Quick summary

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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 1264 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 12 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 and cooling degree days 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].

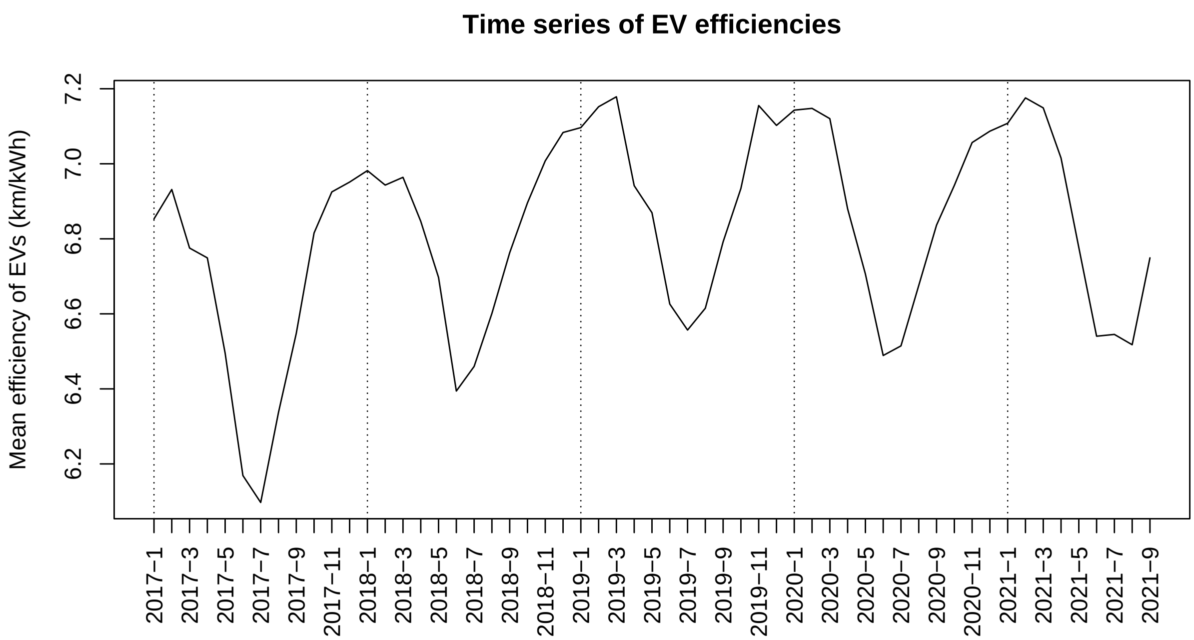
The HDD and CDD was then divided by the length of the month so that HDD and CDD corresponds to average heating degrees days per day for the month. This is so that when comparing to other statistics such as efficiency that are averaged out rather than summed there is less bias.

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 average was then created for all of NZ and also by region of the EV statistics. For average efficiency of the vehicles for each month an adjusted average was used based on the distance traveled by the vehicle so as the vehicles with very low km and therefore more variance in efficiency would have lesser weighting in the data compared to a high mileage vehicle.

