Lawrence Berkeley National Laboratory
Environmental Energy Technologies Division **Behavior Analytics**
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Insights from Smart Meters: The Potential for Peak-Hour Savings from Behavior-Based Programs

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June 2014

behavioranalytics.lbl.gov LBNL 6598E

Acknowledgments

The U.S. Department of Energy funded this document to support the State and Local Energy Efficiency Action Network's Customer Information and Behavior (CIB) Working Group. The working group is co-chaired by Rebecca Wagner, Nevada Public Utilities Commission and Lisa Schwartz, Oregon Department of Energy. The federal staff leads for the Working Group are Michael Li, U.S. Department of Energy and Stacy Angel, U.S. Environmental Protection Agency.

This report was prepared with highly valuable input, direction and comment by members of the CIB Working Group and other technical experts, including: Jim Stewart, Susan Mazur-Stommen, Rebecca Wagner, Lisa Schwartz, Patrick Wallace, Aimee Savage, Brian Urban, Abigail Daken, Alex Orfei, Anne Dougherty, Ram Narayanamurthy, Nicholas Payton, Nick Lange, and Richard Caperton.

The work described in this report was supported by the U.S. Department of Energy's Office of Energy Efficiency and Renewable Energy (DOE EERE) under Lawrence Berkeley National Laboratory Contract No. DE-AC02-05CH11231.

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This document was final as of June 2014. If this document is referenced, it should be cited as:

Todd, A., M. Perry, B. Smith, M. Sullivan, P. Cappers, and C. Goldman. 2014. *Insights from Smart Meters: The Potential for Peak Hour Savings from Behavior-Based Programs.* Lawrence Berkeley National Laboratory, LBNL-6598E. http://emp.lbl.gov/publications/insights-smart-meters-potential-peak-hour-savings-behavior-based-programs.

Table of Contents

Smart Meter Data: the Opportunity

The rollout of smart meters in the last several years has opened up new forms of previously unavailable energy data. Many utilities are now able in real-time to capture granular, household level interval usage data at very high-frequency levels for a large proportion of their residential and small commercial customer population. This can be linked to other time and location-specific information, providing vast, constantly growing streams of rich data (sometimes referred to by the recently popular buzz word, “big data”). Within the energy industry there is increasing interest in tapping into the opportunities that these data can provide.

What can we do with all of these data? The richness and granularity of these data enable many types of creative and cutting-edge analytics. Technically sophisticated and rigorous statistical techniques can be used to pull interesting insights out of this high-frequency, human-focused data. We at LBNL are calling this “behavior analytics”. This kind of analytics has the potential to provide tremendous value to a wide range of energy programs.

For example, highly disaggregated and heterogeneous information about actual energy use would allow energy efficiency (EE) and/or demand response (DR) program implementers to target specific programs to specific households; would enable evaluation, measurement and verification (EM&V) of energy efficiency programs to be performed on a much shorter time horizon than was previously possible; and would provide better insights in to the energy and peak hour savings associated with specifics types of EE and DR programs (e.g., behavior-based (BB) programs).

In this series, “Insights from Smart Meters”, we will present concrete, illustrative examples of the type of value that insights from behavior analytics of these data can provide (as well as pointing out its limitations). We will supply several types of key findings, including:

- **Proof-of-concept analytics techniques** that can be adapted and used by others;
- **Novel discoveries** that answer important policy questions; and
- **Guidelines and protocols** that summarize best practices for analytics and evaluation.

The goal of this series is to enable evidence-based and data-driven decision making by policy makers and industry stakeholders, including program planners, program designers, program administrators, utilities, commissioners, regulators, and evaluators. This series is one of the products we are employing to achieve this goal.

Focus on: The Potential for Peak Hour Savings from Behavior-Based Programs

This report focuses on one example of the kind of value that analysis of this data can provide: insights into whether behavior-based (BB) efficiency programs have the potential to provide peak-hour energy savings. This is important because there is increasing interest in using BB programs as a stand-alone peak reduction program, as well as integrating behavior-based strategies into residential incentive-based demand response (DR) programs and time-based retail rates as a way to augment peak hour energy savings.

