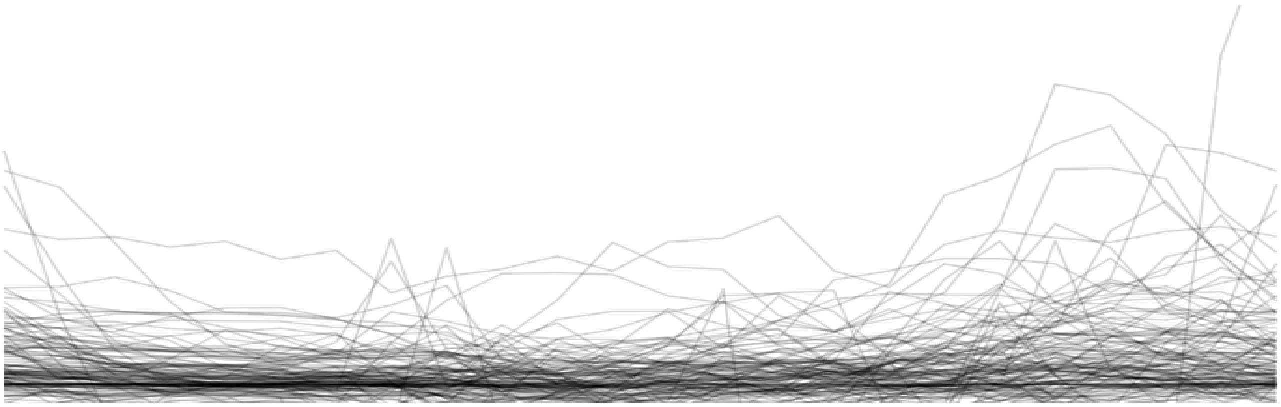
Report on Electric Vehicle Charging for Efficiency Maine
FINAL Report



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Prepared for Efficiency Maine

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Cover image: Estimated charging demand load shapes for households with EVs.

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Overview

This report concludes a study of charging patterns of electric vehicle (EV) owners who received a rebate through Efficiency Maine's Electric Vehicle Rebate program, as revealed through their Smart Meter consumption data. The research focuses on changes in demand (kW) during peak periods due to charging with Level 2 chargers. It also includes estimates of the timing and energy (kWh) associated with charging sessions, with separate estimates for battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs) regardless of charger type.

This report and accompanying analyses were designed to answer the following questions:

1. **Demand:** What is the average peak demand increase during ISO-NE winter and summer peak hours for EV owners using level 2 charging (using BEVs where the average kWh during charging hours was above 5kW as a proxy for level 2 chargers)
2. **Timing:** When are customers charging their vehicles?
3. **Energy:** What is the average daily total energy (kWh) that customers are using to charge their vehicles?

Notably, some of the analyses in this report includes electricity data collected during the 2020 COVID-19 pandemic. The majority of customers changed their energy use patterns substantially during this period, meaning that results drawn from data collected during March or later in 2020 cannot be used with confidence to predict behavior in future years. For this reason, we based the results presented on only data collected during the period from December 2019 through February 2020 (with a pre-EV baseline period covering a full year before those dates), unless otherwise noted. This includes the estimates of demand changes in the ISO-NE weekday summer peak hours of 1-5 PM, which means that the summer peak charging results are based solely on data collected during the winter of 2019-2020. While there are some seasonal differences in driving patterns and battery performance, we expect the typical commute driver to demonstrate generally consistent patterns in charge timing and total energy across seasons.

For this study, Efficiency Maine provided hourly interval AMI data, customer data and vehicle make and model covering November 2018 through May 2020 for 160 past EV Accelerator program rebate recipients. CDA cleaned and combined these data with hourly weather data from NOAA to create a single data set that could be adapted to work with the models we designed to capture the prevailing patterns in EV charging timing, demand, and total energy.

CDA developed three different models to answer the help answer the primary questions listed above. These models all use pre- vs. post-EV adoption changes in electricity use combined with vehicle attributes and weather data to estimate the demand, timing and total energy of charging sessions. Collectively these results establish empirical baselines for:

1. Charging Demand Model – estimates demand increases (in kW) due to BEV charging
2. Charging Timing Model – estimates what times of day customers are charging their EVs
3. Charging Energy Model – estimates the total energy in kWh per day used for charging EVs

ISO-NE on-peak demand periods are 1-5pm non-holiday weekdays Jun-Aug and 5-7pm non-holiday weekdays Dec-Jan, with energy period factors of 7am to 11pm peak. Throughout this report, which is based primarily on data for December through February, we label the 1-5pm period as "Summer Peak Hours" and the 5-7pm period as "Winter Peak Hours" though we are using winter data to estimate demand during both summer and winter peaks.

Table 1 shows the change in demand due to EV charging. The charging demand estimate includes the standard error, converting to 95% confidence intervals, we estimate that the increase in demand for the summer peak hours is 0.3 kW with a 95% confidence interval of (0.2, 0.4) and the demand for winter peak hours is 0.5 kW with a 95% confidence interval of (0.4, 0.7). The primary source of this difference is the time of day.

