Quick summary

Pablo Paulsen

06/12/2021

Introduction

This projects aims to understand how current seasonal trends in driving behavior coupled with seasonal differences in the driving efficiency of electric vehicles (EVs) will impact New Zealand's electricity grid under a future scenario where light passenger vehicles are largely electrified.

Methodology

A variety of data sources were used. Distance traveled and vehicle efficiency (km/kWh) by month, as well as the region of the vehicle was collected from the on-board computers of 1259 vehicles between 2017 and 2021 as part of the 'Flip the Fleet' project.

Weather data was then collected from the NIWA national climate Database for 14 regions around New Zealand that best correspond to the regions of the vehicles.

Fuel trade data including quarterly petrol usage for domestic transport in New Zealand is collected from the Ministry of Business, Innovation & Employment (MBIE).

Vehicle kilometers traveled (VKT) data including quarterly data of 10 regions plus one "other" region was given by Haobo Wang from NZTA for use in this project. Further data on yearly VKT for the "other" regions, the vehicle fuel type and vehicle type was collected from the publicly available fleet statistics page on NZTA's website.

Using the regional hourly temperatures, monthly heating degree days (HDD) and cooling degree days (CDD) were imputed using base temperatures of 16°C and 22°C respectively. The base temperatures were selected to represent the range of comfortable temperatures for most people, as research shows that a majority of the seasonal variation in EV efficiency is due to cabin temperature control[1].

The HDD and CDD was then divided by the length of the month so that HDD and CDD corresponds to average heating degrees days per day for the month. This is so that when comparing to other statistics such as efficiency that are averaged out rather than summed so there is less bias.

The calculated monthly weather statistics by region was then added to the monthly EV data based on the regions of vehicle. This assumes that vehicle stays in it's own region for a majority of the time.

A monthly adjusted average was calculated for the whole of New Zealand and then for each region of NZ. The monthly averages were adjusted by weighting using the distance traveled to give more weighting to vehicles with higher km traveled in that month. this was done using the formula

$$\bar{x} = \frac{\sum_i^n (d_i \times x_i)}{(\sum_i^n d_i) \times n}$$

Power consumption (Wh/km) was calculated using the efficiency (km/kWh). This will be used instead of efficiency in the modeling for reasons that will become apparent later in the analysis.

Results

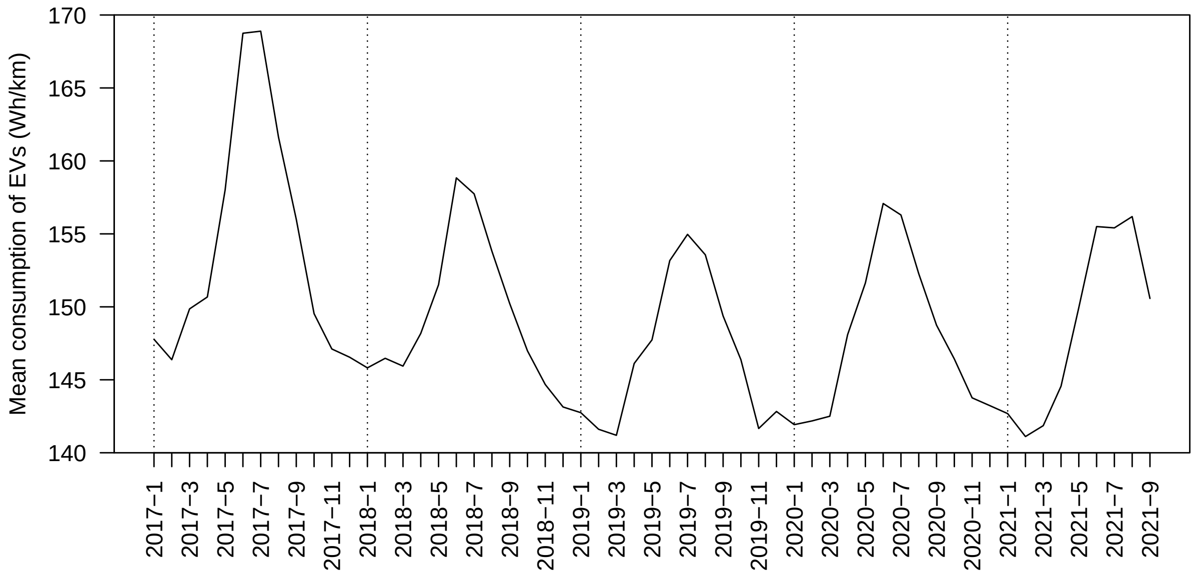

Figure 1: Time Series of EV Consumption

Plotting monthly average consumption for all of NZ we can see that there is a very clear seasonal trend.

Used 2 different methods of decomposition of the seasonal trend of consumption.

- Linear model with each month as an independent factor
  - offers more control and flexibility (could add vehicle type etc in further analysis)
  - shows confidence interval
  - requires to define an arbitrary function that can fit to the overall trend to separate from seasonal trend
  - least squares is sensitive to single large deviation that could just be outlier (such as lockdown)
- Time series Decomposition
  - designed for time series
  - automatically finds an overall trend based on the recent average to isolate the seasonal trend from
  - less sensitive to a large deviation (such as lockdown) as attributed to noise compared to linear model
  - no confidence interval

In the end seems better to use Time series Decomposition for overall consumption trend but is still useful to see from the linear model without assuming any correlation between the months it still has very strong confidence intervals (p-value $< 2^{-16}$). Could be worth doing some more in depth using linear model and adding car as a factor.

