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Spatio-temporal impacts of a utility's efficiency portfolio on the distribution grid

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Abstract

Energy Efficiency has historically focused on delivering savings to offset growth in energy supply. Today's growing emphasis on decarbonization of the energy supply is driving renewables adoption and increased interest in electrification. As a result, energy efficiency is being assessed not just in its ability to offset load growth, but also for its ability to alleviate location-specific constraints on transmission and distribution infrastructure. This work demonstrates that advanced measurement and verification modeling techniques can be used to estimate the spatio-temporal grid impact of a portfolio of energy efficiency programs. It extends measurement-based methods to an entire Demand Side Management portfolio and uses a single model to predict annual as well as seasonal building energy use with near-zero bias. In addition, new metrics are introduced to assess grid level impacts of energy efficiency. The results show that the efficiency program portfolio delivers savings of over 12% at the territory-wide proxy level, with substation and feeder level savings ranging from 0.4%-26%, and -5%-42% respectively. These savings impacted 1.0%-1.4% of the energy used at these locations in the grid. This work provides a methodology with potential to connect efficiency with distribution planning, carrying implications for non-wires alternatives and targeted delivery of efficiency programs.

Keywords: Advanced Metering Infrastructure (AMI), Demand Side Management (DSM), Energy Efficiency (EE), Fractional Savings (FS), Measurement and Verification (M&V), Relative Fractional Savings (RFS), Transmission and Distribution (T&D)

Nomenclature:

E Energy (kilowatt-hour [kWh])

1: Lawrence Berkeley National Laboratory, 1 Cyclotron Road, Berkeley CA, 2: Sacramento Municipality Utility District, 6201 S St, Sacramento, CA 95817, 3: National Cheng-Chi University, Taipei, Taiwan.

T Temperature (degrees Celsius [°C])
t Time (seconds)
P Energy demand (kilowatts [kW])

1. Introduction

Energy Efficiency (EE) is the practice of using less energy to provide the same or an improved level of service to an energy consumer, in an economically efficient way (Goldman et al. 2010). It has historically focused on the delivery of savings as a means to reduce consumer energy costs and offset growth in energy supply. Today, there is growing emphasis on decarbonization of the energy supply chain, which is driving renewables adoption and increased interest in electrification (the practice of switching natural gas consumption to electricity, which is in turn provided by low/no carbon energy sources). Energy efficiency is now being considered not just for its ability to offset growth in supply, but also for its ability to alleviate location-specific constraints on transmission and distribution (T&D) infrastructure as load growth increases unevenly across regions. Also, the EE industry is beginning to consider the time-differentiated value of efficiency, since the increasingly diverse generation mix means that carbon emissions can vary significantly by time of day/year. Moving beyond the traditional approach of average annualized savings for EE surfaces additional insights into the value of efficiency relative to avoided carbon, cost-effectiveness, and grid-level hourly net load shapes.

Targeting EE programs either independently or in concert with demand response (DR) and distributed generation can play a role in deferring capital investments for T&D infrastructure (Chew et al. 2018), which have averaged approximately $45B annually over the last decade in the U.S. (Neme et al. 2015). These 'non-wires alternatives' (NWA) are defined as: "An electricity grid investment or project that uses non-traditional T&D solutions, such as distributed generation, energy storage, energy efficiency, demand response, and grid software and controls, to defer or replace the need for specific equipment upgrades, such as T&D lines or transformers, by reducing load at a substation or circuit level" (Navigant 2017). Studies from as early as the 1990s showed that demand side management (DSM) programs that are carefully matched to local area costs and timing of loads can cost effectively and reliably defer infrastructure investments (Kinert et al. 1992). Due to increasing T&D costs relative to costs of generation, strategies have been tested to develop area-specific marginal costs, loads and DSM load impacts (Orans et al. 1991). This was significant because it allowed for T&D benefits to be emphasized more in DSM program planning. More recently, Chew et al. 2018 summarized case studies of NWAs from leading U.S. projects. The majority of these case studies demonstrated success in helping to delay or permanently defer infrastructure upgrades. For example, the Brooklyn Queens Demand Management (BQDM)

Program, is often noted in the EE industry as a successful effort implemented to delay the construction of a new substation beyond initial load-relief projections (Chew et al. 2018).

Since different EE projects/measures produce savings at different times of day (the so-called “savings shape”), there is opportunity to target measure deployment for maximum temporal value. For example, a commercial lighting EE measure will produce more savings during the day, whereas a residential hot water measure will produce more savings in the morning or evening. From a system perspective, the cost of generating and supplying electricity, and the associated environmental impacts, as well as net load, varies by time of the year and time of day. Therefore, to accurately quantify the system-wide value of energy savings, it is necessary to account for seasonal and hourly variations in energy savings. Mims et al. 2017 show that the time-varying value of energy efficiency savings is important because when calculating the benefits to the power system, the energy savings value will vary by the season and hour of the day that the energy reductions occur (Mims et al. 2017). Boomhower et al. 2017 in their analysis reveal that the value of electricity is highly variable even within a single day, and this variability is tending to grow larger as a greater fraction of electricity comes from solar and other intermittent renewables (Boomhower et al. 2017). In Novan et al. 2018, the authors use meter-based data and are able to estimate not just total energy savings, but also when they occur (Novan et al. 2018).

The consideration of how DSM programs can be coupled with distributed generation and energy storage to deliver more targeted spatial and temporal benefits to both customers and the grid, brings new opportunities for the use of interval meter-based energy savings analysis methods. While demand response programs have typically used interval meter data, energy efficiency savings analyses more commonly use engineering calculations or stipulated savings that represent population average annual energy reduction. However, interval meter-based savings analysis methods offer the ability to disaggregate load, based on time of day, day of week, and season.

