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Electric Vehicle Load Shape Development for Electric Utility Planning

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NOTE

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ABSTRACT

This report focuses on ways electric utilities can estimate electric vehicle (EV) load shapes. EV load shapes are important for utility distribution and system planning and are becoming critical as the number of EVs charging on the electric system increases. Without incorporating the impacts of EV charging into utility planning, the industry risks insufficient capacity on the distribution system and on supply as more and more customers adopt EVs. This white paper provides definitions, presents general background information on EVs, explains why EV load shapes are important, describes considerations and decisions that must be made for a study to develop EV load shapes, and provides examples of key research questions that should be considered in any EV load study.

Keywords
Diversified load shapes
Electric vehicles (EVs)
EV chargers

DEFINITIONS

The following definitions are provided up front to allow the reader a better understanding of this white paper.

AMI = Automated Metering Infrastructure (smart meters capable of interval load capture)

BEV = Battery Electric Vehicle (electric charged battery-only that plug in to charge)

DCFC = Direct Current Fast Charger (sometimes referred to as Level 3 DC charger) typically uses 3-phase 480 V alternating current to deliver greater than 50 kW of DC charging power

EV = Electric Vehicle, including battery electric vehicles and plug-in hybrid electric vehicles

EV Chargers = Includes Level 1, Level 2, DCFC, and Tesla Superchargers

HDV = Heavy-Duty Vehicles; includes transit and tour buses, heavy semi tractors, refuse trucks, and others. Per the Federal Highway Administration, includes vehicles in classes 7 and 8 with gross vehicle weight ratings greater than 26,000 pounds

LDV = Light-Duty Vehicles; includes passenger cars, pick-up trucks, and passenger vans. Per the Federal Highway Administration, includes vehicles in classes 1 and 2 with gross vehicle weight ratings of up to (and including) 10,000 pounds

Level 1 Charging = Charging through a standard 120-volt outlet at less than 2 kW, adding about 4-8 miles[1] range per hour of charge

Level 2 Charging = Charging through a 240-volt outlet at 3.3 kW to 19.2 kW adding 12 - 75 miles of range per hour of charge

LR BEV = Long Range Battery Electric Vehicles (one of two subsets of Battery Electric Vehicles)

MDV = Medium-Duty Vehicles; includes school buses, step vans, bucket trucks, and others. Per the Federal Highway Administration, includes vehicles in classes 3, 4, 5, and 6 with gross vehicle weight ratings of 10,001 to 26,000 pounds

PHEV = Plug-In Hybrid Electric Vehicle (includes a small gasoline engine for range extension)

SR BEV = Short Range Battery Electric Vehicles (one of two subsets of Battery Electric Vehicles)

Tesla Supercharger = A Tesla Supercharger is a 480 Volt DC Fast Charging station built specifically by and for Tesla, Inc. electric vehicles

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[1] Please note, these estimates of range vary depending on the source.

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REPORT FORMAT

The remainder of this white paper is divided into sections focusing on various aspects of the evolving EV market and how best to capture the demand and energy usage characteristics for planning. The sections include:

- **Background.** This section provides foundational information on the different EV types, their range characteristics, and important aspects of the charging infrastructure.
- **Load Profiles for Planning.** This section begins explaining why EVs are becoming increasingly important to utilities and commissions. For utilities, EVs can be viewed as both a blessing – by providing increased load growth – and a curse – if that load growth occurs at the wrong time during the day or at the wrong point in the distribution system.
- **Load Shape Development.** This section highlights decisions that must be made when utilities embark on efforts to collect EV charging load shapes, including what customer characteristics and charging behavior considerations are crucial for structuring a study, and what steps to take in that effort.
- **Research Questions.** The paper concludes with a series of possible research questions and analysis methods to consider during project design.

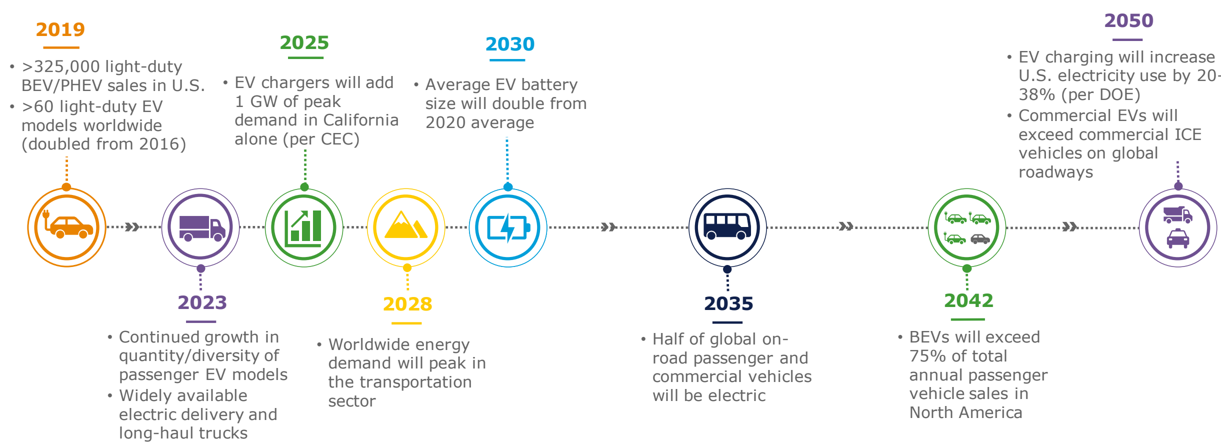
Appendix A includes abstracts related to EVs from the 40th Peak Load Management Association (PLMA) conference held in November 2019 in St. Petersburg, FL as additional references.

2
BACKGROUND

In this section we provide broad background information on EV markets, types of EVs, and types of charging infrastructure.

Market Status

On the road in the U.S. today, there are nearly 1.5 million EVs, including both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs). In the coming decade, EVs will become an increasingly important component of the energy sector. By 2024, light-duty EVs are expected to reach cost parity[2] with their combustion engine counterparts. Moreover, by 2025, DNV GL[3] estimates that there will be a total of 6.14 million EVs on the road in the U.S. with nearly 84% of them BEVs. In the 2019 Energy Transition Outlook (ETO), DNV GL predicts that by 2032, one-half of all light duty vehicles sold in North America will be electric.[4] The ETO predicts this transition will occur even earlier in Europe—by 2027. Figure 2-1 summarizes current EV market status and provides projections through 2050.



Source: DNV GL, 2020

Figure 2-1
EV Market Status – Current and Projected

The electric utility industry views EVs as both an amazing opportunity and formidable challenge. EVs will certainly increase electricity sales but they will also have a significant impact on the distribution network from the sizing of local transformers to the build-out of a nationwide direct current fast charging (DCFC) network. As consumer confidence and EV range extend, energy use per EV will increase. Preliminary data presented at the 2019 Peak Load Management

[2] Based on full lifecycle costs including fuel and maintenance.

[3] Det Norske Veritas is a recognized international leader in the fields of energy program research & evaluation and load research & analytics with extensive offices in the United States.

[4] DNV GL, 2019. Energy Transition Outlook 2019: A global and regional forecast to 2050. Online at https://eto.dnvgl.com/2019/index.html.

Alliance (PLMA[5]) conference from the SmartCharge Nashville project suggests the average annual energy use associated with EVs has the potential to double as consumers shift from PHEVs like the Toyota Prius Prime PHEV6 (2,350 kWh/year) to long range BEVs (LR BEVs) like the Tesla Model 3 (5,000 kWh/year).

Papers and presentations of EVs at industry conferences are becoming more prevalent. At the 2019 PLMA conference, for example, there were several sessions dedicated to various aspects of EVs and electric transportation including utility promotion of residential and commercial fleet electrification, EVs as a flexible load option for utilities, and EV infrastructure expansion. Clearly, EVs will play an increasingly important role in electric utility planning and operations.

An important element for utility planning is the development of a realistic diversified load profile representing the current and future state of EV utilization. This paper provides a discussion guide on the development of diversified residential EV load shapes. Utility planning load shapes need to properly account for several factors including, but not limited to:

- The type of vehicle, including PHEV, short range BEVs (SR BEVs), and LR BEVs, and the current and future level and mix of EV adoption across these types of vehicles;
- The geographical location and clustering of EVs based on the socio-economic or like mindedness of neighborhoods causing localized grid issues even for utilities with a small saturation of EVs;
- The type of charging infrastructure, such as at-home charging versus third-party charging (i.e., charging at work or at public charging facilities);
- The level of alternative charging voltages including Level 1 charging (120V), Level 2 charging (240V), and DCFC (480V);
- Proper identification of the population frame (i.e., understanding who in the market actually owns the different types of EVs); and
- Identification of what to measure (i.e., charging at the home or at the vehicle). Measuring at the vehicle level captures charging that occurs in different locations--such as at work and at home--whereas measuring at the charger level captures charging at that location only.

