Analysis of electric vehicle usage patterns in New Zealand

Statistical Report

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Contents

1 Introduction

The New Zealand government has set a target of increasing the number of electric vehicles (EVs) in New Zealand to 64,000 by 2021 (Transpower New Zealand 2017). High penetration of EVs would cause EV recharging to contribute a substantial portion of total electricity load. A report prepared for lines companies Orion, Powerco and Unison by Concept Consulting Group entitled "Driving change - Issues and options to maximise the opportunities from large-scale electric vehicle uptake in New Zealand" predicts that if all current light private vehicles were electric, annual residential electricity consumption would increase by approximately 30%, whereas if all vehicles including trucks were electric, this would increase the total electricity consumption of New Zealand by approximately 41% (Concept Consulting 2018).

New Zealand's total electricity demand varies throughout the day, with weekdays in particular having two distinct "peaks"; one in the morning, and one in the evening (Transpower New Zealand 2015). Providing the electricity to meet these demand peaks is a costly and inefficient process (Khan, Jack, and Stephenson 2018). Concurrent electric vehicle charging, especially in the early evening when many motorists return home (Speidel and Bräunl 2014, @langbroek_when_2017), would have the potential to negatively impact the operation of the grid through drastically increasing peak loads (Azadfar, Sreeram, and Harries 2015,

@langbroek_when_2017), leading to an increased cost of electricity due to the requirement of expensive upgrades to the electricity grid (Stephenson et al. 2017).

The Concept Consulting report considers different methods of EV charging in its models. The assumption that most drivers would begin charging immediately after returning home is referred to as "passive" charging, while charging that is programmed (either by the driver or by an external entity) to occur during off-peak periods is referred to as "smart". The modelling undertaken in the Concept Consulting report suggests that under a scenario whereby 57% of the current private vehicle fleet were EVs (corresponding to one EV per household), passive charging would cause an increase of peak electricity demand of approximately 3,000MW, whereas if all were charged in a "smart" fashion, there would be no increase in peak demand.

This report extends the work done by Concept Consulting, but utilises actual data collected from electric vehicles, as opposed to using models based on the current New Zealand transport sector. The intention of the report is to provide further insight into the potential effects on the New Zealand electricity grid that may occur with a dramatic increase in EVs, so that these may be planned for and mitigated. It is also inspired by the UK Department of Transport 2018 statistical report (Eyers 2018).

2 Data

2.1 Background

The data used has been provided by 'Flip the Fleet', a community organisation that hopes to increase uptake of electric vehicles in New Zealand. Flip the Fleet have been collecting data on electric vehicle usage patterns, via Exact IOT Limited's blackbox recorder, a small electronic device that connects to the vehicle's internal computer and sends detailed data about the battery health, power demand, charging rate, speed and other performance information to a secure database.

The subset of this data provided to the University of Otago was collected from 52 domestic electric vehicles monitored from April 2018 to March 2019. The data consisted of 1,882,040 1 minute interval observations of timestamped odometer readings (in km) together with measurements of charging power (kW) and battery charge state (% charged) linked by a unique anonymised vehicle identifier. The data received contained *all* available observations but charging was set to 0 kW if the vehicle was non-stationary (speed > 0 km/h) prior to data delivery to the University. This enabled us to automatically exclude charging through regenerative braking from the analysis.

There are a number of important limitations to this data:

- observations were only collected when the car was switched on and/or plugged in and charging. As a result no observations exist for periods when the EV is switched off and so there are large non-erroneous 'gaps' in the data which represent 'no charging' but which are not included as '0 power demand' in the analyses since to do so would require imputation of a very large number of missing timestamps for each vehicle. This means we are only able to analyse power demand profiles for vehicles that were known to be charging, *not for all vehicles in all time periods*;
- data upload relied on mobile 3G data signal and the extent to which gaps in the data are due to data upload errors rather than the vehicle being switched off (as above) is currently unclear;
- these vehicles are driven by 'early adopters' who have opted to install the measuring devices in order to collect their vehicle usage data. As a result the data may not be representative of the usage patterns of current or future EV drivers (Rezvani, Jansson, and Bodin 2015, @li_review_2017).

Even though the use of an anonymised vehicle identifier should prevent the identification of the vehicles in the sample, the fine-grained temporal nature of the data and the relatively small population of EV owners from whom the sample is drawn (Flip The Fleet members) means that the data cannot be publicly released.

Table 1: Summary of original data

	id	date	month	day_of_week	time	charge_power_kw
	Length:1882040	Min. :2018-04-05	Length:1882040	Monday :269050	Length:1882040	Min. : 0.00
	Class :character	1st Qu.:2018-10-12	Class :character	Tuesday :273804	Class1:hms	1st Qu.: 0.00
	Mode :character	Median :2018-11-25	Mode :character	Wednesday:301324	Class2:difftime	Median : 1.30
	NA	Mean :2018-11-22	NA	Thursday :302335	Mode :numeric	Mean : 1.59
	NA	3rd Qu.:2019-01-13	NA	Friday :301212	NA	3rd Qu.: 1.85
	NA	Max. :2019-03-01	NA	Saturday :223379	NA	Max. :74940.42
	NA	NA	NA	Sunday :210936	NA	NA

Table 2: Number of observations and start/end dates for vehicles (6 most scarce)

id	nObs	startTime	endTime	meanWhCharging	maxWhC
0cc746a3f5ae75ee94068a8354b6be08	3	2018-09-09 10:46:30	2018-09-09 10:48:42	0.0000000	0
01583b8a5f0344cc4aa3b3939a27af2a	4	2018-09-09 10:34:12	2018-09-09 10:36:25	0.0000000	0
4a6bb6e7ffc28d9d8eda7b4c6377a027	19	2018-09-08 08:48:38	2018-09-09 10:27:50	4.2251742	27
126c8759ec95ba40070b16a11fe0e587	258	2018-09-30 11:54:18	2018-09-30 19:24:05	1.5869526	1
6e3293c77f562262ed6608db1b596d36	4315	2018-05-15 14:48:15	2018-12-06 13:25:56	0.2872577	47
781f06f7d7bb80b74c399326be0d3e28	5469	2018-09-28 11:25:58	2018-10-15 16:21:57	2.3686450	47

2.2 Initial cleaning

The original supplied data consisted of 1882040 observations for the period NA to NA.

Figure 1 shows the number of unique EVs observed by time of day and date. As we can see the early part of the sample is sparse and indeed the maximum number of EVs observed in any 15 minute time period was only 22 out of a possible total of 52. While this will not affect some analyses, it is likely to introduce error and small sample effects to summary analyses (e.g. means) or month by month analyses. In some sections the analysis will therefore be restricted to the data from September to March.

Figure 2 shows the unique number of EVs recorded on each day and reflects the period over which Flip The Fleet installed the data collection boxes.

Finally, 2 shows that a small number of EVs have very few observations, in some cases not extending beyond 1 day (shown as 0 days observed).

Taking all of the above into account we have therefore discarded:

- the 5 vehicles that had no recorded *charging* observations (this also discarded those with very few observations - see Table 2);
- 45 instances of charging power greater than 120kW. These were considered anomalies and as these exceed the capacity of the highest charging stations currently available in New Zealand (Concept Consulting 2018);
- 61 instances of battery state of charge observations of greater than 100%;
- all observations collected before 1st October and after 1st January in order to focus analysis on the periods with most EVs present in the data. It is hoped that this will reduce the extent to which the charging behaviour of a small number of EV owners will skew the aggregated results.

This left 48 remaining vehicles, and 1,518,388 observations as shown in Table 3.

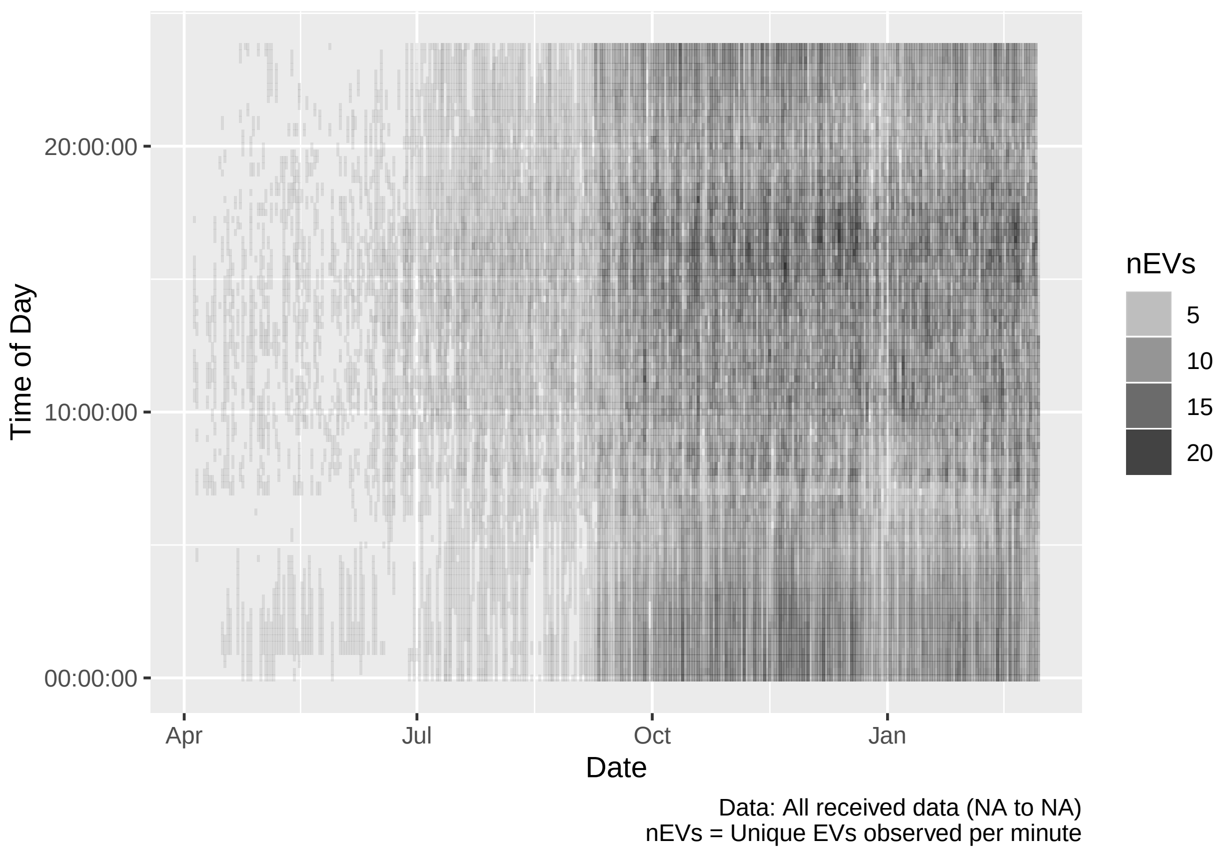


Figure 1: Number of unique EVs observed by time of day and date

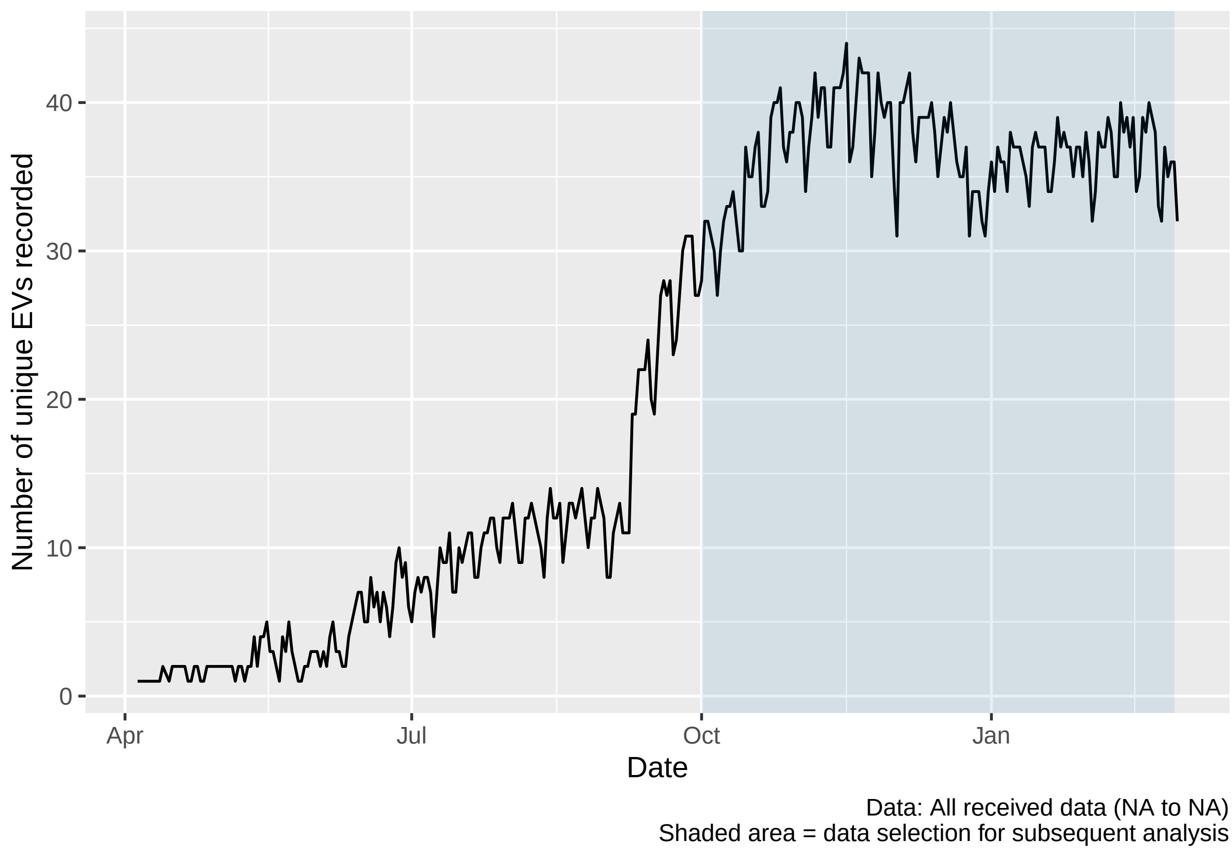


Figure 2: Number of unique EVs observed by time of day and date

Table 3: Number of observations by charge flag (final cleaned data)

	Weekdays	Weekends	NA	Sum
Standard charging	659474	220663	0	880137
Rapid charging	5558	2804	0	8362
Not charging	494990	134899	0	629889
NA	0	0	0	0
Sum	1160022	358366	0	1518388

2.3 Definitions and preparation

2.3.1 Charge type

Charging data has been broadly separated into two separate categories, 'Standard' and 'Rapid'. Standard charging is defined to be when the charger is reading less than 7kW - this is considered the upper limit of ordinary home charging without an expensive wiring upgrade (Concept Consulting 2018). Rapid charging is defined as all charging equal to or greater than 7kW, and would likely occur at designated and purpose-built public charging stations.

It should be noted that this method is not always accurate since we can identify apparent sequences of charging which start at $>$ 7kW and decline to $<$ 7kW over a relatively short period or vice versa (see Section 5.3.1). In this circumstance the first observation will be correctly classified as 'Rapid' but the lower observations, which we assume are lower power 'top-ups' at the end of a rapid charge will be incorrectly classified as 'Standard'. As an example, we know that there are 99 sequences of charging events (out of a total of 16880) where the first and last charge types do not match.

This is clarified and corrected in Section 2.3.2 for charging begin/end pairs (and thus in the results that use this data) but has yet to be resolved in other sections which use all charging observations. As a result we may currently be *under-estimating* the number of rapid charge observations and *over-estimating* the mean power demand of standard charges where we conduct analysis using all charging observations.

Figure 3 shows the distribution of observed charging kW demand by inferred charge type without correcting for potential mis-classifications. Setting aside the small number of potential misclassifications noted above, the plot confirms the validity of our definition and shows that rapid charges were relatively rare in the dataset. rapid charges have two distinct power demand 'peaks' at ~22kW and ~45kW while the far more common standard charging was mostly concentrated around 1.8kW and 3kW, with a smaller concentration around 6kW.

2.3.2 Charge sequences

In order to determine charging durations, we have identified and extracted observations which are the start and end of charging sequences. This is done using the following logic:

- rows were coded as "charging begins" if the charging power was greater than zero and the previous and following row's charging power were (respectively) equal to zero and greater than zero;
- rows were coded as "charge ends" if the charging power was greater than zero and the previous and following row's charging power were (respectively) greater than zero and equal to zero;
- rows were coded as "charge in a sequence" if charging power > 0 and the observations either side were also > 0
- rows were coded as "single charge events" if charging power > 0 but the observations either side were 0.