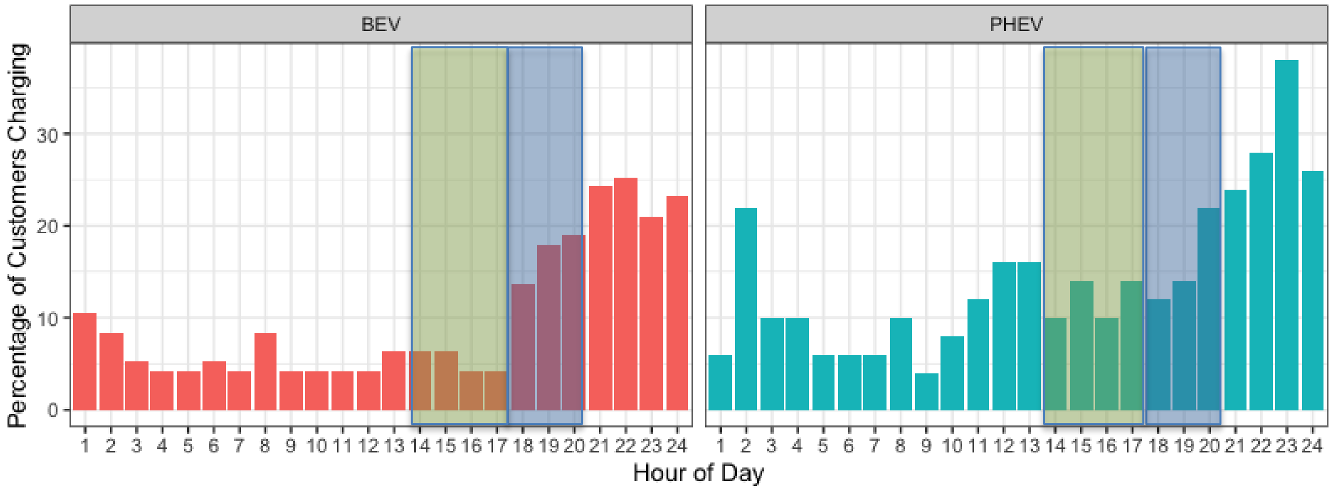
Table 1. Average weekday demand from December 2019 through February 2020

Period	Charging Demand ±SE (kW)	Baseline Demand (kW)	Increase
Morning Off-Peak 12am – 1pm	0.2 ±0.05	0.6	33%
Summer Peak Hours 1pm – 5pm	0.3 ±0.06	0.6	46%
Winter Peak Hours 5pm – 7pm	0.5 ±0.06	1.0	53%
Night Off-Peak 7pm – 12am	0.8 ±0.06	1.5	56%

The charging timing model, designed to identify hours of demand statistically likely to include charging activity, shows that weekday charging hours are primarily from 6pm to 12am, with the highest likelihood of charging occurring in the late evening after 9pm. There is also charging happening during the winter peak hours 5-7 PM. We do not have sufficient data collected outside of the Coronavirus pandemic to estimate what summer charging hours would be during a "normal" year, but with the data from 2019-2020, we find that customers are not charging substantially during the summer peak hours of 1-5 PM, however mid-day charging has been found to be lower than evening charging in other studies of EV charging as well.[1] Figure 1 shows that, on an average weekday, customers are charging more during the evening and night hours, and relatively less in the middle of the day, and that the pattern is more pronounced for BEVs.

Figure 1. Percentage of customers likely charging during each hour of the day on an average weekday by vehicle type (summer peak hours in green; winter peak hours in blue)

[1] This is consistent with variation in time-of-day charging documented in studies of metered charging. See figures 9 and 11 of https://www.energy.gov/sites/prod/files/2014/02/f8/evs26_charging_demand_manuscript.pdf, and for customers on TOU rates see figures 9 and 10 from:
Herter, Karen, and Yevgeniya Okuneva. 2014. EV Innovators Pilot – Load Impact Evaluation. Prepared by Herter Energy Research Solutions for the Sacramento Municipal Utility District (paper available on request).



Blue rectangle shows winter peak hours and green rectangle shows summer peak hours

We estimate average weekday charging energy during December 2019 – February 2020 for BEV vehicles (likely using level 2 chargers) is 9.0 kWh per day. For reference, the most efficient EVs currently on the market can travel just over 4 miles per kWh while the lower end is closer to 2 miles per kWh, so this is consistent with an average of roughly 20-30 miles of electric driving per car per day. Most of the results in this report are split between battery electric vehicles and plug-in hybrid vehicles because their charging characteristics are different due to battery pack sizes. Table 2 shows the average charging energy for BEVs, PHEVs and the group of BEVs that are likely using level 2 chargers.

