

Using EV Telematics to Monitor Real-World Battery Health for EV Owners and Fleet Operators

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Summary

This study of more than 900 electric vehicles examines various ownership conditions that may impact battery state of health over time. Battery electric and plug-in hybrid electric vehicles from Europe and North America were included in the assessment. Through the use of EV telematics technology installed on the vehicles, the battery state of health was monitored on the Nissan LEAF, Toyota Prius Plugin, Ford Fusion Energi, and the Ford Focus EV. Using the vehicle data recorded by the EV telematics devices from the 2011-2012 Nissan LEAF, the battery state of health was correlated to several independent variables including vehicle odometer, annual mean temperature, mean daily charge energy, mean depth-of-discharge, and mean vehicle speed. These correlations identify the environmental or behaviour conditions that lead to battery degradation within electric vehicles.

Keywords: lithium battery, battery SoH (State of Health), data acquisition, BEV (battery electric vehicle), PHEV (plug in hybrid electric vehicle)

1 Introduction

It has been approximately five years since the new age of electric vehicles (EVs) have been introduced to the global mass market. Over that time, new vehicles have become more efficient, offering EV owners extended electric driving range capabilities and faster charging times. The next generation of mass market EVs is expected to deliver even more gains, especially in range; however, consumers and fleets are concerned with the anticipated life and capabilities of the vehicles' battery packs over time. Since lithium ion batteries will be integral in vehicle technology for the foreseeable future [1], these concerns are important barriers and should be addressed to promote future EV penetration into the global mass market.

Battery lifetime and performance loss are known issues for EVs that original equipment manufacturers (OEMs) account for when designing their vehicles. Battery oversizing and usable energy windows are two methods used to ensure that the vehicle meets minimum requirements such as acceleration and range at the end of its lifetime. Power fade and capacity fade are the two primary metrics of degradation [2]. Power fade is caused by an increase in cellular impedance that reduces the power capability of the battery pack. Capacity fade is a slow consistent loss of active lithium within the cells that reduces the energy a battery pack can provide. Both forms of degradation occur during storage and usage, known respectively as calendar and cycling aging. Calendar aging is important to EVs because vehicles in general are parked 80% to 95% of the time [1, 2]. Cycling aging is important because cycling puts the most strain on the cell components such as volume changes in the negative electrode, solid-electrolyte interface (SEI) layer growth at the negative electrode-electrolyte interface, lithium plating on the negative electrode, and active material deterioration or fracturing of either electrode [3].

A significant amount of research has been conducted to identify lithium ion battery degradation factors and mechanisms on a cellular level. A recent review by Rezvanizani et al. [4] identifies environmental temperature [3, 5, 6, 7, 8], discharge rate [3, 6, 9, 10], charging rate [3, 5, 10], depth of discharge (DoD) [3, 5, 6, 10, 11], and the time between full charge [5, 6] as particularly applicable degradation factors for automotive batteries. In addition to these factors, other sources consider extreme battery voltage [3, 10, 11] or state of charge (SoC) [3, 5, 6, 11, 12], Ah-throughput [6], and type of charging (e.g., constant-current constant-voltage) [13, 14] to be important factors. Furthermore, thorough reviews into degradation mechanisms were conducted by Vetter et al. [3], Barré et al. [11], Broussely et al. [15], and Arora et al. [16] to explain the electrochemical and mechanical processes occurring within the cells as a result of the known degradation factors. While it is important to identify the factors and mechanisms leading to degradation, typically only one to two factors are investigated at a time with little consideration for their interaction [17].