Prior work has investigated building-level applications of meter-based savings analysis, for EE and DR. For example, Mathieu et al. 2011 present methods for analyzing commercial and industrial facilities’ advanced metering infrastructure (AMI) data with a focus on DR (Mathieu et al. 2011). Bode et al. 2014 use whole building level interval meter data to screen sites and estimate energy savings (Bode et al. 2014). Jump et al. 2015 used smart meter data to determine how well the whole building level approach to energy savings estimation is applicable and concluded positively that the approaches were viable (Jump et al. 2015). Granderson et al. 2017 show more broadly the commercially available technologies that use AMI data both for energy analytics and advanced M&V (sometimes called “M&V 2.0”) (Granderson et al. 2017b). Most meter-based savings analysis however, in the field and in the literature, have focused on total energy savings and have not considered the time or season in which those savings occur. Other methods that do not use meter-based savings analysis to estimate building load impact on the distribution grid are also present in the literature. Mejia et al. 2020 present a spatio-temporal growth model for estimating the adoption of new end-use electric technologies encouraged by energy-efficiency policies (Mejia et al. 2020). This work uses a geographically weighted regression to capture the spatio-temporal nature of energy efficiency savings. The results show load curves of distribution transformers that provide valuable information regarding the distribution network expansion planning, but the analysis does not quantify actual impacts from specific efficiency programs. Arnaudo et al. 2019 use co-simulation of the electricity grid and buildings to monitor grid capacity to avoid overloading (Arnaudo et al. 2019). They find that given grid capacity limits, different energy efficiency policies could be implemented in buildings to unlock better energy and environmental performance. Even though this work was using simulated data rather than AMI data, it is useful for higher level distribution grid planning including uncertainty analysis.

In previous work, the authors have developed and tested promising advanced M&V approaches to partially automate the savings estimation process through the analysis of time series meter data. Granderson et al. 2015, and Granderson et al. 2016 showed through statistical test procedures that these automated techniques are accurate and robust in modeling and predicting commercial buildings' annual energy use. A literature review did *not* surface prior work that has analyzed time-based energy efficiency savings at different levels of the distribution grid infrastructure (e.g., substation level and feeder level) using meter-based savings analyses.

Addressing this gap in the published research, the goal of this work was to demonstrate the use advanced M&V modeling techniques to estimate the spatio-temporal impact of a portfolio of EE programs, relative to the distribution grid. This paper presents the results of an analysis of interval meter data from over 25,000 accounts from a California utility. The specific research questions that were answered in this work were: 1) what are EE savings at different locations in the distribution grid, and how much do those savings impact the total load at those locations? 2) what is the hourly EE savings shape at different locations in the distribution grid, and how does this shape vary by season?

The paper proceeds as follows: Section 2 describes the methodology underlying the study, Section 3 summarizes the findings, and Section 4 provides a discussion of the results. The final section provides conclusions and ideas for future work.

2. METHODOLOGY

To determine grid-level savings due to energy efficiency, AMI data from a California utility was provided, covering the period 2015 to 2018 that indicated accounts that participated in EE programs in 2016 and 2017. This data was pre-processed and analyzed as shown in Figure 1, to establish aggregate spatio-temporal load impact estimates for both EE program participants and non-participants. Sections 2.1 to 2.4 describe the study method in detail.

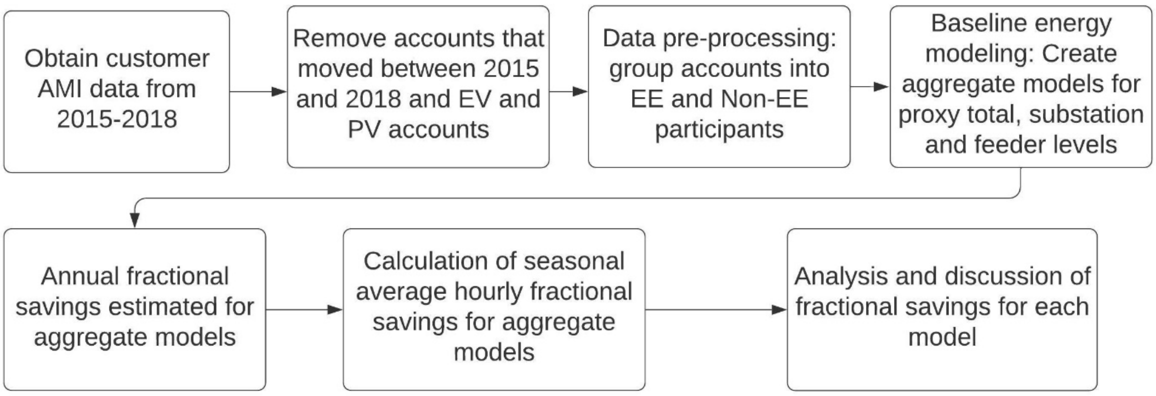

Figure 1: Flowchart showing analytical steps in the study

2.1 Composition of the dataset

A dataset of hourly Advanced Metering Infrastructure (AMI) accounts was used for the analyses presented in this paper. These AMI meters corresponded to 12 different substations and 51 feeders, representing a sample across the territory. The dataset included accounts that participated in EE programs and those that did not; in the remainder of this paper those accounts types are referred to as *EE* and *Non-EE*. For the EE participants, the date of installation of the EE measures were also provided, so that a baseline and analysis period could be defined to analyze the impact of the EE programs. In addition, the data was labeled to indicate customers who had relocated during the analysis period, those who had an electric vehicle (EV), and those who had a photovoltaic (PV) system. Appendix A summarizes the EE customer types at each substation i.e., if they were commercial, residential, industrial, or unlabeled.