EV Types – the Changing Market (PHEVs to BEVs)

The EV market is changing rapidly. Initially, many consumers desired an on-board gasoline engine to help overcome the range anxiety associated with early EVs. However, the ongoing cost reduction and performance improvements of battery technology have resulted in declining EV costs and extended battery range. In 2019, EV sales were just under 330,000 vehicles in the U.S. market. BEVs represented nearly three-quarters of total 2019 EV sales while PHEVs represented approximately 26% (Figure 2-2). Tesla's release of the Model 3 BEV in 2018—with a starting price under $40,000 and range exceeding 200 miles—quickly demonstrated U.S. car buyers'

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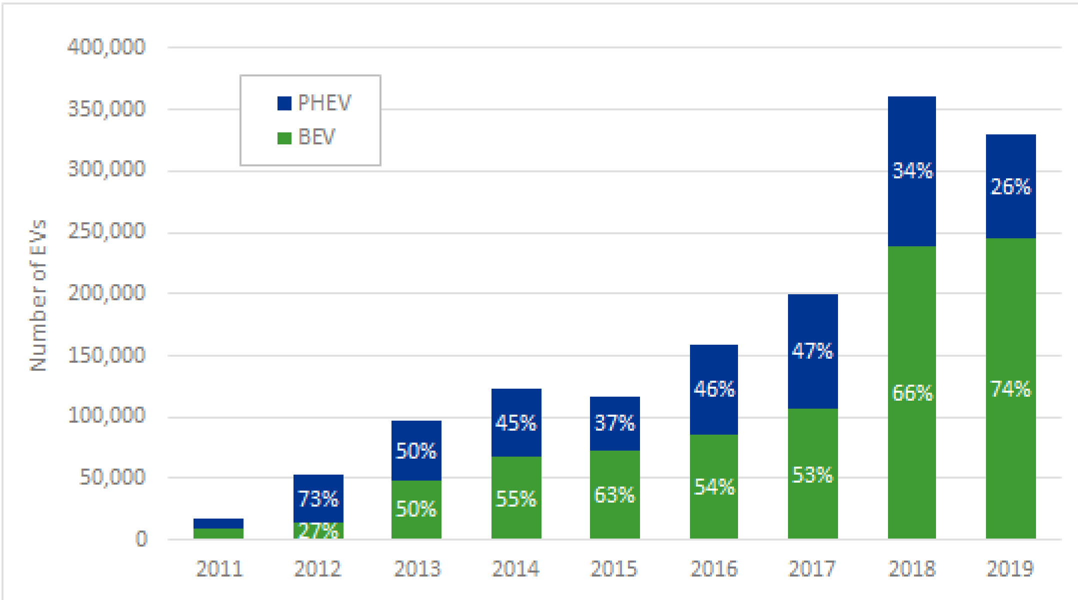
[5] The Peak Load Management Alliance is an industry organization dedicated to sharing knowledge and providing resources to promote inclusiveness in the design, delivery, technology, and management of solutions addressing energy and natural resource integration. https://www.peakload.org. Appendix A includes EV-related abstracts from the most recent PLMA conference.

[6] Please note, these are different from the first-generation gas-electric Prius hybrids (non-PHEV).

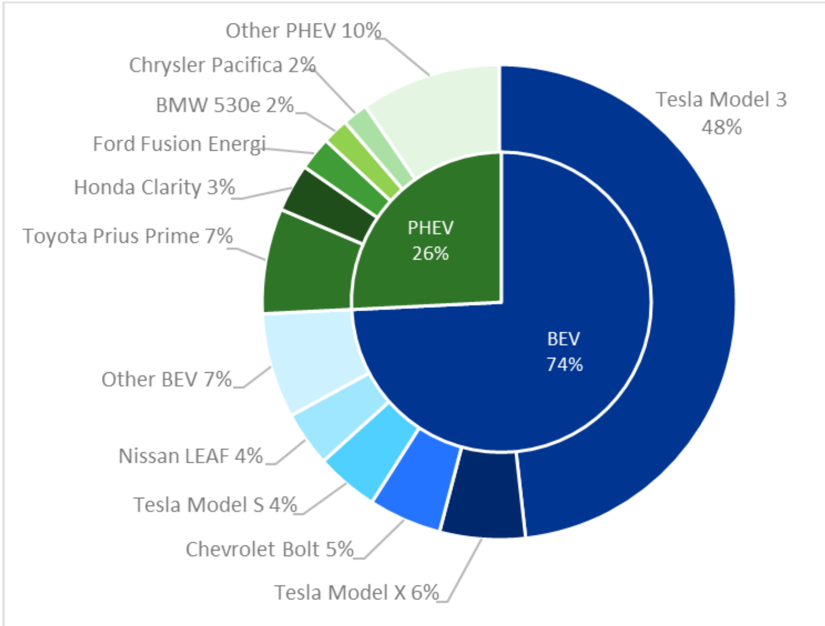
willingness to drive BEVs. The Model 3 alone represented 59% of total U.S. EV sales in 2018 and 48% in 2019, and BEVs represented 66% and 74% of U.S. EV sales in 2018 and 2019, respectively.



Source: DNV GL, 2020 based on InsideEVs, 2020

Figure 2-2
Total U.S. EV Sales and Percentage of Sales by BEV and PHEV, 2011-2019

As mentioned above, the Tesla Model 3 was responsible for nearly half of all 2019 EV sales in the U.S. (48%; see Figure 2-3). Tesla's Model S and Model X—both BEVs—were also among the top ten EVs sold in 2019. The Toyota Prius Prime PHEV was the top-selling PHEV in 2019, representing 7% of total U.S. EV sales and more than a quarter of total PHEV sales (27%).



Source: DNV GL, 2020 based on InsideEVs, 2020; 2019 EV sales = 329,528

Figure 2-3
Share of Total 2019 U.S. EV Sales by Type (BEV and PHEV) and Model

EPRI recently released a 2020 Consumer's Guide to Electric Vehicles, which discusses current BEV and PHEV options.[7] Table 2-1 highlights all BEV makes and models available in the U.S. in 2020 along with their associated driving ranges on a full charge (in miles). Here, we draw the distinction between SR BEV and LR BEV with the latter including vehicles with a range greater than 200 miles on a single charge. Data from a 2015 study suggest Americans drive 29.2 miles per day, on average, with total daily driving time averaging 46 minutes per day. While average daily driving distances vary by gender and age group[8], all EVs on this list are enough to meet at least double the average daily driving distance. However, having enough range to meet the average daily driving distance still may not reduce range anxiety which is more likely tied to the maximum distance a customer expects to drive.

[7] *Consumer Guide to Electric Vehicles, April 2020*. EPRI, Palo Alto, CA: 2020. 3002018113.

[8] See, e.g., Department of Transportation Federal Highway Administration, 2000. Average Annual Miles per Driver by Age Group. Online at https://www.fhwa.dot.gov/ohim/onh00/bar8.htm.

Table 2-1
2019 BEV Models and Associated Range (Miles)

Type	BEV Make and Model	Range (Miles)
Short Range BEVs	FIAT 500e	84
	MINI Cooper SE	110
	Volkswagen e-Golf	123
	Nissan LEAF and LEAF Plus	150 and 226
	BMW i3	153
	Hyundai Ioniq Electric	170
Long Range BEVs	Porsche Taycan Turbo	201
	Audi e-tron	204
	Tesla Model 3	220-330
	Jaguar I-PACE	234
	Kia Niro EV	239
	Chevrolet Bolt EV	249
	Tesla Model X	258-328
	Hyundai Kona Electric	258
	Tesla Model S	287-373
	Tesla Model Y	315

Type of Charging Infrastructure

As of early 2020, industry estimates suggest most charging occurs at home (81%) with 6% occurring at work, 3% at public charging locations, and the remaining 10% undefined or other[9] (however, the share of public charging is likely increased by owners of Tesla vehicles which had free "SuperCharger" use, but had to pay for electricity at home).[10] Approximately three-quarters of this charging occurs at Level 2 (74%[11]), i.e., in the 3.3 kW to 7.2 kW range. This is followed by Level 1 (24%) with the remaining 3% through DCFC. Obviously, Level 1 charging is much slower, occurring at 120 Volts. Some estimates place a 100-mile range on Level 1 charging at more than 24 hours. However, a typical day of driving (29.1 miles, as described above) can be charged overnight. Charging with DCFCs occurs at high voltage and can range from 50 kW to 350 kW (depending on the capabilities of the BEV) resulting in 100-mile charging times of 30 minutes to as low as 10 minutes.[12]

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[9] *Electric Vehicle Driving, Charging, and Load Shape Analysis: A Deep Dive into Where, When, and How Much Salt River Project (SRP) Electric Vehicle Customers Charge*. EPRI, Palo Alto, CA: 2018. 3002013754.