There are many studies that use hourly data estimate the hour-by-hour savings from time-based rate or load control programs, and many studies that use billing data to estimate the annual or monthly energy savings from BB programs.[1] However, few, if any, studies have looked at the hour-by-hour savings from BB programs.[2] The potential for BB strategies as a peak hour energy savings resource is therefore currently largely unknown. Estimating the hour-by-hour savings can help identify whether households in BB programs are saving energy when the energy savings are most valuable (i.e., during peak hours), or if the savings are occurring primarily during off-peak hours.

ANALYTICS TECHNIQUES

Data from smart meters allow us to determine when during the day households are actually saving, through rigorous estimation of hour-by-hour energy savings.

Why does this matter?

If these programs result in peak hour energy savings, and hourly interval data is available to precisely and credibly estimate these savings, then load forecasts can be improved to more accurately represent the impacts of these programs on actual usage. As such, these programs can help utilities by:

- **Reducing short-run supply costs through avoided energy** *by reducing the quantity of energy procured either through forward contracts or spot market purchases;*

[1] There are many examples; we only list a few here. For an example of hourly savings estimates from a control load program, see Freeman, Sullivan & Co. (2012). For an example of hourly savings estimates from a time-based rate program, see SMUD (2013) or EPRI (2011). For an example of monthly and annual savings estimates from a BB program, see KEMA (2010).

[2] Stewart (Work in progress, 2013) examines the peak-coincident demand savings from behavior-based programs.

- **Reducing long-term capital expenditures through avoided capacity** *by deferring investments in infrastructure needed to otherwise meet additional peak demand in order to maintain a reliable system, if these savings are shown to persist over time; and*
- **Increasing the cost effectiveness of these programs** *by helping program administrators to more successfully plan for and achieve peak savings goals at lowest cost.*

KEY RESULTS

Our analysis shows an example of a BB program that provides:

- **Savings during every hour**
- **Disproportionally high savings during peak hours**
- **Disproportionally high savings during high system peak days**

We use data from one particular program rollout as a test-case: we draw upon electricity data from the Pacific Gas & Electric (PG&E) AMI system to analyze the hour-by-hour impacts of a Home Energy Reports (HERs) behavior-based program.

HERs are letters that are mailed to households on a monthly or bi-monthly basis. The letters provide information about the household's own energy use in addition to how their energy use compares to their neighbors. The letters also include some energy savings tips. These programs are designed as randomized controlled trials (RCTs): households are randomly assigned to either the treatment group that receives the letters, or the control group that does not. A well-designed RCT is the "gold standard" of program evaluation design, and thus allows us to produce valid and unbiased estimates of the energy savings during each hour.[3]

We analyze hourly interval electricity consumption data for one particular HER program pilot rollout (called "Wave One" by PG&E). It includes 500,000 households in the top three quartiles of energy use, drawn from most geographic regions in PG&E's service territories.[4] Although it was not a full scale rollout, this large-scale pilot may be representative of households targeted

[3] Although RCTs are the main component of producing valid energy savings estimates, there are many other factors that also matter; see "Evaluation, Measurement, and Verification (EM&V) of Residential Behavior-Based Energy Efficiency Programs: Issues and Recommendations."

[4] There were also two additional pilot "waves" of HERs that went out to different portions of the PG&E residential population previous to Wave One: Beta Wave and Gamma Wave. Wave One was the most representative of what a full scale HER program rollout would be. The Gamma Wave includes fewer households (~150,000), in all quartiles of energy use in a smaller geographic region, and the Beta Wave includes even fewer households (~120,000) in only the top quartile of energy use in an even smaller geographic region. For other reports we will use other data.

in a full scale rollout.[5] The PG&E rollout began on February 2012, but only three months of data were made available for this analysis: August 1st - October 31st 2012. This period includes 6 of the 10 highest hourly consumption levels of 2012.

We provide a prototype for analysis and insights from this test-case. We use it to develop analytical techniques for estimating hourly savings patterns (heretofore untried in this context), and provide novel results with some very interesting insights that answer questions the industry was previously unable to address. However, because these are some of the first results looking at hour-by-hour electricity savings patterns from BB programs, and because we only have data from one utility (with a limited set of data), replication of these results needs to be performed in order to draw more definitive widespread conclusions about the impacts of BB programs on peak hour electricity consumption in different regions of the country.

[5] A full scale rollout would likely also exclude the lowest energy use households because they typically yield lower savings that may not result in a cost-effective program offering to such customers.

