Load Shape Segmentation for Better Grid Stability and Increased Customer Benefit

Efficiency Vermont R&D Project:

Greenhouse Gas Reduction

January 2024

Abigail Hotaling

20 Winooski Falls Way
Winooski, VT 05404

Contents

Executive Summary

Vermont's push to reduce greenhouse gas emissions through beneficial electrification and increased renewable energy production necessitates improvements in energy load management. Using advanced metering infrastructure (AMI) data, Efficiency Vermont can identify and prioritize projects to optimize program goals.

Using a random sample of 50,000 residential customer meters, this study demonstrates the use of load clustering to identify typical load patterns within a population. The study identified load patterns that coincided with grid peaks and evaluated opportunities for technologies to reduce or shift usage out of key times of day. The research team also summarized load patterns across a sample of potentially low-income utility accounts to identify specific energy usage patterns within this sub-sector.

The team also assessed an AMI features–based approach to summarizing energy use data. Example features are baseload, heating and cooling degree day model slopes, and seasonal peak demand. Specific features can help identify use patterns that are well-suited for certain efficiency measures or programs. For example, baseload can capture "always on" appliances such as refrigerators. Other features, like average summer peak demand or energy usage relationship with cooling degree days, can capture time-of-use behavior and loads driven by outdoor air temperature. This features-based analysis allows the team to use specific features depending on program goals to identify customers with the most savings potential.

The research team used a sample of 1,933 previously completed projects with installed measures related to heating, cooling, and domestic hot water efficiency to test using AMI features for customer opportunity identification. Results show that AMI features can identify projects that are more likely to result in positive savings. For example, there is substantial potential in using these methods to identify cooling efficiency opportunities.

This paper only scratches the surface of possible uses for AMI data in population filtering and savings opportunity identification. To further leverage the value of this work, future researchers could combine AMI results with other data sets. For example, the team could isolate usage patterns in geographic regions with significant grid transmission constraints. Combining results with additional equity indicators could point out savings opportunities not just in the highest users, but equitably across the population. This more targeted approach to customer outreach and program design is essential for furthering electrification and managing the resulting increased load on the grid.

Introduction

The beneficial electrification of appliances, heating and hot water systems, and transportation is beginning to align directly with the national prioritization of decarbonization. As most clean-energy market actors know, however, beneficial electrification typically increases overall demand for electricity. If unmanaged, the consequences of this effect are pressure on local and regional electricity grids—and a corresponding increase in carbon emissions from the added electricity generation required to meet the demand. To help clean-energy program designers manage this effect, Efficiency Vermont proposed that targeted analysis of high-frequency energy data could provide valuable information about how to consider beneficial electrification strategies in program planning. The reliability of advanced metering infrastructure in the residential market enables Efficiency Vermont to test and analyze a wide range of beneficial electrification effects to inform subsequent programming strategies.

Efficiency Vermont hypothesized that program designers could use advanced metering infrastructure (AMI) data to maximize temporal energy savings and geotargeting potential. Because of ongoing electrification of residential appliances, systems, and transportation, the research team determined that residential customers could benefit from the most savings opportunities from new program designs.

The research team also hypothesized that a targeted exploration of energy data could support residential programs where barriers related to program outreach can constrain steps toward decarbonization. Within this hypothesis were the following considerations:

- Increased electrification and heat pump adoption can lead to increased energy costs for customers if their homes are not weatherized prior to electrification.
- Increased electrification typically involves electric panel upgrades, which introduce significant added project costs.
- Funding of electrification projects and availability of knowledgeable contractors and Efficiency Vermont program staff, particularly for multifamily buildings, are two factors that require strategic resource allocation. Analysis might inform the optimal allocation of staff time, considering the likelihood for energy savings, the competing costs of customer-requested site visits, contractor expenses, and the specification of certain equipment and appliance purchases.
- Clean-energy program staff can seldom check on heat pump performance after installation to confirm that the owner is using appropriate setbacks and operating strategies. In some building types, information about post-installation heat pumps could lead to customer participation in flexible load programs.
- Energy use patterns can vary among different customer characteristics; clean-energy programs lack visibility into those patterns, especially among vulnerable populations. Greater visibility on these patterns could lead to program design that results in higher levels of equity among customers.

These barriers related to program outreach are essentially customer barriers to program participation. The research team recognized that for greater participation among residential customers in electrifying their buildings, programs must continue to find ways in which energy efficiency can reduce grid constraints—particularly by reducing peak use.

High-frequency reporting from AMI supports data-driven energy management strategies and informs appropriate design elements that can address program and grid barriers. This study has investigated and tested new ways to use high-frequency AMI data to group customers with similar use patterns. This grouping is known as *load shape segmentation*. The results now can guide efficiency investments to serve residential customers who stand to save the most.

Background

In 2022, Efficiency Vermont first reported on the progress of this project in the context of commercial customers. The background portion of that report mirrors this report's background, since the capabilities of AMI data analytics persist across customer classes. That is, AMI data enable energy efficiency program implementers to advance program performance, cost-effectiveness, and grid effects by providing insights into time-of-use, electrification, and at-the-meter program savings. Other clean-energy programs have leveraged energy-use data to pinpoint program participants who might benefit most from specific measures, demand response, or other targeted programs. Efficiency Vermont does not track energy-use data, but explored the analysis methods aligned with the studies described here to inform future applications of energy-use targeting in programs.

Across the country, clean-energy program administrators analyze energy use to test and implement enrollment and outreach strategies in both the commercial and residential sectors. In 2017, Pacific Gas and Electric (PG&E) conducted a retrospective case study that reported significantly greater energy savings in cooling efficiency programs when energy use guided residential customer selection strategies. For example, as targeting based on energy-use data became more strict, program savings increased. Based on these and similar other results, PG&E identified data analytics and targeted customer outreach as key strategies in their *Energy Efficiency Business Plan 2018–2025*. Power TakeOff, a leading software developer for AMI data analytics, demonstrated a successful program design that engaged small and medium-sized business (SMB) customers by load shape characteristic. TECH Clean California, a statewide initiative to advance electric space and water heating, uses electric and gas meter data to encourage participation from customers who will benefit most from heat pump installations. In March 2023, Recurve, an open-source platform company, conducted a study with Exelon's ComEd (Commonwealth Edison, Illinois) to use AMI analysis and customer targeting to increase the total savings of ComEd's energy efficiency programs.

Load shape segmentation has also shown significant potential for effective demand response. Lawrence Berkeley National Laboratory clustered and disaggregated load shapes via AMI data as part of the 2025 California Demand Response Potential Study.

Methods

Data

The research team examined data from residential customers of Green Mountain Power (GMP), the state's largest utility, serving approximately 266,000 customers. The team investigated 15-minute interval AMI data, using methods compatible with any AMI data recorded at least once per hour.

The team used program data to investigate energy use patterns and program performance across program types. The team randomly sampled 25% of the projects from the efficient products program, containing the following measure categories, to investigate customer opportunity identification with AMI data.[1] Table 1 breaks down the study's program data that were sufficient for the analysis and involved electric savings Efficiency Vermont claimed in its annual reporting to regulators. The research team did not analyze projects with claimed fuel savings, because AMI does not capture such savings.

Table 1: Number of projects with sufficient data for analysis by program and primary measure category, with corresponding energy savings

Program	Primary measure category	Number of projects
Upstream / Efficient Products	Air Conditioning Efficiency	410
	Hot Water Efficiency	468
	Space Heat Efficiency	209
	Space Heat Fuel Switch	1085
	Space Heat Replacement	1001

The team did not include sites that did not have utility accounts mapped in Efficiency Vermont's data warehouse. The lack of mapping to the data warehouse inhibits widespread AMI analysis in the residential sector, although some of the lack of information can be overcome by matching addresses from utility accounts. Ideally, utility account data should accompany program data, to minimize the risk of mismatching account information.

Load Shape Clustering

Analysts need to distill thousands of load shapes for each metered account into representative load patterns across a population. The resulting load shape clustering means the team can group individual meters into their corresponding patterns. This helps program administrators understand what types of load patterns are most common in a particular sector or region. This information makes it possible for the programs to categorize energy use types. Knowing the load patterns makes it easier for clean-energy programs to identify energy savings potential,

[1] Due to computation limitations for running the pre/post analysis and resources for this research, the data set could not include more projects.

particularly among customers who participate in programs where time-of-use patterns are important.

