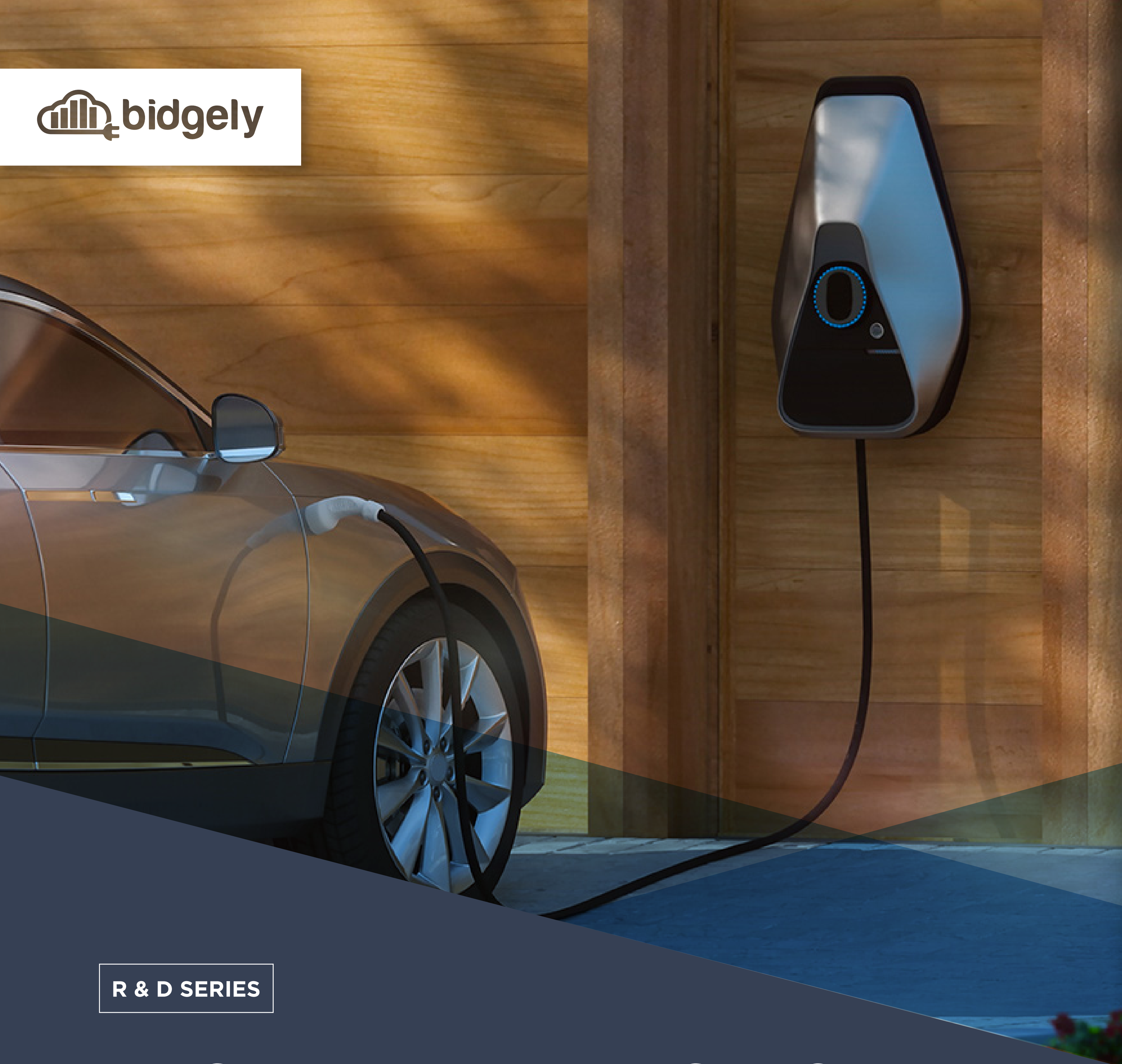

R & D SERIES

BIDGELY EV INTELLIGENCE TECHNICAL BRIEF

UNLOCK SMART METER DATA TO UNCOVER EVs AND UNDERSTAND THEIR IMPACT ON YOUR GRID

Bidgely | September 2023

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MANAGING THE EV REVOLUTION

The International Energy Agency (IEA) notes in its **Global EV Outlook 2023** that “A total of 14% of all new cars sold were electric in 2022, up from around 9% in 2021 and less than 5% in 2020.” This rise in electric vehicles (EVs) has major implications for the grid.

So how do utilities effectively manage the EV revolution if they can’t even “see” the EVs on their grids?

Bidgely’s EV Intelligence solution enables utilities to find the EVs hiding in their smart meter data and visualize their charging patterns.

Our UtilityAI™ data science platform separates out (disaggregates) EV charging signatures from the “noise” of household energy use, enabling utilities to detect EVs at the premises level with a benchmarked accuracy of 90%.

This paper explains our unique, **patented** approach to EV Detection.