Table 4 shows the results of this coding for all clean observations within the selected dates (2018-10-01 - 2019-02-28). As we can see most observations were coded using this scheme and we obtained 8,439 instances of charging starting, and 8,441 instances of charge ending. The additional 2 instances of charge ending than

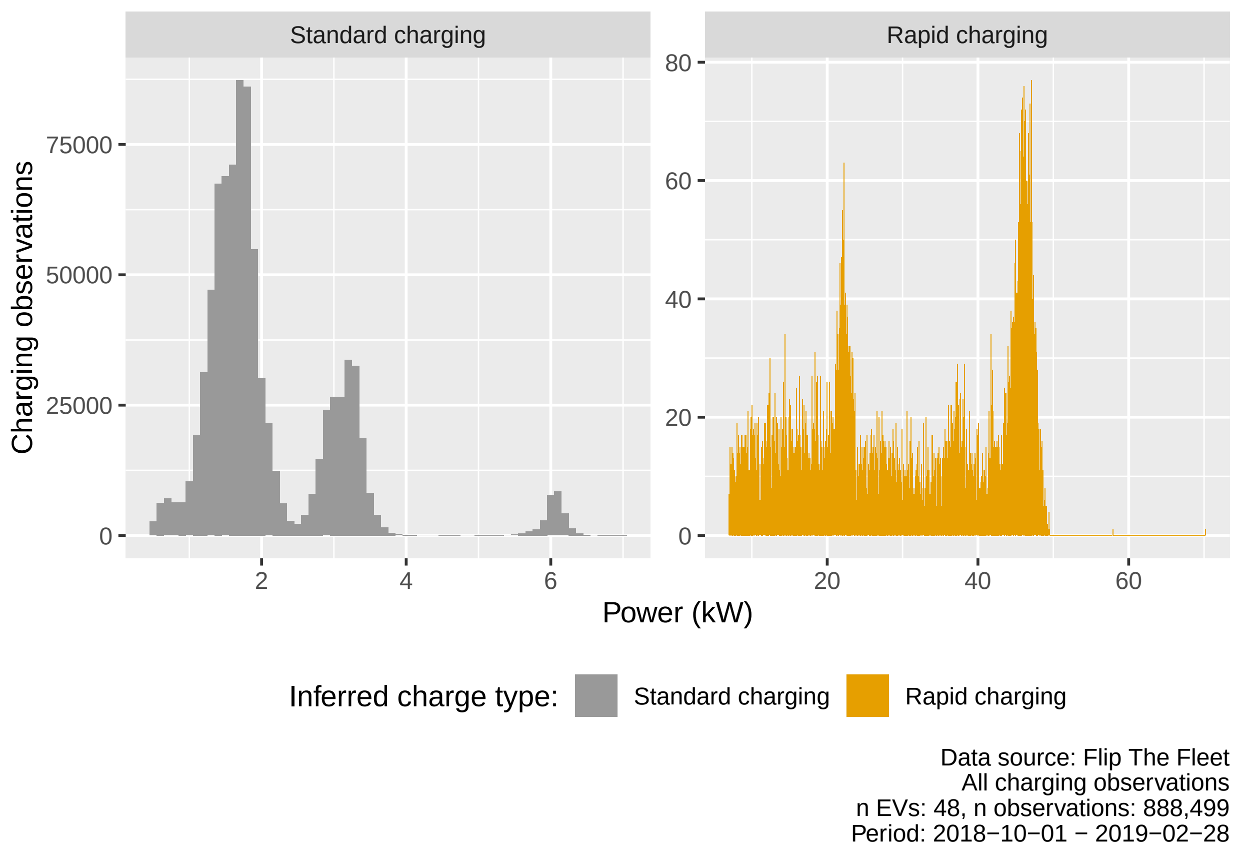


Figure 3: Observed power demand distribution by charge type where charging observed

Table 4: Charge sequence coding results (all cleaned data)

	Standard charging	Rapid charging	Not charging	NA	Sum
Charging in a seq	858209	7375	0	0	865584
First charge obs in a seq	7980	459	0	0	8439
Last charge in a seq	8049	392	0	0	8441
Not charging (0 kW)	0	0	629889	0	629889
Single charge observation	5897	135	0	0	6032
NA	2	1	0	0	3
Sum	880137	8362	629889	0	1518388

Table 5: Charge type errors detected via mis-matching start and end observations vs uncorrected charge type

	Standard charging	Rapid charging	Not charging	Sum
Error: first = Rapid, last = Standard	0	83	0	83
Error: first = Standard, last = Rapid	16	0	0	16
OK: first = Rapid, last = Rapid	0	376	0	376
OK: first = Standard, last = Standard	7964	0	0	7964
Sum	7980	459	0	8439

there are of the charge beginning may be due to the first (or last) instance of data collection occurring during mid-charge for some vehicles.

An alternative classification method, tested in Section 5.3.1, added a 120 second maximim threshold to sequences of observations but was not used as it failed to identify sparse sequences of charging events.

Comparison of the begining and end charge types showed, as suspected, that a number of pairs had mis-matching charge-types (see Table 5). In all cases charge type was set to 'Rapid' if either of the start or end observations was classified as 'Rapid'. However this correction has only been made with the extracted pairs data and how not yet been applied to the full 'all observations' data.

The charge duration was then calculated as being the time duration between each pair of 'first in charge sequence' and 'last in charge sequence' observations.

Figure 4 shows the overall distribution of all charging sequences using the corrected charge type. Clearly there are very small and a few very large values for both charging types.

Table 6 shows the overall distributions and indicates the extent to which the means are skewed by the very small and a few very large values shown in Figure 4.

Table 7 shows the longest duration 'standard' charge events while Table 8 shows the longest duration 'Rapid' charge events.

Figure 5 shows the distribution of very short charging sequences. As we can see these appear to be generally less than 8 minutes in length for Standard Charges.

Manual inspection of the data showed that these short-duration 'standard' charging events generally occurred near the end of a longer-duration charging sequence. It appeared that once the vehicle had reached its highest state of charge, charging would intermittently stop and start again. This is probably due to the behaviour of the charger once the battery was almost full.

Table 9 repeats the same descriptive statistics reported in Table 6 but for all sequences of greater than 8 minute duration. We can now see that the mean and median durations for both Standard and Rapid Charge sequences are closer.

In addition to the many 'short' charging duration values, a small number of unreasonably long charging durations (longer than 14 hours for rapid charging - see Table 8) were calculated. As these exceeded the

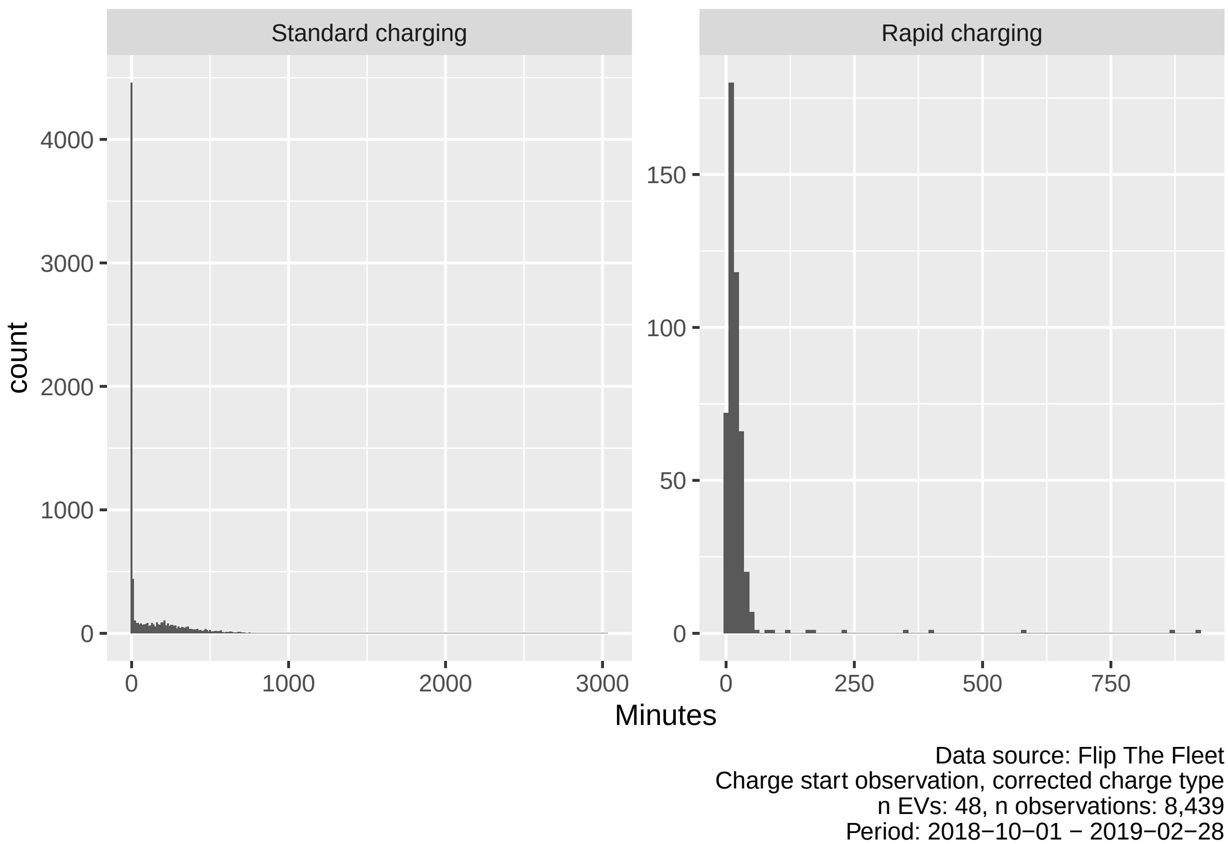


Figure 4: Duration of charging sequences by corrected charge type

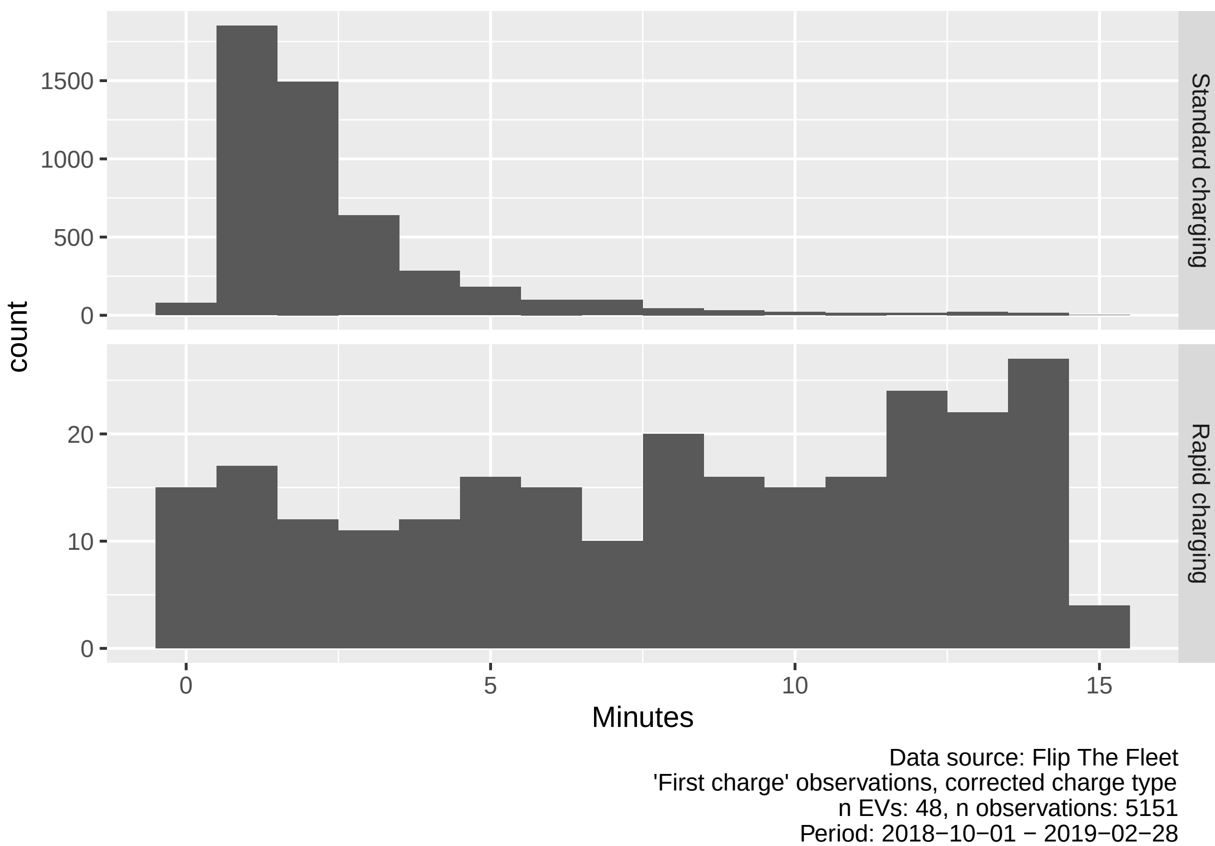


Figure 5: Duration of charging sequences < 15 minutes

Table 6: Duration of all charge sequences by charge type

chargeTypeCorrected	N	mean	median	min	max
Standard charging	7958	98.86 mins	3.40	0.27 mins	3029.12 mins
Rapid charging	475	23.98 mins	14.28	0.02 mins	922.03 mins

Table 7: Duration of longest charge sequences (Standard charging)

dvID	startTime	day_of_week	chargeType	chargeTypeCorrected	pairDuration	duration_hours
Vehicle 37	17:33:33	Saturday	Standard charging	Standard charging	3029.12 mins	50.49
Vehicle 31	12:39:44	Monday	Standard charging	Standard charging	1776.83 mins	29.61
Vehicle 39	10:03:05	Friday	Standard charging	Standard charging	1616.72 mins	26.95
Vehicle 28	13:54:06	Monday	Standard charging	Standard charging	1442.30 mins	24.04
Vehicle 39	15:39:53	Tuesday	Standard charging	Standard charging	1380.53 mins	23.01
Vehicle 34	22:28:58	Saturday	Standard charging	Standard charging	1353.40 mins	22.56
Vehicle 39	17:40:33	Friday	Standard charging	Standard charging	1341.80 mins	22.36
Vehicle 39	10:44:13	Sunday	Standard charging	Standard charging	1324.10 mins	22.07
Vehicle 39	17:52:46	Friday	Standard charging	Standard charging	1323.92 mins	22.07
Vehicle 35	16:58:43	Saturday	Standard charging	Standard charging	1315.95 mins	21.93

expected charge durations of even the highest capacity vehicles currently available, they were also assumed to be anomalies. The analyses in Section 3.3 below was therefore made with the following charge events excluded from the data:

- duration $<$ 8 minutes for standard charging (4747 observations - noting that some of these may be short low power 'Rapid charge' events as discussed in Section 2.3.1)
- duration $>$ 840 minutes (14 hours) for rapid charging (2 observations)

Figure **??** shows the distribution of charging sequences with the excessively long or short events removed. These charging durations appear more reasonable when considering standard battery capacities and available charge power.

Table 8: Duration of longest charge sequences (Rapid charging)

dvID	startTime	day_of_week	chargeType	chargeTypeCorrected	pairDuration	duration_hours
Vehicle 43	09:51:43	Saturday	Rapid charging	Rapid charging	922.03 mins	15.37
Vehicle 36	17:10:19	Wednesday	Standard charging	Rapid charging	865.70 mins	14.43
Vehicle 12	21:08:02	Thursday	Rapid charging	Rapid charging	582.53 mins	9.71
Vehicle 40	12:37:03	Thursday	Rapid charging	Rapid charging	398.27 mins	6.64
Vehicle 40	10:39:13	Tuesday	Rapid charging	Rapid charging	346.25 mins	5.77
Vehicle 43	15:39:24	Tuesday	Rapid charging	Rapid charging	227.85 mins	3.80
Vehicle 1	07:20:46	Thursday	Rapid charging	Rapid charging	173.58 mins	2.89
Vehicle 19	00:52:01	Friday	Rapid charging	Rapid charging	155.42 mins	2.59
Vehicle 49	12:40:40	Tuesday	Rapid charging	Rapid charging	116.37 mins	1.94
Vehicle 21	20:04:03	Sunday	Rapid charging	Rapid charging	90.57 mins	1.51

Table 9: Duration of charge sequences > 8 minutes by charge type (minutes)

chargeTypeCorrected	N	mean	median	min	max
Standard charging	3211	241.89 mins	205.57	8.03 mins	3029.12 mins
Rapid charging	356	30.72 mins	18.14	8.12 mins	922.03 mins

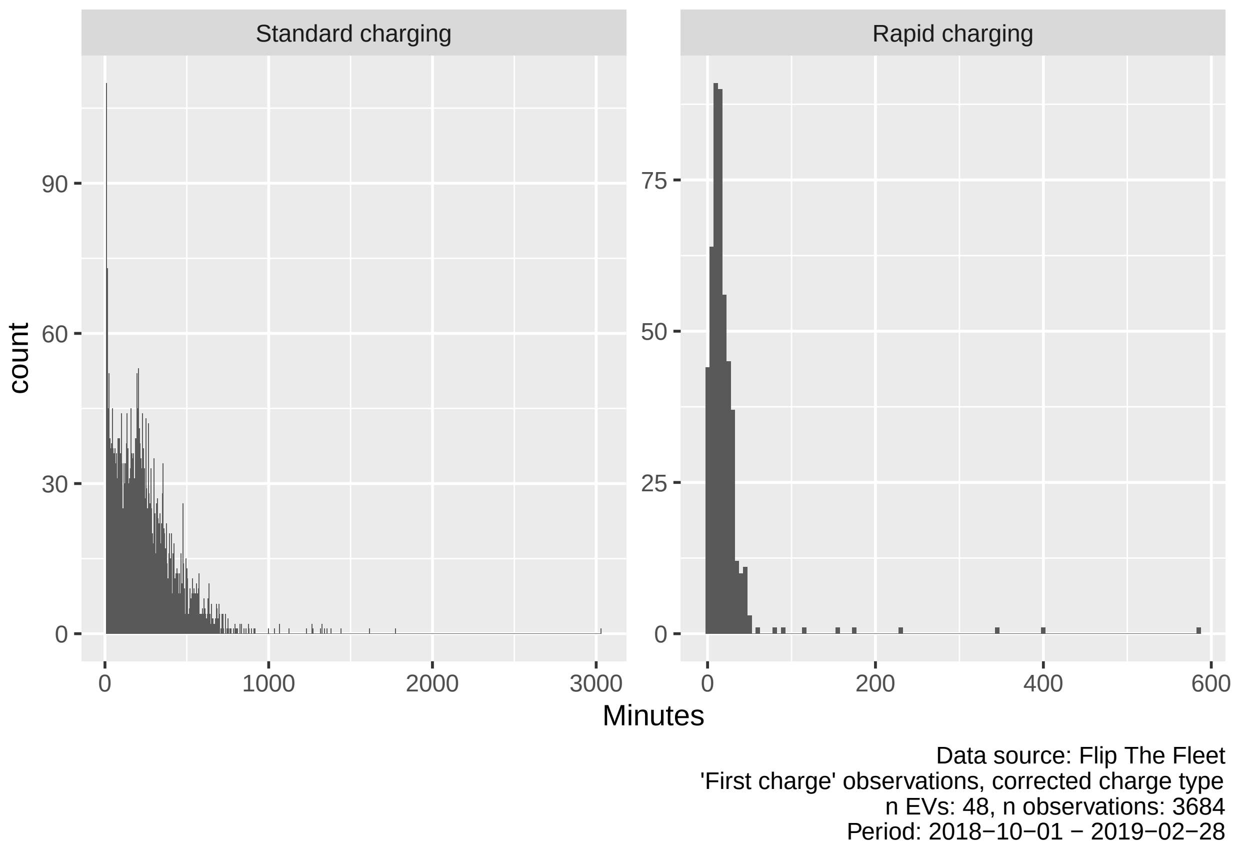


Table 10: Duration of charge sequences, final duration data

chargeTypeCorrected	N	mean	median	min	max
Standard charging	3211	241.89 mins	205.57	8.03 mins	3029.12 mins
Rapid charging	473	20.30 mins	14.27	0.02 mins	582.53 mins

