R & D SERIES

SMB DISAGGREGATION AND INSIGHTS

A TECHNICAL BRIEF BY THE BIDGELY DATA SCIENCE TEAM

1 INTRODUCTION

Small and Medium-sized Businesses (SMBs) make up a large portion of total energy demand on the grid—the Smart Energy Consumer Collaborative estimates roughly 20% of U.S. energy consumption. The potential grid benefits of empowering business owners with energy insights to better manage usage are significant, but historically, energy efficiency programs based on non-intrusive load disaggregation have focused largely on residential customers.

Bidgley, however, has built on our proven residential energy disaggregation science to develop a highly scalable load disaggregation model for SMBs, independent of on-site sensor data. Bidgely SMB insights empower energy providers to realize the same data-science-driven efficiency savings, satisfaction, and engagement from their SMB customers as they have been able to develop with their residential customers.

Historically, in the absence of **appliance-level sub-meter data**, SMB disaggregation has been attempted using statistical rules and heuristics, which can result in highly inaccurate estimates. Bidgely's energy disaggregation for SMBs offers a much more sophisticated and precise approach, personalized for each specific SMB site and delivering accurate usage insights.

This paper explains Bidgley's SMB energy disaggregation and insights capabilities, which give energy providers reliable, appliance-level, and SMB-specific visibility into the usage of these important customers.

2 SMB PROFILE CHARACTERISTICS

Creating an accurate profile of each SMB is essential to delivering energy insights with the greatest value impact for both the business customer and the energy provider.

SMB energy consumption levels vary widely depending on business size, type, location, as well as external factors such as weather and time of year.

One of the primary features of an SMB is its characteristic **working hours**, which usually remain similar throughout the year, with some seasonal/daily variations. During working hours, operation-related appliance usage generally remains the same or is a function of only the hour of the day.

For example, in a small IT business, consumption categories like lighting, computers, ventilation, etc. run continuously only during open hours. Consumption categories such as computers depend on the time of day as per the employee's schedule. We call this component of energy usage **"operational load."** In general, after-hours consumption levels are low, though anomalies or day-specific variations that require special attention sometimes do occur.

Heating Ventilation and Air Conditioning (HVAC) system profiles change with the seasons, heating and cooling as temperatures shift. Most HVAC usage is limited to working hours; however, after-hours spillover is possible due to inefficient behaviors—for example, when an office AC unit is not turned off properly after closing for the day.

When it comes to appliances like refrigeration units, consumption levels depend largely on the type of SMB. For instance, refrigerators have a higher contribution to overall consumption in a restaurant than a shop or office premise.

Likewise, lighting consumption levels are also a function of the type of SMB. For example, while an office-based business might shut off all lights after closure, a 24-hour grocery store would have lighting appliances used throughout the day and night.

3 HI-VALUE USE CASES

1. **Energy disaggregation insights:** Personalized engagement and program design informed by SMB-specific insights about appliance-level energy usage:

    - For an energy efficiency program, Bidgely enables energy providers to select treatment group customers in a way that maximizes savings from each business, since our disaggregation-driven insights enable us to know which customers are saving the most. For example, on the residential side, we have learned that it's not homes with the highest consumption but rather homes with the highest HVAC consumption that save the most.

2. **Efficiency programs:** Targeted SMB efficiency programs are made possible by appliance-level energy consumption, extracted characteristic load, and metadata:

    - Bidgely's analytics can identify customers with high potential to provide value to utility programs based on the level of consumption of key appliances and the times during which the appliances are running. The utility can leverage our Analytics Workbench solution to create versatile and accurate customer segmentation, enabling hyper-personalized customer communications.

3. **Anomaly detection:** Utilities are empowered to send actionable alerts based on consumption pattern anomalies – such as appliances left running 24x7 or anomalous high consumption behavior:

    - When energy consumption from specific appliances spike during a billing cycle, SMB customers should be alerted immediately to avoid a high-bill shock. For example, always-on appliances such as TV screens, desktop computers, coffee makers, and even other specialty devices such as fountain pumps can significantly impact a customer's usage without notice. With Bidgely's Energy Highlight Alerts utilities can educate SMB customers about those potential sources of higher consumption and couple usage insights with tips and utility program recommendations for reducing such loads.

