Accelerated reported battery capacity loss in 30 kWh variants of the Nissan Leaf

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Abstract: Analysis of 1,382 measures of battery State of Health (SoH) from 283 Nissan Leafs ("Leaf/s"), manufactured between 2011 and 2017, has detected a faster rate of decline in this measure of energy-holding capacity for 30 kWh variants. At two years of age, the mean rate of decline of SoH of 30 kWh Leafs was 9.9% per annum (95% uncertainty interval of 8.7% to 11.1%; n=82). This was around three times the rate of decline of 24 kWh Leafs which at two years averaged 3.1% per annum (95% uncertainty interval of 2.9% to 3.3%; n=201). For both variants there was evidence for an increasing rate of decline as they aged, although this was much more pronounced in the 30 kWh Leafs. Higher use of rapid DC charging was associated with a small decrease in SoH. Additionally, while 24 kWh cars with greater distances travelled showed a higher SoH, in 30 kWh cars there was a reduction in SoH observed in cars that had travelled further. The 30 kWh Leafs sourced from United Kingdom showed slower initial decline than those from Japan, but the rate of decline was similar at two years of age. Improvements in the battery health diagnostics, continuous monitoring of battery temperatures and state of charge, and verification of a fundamental model of battery health are needed before causes and remedies for the observed decline can be pinpointed. If the high rate of decline in battery capacity that we observed in the first 2.3 years of a 30 kWh Leaf's lifetime were to continue, the financial and environmental benefits of this model may be significantly eroded. Despite 30 kWh Leafs accounting for only 14% of all light battery electric vehicles registered for use on New Zealand roads at the end of February 2018, there is also the potential for the relatively poor performance of this specific model to undermine electric vehicle uptake more generally unless remedies can be found.

Keywords: Electric vehicle, Nissan Leaf, lithium-ion battery, capacity loss, battery degradation.

Introduction

A barrier to uptake of electric vehicles is the concern amongst prospective purchasers that the batteries will not last long enough to maintain a practical maximum range (Ford et al. 2015, Moller & Ivanov 2017). This concern is potentially more acute in New Zealand where most electric vehicles are purchased second hand and imported from Japan and the UK, and there is not yet a well-developed battery replacement or refurbishment industry. Nissan Motor Company Ltd have so far only guaranteed to supply batteries for the relatively small number of Leafs that were sold new into the New Zealand market (EVTalk, 2017).

A battery's capacity can be measured by a 'State of Health' (SoH) metric, the condition of a battery compared to its ideal condition. It is related to the fraction of electrical energy that the battery can hold as a percentage of the energy that the battery could store at time of manufacture. SoH does not correspond to any particular physical quantity, but rather it's a quantity derived from a number of parameters. The lithium-ion battery SoH is a value officially referred to by Nissan as 'LBSOH' and is generated by the car's battery management system and outputted by the Nissan Consult 3 tool (My Nissan Leaf, 2012). It is also possible to read the SoH of the battery using an OBDII adapter and the LeafSpy application (Pollick, 2018).

Battery capacity is important for electric vehicle owners because it is a primary factor in the maximum range that the car can travel once the battery is fully charged. Limited range and associated "range anxiety" are important perceived barriers for many potential purchasers of the early and less expensive electric vehicle models, like the Leaf (Barton & Schutte 2015, Ivanov & Moller 2017a). The increased range of the 30 kWh Leaf from late 2015 onwards may partially alleviate the "range anxiety" of some purchasers, but these models are currently around a third more expensive to buy on New Zealand's second hand car market than their 24 kWh counterparts.

It is therefore concerning that commentary in electric vehicle social media has asserted that SoH of 30 kWh Leaf batteries declines faster than the 24 kWh models, especially in hotter regions of the USA (NZ EV Owners Group, 2018; My Nissan Leaf, 2018). Given that higher temperatures and warmer climates accelerate battery degradation (Keil, 2016; Mao, 2017), SoH may be higher on average for cars entering New Zealand from the UK compared to those from Japan. To date, well quantified data and robust statistical analysis has not been published to evaluate these claims.

It is normal for the SoH of lithium ion batteries to decrease over time. For example, Nissan estimated that the battery of the Leaf should retain 80% capacity after 5 years (Nissan, 2012; Nissan, 2017). The decrease in the battery's SoH is referred to in this document as the decline. We define the rate of decline as the instantaneous decrease in state of health at a particular point in time (% per annum).

Flip the Fleet is a citizen science project in which electric vehicle owners from throughout New Zealand sign up to provide monthly records on their cars' distance travelled, efficiency, charging patterns, and average speed (Ivanov & Moller 2017b). Over 620 electric vehicles have signed up to contribute data since the testing phase of the project began in July 2016, and the public launch in June 2017. Twenty-two models of electric vehicles provide monthly data, of which 73% are Leafs. A subsample of participants also provide SoH measures at the end of each month from LeafSpy. Here we explore these SoH data of Leafs in New Zealand, and investigate potential factors that are associated with different rates of decline.

