Samorka EV Load Profile Project

Annual Report 2020 Version 4

fleetcarma
a division of GEOTAB

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Executive Summary

This electric vehicle (EV) load profiling project sought to characterize EV load profiles using criteria such as customer type, vehicle make and model, vehicle powertrain, commuting patterns, residence type and charging location. These load profiles can be used to demonstrate how to manage EV load growth for utilities across Iceland.

Vehicle-side data is critical for evaluating infrastructure readiness. It captures the charging load for each vehicle, regardless of charging location or charging level, which is useful when characterizing EV charging behaviour among unique customer groups. Segmenting EV driving and charging data is extremely useful when predicting future EV adoption scenarios. For this EV load profiling project, Samorka recruited participants into one of thirteen groups (refer to Table 2), segmented by residence type, vehicle powertrain, and commuting pattern.

The total number of electric kilometers driving during this project was 2.1 million. The average distance driven by each group varied substantially. On average, Plugin Hybrid Electric Vehicles (PHEVs) drove the farthest but did not drive the farthest electric distance, indicating that these EV owners are heavily dependent on the gasoline engine in addition to the electric battery.

Unsurprisingly, EV owners with longer commutes, those in rural or suburban areas (outside of Reykjavik), drove longer distances.

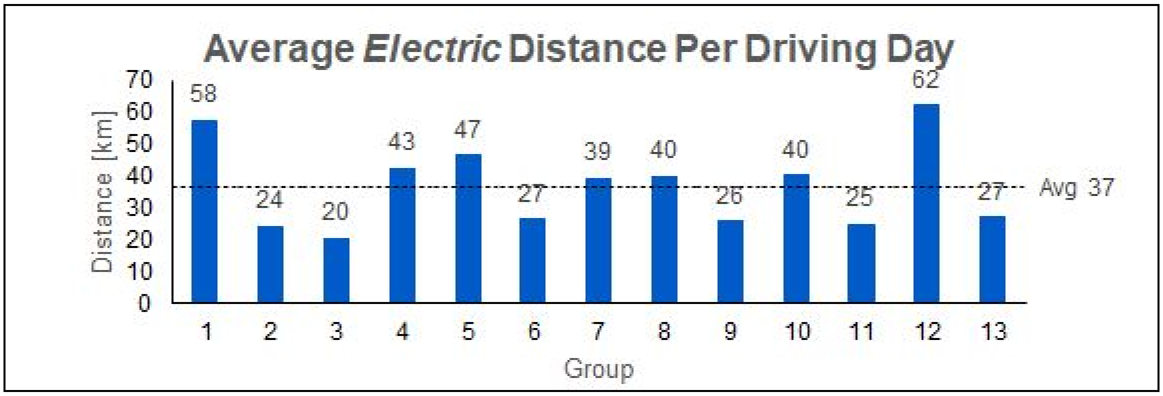

Figure i: Comparison of Average Electric Distance Travelled per Driving Day by Participant Group

The charging behaviour for PHEV groups varied from the SR (short range) and LR (long range) BEV (battery electric vehicle) groups. Although PHEVs consume most of their charging energy during off-peak hours like BEVs, they charge more during the afternoon peak and less during the morning peak. PHEVs also tend to charge more often at home and are less likely to utilize public charging stations or business locations for charging. This behaviour may be due to the hybrid capability to utilize either the gasoline engine or electric battery as a power source for the vehicle, resulting in a less need for a regular charging schedule.

Most EV charging occurs at the home or business location. In fact, all residential (apartment, single family home) groups charge primarily at home. Group 11 which consists of business usage in an urban area primarily charges at commercial offices or industrial locations.

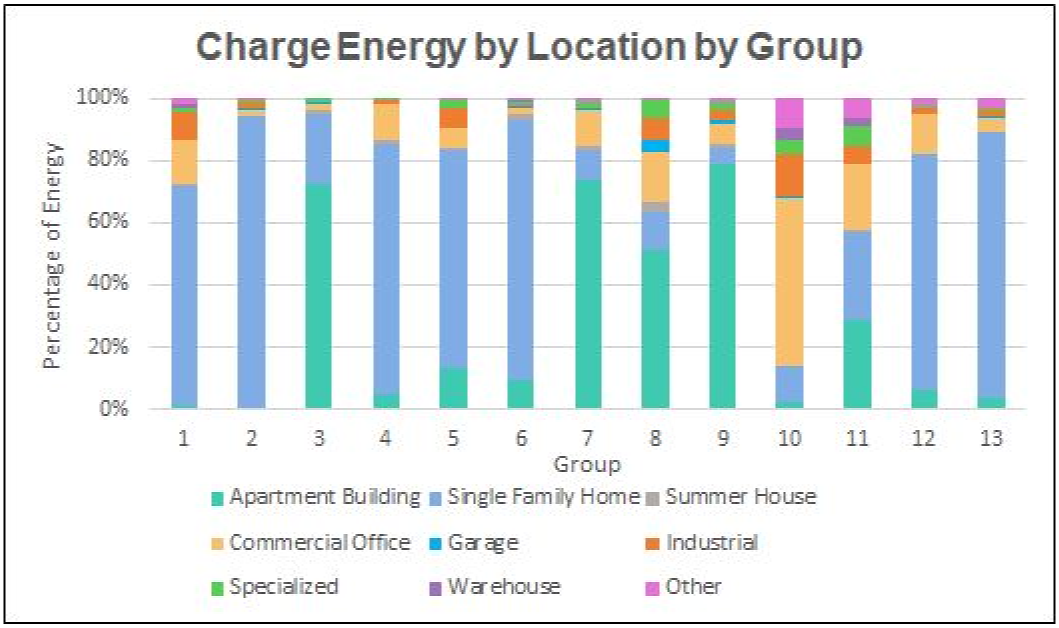

Figure ii: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand

Load curves were created to analyze the aggregate charging load. An average load curve of all vehicles in the project demonstrates a primary charging peak of approximately 0.7 kW per EV in the evening around 19:00. The primary peak may be as expected, occurring when project participants return home from work or other activities and plug-in their vehicles. Interestingly, there is a secondary peak in the morning at 07:30 which is related to EV owners pre-conditioning their vehicles prior to the morning commute. This secondary peak is lower or absent in summer months when EV owners may be on vacation and not traveling to work.

Seasonality and weekday compared to weekday load curves also showed variation from the average daily load curve. More energy is used in colder months than warmer months as the result of battery efficiency and pre-conditioning demands. Weekday load curves closely followed the average daily load curve while weekend load curves demonstrated a primary charging peak in the evening but were lower and less consistent throughout the day.

The effect of EV load on substation infrastructure was modeled at different EV penetration levels. The current penetration level, with 5% all vehicles being EVs, shows very little concern for overloading the existing infrastructure. At penetration levels of 30% there are concerns with smaller, rural substations. At penetration levels of 60%, almost half of all substations will be overloaded. This suggests that consideration should be given to shaping EV load and/or substation upgrades.

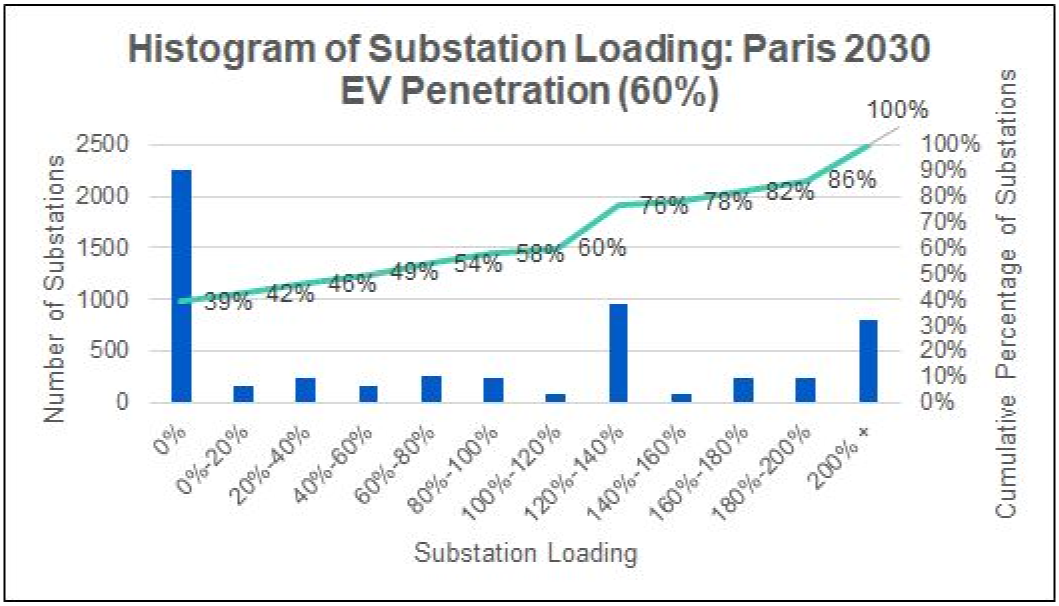

Figure iii: Substation Loading with 60% EV Penetration

In order to improve upon these predictive models, it is recommended that further data collection occur with larger group sizes and more LR BEVs. The larger group sizes will provide more statistical significance for these models and reduce bias. Since LR BEVs are the fastest growing EV segment, with the ability to drive longer distances due to larger battery sizes, it is necessary to examine the impacts of these EVs more directly.

1 Introduction

This electric vehicle (EV) load profiling project was conducted for Samorka with support from several partnering organizations (Appendix A). The project launched in October 2018 with the objective to allow these organizations to evaluate various concepts of EV load management using FleetCarma technology. Specifically, this project aimed to achieve the following:

1. Determine the different EV load profiles by customer type, including vehicle make/model, vehicle segment (short range battery electric, long range battery electric and plug-in hybrid electric vehicles), commuting patterns, residence type, and charging location (rural or urban, capital area or non-capital area, and individual or business location)

2. Demonstrate how to manage EV load growth in a scalable and cost-effective model for the utility and its customers.

In order to achieve these goals, recruitment of 195 EV owner participants were targeted. Project participants were recruited by Samorka in order to diversify the number of participants by residency and vehicle powertrain.

All EV owners that participated in the project received a FleetCarma C2 device. This device was installed in their vehicle by inserting the device into the vehicle's diagnostics port. The diagnostics port is generally located underneath the vehicle's dashboard and can quickly be installed by the vehicle owner, as demonstrated in Figure 1.

Figure 1: Installation of a FleetCarma C2 Device into a Vehicle's Diagnostics Port

The device transmits data from the vehicle to the FleetCarma cloud-based platform for parsing into trip logs (driving data) and charge logs (charging data) by the back-end system. For this project, 12 months of data was logged for each device beginning at the time of device installation. In some cases, the vehicle was sold mid-project and a new EV owner was found to participate in the program. Data collection ended for all devices in January 2020.

The following report includes sections specific to the EV driving and charging behaviour and the potential impacts of the aggregated charging load in general and more specifically on substations within Iceland. These sections are followed with a discussion of the analysis and project conclusions.

2 Data Collection

The driving and charging data collected from project participant vehicles using the C2 device is summarized in Table 1.

Table 1: Summary of Data Collected by the C2 Device in Participant Vehicles

Driving Data	Charging Data
Trip start and end time	Charge interval start and end time
Total and electric only distance [km]	Charge energy [kWh]*
Fuel consumed [L]	Charge energy losses [kWh]**
Battery energy consumed [kWh]	Maximum charge power [kW]
Auxiliary load energy consumed [kWh]	Charge start and end SOC [%]***
Trip start and end SOC [%]***	GPS location of charge session
Ambient temperature [°C]	
Start and end odometer readings	
GPS location of trip [latitude/longitude]	

*Charging energy represents energy flowing into the onboard charger before losses

**These losses are measured as the difference between energy into the onboard charger and battery energy in most models. In the absence of both measurements it is estimated at 12%.

***SOC (state of charge) is the percentage of usable battery energy available.

Driving data is collected on a trip by trip basis, defined from ignition on to ignition off. Charging data is collected in 15-minute intervals throughout the charging session.

All personal data was made unidentifiable in accordance to Act no. 90/2018 on Data Protection and the Processing of Personal Data and also in accordance with Samorka's Agreement with the Icelandic Data Protection Authority. All identifiable data will be deleted after the data processing.

3 Enrollment by Group

The project participants were split into groups by Samorka. These groupings are dependent on their residency and vehicle powertrain. The result was 13 unique groups with approximately 15 participants in each, as shown in Table 2.

Table 2: Description and Number of Vehicles within Each Participant Group

Group	Description	Number of Vehicles with Data in 2019
1	Urban, Outside Reykjavik, Individual, Single Family Home, SR BEV	15
2	Urban, Outside Reykjavik, Individual, Single Family Home, PHEV	15
3	Urban, Outside Reykjavik, Individual, Apartment Building, PHEV	15
4	Urban, Capital Area, Individual, Single Family Home, SR BEV	15
5	Urban, Capital Area, Individual, Single Family Home, LR BEV	15
6	Urban, Capital Area, Individual, Single Family Home, PHEV	15
7	Urban, Capital Area, Individual, Apartment Building, SR BEV	15
8	Urban, Capital Area, Individual, Apartment Building, LR BEV	15
9	Urban, Capital Area, Individual, Apartment Building, PHEV	15
10	Urban, Capital Area, Business, Non-Residential, SR BEV	15
11	Urban, Capital Area, Business, Non-Residential, PHEV	15
12	Rural, SR BEV	15
13	Rural, PHEV	15

4 Aggregate Driving Metrics

Driving metrics were classified by each participant group and, in some cases, by vehicle powertrain: plug-in hybrid electric vehicles (PHEVs), which have a gasoline engine to support driving, and battery electric vehicles (BEVs), which includes both short range battery electric vehicles (SR BEVs) and long range battery electric vehicles (LR BEVs).

4.1 Starting State of Charge

The trip starting state of charge (SOC) can be useful to determine how much charge is needed by EV owners to begin a trip. As Figures 2 and 3 illustrate, the starting SOC of PHEVs and BEVs is very different, with over 29% of PHEV trips starting with an SOC of between 0% and 10%, compared to less than 1% of BEV trips starting with an SOC of between 0% and 10%.

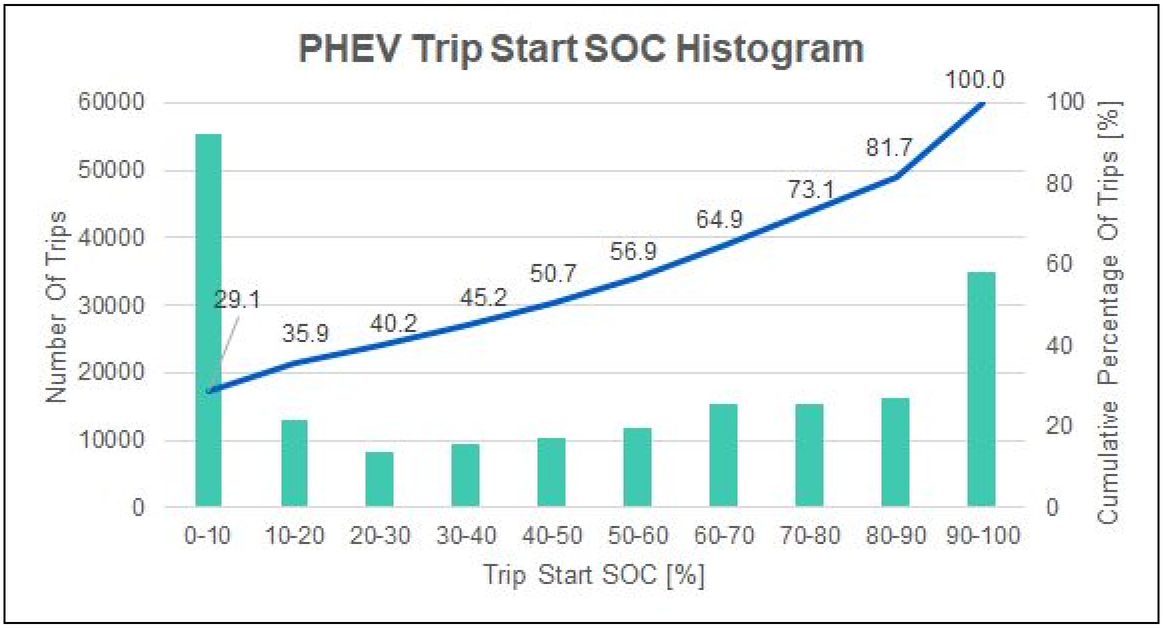

Figure 2: Histogram and Cumulative Distribution for the Battery SOC for All PHEV Trips

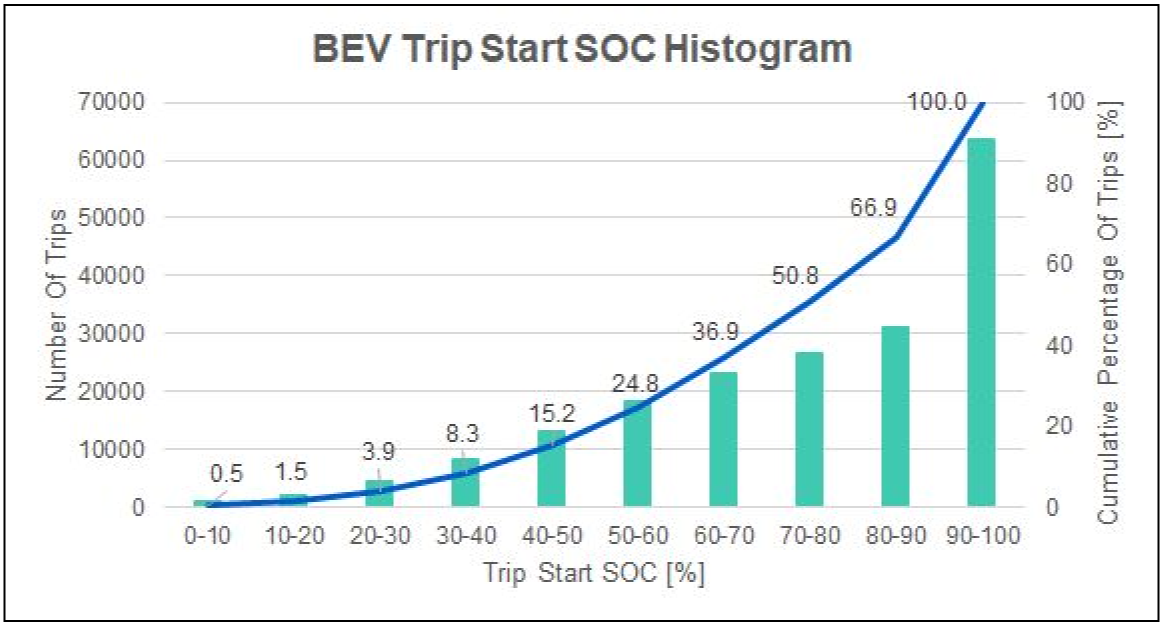

Figure 3: Histogram and Cumulative Distribution for the Battery SOC for All BEV Trips

This indicates that PHEV drivers are relying on the gasoline engine for at least 30% of trips whereas BEV owners, who only have the electric battery as a power source are much less likely to start a trip with a low starting SOC. In fact, more than 50% of all BEV trips start with an SOC of 70% or higher.

4.2 Average Driving Distances

Driving metrics were analyzed in two ways, by 'calendar day' and by 'driving day'. Calendar day distance represents the total distance driven by a vehicle divided by the total number of days the vehicle has been logging data. Driving day distance represents the total distance driven by a vehicle divided by the number of days the vehicle has logged at least one trip. Table 3 shows a summary of the driving metrics collected across all trips.

Table 3: Summary Driving Metrics from Data Collected in All Trips

Group	Average km per Calendar Day	Average km per Driving Day	Average Electric km per Calendar Day	Average Electric km per Driving Day
1	49.5	57.6	49.4	57.5
2	49.8	54.5	22.2	24.4
3	43.1	50.4	17.5	20.5
4	35.2	42.5	35.2	42.5
5	37.9	46.6	37.9	46.6
6	39.6	45.9	22.9	26.5
7	32.4	39.4	32.4	39.3
8	33.3	39.8	33.3	39.8
9	41.5	47.9	22.4	25.9
10	26.8	40.3	26.8	40.3
11	44.8	59.8	18.7	25.0
12	48.2	62.3	48.2	62.3
13	57.9	71.1	22.2	27.2
Total Average (All Vehicles)	41.5	50.6	30.0	36.6

Figures 4 through 7 compare the average distance travelled between each participant group. This analysis shows that Group 13 travels more on average each day than the other groups (both calendar and driving days). Since Group 13 is composed of PHEVs, the average electric kilometers travelled is less than most other groups. The group that travels the most electric kilometers is Group 12, which consists of SR BEVs in rural locations, where longer commuting distances may be necessary.

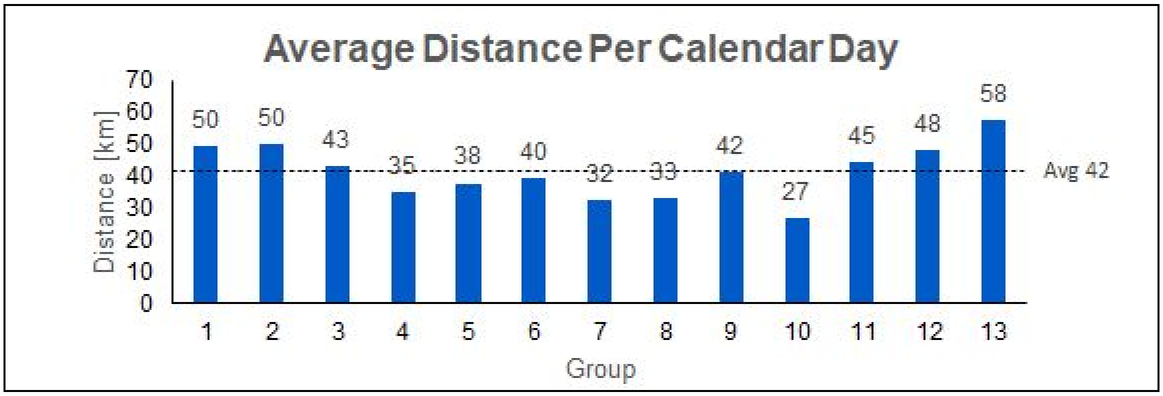

Figure 4: Comparison of Average Distance Travelled per Calendar Day by Participant Group

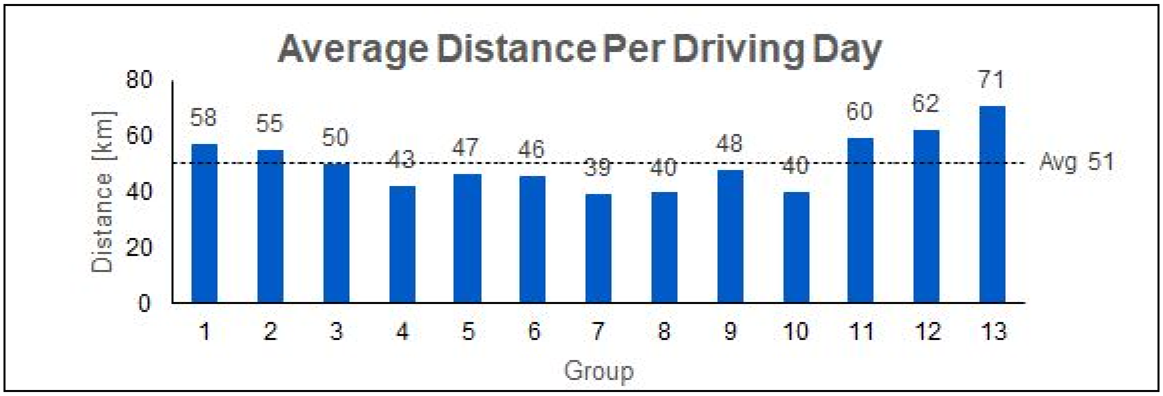

Figure 5: Comparison of Average Distance Travelled per Driving Day by Participant Group

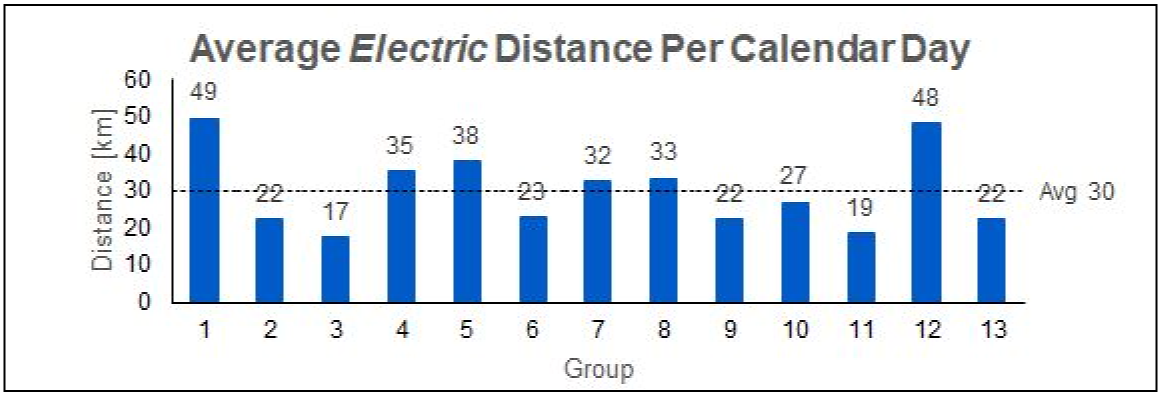

Figure 6: Comparison of Average Electric Distance Travelled per Calendar Day by Participant Group

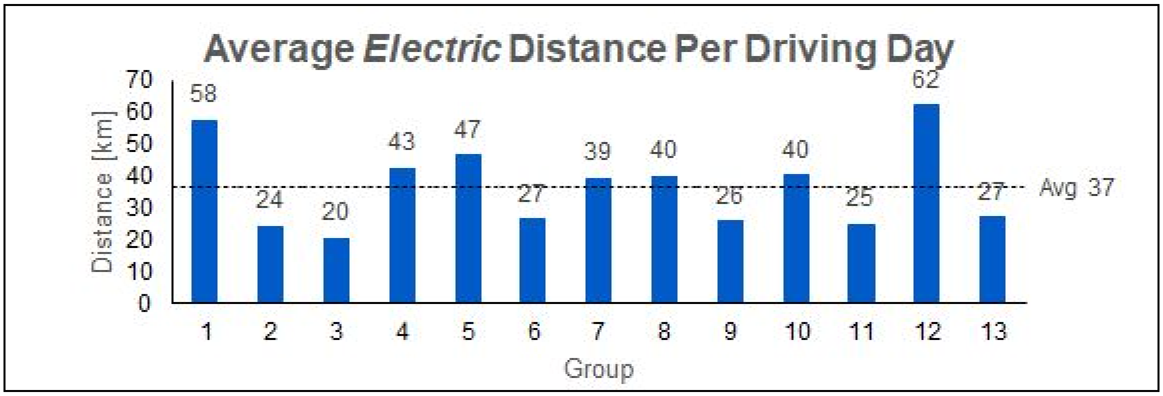

Figure 7: Comparison of Average Electric Distance Travelled per Driving Day by Participant Group

On average, groups with longer commuting distances are those in rural areas and those areas outside Reykjavik. While PHEV participants tend to drive farther overall distances than other vehicle powertrains, their average electric distance per driving day is generally less. This indicates that PHEV participants utilize the gasoline engine for a significant portion of driving distance. The average distance that LR BEV participants drive is similar to the overall project average distance. This may be due to the urban and capital locations these participants are in, indicating that they don't need to drive as often or as far as some of the other groups even though these vehicles are capable of driving longer distances on a single charge.