Table 2. Average weekday charging energy from December 2019 through February 2020

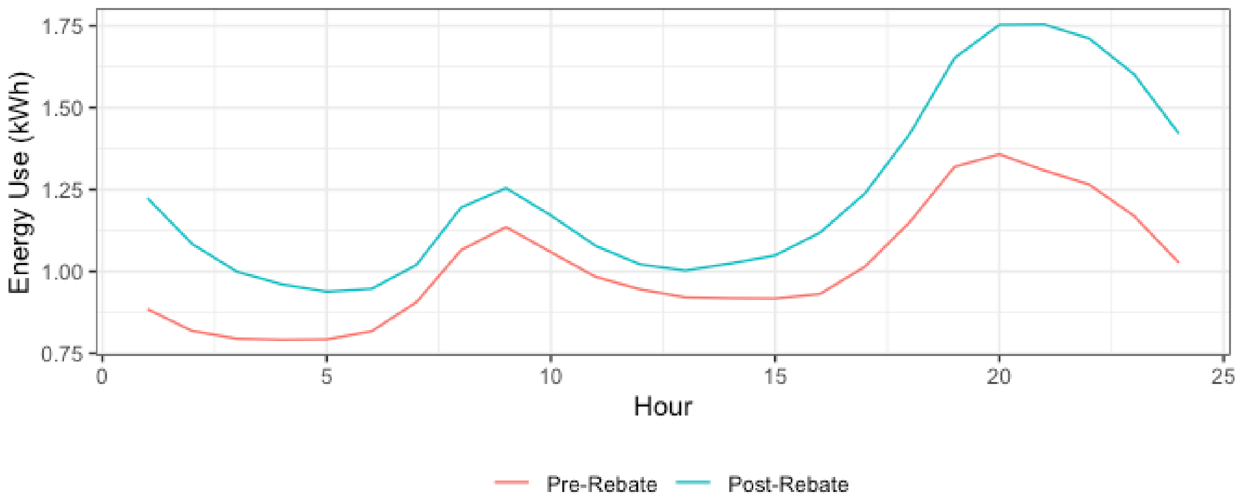
Vehicle Type	Charging Energy (kWh)
BEV + Level 2	9.0
BEV (All)	3.3
PHEV	0.9

We address the three primary questions in more detail in the following section.

Results

Customers are using energy substantially differently after purchasing an electric vehicle. By simply comparing average hourly energy usage before and after EV purchase in Figure 2, one can verify demand increases primarily in the evening and early morning, with more moderate increases mid-day.

Figure 2. Average weekday energy usage



The analysis in this report includes electricity data collected during the 2020 Coronavirus pandemic. Most customers changed their energy use patterns substantially during this period. This means results based on data collected during the months after March 2020 (without a control group) cannot be used to reliably predict behavior or demand in future years. For this reason, we based the results presented below on only data collected during the period from December 2019 through February 2020, though we sometimes include data from the months after February to help understand what happened to charging and electricity usage after early 2020.

The estimates of demand changes in the ISO-NE weekday summer peak hours of 1-5 PM are based on data collected during the winter of 2019-2020, which means that the summer peak charging results could be biased if EV owner driving and charging behavior are different in the summer and winter. In effect, we are assuming that the typical commute driver will demonstrate generally consistent patterns in charge timing and total energy across seasons.

Peak Demand

We estimated increases in demand during summer and winter peak hours using the charging demand model with data from December 2018 through February 2019 (pre-period) and from December 2019 through February 2020 (post-period). We used a model to find the BEV owners we consider likely to have level 2 chargers due to spikes in demand of 5 kW or greater, Then, we put those customers into the peak demand model to estimate demand changes adjusted for weather differences between the winters of 2018-19 and 2019-20. See the methods section for more details on the implementation of the peak demand model.

Figure 3 presents density plots of mean demand across customers during the winter of 2018-19 compared to mean demand during winter of 2019-20 for customers we model as likely to have level 2 chargers. The area under a density curve is = 1 and they function like smoothed out histograms. The vertical lines represent the average demand across customers. There was substantially higher demand during the winter peak hours (5pm-7om) after EV purchase, but the demand increase during the summer peak hours (1pm-5pm) is much smaller.

Figure 3. Distribution of hourly demand before and after EV purchase for customers likely to have level 2 chargers