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

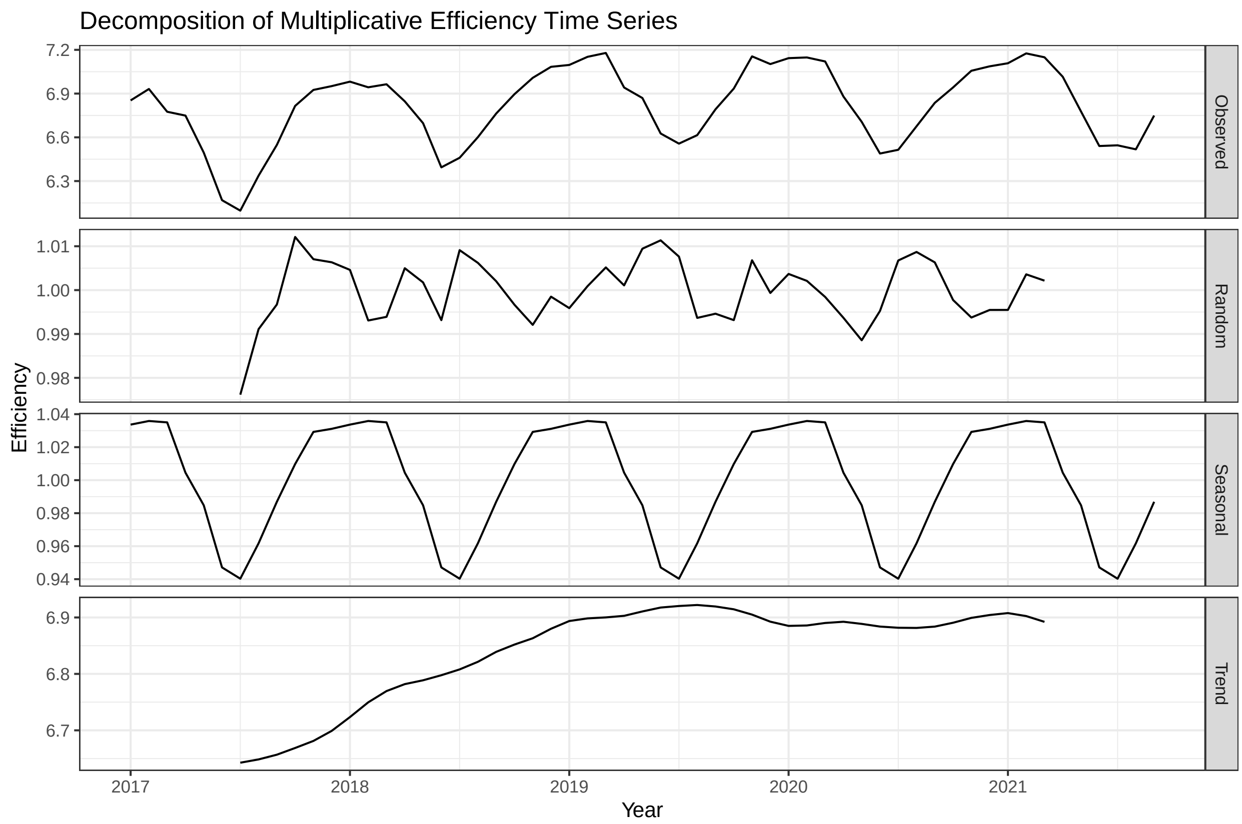


Plotting monthly average efficiency for all of NZ we can see that there is a very clear seasonal trend.

