

Energy Efficiency Program Targeting: Using AMI data analysis to improve at-the-meter savings for small and medium businesses

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Cover image: heat map of pre and post intervention consumption for an anonymous DI customer, with hours of day along the y-axis and days of the year along the x-axis.

1 Introduction

This research paper investigates the potential for predictive targeting methods to improve “at-the-meter savings” outcomes for small and medium business (SMB) energy efficiency (EE) programs.

At-the-meter savings are computed based on changes in customers’ metered consumption¹ before and after program-related interventions. The goal of targeting in this context is increased savings at lower cost through the identification of customers most likely to realize deeper savings, on average, than past participants and targeting those customers with encouragement to participate in future iterations of the program.²

This research is motivated by several questions: What magnitude and depth of savings “gains” over current programs are achievable through targeting? What metrics and methods best support the comparisons necessary to evaluate the performance of different strategies? How are these results determined by the methods of estimating at-the-meter savings? How much variation in optimal targeting strategies can be expected across different types of customers, programs, and measure types?

For this work, two longstanding PG&E programs were used to evaluate data-driven targeting schemes. The first is the Regional Direct Install Program (DI), which focuses primarily on lighting and refrigeration upgrades, and the second is the Commercial HVAC Quality Maintenance Program (HVAC), which services air conditioning equipment based on industry standard maintenance protocols. For both programs, we have identified customer characteristics and usage patterns, all available prior to the program start, that predict at-the-meter savings.

We observe that the best predictive targeting strategies depend on the nature of the interventions being made and the end-uses they impact. High total and peak usage are predictive of lighting savings, high total and baseload usage are predictive of refrigeration savings, and high temperature sensitivity and estimated disaggregated AC usage are predictive of air conditioning savings.

When applied as “targeting filters” that select sub-groups of customers based on threshold values, usage metrics related to baseload and total consumption can roughly **double average DI program savings of the remaining customers when targeting 1 out of every 2 customers and roughly triple average DI savings when targeting 1 out of 4 customers**. For the HVAC program, the results are even more dramatic. The program is fairly light touch and the average savings at the meter for the program were nearly indistinguishable from the background noise of other changes in consumption over time. Filters based on usage characteristics that estimate AC loads were able to **elevate average HVAC savings from 1 kWh/day to 13 kWh/day when targeting 1 out of every 2 customers and to 28 kWh/day when targeting 1 out of every 4 customers**. Those performance gains elevate savings well beyond the background noise of other changes.

Although this research applies targeting methods to two specific PG&E energy efficiency (EE) programs, the methods and results developed here are generalizable to a wide variety of EE programs and customer types. The insights gained through this work can be readily employed to guide future

¹ This research is based on whole premise revenue grade utility meters installed at customer premises.

² Energy efficiency programs are generally open to all utility customers. Targeting does not prevent customer participation but is intended to encourage those customers most likely to achieve the greatest savings.

interventions toward optimized savings results, both for participating customers and for the EE programs.

2 Background

In candid moments, many EE advocates and implementers can readily list interventions that have great potential to save, but nevertheless do not fit within existing program policies and evaluation rules. With the advent of new evaluation and implementation pathways, improved program targeting stands to help unlock some of that untapped potential. Whether it is through lowering acquisition costs by focusing recruitment on viable participants or improving per-customer outcomes by focusing program recruitment on those with the greatest expectation of savings, data-driven targeting and personalization have a lot to teach and offer EE administrators, policymakers, and implementers.

The passage of Assembly Bill 802³ in California established existing conditions baselines⁴ for many energy efficiency (EE) programs with the goal of allowing programs to incentivize and claim savings for the replacement of inefficient equipment with more efficient equipment. AB802 further specified that the savings should be estimated “...*taking into consideration the overall reduction in normalized metered energy consumption as a measure of energy savings.*” The employment of existing conditions baselines directly aligns the savings attributable to a program with the change in a customer’s metered energy usage. This has catalyzed interest in Normalized Metered Energy Consumption (NMEC) based programs.⁵

As a part of this interest, PG&E is running a pay for performance (P4P) pilot where implementers are paid proportionally to their NMEC savings on projects. NMEC-based evaluation will also be an option for implementers under California’s expanded third party solicitation for EE programs. Under such rules, projects that deliver significant metered savings are valuable while projects whose impacts do not manifest at the meter are not. This is in contrast to the deemed savings model in which no direct reward exists for maximizing metered savings. The possibility (and perhaps business imperative) of optimizing metered savings in the P4P paradigm has major practical implications for program design. In particular, it motivates identification and targeting of customers with high savings potential.

3 Key concepts for at-the-meter programs

The central hypothesis evaluated by this work is that customer attributes can predict savings-at the meter, and furthermore, certain patterns in *electric consumption* are correlated with efficiency potential and savings in a manner that complements and extends the performance gains from

³AB 802 instructs the California Public Utilities Commission to authorize EE programs with savings measurement based on “*all estimated energy savings and energy usage reductions, taking into consideration the overall reduction in normalized metered energy consumption as a measure of energy savings*”

https://leginfo.legislature.ca.gov/faces/billNavClient.xhtml?bill_id=201520160AB802

⁴Before AB 802, the standard California baseline for EE measures was set to equal to current code requirements, or industry standard practice (ISP), in cases where no code exists. Before AB 802 EE programs could only incentivize the portion of savings above code. With existing conditions baselines, eligible programs can incentivize the full savings.

⁵ At the time of this writing, the CPUC is taking comments on its proposed ruling on how NMEC-based evaluation will be handled under the expanded third-party solicitation process. The proposed ruling requires it to be subjected to the same level of review and oversight as custom projects.