[10] *Electric Vehicle Driving, Charging, and Load Shape Analysis for Tesla Drivers: A Deep Dive into Where, When, and How Much Salt River Project (SRP) Tesla Electric Vehicle Customers Charge*. EPRI, Palo Alto, CA: 2019. 3002015601.

[11] *Electric Vehicle Driving, Charging, and Load Shape Analysis: A Deep Dive into Where, When, and How Much Salt River Project (SRP) Electric Vehicle Customers Charge*. EPRI, Palo Alto, CA: 2018. 3002013754.

[12] Charging times will depend on several factors, including battery temperature, ambient temperatures, battery state of charge, and charging station power capacity. Most current vehicles are only able to sustain maximum charging power with low battery state-of-charge (battery is almost empty) and favorable ambient temperatures.

Not all EVs are compatible with DCFCs. Figure 2-4 presents the percentage of BEV sales that are compatible with DCFC greater than 100 kW. The increase in percentage is directly related to the popularity of the Tesla Model 3—released in mid-2017—which has a maximum charging power capacity of 250 kW.

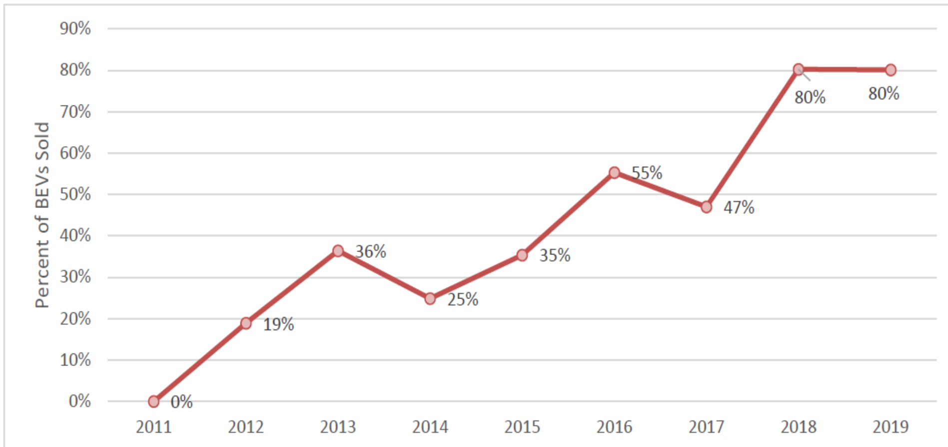
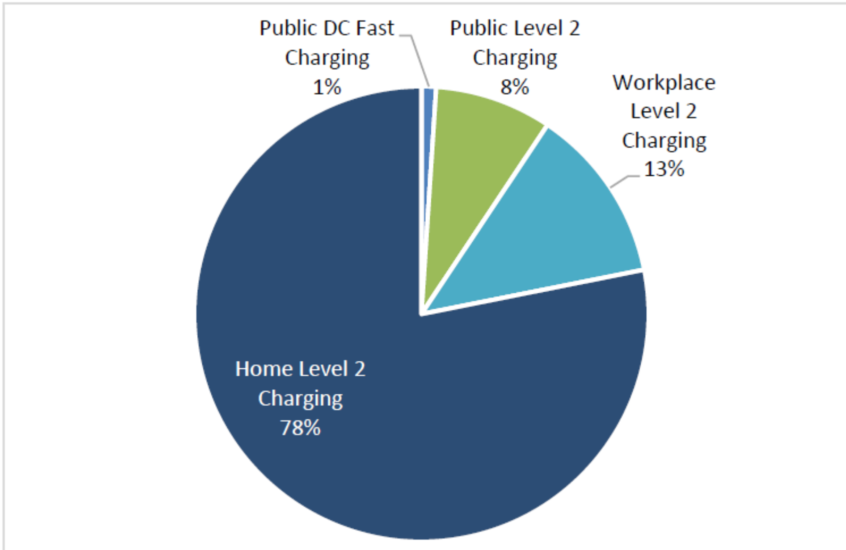


Figure 2-4
Percent of BEVs Sold That Are Compatible with >100 kW Max Charging Power, 2011-2019

As we assess the value of capturing the load profiles associated with EV charging it is important to note where the charging is likely to occur during the planning horizon. Even by 2030, the Institute for Electric Innovation and the Edison Electric Institute estimate that most charging will be Level 2 and will occur at home (78%; see Figure 2-5). Workplace Level 2 charging will account for 13% and public charging will account for an additional 8%. Public DCFC will play a minor role at just 1%. The continued reliance on at-home charging will place added burden on the electric utility infrastructure to ensure the distribution system can handle the increase in load.



Source: Institute for Electric Innovation and Edison Electric Institute, 2018.

Figure 2-5
Projected Share of Total EV Charging Infrastructure by Type and Location, 2030

3

LOAD PROFILES FOR PLANNING

For planning purposes, utilities are developing load profiles for EVs based on any available data. For companies with AMI data and a well-defined population, this can be a relatively simple task. For others, this exercise is more complicated and often turns out to be a modelling exercise built on assumptions.

Figure 3-1 presents an illustrative example of a diversified load profile for Level 1 charging. The figure presents an EnergyPrint of the EV load. The horizontal EnergyPrint presents a full year of data with the time of day on the vertical y-axis, the month of the year on the horizontal x-axis, and the diversified load of the EV shown as a color gradient with low levels of load in the black-blue spectrum and high levels of load in the yellow-white spectrum. This example assumes that the load is mostly off-peak beginning after 6pm and ending just after midnight. There was some assumed monthly variation included and no load management applied. Under this scenario, the modelled load is estimated to have an average annual use of 2,753 kWh with a maximum diversified demand of 0.80 kW. This translates into an annual load factor of 39%.

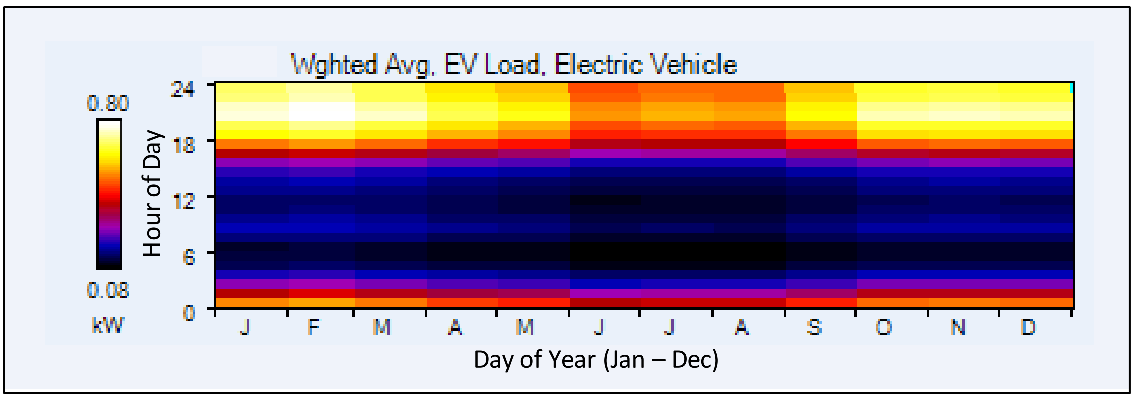
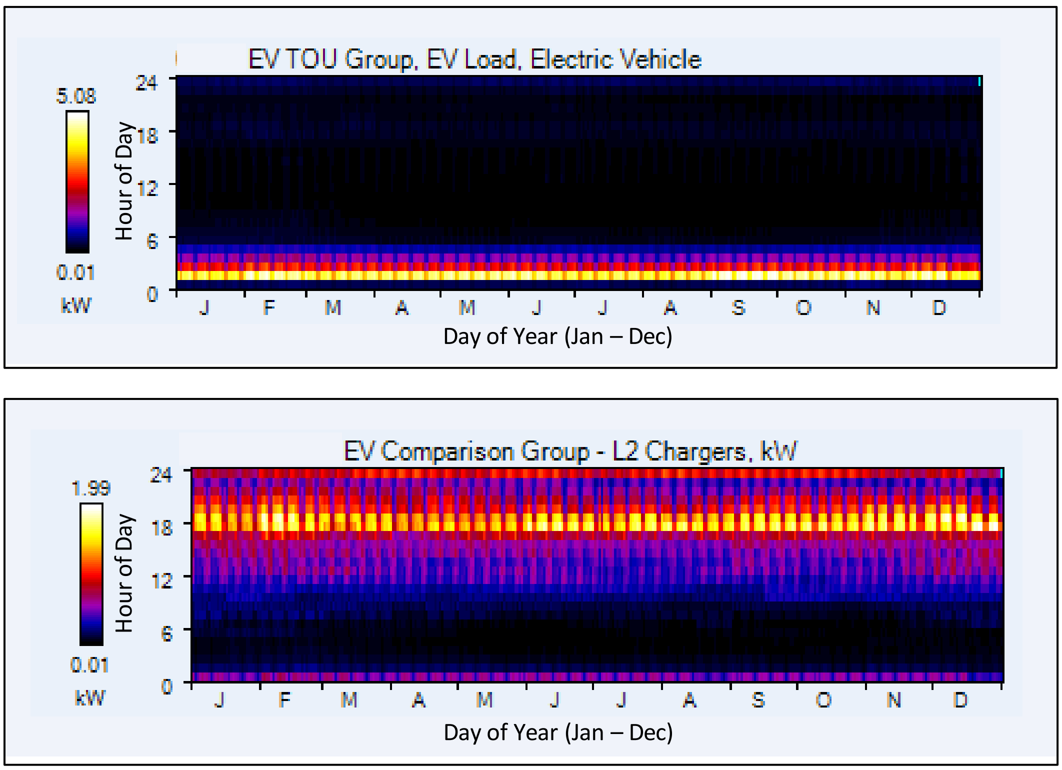


