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Automated Measurement and Verification of Transactive Energy Systems, Load Shape Analysis, and Consumer Engagement

Phillip N. Price, Mary Ann Piette, Jessica Granderson and John Elliott
Lawrence Berkeley National Laboratory

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Abstract
A key goal of transactive energy systems is to facilitate scalable adoption of intermittent and distributed resources in grid modernization and improve overall operational efficiency of the electric grid. Given that buildings are 70% of the load on today's grid, it is critical to better understand electric load shapes, how to change them, and how to improve energy efficiency in buildings. Transactive energy systems must be able to transmit information about and facilitate changes in electric loads. A transactive system should provide an application platform that provides access to building data, allows analyses of energy transactions, and generates actionable information for building systems and operators, occupants, owners, and service providers. We present four use cases for a transactive energy network that show that in addition to the societal and economic benefits provided by real-time energy transactions, there are large benefits that are enabled by the transactive system infrastructure. We show that energy and outside temperature data provide useful information for evaluating electric loads in many buildings. We also present an example of the use of proxy occupancy data that help demonstrate the value that such data provide in identifying operational performance issues.

Introduction
The goal of transactive energy systems is to facilitate scalable adoption of intermittent and distributed resources envisioned in grid modernization and improve overall operational efficiency of the electric grid. The term "transactive energy*" is used to refer to …"techniques for managing the generation, consumption or flow of electric power within an electric power system through the use of economic or market based constructs while considering grid reliability constraints The term transactive comes from considering that decisions are made based on a value (GWAC, 2014*)."

Given that buildings are 70% of the load on today's grid, it is critical to better understand how electric load shapes, how to change them, and how to improve energy efficiency in buildings. Transactive energy systems must be able to transmit information about and facilitate changes in electric loads. A transactive system should provide an application platform that provides access to these data, allows analyses of energy transactions, and generates output targeted to inform building systems and building operators. In a previous report we described the development of an autonomous agent that automatically provides measurement and verification of energy transactions as part of a transactive network (Piette et al, 2014).

In this paper we present four case studies that illustrate different use cases for a transactive energy network. In addition to the societal and economic benefits provided by real-time energy transactions, there are large benefits that are enabled by the transactive system infrastructure. New smart meters and ever more granular energy use data from buildings provide great opportunities for providing consumers with better information about their energy usage patterns. In addition, transactive communication and control platforms make system-level data and controllers

accessible, for improved operational efficiency. This paper summarizes recent work on transactive energy systems related to measurement and verification, load shape benchmarking, anomaly detection, and pattern analysis. Our research framework is consistent with a recent reference guide on transaction-based controls (Somasundaram et al., 2014). This framework outlines several use cases for transactive energy systems, including end-user services, energy market services, grid services, and societal services. The guide describes the need for energy analysis tools that track energy consumption by building systems or for the building as a whole. This can include simple trending of systems; typically used to verify schedules and device functionality. It can also include more rigorous tracking of energy consumption patterns within a building that can be used to verify energy savings from efficiency measures. We will illustrate our points with four case studies, each related to the end-user services transactive energy use case:

1. Analysis of interval electric load data, in absence of other data, to determine that a specific building is a likely candidate for improvements in its ability to "shut down" at night;
2. Analysis of load data in conjunction with weather data to determine that a building is a candidate for improved HVAC systems or operations;
3. Analysis of load data in conjunction with interval water usage data to determine that a building that operates 24/7 does not need to do so; and
4. Analysis of interval load data and weather data to determine that a building's HVAC system is behaving non-optimally and to diagnose the specific problem.

Methods and Results

Over 50 million smart meters have been installed in the United State (EEI, 2012). Typically the electric load data are reported for each 15-minute period. We obtained electric load data from several buildings and analyzed them using software tools currently under development (Piette et al, 2014). One of the tools is a load shape analysis program that generates several plots and parameter estimates to develop metrics to characterize the energy performance of the building. For example, it quantifies typical base and peak load for each day of the week, and the dependence of the load on outdoor air temperature at different times of day and in different temperature regimes. Another tool uses automatically generated baseline models to quantify the change in the electric load shape. This tool evaluates the impact of operational changes by predicting building electric loads based on historical electric load data and explanatory variables, and comparing those loads to the actual loads in the building after an energy conservation measure is implemented. These models are used to fit the data from a "training period" and are used to predict the load in the "prediction period." The key output of a baseline model is the "projected baseline," which is a time series of the predicted energy use if the building is operated during the prediction period the same way it was operated during the training period. Ideally, a baseline prediction will account for all of the scheduled and routine uses of electricity in the building as well as electric load that varies with outdoor air temperature.

