Smart Electric Power Alliance

Insight Brief: AI for Transportation Electrification

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Insight Brief: AI for Transportation Electrification

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About SEPA

The Smart Electric Power Alliance (SEPA) helps all electric power stakeholders accelerate the transformation to a carbon free electricity system. SEPA concentrates our focus on the following areas to maximize impact: Transportation, Storage, Resilience, Emerging Technology, Policy, and Energy Equity.

SEPA delivers value to our members through research, education, events, working groups, peer engagements, and member projects. We facilitate collaboration, develop innovative strategies and guidance for regulatory and business innovation, and provide actionable solutions for our members and partner organizations. For more information, visit www.sepapower.org.

About Bidgely

SEPA would like to acknowledge Bidgely, our teaming partner, who made this report possible.

For more than a decade, Bidgely has been at the forefront of AI-based meter data disaggregation, building patented algorithms that turn data into detailed insights about each customer's appliance ownership and energy use.

On the grid side, this behind-the-meter intelligence enables utilities to understand their grids from the premises up, analyze the load impacts of EVs, Solar, HVAC systems, and other appliances on specific grid assets, and then make informed planning decisions.

On the customer side, Bidgely's suite of engagement solutions let utilities engage customers with hyper-personalized energy insights and recommendations and empower them to become engaged energy partners.

Applied to the EV management use case, Bidgely is able to detect EVs at the premises level with 95+% accuracy, target EV-owning customers based on charging profiles and load-shift value, recruit them into EV TOU and other Managed Charging programs, and then coach them to maximize load shift value. To learn more about Bidgely, visit www.bidgely.com or to see Bidgely's AI-enabled insights and engagement in action, visit their demo portal at demo.bidgely.com.

Acknowledgements

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Executive Summary

As electric utilities explore how best to serve expected, near-term demand growth from electric vehicle (EV) charging, the role of accurate information about their EV-driving customers has never been more important. This information helps planning teams identify potential complications, such as transformer overloading, and helps program managers develop strategies to turn challenges into opportunities, such as using EVs for load flexibility and virtual power plants. EVs are reaching the mainstream, with adoption predicted to grow by 16x through 2035, from 4.8 million EVs in 2023 to 78.5 million EVs in 2035. Utilities are expanding their capabilities to both track EV adoption and determine impacts for their load forecasts. Surveys and basic assumptions provide an adequate initial view, but robust datasets and rigorous analysis are becoming essential in many areas. **This brief explores how utilities can use AI to get ahead of transportation electrification trends and prepare to implement managed charging programs.**

Artificial intelligence (AI) and machine learning (ML) can provide utilities with a more advanced understanding of EV impacts on the distribution grid and allow them to better plan for EV demand growth. These software solutions are helping early-adopting utilities accelerate their efforts in detecting EV-driving customers, create direct marketing and engagement strategies with those customers, and account for EV charging within broader distribution system management strategies.

Why Now?

AI tools make it easier to create value from data—including finding trends in extremely large datasets and moving towards real-time analysis of device, customer, and utility data. Machine learning models are a subset of AI that have been used for decades to support well-defined utility tasks, such as load forecasting. Machine learning models have become more powerful and widely applicable due to grid digitization, yielding new data streams to analyze, computer science advancements, and broader access to cloud computing.

In 2024, the Smart Electric Power Alliance's (SEPA's) Transportation Electrification and Emerging Technology teams joined forces with Bidgely to capture the current status of AI for EV customer engagement. In this report, we explain how utilities are using a type of AI called deep learning to disaggregate advanced metering infrastructure (AMI) data into EV loads.[1] Disaggregating AMI data into EV loads allows utilities to identify EV drivers more efficiently, design better-targeted EV managed charging programs, and map transportation electrification trends to distribution grid assets. This resource is intended to educate utility staff and their stakeholders with limited previous exposure to machine learning and other forms of AI.

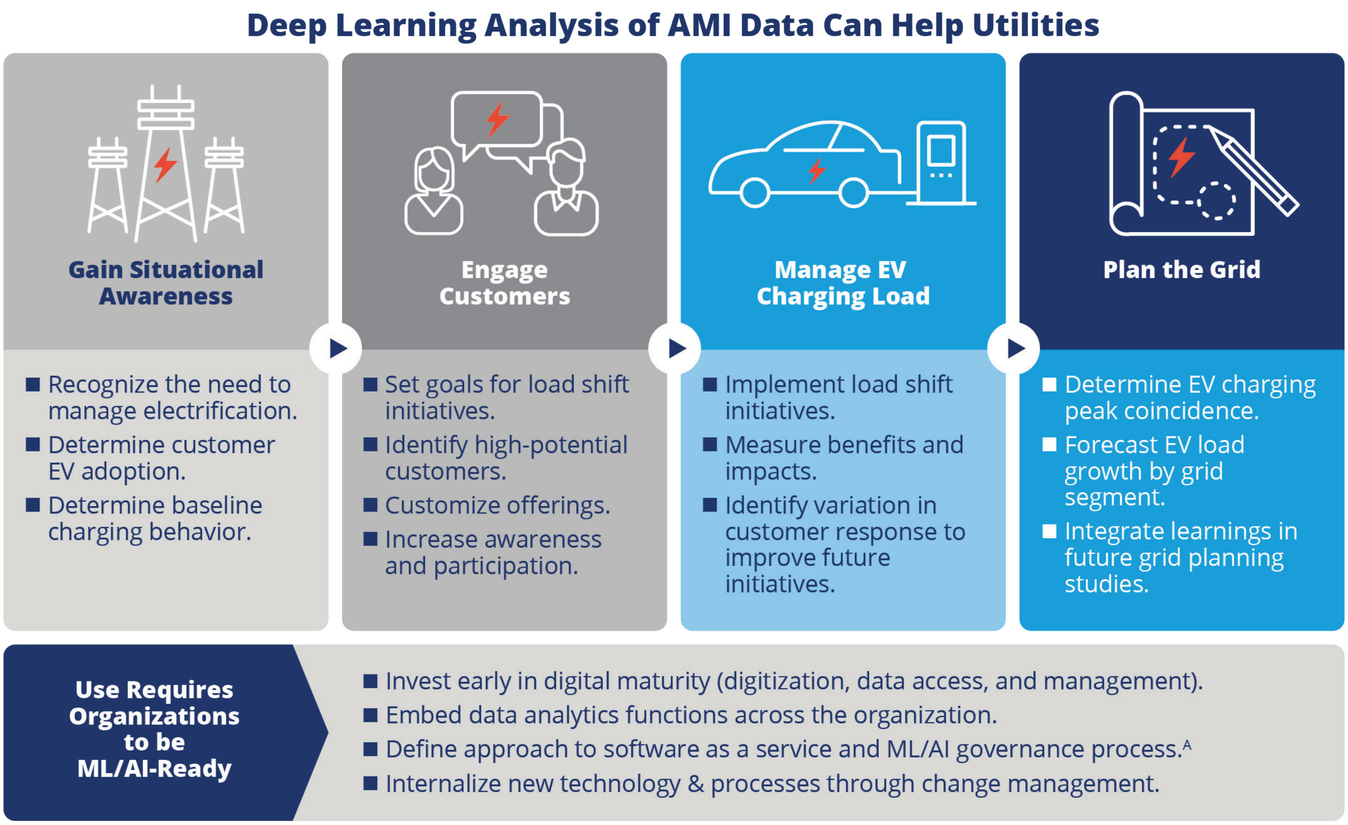
At its core, the benefit of using AI for EV detection is improved situational awareness, unlocking more efficient and effective EV load management. Three core benefits discussed in this brief and case studies include:

- **Easier to find and engage EV-driving customers:** Utility staff can use AI analytics to find more EV-driving customers than self-report or basic analysis and can more efficiently target those with high potential to help meet load flexibility goals. Outcomes for utilities include more efficient customer analytics, customer outreach, program implementation, and more effective programs.
- **Access to a novel source of EV charging data:** Utilities with AMI can use AI analytics to identify EV charging sessions from hourly or 15-minute meter data. For some utilities, this will open a new door to EV detection analytics (e.g., those without a managed charging program or third-party access to EV telematics or EVSE data).
- **Higher-quality EV charging characteristics:** By using more granular data like these, utilities can strengthen their understanding of (and better account for) local variability in how, when, and how much customers charge their EVs. As EV adoption rises and driving and charging patterns diversify, this granularity becomes crucial to pinpoint EV-grid integration challenges and devise programs, services, and grid upgrades that reflect this diversity and dynamism.