Figure 3-1
EV Modelled Load Profile

It is important to note here the meaning of a diversified load shape and how that differs from an individual charging load shape. Individual shapes represent a single charger, without averaging. When charging, the shape is dependent on the charging characteristics of the vehicle when being charged. There is considerable variation in the shape of the charge curves across models, with certain models capable of a stepped decline, a gradual decline, a sharp linear decline, or almost no decline. Clearly, this is another element for consideration in a study design.

When the charger is not charging, there is no electricity usage. But when many chargers are aggregated together or averaged, the resulting load shape is diversified, meaning that at most times, there are zero and non-zero values being averaged together. The diversified shape indicates the overall charging behavior of the group but does not usually look the same as a single, individual charging load shape. One key aspect of diversified averages is that the peak of the average is nearly always less than the average of the peaks, since those peaks generally do not all happen at the same time. The diversified average shape is almost always more useful to utility planners, since it represents the collective behavior of multiple charges, and indicates the impact that the group has on the system. However, the size and diversity in the group is important as it affects how coincident the charging behavior is across customers.

A long-term project for Dominion Energy Virginia used data loggers installed on at-home EV chargers to collect direct usage data.[13] The EV chargers included a combination of Level 1 and Level 2 chargers, however most were Level 2 chargers. Figure 3-2 shows the diversified average EV load of participants on a "super off-peak" time-of-use (TOU) rate program[14] compared to a comparison group of customers with Level 2 chargers but not on the TOU rate. For the TOU customers, most of the energy was consumed in the 1am to 5am period (81%). The average annual use was just over 4,000 kWh with a non-coincident peak demand of 5.08 kW translating into an annual load factor of just under 9%. The TOU rate participants showed less diversity and therefore a much higher diversified demand than the comparison group participants. Clearly, having data at the charger provides a very clear indication of the load profile associated with the EV charging equipment.



Source: Dominion Energy, 2017

Figure 3-2
EV Only Load "Super Off-Peak" TOU Rate versus Comparison Group

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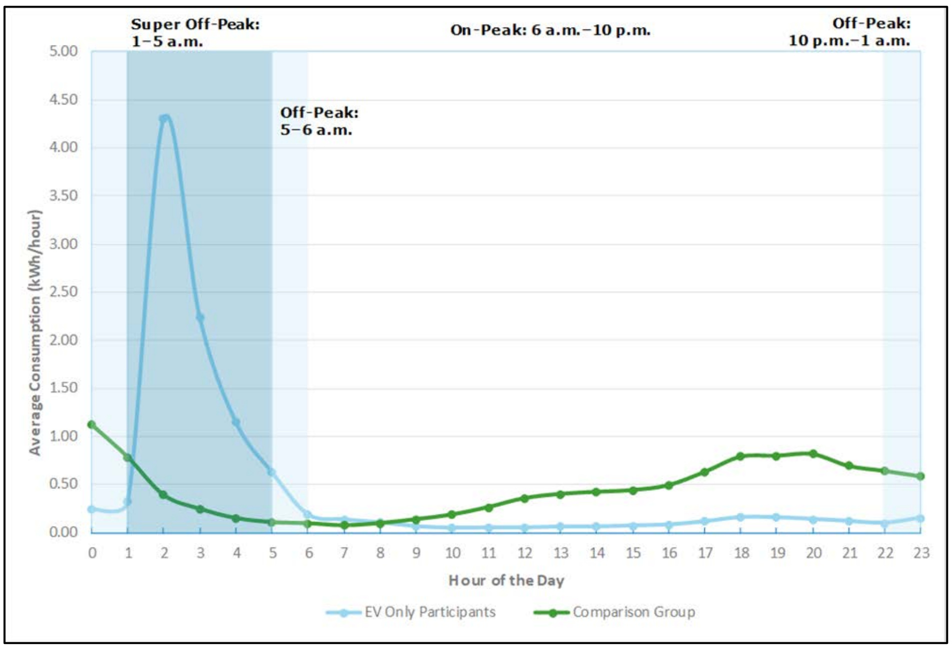
[13] Electric Vehicle Program, Evaluation, Measurement & Verification Report, Dominion Energy, 11/1/17.

[14] The term super off-peak is coined by the authors with the hours defined as 1am to 5am, the rate was not marketed as such. The super off-peak generation plus distribution charge was $0.00695/kWh compared to the on-peak rate of $0.13300. The transmission charge was the same for both time periods at $0.00970/kWh.

Figure 3-3 shows the average daily diversified, “charger only”, load profiles for the TOU and comparison group customers on the same graph. The TOU customers clearly took advantage of the super off-peak rate and charged during this period. In contrast, the comparison group customers charged during the 5pm to 9pm period with an additional bump in the midnight to 1am period.

For the TOU customers, the average daily demand approached 4.4 kW or 87% of the maximum diversified demand of 5.08 kW displayed in Figure 3-2. In contrast, the average daily demand of the comparison group peaked at just over 1 kW or about 50% of the 1.99 kW maximum diversified demand. For the average day profiles, the TOU customers use a substantially compressed time frame of charging, nearly eliminating charging outside of the super off-peak window. This produces a daily diversified peak that is over four times their comparison group counterparts. If we assume that the system peak occurs at hour ending 1600 (4pm) then we can see that the TOU customers contribute very little to the system peak, whereas, their non-TOU counterparts contribute just over 0.5 kW per customer.



Source: Dominion Energy, 2017

Figure 3-3
Annual Average 24-Hour Diversified Load Profile (Charger Only Load)

Table 3-1 presents a classic load profile representation of an annual load profile by presenting the peak-like days, average weekday, and average weekend day for the summer, winter and spring/fall seasons. The table presents the number of days and the average hour ending profile. This particular year was a leap year and contained 366 days

Table 3-1
Classic Load Profile Layout (Hour Ending)