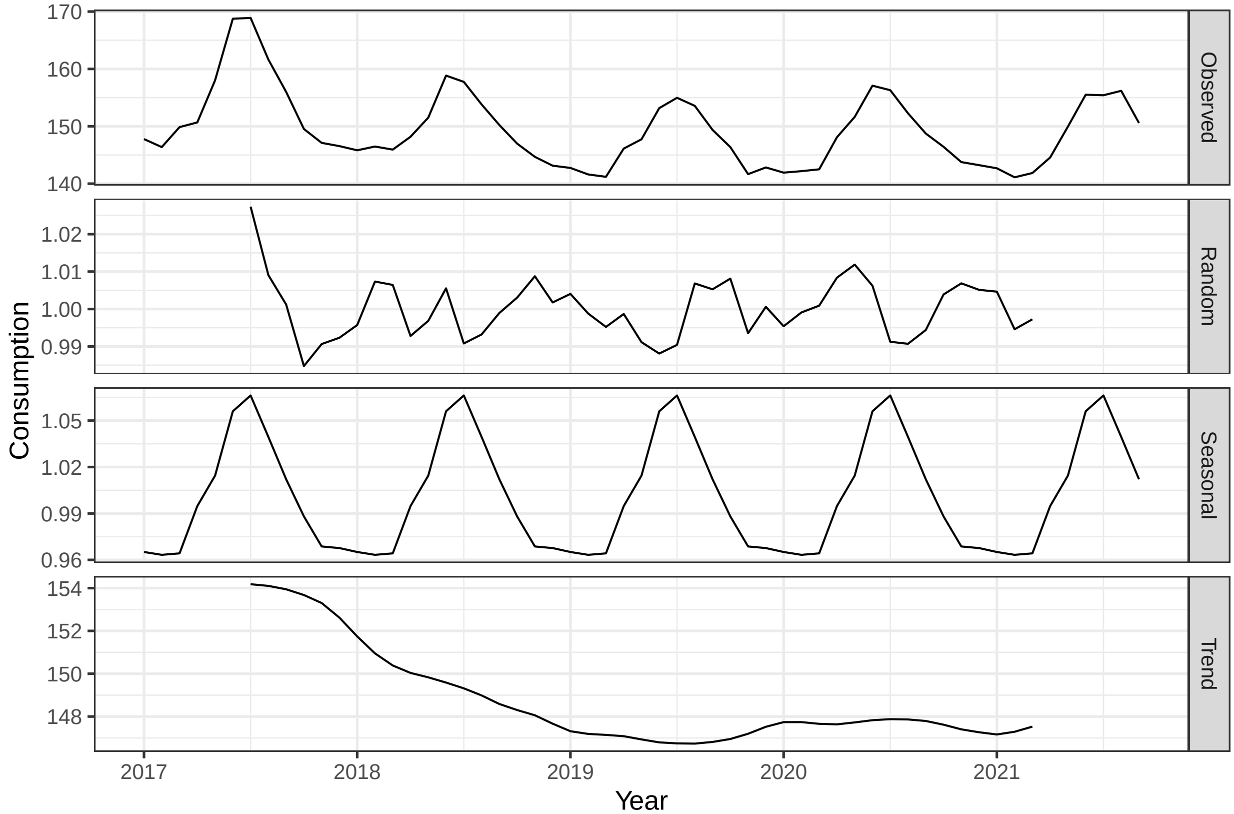

Figure 2: Decomposition of Multiplicative Consumption Time Series

The decomposition shows that the seasonal trend goes from 0.96 times the mean consumption in February to 1.07 times the mean consumption in March, A peak to peak difference of 10.7%.

Looking at the plot there is a very obvious seasonal trend to EV consumption. To compare this to I limit this to just Auckland EVs.

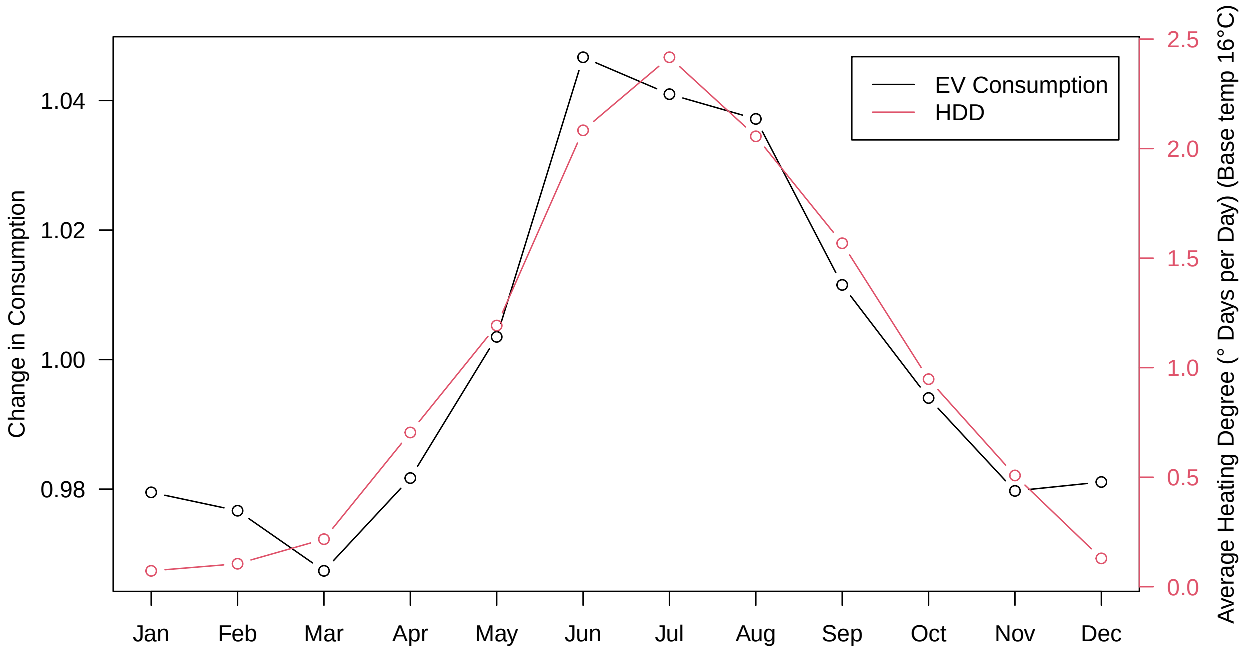

Figure 3: Auckland Seasonal component Decompostions

Within Auckland looking at the plot it is very clear that HDD and consumption of EVs are highly correlated. There is a slight increase in consumption in January and February and it can be questioned if that is due to AC usage which would decrease range [1] or other factors such as holiday travel which could involve highway driving which EVs are generally less efficient at [2]. This effect is not obvious in the overall trend this could be as Auckland for the most part is a warmer climate than the rest of NZ.

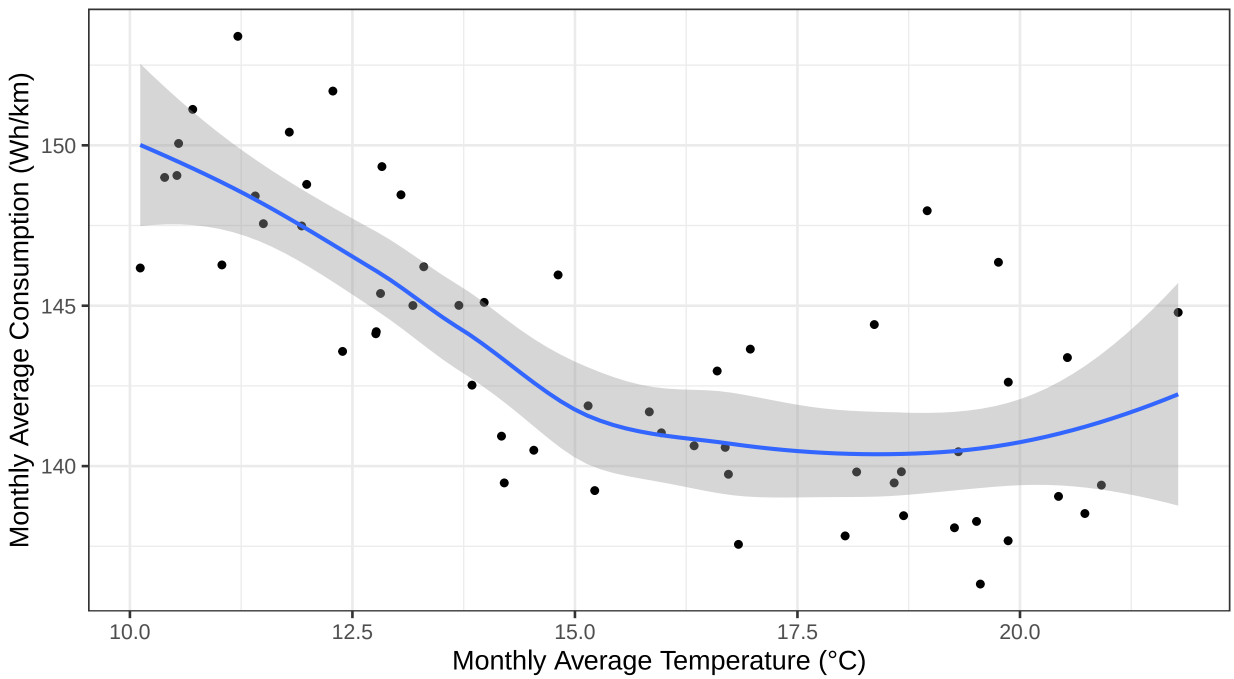

Figure 4: Auckland Monthly Consumption by Temperature

Further looking into this we can see that in Auckland as the average temperature of the month starts increasing past 17.5°C there appears to be a trend towards increasing EV consumption. As stated before research [1] suggested AC also increases consumption of the EV. This suggest it may be worth including cooling degree days and heating degree days in analysis. This could also be useful to explain the points well above the trend line that may be from a month where there was both cold and warm days contributing to a high usage of cabin temperature control increasing consumption but average temperature would not be able to show this.