4. **Demand-Side Management:** Utilities are better able to plan for energy demand at the feeder level when they are able to leverage information regarding SMB appliance-level time of use and work hours:

    - Using Analytics Workbench, the utility can visualize its grid by demand capacity. Bidgely breaks down up-to-date grid loads into the individual service point end-use consumption, and peak demand, which can show different load shapes by grid asset. This detailed visibility enables utilities to identify granular opportunities to reduce demand or implement targeted infrastructure improvements.

4 THE BIDGELY SOLUTION

Bidgely's AI-powered algorithms disaggregate overall SMB electrical energy consumption at the appliance level, including heating, cooling, ventilation, lighting, refrigeration, always-on, operational load, and more. The algorithms receive utility-supplied smart meter AMI data and appliance level estimates are made at the data sampling level. The operational load is specific to work hours and varies with the size and type of SMBs.

In order to give accurate estimates, we have developed machine learning models that classify the consumption pattern as a specific category of SMB including offices, restaurants, Quick Service Restaurants, salons, churches, hotels, grocery stores, shops, clinics, and hospitals.

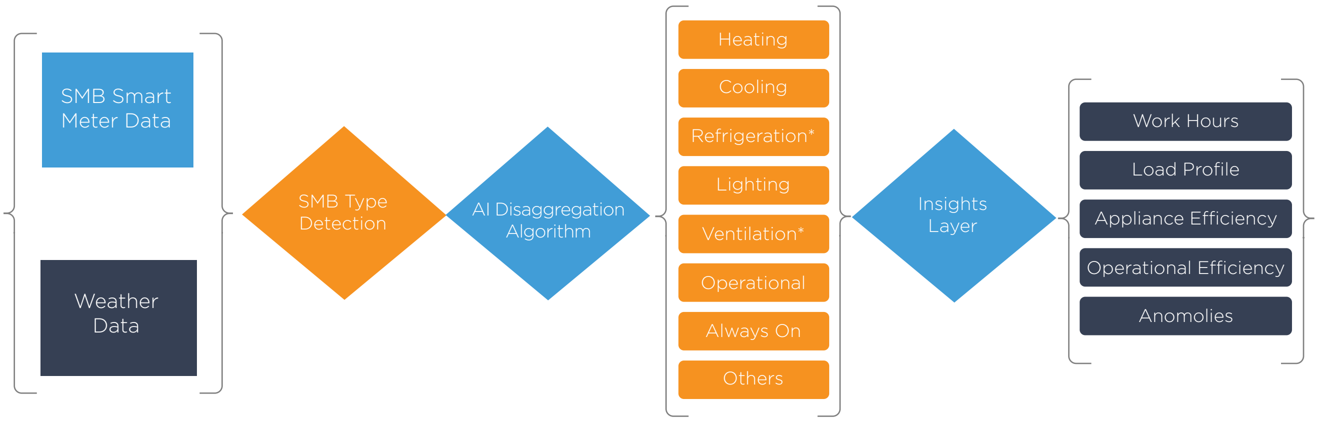

Figure 1: Bidgely's process to extract disaggregation information and actionable insights for SMBs

Based on appliance-level estimates, the type of SMB, and consumption patterns, Bidgely's SMB data science also extracts other useful information for utilities, including:

- Work hours
- Premise load profiles
- Appliance efficiency scores
- Operational efficiency
- Anomalies

Understanding work hours and load profile helps utilities plan for demand-side management. Appliance efficiency and operational efficiency intelligence enables utilities to run targeted energy efficiency programs. The anomalous behavior information helps utilities send proactive alerts that improve customer satisfaction.

Figure 1 shows the process flow for Bidgely's disaggregation-based insight extraction. Appliance categories marked with a star are available for SMB types where applicable.