Cluster analysis uses unsupervised learning algorithms to group together data clusters that are more similar to each other than they are to any other group. The research team used the K-Means algorithm to cluster a sample of utility AMI data, as it did with the 2022 Efficiency Vermont R&D research project for commercial customers.

Grouping the data into meaningful load patterns makes it possible to explore other questions, such as:

- What customer demographics comprise the identified load patterns?
- For a specific subset of the grid—for example, a substation or town—what are the dominant load patterns?
- What proportion of residential meters falls into each load pattern?
- Which load patterns contribute most to grid constraints or greenhouse gas (GHG) emissions?
- What rates and technology would best incentivize non-optimal load patterns to become optimal load patterns for the grid?

Use Metrics

In addition to load shape clustering, the research team investigated a features-based method for summarizing energy use data. Specific features of the load—such as total use or winter peak demand—can identify use patterns that are well-suited for certain efficiency measures or programs. Table 2 summarizes the features the team investigated. The team could derive more specific metrics, basing them on program goals, but the table identifies the features most applicable to the projects the team analyzed.

Table 2: Energy-use metric definitions

Feature	Applicable programs	Definition	Units
Total use	EE (Energy efficiency)	Total annual consumption	kWh
Base use	EE	Mean of daily minimum hourly demand x 24	kWh/day
Percent base use	EE	Base energy use as a percent of total consumption	%
Summer on-peak demand	EE, FLM (Flexible load management)	Average demand during summer peak periods[2]	kW

[2] Sumer peak period is defined as hours 3 PM to 8 PM during June through August.

Feature	Applicable programs	Definition	Units
Winter on-peak demand	EE, FLM	Average demand during winter peak periods[3]	kW
Upper demand range	EE, FLM	97th percentile−75th percentile identifies long demand tails	kW
Percent of energy on peak	FLM	Ratio of average demand in hour 3 PM to 10 PM over average daily consumption	%
Ramp rate during peak hours	FLM	Average ramp rate between 3 PM and 10 PM	kW
Cooling degree day (CDD) slope	EE, FLM	Incremental change in energy use per day for every additional cooling degree day	kWh/day/CDD
Percent cooling degree day (CDD) slope	EE, FLM	Incremental change in energy use per day for every additional cooling degree day as a percent of total consumption	%
Heating degree day (HDD) slope	EE, FLM	Incremental change in energy use per day for every additional heating degree day	kWh/day/HDD
Percent heating degree day (HDD) slope	EE, FLM	Incremental change in energy use per day for every additional heating degree day as a percent of total consumption	%

Efficiency Vermont can use these features to target different components of a home's energy load at different times of the day or year. For example, base use can capture equipment that is always on, such as refrigeration equipment. Residents tend to use lighting and HVAC more during occupied hours (consumption), and outdoor temperatures tend to drive HVAC load (demand). Customers with very high heating and cooling loads are excellent candidates for flexible load programs. If customers have a very high cooling load, installing a more efficient cooling system like a heat pump could provide significant reductions in customer costs. If a customer has little to no cooling load, a clean-energy program can still incentivize efficient cooling systems to improve occupant comfort and health and safety. That is, efficient cooling

[3] Winter peak period is defined as hours 7 PM to 9 PM during December through February.

systems can still decrease incidence of mold and heat-related illnesses associated with warm and humid environments.

Deploying the features-based strategy to identify customer opportunities could increase the reach of Efficiency Vermont's programs and engagement with customers, while continuing to deliver energy savings and grid benefits.

AMI Data for Identifying Customer Opportunity

After running the analysis to summarize a customer's load patterns using AMI features, Efficiency Vermont can specify opportunities for intervention based on feasibility, potential savings, and programming considerations.

To test the likely correlation of different features on at-the-meter savings after an efficiency upgrade, the research team conducted a retrospective case study of completed residential projects. The participant group consisted of residential customers' energy efficiency retrofit projects from 2020 to 2022. After filtering for utility data requirements and baseline uncertainty requirements, the analysis contained 1,933 projects.[4]

The team used AMI data to model pre-and post-project savings,[5] then used the AMI data (and the same pre- and post-assessment points) to compute savings for a matched comparison group that did not have intervention. The team estimated the net savings of the interventions as the difference between participant group savings and comparison group savings. Efficiency Vermont's 2022 study offers more information on how the team defined matched comparison groups.

To estimate savings for the cohort of retrofit projects, the team computed average customer savings for the participant group and for the comparison group, then subtracted average comparison group savings from average participant group savings. Table 3 shows these savings by primary measure type.

Table 3: Average customer savings by primary measure type

Program	Primary measure category	Number of projects	Participant average savings (kWh / day)	Comparison group average savings (kWh / day)	Net average savings (kWh / day)
Upstream / Efficient Products	Air Conditioning Efficiency	238	-0.92	-0.09	-0.83
	Hot Water Efficiency	271	-1.66	-0.09	-1.57

[4] The research team followed the International Performance Measurement and Verification Protocol, which requires 12 months of pre- and post-period data. Further, the team applied ASHRAE-14 guidelines, which recommend fractional savings uncertainty within 50%. Industry experts at the Lawrence Berkeley National Laboratory recommend a normalized mean bias error within 0.5%.

[5] The research team used baselines for pre-and post-project modeling via an hourly time-of-week and temperature model from OpenEEMeter's CalTRACK library.

Program	Primary measure category	Number of projects	Participant average savings (kWh / day)	Comparison group average savings (kWh / day)	Net average savings (kWh / day)
	Space Heat Efficiency	127	-0.99	0.00	-0.99
	Space Heat Fuel Switch	494	-2.46	0.60	-3.06
	Space Heat Replacement	801	-3.39	0.06	-3.45
All projects		1,933	-2.45	0.15	-2.60

Results

Load Shape Clustering

Figures 1 and 2 show the typical summer and winter load patterns that the clustering algorithm determined using a random sample of 50,000 residential GMP meters in Vermont. The load patterns represent the center of each cluster. The normalized load over each hour is the ratio of average energy used for each hour over the average total daily energy use—in other words, the proportion of daily energy usage occurring each hour. The analysis showed 8 load patterns typical of summer; for interpretability, the researchers grouped two load patterns with very similar *demand response* load signatures. The research team named these load patterns to describe the timing and frequency of customer peaks, as well as the types of programs to which they might belong, based on the exhibited energy use behavior. The patterns identified were *afternoon peak, demand response, evening peak, mid-day peak, dual morning and evening peaks, demand response* with *morning peak,* and *solar.*

Tables 4 and 5 highlight that afternoon and evening peak patterns characterize most energy-use behaviors for households in residential sectors. Opportunities for considerable grid benefits for energy efficiency and demand-management improvements appear in these usage patterns. With only 5% and 5.1% of households exhibiting demand-response load signatures in summer and winter, respectively, there are still clear opportunities to expand demand management, but Efficiency Vermont is off to a great start.

