Faster, Cheaper, Better – Can Utilities Keep Up?
New EM&V and Program Approaches for Smart Connected Devices

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ABSTRACT

A new generation of smart and connected devices promises energy savings, but traditional participant/control group field trials taking 12 to 18 months are not in step with these rapidly evolving software-based products. To keep pace with these smart technologies, we believe it is important for electric utilities to develop methods for measurement and verification (M&V) that use data from Internet-connected systems. This paper explores new M&V approaches, including aggregating vendor's anonymous data sets, post/post analysis approaches, and baseline estimation techniques.

Results from analysis of field data from residential smart thermostats, digital lighting controls, and rooftop unit controllers are presented. Techniques and results for HVAC baseline emulation, survey-based lighting baselines, and thermostat metrics are presented. Issues explored include proprietary data, vendor-biased data, sampling protocols, and potential dramatic time and cost reduction for M&V.

Introduction

Some of the leading examples of the new generation of intelligent, Internet-connected devices include residential smart thermostats, advanced digital lighting controls, and commercial HVAC controllers. These emerging technologies promise energy savings but to date there has been limited verification by third-parties. As the number of installed devices is increasing, there are a number of utility-sponsored field studies in progress exploring both energy efficiency and demand response capabilities. Many of these pilots are using traditional methods for verifying energy savings, including utility whole-building smart meter analysis and end-use sub-metering. A typical experimental approach is to use large randomized field trails with participant and control groups. While these traditional methods can be effective, we believe the related costs and timelines are not the best match for these rapidly evolving, smart, Internet-connected devices.

We further believe there is a key innovation that differentiates these smart, Internet-connected devices***: It is now possible to collect real-time, high-resolution performance data and use this data to measure and improve system performance. This data enables manufacturers to conduct rapid testing and improvement of algorithms and other control features, as well as enabling third-party performance monitoring.***

Our current efforts are focused on development of measurement and verification (M&V) approaches that leverage the self-reporting strength of these connected devices. At Bonneville Power Administration (BPA), our ongoing research is guided by roadmaps in the 2013 National

Energy Efficiency Technology Roadmap Portfolio (pages 352 – 394), specifically: *Smart Device Level-Controls Responsive to User and Environment, Easy/Simple Interface Controls, Energy Management Services, Low Cost Savings Verification Technique.*

Although there is considerable promise for leveraging these connected devices for rapid and low-cost measurement and verification of energy savings, there are some significant challenges, including:

- Ownership and access rights that limit third-party use of data;
- Concerns for personal privacy and intellectual property of service providers;
- Lack of metrics and protocols for savings verification;
- Obtaining baseline data for existing equipment.
- Measurement accuracy of power and energy consumption.

In this paper, we investigate three applications of self-reported data from connected devices: 1) Digital Lighting Controls, 2) Smart Thermostats, and 3) Advanced Roof Top Unit (RTU) Controller. Each of these three trials is described in separate sections below.

Digital Lighting Controls

Background

As the Solid State Lighting (SSL) market expands, new opportunities are becoming available for energy savings with advanced controls. Meta-analysis by Williams et al. (2012) plus recent case studies (Mutmansky and Berkland 2013, Cortese and Scherba 2013) indicate that deep energy savings are available from lighting controls, but results vary broadly with product functionality, commissioning and application. In addition, the performance of software-based products can change over time—positively with software upgrades and continuous commissioning, or negatively with manual overrides. In order for utilities to promote products such as this with variable energy savings, accurate data is needed about energy performance.

BPA's research need is to quantify energy savings from digital lighting control systems. We would like to know which control functions and which products provide reliable and quantifiable savings. The traditional approach for this research, and for site-based M&V to support performance-based incentives, would use electric submeters to monitor each luminaire or each lighting circuit. This "Digital Lighting Controls" section of this paper explores vendor-reported data as an alternative to submeters, to evaluate energy savings from networked lighting control systems.

Methods

Before embarking on a research proposal to spend 3 years and over $300,000 on a few conventional submetered case studies of lighting control systems, BPA contacted some manufacturers of networked lighting controls, to explore the potential for collecting data to augment or replace data from case studies. Digital Lumens promptly responded with an anonymized spreadsheet with data from sites with their LightRules software application, a web-based system for industrial facility managers to manage their lighting.