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

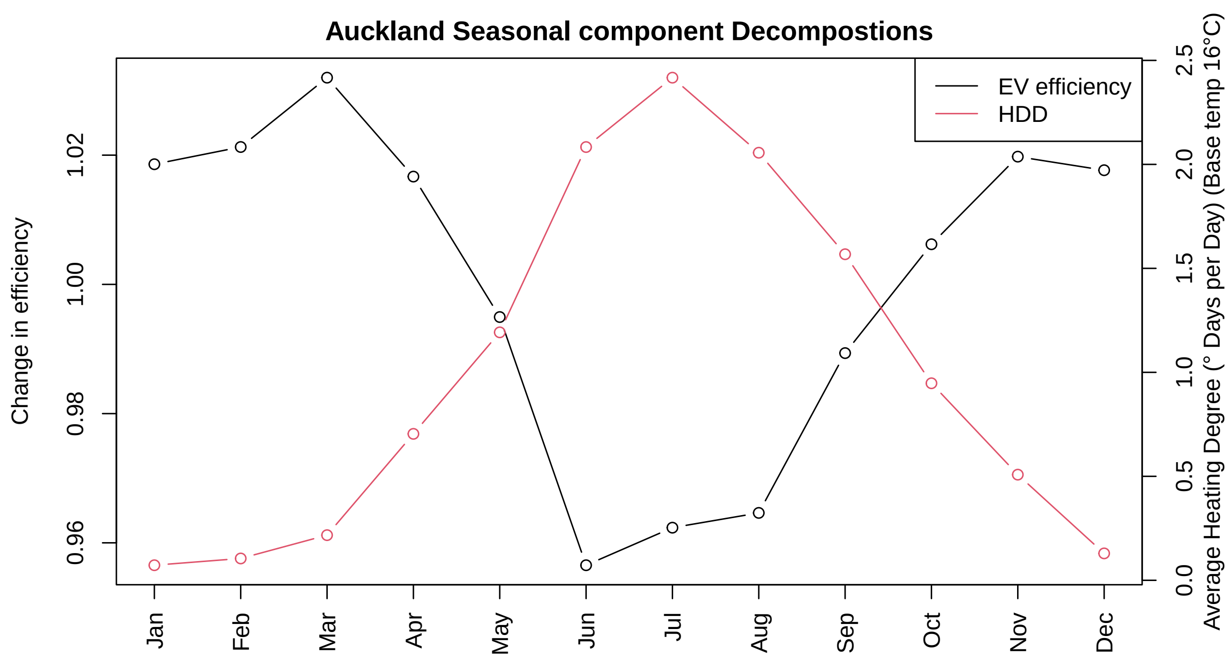
- Linear model with each month as an independent factor
  - offers more control and flexibility (could add vehicle type etc in further analysis)
  - shows confidence interval
  - requires to define an arbitrary function that can fit to the overall trend to separate from seasonal trend
  - least squares is sensitive to single large deviation that could just be outlier (such as lockdown)
- Time series Decomposition
  - designed for time series
  - automatically finds a overall trend based on the period 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 efficiency 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.