Case 1: Simple analysis of operational patterns

One of the simplest types of analysis requires only 15-minute or hourly electric load data. Our load shape analysis program uses an algorithm to automatically determine when during each day a building is "operating" or "not operating." This is an empirical determination of the duration of time that the building systems spend on a given day at a load that is substantially above its minimum. This is not the same as determining how long during the day the building is occupied, but can be related to occupancy.

Figure 1 shows an example: a summary of electric load data for a public library, an example we further describe in the next section. The number of "operating hours" varies by day of the week, as illustrated in the figure by the varying width of the bars. When the building is operating it uses more than three times more energy as when it is not operating. A high ratio is not *necessarily* good and a low ratio is not necessarily bad – a high ratio could be the result of exceptionally high load during operating hours, and a low ratio could be the result of a necessarily high load during non-operation hours, from a computer server room for example – but it is often the case that a high ratio of operating load to non-operating load indicates that the building is shutting down effectively when it is not occupied.

In this building, the number of operating hours varies by day of the week; the mean load during operating and non-operating hours is nearly the same for each day of the week. In terms of the parameters presented on this plot, this is a well-behaved building: it shuts down well each night, and as it happens its daily operating hours as determined by the algorithm are a good match to the hours the building is operating.

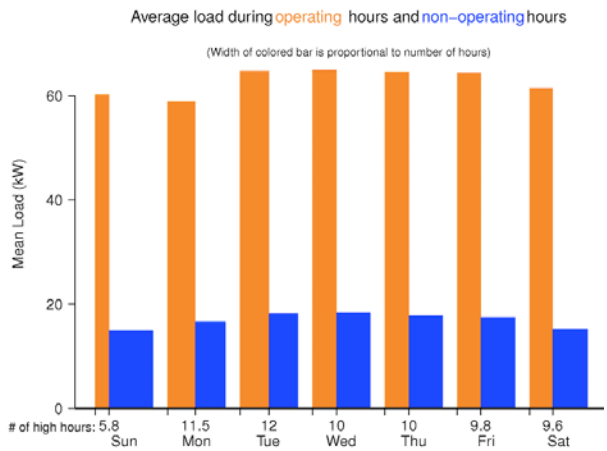

Figure 1: Average electric load during "operating hours" and "non-operating hours" on each day of the week, for a library. Width of each bar is proportional to number of hours; height is mean load.

In contrast, Figure 2 shows mean load for operating and non-operating hours in a building that includes a homeless shelter. The load in this building is much lower than in the large library building discussed above, but the noteworthy characteristic for the present discussion is that the building does not *turn down* at the same rate, or for very long: the mean load during non-operating hours is only about 30% lower than the mean load during operating hours, and (as determined empirically by our algorithm) the building operates about 17 hours per day. This might represent correct behavior, since unlike the library this building is occupied overnight. Ultimately, knowing whether the building is operating correctly will require more information about how the building *should* be operating; we return to this issue in a later case study.

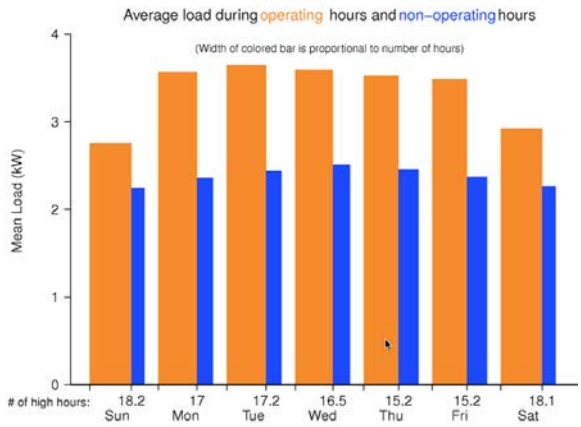

Figure 2: Average load during "operating "and "non-operating hours" on each day of the week, for a building that includes a homeless shelter.

Case 2: Analysis of load data in conjunction with weather data

We now return to the public library data. As we saw in the previous section, analysis of load data alone did not suggest that this building is operating poorly: the building turns down well during non-operating hours, and its operating hours match the hours the building is occupied. However, once outdoor air temperature data are considered, the picture changes. Figure 3 shows the mean load (y-axis) versus mean outdoor air temperature (y-axis) for four different time periods during each day (four panels), for June through August. Each day during the season produces a point on each panel.