Methods

A convenience sample (non-random, self-selecting participants) of 82 of the 30 kWh and 201 of the 24 kWh Leafs contributed 1,382 battery SoH measurements for this analysis. Most records were taken between June 2017 and the present, and submitted to *Flip the Fleet* (http://www.flipthefleet.org/). There were also 76 participants who submitted 359 historical records of SoH from July 2014 to June 2017. In addition to cars enrolled in *Flip the Fleet*, there were 39 records from 24 kWh and 30 kWh cars presented for auction and randomly measured in the Osaka, Nagoya, and Kobe regions of Japan in early February 2018. We also included 14 SoH measurements from 6 of the 30 kWh vehicles in use on New Zealand roads that had not been signed up to *Flip the Fleet*. There was no evidence that these additional samples differed in nature from the samples from *Flip the Fleet*.

Most (81%) of the sample are in private ownership and used for domestic travel and the remainder are part of fleets operated by companies. Here we present data from Leafs divided into two groups: 201 with a 24 kWh lithium ion battery (manufactured in 2011 - 2016), and 82 with a 30 kWh battery manufactured in late 2015, 2016 and 2017. Most of the vehicles in our sample were sourced second-hand from either Japan (89%), United Kingdom (7%), Australia (<1%), or Europe (<1%). There was a small fraction (3%) that were NZ-new 24 kWh Leafs. Overall, 32% of the total life of all vehicles, and 49% of the total distance travelled by the Leafs occured in New Zealand.

Bayesian hierarchical models (Gelman, 2006), taking into account the correlated nature of measurements from the same car, were fitted to the data. This model choice is particularly appropriate to analyse this dataset because of the wide and increasing scatter of the measurements with age of car, repeated measures of SoH from the same cars, and varying number of measurements per car. The R statistical environment (R core team, 2016) was used for analysis, with the packages *dplyr* (Wickham, 2017) for data manipulation, *brms* (Bürkner, 2017) for Bayesian models, and *ggplot2* (Wickham, 2016) for graphical display.

The predictor included in the primary model was age by battery capacity type. The date of manufacture, or date of first registration in the country of origin when this was not available, was used to calculate the age of the car at each measurement. To allow for a model with no intercept, the dependent variable SoH was linearly transformed so that the origin corresponded to a 100% SoH at age 0. The rate of decline of battery SoH by age was allowed to vary by vehicle within the model, and model predictors were assumed to be of a Gaussian form. A second model was fitted which additionally allowed the decline by age to vary by the battery capacity and country of origin. A third model also included predictors of odometer and rapid charges per unit of distance travelled.

Statistical models where age had a linear or quadratic relationship with SoH were compared using "leave-one-out" cross-validation information criteria with a lower value representing a model that provides a better "out-of-sample" fit to the data (Vehtari, 2017). The rate of decline of SoH by each Leaf model is presented as the mean rate at a given age. The mean posterior values are given, along with the 95% uncertainty intervals, which contain the value for the population with 95% probability given the model and data.

Results

Battery SoH declined at a population level consistently with age, but there was considerable variation between vehicles of a given age (Fig. 1 & 2). Some individual vehicles maintained a steady SoH, others inflected sharply downward after stable periods, and some even increased up to 100% for reasons we cannot identify (Fig. 2). Several participants reported that their SoH builds steadily after several rapid charging events in quick succession when on long journeys, followed by decline when the vehicle has once again been slow-charged at home at daily intervals.

A quadratic model provided better out-of-sample predictions than a linear model (leave-one-out cross-validation information criteria of 4985 for the quadratic model versus 5475 for the linear model, with a lower score indicating a better fit to the data). This improvement was largely driven by the 30 kWh cars benefiting from a quadratic term (coefficient value -1.4%, 95% uncertainty interval -2.0% to -0.7%). In contrast, the coefficient for the quadratic term for the 24 kWh Leafs had a much small magnitude (-0.1%, 95% uncertainty interval -0.2% to 0.0%).

The decline in the 30 kWh Leafs was much faster than the 24 kWh Leafs (Fig. 3 & 4). The mean rate of decline of 24 kWh Leafs at one year of age was 2.9% per annum (95% uncertainty interval of 2.6% to 3.2%). In contrast, the mean rate of decline of 30 kWh Leafs at this age was 7.2% p.a. (95% uncertainty interval of 6.7% to 7.6%). At two years, the rate of decline in the 24 kWh Leafs was relatively unchanged at 3.1% p.a. (95% uncertainty interval of 2.9% to 3.3%), but the rate of decline in the 30 kWh Leafs increased to 9.9% p.a. (95% uncertainty interval 8.7% to 11.1%).