The data from each site included fixture count, % occupancy detected for a month, kWh usage for a month, building type, etc. No data was included for time intervals of less than or more than a month. Prior controls, if any, were not described. Additional data describing the wattage of each new fixture was provided upon request for most sites. The average new fixture wattage from those sites, 163 Watts, was used to estimate the fixture wattage at remaining sites.

At BPA, the baseline installed wattage for a typical retrofit incentive project is estimated using the fixture count and the nominal lamp wattage of each fixture. For large or research projects, more accurate estimates are based on measured wattage. For this study, nominal baseline wattage data was available for 10 of 36 sites. For these 10 sites, the average reduction in installed wattage by the LED lighting retrofit was 58%.

Additional analysis focused on lighting controls, rather than installed wattage. To analyze the performance of controls, a baseline is needed for Hours of Use (HOU). For BPA's new performance-based incentive for advanced lighting controls, a site-specific baseline HOU is estimated with a site survey (RTF 2014). Alternatively, at some networked lighting control sites, the advanced control functions are disabled during the first few weeks of operation, to capture a site-specific baseline HOU. For this study, the baseline HOU was assumed to be the site-specific operating hours at each of 9 sites, with an average of 139 hours per week (range from 105 to 168 hours). For the remaining sites where no operating hours were specified, the baseline HOU was estimated from a national survey of comparable buildings (Ashe et al, 2012): 78 hours per week for storage and misc. commercial, and 91 hours per week for manufacturing. The national HOU data was collected more than 10 years ago, and is lower than the HOU reported at the 9 sites.

Results

The dataset was analyzed for 3 applications: storage, manufacturing, and miscellaneous. Histograms are shown for occupancy and for energy savings from controls. Additional energy savings from fixture wattage reduction (average 58%, range from 37% to 65%) are not shown.

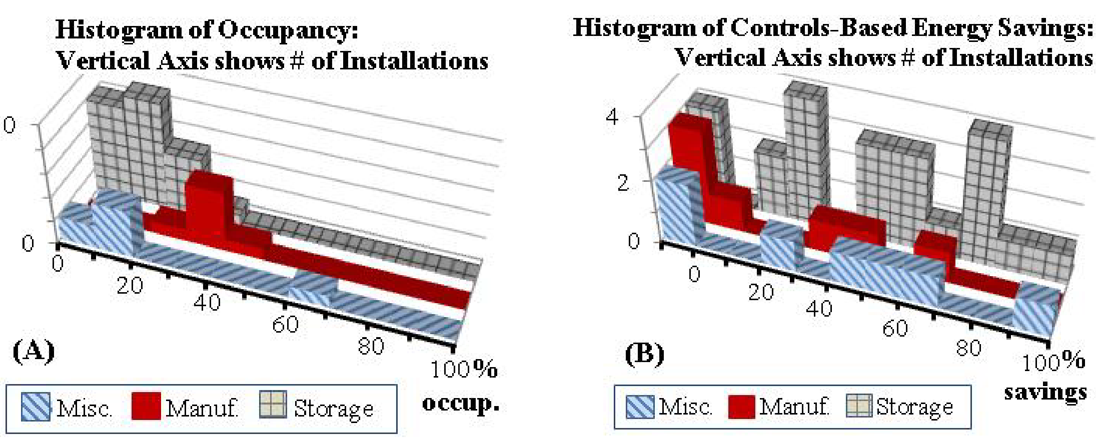

Figure 1. Histograms of occupancy, and of controls-based energy savings. Figure 1(A) on the left shows a histogram of occupancy for the miscellaneous, manufacturing, and storage buildings surveyed. Histogram buckets cover 0-9%, 10-19%, 20-29%, etc. Figure 1(B) on the right shows a histogram of controls-based lighting energy savings. The leftmost bin includes all estimated savings less than 0%. *Source: BPA & Digital Lumens.*

Figure 1(A) shows that all but 2 of the buildings were occupied less than 40% of the time. This is considerably lower than the average 139 hours per week that 9 sites with records were open for business (139 hours are 83% of the total 168 hours in a week). Figure 1(B) shows that, based on the HOU baseline, the energy savings from lighting controls varied broadly, and savings were positive in most buildings. Eight of the buildings that were assigned the average HOU baseline from the national survey, had negative savings from controls, suggesting that their actual site-specific baseline HOU might have been higher than the average (however these actual baselines are unknown, so this hypothesis cannot be tested). Figure 1(B) indicates that in storage buildings, the lighting control systems saved more than 20% energy in 17 of 22 buildings, and saved more than 40% energy in 13 of 22 buildings. In miscellaineous and manufacturing applications, lighting controls saved more than 20% energy in 8 of 14 buildings, and saved more than 40% energy in 6 of 14 buildings. In one storage building plus one miscellaineous building, controls-based savings on lighting energy were over 90%.