A linear model is used to model power consumption by HDD and CDD.

As with the case of the adjusted monthly average power consumption (Wh/km) in the linear model a weighting is added to the points in order to give more weighting to cars with longer distance traveled. This may give a slight bias towards EVs with proportionally higher highway mileage. However, from the electricity grids perspective it makes sense to give less weighting to cars that have traveled 0 or very low km. Mathematically this means instead of estimating the coefficients by minimizing the RSS given by the function $\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$ we minimize the function $\sum_{i=1}^{n} d \cdot (y_i - \hat{y}_i)^2$ where d is the distance traveled by a car in that month, y_i is the actual power consumption, and $\hat{y}_i$ is the power consumption of that vehicle as predicted by the model.

Power consumption is used in conjunction with a linear model as with the correct base temperature the usage of power to warm/cool the cabin should be roughly linear to the HDD/CDD [3]. This would allow energy used to heat/cool the car to be isolated for analysis from drivetrain power consumption. Conceptually it makes sense that extra power usage due to heating/cooling demand to be independent from drivetrain demand as unlike in traditional internal combustion engine (ICE) vehicles where the energy to heat and cool the cabin comes from the engine, an EVs heat pump and AC can draw power independently from the engine. Unfortunately, this linear correlation may break down as cars unlike houses or buildings are often only used at particular hours of the day for short periods so this may break down or have more dependency towards the temperature at times such as the morning or evening commute hours.

A different intercept is used for each model of car as a majority of the variation in efficiency will be due to different vehicle models, therefore, including the vehicle model allows for much better model fit and smaller confidence intervals. A different intercept is also used for each weather region as weather might be measured in a cold or hot section of region and also the region may have more or less hill/highway which could influence driving patterns impacting efficiency (for simplicity preferable if not included but model is much better fit if is included). However the Gradient of HDD term and CDD term is kept same for all regions and models as this is the number we are trying to find to see how the number of HDD and CDD affect the efficiency of the EV. A baseline of Auckland and Nissan Leaf (24 kWh) 2013-2016 are used for the region and model as there is the most amount of data in them.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	132.1	0.2867	460.8	0
HDD	2.195	0.05096	43.07	0
CDD	2.347	0.5722	4.102	4.113e-05
weather_regionUpper Hutt	-0.4796	0.3036	-1.58	0.1141
weather_regionChristchurch	-0.9073	0.3257	-2.786	0.005348
weather_regionDunedin	12.06	0.3835	31.45	1.705e-212
weather_regionHamilton	8.513	0.5298	16.07	8.999e-58
weather_regionNelson	2.711	0.4806	5.642	1.7e-08
weather_regionRotorua	5.015	0.5462	9.182	4.597e-20
weather_regionClyde	4.53	0.7491	6.048	1.494e-09
weather_regionPalmerston North	14.11	0.6652	21.21	6.519e-99
weather_regionStratford	10.36	0.9497	10.91	1.254e-27
weather_regionNapier	6.316	0.8473	7.455	9.311e-14
weather_regionInvercargill	3.191	1.758	1.815	0.06949
modelNissan Leaf (30 kWh)	3.401	0.2524	13.47	3.276e-41
modelNissan Leaf (24 kWh) 2011-2012	12.39	0.3246	38.17	7.229e-309
modelNissan Leaf (40 kWh)	10.68	0.5174	20.63	1.046e-93
modelNissan e-NV200 (24 kWh)	32.71	0.5367	60.95	0
modelHyundai Ioniq (EV)	-18.32	0.685	-26.75	3.342e-155
modelBMW i3	-1.335	0.7873	-1.695	0.09006
modelHyundai Kona (EV)	0.6822	0.86	0.7933	0.4276
modelRenault Zoe	11.55	0.8507	13.57	8.383e-42
modelTesla Model 3	10.55	1.022	10.32	6.485e-25
modelNissan Leaf (62 kWh)	25.46	1.752	14.53	1.295e-47
modelKia Niro (EV)	11.34	1.193	9.511	2.075e-21
modelTesla Model S	48.38	1.69	28.63	4.806e-177
modelVolkswagen e-Golf	1.208	1.538	0.7853	0.4323
modelTesla Model-X	104.1	1.296	80.34	0
modelKia Soul	6.276	1.25	5.022	5.15e-07
modelMG ZS EV	22.12	3.9	5.671	1.439e-08
modelRenault Kangoo (van)	56.63	1.537	36.84	1.301e-288
modelJaguar I-PACE	73.02	2.951	24.75	1.949e-133
modelPeugeot e-208	10.96	9.581	1.144	0.2525

Table 2: Fitting linear model: consumption ~ HDD + CDD + weather_region + model

Observations	Residual Std. Error	R^2	Adjusted R^2
22592	492.2	0.4855	0.4848

The HDD term suggests that as the average number of heating degree days per days increases by 1 the average power consumption of EVs for the month increases by 2.19Wh/km. With a p-value of $< 2 \times 10^{-16}$ we are quite confident on this value.

The CDD term suggests that as the average number of cooling degree days per days increases by 1 the average power consumption of EVs for the month increases by 2.35Wh/km. With a p-value of 4.11×10^{-5} we are less confident on this value. This is likely as there is much less data in New Zealand regarding cooling degree days as NZ is a much cooler climate compared to where a lot of the other research on EVs is going on.

If we know that EVs have higher consumption in the winter due to heating requirements and to a much lesser extent in NZ higher consumption on warm days due to AC in order to see how this will affect the grid we need to see how this correlates with NZ populations driving pattern.

For now I have 3 data sets regarding fuel usage

- monthly card sales data
  - monthly data for all of NZ credit card transactions at fuel stations
- quarterly regional fuel sales data
  - quarterly data for all sales at fuel stations broken down by region from MBIE
- quarterly fuel trade data
  - quarterly data of fuel used for transport by type of fuel

As an initial analysis of the fuel usage in NZ I load the quarterly fuel trade data so that I can isolate only petrol usage in domestic land transport which should be an accurate representation of the fuel usage by light passenger vehicles. Will be just combining regular petrol and premium for analysis. (Premium used to be more popular. Was there a definition change on premium and regular used in the data?)