There was reasonable variation between vehicles, with some cars showing minimal decline as a function of age while others showed substantial decline. This was especially the case with 30 kWh Leafs, which after 1.4 years some had 100% SoH while others were at 85% SoH.

SoH was positively associated with distance travelled in 24 kWh Leafs, but negatively associated in 30 kWh Leafs: for every 10,000 km that a 24 kWh Leaf had traveled above the mean for a given age, SoH increased by 0.3% (95% uncertainty interval 0.0% to 0.5%); whereas for every 10,000 km above the mean for 30 kWh Leafs, SoH decreased by 0.6% (95% uncertainty interval of 0.1% to 1.0%). The number of rapid charges per 100 km travelled was associated with a decrease in SoH of 0.6% (95% uncertainty interval of 0.3% to 1.0%) in both 24 and 30 kWh models. That is, a Leaf with an odometer of 10,000 km and 150 rapid charges, is expected to have a SoH 0.9% lower than a Leaf with an equivalent odometer and no rapid charges.

There was no evidence that the rate of decline of 24 kWh Leafs differed between source countries, with a mean rate of decline close to 3.0% in both Japanese and UK sourced Leafs. In contrast, the rate of battery decline in 30 kWh Leafs was at first slower in cars sourced from UK compared to Japan before rates converged: UK-imported Leafs (n = 21) had a mean rate of decline of 5.7% p.a. (95% uncertainty interval 5.0% to 6.5%.) compared to Japan-imported Leafs (n = 67) which had a mean rate of decline of 7.5% p.a. (95% uncertainty interval 7.1% to 7.9%). By age two, UK-imported Leafs mean rate of decline had increased to 11% p.a. (95% uncertainty interval 8.8% to 13.4%) compared to Japan-imported Leafs increasing to 9.3% p.a. (95% uncertainty interval 7.7% to 10.9%).

The decline in the winter range of vehicles due to the decline in SoH was calculated using *Flip the Fleet*'s mean winter efficiency of 6.25 km/kWh in July 2017, and the usable capacity of the battery packs of 21.3 kWh for 24 kWh (Lohse-Busch, 2012) and 28 kWh for 30 kWh (based upon reported LeafSpy values). This range in 30 kWh Leafs had reduced by 29 km on average over 2.3 years (the

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oldest of these models), compared to a decline of 9 km in 24 kWh Leafs over the same period (Fig. 5).