1 AMI is the combination of two technologies: digital meters that measure energy consumption and other data at a premise, as well as a two-way communication component to transmit meter data to the utility and to send utility signals to the meter.

Figure 1 includes an overview of how using deep learning to analyze existing utility data like AMI interval data can help utilities accelerate and improve their grid visibility, customer engagement, and load shift implementation. These themes are elaborated on in the brief.

Figure 1. AI-Based EV Detection Enables Downstream EV Load Management



A: For more information about Software as a Service, see National Association of Regulatory Utility Commissioners (2020). Financial Toolbox Series: Cloud Computing Brief.

Source: SEPA (2024).

Introduction

As EVs reach the mainstream, adoption is predicted to grow from over 4.8 million EVs on U.S. roads today to 78.5 million EVs in 2035, or more than 26% of the cars and light trucks on the road that year.[2] Electricity load growth from new EV charging can also place new strain on the distribution system depending on the location and time of day. Studies forecast that unmanaged charging could cost billions of dollars in distribution grid infrastructure investments by 2035.[3] ***Being proactive is key to managing these costs.*** EV TOU rates, active managed charging programs, and other interventions reduce and delay the need for such investments and their associated costs.[4] Luckily, consumers are often flexible about when and how they charge their vehicles.[5]

This brief is about how utilities can use AI to get ahead of transportation electrification trends and prepare to implement managed charging programs. The utility industry is awash in many types of AI, from large language models to analyze regulatory documents to advanced wildfire detection and renewable energy optimization tools. For transportation electrification, machine learning tools exist to detect EVs and other sub-meter-level appliances from premise-level AMI data. This is a way to understand more of their customers, with greater nuance, than basic analyses or sample-based surveys. Machine learning also opens the door for dynamic automations that could help utilities better keep pace with rapid EV adoption. However, building trust among utilities, customers, and stakeholders about machine learning and other AI tools can be gained only through experience and the ability to validate results and understand value.[6]

This brief takes a closer look at where AI dovetails with transportation electrification, how AI-based EV detection and EV characterization with AMI data work, and how two utilities have been using machine learning insights to inform transportation electrification plans and programs. We present:

- How AI works, using deep learning trained on AMI data as an example
- Why there is an opportunity to expand the use of AI in transportation electrification planning
- Utilities' experiences using one form of AI to strengthen their EV initiatives
- Considerations for utilities exploring AI tools for their work
- A glossary with the key terms at the intersection of AI and EVs

What is AI? A Machine Learning Focus

Utility staff are all on unique journeys to using AI. In 2024, multiple industry surveys suggested that about one-third of utilities were actively using generative AI somewhere in their operations,[7] but utilities have been using other forms of AI—namely, machine learning models—for much longer. Before discussing AI for EVs specifically, this section provides a brief primer on AI for those who want to develop or refresh their understanding.

Artificial intelligence is all about computers solving difficult tasks through experience and observations. It is also an evolving field of study and practice with many branches. In 2024, most of the AI being discussed in the energy sector involved *machine learning* to improve pattern recognition and prediction.

2 *Inclusive of battery electric vehicles and plug-in hybrid electric vehicles.* Edison Electric Institute (2024). Electric Vehicle Sales and the Charging Infrastructure Required Through 2035.

3 Kevala Inc. (2023). Electrification Impacts Study Part 1: Bottom-up Load Forecasting and System-Level Electrification Impacts Cost Estimates. *Prepared for the California Public Utilities Commission Proceeding R. 21-06-017.*

4 National Renewable Energy Laboratory, Lawrence Berkeley National Laboratory, Kevala Inc., and U.S. Department of Energy (2024). Multi-State Transportation Electrification Impact Study: Preparing the Grid for Light-, Medium-, and Heavy-Duty Electric Vehicles. DOE/EE-2818, U.S. Department of Energy.

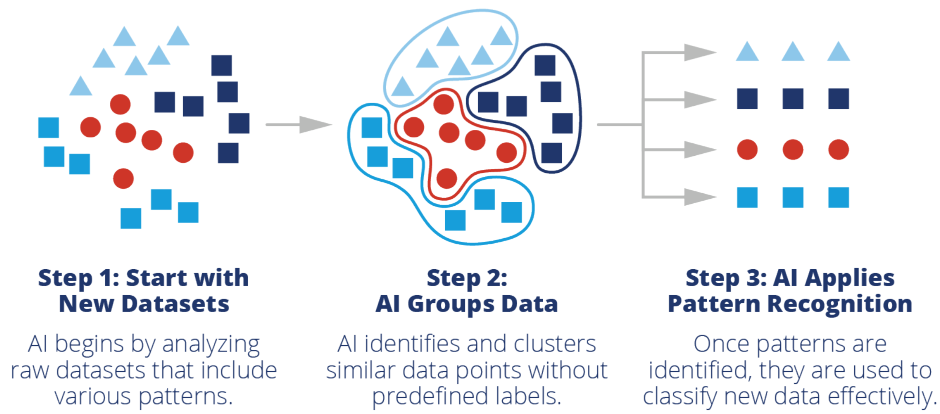
5 The Smart Electric Power Alliance tracks the many ways to manage EV charging patterns to meet consumer needs while maximizing utility benefit. See, for example: Smart Electric Power Alliance (2024). The State of Managed Charging in 2024.

6 Smart Electric Power Alliance (2024). Expert Takeaways from the Early Days of AI.

7 For example: IBM (2024) Global AI Adoption Index 2023; CapGemeni Research Institute (2024) Harnessing the Value of Generative AI: Top Use Cases Across Industries.

- **How AI Works:** AI is a system of input data (numbers, images, text, etc.), human instructions (programs) and outputs (predictions or estimations). Programs are designed to learn about and classify the data independently, and then apply learnings to make inferences about new data (Figure 2). Software developers design these models to work iteratively and with relatively little human involvement after the initial instruction. Therefore, resulting algorithms may reveal different patterns or predictions than a manual approach might find.
- **What Could AI Replace?** Not all analyses need AI. AI is seen as a way to find patterns and make predictions faster, at a broader scale, and/or when the environment is *highly complex or dynamic*. For example, a midsize utility with 15-minute AMI data for its 50,000 customers amasses 144 million data points per month. Conventional data science and statistical methods can reveal a great deal of insight on these data, but machine learning can help data scientists detect and model especially nuanced trends.
- **Why Now?** Utility staff who perform load forecasting likely have some basic experience with AI, because machine learning—a subset of AI—underpins many of these models. Basic machine learning models have long supported a variety of other well-defined tasks. More recently, machine learning models have become more powerful and widely applicable due to the broad digitization of the grid, alongside computer science advancements and broader access to cloud computing.

Figure 2. Deep Learning Identifies Patterns and Applies the Trends to New Data



Example Result

Outcome with 15-Minute Interval AMI Data

- Level 2 EV charger detected at 98% accuracy (+/- 1%)
- Level 1 EV charger detected at 92% accuracy (+/- 3%)
- Cooling load detected at 97% accuracy (+/- 2%)
- Pool Pump detected at 96% accuracy (+/- 2%)

Source: Bidgely. Reproduced by SEPA.

Framing the Utility Path to AI-Supported Transportation Electrification

Three years ago, in 2022, 59% of U.S. electric utilities in SEPA's network had already established a strategic plan for managing transportation electrification.[8] Situational awareness has always been key to these types of plans. Analysis of customer surveys, public records (e.g., EV registrations), and AMI meter data all yield useful insight. AI tools can speed up these analyses and make it possible to incorporate more complex data.[9] Utility staff have and are working through a variety of questions as they evaluate AI across their organizations, from digital readiness to use cases, to value. Figure 3 shows the questions that various teams might ask about AI tools specifically for transportation electrification. Because transportation electrification—and AI tools—are both dynamic topics today, the central question linking these perspectives is, *"How can I begin preparing today for future opportunities and challenges?"*

Figure 3. Early Questions to Answer in AI-Supported Transportation Electrification

Source: SEPA (2024). Research synthesis and industry interviews.