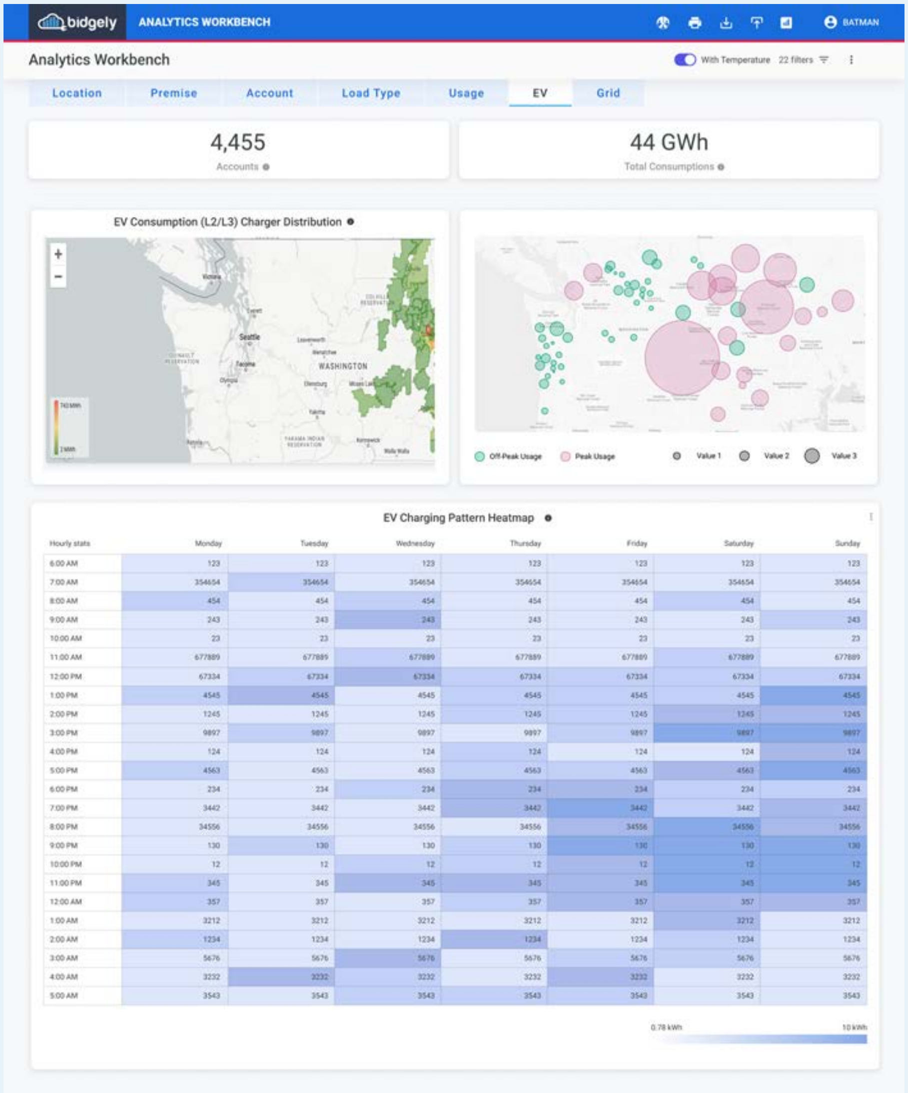
THE BIDGELY SOLUTION

Historically, determining the location of an EV and its charging load has been difficult. DMV data lacks granularity and is often out of date. Customer-provided methods like telematics only provide a limited view of EV activity.

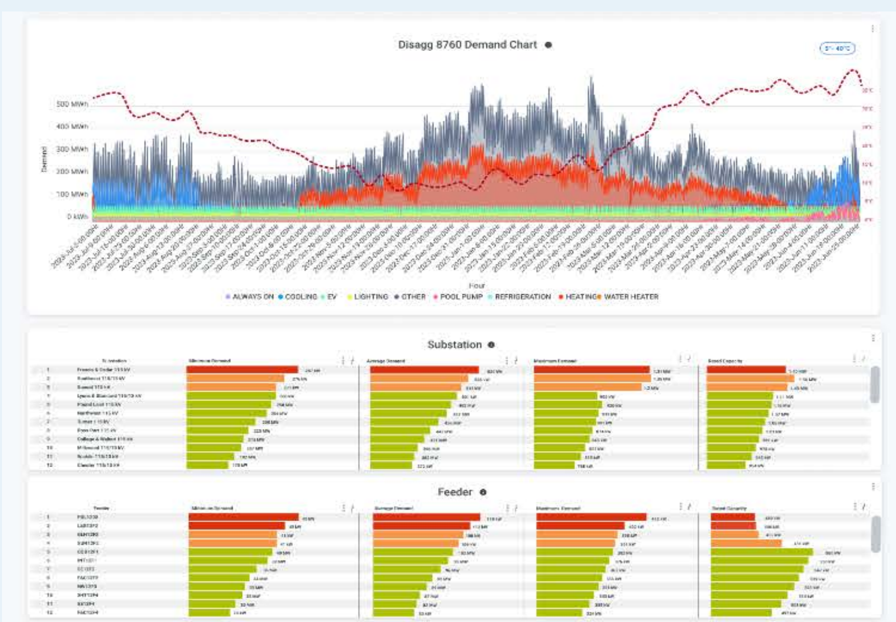
To solve this challenge, Bidgely uses AI and machine learning to detect EV charging signatures buried in smart meter data as well as relative intelligence essential to the management of EV load, including:

1. Differentiation of Level 1, 2, and 3 chargers
2. Charging estimation, hour by hour for each EV customer
3. Average hourly charging patterns
4. Geographic patterns of EV charging and growth
5. Amplitude of chargers

This granular EV visibility enables utilities to not only detect EV charging but also build 8760-hour EV charging load curves for each customer and for each grid asset to understand the real-world impact of EVs across the grid.



See EVs on your Grid
Because Bidgely's UtilityAI algorithms can spot EVs behind the meter of each household and then correlate those EVs to the relative grid assets, utilities can understand the presence, growth, geographic concentration, and load impacts of EVs in near real time.



8760 View of EV Demand
See your EV demand across all 8,760 hours of the year to spot trends, identify stress points, and guide EV program planning and engagement strategies.

Grid Asset Impact
Map EVs to grid assets to identify constraints and hot-spots, predict failure, and plan for operational changes needed.

THE DATA SCIENCE: EV DISAGGREGATION & DETECTION

Building an EV Detection Model

Our EV Detection model has been developed using behavioral energy consumption studies to isolate EV owner energy patterns from a set of real-world users across varied geographies, including but not limited to North America, Europe, and Australia.

These EV profiles are then used to train a supervised machine learning model that accounts for variables such as seasonal dependency, time-of-usage habits, duration of charging, and other inputs. Our research has revealed that a tree-based model performs best in connection with EV detection. Bidgely employs state-of-the-art computer vision and deep learning techniques such as box filtering, box refinements, and object detection to extract EV charging instances from user energy consumption data.

Bidgely's EV detection and estimation algorithm requires only smart meter data with different sampling rates (such as 15 mins, 30 mins, and 1 hour) and weather data. **No ancillary equipment or inputs are required**, although these are leveraged to build and test our algorithms.

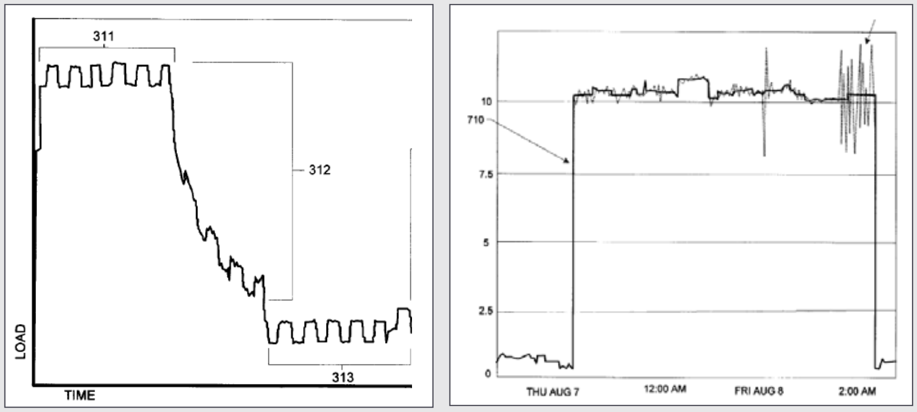
Owing to the quality of algorithms and comprehensiveness of the training data used, the trained model is extremely robust and is able to provide an accurate sampling-rate-level estimation.

EV "Signatures" in Meter Data

EVs have distinctive charging signatures. In addition to consuming large contiguous blocks of energy, EVs generally exhibit a clear pattern of sloping decay toward the end of charging. This sloping decay is due at least in part to electrochemical properties of battery cells (lithium ion based, or otherwise) used in EVs. As batteries approach a full 100% charge, internal resistance of the battery cells may increase, thereby at least in part leading to lower power consumption.

Moreover, some chargers for EVs may employ a step-charging method, in which a voltage held across the battery cells may be gradually decreased. Such methods further contribute to the decreasing charging signature.

The type of EV and the capacity of the EV may alter the charging signature. For example, large capacity EVs (such as, but not limited to the Tesla Model S) may have the distinctive charging pattern discussed above. In contrast, small capacity EVs (including but not limited to the plug-in Toyota Prius) may have a less distinctive box-shaped signal. Although a box-shaped signal stemming from a low-capacity EV pattern may be simpler to detect, care must be taken to disambiguate the EV signal from other appliances with similarly long-running, box-shaped signatures.