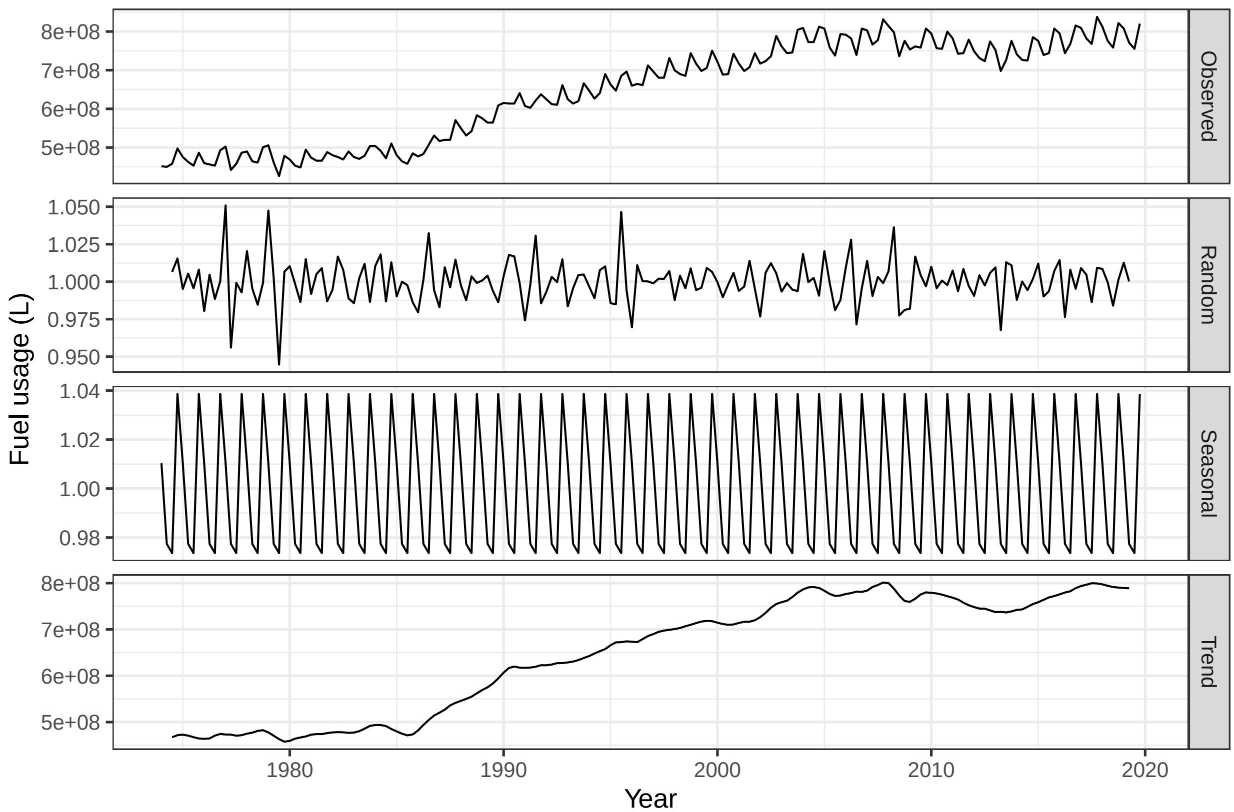

Figure 5: Decomposition of Multiplicative Petrol Usage Time Series

Fuel trade data from 2020 was excluded as lockdowns were not an accurate representation of the general driving patterns of the NZ population. Looking at the decomposition above there is a clear seasonal trend however it not that significant and is smaller than the larger deviations of the random variations.

Fuel trade data can be compared to the VKT data from NZTA. This data was given by Haobo Wang from NZTA and is collected using VKT based on WoF/CoF odometer [4].

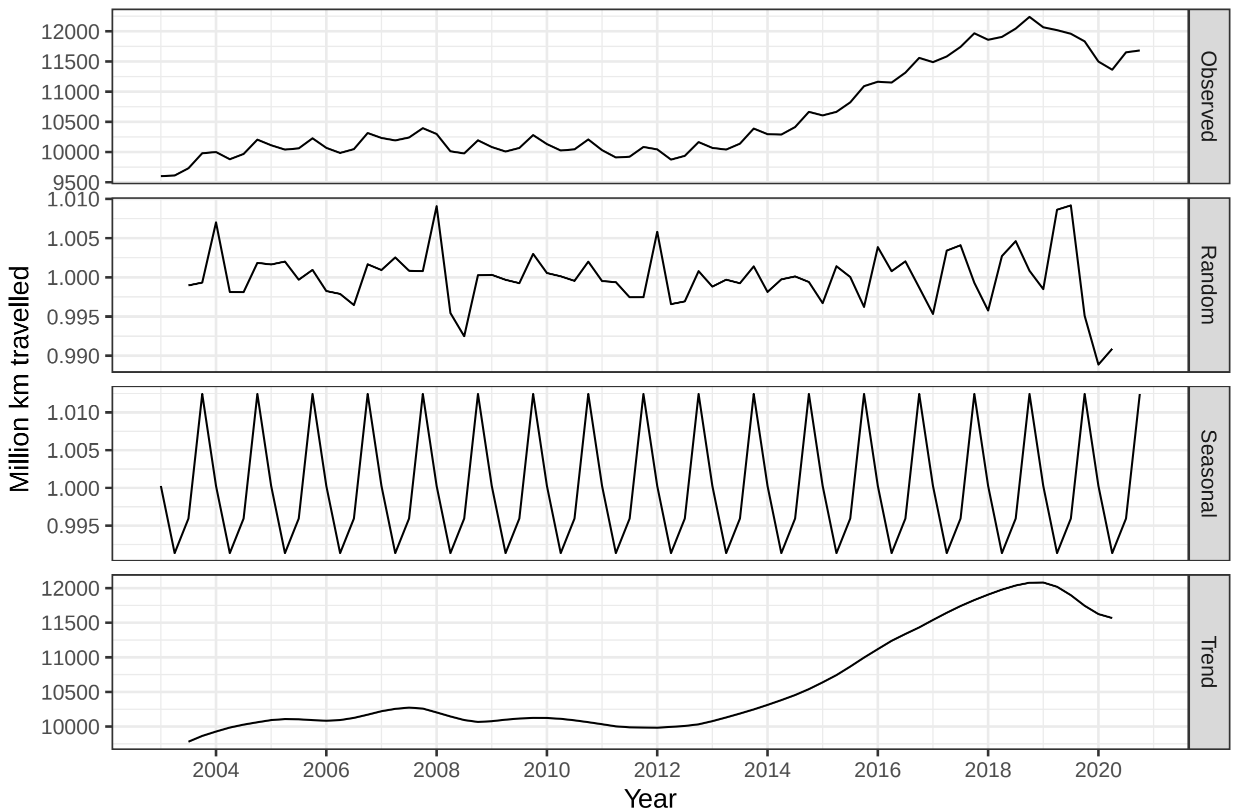

Figure 6: Decomposition of NZ VKT Time Series

The time series decomposition of the NZ VKT data shows a clear seasonal trend, albeit smaller than the trend from the fuel sales data. There is, however, clearly a large amount of smoothing going on with this data. This is shown in a couple of different ways including.

- The drop of VKT due to lockdown which started in 2020 March is already visible in the data from early 2019.
- Related to the previous point, the Random component of Time Series Decomposition shows only a 10% decrease in VKT spread out over a 1 year period from lockdown compared to 30% drop in fuel usage only during 1 quarter shown in the MIBE fuel trade data.
- Random variation in MIBE fuel trade data shows around a 3 times greater random variation. There could be a seasonal effect on fuel efficiency which could change seasonal fuel trend relative to VKT but there is no reason there would be any randomness in fuel efficiency so randomness should be of similar magnitude.

This smoothing likely occurs due to the method of data collection using the odometer readings during WoF/CoF. For a majority of vehicles WoF is only done once a year and in the case of new cars that could be up to 3 years. This likely causes the data to show less seasonal trend than may exist in the real world.

Looking at the long term trend VKT remained largely flat between 2004 and 2012 after which there was a steady but significant increase until 2019. After which there is a decrease in VKT due to lockdown, which in this data set for the above reasons likely started showing its effects in 2019.