8 Smart Electric Power Alliance (2023). 2023 Utility Transformation Profile.

9 U.S. Department of Energy (DOE) (2024). AI For Energy: Opportunities for a Modern Grid and Clean Energy Economy.

Information managers within utilities can help transportation staff determine whether their organization supports AI and is ready to adopt it (Table 1). For example, AI is valuable for its ability to analyze vast digital data, but this capability requires the AI user or vendor to have both gathered the digital data itself and secured the computing power to store it and perform analyses. AI's predictive elements introduce some new business and consumer risks, so data governance teams may need to be formed or strengthened to manage them.[10] Finally, as customer-centric businesses, it is important to be aware of the potential for negative perceptions of AI-based insights, and ensure that AI-based outputs are accurate. Utilities can leverage internal expertise or bring in external vendors to help manage these issues.

Customer program staff at utilities can use AI to replace or supplement existing processes. Table 2 highlights a few ways that AI-based EV analytics work to replace or supplement manual or digital approaches to early stages of managing transportation electrification. For example, to detect EVs, AI analytics would replace manual data gathering and conventional data analysis to identify usage spikes characteristic of EV charging. Layering AI analysis with automation tools further empowers utility staff to access current analysis results in real-time (e.g., dashboards that refresh when new AMI data are received).

As utilities progress from manual to digital and dynamic analytics, they may encounter new considerations. While detailed analyses of utility change management and digitalization are beyond the scope of this brief, four perspectives emerged in our research for this brief, which may help utilities envision their path to AI adoption to manage EV electricity demand growth.

- **Technology Roadmap:** AI provides a path to get more insight from existing data, but requires linking hardware systems that generate the data with software

Table 1. Digital Maturity Enables ML/AI Adoption

Enabling AI for Transportation Electrification Requires Investments in Digital Maturity					
Acquire Digital Data on Physical Assets	Establish Data Management	Access Cloud Computing	Invest in Software Capabilities (in-house or third-party)	Update Data Governance to Include AI	Pilot AI, Validate Impact, and Implement

Source: SEPA (2024).

Table 2. AI is a Continuation of Transportation Electrification Digitization

Task	Manual Hard copies, one-by-one approaches	Digital Collect, store, transmit, and analyze digital data	Automatic and AI-Enabled Software automations, AI analysis, and more
Detect EVs	▪ Survey customers. ▪ Process vehicle registration data.	▪ Periodically query meter data for high energy use, using simple assumptions (e.g., what does EV load look like). ▪ Obtain third-party networked EVSE or EV telematics data.	▪ Use **machine learning** to isolate EV charging loads from other large loads. ▪ Automate staff analysis and reporting with live dashboards.
Engage EV Drivers	▪ Open recruitment for managed charging programs. ▪ Send mass-market outreach to all customers or to manually identified EV drivers.	▪ Send outreach to EV customers after EV detection analysis. ▪ Target outreach to customers with high load shift potential (identified with **deep learning**).	▪ Run **machine learning** analysis to detect new EVs when AMI data refreshes. ▪ Design automated email campaign to contact new EV drivers.[A] ▪ Customize customer communications based on their behavior & devices.

A: Limited use today but possible to deploy; see discussion below on customer program operations.
Source: SEPA (2024).

10 See NIST (2024) AI Risk Management Framework. The IEEE 'Flexible Maturity Model for AI Governance Based on the NIST AI Risk Management Framework' is designed to help entities assess their relative maturity on various dimensions of AI governance. TechBetter's "Responsible AI Governance Framework" is based on the NIST AIRMF and denotes nine key risk categories, including performance, safety, privacy, security, third-party access and intellectual property, fairness, ecology, explainability, and transparency.

systems to analyze it. A technology roadmap can help stakeholders understand what and when to expect these investments to return value and ensure that investments are fully leveraged for customer benefit.[11] Incorporating AI disaggregation tools in AMI technology plans increases the value of AMI data to EV rate design, programs, and services. In this process, it is important to bring together the varied people or teams that address individual pieces of transportation electrification and learn how they would like to make better use of AMI data, telematics, EVSE, or other data.

- **Risk Management:** All AI tools are based on predictions and therefore have risks and limitations related to uncertainty. Before purchasing AI software, decision-makers and users should review the software's reported technical performance in terms of metrics like accuracy, precision, and recall. If desired, they can also compare a sample of results to their own ground-truth data to check for common-sense alignment. Staff may also need to be trained on any utility governance best practices for data sharing with third-party vendors and the ethics and best practices for using AI for customer-facing services and communications. Interested utilities can engage AI ethics experts, AI software providers, consumer advocates, or community members to chart the path forward.
- **Customer Program Operations:** As programs incorporate more complex EV charging management, they should maintain ease of customer use. SEPA's report "Managed Charging Programs: Maximizing Customer Satisfaction and Grid Benefits" discusses how utilities can better design programs to increase customer participation and partner with software providers and other program entities to deploy those programs. While this brief focuses on the benefits of AI to utility program staff, the same tools can be used to present enhanced data insights to customers as well. AI vendors can provide utilities with strategies for presenting AI-derived insight to customers to inspire trust and position the utility as a partner.

Improving EV Detection & Characterization with AI

Customers do not have to share their EV purchases or charging behavior with their utility. This type of data gap limits utilities' ability to plan the distribution system most efficiently and implement EV load management programs. Finding another source of data regarding customer EV adoption, charging behavior, and the impact EV charging has on the distribution and bulk-level grids is, therefore, essential for planning for EV adoption.

There are a variety of data sources and methods that utilities can choose from to fill in the gaps.[12]

- **Public records**, such as vehicle registration data, can in some cases be obtained to identify customers with registered EVs, but not where, when, or how they are being charged. Data lags may also limit how quickly action can be taken.
- **Networked EVSE** and **vehicle telematics** data from vehicle manufacturers and charging equipment companies directly show where and how customers are charging EVs. As these are generally customer-owned and behind-the-meter assets, utilities must arrange third-party data-sharing agreements with vehicle OEMs and EVSE suppliers to obtain the data, such as in some managed charging programs.
- **Customer surveys** are timely and relatively easy for the utility to implement, but as sample-based data, they cannot provide complete insight on all customers.
- **Utility meter data analytics** include all customer accounts. Utilities with AMI meters installed have a relatively direct route to using the data to reveal EV adoption and charging. However, they must work through internal data-sharing processes and develop analytic methods and assumptions to reveal which AMI data indicate an EV present behind the meter.

Each of these methods is an improvement compared to limited knowledge about customer EV adoption. Still, lower-coverage data and/or lower-certainty analyses may under-count the true number of EVs charging in a service territory. This cascades into reduced visibility into charging behavior, reduced ability to reach and engage

11 American Council for an Energy Efficient Economy (2020). Leveraging Advanced Metering Infrastructure To Save Energy.

12 See detailed discussion in SEPA (2024). State of Managed Charging in 2024.

eligible customers in EV managed charging, and increased uncertainty in EV load growth forecasts (Figure 4).

In the software market today, there are a variety of AI-based EV detection and charging characterization tools designed to better utilize the data listed above Figure 6, create higher-accuracy estimates at territory-wide scales, and link these data to distribution system planning. The class of tools using **AMI data** for this purpose *indirectly* reveal EV charging through **meter data disaggregation** analyses. Meter data disaggregation analyses examine hourly or 15-minute consumption data for energy use signatures typical of EVs or other electricity loads. Finer-resolution data provide higher accuracy results. The following sections provide details and examples of this technique.

Figure 4. EV Adoption Data Improves Efforts Across Key Steps of Vehicle-Grid Integration

Step 1: Identify Customers With EVs and Their Charging Behaviors
Utilities seek to understand customer EV adoption and charging behavior to understand system impact and opportunities for managed charging.

Step 2: Create Managed EV Charging Programs
Utilities use information about customer EV adoption and charging (kWh, kW) to design programs to meet grid needs, avoiding grid strain and lost savings.

Step 3: Incorporate EVs into Load Forecasts
By understanding EV adoption, charging behavior, and grid impact by distribution grid segment (transformer, circuit, substation), utilities can incorporate EVs into load forecasts to prevent overload or capacity issues.

Step 4: Map EV Load Growth by Geography
Understanding EV adoption by geography provides an opportunity to detect local reliability risks that may appear before system-level issues arise, preventing delays in addressing localized outages and risks.

Comprehensive Data is Key to Effective EV Integration
Insufficient data on EV adoption and charging behaviors can lead to missed opportunities, grid instability, and delayed responses to risks. Utilities must prioritize enhanced data collection methods. AI-based tools can help bridge the gap by improving EV detection and the accuracy of load forecasting.

