bidgely

UNLEASHING THE POWER OF DISAGGREGATION

TIME OF USE APPROACH

Bidgely | February 2021

INTRODUCTION

The rise of artificial intelligence and growing consumer energy consciousness has positioned energy disaggregation as an essential tool to deliver a personalized energy experience and simplify utility operations. With the reach of Advanced Metering Infrastructure (AMI) expanding at a rapid pace, energy consumption can be measured at a meter level, while disaggregation technology breaks this customer data down further each bill cycle into appliance categories.

This white paper examines how Bidgely is advancing the science of disaggregation with Time of Use (ToU) disaggregation that breaks down consumption with never-before-achieved granularity., For example, we're able to identify if an EV is being charged during peak time, alert the consumer about the situation and offer corrective actions. This precision unleashes a new generation of applications and business intelligence.

HOW DO WE DISAGGREGATE?

Disaggregation is the process of breaking down combined energy consumption data on a device-by-device or or categories basis to isolate what appliances and energy habits are contributing to that total consumption. Disaggregation enables both consumers and utilities with personalized information and analytics to make better energy decisions.

Historic energy disaggregation approaches can be broadly classified as software- or hardware-based. Software-based approaches make up the bulk of the market today because they are cost effective and don't require any device installations. Typical software-based disaggregation products sample AMI data at multi-minute intervals, and provide energy use breakdowns at a monthly, bill cycle, weekly or daily level.

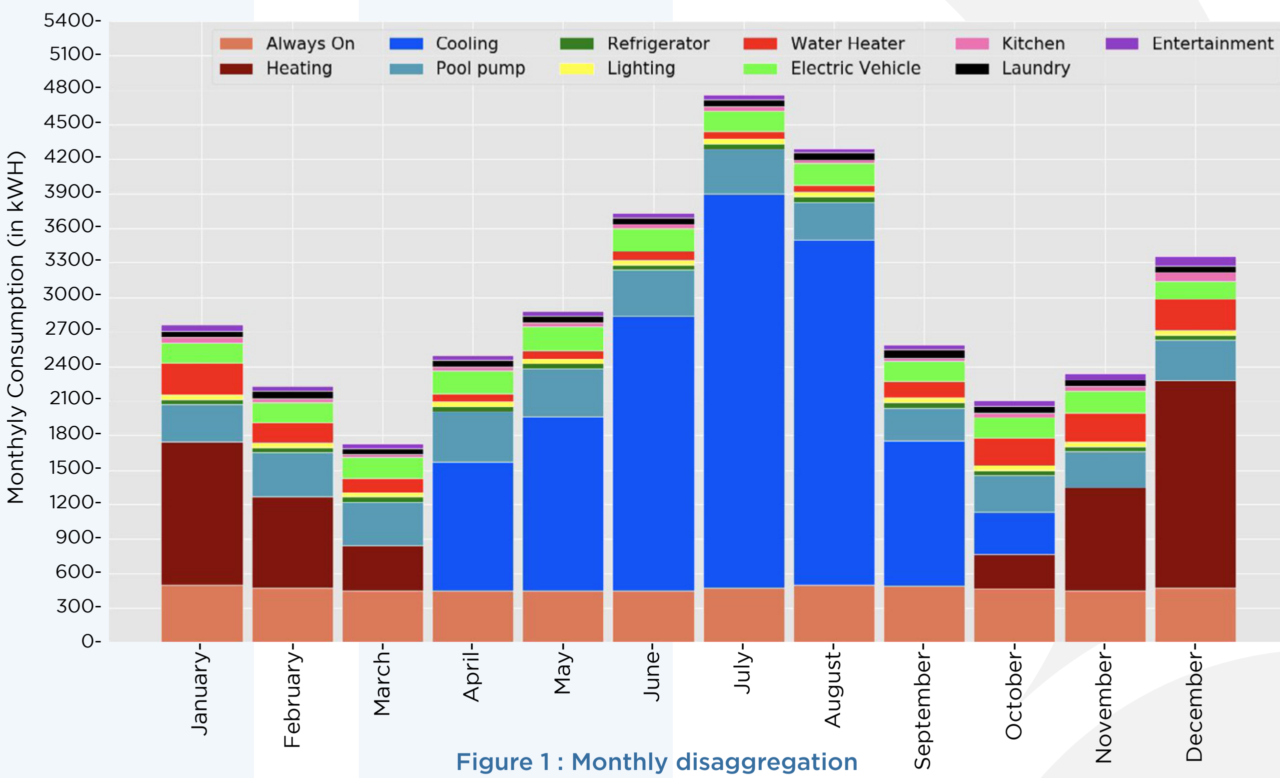


Figure 1 : Monthly disaggregation

What this disaggregation approach lacks is the ability to determine either when an appliance is used or to define the **consumption patterns within a day.**

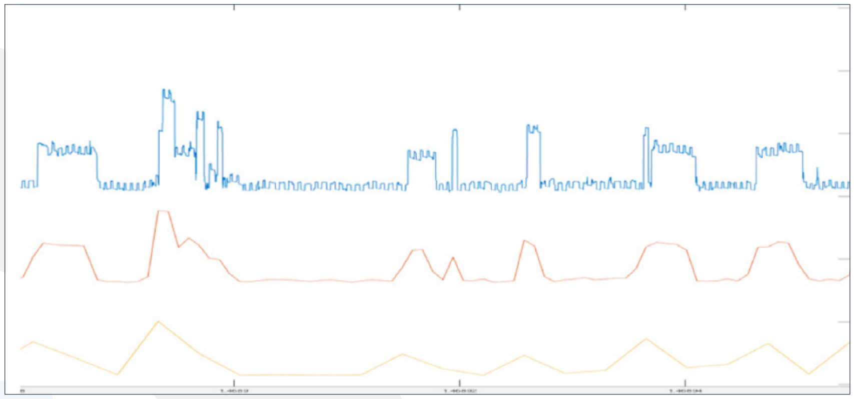


Figure 2a : Loss of information by sampling rate

It is important to note though that performing disaggregation on AMI data is incredibly complex. Figure 2a shows signal information loss rates when sampled at a 10s frequency, a 15 minute frequency and a 1 hour frequency. At longer frequencies, clear signatures that can be attributed to specific appliances with distinct start and end times converted to indistinguishable energy consumption bumps. This loss of information makes disaggregation at TOU level of AMI data significantly tougher.

THE NEED FOR TOU DISAGGREGATION

The value of data lies in its specificity and actionability. Imagine that you received a high credit card bill and are looking to identify ways to reduce your spending. A monthly breakdown would provide you information like, “you spent $500 on restaurants, $200 on groceries, $170 on gas etc. in the last month”, which reveals restaurant spending as the potential source of the problem but doesn’t give you enough information to take corrective measures. By contrast, if you had the actionable information about when and where those restaurant expenses were incurred and the amount of each expense, you could pinpoint what actions to take.