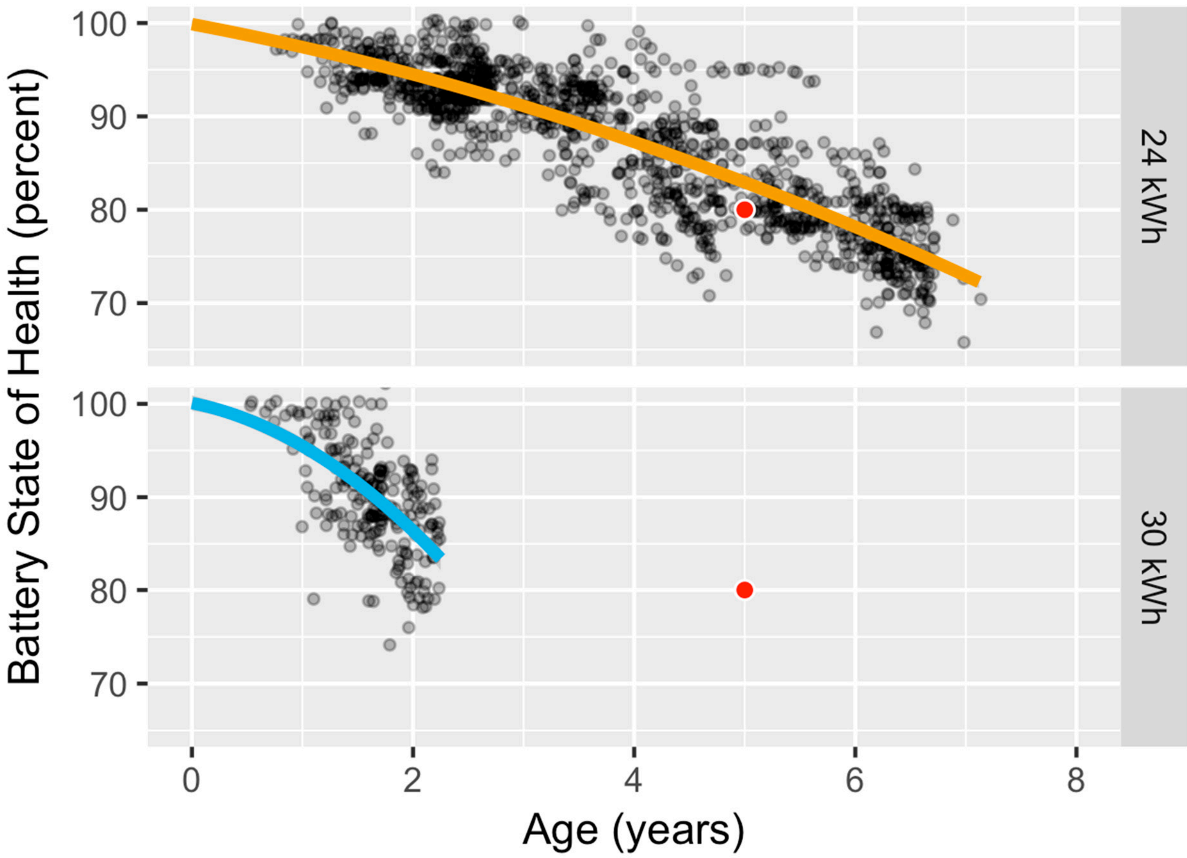

Figure 1: All individual battery SoH measurements as a function of age with average 2nd-degree polynomial fits for both 24 kWh and 30 kWh models. Nissan's estimate for decline is 80% SoH after 5 years (Nissan, 2012; Nissan, 2017) and is shown by a red dot. There was large variability between cars, but both battery models showed increasing decline with age.

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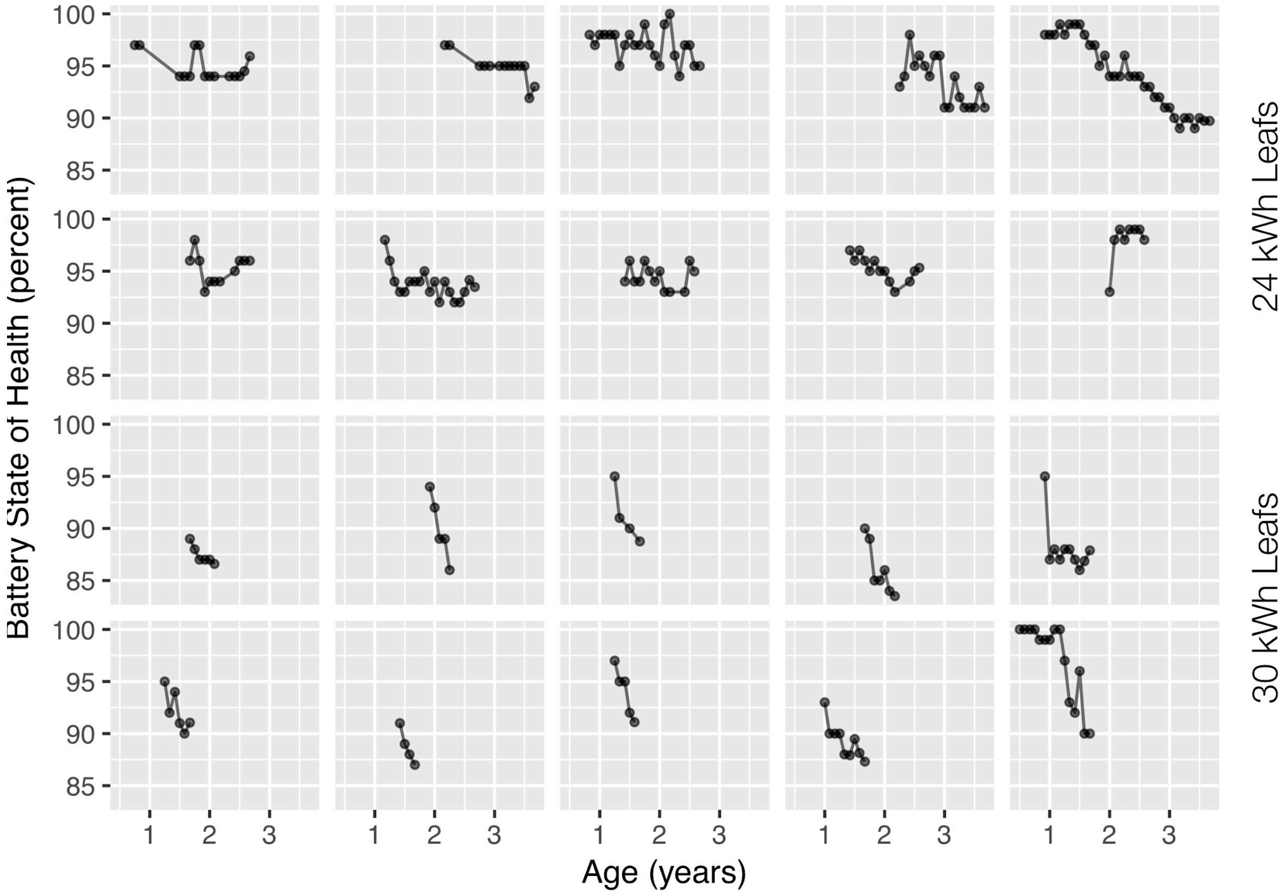