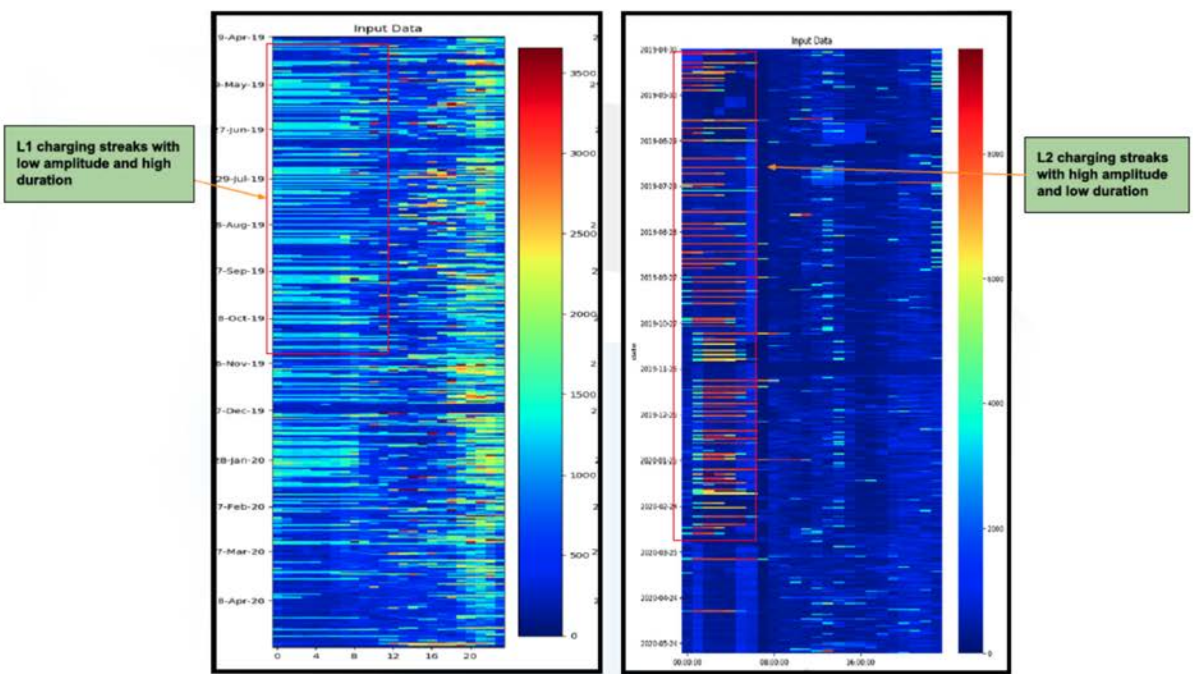
Left: large capacity EV charging signature. Right: small capacity EV charging signature.

Charger Type Detection

Because Level 1, 2 and 3 chargers have different demand profiles (amplitude + charging time), Bidgely's algorithms can differentiate between charger type easily:

- **L1:** Low power rating (< 3kW) and longer charging time (> 6 hours)
- **L2:** Medium power rating(3.5 - 7kW) and shorter charging time (3-6 hours)
- **L3:** High power rating (> 7kW) and very short charging time (60 minutes)

The heat maps below demonstrate how charging amplitude and duration illuminates EV charger level.



The heatmap displays the power consumption of 365 days, where each day is represented by one row.

Color is most intense (red) for high energy values and least intense (blue) for low energy values. EV charging events are clearly visible in both heatmaps, with blue streaks in the heatmap on the left indicating the lower demand from L1 chargers but stretched over a longer window of time each day.

On the right heatmap, the red streaks indicated greater intensity of demand over a shorter period of time, as is characteristic of an L2 charger.

Because L2 charging is roughly 5.6% more efficient than L1, Bidgely's machine learning algorithms easily pinpoint the type of charger in use.

WHAT SETS BIDGELY EV DETECTION APART?

Electric vehicles are not easy to detect—the power draw of even an L2 charger (often 3-7 kW) can fall within the same range as HVAC (3-6 kW) or electric water heaters (3-7 kW). Other technologies confuse these conflicting appliance signatures, resulting in poor detection. It's crucial to ensure both model performance against a data set and performance in a full population scenario.

Many vendors will list only results from a small sample set, which does not accurately reflect the success you will see in the field. It is relatively easy to detect the top 30% of EVs that have large charging amplitudes in comparison to the remainder of the appliances in the household load, however, it becomes increasingly harder to separate EVs when charging amplitudes are lower (L1) and closer to the range of consumption patterns that large appliances like Water Heater and HVAC also exhibit.

Ultimately, Bidgely not only provides the highest quality disaggregation in the market but the only disaggregation that will yield hourly results for each customer.