4.3 Electric Efficiency

The electric efficiency of an EV's battery is useful to determine the optimal operating temperature of the project vehicles. Figure 8 plots the electric efficiency with temperature. This shows that the optimal operating range is between 15 and 21 degrees Celsius. Range losses will occur with temperatures less than 15 degrees or more than 21 degrees and are more substantial with temperatures of less than zero. This means that it will require more energy to drive the same distance in extreme cold.

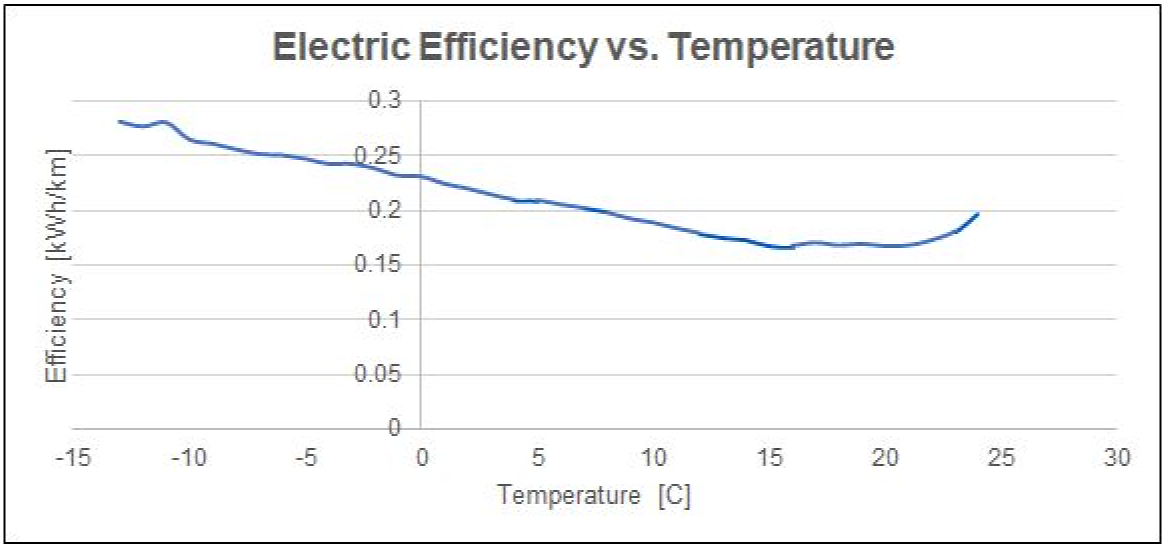

Figure 8: Electric Efficiency vs Average Outdoor Temperature

4.4 Carbon Offset

Across the 195 vehicles reporting data during 2019, the total number of electric kilometers driven is 2.1 million. From the charging data, the efficiency of the vehicles in this program is calculated at 0.23 kWh/km.

The following assumptions are used in converting electric kms to a carbon emissions offset:

- The average fuel economy of a conventional vehicle in iceland is 7.1 L/100 km
- Tailpipe fuel emissions are 2345 g CO_2/L
- 740 g CO_2/L are emitted in the production of gasoline
- 11.2 g CO_2/kWh are emitted in the production of electricity in Iceland

The total carbon offset by the electric vehicle kilometers travelled by project participants is therefore 457,188,125 g CO_2 (457.2 metric tons of CO_2).

5 Aggregate Charging and Energy Metrics

When and how electric vehicles are charged can be sporadic and unpredictable, especially as vehicles travel longer trips and utilize public charging stations. To understand charging energy metrics, the data was analyzed in two ways, by 'calendar day' and by 'charging day'. Calendar day charging represents the total kWh charged by a vehicle divided by the total number of days the vehicle has been logging data. Charging day statistics represent the total kWh charged by a vehicle by the number of days on which the vehicle had any charging events. Table 4 shows a summary of the charging metrics collected for all 13 groups.

Table 4: Summary Metrics from Data Collected in All Charging Sessions

Group	Energy per Calendar Day [kWh]	Energy per Charging Day [kWh]	Max Charging Power [kW]	Average Charging Power [kW]
1	11.1	16.3	48.5	3.6
2	5.7	7.6	19.5	2.2
3	4.2	7.0	19.5	2.2
4	8.6	11.8	48.9	3.1
5	8.3	16.0	48.5	4.6
6	6.5	8.9	48.0	2.4
7	7.1	11.3	49.0	3.1
8	6.6	15.4	49.0	4.4
9	5.7	8.7	19.5	2.1
10	6.2	10.8	49.1	3.0
11	4.5	7.9	19.5	2.3
12	10.8	15.7	49.0	3.5
13	5.3	7.9	19.5	2.1
Total Average (All Vehicles)	7.0	11.0	49.1	2.9

The values shown in Table 4 are compared through Figures 9 through 12. In Figure 9, Groups 1 and 12 used the most charging energy on average per calendar day and per charging day. Both of these groups are composed of SR BEVs, with Group 1 in a suburban setting (outside of Reykjavik) and Group 12 in a rural setting.

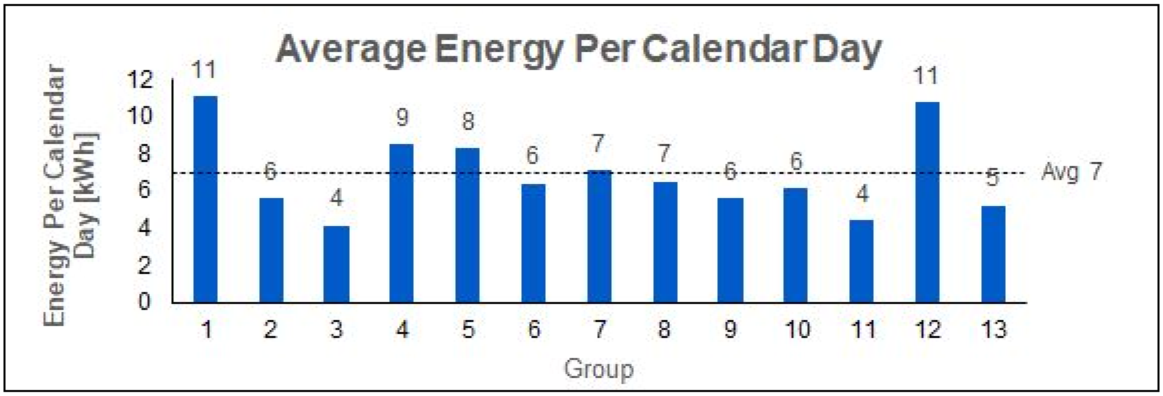

Figure 9: Comparison of Average Charging Energy per Calendar Day by Participant Group

As Figure 10 shows, the average charging energy per charging day ranges from approximately 7 kWh to 16 kWh amongst the participant groups, with an average of 11 kWh for all 195 vehicles in the project. Overall, participant groups with PHEVs use less charging energy on average than the other participant groups.

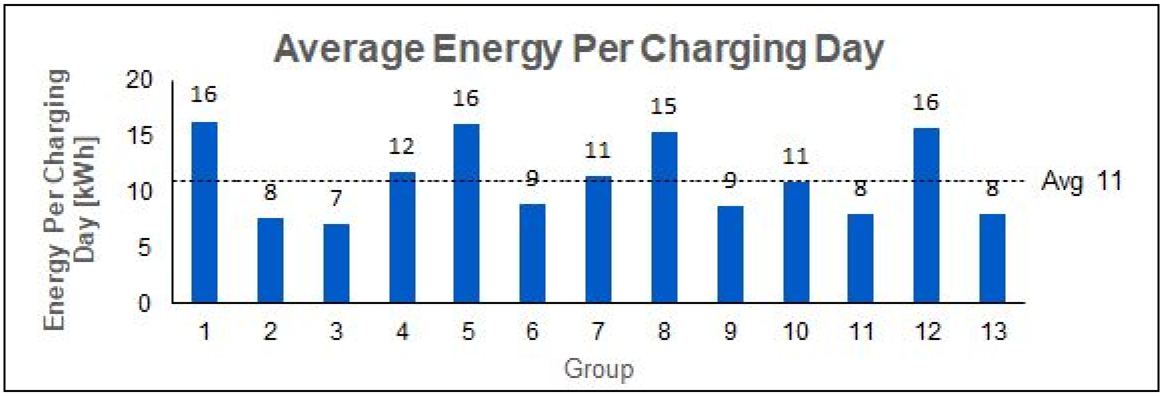

Figure 10: Comparison of Average Charging Energy per Charging Day by Participant Group

The maximum power of a charge interval for each participant group is plotted in Figure 11. This shows several groups with a maximum power of 48-49 kW, which typically corresponds to DC Fast Chargers (~50 kW maximum output). The other participant groups reported a maximum charging power of 19-20 kW which corresponds to a 'Level 2' (240 V) charging station.

The participant groups with PHEVs are more likely to utilize Level 2 chargers, with the exception of Group 6. Groups in more urban areas were more likely to utilize DC Fast Chargers (DCFC).

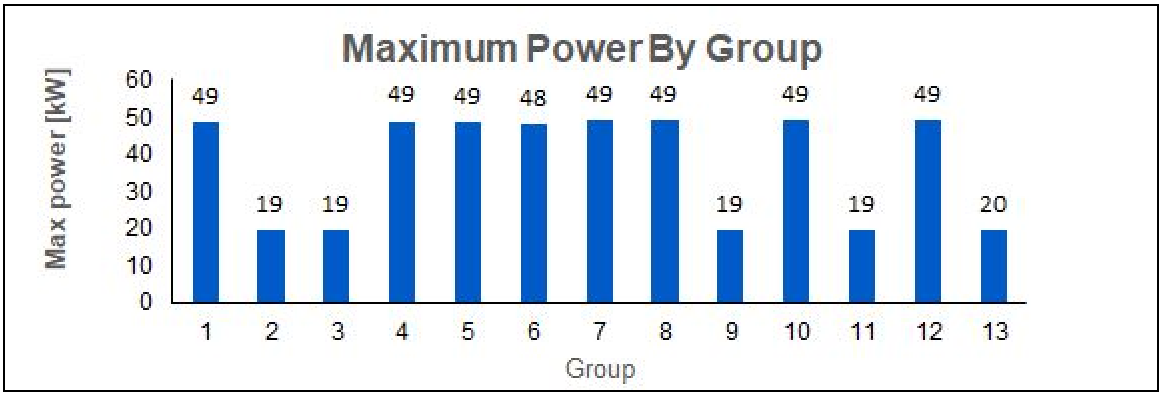

Figure 11: Comparison of Maximum Charging Power by Participant Group

As anticipated, participant groups with LR BEVs (i.e. Groups 5 and 8) have a higher charging power on average. Groups 1 and 12 also have a higher charging power, likely due to the longer, on average, electric distances travelled when compared to the other groups. This can be seen in Figure 12.

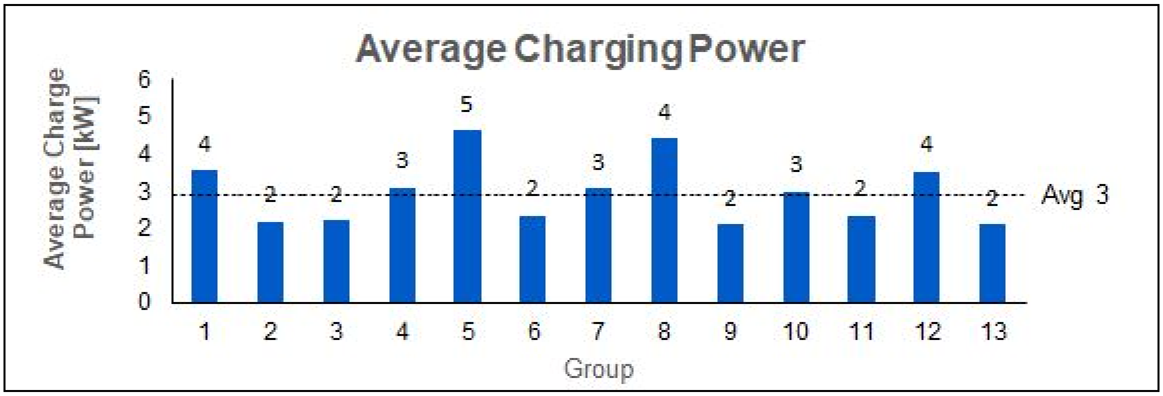

Figure 12: Comparison of Average Charging Energy per Calendar Day by Participant Group

The annual charge energy demand per vehicle has been plotted in a Box and Whisker plot in Figure 13. To understand this plot, the ends of the boxes represent the 25th and 75th percentiles of the charge energy reported. The line in the box is the median total charge energy for all vehicles within that group. The whiskers (lines outside of each box) represent the minimum and maximum annual charge energy reported by individual vehicles within the group.

In general, vehicle groups that cover more kilometers charge more per calendar and charging day. However, there are several groups that have vehicles doing no or very little charging. These groups are composed of PHEVs and only one group, Group 2, had a vehicle that did not charge at all during the data collection period.

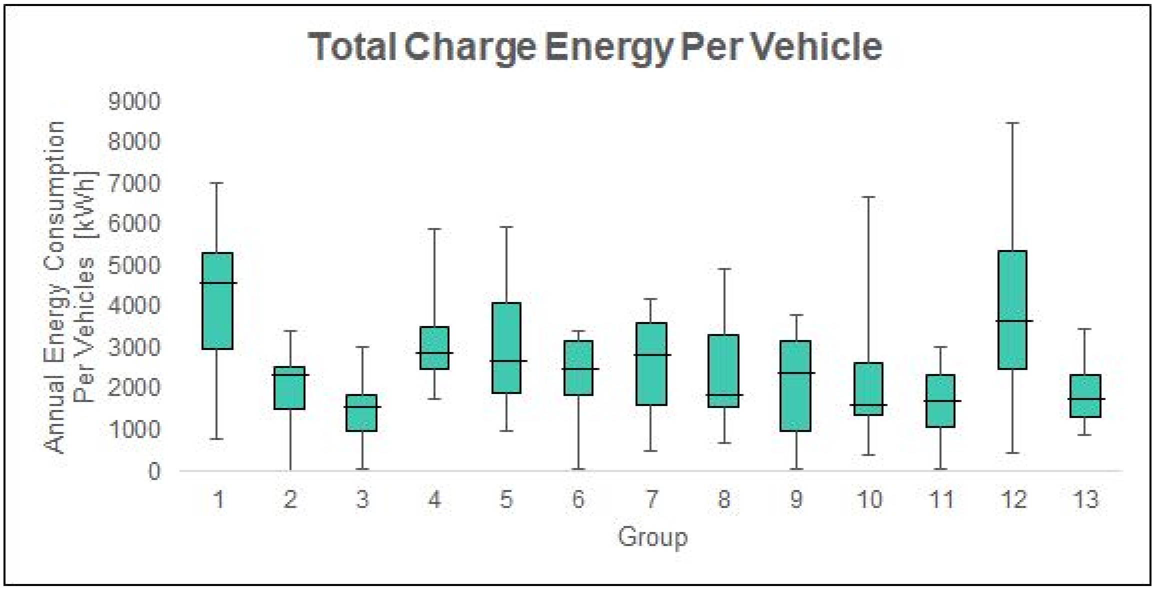

Figure 13: Box and Whisker Plot Showing the Total Charge Energy per Vehicle Group

The daily charge energy per vehicle was also plotted using a Box and Whisker plot. This shows a wide range of charge energy consumed on a daily basis. All groups and vehicles show a minimum value of zero, representing the days when they are not charging. Groups 5 and 8 show higher maximum values, likely due to the LR BEVs ability to consume more energy in a single charge.

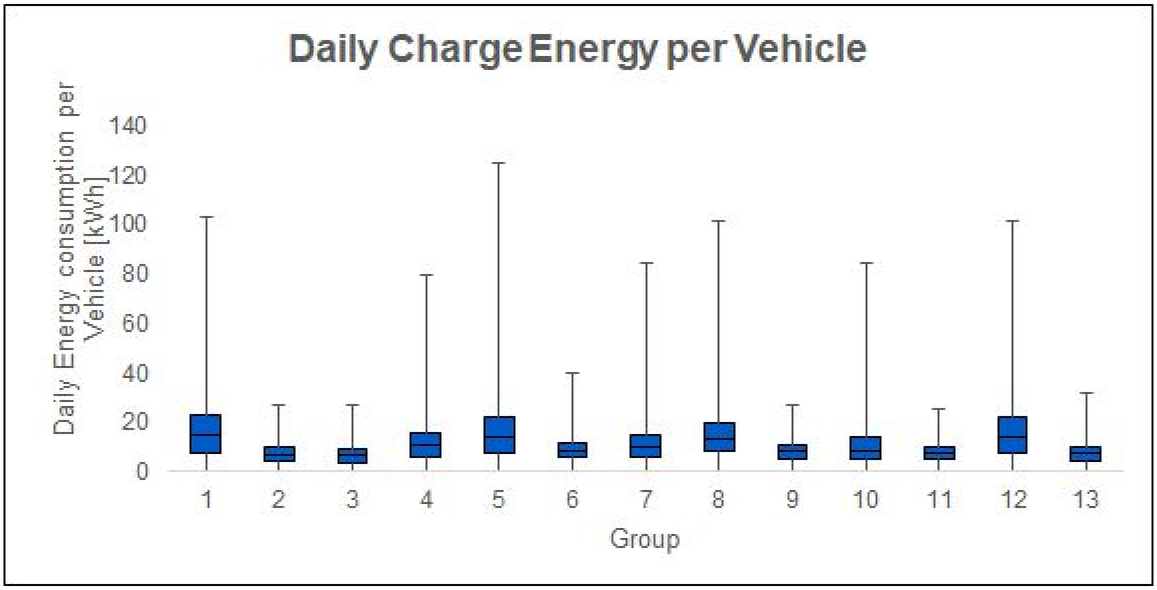

Figure 14: Box and Whisker Plot Showing the Daily Charge Variation within Each Group

5.1 Charging During Peak Periods

The amount of charging energy consumed by each participant group was analyzed by peak periods. The peak periods were defined as: Morning Peak (08:00 to 11:00), and Afternoon Peak (17:00 to 19:00). All charging energy consumed outside of these peak periods was considered off-peak. For each group, the total kWh charged for each period in 2019 was summarized in Table 5.

Table 5: Percentage of Charging Energy by Peak Period for Each Group

Group	Morning Peak Energy	Afternoon Peak Energy	Off Peak Energy
1	16.1%	14.4%	69.4%
2	6.8%	27.9%	65.3%
3	4.1%	21.0%	74.9%
4	9.4%	17.1%	73.4%
5	10.8%	14.6%	74.6%
6	7.1%	27.4%	65.6%
7	7.7%	14.2%	78.1%
8	17.2%	14.8%	68.0%
9	10.9%	25.1%	64.1%
10	17.0%	21.7%	61.3%
11	16.4%	18.8%	64.8%
12	11.1%	18.2%	70.7%
13	10.5%	25.1%	64.4%
Total (All Vehicles)	11.5%	19.2%	69.3%

Overall, the percentage of charging energy consumed during the morning peak period ranges from 4% in Group 3, to 17% in Groups 8 and 10. The percentage of charging energy consumed during the afternoon peak period ranges from 14% in Groups 1 and 7, to 27% in Group 6. The Group that is consuming the most charging energy for both peak periods is Group 10, which may correspond to workplace charging. These percentages are visually illustrated in Figure 15.

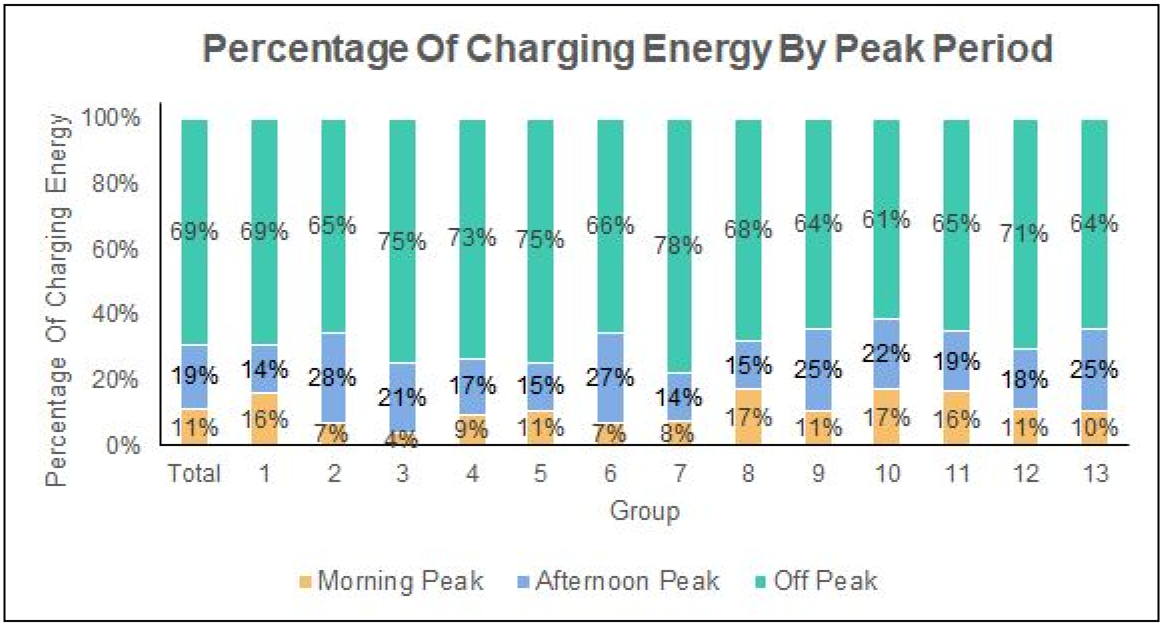

Figure 15: Percentage of Charging Energy by Peak Period for Each Participant Group

The majority of charging for all groups occurs off-peak. Groups with PHEVs are most likely to charge on-peak, specifically during the afternoon peak. Non-residential groups, those that use their vehicles for business purposes, are charging during peak periods most often. The breakdown of charging done by vehicle segments at specific times can be seen in Figure 16.

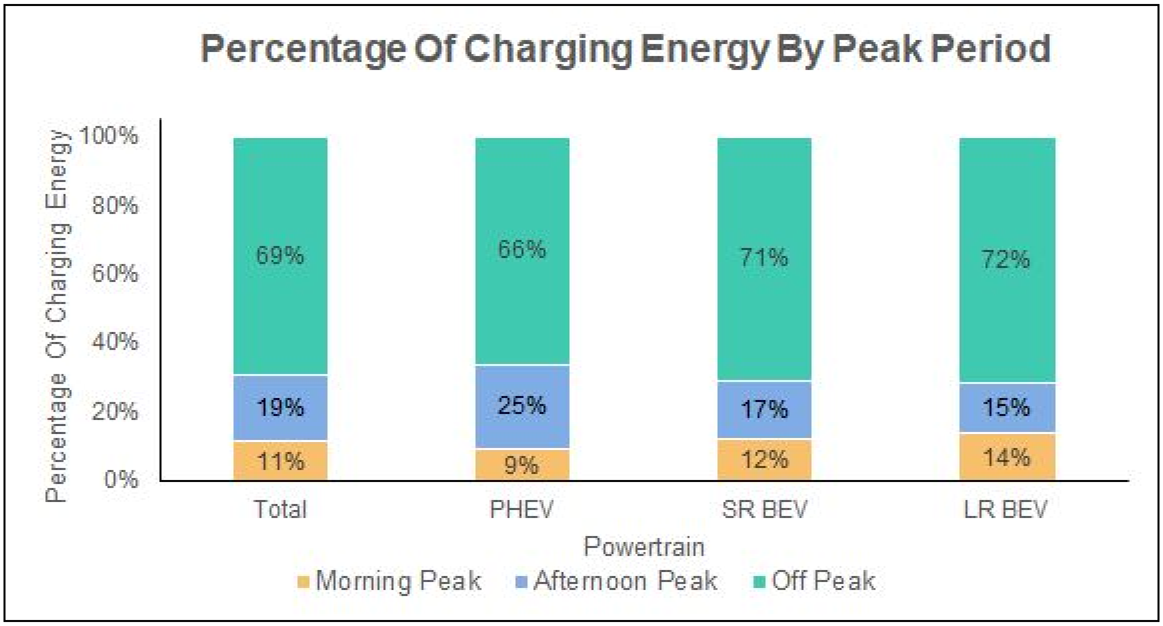

Figure 16: Percentage of Charging Energy by Peak Period for Each Vehicle Powertrain

When analyzing the charging energy by peak period for each vehicle powertrain, BEVs tend to charge at similar times with the majority of charging occurring off-peak, and similar percentages of charging during the morning and afternoon peak periods. PHEVs charge significantly less in the morning peak period and more in the afternoon peak period. They also charge less during the off peak period than SR or LR BEVs.

5.2 Charging by Location

The locations at which charging occurred can be classified as the following: home, summer house, workplace or service center, work base, service center, DCFC station or other. These charging locations are based on the locations provided by Register Iceland with specific charging definitions applied (refer to Appendix B for charging location definitions). These definitions combine the different types of commercial properties and the different types of homes. The definitions are further refined for business locations and DCFC.