Discussion

For energy-efficiency field research based on conventional submetering, BPA's research budget often exceeds $15,000 per field site, and may range as high as $100,000 per site. For a study of 36 submetered sites, the budget would exceed $500,000, and the duration would be more than a year. In comparison, the only cost of this report was staff time, for a few weeks of analysis and review. Compared to a conventional research project of comparable 36-site scale, this trial yielded results 10x faster and 10x cheaper. Compared to a conventional research project constrained by budget to 3 or 4 sites, this trial yielded 10x more sites.

This trial does have some drawbacks. Without complete baseline data, some conclusions may be incorrect, such as negative controls-based energy savings at 8 sites. A case study such as Mutmansky and Berkland (2013) could provide performance data for each control function, and interval data of higher resolution and/or longer duration than the 1-month data of this trial. Interval data may be available from some vendors, if it does not reveal proprietary algorithms.

Concerns are sometimes raised about the potential for a vendor to introduce sampling bias, by "cherry picking" data from the best-performing projects. Note that a similar sampling bias is likely in a meta-analysis of case studies from diverse sources, because few project teams publish their failures. For vendor-reported data, the risk of sampling can be managed. For instance, access to data from newly commissioned sites, where the operational performance is not known yet, could be negotiated with a networked controls vendor. Some sites might even disable the advanced control functions for a few weeks, for site-specific baseline HOU.

The accuracy of vendor-reported energy data presumably varies by product. For instance, some streetlight control vendors offer optional utility-grade meters for increased accuracy. Cortese and Scherba (2013) used individual luminaire-level submeters to validate the accuracy of three pilot installations of the Enlighted networked lighting control system. Future work is needed for third-party validation of the energy savings reported by other lighting control systems. This will validate (or discount) the usefulness of research such as this trial based on vendor-reported data. Note that some alternatives to vendor-reported data about lighting energy are subject to their own inaccuracies, such as difficulties in excluding non-lighting loads from circuit-level submeters, nominal vs. actual fixture wattages, and unrecorded baseline HOU.

Trials like this, with data from many sites, can help utilities and building owners see a range of possible outcomes before embarking on new programs or projects. The rapid speed and low cost of this trial offer hope of keeping up with innovations in this rapidly developing field. While this particular data set had limited resolution, incomplete information about pre-existing baselines, and limited information about performance differences between various energy-saving functions, these limitations do not necessarily apply to all vendor-reported data.

Smart Thermostats

A new class of control system is emerging for residential HVAC equipment, from innovations in technology for electronic sensing, communicating, and computing. We call this new class of control system "smart thermostats." Vendors of smart thermostats have reported their successful use to increase efficiency of space conditioning (Kerber 2013 and Nest 2013). Our objective for this research was to develop methods for evaluating efficiency of these control systems, using data collected from smart thermostats. In doing so, we hoped to replace site visits and instrumentation with lower-cost, Internet-based methods for data collection.

Methods

Through interview with industry stakeholders and other research, we created an inventory of data types that could be accessed by an analyst at an electric utility through the Internet. Of primary interest to a measurement of efficiency were indoor temperature set point, indoor temperature, run time of heating system(s), and outdoor temperature. Vendors of smart thermostats and service providers were asked to provide, by e-mail, data for these parameters. We requested a sample from systems heating single-family homes in climates similar to those found in the Pacific Northwest. From data acquired through those methods, an historical data set was compiled.

A function, *heating system run time = f(set point – outdoor temp),* was fit to the data set for each home, using standard methods for linear regression in Microsoft Excel. The slope and intercepts of this function are understood to be unique to the thermal properties of the home and the performance of the furnace.

Changes in efficiency of control logic are difficult to evaluate. We ruled out methods which required measuring system conditions, prior to installation of a smart thermostat. A prototypical set point schedule was derived from a recent survey of more than 1,400 single-family homes in the Pacific Northwest (Baylon et al. 2012). Participants in that survey reported an average heating set point of 69°F. More than two thirds reported adjusting the set point down an average of 7°F at night. Hours of set back were assumed to be 10pm through 6am, leading to our assumption of a day-averaged set point of 67°F for baseline conditions.