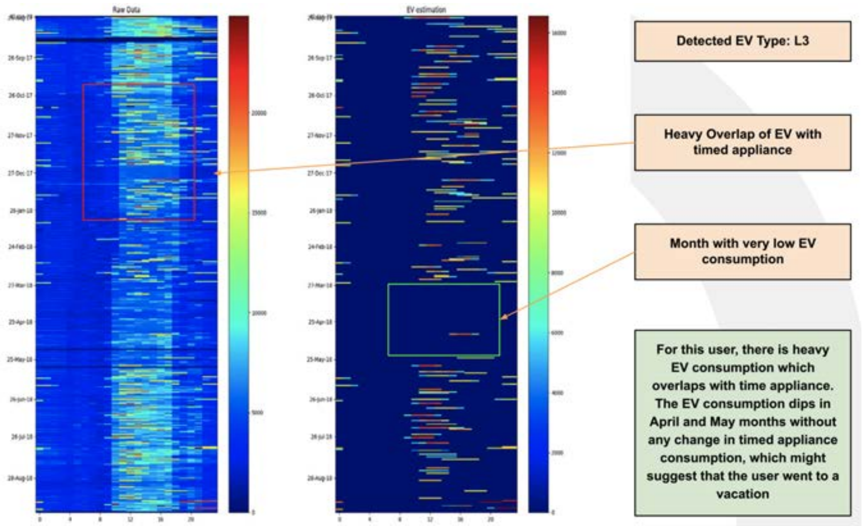
APPLIANCE	ELECTRIC VEHICLE(L2/L3)*
MIN DATA REQUIREMENT (DAYS)	180
PRECISION	75(+-5)%
RECALL	88(+-2)%
ACCURACY	98(+-1)%
FP RATE	<1%
ESTIMATION ACCURACY (100-MAPE)	90(+-5)%

*Based on residential 15-min. data sampling. Since EV and Pool Pump appliances are not commonly prevalent, having user survey data improves Precision to 95%+.

Three Real-World Examples

EV Owner 1 - L3 EV usage disaggregated against other high power-consuming timed appliances.

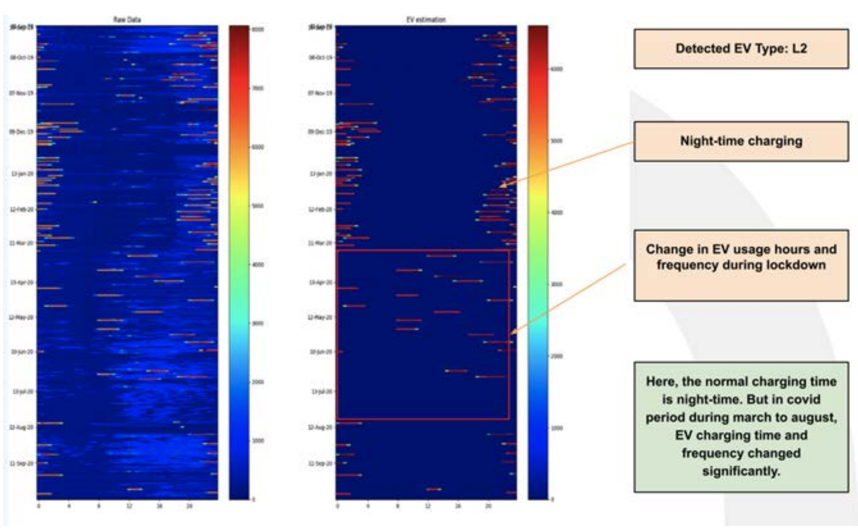
This EV user (Figure 3) has another high-power-consuming timed-appliance which is a potential hindrance in EV detection(left) which the algorithm removes before estimating the EV usage(right).



Extraction of EV streaks from raw energy data in the presence of another high-power-consuming appliance.

EV Owner 2 - Disaggregating EV with limited data during COVID-19.

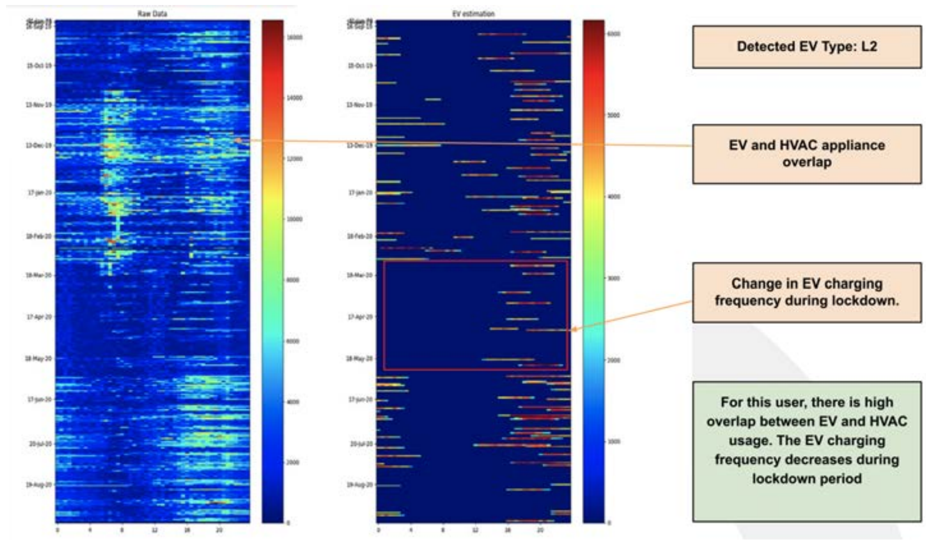
The EV usage frequency for this user (Figure 4) has declined dramatically and charging time has also shifted to day time during the period starting May 2020, as a result of COVID-19 lifestyle changes(left). The algorithm has successfully detected the presence of an EV even when the pattern was inconsistent with prior usage patterns (right).



