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Meter-Based Assessment of the Time and Locational Benefits of a Large Utility's DSM Portfolio

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ABSTRACT

As decarbonization goals drive increasing levels of renewable generation, there is a need to understand the time- and location-based savings benefits of demand-side management (DSM) programs. The challenges of the 'duck curve' are driving the utility industry to consider how programs can be optimized to match demand profiles with low carbon generation resources. From an infrastructure standpoint, time- and location-targeted DSM could serve as a 'non-wires alternative' (NWA) to defer equipment upgrades.

Additional DSM value streams are motivating innovation in savings evaluation, providing more resolved insights beyond the total annual program impact. Methods grounded in the principles of billing analysis, leveraging hourly metering at the distribution grid, can provide new visibility into the spatial and temporal savings achieved through DSM. A large body of work has investigated related topics including interval meter-based savings analysis, the time-varying nature of efficiency measures, and NWA. A less studied topic concerns the impact of DSM on the grid, based on metered consumption.

This paper presents an analysis of interval data across more than 25,000 customers and twelve substations, from the Sacramento Municipal Utility District. The results show for different locations on the grid: achieved savings and the impact on grid consumption; hourly savings shapes for DSM program participants and non-participants, and how those shapes vary with season; and the impact of the programs on peak demand. These findings show the current impact of DSM, with implications for future, more intentional targeting as the utility continues to pursue aggressive electrification, efficiency, load flexibility, and reliable NWA.

Introduction

The past decade has seen a significant shift in industry activities and policy regarding energy efficiency. The longtime focus on reducing consumption (kWh, therms) evolved to place increasing emphasis on peak demand (i.e., at times when the most carbon-intensive generation assets are mobilized). However, the significant growth in solar generation in some regions resulted in the so-called electric consumption "duck curve," whereby the peak generation requirements had become disconnected from peak consumption because such a high portion of consumption was being met by PV power (i.e., the timing of peak consumption doesn't correspond to the timing of peak generation needed from the utility). As a result, it is becoming far more important to understand when electric load reductions from energy efficiency programs occur, both by time of day and seasonally.

In concert with the evolution of thinking around generation, a parallel evolution is happening with respect to transmission & distribution (T&D) planning. T&D Investments in the United States are in the billions of do3llars, and the evolving landscape of distributed energy resources (DERs) is increasing the return-on-investment risk for those investments. T&D constraints affect different locations to differing degrees (e.g., significant population/activity

growth may happen adjacent to one particular substation), so some regulators and utilities are exploring ways to defer T&D expansion investments by investing in demand-side management (DSM) strategies targeted at specific regions. These emerging strategies, also known as non-wires alternatives (NWAs), were successfully demonstrated through the Brooklyn-Queens Demand Management program which met its 52MW reduction target in the summer of 2018, thereby avoiding a $1.2 billion substation upgrade. To support NWA efforts, the focus is not only on load reductions at specific times of day/year but also by geographical location.

Whether targeting DSM efforts by time of day/year or by location, good quality data is key to successfully optimizing the programmatic approach. The major growth in Advanced Metering Infrastructure (AMI) deployment over the past decade presents an opportunity to quantify and target load reductions by time of year and/or by location. The emergence of advanced measurement & verification (M&V) over the past decade has shown the potential for capturing DSM program energy impacts at the meter, using established analytical methods and software. However, advanced M&V has generally focused on quantifying savings impacts for individual projects, or in some cases annualized savings for an aggregation of projects under a given program; advanced M&V literature is lacking when it comes to quantifying energy impacts at the grid level, both by time of year and by distribution substation.