Results

We interviewed with several vendors and industry participants. Those conversations revealed significant constraints on access and use of data. Most data is stored and collected by manufacturers of smart thermostats and service providers. Threats to security and privacy of personally-identifiable information were concerns that demanded extreme caution. Another barrier to accessing data appeared as intellectual property protection: one service provider claimed their proprietary control logic could be synthesized through analysis of raw data from the thermostat. Many of these issues were resolved through anonymity and aggregation of data to time intervals greater than ten minutes, to provide needed protection.

An anonymous, historical account of data was acquired for ten smart thermostats, from a seven-day period in January 2013. This data set included, at hourly intervals, average indoor temperature set point, run time of a natural gas forced-air furnace, and average indoor air temperature. All data were believed to be produced by smart thermostats operating the primary heating system, in heating mode, for single-family homes with a single conditioned zone. The provider of data reported that outdoor dry-bulb air temperature was acquired from the nearest meteorological station to each site. Over the study period, hour-averaged outdoor temperature ranged from 7°F to 59°F.

We selected a set of data for a single home, for testing of proposed methods. Figure 2 illustrates that data set. Note how the set point changes throughout each day, indicating a schedule.

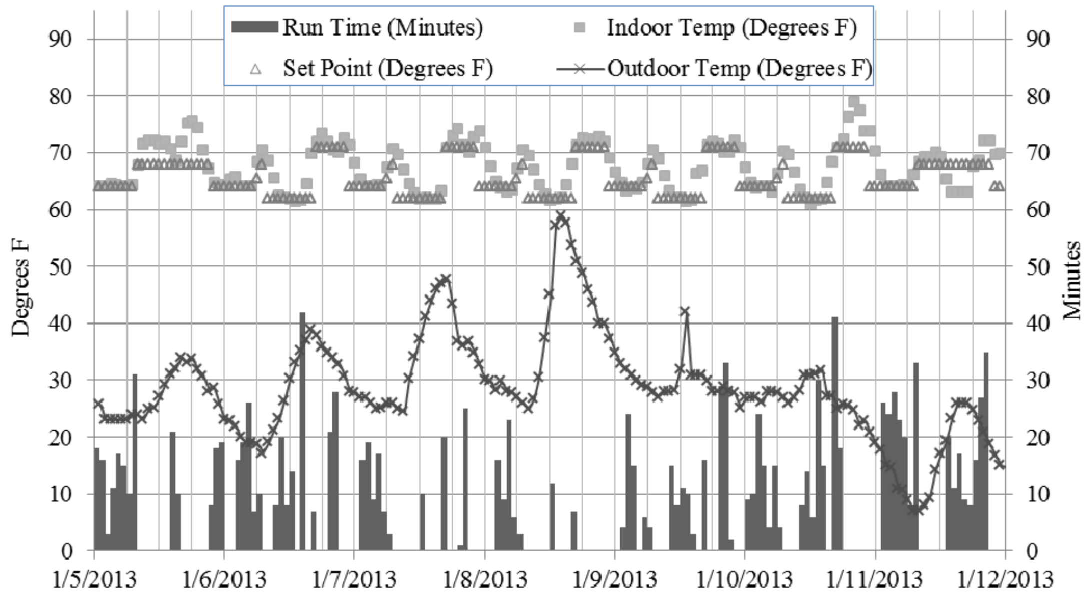

Figure 2. Illustrative data from a single thermostat.

A linear regression function, *heating system run time = f(set point – outdoor temp),* was fit to daily averages across the seven-day study period, with an R-squared value of 0.95, shown in Figure 3.

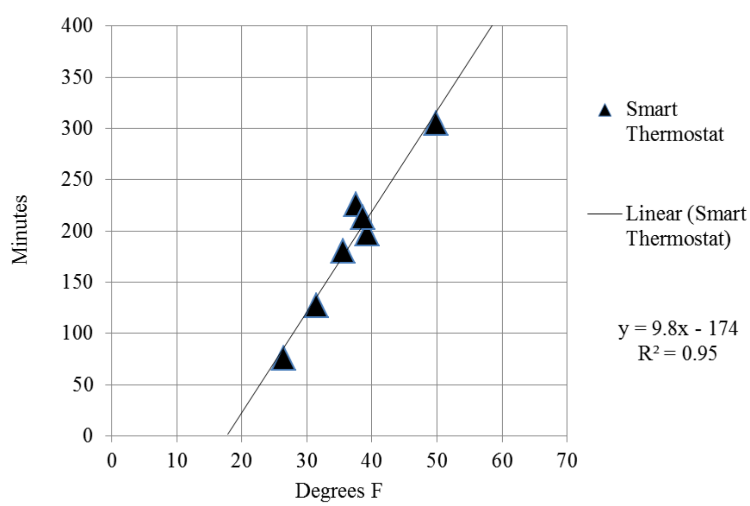

Figure 3. Comparison of furnace run time (minutes) and average difference between indoor set point and outdoor air temperature (degrees F), for each of seven days during the study period.

