ELECTRIC VEHICLE ANALYTICS: THE FUTURE IS NOW

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TABLE OF CONTENTS

INTRODUCTION

With an all-time high global adoption rate, the proliferation of electric vehicles is impacting commercial and residential energy demand like never before. According to the Global EV Outlook 2020, the sales of electric cars reached a record-setting 2.1 million worldwide in 2019, bringing total EV ownership to 7.2 million EVs. At the end of 2019, 7.3 million EV chargers had been deployed worldwide, 2.1 million more than in 2018, including 6.5 million private chargers. Looking ahead, the electric vehicle market is projected to reach 27M units by 2030, at a CAGR of 21.1% during the forecast period as depicted in Figure 1.

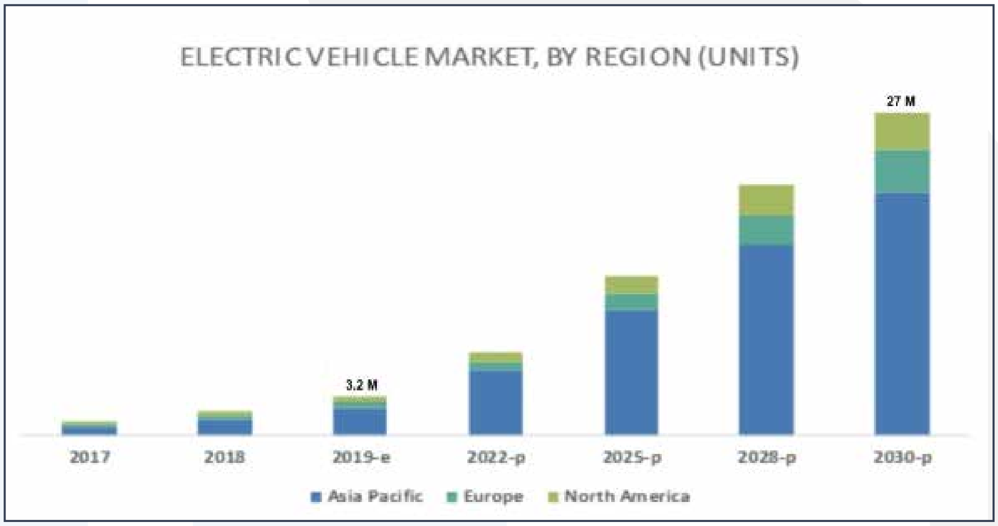


Figure 1 : Industry trends on the Electric Vehicle market. Image source: https://www.marketsandmarkets.com/Market-Reports/

The world is nudging towards a more environmentally aware and energy-efficient society and the automotive and energy sectors are evolving rapidly to keep pace. In times like these when innovation and the ability to pivot are crucial, AI-driven solutions help utilities remain future-ready.

UNDERSTANDING EV USAGE

Due to the increase in the number of electric vehicles and private chargers, the task of dynamic load management and demand forecast for grid companies at scale is becoming increasingly challenging. Take for example, one scenario where large numbers of EV owners in one geographic location start charging their vehicles during the same time interval illustrated in Figure 2.