Figure 2: Example longitudinal battery SoH data from ten 24 kWh Leafs (top two rows) and ten 30 kWh Leafs (bottom two rows). There is large variation between cars, although the overall longitudinal trend is a decline in SoH over time, especially in the 30 kWh Leafs.

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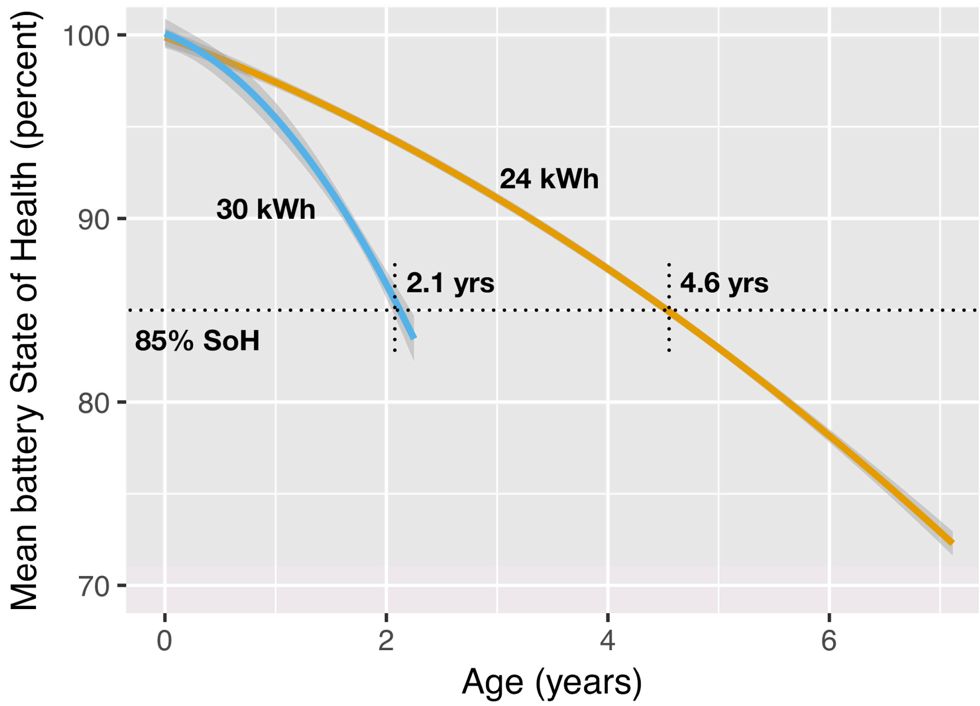

Figure 3: Comparison of the decline in mean battery SoH in the 24 kWh compared to the 30 kWh Leafs. These two lines are identical to those presented in Fig. 1. While it took 4.6 years for the 24 kWh Leafs to reach a mean 85% SoH, the 30 kWh Leafs reached this in 2.1 years. The 85% threshold is where the first 'bar' is lost in a 24 kWh state of health indicator on the dashboard. This has been adjusted to approximately 80% on the 30 kWh Leaf (My Nissan Leaf, 2018).