In the spirit of improving the actionability of disaggregation-based information and unlocking new use cases, Bidgely has developed cutting-edge ToU disaggregation for AMI data. This next generation of AMI disaggregation **provides energy consumption breakdown at the sampling frequency of the data.** With ToU disaggregation, utilities can derive a better understanding of their customers and their energy consumption habits as a means to scientifically enhance operational efficiency, improve customer satisfaction, drive targeted actions and much more.

The analytics and insights derived through ToU disaggregation are easily verified. For consumers, it provides a granular understanding of their energy consumption, actionable insights. It also instills higher consumer confidence with respect to the validity of the information being provided, making it likelier for them to take action.

TOU DISAGGREGATION : A PEEK BEHIND THE CURTAIN

Bidgely disaggregation algorithms are designed to produce 100% itemization of total energy consumed. Irrespective of geography, we are able to break down total energy consumption to the appliance level, isolating electric vehicles, pool pumps, heating, cooling, water heaters, refrigerators, lighting and more.

Bidgely's patented disaggregation technology includes sophisticated machine learning models and signal processing algorithms, trained over millions of households worldwide. **These algorithms are capable of estimating appliance energy consumption at the AMI data sampling level to produce time of usage disaggregation precision.**

Energy data visualization - understanding heatmaps

AMI meters record energy consumption data periodically with a measurement interval in the order of minutes. This gap is called the "sampling rate." For example, a utility may record 365 days of energy consumption data available at 15 minute intervals.

ENERGY CONSUMED IN WATT-HOURS (EVERY 15 MINUTES FOR EACH DAY)																					
DAY 1	10.1	15.7	13.2	12.2	18.4	30.1	33.7	34.3	32.6	33.3	...	48.2	63.7	79.6	78.4	72.9	75.1	64.9	42.7	34.6	21.5
DAY 2	11.5	17.4	15.1	14.7	21.5	29.2	35.4	31.9	30.7	35.3	...	41.9	66.6	71.2	80.8	83.4	72.2	61.4	40.3	31.7	20.4
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
DAY 365	18.4	25.5	23.3	22.6	28.6	34.5	31.4	31.8	33.9	31.1	...	43.5	61.5	69.1	70.9	69.7	65.6	60.9	51.6	40.6	23.8

A convenient way to visualize this data is through a heatmap, where color is most intense (red) for high energy values and least intense (blue) for low energy values. Figure 2 illustrates the energy consumption values in heatmap form, for the entire data 365-day data set.

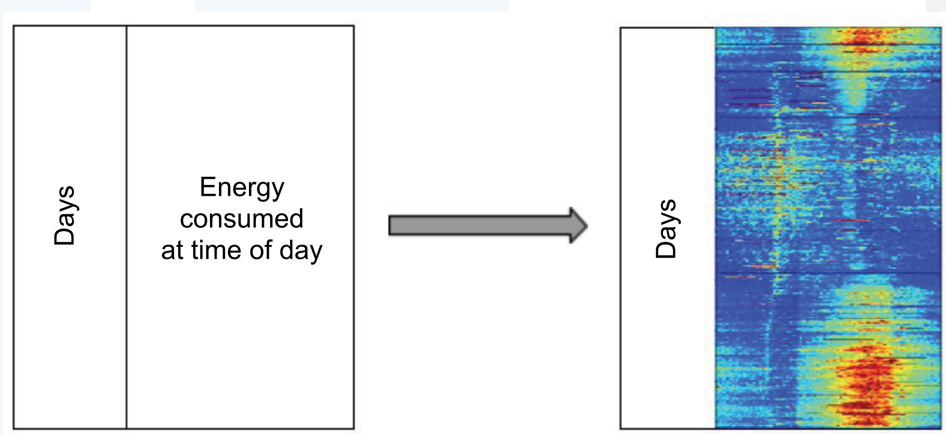


Figure 2b : Extraction of EV estimates from raw energy consumption

APPLIANCE CHARACTERISTICS

As illustrated in Figure 3, residential appliances exhibit characteristic behavior.

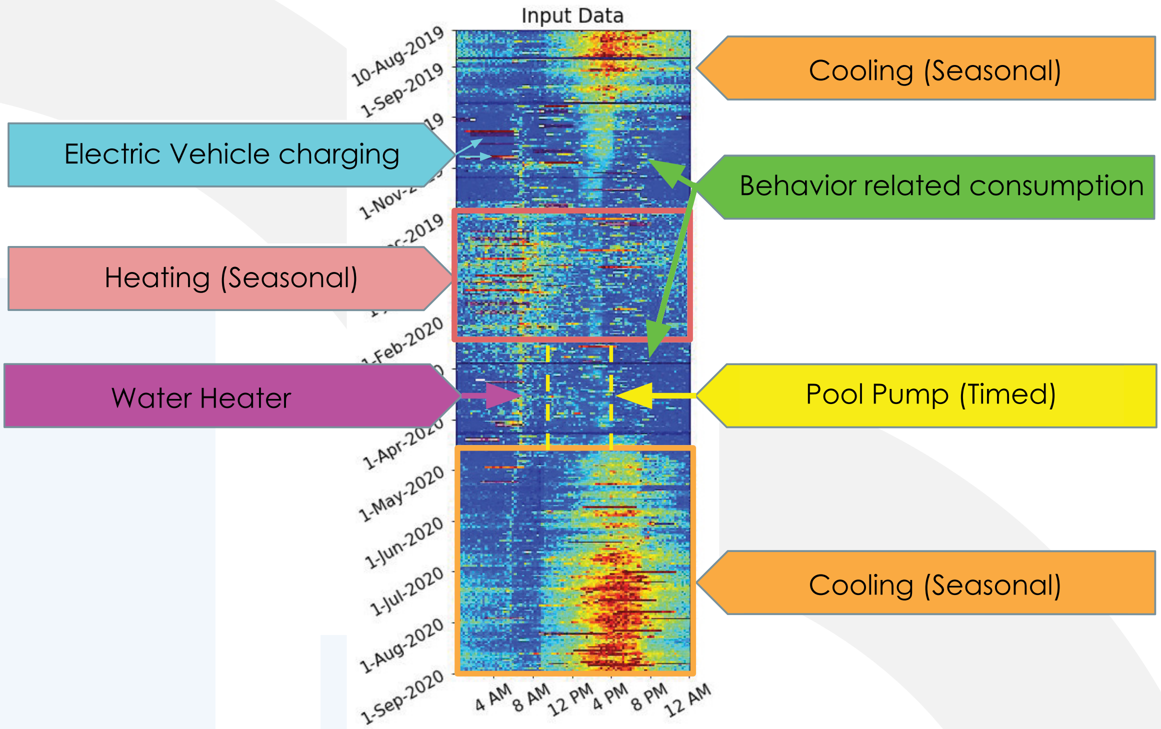


Figure 3 : Key Appliance Characteristics

Heating ventilation and cooling (HVAC) are seasonal appliances and with temperature-sensitive energy consumption patterns. Pool pumps most often operate on a daily schedule. Appliances like water heaters may reveal seasonal, timed or instantaneous usage patterns. EVs consume more energy than typical home appliances, whereas lighting and refrigerators fall in the lower end of the energy consumption spectrum.