To estimate run time of the furnace under baseline conditions, we calculated *delta-T*, the difference between our baseline set point of 67°F and outdoor air temperature, for each day during the study period. Figure 4 illustrates the estimated run time under baseline conditions for the seven days in our study period. Table 1 provides a comparison of smart thermostat observations and estimated baseline. The smart thermostat is estimated to run the furnace 109 minutes (8 percent) less than expected under baseline conditions.

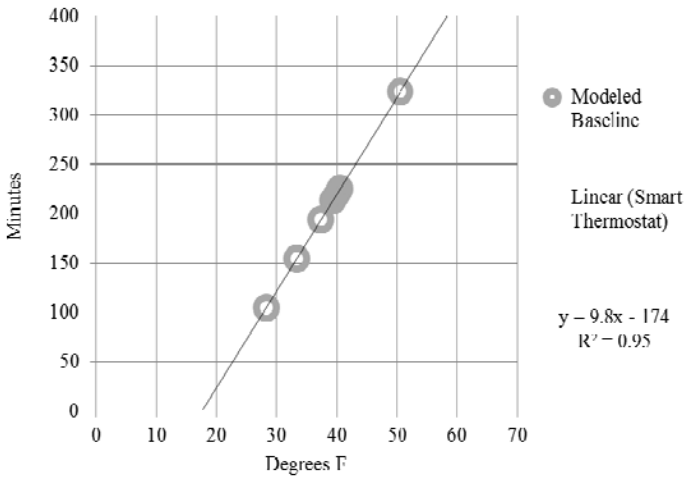

Figure 4. Estimated run time under baseline conditions, using the regression function constructed from smart thermostat data.

	Modeled Baseline		Smart Thermostat	
Day	delta-T (F)	Run Time (min)	delta-T (F)	Run Time (min)
6	40	219	39	197
7	39	213	38	226
8	33	154	31	127
9	28	105	26	76
10	37	194	36	180
11	41	225	39	213
12	51	324	50	305
Total		**1433**		**1324**
Savings				**(109)**

Table 1. Comparison of observed run time and estimated run time under baseline condition.

To further develop these methods, we hope to test against a set of data with a wider distribution of key variables, such as set point, outdoor air temperature, HVAC system type, and plug loads. One such data set may soon be available from a group of 140 single-family homes in the Pacific Northwest, which were extensively sub-metered (Larsen et al. 2014). The proposed methods may also be improved by constructing a unique baseline for each home. We envision several methods for doing so, the simplest of which seems to be a survey, similar to the one administered in Baylon (2012), in which a participant reports their preferred indoor air temperature during a commissioning period for the smart thermostat.

Advanced Rooftop Unit Controller

Methods

The Catalyst controller manufactured by Transformative Wave (TW) is a retrofit technology for constant speed commercial rooftop units (RTUs) providing cooling, heating and ventilation. It saves energy by decreasing the supply fan speed to 40% when the RTU is in ventilation-only mode, and to 75% and 90% in other modes. It also optimizes economizer control and implements demand control ventilation (DCV) with the addition of a CO_2 sensor in the return air stream. There is no effect on occupant comfort since thermostat settings are not changed and interior thermal loads are fully met. Catalyst controllers can be wirelessly networked to TW's eIQ platform, enabling web access for programming, real-time energy consumption monitoring and fault detection. Of particular interest to utilities is the ability to cycle between modes of operation, allowing savings verification with an emulated baseline that doesn't require pre-monitoring.

BPA co-funded a field-study of the Catalyst, conducted by the Pacific Northwest National Lab (PNNL) to determine the magnitude of kWh savings achievable by retrofitting constant volume RTUs with advanced control strategies not ordinarily used for this type of equipment (Wang et al. 2013). The study included 66 RTUs, with data from true-power meters and an array of sensors and control signals collected by the Catalyst eIQ platform. The energy savings ranged between 22-91% of total unit kWh, with an average of 56% ± 25%. The savings associated with economizers and DCV were difficult to isolate because they were relatively small. Data was collected by TW, and then independently analyzed by the researchers.