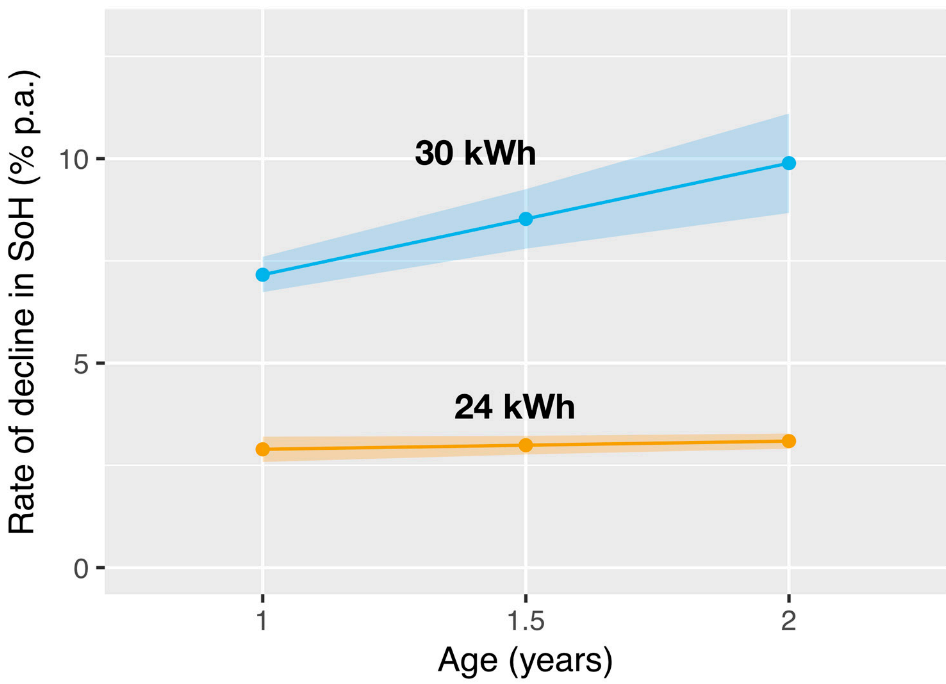

Figure 4: The rate of decline in SoH by battery model between one and two years. The age bracket of 1-2 years made a fair comparison possible, as the 30 kWh models have only been on sale for just over 2 years. Shaded regions represent 95% uncertainty intervals. While 24 kWh models have a slight increase in the rate of decline as they age, the 30 kWh model has shown a moderately increasing rate of decline as the battery ages.

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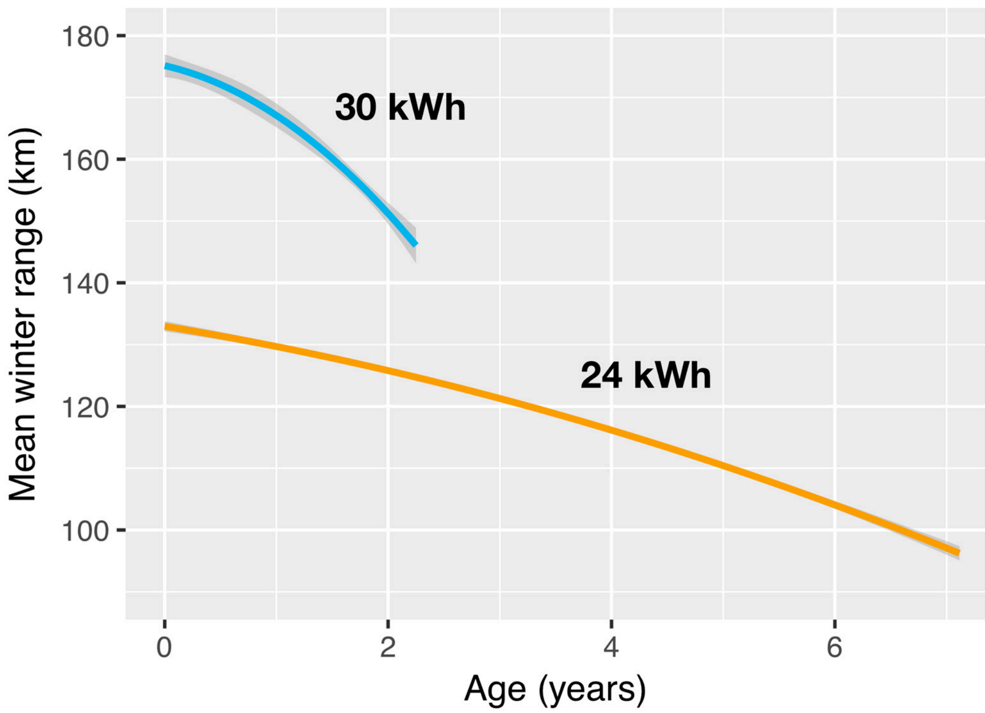

Figure 5: Comparison of the reduction in mean winter range (at an efficiency of 6.25 km/kWh) in the 24 kWh compared to the 30 kWh Leafs. This is calculated using the usable capacity of the battery packs of 21.3 kWh for 24 kWh (Lohse-Busch, 2012) and 28 kWh for 30 kWh (based upon reported LeafSpy values). The available range on a full charge is decreasing faster in the 30 kWh than 24 kWh Leafs.

Discussion

Our data indicate that the batteries of 30 kWh Leafs are declining at a faster rate on average than observed in 24 kWh Leafs. Otherwise, the dominating predictor of SoH was the age of the car. Somewhat paradoxically, SoH increased with greater distance travelled in 24 kWh Leafs, but decreased when greater distance had been travelled by a 30 kWh Leafs. SoH also decreased slightly with increased use of fast charging per distance travelled. Considerable variation between rate of decline of individual cars have been observed overlaying these broad patterns, especially in the 30 kWh model.