Season	Day Type	Number of Days	HE1	HE2	HE3	HE4	HE5	HE6	HE7	HE8	HE9	HE10	HE11	HE12	HE13	HE14	HE15	HE16	HE17	HE18	HE19	HE20	HE21	HE22	HE23	HE24
Summer	Peak Day	12	1.23	0.79	0.33	0.21	0.12	0.08	0.08	0.07	0.09	0.11	0.16	0.25	0.33	0.33	0.35	0.38	0.43	0.59	0.86	0.83	0.80	0.62	0.62	0.56
	Weekday	77	1.28	0.81	0.37	0.21	0.11	0.07	0.07	0.06	0.09	0.12	0.18	0.25	0.35	0.35	0.37	0.38	0.46	0.69	0.93	0.93	0.92	0.75	0.67	0.64
	Weekend	34	1.09	0.79	0.36	0.21	0.11	0.07	0.06	0.04	0.04	0.11	0.15	0.28	0.44	0.46	0.48	0.49	0.51	0.57	0.59	0.50	0.46	0.37	0.38	0.39
Winter	Peak Day	4	0.98	0.74	0.41	0.32	0.22	0.17	0.18	0.11	0.14	0.20	0.23	0.29	0.37	0.46	0.53	0.52	0.53	0.69	0.82	0.85	0.92	0.77	0.71	0.62
	Weekday	80	1.06	0.82	0.43	0.30	0.20	0.14	0.14	0.12	0.16	0.17	0.20	0.27	0.34	0.43	0.45	0.45	0.51	0.69	0.89	1.01	1.08	0.91	0.81	0.71
	Weekend	37	0.92	0.81	0.44	0.30	0.20	0.14	0.12	0.08	0.08	0.16	0.18	0.30	0.44	0.57	0.60	0.59	0.58	0.58	0.58	0.55	0.54	0.46	0.47	0.44
SpFall	Weekday	85	1.27	0.80	0.39	0.24	0.14	0.10	0.09	0.06	0.09	0.13	0.21	0.26	0.32	0.35	0.37	0.41	0.49	0.66	0.89	0.92	0.96	0.86	0.78	0.68
	Weekend	37	1.11	0.79	0.40	0.24	0.14	0.10	0.06	0.04	0.05	0.12	0.18	0.28	0.41	0.46	0.48	0.53	0.54	0.55	0.58	0.49	0.49	0.44	0.45	0.42
	Totals	366	Sample Size (n=18)																							

Notes (for this table):

- Customers were under the standard (non-TOU) residential rate
- Summer is defined as May 16 through September 15
- Winter is defined as November 16 through March 15
- Spring/Fall is defined as September 16 through November 15 and March 16 through May 15
- Summer Peak days are defined as summer days whose peak hour falls within five percent of annual system peak (number may vary from year to year but a minimum of one day)
- Winter Peak days are defined as winter days whose peak hours fall within five percent of the annual system peak (number may vary from year to year but a minimum of one day)
- Weekends include holidays of New Years, Presidents, Memorial, Independence, Labor, Columbus, Thanksgiving and Christmas

As noted, Table 3-1 shows a sample load profile that could be used for utility planning and perhaps for market potential and rate studies. In this example the sample size is 18 and reflect level 2 chargers on non-time differentiated rates.

What is interesting in this mapping is that the likely system peak hours HE18 in the summer and hour HE6 in the winter. There are not substantial differences between different peak days, average weekdays or weekend days throughout the seasons.

These data may be used for baseline EV forecasting and for subsequent time differentiated rate system peak impacts. Further details on designing a study and their level of statistical significance may be found in Appendix B.

4

LOAD SHAPE DEVELOPMENT

In this section, we review several considerations and decisions analysts need to make during the planning phase of an EV load shape development project. We examine the following elements in more detail in this section:

1. **Who has EVs?** A fundamental question in any project is the proper identification of a population frame. If the population is not known, it is impossible to know whether the results are representative of that unknown population.
2. **What data are you going to collect?** There is a substantial amount of data that should be collected during the study. This includes information regarding the EV, EV chargers, customer characteristics, demographic characteristics, and so on. Considerations on the data resolution should also be considered, depending on the questions being asked.
3. **What level of charger is important?** With the likely prevalence of Level 2 chargers, are these the only ones that need to be studied? Should any effort be dedicated to Level 1 chargers? Will utilities have the DCFC chargers on a separate rate (as they are often in commercial locations) or require interval load metering so that they can be more readily tracked and captured?
4. **What about charger location?** The location of the charger is an important planning consideration. Utility planning may require several different perspectives to be represented, e.g., at-home charging, workplace charging, public charging, or charging that occurs in transit corridors (such as DCFC charging on highly travelled routes). EPRI and other governmental agencies reference a standard set of definitions of home, work, and community. Distribution planners will be concerned about the number and location of chargers on a circuit or tied to specific distribution assets. In addition, the utility planners will need to engage and play an important role in helping community planners to design and build out public charging infrastructure.
5. **How do you capture the necessary data?** Do you isolate the EV charger-only load or capture the whole facility loads of customers with chargers? Isolating the charger load will require a separate meter at the EV charger whereas the whole facility load may be available through the AMI system. There are systems that capture data at the vehicle through putting a physical device on the vehicle that logs the data. Teslas allow data logging remotely through their publicly available API and therefore a physical device is not needed, making data collection easier and in most cases less expensive.[15] Other vehicle manufacturers may offer a similar option in the future. The device can capture all charging data for any station type and at any location – not just at home.
6. **What are you going to monitor?** The EV charger or the EV? Most charging occurs at home using the EV charger installed at the residence. However, charging can also occur at work or

[15] https://www.epri.com/research/products/3002018605

at public charging infrastructure. Analysts must decide whether to simply monitor a specific charger (at-home or other) or to monitor the a specific EV's charging, regardless of where charging it takes place. This is also a question of how the population is defined: are you studying a population of EVs or a population of EV chargers?

7. **What other elements should the utility planner consider?** These may include interval length, frequency of data transfer, storage medium, other topics?

The following sections explore these questions in greater depth.

Population Frame Identification

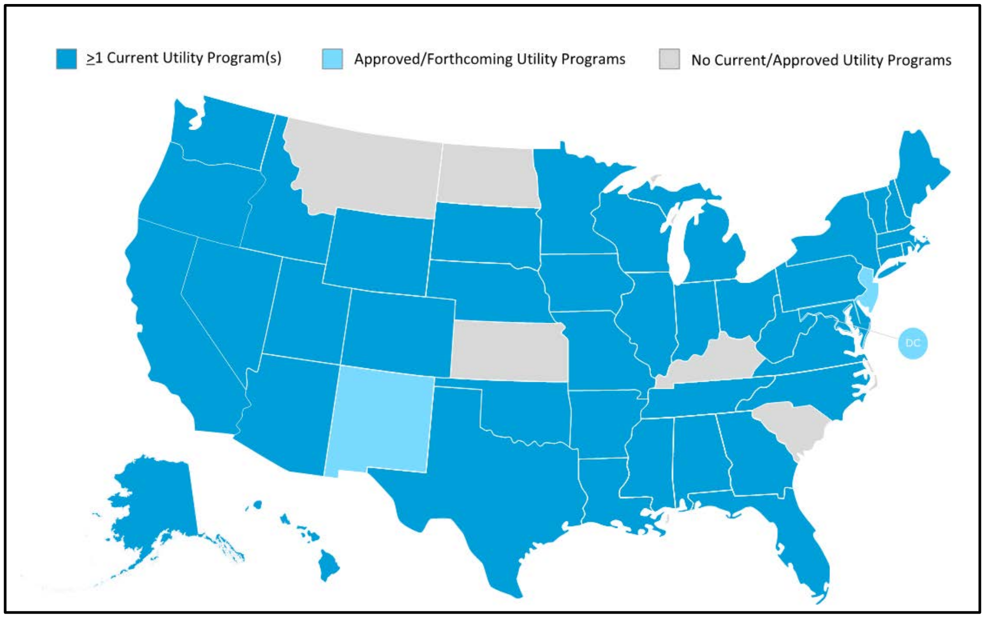
One of the significant challenges confronting utility research regarding EV load characteristics is the ability to adequately develop and define a population frame for sampling. How can researchers know who has EVs, where they are, and the types of EV chargers they are using? There are several possible approaches to address this issue.

Utility and State EV Programs. As of early 2020, utilities in at least 45 U.S. states had active customer programs offering discounted rates or other incentives for off-peak EV charging and/or incentives to defray the purchase costs of EVs and/or EV chargers. These programs target residential and/or non-residential utility customers (ratepayers) and a variety of EV charger applications (e.g., to serve single-family homes, workplaces, public sites, multi-unit dwellings, fleets, and/or government/institutional properties). Table 2 summarizes the types of EV programs found in the U.S. market. For utilities implementing these types of programs, at least a partial population frame can be constructed from the customers who are taking advantage of the various program offerings. But it is important to note that these will only be partial frames, excluding those who own EVs but do not participate in utility programs.

Table 4-1
Types of U.S. Utility EV Program Offerings

Program Type	Description
Rates or Load-Shifting Incentives	Discounted rates, rebates, or similar incentives to utility customers for EV charging during off-peak periods. Typically for residential customers.
Residential **EV** Incentives	Rebates, purchase discounts, or similar incentives to residential utility customers. Typically for new EVs; occasionally for used/leased vehicles.
Commercial **EV** Incentives	Rebates, purchase discounts, grants, or similar incentives to non-residential utility customers for new EVs. Typically for light-duty EVs; occasionally for off-road and/or medium-/heavy-duty EVs.
Residential EV Charger Incentives	Rebates or similar incentives to residential utility customers for Level 2 EVSE for the home. Typically for residential customers in single-family homes, occasionally for residents of multi-unit dwellings.
Commercial EV Charger Incentives	Rebates, grants, or similar incentives for either Level 2 EV chargers or DCFC to commercial utility customers including owners/managers of multifamily dwellings and/or non-residential properties (including government) for public, workplace, and/or fleet charging applications.