Source: SEPA (2024). Research synthesis and industry interviews.

ML Solving the Difficult Task: Is There an EV Behind This Meter?

Advanced metering infrastructure (AMI) is an integrated system of 'smart' meters and two-way communication between customer and utility that records electricity usage (kWh) and automatically sends the data to the utility. For residential meters, this information is often collected at hourly or 15-minute intervals. By 2022, utilities had deployed AMI meters at 73% of U.S. households and businesses;[13] coverage continues to extend as utilities in some states begin their first deployments.[14]

AMI meters are a useful source of information about customer energy usage. Utilities often query AMI data to find customers with high overall energy use, high peak demand, or who have started using more energy. Because utilities do not know what appliances or equipment customers own or how they use them, determining

13 U.S. Energy Information Administration (2023). How many smart meters are installed in the United States, and who has them?

14 The Edison Foundation Institute for Electric Innovation (2023). Smart meters at a glance.

the reason for these trends requires modeling and assumptions. For example, if interested in finding out whether EVs are charging at customer premises, analysts need a way to parse out EV usage from other high-usage electric appliances such as hot tubs, electric heat, or other equipment. EVs are a diverse appliance. A variety of simplifying assumptions can be made (Table 3), but as EV charging spreads and average customer behavior diversifies, there is growing interest in performing more sophisticated assessments.

For nearly 30 years, data scientists have been developing machine-learning tools to interpret electric meter data. **With the increasing need to understand and manage transportation electrification, there is a *new wave of using and improving on existing machine learning techniques* to identify EV usage and charging characteristics.**

The approach has roots in the early utility AMI rollout in the 2010s, when various companies and research institutions developed machine learning tools to parse meter-level usage into the individual types of appliances and equipment that contribute to total usage.[15,16] In the years since, software innovation has progressed, AMI coverage has increased, and AMI meters themselves have been improved to provide more data and better communication capabilities.

AMI disaggregation with machine learning can be distilled into five core steps:

1. **Compile** a large time-series dataset of AMI interval data
2. **Classify** energy usage patterns in the historical AMI data
3. **Associate** unique patterns with end-use devices (EVs, lighting, water heaters, etc.)
4. **Predict** which end uses are contributing to ***new*** meter data, based on past classifications and associations
5. **Format results** in ways meaningful to utility staff and customers

Today, a variety of software vendors provide end-use load disaggregation, including Bidgely, Uplight, Sense, Sagewell, Powerly, Oracle, and others. Each has developed unique algorithms and analytic approaches to disaggregating load, although in general the goal is to provide utilities and their customers about what appliances are present and when and how much energy they use (Figure 5). The Appendix contains a technical explanation of how these algorithms work and what utilities are doing with them, using Bidgely's software as an example.

Table 3: Approach and Limitations of Simple EV Detection Methods

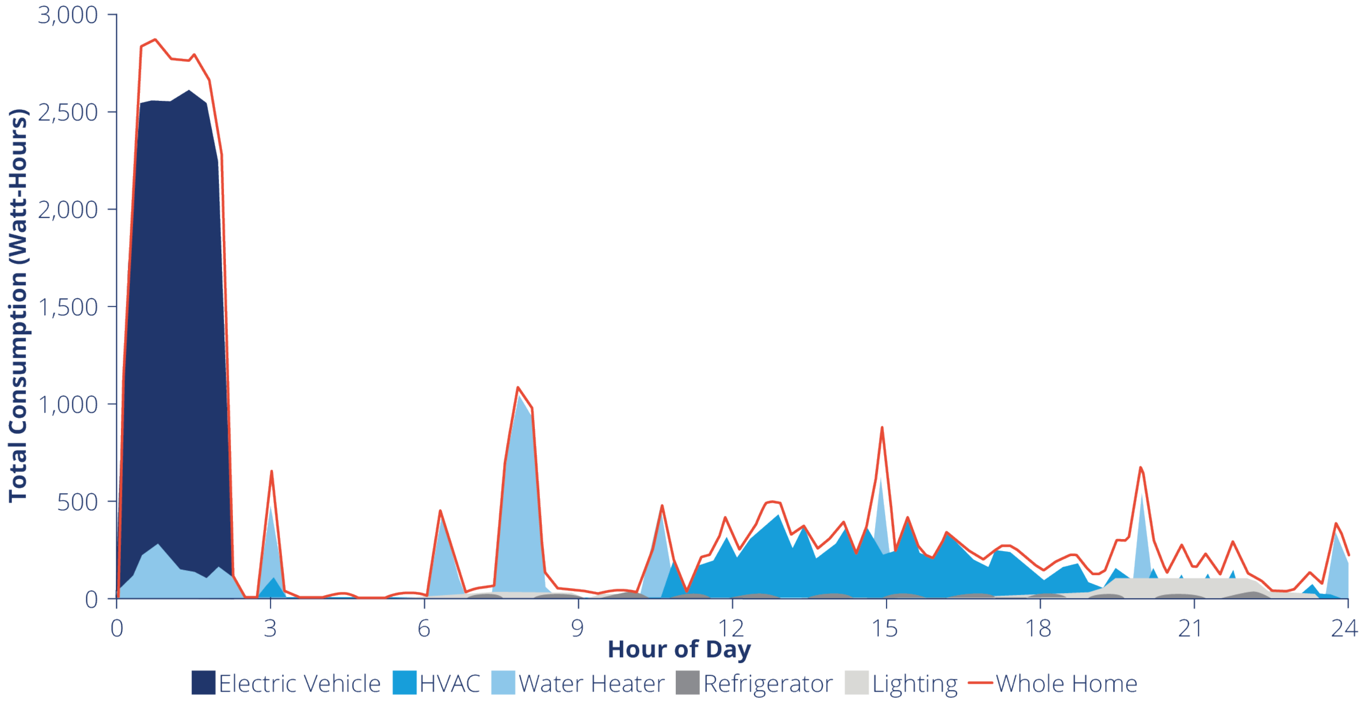
	Amplitude	Load Shape
Initial Simplifying Assumptions	High power draw over several hours could represent a charging session, such as when an owner comes home and plugs in their car. Relative amplitude differentiates EV charging from other loads.	Modelers tend to look for the most-classic EV load shape: a large load overnight (4kw to 8kW, for 6 to 8 hours).
Limitation of the Basic Approach	Charging behaviors and EV battery depletion can vary widely; these characteristics result in varying power draw and charging durations. Using a standard estimation of demand across all EV owners may over- or under-estimate grid impact.	Not all charging is equal. Plug-in hybrids have a different charging profile than BEVs, and Level 1 chargers have different load profiles than Level 2 chargers. These characteristics can impact EV visibility and the demand over time. EV detection with just one assumed load shape will miss some EV charging sessions.

Source: Bidgely and SEPA (2024).

15 Butner, R.S., Reid, D.J., Hoffman, M., Sullivan, G. and J. Blanchard (2013). Non-Intrusive Load Monitoring Assessment: Literature Review and Laboratory Protocol. Pacific Northwest National Laboratory.

16 Mayhorn, E.T., Sullivan, G. P., Petersen, J., Butner, R.S., and E. M. Johnson (2016). Load Disaggregation Technologies: Real World and Laboratory Performance. Proceedings of the 2016 ACEEE Summer Study on Energy Efficiency in Buildings.

Figure 5. Representative Customer Consumption by Behind-the-Meter Asset



Source: Bidgely (2023). Empowering Utilities with True, Behind-the-Meter Disaggregation. Dotted line is whole-home energy consumption from AMI meter. Shaded areas reflect outputs of deep learning AMI data disaggregation. Recreated by SEPA.

Utility Case Studies

As with AI adoption generally, utilities are at varying stages of using AMI data for EV detection. In recent decades, many utilities have used AMI data disaggregation results to engage customers about their energy usage and encourage energy-efficient behavior. For example, a 2020 SEPA survey of 135 electric utilities found that 33% were using AMI data load disaggregation tools to determine or measure EV connections.[17] EV and managed charging program managers who want to begin using these solutions can look to earlier adopters for learnings and best practices.

The following two case studies illustrate how utilities are using AI to disaggregate AMI data for EV detection, program design, and forecasting, thereby increasing utility situational awareness and load management capability.

- **Hydro One used EV detection** with disaggregated AMI data to expand customer recruitment for an opt-in load shift program.
- **NV Energy used EV charging characterization** with disaggregated AMI data to explore the need and value of EVMC and support a program trial.