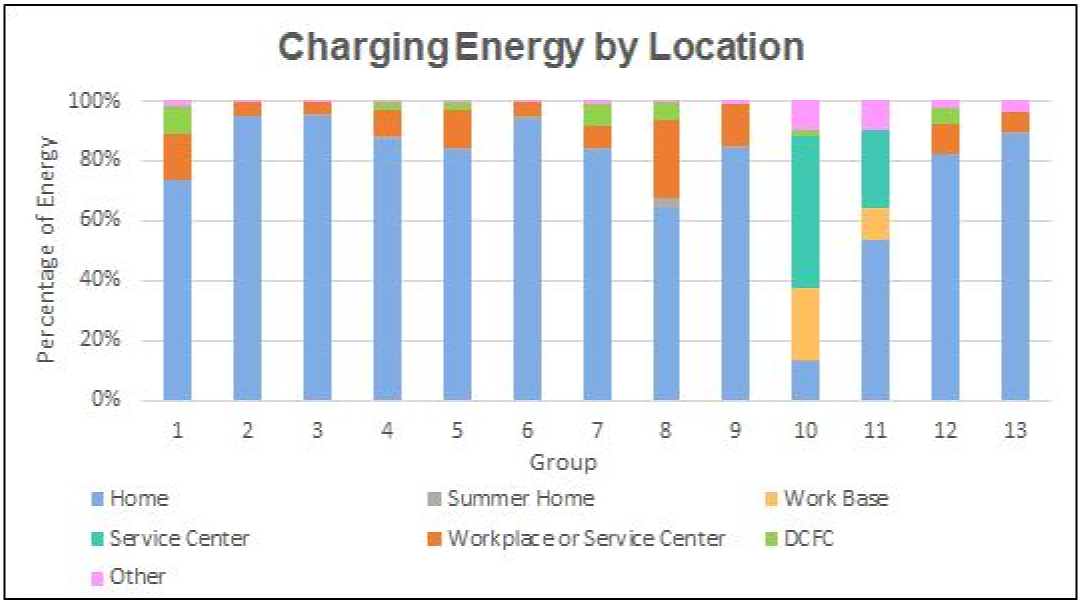

Figure 17: Total Charge Energy by Group for Defined Charging Point Locations

Figure 17 indicates that the majority of charging occurs at home. Business owned participant groups show more variation in charging with much less charging occurring at home. Individual owned and business owned vehicles were further analyzed in Figure 18 below.

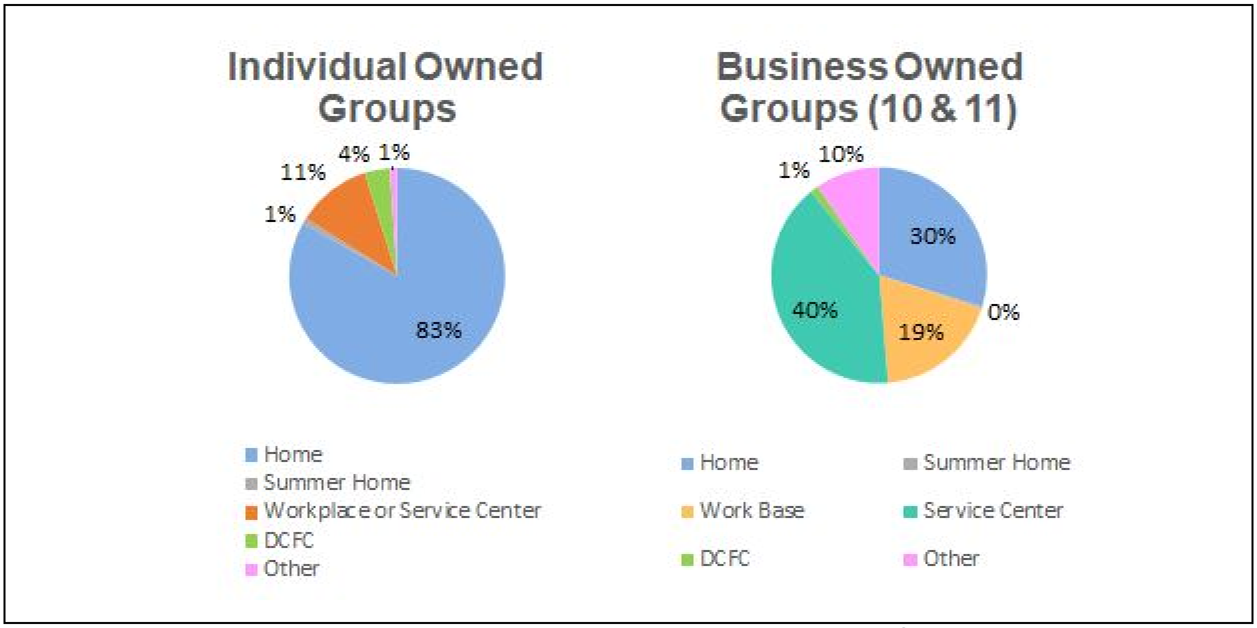

Figure 18: Charging Energy Percentage by Individual and Business Owned Groups For Defined Charging Point Locations

The charge energy distribution for business owned vehicle participant groups is different than for individual owned vehicle participant groups with significantly more charging energy used at service centers, work bases and other charging locations.

In addition to charging at defined charging locations, the charging locations defined by Register Iceland were also analyzed. These locations can be classified as the following: apartment building, single family home, summer house, commercial office, garage, industrial, specialized, warehouse or other. The percent distribution of charging locations can be seen in Figure 19. A table of these results can be found in Table B-2.

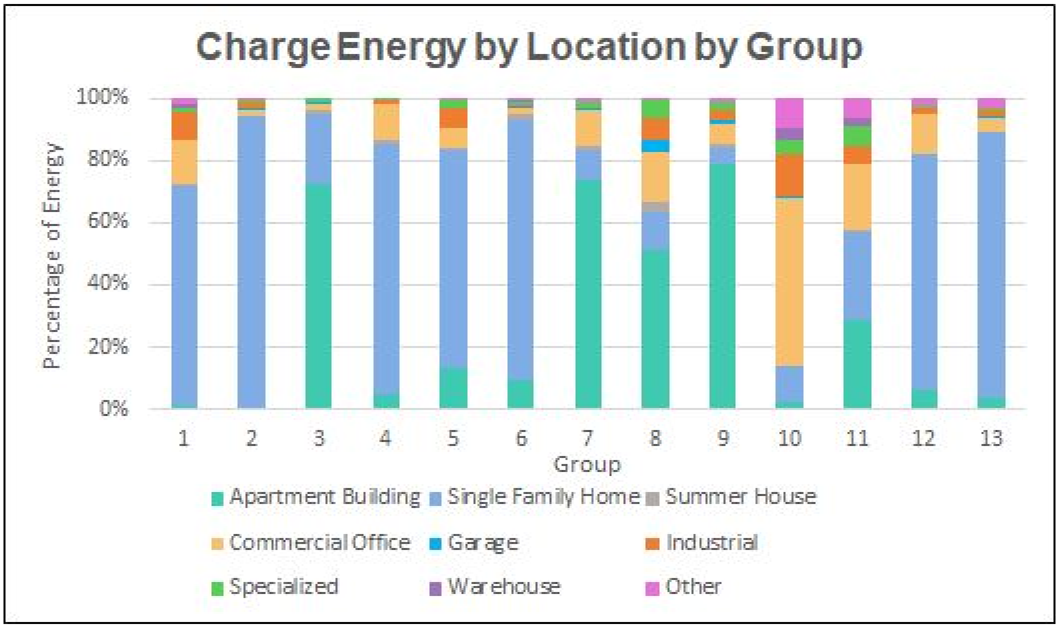

Figure 19: Charge Energy Percentage by Housing Location for Each Participant Group

It is apparent that most charging occurs at the home (apartment or single family home) or commercial locations. In fact, all residential (apartment, single family home) groups charge primarily at home. Non-residential groups (Groups 10 and 11) do more charging in commercial, industrial or other locations. A table comparing residential with non-residential groups is available as [Table B-3].

All groups show both charging at apartment buildings and single family homes, regardless of the participant's residence. Groups 1 and 2 are the only exceptions, these participants are outside of Reykjavik, living in single family homes and may only use their residences for home charging. Very little charging occurred at summer homes, only participants in Group 8 with LR BEVs showed any significant portion of charging at this type of location.

The overall breakdown of charging by location for all groups can be seen in Figure 20. The majority of charging occurs at single family homes or apartment buildings. Commercial locations are the next most significant location for charging however, this proportion is reduced to 9% if Groups 10 and 11 are removed from this analysis. Both Groups 10 and 11 contain non-residential EVs which charge more often at commercial or industrial locations.

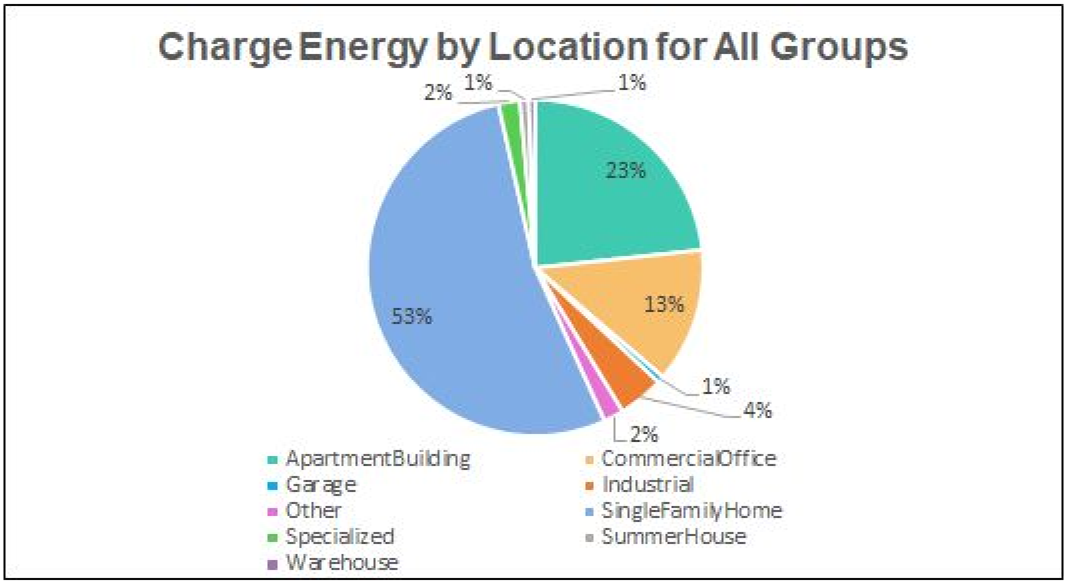

Figure 20: Charge Energy Percentage by Charging Location across all Participant Groups

The EVs within this project utilized public DCFC stations on average 54 km away from their home or business location (as shown in Figure 21). Groups 2 and 13 tend to utilize DCFCs from farther away, but also tend to fast charge less frequently. This may indicate that these EV drivers are likely on longer trips, and only using these chargers when necessary or the location of these public charging stations is inconvenient.

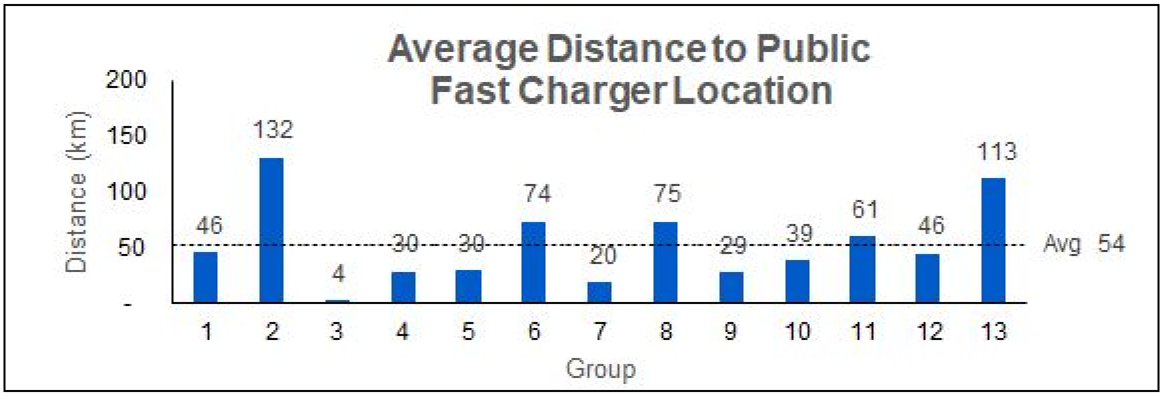

Figure 21: Average Distance from Home when DC Fast Charging

The utilization of public Level 2 charging stations tends to occur more closely to the EV driver's home or business location, on average 38 km away (as shown in Figure 22). Group 3 has a much higher average distance than the other participant groups but only utilizes these public charging stations 2% of the time. Participants in this group are also the closest to a DCFC, indicating that this may be the preferred public charging location. PHEVs tended to use public charging stations less frequently than other vehicle powertrains.

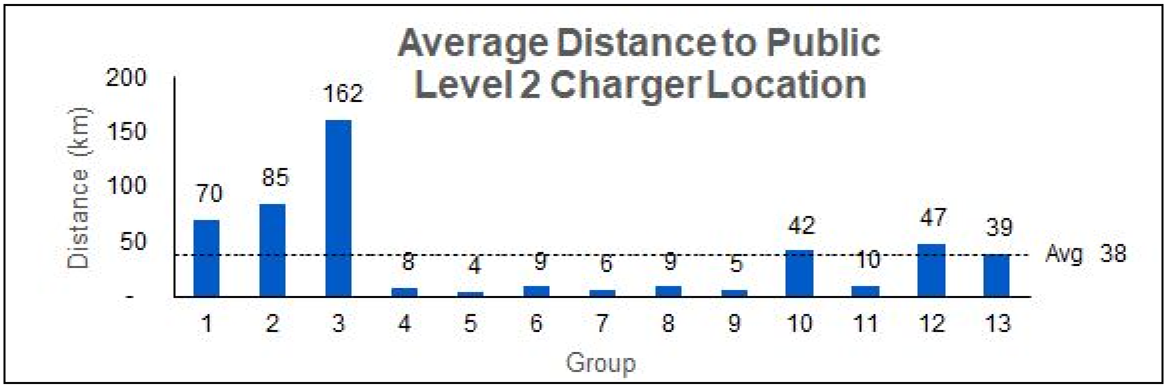

Figure 22: Average Distance from Home or Business When Level 2 Charging

Overall, the distance to public charging stations and frequency in which these are used is useful in managing the public charging station network within Iceland. Those participants who are closer and utilizing public DCFC charging stations are generally located further away from the public level 2 charging stations and vice versa. This may indicate that the public charging station availability is spaced conveniently from the homes of the majority of project participants. Only participants in Group 2 have a much higher than average distance from both the DCFC and level public charging stations.

6 Aggregate Charging Load Impacts

Understanding the load impacts from electric vehicles is complicated by the nature of the charging events and the differences in charging speeds (kW) possible. This is especially true for SR BEVs and LR BEVs that can use public DCFCs capable of providing 50-150 kW of power over short periods of time (<30 minutes).

Load curves are used to provide a graphical representation of the power demand over time. This allows the complexity of EV owner charging behaviours, along with the wide variety of EV makes, models and model years with varying battery sizes, to be compared together.

The total charging load recorded for all vehicles in the project is plotted in Figure 23 for each hour in 2019. This curve shows significant variability in the day-to-day EV energy demand. At a high level, there is some seasonality in the data, where there is less charging in the summer and more in the colder months. The lowest value of 2 kW is reached occasionally during the summer months. The maximum peak of 339 kW occurred in October.

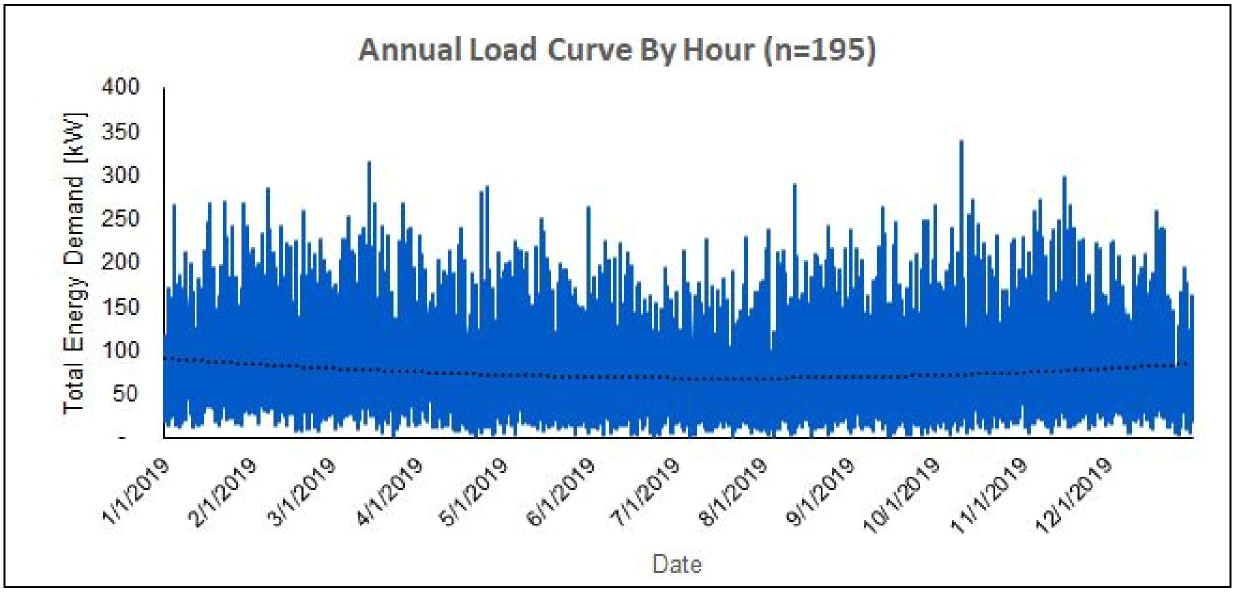

Figure 23: Annual Load Curve for All Project Vehicles

An average daily load curve (Figure 24) has been constructed, and represents the average load for all vehicles in the project at each 15 minute interval throughout the day. The average load is lowest in the early morning hours and peaks slightly around 07:30. This small peak may be the effect of EV preconditioning prior to the EV owner's morning commute. The average load then remains relatively consistent until 16:00 when the load begins to increase. The consistent daytime charging may be reflective of workplace charging which would occur throughout the workday. The increase of charging in the evening and the consistency overnight may be reflective of home charging as the EV owner returns home from work and plugs in.

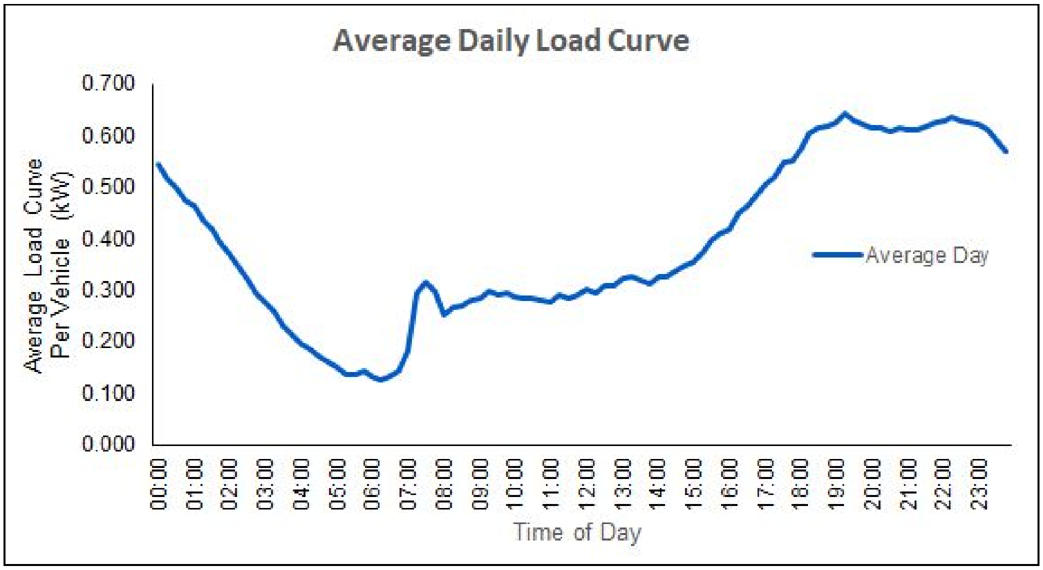

Figure 24: Average Daily Load Curve for All Vehicles

Average daily load curves comparing each of the participant groups to the project average daily load curve are included in Appendix C.

6.1 Coincidence Factor

Coincidence factor is the peak of a system divided by the sum of peak loads of each individual EV. This is a measure of how likely the EVs would peak at the same time. The highest factor is 1, indicating that all vehicles are peaking at the same time.

The peak of the system was calculated based on the annual load curve for each sample size. A curve was created and then fit and extrapolated to model for additional EVs beyond the 195 EVs in the project. This curve can be seen in Figure 25.

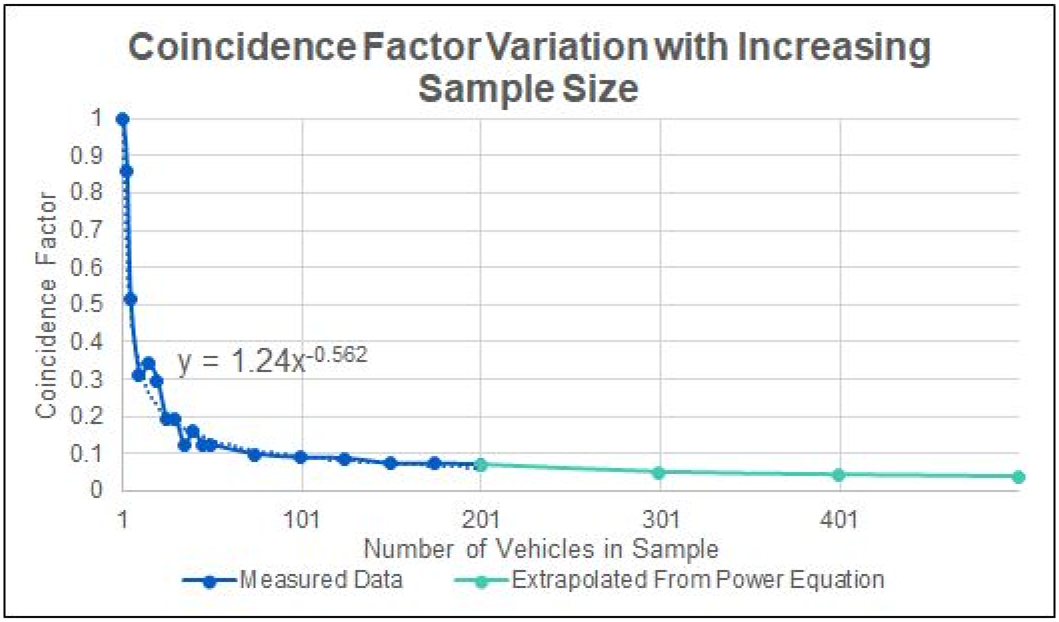

Figure 25: Coincidence Factor Variation with Increasing Sample Size

Coincidence factors for each participant group were calculated and have been included in Appendix D. These show that the PHEV groups in the urban, capital area (both single family homes and apartment buildings) have the highest coincidence factor.

The coincidence factor is a useful metric as it can be used to determine how likely individual EVs will peak at the same time. This is useful for future projections with a growing number of EVs as it can be used to create a measure of the possible maximum peak for any number of vehicles. The coincidence factor calculated in Figure 25 above was used to determine substation impacts for varying levels of EV penetration, as seen in Section 7.2.

6.2 Weekend and Weekday Load Curves

Since charging behaviour often varies from weekdays to weekends, an analysis of these load curves has been included as Figure 26. Both the weekend and weekday load curves peak in the evening as expected. The peak load is noticeably higher on weekdays, and the load shape contains a secondary peak in the early morning hours as drivers pre-condition their vehicles before work or plug in upon arriving at the office. An analysis of the weekend versus weekday load curves is included in Appendix E.

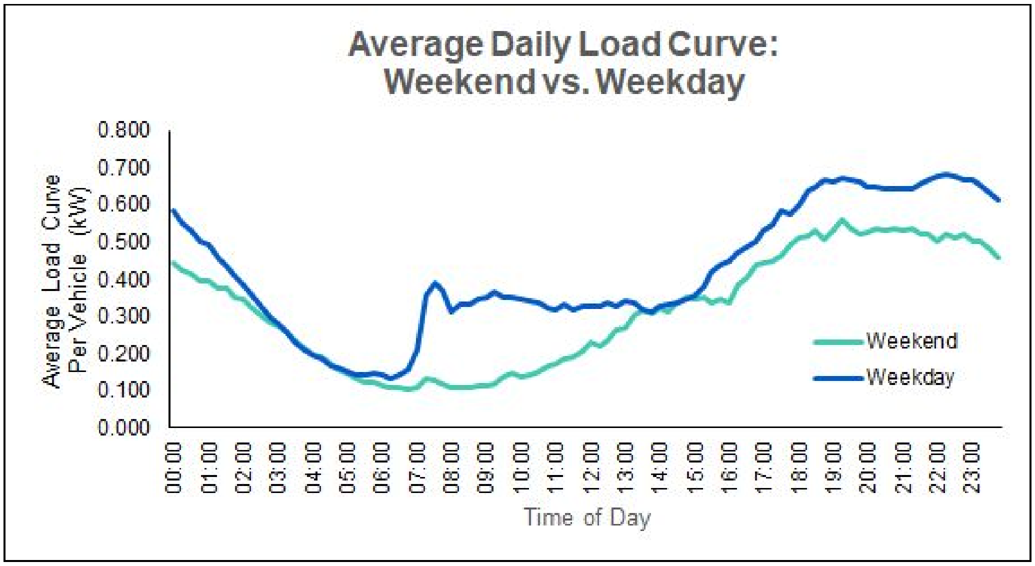

Figure 26: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand

6.3 Seasonality of Daily Load Shapes

The effects of seasonal variation in EV charging was analyzed by comparing the load curve for all vehicles by month to the average daily load curve (as seen in Figures 27 through 38). In colder months, the average load curve per vehicle increases in the evening. This may be related to the relationship of battery efficiency and temperature. Since it requires more energy to drive the same distance in colder temperatures, load curves during these months are expected to be higher. In moderate months, the load curve more closely matches the average. In warmer months, the average load curve decreases in the evening.