Sacramento Municipal Utility District (SMUD) is one of many utilities looking to address the above-mentioned challenges, along with another shift that has significant long-term implications for the grid: electric vehicle (EV) growth. SMUD recently became the first utility in the United States to change their key energy efficiency metric to “avoided carbon,” through their Integrated Resource Plan (IRP) (SMUD 2019). In this work we demonstrate the application of 'bottom-up' advanced M&V savings analysis to characterize the time and locational savings achieved by participants in SMUD’s DSM programs. These programs included customers from residential, commercial, and industrial market segments. There were seven different DSM programs that included measures such as LED lighting, HVAC equipment upgrades, sealing and insulation among others. A majority of the participants in this study fell into the Equipment Efficiency program category, which included sealing, insulation, and heat pump water heater upgrades. The other programs that had a significantly large number of customers were the Appliance Efficiency and Pool Pump Programs. The Appliance Efficiency program included refrigerators replacements, cooktops, and clothes washers while the Pool Pump Program included the installation of efficient variable-speed pumps.

Research Method

A dataset of hourly AMI electric consumption accounts was analyzed to understand the change in consumption for participants in energy efficiency programs (a) compared to accounts where no energy efficiency (EE) program participation occurred, and (b) relative to the total consumption at their grid location (i.e., the feeder or substation to which the meter is connected). The analysis results include whole-year energy impacts, hourly impacts, and load reduction on the single day with the highest peak load. Where accounts were marked as EE program participants, that participation took place during the 2016 - 2017 period.

Data preparation

Data preparation steps included:

- Dividing dataset into a 2015 baseline period and 2018 reporting period;
- Removal of certain accounts (i.e., meters) from the dataset:
    - Accounts with owner relocations (i.e., moves) between 2015 and 2018;
    - Accounts marked as having PV or EV (a small percentage of accounts, with highly variable usage patterns);
    - Accounts for which data was incomplete in either the baseline or reporting period.

The resulting analysis data sample included 1,372 EE program participant accounts and 25,841 Non-EE participant accounts. This represented 12 distribution substations (a sample of SMUD's >200 substations) and 51 feeders. When combined, the total sample is taken as a proxy for whole grid-level analysis in this analysis ("proxy grid" level).

Energy modeling approach

Several advanced M&V modeling approaches have been developed and shown to provide reliable predictive capabilities for development of annual savings estimates. A key component of this study was to review EE load impacts by time of year, so it was important to verify that the chosen modeling approach is robust to seasonal effects. Two modeling options were considered: The Gradient Boosting Machine (GBM) baseline model (Touzani et al. 2018), which is an ensemble tree-based machine learning method, and the Time-of-Week-and-Temperature (TOWT) model (Mathieu et al. 2011), which is a piecewise linear model where the predicted energy consumption is a combination of two terms that relate the energy consumption to the time of the week and the piecewise-continuous effect of the temperature. In previous studies (Granderson et al. 2016, Touzani et al. 2018) both of these models were shown to be highly accurate at predicting annual consumption, equaling or outperforming other models.

The GBM model was configured with input variables for outside air temperature, time of the week, an indicator to specify if the day of the observation is a holiday, an indicator to specify if the day of the observation is a week day or a weekend and an indicator to represent the season of the observation (where "winter" covered the period December to February, etc.). The TOWT model uses only time (i.e., hour) of the week and the outside air temperature as input variables.

Comparison of TOWT versus GBM model quality was based on three statistical model fitness metrics, in alignment with prior work and industry guidelines such as ASHRAE Guideline 14 (ASHRAE 2014) and industry best practice (Lawrence Berkeley National Lab oratory 2019):

- Coefficient of determination or R^2, target > 0.7,
- Coefficient of Variation of the Root Mean Squared Error (CV(RMSE)), target <25%;
- Normalized Mean Bias Error (NMBE), target within -0.5% to +0.5% range.

In short, these metrics respectively characterize: the amount of variance explained by the independent variables; the difference between the modeled and measured data relative to the mean; and the percent difference between the modeled and measured data.

Baseline models were created for a variety of aggregations of the 2015 calendar-year meter data: firstly, for all EE participants and for all Non-EE participants, and then similar pairs of models for all 12 substations and all 51 feeders. Model fitness metrics were then calculated for each season, by comparing model-predicted consumption to actual metered values for each season.