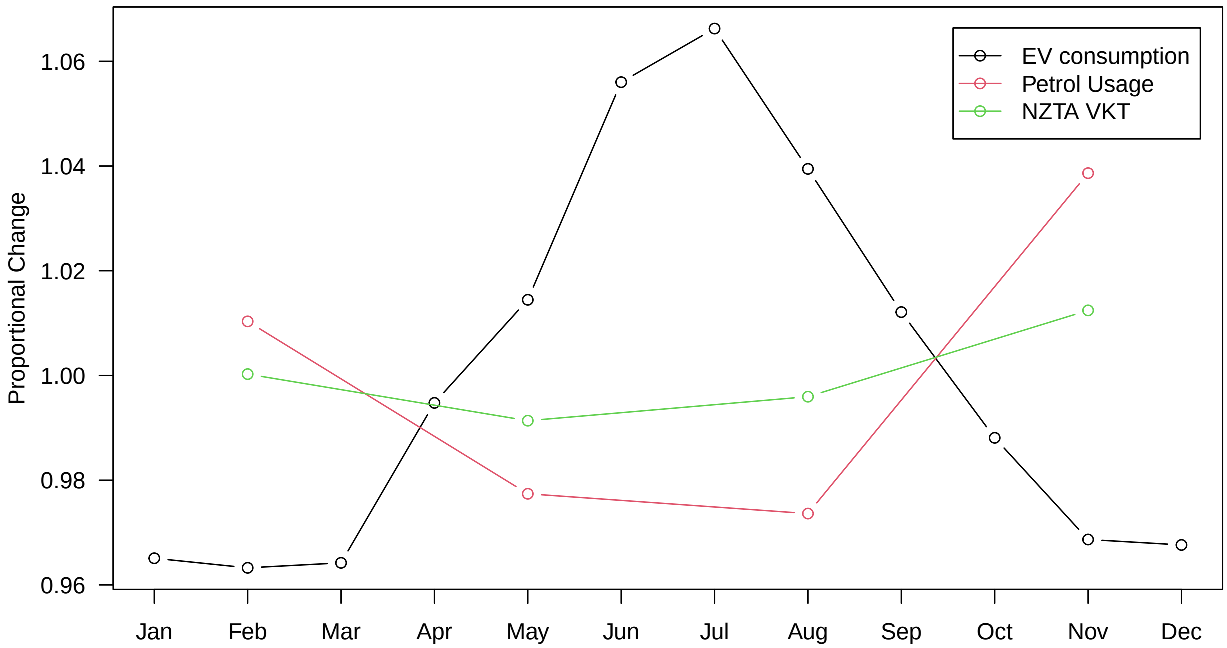

Figure 7: NZ Seasonal Component Decompostions

Looking at the Seasonal trend of Petrol Usage and VKT data from NZTA we can see an obvious decrease in the winter months with a peak in the 4th quarter likely corresponding to holiday travel. Petrol Usage shows this variation to be much larger than the VKT data from NZTA. It is unclear whether this would be due to the smoothing effect as was previously discussed on the NZTA data or perhaps a change in efficiency for petrol vehicle by seasons similar to that of the EV. However if this was a seasonal effect it is odd that the increase in petrol usage occurs in 4th quarter rather than the 1st quarter, as the 1st quarter is generally warmer than the 4th quarter, as shown by the EV efficiency increasing more significantly in 1st quarter than 4th quarter. Combining these 2 data sets it is reasonable to suggest that in New Zealand, compared to the winter (Q2 and Q3) VKT, the true VKT in the summer (Q1 and Q4) is between 1.3% higher, as suggested by the VKT data from NZTA, to 5% higher, according to the petrol usage data.

Looking at the seasonal trend of EV consumption we can see much larger increase in consumption in the winter months with average consumption in July being 10.7% higher consumption than in February. From the plot we can see that when consumption of EVs increases, VKT goes down, suggesting that some increase in total power usage due to EVs increase in consumption will be countered by the decrease in VKT. However, the increase in consumption is much larger than than the decrease in VKT. This combined with the fact that winter is when our electricity grid in New Zealand is already under strain due to heating demand suggests that if we ignore the relatively small change in VKT in our model we can effectively model a worst case scenario.

In order to predict the the effect that EVs will have on New Zealands electricity grid the yearly regional VKT data from 2019 in used in conjunction with the consumption linear model from above, with weather data from 2017 to 2021 matched to the best corresponding VKT regions and the vehicle model make up of the Flip the Fleet data.

Assumptions made are therefore,

- Regional VKT data remains relatively consistent with 2019 VKT data. 2019 is chosen as in NZ there has been a significant increase in VKT in recent years excluding 2020 as there was a significant decrease due to lockdown. As lockdown is an outlier event it would be preferable to not include this in the model so 2019 is used.

- Regional weather data from 2017 to 2021 remains consistent with future climate of NZ.
- Flip the Fleet's fleet is representative NZs future EV fleet.
- Actual VKT of each region remains relatively constant throughout the year.

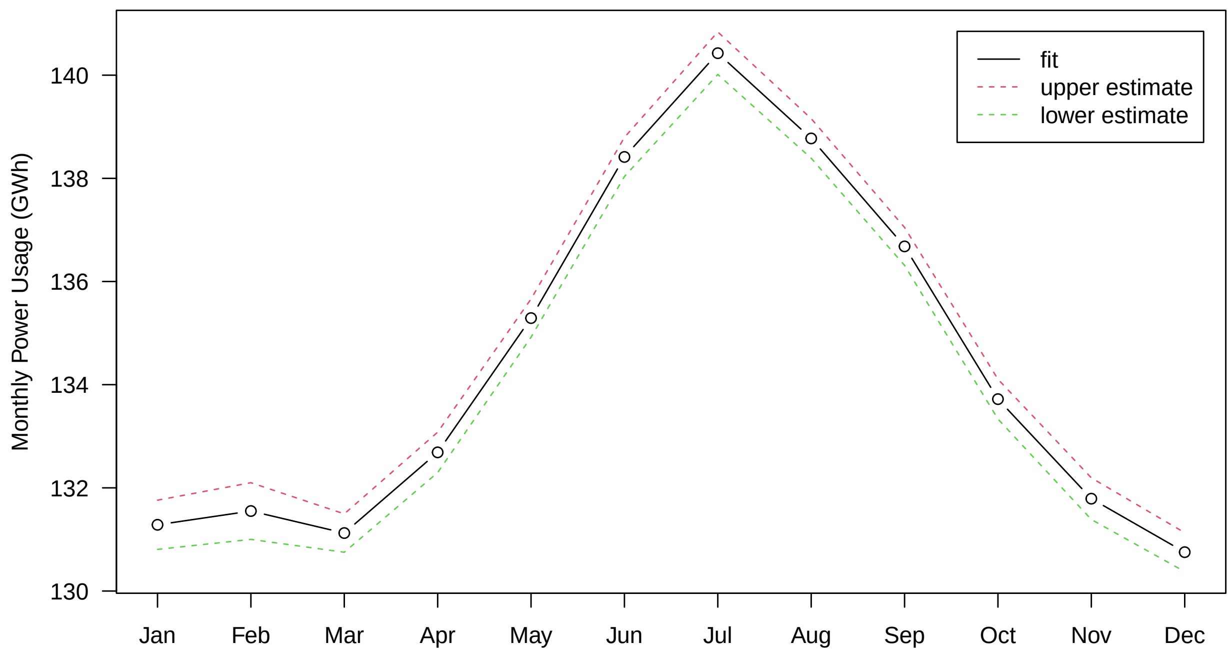

Figure 8: Auckland Region 100% EV Case Total Power Usage per Month

Combining Auckland only VKT with the consumption linear model we can see the estimated power usage per month showing a clear seasonal trend from around 130.8 GWh per month in summer to around 140.4 GWh per month in the winter.