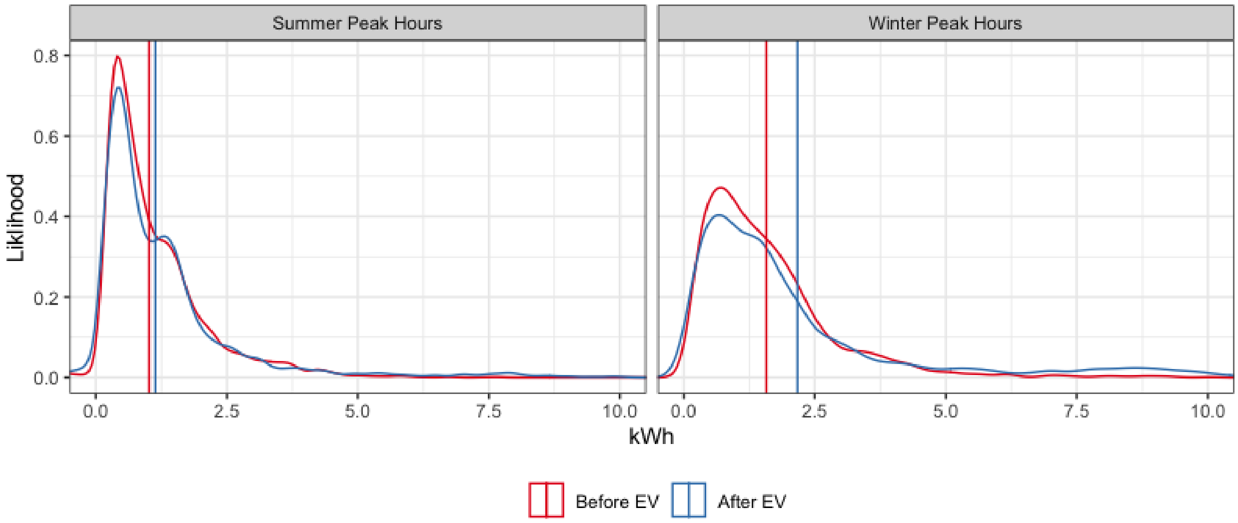


Table 3 shows how the number of hours with higher demand has increased after EV purchase for the BEV owners with likely level 2 charging. The first column shows the demand for the hours in that category. The second column shows the percentage of hours at that particular demand level before EV purchase, while the third column shows the percentage after EV purchase. The fourth column shows the ratio of post to pre, so numbers above 1 show an increase of hours at that level of demand. There is a marked increase in the number of hours with demand in excess of 5 kW (e.g. there is a 14.6-fold increase in the number of hours with a demand of 9 kW after EV purchase compared to before).

Table 3. Ratio of percentage of hours at each level of demand

Demand (kW)	Pre-Purchase Percentage of Hours (%)	Post-Purchase Percentage of Hours (%)	Ratio of Post to Pre Hours
0	51.4	48.7	0.9
1	30.7	30.0	1.0
2	10.9	10.0	0.9
3	4.4	3.8	0.9
4	1.6	1.9	1.1
5	0.54	1.3	2.4
6	0.21	0.75	3.5
7	0.15	1.2	8.0
8	0.11	1.1	10.0
9	0.05	0.69	14.6
10+	0.01	0.74	62.6

Ratio may not exactly equal post divided by pre due to rounding

Table 4 shows the average demand increase across each period for BEV owners with likely level 2 charging. These results are weather adjusted for a winter similar to 2019-2020.

Table 4. Average weekday demand change from December 2019 through February 2020

Period	Baseline Demand (kW)	Demand Increase (kW±SE)	Percentage Increase
Morning Off-Peak 12am – 1pm	0.6	0.2 ±0.05	33%
Summer Peak Hours 1pm – 5pm	0.6	0.3 ±0.06	46%
Winter Peak Hours 5pm – 7pm	1.0	0.5 ±0.06	53%
Night Off-Peak 7pm – 12am	1.5	0.8 ±0.06	56%

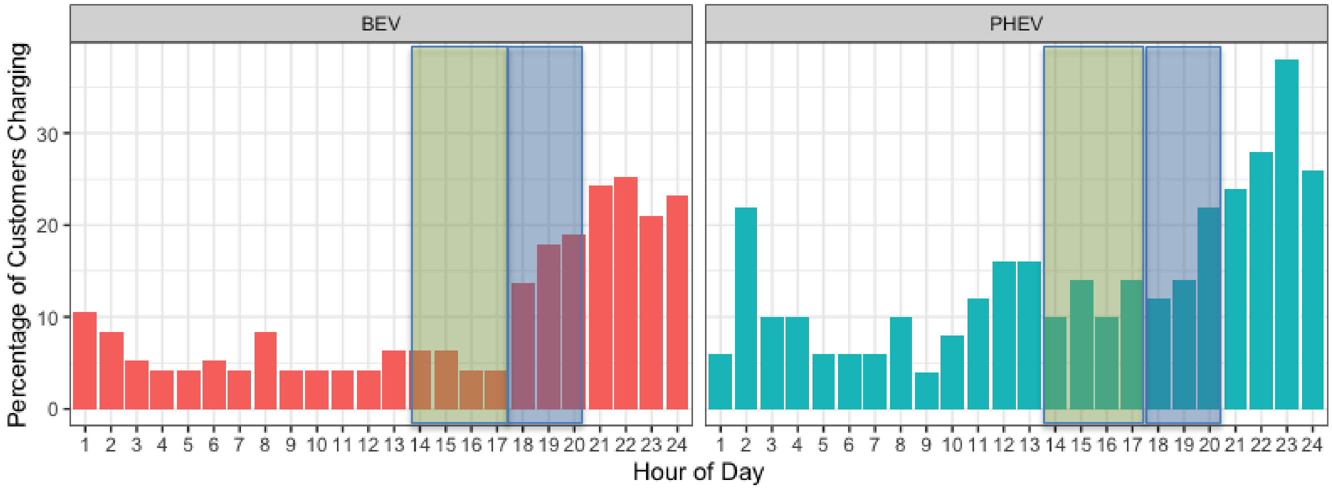
Overall Charging Hours

CDA estimated which hours customers are charging, on average, using the timing model. This model is designed to find the hours where it is most likely that each customer was charging, and then combine the results from all customers to discern which hours of the day more customers are charging. These results can be used to understand what times of day EV charging is most likely to have a substantial effect on demand as more EVs are purchased.

In order to discern which hours customers are charging their vehicles, we set a threshold on the increases in demand from pre- to post-EV periods that are large enough to suggest that charging is occurring. We tested a range of threshold levels and found that a modeled increase of demand of 1 kW for BEVs and 0.5 kW for PHEVs produce stable estimates of which hours of the day tend to have the most charging.