2.2 Data pre-processing

For the assessment of EE program impacts, 2015 was taken as the baseline year and 2018 was selected as the analysis year. Meter data from the following account types were removed from the analyzed dataset:

- Accounts that relocated in 2015 or 2018, because the change in energy consumption could have been caused by occupancy change rather than by the EE measure.
- Accounts that had an EV or a PV, because they were a very small number in the sample and their load shape patterns were highly variable.

- Accounts for which data was missing in either the baseline year or analysis year.

After completing the data pre-processing, 1,372 EE accounts and 25,841 Non-EE accounts were included in the study sample.

The analysis was performed at three levels of account grouping: 1) The sum of data from all meters across all substations, which can be viewed as a proxy for the utility's territory-wide distribution grid. This is referred to as "*total level.*" 2) The sum of data from all meters associated with a given substation, for all 12 substations. 3) The sum of data from all meters associated with a given feeder, for all 51 feeders.

For each of the three account grouping levels the accounts were split into two subsets: EE and Non-EE. Then, in order to decrease the variability of the energy use time series, and thus improve the prediction accuracy of the considered baseline modeling method, the hourly energy use was aggregated for all of the accounts within a subset (i.e., EE and Non-EE). This was conducted for the baseline year (2015) and the analysis year (2018). Thus, for each time step *t* the energy use for the EE and Non-EE accounts was defined in Equations 1 and 2 as:

$$E_t^{NonEE} = \sum_{j=1}^{N_{NonEE}} E_t^j \qquad (1)$$

$$E_t^{EE} = \sum_{j=1}^{N_{EE}} E_t^j \qquad (2)$$

where N_{NonEE} is the number of accounts in the Non-EE subset, N_{EE} is the number of accounts in the EE subset, and E_t^j is the energy use of account *j* at the time step *t*.

Note that: at the total level N_{NonEE} is equal to the total number of Non-EE accounts that are in the dataset (i.e., 25,841) and N_{EE} is equal to the number of EE accounts that are in the dataset (i.e., 1,372); at the substation level N_{NonEE} and N_{EE} are respectively equal to the number of Non-EE and EE accounts that are connected to a specific substation; at the feeder level N_{NonEE} and N_{EE} are respectively equal to the number of Non-EE and EE accounts that are connected to a specific feeder.

For the remainder of this paper, both EE and Non-EE accounts will be referred to as *account types* and the total, substation and feeder level aggregations will be referred to as *analysis levels.*

2.3 Baseline Energy Modeling

Regression methods are a standard approach used for developing baseline models that aim to model the relationship between energy use and a set of independent variables (also known as explanatory variables) $\boldsymbol{x} = (x^{(1)}, \dots, x^{(d)})$, where d is the number of independent variables. The most commonly available independent variables in energy use baseline modeling are the time of the week and the outdoor air temperature. Mathematically the regression problem can be represented for a given observation set $\{(\boldsymbol{x}_1, y_1), \dots, (\boldsymbol{x}_T, y_T)\}$, as

$$E_t = f(\boldsymbol{x}_t) + \varepsilon_t, \quad \varepsilon_t \sim N(0, \sigma_\varepsilon^2) \qquad (3)$$

where $\boldsymbol{x}_t = (x^{(1)}, \dots, x^{(d)}),\ t = 1, \dots, T$ are d dimensional vectors of inputs variables, ε_t is independent Gaussian noise with mean 0 and variance σ_ε^2. Building a baseline model consists of approximating the function $f(\boldsymbol{x})$ given a set of T observation $\{(\boldsymbol{x}_1, y_1), \dots, (\boldsymbol{x}_T, y_T)\}$.

In recent years several baseline energy modeling approaches that use interval meter data have been introduced in the academic literature and in the industry. For instance, Mathieu et al. present a regression-based electricity load model that uses a time-of-week indicator variable and outdoor temperature to characterize demand response behavior (Mathieu et al. 2011). Heo and Zavala present a Gaussian process (GP) modeling framework to determine energy savings and uncertainty levels in M&V (Heo and Zavala 2012), while Burkhart et al. present a Monte Carlo expectation maximization framework for M&V (Burkhart et al. 2014). More recently Touzani et al. presented a Gradient Boosting Machine baseline model for M&V (Touzani et al. 2018). These methods are based on traditional linear regression, nonlinear regression, and machine learning regression methods. The temporal variation in electricity consumption in buildings can be driven by several factors, including weather, occupancy schedule, and daily and weekly periodicity. In practice and in the literature, to capture these effects, it is common to use two different input variables - outside air temperature and time of the week. Historically, energy savings analysis has focused on total annual energy savings.

Since one of the key research questions associated with this work concerns the seasonality of hourly savings shapes, an analysis was performed to evaluate the impact of including season as independent variable on seasonal model goodness of fit metrics. Two models were considered: The Gradient Boosting Machine (GBM) baseline model (Touzani et. al 2018), which is an ensemble tree-based machine learning method, and 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. 2017, Touzani et al. 2018) GBM and TOWT were shown to be highly accurate at predicting annual consumption, equaling or outperforming other M&V industry standard 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 of the week and the outside air temperature as input variables.

The goodness of fitness of each model was assessed using three statistical model fitness metrics: NMBE, CV(RMSE) and R^2 (see definition and description of the metrics in Granderson et al. 2017a). Figure 2 shows the three model fitness metrics for both GBM and TOWT models by season and by analysis level. Each chart shows data points for EE models and Non-EE models, e.g., at the total proxy level there are two TOWT R^2 data points for Autumn, one for the EE model and one for the Non-EE model. Overall the GBM models outperformed the TOWT models, having higher R^2, lower CV(RMSE), and NMBE closer to zero. The most significant improvement can be seen in the NMBE metric where GBM models have near-zero bias (NMBE) across all seasons, which is most desirable for accurate seasonal savings quantification. Given its near-zero bias for both annual as well as seasonal time horizons, the GBM model was used in this work.