The upper and lower estimate are 95% confidence interval on the linear model. As confidence intervals are unknown for the future VKT and future weather the confidence intervals do not include this uncertainty. (should i just remove from the plot as do not have much meaning)

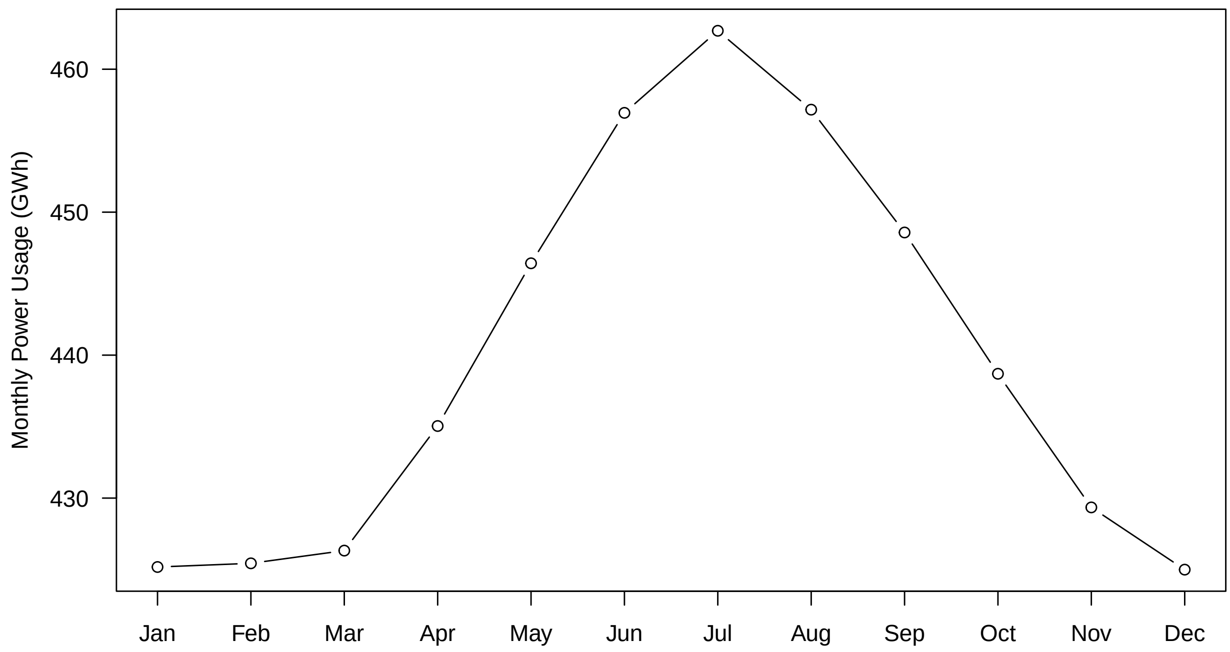

Figure 9: NZ 100% EV Case Total Power Usage per Month

Similarly for all of NZ each VKT region is combined with the consumption linear model for each best corresponding weather region. Again estimated power usage per month is showing a clear seasonal trend from around 425 GWh per month in summer to around 463 GWh per month in the winter.

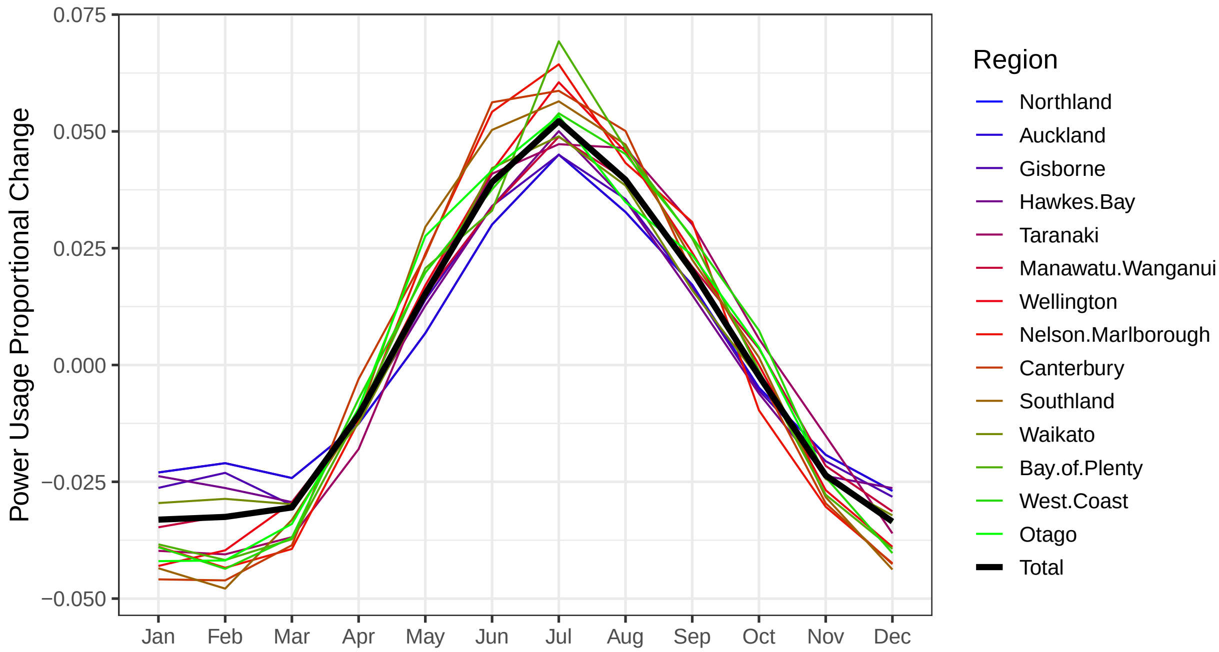

Figure 10: All NZ Regions Monthly Proportional Change in Power Usage Relative to its Yearly Average

Using the weather data only we can see the proportional change in power usage for each region in NZ. All regions follow a similar seasonal change in power consumption. Of note regions like Northland and Auckland appear to have less of a seasonal trend compared to regions such as Otago and the West Coast likely due to a warmer climate leading to increased AC usage during the summer months decreasing efficiency in the summer month.

