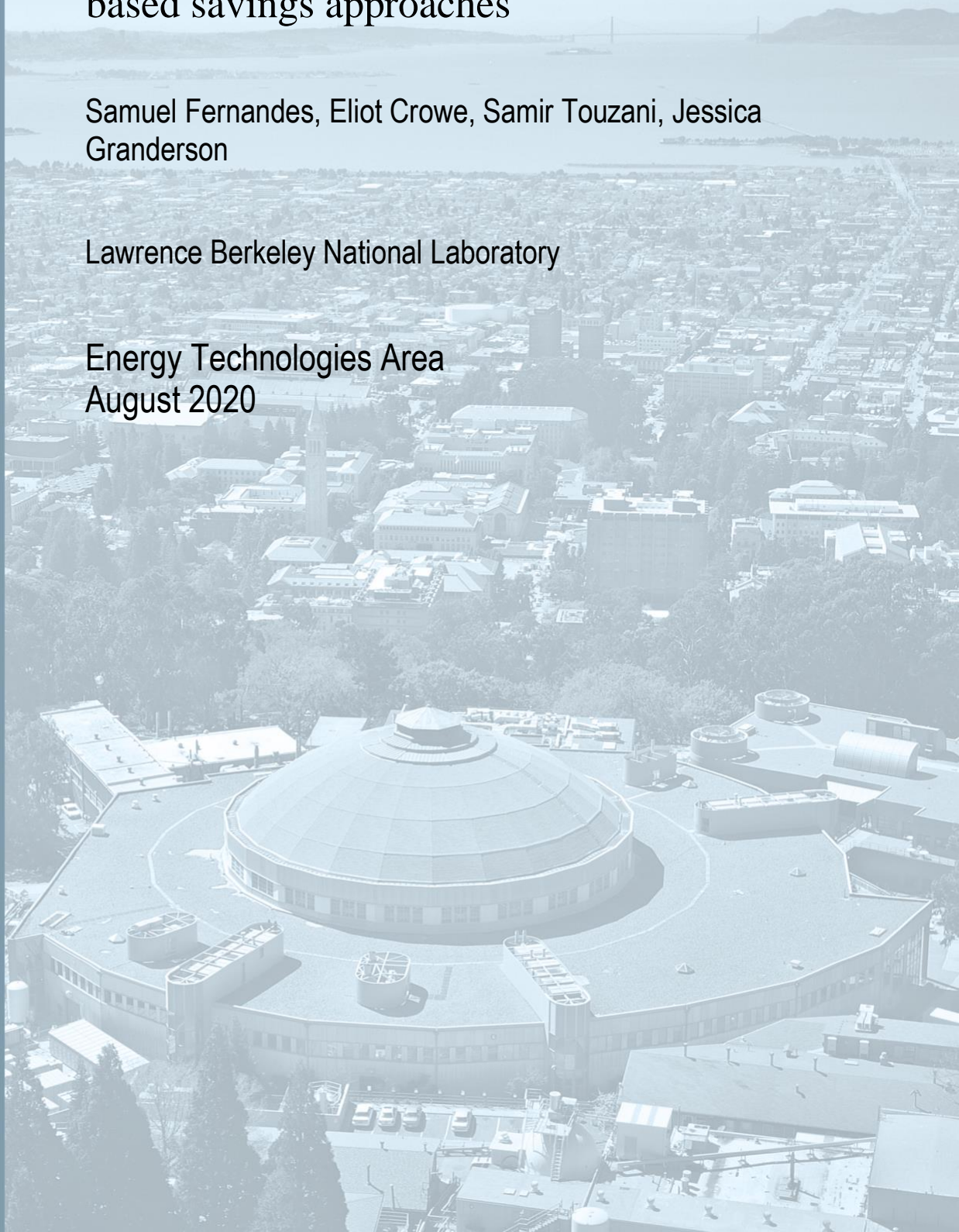
Lawrence Berkeley National Laboratory

Detecting the undetected: Dealing with non-routine events using advanced M&V meter-based savings approaches

Samuel Fernandes, Eliot Crowe, Samir Touzani, Jessica Granderson

Lawrence Berkeley National Laboratory

Energy Technologies Area
August 2020



Disclaimer:

This document was prepared as an account of work sponsored by the United States Government. While this document is believed to contain correct information, neither the United States Government nor any agency thereof, nor the Regents of the University of California, nor any of their employees, makes any warranty, express or implied, or assumes any legal responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by its trade name, trademark, manufacturer, or otherwise, does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof, or the Regents of the University of California. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof or the Regents of the University of California.

Detecting the undetected: Dealing with non-routine events using advanced M&V meter-based savings approaches

*Samuel Fernandes, Eliot Crowe, Samir Touzani, Jessica Granderson
Lawrence Berkeley National Laboratory*

ABSTRACT

In a rapidly evolving energy industry, utilities are dealing with new challenges like integrating distributed energy resources and market saturation for advanced lighting retrofits. Demand-side management programs require new approaches to meet aggressive carbon reduction goals. Advanced measurement & verification (M&V) is an energy data analysis method using smart meter data in combination with analytics to quantify energy efficiency project savings. Advanced M&V shows great promise for supporting next generation commercial programs including retro commissioning, multi-measure retrofits, and behavior change programs.