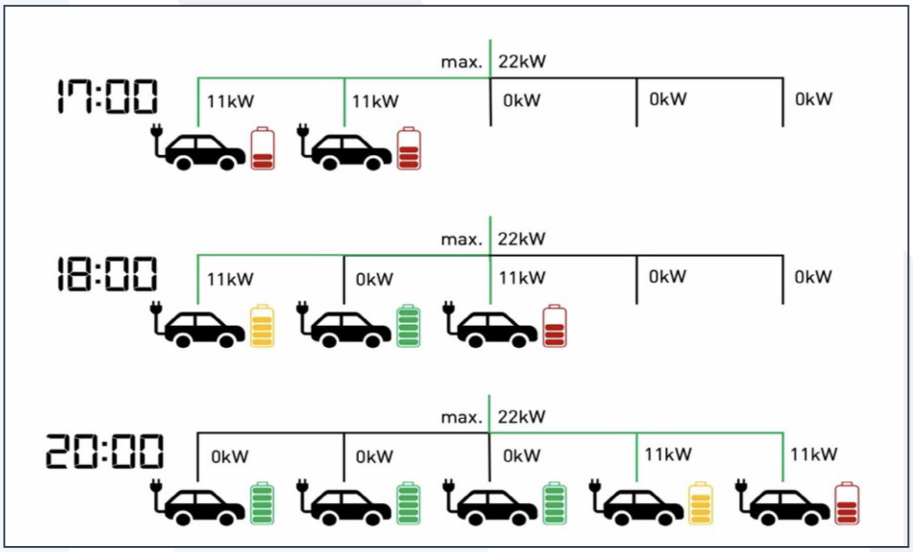


Figure 2: Usually during working office hours, more vehicles line up for charging their EVs resulting in a surge in demand. As seen in the figure, these demands are not fully met in the peak time. Image source: https://evse.com.au/blog/load-management-electric-car-charging/

The power grid would experience unanticipated demand. In extreme cases, this demand has the potential to lead to outages. With an intelligent toolkit, utilities are able to balance this demand-supply paradigm and avoid major setbacks.

Data can also inform the strategic, staged development of infrastructure as EV adoption increases. For example, current logistics of public docking stations may not fully account for forecasted EV growth. AI-powered analytics help utilities look forward to anticipating how EV charging demand will grow over time,not only at the neighborhood level but also for cross-city routes. With this insight, utilities are able to build an efficient network of EV charging stations as depicted in Figure 3.

HIGHLY ACCURATE EV DETECTION & ESTIMATION

EV owners tend to be much more engaged and interested in their energy behaviors, they want to know how their EV usage statistics stack up against their neighbors. They also appreciate information about how upgrading to more efficient EV chargers or better rate-plans can lower their costs, providing utilities with an opportunity to smooth EV adoption and protect the grid.

Bidgely's UtilityAI platform makes targeting EV owners with personalized insights and advice efficient and effective. Bidgely's proprietary algorithm suite detects EV chargers. There are two primary types of EV chargers: L1 and L2. Power consumed by L1 chargers is roughly the order of 1kW-3kW. L2 chargers, on the other hand, consume more power but run for a comparatively shorter period of time.

Figure 3: Depending on the routes frequented, EV docking stations need to be installed accordingly to enable cross-city travel as well. Image Source: https://www.engadget.com/electrify-america-ev-charging-cross-country-route-185900913.html

Figure 4 presents heat maps that depict the amplitude of power consumed. Color is most intense (red) for high energy values and least intense (blue) for low energy values. The heatmap displays the power consumption of 365 days, where each day is represented by one row. The EV strikes are clearly visible in both heatmaps, with blue streaks in the heatmap on the left and smaller red strikes in the heatmap on the right. Because L2 charging is roughly 5.6% more efficient than L1, Bidgely's machine learning algorithms easily pinpoint the type of charger in use and provide an opportunity to transition an L1 customer to an L2 charger.