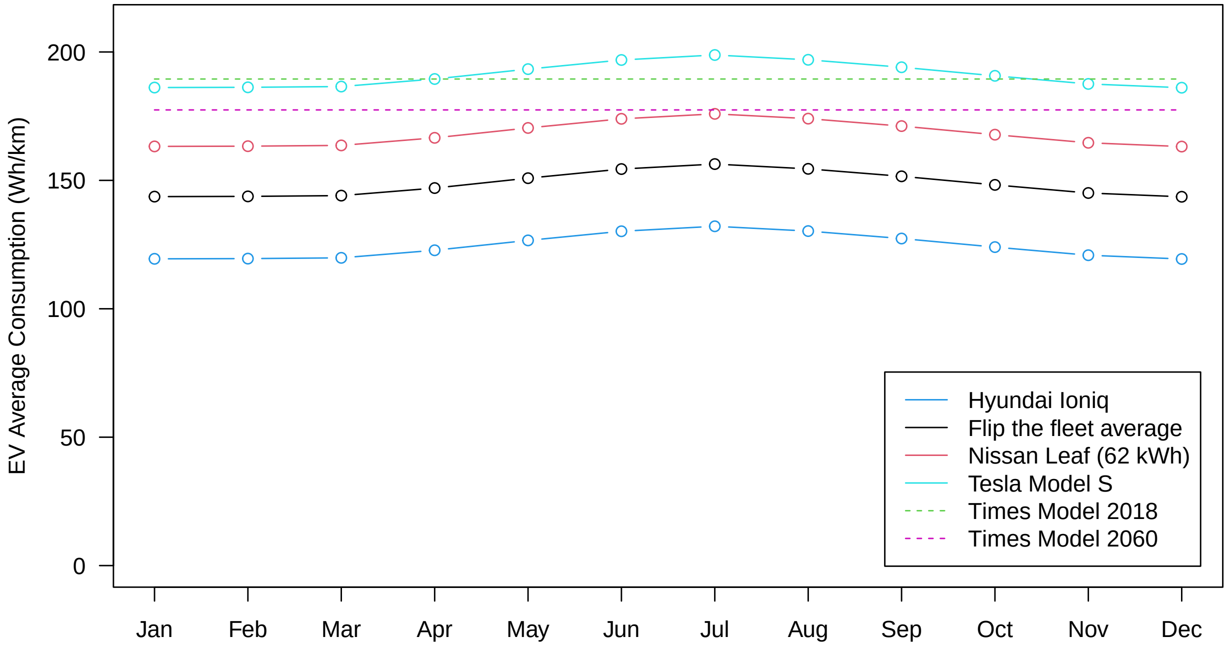

Figure 11: NZ Vehicle Average Consumption Scenarios

Comparing flip the fleet consumption numbers to EECA's times tui model [5] consumption we can see that ECCA's times model is based on a much higher consumption (lower efficiency) than the flip the fleet data would suggest. With the consumption model using the flip the fleet vehicle make up suggests an average of 148.6Wh/km. However, this is consisting of primarily of Nissan leafs with 1078 out of 1264 vehicles included in the flip the fleet data being Nissan leafs which is a quite light and efficient EV. The 2018 times model consumption is much more comparable to much heavier and less efficient Tesla Model S (based on 81 months of efficiency data from 5 vehicles).

Figure 11, while showing a seasonal trend, shows that the vehicle make up of the fleet can have a much greater impact than anything else on the actual power consumption that EVs will have on the power grid.

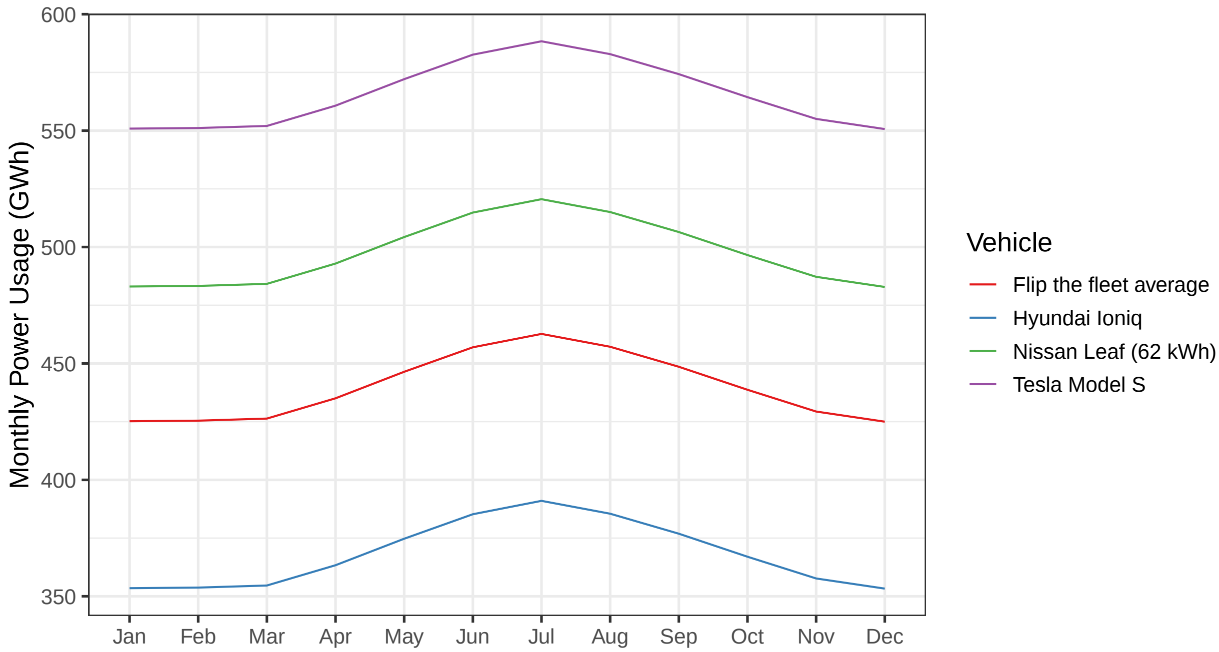

Figure 12: 2019 VKT 100% EV Case NZ Total Power Usage Scenarios by Vehicle Fleet Model Makeup

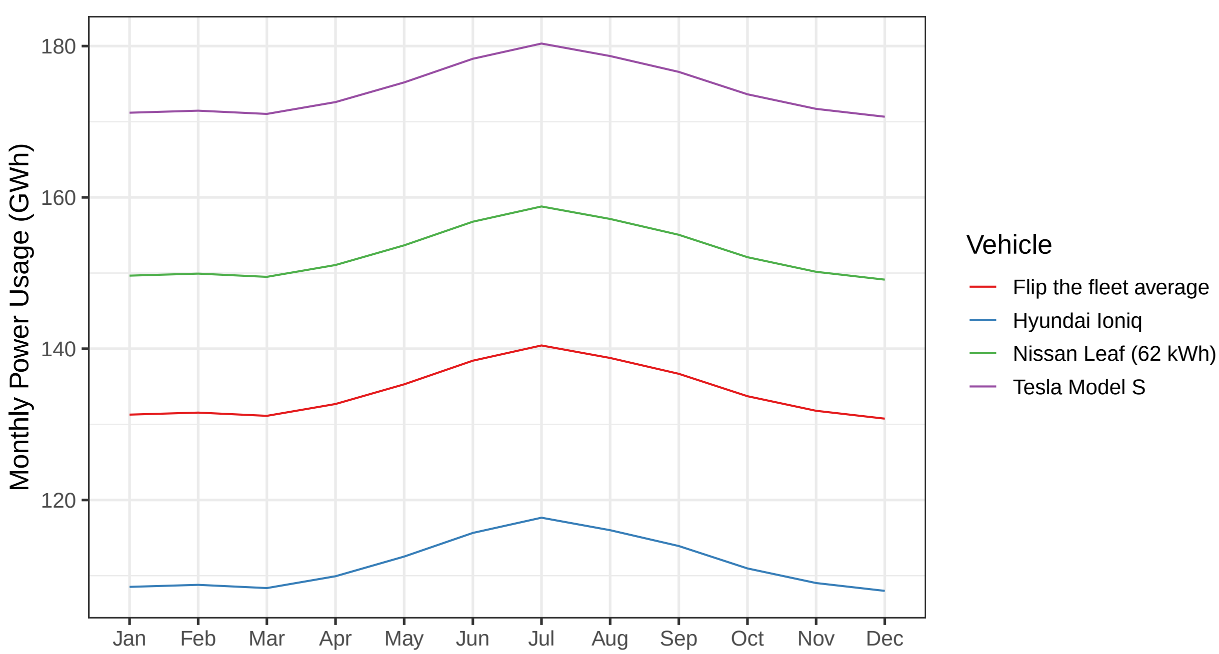

Figure 13: 2019 VKT 100% EV Case Auckland Total Power Usage Scenarios by Vehicle Fleet Model Makeup