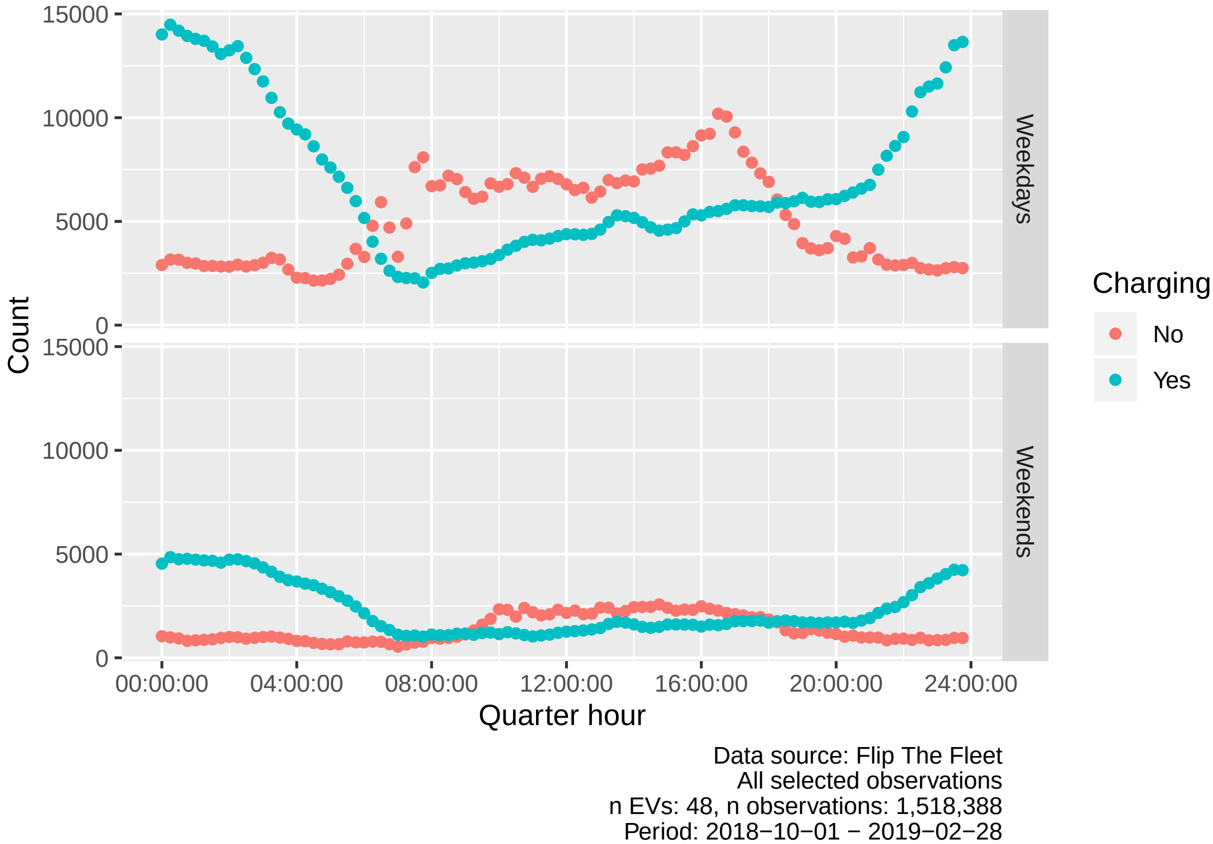


Figure 6: Frequency of charging observations (all days)

3 Results

3.1 Time of charging

It has been suggested that EV charging is more likely to occur in the early evening when drivers return from daily commutes or school pick-ups (Langbroek, Franklin, and Susilo 2017).

Figure 6 shows counts of charging events by type and time of day while Figure 7 shows the percent of observations that were charging events by quarter hour for the cleaned data set.

Both figures point to a high incidence of overnight charging which declines rapidly to 08:00 on weekdays but later at weekends, before trending upwards again throughout the day with noticeable ‘blips’ just before 14:00 and just before 16:00. However we do not see a sharp rise in the frequency of charging events between 16:00 and 18:00 when the incidence of driving declines (non-charging in Figure 6). This, together with the increase in charging frequency after 20:30 suggests that owners manually or automatically start to charge vehicles later in the evening. It should be noted therefore that the apparent rise in the percentage of vehicles charging from 17:00 onwards is driven by the reduction in the number observations of non-charging rather than an actua increase in charging behaviour.

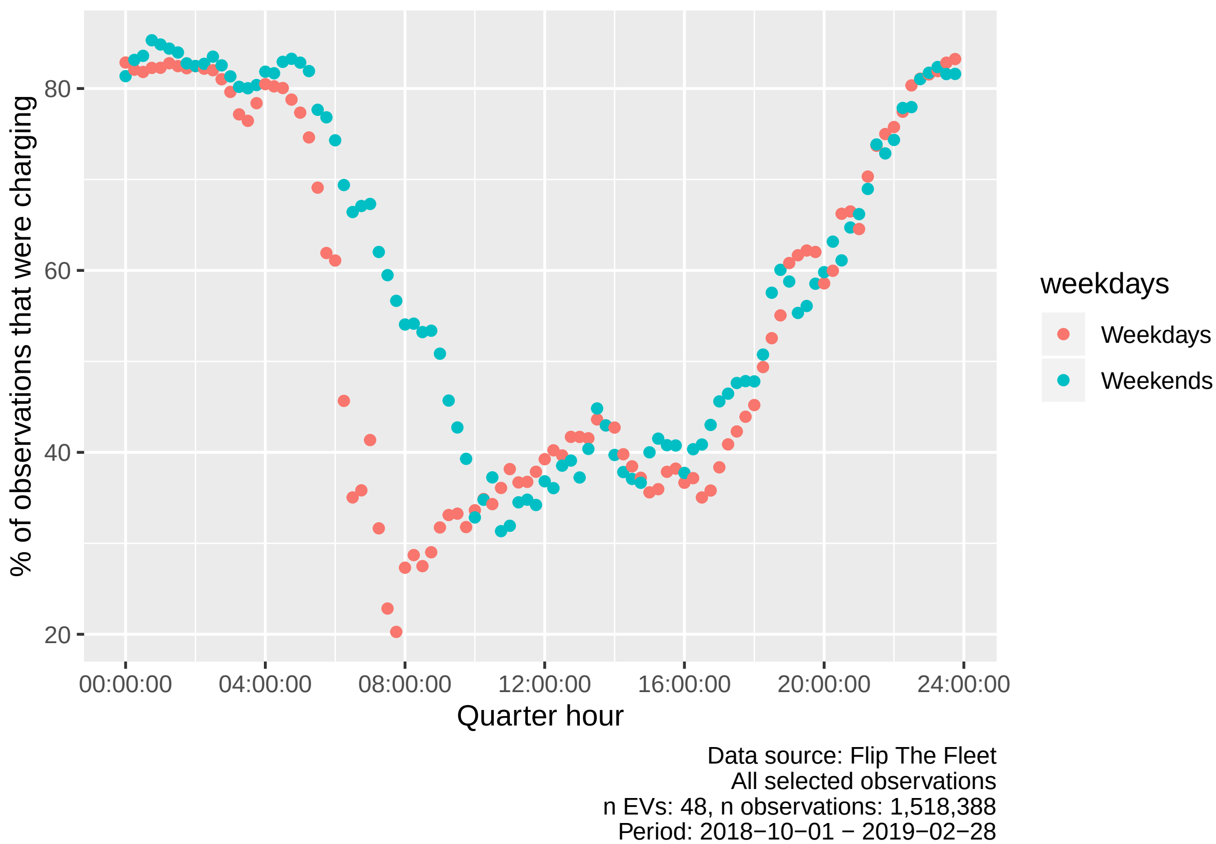


Figure 7: % of observations which are charging (all days)

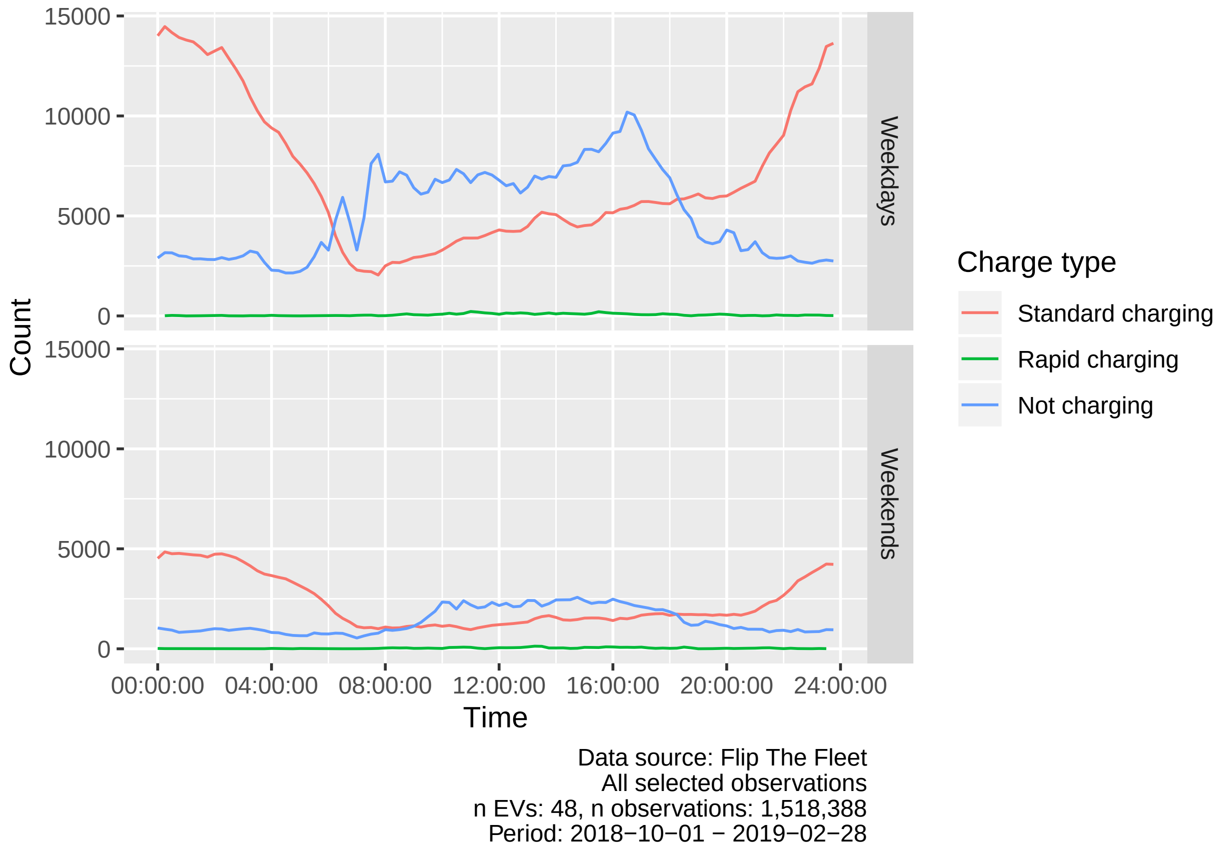


Figure 8: Density plot of charging start times during weekdays

Figure 8 plots the distribution of each charge type over time of day and confirms the very low incidence of rapid charging. It also supports the suggestion that standard charging (at home) does not appear to begin until later in the evening.

Figure 9 extends this analysis by showing charging and non-charging observations at different times of day by weekday vs weekends using a density plot to show releative distributions over time within each type. The plot clearly shows non-charging during day-time use and also shows a bi-model distribution for rapid charging (non-corrected categorisation). Standard charging also shows a bi-modal distribution with a peak around 22:00 on weekdays and another at 01:00 presumably indicating the use of timed or 'smart' charging or trickle events.

In general, these results indicate that the greatest frequency of standard charging events occurs between 20:00 and 08:00, with very low occurrences of charging during morning and evening grid peaks. Rapid charging on the other hand is a day-time activity on both weekdays and weekends.

To make the patterns of 'initial charging' clearer, we use just the 'first' charge observation in a pair (see above) and also exclude automatic battery 'top-ups' (refer to Section 3.4) by filtering out any data where a charging observation begins while the state of charge is greater than 90%. Having done so, Figure 10 shows the distribution of the start of 'charge sequences' and shows that the number of charging event starts increases steadily through the day before an apparent brief lull between 19:00 and 21:00 and then increases substantially thereafter.

Figure 11 uses a density plot to represent the proportion of charging sequences that start at different times of the day on weekdays vs weekends for standard and rapid charging (corrected classification).

As we can see, standard charging sequences (as opposed to single observations) have a noticeably different

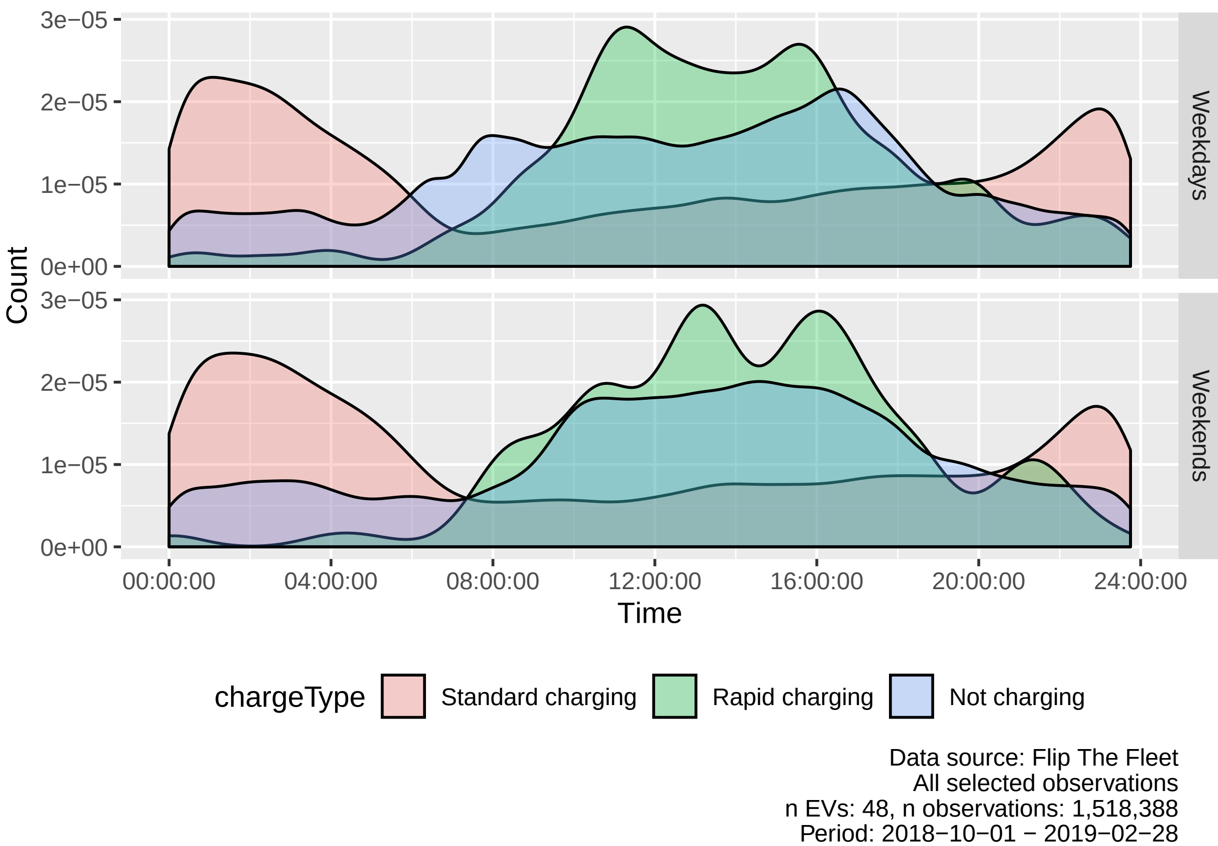


Figure 9: Density plot of charging start times during weekdays

Figure 10: Charging start times where state of charge $< 90\%$

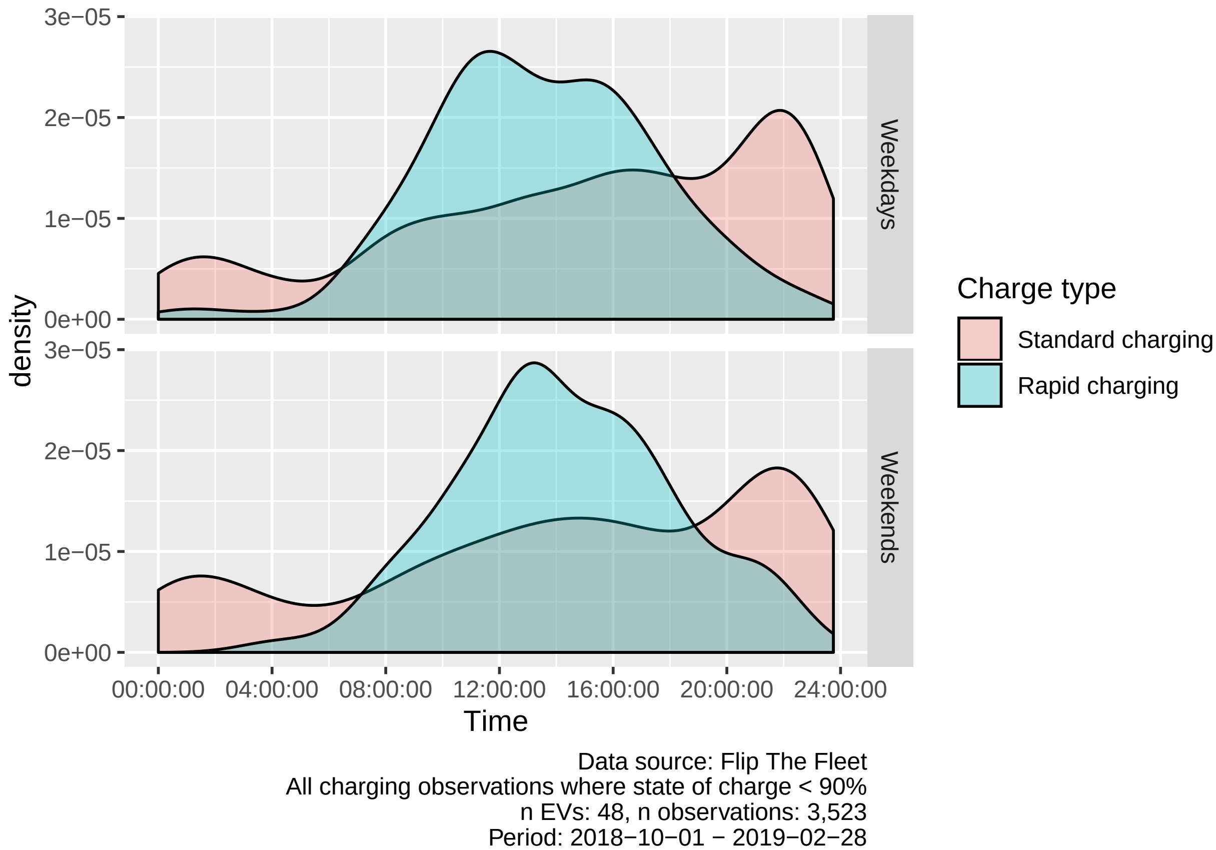


Figure 11: Density plot of charging start times where state of charge $< 90\%$

profile to charging patterns for rapid charges. It suggests that the largest number of standard charging events start between 20:00 and 22:00 and run overnight, and perhaps use the more powerful public charge points to top up during the day. However the plot also show a substantial proportion of charging events start earlier in the day, including during the NZ peak demand periods of 07:00 - 09:00 and 17:00 - 21:00.