4.1. Data Requirement

SMB disaggregation and insights extractions are performed using AMI smart meter data at a 15-, 30- or 60-minute sampling. The data requirements are as follows:

1. Energy consumption information (from the utility)
2. Postal Code information of SMB premises (from the utility)
3. Weather information based on postal code (available from a third party)
4. Any available metadata such as floor area or type of SMB (from the utility)

4.2. SMB Insights Methodology

In this section, we will discuss the methodology taken to perform the SMB disaggregation and extract actionable insights.

4.2.1. Data Pre-Processing

Unsupervised algorithms used in building the disaggregation process are sensitive to data outliers. In order to handle such issues, we preprocess the consumption and temperature data by handling anomalous consumption and temperature points and then inserting missing consumption or temperature data if required.

4.2.2. Working Hours Estimation

Working hours estimation is carried out in two steps. First, we estimate working hours based on general local practices, which remain consistent with slight variations. Second, we capture deviations from the general trend caused by holidays, days of the week, vacation seasons and other factors that result in extended or shortened working hours.

Figure 2 shows the working hours of a specific SMB on a particular day.

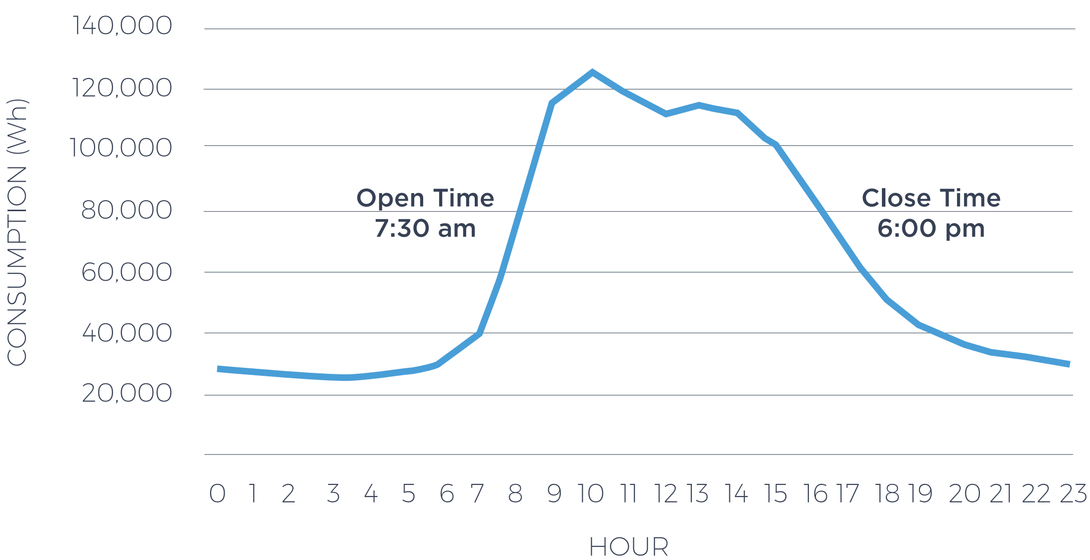

Figure 2: Illustration of load pattern for an SMB on a particular working day

4.2.3. SMB Type Detection

Information about SMB type is essential to draw insights based on disaggregation. There are three main sources of this information:

1. SMB type information available from the utility's database
2. SMB type information taken through surveys, either by Bidgely or by the utility
3. SMB type information available from third parties

If none of the sources above are able to provide SMB type information, Bidgely has developed an AI-based model based on a large dataset to classify the AMI smart meter data into specific categories including: office, restaurant, Quick Service Restaurant, salon, church, hotel, grocery store, shop, clinic, and hospital.

Characteristic SMB type features are extracted from AMI smart meter data based on energy consumption patterns and consumption levels. This feature set is further fed into a classifier that has the capability to perform multi-class classification. For a new SMB AMI dataset, the probability model identifies the most likely SMB type based on the detected consumption pattern.