Combining the regional consumption used to plot figure 11 with the 2019 VKT number we can get an expected power usage for all of NZ and also for each VKT region. Figure 12 shows with a 100% EV penetration and an EV fleet comparable to the Flip the Fleet, the monthly power usage for all of NZ goes from 425 GWh minimum in the summer to 463 GWh maximum power usage in the winter. If the fleet consisted of heavier less efficient vehicles like the Tesla Model S this would increase to 551 GWh minimum in the summer to 588 GWh maximum power usage in the winter. Figure 13 shows with a 100% EV penetration and an EV fleet comparable to the Flip the Fleet, the monthly power usage of Auckland goes from 131 GWh minimum in the summer to 140 GWh maximum power usage in the winter. If the fleet consisted of heavier less efficient vehicles like the Tesla Model S this would increase to 171 GWh minimum in the summer to 180 GWh maximum power usage in the winter.

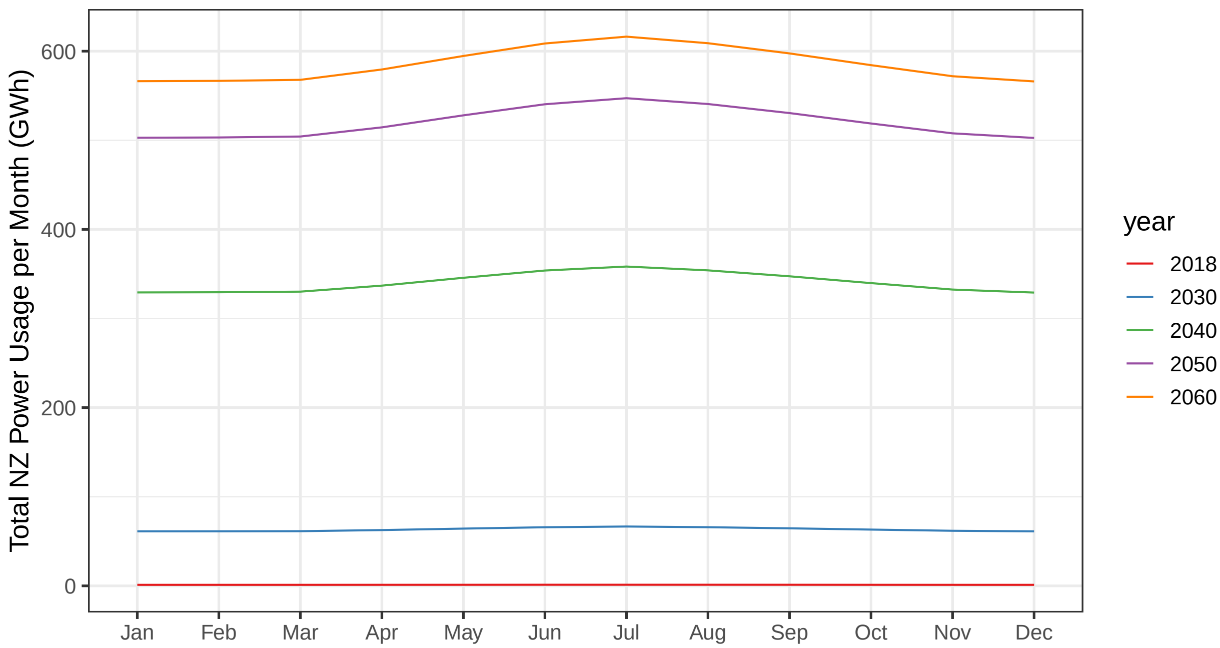

Figure 14: NZ EVs Power Usage per Month using EECAs kea VKT and Flip the Fleets Average Consumption

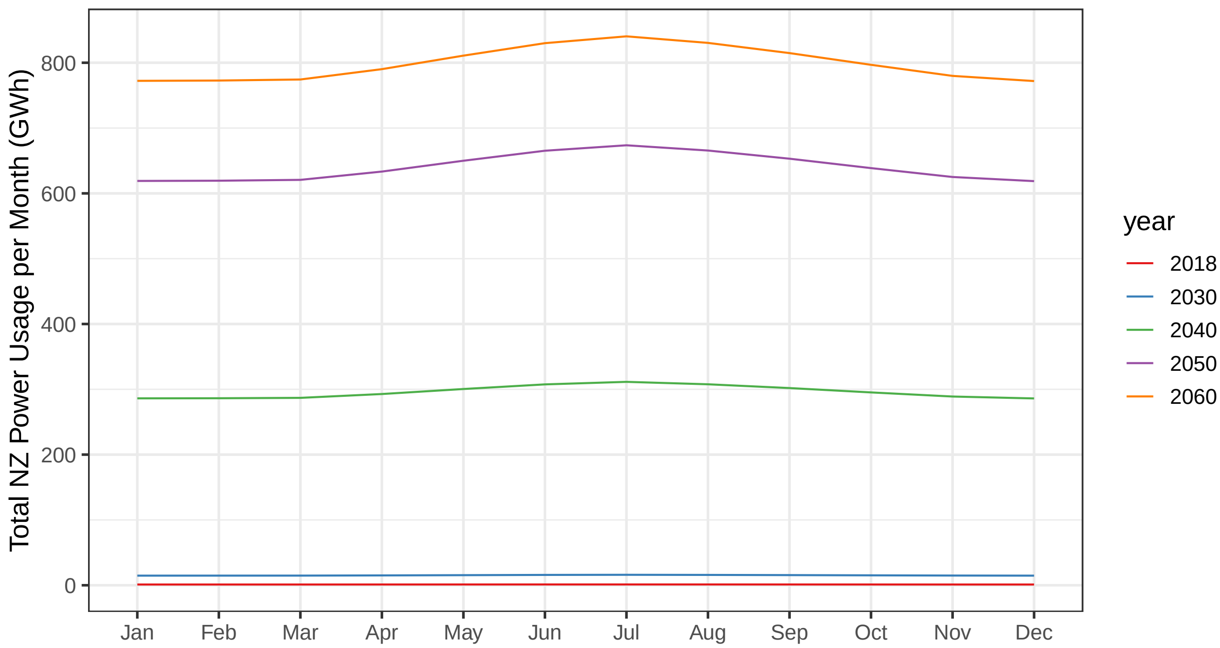

Figure 15: NZ EVs Power Usage per Month using EECAs Tui VKT and Flip the Fleets Average Consumption

References

[1] *To what degree does temperature impact EV range?*
`https://www.geotab.com/blog/ev-range/`

[2] *Why is the range of an EV less on the freeway than the city?*
`https://evcentral.com.au/why-is-the-range-of-an-ev-less-on-the-freeway-than-the-city/`

[3] *Bayesian estimation of a building's base temperature for the calculation of heating degree-days*
`https://www.sciencedirect.com/science/article/abs/pii/S0378778816312907`

[4] *NZTA VKT data website*
`https://www.transport.govt.nz/statistics-and-insights/fleet-statistics/vehicle-kms-travelled-vkt-2/`

[5] *ECCA Times Model*
`https://www.eeca.govt.nz/insights/data-tools/new-zealand-energy-scenarios-times-nz/`