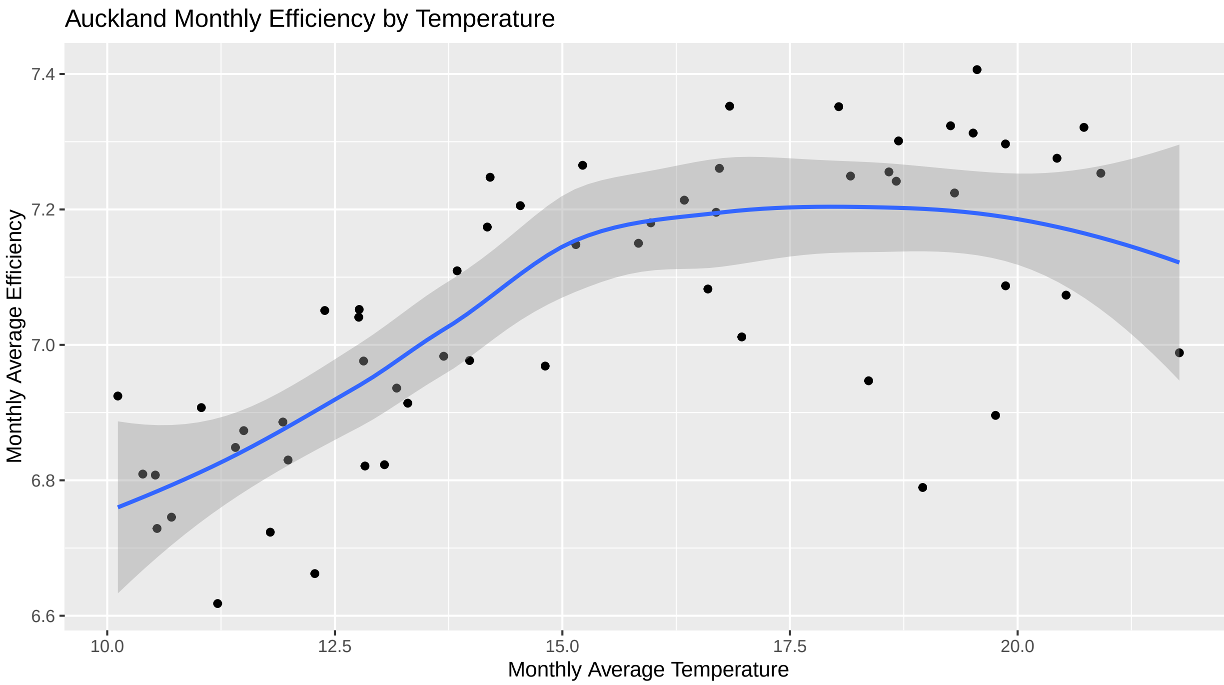


The decomposition shows that the seasonal trend goes from 0.94 times the mean efficiency in June to 1.04 times the mean efficiency in March, A peak to peak difference of 9.2%.

Looking at the plot there is a very obvious seasonal trend to EV efficiency but so that I can compare it to HDD I limit this to just Auckland EVs.



Within Auckland looking at the plot it is very obvious that as number of heating degree days increases the efficiency of the EV decreases. I do notice a slight dip in efficiency during Jan and Feb 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.



Further looking into this we can see that in Auckland as the average temperature of the month starts increasing past 17.5 there appears to be a trend towards decreasing EV efficiency. As stated before research [1] suggested AC also decreases efficiency of the EV. This made me think what if we include cooling degree days and heating degree days in analysis? This could also be useful to explain the points well below 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 decreasing range but average temperature would not be able to show this.

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

As with the case of the adjusted monthly average for efficiency (km/kWh) and 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 slightly 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 drive train power consumption. Conceptually it makes sense that extra power usage due to heating/cooling demand to be independent from driven train demand as unlike in traditional internal combustion engine (ICE) vehicles where the energy to heat and cool the cabin comes from the engine a 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 period 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 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 it this is the number we are trying to find to see how the number of HDD and CDD effect 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.

```
##
## Call:
## lm(formula = consumption ~ HDD + CDD + weather_region + model,
##     data = EV_data[year >= 2017, ], weights = distance, na.action = na.omit)
##
## Weighted Residuals:
##     Min      1Q  Median      3Q     Max
## -2330.0  -336.0   -58.9   233.7  4076.6
##
## Coefficients:
##                                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)                        132.10910    0.28682 460.596  < 2e-16 ***
## HDD                                  2.19587    0.05098  43.077  < 2e-16 ***
## CDD                                  2.38447    0.57237   4.166 3.11e-05 ***
## weather_regionUpper Hutt            -0.47884    0.30368  -1.577  0.11486
## weather_regionChristchurch          -0.91050    0.32585  -2.794  0.00521 **
## weather_regionDunedin               12.06167    0.38363  31.441  < 2e-16 ***
## weather_regionHamilton               8.51143    0.53005  16.058  < 2e-16 ***
## weather_regionRotorua                5.01376    0.54639   9.176  < 2e-16 ***
## weather_regionNelson                 2.71181    0.48076   5.641 1.71e-08 ***
## weather_regionClyde                  4.52313    0.74940   6.036 1.61e-09 ***
## weather_regionPalmerston North      14.11267    0.66544  21.208  < 2e-16 ***
## weather_regionStratford             10.36010    0.95003  10.905  < 2e-16 ***
## weather_regionNapier                 6.31241    0.84758   7.448 9.85e-14 ***
## weather_regionInvercargill           3.19161    1.75860   1.815  0.06956 .
## modelNissan Leaf (30 kWh)            3.40104    0.25253  13.468  < 2e-16 ***
## modelNissan Leaf (24 kWh) 2011-2012 12.38655    0.32468  38.150  < 2e-16 ***
## modelNissan Leaf (40 kWh)           10.67590    0.51761  20.625  < 2e-16 ***
## modelNissan e-NV200 (24 kWh)        32.71507    0.53694  60.929  < 2e-16 ***
## modelHyundai Ioniq (EV)            -18.32449    0.68530 -26.739  < 2e-16 ***
## modelBMW i3                         -1.33423    0.78757  -1.694  0.09026 .
## modelHyundai Kona (EV)               0.68179    0.86030   0.793  0.42808
## modelRenault Zoe                    11.54664    0.85101  13.568  < 2e-16 ***
## modelTesla Model 3                  10.54916    1.02253  10.317  < 2e-16 ***
## modelNissan Leaf (62 kWh)           25.45888    1.75280  14.525  < 2e-16 ***
## modelKia Niro (EV)                  11.34407    1.19319   9.507  < 2e-16 ***
## modelTesla Model S                  48.37587    1.69060  28.615  < 2e-16 ***
## modelVolkswagen e-Golf               1.20791    1.53830   0.785  0.43233
## modelTesla Model-X                 104.12524    1.29657  80.309  < 2e-16 ***
## modelKia Soul                        6.27576    1.25011   5.020 5.20e-07 ***
## modelMG ZS EV                       22.12031    3.90177   5.669 1.45e-08 ***
## modelRenault Kangoo (van)           56.62978    1.53753  36.832  < 2e-16 ***
## modelJaguar I-PACE                  73.02598    2.95178  24.740  < 2e-16 ***
## modelAudi A3 e-tron                 33.38171    4.85534   6.875 6.35e-12 ***
```

```
## modelPeugeot e-208                  10.96685    9.58439   1.144  0.25254
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 492.4 on 22497 degrees of freedom
##   (67 observations deleted due to missingness)
## Multiple R-squared:  0.4855, Adjusted R-squared:  0.4847
## F-statistic: 643.2 on 33 and 22497 DF,  p-value: < 2.2e-16
```