Figure 4-1 highlights the states with current or approved and upcoming EV programs and/or rates designed to support EV charging (e.g., TOU rates) as of February 2020. The utility programs can be looked at as a source for constructing at least a partial population frame, however, this may be an optimistic view.



Source: DNV GL, 2020 based on U.S. DOE Alternative Fuels Data Center, 2020 and supplemental research.

Figure 4-1
Utilities Offering Incentives and Rates for Off-Peak EV Charging, EVs, and/or EV Chargers by U.S. State, February 2020

For utilities not offering an incentive or rate program, it may be a good strategy to start a low-cost incentive or registration program in order to get a list of EV ownership. In the absence of a program, utility analysts will need to turn to secondary sources--for example, information from the state Department of Motor Vehicles (DMV) coupled with utility surveys may provide some insight based on geographic area.

Other List Sources. In the absence of a utility-sponsored program—or to supplement utility program information—various resources provide information on EV ownership. The Alliance of Auto Manufacturers has a website—the Advanced Technology Vehicle Sales Dashboard—that shows sales and market share information by state by month since 2011.[16] The DMV for various states may provide summaries of EV ownership to the utilities based at the zip code level, and private companies provide similar information at a cost. EPRI provides members of the Electric Transportation Program with reports on registrations within their service territory.

Leveraging AMI Data. With the advent of AMI data, utilities are well positioned to investigate the load characteristics of virtually any domain of interest if that domain can be identified in the population. Of course, the challenge is identifying customers with EVs from the general population.

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[16] See https://autoalliance.org/energy-environment/advanced-technology-vehicle-sales-dashboard/.

For those utilities with AMI deployed for all or nearly all customers, advanced analytics offers possibilities for identifying the population frame. Customers with EV chargers at their homes may have distinctive patterns in their energy use that could allow utility researchers to define a more complete population frame. Identifying Level 2 charging based on fifteen-minute or five-minute interval data should be possible. Level 1 charging, on the other hand, will be difficult to identify due to the smaller magnitude of load. And because many AMI systems collect data in hourly increments, there would be more challenges in detecting even Level 2 charging of short duration. One early attempt at using AMI data by Pacific Gas & Electric staff was not particularly successful in identifying EVs.[17] However, data mining algorithms have improved.

Survey and Third-party Data. Another option for defining a population frame would be to augment third-party data with targeted survey research to ask customers about EV ownership. Data collected from the state DMVs or other third-party information providers may provide a means to isolate concentrations of EVs. For example, state DMVs may not provide information on exact location but may provide counts of EVs by zip code. In turn, the utility could survey customers in the identified zip codes to identify EV ownership. A targeted web survey could be a means to increase the utility's knowledge of EV ownership. A targeted pre-study survey, e.g., targeting customers with high AMI usage during the off-peak periods, could be a means to identify additional EV owners and lessees.

Alternatively, third-party data coupled with AMI data and known EV ownership data could help develop a "customer profile" of current EV users that analysts could use to identify other possible EV owners. The customer profile could include location, demographic data (like age, income level, and so on), and load shape characteristics that would help to identify other EV owners.

What Data to Collect

EV Data Elements. The study purpose must dictate the data to be captured, but analysts should consider the following attributes:

- Make, model, and model year of vehicle;
- Categorization of vehicle, i.e., PHEV, SR BEV, or LR BEV;
- Home charger voltage, i.e., Level 1, Level 2, DCFC;
- Whole house energy interval data;
- Charger energy interval data;
- The amount of time the vehicle is charging, i.e., plugged in and/or charging,
- Frequently used charging location(s),
- Miles driven (weekly, monthly, annual, shortest trip, and longest trip),
- Geography, particularly the terrain characteristics, i.e., flat, hilly, mountainous, and
- Outside ambient temperature.

[17] EV Owner Identification Study, Pacific Gas & Electric, Erin Boyd and Andrew Lee, April 2016.

Survey data. To the extent that whole house AMI data are being used in the analysis, survey data provides valuable insights regarding the composition of appliance stock and the subsequent demand and energy characteristics of load in the rest of the house. EV-specific surveys directed at identifying the charging habits of the car owner or lessee could be valuable in characterizing the frequency of charging at home versus elsewhere[18]. Survey data also provides information and insight into the specific attributes of current EV owners, e.g., typical driving distance, income, age, family size, and so on. As suggested earlier, it may be possible to use AMI and survey data to create a population frame for utilities that do not have existing incentive or rate programs.

How to Collect Data

Whole building or directly measured end-use. Both whole building and EV charger interval load data would be extremely valuable to the utility planning team. Both profiles contribute to a more complete understanding of how EVs are changing the residential load shape. As discussed earlier, EVs have the potential to be either the first or second largest energy user in a home. For example, the current estimate of approximately 5,000 kWh per vehicle per year for Level 2 charging of a LR BEV represents a 75% increase in the average residential use of a customer in California (estimated at 6,684 kWh per year).[19] Furthermore, this is nearly a 45% increase in the average use of the typical U.S. home, which is estimated at 10,972 kWh annually.[20] Clearly, the presence of an EV will have a significant impact on the energy and demand characteristics of customers in the residential class.

Measurement at the EV charger or at the vehicle. Measurement at the EV charger provides a direct measurement of EV charging load characteristics at that site. It provides information on the number and timing of charge events, the duration of charging, and associated load characteristics. It does not capture other charging events that occur at locations other than the EV charger measured. Measurement that follows the vehicle is possible, either via the EVs onboard telematics systems or using a third-party measurement device. For example, in the SmartCharge Nashville project, the project team is using monitoring devices that plug directly into the EV's self-diagnostic port. The device captures all charging data for any station type and in any location – not just at home, but wherever charging occurs.[21]

Equipment choices absent AMI. As indicated, equipment choices depend on the focus of the measurement.

- If measurement is taken at the whole house, standard monitoring equipment could be used to capture the whole house load (e.g., pulse initiators and load recorders, or recorders under glass).
- If measurement is taken at the device, the type of end-use metering equipment is fairly open and can include various submeters coupled with appropriate data loggers.

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[18] Of course, if you can arrange access to the vehicle onboard charge/discharge logs, then these data will tell the vehicle's charging profile and where it occurred.

[19] www.electricchoice.com/

[20] www.eia.gov

[21] However, by default, GPS data are not collected while driving (for privacy purposes), so this method will not identify the specific charging locations.

- If measurement is taken at the car, specialized devices may be needed for data capture if the vehicle's onboard systems are insufficient to capture and transfer this information.

Other Considerations

Interval length (or data resolution). The Association of Edison Illuminating Companies (AEIC) load research manual provides direction on the factors to consider when defining the desired interval length for a load study.[22] These include:

- Characteristics of the attributes and parameters being measured or estimated;
- Compatibility with methodologies that utilize the results (e.g., planning, reporting, forecasting, etc.); and
- Data processing and storage resources and limitations (e.g., 5-minute data have twelve times the number of intervals as 60-minute data and, therefore, require twelve times as much data storage).

Please note, the study of end-use load patterns may require interval measurements of 1- or 5-minute duration to provide needed resolution or detail in the data profile. The interval length should be dictated by the information needed in the planning process—either 1, 5, 15, or 60-minute data. For most projects, 15-minute data is likely to be adequate, however, a higher resolution may be necessary to capture the actual peak demand.

Frequency of data transfer/collection. Data logger storage capacity and timing of reporting needs should dictate the frequency of data transfer. Where possible, the authors suggest that data be transferred daily to allow for continuous monitoring and quality control over the data stream. Historically, analysts have typically collected data at less frequent intervals (e.g., once or twice a month).

[22] Association of Edison Illuminating Companies, Load Research Manual Third Edition, 2017.

5

SAMPLING STRATEGIES AND RECOMMENDED SAMPLE DESIGNS

The appropriate sampling strategy depends on the quantity and quality of information available for the population frame as well as the precision required. We begin our discussion about sampling in the "ideal" world where information is available on the various attributes deemed important in the analysis. Ideally, the analyst would have the following information on the population of EV customers in their service territory:

- Customer rate and/or rate rider consideration;
- Make, model, and model year of the EV – used to stratify into PHEV, SR BEV, and LR BEV;
- At-home charging level – this could be used to stratify based on Level 1 and Level 2 charging to examine differences in distribution loads;
- Geographic location of the customer – used to stratify geographically – important for distribution planning purposes;
- Household electric consumption history pre and post EV purchase – the electric consumption data can be used to stratify the population, however this may or may not be related to EV usage.