Advanced M&V captures real project impacts at the meter, but sometimes non-project events can also impact consumption (so-called “non-routine events” [NREs]). Accurately detecting and accounting for NREs is important for reducing uncertainty of savings estimates and helps manage investment risk for different stakeholders (e.g., utilities, building owners, ESCOs). Recent research has shown promise in establishing data-driven techniques to identify and adjust for NREs, but fundamental questions still remain, such as: how can you distinguish NREs from acceptable noise in energy consumption profiles? What is the frequency and magnitude of NREs? Can their detection and adjustment be automated and streamlined?

This paper documents the state of the art in NRE quantification and analysis. The results of research to quantify the frequency, nature and direction of NREs, and methods and metrics for determining a trigger threshold for taking action on NREs are presented. The paper also documents the latest technical guidance on application of NRE detection and adjustment methods.

Introduction

Advanced measurement & verification (AM&V), or M&V 2.0, is an energy data analysis method using advanced metering infrastructure (AMI) data in combination with analytics to quantify energy efficiency project savings. Advanced M&V is viewed as an enabler for underutilized behavioral, retro-commissioning, and holistic multi-measure efficiency efforts, as quantifying savings for these programs with existing methods has typically been very challenging.

The growing availability of AMI interval energy use data together with the rapid expansion of energy analytics tools presents great promise to both enable efficiency savings and automate savings quantification. Industry-wide, there is a desire to streamline the M&V process and to base project savings claims on actual meter data. Utility program evaluators have shown an interest in advanced M&V but have needed guidance on different application methods and tools applicable to those methods (Molina, Novak, and Kushler 2017, Gold, Waters, and York, 2020). Utilities and energy efficiency program administrators (PAs) are also exploring new

programs and analysis tools that leverage AMI data. In addition, as efficiency efforts ramp up to meet aggressive building energy reduction goals at national and state levels, there is increasing interest in moving toward performance-based outcomes - whether in codes, utility incentive programs, or operational energy goals. Innovative utility “pay-for-performance” programs are emerging, and these measured savings approaches can reach underserved markets such as commercial real estate (Pearce, Dearth and Schantz 2018).

Alongside the many opportunities, deployment of advanced M&V has also faced challenges. Many of the challenges relating to modeling methods, implementation guidance, and software tools have been largely addressed. One significant challenge remains for meter-based savings estimation approaches, however: how to distinguish the energy efficiency project savings from non-project impacts on energy consumption (so-called non-routine events [NREs]).

While some methods have been proposed to identify NREs and quantify their impacts, there are still a number of questions that need to be addressed, such as: how can NREs be distinguished from acceptable data noise? What is the frequency and magnitude of NREs? To what extent can their detection and adjustment be automated and streamlined? This paper aims to document the state of the art in NRE quantification and analysis.

The methodology applied in this research is a visual inspection of AMI time series meter data to identify changes in consumption that may indicate NREs. Certain consumption patterns that may be indicative of an NRE were defined prior to visual inspection. Visual inspection was then performed, and when one of the patterns was observed, an NRE was documented. This paper highlights the results of visual inspection to quantify the frequency, nature and direction of potential NREs, and documents the latest technical guidance on application of NRE detection and adjustment methods.

This paper first provides a brief background on state-of-the-art methods for addressing NREs, explains the analysis methodology applied in this paper, showcases characteristics of NREs that were identified using the analysis methodology, addresses some approaches to savings adjustment for NREs and finally includes a discussion section with comments about potential future work.

Background

Advanced M&V utilizes AMI data (at hourly or shorter intervals) from before an efficiency intervention (the “baseline period”) and after the intervention (the “reporting period”) to determine project savings. This is achieved through development of energy model(s) that correlate energy consumption with independent variables. The International Performance Measurement and Verification Protocol (IPMVP) (EVO 2012), Option C, defines energy savings as:

$$\text{Savings} = \text{Baseline minus Reporting Period Energy Consumption} \pm \text{Adjustments}$$

The “Adjustments” term breaks down into both routine and non-routine adjustments:

- Routine adjustments based on variation in the independent variables that were used to develop the baseline model (most commonly time of week and ambient temperature, since they are the most dominant drivers of energy consumption for the majority of medium-to-large commercial buildings, the typical targets for advanced M&V methods to date);

- Non-routine adjustments, for energy-influencing factors that were not selected as independent variables, and which changed at some time between the start of the baseline and the end of the reporting period.