This indicates that more energy is being consumed on average in colder weather than warmer. Additionally, the secondary peak at 07:30 for pre-conditioning is more pronounced in the colder months, likely because vehicles have to use more energy to get to a comfortable temperature than in summer. This secondary peak is lower or absent in warmer months when the energy needed for pre-conditioning or cabin temperature is less, specifically from June to August. In August, the secondary peak is completely absent. This could be related to more participants on vacation during this month and not using their vehicles for the regular morning commute to work.

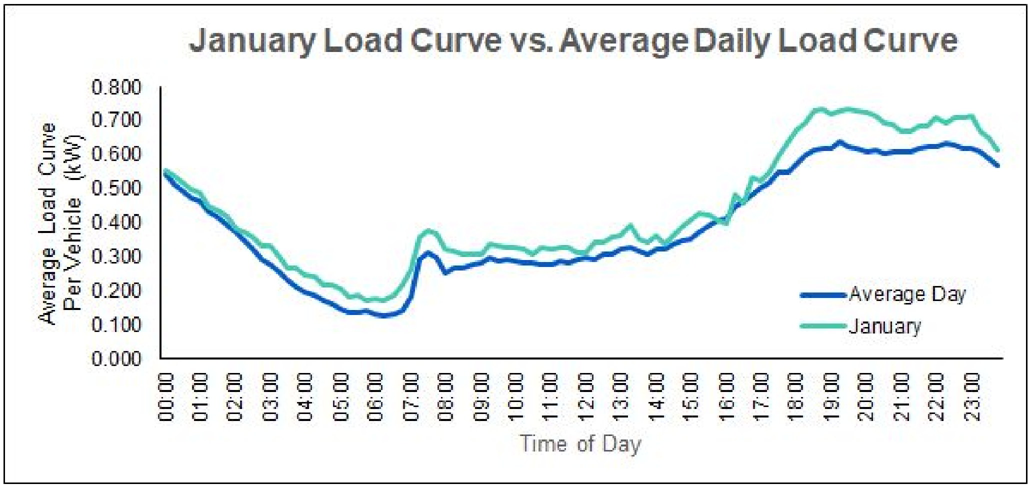

Figure 27: Monthly and Average Daily Load Curve Comparison (January)

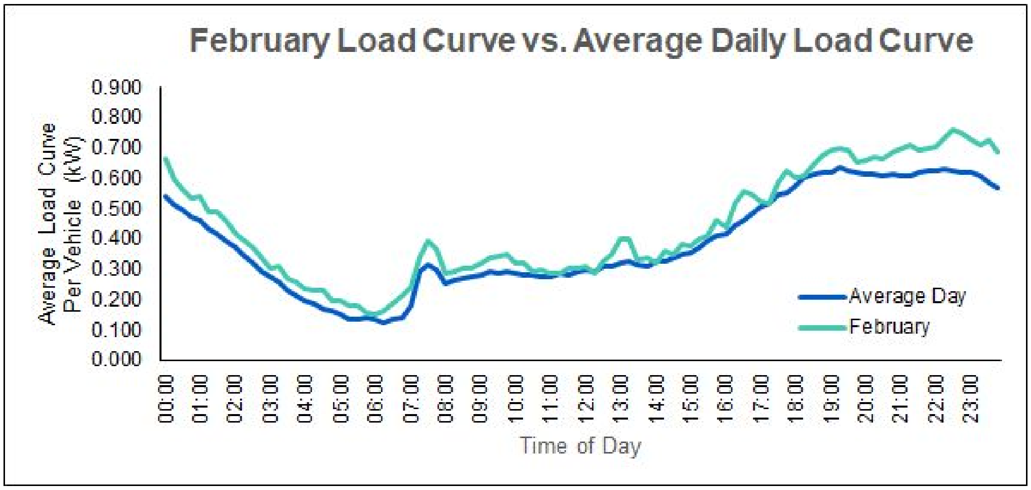

Figure 28: Monthly and Average Daily Load Curve Comparison (February)

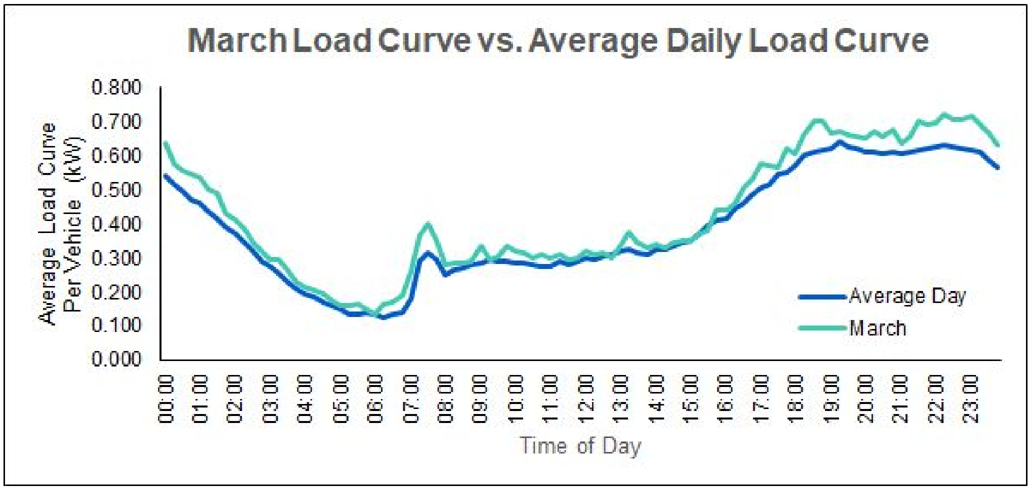

Figure 29: Monthly and Average Daily Load Curve Comparison (March)

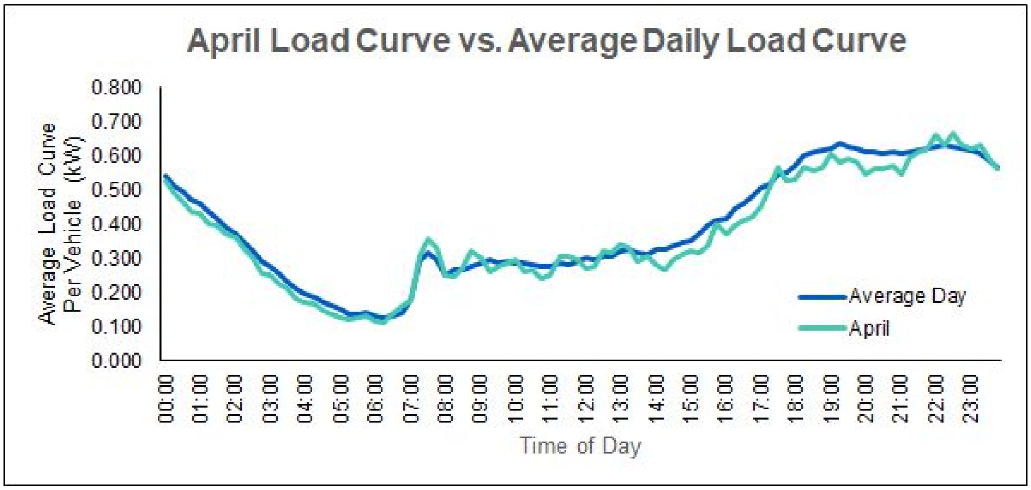

Figure 30: Monthly and Average Daily Load Curve Comparison (April)

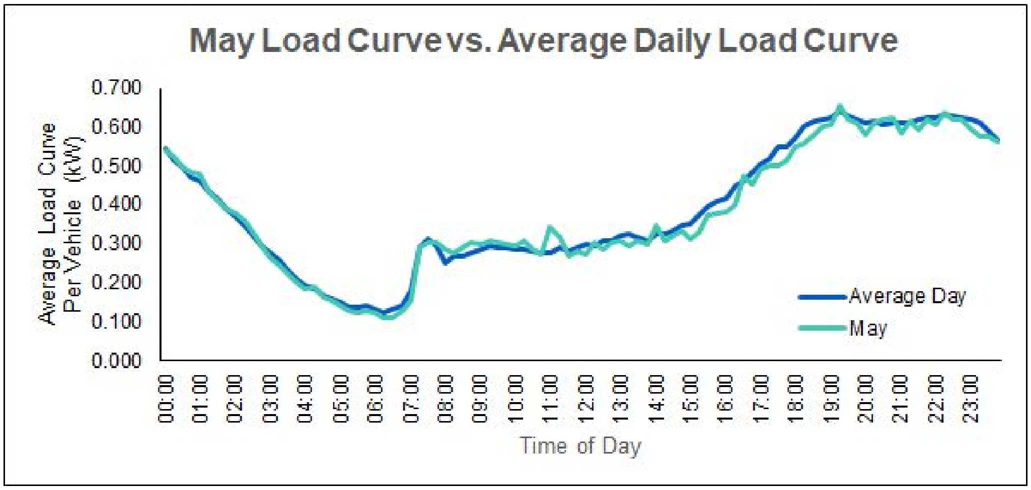

Figure 31: Monthly and Average Daily Load Curve Comparison (May)

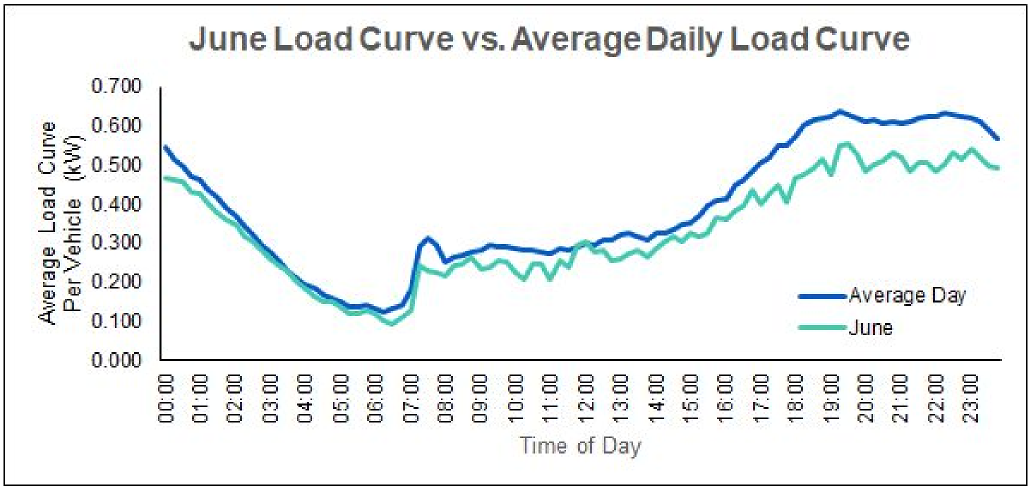

Figure 32: Monthly and Average Daily Load Curve Comparison (June)

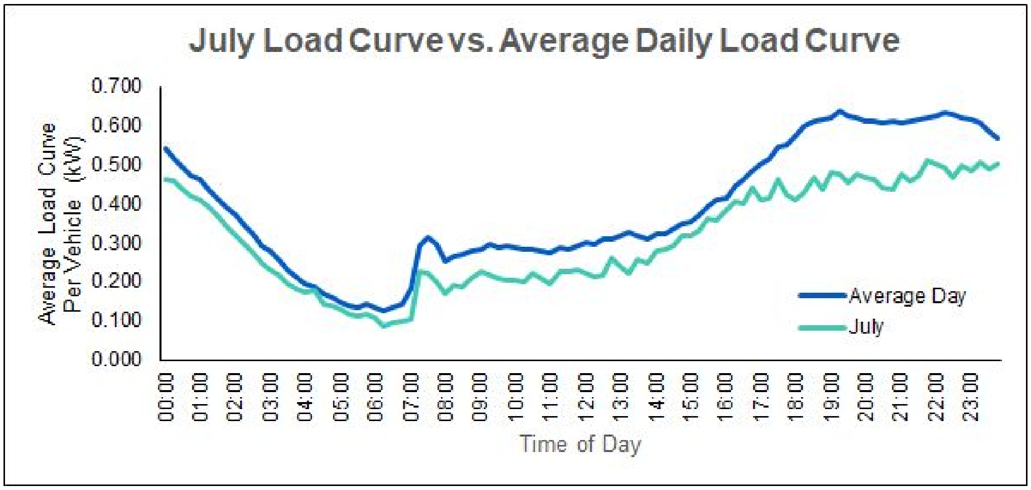

Figure 33: Monthly and Average Daily Load Curve Comparison (July)

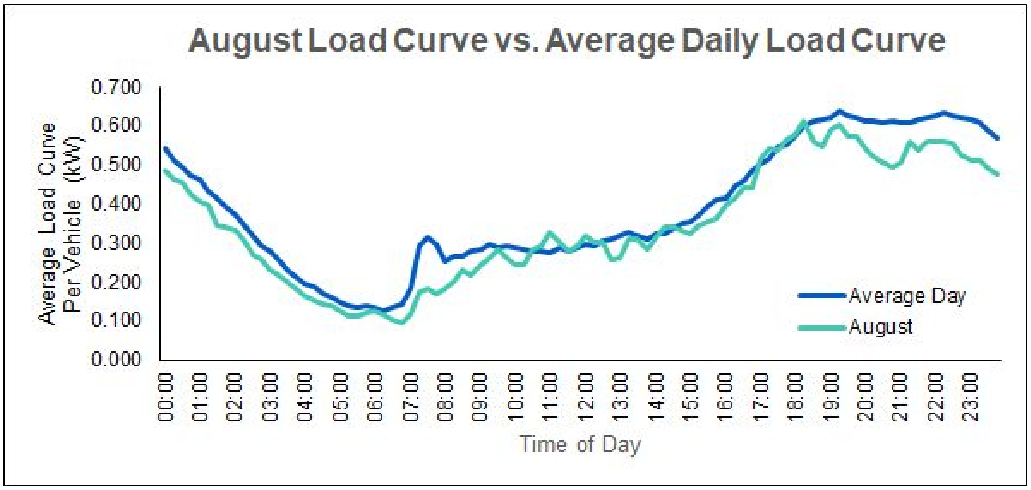

Figure 34: Monthly and Average Daily Load Curve Comparison (August)

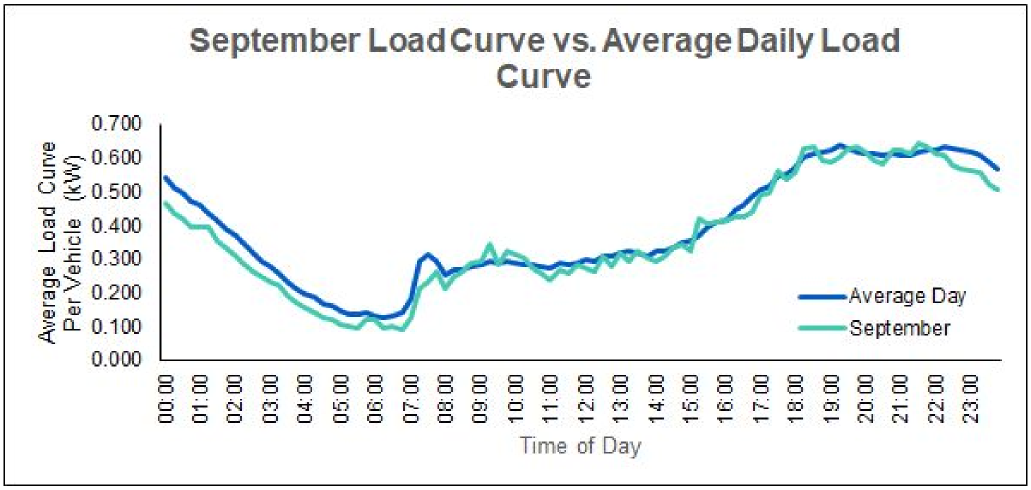

Figure 35: Monthly and Average Daily Load Curve Comparison (September)

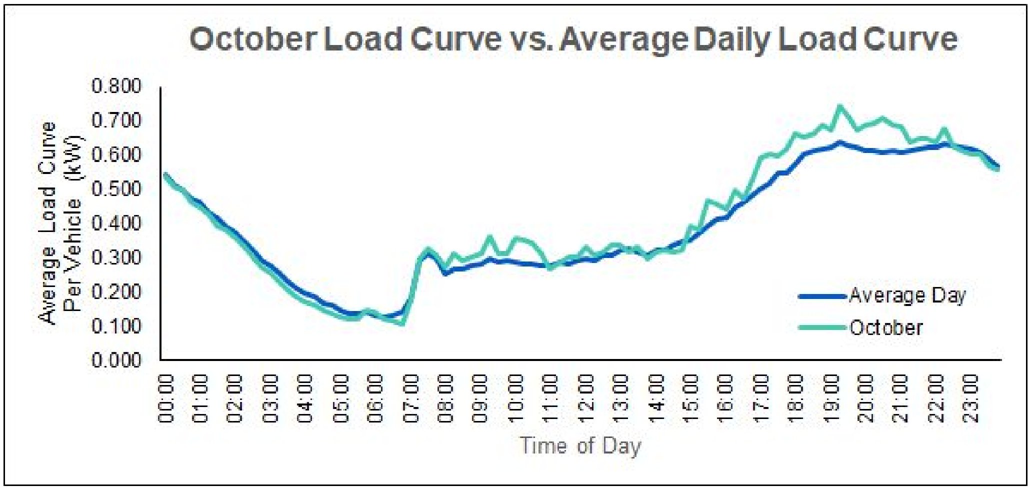

Figure 36: Monthly and Average Daily Load Curve Comparison (October)

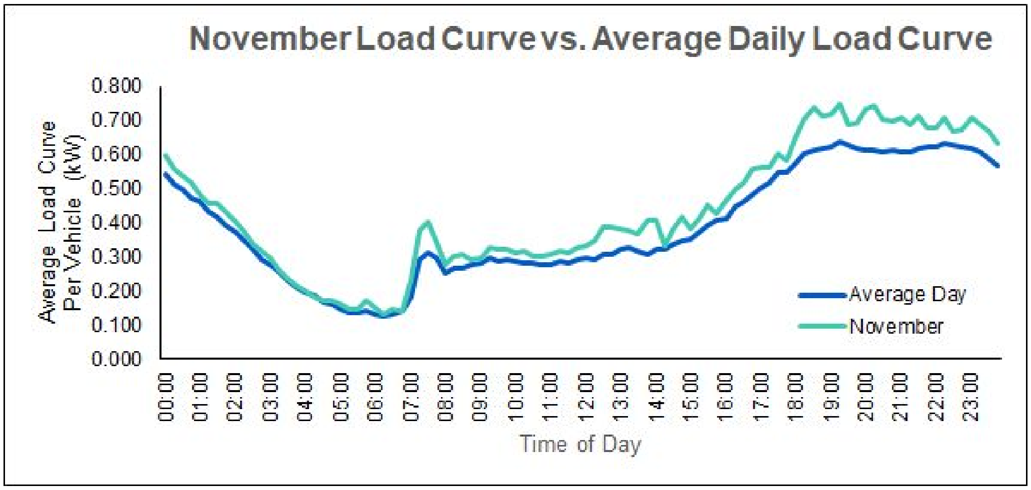

Figure 37: Monthly and Average Daily Load Curve Comparison (November)

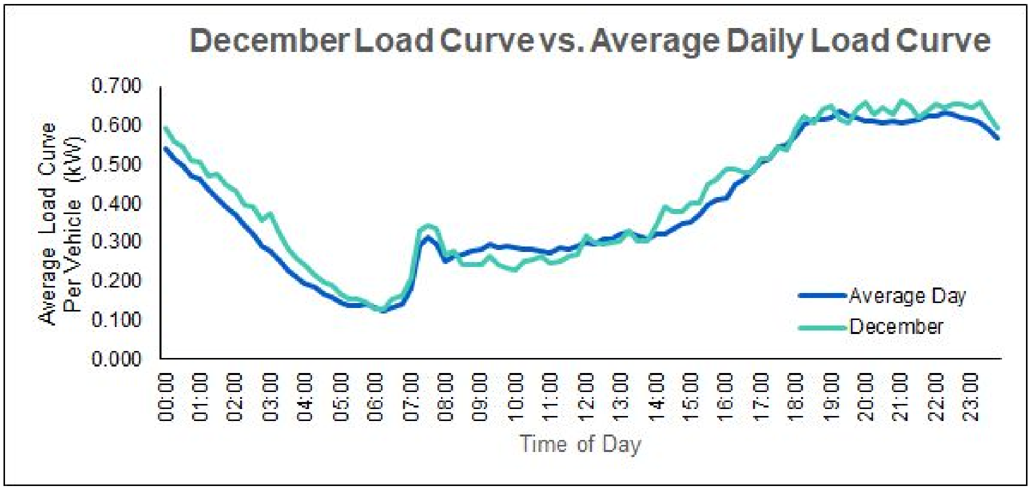

Figure 38: Monthly and Average Daily Load Curve Comparison (December)

The average daily energy use per vehicle for each 15 vehicle group over the course of a month is included in Table 6. The cells are shaded on a scale of white (lower loads) to dark green (higher loads) with a new colour scale for each column. The colours are consistently lighter June through August, representing lower average daily energy use in the summer months. Group 3 and Group 12 are unique since their lowest energy consumption happens in January and April respectively. In general the average energy used monthly by each group follows the same trend as power across all groups. There is a greater electricity demand in terms of energy and power consumption in the winter months.

Table 6: Average Daily Energy Consumption per Vehicle per Calendar Day By Group and Month

Month	Group 1	Group 2	Group 3	Group 4	Group 5	Group 6	Group 7	Group 8	Group 9	Group 10	Group 11	Grou p12	Group 13
Jan	11.8	6.2	3.5	10.6	10.2	7.5	9.2	7.6	5.4	6.9	4.8	11.2	6.1
Feb	13.1	6.4	3.8	9.7	8.5	6.9	8.1	6.9	4.9	5.9	4.8	10.7	4.7
Mar	12.0	6.3	4.5	9.6	8.8	7.4	8.0	7.3	5.8	6.4	5.8	10.9	5.4
Apr	10.5	5.8	3.8	7.5	6.6	6.5	7.2	6.3	5.8	5.6	5.1	9.2	5.6
May	10.5	5.6	4.5	7.1	7.9	6.8	6.8	6.8	5.9	6.6	4.6	10.6	5.5
Jun	9.3	5.4	3.6	5.6	7.6	4.9	5.7	5.6	5.6	6.3	3.4	9.8	4.9
Jul	8.0	5.3	3.9	6.0	6.2	5.2	5.1	5.4	4.9	5.3	2.9	9.6	4.7
Aug	10.2	4.7	4.4	8.1	7.1	6.0	5.3	6.2	5.2	5.2	3.1	10.9	4.2
Sep	10.3	4.7	4.5	8.4	8.5	6.5	6.3	5.1	5.2	5.7	4.1	10.1	5.3
Oct	11.2	5.1	4.0	8.9	9.6	5.7	6.5	6.7	5.5	6.4	4.6	12.1	5.0
Nov	16.0	5.8	3.7	10.2	8.9	6.5	7.5	7.3	5.6	6.9	5.4	11.7	4.7
Dec	10.0	5.7	4.4	9.1	8.8	6.0	8.9	6.7	5.2	6.2	4.7	10.2	5.8

6.4 Load Factors

Load factor is one way to measure the shapeability of a load curve. Defined as the average load divided by the maximum load, load factors close to 1 represent a consistent load throughout the day, with a peak that would be difficult to reduce. Load factors closer to 0 represent a high peak and low average, meaning the demand at peak could be shifted to another time of day to smooth the curve and lower the overall peak. The load factors for weekends and weekdays respectively can be seen in Figure 39.

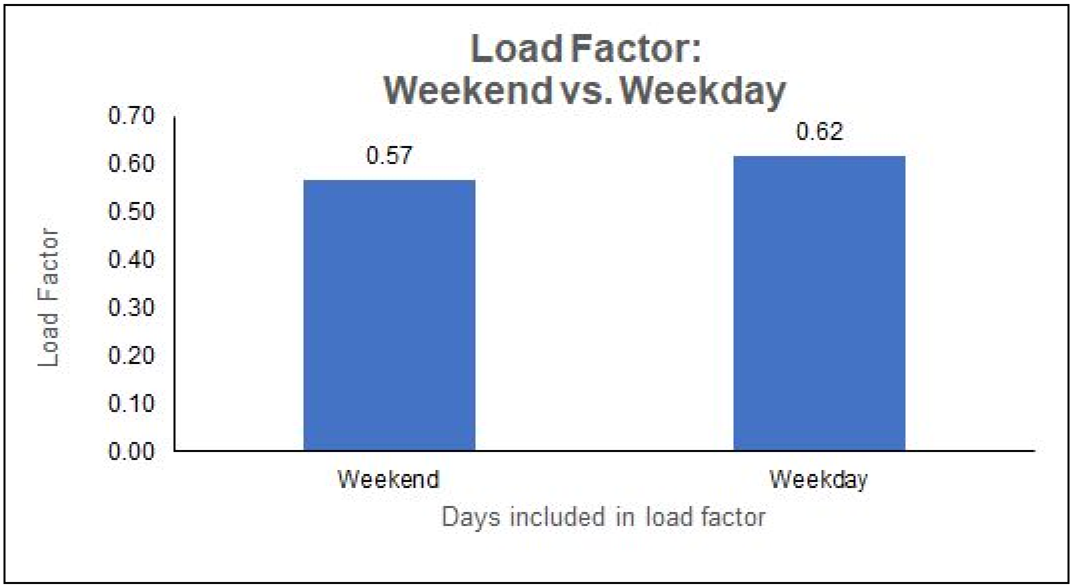

Figure 39: Load Factor for Weekends and Weekdays

The weekend load has a load factor of 0.57, while the load factor on weekdays is 0.62. This indicates that the load may be more shapeable by shifting peak demand to another time during the day. A load factor on weekdays is sometimes more useful when calculated only during the evening and overnight hours, when load has the opportunity to be shifted. Including the low daytime average load can be misleading as it gives the impression that load can be shifted to midday when, in reality, those vehicles are in use or parked in lots without charging equipment. The weekday load factor when calculated between 6:00 pm and 6:00 am (when vehicles are expected to be parked at home) is higher at 0.70.

The load factors for each participant group are available in Appendix F of this report. The load factors for Groups 2, 3 and 6 were all below 0.5, indicating that the load generated by these participants could be shaped to improve generation efficiency. This indicates that PHEVs in urban (within and outside of Reykjavik) areas may be more receptive to load shaping.