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 2.20Wh/km. With a p-value of $< 2 \times 10^{-16}$ we are quite confident on this value.

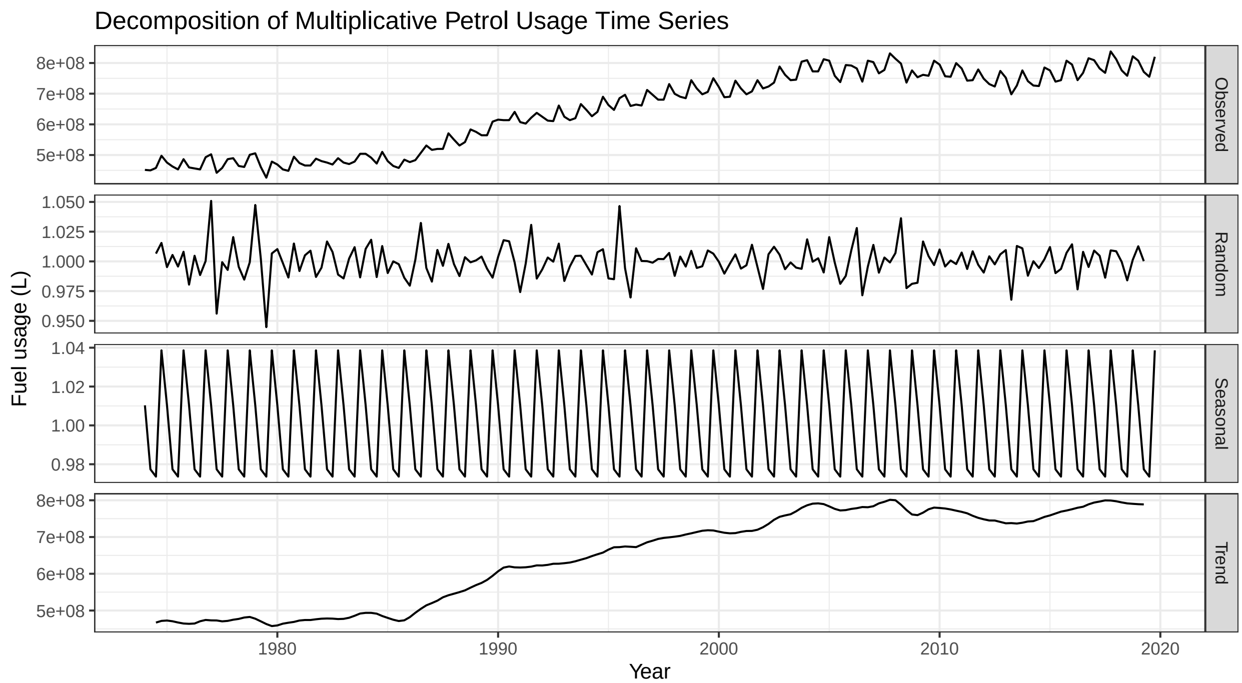
The CDD term suggests that as the average number of cooling degree days per days increases by 1 the average power consumption of EVs for the month increases by 2.38Wh/km. With a p-value of 3.11×10^{-5} we are less confident on this value. This is likely as there is much less data in New Zealand regarding 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 are less efficient in the winter due to heating requirements and to a much lesser extent in NZ less efficient 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