It is difficult to fully understand the interactions between these battery degradation factors on a system level due to complex electrochemical and mechanical processes within the cells and the dynamic operating conditions of EV battery packs [4]. Since each drive cycle is unique, battery packs experience different environmental conditions and performance requirements that lead to different degradation rates [18]. For example, battery temperature is a known degradation factor that depends upon ambient temperature, heat evolution during usage, and any cooling system on-board the vehicle. The vehicle speeds, accelerations, and grades that represent a unique drive cycle will impact battery temperature differently from another unique drive cycle [11]. In other words, different drive cycles will evolve different amounts of heat and different EVs will handle that heat in different ways, e.g. no-cooling, air cooling, active cooling. In an attempt to capture real-world utilization impacts on battery degradation, aging tests of cells have been conducted on realistic or typical duty cycles [1, 19]. However, due to the lack of EV data available [4], these realistic duty cycles are approximations and do not account for the daily variation and unpredictability inherent in such a system. Furthermore, simulations typically conducted on these approximated duty cycles are rarely confirmed using experimental data [17].

This paper provides real world battery degradation data of commercially available EVs using plug-in telematics equipment to monitor the vehicle and battery signals from the on-board diagnostics (OBD II) port. The battery signals are used to monitor the battery state of health (SoH) and the vehicle signals are used to analyze and identify system-level degradation factors impacting EVs. The Nissan LEAF, Toyota Prius Plugin, Ford Fusion Energi, and the Ford Focus EV degradation rates are presented, and the 2011-2012 Nissan LEAFs model years are used to identify the probable degradation factors.

2 Methodology

With more than three years of data collection, this study examined the battery performance of more than 900 plug-in electric vehicles in different geographical regions and climates in North America and Europe. All of the vehicles were equipped with FleetCarma EV telematics devices. A mix of individual EV owners and fleet operators had access to data from their vehicles through an online portal or mobile application, including dashboards and exportable reports to help track metrics of interest from their vehicle. This included personalized data on driving efficiency, battery SoH, trip and charging logs, charging efficiency, range capabilities, greenhouse gas emissions savings, and benchmarking to other EV owners or fleets.

A data-driven battery SoH estimation method (Eq. 1) is used in the FleetCarma System based on the real world driving data collected using the EV telematics devices,

$$SoH = \frac{1}{20} \cdot \sum_{i=1}^{20} \left(\frac{E_{trip,i}}{\Delta SoC_{trip,i}} \cdot \frac{100\%}{E_{new}} \right) \quad (1)$$

where the *SoH* represents the remaining percentage of a new vehicle's energy at any given time calculated from the previous 20 trips with a minimum distance of 10 km and SoC depletion of at least 10%, $E_{trip,i}$ is the *i*-th trip's energy consumption in kWh, $\Delta SoC_{trip,i}$ is the *i*-th trip's SoC depletion, and E_{new} is the energy of a new vehicle.

There are two possible forms of SoH, usable and actual, which represent the remaining percentage of a new vehicle's usable and rated energy, respectively. The usable SoH is more meaningful to drivers because it indicates the amount of energy available to them as a percentage of the vehicle's usable energy; however it is susceptible to alteration by the OEMs that expand their SoC windows as the battery pack degrades. The actual SoH is less meaningful to drivers because it represents the percentage of the full battery pack available to them, but is a more true value of the battery's real age. A list of the vehicles included in this study and their energy values are presented in Table 1.

Table 1: Vehicle Energy Values			
Model Year	Vehicle	New Energy [kWh]	Type of SoH
2011-2015	Nissan LEAF	24	Actual
2012-2014	Prius Plugin	2.728	Usable
2013-2015	Ford Fusion Energi	19.55	Usable
2012-2014	Ford Focus EV	23	Usable

For this analysis, only the Nissan LEAF was analysed with actual SoH because it was the only vehicle with the actual SoC signal available. Each vehicle model and their model years are assessed for degradation over time by averaging the data from that model year on a per month basis and applying a three-month moving average filter.

For the purpose of this study, the statistical relationship between potential degradation factors and battery SoH are examined using linear regression in Microsoft Excel with 95% confidence. Only the degradation factors that produced a p-value less than 0.1 were included in this paper. The degradation factors are calculated from the vehicle data recorded using the FleetCarma EV telematics devices. Thus, the factors do not represent the entire history of the vehicle unless the telematics devices were installed on newly purchased vehicles. Therefore, it is assumed that the recorded data is representative of the vehicle's entire history. The exception to this assumption is the vehicle's odometer because it is a state-variable tracked by the vehicle and does not need to be calculated externally.