2.4 Analysis framework

The GBM baseline model was fit to the data for the two account types and the three analyzed levels of the distribution grid. Model goodness of fitness metrics R^2, CV(RMSE) and NMBE were evaluated to verify model sufficiency. The threshold values of model fitness metrics for CV(RMSE) and NMBE were from ASHRAE Guideline 14 (ASHRAE 2014), while the R^2 value is an industry best practice. These were:

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

Using the baseline models, energy use predictions for the analysis year (2018) were generated. The annual savings for the EE and the Non-EE groups was calculated as the difference between the baseline predictions and the actual consumption in the analysis period (known as the "avoided energy consumption" approach to estimating savings). The analysis result was expressed as a percentage reduction in consumption, the *fractional savings* (FS), defined in ASHRAE Guideline 14 as shown in Equation 4:

$$FS = \frac{\hat{E}_{post} - E_{post}}{\hat{E}_{post}} = \frac{E_{save}}{\hat{E}_{post}} \qquad (4)$$

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

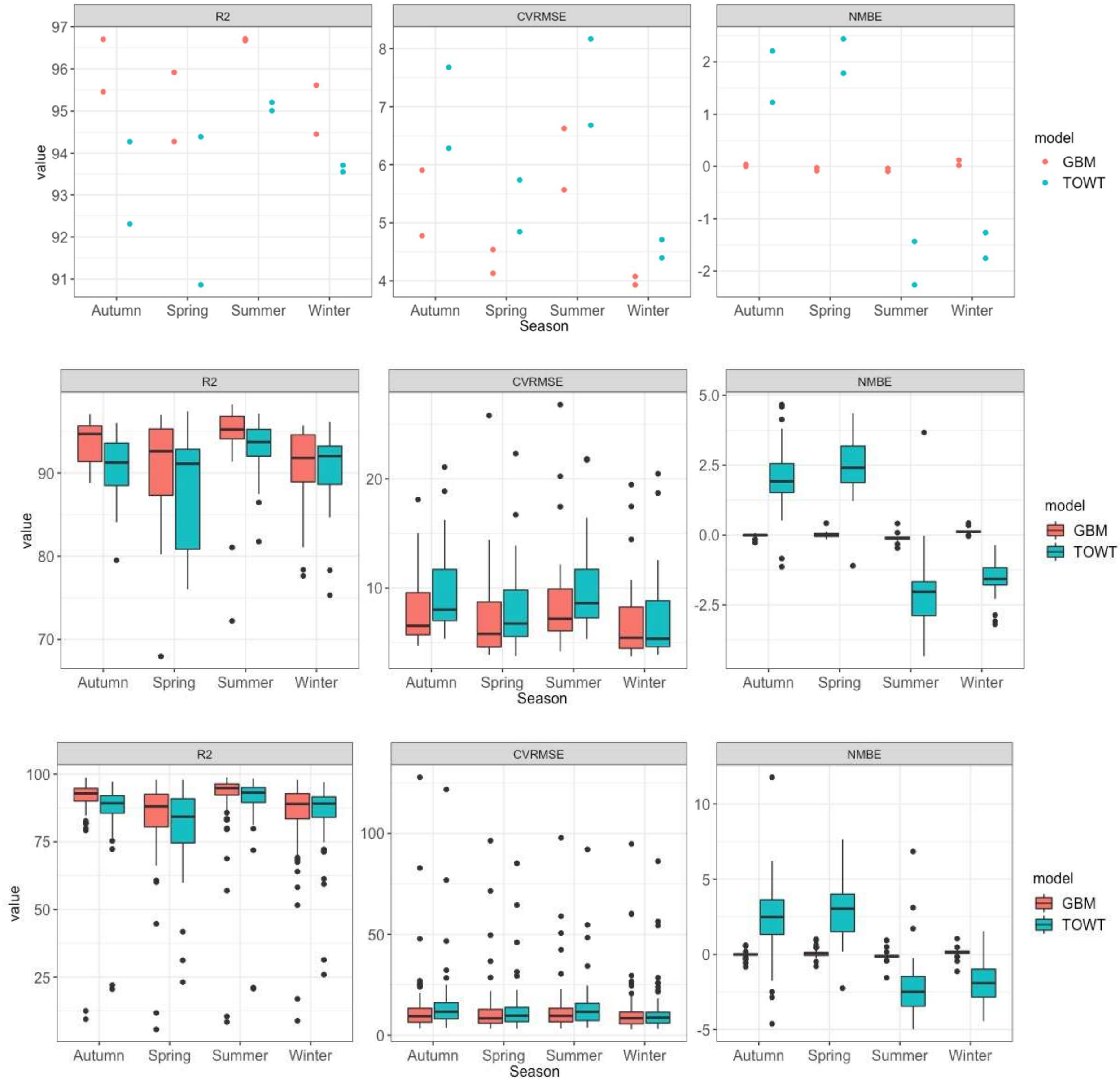

Figure 2: Seasonal goodness of fit metrics for GBM and TOWT models at the proxy total (top), substation (all substations in middle), and feeder levels (all feeders at bottom).

The FS of the EE group was compared to the FS of the Non-EE group as an additional verification of the validity, or reliability of the savings results, that complemented the assessment of baseline model goodness of fit. The expectation is that the savings observed for EE program participants will be significantly different from changes in consumption for the Non-EE program participants (which may reduce or increase over time). Confirming that this is indeed the case in the analysis results was used to verify that the EE savings signal was above some level of energy consumption change that may affect all accounts, EE and Non-EE, independent of their participation in energy efficiency programs (For example, changes in the economy, naturally occurring efficiency, or upstream utility efficiency interventions). In the following, for simplicity this change in energy use for NonEE accounts, that may occur independent of efficiency program participation, is called 'noise.'