Key Findings: Insights from the data

Previous to the rollout of smart meters, monthly utility billing data was used to estimate monthly and annual energy savings for BB programs. Without higher-frequency electricity consumption data, it was it was not possible to determine when during the day that these savings occurred. The analysis in this report is the one of the first to estimate the hourly profile of these savings.

New types of analysis enabled by investments in smart meters AMI allow us to examine hourly patterns of electricity usage and savings by customers participating in BB programs and perform statistical tests of whether savings during peak hours are higher than other hours. We employed a regression technique that compares the electricity use of the treatment group to the electricity use of the control group jointly for each hour of the day.[6] In addition, we used similar techniques to estimate the savings during all of the peak hours (which allows us to test whether or not the peak hours showed savings that were statistically significantly higher than savings during other hours), and the savings on the highest system peak days.

New kinds of results from the hour-by-hour electricity savings estimates are shown in Figure 1 (along with the 95% confidence intervals). The savings are shown with three different scales: first, *kWh savings* (left-hand y-axis on the top graph); second, *normalized savings* (right-hand y-axis on the top graph) as a percent of the total average energy usage of the control group across all hours (in order to give a sense as to how large the kWh savings are); and third, *proportional savings* (y-axis on the bottom graph) as a percentage of each hour's average energy usage for the control group (in order to show the proportional savings relative to the energy consumed for each hour).

[6] More details about the analysis specification are in the Appendix. We used difference-in-averages estimators with dummy variables that indicated treatment during each hour of the day. To account for correlation within customers but across days and hours, the standard errors are robust and clustered at the household level. Because of computing limitations, we maintained unique observations for each customer, but we aggregated all weekday data within a week for each hour, so that there were 24 hourly observations per week for each customer. To test peak vs. off peak, we used a similar approach but with dummy variables that indicated treatment during peak hours.

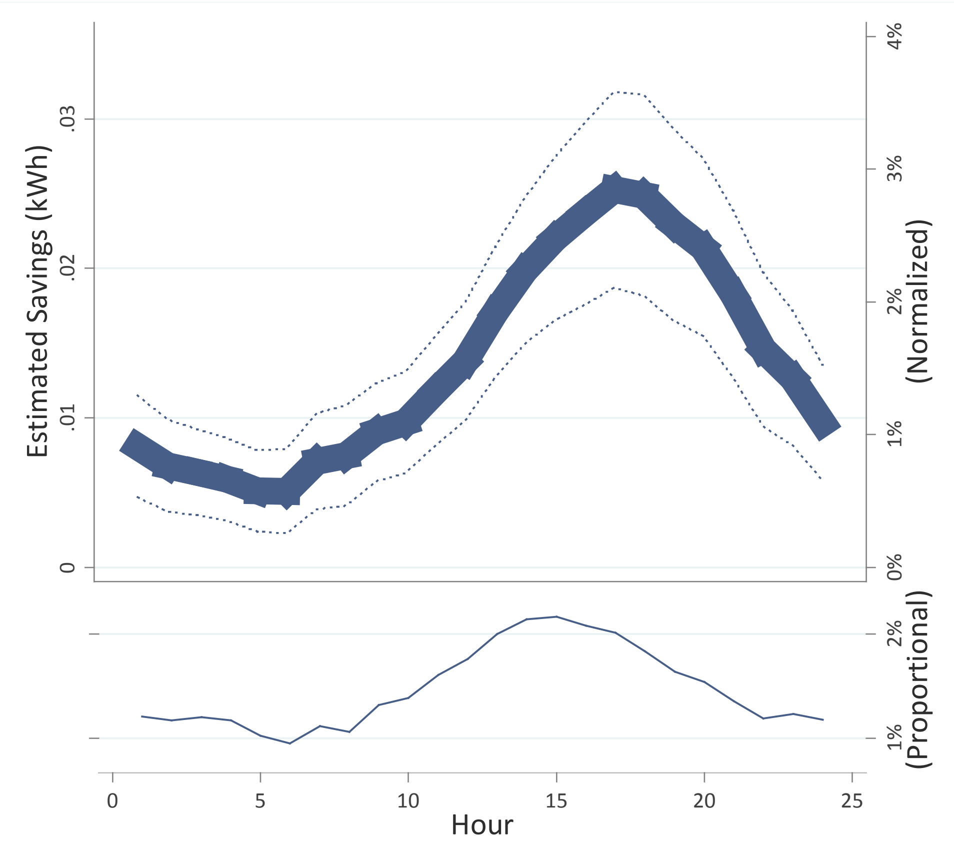

Figure 1. Hour-by-hour electricity savings

For analysis of the particular program rollout that we are using as our test-case (shown in Figure 1), we find:[7]