BPA is seeking to define a methodology for Catalyst and similar controllers, to verify "post-post" savings using self-reported data, with acceptable certainty. (We define "post-post" as using only post installation data for M&V.) Once a methodology is established, savings can be evaluated after retrofits, rather than being metered before and after the project, streamlining program implementation and lowering program delivery costs.

The Catalyst can simulate baseline operation, allowing the RTU to be cycled between baseline mode and Catalyst mode at a user-determined interval. This eliminates the need for baseline metering, allowing "post-post" savings verification, and nullifying the effects of other changes during the monitoring period. This has the disadvantage of not being able to discern the effects of O&M improvements, such as economizer repairs, coil cleaning or refrigerant charge correction. This does not affect the programmatic savings since the installation protocol for the controller calls for all repairs to be completed at that time.

Daily cycling for a full year was used in the PNNL study, and several owners did not want to participate because they would only have half the energy savings. This concern can be addressed by using either by an abbreviated monitoring period or a generic baseline. Bonneville is researching a simplified data analysis method for program evaluation. In the PNNL study, most of the electrical savings were associated with fan speed reduction; so it is posited that fan kW alone can be used to estimate and evaluate RTU savings. If feasible, this greatly simplifies quantifying baseline energy, which would be the supply fan running at 100% speed during all scheduled operating hours. Since the controller adjusts the fan speed to fixed percentages according to the mode of operation, savings could be derived by monitoring only the system status, or only the fan speed. This assumes that the fan power is accurately measured for each operating mode. The final simplified method needs to meet an 80% confidence interval. Now the energy savings may be calculated by a simple equation such as:

$$kWh\ Savings = \sum_{1}^{n} (fankW_{100\%} - fankW_n) * Runtime_n$$

Where: n = number of fan operating modes

$fankW_n$ = fan power draw in mode n, kW

$Runtime_n$ = time in mode n, hours

Results

Catalyst data is available through the optional eIQ platform, and TW has been cooperative in facilitating access. If required by incentive agreements, other manufacturers may also enable data access. With the owner's permission, utility program evaluations can be done without publishing identifying information. Cleaned data sets rolled up to hourly values for the PNNL study were posted to the Regional Technical Forum (RTF) website.

Catalyst comes with several sensors that can be replaced or augmented for savings verification purposes. Additional information is generated by the controller and variable speed drive. In the PNNL study, sensors were added for total RTU power, mixed air temperature and space temperature. The standard package includes unit power calculated from current measured in one leg of power and an assumed voltage. The standard sensors and a sampling of other available monitoring points are shown in Table 2.

Table 2. Sample of available catalyst monitoring points

Field Name	Unit	Notes
Timestamp		Local time , yyyy-mm-dd hh:mm
ESMMode	True/ False	True = Advanced control logic; False = Standard control logic
FanSpeed; FanPower	%, kW	Supply fan speed and power from the variable speed drive
OaTemp; RaTemp; DaTemp	°F	Dry-bulb temperature of the outdoor air, return air and discharge air
VentMode; CoolCall1,2; CoolCmd1,2; Econ Mode, AdvanceCool; HeatCall1,2; HeatCmd1,2	True /False	Command and status signals
UnitPower	kW	Total electric power for the unit

Sampling rates can be set by the user. Since data is available as CSV files, the analysis method is left to the discretion of the utility engineer or researcher. For its own savings analysis, TW appears to rely on a standard change point regression. In at least one instance they published a case study with a link to the raw data (TW 2013).

The dataset posted on the RTF website was used to test the validity of the proposed simple calculation, along with a table in the PNNL report that shows the percent time in each mode for each RTU in the study. Since the run time in a particular mode is represented by a fraction of total unit run time during the study period, the result is in units of average kWh/hour of RTU run time. The data used are shown in Table 3 and the results are in Table 4. Because the power measurement from the variable speed drive is a calculated value of power output to the fan, the final result from the equation was divided by the drive efficiency of .968.