Each case study discusses the context, application, and results of using AI software. Each also focuses on learnings about how various utility teams prepared to implement or expand their use of AI, whether finding new ways to apply AI insights for situational awareness, using them to refine customer engagement, or strengthening their grid planning to solve unique challenges posed by EV adoption (i.e., Figure 1).

17 SEPA (2021). 2021 Utility Transformation Profile.

Case Study: Hydro One Used AI to Identify EVs, Accelerate Recruitment, and Inform Planning[18]

Context

Hydro One distributes electricity to about 1.5 million residential and business customers in the Canadian province of Ontario. EV adoption has been modest to date but is now growing, particularly in areas already facing load growth from new construction. Hydro One had been using customer surveys to identify EV drivers.

Establish AI-Readiness

Hydro One already had the AMI data necessary to provide the inputs to Bidgely's AI models. In 2019, Hydro One created a customer energy marketplace to engage its customers about energy, following the transfer of all Ontario utilities' demand side management programs to IESO. Bidgely ran the new marketplace and provided customers with AMI data disaggregation insights based on Hydro One's hourly AMI data.

Gain Situational Awareness

Hydro One realized it could repurpose AMI disaggregation insights for its own staff to learn more about EV load, how that load was contributing to localized grid constraints, and the value and necessity of programs to manage EV loads that could defer or offset future grid investments. Hydro One turned to Bidgely's disaggregation-based EV intelligence analytics to identify EVs across its service territory and understand their load impact.

- Hydro One identified 20,000 customers with EV charging activity — approximately 10 times more than were identified via customer surveys.
- The utility has built confidence in these results via a field validation study.

Engage Customers

Hydro One's customer program team used the results to support outreach for a pilot EV demand response program. According to staff, targeted email recruitment sent to identified likely EV drivers resulted in the "highest click-through rate" in recent history. Three hundred customers signed up within 24 hours, and today over 1,000 customers are enrolled. In Hydro One's view, presenting customers with targeted offerings personalized to their energy consumption has been a success.

Plan the Grid

Distribution system management staff now incorporate these meter-level EV insights into their work, creating territory-specific EV charging load shapes and diversity factors.

- Staff use the software to estimate EV load, calculate average EV charging load shapes, and estimate a territory-specific EV diversity factor.[19]
- For the first time, by mapping results to grid assets, staff can assess EV adoption, incremental charging impacts (kWh and kW), and load profiles by feeder or substation. This added visibility supports design studies and can strengthen future system planning with territory-specific insights.

18 Hydro One (2024) Investor Overview: Post Second Quarter 2024, Bidgely (n.d.) Hydro One Case Story: Gearing Up for the EV Revolution, and SEPA's discussions with Hydro One and Bidgely staff (2024).

19 Customers do not all charge their EVs at the same time. Diversity factors help utilities understand how much of the time an EV will be charging and, at a neighborhood level, what share of EVs are likely to charge at the same time and how their total load compares to system capacity. Knowing how many EVs are likely to charge at a given point in time helps utilities correctly plan the right size and location of new distribution system equipment. See also: Electrical Engineering Portal (2024). Energy Demand Factor, Diversity Factor, Utilization Factor, and Load Factor.

Case Study: NV Energy Used AI to Facilitate Load Shift Trial for Diverse EV Charging[20]

Context

NV Energy is an electricity generation, transmission, and distribution utility serving 1.4 million residential and commercial customers in Nevada, including Las Vegas. With growing EV adoption, NV Energy wanted to better understand customer preferences and charging trends. They also aimed to identify and test technology that could help improve NV Energy's distribution and resource planning processes to prepare for future grid constraints that might develop because of additional EV load.

Establish AI Readiness

NV Energy has used AMI-based programs for customer engagement and energy efficiency purposes since 2017, and also offers an opt-in EV time of use rate. In 2023, Bidgely performed a trial AMI disaggregation analysis of 100,000 NV Energy customers in the Las Vegas area to identify EV drivers, understand how often drivers charge on-peak and learn how their behavior contributes to overall electricity demand. Bidgely also supported a telematics-based EV managed charging trial with 50 customers using peak-time demand response via informal telematics.

Situational Awareness

The trial disaggregation helped NV Energy determine that "EVs are largely pocketed, and growth is likely going to be centered around hot spots where infrastructure investment will likely be needed first… EV behavior is not fully coincident with peak, but there is a substantial opportunity to shift load into off-peak hours."[21]

Engage Customers

The goal of the managed charging trial was to explore what types of offerings would reach high-value candidates, meet customers' needs, and provide system resilience as EV charging increases. Las Vegas is a "24/7" city, and customers need to charge their EVs at all times of the day and night. Accordingly, NV Energy also wanted to understand how best to help high-potential customers curtail charging during peak hours (8 pm-12 am) in balance with grid needs. For the trial, high-value customers were defined as those with high amplitude chargers (higher kW pull), charging frequently during the program event window (frequency of charging), and charging a lot during the event window (total KWh). Bidgely applied its AI models to NV Energy meter data to identify these types of customers.

Manage EV Charging

Typical managed charging programs achieve an average load shift of 0.2 - 0.8 kW/vehicle per event, accounting for the zero (0 kW) load shift from opt-outs and EVs not plugged in during events.[22] This range reflects the variety of EV drivers enrolled in these programs and their plug-in habits (many customers plug-in every three days, often during non-peak times). In contrast, by using AI to detect 50 customers with high-value baseline charging behavior, Bidgely was able to achieve a higher load-shift potential of 2 - 4 kW/vehicle per event (Figure 6). By engaging only the highest-potential EV drivers, Bidgely's approach achieved a 2.5 times to 10 times greater load-shift on average.

AI-powered analysis can increase EV customer program portfolio cost-effectiveness. Utilities benefit from targeting recruitment to customers who can respond to managed charging in ways most closely aligned with the program's purpose, whether that is based on availability to reduce their charging by a specific amount, at a specific time or

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20 Bidgely (2023). EV Preparedness Starts with EV Intelligence. NV Energy (n.d.) Electric Vehicle Rate; and SEPA's discussions with NV Energy and Bidgely staff (2024).

21 Nevada Power Company d/b/a NV Energy and Sierra Pacific Power Company d/b/a NV Energy. (2024). 2024 Joint Integrated Resources Plan. Distributed Resources Plan, Section 10. Transportation Electrification Plan. Accessed November 2024.

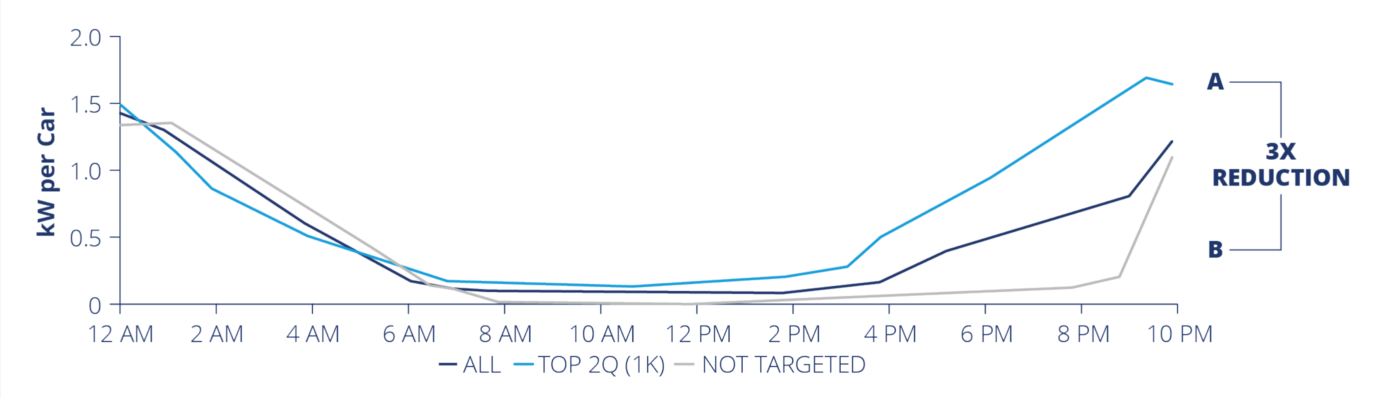
22 Including programs incorporating TOU, DR, and dynamic controls. See: Smart Electric Power Alliance (2024). The State of Managed Charging in 2024. Table 6.

location, or other factors.[23] This can reduce outreach costs, increase the load flexibility potential (kW/vehicle), and further increase the cost-effectiveness of EV time-of-use rates (Figure 7). For NV Energy, a targeted approach to managed charging yielded cost efficiencies for the utility and customers. Seeing that they could achieve load-shift goals with fewer, higher-potential customers than anticipated, NV Energy reallocated its incentive funds to provide each of the targeted participants with a higher participation incentive.