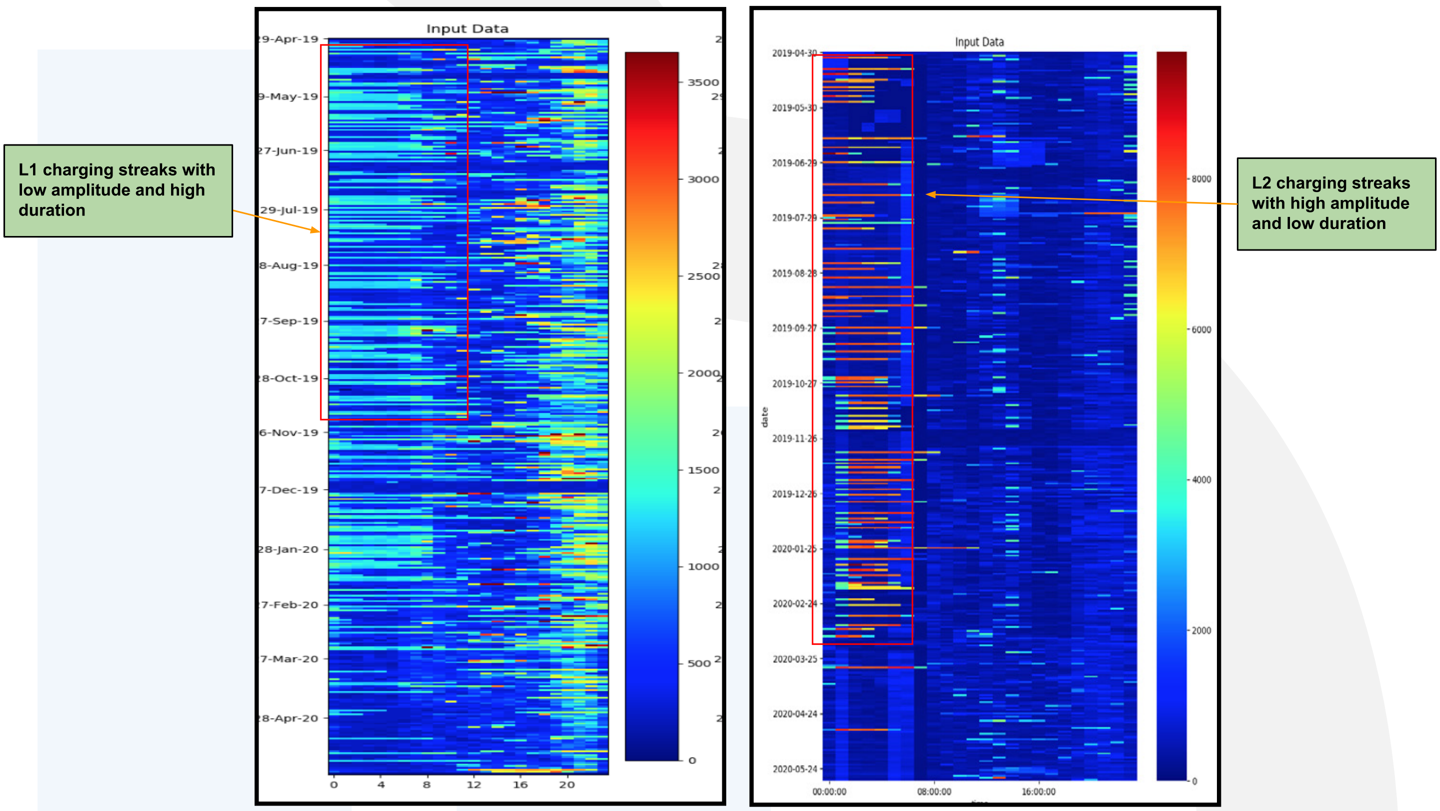


Figure 4: Type of EV chargers: L1(Amplitude ~1kW-3kW)(left), L2(3kW-20kW)(right)

Never before have we been able to understand so much about customers that have EVs and are drawing from the grid without the use of hardware sensors of excessive survey efforts. Just using AMI data, machine learning and artificial intelligence we're able to help utilities understand EV owners quickly and cost-effectively.

ROADBLOCKS TO EV DETECTION AND ESTIMATION

Developing robust EV solutions that algorithmically detect EV ownership and estimate EV usage is challenging due to the following factors::

a. EV penetration is skewed to select geographies and public research on EV penetration is limited.

b. There are few publicly available datasets in this domain.

c. Building solutions and platforms for grid companies that have witnessed a sudden surge in demand have no prior playbook upon which to base one's hypotheses.

d. It is difficult to forecast demand, manage power load on the grid, and determine optimal, surge-preventing logistics for charging docks in an ever-evolving market.