AM&V can be conducted at a site level, to estimate savings for an individual building or more broadly at a population level for multiple buildings to assess program level savings. Non-routine adjustments are more commonly associated with site level M&V. Ignoring NREs can result in biased savings estimates. For example, if an efficiency measure is installed concurrent with a reduction in building occupancy (an example NRE), it would be challenging to determine which portion of the energy consumption reduction could be attributed to the measure versus the occupancy change. This type of savings attribution has typically been a critical consideration for ratepayer-funded efficiency programs. In practical terms, there are myriad factors that influence a building’s energy consumption and which cannot feasibly be factored into an energy model. The key objective is to identify and adjust for those NREs that have a *significant* impact on energy consumption. Figure 1 provides an example time series energy consumption chart for a building, indicating a possible NRE, and also illustrates the extent of normal ‘noise’ in the data that may not be significant enough to warrant adjustment of savings estimates.

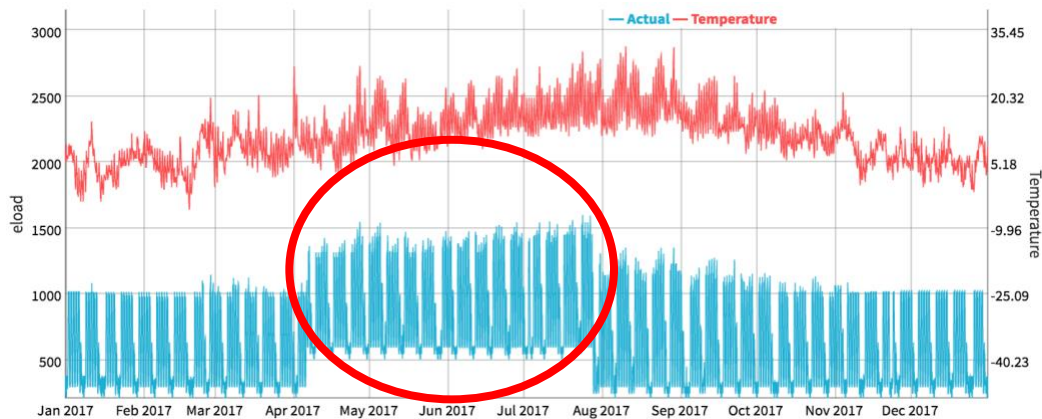


Figure 1: Sample data of approximately one year of metered electric load data (blue), and outside air temperature (red); the change in load between April to August does not appear to be correlated with weather, and could indicate the presence of an NRE

NREs may be characterized as temporary or permanent, as load is added or removed, and as having a constant or variable impact on load (Granderson et al. 2019). Energy efficiency industry methods to conduct non-routine adjustments are currently manual and not standardized. These methods span a variety of solutions that rely upon site audits, surveys and interviews, and inspection of system-level data should it be available. System-level data could include building heating, ventilation and air-conditioning, lighting and security systems. There are a number of different guidelines that offer steps to handle non-routine adjustments within the M&V process (BPA 2018, CPUC 2020, EVO 2012, and Southern California Edison 2017, for example). However, these highly manual methods are not economical at scale and would likely produce inconsistent results due to their manual nature.

While existing guidance focuses on highly manual approaches, there is some emerging work on more data-driven analytical approaches to NRE identification and adjustment. Tools like the cumulative sum (CUSUM) chart monitor the accumulation of savings relative to baseline conditions, and can provide an indication of potential NREs (See Figure 2 for an example). While the use of CUSUM charts for NRE identification has been demonstrated at pilot scale (Crowe et al. 2019, Wallace and Greenwald 2007), they still require manual visual review, and the extent to which they could be applied across a range of efficiency measures and building types for this purpose has not been studied.

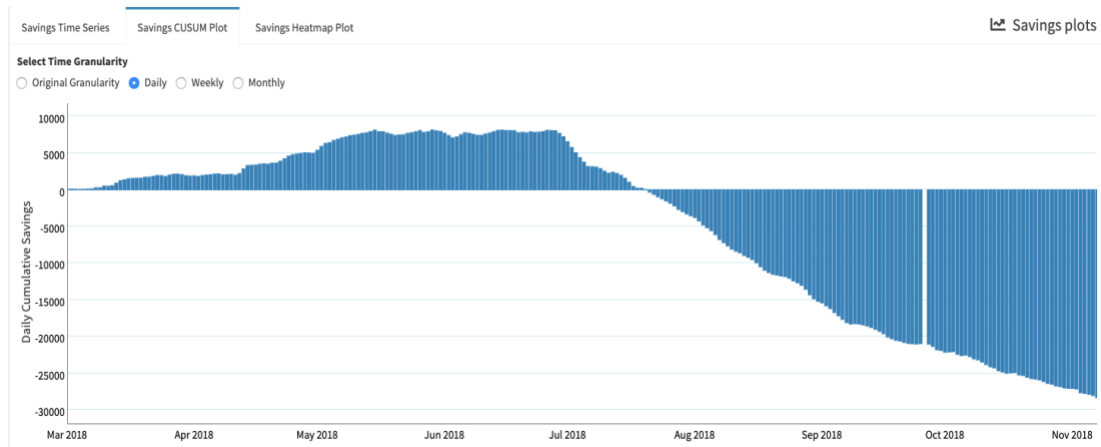


Figure 2. Example CUSUM chart for an efficiency project reporting period, with changes in gradient indicating potential NREs in May and July

In recent work, Touzani et al. developed a statistical approach to change detection in the savings time series (Touzani et al. 2019). Change points were defined as those points in the savings time series where a change in the statistical properties were observed. The approach assumed that if there is no NRE the difference in the behavior of the baseline and reporting period energy consumption time series is stable. When there is an NRE, the difference in behavior between baseline and reporting period is estimated using a proximity measure known as a dissimilarity index. This work also introduced a data-driven NRE adjustment methodology. These data-driven identification and adjustment methods showed promise as early steps toward more automated approaches, though it is noted that the methods were applied to simulation-generated data that is by nature less subject to data noise.