3 Results and Discussion

3.1 Degradation Rates

The FleetCarma System contains recorded data for hundreds of vehicles that have been equipped with EV telematics devices for up to four years. This wealth of data enables an analysis of battery SoH over time for the five vehicles listed in Table 1.

3.1.1 Nissan LEAF

The Nissan LEAF contained the largest data set across five model years with more than three years of historical data (Fig.1). There is a clearly defined negative trend in battery SoH over time for the 2011 to 2012 model years, but the 2013 to 2015 model years show little signs of aging compared to their predecessors. Such a change in degradation rate would indicate an improvement to the vehicle powertrain and/or battery pack between the 2012 and 2013 model years.

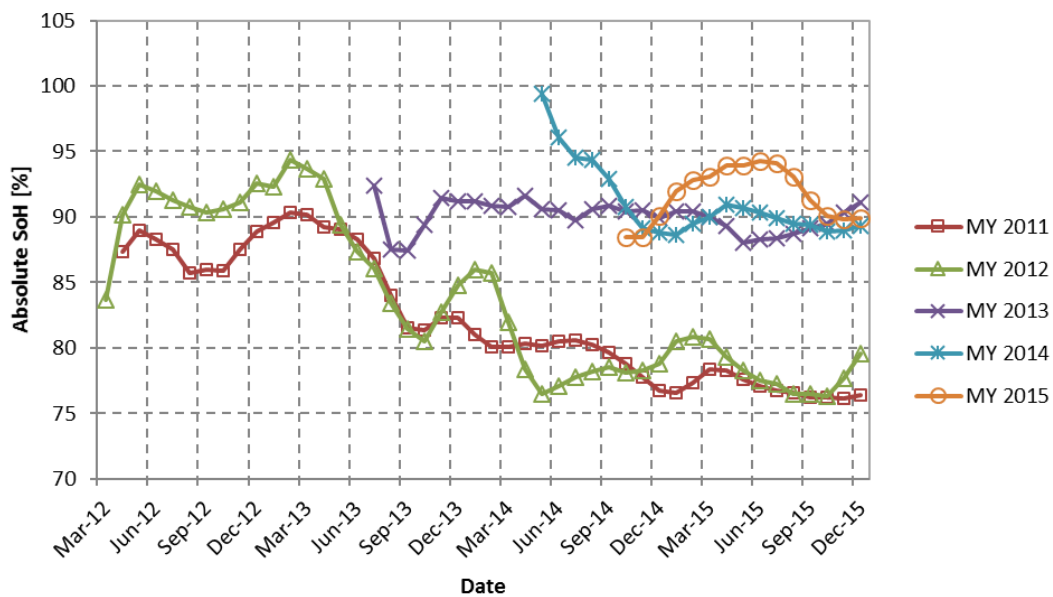


Figure 1: Progression of Nissan LEAF battery SoH over time using a three-month moving average filter

There are two interesting features when considering the Nissan LEAF degradation trends. The first feature is the similar SoH values between the 2011 to 2012 model years according to the date instead of the elapsed time since their production. It is possible that the battery packs were built at the same time and calendar aging is the primary degradation source; meaning that the battery pack for the 2013-2015 model years originated from a later batch. It is also possible that the usage history of these vehicles led to the coincidental alignment of battery SoH values between the model years. Another possibility is that there are degradation plateaus experienced by the vehicles; leading to the second interesting feature. Plateaus appear for the 2011 and 2012 model years between March 2012 and March 2013 before degradation sets in. Then 2011 to 2012 model years plateau between June 2014 and December 2015. The 2014 model year shows a large amount of degradation early on, but plateaus with the 2013 and 2015 model years at a similar value to the 2011 and 2012 model years' first plateau.

