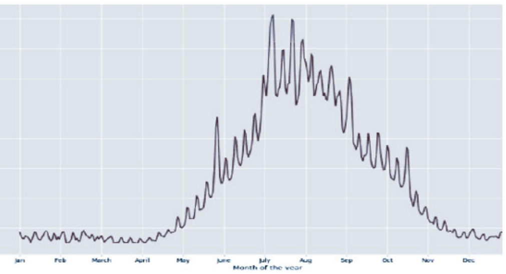
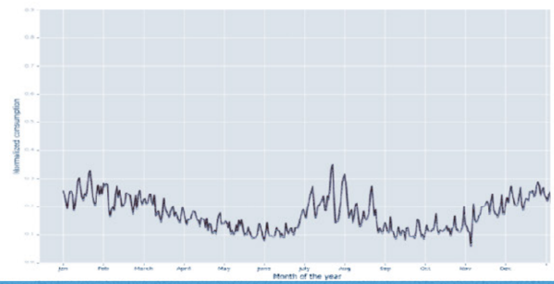
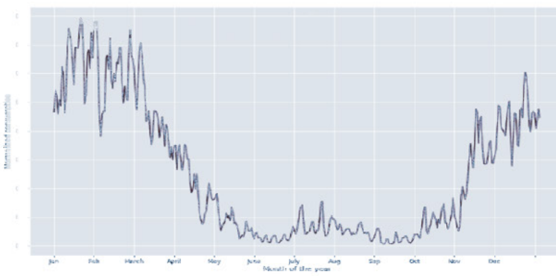






ADVANCED RATE DESIGN WITH ANALYTICS

Bidgely | January 2022

EXECUTIVE SUMMARY

Rate design is a crucial activity all utilities must undertake to ensure that customers enjoy reliable and affordable service while the utility generates necessary revenue. It's where the rubber meets the road and a utility determines the most equitable way to charge customers for energy services. More than a simple optimization problem, rate design is a complex equation that balances covering the costs to reliably provide services and charging a fair and transparent amount to all customers, while not overburdening any given customer.

When applied to Advanced Metering Infrastructure (AMI) data, advanced analytics provide an essential input to the rate design equation that enables more effective rates that better satisfy utility objectives.

New Hampshire Electric Cooperative (NHEC) partnered with Bidgely to identify additional value for rate design in its AMI data. While many utility rates are designed to encourage customers to modify their behavior and shift energy use to lower cost hours (Time of Use rates), NHEC approached Bidgely with a different question. They wanted to determine whether there were existing segments of its member base (NHEC's customers are members of the cooperative) that could be offered lower overall rates because their current time of use consumption was less expensive to serve. They sought to proactively reward members for positive power use behaviors rather than incent them to use it differently. To inform their efforts, NHEC leveraged its AMI investment to capture each member's energy use data. They turned to Bidgely to transform that data into customer energy use profiles upon which they could base their program.

NHEC and Bidgely explored how advanced machine learning techniques could augment rate analysis and design practices and answer the question: "Can member value be created by grouping members by their current use and developing a rate to serve them?" Through its Analytics Workbench tool, Bidgely deployed unsupervised learning algorithms to identify clusters of customers who fell into patterns of electricity use by annual consumption, seasonal consumption, and even daily consumption.

The project was a success. NHEC discovered that multiple segments of its member population used energy in a way that was less expensive to serve. In particular, three segments (night load, all-year baseload, and heavy winter peak) demonstrated the potential for 3-4% of savings per year [while not impacting the overall population more than 1% once they were removed]. NHEC used Analytics Workbench to verify the initial findings by recalculating the costs to serve each segment using hourly avoided costs .

While the results were promising, the application of the results to create an easy-to-understand rate structure proved challenging. The unsupervised learning developed interesting segments with many attributes – attributes that may prove difficult to define in a tariff. In addition, questions were raised as to how and when a member might be removed from the preferred rate should they no longer fit the characteristics of the segment, or how a member might be notified about changes in their usage behavior that had disqualified them from the discounted rate segment.

Though more analysis is needed to help answer these questions, NHEC's research has clearly revealed that when powerful analytics are applied to AMI data, it is possible to create innovative rates that provide higher member value.