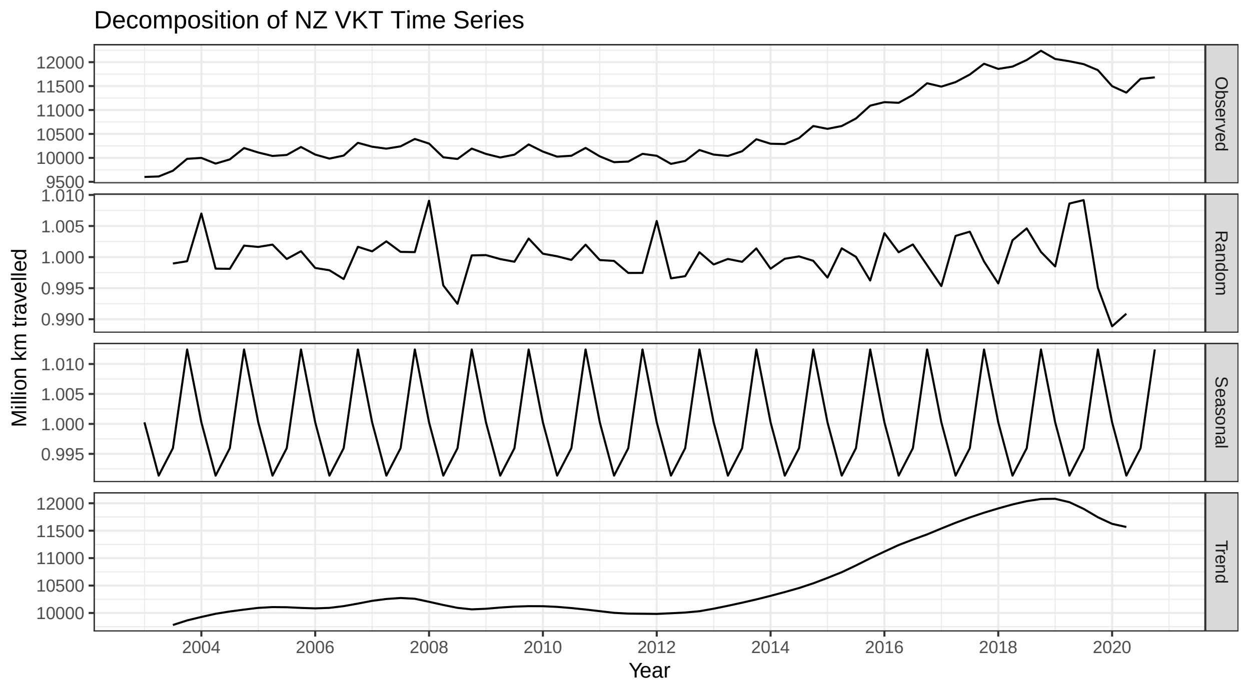
- monthly card sales data
  - monthly data for all of NZ credit card transactions at fuel stations
- quarterly regional fuel sales data
  - quarterly data for all sales at fuel stations broken down by region from MBIE
- quarterly fuel trade data
  - quarterly data of fuel used for transport by type of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