Plan the Grid

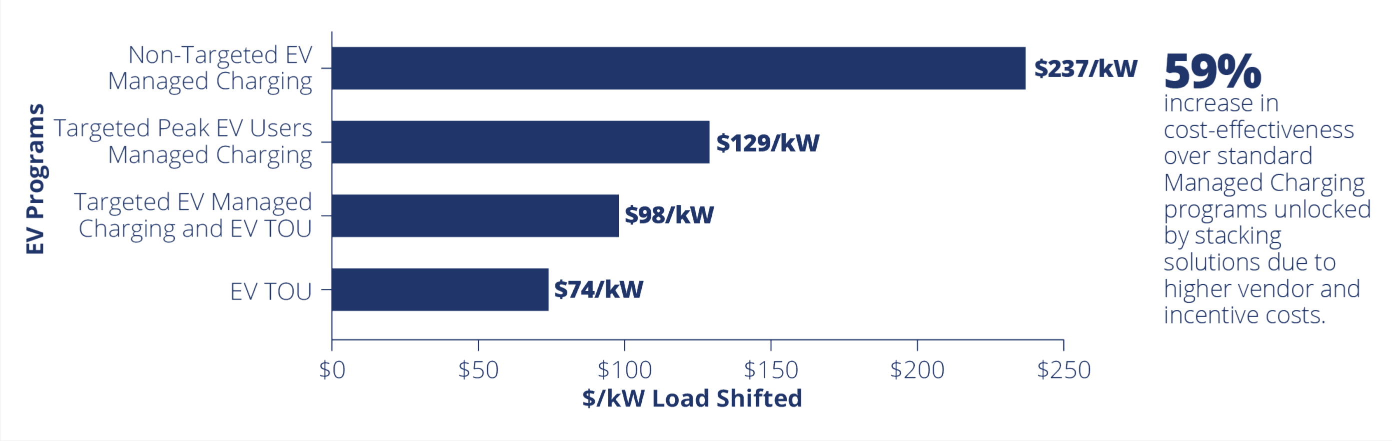
NV Energy used learnings generated in these trials to help design its 2025 - 2027 Transportation Electrification Plan, filed with the Public Utilities Commission of Nevada as part of its integrated resources plan.[24] This included a request to expand the trial to a full pilot, allowing "for the nuances of the full territory to be studied; [allowing] a wider array of customers to participate; and [focusing] on enrolling customers who have the biggest system impact."

Figure 6. EV Load Profiles of High-Value Drivers Before and After AI-Targeted Load Shift



Source: Bidgely (2024). The medium blue line (A) indicates the targeted EV load of customers in the top two quartiles of demand. In contrast, the average EV charging profile of other customers (B) has significantly less charging occurring during the peak time (1-9 p.m.). With targeting in place for a targeted sample of higher-demand customersat NV Energy, the result was an average of 1kW/car for over 20 events, far exceeding the industry average of 0.2-0.3 kW/car. Recreated by SEPA.

Figure 7. Bidgely Has Realized EV Customer Program Cost-effectiveness



Source: Bidgely (2024). Based on Bidgely's analysis of solution performances and market-published program performance from other vendors.

23 See additional examples in: Smart Electric Power Alliance (2023). Managed Charging Programs: Maximizing Customer Satisfaction and Grid Benefits.

24 Nevada Power Company d/b/a NV Energy and Sierra Pacific Power Company d/b/a NV Energy (2024). 2024 Joint Integrated Resources Plan. Distributed Resources Plan, Section 10. Transportation Electrification Plan. Accessed November 2024.

Summary & Future Directions

Incorporating transportation electrification trends into distribution system planning helps utilities best target investments and support customers in managing costs and providing flexibility. Utilities can use AI tools to gain situational awareness, engage customers, manage EV charging load, and plan the grid.

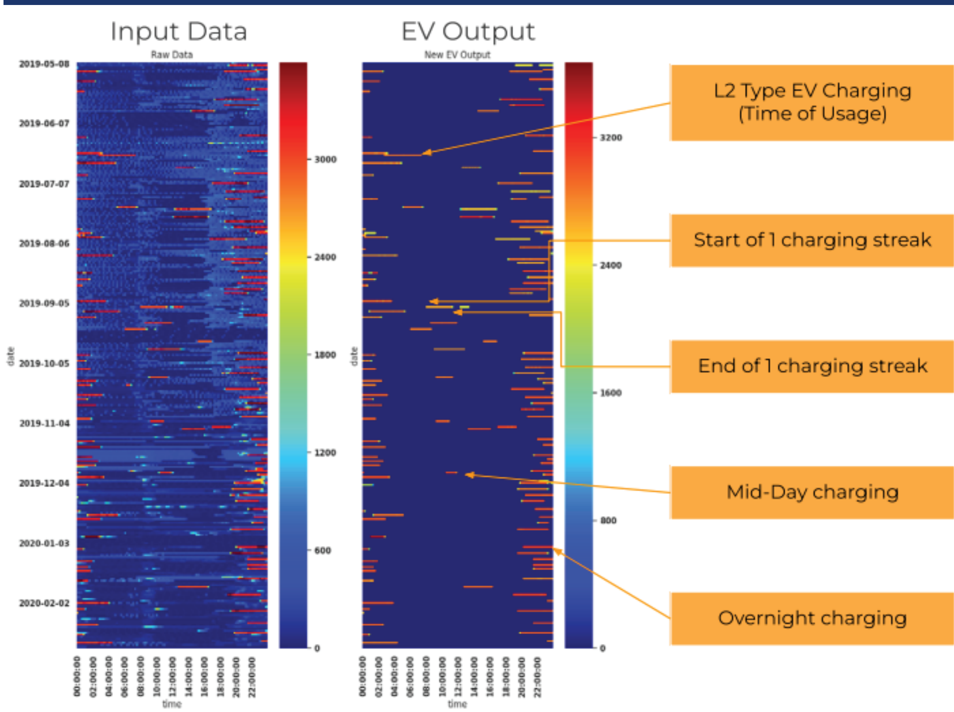
Looking ahead, as utilities advance their distribution system planning capabilities for the two-way, digitalized, dynamic grid of the future, improved EV insight can inform utility decisions about a cascade of other investments. Utilities can deploy AI's capabilities in classification, assessment, automation, prediction, and customer engagement to support staff in moving from strategic planning to system investments and operations.

Appendix: More Detail—Using Machine Learning to Detect & Characterize EVs

Bidgely's UtilityAI™ software provides one example of how machine learning analysis of AMI data can work. Elaborating on the same four steps discussed in the report above, Bidgely developed its model by taking the following actions:

- **Compile:** To develop its models, Bidgley collected billions of high-resolution sub-second-level data on all major appliances. This high-resolution data was the foundation for creating diverse appliance profiles. Bidgely additionally gathered a historical time series of AMI interval data from a variety of electric utilities in North America, Europe, and Australia. Bidgely has refined methods to sanitize the data for reliable analysis because the raw data collected is not always clean or complete.
- **Classify:** Bidgely developed supervised and unsupervised machine learning algorithms to classify AMI data points based on a range of factors (amplitude, total energy consumption, time of day, day of the week, season, and weather data).[25] The results of this classification can be visualized in a heat map (Figure 8).[26]
- **Associate:** Bidgely used deep learning to group AMI data points that represent unique energy "signatures." These unique appliance signatures provide deep insights into appliance penetration and usage.

Figure 8. One Type of Deep Learning Dataset used for End Use Disaggregation



User Profile

Charger Type	L2
Amplitude	11900 W
# runs peak hours (winter)	3
Consumption Peak Hours (winter)	64.437 kWh
# runs peak hours (summer)	10
Consumption Peak Hours (summer)	425.814 kWh
Interval start-end time (avg)	8pm - 4am
Charging frequency (avg)	4 times / week
Load profile and flexibility analysis	

An individual user profile can be extracted from the data

Source: Bidgely (n.d.). Empowering Utilities with True, Behind-the-Meter Disaggregation. In the blue heat maps, the y-axis represents every day of a year while the x-axis represents every hour of a day. The "Input Data" heat map shows an entire year's worth of meter data, while the "EV Output" heat map shows the EV charging sessions extracted by Bidgely's algorithms, showing the time of charging, length of charging session, and demand amplitude (coloration). These insights are then extracted into an individual user profile for each EV owner.