THE OPPORTUNITY

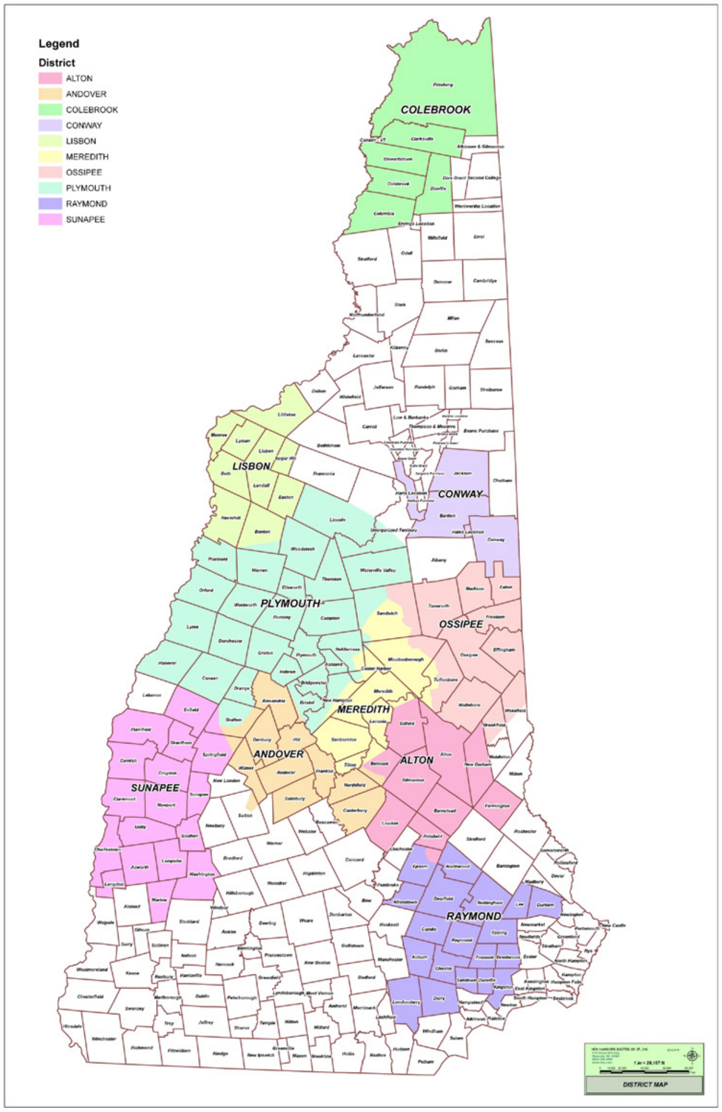
New Hampshire Electric Cooperative (NHEC) is a not-for-profit electric utility owned by customer-members. It’s 86,000 members are predominantly residential and sparsely populated over 115 communities, with a density of 15 members-per-mile of distribution line. Nearly 88% of all members served by NHEC’s default service rate are residential customers, and almost all of these members are on the base rate. Member value and service is at the core of NHECs mission, so determining f how to provide the most customer value through rates was a natural innovation point

The broad grouping of NHEC’s members on one rate provided opportunity for greater differentiation among a substantial sample size. NHEC approached Bidgely to see if advanced analytics could enhance rate design by grouping members based on usage patterns. This would allow NHEC to determine if a rate could be created to reward customers for existing “low cost to serve” behaviors while not overburdening other customers.

AN INNOVATIVE APPROACH

Bidgely’s load disaggregation solution leverages artificial intelligence and advanced analytical models to itemize 100% of residential customer loads and provide visibility into usage patterns at the whole-home and appliance levels. This advanced data science enabled NHEC to explore opportunities to design rates that better aligned with member usage patterns.

Bidgely’s Analytics Workbench dramatically reduces the resources and time required to conduct analyses on load profiles. Requiring no customer surveys or additional metering/submetering, Bidgely uses AMI meter data and supplemental customer data from the utility to generate up-to-date analyses of major appliance ownership, usage in kWh (including time of use) and additional attributes such as major appliance power draw in kW. Beyond informing more advanced rate design, Bidgely’s customer intelligence is valuable for a host of customer segmentation and utility planning activities.



THE SOLUTION

Bidgely and NHEC's innovative customer-value driven rate design project included four phases:

01 DATA INGESTION

02 DISAGGREGATION

03 UNSUPERVISED MACHINE LEARNING - CLUSTERING

RESULTS VIA ANALYTICS WORKBENCH

01 Data Ingestion

NHEC provided hourly meter data for the period of October 1, 2018 to September 30, 2020 for 85,640 unique individual residential members and location combinations. In some cases, information for multiple customers residing at the same location during the 24 month period was included, creating a higher member count. The data provided also included members determined to be seasonal residents. Generally such cases are excluded from Bidgely's analysis because they tend to skew the averages for the population. However, for this project, we chose to include seasonal residences in our analysis because seasonal users made up a significant proportion of the sample. Similarly, the data also showed that a large portion of NHEC's members had been members for less than one year. We elected to omit unique users with less than 12 months of data. In total, approximately 30% of the data was removed from the analysis in order to achieve 100% itemization. Ultimately, Bidgely's disaggregation was performed on 59,879 NHEC unique residential member locations.