Figure 4 plots the count of hours with changes beyond the relevant threshold for BEVs (left) and PHEVs (right). The actual counts are sensitive to the threshold selected, but the timing model is focused on relative count from hour-to-hour, so the y-axes are left unitless. In December through February (the study period), the charging happens after 6 pm and into the early morning for both BEVs and PHEVs. These results align with previous studies showing that most charging is occurring overnight and into the morning hours rather than during peak periods.

Figure 4. Percentage of customers likely charging during each hour of the day on an average weekday by vehicle type (summer peak hours in green; winter peak hours in blue)



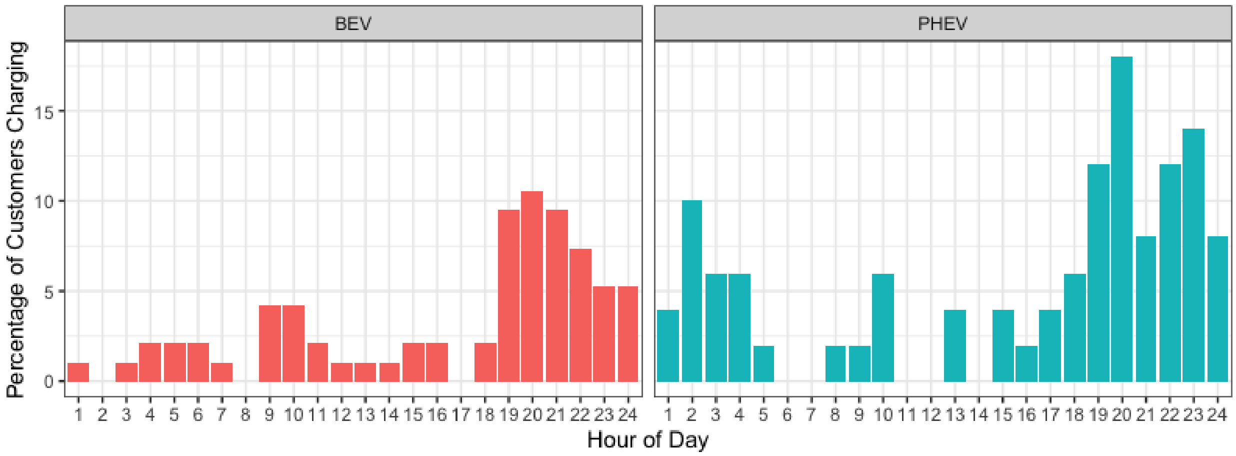
Blue rectangle shows winter peak hours and green rectangle shows summer peak hours

Charging Hours During Coronavirus

CDA found that data from months after February 2020 are not reliable for estimating future charging hours because of the 2020 coronavirus pandemic and subsequent shelter-in-place orders, which substantially reduced vehicle miles traveled[2] and changed customer's energy usage patterns due to spending more time at home. This makes it difficult to compare charging hours during the winter with charging hours starting in March, since shelter-in-place is confounded with vehicle charging. Figure 5 shows that the pattern of charging has changed, and is somewhat harder to discern, though most of the charging still happens during the evening and overnight hours.

[2] https://www.fhwa.dot.gov/policyinformation/travel_monitoring/20martvt/

Figure 5. Coronavirus pandemic months (April and May 2020) percentage of customers charging in each hour of the day by vehicle type



There is a 45% drop in charging hours in spring and summer compared to winter. We believe that the drop in charging in the spring and summer is likely due to shelter-in-place rather than the driving and charging patterns we would expect to see in a normal year. See the appendix on Caveats and Potential Next Steps for more discussion of this issue.

Charging Energy

The daily total charging energy averages 2.5 kWh and varies substantially between customers. Table 3 shows the average total charging energy by vehicle type across the months where we have sufficient data (December through February). The average total charge kWh is lower in March through May, so they are not included here due to shelter-in-place requirements that substantially reduced most people's miles driven. We believe that the charging model is much less effective in these months for the same reason. For this report, we recommend using the December through February daily averages of 3.2 kWh for BEVs overall, 9.0 kWh for BEVs with likely level 2 charging, and 0.9 kWh for PHEVs.

Table 5. Average weekday charging energy in kWh from December 2019 through February 2020

Month	BEV (All)	BEV (likely level 2)	PHEV
Dec	5.1	9.0	1.2
Jan	3.8	8.8	1.0
Feb	1.2	9.1	0.6

Methods

Data Sources

To perform this analysis, CDA used data from a variety of sources. With the exception of weather data, these data were provided by EMT, including customer data, rebate data, and hourly electrical meter data. We used customer zip codes to match each customer to their nearest weather station and downloaded hourly weather data from NOAA to weather normalize the electricity consumption models.

Direct charging data from internet connected chargers was not available for this analysis. Instead, CDA used hourly whole home meter utility meter data. For most customers, as of June 2020, there is at least a year of hourly data prior to the EV purchase and 3-7 months after purchase.

Customer Data

Efficiency Maine provided customer data for customers participating in the EVA rebate program. This data includes customer ID, address and application date. It covers 196 of the customers who received rebates between 2019-08-29 and 2020-02-26.