In virtually all cases the CV(RMSE) and R^2 values met best practice targets across all four seasons, but NMBE results uncovered a marked difference between the TOWT and GBM models. Figure 1 shows a subset of these results, illustrating that all substation-level GBM models met NMBE best practice targets, while very few of the TOWT models met them. Similar trends were observed at the proxy grid level and feeder level. While the TOWT model has been demonstrated to be robust for quantifying annual savings impacts it appears biased when isolating individual seasons; all savings analysis was therefore conducted using the GBM model.

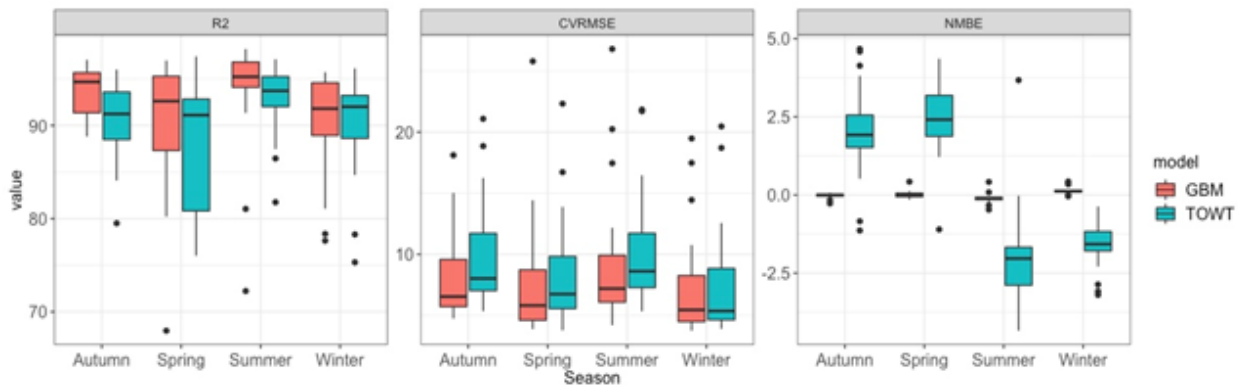

Figure 1. Seasonal model fitness metrics for GBM and TOWT models at substation level.

Using 2015 GBM baseline models, energy use predictions for 2018 (the "reporting period") were generated. The annual savings was calculated as the difference between the model predictions and the actual consumption in the reporting period (known as the "avoided energy consumption" approach), for EE and Non-EE meters at proxy grid level and for all substations/feeders. The analysis result was expressed as a percentage reduction in consumption, the fractional savings (FS), defined in ASHRAE Guideline 14 and shown in Equation 1:

$$FS = \frac{\hat{E}_{post} - E_{post}}{\hat{E}_{post}} = \frac{E_{save}}{\hat{E}_{post}} \qquad (1)$$

Where $\hat{E}_{post}$ is the model-predicted energy consumption in the reporting period, and E_{post} is the actual energy consumption in the reporting period.

To assess the impact of EE accounts' FS on overall energy used at different locations in the grid, a new metric was developed: relative fractional savings (RFS). Defined in Equation 2, the RFS expresses the savings of a given set of EE program participants as a fraction of the energy used at the level of the distribution grid in which the EE accounts are located. For example, it would express the energy impact of those EE participants attached to substation 'X' on the total consumption of substation X (including those who didn't participate in any EE program).

RFS is defined as:

$$RFS = \frac{E_{save}}{\sum \hat{E}_{post}} \qquad (2)$$

Where $\hat{E}_{post}$ is the model-predicted energy consumption in the reporting period, and E_{save} is defined in Equation 1. The denominator of equation 2 corresponds to the sum of EE and the Non-EE groups for each location in the distribution grid.

To determine the hourly EE savings shapes at different locations in the distribution grid, and how those shapes vary with season, average hourly FS was quantified for weekdays, for both EE and Non-EE accounts types. These hourly savings were computed for the full year of the 2018 reporting period, for each of four seasons, and for the day with the highest peak demand (July 25, 2018). For the peak day load reduction analysis an uncertainty band was calculated around the model prediction.