7 Substation Impacts

Knowing that the majority of charging occurs at home, projecting the power demands of more EVs on the local substations is paramount. The power demand on any given day can be substantially different than the average. There will likely be days where multiple individuals happen to charge at the same time, creating a high demand point.

7.1 Reykjavik Substations

In Reykjavik, three substations of varying ratings were modeled with project EV data from EV owners with residences in matching locations e.g. only EVs from apartment buildings were used when modeling substations that service only apartment buildings.

7.1.1 Substation 472

Figure 40 shows the expected power increase with additional electric vehicles on substation 472. The blue line indicates the transformer rating, while the green portion is the expected maximum power demand over the course of a year. Samples for these vehicles were taken from all participant groups living in single family homes with an equal ratio of LR BEVs, PHEVs, and SR BEVs. Substation 472, which currently powers 153 houses, is rated at 800 kVA, and has had a previous high demand of 360 kW. It would take a significant number of additional EVs before the maximum potential power demand approached the maximum rating.

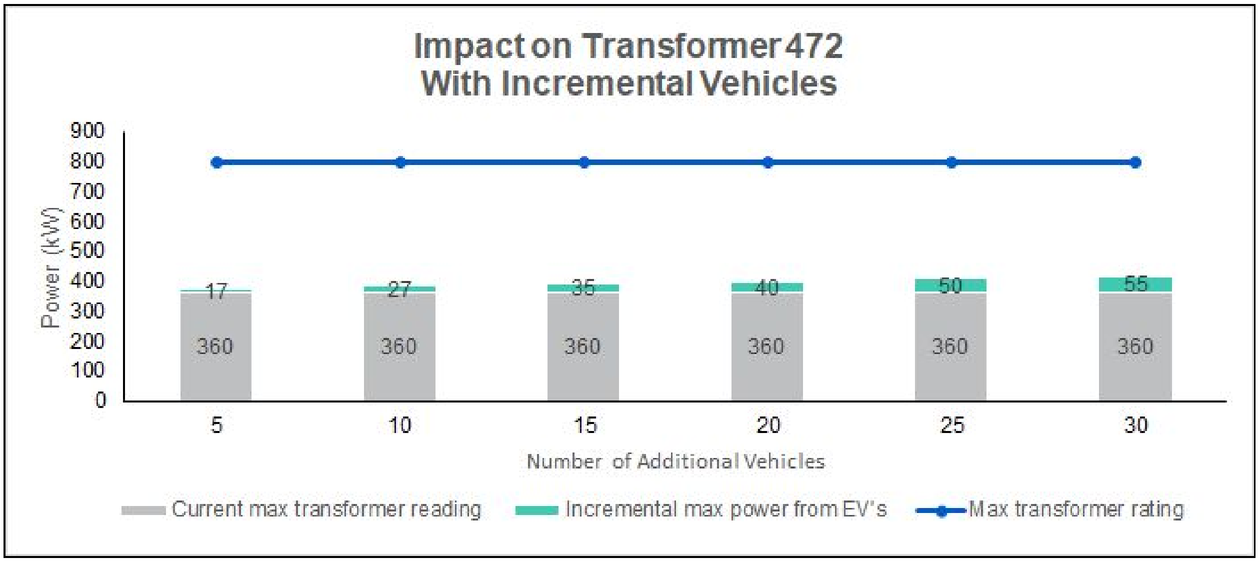

Figure 40: The Impact of Adding Additional EVs onto Transformer 472

7.1.2 Substation 350

Substation 350, which powers 163 apartment residences, is rated at a maximum of 500 kVA and has a previous high demand of 224 kW. There is still a significant buffer between the potential demand and the maximum rating, as shown in Figure 41. All participant groups in apartment buildings consume average or lower than average charge energy per calendar day. These participant groups (Groups 3, 7, and 9) are less likely to have a significant coincidence load. Only Group 8 participants, which consists of LR BEVs, have above average energy demands, may cause a higher coincidence load.

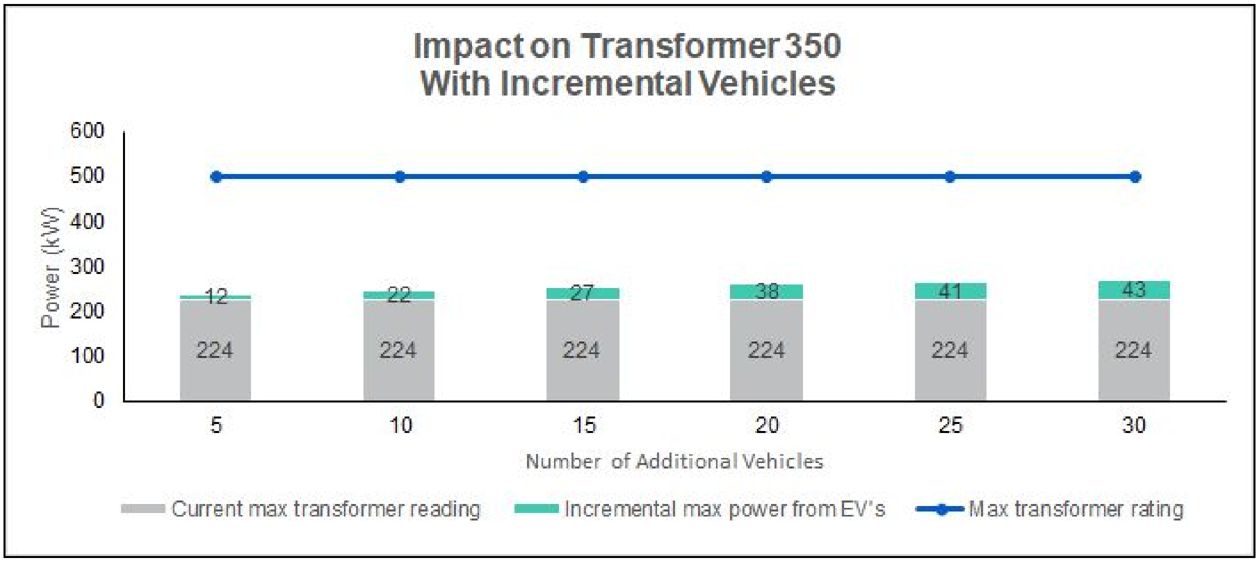

Figure 41: The Impact of Adding Additional EVs onto Transformer 350

7.1.3 Substation 293

Finally, Substation 293, which powers 292 apartments and houses, is rated at a maximum power of 800 kVA and has a previous high demand at 541 kW. Of the three transformers analyzed in this report, Transformer 293 is the closest to the maximum rating. Thirty incremental EVs would increase the total potential demand to 585 kW (as shown in Figure 42). The potential demand will increase if residents prefer more LR BEVs, which would alter the ratio of PHEVs, LR BEVs and SR BEVs from the ratio analyzed for this report.

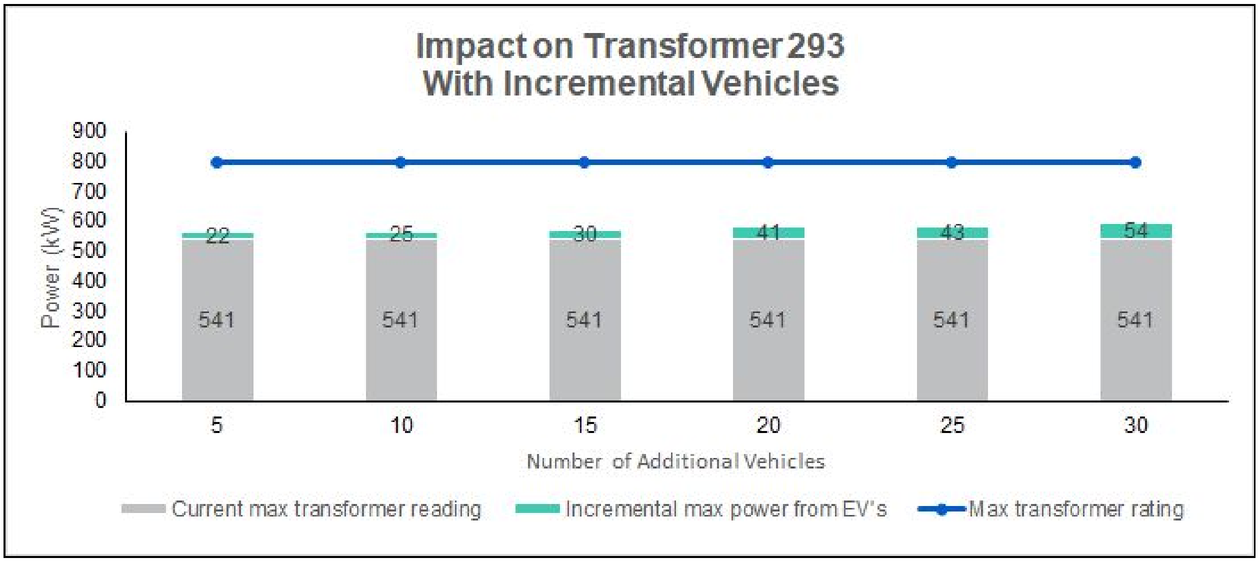

Figure 42: The Impact of Adding Additional EVs onto Transformer 293

The three substations modeled for this project are more than able to support current and near future EV load. A discussion of the anticipated number of additional EVs required to pose a risk to these substations is included in the Discussion section of this report.

7.2 RARIK Substations

The substation ratings and the number of units each substation serves for 5,695 RARIK substations were analyzed to determine the impact of EV load on each substation. The impact of EV load on each substation was studied with the following assumptions:

- In rural areas 100% of residential units own an EV.
- In urban areas 50% of residential units own an EV.
- The maximum power drawn annually by a PHEV is 19.5 kW (see Table 4).
- The maximum power drawn annually by a BEV is 49 kW (see Table 4).
- The maximum possible power drawn annually by a BEV at a level 2 charging station or home location is 19.5 kW.
- The coincidence factor for each substation follows the trendline in Figure 23.

The analysis of aggregated charging indicated that the maximum power for SR and LR BEVs was similar. It is possible that the coincidence factor of LR BEVs may have been different if more LR BEVs were included in this project, as these vehicles are more likely to have higher loads more frequently.

7.2.1 EV Penetration Level 1: Present Day (5%)

The current EV penetration level in Iceland is that 5% of all vehicles are either EVs, of that number, 32% are BEVs and 68% are PHEVs. In Figure 41, the blue bars represent the number of substations and their substation loading from EVs. The green line shows a cumulative percentage of all analyzed substations. At the current penetration level, 93% of substations currently do not support any EVs. There are no substations with a loading of 100% or higher which indicates that no substations are predicted to be overloaded with the current EV penetration. The substations with the highest loading are all rural substations rated at 50 kVA serving mostly summer homes.

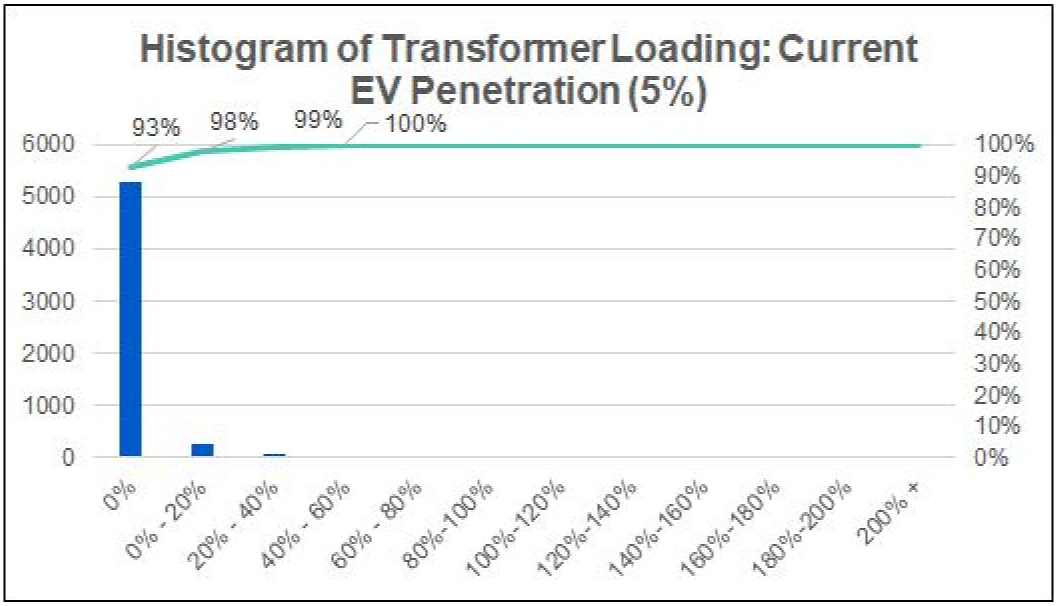

Figure 43: Substation Loading with Current EV Penetration

7.2.2 EV Penetration Level 2: 2026 (30%)

The Paris agreement has a goal of 30% targeted for achievement in 2026, this is the halfway point to reaching the overall goal of the Paris agreement. For this goal to be achieved, it is anticipated that 30% of vehicles in Iceland will be either BEVs or PHEVs by the year 2026. For this EV penetration level, it is anticipated that 30% of these vehicles are to be PHEVs while 70% will be BEVs. At this EV penetration level, there is still a significant percentage (71%) of substations that have no added load from EVs (as shown in Figure 44). However, about 1% of RARIK substations are at risk of overloading. All of these substations are servicing rural areas and rated under 200 kVA.

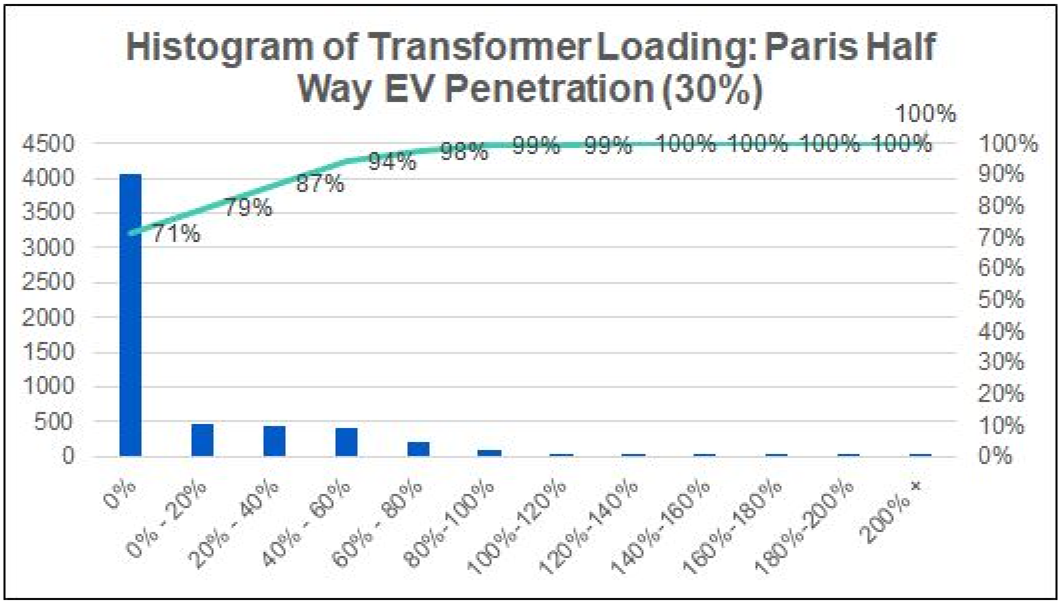

Figure 44: Substation Loading with 30% EV Penetration

7.2.3 EV Penetration Level 3: 2030 (60%)

The Paris agreement expects 60% of vehicles in Iceland to be BEVs by 2030. For this EV penetration level, 100% of these vehicles will be BEVs. At this EV penetration level about 14% of substations are at risk of overloading (as shown in Figure 45). Some urban substations with ratings up to 315 kVA are likely to be at risk, in addition to the smaller rural transformers. In addition, there is a significant percentage of substations (2%) with a demand of more than twice the substation rating.

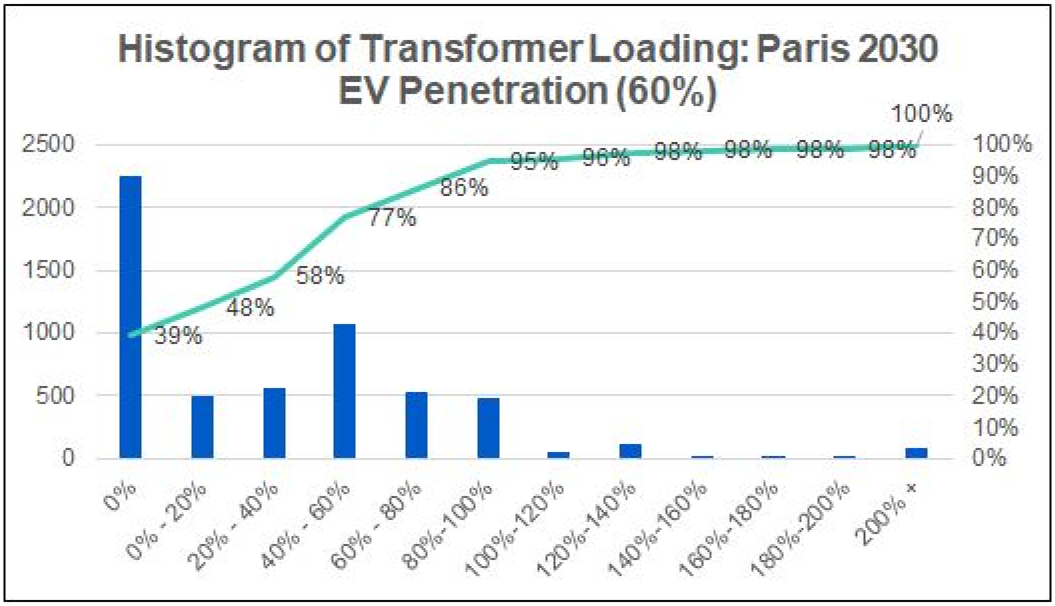

Figure 45: Substation Loading with 60% EV Penetration

7.2.4 EV Penetration Level 4: 2030 (100%)

The final scenario modelled assumed 100% of vehicles in Iceland are BEVs. This means that 100% of rural households and 50% of urban households modelled are driving a BEV. Figure 46 shows that in this scenario, over 22% of substations are at risk of overloading. Some substations rated at only 10 kVA may be overloaded by more than 10 times their rated capacity. The least likely substations to overload are those rated at over 1000 kVA supporting only single family homes or farms.

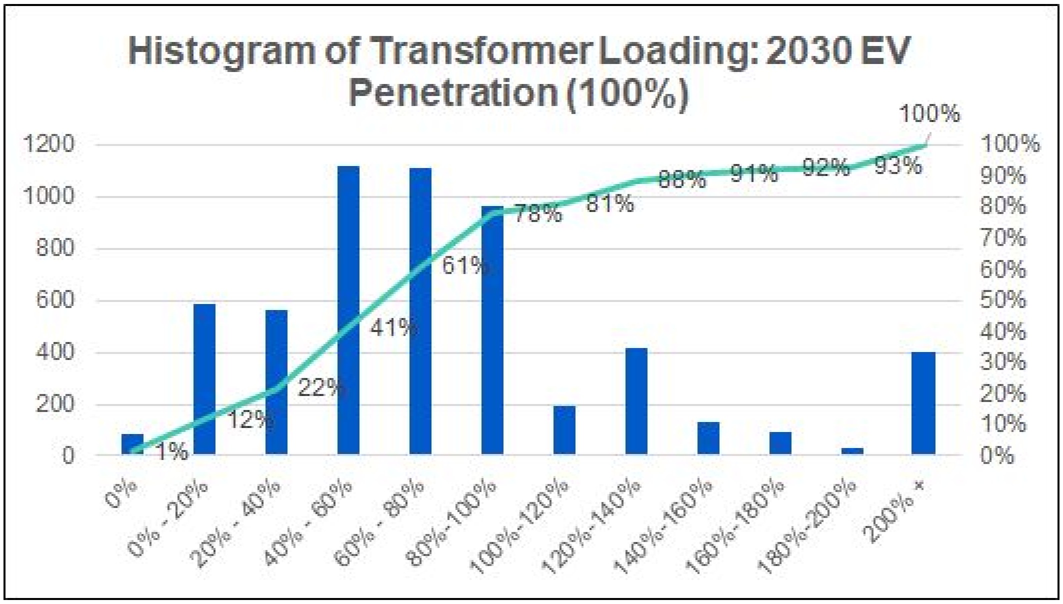

Figure 46: Substation Loading with 100% EV Penetration

Overall, as EV adoption rates increase, the potential for substation overloading also increases. The substations most at risk are those with a rating of <200 kVA and servicing rural areas. The potential for overloading on higher rated substations supporting single family homes or farms

8 Discussion

This EV load profiling project aimed to determine different EV load profiles based on criteria such as customer type, vehicle powertrain, residence type and charging location. It also examined the ability of existing substations to handle current EV load and future growth with further EV adoption.

8.1 Impact of Driving Behaviour and Powertrain Type on EV Charging

Through the analysis of data, it was identified that drivers in the urban, capital-area urban drive the fewest kilometres per calendar day (35.2 km/day to 44.8 km/day), while rural participants drive the farthest (48.2 km/day to 57.9 km/day). PHEVs drivers have different driving and charging behaviours than BEVs. On average, PHEVs travel approximately 20% more than other SR BEVs, but they do not travel the most electric kilometers. The number of electric kilometers travelled for each PHEV group was consistently below the average. This indicates that PHEV drivers are utilizing the gasoline engine for a significant portion of their trips.

Participant Groups 1 and 12, consisting of SR BEVs in suburban and rural areas consumed the most energy (~335 kWh/month). This may be as expected given the possibility of a longer commute time each day. It is anticipated that if additional groups of LR BEVs had been included in this project, the overall distance travelled and charge energy demand would increase.

The charging behaviour for PHEV groups also varied from the SR and LR BEV groups. Although PHEVs consume most of their charging energy during off-peak hours like BEVs, they charge more during the afternoon peak (17:00 to 19:00, 25% of the energy consumed) and less during the morning peak (08:00 to 11:00, 9% of the energy consumed).

PHEVs tend to charge more often at home and are less likely to utilize public charging stations or business locations for charging. This behaviour may be due to the hybrid capability to utilize either the gasoline engine or electric battery as a power source for the vehicle, resulting in a less demand for a charging schedule. It should be noted that if PHEV drivers in Iceland leverage the electric battery in these vehicles, the overall charging behaviour may change to something more closely resembling an SR BEV increasing overall power demand.

8.2 System-Wide Impacts

An average load curve of all vehicles in the project demonstrates a primary charging peak of approximately 0.7 kW per EV in the evening around 19:00 and a secondary peak in the morning at 07:30. The primary peak may be expected, as project participants return home from work or other activities and plug-in their vehicles. However, since the study has a high proportion of PHEVs, it is understood that this will be significantly higher as more LR BEVs are introduced into the Icelandic market over time. Analyses in similar North American studies, including just over

50% LR BEVs, for example, shows that this unmanaged EV evening peak is approximately 1.5 kW and is expected to increase over 2.0 kW per evening peak period as these vehicles become more popular (more information available from FleetCarma, but not included in the scope of this study).

The secondary morning peak may be related to vehicle pre-conditioning prior to a morning commute. This theory is supported by the absence of this secondary peak when comparing weekend to weekday load curves and when reviewing the August load curve when more participants are expected to be on vacation. The average load after the secondary morning peak plateaus throughout the day until the evening peak at 19:00, which may be related to workplace charging at various times throughout the day.

Load curves were generated to analyze the charging profiles for each group. The load curves for each group are relatively consistent in shape to the average load curve. PHEVs utilized less power than average. Group 10, a group consisting of SR BEVs at businesses, demonstrated much more daytime charging. Group 12, a group consisting of SR BEVs in rural locations, demonstrated a much higher average load overall, which aligns with the greater average distance travelled by participants in this group.

Load curves were also developed to analyze weekend versus weekday charging behaviour and seasonality. Weekday charging energy demands are typically higher than those on weekends and are more consistent, indicating that weekend load may be more shapeable than the charging behaviour seen throughout the week. Charging energy demand was higher in colder months than warmer, as might be expected due to battery efficiency reduction and pre-conditioning.

8.3 Distribution Impacts

An analysis of the EV load impacts to substations within urban and rural areas within Iceland has been included in this report to determine the effect of a growing number of EVs charging at these locations.

8.3.1 Reykjavik Substations

The analysis showed that the incremental EV load projected at each of the substations is under the maximum threshold. Extending on this analysis, and using all project vehicles with the correct residential locations for each substation, the incremental EV load varies across all three substations. The results of this analysis can be seen in Table 7. This analysis indicates that it would take a very significant increase in the number of vehicles and/or LR BEVs to exceed these substation ratings with the residences charging multiple EVs at the same time.

Table 7: Maximum Incremental Load Per Substation from Project Vehicles

Substation	Incremental Load (kW)	Number of Residences Serviced	Number of EVs to Exceed Transformer Rating
472	133	153	348
350	94	163	177
293	163	292	263

This analysis contains several inherent assumptions:

- Only vehicle data from project participants was included in this analysis.
- Only participants matching the residential requirements were included in this analysis on a per transformer basis.
- There were a limited number of LR BEVs included (30 vehicles).
- The power levels are based on the maximum reported load occurring during home charging.

Since this analysis used participants from several groups, it also assumes that the behaviours of the participants varies, as seen in the Appendix B load curves. If the behaviour of EV drivers on a single transformer is more similar, there is more opportunity for higher coincidence load as these EV drivers may plug-in at the same times.

It is important to note that although the analysis completed does not indicate an immediate need for concern, the substations modelled in Reykjavik were all rated at over 500 kVA. Based on our analysis with the RARIK substations, it was those transformers with lower ratings that were more likely to fail. It is not that the Reykjavik substations are 'safe' but the analysis did not include information on any smaller substations that might be at a greater risk of failure.

8.3.2 RARIK Substations

Using data provided by RARIK, the effects of EV charging on substations across Iceland was modelled with a growing number of EVs in relation to the Paris agreement. As anticipated, demand increases with a growing number of EVs. A penetration level of 5% does not pose any immediate risk for the current substation infrastructure. When the penetration level approaches 30%-60% there is a significant number of substations at risk of being overloaded.

Substations with lower ratings are more likely to fail. As EV adoption increases, very small substations ~10 kVA may be overloaded by 10 times their capacity. If these smaller substations are supporting summer homes with LR BEV owners, the impact could be amplified.