- **Statistically significant electricity savings during every hour;** the savings average 0.014kWh per hour per household, or around 2% of total energy consumption
- **Higher kWh savings during peak hours;** the average savings during peak hours are more than double the savings during off-peak hours (0.023kWh savings per hour per household for on-peak versus 0.010kWh for off-peak), and
- **A higher percentage of savings during peak hours, relative to the energy usage in each hour.**

These results show that this pilot program rollout resulted in savings that are higher during peak hours. It is particularly interesting because the savings disproportionately *increase* during

[7] Electricity savings during each hour are statistically significant. Peak savings vs. off-peak kWh savings are statistically significantly different. Results and standard errors for all analyses are shown in the Appendix.

the peak hours. Without hourly data, one assumption that was commonly used (based on anecdotal evidence) was that this was not the case; that either the savings are spread out evenly in proportion to the electricity usage, or that savings are actually harder to achieve during peak hours.

Figure 2 displays hour-by-hour savings, but for only the ten highest and ten lowest system peak days included in our dataset. The X and Y-axis scales are similar to the previous graph: first, *kWh savings*; second, *normalized savings* as a percent of the total average energy usage of the control group across all hours; and third, *proportional savings* as a percentage of each hour's average energy usage for the control group during the ten highest and ten lowest system peak days. For reference, Figure 2 also includes the savings during all days from Figure 1.