The FS was calculated to quantify the efficiency savings achieved by accounts at different points in the distribution grid. To assess the impact of those savings on the energy used at these points in the grid, the metric *relative fractional savings* (RFS) was developed. Defined in Equation 5, the RFS expresses the savings of a given set of EE program participants as a fraction of the energy used at level of the distribution grid in which the EE accounts are located. This is in contrast to the fractional savings (FS), which quantifies savings for a particular aggregation of accounts with respect to *their own historical consumption.*

RFS is defined as:

$$RFS = \frac{E_{save}}{\sum \hat{E}_{post}} \qquad (5)$$

where $\hat{E}_{post}$ is the model-predicted energy consumption in the analysis period, and E_{post} is the actual energy consumption in the analysis period. The denominator of equation 5 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 savings were quantified for weekdays, for both accounts types. These hourly savings were computed for the full year of the 2018 analysis period, and also for the each of four seasons. Winter was taken as spanning December through February, spring as March through May, summer as June through August, and fall as September through November. In this analysis only the FS metric was analyzed, due to the fact that the RFS is less visible at the hourly level. As in the analysis of *annualized* EE at different points in the grid, the *hourly* FS for EE participants was compared to the FS for Non-EE participants to verify that they EE savings signal was indeed above the 'noise'.

3. FINDINGS

This section first presents the utility's EE programs energy savings at different points in the distribution grid. These annualized results are followed by findings that illustrate hourly savings profiles for the full year, and for the different seasons of the year.

3.1 Annual efficiency savings in the distribution grid

For the proxy total distribution grid level (the aggregate of twelve substations, containing 1,372 EE accounts and 25,821 Non-EE accounts, with EE accounts comprising 5.4% of the total number of accounts in the analysis). The left plot in Figure 2 shows that the EE accounts saved 12.6% from the baseline year to the analysis year, while the Non-EE accounts 'saved', i.e., reduced their consumption, by 2.7%. As noted in the methodology section, the reduction in energy use observed in the Non-EE accounts group could be due to a number of exogenous factors, however as expected, the EE accounts are savings significantly more, verifying that the savings signal is discernible from the 'noise'.

The right plot in Figure 3 shows that the 12.6% savings that were achieved by the EE accounts manifested as a 1.3% reduction in the total energy used across the twelve substations. That is, energy efficiency was observed to impact grid-level energy use by 1.3%. However, the impact of the Non-EE accounts was even larger, with 2.7% FS translating to an RFS of 2.4%. This is due to the large number of Non-EE accounts versus EE accounts. Even though the 1,372 accounts in the EE group saved over 12%, the impact of these savings on energy used in the distribution grid was surpassed by the 2.7% savings were observed in the 25,821 Non-EE accounts.

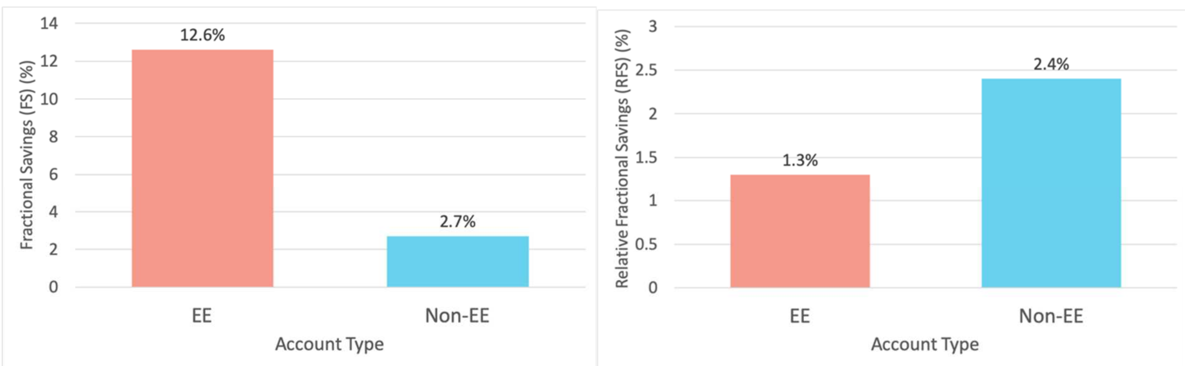

Figure 3: FS and RFS for EE and Non-EE accounts at the proxy total distribution grid level.

Figure 4 shows the fractional savings and relative fractional savings for each of the 12 substations individually. Across substations the average number of EE accounts was approximately 5% of the total number of accounts, as was the case for the total grid-level proxy. Of the 11 substations with EE account savings larger than Non-EE accounts, 4 substations also had an RFS for the EE accounts that exceeded that of the non-EE accounts. At the substation level, the FS achieved by EE participants ranged from near zero, to above 25%, with an average of 11%.

This indicates that even without the utility explicitly conducting location targeting, efficiency is delivering observable impacts for a portion of the substations in the distribution grid.

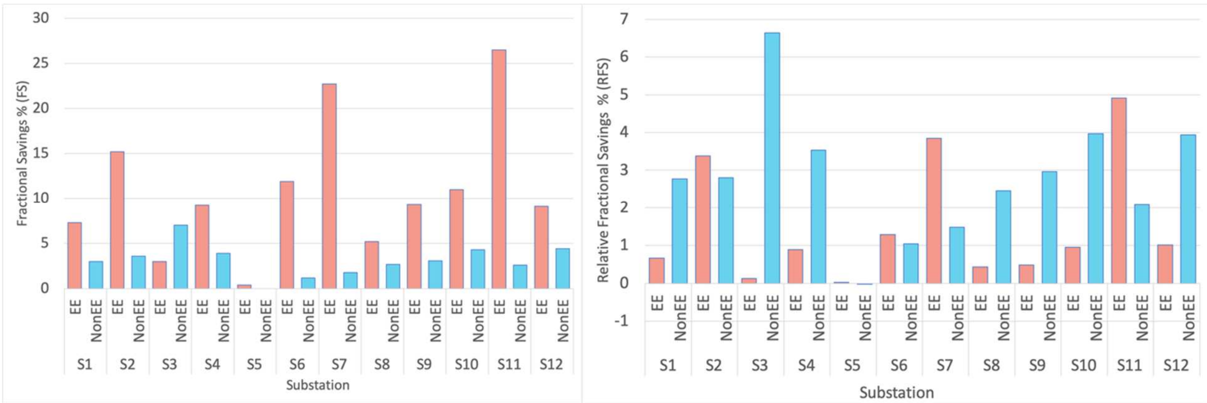

Figure 4: FS and RFS for EE and Non-EE accounts at the substation level.