To further explore the potential of observing patterns in interval energy use data, SBW Consulting explored techniques to indicate the presence of NREs (SBW Consulting 2019). The exploration of data yielded groups of data anomalies that could indicate NREs, but on further investigation they found that the occurrence of significant NREs were small.

Goldberg et al. analyzed both residential and commercial data sets to test and refine methods to detect NREs (Goldberg and Mahone 2019). Their research tested two analytical methods using actual consumption data from both program participants and general populations, as well as actual data with simulated events. Their results indicate that both a relatively simple (F-Test) and a more sophisticated approach (based on Touzani et al. 2019) can generally detect a large NRE when it occurs. However, these methods also tend to detect apparent NRE in large fractions of actual premises where no known intervention occurred. Goldberg and Mahone also noted that accurately addressing NREs through energy data monitoring requires a mechanism to monitor for a consumption change, guidance on a threshold that triggers a need to adjust for an

NRE, gathering sufficient information and data surrounding the change in static factors, along with ways to account for this change. Static factors are those parameters that are expected to remain unchanged throughout the baseline and reporting periods, which may include occupancy type, operating conditions or activity levels.

Koran and Rushton (Koran and Rushton 2019) found that NREs have the potential to strongly influence savings estimates in some cases. The authors also noted the risk that treatment of NREs may tend to bias savings estimate upwards if analysts had a tendency to increase scrutiny when meter-based savings estimates are significantly lower than expected, and apply less scrutiny if the opposite is true. They also identified that additional guidance is needed for identifying NREs and modifying savings calculations to account for NRE as appropriate.

Analysis

To extend and complement the current state-of-the-art NRE work and address the gaps in published research, an analysis was undertaken to visually inspect AMI meter data to identify consumption patterns that suggest a possible NRE. Once a suspected NRE was visually identified, the characteristics were documented. The dataset included time series meter data of 509 commercial buildings, with 24 months of data that was divided into 12 months of year 1 and 12 months of year 2 data with no known measures installed in either year. Data with no known measures was selected to extrapolate effects due to other non NRE related changes. The main goals of the visual inspection were to:

- a. Identify consumption profiles indicative of an NRE, distinct from noise (i.e., routinely varying factors or non NRE related anomalies); and
- b. Quantify the frequency, nature and direction of NREs.

For the purposes of standardization and repeatability, it is important to develop a repeatable procedure for a suspected NRE to be identified. For the purposes of this paper, when the following consumption patterns were present in the AMI time series year 2 data, a suspected NRE was documented:

- a. The energy consumption load profile had a step change up or down in year 2 for a given meter's data;
- b. There was a gradual increase or decrease in the energy consumption load profile over a period of a few weeks to a month and then the energy consumption returned to its previous level;
- c. The energy consumption load profile was scaled up by a factor and then returned to a previous level;

After a suspected NRE was identified as described above, the year 1 time-series data was inspected to check if the same energy consumption load profile patterns were observed in year 1. If a similar consumption pattern was observed, it would indicate that it was not an irregular event and the site was therefore not considered to have experienced an NRE. For example, educational institutions often show a step down in energy consumption through the summer months; this type of consumption characteristic is not classed as an NRE within the scope of this study.

Findings

In this section we present findings of the visual inspection of the AMI meter data. Figures 3-9 display examples of the time series of the year 2 data at hourly granularity and the corresponding suspected NREs that were documented. In these figures, the top plot indicates normal operations in blue and the temperature in red, and the suspected NRE in a red circle. A summary of these characteristics observed in the NREs is given below:

- *Frequency:* A total of 151 suspected NREs were identified and documented in the sample dataset (n=509).
- *Nature:* Of the suspected NREs, 58% (n=87) lasted for less than two weeks, 13% (n=21) lasted between two weeks and one month, 22% (n=33) lasted between one and three months and 7% (n=10) lasted for more than three months.
- *Direction:* 56% (n=85) suspected NREs had a decrease in energy consumption during the event, while 44% (n=66) showed an increase in consumption.

Examples of some of the suspected NREs identified are shown in the figures 3-6. Figure 3 shows an example where the NRE lasted for less than one week before resuming to a regular consumption pattern.