3.1.2 Toyota Prius Plugin

The Toyota Prius Plugin shows consistent degradation across all three model years (Fig.2). Since the SoH values are calculated according to the same estimated usable energy for this vehicle, the real SoH values could be slightly higher or lower for each model year. The 2014 model year has a noticeably lower SoH possibly due to a decreased usable energy that model year or an accelerated degradation compared to the earlier model years. There is no particular difference in location or odometer that would account for an accelerated degradation of one model year over any others, so it is likely a change in the 2014 model year battery pack or control strategy.

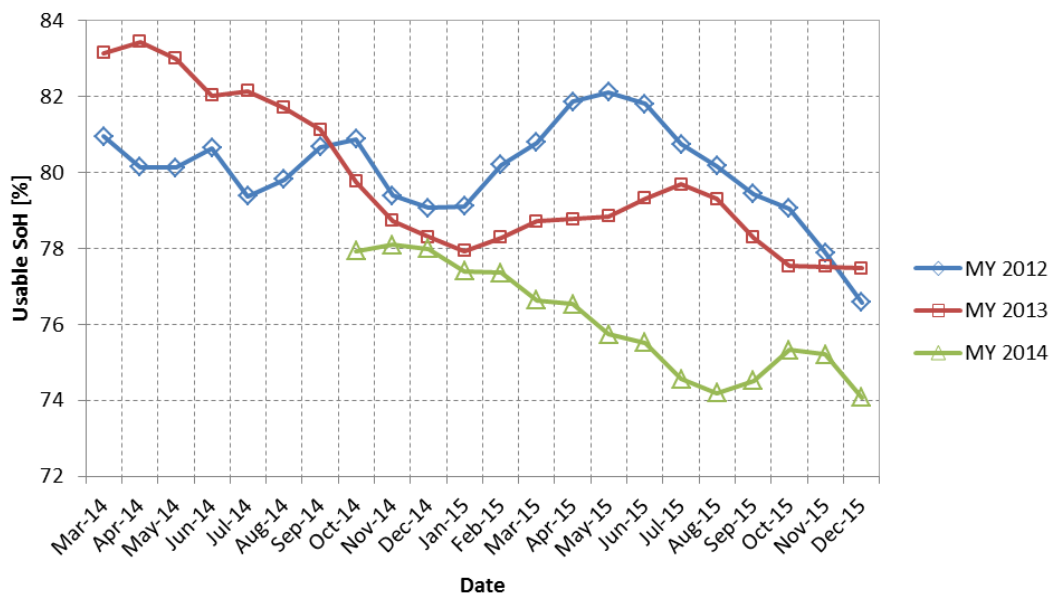


Figure 2: Progression of Toyota Prius Plugin battery SoH over time using a three-month moving average filter

3.1.3 Ford Fusion Energi

The Ford Fusion Energi also shows degradation over time with the 2013 model year degrading the most, followed by the 2014 model year, and then by the 2015 model year (Fig.3). Such an order is expected because the 2013 model year is older than its successors and therefore has experienced more calendar aging and likely more cycling aging. The 2014 model year SoH data appears to begin with significant degradation, but it is more likely that the SoH trend is decreasing as summer transitions to fall or winter. A similar deviation from the overall degradation trend occurs during the summer months of 2015 for all three model years. Similarly, all three models show a dramatic loss in SoH during the fall of 2015, but it is unlikely to continue at that rate when considering their historical trends. The 2015 model year shows very little degradation after one year of recorded data. Overall, the SoH values are high for this vehicle; even above 100%. This means that the battery provides more energy to the user per percent usable SoC than expected from the battery specifications since SoH is a relative value.