Rebate Data

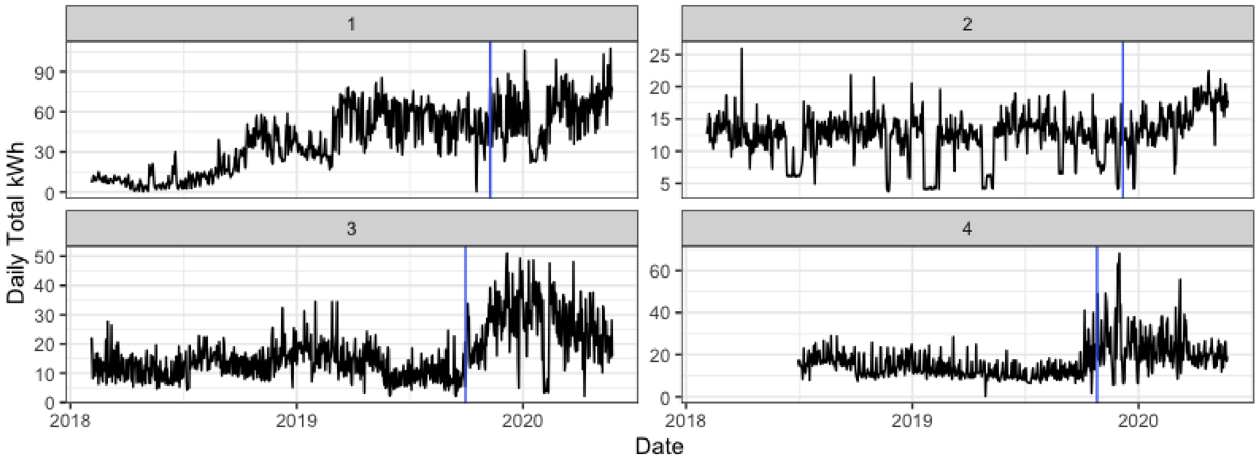
Efficiency Maine provided program rebate data[3] that shows vehicle make, model, battery type (PHEV or BEV), battery size, and purchase date for all customers participating in the rebate program. A total of 434 rebates are included in this data, including 257 battery only electric vehicles (BEV) and 177 plug-in hybrid vehicles. Customer data is only available for 172 of the rebates.

Hourly Electricity Meter Data

Efficiency Maine provided hourly interval meter data for 169 customers. Figure 6 highlights the heterogeneity in meter data across four customers, rolled up to daily totals. The vertical blue line shows the date of EV purchase.

[3] See the program website for details: https://www.efficiencymaine.com/ev/electric-vehicle-rebates/

Figure 6. Example hourly data for 4 customers



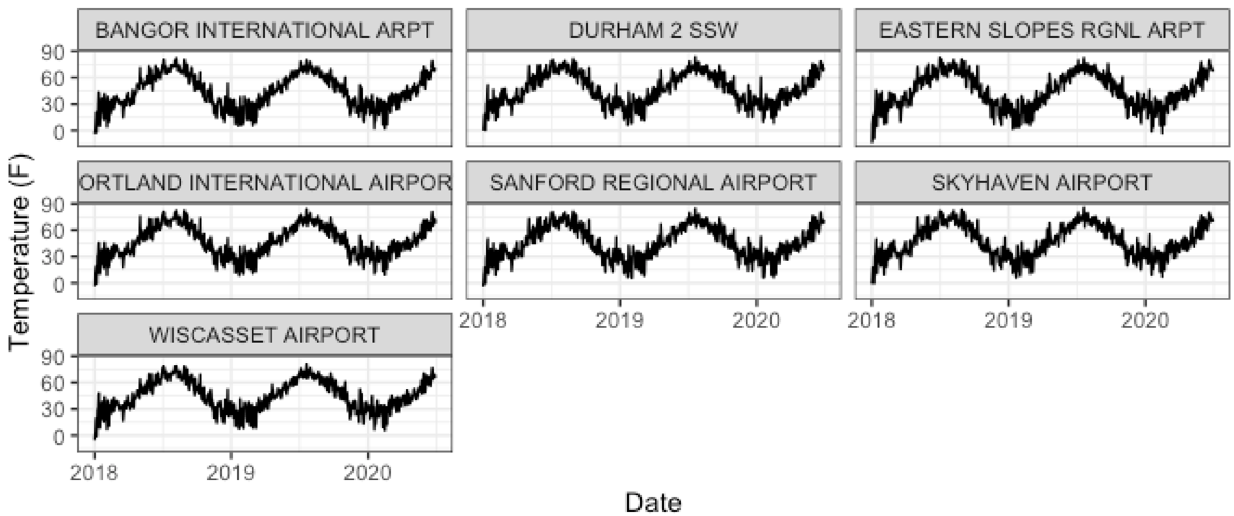
For customer #1 we see step increase in daily consumption after early 2019, but with greater day-to-day variability, with possibly another small step increase after EV purchase. For customer #2 we see a modest increase in consumption during 2020, but no step-change until EV purchase. For customer #3, we see a notable increase in consumption at the time of EV purchase, with a seasonal pattern of increased electricity usage during the winter. For customer #4 we see a large increase in electricity consumption after EV purchase.

Weather Data

CDA used hourly temperature data downloaded from NOAA National Centers for Environmental Information's Integrated Surface Hourly Database. These data include hourly values from most government-operated weather stations operating in the US. We match customers using their zip code centroid to their nearest weather station. In some cases, weather stations are missing data, and if the weather station does not pass our data quality and completeness checks, we use the next closest station. This set of checks helps to assure that no customers or data points will be dropped due to missing weather data.