Bidgely is one of the only companies in the world to develop patented EV detection & estimation algorithms that solve these challenges for utilities. In one project with a large northeastern utility we have compared our results to a hardware EV monitoring device and achieved 90% accuracy in detection and estimation of EV load charge for a selected population of their territory. Software solutions prove to be more scalable and fast-acting than hardware monitors/sensors which require much more work on the user's part to ensure an accurate measurement.

BIDGLEY'S AI-POWERED APPROACH

Bidgely's EV detection and estimation algorithm requires only smart energy meter data with different sampling rates (such as 15 mins, 30 mins, and 1 hour), and weather data. No ancillary equipment is required. The EV detection algorithm also relies on behavioral energy consumption studies to isolate EV owner energy patterns. These behavioral patterns then inform the supervised machine learning model, including seasonal dependency, time of usage habits, duration of charging, and many more. Bidgely's research revealed that a tree-based model performs best in connection with EV detection. The aforementioned model was trained on users from varied geographies including but not limited to North America, Europe, and Australia.

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. We also borrow learnings from image processing methods for multiple post-processing steps. 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.

The following examples illustrate the capabilities of the machine learning model and what insights we can derived from EV owners:

Example 1: Disaggregating L3 EV usage against other high power-consuming timed-appliances

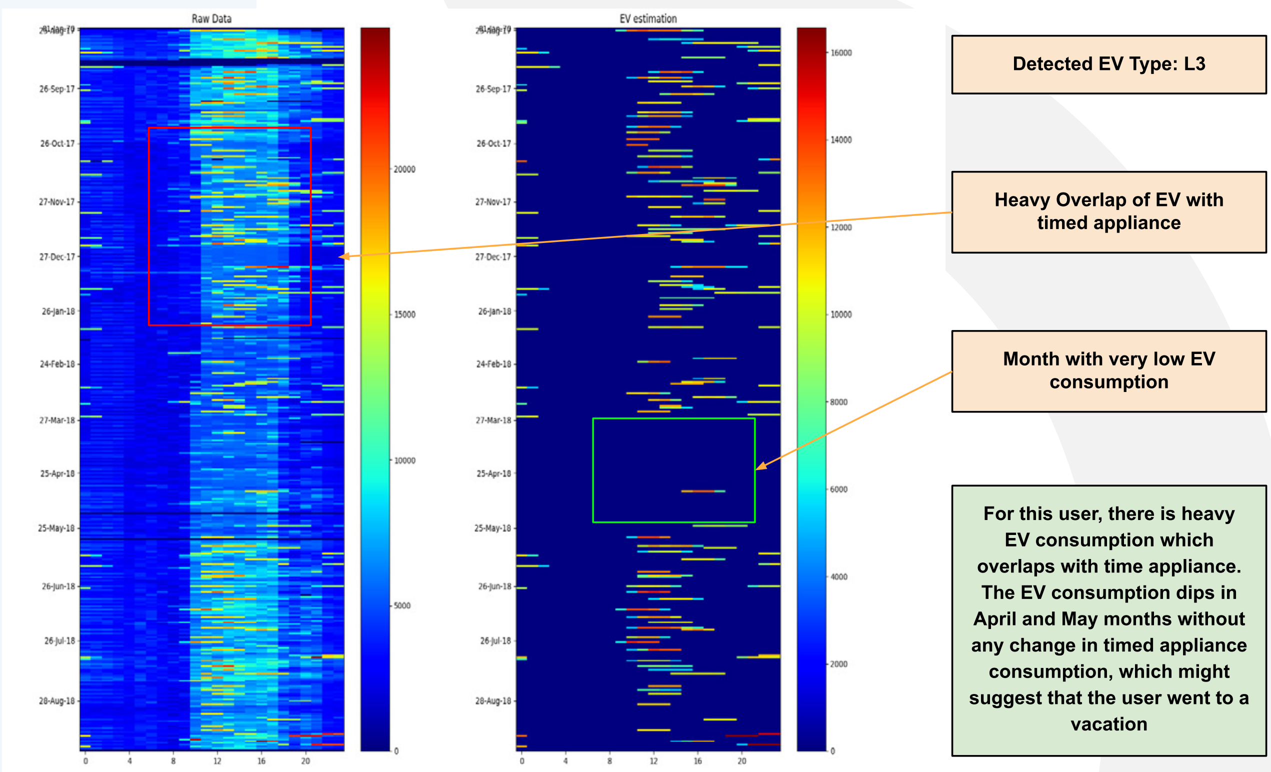


Figure 5: Extraction of EV streaks from raw energy data in the presence of another high power-consuming appliance. The type of charger is L3 here, owing to the amplitude and duration of consumption.

This EV user has another high power-consuming timed appliance which is a potential hindrance in EV detection(left). The algorithm first checks for the presence of timed appliances within bounds and removes them from the background before estimating the EV usage(right). It also runs sophisticated EV streaks refinement operations after detection as part of post-processing steps. By doing so, we're able to accurately identify when the EV consumption dips in April and May months which may suggest the user went on vacation. Each streak here represents the EV usage in a day and the coloration is the representation of the amplitude of consumption. The abrupt change in coloration within a streak is due to the switch from L2 to L3 charging. This flexibility of switching from L2 to L3 is applicable for some chargers.