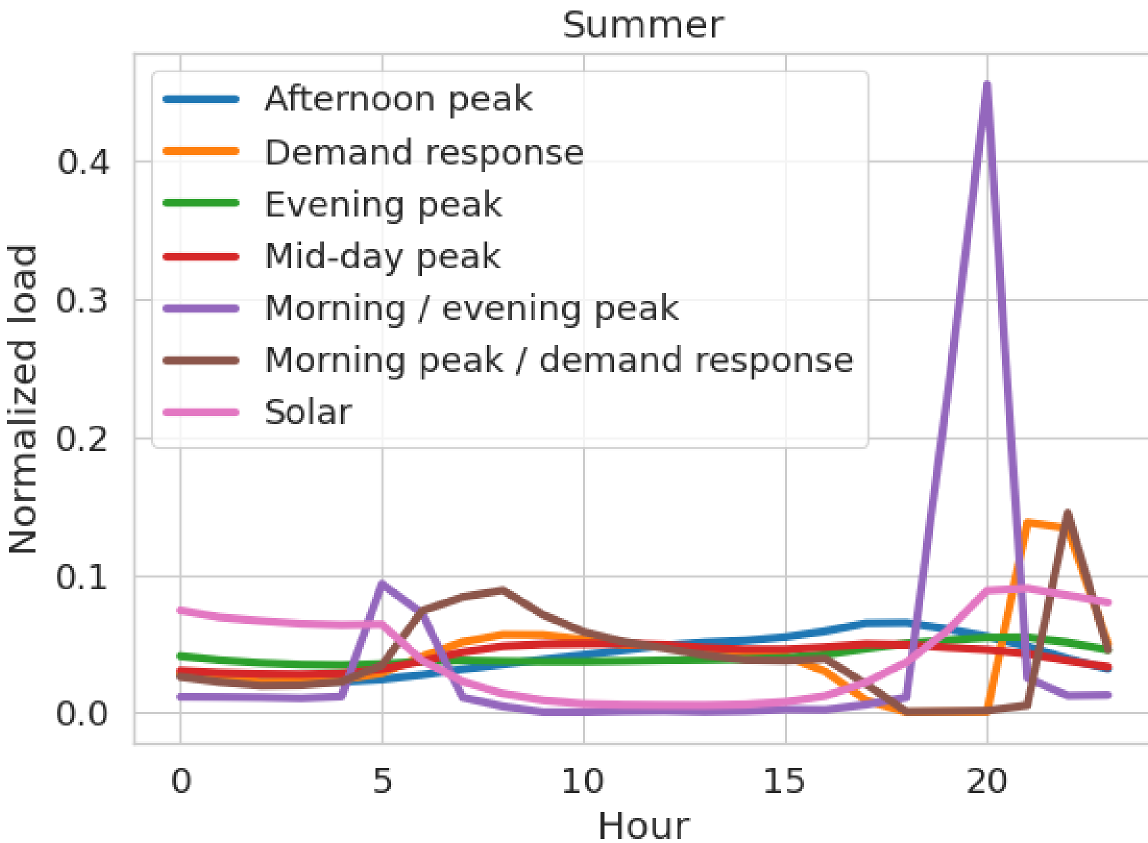

Figure 1: Summer normalized load patterns for residential utility meters

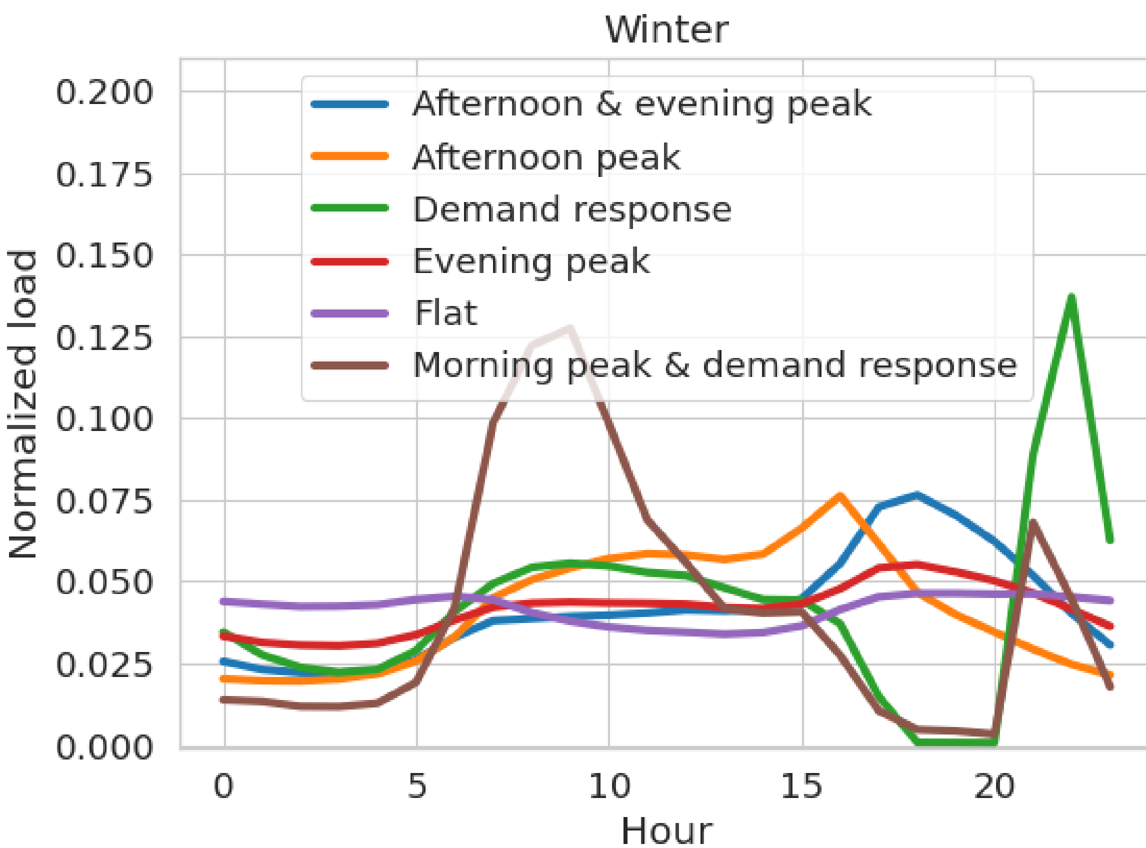

Figure 2: Winter normalized load patterns for residential utility meters

Table 4: Distribution of summer residential load patterns

Load Pattern	% of sample within pattern
Afternoon peak	22.3
Demand response	3.6
Evening peak	36.3
Mid-day peak	29.2
Morning and evening peak	1.1
Solar	6.1
Morning peak and demand response	1.4

Table 5: Distribution of winter residential load patterns

Load pattern	% of sample within pattern
Afternoon and evening peak	17.6
Afternoon peak	10.5
Demand response	4.4
Evening peak	41.1
Morning peak and demand response	0.7

Flat	25.6

The research team also generated similar results for residential meters that were considered potentially low income based on existing EVT program participation or qualification for a low-income utility rate code. Figures 5 and 6 the summer and winter load patterns identified out of a sample of 19,000 potentially low-income meters. Similar load patterns exist as compared to the overall residential population. The majority of meters showed afternoon and evening peak usage patterns. The results show that among this sample of meters, 1.4% showed a summer load signature likely influenced by onsite solar generation. Within the overall residential population 6.1% showed potential for solar generation in the summer load pattern. In the potentially low-income meters 4.3% of meters shows a demand response behavior in the pattern.