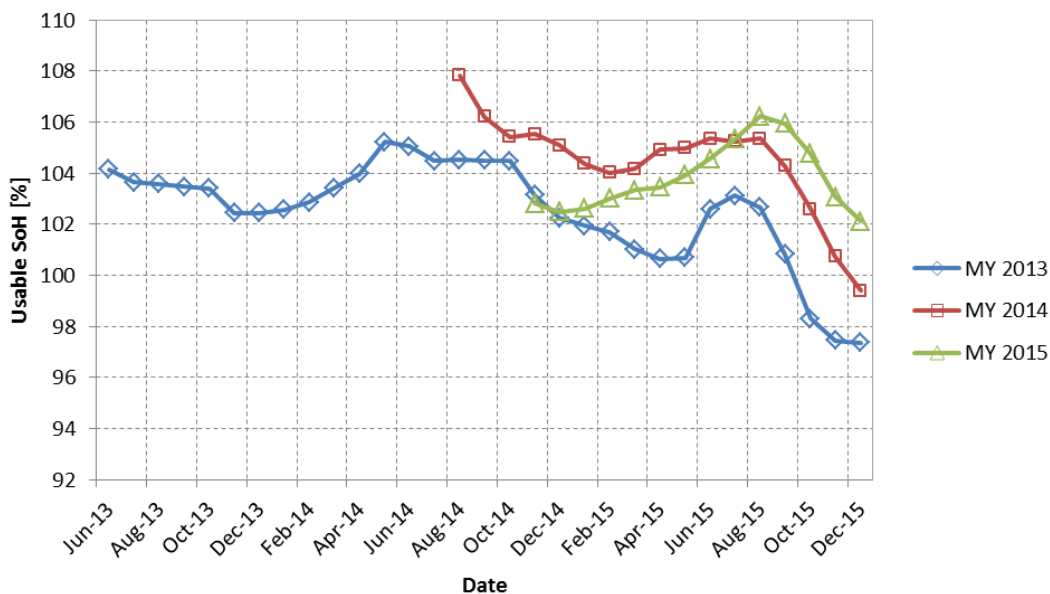


Figure 3: Progression of Ford Fusion Energi battery SoH over time using a three-month moving average filter

3.1.4 Ford Focus EV

All three model years of the Ford Focus EV show signs of degradation, but the trends are showing interesting behaviour (Fig.4). The 2013 model year has the lowest SoH, followed by the 2012 model year and the 2014 model year. Normally, the oldest model year should have the lowest SoH because it should experience more calendar and cycling aging compared to the newer model years. The steep degradation rate of the 2013 model year indicates it is degrading at a faster rate than the 2012 model year, which explains why its SoH is at 2012 model year levels. The mean odometer across all vehicles for a given model year are 28295 km, 32032 km, and 11086 km for the 2012, 2013, and 2014 model years, respectively. Despite the 2013 model year being newer, it has been driven further on average and should therefore experience more degradation than the 2012 model year. While the 2014 model year's degradation rate agrees with the analysis thus far, it does show significant seasonal dependency that the other model years do not. This is due to the large number of trips recorded by one vehicle in Maine, USA, which experiences more temperature variations between seasons compared to the other vehicles in California, USA, with fewer recorded trips. The other model years do not share this seasonality because they have a more distributed sample set.