Figure 7 shows the temperature time series for the 7 weather stations across Maine we used for this analysis.

Figure 7. Daily mean temperatures by weather station



Modeling Methods

Model Data

CDA built a single data set to serve all three models by combining all four data sources. This leads to some data loss and dropping some customers because of missing data from one or more of the data sources. The final data set contains weekday data for 2.6 million hours for 168 customers, with an average of 563 days for each customer. The modeling used only data from the months of December through February to remove bias that would likely be introduced if we were to include data collected during the coronavirus pandemic and shelter-in-place orders.

Models

All three of the models we developed for this report are tested against similar alternatives, checked for issues in data and assumptions, and assessed on performance.

CDA always checks a variety of model formulae, simple data descriptions and, where possible, alternative modeling approaches. These checks are often not included in the report because they add a large quantity of information that is superfluous for nearly all users of the report.

We use standard statistical practice methods for assessing model assumptions, including model fit statistics, plots of error distribution against assumed distribution, plots of error against estimated and actual data to assess heteroskedasticity, and other checks as appropriate.

Our primary tool for assessing performance is comparing model estimates to actual data. We produce a time series of estimates using historical weather and actual covariate values, and then compare those estimates to the actual demand or energy usage during those same periods. This shows where there are differences between the model and reality, and we can adjust the model as necessary. It is neither possible nor preferable to exactly match modeled data to historical data because doing so likely "over fits" the model to that data, degrading model performance when used for prediction.

Charging Demand Model

CDA developed a model for estimating average electricity demand (kW) used for charging during different times of day. This model is a linear fixed effects panel regression model that uses customers' weekday meter data. Once we fit the model, we calculate what demand would have been without the EV purchase and compare it to the demand after EV purchase to estimate average demand.

The following equation shows the form of the model.

$$kW = \beta_i + \beta_0 + \beta_{post} post + \beta_{hdd} hdd65 + \beta_{peak} peakPeriod + \beta_{post \cdot peak} post \cdot peakPeriod + \beta_{post \cdot batterykWh} post \cdot batterykWh + \beta_{post \cdot hdd} post \cdot hdd65 + \varepsilon_{it}$$

Where all of the β are coefficients that are estimated by the model fitting algorithm to best fit the equation to the data. The subscript i refers to individual customer i. In the formula, the variables we use are:

- kW – the average electricity demand during the peak period
- peakPeriod – Indicator for Morning Off-Peak (Midnight to 1 PM), Summer Peak (1 PM – 5 PM), Winter Peak (5 PM – 7 PM), Evening Off-Peak (7 PM – Midnight)
- post – an indicator for the time period after the EV purchase + rebate
- hdd65 – heating degree days with a base of 65 degrees Fahrenheit
- battery kWh – the size of the vehicle battery in kWh

Charging Timing Model

CDA tested a range of models to examine charging behavior and found that the most effective of those we tried are individual adaptive linear models fit separately for each customer, allowing the model to adjust for that customer's specific patterns of energy usage.

Determining charging hours requires developing a model of how each customer uses energy under different circumstances (outside temperature, time-of-day, etc.). CDA developed a model structure that uses the available information about each customer's historical electricity use, weather, month of the year and time-of-day to create a scaffold for individual statistical learning models. We fit these individual regularized linear regression models to each customer's weekday electrical usage data. The regularized linear models use an algorithm called elastic-net[4] that selects the best-fitting model from a specified set of possible models by dropping explanatory variables that don't contribute to the fit, and adjusting the remaining parameters to reduce the likelihood of fitting to noise (i.e. over fitting the model to the data it is trained on at the expense of degrading predictive performance). In other words, each customer gets a model whose parameters are selected to be the subset that best explains their individual consumption patterns.

Then, for the period after they purchased the EV, we used the fitted model to predict what their electricity use would have been had they not purchased the EV and subtracted that "baseline"

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[4] Zou, Hui, and Trevor Hastie. "Regularization and variable selection via the elastic net." (2005).

from the monthly average weekday load shape from post-adoption data to get an estimated charging load shape. We then found the charging hours where the difference between the estimated non-EV electricity use and the actual measured electricity use (with the EV) exceeds a threshold, typically 1kW if we want to be sure we are not capturing other smaller drivers of change in electric consumption.

The structure of the model can be different for each customer, depending on their energy usage patterns and household characteristics. All of these models are subsets of the full model, shown below.

$$kWh = \beta_0 + \beta_{post} post + \beta_{month} month + \beta_{hour} hour + \beta_{hdh} hdh65 + \beta_{cdh} cdh70 + \beta_{post \cdot month} post \cdot month + \beta_{post \cdot hour} post \cdot hour + \beta_{month \cdot hour} month \cdot hour + \beta_{month \cdot hdh} month \cdot hdh65 + \beta_{month \cdot cdh} month \cdot cdh70 + \varepsilon_t$$

Where all of the β are coefficients that are estimated by the model fitting algorithm to best fit the equation to the data. Each customer has a different set of coefficient estimates. In the formula, the variables we use are:

- kWh – the electricity used during the hour
- post – an indicator for the time period after the EV purchase + rebate
- month – a set of indicator variables for month of the year
- hour – a set of indicator variables for hour of the day
- cdh70 – cooling degree hours with a base of 70 degrees Fahrenheit
- hdh65 – heating degree hours with a base of 65 degrees Fahrenheit

Charging Energy Model

CDA also developed a model for estimating total daily energy (kWh) used for charging. This model is a linear fixed effects panel regression model that uses all customers' meter data. Once we fit the model, we calculate what energy usage would have been without the EV purchase and compare it to the energy usage after EV purchase to estimate total charging energy. We do this for the full group and for subgroups of vehicle type and battery size.