Extraction of L2 EV streaks from raw energy data with change in usage behavior

EV Owner 3 - Disaggregating EV with limited data during COVID-19.

For this EV owner (Figure 5), the high energy consumption pattern reveals seasonality indicating the presence of an HVAC appliance which the algorithm can differentiate based on typical usage patterns. This can be useful in preparing users for seasonal bill changes.



Extraction of L2 EV streaks from raw energy data with an overlapping high power-consuming appliance.

Efficacy

To demonstrate the efficacy of Bidgely's true disaggregation approach to EV detection, we conducted a study for a large investor-owned utility in the Northeast United States. For the study, we developed a "layman's approach" to identifying potential EVs within sample meter data. This approach and our disaggregation-based detection were both run against the same sample data and results were compared.

The study analyzed three months of raw meter data at a granularity of 15 minute intervals across two postal code regions. Region 1 included **1,122** customers and Region 2 included **2,826** customers, for a total of **3,948**.

Layman's Approach Model

The layman's model looked for combinations of kW intensity and frequency to spot potential EV charging. A frequency threshold of 100 or more high consumption instances was used to develop proxy scenarios for EV charging, defined as follows:

1. Users with more than 100 consumption points above **1.5 kW** were used as a proxy to hourly consumption of 6kWh.
2. Users with more than 100 consumption points above **2.25 kW** were used as a proxy to hourly consumption of 9kWh.
3. Users with more than 100 points above **>3 kW** were used as a proxy to hourly consumption of 12kWh.

This proxy detection approach yielded the following breakdown of **potential EV candidates detected (labeled UUIDs)**.

REGION	POPULATION	CONSUMPTION PER 15 MIN	UUIDs	ESTIMATED % EV CHARGING
1	1,122	No EV	409	36.45%
1	1,122	1.5 - 2.25 kW	114	10.16%
1	1,122	2.25 - 3.0 kW	41	3.65%
1	1,122	> 3.0 kW	558	49.73%
2	2,826	No EV	2,187	77.39%
2	2,826	1.5 - 2.25 kW	187	6.62%
2	2,826	2.25 - 3.0 kW	56	1.98%
2	2,826	> 3.0 kW	396	14.01%

In stark contrast, Bidgely's AI-based true disaggregation detection identified:

- Region 1: **47 EVs** (4.19%)
- Region 2: **26 EVs** (0.92%)

Additional Findings

- In the layman's approach, the Region 1 possible EV detection percentage is **84.8%**, whereas the disaggregation solution provided an actual EV detection rate of **4.19%**.
- In the layman's approach, the Region 2 possible EV detection percentage is **63.3%**, whereas the disaggregation solution provides an actual EV detection rate of **0.92%**.
- The former approach gives **unacceptably high EV detection** and does not even provide an estimate of actual EV detections. Therefore, this approach could be highly misleading.
- The resulting **excessive false positives could hurt customer experience** and give the utility a misleading impression of EV penetration, resulting in over-investment.
- The layman's approach was **unable to deduce a logical pattern** in detecting EVs when the high consumption intervals (>12kwh or >9kWh or >6kWh) were analyzed.

Accuracy

Bidgely measures accuracy across two key parameters:

1. Detection identifies if an appliance has been used within a given time period. From a customer engagement standpoint, accurate detection is critical; simply put, customers know when they use an appliance. Inaccurate detection can erode customer confidence.

2. Estimation accuracy is the difference between disaggregated consumption and actual consumption. Minor inaccuracies in appliance-level consumption estimation don't have a significant impact on the consumer's bottom line (e.g. a 10% error on an appliance that consumes 20% of the home's energy is only a 2% error in terms of whole home consumption).

Bidgely's true disaggregation of AMI data at 15-minute intervals delivers 98(+/-1)% accuracy for detection and 90(+/-5)% accuracy for estimation.

Bidgely stating 98% EV detection accuracy and another vendor stating 98% can mean two different things—it is essential to understand the definition behind "accuracy."

If you are trying to determine if an EV is present in a home, and there are 30 instances of charging, detecting 5 of them with high confidence would allow you to confidently conclude that the home has that appliance, resulting in almost 100% detection accuracy at the home level. However, if you define detection accuracy as detecting each occurrence of the appliance individually, detecting it only 5 out of 30 times would translate to only 16% accuracy.