It is unknown what causes the accelerated reported battery capacity loss that we have observed in 30 kWh Leafs, but other research suggests plausible hypotheses for further test. It is well known that capacity declines if batteries experience high temperatures. The chemistry in Leaf batteries was changed from lithium manganese oxide (LMO) in the 24 kWh batteries (AESC, 2013) to nickel manganese cobalt (NMC) in the 30 kWh batteries (Lima, 2015). It is not clear exactly what variation of NMC was used, however an NMC-LMO blend shows reasonable loss when stored at high temperatures and high State of Charge (SoC), with 10% loss in capacity occuring at 35°C when stored at 100% SoC for 9 months (Mao, 2017), and NMC111 showed 11% loss at 40°C when stored at 80% SoC for 10 months (Keil, 2016).

In addition, the 30 kWh batteries may experience more extended periods at higher temperatures. The higher energy density, higher volumetric mass density, and faster DC charging currents (Lima,

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2016) may lead to higher battery temperature in the 30 kWh Leaf, through higher peak temperature at the end of the charging event, and then slower cooling afterwards. A 'long life 80% mode' which terminates AC charging when the battery reaches 80% SoC is an option in many of the 24 kWh models, but is not available in 30 kWh models (Nissan, 2017). This will most likely increase the time the 30 kWh battery spends at higher states of charge which, if combined with high temperature over time, may cause an increased rate of battery decline. Hence, the change in chemistry, potentially higher temperature experienced, and higher SoC may partly explain the greater capacity loss observed.

Trajectories of SoH change are so variable between individual vehicles, and there are instances of sharp inflections in SoH (Fig. 2). There was sometimes a quick drop in SoH following the purchase of a second-hand Leaf in New Zealand. This may be because these cars had been predominantly rapid charged in Japan, and so had inflated SoH at the time of transfer to New Zealand. There might also be loss of capacity during the storage, auction, and shipping process if the car is stored at a high SoC and a high temperature for many months (Keil, 2016; Mao, 2017). SoH of many 30 kWh cars has continually declined, and some show decline before stabilising. It is possible that the cars that have stabilised are being used under conditions that are favourable for the battery or, alternatively, driving/charging patterns are masking the decline in SoH. The hierarchical Bayesian model took this individual variation into account by allowing the fit to vary by car, and confirms that the overall population-level trend is for continuing decline as they age.

We cannot discount the possibility that some of the observed variation between individual cars results from disparity between the SoH calculation and the actual battery capacity. Actual battery capacity for a measured SoH, and so inferred range, could be higher or lower than indicated, and on average even different between 24 kWh and 30 kWh types. Verification of actual battery capacity compared to reported SoH, in both 30 kWh and 24 kWh types, is required to measure the size of "nuisance" variation that any such errors may have introduced and to improve estimation of the model parameters around model, age, distance and fast charging. Research to discover the short-term causes of fluctuations of the SoH index would be valuable if it identified covariates that can help eliminate nuisance variation and better estimate underlying battery health in absolute terms in future. In the meantime SoH is, at best, treated as a relative indicator rather than an absolute measure of battery health.

Some of the observed variation could also be from the non-random nature of the sample. Our data are based on a 'convenience sample' provided by volunteers, rather than a formal random sample. Most observations in the panel began well before any collective signs of lower SoH were detected, and the majority of participants do not measure their SoH regularly, or they only started to do so recently once prompted by us. Therefore we do not expect bias in the sample of SoH measurements. Nor is there any reason to suspect any bias to be stronger in one variant than the other, in which case sampling bias can not be a sufficient explanation for why the rapid decline in SoH is so much higher in the 30 kWh variant. Finally, the observed difference in SoH decline is so large for 30 kWh that it seems extraordinarily unlikely that sampling bias could explain the observation.

We cannot also exclude the possibility that the faster rate of decline seen in some cases is the result of manufacturing faults, rather than the more systemic stresses discussed above. Tracing the place, time and batch of batteries that are showing premature SoH loss is therefore an important next step to see if the problem is localised and has already been eliminated.

More vehicles and especially longer runs of data for the same Leafs in New Zealand conditions are needed to refine our models. Many (49%) of the Leafs in our study have provided only three or fewer data points. Also, much of the travel and life of the Leafs studied was spent in their country of origin where charging and climatic influences may have been very different than those in New Zealand. This mix of two phases of the vehicle's life, and the potential for lagged or legacy effects of the way the vehicle was treated before reaching New Zealand where our monitoring starts, may also have hampered our ability to detect other significant drivers of the wide range in individual battery SoH trajectories observed. This will also have likely hampered our ability to identify strategies to minimise rate of decline in the remaining life of the car in New Zealand.