Results

FS and RFS

At the proxy grid level, EE participants saw an FS of 12.6% in 2018 (n = 1,372 aggregated accounts), compared to a 2015 baseline year. This is almost 10% higher than Non-EE accounts, which saw an FS of 2.7% (n = 25,821). This indicates a significant impact from EE program participation, though it should be noted that the analysis did not attempt to attribute the savings directly to the EE programs. The positive FS of non-participants is noteworthy (especially as it is aggregated across over 25,000 accounts), and may be caused by many exogenous factors such as 'green' marketing, energy efficient product promotions, social trends, etc.

While EE accounts' FS was higher than Non-EE, the opposite was true for RFS. EE accounts saw RFS of 1.3% in 2018, compared to 2.4% for Non-EE. This was not unexpected, as the Non-EE participants achieved FS of 2.7% and Non-EE sample size was 19 times larger than the EE sample. Comparing these two values is somewhat arbitrary, as RFS for Non-EE accounts may be positive or negative, varies over time, and cannot easily be influenced. The more significant point (from a utility's perspective) is that EE program adoption by just 5% of the population reduced overall grid consumption by 1.3%, an achievement that aligns well with typical statewide reduction targets.

At the substation level, a wider variation in FS is observed for the EE accounts. As shown in Figure 2 (left-hand chart), FS for EE accounts ranged from near zero (S5) to 26% (S11). In all but one case, FS for EE accounts was higher than FS for Non-EE accounts (substation S3 being the exception). The causes for variation in EE account savings was not studied, but may be due to the types of EE program measures installed, exogenous factors, etc.

The right-hand chart in Figure 2 illustrates the RFS at substation level. In 4 out of 11 cases (S2, S6, S7, and S11) the RFS of EE accounts exceeded the RFS of Non-EE accounts, and in 3 of those cases the RFS of EE accounts exceeded 3%, a significant impact. In one case (substation S4) RFS was virtually zero for both EE and Non-EE accounts. Even in the absence of specifically targeted measures, the EE RFS analysis results indicate that just a small cohort of program participants can have a significant impact on substation load.

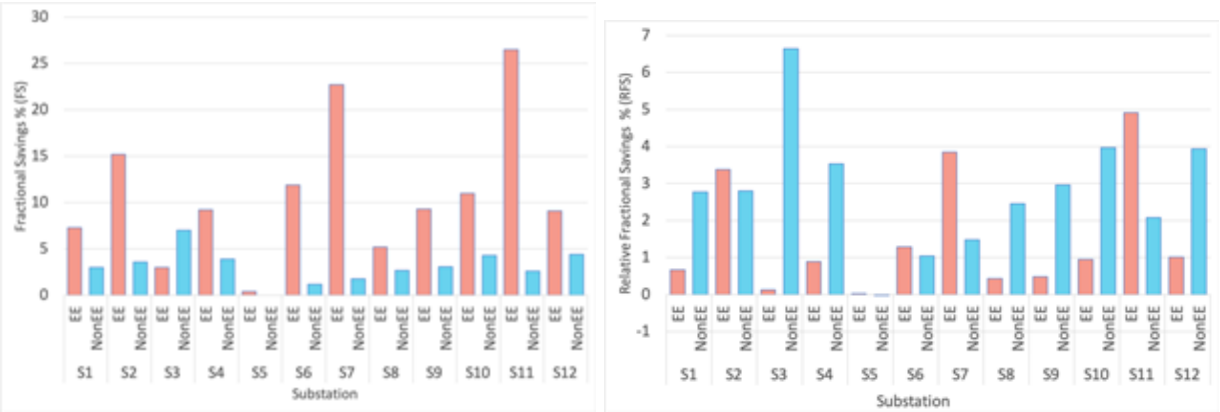

Figure 2. FS (left) and RFS (right) by substation, for EE accounts (red) and Non-EE accounts (blue)