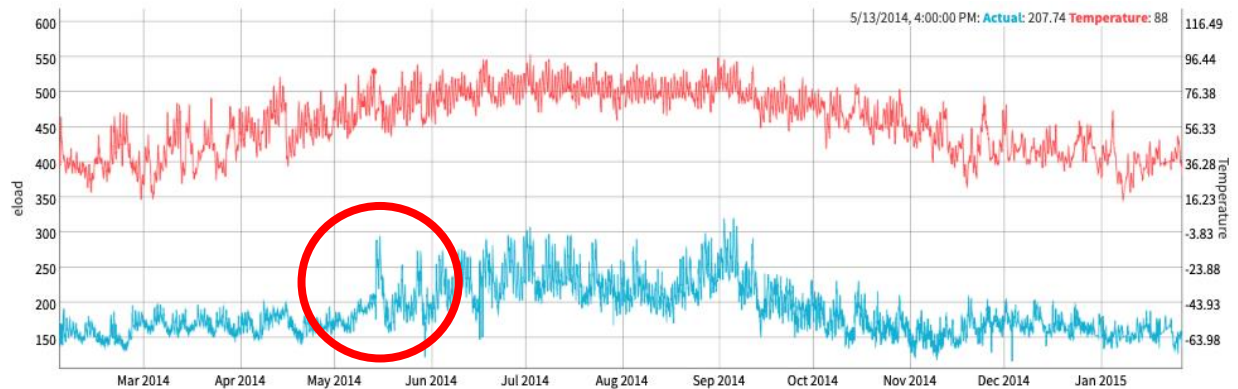


Figure 3: Example of a suspected NRE showing a step change up in energy consumption and lasting for less than a week.

Figure 4 shows an example where a single NRE lasted for up to a month with a step change down in energy consumption before resuming to a regular consumption pattern.

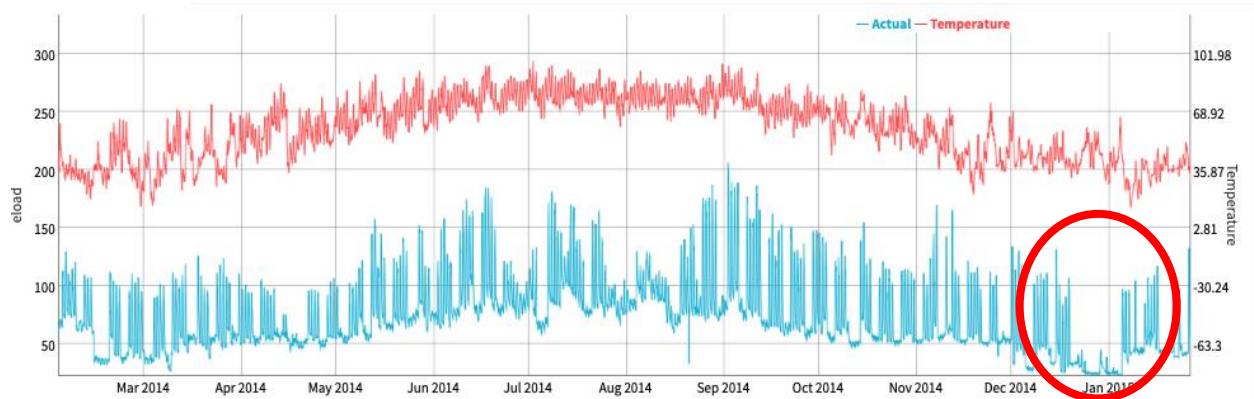


Figure 4: Example of a suspected NRE showing a step change down in energy consumption and lasting for up to a month.

Figure 5 shows an example where there was a gradual change down in the energy consumption during the NRE and it lasted for less than a month before resuming a consumption pattern that was scaled lower.

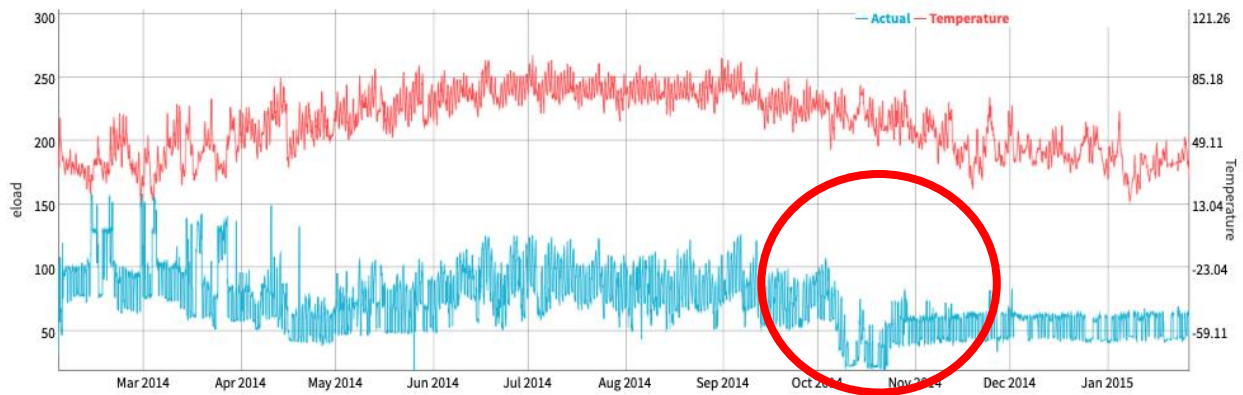


Figure 5: Example of a suspected NRE showing a gradual change down in energy consumption and lasting for up to a month.