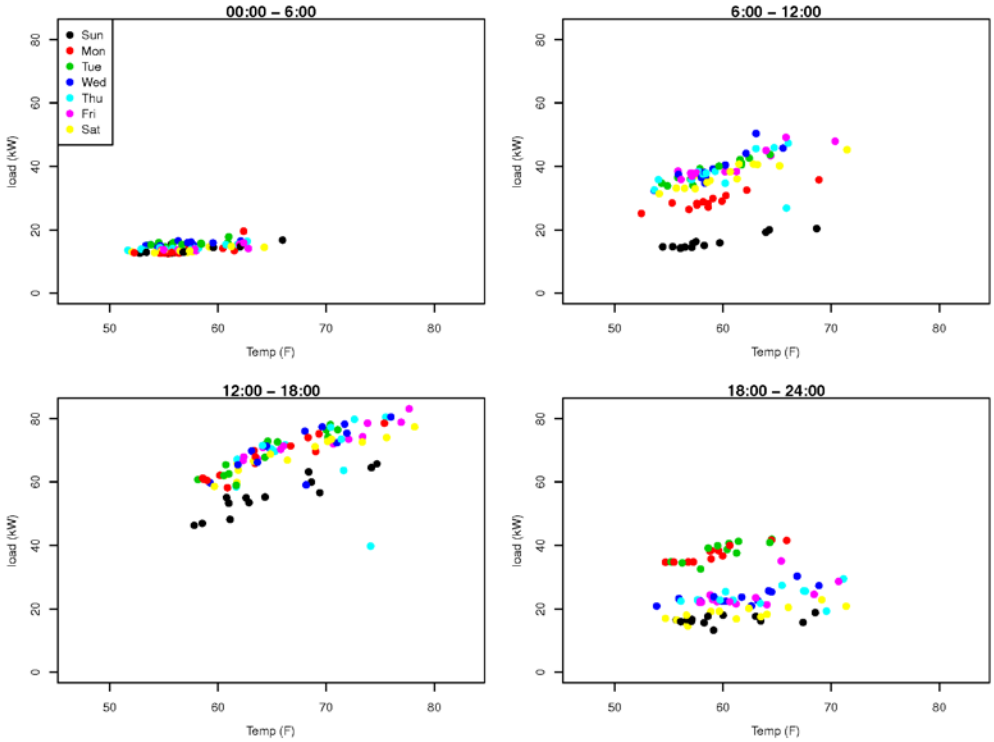

Figure 3: Average load as a function of average outdoor air temperature, for 4 quarters of each day.

The slope of the load-versus-temperature relationship – the additional energy used per degree of outdoor air temperature – is about the same at all temperatures from below 50 °F to above 75 °F. This would not be expected if the building is making effective use of an economizer mode. We expect that at relatively low outdoor air temperature the building could meet its cooling needs by ventilating with cool outdoor air, while at higher outdoor air temperatures the building should modulate to use less outdoor air as is necessary to meet ventilation requirements. Such behavior would lead to a lower slope in the relationship at low outdoor air temperatures than at high temperatures. No such change is evident in this building, which suggests that there may be an opportunity for improving the energy performance of this building. We would suggest checking to see if the building has an economizer and if it is operating correctly. This might result in substantial energy savings.

Case 3: Analysis of load data in conjunction with interval water usage data

In Case 1 we discussed a building that does not seem to shut down effectively at any time during any day of the week. In that case, such load shape behavior may or may not indicate a problem with building operation; the building might be continuously occupied and in use, and therefore *should* be operating continuously. We now discuss a building that would pose a similar problem, except for the availability of additional interval data. This building is a "user support facility" at Lawrence Berkeley National Laboratory (LBNL). The building provides office and lab space for users of the Advanced Light Source, a large experimental device with an electron accelerator that operates around the clock. The user support facility provides workspace for researchers.