At feeder level the picture was similar to substation level but with a wider distribution of results; this is most likely due to the wider spread in the number of accounts per feeder and percentage of those accounts participating in EE programs. FS for EE accounts ranged from -4.7% to 42%, and was higher than the FS for Non-EE accounts in 39 out of 51 cases. RFS for EE accounts ranged from -2% to 12%, and exceeded the RFS of Non-EE accounts for 12 out of 51 feeders. As with the substation-level analysis, the results suggest that targeted DSM efforts have potential to significantly affect feeder-level load. In contrast, however, feeder-level loads will be far more sensitive to exogenous factors, especially if those factors result in significant load increases for large customers attached to a given feeder (e.g., expansion of an industrial facility attached to a relatively small feeder).

Savings shape

Hourly FS at proxy grid level is shown in Figure 3, for the whole year (left-hand chart) and for each season. For each season and the whole year, the FS of EE accounts is higher than for Non-EE accounts, reflecting the validity of the EE load reductions. The whole-year FS profile shows daytime load reductions peaking around 17% between 12:00 and 1:00pm, and 7% - 10% load reduction between 11:00pm and 6:00am. The EE savings shape is similar for each season, though Autumn trends a few percent higher than other seasons and the summer peak FS occurs a few hours earlier in the day. The Non-EE savings shape is generally flatter and shows less consistency from season to season. It is also noteworthy that while the annual FS for Non-EE accounts is 2.7% (as noted in the prior section), there are some time periods in Spring and Summer where FS is below zero (i.e., load increased relative to baseline for some hours of the day). This emphasizes the benefit of hourly load shape analysis over annual total FS, as T&D capacity constraints are time-bound rather than based on average annual consumption.