Apart from appliance-specific loads, residential customers also demonstrate an always-running living load. Appliances like routers, light indicators, security sensors and doorbells contribute to always-running measures. We remove the always-on signature before beginning the core appliance disaggregation steps.

TOU DISAGGREGATION : APPLIANCE BY APPLIANCE

Electric Vehicle (EV) Extraction: EVs draw more power than virtually any other residential appliance. There are three main types of EV chargers: L1, L2 and L3. L1 chargers draw lower power whereas L2 and L3 chargers draw much higher power and run for relatively short periods of time. The series of heatmaps in Figure 4 shows L2 charger consumption extracted out of total energy and the resulting residual energy.

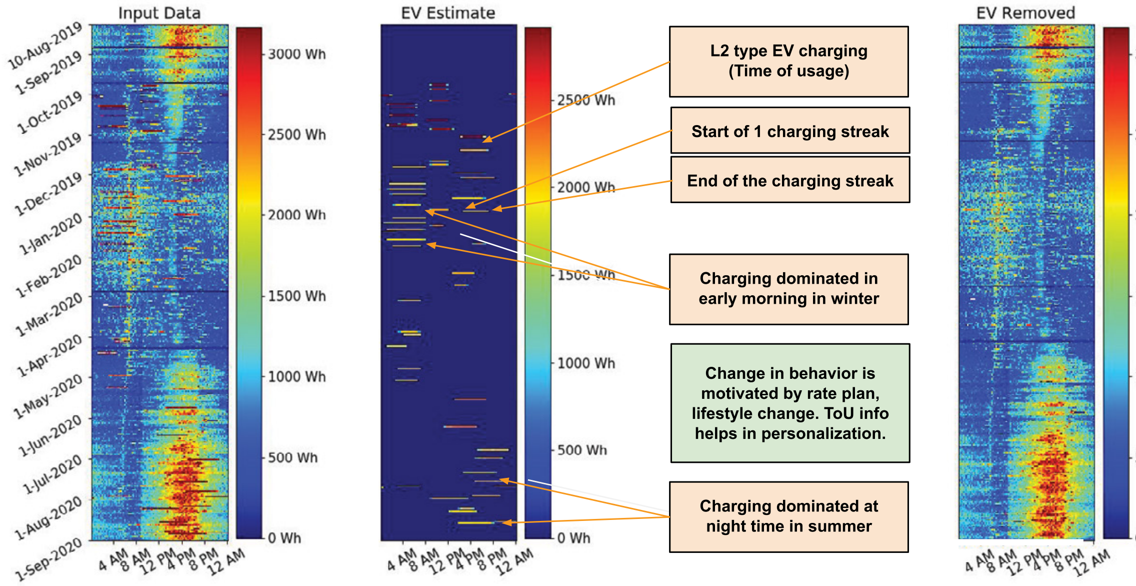


Figure 4 : Extraction of EV estimates from raw energy consumption

Bidgely's algorithm not only detects the presence of L1/L2/L3 chargers but also provides an accurate charging estimate to the time-of-day-level.

Pool Pump (PP) Extraction: Residential pool pumps are operated by a pre-programmed controller that runs the pump according to a set schedule. A pool pump may also be programmed to operate at different amplitude levels. Bidgely's robust timed appliance detection algorithm takes into account all such variations.

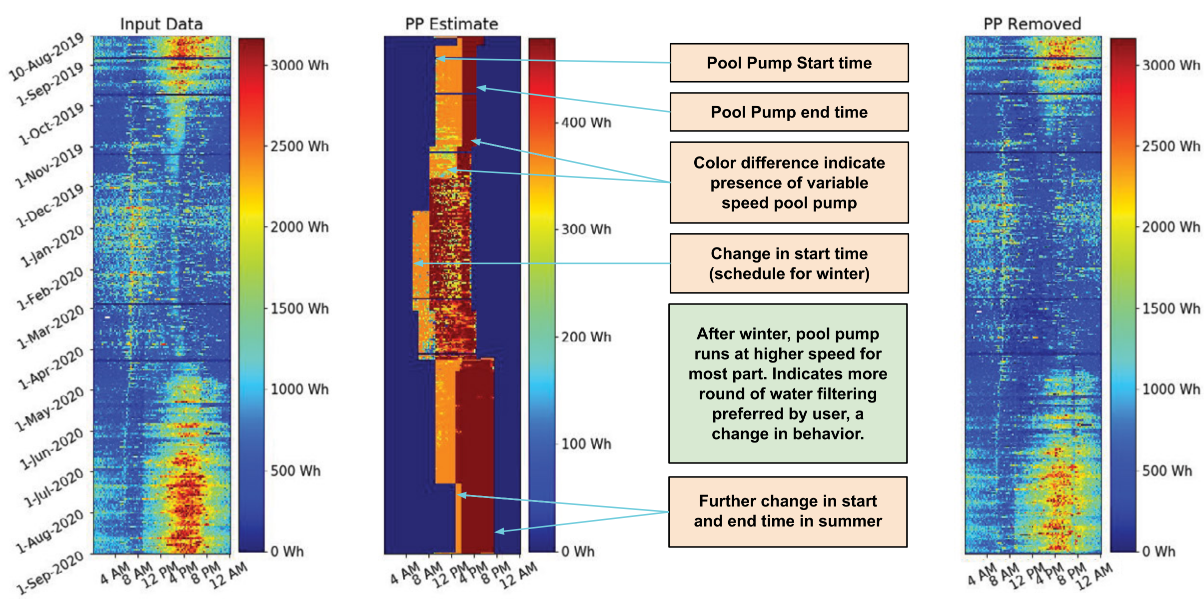


Figure 5 : Extraction of PP estimates from remaining energy consumption

The heatmaps in Figure 5 illustrates how pool pump consumption can be extracted from even the most complex energy usage data. Evidently the pool pump schedule, any associated changes and underlying amplitude is accurate for any time of day.

Cooling Extraction: Cooling units are one of the largest contributors to total summer season energy consumption. Globally, a wide variety of cooling appliances exist, including Split units, heat pumps, packaged units, mini split and PTAC A house may have a combination of cooling units running concurrently, and some units may left on to run throughout the day.