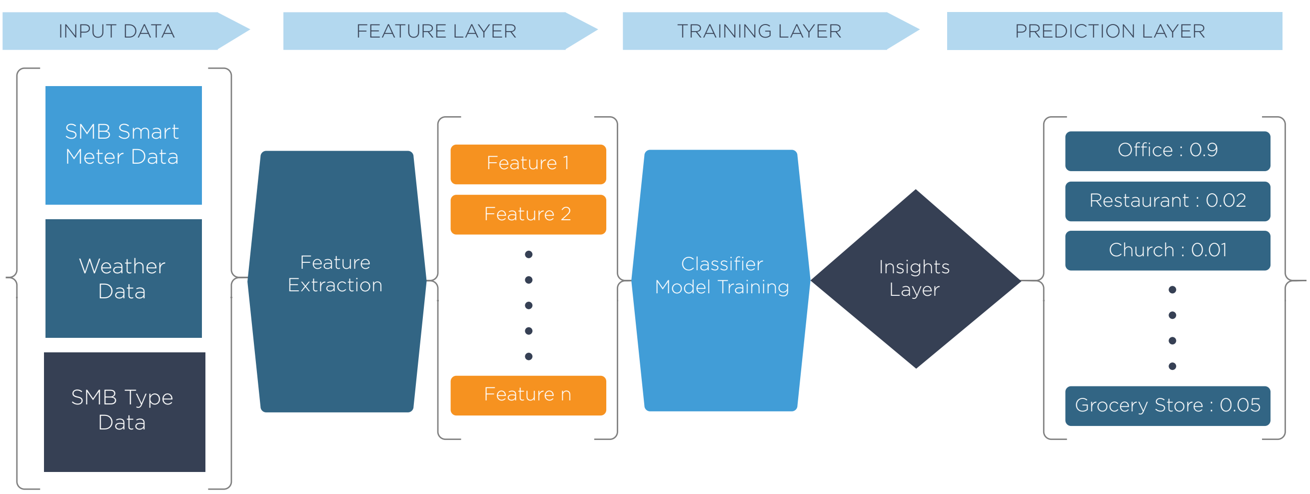

Figure 3: Bidgely's approach to SMB type classification

Figure 3 shows the classification process for an unseen SMB based on the features extracted from its AMI smart meter data. The prediction layer classifier gives the probabilities of one of the 10 contender classes. The most probable class in this example is the "Office" class, with a probability of 0.9.

4.2.4. Disaggregation Description

Different appliances display unique patterns based on their usage. For example, appliances responsible for heating and cooling are mainly seasonal in nature and are used in winter and summer respectively. In addition, refrigeration usage varies based on the type of SMB. Likewise, lighting appliance usage may vary over time throughout the day depending upon the type of SMB. There may also be a standby load for an SMB that falls into the always-on category. Depending on the size of the SMB, the always-on load may be large or small in comparison to other SMBs of the same type. Certain appliances may only run during operational hours. We have the capability to extract the aggregate of such appliances as part of the operational load.