25 Bidgely (2023). Bidgely EV Intelligence Technical Brief.

26 Ibid.

Signatures are continuously refined with Bidgely's extensive library of ground truth derived from plug-level sensors, manually labeled data, EV telematics data, customer surveys, etc. According to Bidgely, battery EVs using level 2 and level 3 chargers have distinctive charging signatures. Bidgely's algorithms can differentiate vehicles from other appliances and identify the type and capacity of EVs and the type of charger.

- **Predict:** By applying these classifications to new interval data, Bidgely's machine learning model has correctly identified the presence of Level 2 EV chargers with 96(+/- 2)% to 98(+/- 1)% accuracy hourly and 15-minute data, respectively.[27] Bidgely has also identified Level 1 charger consumption with 85(+/- 3)% to 92(+-3)% accuracy across these same intervals.

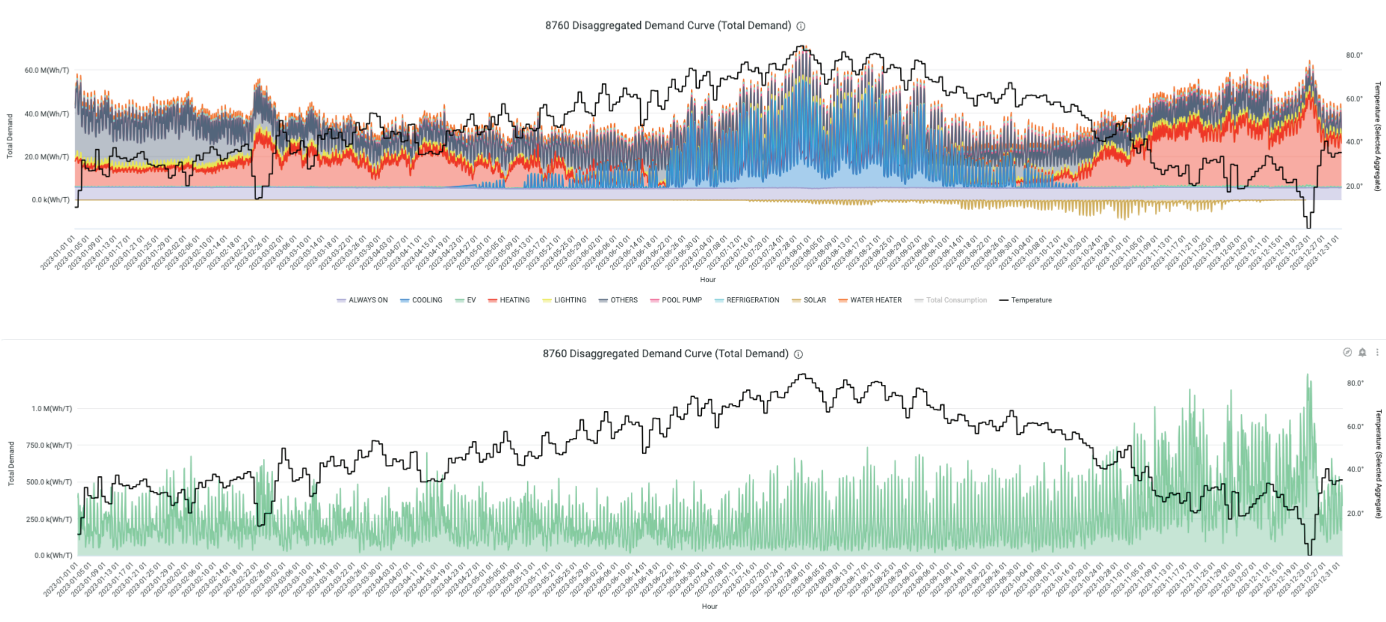
Applying Insights to Shift Load in the Real World

Software providers can present disaggregation results to end-users (utility staff or utility customers) in a variety of ways, such as through load shape charts (Figure 9), customer home or business energy usage reports, or distribution planning dashboards that aggregate the detected EV load to the transformer, substation, or other grid units for EV loading and other analyses (Figure 10).

With this appliance-level, behind-the-meter visibility across the grid, utility grid planners can identify which loads need to be shifted based on appliance (e.g. EV charger), location, grid asset impact, or other filter criteria and then define targeted mitigation approaches and customer segments. Likewise, program managers can tailor load-shift pilots and programs to these customer segments and engage them with hyper-personalized messaging and incentives to participate.

Bidgley has worked with multiple utilities to identify and target EV owners for time-of-use rate enrollment and managed charging initiatives, resulting in high levels of peak load shift for EV charging. This includes layering multiple EV load shift solutions together, including EV managed charging, EV time-of-use rates, and behavioral load shifting. Engaging with EV owners beyond enrollment, using continued coaching touch points, helps customers stick with the desired EV load-shift behaviors (Figure 11).

Figure 9. Appliance-Level 8760 Demand Curves



Source: Bidgely (2024). Bidgely demo portal. The top chart shows total consumption across appliance categories for all 8,760 hours of a year. The lower chart shows segmented EV load only, demonstrating an upward trend in EV charging demand in the later months of the sample year.

27 Bidgely (2023). Bidgely EV Intelligence Technical Brief.

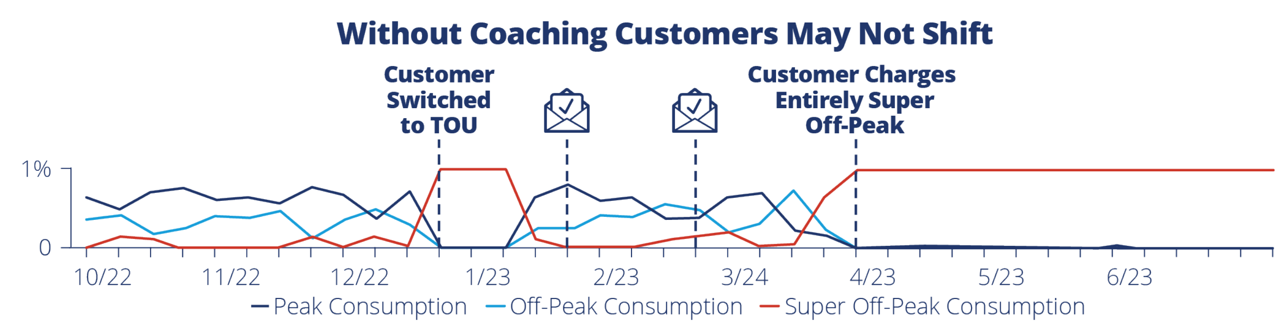
Figure 10. EV Demand Impact on Grid Assets