Example 2: Disaggregating EV with limited data during COVID

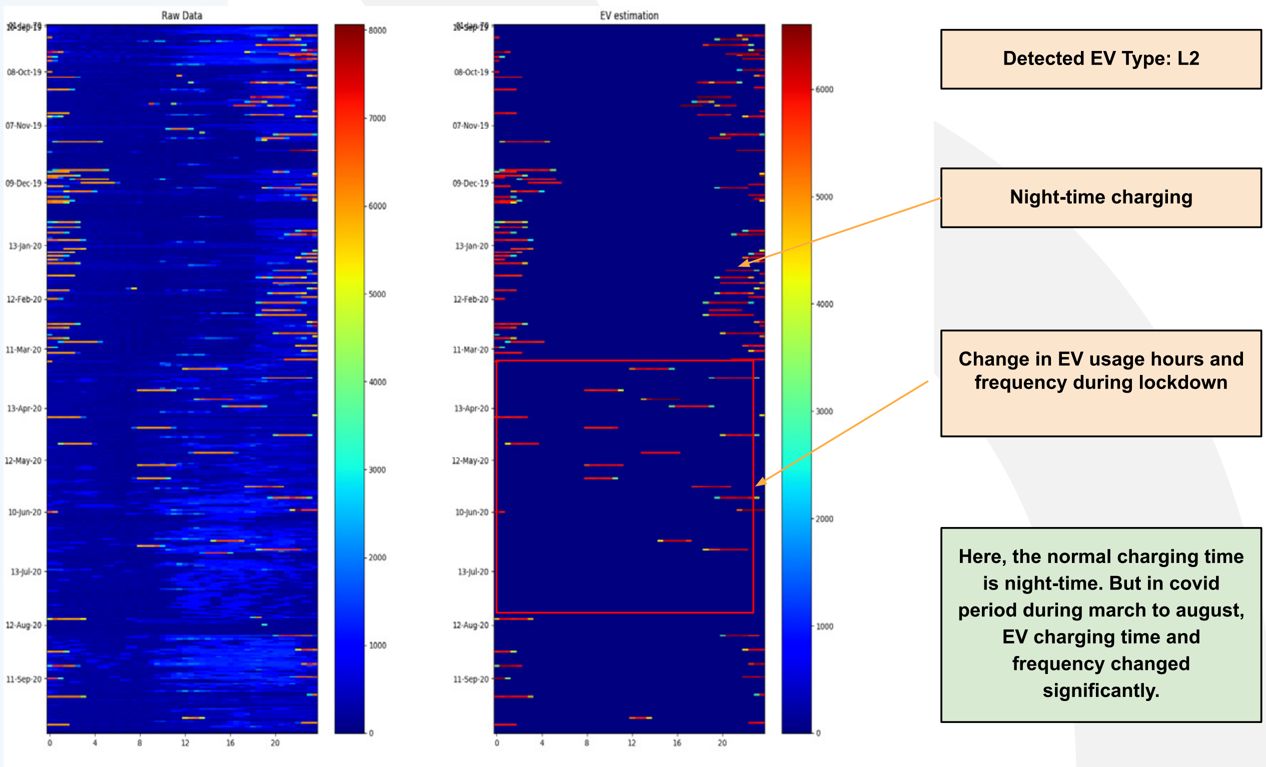


Figure 6: Extraction of EV streaks from raw energy data with low activity in one phase of the year. The type of charger is L2 here, owing to the amplitude and duration of consumption.

The EV usage frequency and EV usage time of the day for this user have declined dramatically from 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). In