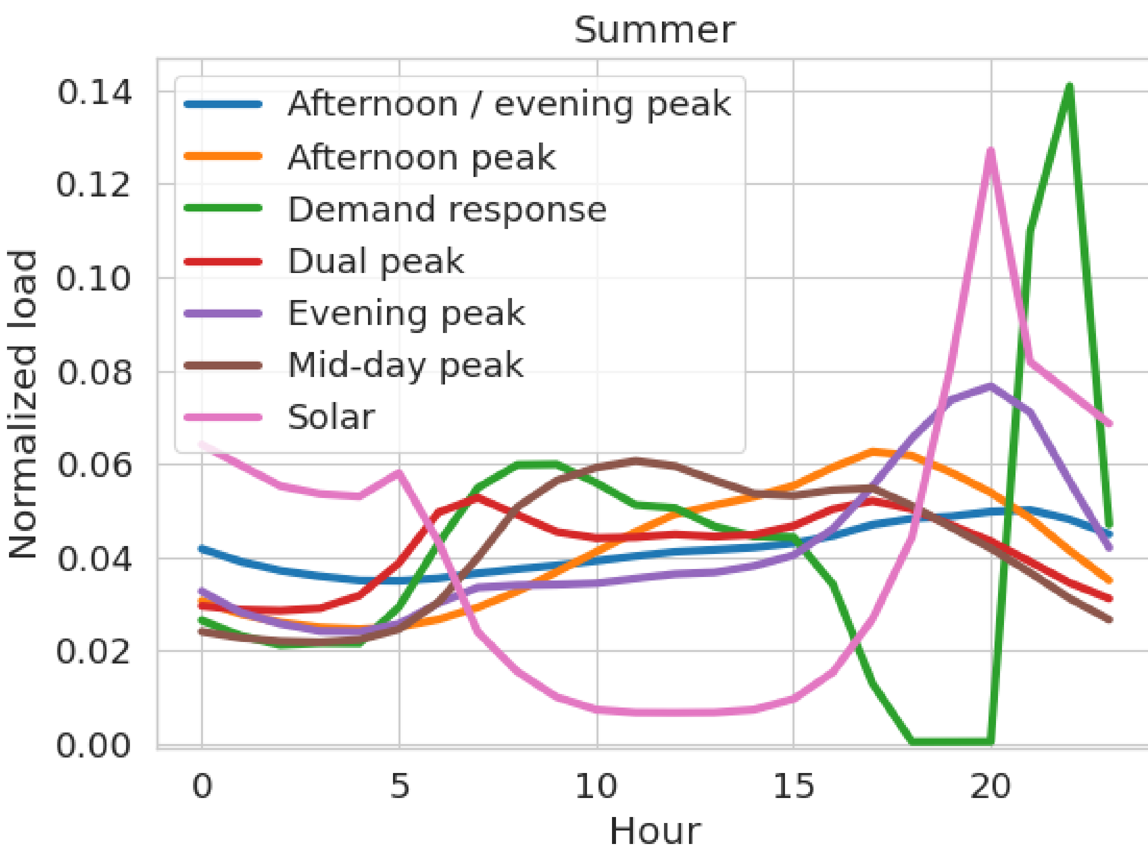

Figure 3: Summer load patterns for potentially low-income utility meters

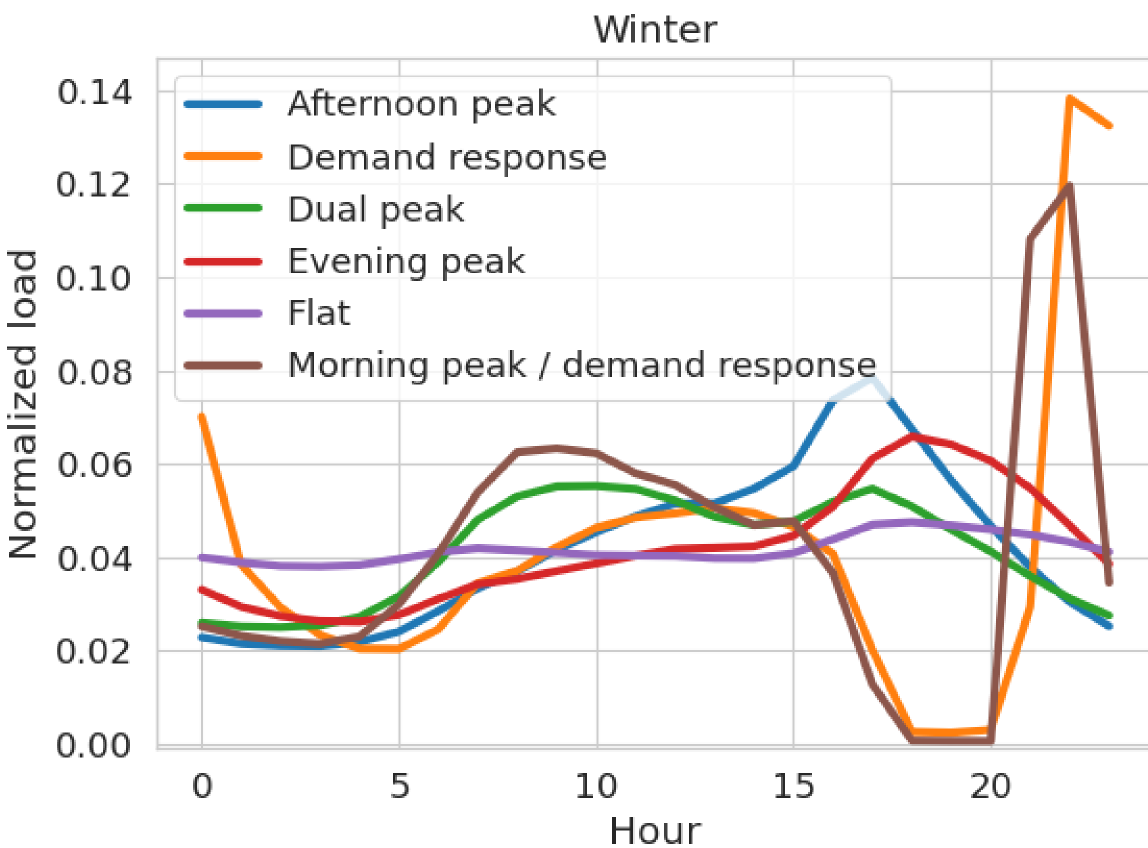

Figure 4: Winter load patterns for potentially low-income utility meters

Table 6: Distribution of summer load patterns for potentially low-income utility meters

Load Pattern	% of sample within pattern
Afternoon and evening peak	40.0
Afternoon peak	24.8
Demand response	4.3
Dual peak	11.2
Evening peak	5.2
Mid-day peak	12.9
Solar	1.4

Table 7: Distribution of winter load patterns for potentially low-income utility meters

Load Pattern	% of sample within pattern
Afternoon peak	8.4
Demand response	1.0
Dual peak	21.1
Evening peak	23.4
Flat	42.4

Morning peak and demand response	3.6

Identifying Customer Opportunities with AMI Data Analysis

Using load shape and AMI data to identify customer opportunities for efficiency measures has the potential to increase savings beyond current achievements. The following sections demonstrate how opportunity identification techniques informed by AMI data analysis could affect the *average savings per project* and the *average percent savings relative to load* under such a program model.

Figure 5 shows how using AMI data analysis to identify customers shifted the distribution of savings and increased the average savings per project. In this example, the team categorized participants based on cooling degree day slope variable and focused on the 50 percent of meters with the highest cooling loads. For all participants, the average savings per project was -0.39 kWh/day. Focusing only on the top 50 percent of users resulted in an average savings per project of 0.14 kWh/day. This example demonstrates a comparison of results. There is uncertainty in these values; a larger sample could better quantify potential savings increases from this approach.

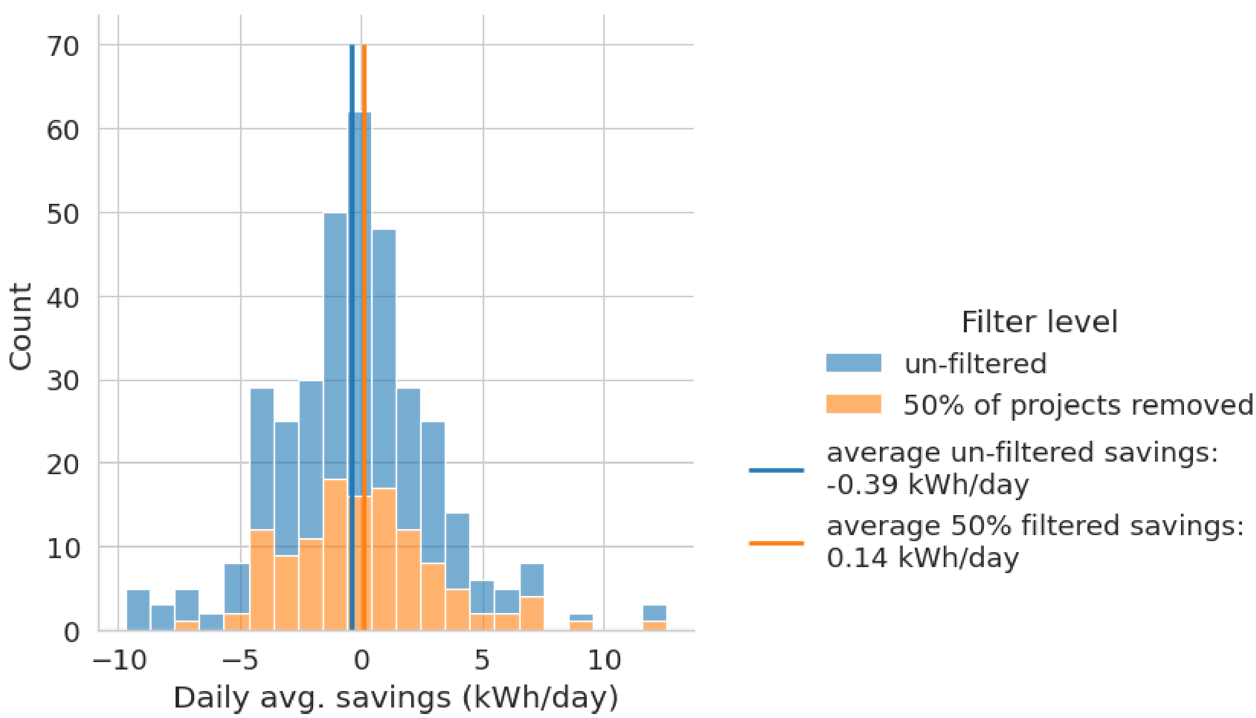

Figure 5: Average net daily savings (kWh/day) for all participants and for the 50 percent with highest total annual use

Savings per project

As shown in Figure 6, filtering by various magnitude and normalized features influences the average daily savings. This analysis shows that for nearly all order-of-magnitude features tested, the customer opportunity identification approach based on AMI data analysis resulted in higher average daily savings per project. In other words, focused program participation resulted in higher average savings per project. The dotted grey line displays average savings results across all participants. Focusing on the top 50 percent of participants based on total usage resulted in a 29% increase in average savings per project.