9 Conclusions

This EV load profiling project provided many insights into EV driving and charging behaviour in Iceland. It was able to assess EV load profiles for groups of project participants with similar characteristics. Through data analysis, the impact to three substations in Reykjavik with EV load growth was assessed and may not be problematic in the near future on distribution assets of similar capacities. The three substations analyzed were highly rated, ranging from 500-800 kVA. It may be useful to further analyze substations with varying ratings within Reykjavik to determine if there are any districts within the city at risk.

Participant retention for this project was very successful. There were a limited number of participant withdrawals and Samorka was very effective at finding replacement EV owners as needed. However, a limitation in the data analysis was the small sizes (15 participants) for each participant group. Small sample sizes can result in high variability in the data leading to bias. The participants in each group may not be reflective of the population with similar demographics. The impact of an individual's behaviour on overall group performance is substantial.

When analyzing data from RARIK for over 5000 substations, there is a growing concern. If EV adoption continues and meets the goal of 60% electrification by 2030, an estimated 14% of all substation assets may become overloaded. As anticipated substations with smaller ratings are more likely to be overloaded. These substations are primarily in rural locations and may support both commuters and summer homes, both of which are common to LR BEV drivers. The LR BEV vehicle segment is growing quickly and since LR BEVs have larger battery sizes, a higher power demand is needed, this will amplify the problem.

The project was restricted to data from only 30 LR BEVs (as shown in Table 9). In addition to this being a growing vehicle segment, LR BEV drivers tend to charge at more varied locations (Group 8) and have the ability to drive much farther than SR BEVs and PHEVs on a single charge. When the EV battery is drained, these vehicles require more charging energy and have the ability to charge at different rates. Some Tesla models are able to draw up to 17.2 kW at a residential Level 2 charger. It is expected that a larger number of LR BEVs in the electric vehicle sample would demonstrate more significant impacts on overall substation load.

Table 8: Number of Participant Vehicles by Powertrain

Powertrain	Number of Vehicles
PHEV	90
SR BEV	75
LR BEV	30

Ideally, data collection for this project would continue and would increase the sample size of each of the distinct groups. Additionally, more LR BEVs would be included to better represent this growing vehicle segment. Further analysis on the substations across Iceland may also be considered, with smaller substations in Reykjavik as a point of interest for further work.

10 Appendix A - Partnering Organizations

Table A-1: Project Partnering Organizations

Organization Name	Location	Key Contact
Samorka	Borgartún 35, 105 Reykjavík	Páll Erland
Landsvirkjun	Háaleitisbraut 68, 103 Reykjavík	Auður Nanna Baldvinsdóttir
Landsnet	Gylfaflöt 9, 112 Reykjavík	Sverrir Jan Norðfjörð
Orka Náttúrunnar	Bæjarhálsi 1, 110 Reykjavík	Berglind Rán Ólafsdóttir
Veitur	Bæjarhálsi 1, 110 Reykjavík	Tómas Hansson
RARIK	Dvergshöfða 2, 110 Reykjavík	Kjartan Rolf Árnason
HS Veitur	Brekkustíg 36, 260 Reykjanesbæ	Júlíus Jón Jónsson
HS Orka	Svartsengi, 240 Grindavík	Friðrik Friðriksson
Orkusalan	Dvergshöfða 2, 110 Reykjavík	Magnús Kristjánsson
Norðurorka	Rangárvellir, 603 Akureyri	Helgi Jóhannesson
Orkubú Vestfjarða	Stakkanesi 1, 400 Ísafirði	Elías Jónatansson
Fallorka	Rangárvellir, 603 Akureyri	Andri Teitsson

11 Appendix B - Charging by Location

Charging Location Category Definitions

The GPS coordinates from the charging locations were used to create geofences that captured charging occuring in the same space. In cooperation with Register Iceland, each of these geofences were identified with the type of housing found within the geofence.

The types of housing (Categorization 1) as described from the Register Iceland's Property Register are:

- Single family home
- Apartment building
- Warehouse
- Commercial/office
- Industrial
- Specialized
- Garage
- Summer house
- Other

The following definitions (Categorization 2) were used to further classify the charging location:

- Home
- Work base
- Summer house
- Service Center/workplace
- Direct current fast charging station (DCFC)
- Other

The following criteria was then used to classify each charging into the above noted categories (Categorization 2):

Table B-1: Charging Location Definitions (Categorization 2)

Location	Definition
Home	If a car is individual owned, then the owners address is registered as **Home**. If a car is owned by a business and the address of the company is registered at a person's home, then the charging point shall be registered as **Home** instead of **Work base**.

Work Base	If a car is owned by a business and the address of the company is registered at a business housing, then the charging point shall be registered as a **Work base**.
Workplace or Service Center	If an individual owned car is charged at a business address, we assume that it is a **Workplace**. If housing is: ● Commercial/office ● Specialized ● Industrial ● Garage ● Warehouse ● Public charging stations that is not a fast charging station and it is: ● neither Work base ● nor Workplace then the charging point shall be registered as a **Service center**.
Summer House	If a charging point is located at a summer house, then it shall be registered as **Summer house**.
DCFC	If GPS coordinates of the charging point belong to a direct current fast-charging station, then the charging point shall be registered as **DCFC**.
Other	If nothing of the above applies, then the charging point shall be registered as **Other**.

It was not possible to confidently establish people's workplaces based on their charging behavior in the data collected in this study. Therefore, the original plan to separate charging into the two categories of *Workplace* and *Service Center*, was not possible. Thus, they were combined into one category, *Workplace or Service Center*.

Charging Location Categorization 1

The following tables show the percentage of total charging energy by charging location for each participant group. Table B-2 compares the average overall charging location for all participant groups to those groups with non-residential participants.

Table B-2: Percent of Charging Energy by Charging Location (Register Iceland)

Group	Apartment	Commercial	Garage	Industrial	Single Family Home	Specialized	Summer House	Warehouse	Other
1	1%	14%	0%	9%	71%	1%	0%	1%	2%
2	0%	2%	0%	2%	94%	0%	0%	0%	1%
3	72%	3%	0%	0%	23%	1%	1%	0%	0%
4	5%	11%	0%	1%	81%	1%	1%	0%	0%
5	13%	6%	0%	6%	70%	3%	0%	0%	1%
6	9%	2%	0%	1%	84%	1%	2%	1%	0%
7	73%	12%	0%	1%	10%	2%	1%	0%	1%
8	51%	16%	4%	7%	12%	5%	3%	0%	1%
9	79%	7%	1%	3%	5%	3%	1%	0%	1%
10	2%	54%	0%	14%	11%	5%	0%	4%	9%
11	29%	21%	0%	6%	28%	6%	0%	3%	6%
12	6%	13%	0%	2%	76%	1%	0%	0%	2%
13	4%	4%	1%	2%	86%	1%	0%	0%	3%

Table B-3: Percent of Charging Energy by Location Comparing Residential and Non-Residential Vehicles

Group	Apartment	Commercial	Garage	Industrial	Single Family Home	Specialized	Summer House	Warehouse	Other
All	23%	13%	1%	4%	53%	2%	2%	1%	1%
10 & 11	13%	40%	0%	10%	18%	8%	5%	0%	3%
All but 10 & 11	25%	9%	1%	4%	58%	1%	2%	1%	0%

Charging Location Categorization 2

Table B-4: Percent of Charging Energy by Charging Location Definition

Group	Home	Summer Home	Service Center	Work Base	Service Center or Workplace	DCFC	Other
1	73%	0%	0%	0%	15%	9%	2%
2	95%	0%	0%	0%	4%	0%	1%
3	95%	1%	0%	0%	4%	0%	0%
4	87%	1%	0%	0%	9%	3%	0%
5	84%	0%	0%	0%	13%	2%	1%
6	93%	2%	0%	0%	4%	0%	0%
7	84%	1%	0%	0%	7%	7%	1%
8	64%	3%	0%	0%	26%	6%	0%
9	84%	1%	0%	0%	14%	0%	1%
10	13%	0%	51%	25%	0%	2%	10%
11	53%	0%	26%	10%	0%	0%	10%
12	82%	0%	0%	0%	10%	6%	2%
13	89%	0%	0%	0%	7%	0%	3%

12 Appendix C - Participant Group Load Curves

The load curves in this appendix (Figures C-1 through C-13) compare the average daily load curve containing all 195 project vehicles with the average daily load curve for each participant group. The load curve for all project vehicles is generally smoother as the data is analyzed over more vehicles. This means that the impact of an individual's charging behaviour may be less significant in the load curve, than in a load curve with fewer vehicles. This is demonstrated by the volatility of the participant group load curves, particularly as seen with Group 1.