At the feeder level the average number of EE accounts was 5% of the total number of accounts, as was the case for the substation and proxy total levels. However, at this level of the distribution grid, the EE savings signal was more variable, and less discernible. The FS for the EE group was larger that of the Non-EE group for 39 out of 51 feeders analyzed, and ranged from -4.7 to 42% with an average of 9%. The RFS for the EE accounts ranged from -2 to 12% with an average of 1%, and exceeded that of the Non-EE accounts for 12 out of the 51 feeders.

3.2 Hourly efficiency savings shapes in the distribution grid

Figure 5 shows the average savings for each hour of the day at the proxy total distribution grid level. The left-most plot shows hourly savings for the full year, and the four plots to the right show the hourly savings profiles for each season. For every hour of the day, the savings for the EE accounts is larger than that of the Non-EE accounts, reflecting the validity of the savings results. Annually, the hourly EE savings range from approximately 7% to over 17%. The annual and seasonal savings profiles reflect similar shapes, with savings peaking around noon, and minimum at around 5:00 am. In the summer, the peak savings appear a couple of hours earlier at 10:00 am. It is also notable that, while Non-EE accounts saw a reduction in consumption overall (as stated earlier), Figure 4 indicates that consumption actually increased (i.e., a negative savings value) for some hours in spring and summer.

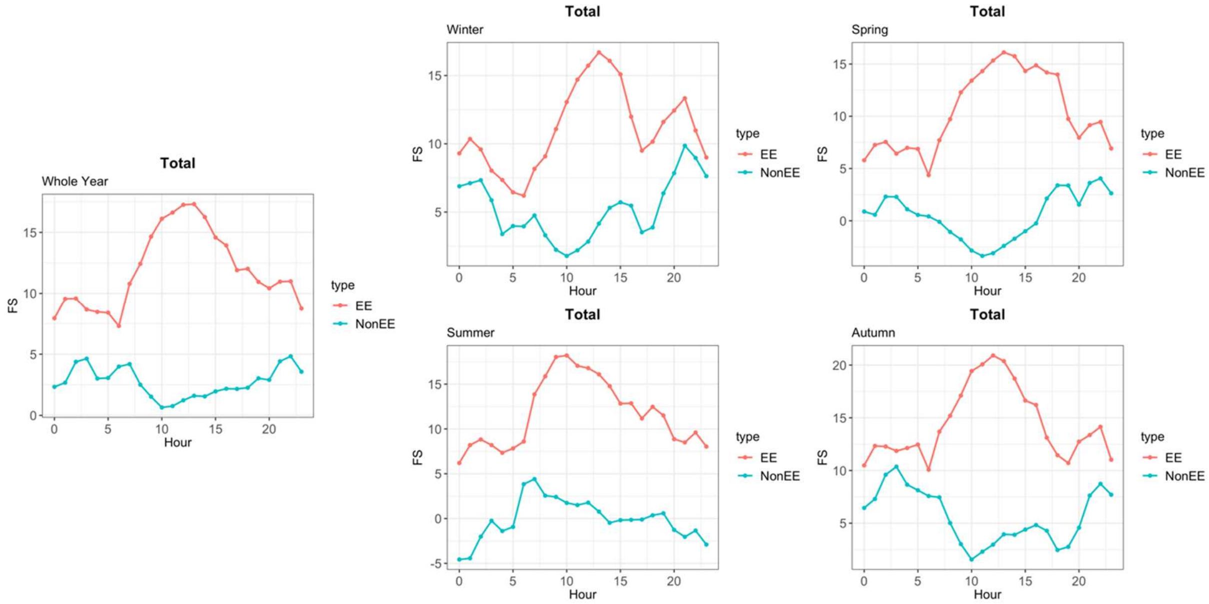

Figure 5. Average hourly FS for EE and Non-EE accounts at the proxy total distribution grid level, annually (left), and seasonally.

Figure 6 shows the annual hourly savings profiles for the proxy total distribution grid level, and also for each of the twelve substations that were analyzed. In contrast to the proxy total grid level, at the substation level, there *are* hours of the day for which the savings for EE accounts group are *not* larger than that of the Non-EE group. These hours of the day are shaded gray in the plots, and although relatively few in number, represent time periods for which the hourly savings signal cannot be distinguished from the 'noise' (Substation S3 being the most extreme example). These substations are dominated by single miscellaneous or industrial accounts, which have very different consumption patterns and usage levels than typical residential and commercial accounts. At the substation level the hourly savings shapes are highly varied, with more diversity of shapes, and also timing of the peak savings. This likely reflects the number and type of accounts associated with each substation, and the degree and type of efficiency deployed.