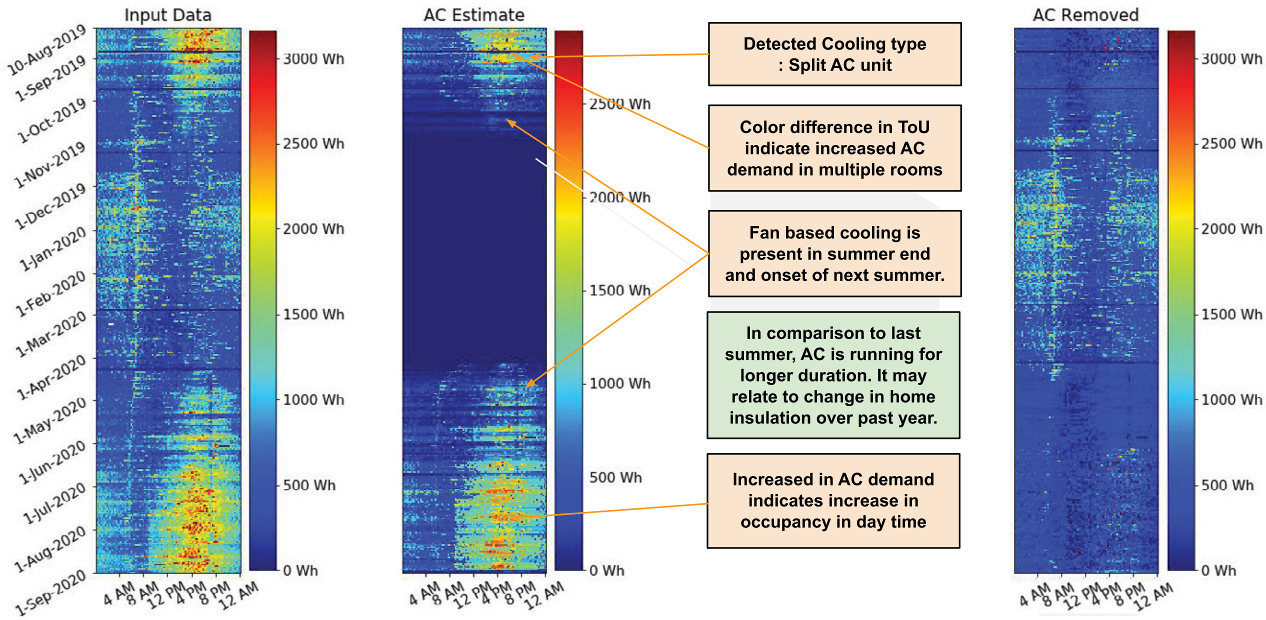


Figure 6 : Extraction of AC estimates from remaining energy consumption

Heatmaps in Figure 6 show cooling estimates accurate to the data sampling level, extracted through a collection of classification and regression models. It is worthwhile to note the on-demand, and all-day use of cooling which reveals the presence of multiple cooling units. The attributes help us in building probabilistic classification models to identify different types of cooling units along with their efficiency and capacity.

Heating Extraction: Like cooling extraction in summer months, heating extraction during winter months looks for heating signatures associated with the full range of heating appliances, including electrical furnaces, baseboard heating, heat pumps, mini split and PTAC. An electric-powered heat circulation component of gas- heating may also be present. From a usage perspective, on-demand usage is most common, but a heating device may also run all e day. Heatmaps in Figure 7 illustrate the ToU heating consumption extracted from energy data using our disaggregation algorithms.

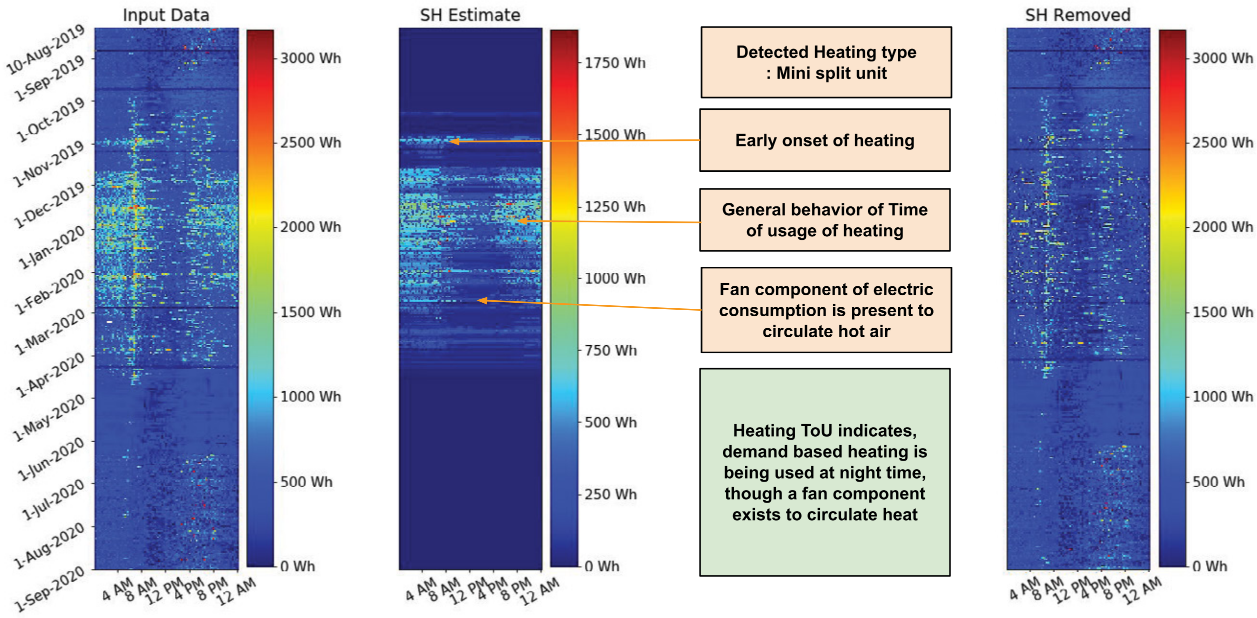


Figure 7 : Extraction of SH estimates from remaining energy consumption

Depending on the always-on component, the heating device fuel type can be predicted with a high accuracy.

Water Heater (WH) Extraction: Based on usage style, we can categorize water heaters as either storage or timed. Each type of water heater has two modes of operation: 1) passive usage, where a set temperature has to be maintained by a water heater for use at a later time of day; and 2) active usage, where the device runs for a relatively longer duration when hot water is in use.