Standard charging events were most likely to begin around 10pm during both weekdays and weekends. As it seems unlikely that this is due to vehicle drivers returning home at this hour, this effect may be due to drivers setting the charger on a timer to take advantage of cheaper "off-peak" electricity times, which frequently begin around 10pm.

Rapid charging events were most likely to begin at 11:30am on weekdays and 1pm during weekends.

3.2 Patterns of power demand

Given this distribution of charging events, it is important to understand their magnitude to understand the potential effect on the electricity network. Although we are hampered by the lack of observations when the EV is inactive, this section analyses the patterns of power demand for the observations we have.

Overall 75% of standard charging observations were 1.47 kW or more but the figure was 19.44 kW or more for rapid charging.

Figure 12 shows the mean charging demand in kW calculated across all observations after setting rapid charge observations to 0 kW. As we would expect the kW load due to the EVs follows essentially the same shape as the charging event proportions shown above but with slightly more evidence of a 13:00 and 16:00 mini-peak and distinct differences between weekday and weekend mornings. As before, the apparent rapid increase in demand (and the pre-20:00 spike) are more likely to be due to decreasing numbers of 'non-charging' observations than increases in charging (see Figure 7.

Figure 13 repeats this analysis but shows the mean charging demand in kW calculated across all observations after setting standard charge observations to 0 kW. Again, the kW load due to the EVs follows essentially the same shape as the charging event counts shown above and the low mean value should remind us that rapid charging was relatively rare in the data.

In next plots we use transparency to indicate the number of EVs contributing to each of the mean calculations to give a guide to their reliability and indicate the relative proportion of sample EVs that contribute to each mean value. Dots with stronger colours indicate means calculated from a larger number of EVs and, given the data gaps noted in Section 2.1, this therefore indicates patterns which are generally shared across a larger number of EVs. We would therefore expect darker dots (most vehicles) durng overnight charge times and lighter plots (fewer vehicles co-incidentally charging) through the day.

Figure 14 shows the mean power demand for standard charging observations by time of day and weekdays vs weekends for the selected time period. This plot appears to show that there are three peaks in standard charging, one at 10:00, one at 18:00 (possibly based on fewer EVs) and one after midnight on weekdays. There are also noticeable 07:00 and 16:00 charging blips. On the other hand at weekends the daytime peak shifts to 14:00. Thus, while our previous analysis suggested that charging events were more likely to start later in the evening, the power demand of earlier charging events may actually be relatively high and co-incide with existing peak demand periods.

Rapid charging however has no detectable pattern other than a clear increase in density during weekday daytimes (Figure 15). However, we can now see the effect that rapid charging may have with significant EV uptake.

It is possible that the 'standard charge' day-time peak is skewed by mis-classified short low power 'Rapid charge' observations (see Section 2.3.1). Figure 16 attempts to allow for this misclassification by plotting the median rather than the mean. The plot more clearly shows the 10:00 weekday spike which, if we assume that the mis-classified 'Rapid charges' will be skewing the standard charge mean value upwards, is likely to be due to mis-classified 'Rapid charging'. However the 18:00 peak persists as does the 14:00 weekend peak while overnight charging levels are relatively stable as we would expect from 14.

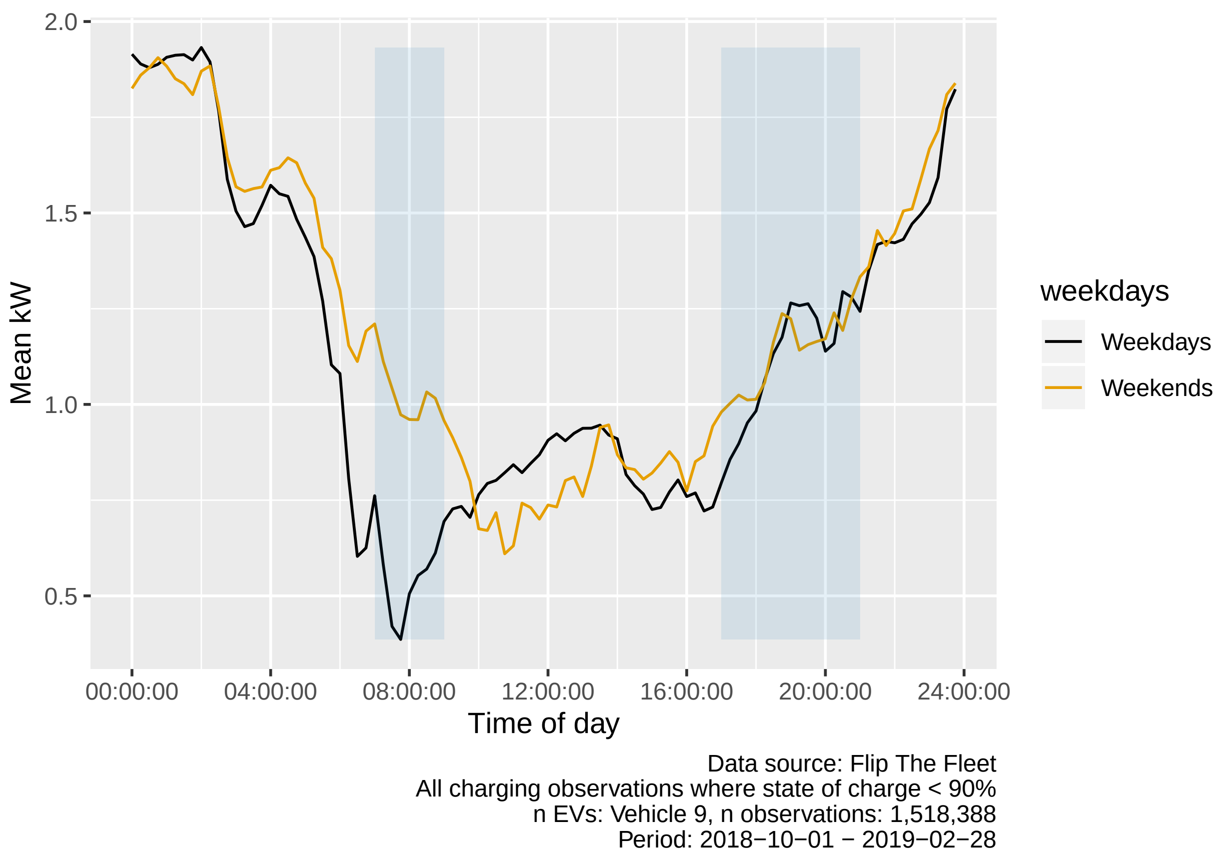


Figure 12: Mean kW per quarter hour (treating rapid charging as 0 kW)

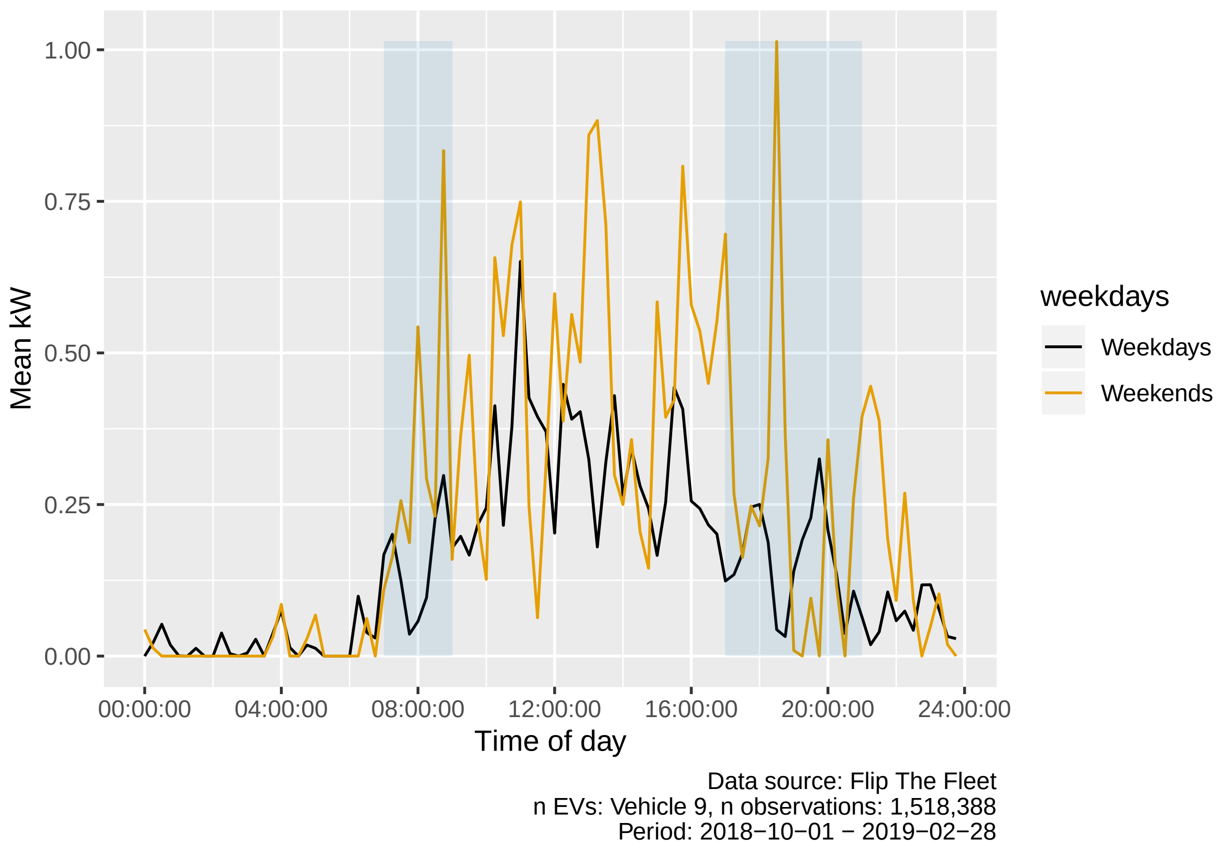


Figure 13: Mean kW per quarter hour (treating standard charging as 0 kW)

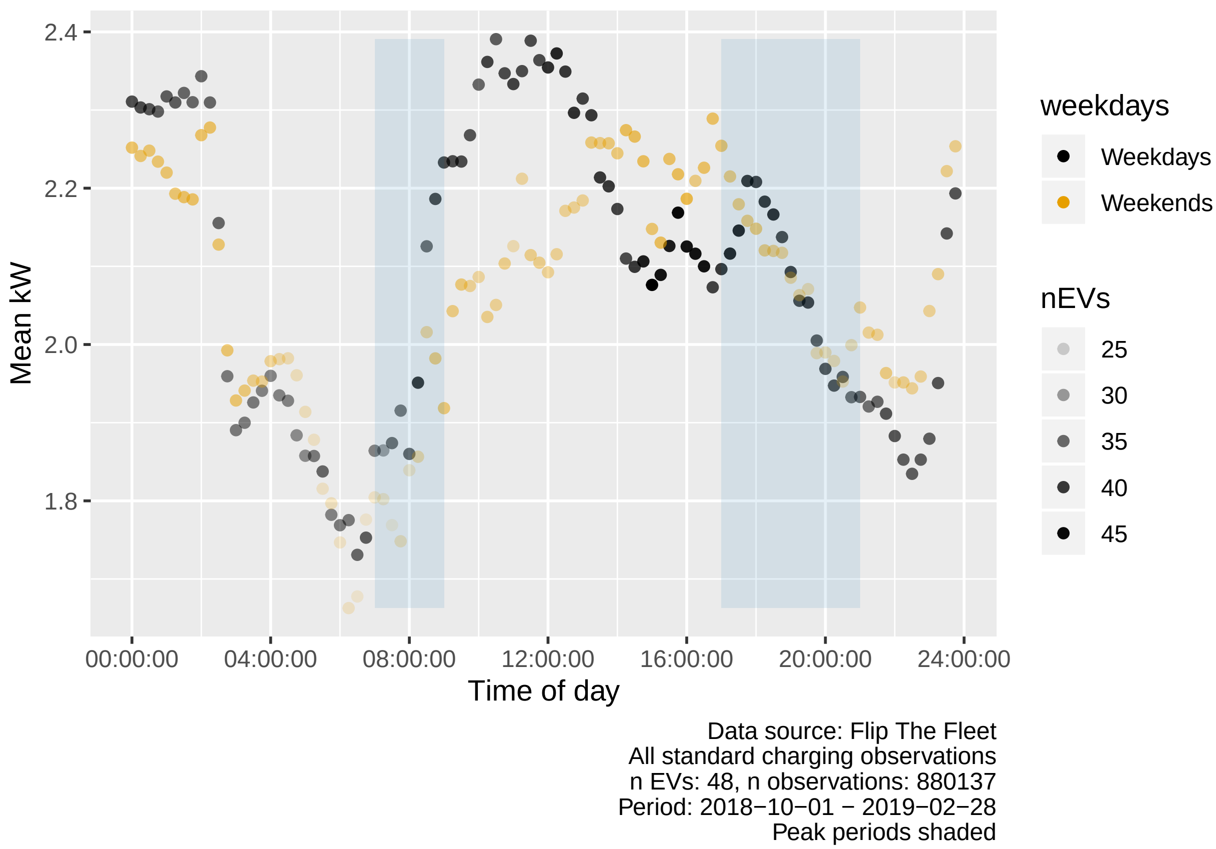
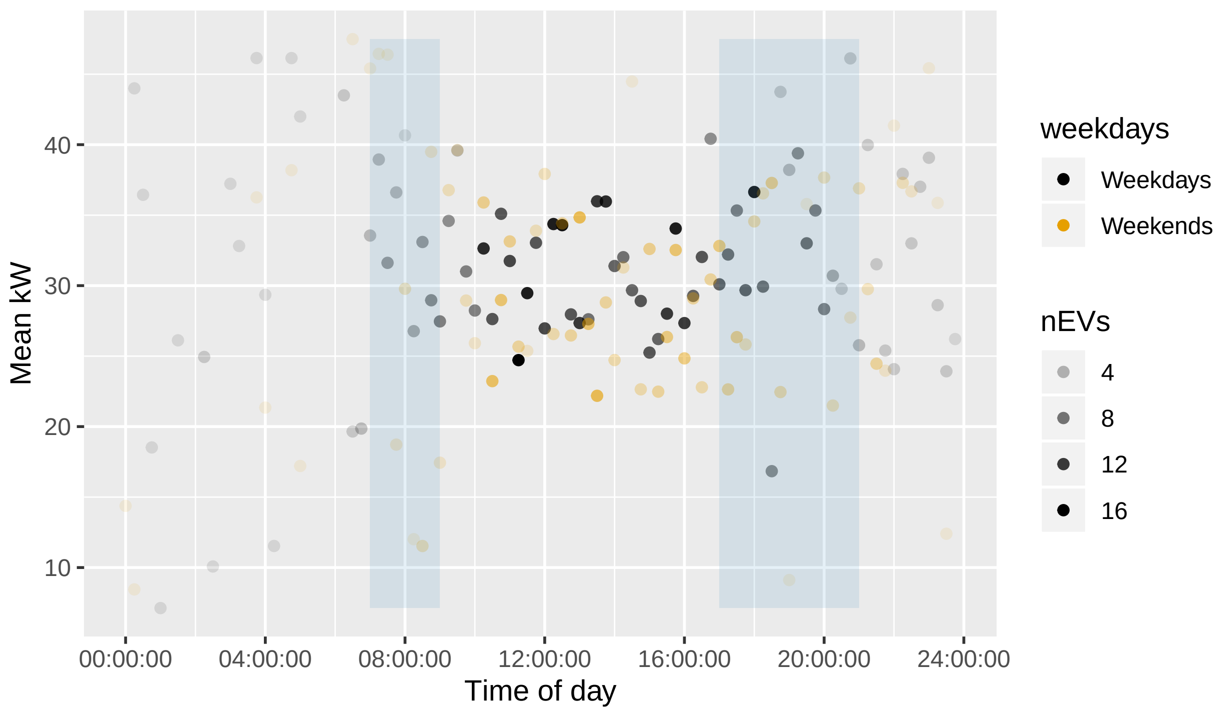


Figure 14: Mean charging power demand (kW) by time of day ('standard' charging)



Data source: Flip The Fleet
All Rapid charging observations
n EVs: 46, n observations: 8362
Period: 2018−10−01 − 2019−02−27
Peak periods shaded

Figure 15: Mean charging power demand (kW) by time of day ('rapid' charging)