02

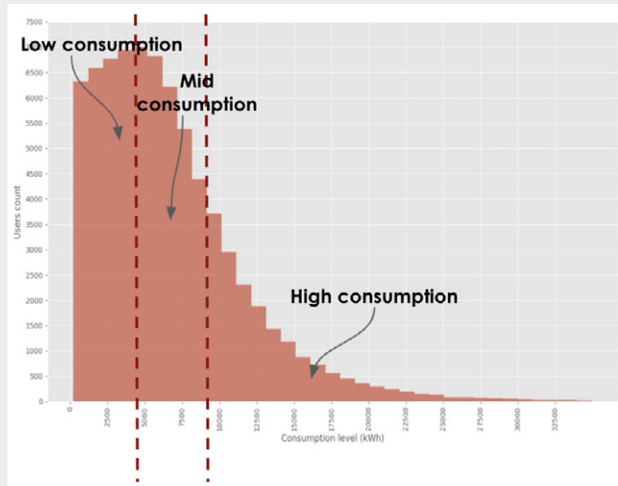
Disaggregation Categories	Time of Use Granularity Available	Using 15/30 Minute Data	Using 60 Minute Data
Always On	Yes	True Disagg	True Disagg
Heating	Yes	True Disagg	True Disagg
Cooling	Yes	True Disagg	True Disagg
Pool Pump	Yes	True Disagg	True Disagg
Always On	Yes	True Disagg	True Disagg
Electric Vehicle	Yes	True Disagg	True Disagg
Lighting	Yes	True Disagg	**True Disagg**
Water Heater	Yes	True Disagg	**True Disagg**
Refrigeration	Yes	True Disagg	**True Disagg**
Laundry	No	User-Centric Disagg	User-Centric Disagg
Entertainment	No	User-Centric Disagg	User-Centric Disagg
Cooking	No	User-Centric Disagg	User-Centric Disagg

03 Bidgely Unsupervised Machine Learning

Bidgely expanded upon its industry-leading disaggregation to find clusters of members that use electricity in a similar fashion throughout the NHEC service territory. This exploratory analysis identified distinct usage patterns grouped around naturally occurring clusters. Bidgely found insights from this "unsupervised" clustering analysis (driven by machine learning) to generate groups of members with 14 distinct lifestyle clusters:

Three clusters of annual consumption usage were identified using this methodology:

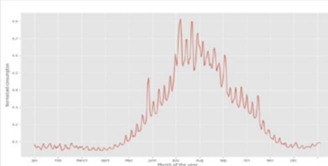
- High annual consumption
- Medium annual consumption
- Low annual consumption



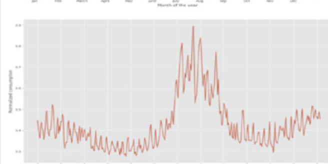
Typical Non-Normal Distribution

Five clusters of seasonal consumption were identified using this methodology:

- A heavy summer peak
- A heavy summer and mild winter peak
- A heavy winter peak
- A heavy winter and mild summer peak
- An all year baseload

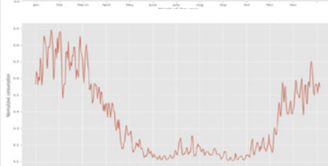


- Heavy summer cluster
- Heavy consumption between May to October
- Probably on vacation during winters

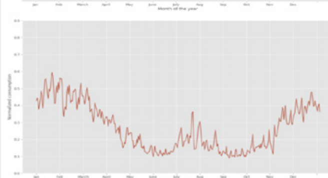


- Heavy summer mild winter cluster
- Consumption throughout the year
- Less consumption in winter months compared to summer months

- All year baseload
- Same level of consumption throughout the year
- Seasonality is less compared to other seasonal patterns