The following equation shows the form of the model.

$$kWh = \beta_i + \beta_0 + \beta_{post} post + \beta_{hdd} hdd65 + \beta_{cdd} cdd70 + \beta_{post \cdot vehicleType} post \cdot vehicleType + \beta_{post \cdot batterykWh} post \cdot batterykWh + \beta_{post \cdot hdd} post \cdot hdd65 + \beta_{post \cdot cdd} post \cdot cdd70 + \varepsilon_{it}$$

Where all of the β are coefficients that are estimated by the model fitting algorithm to best fit the equation to the data. In the formula, the variables we use are:

- kWh – the electricity used during the hour
- post – an indicator for the time period after the EV purchase + rebate
- cdd70 – cooling degree days with a base of 70 degrees Fahrenheit
- hdd65 – heating degree days with a base of 65 degrees Fahrenheit
- vehicle type – an indicator variable for BEV or PHEV

- battery kWh – the size of the vehicle battery in kWh

Summary

The primary weekday charging hours for both BEVs are from 6 PM through midnight, while PHEV charging starts a bit later, running from 8 PM through midnight. The results show that there is some charging occurring during the winter peak hours of 5-7 PM for BEVs. We don't see substantial charging during the summer peak of 1-5 PM for PHEVs, but do see some for BEVs.

We estimate that the increase in demand for the summer peak hours is 0.3 kW with a 95% confidence interval of (0.2, 0.4) and the demand for winter peak hours is 0.5 kW with a 95% confidence interval of (0.4, 0.7).

The weekday charging energy for PHEVs is 0.9 kWh/day, 3.3 kWh/day for BEVs, and 9.0 kWh/day for BEVs in with likely level 2 charging.

We believe that the sample size is large enough that these results may apply as more EVs are purchased and being charged in homes because the demand estimates are statistically significant. That said, early EV adopters are likely wealthier and more likely to live in a single-family home than the average citizen of Maine, so as EVs become available to a more representative population, we expect the amount of charging and charging patterns to evolve. We also expect vehicle technologies to continue to evolve, with the most likely outcome being an increase in BEV range even as their costs come down, with PHEVs and short-range BEV possibly being replaced in the process.

These results are all based on just two winters of data, with a pre-purchase period of December 2018 – February 2019 and a post-purchase period of December 2019 – February 2020. We suggest revisiting the summer peak hours when post-coronavirus pandemic data is available, as it should be expected that customer's driving and charging patterns would be somewhat different during the summer months.

Appendix: Caveats and Potential Next Steps

This section summarizes our views on the limits of our methods and options for future improvements to the approaches taken.

Pre/post baselining and "drift": one of the most important assumptions supporting the use of a customer's pre-EV adoption consumption as the basis for their post-adopting baseline is that no other major changes in electric use (something that we call "drift" when looking at our model results) occurred over the time elapsed between the two periods. Since we are controlling for seasonal effects (for example seasonal occupancy) in part by comparing the same months of usage pre- and post-adoption, the minimum time between the baseline period and post-adoption period is 1 year. If other structural changes in consumption occurred with that yearlong window, our pre-post difference will include them. Examples might include having a baby, having an older child move out (or back in!), or adoption of large electricity-using (or producing) equipment, like heat pumps, rooftop PV, major electric appliances, etc. In aggregate analysis, this assumption is weakened to the assumption that for every household with a change that increases consumption, there is another with a change that, on average, decreases consumption. However, especially in households adopting EVs, we might hypothesize correlation with end use electrification and PV adoption, as all three are understood to be ways of reducing one's carbon footprint.

COVID-19: The shelter in place outcomes of our response to COVID-19 mean that virtually everyone is spending a lot more time at home and many of us are no longer commuting to work. This has altered both background electricity consumption and driving and therefore charging patterns. Such a big "drift" between the pre-COVID period to Spring of 2020 onwards means it is harder to isolate the EV charging signal and it will not be representative of the "normal" usage anticipated in the future anyway.

Charge event labeling: An alternative to pre/post baseline analysis would be available to us if we knew which days customers charged their cars and which days they do not (this approach would require a statistically significant number of days without charging to work). The baseline for charging days could become non-charging days from the same time period. This would offer a very good control against both conventional and COVID-19 "drift" since the baseline days would be intermixed with the charging ones. Since we do not know which days are which, we could alternately apply statistical tools to daily load patterns to perform charging/non-charging day classification, but there would be uncertainty in those results that would tend to lead to under-estimates of charging magnitudes. It is an empirical question (i.e. it would need to be tried to know for sure) whether the classification of day types would work well enough in practice to be a viable solution to drift, but early exploration shows some promise.

Data updates: The statistical modeling for this project was done in R and that code was designed to support data updates *as long as the data file formats do not deviate from the original data set*. It should be possible to efficiently update these results as new data becomes available.