Finally, figure 6 shows an NRE that lasted between 1 and 3 months. In cases where a suspected NRE was detected by visual inspection in the year 2 data and when the consumption pattern was the same in year 1, the site was considered a non-NRE.

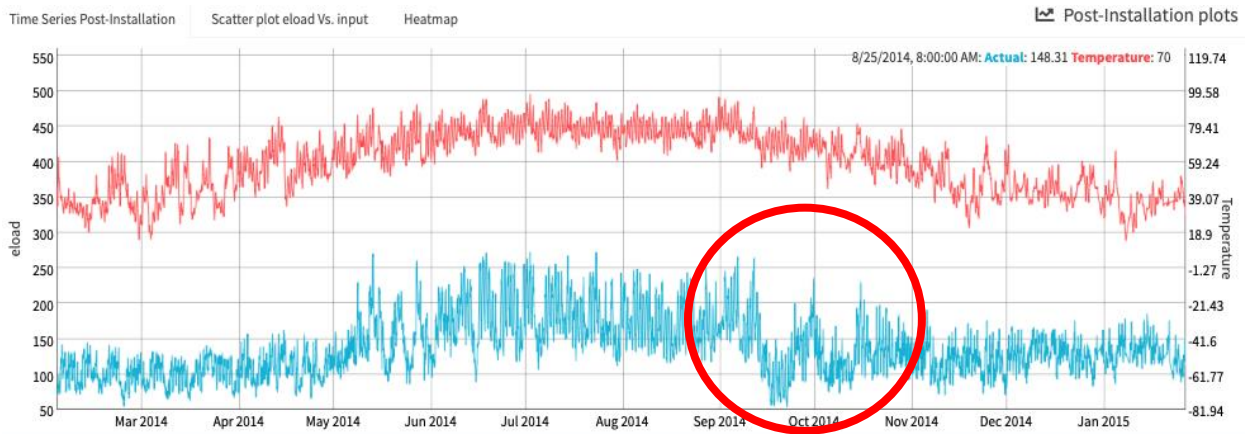


Figure 6: Example of a suspected NRE showing a gradual change down in energy consumption and lasting between 1 and 3 months.

Adjusting Savings Estimates in Response to NREs

There are several non-routine adjustment approaches that may be adopted to determine the impacts of NREs, including engineering calculations and statistical based or simulation-based models. Methods documenting NREs in existing literature are summarized below.

1. **Statistics-based models:** To account for the effects of the NRE, BPA’s MT&R guidelines (BPA 2018) outline the utilization of an existing baseline model, with the addition of an “indicator variable” placed in the data set at the time of the change. The impact of the change is thereby quantified by solving for the indicator variable coefficient using regression, following a suitable data collection period. BPA’s Potential Analytics for Non-Routine Adjustments outlines the following four statistics-based approaches to quantifying the impact using a model (BPA 2019).
 - a. Analyzing the time series data of residuals for a model that includes the time period of change and estimate the magnitude of the change from the change in the residuals;
 - b. Developing pre-post model with a ‘mini baseline’ and ‘mini post’ period. The pre-post model uses an indicator variable for the mini post period, and the coefficient on the indicator variable is the NRE impact.
 - c. For a change of longer duration, especially one that is ongoing through the time period, treat the time periods around the non-routine change as a mini baseline and a mini post period, and model the change by subtracting the mini post period energy use from an adjusted baseline developed from the mini baseline period. This can be done using either a forecasting or backcasting approach, depending upon which mini period has better coverage for the independent variables.
 - d. For a temporary NRE of relatively short duration, modeling the entire period excluding the portion of the period that includes the non-routine change. Use this model in conjunction with the independent variable(s) for the times that include the non-routine change to estimate energy use for the entire period as if the non-routine change had not occurred. Subtract this estimate from the actual energy use for the period to estimate the impact of the change.

Touzani et. al also propose a statistical methodology for NRE adjustment that involves the NRE detection algorithm, M&V practitioners' knowledge and a regression model (Touzani et al. 2019)

2. Sub-metering-based approaches: According to ASHRAE (ASHRAE 2014), the most straightforward and possibly easiest way to account for the changes due to an NRE, is to submeter the effect of any addition to the structure, operation or use of the facility. However, this method will come with its own set of challenges because installing submeters in a building may be time-consuming and costly, and may extend M&V time frame. However, it may be suitable for permanent added or removed load that is not variable.
3. Calculation based approaches: An industrial SEM program impact evaluation report recommends non-routine adjustments during the baseline or reporting period energy consumption be made using an engineering estimate (BPA 2017). This approach can vary widely in complexity. The comprehensive methods are typically hourly models to calculate facility's energy consumption by factoring in external climate conditions, facility construction, operation, and HVAC equipment, and other inputs. On the other hand, simplified methods are more localized approaches based on aggregate models where the energy consumption of a system or a subsystem is calculated based on engineering principles, with certain reasonable assumptions.
4. Simulation based approaches: These approaches are also based on engineering principles built on elaborate physical functions or thermal dynamics to precisely calculate the energy consumption for the whole building level or for sub-level components. Since these are very intricate and detailed models, they employ commercially available software. Building these models and running the analysis involve specialized skills and can be resource intensive. Calibration of such a model may also be challenging if the energy data for that calibration includes NRE periods.