Actuals

In order to measure success you need to define what is a true positive / true negative / false positive / false negative.

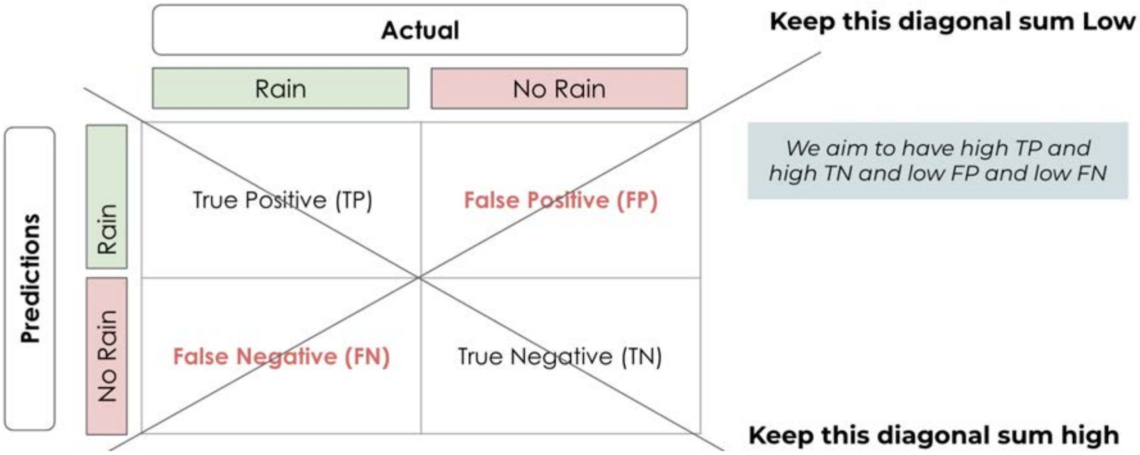
Let's consider the example of predicting whether it will rain or not.

True Positive: Interpretation: You predict rain (positive) and it rains (true) ... CORRECT / GOOD RESULT

True Negative: Interpretation: You predict it won't rain (negative) and it does not rain (false) ... CORRECT / GOOD RESULT

False Positive: (Type 1 Error) Interpretation: You predict rain (positive) and it does not rain (negative) ... INCORRECT / BAD RESULT

False Negative: (Type 2 Error) Interpretation: You predict it will not rain (negative) and it rains (false) .... INCORRECT/BAD RESULT



Accuracy is the ratio of number of correct predictions to the total number of input samples.

$$\text{ACCURACY} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{False Positive} + \text{True Negative} + \text{False Negative}}$$

Accuracy is a great predictor of success when true positives and true negatives are in roughly in proportion, but **for EV detection, this kind of Accuracy is not the best measure of success.**

A better approach is to look at Accuracy in context with other data science metrics, including Precision, Recall, and False Positive Rate.

There are various ways to measure (metric) a classifier. In a balanced data set, each metric individually gives similar perception.

However, in an extremely imbalanced data-set, depending on the bias of population, some individual metric may seem pretty off and gives bad perception about a classifier.

Always analyze the complete picture of confusion metric to measure a classifier.

Precision

When the model predicts 'Yes' how often is it correct?

Precision = TP/ (TP + FP)

Higher the better

Accuracy

Overall how often is the classifier correct? Includes both classes

Accuracy = (TP + TN)/ (TP + TN + FP + FN)

Higher the better

Recall

How many of the 'Yes' class items did the classifier predict?

Recall = TP/ (TP + FN) = TP/P

Higher the better

False Positive Rate

When it's actually 'No', how often does it predict 'Yes'?

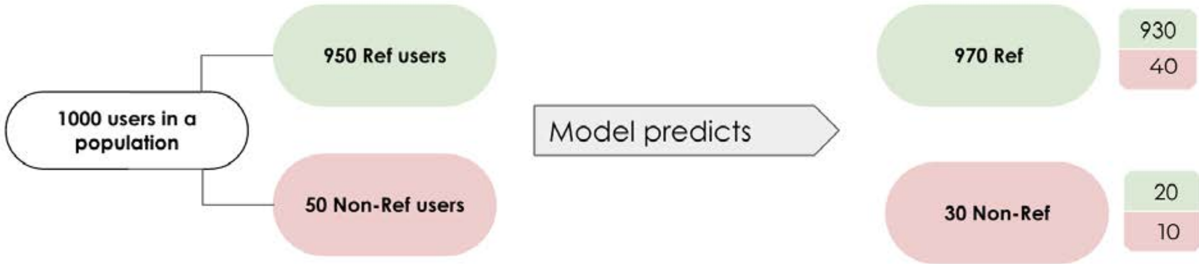
FP rate = FP/ (FP + TN) = FP/N

Lower the better

To better explain the nuanced differences of measuring success, let's consider the following scenarios.