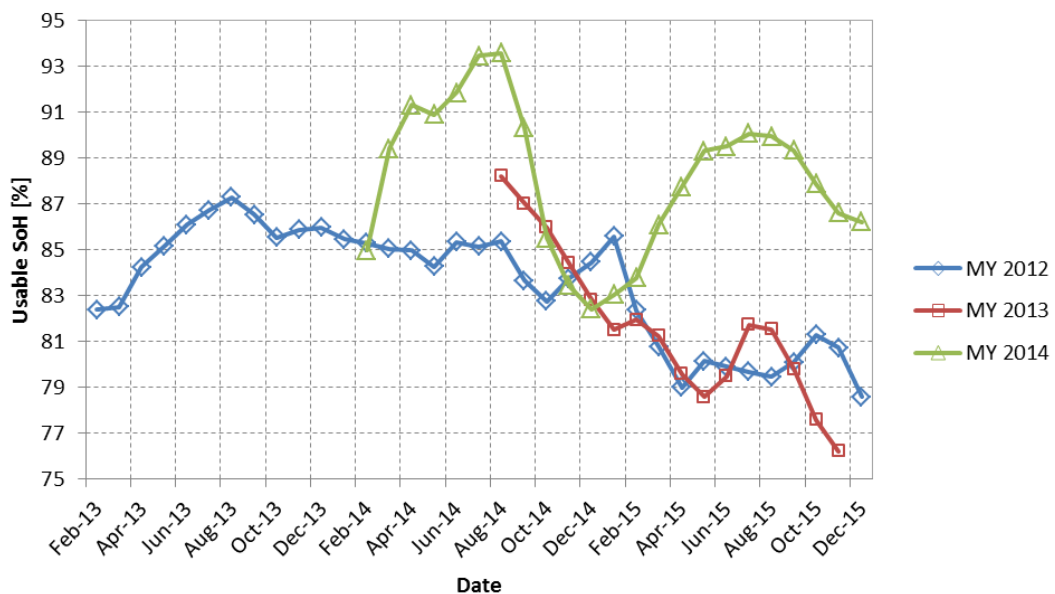


Figure 4: Progression of Ford Focus EV battery SoH over time using a three-month moving average filter

3.2 Degradation Factors

The 2011-2012 Nissan LEAF model years provide a large data set of actual SoH values ideal for assessing degradation factors involved in aging the battery pack. Over 30 degradation factors were considered, but only vehicle odometer, annual mean temperature, mean daily charge energy, mean daily DoD, and mean vehicle speed had a statistically relevant correlation with SoH.

The first degradation factor to be considered is vehicle odometer because it represents the age of the vehicle in terms of usage (Fig.5). The driven distance of a vehicle is generally proportionate to the number of charge/discharge cycles that battery lifetime curves are typically plotted against. It was determined that vehicle odometer has a linearly negative correlation with SoH that accounts for 7.57% of the variability in SoH. Therefore, to some extent, the further the vehicle is driven, the more the battery degrades.

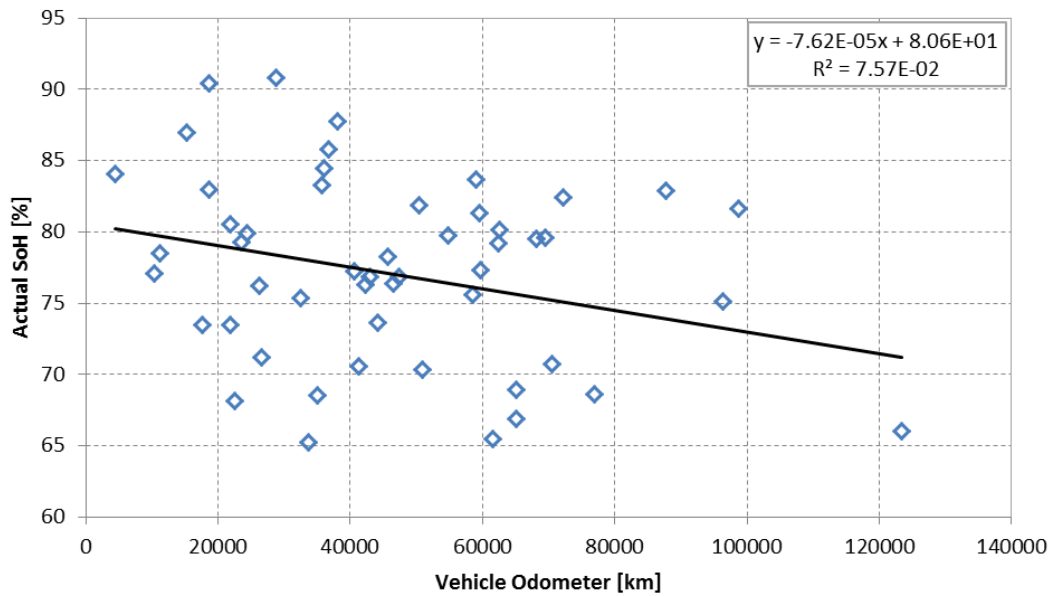


Figure 5: Linear regression fit of battery SoH for 2011-2012 Nissan LEAFs with vehicle odometer, p-value = 0.0484

Since the vehicle odometer is clearly a degradation factor and represents the vehicle's usage, the subsequent degradation factors will be analysed against an actual SoH value corrected to a vehicle odometer of 60000 km. This correction was necessary to be able to compare vehicle data assuming the vehicles have the same amount of usage.