DISCUSSION

There is a clear lack of useful real-world data on the topic of NREs and the risk they pose to savings estimation. While we have tried to provide examples of suspected NREs from real world data and attempted to identify their characteristics, further data on the statistical properties of the types of the NREs would be really useful. While visual inspection methods were used to address certain research questions on the characteristics of NREs, they may not be a scalable solution. In addition, it would be useful to correlate the NREs observed from the data with actual information about what occurred at each of the sites. This data could be sourced directly from programs and participants, in order to provide more accurate information to inform adjustments. More case studies with that kind of information would be a valuable resource for informing savings accuracy and uncertainty. In addition, PAs should require monitoring for NREs and implementers should facilitate the process of logging them, with the goal of minimizing introduction of new steps in work flow, e.g., use existing facility management systems such as work orders and invoice tracking.

At a basic level it is not too cost prohibitive to monitor for NREs if AMI meter data is available. Establishing visual inspection rules to identify some patterns that indicate the presence of an NRE could be used to identify NREs. This does not require the development of complex

modeling techniques, but only ongoing data collection and inspection. If AMI meter data is not available and meters need to be installed, or if NREs need to be detected and adjusted for a large population of buildings at a program level, it could be cost prohibitive. In addition, the cost relates to how often you decide to check the data. Making NRE detection and adjustment at a population level cost effective is a future area of research that would require newer methods. Large scale shutdowns like those occurring during the COVID-19 pandemic between March and June 2020, could be used to gather data for studying occupancy-related NREs further. In such an instance, the NRE is known and more quantifiable and the data could be used for research on treatment and adjustment methodologies.

Looking at certain characteristics of NREs such as those defined and identified in this study could be a good way towards further industry standardization of NRE detection and adjustment. These characteristics could be used to determine a trigger threshold for taking action on an NRE. If defined accurately, the rules defined to visually inspect the consumption patterns to identify a NRE could be used to take an action, for instance, if the step down change in energy consumption pattern lasts more than a week, the site could be inspected and adjustment procedures initiated if the presence of an NRE was verified. However, if performing a visual inspection, the role of PAs becomes even more important in verifying and validating the NRE. While the summary statistics of the defined NRE characteristics may differ in other sample datasets, there is value can be extracted from each of these characteristics for PAs and M&V practitioners. Characteristics such as the frequency and nature of the NRE could be used to distinguish them from acceptable data noise. Prior work has shown an automated statistical change point algorithm to be oversensitive (Touzani et al. 2019). Visual inspection of NRE coupled with an automated algorithm can help reduce the high number of false positives detected by the algorithm alone.

The rate of NREs detected in this study (29.5%) is comparable to those identified as part of the small-sample advanced M&V pilot reported by Crowe et. al (34.5%) (Crowe et al. 2019). However, additional guidance is needed to understand what approaches to use given the specific case of NRE and when it occurred so that the costs and savings uncertainties are balanced. A key step in this adjustment process is to determine whether the impact of the event is material e.g a utility program regulator may define policies for acceptable levels of error in savings claims that merits quantification and adjustment. This involves establishing some kind of threshold for what is considered ‘material’, so only the “correct” NREs are addressed. More research needs to be done on how these existing approaches for determining the uncertainties can be used towards developing a more specific guidance for the M&V practitioners.

CONCLUSIONS AND FUTURE RESEARCH

NRE detection is not trivial, given continuous changes in a building load profile due to many different factors. Standardizing the definition of what load profile should be normal and what should be an NRE is an important step for the industry to gain deeper understanding of how to deal with NREs. Developing more examples of real-world datasets and the rules used to characterize the NREs could significantly help in this effort to standardize NRE detection.

This paper documented the state of the art in NRE quantification and analysis. The paper characterized the frequency, nature and direction of NREs based on visual inspection, explored

questions around determining trigger thresholds for taking action on NREs, and also documented the latest technical guidance on application of NRE detection and adjustment methods.

Programmatically, there is a need to define standardized NRE detection/adjustment approaches and the characteristics of NREs such as frequency, nature and direction could play a role in helping to develop standardization. While this research offers some rules to define an NRE in an energy consumption time series, further research is needed to define standard consumption patterns that could reveal the presence of an NRE more accurately. Research and guidance are needed to establish a process to calculate these thresholds to identify if the adjustment is warranted by taking into account the baseline energy consumption, savings and model uncertainty. Irrespective of what approach is used to detect and quantify these adjustments, there is inherent uncertainty that need to be assessed.