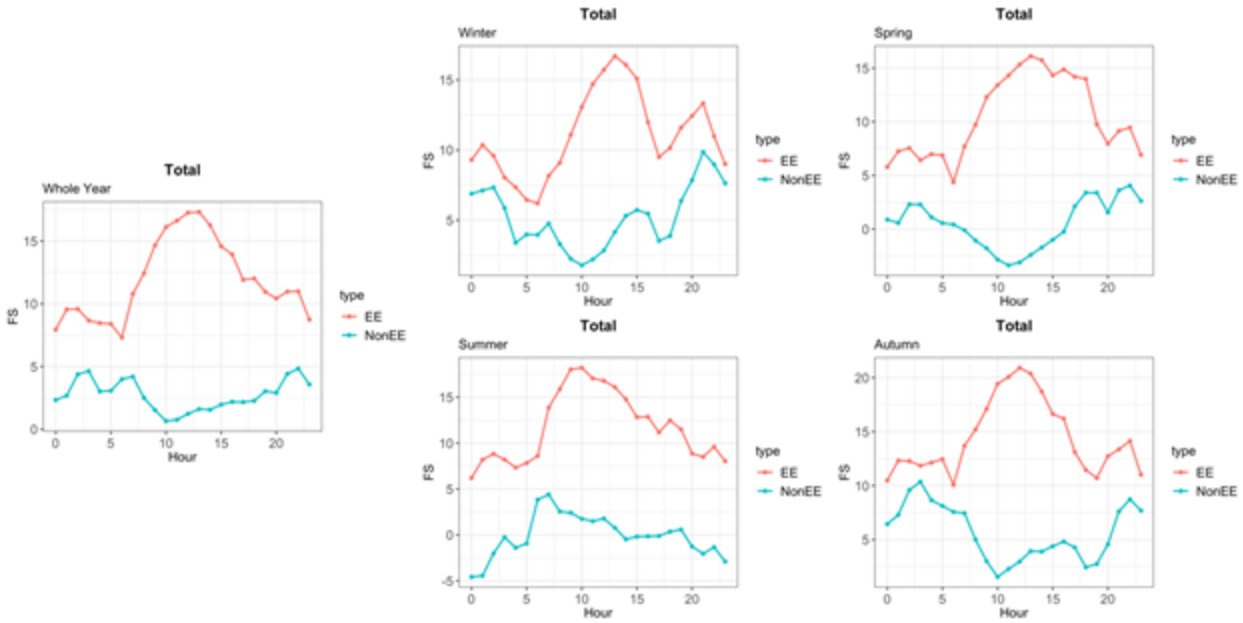

Figure 3. Hourly FS at proxy-total level, for the whole year and for each season

Whole year and seasonal FS profiles were analyzed for each substation, and the hourly profiles for Summer are shown in Figure 4 as an example. Figure 4 illustrates the greater diversity in FS profiles when looking at the substation level, with some substations experiencing higher FS for Non-EE accounts than for EE accounts at some hours of the day (indicated by gray shaded areas on some charts). These substations (with substation S5 being the most extreme example) are dominated by single industrial or miscellaneous accounts, which have very different consumption patterns and usage levels than typical residential and commercial accounts. Other seasons saw similar diversity in hourly FS shapes; this diversity likely reflects the number and type of accounts associated with each substation, and the type of efficiency program deployed.

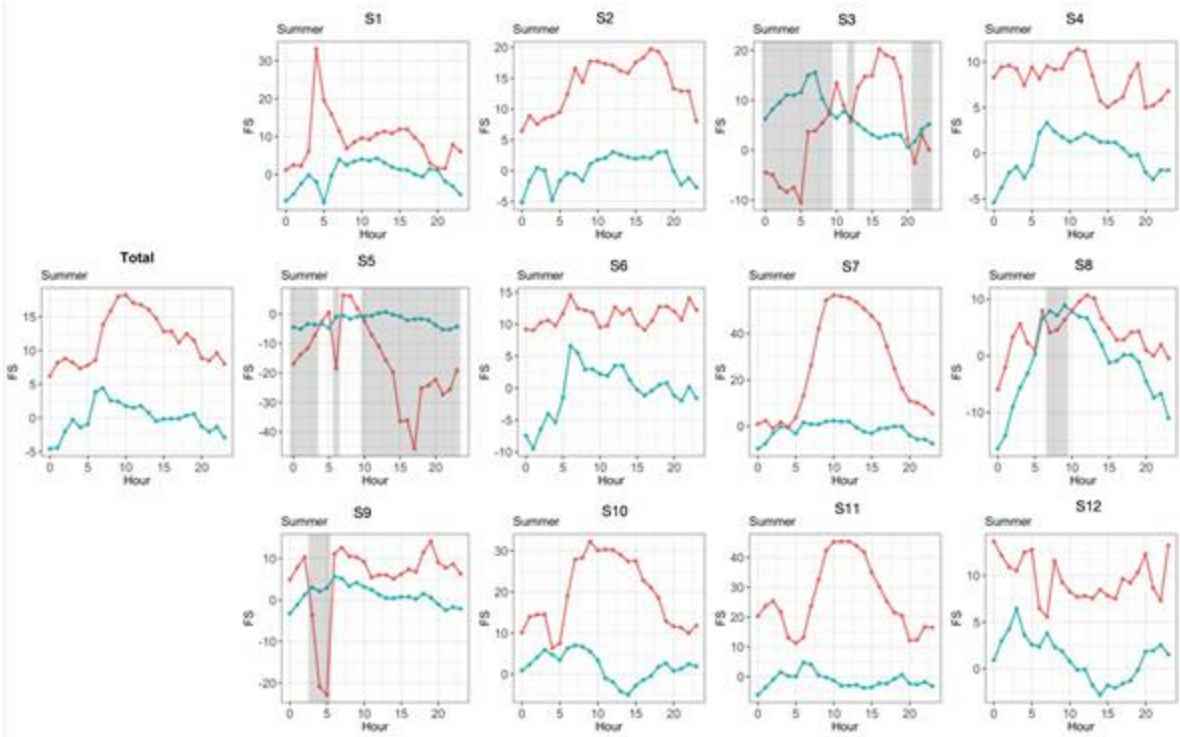

Figure 4. Summer hourly FS at substation level

When replicating the hourly FS analysis at the feeder level, more diversity was seen in terms of EE savings shape (as was seen in the annual savings estimates in the prior section). While substations were typically seeing 3 - 7 hours where Non-EE FS was higher than for EE, feeders were seeing this for 7 - 9 hours. This illustrates that it is harder to distinguish EE FS from the 'noise' of Non-EE load shape changes when data is analyzed by feeder.