Table 3. Fraction of fan runtime and fan power in each mode of operation

Fan Speed, %		40%		75%		90%		100% Baseline	
RTU ID	Tons	Time Fraction	Fan kW	Time Fraction	Fan kW	Time Fraction	Fan kW	Time Fraction	Fan kW
202	10	0.98	0.16	0.02	1.02	0	1.71	1	2.42
212	25	0.57	0.45	0.38	2.67	0.05	4.58	1	6.49

Table 4. Calculated fan savings vs. measured RTU savings

	kWh/hour/ton	
RTU ID	Calculated	Measured
202	0.255	0.258
212	0.227	0.307

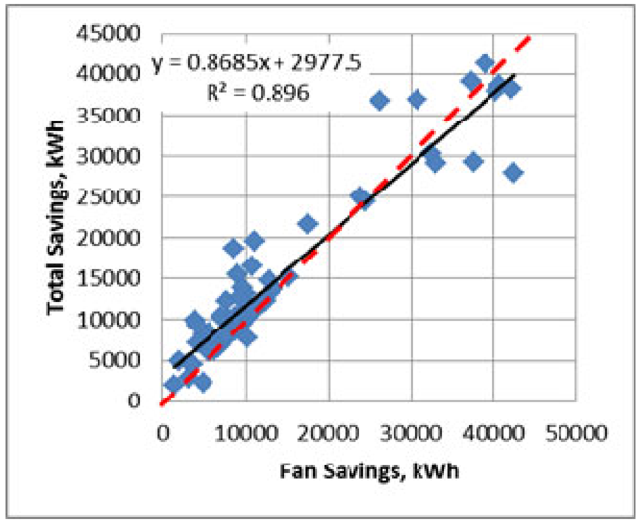

Figure 5. Fan savings vs unit savings

The calculated savings, which are fan-only savings, are less than the full measured savings in both instances. The shortfall is greater for unit 212 which was in ventilation-only mode at the lowest speed 57% of the time, while unit 202 was in ventilation mode for 98% of the time. This illustrates that, for individual units where there is a higher proportion of run time spent in cooling and heating, savings could be significantly underestimated by considering only the change in fan power. Figure 5 above shows the PNNL dataset of savings for all 61 RTUs in the study with fan savings plotted against total unit savings. While there is a good correlation between fan savings and total savings, it is easy to see that most points are above the dashed line where fan savings would equal the total savings.

For this technology, the self-reported data is comprehensive, reliable and accurate. It allows for a simplified post-post methodology for savings estimation, although a utility would have to weigh the drawback of savings underestimation against M&V cost savings.

Conclusions

This paper set out to explore faster, cheaper, and better M&V for smart, Internet-connected devices. In all three cases, digital lighting controls, smart thermostats, and the advanced RTU controller, we were able to get data from existing installations at no direct cost other than our staff time for outreach and analysis. The vendors we worked with all kept extensive historical data archives that were quickly aggregated and transferred to us for analysis.

In comparison to traditional end-use submetering or large randomized field trials, M&V methods using data from connected devices was dramatically faster and cheaper.

For digital lighting controls trial, *data sets were available, but not* standardized. Our trial data set had limited resolution and incomplete information about pre-existing baselines; however, these limitations do not necessarily apply to all vendor-reported data. When unbundled from lighting fixture retrofits, post/post methods appear valid for comparing advanced lighting controls with scheduled controls.

For the advanced RTU controller trial, the self-reported data was comprehensive, reliable and accurate. It allows for a simplified post-post methodology for savings estimation, although a utility would have to weigh the drawback of savings underestimation against M&V cost savings. A desired method to eliminate the need for kW data was not achieved, so we plan future work for this.

For the smart thermostats trial, the data we received included key variables (run time, set point, indoor temperature, outdoor temperature) for useful analysis of energy savings. Although we were lacking needed data for indoor temperatures during the pre-installation period, the method of combining post-installation run time regression with independently-obtained indoor temperature data appears promising from our very limited data set.

We encountered challenges in connecting with vendors and did not obtain the extensive and robust data sets we desired. Intellectual property and barriers were generally not issues because key data was made anonymous, except for several smart thermostat vendors who cited these reasons for not providing any data for our trials. However, standardization of data points, recording intervals, and performance metrics were not solved with these trails and remain key challenges.

Our central thesis that high-resolution real-time data will be used by vendors to improve product performance remains to be fully tested. Nevertheless, once agreements for sharing data were reached, the rapid speed, low cost, and easy scalability of these trials offer hope of utility M&V keeping up with innovations in this rapidly-developing field.

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