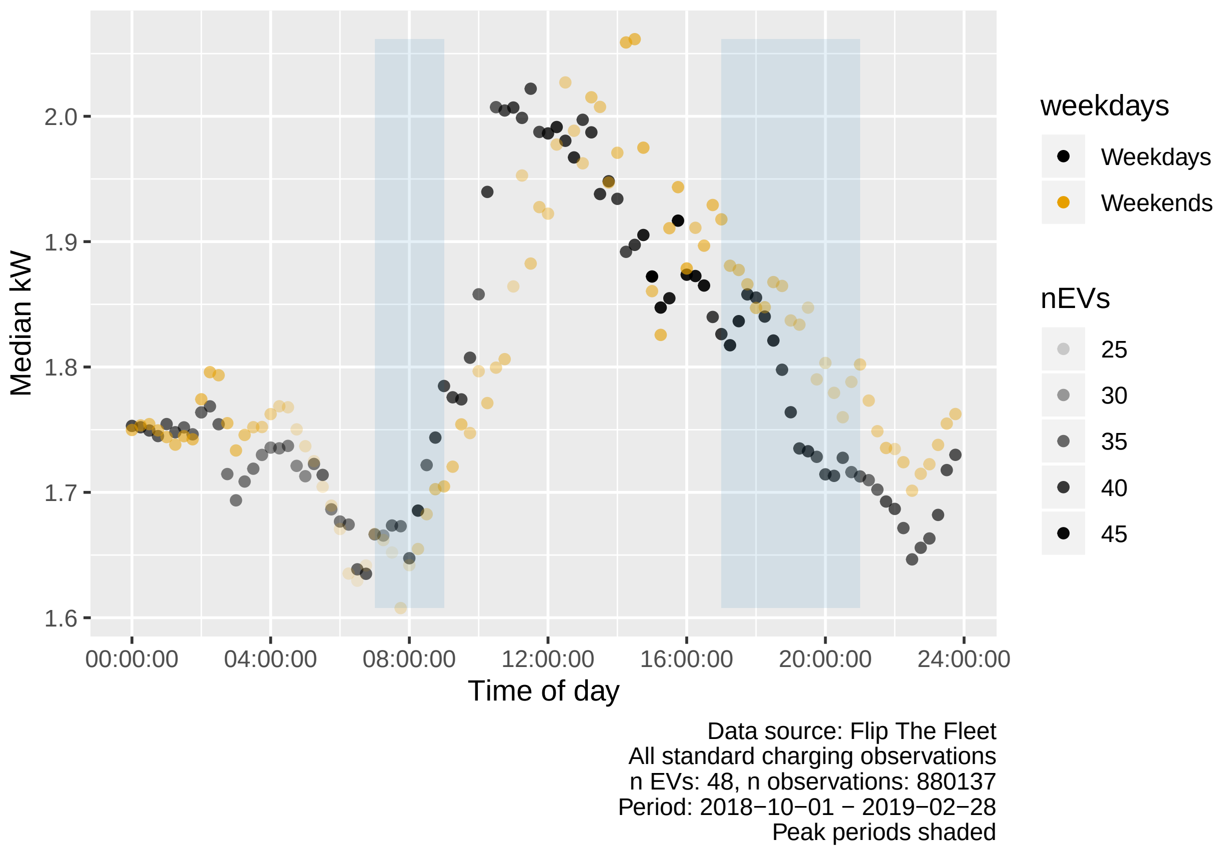


Figure 16: Median charging power demand (kW) by time of day

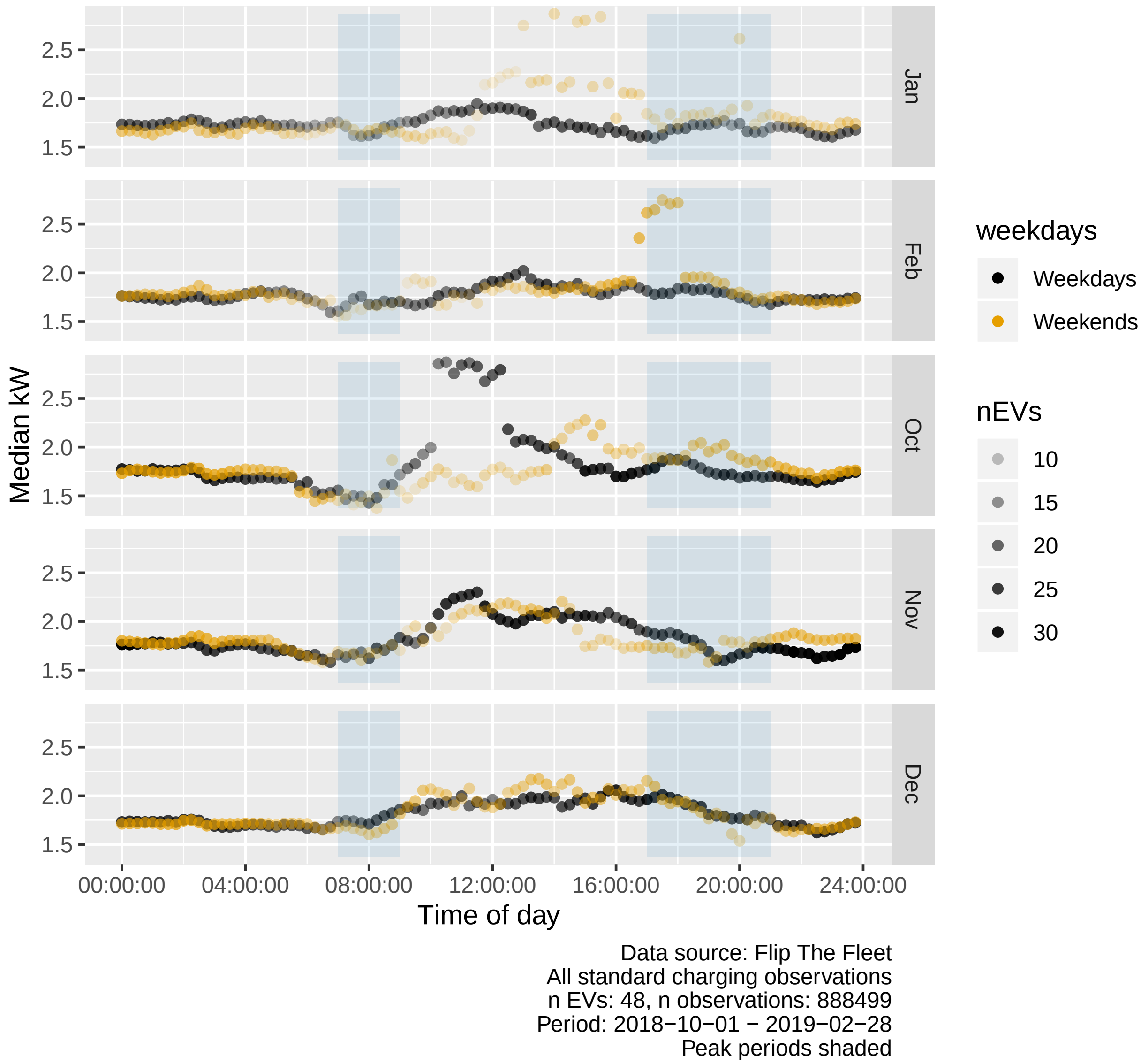


Figure 17: Median charging power demand (kW) by time of day and month

Figure 17 repeats the median power-based analysis for 'Standard charging' but shows the results by month. While the sample size is probably too small to draw robust conclusions there appear to be differences between months with December showing few discernable peaks and September and January showing much lower daytime weekday charging. In addition, weekdays and weekends are much more similar in November and December.

On face value the results suggest that EVs could be placing additional power demand on local and national networks during well-known periods of peak demand although this appears to vary by month for this small sample of EV owners.

> Clearly this analysis should be revisited once the potential misclassification of 'rapid' as 'standard' charging observations has been resolved and the 'missing' non-use (zero charging) observations have been imputed.

Table 11: Mean duration of charge events by charge type (filtered data, corrected charge type)

chargeTypeCorrected	mean	median	min	max	sd
Standard charging	241.89 mins	205.57 mins	8.03 mins	3029.12 mins	196.77
Rapid charging	20.30 mins	14.27 mins	0.02 mins	582.53 mins	39.41

Table 12: Mean duration of charge sequences (values > 480 minutes)

qHour	chargeTypeCorrected	weekdays	meanDuration	nEVs
21:00:00	Standard charging	Weekends	484.05 mins	10

3.3 Charging duration

This section analyses the duration of observed charging events to understand when longer charging sequences are likely to occur. Table 11 shows the mean durations for all all charging events by event start time for standard charging durations greater than 8 minutes (see Section 2.3.2) and all rapid charging events for observations collected after 01 October 2018.

Figure 18 plots the mean duration by time of day and weekday vs weekend and charge type. As before we use transparency to indicate the number of unique EVs contributing to the mean values and we have removed a small number of very large duration outliers (mean duration > 540 minutes or 9 hours) which appears to be based on just 1 or 2 EVs (see Table @ref:(tab:makeDurationTimeMean)).

As we would expect, the plot shows that for standard charging mean 'forward' duration generally decreases from midnight, presumably as batteries are becoming fully charged through to 06:00 and then increases as the time of starting to charge increases through the day before trending downwards before midnight. Again, this confirms that charge events starting in or just after the evening peak demand period on both weekdays and weekends are likely to be longer, possibly reflecting the lower state of charge at this time of day (following use).

Duration of rapid charge events by start time appear to be more randomly distributed, although very few events were recorded between midnight and 7am. This, along with the comparatively low number of recorded rapid charge events indicated in Fig. 3 suggests that drivers utilize rapid charging only "as necessary" to ensure they have enough battery capacity to complete their journey or when 'at work' or conducting some other mobility related task such as shopping.

3.4 State of charge

The state of charge is the percentage of energy still available to be used in the battery. In future, electric vehicles may be able to discharge any remaining battery charge as electricity into the grid, a process known as vehicle to grid (V2G) energy transfer. This may allow electric vehicles to have a net beneficial effect on the grid, reducing the evening peaks by providing electricity to the home during this period, and then recharging later in the evening or early the next morning when peak demand has diminished.

This section provides an indication of the state of charge of electric vehicles upon charging, so that the potential of V2G technology can be assessed.

As can be seen in Figure 19, using the cleaned complete observations data, the state of charge for the majority of standard charge observations is above 90%. This is most likely due to the manner in which the charger regularly turns off and on again near the end of the charging cycle as described in Section 2.2.

Figure 20 shows the state of charge values for all charging events but with state of charge greater than 90% removed from the data for clarity. The figure indicates that many vehicles begin charging despite having greater than 50% charge remaining. This has clear implications for battery life management since continually top-up charging is known to substantially shorten the lifetime of EV batteries (XX ref needed XX). However

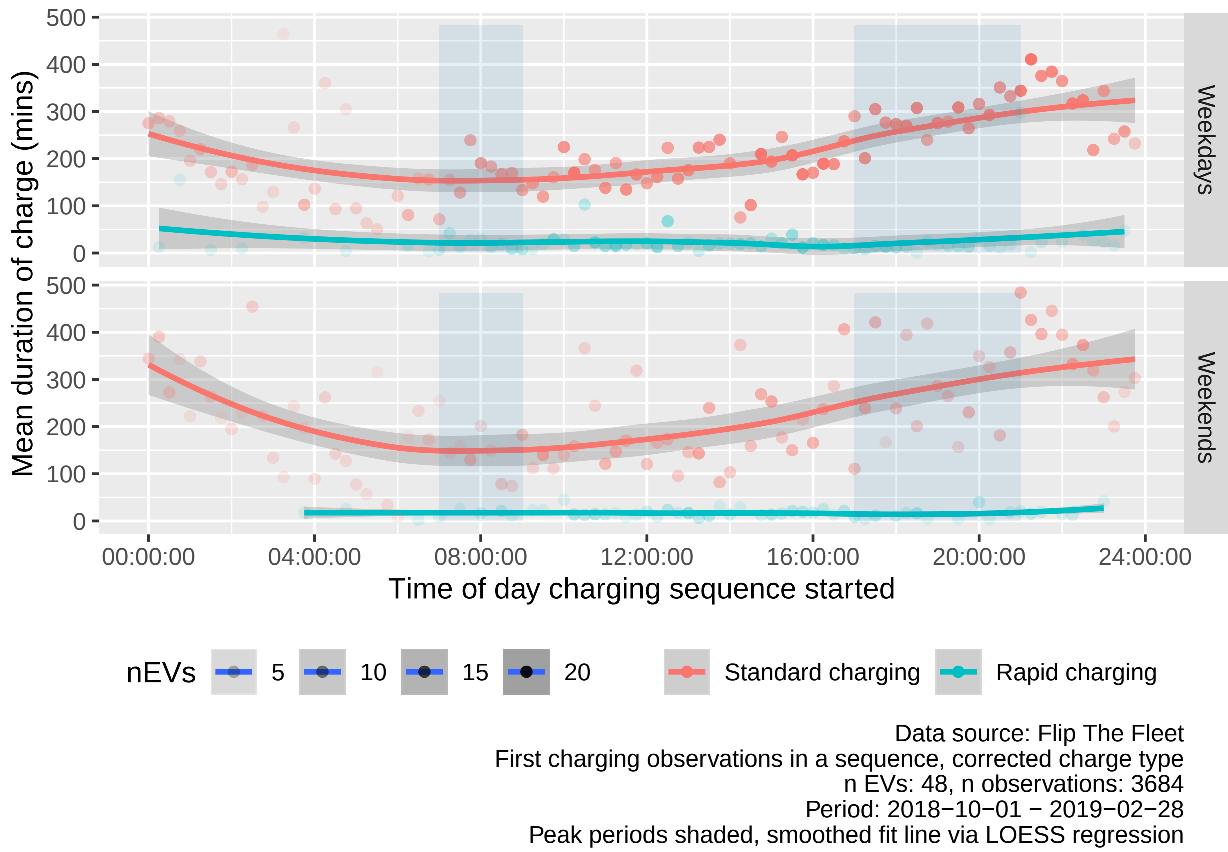


Figure 18: Mean duration (within quarter hours) by time of charging start

Figure 19: Value of state of charge (all charging observations)

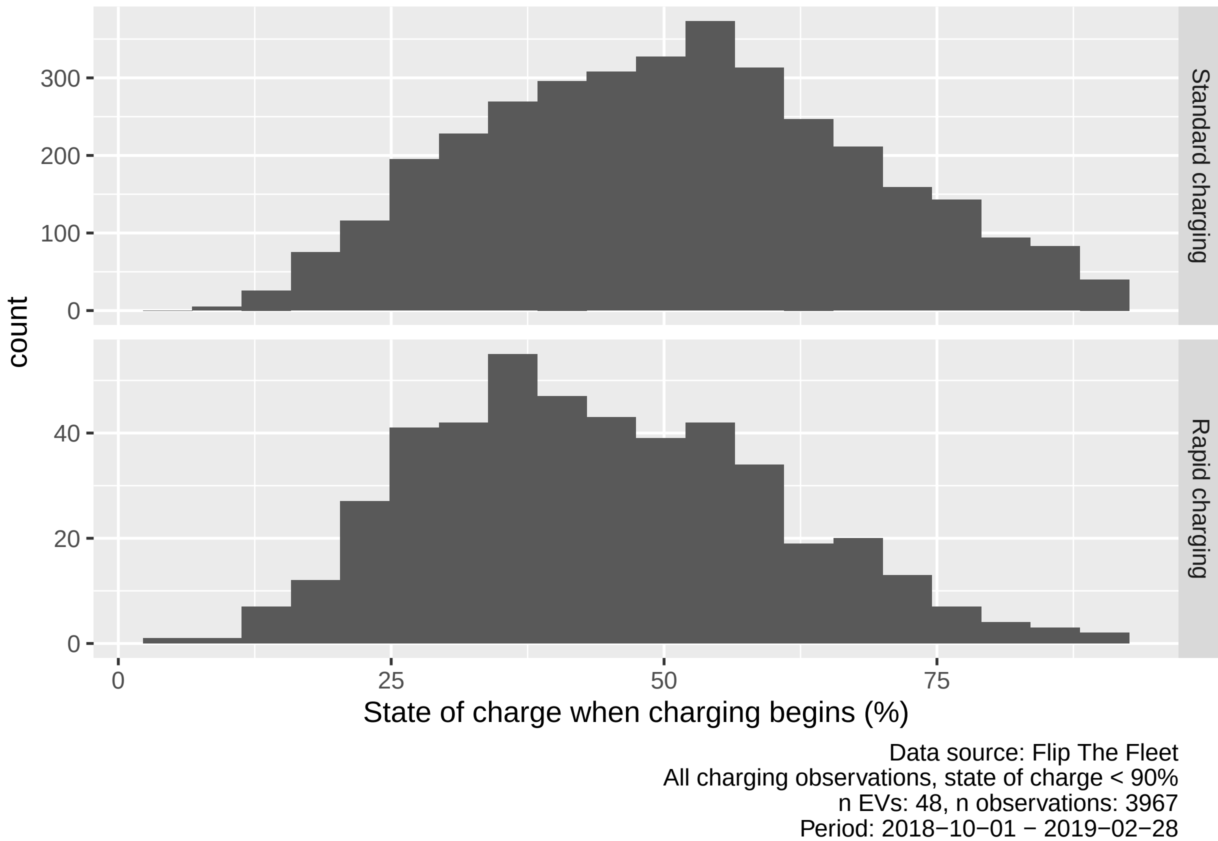


Figure 20: Value of state of charge (values > 90% removed)

it also indicates the potential to use the charge in the battery to feed into the grid, especially in the residential context.

Figure 21 repeats this analysis but uses the cleaned and corrected inferred start/end of charging sequence data instead of all charging observations. Figure 21 shows very similar distributions to the previous 'all-observations' plot (Figure 20) and confirms that sequences of standard charging in particular most frequently start with battery state of charge over 50%.

Finally, Figure 22 shows the mean % charge by time of first charging observation in a sequence using the cleaned and corrected inferred start/end of charging sequence data. The plot suggests that this capacity may be relatively stable throughout the day albiet with slightly higher mean capacity around the morning peak as we would expect given over-night charging. It is unlikely that this early morning capacity would be willingly made available for V2G since the EV may be used in the near future although this may not always be the case. However it is interesting to note that mean capacity at start of charge in the evening peak period is still roughly 50% indicating relatively substantial power availability.