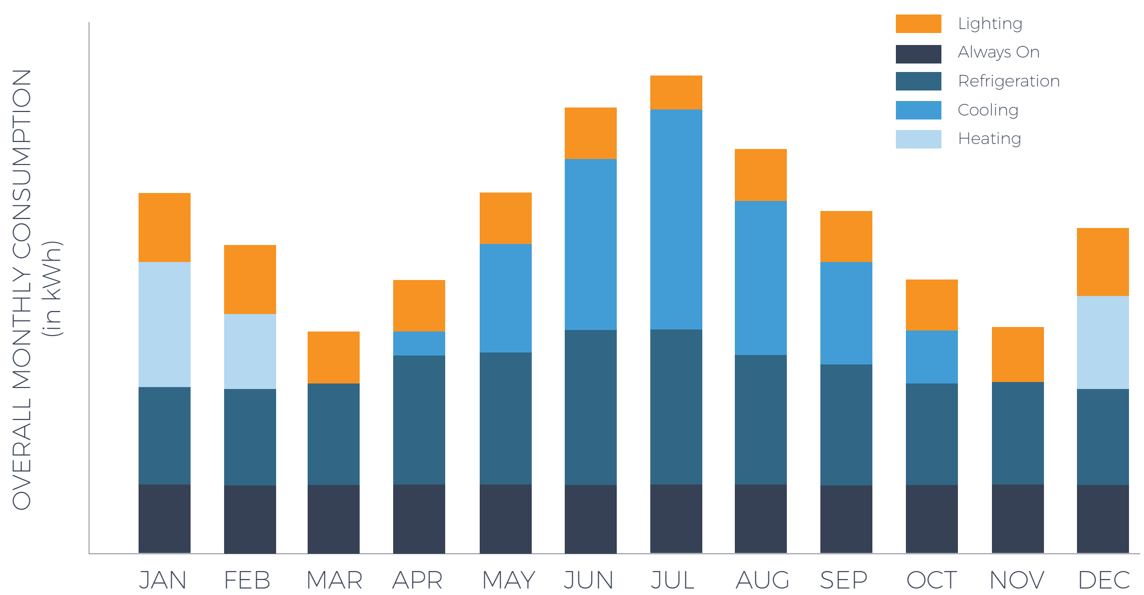

Figure 4: The month aggregate-level energy disaggregation for a SMB

Bidgely's AI-based disaggregation algorithm is able to extract appliance-specific patterns from overall consumption data and make estimates for appliances at the data-sampling level. The data sampling-level appliance estimates are further aggregated to the billing cycle level in order to identify appliance-specific expenses incurred by the SMB.

Figure 4 shows the monthly consumption and appliance-level disaggregation of a restaurant. The disaggregation shows consumption of lighting, refrigeration, cooling, heating, and always-on for the restaurant over the course of one year.

4.2.5. Disaggregation-Based Insights

The appliance-level energy consumption, hours of operation and SMB-type information enables utilities to make insights-based recommendations for each SMB customer. Utility-provided meta information further improves the recommendation efficacy. Potential recommendations include:

1. **HVAC inefficiency:** The HVAC disaggregation extracts appliance-specific characteristics such as the amplitude of operation, consumption level, and more. These characteristics are then compared between SMBs of a similar type to identify the premises where HVAC systems are running inefficiently. The SMB premises are ranked based on the gaussian distribution of characteristic parameters. Using the rankings, utilities can plan to run efficiency programs to target the subset of SMB customers best aligned with their program goals.

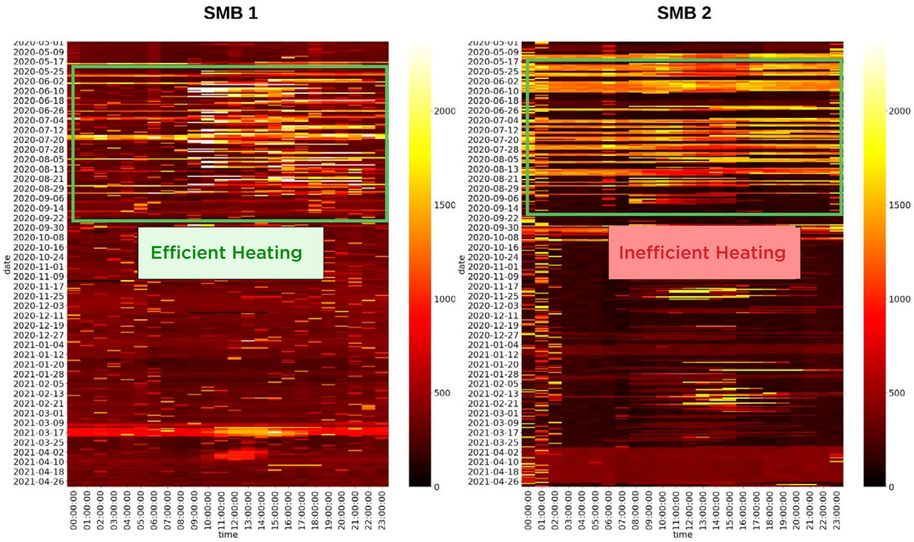

Figure 5: Proof point of heating inefficiency between two SMBs of same type in Australia region

Figure 5 shows heatmaps of heating inefficiency for two SMBs of the same type from Australia's Melbourne region. SMB 1 on the left shows efficient heating usage, while SMB 2 on the right exemplifies inefficient energy usage. This detection can be expanded to identify inefficient SMBs across a given territory.