The team also tested for features that were normalized to reflect a percentage of total energy usage (bottom of Figure 6) to identify customers with high relative use. These normalized-feature analyses showed mixed results and not a clear relationship with savings. Selecting customers based on normalized *percent of base use* showed the highest positive correlation with average net daily savings. Other normalized features showed a negative correlation with this AMI data–informed customer opportunity identification. Given the small sample and variability in results, the research team was unable to distinguish significant trends in the effectiveness of an AMI data–informed approach using normalized features.

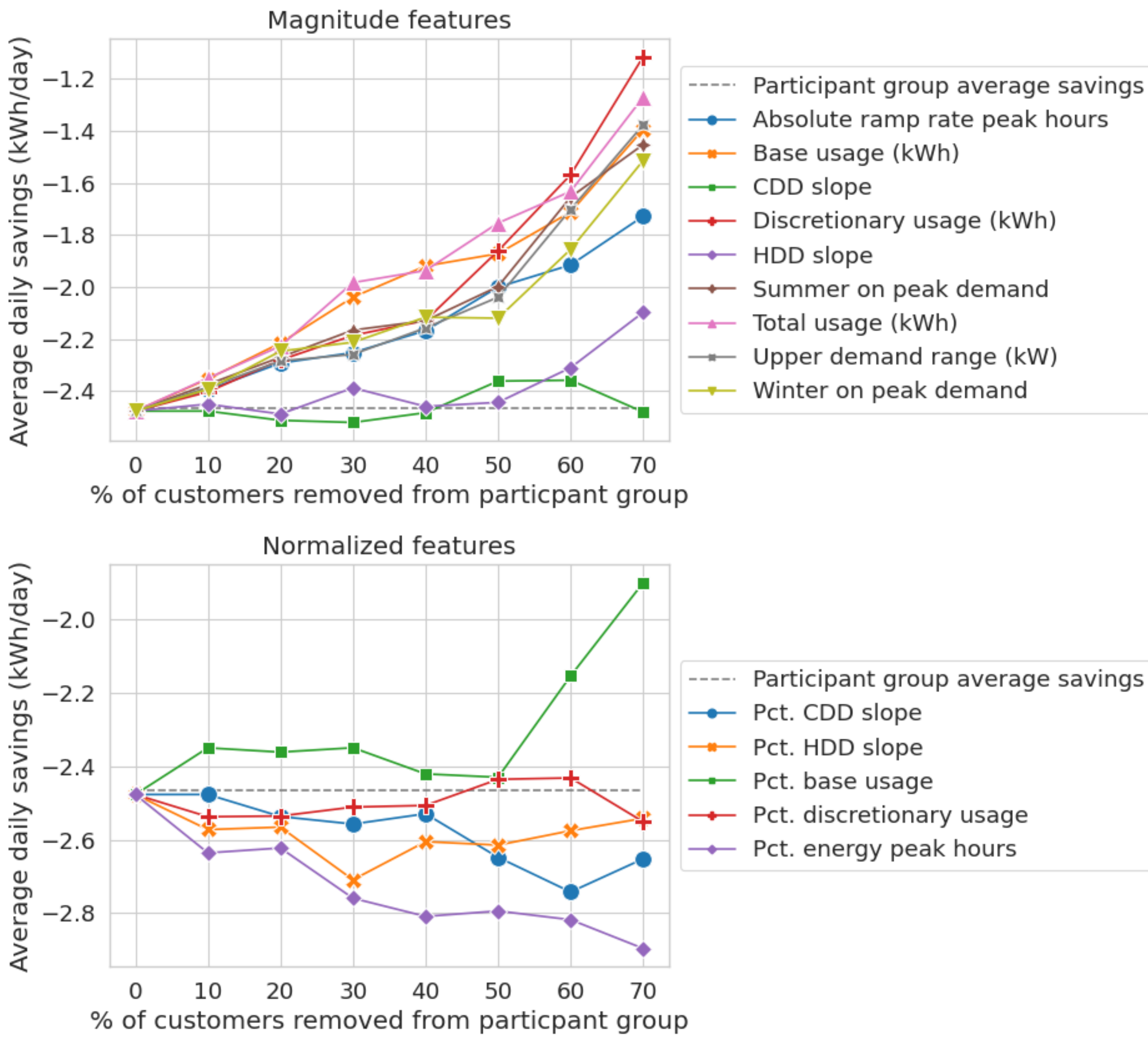

Figure 6: Average daily savings (kWh/day) for a range of customer selection thresholds, and magnitude (top) and normalized (bottom) features

Depending on the program goals, administrators might focus more on summer or winter peak demand savings. Figure 7 shows summer peak demand savings for various levels of filtering across magnitude and normalized features. This example illustrates that different features correlate more with savings depending on program goals. Both the *percent cooling degree slope* and *cooling degree slope* show strong relationships with increased summer demand savings. Targeting the top 60 percent of projects based on *percent cooling degree slope* results in a nearly 10 times increase in average summer peak demand savings.

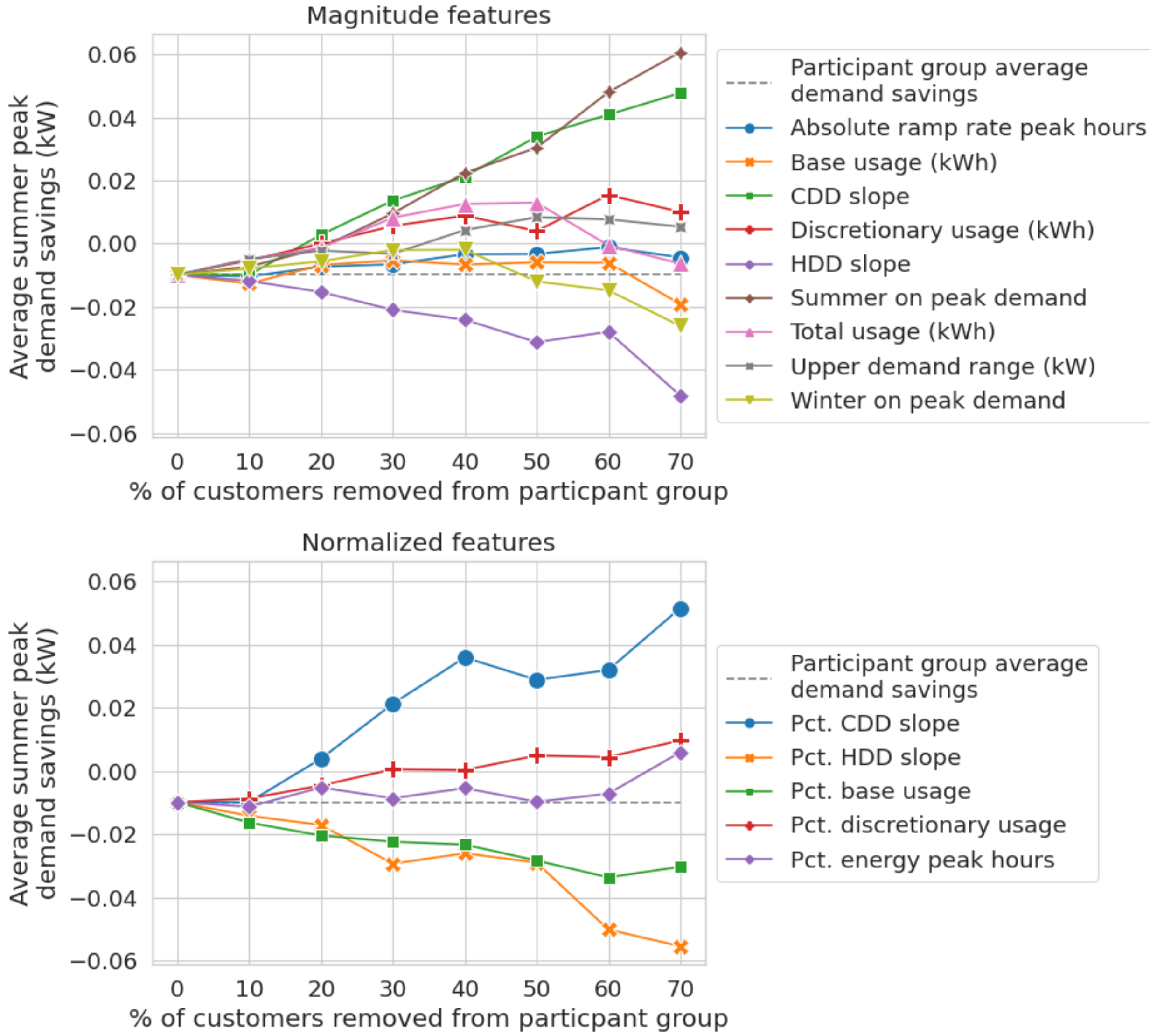

Figure 7: Average summer peak demand savings (kW) for a range of customer selection thresholds, and magnitude (top) and normalized (bottom) features

Figure 8 shows how various filtering requirements influence average percent savings. Similarly, to the example above, the magnitude features (top of Figure 8) show consistent increases in savings as more projects are filtered out. Focusing on the top 50 percent of participants based on *total usage* resulted in a 56% increase in the percent savings per project. The *percent cooling degree slope* feature showed the highest increase in the percentage savings of the normalized features. Focusing on the top 50 percent of projects based on *percent cooling degree slope* resulted in a 5% increase in the percent savings per project.