An experimental study in Phoenix, Arizona found slightly increased rates of SoH decline in two 24 kWh Leafs that were always rapid charged compared to two others that were slow charged (Shirk, 2015). The sample size was small, the experiment lasted only a year and a half, and the vehicles were driven extraordinarily long distances in much hotter conditions than prevail in New Zealand. With a much larger sample and under normal-use situations, our analysis has replicated this finding, showing a small increased SoH loss in cars with a greater proportion of DC rapid charging. While successive rapid charging may increase SoH in the short term, our modelling suggests that it causes a slight decline in SoH in the longer run. The effect may be stronger than indicated by our modelling because of this short term elevation of SoH after fast charging, or if longer distance travelled is in part conflated with increased use of fast chargers.

Another battery index, denoted Hx by LeafSpy, which is understood to be a measure of internal battery susceptance, has a similar value to the SoH metric just after manufacture, but then it generally declines faster than SoH itself as the Leaf ages. *Flip the Fleet* has only recently begun collecting Hx and battery temperature data with a goal to build models like those presented here for SoH to predict Hx. Increased internal resistance will increase the internal pack energy loss while rapid charging and during high speed driving. This will increase overall battery temperature which may accelerate the decline in SoH. Near continuous monitoring of both 24 kWh and 30 kWh battery SoH, Hx and battery temperature during charging and discharging cycles are needed to test these predictions and better discern the effect of rapid charging, number of charging cycles, age and especially temperature on SoH.

There is a need to test and refine an underlying model of battery SoH decline, partly so that Leaf owners can do all they can to prolong battery life, and partly so we can better project the longer term future of SoH, vehicle range and repairs and maintenance costs. An important aspect is to understand whether loss in reported battery capacity will progress in the quadratic fashion detected by our model so far (Fig. 1 & 3). A simple geometric rate of decline model (decreasing rate of decline over time) would result if a constant fraction of ions are immobilised in the batteries each year, in the way projected by Larsen (2016) for Leafs. Our observed pattern rejects this geometric model. Sharp downward inflections in battery health are expected in generalised battery health scenarios (Buchmann, 2014; Warnecke, 2017) and the technology applied to electric vehicles in general. Leafs, with their battery chemistries, have not been in place long enough to know if and when such downturns will occur, nor how sharp they will be. The declines observed in Fig. 1 indicate a largely linear decline over time in 24 kWh models, but a much faster increase in decline over time in 30 kWh models.

We hypothesise that 30 kWh models experience a greater battery temperature increase during charging. The chemistry of the 30 kWh batteries are also possibly more sensitive to degradation due to elevated temperature, compared to the batteries in 24 kWh Leafs. If so, elevated battery temperature could, at least in part, be driving faster decline in the 30 kWh Leafs. Active thermal management systems have been developed to prolong battery life (Dincer et al. 2017), but Leafs do not have battery thermal management systems like those used by Tesla (Eberhard, 2016), BMW (Bower, 2015), Chevrolet (Chevrolet, 2018) and Renault (Prochazka, 2017). Nissan included active air cooling for the e-NV200 which uses the same battery modules as the 24 kWh Leaf (Loveday, 2014). Tesla S battery packs with thermal management systems have shown minimal decline over time (Lambert, 2016).

Our results for 30 kWh Leafs show cause for concern because of rapidly reducing indicated range, the possible cost of early replacement of batteries, and the increased lifetime carbon emissions that will result due to early replacement. A new complete battery pack replacement may come at a very considerable cost for a New Zealand Leaf owner and rapid battery health decline may undermine the resale value and utility of 30 kWh Leafs. Many early adopters of electric vehicles are motivated by a desire to reduce greenhouse gas emissions and thereby mitigate climate change (Peters et al. 2018). The environmental benefits will be reduced and toxicity impacts from battery manufacture increased if three or more batteries are required in the course of a 210,000 km life of a 30 kWh Leaf (Arup 2015). The observed trajectory of SoH decline suggests that an 80% threshold where the first bar is lost from the dashboard indicator of battery health will be reached by many of the 30 kWh Leafs manufactured in 2015/2016 in the next 6 months (Fig. 3). The majority of 30 kWh leaf owners in *Flip the Fleet* do not obtain the SoH of their batteries regularly and so will not be aware of their cars declining SoH. The first indication of the problem identified in this study will not be evident to most until this first bar is lost.

There is risk that rapid decline in the reported capacity of battery, a core and expensive component of an electric vehicle, will exacerbate uncertainty amongst prospective purchasers of any electric vehicle rather than just the 30 kWh Leaf. Our analysis confirms an acceptable and cost effective longevity of the 24 kWh Leaf battery in Japan, UK and New Zealand conditions (Figs. 1-5). Identification of the cause of the accelerated reported decline in battery capacity of 30 kWh Leaf batteries and remedies for it are therefore an urgent New Zealand and international priority.

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