Peak day analysis did not provide reliable quantification of load shape changes. Figure 5 shows the GBM model-predicted load shape at the proxy grid level for the peak day (July 25th, 2018) in red, with red dashed lines indicating the uncertainty band around the prediction. Actual consumption is shown in black. The difference between the predicted and actual consumption is relatively small, and actual consumption falls well within the prediction uncertainty band. While some marginal variation in load shape may have occurred, this analysis cannot quantify it with statistical certainty.

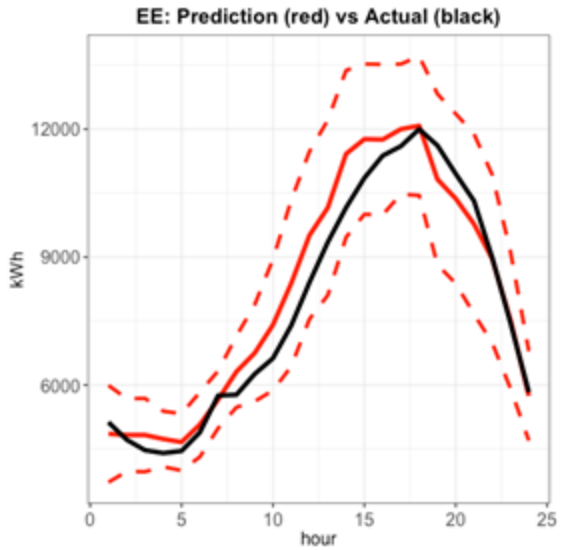

Figure 5. Peak day load analysis at proxy grid level.

As with all other types of analysis in this study, greater variation was observed when moving from proxy grid level to substation level. However, even when plotting the substation with the greatest difference between predicted and actual load, 22 out of 24 hours were inside the prediction uncertainty band (Figure 6). In this case it can be seen that peak demand was reduced by approximately 250kWh (17%) and moved two hours later, but was still within the uncertainty band. Values for 5:00pm and 6:00pm were outside of the uncertainty band but were the exceptions when looking across all substations.

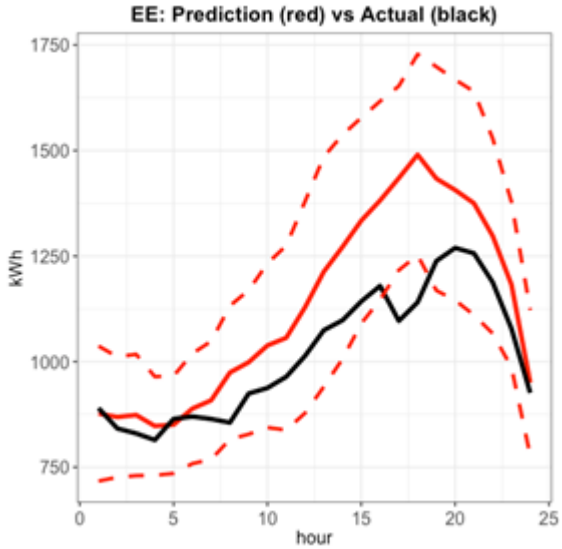

Figure 6. Substation that has the highest hourly difference between predictions and actual energy consumption

Given that the prediction uncertainty band was around 15% - 20% of predicted values, and that an aggregate impact of 15% from DSM programs is very high, we conclude that the

analysis method is insufficient for capturing peak day loadshape changes (i.e., this method would be appropriate for program efforts yielding >20% load reductions, which is highly unlikely).