Figure 6 shows the distribution of SMBs in Melbourne as per their heating inefficiency. The SMBs marked in red are inefficient and those in blue are efficient. Additionally, the shades of red/blue are darker depending on the score of inefficiency.

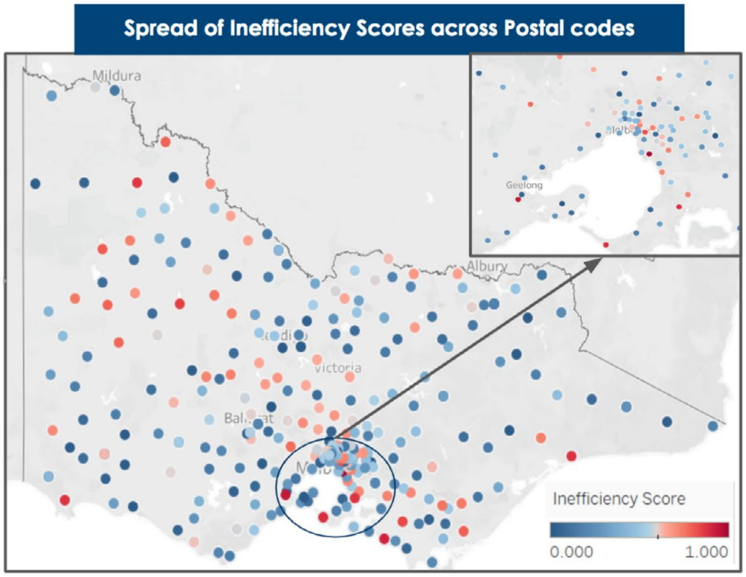

Figure 6: Distribution of efficient heating (Blue) and inefficient heating (Red) for SMBs of same type in Melbourne

2. **HVAC Usage inefficiency:** In some instances, SMBs leave HVAC appliances running beyond their operational hours. Since we have operational hours and data sample-level HVAC estimates, utilities can use this information to target SMBs that are running HVAC equipment after hours. The resulting energy savings would help achieve both energy efficiency and customer satisfaction goals.

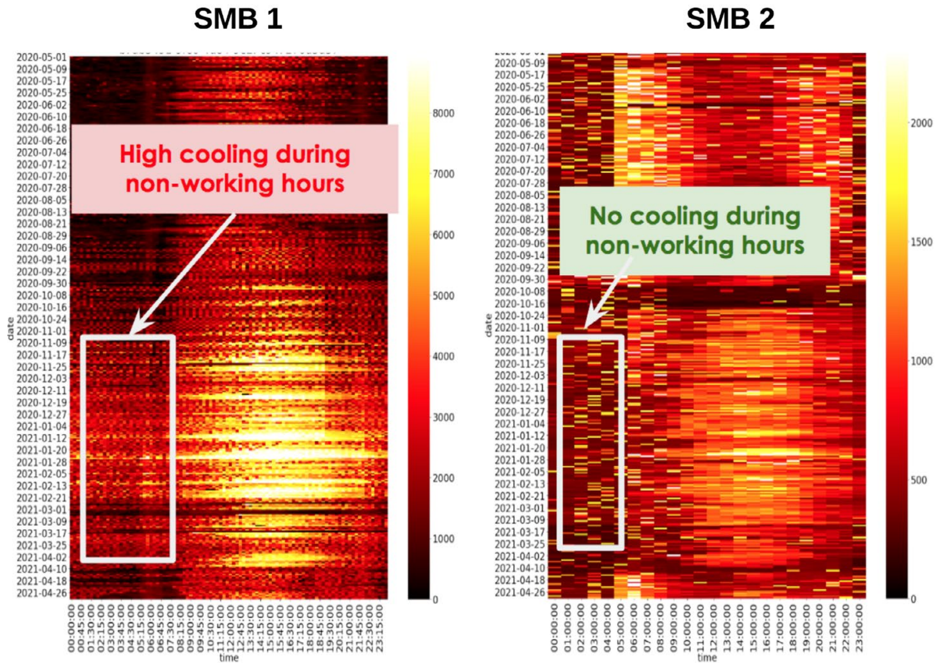

Figure 7: Heatmaps of cooling usage between two SMBs of same type in Melbourne region of Australia