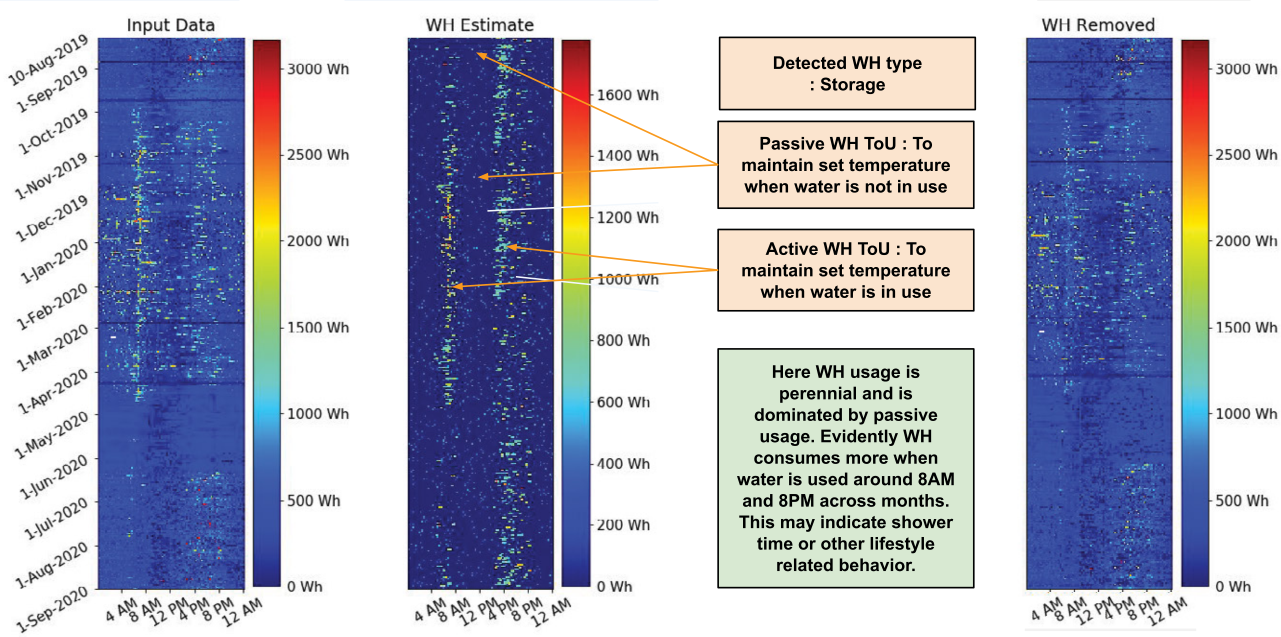


Figure 8 : Extraction of WH estimates from remaining energy consumption

The heatmaps in Figure 8 show net water heater usage derived at sampling rate. The algorithm's output consists of both passive usage (intermittent usage) and active (bright usage chunks) accurate for any hour of a day. A higher thin pulse contribution can help in identifying if there are insulation issues with the water heater tank.

Lighting Extraction: The amount of lighting consumption is sensitive to sunrise-sunset time, lifestyle, home size and other factors. Lighting consumption in general falls in the low-energy range, and is easily convoluted by high consumption appliances as shown in heatmap of Figure 9.

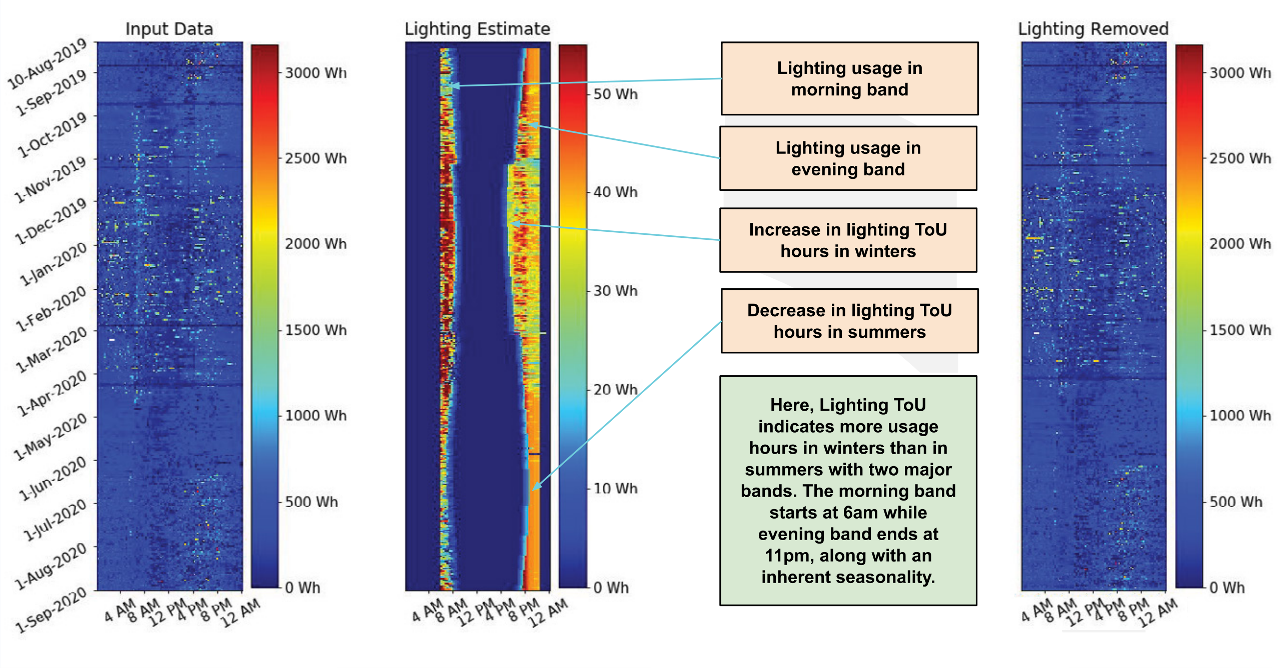


Figure 9 : Extraction of Lighting estimates from remaining energy consumption

Bidgely's algorithms are designed to model residential lifestyles, which helps us to extract the time of day where lighting is on and the associated amount of energy consumed by lighting appliances. The derived consumption depicts the seasonal variation in lighting usage inline with the daylight hours.