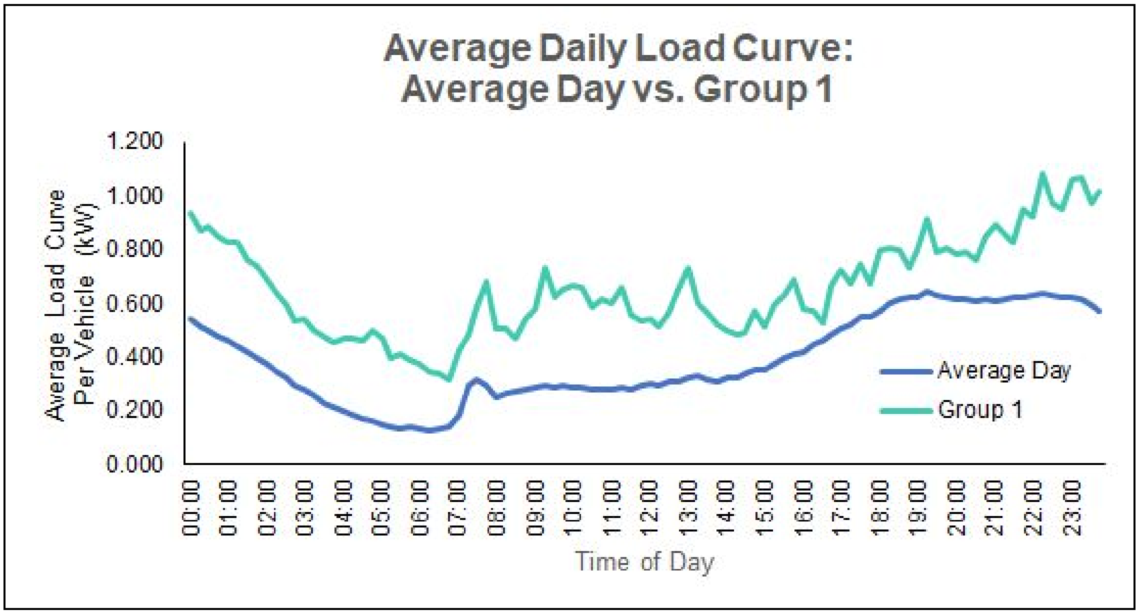

Figure C-1: Average Daily Load Curve for Group 1 Participants

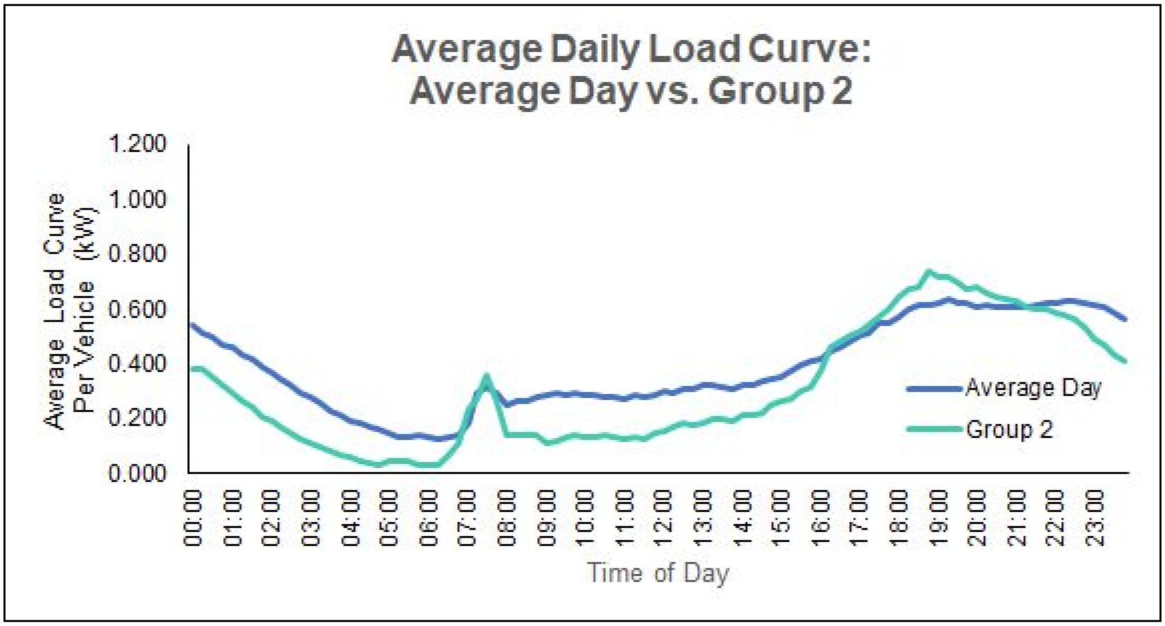

Figure C-2: Average Daily Load Curve for Group 2 Participants

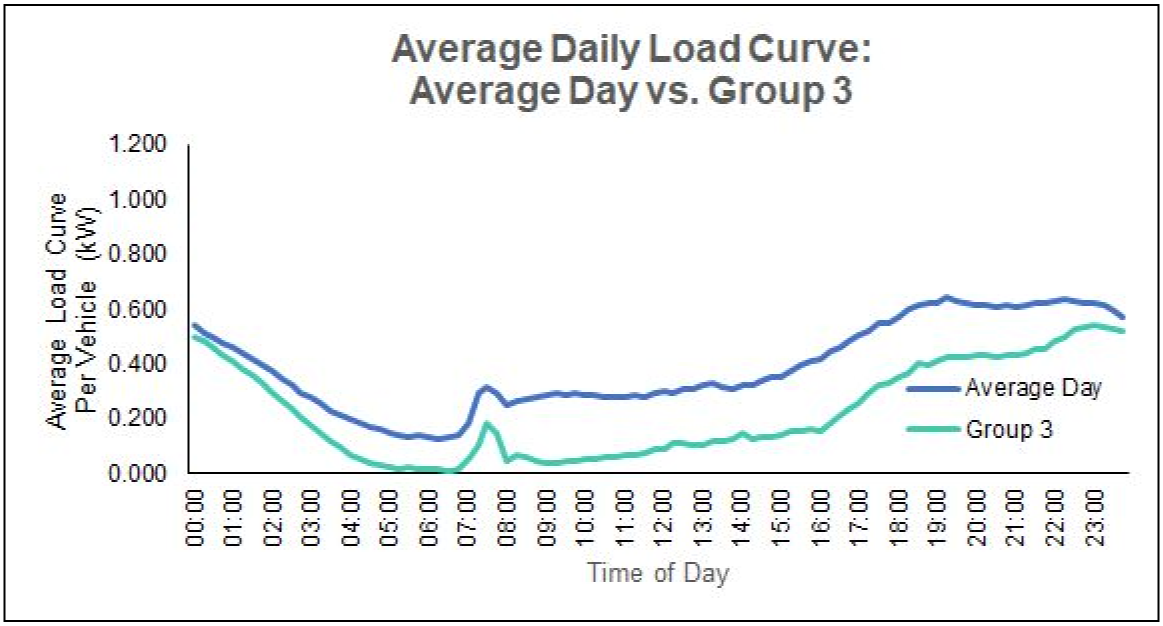

Figure C-3: Average Daily Load Curve for Group 3 Participants

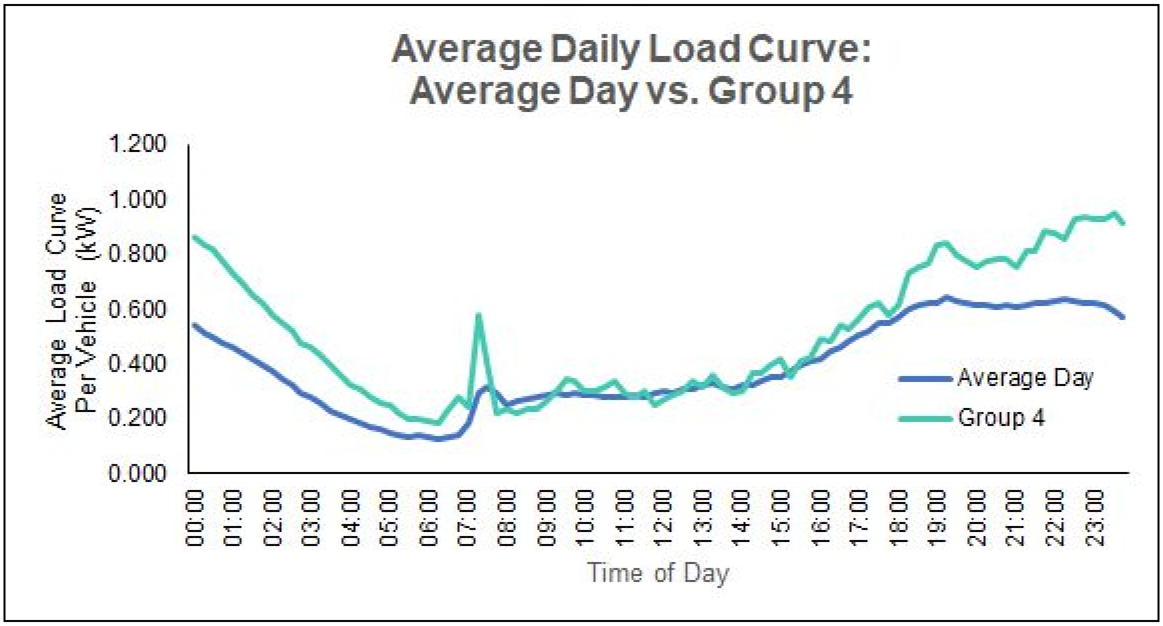

Figure C-4: Average Daily Load Curve for Group 4 Participants

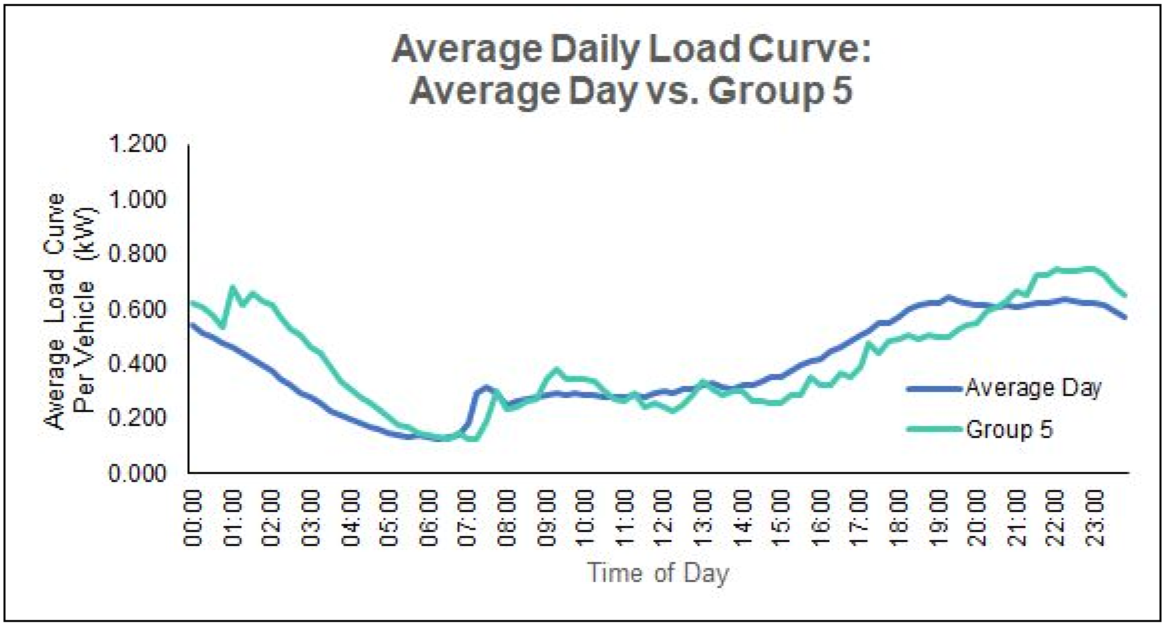

Figure C-5: Average Daily Load Curve for Group 5 Participants

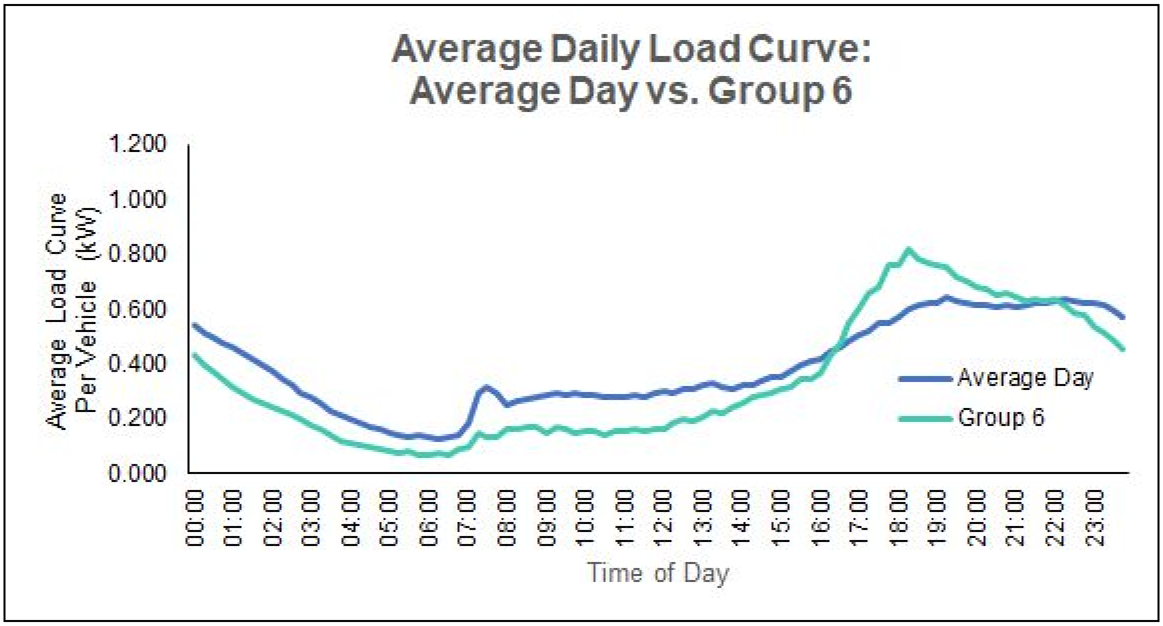

Figure C-6: Average Daily Load Curve for Group 6 Participants

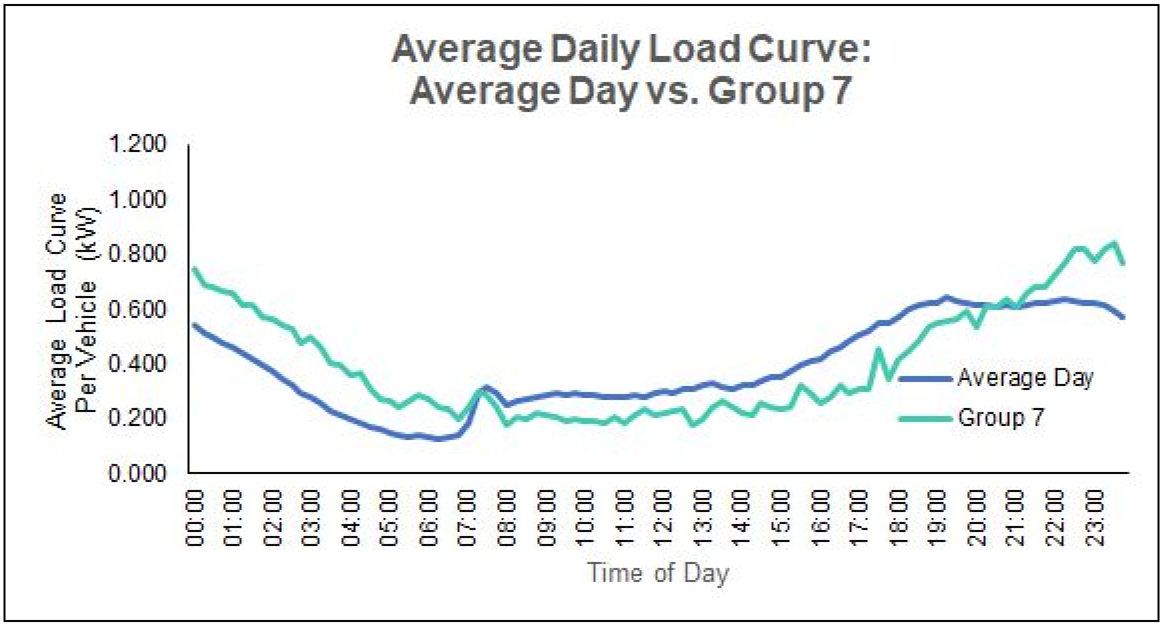

Figure C-7: Average Daily Load Curve for Group 7 Participants

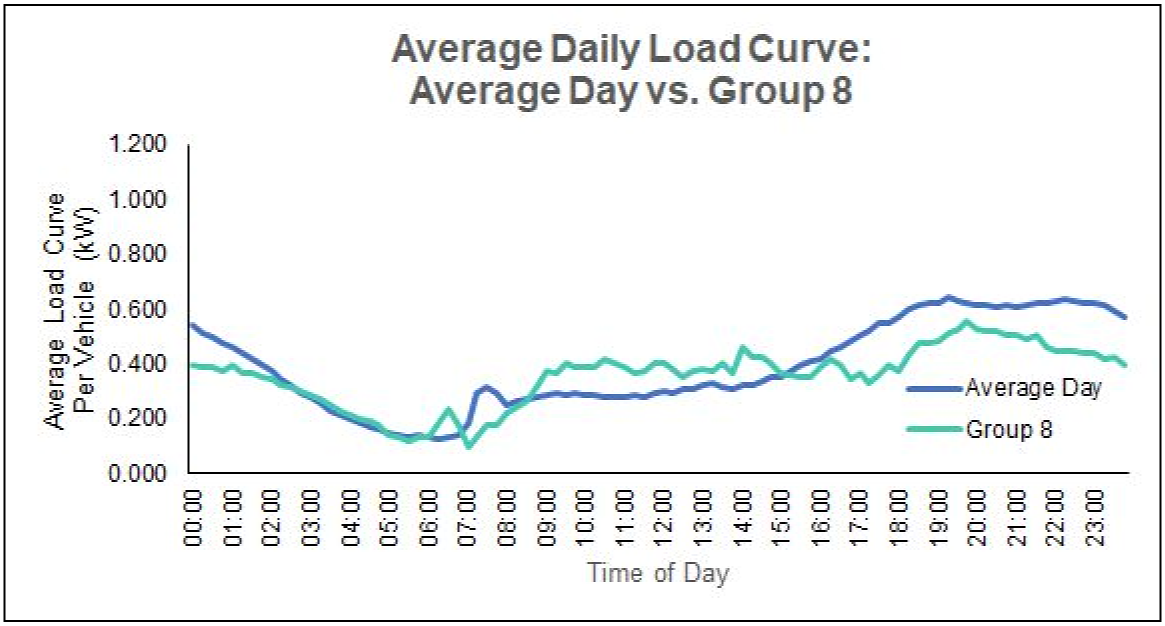

Figure C-8: Average Daily Load Curve for Group 8 Participants

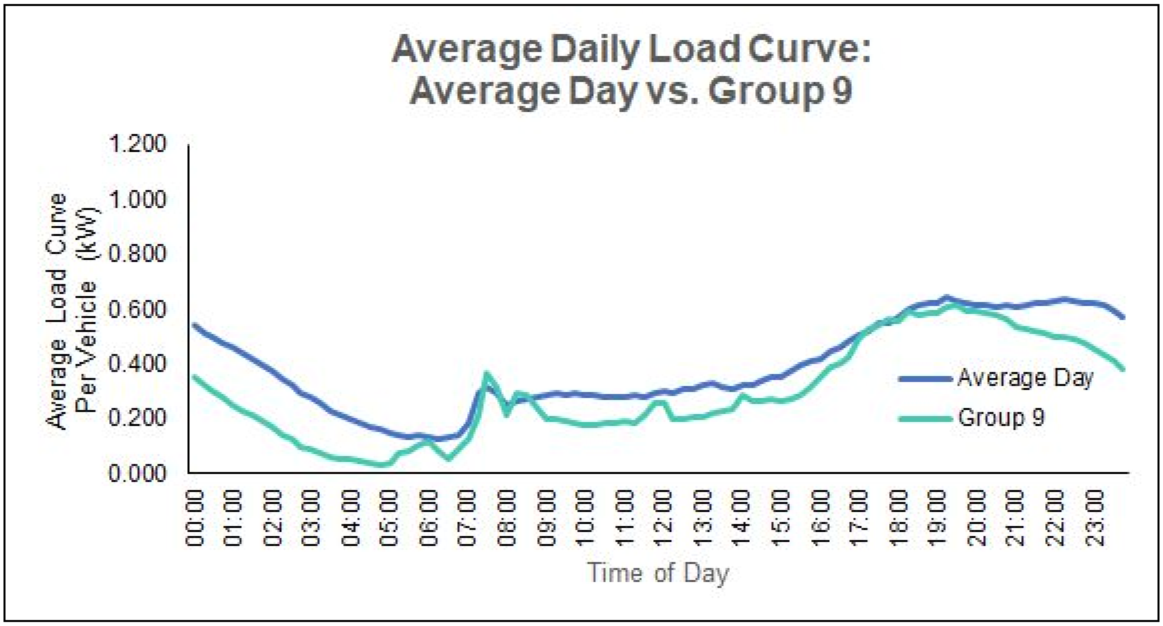

Figure C-9: Average Daily Load Curve for Group 9 Participants

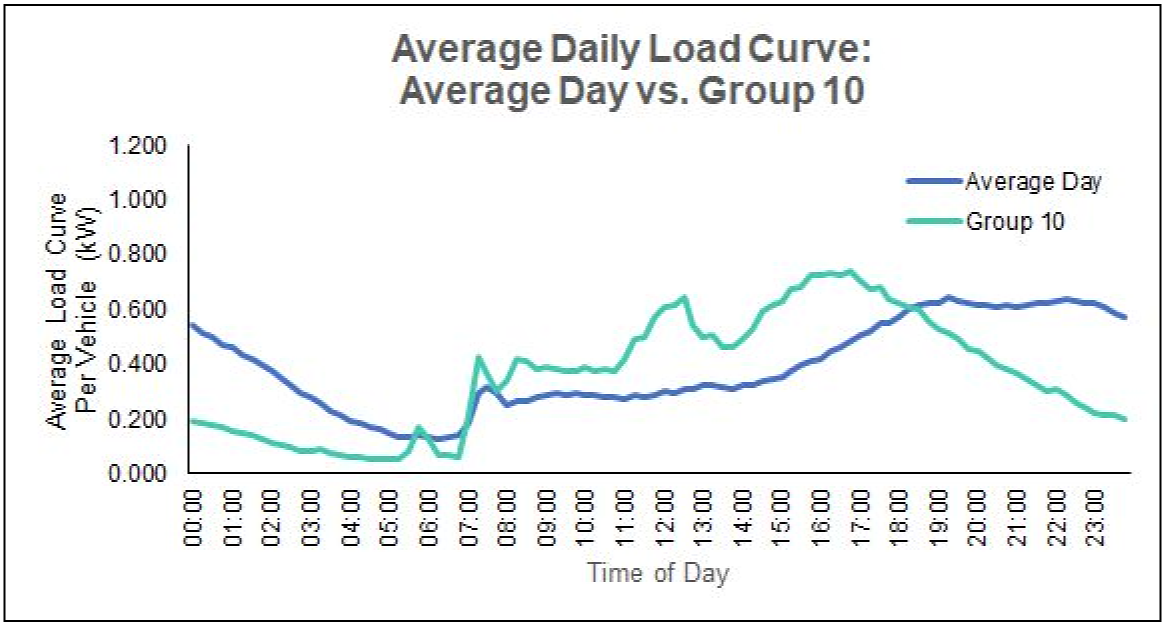

Figure C-10: Average Daily Load Curve for Group 10 Participants

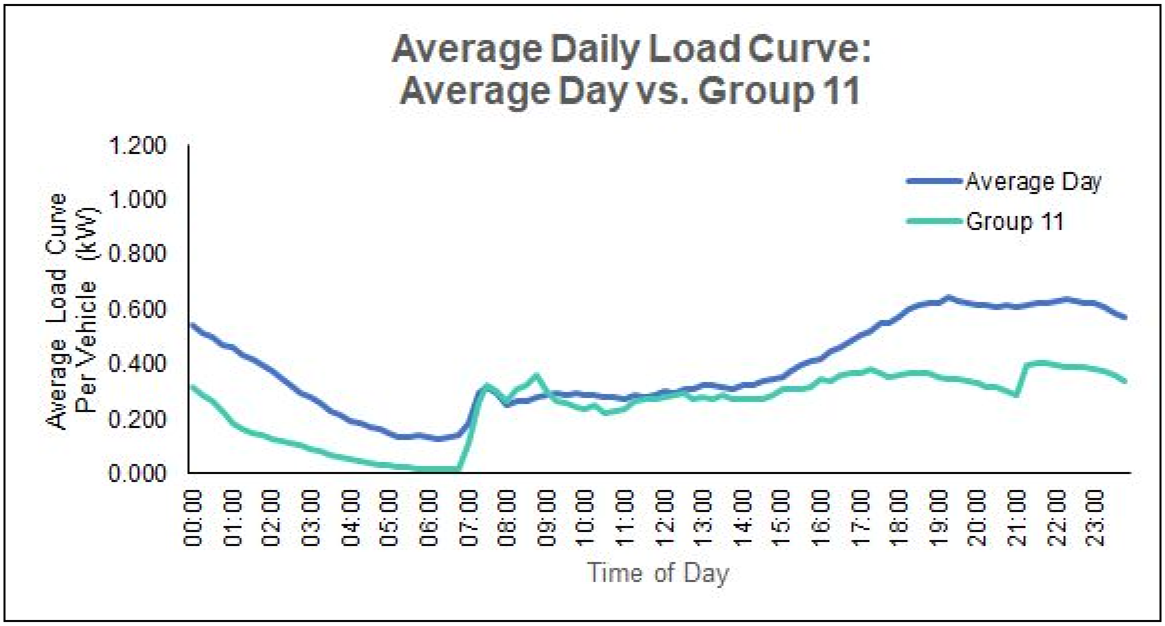

Figure C-11: Average Daily Load Curve for Group 11 Participants

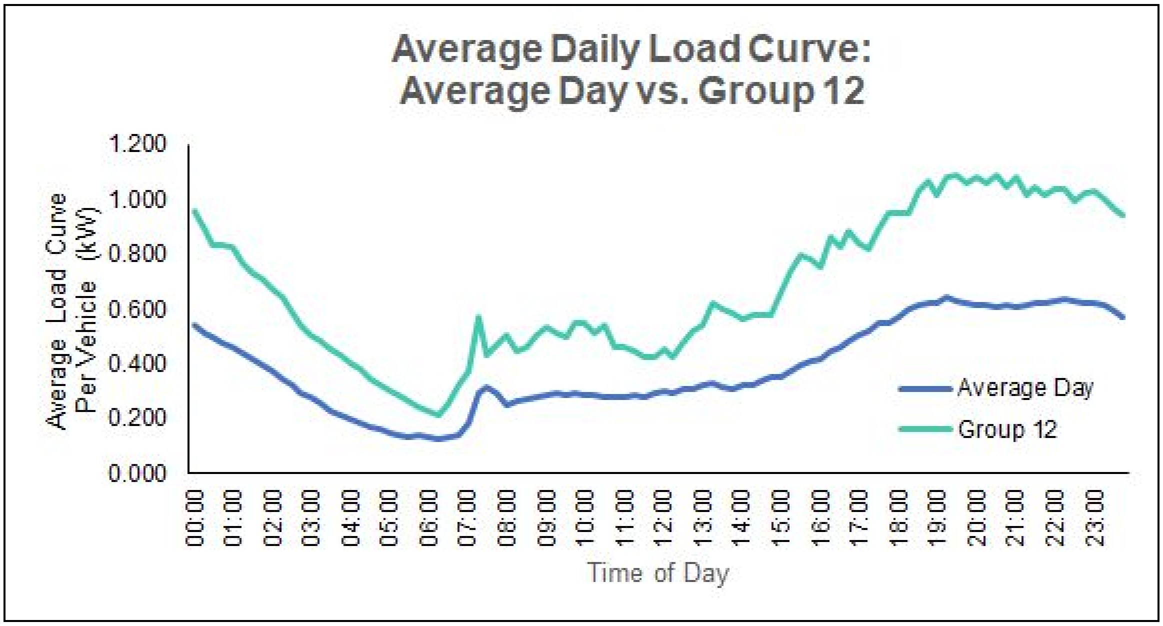

Figure C-12: Average Daily Load Curve for Group 12 Participants

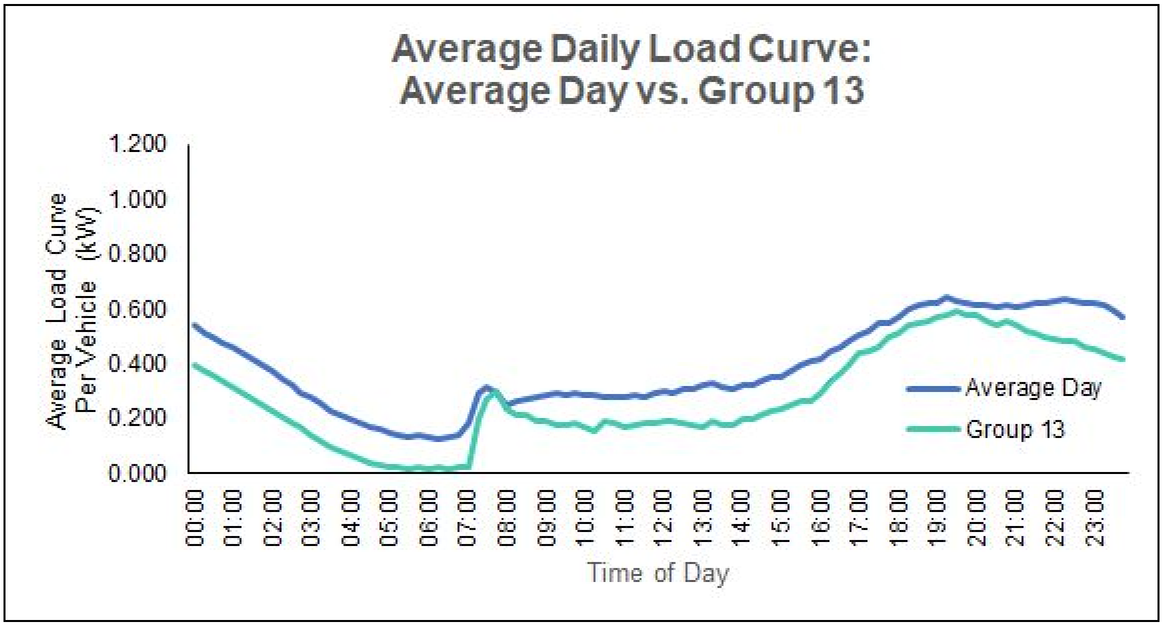

Figure C-13: Average Daily Load Curve for Group 13 Participants

13 Appendix D - Participant Group Coincidence Factors

Figure D-1 shows the calculated coincidence factor for each participant group. The lower the coincidence factor, the smaller the probability that all EVs within the group will be peaking at the same time. Groups 6 and 9 have the highest coincidence factor, these groups both consist of PHEVs within the urban, capital area.

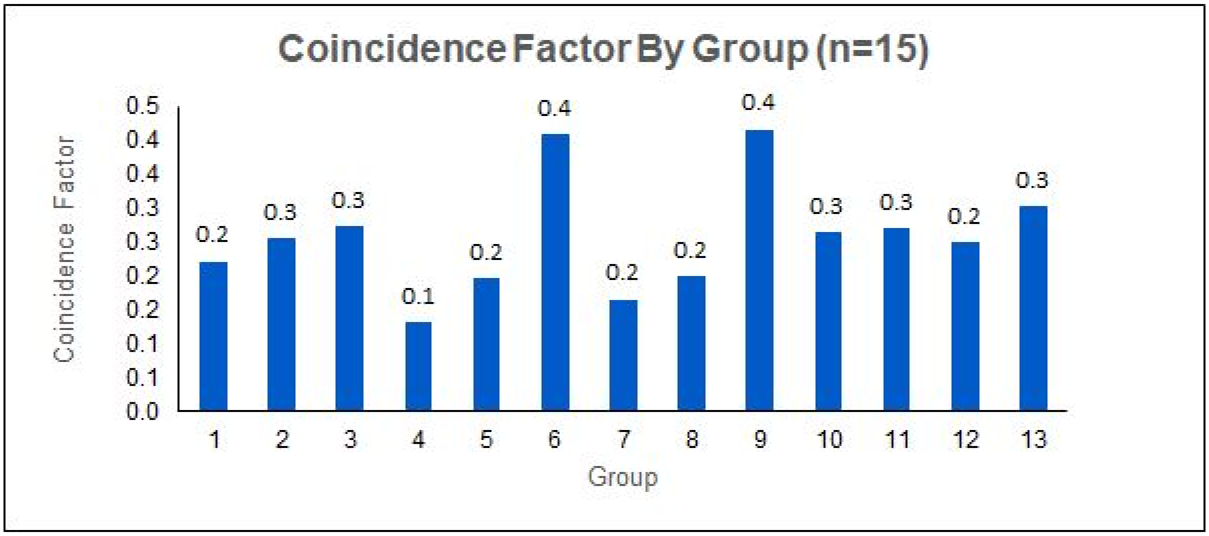

Figure D-1: Coincidence Factors by Participant Group

14 Appendix E - Participant Group Weekend vs. Weekday Load Curves

The load curves in this appendix (Figures E-1 through E-13) compare the weekday and weekend average daily load curves for each participant group. All groups have a lower weekend average load curve than weekdays. In some cases, like in Groups 10 and 12, there is very little or no weekend charging occurring. This likely due to the usage of these vehicles, for business or commuting, respectively.

The secondary peak identified in the average daily load curve, occurring at 07:30 is visible in all weekday load curves. However, this secondary peak is absent in all weekend load curves, indicating that this is very likely related to commuting activities.