Figure 7 shows heatmaps of consumption for two SMBs of the same type in Melbourne. SMB 1 on left shows evidence of after-hours cooling usage while SMB 2 on the right is using cooling efficiently only during working hours.

Figure 8 shows the distribution of SMBs of the same type with efficient cooling usage and inefficient cooling usage in the Melbourne region of Australia.

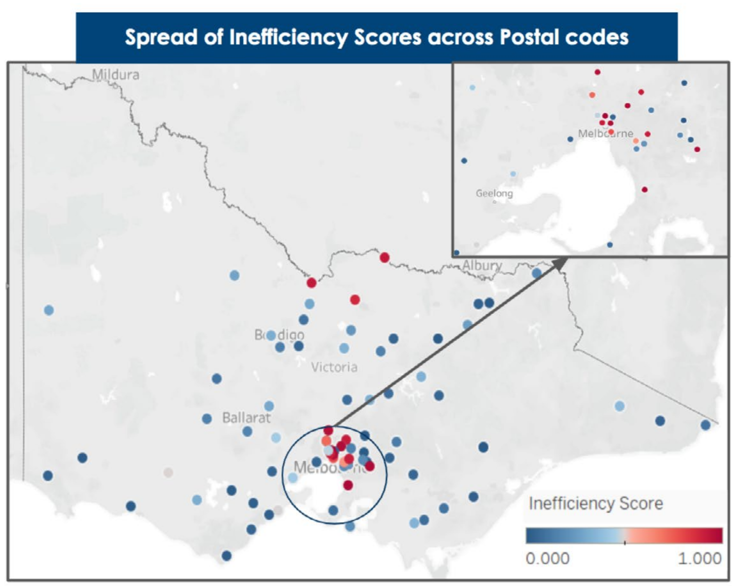

Figure 8: Distribution of efficient cooling usage (Blue) and inefficient cooling usage (Red) for SMBs of same type in Melbourne region of Australia

3. **Energy disaggregation insights:** The appliance-level disaggregation information in itself serves as a good basis for SMB electric bill insights and empowers SMB stakeholders with a better understanding of their energy usage behavior.