doing so, we're able to see how the user's charging time and frequency has changed from mornings/nights to midday and evenings.

Example 3: Disaggregating EV charging from similar heating & cooling amplitude

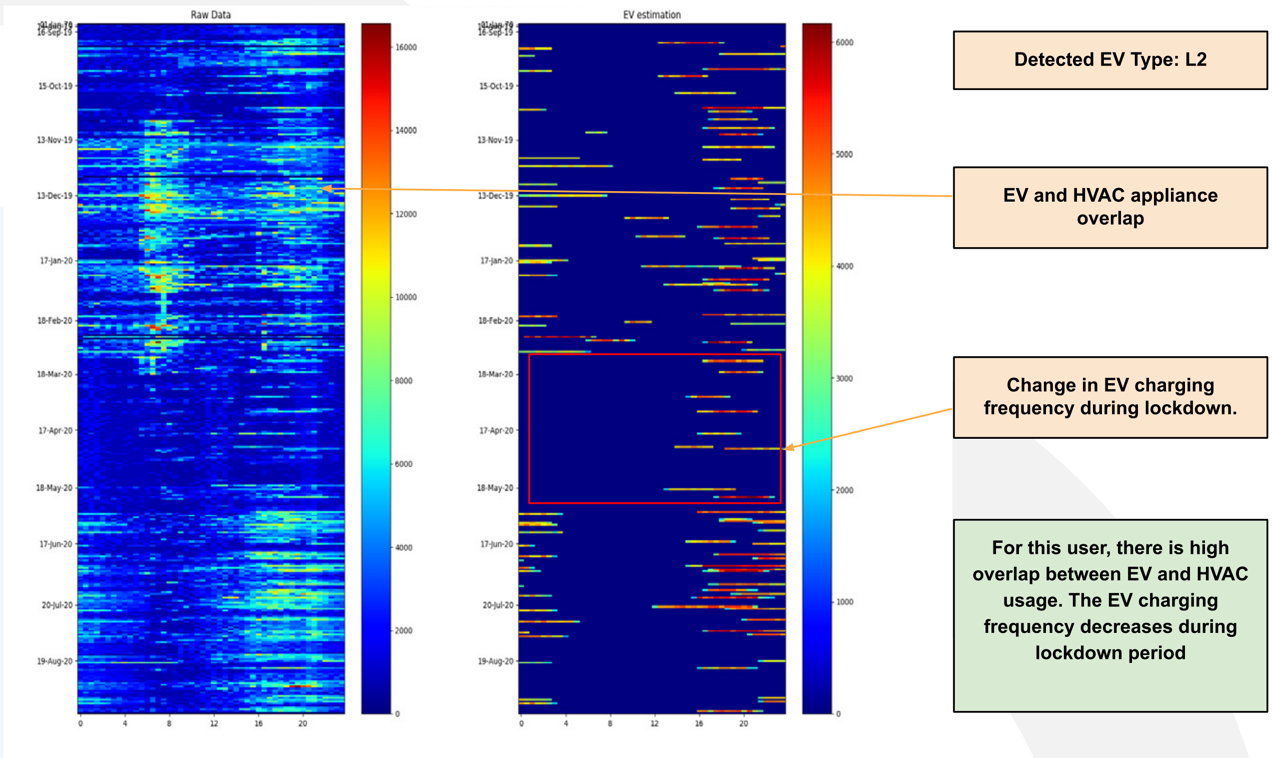


Figure 7: Extraction of EV streaks from raw energy data with an overlapping high power-consuming appliance. The type of charger is L2 here, owing to the amplitude and duration of consumption.