Transformer

	Transformer	Asset User Count	Hourly Minimum Demand	Hourly Average Demand	Hourly Maximum Demand	Capacity	Utilization
1	ORI12F3-T2 ...	13	0.78 kW	8.12 kW	97.29 kW	110.00 kW	88%
2	MIL12F3-T10 ...	13	0.54 kW	8.27 kW	123.15 kW	140.00 kW	88%
3	GLN12F2-T24 ...	5	0.43 kW	4.44 kW	43.42 kW	50.00 kW	87%
4	EFM12F2-T5 ...	12	0.20 kW	3.74 kW	43.14 kW	50.00 kW	86%
5	FWT12F4-T9 ...	14	0.22 kW	5.60 kW	84.53 kW	100.00 kW	85%
6	9CE12F2-T1 ...	6	0.64 kW	4.32 kW	83.66 kW	100.00 kW	84%
7	GLN12F2-T25 ...	19	3.30 kW	14.14 kW	162.28 kW	200.00 kW	81%
8	CLV12F4-T9 ...	6	0.41 kW	4.06 kW	32.28 kW	40.00 kW	81%
9	LIB12F3-T16 ...	11	0.29 kW	4.53 kW	63.72 kW	80.00 kW	80%
10	KET12F2-T3 ...	12	2.37 kW	19.98 kW	79.40 kW	100.00 kW	79%
11	C&W12F2-T4 ...	6	0.18 kW	1.83 kW	47.02 kW	60.00 kW	78%
12	3HT12F4-T19 ...	11	0.30 kW	5.40 kW	37.77 kW	50.00 kW	76%
13	FWT12F4-T3 ...	9	1.70 kW	7.10 kW	59.46 kW	80.00 kW	74%
14	F&C12F2-T11 ...	13	1.72 kW	6.07 kW	72.97 kW	100.00 kW	73%
15	SUN12F1-T8 ...	11	0.11 kW	4.54 kW	57.99 kW	80.00 kW	72%
16	GRN12F1-T9 ...	6	0.19 kW	2.09 kW	35.54 kW	50.00 kW	71%
17	GLN12F2-T9 ...	7	2.65 kW	10.31 kW	35.32 kW	50.00 kW	71%
18	SUN12F3-T20 ...	9	0.15 kW	1.13 kW	70.00 kW	100.00 kW	70%
19	NW12F3-T18 ...	5	2.34 kW	9.04 kW	52.24 kW	75.00 kW	70%
20	MLN12F1-T5 ...	14	1.02 kW	15.37 kW	68.72 kW	100.00 kW	69%
21	LIB12F3-T18 ...	15	1.61 kW	10.01 kW	54.43 kW	80.00 kW	68%
22	CHW12F2-T3 ...	4	0.27 kW	5.07 kW	40.81 kW	60.00 kW	68%
23	EFM12F2-T3 ...	10	1.10 kW	5.27 kW	50.84 kW	75.00 kW	68%
24	C&W12F1-T8 ...	5	0.01 kW	3.10 kW	33.73 kW	50.00 kW	67%
25	GLN12F1-T25 ...	8	0.70 kW	4.09 kW	26.91 kW	40.00 kW	67%
26	3HT12F4-T23 ...	10	0.19 kW	5.84 kW	53.57 kW	80.00 kW	67%
27	ARD12F2-T5 ...	9	0.42 kW	13.17 kW	46.05 kW	70.00 kW	66%
28	RDN12F2-T9 ...	3	0.90 kW	8.00 kW	65.55 kW	100.00 kW	66%
29	GRA12F2-T18 ...	9	0.65 kW	6.55 kW	45.82 kW	70.00 kW	65%
30	MIL12F4-T11 ...	5	0.75 kW	3.48 kW	32.67 kW	50.00 kW	65%
31	CHW12F2-T10 ...	6	0.56 kW	4.35 kW	32.37 kW	50.00 kW	65%

Source: Bidgely (2024). Bidgely demo portal. This example is from Bidgely's EV and Grid analytics solution and shows transformer utilization, filtered for EV-owning customers only. Grid planners can also perform this analysis at the substation and feeder levels.

Figure 11. Customer Engagement Increases the Effectiveness of Time-of-Use Rates



Source: Bidgely (2024). In working with one utility to drive EV time-of-use (TOU) rate adoption, Bidgely found that after onboarding customers into the rate, their EV peak-time charging decreased by 70%. Once they were on the rate, the ongoing coaching (signified by letters in the time series above) helped reduce EV peak-time charging by an additional 26%. Recreated by SEPA.

Glossary

Advanced Metering Infrastructure: AMI is the combination of two technologies: digital meters that measure energy consumption and other data (i.e., kilowatt hour (kWh); usually at 1-hour, 30-minute, or 15-minute intervals) and a two-way communication component to transmit meter data to the utility (usually daily or more often), and to send utility signals to the meter. Utility AMI deployment accelerated circa 2010; by 2022, 72% of electric meters were AMI.[28,29] Recently, some utilities have started deploying second-generation AMI meters ("AMI 2.0"), which include better on-board computer processors, more memory, and on-board software to improve data capture, communications, and analysis at the meter (also known as grid-edge computing).[30] Utilities typically request regulatory approval to invest in AMI.[31]

Artificial Intelligence (AI): Computer systems that perform complex modeling in ways that mirror human cognition. AI systems are designed to perceive environments (real or virtual), to abstract perceptions and model trends in an automated way, and to use the models to make predictions, recommendations, or decisions.[32,33] Most AI available today involves an AI technique called machine learning:

- **Machine Learning:** AI models designed to find patterns in data, iteratively learn from both the inputs and outputs, and improve model performance through trial and error. Machine learning models differ from statistical analysis in terms of their ability to handle more data, to handle unlabeled data, and in how they are 'trained' through many layers of analysis to extract complex relationships. These layers are called neural networks because they work in a manner "suggestive of the connections between neurons in a human brain..."[34]
- The most complex machine learning algorithms are called 'deep learning' and use thousands of layers of these neural networks. Whether applied to numerical data, such as AMI data, or text, sound, and image data, such as generative AI, deep learning is effectively a tool for predicting complex trends and outcomes.[35]

Disaggregation: The process of breaking down meter-level electricity consumption data on a device-by-device or categorical basis to isolate what equipment or usage is contributing to the total consumption.[36] This is accomplished through deep learning analysis, sub-metering or sensors, population-level statistical assumptions, or a combination. In the deep learning approach, analysis of large meter-level datasets extracts and categorizes the unique energy use signatures of appliances and other behind-the-meter devices. Results can be used to identify equipment presence, characteristics, on/off state, time-stamped consumption (kWh/interval), demand (kW at peak) at specified confidence, and precision. Deep learning is typically more accurate than statistical approaches and much more scalable than sensor-based approaches and can be personalized to a cohort of one customer.

Electric Vehicle Supply Equipment (EVSE): Also known as an electric vehicle (EV) charger. The equipment that connects the AC electricity grid at a site to the EV. It can be Level 1 (typically 1 kW), Level 2 (typically 7 - 19 kW), or Direct Current Fast Chargers (DCFC) charging (typically >50 kW).[37]

EV Telematics: EV telematics refers to the communication of data between the vehicle and a data center (or "cloud"), enabling a range of consumer functions like remotely locking or unlocking a car, pre-conditioning the car's temperature, accessing emergency assistance, and for

28 U.S. Energy Information Administration (U.S. EIA) (2017). Nearly half of all U.S. electricity customers have smart meters.

29 U.S. EIA (2023). How many smart meters are installed in the United States, and who has them?

30 Deloitte Consulting (2022). Enabling the clean energy transition: Planning for next-generation advanced metering infrastructure and grid technologies.

31 NARUC (2022). Regulator's Financial Toolbox: Advanced Metering Infrastructure - Unlocking Resilience.

32 U.S. Department of Energy (n.d.) DOE Explains...Artificial Intelligence. Accessed: October 2024.

33 Executive Office of President Biden (2023). Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. Executive Order 14110.

34 Merriam-Webster (n.d.). Neural network. In Merriam-Webster.com Dictionary. Accessed: October 2024.

35 Dotan, R. (2024). How Does Generative AI Work? TechBetter. Accessed: November 2024.

36 Bidgely (n.d.). Empowering Utilities With True, Behind-the-Meter Disaggregation: Bidgely's Proven Approach And Real-World Impact. Accessed: October, 2024.

37 U.S. Department of Transportation. (n.d.). Electric Vehicle Charger Types and Speeds.

location and navigation services. Telematics also can be used to send control commands to the vehicle from a utility or third-party aggregator for active managed charging and retrieving charging session data for program participation verification.

Managed Charging: Approaches that shift EV charging to reflect utility, customer, and grid priorities. See SEPA's State of Managed Charging in 2024 for extensive discussion and outlook.[38]

- **Active Managed Charging:** EV charging is controlled (e.g., temporarily throttled or paused entirely) by signals sent to a vehicle or charger at discrete events or on a continuous basis.
- **Passive Managed Charging:** Also known as behavioral load control, relies on customer behavior to align charging patterns with grid needs. Price signals such as Time-of-Use rates are often used to influence behavior, but ultimately, the customer remains in control of the vehicle charging.

Time-of-Use (TOU) Rates: A TOU electricity rate reflects the cost of electricity at different times of day. Generally, a customer on a TOU rate will pay higher rates during a block of time when electricity demand is at its peak and electricity is most expensive, and lower rates off-peak when these factors subside.

Vehicle-Grid Integration: Vehicle-grid integration (VGI) refers to technologies, policies, and strategies for EV charging, which alter the time, power level, or location of the charging (or discharging) in a manner that benefits the grid while still meeting drivers' mobility needs.[39]

38 Smart Electric Power Alliance (2024). The State of Managed Charging in 2024.

39 California Energy Commission (n.d.). Vehicle-Grid Integration Program. Accessed: October, 2024.

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