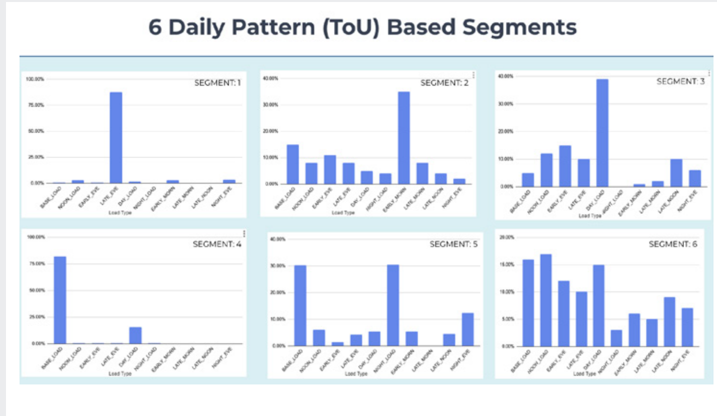
- Heavy winter cluster
- Heavy consumption between November to April
- Probably on vacation during summers



- Heavy winter, mild summer
- Consumption throughout the year
- Less consumption in summer months compared to winter months

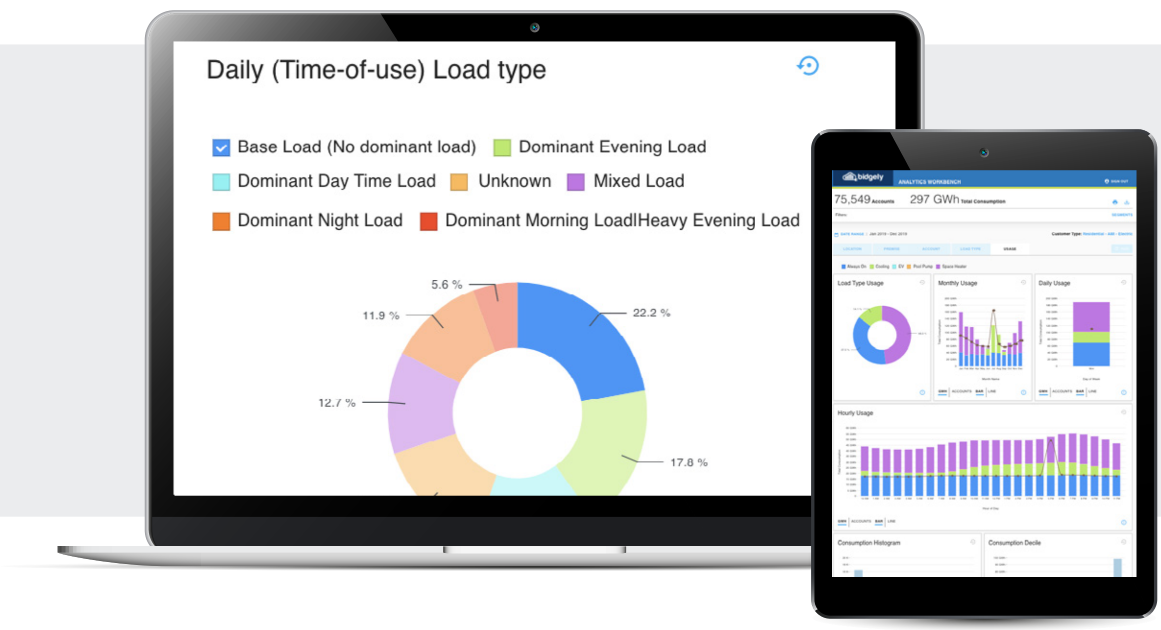
Six clusters of daily load consumption

- Dominant evening load
- Dominant morning load
- Dominant daytime load
- Dominant base load
- Dominant overnight load
- Mixed load patterns



04 Analytics Workbench

Analytics Workbench is a business intelligence tool that provides data stream visualizations of usage, appliance ownership and consumption, geographic impacts, and more. Analytics Workbench helped NHEC visualize each unsupervised learning cluster and provided the ability to share results easily across internal teams. Analytics Workbench also allowed NHEC to filter members by identified lifestyle clusters and/or any other characteristics identified through Bidgely's analytics, such as appliance ownership, geographic location, or time of use in order to unlock deep cost analysis with many different variations. After filtering the data by clusters or segments, it was possible to observe the unique load characteristics of that segment and then compare that to other segments.



Additionally, Analytics Workbench flexibility allowed additional data streams to be analyzed in combination with Bidgely analytics. For this particular analysis, NHEC provided "cost-to-serve" data for their customers which was a cost-per-hour over the entire year. This data was incorporated into Analytics Workbench and used to analyze the cost to serve each segment or membercluster.