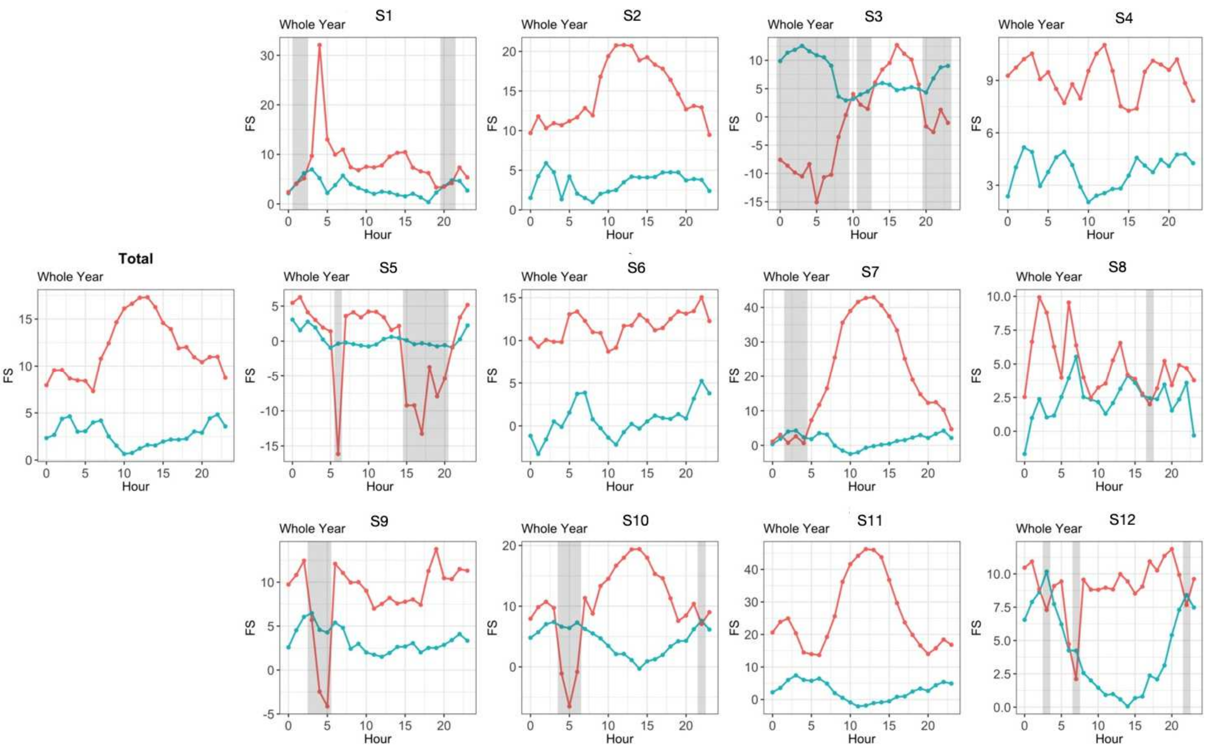

Figure 6: Average hourly FS for EE (red line) and Non-EE (blue line) accounts annually, at the proxy total distribution grid level (left), and at each substation analyzed.

Figure 7 shows the summer season hourly savings profiles for the proxy total distribution grid level, and also for each of the twelve substations that were analyzed. Summer is a period of particular interest, as it is the time of year when loads are typically at their highest, putting the highest demand on the distribution grid. With the exception of substations S3 and S4, the hourly savings for the EE group are validated as higher than the Non-EE group for most hours of the day. Overall, for each substation, the summer savings shapes are similar to the full-year savings shapes, and there remains significant variability between substations.

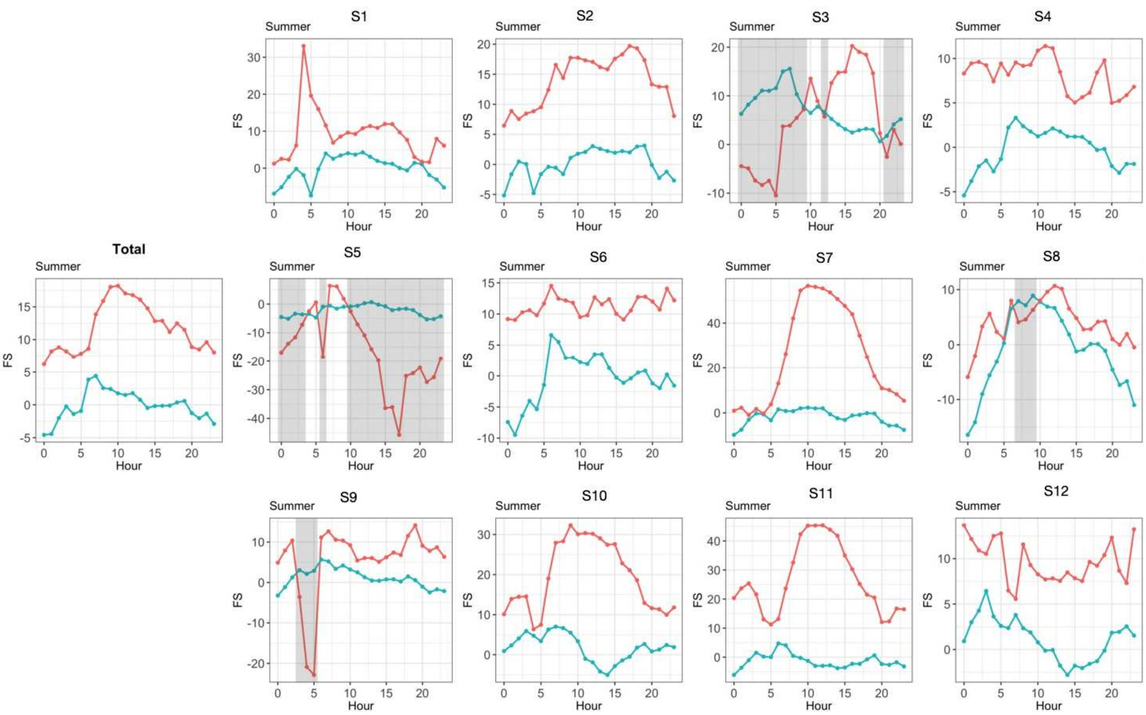

Figure 7: Average hourly FS for EE and Non-EE accounts in summer (June, July, August), at the proxy total distribution grid level (left), and at each substation analyzed.