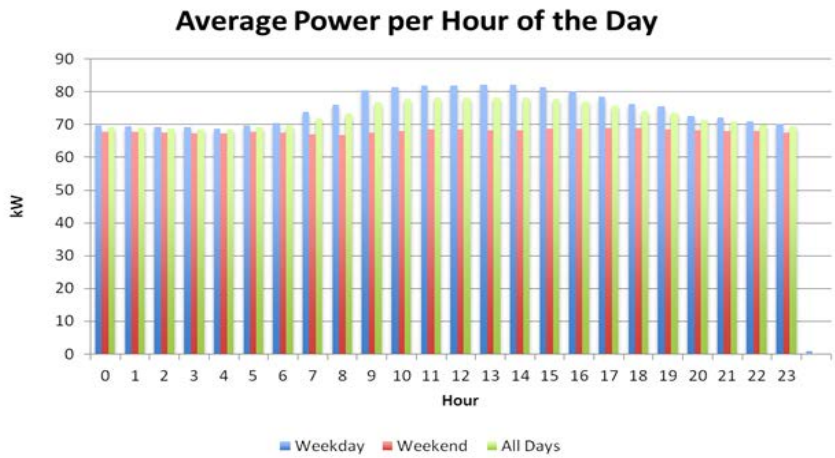

Figure 4: Average load by hour of the day, for weekdays and weekends.

Figure 4 shows the average electric load during each hour of the day, on weekdays and weekends. There is little load variability, either by hour or weekend versus weekday. The nearly constant load made the building operator suspicious: surely there should be some variation in occupancy, and variation in load. On the other hand, this building exists to support researchers at the Advanced Light Source, which does operate continuously nights and weekends during experimental sessions when many researchers are present. We asked the question *is the facility actually occupied all hours of the day*?

Unlike the homeless shelter discussed in Case 1, additional data are available for this building: the building's water consumption is monitored with a 15-minute interval meter. Water data are shown in Figure 5.

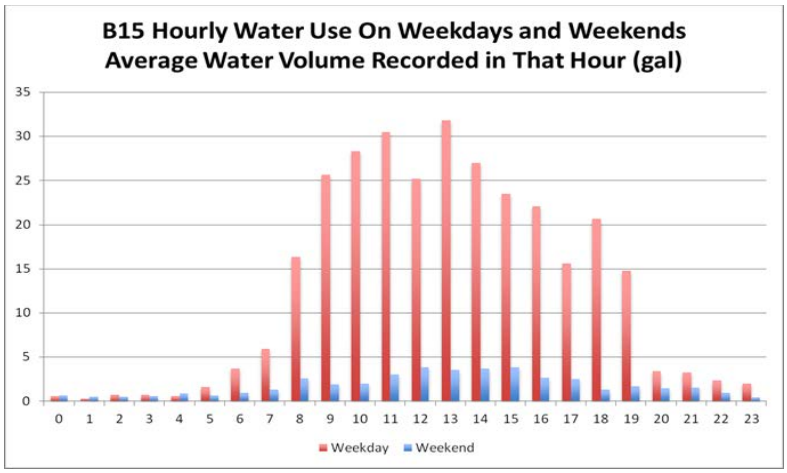

Figure 5: Average water consumption by hour, on weekdays and weekends.

Water consumption data can be a reliable indicator of occupancy because bathroom use is fairly consistent in terms of toilet flushes per person per hour: if there are people in the building there will be some water consumption. In buildings such as this one there are also other substantial uses of water. Variables such as water consumption that are closely associated with the number of people in a building are known as "proxy" occupancy variables. We are currently evaluating how interval data that are commonly available in buildings, such as the number of Wi-Fi connections, can be useful as proxy occupancy variables. It is immediately apparent from Figure 5 that this building is normally unoccupied from midnight to around 5 a.m. on weekdays, and from midnight to around 8 a.m. on weekends. Although Figure 4 alone was suggestive, together with Figure 5 we see that this building is consuming a great deal of energy even at times that the building is completely unoccupied. There are large energy savings opportunities in this building that, because of these data, are being aggressively pursued by LBNL facilities staff.

Case 4: Analysis of interval load and weather data to identify energy savings

Another real-world case in which data collected for a transactive energy application served multiple pursues, allowing an energy saving opportunity to not just be detected but also diagnosed.

Figure 6 shows electric load data (black line) from a small office building at Lawrence Berkeley National Laboratory. This building has been used as a test case for our multi-laboratory collaboration on transactive energy networks (Piette et al., 2014). Whole building electric load data and a large set of operating data from the building are posted to a data repository, and we are using data from this building to test the performance of a publically available open source statistical model that predicts baseline energy use. To this end we have created a baseline-modeling agent that runs on the transactive network. The model is an improved version of the one described in Mathieu et al. (2011). The software is available as an open-source project from the Python Package Index (PyPi) under module name loadshape.