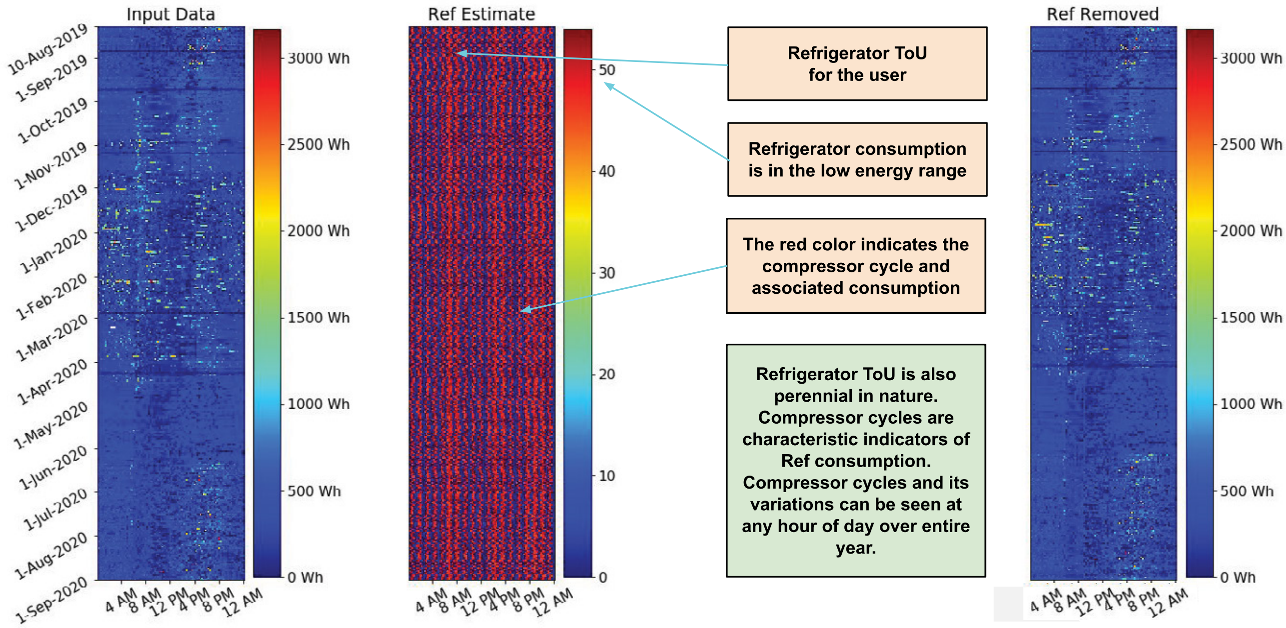
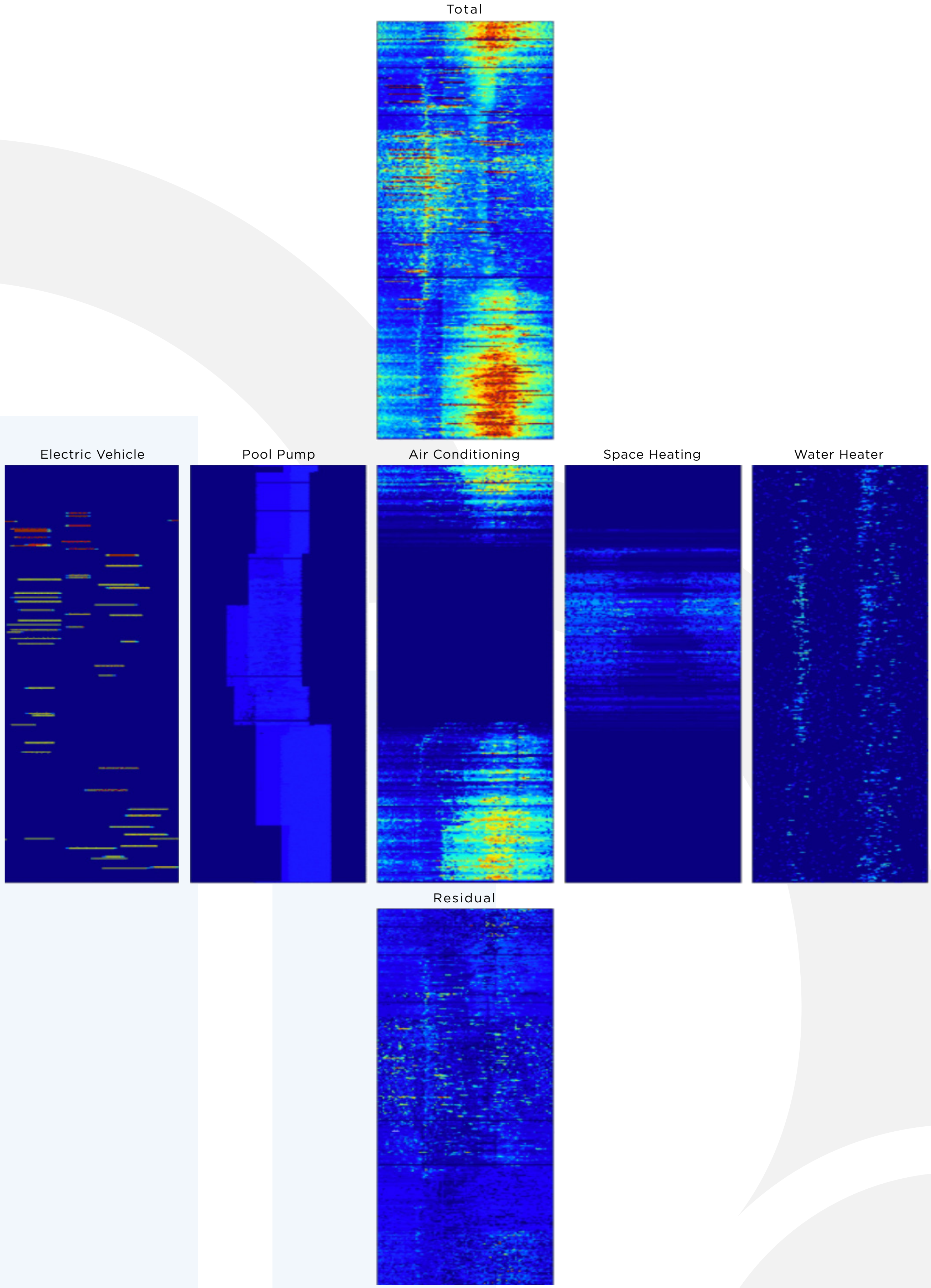
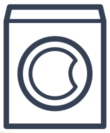


Figure 10 : Extraction of Refrigerator estimates from remaining energy consumption

Refrigerator (Ref) Extraction: Refrigerators irun throughout the year and demonstrate key compressor cycle characteristics. We detect the compressor cycles through signal processing and statistical modeling techniques. Bidgely's modeling also provides compressor duty cycle attributes which enables the accurate estimation of refrigerator consumption to the data sampling level. Figure 10 shows time of usage for refrigerator consumption.



Bidgely's Time of Use Disaggregation



Disaggregation of Non-signature appliances: Appliance categories such as laundry, cooking and entertainment do not exhibit discernible signatures in raw energy data at AMI sampling rates.