If there is a specific rate or rate rider in place for EV owners and lessees, then it is appropriate to use this element in the sample design process. This likely provides the clearest indication of the EV population within the utility service territory. Of course, it is still possible to have additional EVs that are not part of the rate program in the service territory. At a minimum, an n-dimensional stratification based on vehicle type and at-home charging type would be effective, possibly also including geographical and consumption dimensions.

If the goal is to estimate the load for the population of public charging stations, and AMI data are available, then there is no need for sampling. But if a sample is needed, an appropriate stratification could be based on the number of plugs at each station, if that is known. Stratifying based on billing energy would also help group more heavily used stations together, stations that would have similar loads. This population should be well-defined, since the utility will usually know where the public charging stations are in their service territory.

If there is insufficient information on the populations of interest, then the analyst must invest considerable effort into identifying a suitable population frame for sampling. Please refer to Chapter 4 – Load Shape Development under the Population Frame Identification section. For help in determining appropriate sample sizes for study, please refer to Appendix B – Note on Sample Design.

6
RESEARCH QUESTIONS AND ANALYSIS METHODS

In this section we propose research questions and the associated analysis methods to be considered in the development of information and insight related to charging load shapes.

Table 6-1
Sample Research Questions and Proposed Approaches

Sample Research Questions	Overview of Approaches
What is the incremental load (kWh and kW) associated with adoption of an EV? ▪ **How does the load vary by month and day of week?** ▪ **How does the load vary by time of day?** ▪ **Do customers charge their EVs every day?**	▪ End use metering analysis ▪ Compare load shapes of customers with chargers versus a comparison group using whole building hourly load analysis ▪ Compare load shapes of customers with chargers versus comparison group using end use metering approaches to determine incremental EV load
What is the load shape measuring? ▪ **Home charging, level 1 and level 2?** ▪ **Workplace charging?** ▪ **Public charging, level 2 and DCFC?**	▪ Design sample for all charging ▪ Analyze domains for individual types and levels of charging
What is the difference in EV energy consumption due to other attributes? ▪ **What is the net consumption changes from Level 2 chargers versus a Level 1 chargers?** ▪ **What is the average number of hours under charge for Level 1 versus Level 2 charging?** ▪ **What is the added load due to program attributable EV adoption versus non-program EV adoption?** ▪ **Vehicle type**	▪ Compare load shapes of customers with different types of attributes, e.g., different chargers, using whole facility or end-use metering ▪ Compare charging load shapes from whole building hourly load analysis and end use metering approaches to determine incremental EV load ▪ Develop pre/post Load shapes
How does customer charging behavior change in response to time-of-use rates?	▪ Using a pilot and randomized assignment compare EV customers on a TOU charging rate with EV customers on a standard rate ▪ Compare either whole building or end-use load shapes
What are the differences in charging behavior for customers who drive for ride share services (Lyft, Uber)?	▪ Identify these drivers using survey or other data sources ▪ Measure load shapes, compare with general population ▪ Charging will likely need to be tracked at the vehicle

7
SUMMARY AND CONCLUSIONS

This focus of this paper was to familiarize the reader with various aspects of the EV market including why utilities and commissions need to include EVs in future planning scenarios. The paper examined the key factors needed for the design and launch of a successful EV diversified load project. Our intent was to shine a light on the importance of the following key factors:

- **Who has EVs?** A fundamental question in any project is the proper identification of a population frame. If the population is not known, it is impossible to know whether the results are representative of that unknown population.
- **What data are you going to collect?** There is a substantial amount of data that should be collected during the study. This includes information regarding the EV, EV chargers, customer characteristics, demographic characteristics, and so on.
- **What level of charger is important?** With the likely prevalence of Level 2 chargers, are these the only ones that need to be studied? Should an effort be dedicated to Level 1 chargers? Will utilities have the DCFC chargers on a separate rate or require interval load metering so that they can be more readily tracked and captured?
- **What about charger location?** The location of the charger is an important planning consideration. Utility planning may require several different perspectives to be represented, e.g., at-home charging, workplace charging, public charging, or charging that occurs in transit corridors (such as DCFC charging on highly travelled routes).
- **How to capture the necessary data?** Do you isolate the EV charger only load or capture the whole facility loads of customers with chargers?
- **What are you going to monitor?** The EV charger or the EV? Most charging occurs at home using the EV charger installed at the residence. However, charging can also occur at work or at public charging infrastructure. Analysts must decide whether to simply monitor a specific charger (at-home or other) or to monitor the a specific EV's charging, regardless of where charging it takes place. This is also a question of how the population is defined: are you studying a population of EVs or a population of EV chargers?
- **What other elements should the utility planner consider?** These may include interval length, frequency of data transfer, storage medium, and/or other topics.

A
40TH PLMA ABSTRACTS

This appendix includes abstracts for EV-related presentations from the 40th Peak Load Management Association conference held in St. Petersburg, FL, in November 2019.

Profiling and Managing EV Charging Load – TVA and FleetCarma
Drew Frye, TVA and Eric Mallia, FleetCarma

Tennessee Valley Authority (TVA), in conjunction with FleetCarma, has launched an electric vehicle load profiling program called SmartCharge Nashville to better understand the current and future impact electric vehicle charging has in their service territory. Using real-world EV charging and driving data, Drew and Eric will evaluate and discuss interim results from the SmartCharge Nashville program. They will also share insights into how utilities can leverage real-world charging data to make data-driven decisions for system planning, demand-side management strategies, and customer engagement. The SmartCharge Nashville program collects EV driving and charging from 200 participants. This data is utilized to compare weekday/weekend charging, energy consumed during on/off-peak, % of charging conducted with L1/L2/DCFC stations, and home vs. away charging. TVA is also utilizing this data to address questions such as how TOU rates affect EV load and determining the amount of manageable EV load now and into the future.

Vehicle Electrification Programs at JEA – Past, Present, Future
Payson Tilden, JEA and Josh Duckwell, GDS Associates

JEA's Non-Road Electrification programs and passenger car EV charging programs have evolved substantially over the past few years, incorporating lessons learned from around the country as well as from its own evaluations. By engaging community involvement and keeping a close relationship with its customers, these programs are now some of the best examples of progressive thinking in the southeast and are still growing. From well-designed incentive offerings to a forward-thinking strategic team, JEA will highlight some of the key lessons learned along the way and provide a glimpse into the future of the electric transportation efforts to serve its over 460,000 electric customers.

Ahead of the Curve – EVSE Billing & Control
Brian Raines, Seven States Power Corporation and Matt Kiesow, OATI

Seven States Power Corporation is working with a group of Electric Vehicle Network Providers and OATI to help promote adoption of Electric Vehicles. Specifically, their focus is on managing Electric Vehicle Supply Equipment (EVSE) in the public and fleet charging spaces to ensure easy planning, integration, and control of these demand profiles. The OATI EVolution system is one of the EVSE Network Management Services offered by 7SP. Each EVSE managed in EVolution supports dynamic billing and pricing strategies and is enrolled as a controllable DR asset to 7SP member cooperative demand response system. This new program model of extending the home rates members are familiar with to their public charging needs and allowing easy direct to utility billing charges will push greater EV adoption.

B
NOTES ON SAMPLE DESIGN

The 3rd Edition of the AEIC Load Research Manual[23] covers Sample Design and Selection for interval load analytics projects in Chapter 4. The manual does a good job of laying out the sample design process. We suggest this as both a reference and a guide.

The key to knowing how many sample points to deploy is in the customer-to-customer variability of the variable(s) of interest. The variables of interest are usually demands including the contribution to the system peak demand (i.e., coincident peak demand), the class or group peak demand (i.e., maximum diversified demand), the individual customer demand, or all hourly or 15-minute interval demands. In practice, we can examine the coefficient of variation or the error ratio for any number of variables and select a robust sample size that can be expected to yield adequate precision across the spectrum of target variables.

Of course, as you plan the initial study, knowing how much variation you are likely to encounter will be a challenge, since you are unlikely to have any data to use to determine that variation. However, once data have been collected, even for a small sample, then these sampling parameters can be estimated from the actual data. Sizing the sample is dependent on several factors including sampling method, estimation technique, and required accuracy. However, there are additional non-statistical factors that play a role, including ability to identify an appropriate population frame, availability of equipment, timing of results, and size of available budget. But setting those elements aside, let's examine how we might approach determining an appropriate sample size for an upcoming study.