In this example, we can see the high energy consumption pattern reveals some seasonality in the left heatmap. This indicates the presence of a heating and cooling appliance that runs on an amplitude similar to an EV. As such, segregating EV streaks from this consumption data is difficult, but the machine learning algorithm is able to differentiate on the basis of typical EV-usage patterns, especially since EV usage is not seasonal(right). By separating the two usages - users can more easily understand what is driving their cost: seasonal heating & cooling versus their EV consumption which may be raising their overall consumption more than expected. This can be especially useful in preparing users for seasonal bill changes.

Example 4: Disaggregating EV usage from high consumption throughout the year

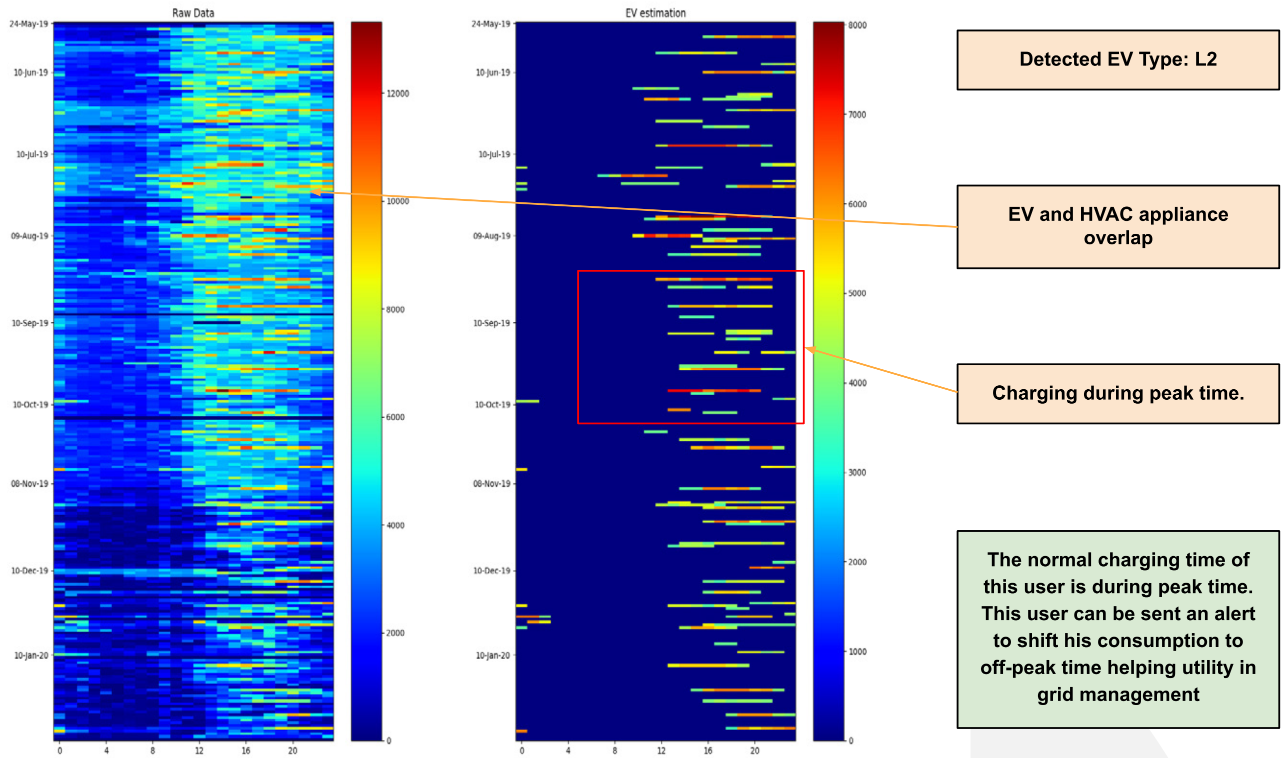


Figure 8: Extraction of EV streaks from raw energy data in the presence of another high power-consuming appliance with no seasonal differentiator. The type of charger is L2 here, owing to the amplitude and duration of consumption.