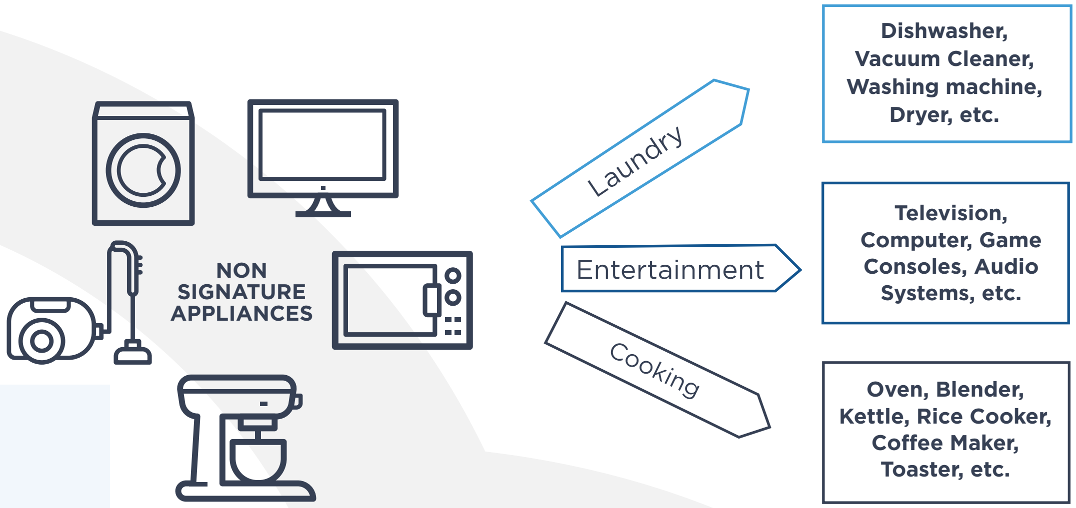


Figure 10: Categorization of Non-signature appliances

For example, entertainment appliances contribute a less significant amount of energy in the days when HVAC energy usage is high. Their consumption is hidden by high consumption HVAC appliances, making it challenging to extract their energy usage. Cooking appliances including ovens, rice cookers and coffee makers are used differently by every customer and are in use for very short spans of time. Similarly laundry appliances like washing machines and dryers are not used on a regular basis.

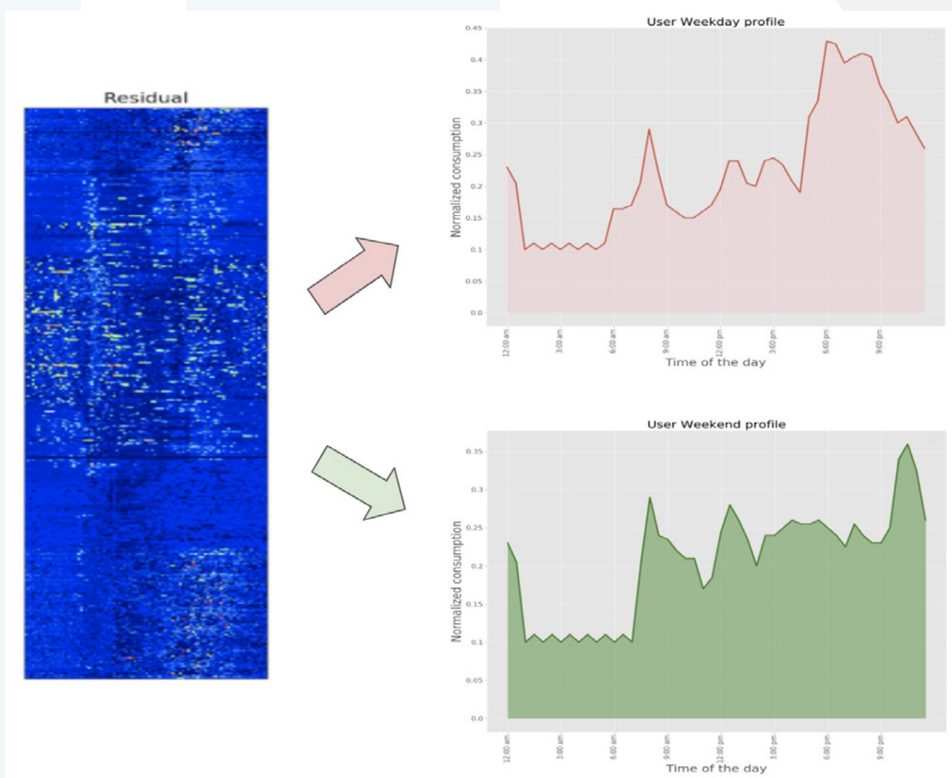


Figure 11: (a) Electrical activity curve

Hence, In order to estimate their ToU consumption, Bidgely's algorithms shift from pattern recognition to user-profile-based analysis to discern further insights about probable target appliance usage hours. Bidgely solutions employ Intelligent methods to extract hidden user behavioral attributes. Fig 11(a) illustrates temporal and quantitative details of residential user behavior-dependent electrical activity. Fig 11(b)-(c) depicts user attributes derived from the activity curve. Finally, by associating the residual energy data with derived user attributes reveals the ToU disaggregation of these appliances.