Scenario 1: Extremely Imbalanced Population biased towards positive class

In a real classifier doing great job but if judged based on FP rate only, classifier seems very **bad.**

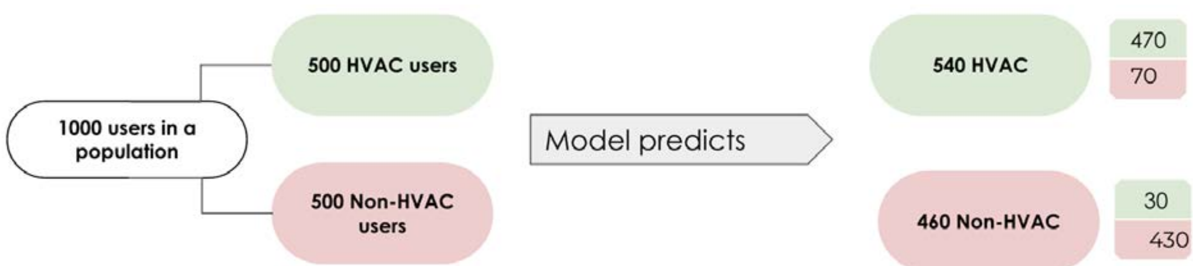


Confusion Matrix	
TP - 930	FP - 40
FN - 20	TN - 10

Metrics		Perception
Precision	96	Good
Recall	98	Good
Accuracy	94	Good
FP rate	80	Bad

Scenario 2: Perfectly Balanced Population

In real classifier doing good job and even if judged based on any individual metric the numbers look **good**.

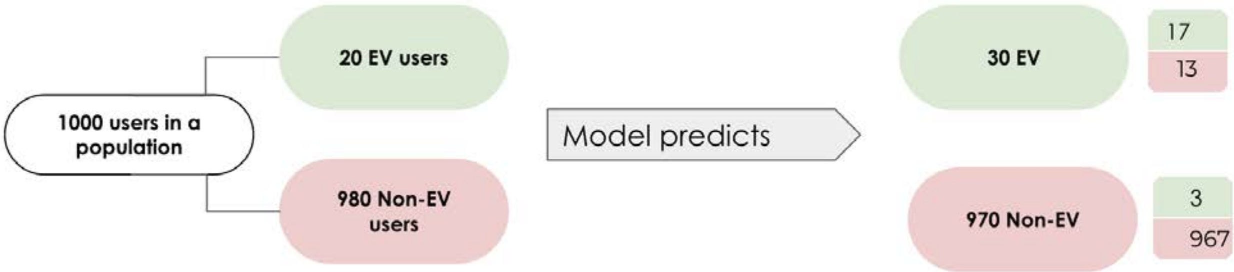


Confusion Matrix	
TP - 470	FP - 70
FN - 30	TN - 430

Metrics		Perception
Precision	87	Good
Recall	94	Good
Accuracy	90	Good
FP rate	14	Good

Scenario 3: Extremely Imbalanced Population biased towards negative class

In a real classifier doing great job but if judged based on Precision only, classifier seems very **bad.**In fact, this classifier has least number of false positives with regard to previous two classifiers, but the general perception is that we have lot of false positives.



Confusion Matrix	
TP - 17	FP - 13
FN - 3	TN - 967

Metrics		Perception
Precision	56	Bad
Recall	85	Good
Accuracy	98.4	Good
FP rate	1.3	Good

Ground Truth

We use something called "ground truth" which is considered the "actual" value. For example, in the case of EVs this would be validation that a premise had a level 2 charger installed. We can obtain ground truth in 3 ways including:

1. **Customer Surveys:** For appliance detection accuracy, customer survey data is used. We have more than gathered unique appliance survey data across different geographies of the world from which we validate our accuracy against customer provided ground truth

2. **External Validations and Pilots:** In last 8+ years we have done numerous disaggregation pilots with different clients where they have measured our appliance detection and estimation accuracy against the ground truths they collected. Mostly utilities collected ground truth by deploying sensor plugs on sample of homes. We have done more than 20 such exercises with evaluations across different geographies.

3. **Manual ground-truth labeling and visual validations:** At high frequency data, the signature of appliances are clearly visible in raw energy data. We have a team which has accumulated vast amount of manual ground-truth data over 8 years of effort. We have created a ground truth pool of around user data for various appliances manually labeled against which we keep validating and iterating our algorithms.

Due to the limited public data available, to create a training dataset, Bidgely surveyed thousands of people about EV ownership from various geographies including North America, Europe, and Australia, making the dataset robust.

A user-set of size ~13k was gathered from North American and European utilities. Out of this, ~5k resulted in positive EV identification instances and the remaining are negative.

The complete set ~13k is run on both the models and the results are as follows:

GEOGRAPHY	PRECISION	RECALL
NA 0.92 0.81	0.92	0.81
EU 0.85 0.89	0.85	0.89

High Precision and Recall

Learn More at: https://www.bidgely.com/technology

To see our EV Analytics in action, visit our demo portal.