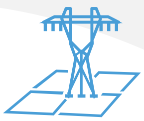
For this example, the raw data heatmap on the left shows high consumption throughout the year, so there isn't much of a visual difference between seasonal loads (like heating and cooling) from EV loads. However, Bidgely's algorithm can successfully detect and estimate EV load still by using the duration of usage, high amplitude, and the time of usage. For this user, their charging is clearly occurring regularly at peak times so they would make for an ideal candidate of demand response alerts to shift their charging to off-peak times.

Bidgely's EV solution also keeps an active validation track to monitor both algorithmic and business evaluation metrics. For the assessment of the model performance of EV detection and estimation, an amalgamation of survey information, ground truth tagging, and manual analysis are used. We constantly evaluate the trade-offs of improving the precision and the recall of the algorithm against customer satisfaction in order to meet specific use-cases for example being more conservative or aggressive in detection EVs in order to promote EV rate plans and programs.

EV ANALYTICS IN ACTION

Bidgley UtilityAI delivers meaningful results in connection with a broad range of utility use cases, including:

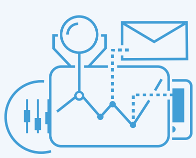
1. **Customer Satisfaction:** The EV disaggregation module detects and estimates EV power consumption through an AI-enabled solution applied to consumers' power meter readings. This serves as a credible behavioral analysis source to consumers and nudges them to be more mindful of their usage.



2. **Grid Planning and Management:** With load management and demand forecasting solutions, grid companies are better equipped to solve demand-supply issues. Bidgely's EV detection and estimation algorithm determines if a household is charging an EV and the amount consumed through machine learning models. The intricacies lie in deciphering this information at timestamp level just on the energy meter readings. The model doesn't only boast high performance and low latency but is also easily explainable. This model is part of the energy disaggregation solution, where energy readings are dissected for the detection of many appliances.

3. **Energy Efficiency:** Using UtilityAI's hyper-personalized recommendation engine, consumers are propelled to take actions like upgrading to a more desirable rate-plan for EV charging, to consume less energy. The grid companies also benefit as participants in government initiatives to advance clean energy and achieve net zero targets. With the availability of historical energy data and meta information on users through third-party sources, the hyper-personalized engine targets the EV consumers with the most relevant insights and actions.

4. **Targeting:** Leveraging rich data and intelligent algorithms enables grid companies to pinpoint customer needs, such as estimating the propensity to buy an EV or upgrading to a more efficient charger. This dramatically reduces the acquisition cost for EV companies looking to target customers.



5. **Demand Side Management:** The solution also caters to many ad-hoc requests from grid companies to facilitate detection and estimation at the most granular level. Bidgely is currently running a utility program where users are rewarded for charging EVs outside a peak time window. We detect if a user is in violation of the requirements every day and send alerts in case a strike occurs.

CONCLUSION & FUTURE EFFORTS

As the world transitions to electrified transportation, AI-enabled solutions will serve as the foundation for successfully mitigating hurdles and inefficiencies by making possible advanced analysis, planning and engagement capabilities. The Bidgely AI-powered UtilityAI platform has evolved from detecting and estimating EV usage at the time-stamp level to devising rate-plans and suggesting more effective measures towards lower load on the grid and better pricing for customers. We're excited to work with you on your EV challenges and look forward to being part of your customer's EV experience.

Learn More at: https://demo.bidgely.com/solutions/ev/

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