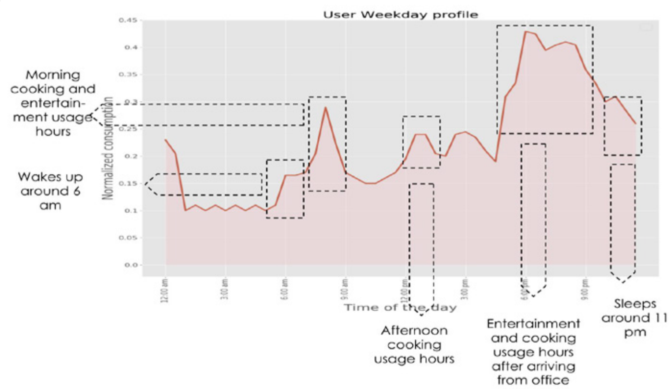


Figure 11 (b): Residual energy profile on weekdays

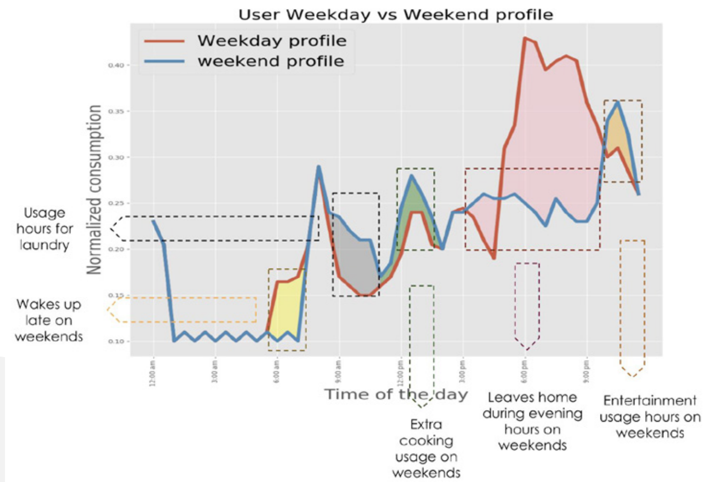


Figure 11 (c): Residual energy profile on weekends

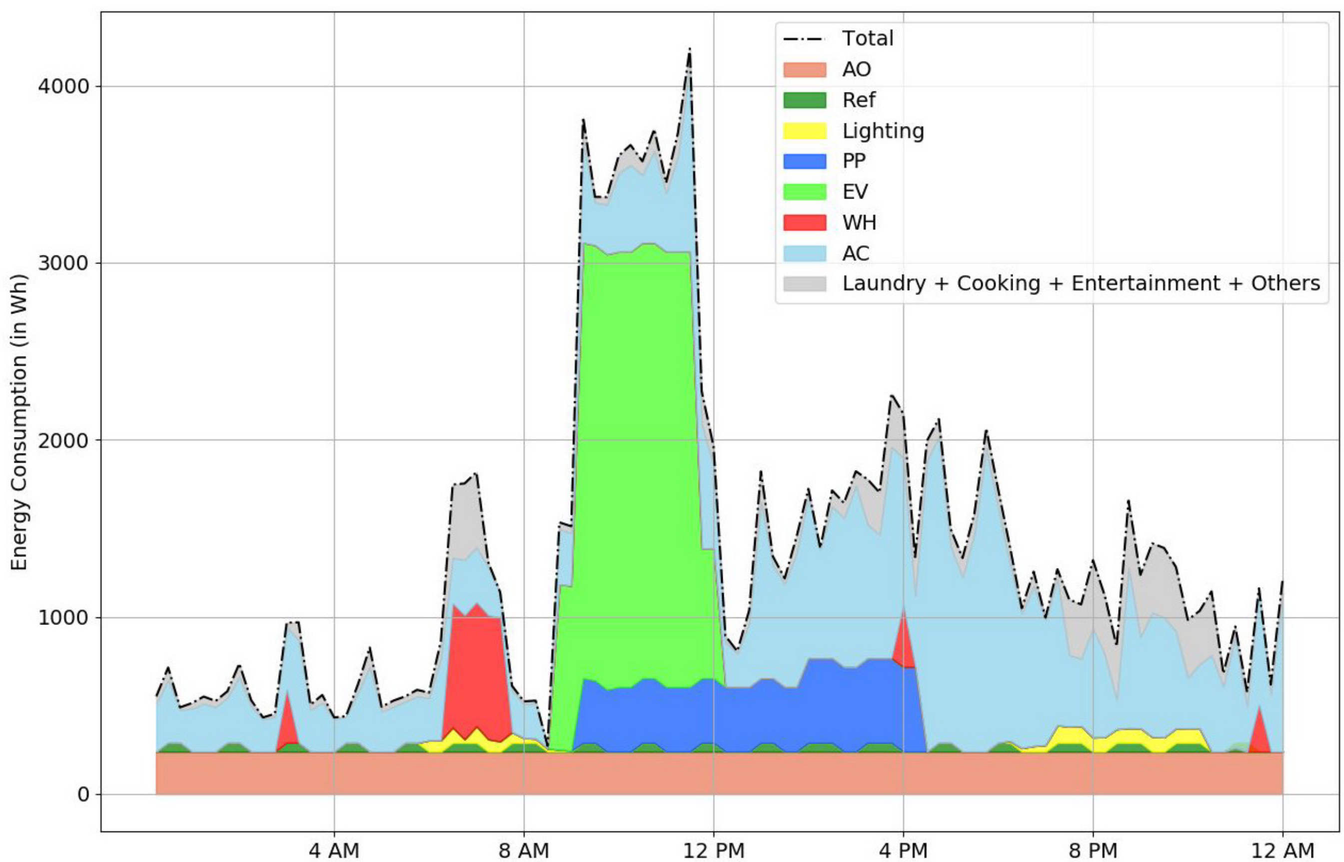


Figure 12: Day view of ToU disaggregation

Fig 12 depicts the timestamp level energy estimation for all appliances, including signature and non-signature .

TOU DISAGGREGATION : POTENTIAL UNLOCKED

ToU Disaggregation at a high granular level opens new possibilities for practical applications. ToU disaggregation helps us understand the user's energy consumption behavior in a superior way. For example, knowing that a person has an EV is not enough. Insights such as the time at which the user usually charges the EV, any variations in seasonal charging time or duration and more enables the type of hyper-personalized communication and service that improves the user experience and helps utilities better achieve their strategic goals.

Demand Side Management(DSM): Demand-side management is the modification of consumer energy demand . Usually, the goal of DSM programs is to encourage consumers to use less energy during peak hours, or to shift their time of energy-use to off-peak hours. Historically, identifying the precise subset of customers to target with relevant recommendations has been difficult. But now, with the help of ToU disaggregation, utilities can not only identify users but also generate personalized recommendations for altering consumption patterns. For example, utilities can send an alert to a customer who is using a pool pump during peak hours recommending the customer change the pool pump timings to non-peak hours in order to save, which serves to help utilities reduce peak-time load. Precisely targeting users with actionable insights reduces outreach costs and improves campaign success metrics.

Read more about NV Energy's use of AMI analytics for program design: https://go.bidgely.com/Virtual-Assessment-CARE-DSM-Case-Study.html

Grid Planning and Management: ToU disaggregation can help utilities understand the energy needs and consumer behavior in a given locality or zip codes. This understanding helps design rate-plans tailored to the target populations' consumption behavior. Customized rate-plans have proven to be an effective way to manage load and increase revenue without negatively impacting user satisfaction. ToU disaggregation plays a pivotal role in making accurate user-specific rate plans, and also helps utilities boost infrastructure at a micro-level to ensure smooth and efficient operations.

Listen here on how Duke Energy is using ami disaggregation in their next generation peak load management: https://go.bidgely.com/informing-ev-and-propensity-modeling-duke-energy-reynolds-full-session.html

Energy Efficiency: Improving energy efficiency remains a top utility priority. An accurate ToU-level disaggregation plays an important role in identifying the target population and providing hyper-personalized actionable insights for achieving energy efficiency. Also, granular disaggregation helps to identify appliance degradation and inefficient usage, which makes it easier to pinpoint and act upon the root cause of inefficiency. This opens up opportunities to drive utility marketplace commerce by targeting customers who have inefficient appliances with replacement product or service offers.

Check out Hydro-One's new personalized marketplace solution: https://www.hydroone.com/saving-money-and-energy/residential/myenergymarketplace

Customer Satisfaction: Insights based on granular disaggregation better explain customer energy consumption and equips customer representatives to better handle customer queries and deliver satisfactory resolutions at a faster pace. This strengthens consumer confidence in utility insights and analytics.

Listen to how VSE is using this intelligence to create stickiness with their customers: https://go.bidgely.com/use-of-ai-to-fight-electricity-loss.html

CONCLUSION

The power of artificial intelligence can be harnessed to accurately determine the operating status of home appliances with a timestamp-level consumption estimate, based on only AMI data. Bidgely's patented TOU disaggregation algorithms solve for DSM, energy efficiency, customer satisfaction and more.

Bidgely continues to lead the industry in developing the most advanced applications at the intersection of AI-powered disaggregation and fast-evolving utility operations and customer requirements.

GET STARTED

Interested in learning more about how Bidgely's UtilityAI Platform for Hyper-Personalization can improve your utility programs? Contact one of our representatives at utilityai@bidgely.com to schedule a demo and see how UtilityAI can drive more value for your customers and your business.

Experience it for yourself at: https://demo.bidgely.com/

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