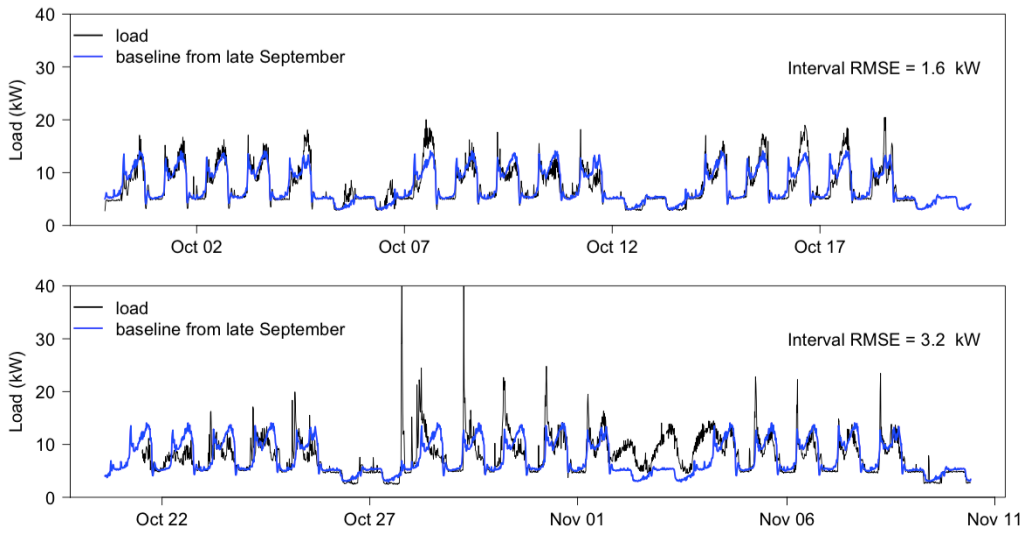

Figure 6: 15-min electric load as function of time (black line) and baseline prediction (blue line).

The motivating use case for the baseline prediction is to perform measurement and verification (M&V) of short-term electric load shape changes (within hours) and of long-term energy conservation measures (over days, weeks or months). The short-term demand response case is a prime example of an energy transaction that could be performed by a transactive system. As part of routine testing our M&V model was "trained" on load and outdoor air temperature data from August and September 2013, and used to predict the load for October and November. The model correctly captures the existence of a start-up peak each morning, whose magnitude depends on outdoor air temperature, as the building's heat pumps bring the model to the desired indoor temperature. The data followed the predictions fairly well for the three weeks shown in the upper panel of the figure: the root-mean-squared error (RMSE) in the hourly load is 1.6 kW, as indicated in the upper right of the panel.

In late October and early November (lower panel) the RMSE doubled to 3.2 kW. Investigation showed that almost all of the increase is due to an unpredicted spike in load every weekday morning, far above the load prediction based on the building's previous behavior. A building energy expert correctly guessed the cause as soon as the phenomenon was noted: the building was switched into its winter heating mode at the end of October, whereupon electric resistance heating began turning on each morning to supplement the heat pumps. This behavior might be necessary on exceptionally cold mornings (which are rare in this building's climate zone) but on most mornings the heat pumps would be adequate to achieve and maintain a comfortable temperature in the building, given time, and that approach would be much more energy-efficient (and cheaper). A control change to give the heat pumps an hour to work before the resistance heating is activated will reduce the size of the startup peak (and the associated demand charges) and will save energy. This change to the HVAC control is also being pursued by the facilities staff to lock out the resistance heat at moderate outside temperatures.

Conclusions

Transactive energy systems require the collection of 15-minute or similar electric load data. These data should be collected and archived. Transactive systems also require the ability to quantify changes in building energy performance in order to track the energy savings associated with operational improvements or short-term load interventions, and to conduct continuous energy

anomaly and fault detection. As we have illustrated in this paper, once multiple data streams are provided, along with programs to quantify features of those data streams, other capabilities are enabled. Future research will explore how to automatically include occupant data in the M&V tools. We are also developing a load shape-benchmarking tool for small commercial buildings to allow quick feedback on energy efficiency recommendations based on operational improvements. These models are being evaluated at several large corporate campuses to measure energy efficiency and short-term changes in electric load shapes. There are many opportunities to organize time series electricity data to provide actionable information for facilities managers and building owners.

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