The following equations provide the sample size calculations depending on the intended allocation strategy.

Equation 1 – Sample Size Calculation[24]

Proportional allocation:

Without fpc / With fpc

$$cv_1 = \frac{\sqrt{\sum_{h=1}^{L} W_h \sigma_h^2}}{\mu} \qquad n_0 = \left(\frac{z\, cv_1}{D}\right)^2 \qquad n_1 = \frac{n_0}{1+n_0/N}$$

Neyman allocation:

Without fpc / With fpc

$$cv_2 = \frac{\sum_{h=1}^{L} W_h \sigma_h}{\mu} \qquad n_2 = \left(\frac{z\, cv_2}{D}\right)^2 \qquad n_3 = \frac{n_2}{1+n_0/N}$$

(Here n_0 is not a typo)

[23] 3rd Edition of the AEIC Load Research Manual can be located at https://www.techstreet.com/aeic#lrm

[24] AEIC Advanced Applications, Session 3 – Sample Design, slide 10.

Where,

N=population size;

W_h=Stratum weight (N_h/N);

z = standard normal deviate based on the desired confidence level, or 1.645 for 90% confidence and 1.96 for 95% confidence;

cv_1=the coefficient of variation (i.e., standard deviation divided by the mean) of the target variable of interest, e.g., average demand during a selected period;

D=the desired level of precision, typically, ±10%; and

fpc stands for the finite population correction; if the population is infinite, or very large relative to the sample, the first formulas hold; if the population is not as large, then the use of the fpc formulas result in smaller and more appropriate sample sizes.

A similar calculation is available for the use of stratified ratio estimation and strong stratification[25] that yields Equation 2.

Equation 2 – Sample Size Using Ratio Estimation

$$n \approx \left(\frac{z\ er}{D} \right)^2$$

Where,

er=error ratio which is similar to the coefficient of variation (i.e., standard deviation divided by a mean) presented above.

So, the key is to identify a reasonable estimate of the error ratio (or coefficient of variation) in order to make a preliminary sample size estimate. Table B-1 provides a listing of some "rules of thumb" for sizing the sample. Of course, the study of electric vehicles is new, and the entries display the authors' best estimates with limited data. This table will need to be updated when more practical experience has been ascertained.

If actual interval data for the charging shape being estimated is available, that interval data can and should be used to calculate a more appropriate value for the coefficient of variation or error ratio and will give a better sample size.

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[25] Strong stratification allocates the sample based on the percentage of modeled standard deviation.

Table B-1
Error Ratios for Use in Sizing a Sample

Error Ratio	Description of Association	Examples
>1	Extremely weak but possible	DSM end-use metering with poor tracking data Electric vehicles at the charger not on a TOU rate
1	Very weak, conservative assumption	Market research with poor supporting data
0.8	Rather weak	Residential whole facility load study
0.6	Weak	General service load study Residential whole facility with electric vehicles during evening hours
0.5	Typical	End-use study with good supporting data
0.4	Strong	Large C&I whole facility load study Electric vehicles at the charger on a TOU rate during super off-peak periods
0.2	Very strong	End-use metering supported by simulations
0.1	Extremely strong	1^{st} year persistence study for motors
0.0	Least possible value, perfect association	Not expected

C
SIMULATION FOR LOAD SHAPE DEVELOPMENT

Another potential approach for developing load shapes, either for analysis or for sample design and planning, is to use simulation. If data are available, simulation can be used to generate multiple realizations of synthetic load shapes that reflect certain assumptions about the number of EVs and the type and frequency of charging. These load shapes can be used as possible load shapes for analysis, they can be averaged to get a diversified load shape, and they can be used as individual shapes for estimating variances or error ratios for sample design.

The Tennessee Valley Authority (TVA), in partnership with Nashville Electric Service and Middle Tennessee Electric Membership Corporation, collected extensive charging data as part of the Smart Charge Nashville (SCN) program operated by FleetCarma, a division of Geotab. These data were used to develop probability distributions for charging behavior, distributions which were used to generate simulations of a charging station. The SCN data was made up of records for every 15-minute interval when a vehicle was charging. The data included a vehicle ID, the charging location, the maximum charging demand during the period, the energy consumed for charging, and the start and end times for charging. For intervals when the vehicle was charging for the full 15 minutes, the start and end times corresponded to the beginning and end of the interval. This data was aggregated into data by charging event, with all intervals related to a single charging event aggregated, including total charge energy, peak charge demand, and start and end times for the charge.

While the SCN data was used for extensive analysis of many types, the simulation we discuss here was used to generate load shapes for public DC Fast Charging (DCFC) stations. TVA wanted to know what potential impact public DCFC stations would have on their load, and how different rate designs would influence the bills of these station, which may in turn influence how many of the stations would be built.

The first step was to limit the SCN data to charging sessions that likely occurred at DCFC stations. This was done by filtering the charging sessions, including only those that had a charging demand of 19 kW or greater.

The filtered SCN data was used to generate two specific probability distributions. The first was the probability of a charging event starting in each hour on either weekdays or weekend days. These 48 probabilities were calculated as the total number of charging events started in that hour on that daytype divided by the number of occurrences of that hour on that daytype in the dataset.

$$P\left[event\ in\ hour_{i,j}\right] = \frac{count\ of\ events\ starting\ in\ hour\ i\ on\ daytype\ j}{total\ count\ of\ hour\ i\ on\ daytype\ j}$$

Where

i = 1 to 24 is the hour of the day, and
j = 1 to 2 for weekdays and weekend days.

The second probability distribution needed was the charging energy. This distribution was created as the proportion of the charging events with each level of energy (rounded to the nearest kWh) in the dataset. The charging energy values ran from 0 to 70 kWh, each with an associated probability, all of which summed to 1.0. As with the probability of a charging event, this was based on the proportions of values in the SCN dataset.

Some additional simplifying assumptions were made, and then the 48 hourly probabilities of charging were adjusted to achieve a target number of charges per plug per year. The SCN data had an inherent number of charges for the period of the data, but by multiplying the probabilities by the ratio of the target number of charges per year to the actual number of charges, the expected value of the number of charges per year would match the target. This allowed us to scale the assumed amount of charging at the DCFC station up or down but still retain the random nature of the charging.

Once the probabilities were determined, the simulation was run as follows, creating 1,000 simulated loads for a DCFC charging station with 5 plugs.

1. A calendar for a future year was created with 8,760 hours to be filled in with simulated data.
2. For each hour, a uniform random number from zero to one was generated, and if it was less than the probability of an event starting in that hour for that daytype, a charging event was deemed to have happened in that hour, and a charging energy was selected from the possible values based on the appropriate probabilities. If the original random number was greater than the probability of an event starting in that hour, then no event occurred in that hour, and the hourly energy for the plug load was set to zero.
3. Step 2 was done 8,760 times to simulate one DCFC plug. This was repeated five times, to simulate one realization of the DCFC charging station with 5 plugs.
4. This process was repeated 1,000 times, to create a distribution of possible DCFC charging station load shapes for a given set of assumptions.

The resulting distribution of load shapes were used in several different ways. An average of the 1,000 was calculated, representing a diversified average load shape. A diversified average is appropriate to understand the overall impact on a system of multiple DCFC charging stations but is not an appropriate characterization of a single charging station, especially regarding demand. The 1,000 load shapes were sorted by individual max demand, and the median was then used to represent a typical DCFC charging station. This typical shape could be used for assessing demand impacts. To get a fuller understanding of the range of possible impacts of a demand rate, that rate can be assessed on all 1,000 load shapes, which will provide a distribution of possible impacts.

While this project focused on simulating DCFC charging stations, this same approach could be used to generate workplace or home charging as well, though some of the assumptions would need to change. One of the benefits of simulation is that you can change assumptions or inputs and see how those changes affect the outcomes of a distribution, particularly the variability of that distribution, rather than of just a single engineering estimate.

The Electric Power Research Institute, Inc. (EPRI, www.epri.com) conducts research and development relating to the generation, delivery and use of electricity for the benefit of the public. An independent, nonprofit organization, EPRI brings together its scientists and engineers as well as experts from academia and industry to help address challenges in electricity, including reliability, efficiency, affordability, health, safety and the environment. EPRI also provides technology, policy and economic analyses to drive long-range research and development planning, and supports research in emerging technologies. EPRI members represent 90% of the electricity generated and delivered in the United States with international participation extending to nearly 40 countries. EPRI's principal offices and laboratories are located in Palo Alto, Calif.; Charlotte, N.C.; Knoxville, Tenn.; Dallas, Texas; Lenox, Mass.; and Washington, D.C.

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