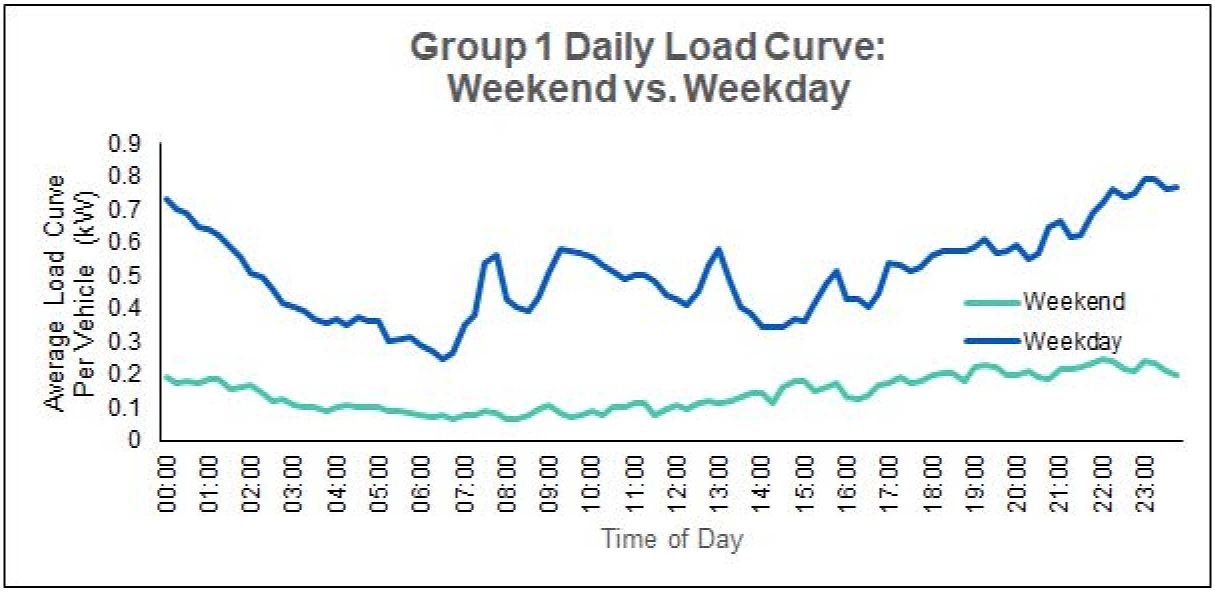

Figure E-1: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 1

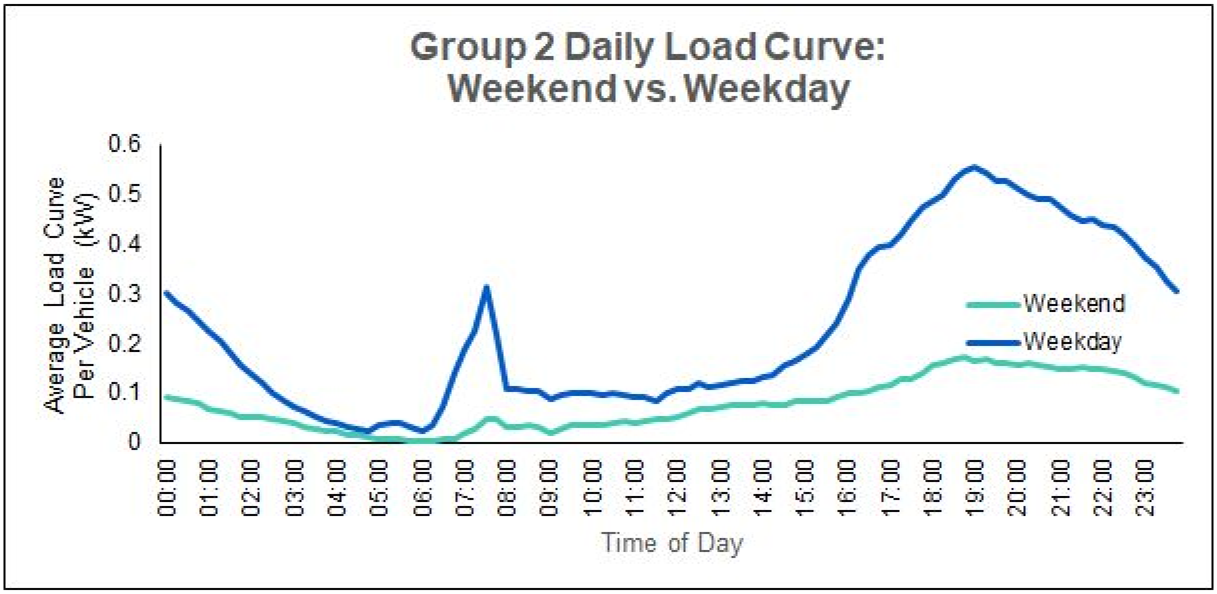

Figure E-2: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 2

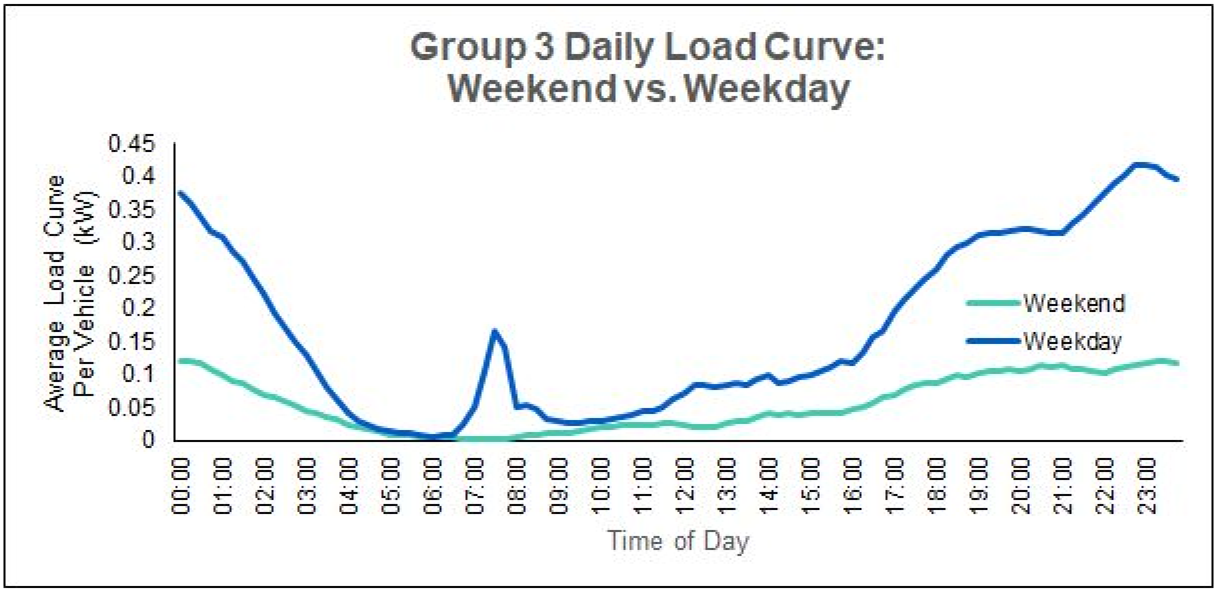

Figure E-3: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 3

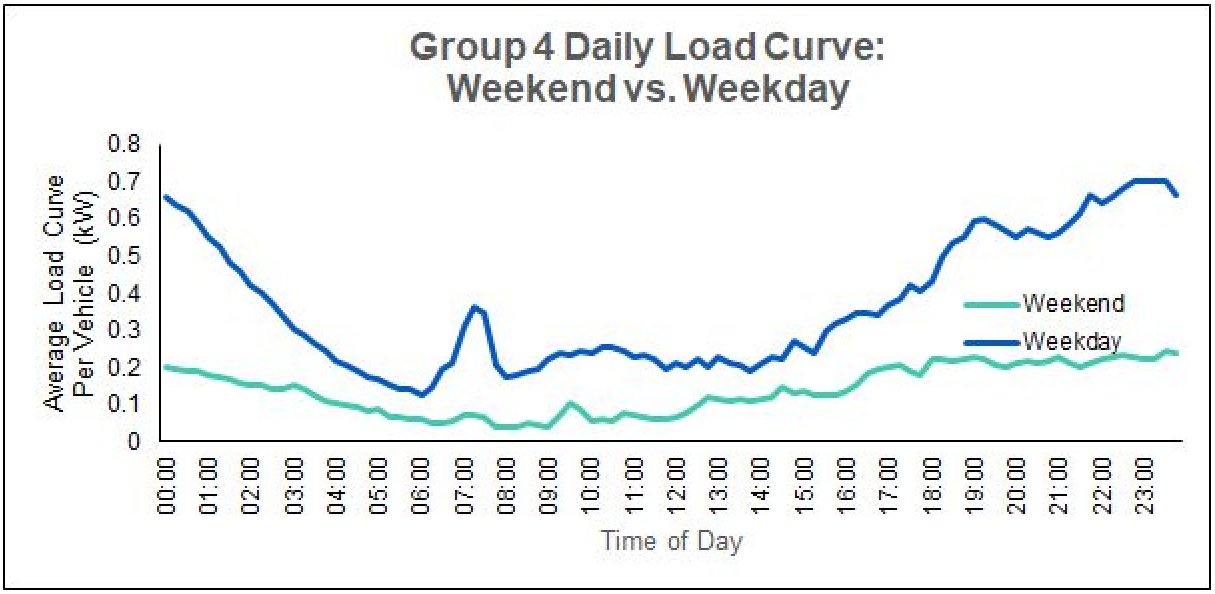

Figure E-4: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 4

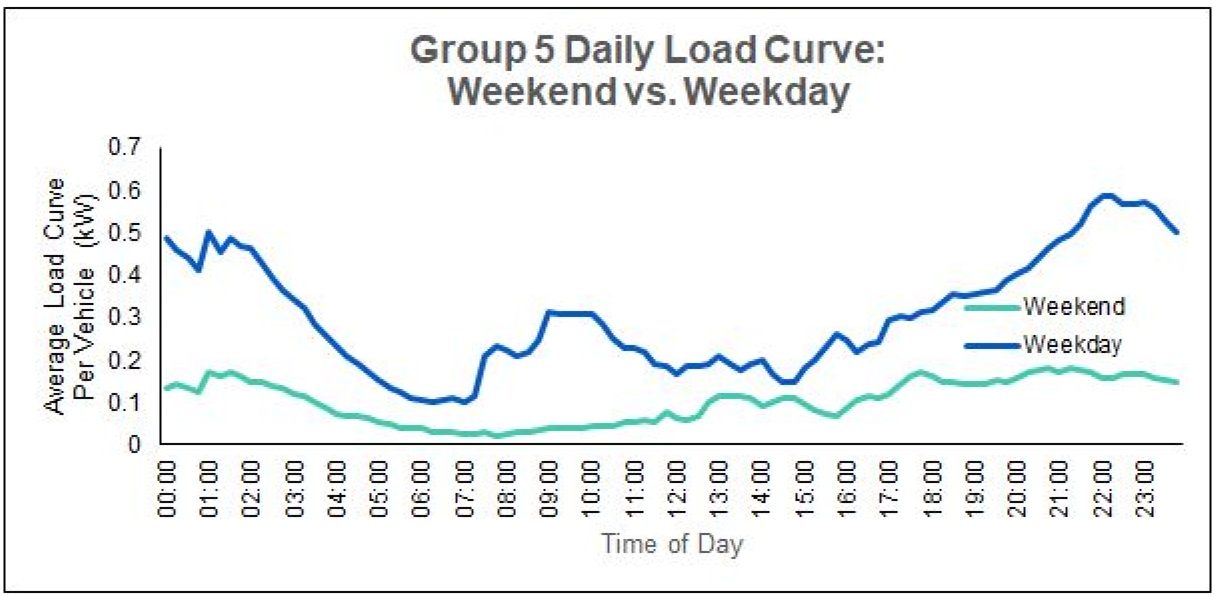

Figure E-5: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 5

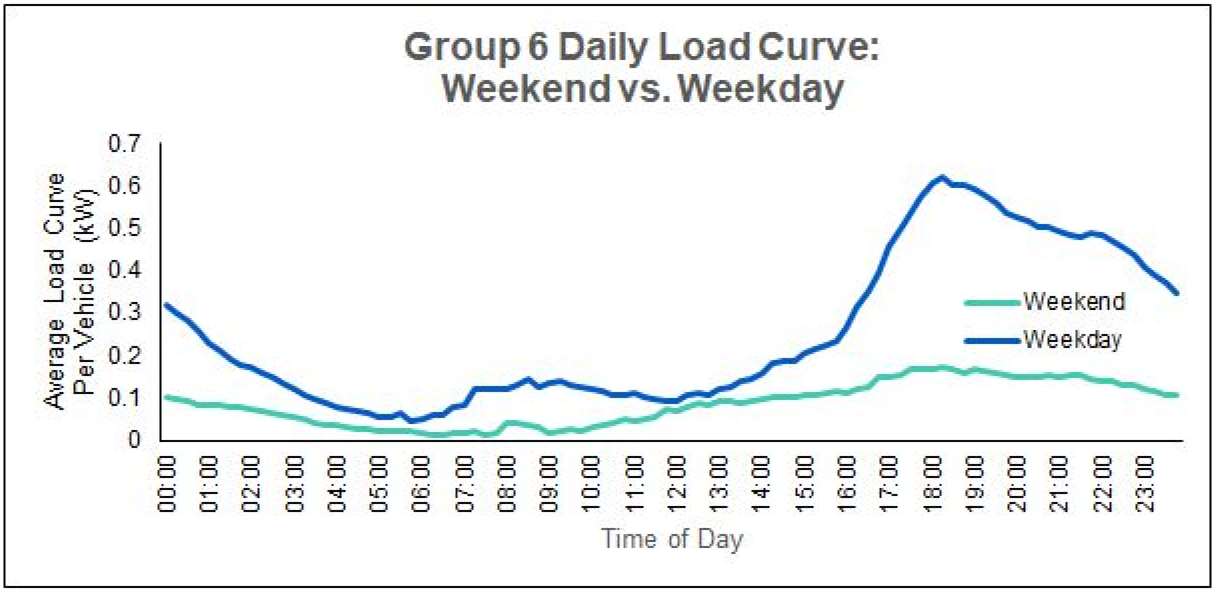

Figure E-6: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 6

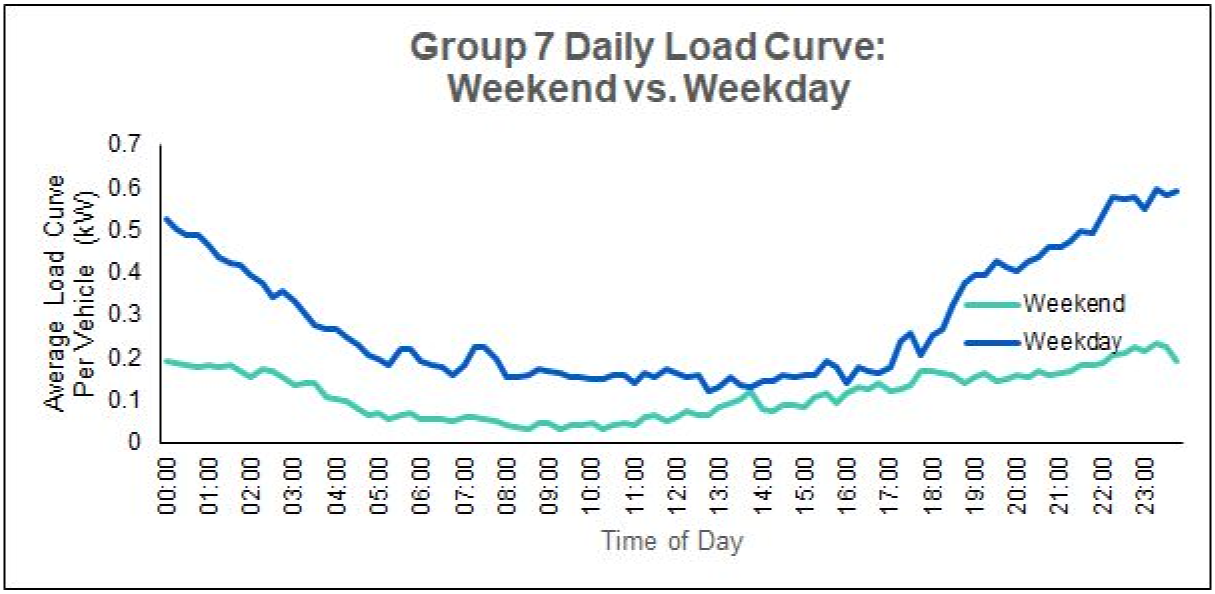

Figure E-7: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 7

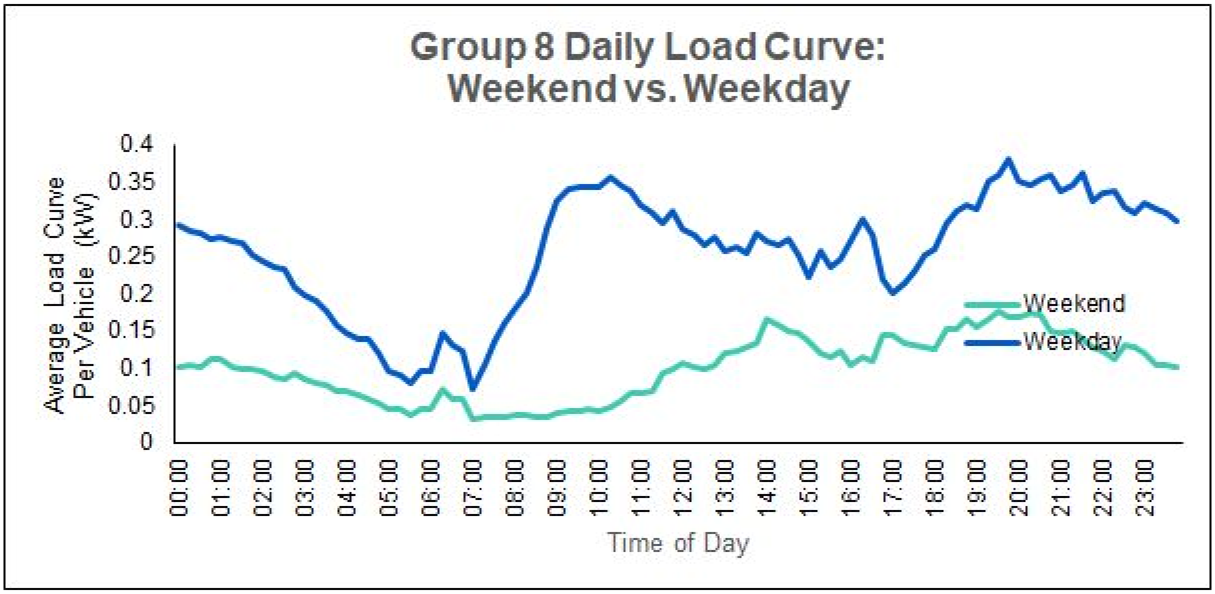

Figure E-8: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 8

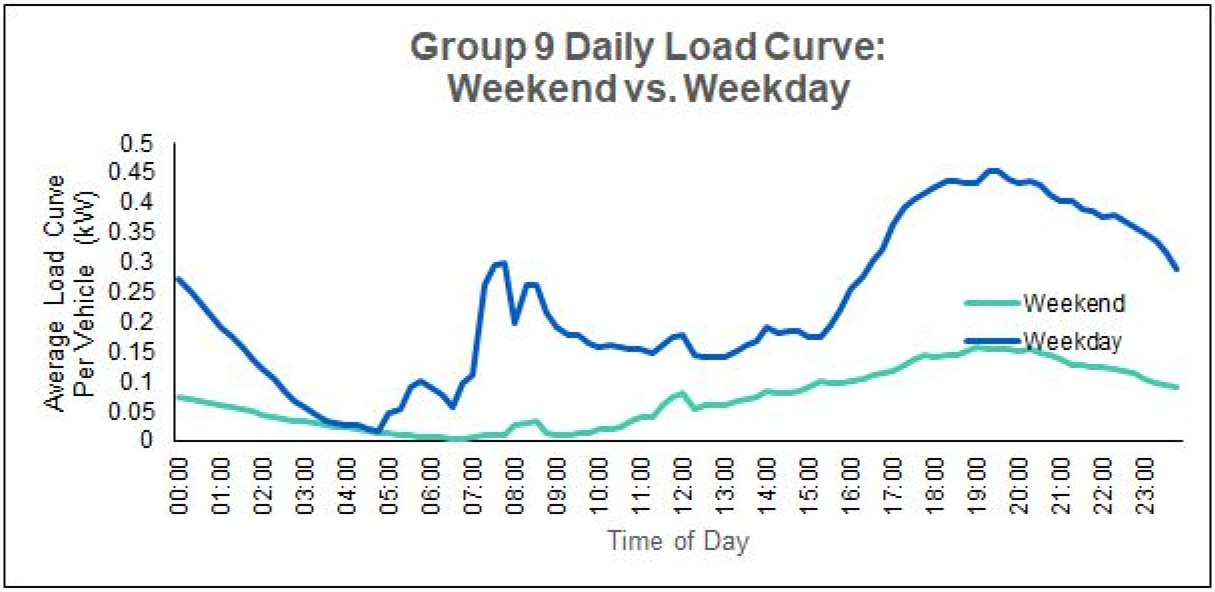

Figure E-9: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 9

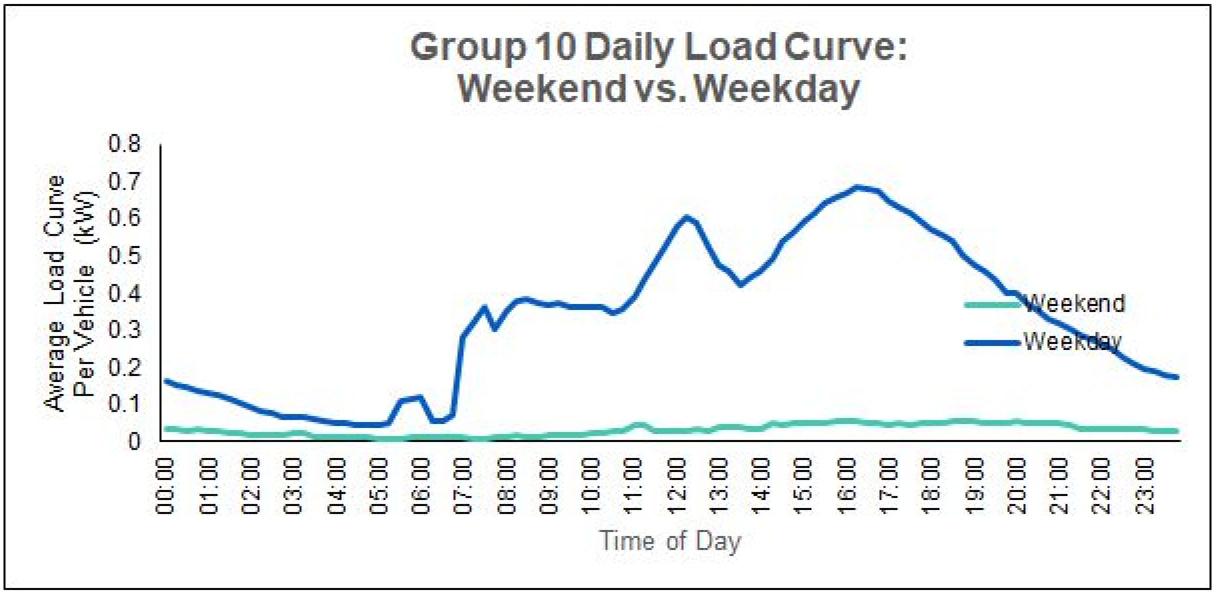

Figure E-10: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 10

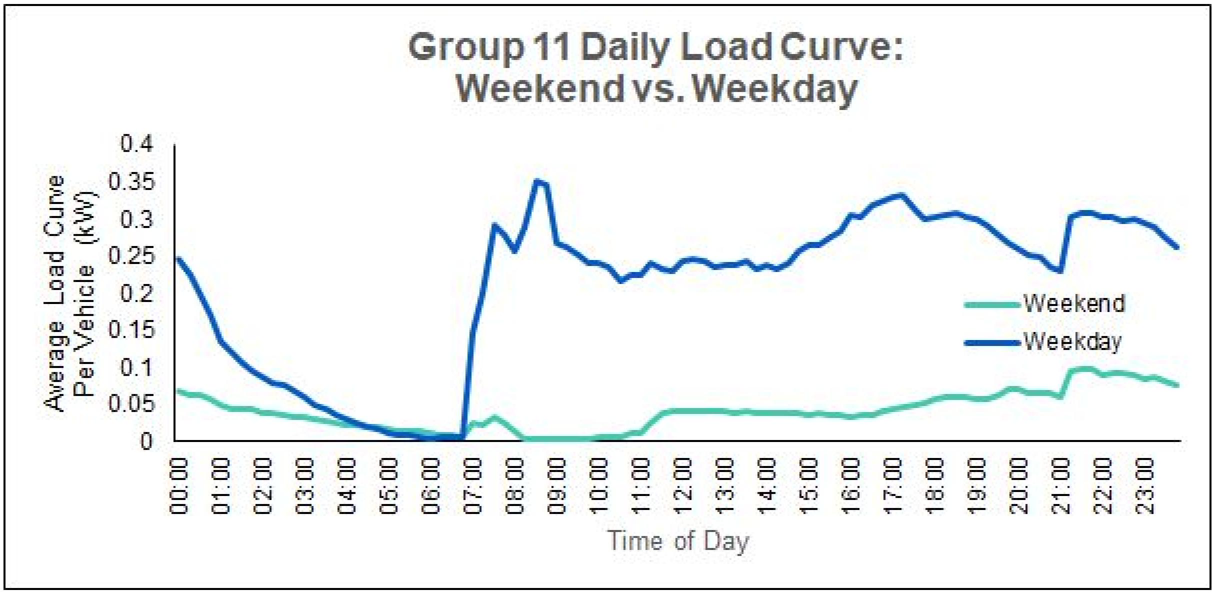

Figure E-11: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 11

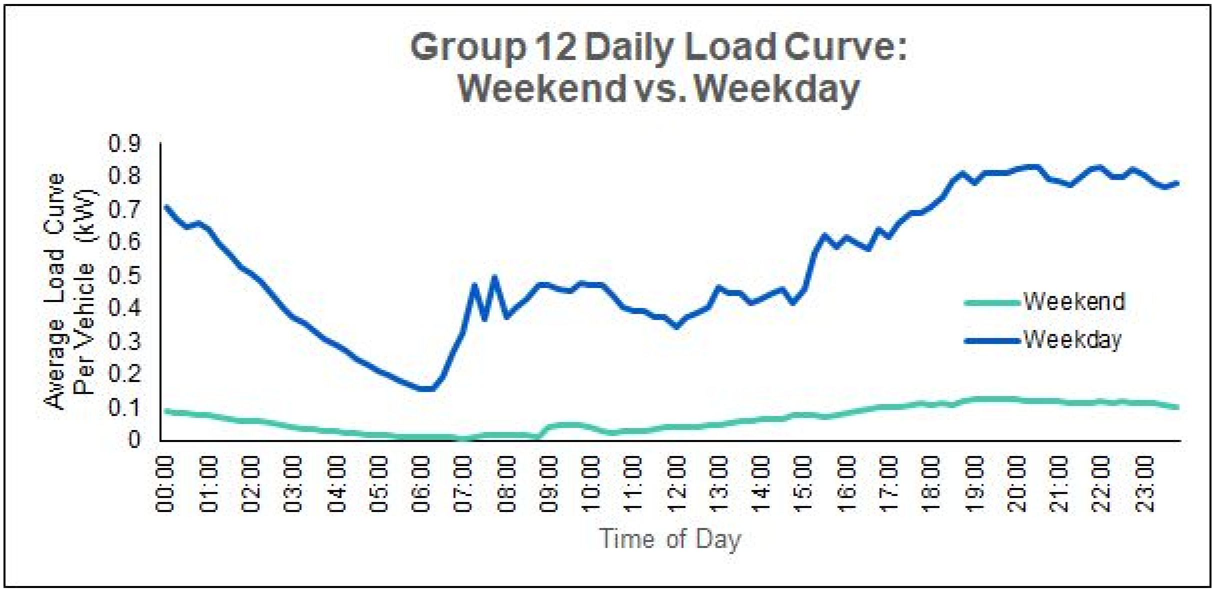

Figure E-12: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 12

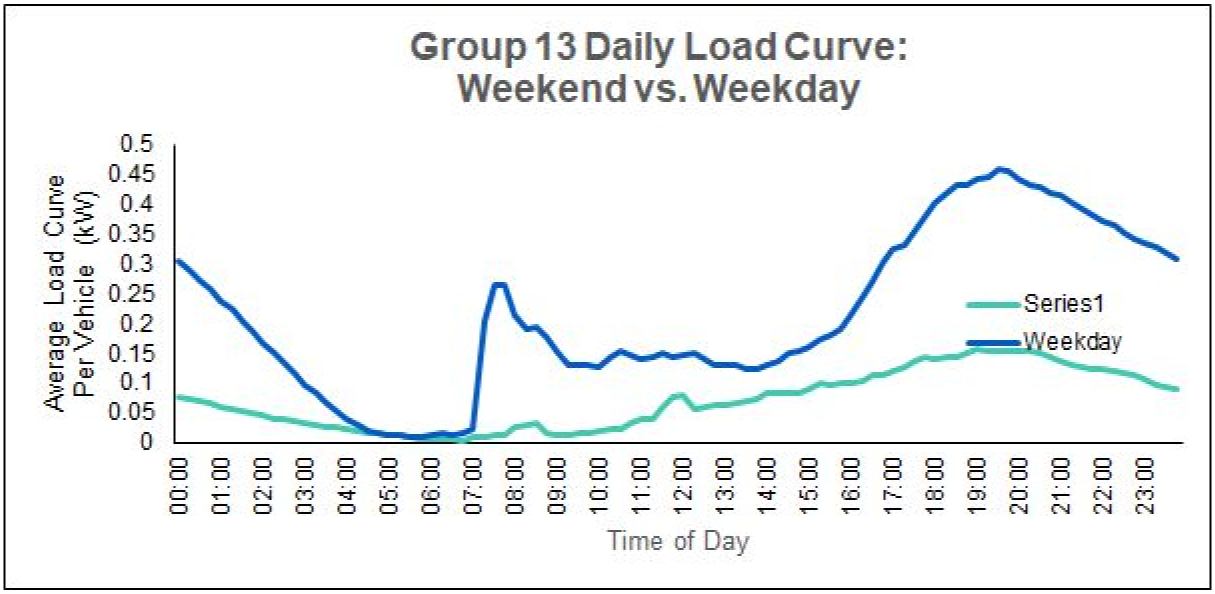

Figure E-13: Average Daily Load Curve Comparing Weekend to Weekday Energy Demand for Group 13

15 Appendix F - Participant Group Load Factors

Figure F-1 shows the load factor by each participant group. The load factor is the ratio between average power and maximum power over an average day. For example, with Group 1, the average day has an average power of 0.7 kW, but maximum power of 1.1 kW, yielding a load factor of 0.6 (i.e. 0.7 / 1.1 = 0.6). This load factor is useful for determining how evenly the load is being spread out throughout the day. The closer the load factor is to 1, the closer the average and maximums are, meaning the load is consistent throughout the day. Conversely, if the load factor is closer to 0, the demand is concentrated in more specific time intervals over the course of a day.

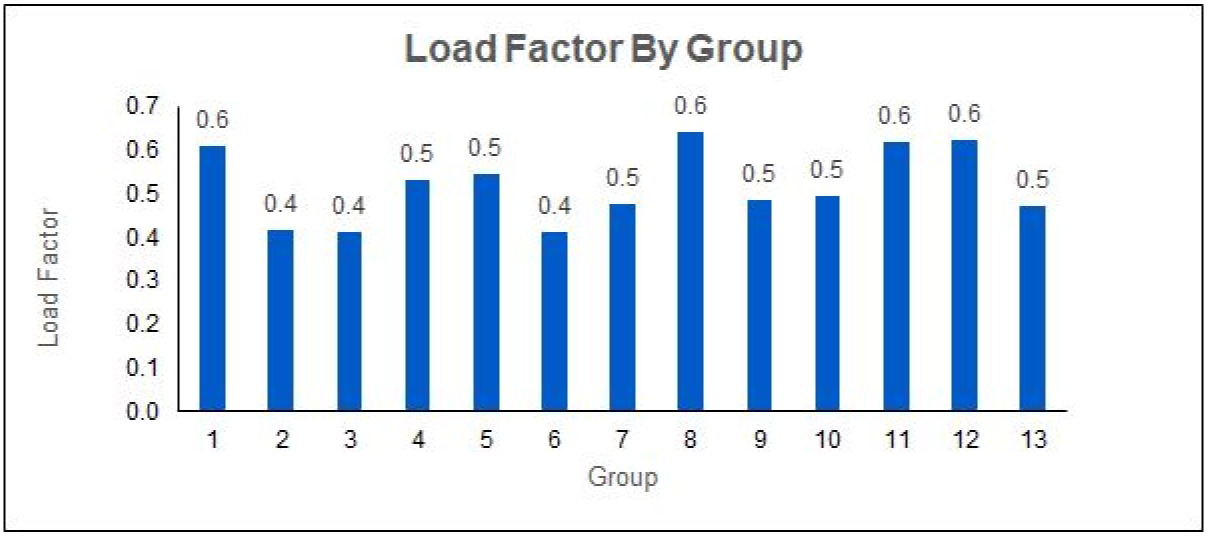

Figure F-1: Load Factors by Participant Group

16 Glossary

C2 Device - a telematics hardware device, from FleetCarma, that is capable of logging driving and charging data from electric vehicles.

Calendar Day - a full civil day from midnight to midnight. This is used to calculate average charging energy or driving distance for every day from the first date data was received for that vehicle..

Charger Types - in today's market, three different charge types exist: Level 1 (L1), Level 2 (L2) and DCFC (Direct Current Fast Charger). While other parts of the world may use a different nomenclature for the charger types, this report uses terms relevant to Canada.

Charging Day - a day, midnight to midnight, in which the vehicle was driven. This is used to calculate averages only for days that the individual vehicle was plugged in.

Coincidence Factor - the peak of a system divided by the sum of peak loads of each individual EV. This is a measure of how likely the EVs would peak at the same time.

Coincidence Load - the sum of load from all vehicles in a set that are charging simultaneously.

Direct Current Fast Charge - there is no standard for DCFCs but they range in charge power from 50-140kW and can deliver a charge of approximately 80% in 30 minutes.

Driving Day - a day, midnight to midnight, in which the vehicle was driven. This is used to calculate averages only for days that the individual vehicle drove some distance.

Kilowatt hour (kWh) - a common unit of energy used by electric utilities.

Level 1 Charging - a Level 1 (L1) charger is included with most EVs. It plugs into a traditional 110-120v household outlet and is capable of a charge power of 1.5kW. This can generally supply an EV with 5-10km of range per hour of charge.

Level 2 Charging - a Level 2 (L2) charger can be found in areas for public parking and also be installed at a residential location for personal use. They provide power at 220-240 V and up to 30 amps. On average, EVs can add 20-50 km of range per hour of charge.

Load Curves - a load curve or load profile is a graph of electrical load over time. This is useful for utilities to determine how much electricity will need to be available at a given time for efficiency and reliability of power transmission.

Long Range Battery Electric Vehicle (LR BEV) - a battery electric vehicle with a larger battery capacity, powered only by its high voltage battery.

Paris Agreement - an agreement within the United Nations Framework Convention on Climate Change where each county must determine, plan and report on the contribution that it undertakes to mitigate global warming.

Pre-conditioning - the process of warming up the electric vehicle batteries in cold temperatures to improve battery efficiency. Also includes the warming or cooling of the vehicle cabin for passenger comfort prior to driving.

Plug-in Hybrid Electric Vehicle (PHEV) - a vehicle which combines a conventional engine with an electric motor and rechargeable battery that allows the battery to be recharged from an outlet

Short Range Battery Electric Vehicle (SR BEV) - a battery electric vehicle with a smaller battery capacity, powered only by its high voltage battery.

State of Charge (SOC) - the percentage of usable battery energy available.