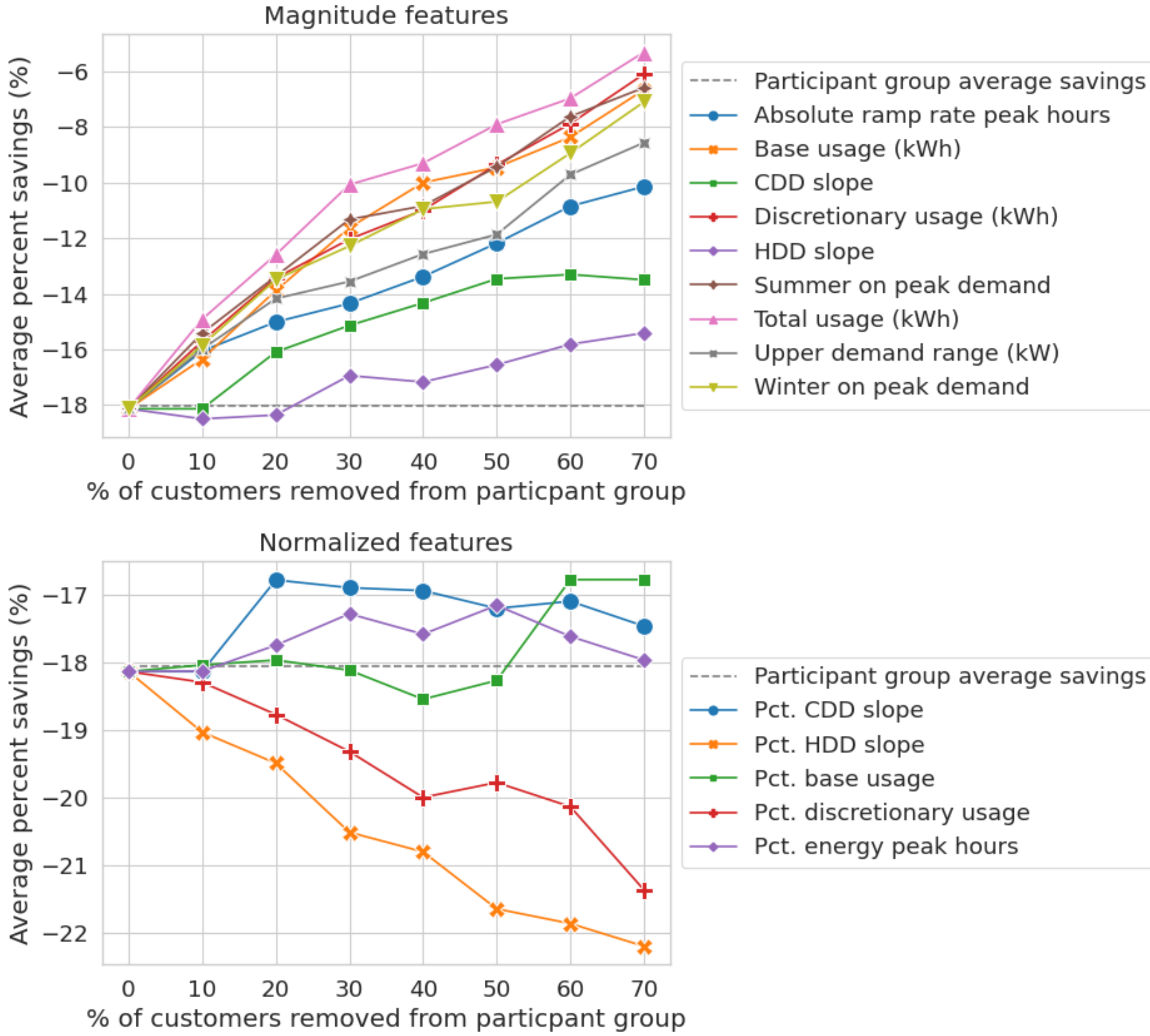

Figure 8: Average savings as a percent of baseline use over a range of customer selection thresholds, and magnitude (top) and normalized (bottom) features

Discussion

Consistent with the 2022 report's findings, this analysis shows that load shape segmentation presents an opportunity to gain a deeper understanding of the time-of-use patterns in a sector or region. The time-of-use patterns are critical to further understand potential FLM opportunities and which technologies, incentives, and rates would best optimize these patterns.

Using completed efficient product projects shows that this analysis can identify customers that are more likely to show positive savings and grid impacts for a given measure. Given the limited sample sizes of this analysis, the team is not certain of the amount of savings increases that a targeted opportunity identification approach could produce. This research also does not capture effects of customers' propensity to participate in energy efficiency programs. Even with these limitations, the findings show how AMI data can inform Efficiency Vermont's approach to customer outreach and identification of ideal program participants.

Additional Use Cases

This research began to explore the possibilities of analyzing population-wide AMI data. The following examples offer guidance for building on this approach to meet the organization's use cases.

Panel upgrades can be a big barrier for electrification due to the added cost. Efficiency Vermont is interested in understanding customers' peak demand and how it relates to panel upgrades to meet electrification goals. Using AMI data, Efficiency Vermont could calculate the maximum load demand on meters and spare capacity assuming a 100-amp or 200-amp service.

Flexible load management is another program that has significant alignment with using energy data for opportunity identification. Impacts from demand management depend on the coincidence of existing load with system peaks, meaning customers who use more energy during peak times might have more load to shift into other times of the day. Load that is weather-dependent often has capacity to be flexible using thermal storage to shift heating or cooling loads outside of peak times. AMI data can effectively disaggregate heating and cooling loads and coincident demand to identify customers with the most flexibility. For example, as we increase heat pump adoption in the residential sector, we can use AMI analysis to identify customers who are most suitable for demand management given these characteristics.

To increase the benefit of this work, Efficiency Vermont can pair data from additional sources with AMI data to expand the filtering and alignment with program goals. Via the Efficiency Vermont project database, utility data, publicly available census data, or purchased data sets, Efficiency Vermont can match additional information about the customer to their energy use behavior. Additional variables that would increase the value of this analysis include:

- Grouping usage patterns by geographic regions; for example, regions of the grid that are particularly transmission-constrained.
- Equity indicators like income, to identify savings opportunities equitably across the population.
- Utility rate codes and existing project data, to indicate existing assets that could enable new demand management or energy efficiency opportunities (for example, customers with behind-the-meter generation or customers with previously installed heat pumps).

Challenges

This AMI data approach to load shape segmentation identifies opportunities that could result in higher energy savings. Despite this, the prescriptive savings approach of most residential programs means that savings claims are fixed for specific measure types. If Efficiency Vermont implemented customer opportunity identification into residential programs, there would not be direct benefit for program cost-effectiveness and other performance indicators if the prescriptive savings model stayed the same.

There is also opportunity to adjust program incentive models based on savings opportunity indicators from energy data. For example, if analysis determines that a subset of a low-income population has significant cooling efficiency opportunities, Efficiency Vermont could consider an incentive bonus to facilitate energy efficiency upgrades. Such a model has not been explored and would require program design.

Efficiency Vermont must consider data challenges as it considers deploying these methods in program process. For example, in the residential sector, mapping between historical program data and utility data is often incomplete, making it difficult to link program participants with AMI data without using address matching—which can be less reliable.