4 Summary

Based on a relatively small and probably non-representative sample of 48 domestic electric vehicles provided by our research partner FlipTheFleet and which were monitored from April 2018 to March 2019 we have found that:

- *Power supplied*: The median power supplied during a charging event coded as 'standard' was 1.76 kW. The mean was slightly higher at 2.09 kW. Charging observations coded as 'Rapid' had a median of 1.76

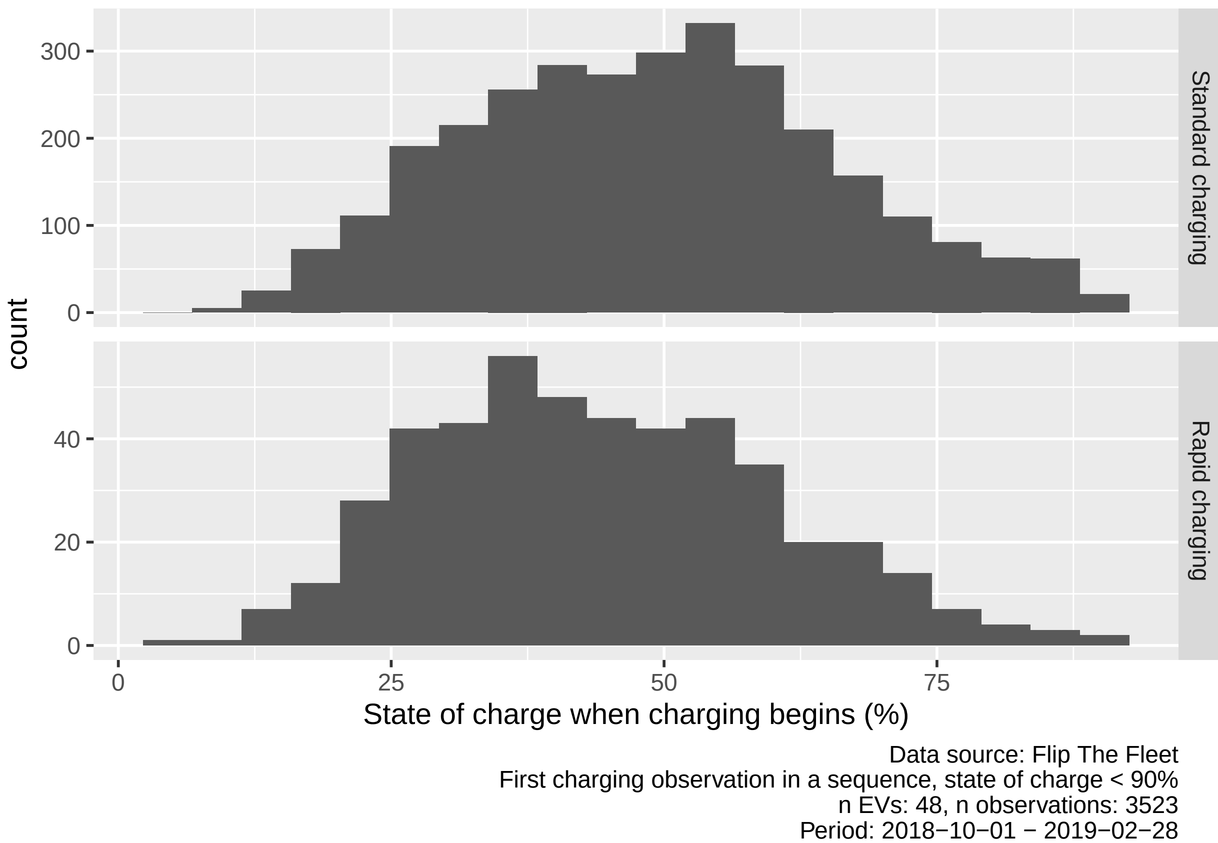


Figure 21: Value of state of charge at beginning of charging sequence (chargeType corrected, values > 90% removed)

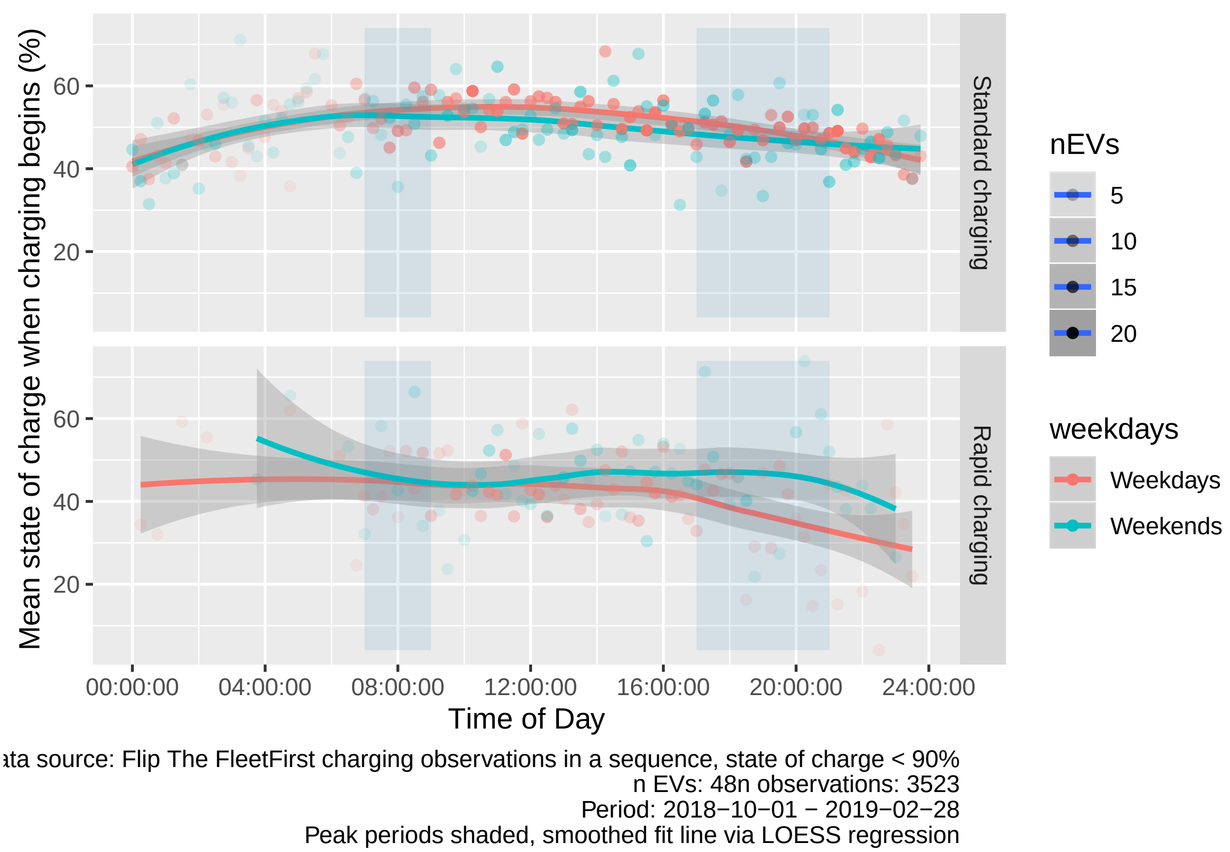


Figure 22: Mean state of charge at beginning of charge sequence by time of day (chargeType corrected, values > 90% removed)

kW (mean = 2.09 kW). Mean power when charging showed a complex temporal profile for weekday standard charging (Figure 14) with a peak of ~ 2.5kw at 10:00 and a second of the same value at around 18:00 with further peaks just after midnight. The inverse is seen on weekends with a charge peak during the middle of the day;
- *Charging duration*: Charging durations tended to fall into one of two groups. Longer 'standard' charges had a median duration of 205.57 minutes and a mean duration of 241.89 minutes. High power 'Rapid' charge events had a median duration of 14.27 minutes and a mean duration of 14.27 minutes;
- *Time of day*: Standard charging events tended to be the most frequent around 22:00 on both weekdays and weekends, suggesting the drivers in our dataset utilise timers to take advantage of off-peak electricity although this is not universal with a substantial proportion of charging events starting earlier in the day and potentially at higher power levels (see above). Rapid charging events tended to begin at 11:30am on weekdays and 1pm during weekends;
- *State of charge*: As has been previously shown (Speidel and Bräunl 2014), any drivers begin recharging with greater than 50% charge still remaining in the battery for both standard and rapid charge events. This has clear implications both for the management of battery life and also for the potential for vehicle-to-grid power flows during peak demand periods where vehciles may be at or arriving home with substantial available charge.

In the data provided for this study, most charging occurs at home using either a 1.8kw or 3kW charger, and commonly occurs both in the evening peak period and through the night. In addition, many vehicles begin charging with significant battery capacity remaining, providing them with the ability to provide vehicle to grid energy transfer should that technology become widely available.

These preliminary findings support recent modelling work (Concept Consulting 2018) that suggests that any negative effects electric vehicles may have on the evening national electricity grid peaks should be mitigable through 'smart' charging methods. In addition, our analysis indicates that this may already be occurring to some extent in this sample of EV owners. If later adopters of electric vehicles can be induced to follow the same 'smart' charging patterns as those displayed in some of our data sample, it is likely that the effects that electric vehicles are otherwise likely to have on the electricity grid may be mitigated.

5 Statistical Annex

Data used:

- ~/working/ftf/output/EVBB_processed_all_v2.0_20190604.csv

If this is not what you expect this may be a test run using preliminary data.

5.1 Flip The Fleet data description

5.1.1 Raw data

Data description for original data supplied (before processing or filtering).

```
skimr::skim(rawDF)
```

```
## Skim summary statistics
##  n obs: 1882040
##  n variables: 8
##
## -- Variable type:character ------------------------------------------------------------------------
##     variable missing complete       n min max empty n_unique
##  day_of_week       0  1882040 1882040   6   9     0        7
##           id       0  1882040 1882040  32  32     0       52
```

```
##       month       0  1882040 1882040   3   3     0       12
##
## -- Variable type:Date ----------------------------------------------------------------------
##  variable missing complete       n        min        max     median
##      date       0  1882040 1882040 2018-04-05 2019-03-01 2018-11-25
##  n_unique
##       328
##
## -- Variable type:difftime ------------------------------------------------------------------
##  variable missing complete       n    min        max     median n_unique
##      time       0  1882040 1882040 0 secs 86399 secs 44877 secs    86400
##
## -- Variable type:numeric -------------------------------------------------------------------
##                 variable missing complete       n    mean      sd     p0
##          charge_power_kw       0  1882040 1882040    1.59   63.73      0
##              odometer_km 1255614   626426 1882040 7789.97 8268.44 -62920
##  state_of_charge_percent       0  1882040 1882040   69      20.66      0
##      p25     p50      p75     p100     hist
##     0       1.3      1.85 74940.42
##  2166.25 5309    11154    73607
##    56.31   70.41    83.05  1677.72
```

5.1.2 Processed and cleaned data

Data description for cleaned data (all observations).

```r
skimr::skim(cleanDT)
```

```
## Skim summary statistics
##  n obs: 1518388
##  n variables: 21
##
## -- Variable type:character -----------------------------------------------------------------
##     variable missing complete       n min max empty n_unique
##   chargeFlag       3  1518385 1518388  17  25     0        5
##  chargingStr       0  1518388 1518388   2   3     0        2
##         dvID       0  1518388 1518388   9  10     0       48
##           id       0  1518388 1518388  32  32     0       48
##   peakPeriod       0  1518388 1518388   8  12     0        3
##     weekdays       0  1518388 1518388   8   8     0        2
##
## -- Variable type:Date ----------------------------------------------------------------------
##  variable missing complete       n        min        max     median
##      date       0  1518388 1518388 2018-10-01 2019-02-28 2018-12-12
##  n_unique
##       151
##
## -- Variable type:difftime ------------------------------------------------------------------
##      variable missing complete       n    min          max     median
##  dateTimeDiff      15  1518373 1518388 0 secs 2486002 secs    50 secs
##         qHour       0  1518388 1518388 0 secs   85500 secs 43200 secs
##     startTime       0  1518388 1518388 0 secs   86399 secs 43969 secs
##          time       0  1518388 1518388 0 secs   86399 secs 43969 secs
##  n_unique
```

```
##     14681
##        96
##     86400
##     86400
##
## -- Variable type:factor --------------------------------------------------------------------------
##     variable missing complete       n n_unique
##   chargeType       0  1518388 1518388        3
##  day_of_week       0  1518388 1518388        7
##        month       0  1518388 1518388        5
##                                     top_counts ordered
##         Sta: 880137, Not: 629889, Rap: 8362, NA: 0   FALSE
##  Thu: 244939, Wed: 240497, Fri: 232824, Mon: 222218    TRUE
##  Nov: 332960, Oct: 309239, Dec: 299216, Jan: 291236   FALSE
##
## -- Variable type:numeric -------------------------------------------------------------------------
##         variable missing complete       n    mean      sd     p0     p25
##  charge_power_kw       0  1518388 1518388    1.38    2.68      0    0
##         charging       0  1518388 1518388    0.59    0.49      0    0
##      odometer_km 1058334   460054 1518388 8139.03 8632.56 -62920 2530
##     odometerDiff 1067454   450934 1518388    1.07 2549.69 -64324    0
##      SoC_percent      53  1518335 1518388   68.82    18.5      0   56.15
##           tempkW       0  1518388 1518388    0.17    2.44      0    0
##      p50      p75     p100     hist
##     1.34     1.84    70.16
##     1        1        1
##  5659    10343.75 73607
##     0        1    64261
##    70.19    82.84    98.1
##     0        0       70.16
##
## -- Variable type:POSIXct -------------------------------------------------------------------------
##  variable missing complete       n        min        max     median
##  dateTime       0  1518388 1518388 2018-10-01 2019-02-28 2018-12-12
##  n_unique
##   1429770
```

Data description for cleaned data (first observations in a charging sequence).

```r
skimr::skim(firstCleanDT)
```

```
## Skim summary statistics
##  n obs: 3684
##  n variables: 23
##
## -- Variable type:character -----------------------------------------------------------------------
##         variable missing complete    n min max empty n_unique
##       chargeFlag       0     3684 3684  25  25     0        1
##  chargeTypeError       0     3684 3684  31  37     0        4
##             dvID       0     3684 3684   9  10     0       48
##               id       0     3684 3684  32  32     0       48
##       peakPeriod       0     3684 3684   8  12     0        3
##         weekdays       0     3684 3684   8   8     0        2
##
## -- Variable type:Date ----------------------------------------------------------------------------
```

```
##  variable missing complete    n        min        max     median n_unique
##      date       0     3684 3684 2018-10-01 2019-02-28 2018-12-05      142
##
## -- Variable type:difftime ------------------------------------------------------------------
##      variable missing complete    n                  min
##  dateTimeDiff       0     3684 3684  0 secs
##       endTime       0     3684 3684 31 secs
##  pairDuration       0     3684 3684       0.01666667 mins
##         qHour       0     3684 3684  0 secs
##     startTime       0     3684 3684 40 secs
##          time       0     3684 3684 40 secs
##                  max             median n_unique
##  230025 secs           318 secs            1994
##   86342 secs              41046.5 secs       3573
##        3029.117 mins        178.275 mins     3345
##   85500 secs          54900 secs              96
##   86246 secs          55665 secs            3514
##   86246 secs          55665 secs            3514
##
## -- Variable type:factor --------------------------------------------------------------------
##             variable missing complete    n n_unique
##           chargeType       0     3684 3684        2
##  chargeTypeCorrected       0     3684 3684        2
##          day_of_week       0     3684 3684        7
##              endType       0     3684 3684        2
##                month       0     3684 3684        5
##                              top_counts ordered
##      Sta: 3226, Rap: 458, Not: 0, NA: 0   FALSE
##      Sta: 3211, Rap: 473, Not: 0, NA: 0   FALSE
##  Wed: 568, Thu: 564, Fri: 563, Mon: 533    TRUE
##      Sta: 3293, Rap: 391, Not: 0, NA: 0   FALSE
##  Nov: 912, Oct: 846, Dec: 810, Feb: 641   FALSE
##
## -- Variable type:numeric -------------------------------------------------------------------
##         variable missing complete    n    mean      sd        p0     p25
##  charge_power_kw       0     3684 3684    6.64   12.04      0.5     1.57
##      odometer_km    2905      779 3684 7600.63 8311.28 -52352    2022
##     odometerDiff    2923      761 3684  136.5  3704.63 -45299       0
##      SoC_percent       0     3684 3684   50.38   19.04      4.11   36.41
##      p50      p75     p100     hist
##     2.08     3.3     70.16
##  5110    10545    54443
##     0        0    44500
##    49.07    61.24    98.1
##
## -- Variable type:POSIXct -------------------------------------------------------------------
##  variable missing complete    n        min        max     median n_unique
##  dateTime       0     3684 3684 2018-10-01 2019-02-28 2018-12-05     3684
```

5.2 Odometer data checks

There are many NAs in the odometer data and also -ve values as Table 13 shows. Given the apparently poor quality of the data we do not use odometer data in this report.

```
rawDT[odometer_km < 0, odometerFlag := "-ve" ]
rawDT[odometer_km == 0, odometerFlag := "0" ]
rawDT[odometer_km > 0, odometerFlag := "+ve" ]

t <- with(rawDT, table(id,
     odometerFlag, useNA = "always"))

kableExtra::kable(t, caption = "Count of -ve, 0, +ve and NA odometer readings by vehicle (original data
  kable_styling()
```

5.3 Coding checks

5.3.1 Charge flag

This is used to identify observations that form part of a sequence. The logic is given in Section 2.3.2. Here we show the results of applying an additional 120 second rule. In this case a sequence only exists where we have charging observations which have less than 120 seconds between them.

```
kableExtra::kable(sequenceMethod1_T, caption = "Charge sequence flags (120 second rule)") %>%
  kable_styling()
```

```
kableExtra::kable(sequenceMethod2_T, caption = "Charge sequence flags (no 120 second rule)") %>%
  kable_styling()
```

As we can see, applying the 120 second rule reduces the number of observations categorised as part of a sequence as it will not know what to do with:

- charge -> gap of > 120 secs -> charge 120 secs -> charge

For now we therefore do not use the 120 second rule.

```
# Check chargeFlag ----
message("chargeFlag is used to classify charging events - check against charge type:")
```

```
## chargeFlag is used to classify charging events - check against charge type:
```

```
t <- table(cleanDT$chargeFlag, cleanDT$chargeType, useNA = "always")
kableExtra::kable(t, caption = "chargeFlag errors (clean data)") %>%
  kable_styling()
```

```
message("There are a few observations that have chargeFlag = NA but are charging... why?")
```

```
## There are a few observations that have chargeFlag = NA but are charging... why?
```

We also test the patterns of charging that this classification produces. We do this first for 'standard' charging sequences and then for 'Rapid' charging sequences.

```
# debug sequences visually ----

# start & end charge rate ----
firstLastDT <- firstLastDT[, startChargekW := charge_power_kw]
firstLastDT <- firstLastDT[, endChargekW := shift(charge_power_kw, type = "lead")]

# start & end batter state
firstLastDT <- firstLastDT[, startSoC_pc := SoC_percent]
firstLastDT <- firstLastDT[, endSoC_pc := shift(SoC_percent, type = "lead")]
```

```
# calc duration so we can decide what to do where it is -ve - i.e. event spanned midnight ----
firstLastDT <- firstLastDT[, notDuration := difftime(endTime, startTime, units='mins'), by = id] # set
# fix # 1
firstLastDT <- firstLastDT[, endTimeTrunc := ifelse(notDuration < 0,
                                                    hms::parse_hm("23:59"),
                                                    endTime)] # this truncates charge periods that span

# charge rate & state of charge deltas ----
firstLastDT <- firstLastDT[, chargePowerDelta := endChargekW - charge_power_kw] # should be -ve where w
firstLastDT <- firstLastDT[, SoC_pcDelta := endSoC_pc - startSoC_pc] # should be -ve where we start hig
```

Figure 23 plots the first and last charge observation in a sequence for all pairs and for all vehicles where events were classified as (corrected) 'standard' charges. The y value is charging rate (kW) at the start and end of the sequence. Colour (red end of the scale) is used to highlight pairs which show an 'odd' pattern - e.g. the charge rate increased.

```
# format labels function
# https://stackoverflow.com/questions/53804629/how-to-format-difftime-as-hhmm-in-ggplot2
format_hm <- function(sec) stringr::str_sub(format(sec), end = -4L)
# plotting function
makeSeqChargePlot <- function(dt, y = y, yend = yend, colour = colour){
  p <- ggplot2::ggplot(dt) +
    geom_segment(aes(x = hms::as.hms(startTime), # start x value
                     xend = hms::as.hms(endTimeTrunc), # end x value
                     y = get(y), # start y value
                     yend = get(yend), # end y value
                     colour = get(colour))) + # colour to highlight some value
    labs(x = "Sequence start and end time") +
    theme(legend.position = "bottom") +
    scale_x_time(labels = format_hm) +
    facet_wrap(. ~ dvID)
  return(p)
}

dt <- firstLastDT[chargeTypeCorrected %like% "Standard" &
                    #startChargekW < 5 & #use this to filter out the few that seem to have 6kW chargers
                    chargeFlag %like% "First"]

p <- makeSeqChargePlot(dt, y = "startChargekW",
                       yend = "endChargekW",
                       colour =  "chargePowerDelta")
p <- p +
  labs(y = "Charging rate (kW)",
       caption = "Standard charging (corrected) \n
       Pairs spanning midnight truncated at 23:59 \n
       Peak periods shaded") +
  guides(colour = guide_legend(title = "Charge rate delta (kW)")) +
  scale_color_continuous(low = "green", high = "red") # highlight ones that went up
yMin <- min(dt$startChargekW) # might not quite work if end is higher...
yMax <- max(dt$startChargekW) # might not quite work if end is higher...
addPeaks(p)
```

```
#ggsave("plots/standardChargePairs_kW_LineSegments.png", p, height = 10)
```

Figure 24 shows the distribution of charge power deltas by peak/not peak period (of start time) for 'standard'

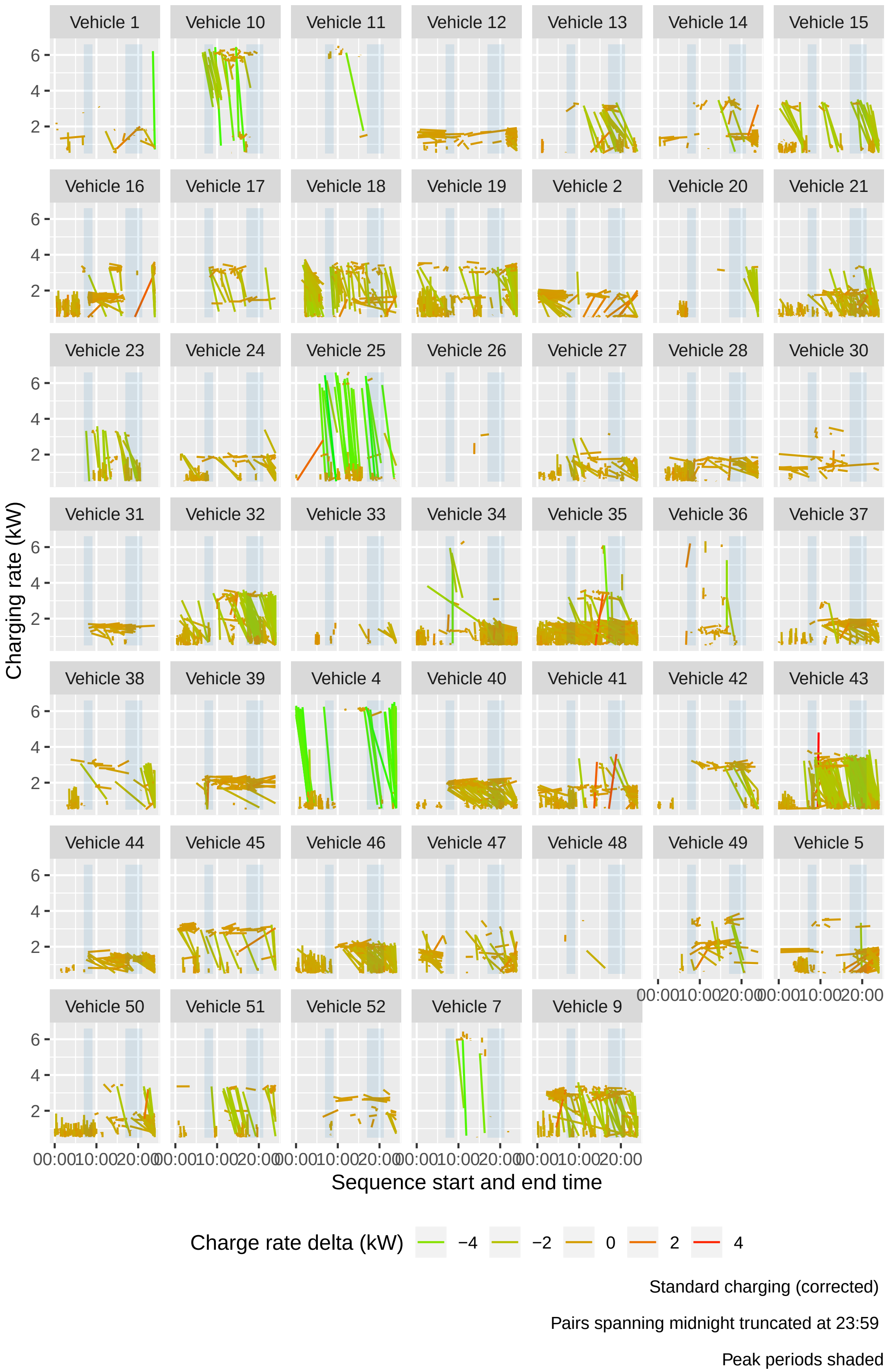


Figure 23: Standard charging (corrected) - rate of charge

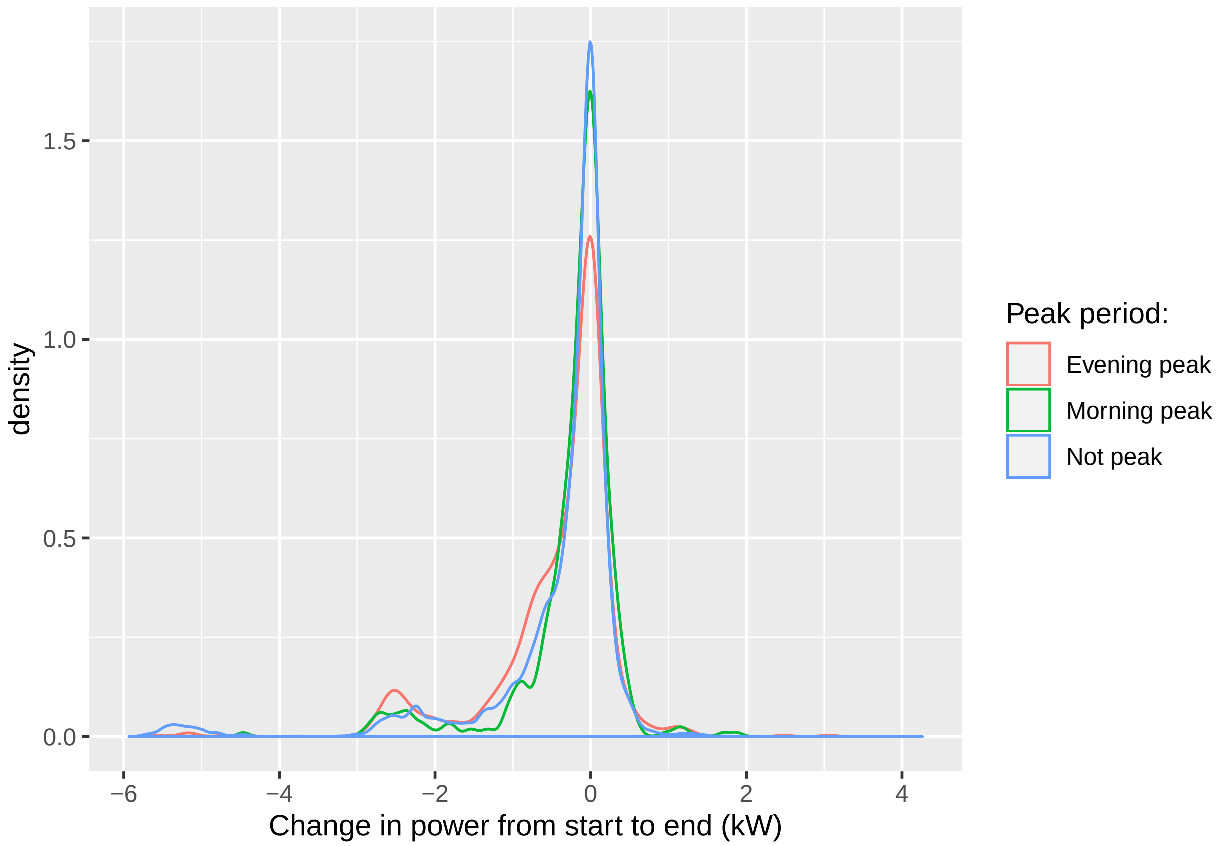


Figure 24: Histogram of charge power deltas by peak/not peak period

charge events. This suggests that the majority of charging events either hold power constant or decline over time with some sort of shoulder effect. A few increase. More of those which start in the 'evening' and 'not peak' period seem to hold the power level constant, presumably because the battery capacity is slightly lower at this time following day-time use.

```
p <- ggplot2::ggplot(dt, aes(x = chargePowerDelta, colour = peakPeriod)) +
  geom_density(alpha = 0.5) +
  guides(colour = guide_legend(title = "Peak period:")) +
  labs(x = "Change in power from start to end (kW)")
p
```

Figure 25 uses the same approach but in this case the y value is charging rate (kW) at the start and end of the sequence. Colour (red end of the scale) is used to highlight pairs which show an 'odd' pattern - e.g. the battery state of charge decreased.

```
#dt <- dt[, SoC_pcDelta := SoC_pcDelta * -1] # invert so big drops become red in plot
p <- makeSeqChargePlot(dt, y = "startSoC_pc",
                       yend = "endSoC_pc",
                       colour =  "SoC_pcDelta")
p <- p +
  labs(y = "State of charge (%)",
       caption = "Standard charging (corrected) \n Pairs spanning midnight truncated at 23:59") +
  guides(colour = guide_legend(title = "State of charge delta (%)")) +
  scale_color_continuous(low = "red", high = "green") # highlight ones that went down
yMin <- min(dt$startSoC_pc) # might not quite work if end is higher...
```

```r
yMax <- max(dt$startSoC_pc) # might not quite work if end is higher...
addPeaks(p)
```

```r
#ggsave("plots/standardChargePairs_SoC_LineSegments.png", p, height = 10)
```

Figure 26 and Figure 27 repeat these plots but for (corrected) 'Rapid' charge events.

```r
dt <- firstLastDT[chargeTypeCorrected %like% "Rapid" &
                    #startChargekW < 5 & #use this to filter out the few that seem to have 6kW chargers
                    chargeFlag %like% "First"]

p <- makeSeqChargePlot(dt, y = "startChargekW",
                       yend = "endChargekW",
                       colour =  "chargePowerDelta")
p <- p +
  labs(y = "Charging rate (kW)",
       caption = "Rapid charging (corrected) \n Pairs spanning midnight truncated at 23:59") +
  guides(colour = guide_legend(title = "Charge rate delta (kW)")) +
  scale_color_continuous(low = "green", high = "red") # highlight ones that went up
yMin <- min(dt$startChargekW) # might not quite work if end is higher...
yMax <- max(dt$startChargekW) # might not quite work if end is higher...
addPeaks(p)
```

```r
#ggsave("plots/RapidChargePairs_kW_LineSegments.png", p, height = 10)
```

```r
#dt <- dt[, SoC_pcDelta := SoC_pcDelta * -1] # invert so big drops become red in plot
p <- makeSeqChargePlot(dt, y = "startSoC_pc",
                       yend = "endSoC_pc",
                       colour =  "SoC_pcDelta")
p <- p +
  labs(y = "State of charge (%)",
       caption = "Rapid charging (corrected) \n Pairs spanning midnight truncated at 23:59") +
  guides(colour = guide_legend(title = "State of charge delta (%)")) +
  scale_color_continuous(low = "red", high = "green") # highlight ones that went down
yMin <- min(dt$startSoC_pc) # might not quite work if end is higher...
yMax <- max(dt$startSoC_pc) # might not quite work if end is higher...
addPeaks(p)
```

```r
#ggsave("plots/RapidChargePairs_SoC_LineSegments.png", p, height = 10)
```

Figure 28 shows the distribution of charge power deltas by peak/not peak period (of start time) for all 'Rapid' charge events. These show a rather different pattern.

```r
p <- ggplot2::ggplot(dt, aes(x = chargePowerDelta, colour = peakPeriod)) +
  geom_density(alpha = 0.5) +
  guides(colour = guide_legend(title = "Peak period:")) +
  labs(x = "Change in power from start to end (kW)")
p
```

5.3.2 Charge type

`chargeType` is used to classify charging events into standard vs rapid using the 7 kW threshold. But there may be misclassfications where a sequence starts on a rapid charger but power demand declines below the threshold. We can check this and have corrected it in some sections above using the start/end pairs.