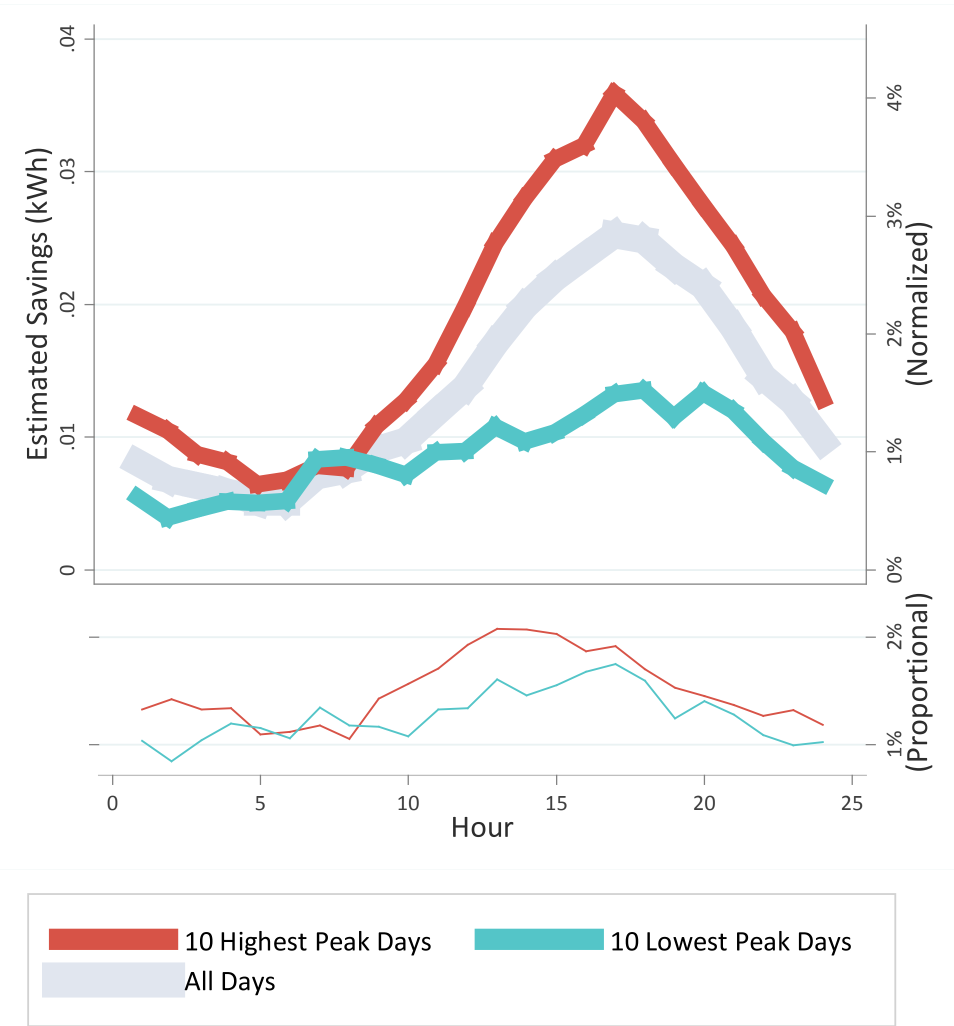

Figure 2. Hour-by-hour savings for the 10 highest and 10 lowest system peak days

Figure 2 shows additional key findings: [8]

- **Higher peak savings during the ten highest system peak days;** average peak-hour savings during the ten highest days are more than three times as much as during the ten lowest days (0.033kWh peak-hour savings per hour per household for the highest days versus 0.012kWh for the lowest), and
- **Slightly higher proportional peak savings during the ten highest system peak days**

Together with the findings from Figure 1, this implies that BB programs have the potential to induce electricity savings exactly when they are most needed; the savings are disproportionately high during peak hours on peak days.

[8] Savings during each hour are statistically significant for both the 10 highest and 10 lowest system peak days. Peak savings during high system peak days versus during low system peak days are statistically significantly different. Results and standard errors for all analyses are shown in the Appendix.

Key Finding 1: Proof-of-concept analytics tool

High-frequency data from smart meters enable new forms of analysis techniques that allow us to examine hourly usage patterns and determine when during the day households in BB programs are actually saving. This includes hour-by-hour savings estimates and rigorous peak versus off-peak statistical tests.

Implication: This allows measurement of the effectiveness of BB programs in producing peak-hour savings and improves the prediction accuracy of load forecasts.

Key Finding 2: Novel result

Our results show an example of one rollout of a BB program that provides savings during every hour, with disproportionally high savings during peak hours and during high system peak days.

Implication: BB programs have the potential to provide peak-hour savings, and should be considered as a potential (non-dispatchable) resource for improving short-run reliability. If the peak hour energy savings can be maintained and accurately predicted over time, system planners can assess whether this type of program is treated as a planning capacity resource.

While we show that it is feasible for such BB programs to provide peak-hour savings, these results may be specific to this particular program in this specific situation. Because this is only one example of a BB program that provides peak-hour savings, this does not imply that these results can be generalized and that all BB programs can provide this kind of savings.[9] Until we have a better understanding of what is driving these savings levels and their differences across different populations and under different circumstances, it is not possible at this time to definitively conclude that all BB programs will produce peak hour savings.

[9] In other words, even though the RCT design ensures that the results are *internally valid* (e.g., unbiased for a particular program, with a given participant population and a given time frame) does not mean that the results are *externally valid* (e.g., can be generalized and applied to new populations, circumstances, and future years).

Next Steps & Future Research

In this report, we presented illustrative examples of some of the new types of analyses and valuable insights that smart meter data enable. Using one test-case BB program rollout, we show that BB programs have the potential to provide peak-hour savings.

More research is needed in the future to better understand how BB programs can be considered as a resource capable of providing dependable and predictable peak-hour electricity savings. In order to determine whether this finding is common in all kinds of contexts, this analysis will have to be replicated across many different BB programs, in many different situations and with many different customer populations. In order for system planners to be able to rely on these peak hour savings, this analysis will need to be replicated over time to understand the degree to which these savings are maintained or degrade over time, and to understand if that happens in a predictable manner. In order for utilities to be able to claim capacity credit for these resources, new EM&V protocols would also have to be developed and adopted. Fortunately, the ability to perform this type of analysis and see if the results are replicable across a variety of different BB program offerings should become easier and more commonplace as the availability of AMI data continues to expand.

There are also several other novel types of analyses enabled by smart meter data that might provide additional valuable insights. Savings during peak hours and high system peak days hint at a relationship of temperature to electricity savings; exploring this may help us understand what is driving these savings. Examining the hourly savings over time may allow us to better understand how households respond to BB programs.

This series will continue to explore the kinds of insights which can be pulled from the newly available data captured by smart meters and other sources, and to report our key findings in this series *Insights from Smart Meters*.

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