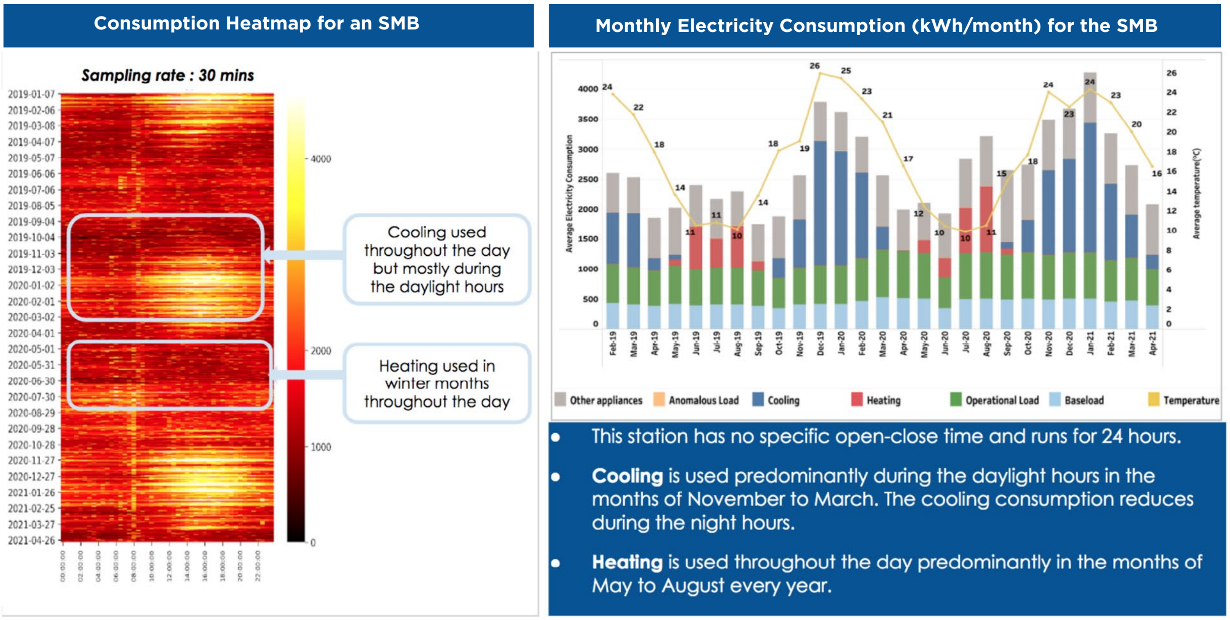

Figure 9: The illustration of insights from disaggregation of one of the SMBs from Melbourne region of Australia

Figure 9 shows an example of the insights based on disaggregation for one SMB in the Melbourne region of Australia.

4. **Anomaly detection:** This feature helps utilities raise alerts and provide SMB customers with actionable insights when a consumption pattern anomaly is identified. The anomalies often correspond to unexpectedly high energy usage, such as a high always-on usage on certain days. Figure 10 shows an SMB high consumption anomaly.

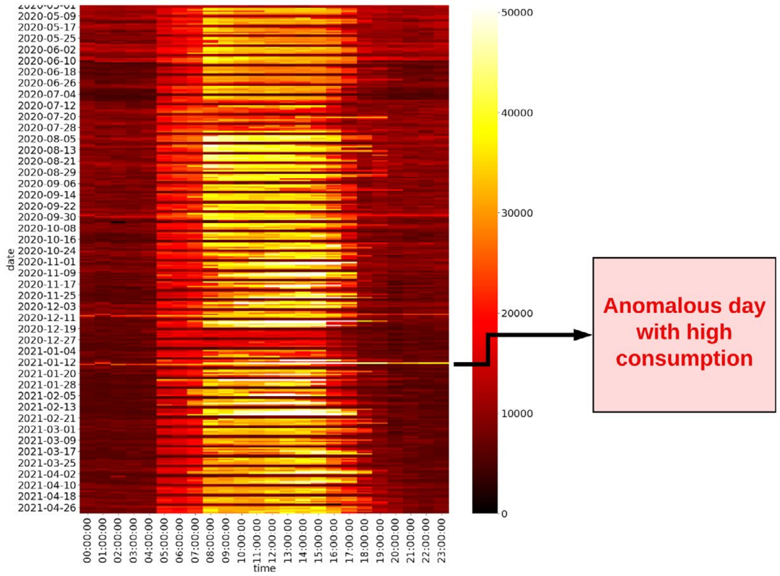

Figure 10: Consumption heatmap showing an anomaly in consumption for one SMB in the Melbourne region of Australia.

5. **Demand-Side Management:** Data sampling-level appliance estimates provide an overall perspective of energy demand within a population of SMBs. Using timestamp disaggregation information, utilities can target a segment of premises to shift or manage load when overall energy demand is high. Appliance-level consumption information enables utilities to conduct this targeted load-shift in a meaningful way, improving the chances of moving demand to off-peak hours.

5 CONCLUSION

Bidgely's SMB disaggregation solution is scalable and can be applied to large SMB populations using AMI data alone, without installing any additional equipment. Disaggregation-based insights empower utilities to design and implement more effective energy efficiency programs, improve SMB customer engagement and satisfaction, and better inform grid planning efforts.

Learn more at:
https://www.bidgely.com/solutions/small-medium-business