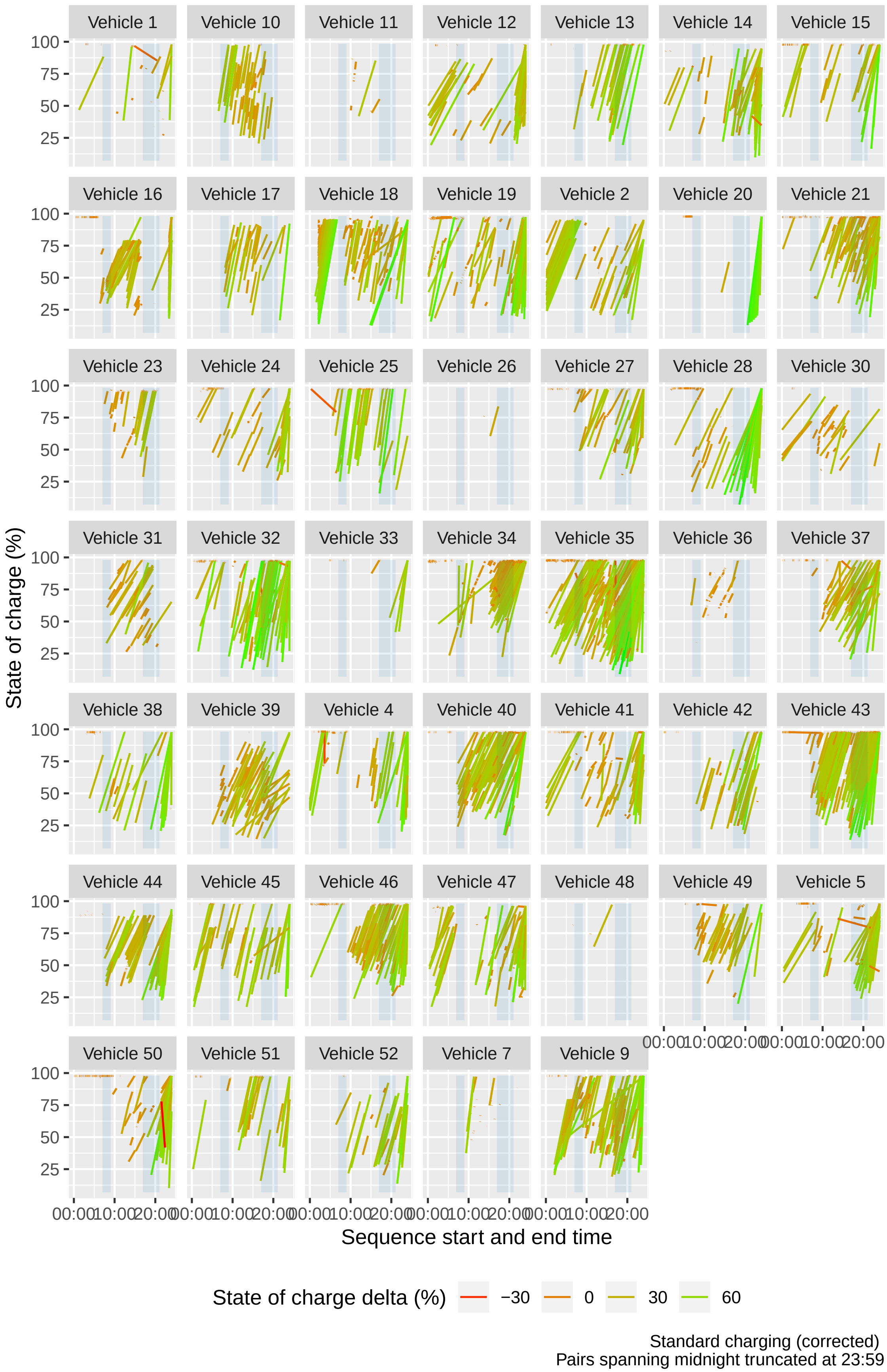


Figure 25: Standard charging (corrected) - state of charge

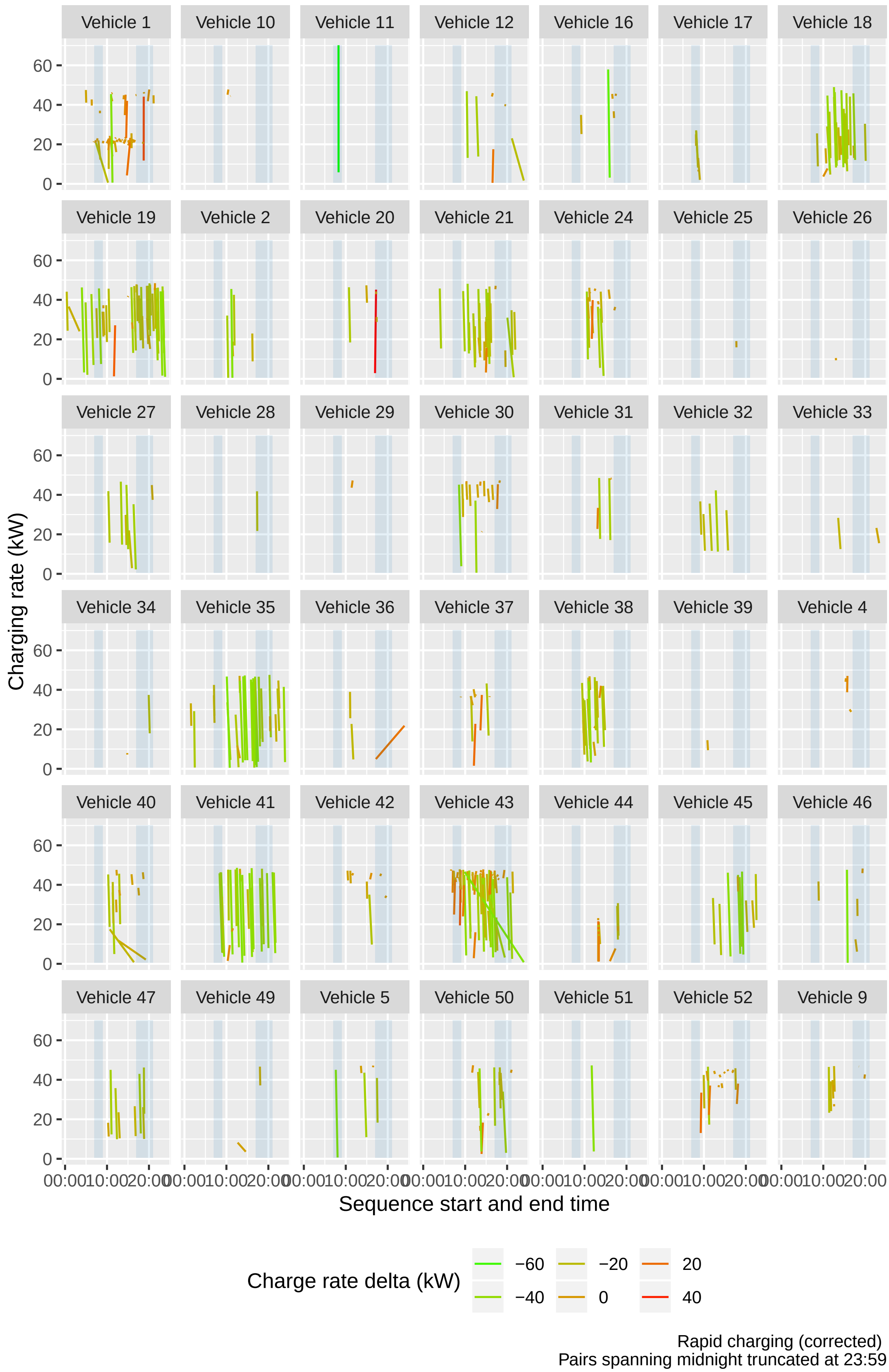


Figure 26: Rapid charging (corrected) - rate of charge

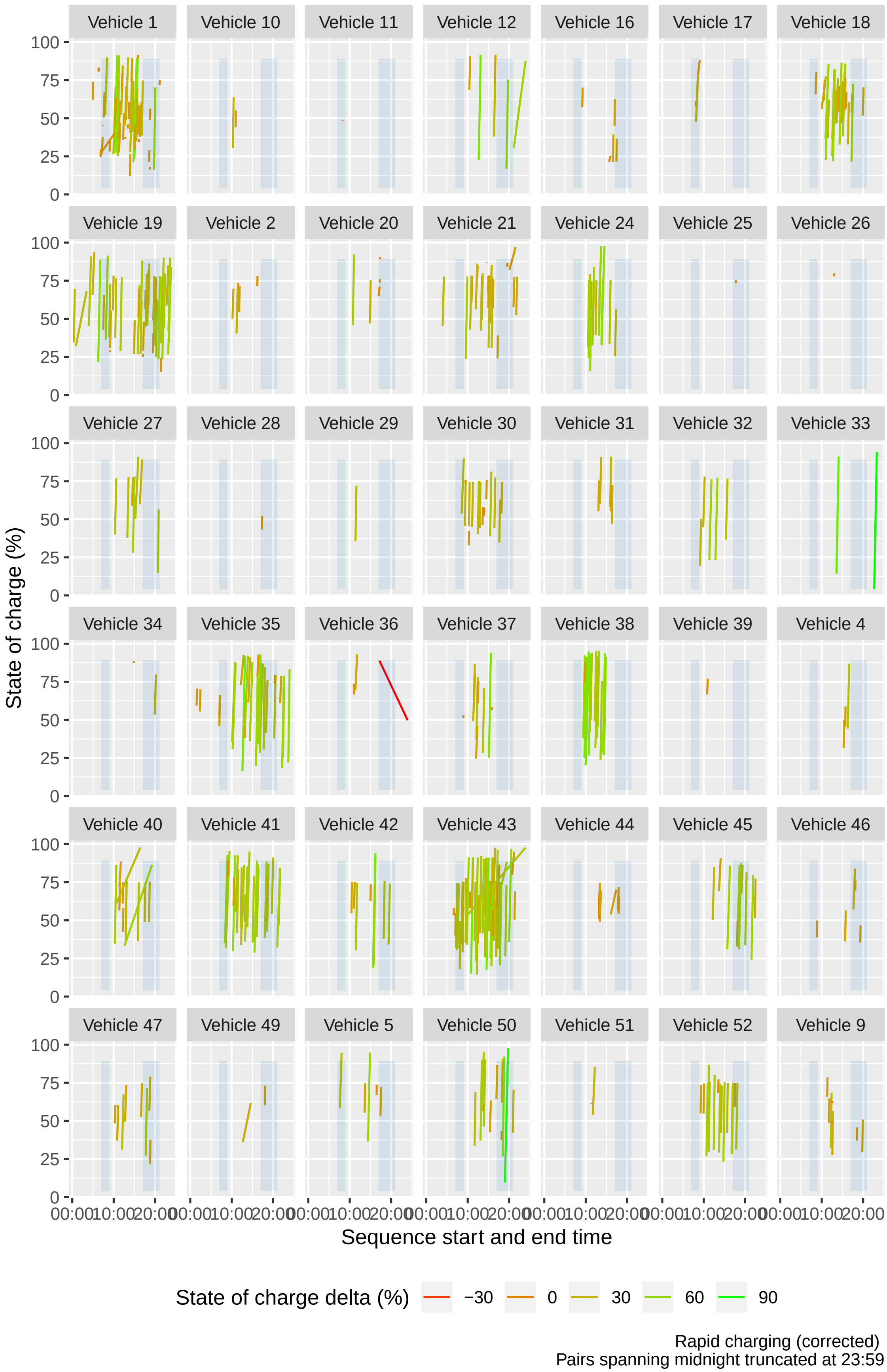


Figure 27: Rapid charging (corrected) - state of charge

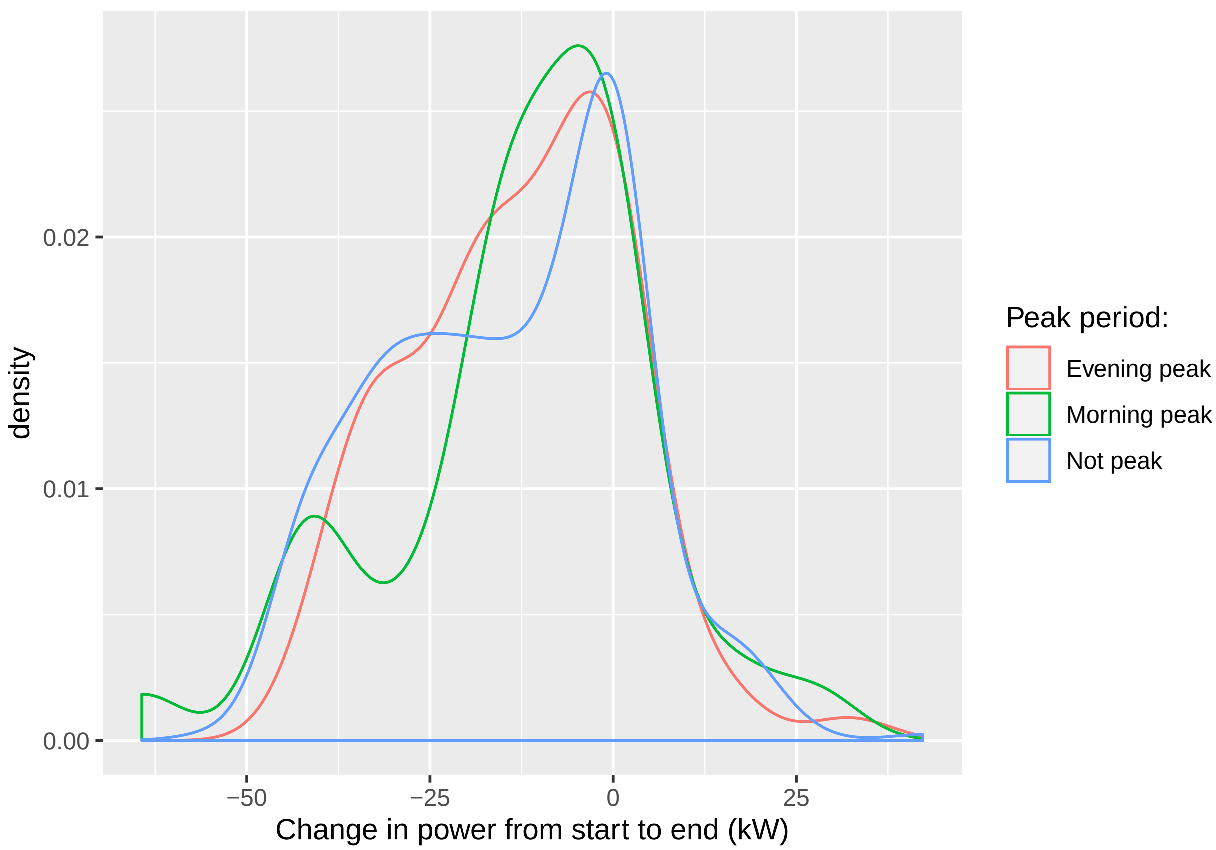


Figure 28: Histogram of charge power deltas by peak/not peak period

```
# Check chargeType ----

t <- table(firstLastDT$chargeTypeError, firstLastDT$chargeType, useNA = "always")

kableExtra::kable(t, caption = "chargeType errors detected") %>%
  kable_styling()
```

```
nError <- nrow(firstLastDT[chargeTypeError %like% "Error"])
nErrorEVs <- uniqueN(firstLastDT[chargeTypeError %like% "Error"]$dvID)
message("There are ", nError, " pairs (out of a total of ", nrow(firstLastDT)/2,") from ", nErrorEVs ,"
```

```
## There are 99 pairs (out of a total of 8440) from 27 EVs where charge type doesn't match.
```

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Table 13: Count of -ve, 0, +ve and NA odometer readings by vehicle (original data)

	-ve	+ve	0	NA
009e8a24229d1c7723588ceec2b95f6a	186	82476	0	2537
0155fb80d2ef801d7086a159c5fe8df0	11	7876	3	32998
01583b8a5f0344cc4aa3b3939a27af2a	4	0	0	0
0564346e7607d1c21e5a6e3878399307	40	15940	2	39263
0af7e964b7e72ab184fbead5d30106e3	22	10751	5	77445
0cc746a3f5ae75ee94068a8354b6be08	0	3	0	0
1256011bed883244df94d560795904e8	310	33783	0	1364
126c8759ec95ba40070b16a11fe0e587	3	0	0	255
12f1e87977249e72358c12dcd197f753	153	16504	1	50609
16b47e88aec68658c5f03db9546db91b	2	2711	2	4185
19c4d7520e9d65c364ff0729a7caf426	117	12847	1	480
1c43f265e57e648c89a427add181e58f	73	16525	0	47822
2f1aeb0d0c5d7a823533b8633d808332	4	3230	4	6707
32346e168dbccf81c465ed657e5fc371	76	19917	17	50582
3993011700868644dc948d58dd3bf9d7	93	3494	9	11768
3aa51bc2789088cf6a3804c50f362f34	4	11685	1	50299
3c218d73c404cc8a552f3449b64f403a	19	3204	47	4097
3dfd17f381f439bc351065cff0d83c69	851	21524	1	54441
3fcc39331391ecd9280917d6bdf321bb	414	14609	2	34223
41930b96d7e6cc4a5eb6542ca36f09e2	0	5256	3	11877
49be6e824b8a4196cc514c2ce4cb6e68	296	31792	0	26927
4a6bb6e7ffc28d9d8eda7b4c6377a027	16	3	0	0
4e48f4155c29c763ffe6d9e17a495200	79	1854	2	4338
5580d13143df1b944fdc1d89ec402b8e	175	20005	15	37670
5bf3a96857982acaa939fd1adc988e07	0	5745	4	9862
5ddc10f96e80630519747ba6a8fe682f	1	9631	1	80
60593731dff536355c4bd88c1c1e5cdb	103	5100	4	14445
616cde60ad25ddc1db4dd832ff1231ca	126	6782	2	33292
6e3293c77f562262ed6608db1b596d36	0	4288	0	27
70102a8511c6454814b7ca1506d461dd	33	5308	45	12491
7023838bd3a5004be2d10784bc116d54	0	1619	1	6974
746039182479252e9d1c9eeb071695ec	349	11902	2	23483
781f06f7d7bb80b74c399326be0d3e28	419	1419	14	3617
7c234b2fb2fc9db5a1a1321167606eba	97	29619	1	69761
80160eb40e4f12004b46d4cf77dcd62f	131	21159	2	117518
8a217a62f385a9c6698033b38b169d70	97	28408	0	1541
8ccb51191dcf0dd9152b867f6e1f74d4	176	3970	1	20941
8d4a65c57c5d778786189f96df2c65c5	227	9130	2	15644
9447d58925397798b076e4b5bf42fd43	9	5829	5	18892
a1c8e57bfcf815f25844c49f4535a8ef	4	7832	2	27540
bb1a2db7ae160eba9d77bb7c35c57f05	2	8931	3	32765
bc3bd38c67b3b2cb2757c94b54a5b408	36	7147	0	9816
bdbbb99fdb70e1e108bb69eff77ee48a	141	24744	2	65667
c05b76de4b11ef7ec0c84e6dc3d05f9c	16	14598	339	52110
da5dcd6efbca045af6759f645f51b6a0	137	9617	2	24606
e11e3f82945d94d288a7e47c06515f26	26	7558	1	38693
f616ac16a4a9af35eacd2afa9a98f7f1	19	10146	3	31736
f8afdd8b06b89cfcfadd75f5146736cd	44	14552	0	1678
f99c233aec9005793d82e64afb45aa23	41	4637	3	10469
fc6a67af46efb8ab97e2e014173af954	128	11862	5	46543
fc9cb5463304eb870e70f6720185d653	0	6646	1	6942
fd60aa4d6f3748b3f36495ff1a823407	0	6383	5	8594
NA	0	0	0	0

Table 14: Charge sequence flags (120 second rule)

	Standard charging	Rapid charging	Not charging	NA
Charging in a seq	1015294	11992	0	0
First charge obs in a seq	7540	562	0	0
Last charge in a seq	10344	651	0	0
Not charging (0 kW)	0	0	805358	0
Not classified (what is this??)	20357	675	0	0
Single charge observation	8584	400	0	0
NA	230	53	0	0

Table 15: Charge sequence flags (no 120 second rule)

	Standard charging	Rapid charging	Not charging	NA
Charging in a seq	1032623	12388	0	0
First charge obs in a seq	10453	817	0	0
Last charge in a seq	10602	677	0	0
Not charging (0 kW)	0	0	805358	0
Single charge observation	8584	400	0	0
NA	87	51	0	0

Table 16: chargeFlag errors (clean data)

	Standard charging	Rapid charging	Not charging	NA
Charging in a seq	858209	7375	0	0
First charge obs in a seq	7980	459	0	0
Last charge in a seq	8049	392	0	0
Not charging (0 kW)	0	0	629889	0
Single charge observation	5897	135	0	0
NA	2	1	0	0

Table 17: chargeType errors detected

	Standard charging	Rapid charging	Not charging	NA
Error: first = Rapid, last = Standard	0	83	0	0
Error: first = Standard, last = Rapid	16	0	0	0
OK: first = Rapid, last = Rapid	0	376	0	0
OK: first = Standard, last = Standard	7964	0	0	0
NA	8049	392	0	0