Table 1 summarizes the difference in the calculated hourly fractional savings between the EE and Non-EE groups, at each level of analysis in the distribution grid (total proxy, substation, and feeder), for the full year, and also for each season. This difference indicates the validity, or quantifiability of the hourly savings results, and is expressed as the average number of hours (out of 24), for which the fractional savings of the EE group was larger than that of the Non-EE comparison group. The results indicate that the hourly savings results are most often valid at the total proxy level (EE higher than NonEE for all 24 hours of the day), decreasing down the hierarchy to the substation and feeder levels (e.g., in the Spring, EE savings are higher than NonEE for an average of just 15 hours of the day). At the substation and feeder level, savings validity is higher in Summer than in other seasons.

Table 1. Validity of hourly EE savings results, as indicated by the average number of hours out of 24 for which the fractional savings of the EE accounts are larger than those of the Non-EE accounts.

Time Period	Total Proxy	Substation	Feeder
Whole year	24	21	17
Winter	24	17	17
Spring	24	18	15
Summer	24	21	17
Autumn	24	20	16

4. DISCUSSION

The results of the analysis showed that the utility's DSM portfolio is delivering significant energy savings at each location in the distribution grid - from over 12% at the proxy total level, to average substation and feeder level savings of 11% and 9% respectively. At the substation level, the savings ranged from 0.4% to 26%, and at the feeder level the range was -5% to 42%. The possible causes of these wide ranges were not directly studied, but are expected to be driven by differences in the number of accounts participating in the efficiency programs, the specific measures installed, and the types of facilities represented, e.g., residential, commercial, industrial, and agricultural. These savings had a measurable impact on the energy used at these locations in the grid, with RFS of 1.3% at the proxy total level, to average 1.4% and 1.0% at the substation and feeder levels. These RFS impacts at the substation and feeder level were also highly variable, ranging from 0% to 5% (substations), and -2% to 12% (feeders), for the same reasons.

The total average efficiency impact (RFS) of 1.4% is reasonable with respect to the utility's load reduction planning targets that aim for annual reductions on the order of a couple of percent, due to building code improvement efforts and energy efficiency programs (which include midstream/upstream programs with subcontractors and retailers, which weren't captured by the "EE" marker in the dataset used for this study). While the utility's load reduction estimates are based primarily on calculated or stipulated savings, the analyses presented in this work provide a measurement-based lens into the achieved impacts of efficiency on the grid. These observed impacts were present even *without* explicit locational targeting of DSM delivery by the utility, suggesting compelling potential for the more aggressive use of efficiency as a non-wires alternative. These results were validated through comparison of the reductions in energy use for accounts that participated in efficiency programs, and those that did not. Another means of validating the results was to ensure high levels of model goodness of fit to the baseline data.

When the annual efficiency savings were disaggregated into average hourly savings shapes, the results showed that savings at the proxy total grid level peaked at around 12PM-1PM, and ranged from approximately 7% to 17%. The timing of the peak savings is driven by the measure types that are implemented in the programs (e.g., lighting, appliance, and equipment efficiency are common), and the end uses that those measures affect. The seasonal effects on the saving shapes were modest, with a shift of the summer peak savings to a couple of hours earlier in the day.

At the substation and feeder level, hourly savings results became less quantifiable, as indicated by the comparison of the EE group to the NonEE group and by the degree of variation between savings shapes. With the exception of substations that were known to be dominated by industrial or other special building types, the effect was not large, but as expected, the hourly savings results became less quantifiable in moving from the proxy total to the feeder level, and in moving from the higher temperature and daylight summer period to the other seasons of the year.

5. CONCLUSIONS AND FUTURE WORK

As the efficiency industry (particularly utilities and their respective regulatory bodies) moves to consider how energy efficiency can meet the more nuanced needs of a decarbonized renewables-integrated energy system, there is increased need to better understand the time and location of realized efficiency savings. Using a single model that can predict annual as well as seasonal building energy use with near-zero bias, this work demonstrated new metrics and methods to apply meter-based savings analysis to assess grid-level spatio-temporal impacts of energy efficiency. These approaches provide a methodological and modeling foundation that offers potential to connect efficiency programs with grid and distribution planning, carrying implications for non-wires alternatives and targeting the delivery of efficiency programs, as well as tracking achieved efficiency with respect to forecasts.

There are several immediate directions for future work to expand upon the initial analyses presented in this paper. The DSM portfolio-wide analysis could be disaggregated to assess program-specific effects, and to characterize how the results vary with different distributions of residential versus commercial and industrial customers. This would provide further insights to program administrators seeking to design the most impactful portfolio of program offerings, and could be combined with additional work to enable integration of the customers with EVs and on-site PV. To couple different levels of consumption measurement, the bottom-up analysis using AMI data could be complemented with an analysis of SCADA measurements at the distribution level. Finally, the analyses presented in this work can be applied to NWA projects in the field, and to future pilots of location- and time-based targeting of EE program delivery.

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Appendix A

Table 2. Market segmentation of EE customers at substations analyzed

SUBSTATION	RESIDENTIAL	COMMERCIAL	INDUSTRIAL	MISC
S1	88	2	NA	1
S2	57	7	NA	NA
S3	14	NA	NA	1
S4	159	10	2	1
S5	25	19	1	1
S6	267	3	NA	NA
S7	145	2	NA	NA
S8	127	2	NA	2
S9	200	6	NA	NA
S10	84	7	NA	NA
S11	90	3	NA	3
S12	30	12	NA	1