I excluded the fuel data from 2020 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.

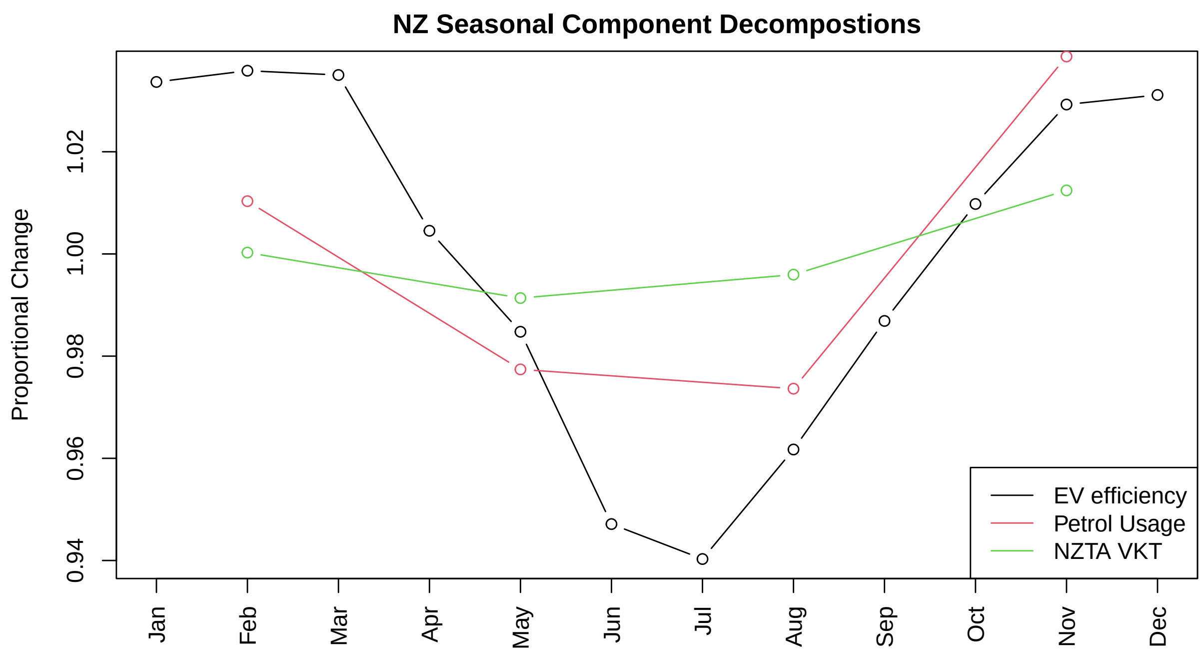
We can also compare this to the VKT data from NZTA. This data was given by Haobo from NZTA and is collected using VKT based on WoF/CoF odometer [4].



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 1 time 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 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 (Q1 and Q4) VKT, the true VKT in the summer (Q2 and Q3) 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 efficiency we can see much larger decrease in efficiency in the winter months with average efficiency in July being 9.2% less efficient than in February. From the plot we can see that when efficiency of EVs go down, VKT also goes down, suggesting that some increase in power usage due to EVs decrease in efficiency will be countered by the decrease in VKT. However, the decrease in efficiency 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 the worst case scenario.

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/sheet/vehicle-kms-travelled-vk