Suggested future research includes work to correlate the NREs observed from data with actual information about what may have occurred at each of the sites, for a large data set. Programs such as Strategic Energy Management (SEM) could be used for testing such an approach as SEM participants document the information as part of the program participation process. This data could be sourced directly from programs and participants, in order to provide more accurate information to inform adjustments. In addition, research to quantify the impacts of NREs across a large data set (possibly using several adjustment methods) would be very useful for informing discussions around trigger thresholds for adjustments, and would deepen the understanding of frequency and magnitude of NREs.

Acknowledgement

This work was supported by the Assistant Secretary for Energy Efficiency and Renewable Energy, Building Technologies Office, of the U.S. Department of Energy (DOE) under Contract No. DE-AC02-05CH11231. The authors would like to thank Sarah Zaleski from DOE for her support of this work.

References

ASHRAE. 2014. “*ASHRAE Guideline 14-2014, Measurement of Energy and Demand Savings.*” American Society of Heating Refrigeration and Air Conditioning Engineers, 2014, ISSN 1049- 894X.

Bonneville Power Administration (BPA). 2017. “*Industrial Strategic Energy Management Impact Evaluation Report.*” https://www.bpa.gov/EE/Utility/research-archive/Documents/Evaluation/170222_BPA_Industrial_SEM_Impact_Evaluation_Report.pdf

Bonneville Power Administration (BPA). 2018. “*Monitoring Targeting and Reporting (MT&R) Reference Guide.*” <https://www.bpa.gov/EE/Policy/IManual/Documents/MTR-Reference-Guide-Rev7.pdf>

Bonneville Power Administration (BPA). 2019. “*Potential Analytics for Non-Routine Adjustments.*” <https://www.bpa.gov/EE/Policy/IManual/Pages/IM-Document-Library.aspx>

California Public Utilities Commission (CPUC). 2020. “*Rulebook for Programs and Projects Based on Normalized Metered Energy Consumption.*”
<https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442463694>

Crowe, E., Granderson, J., Fernandes, S. 2019. “*From theory to practice: Lessons learned from an advanced M&V Commercial Pilot.*” International Energy Program Evaluation Conference 2019.

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

Gold, R., Waters, C., & York, D. 2020. “*Leveraging Advanced Metering Infrastructure to Save Energy.*” <https://www.aceee.org/sites/default/files/pdfs/u2001.pdf>

Goldberg, M. L., Mahone, T. 2019. “*Can the Non-Routine become Routine? Dealing with Non-Routine Events in Normalized Metered Energy Consumption Analysis.*” In proceedings of the 2019 International Energy Program Evaluation Conference.

Granderson, J., Greundling, P., Torok, C., Jacobs, P., Gandhi N. 2019. “*Site-Level NMEC Technical Guidance: Program M&V Plans Utilizing Normalized Metered Energy Consumption Savings Estimation.*” <https://www.cpuc.ca.gov/WorkArea/DownloadAsset.aspx?id=6442463695>

Hawkins, D. M., Qiu, P., and Kang, C. W. 2003. “*The changepoint model for statistical process control*”, Journal of Quality Technology, 35(4), pp. 355–366.

Killick, R., Eckley, I. 2014. “*Changepoint: An R package for changepoint analysis.*” Journal of Statistical Software, 58(3), pp.1-19.

Koran, B., Rushton, J. 2019. “*Reliability of energy savings estimates based on commercial whole building data*”. <https://rtf.nwccouncil.org/meeting/rtf-meeting-may-21-2019>

Molina, M., Nowak, S., Kushler, M. 2017. “*Evolution of EM&V: State experience that looks to the future.*” In proceedings of the 2017 International Energy Program Evaluation Conference.

Pearce, E., Dearth, F., Schantz, M. 2018. “*Getting Ahead of the Savings Curve: Utility Pay-For-Performance Program Design for Commercial Real Estate Customers.*” In proceedings of the 2018 ACEEE Summer Study on energy Efficiency in Buildings.

SBW Consulting Inc. 2019. “*PG&E Commercial Whole Building Demonstration Early M&V Report*”. Pacific Gas and Electric Company.

Southern California Edison. 2017. “*Normalized Metered Energy Consumption Savings Procedures Manual.*” <https://www.etcc-ca.com/reports/normalized-metered-energy-consumption-savings-procedures-manual>

Touzani, S., Ravache, B., Crowe, E., and Granderson, J. 2019. “*Statistical Change Detection of Building Energy Consumption: Applications to Savings Estimation.*” *Energy and Buildings*, 185, pp. 123–136

Touzani, S., Granderson, J., & Fernandes, S. 2018. “*Gradient boosting machine for modeling the energy consumption of commercial buildings*”. *Energy and Buildings*, 158, 1533-1543.

Wallace, K., & Greenwald, R. 2007. “*Monitoring, Targeting and Reporting: a Pathway to Continuous Improvement in Energy Management.*” *Proceedings of ACEEE Summer Study in Energy Efficiency in Industry.*