Future Work

Based on the results from this report and the 2022 study, the research team proposes a pilot program to take this work beyond research and development. Given the challenges with the prescriptive program model, the team should start with a small or medium-sized business pilot. The pilot program should isolate a specific program initiative and set of measures for implementation. This pilot can implement the infrastructure needed to provide program staff visibility into the energy features most related to program goals. Based on analysis results, staff can define targeted customer outreach or program participation requirements. Findings from such a pilot can steer the longer-term implementation plan for these methods.

Conclusion

Beneficial electrification is one of the leading pathways to decarbonization. As the overall demand for electricity increases, if it is not appropriately managed, it will create pressure on local and regional electricity grids. This will result in a corresponding increase in carbon emissions from the added electricity generation required to meet the demand.

In response, clean-energy program designers must consider beneficial electrification strategies in their planning, and analysis of high-frequency energy data could provide substantial value in that effort. Efficiency Vermont used advanced metering infrastructure data within the residential market to show how program designers could use data analysis to maximize temporal energy savings and customer targeting potential. The results of this paper demonstrate that energy-use patterns and features can identify residential customers who would benefit from increased savings and deliver grid impacts if they employed certain measures. This analysis can smooth the path to and enhance the benefits of decarbonization.

Appendix

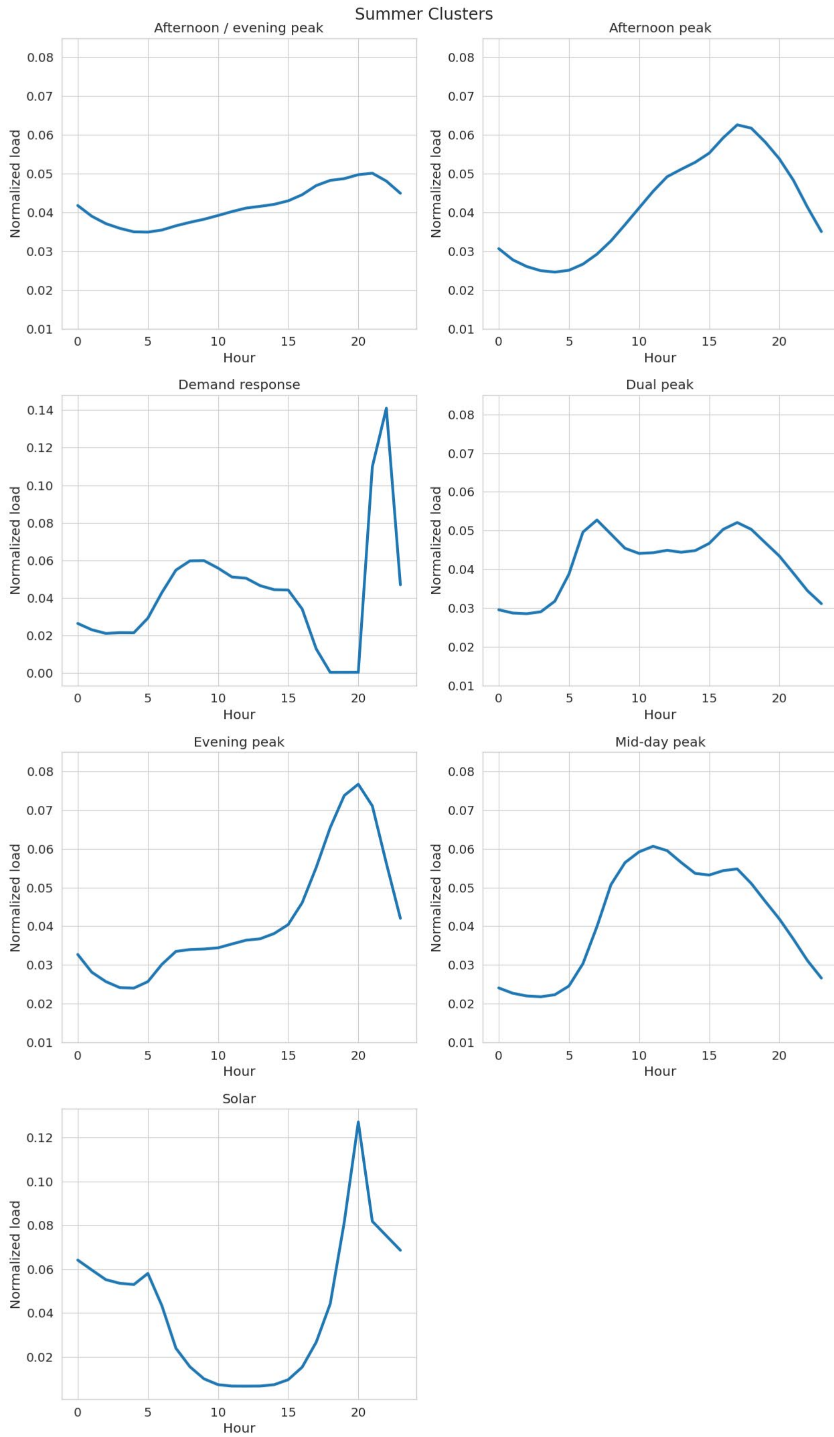

Figure 9: Summer load patterns for potentially low-income utility meters

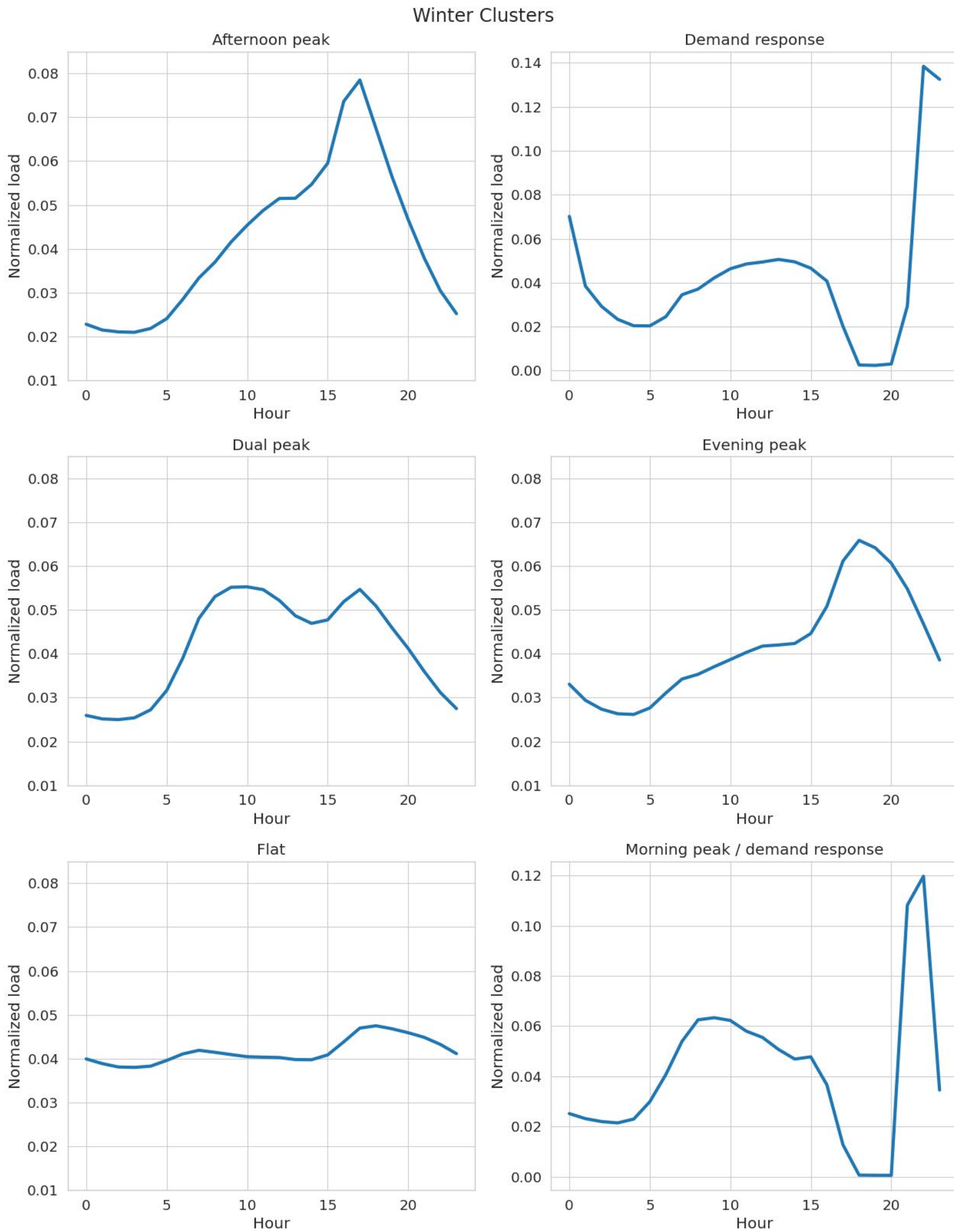

Figure 10: Winter load patterns for potentially low-income utility meters

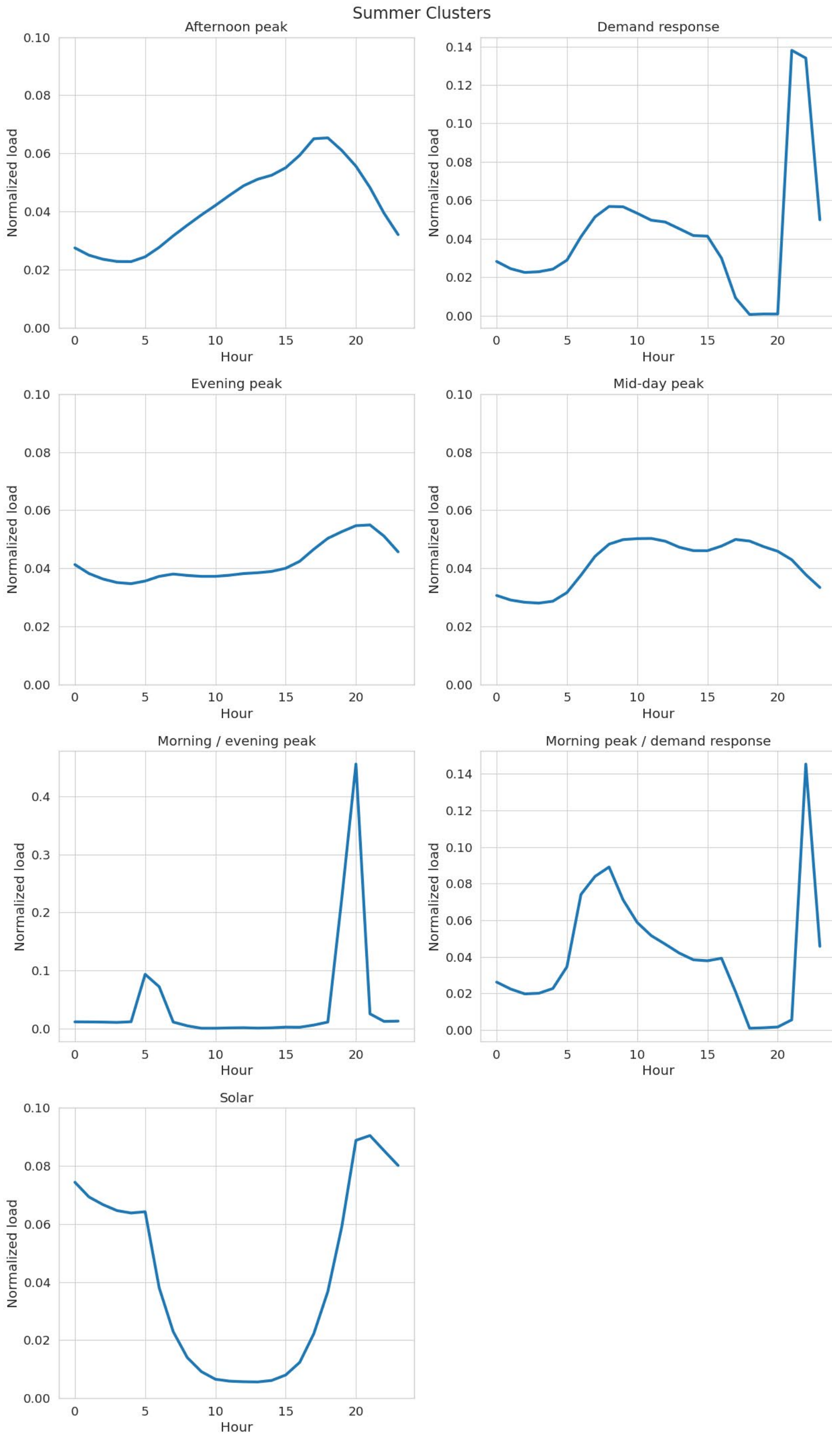

Figure 11: Summer load patterns for sample of residential meters.

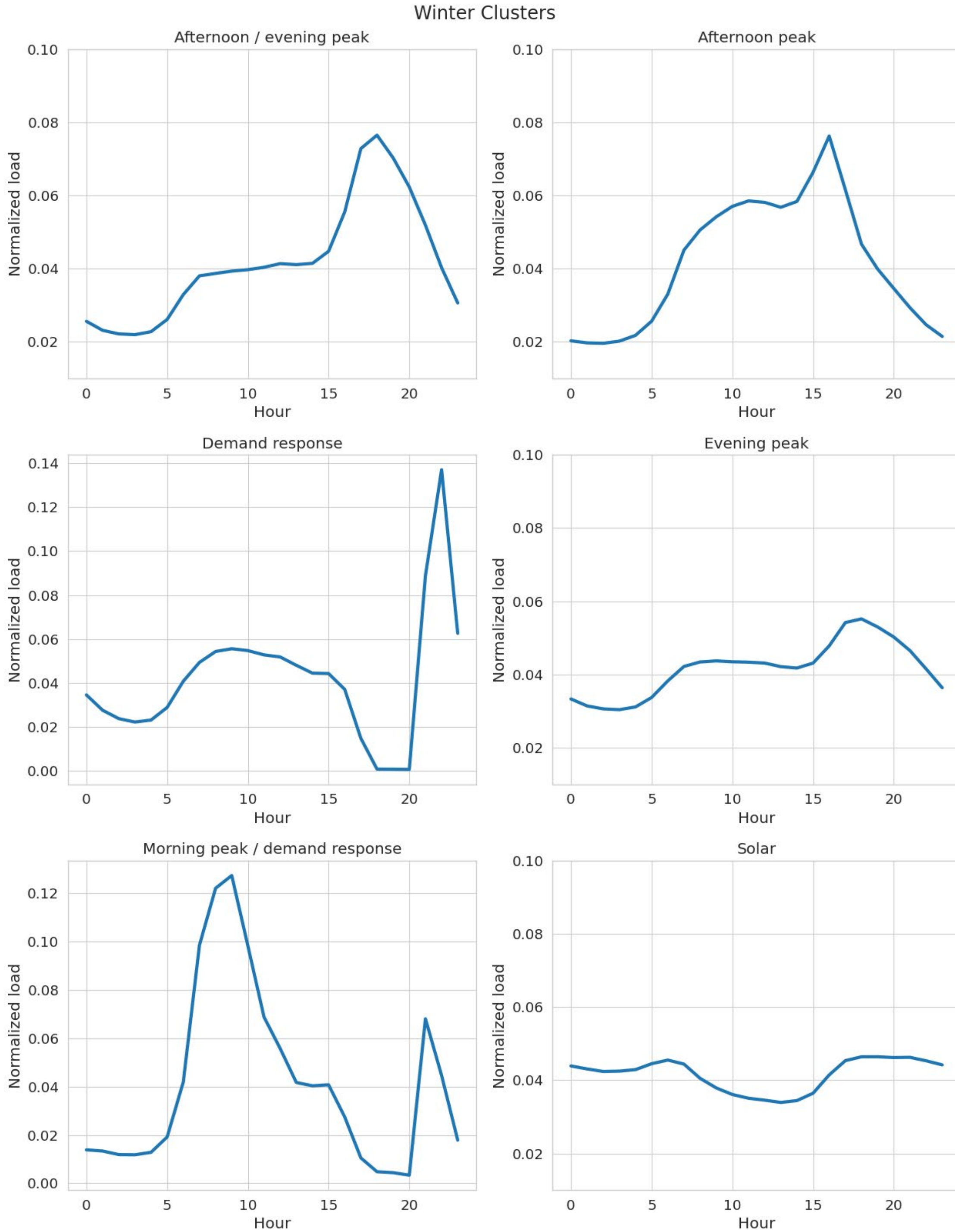

Figure 12: Winter load patterns for residential utility meters