Discussion

The results of the annual savings analysis showed that EE program participants are, on average, achieving an almost five-fold reduction in energy consumption compared to non-EE participants. This pattern was largely replicated at substation and feeder level, though to varying degrees across the 12 substations and 51 feeders analyzed. The causes of variation in FS between EE accounts at different substations/feeders was not studied, but two possible drivers of the variation are the applicable programs (which may have some correlation to the building types attached to the substations/feeders) and exogenous factors. Further study of FS results in relation to participation in different programs and the mix of residential/commercial/industrial properties in the analysis may provide valuable additional insights for future targeting of programs.

The development of the RFS metric allowed for an assessment of the impact of EE programs on the grid (and on specific geographical locations within the grid infrastructure). The grid-level RFS of 1.3% was reasonable with respect to the utility's load reduction targets, which aim for annual reductions in the order of a couple percent (which include midstream/upstream programs with subcontractors and retailers, which weren't captured by the "EE" marker in the dataset used for this study). At the substation and feeder level, a wider distribution of RFS results illustrate that, as the sample size is reduced, there is more chance for exogenous factors and variation in EE participation rates to lessen the visibility of EE impacts. However, it should be remembered that there was no explicit effort to target DSM efforts geographically. When taken in combination, FS and RFS analysis results provide strong encouragement to program implementers wanting to target EE programs geographically and to clearly quantify the benefits of those efforts.

Reporting hourly FS enabled temporal analysis of EE impacts, which is becoming ever more important as the evolving duck curve is driving utilities and regulators to review the time-specific impacts of their programs. At the proxy-grid level, hourly FS ranged from approximately 7% to over 17%, with some relatively minor variations between seasons. Maximum savings were observed to occur between 12:00pm and 1:00pm. Solar generation is also high during these hours, suggesting that in a decarbonized world with increased building electrification, the ability to time-shift savings will have implications on the value of efficiency.

In moving to substations and then to feeders the hourly profiles saw increasing levels of variety (in savings shape, and also in whether FS for EE accounts was higher than for Non-EE). These results showed that, with more intentional DSM targeting, there is potential to target specific locations based on intended FS magnitude and savings shape. To support this, further study into the impacts of factors such as program type and building type may be very useful for program developers. Supplementing FS charts with hourly charts of absolute carbon reductions (using variable hourly carbon emission rates) may also help inform and prioritize DSM planning.

Analysis of peak day FS was inconclusive; results indicated a trend of modest load reductions across all substations, but those reductions couldn't be expressed with statistical certainty. Refinements to the analysis method could include: (a) more selective curation of data used to create the baseline model; (b) quantifying average load reduction for several peak days in the reporting period; and/or (c) considering other model types. Analysis of data from other

regions (perhaps with peaks occurring in different seasons or at different times of day) may also provide some interesting insights into peak demand reduction.

Conclusions and Future Research

As the efficiency industry is moving toward application of energy efficiency to meet the needs of a renewables-integrated energy system, there is a strong need to understand time- and location-based energy impacts of DSM efforts. This work demonstrated new metrics and an accurate modeling method to assess grid-level spatio-temporal impacts of energy efficiency. These approaches provide a methodological and modeling framework that can connect efficiency programs with grid and distribution planning. In turn this will support the achievement of aggressive targets for electrification and efficiency through targeted DSM, load flexibility, and reliable NWA.

Future work on grid level AMI data analysis can expand upon the initial analyses presented in this paper. Disaggregation of the data set would enable assessment of program-specific effects, and characterization of how energy savings vary with different distributions of residential, commercial, and industrial customers (the analysis could also be replicated with data from different geographical regions). This would provide valuable insights to program implementers seeking to optimize a portfolio of program offerings, and could be combined with the development of analytical methods to address meters with EVs, on-site PV, and other meters that had to be excluded from this study. Improvements to the quantification of peak day load reduction are needed; this may be achieved through more selective curation of baseline and reporting period data, review of model terms, and consideration of other model types. Finally, the analyses presented in this work can be applied to NWA projects in the field to study longer term impacts, and to future pilots of location- and time-based targeting of EE program delivery.

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