CHALLENGES

As the project unfolded, several blockers were revealed, including the initial data ingestion, inclusion of non-residential meters, data cleanliness, and the availability of ground truth to refine disaggregation. Different customer types have different data requirements and types, making the simultaneous ingestion of residential, small and medium business, and commercial and industrial customers difficult. For this project only residential meters were ingested. Additionally, while the project intended to segment customers based on heating types rather than lumping all heating into one category, the necessary ground truth data was not available to make that distinction possible.

FUTURE CONSIDERATIONS REQUIRING ADDITIONAL ANALYSIS

The initial study revealed important philosophical questions that must be addressed, including:

How to communicate with members the patterns or clusters of use and their new rate class.

When communicating rates and billing details to members, it's essential to be transparent and clearly communicate applicable charges and eligibility. While it is easy to see which members fall into each cluster, explaining that classification to the members themselves is not as straightforward. For example, it's not useful to tell a member that their classification is "dominant evening load." Therefore, it's important to further define the clusters in terms of what the usage patterns means to a customer. Additionally, it's very important to map out the entire customer journey toward adoption of a new rate to anticipate positive and negative outcomes. For example, while a customer may qualify for a beneficial rate based upon the 2019 analysis, they may eventually "disqualify" themselves if their lifestyle changes, which presents a critical customer engagement and communication challenge.

Future time based costs may not follow the same pattern (Capacity shift)

While we incorporated the cost to serve (or avoided cost) in the models today, they may not be consistent going forward and therefore the rates designed with this information could become obsolete as capacity shifts. Therefore rates cannot be based upon a one-time analysis, but rather must be developed and refined as part of an ongoing process where revenue, cost, and various usage clusters are continuously evaluated. For this reason it's important to leverage Analytics Workbench to future-proof rate design and ensure ongoing analysis is both quick and low cost.

Length of time considered for cluster identification

The unsupervised learning algorithms identified clusters based only on a single year of usage (2019). This timeframe was long enough to capture necessary seasonal usage patterns. However, the question remains as to how a longer time frame of two, three or more years would alter the clusters.

Does averaging create a poor member experience?

It is possible that some members fall within a particular cluster, but have unique outlying behaviors that could result in a negative billing experience. For this reason, rate design must be conducted carefully, evaluating the impacts on all customers both in the discounted group as well as in the base group.

DISCOVERIES

This project served as an important proof of concept that revealed several very positive discoveries that will shape the future of rate design for Bidgely and NHEC. First, we identified ideal candidates that could benefit from new residential rates by applying an unsupervised clustering analysis and NHEC cost to serve data. NHEC was in search of identifying a cluster to reward with a lower rate, without adversely affecting other members. To do this, they evaluated the cost to serve each cluster, the bill impact to that cluster, and the overall bill impact to the remainder of the population. The following clusters have beneficial results when isolated and provided a discounted rate.

Seasonal Clusters

The heavy winter peak cluster, comprising 10,993 customers, has a lower relative cost to serve than other segments. Customers belonging to this cluster would see a 3% annual benefit, while the remaining customers would only see a 1% annual increase.

The all-year baseload cluster also has a net-positive benefit when isolated from the remainder of the population. Customers belonging to this cluster would see a 4% annual benefit, while the remaining customers would only see a 1% annual increase

Time of Use

When examining the clusters relating to time of use, two clusters showed positive results when evaluated for overall customer benefit. First, the “no favored shape” cluster resulted in a 3% annual benefit for cluster members with only a 1% increase for the remaining customers. Second, the night load cluster also had a 3% annual benefit for those cluster members while having a <1% increase on the remainder of the population.

Rate & Cost Discovery

At the beginning of the project, we anticipated that individual member usage patterns would provide sufficient insight to indicate which groups would be best suited for a new rate. However, after analyzing cluster results, it became clear that it was not going to be that straightforward. Instead, cost-to-serve data was revealed to be an important additional input into the analysis to better define the clusters who had the least and greatest impact on cost. With cost-to-serve added to Analytics Workbench, clusters could be analyzed based on their cost to serve which tied directly to their usage pattern.

CONCLUSION

Designing customer-centric rates based on AMI data is the future of rate design innovation. This project revealed several essential takeaways to inform future AMI-based rate structures and customer rate engagement strategies. Bidgely’s full suite of customer engagement tools and timely rate comparisons offer a value-driven way to engage customers/members by leveraging their actual consumption data.

From a broader point of view this project demonstrated the power of leveraging AMI analytics for a broad-range of utility business decisions and the ability of Analytics Workbench to serve utilities in unique and flexible ways.