After correcting for odometer, the geographical location of each vehicle was identified and the mean temperature in 2015 for that location was recorded. The odometer-corrected actual SoH values were then compared to the annual mean temperatures to show a linearly negative correlation that accounts for 25.68% of the variation in SoH (Fig.6). Such a correlation indicates that the battery SoH decreases as the environmental temperature rises, within the temperature range studied. This result agrees with reports from Nissan LEAF owners in Arizona, USA that experienced accelerated degradation from the excessive heat. It also agrees with many sources reviewed by Rezvanizani et al. [4] that suggest battery life should decrease more rapidly with hot temperatures. Battery life is also expected to decrease with very low temperatures [4], but this study did not include enough data in very cold weather to make a definitive conclusion on this matter. Some variation in the results below could be due to the vehicle owners storing the vehicles indoors, effectively increasing the annual mean temperature that the vehicle actually experiences.

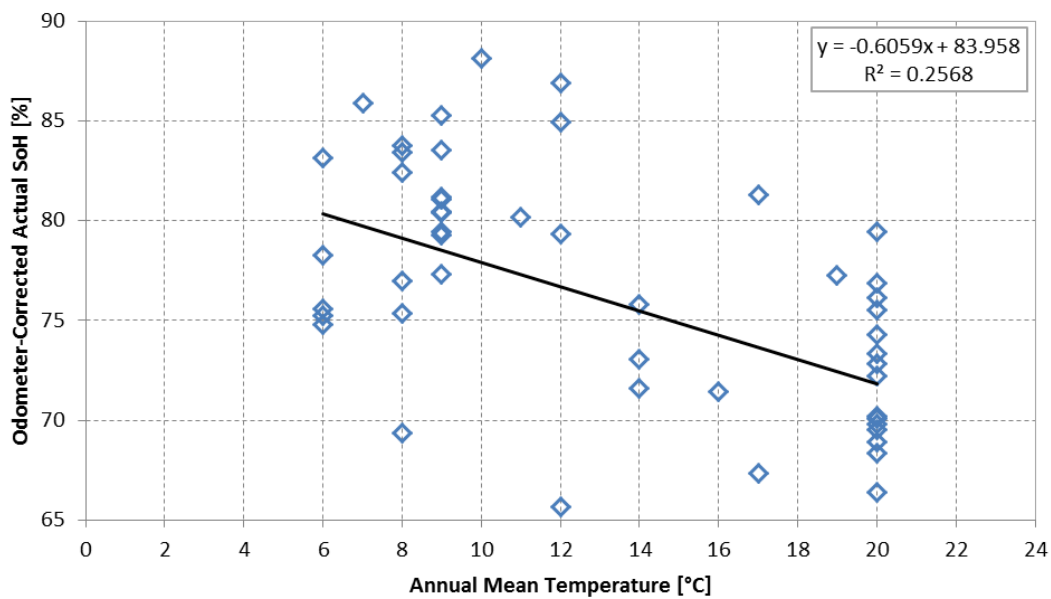


Figure 6: Linear regression fit of battery SoH for 2011-2012 Nissan LEAFs with annual mean temperature, p-value = 0.0001

The residuals from the previous analysis indicate that there are more degradation factors affecting battery SoH that have not been considered yet. The mean daily charge energy is another degradation factor expected to impact battery life since the parasitic reaction that occurs in lithium ion cells is most prevalent during charging. The statistical analysis highlights this relationship with a negative correlation between the odometer-corrected absolute SoH and the mean daily charge energy that accounts for 7.5% of the SoH variation (Fig.7). Therefore, drivers that charge more in a given day than their counterparts will degrade their battery packs more quickly.

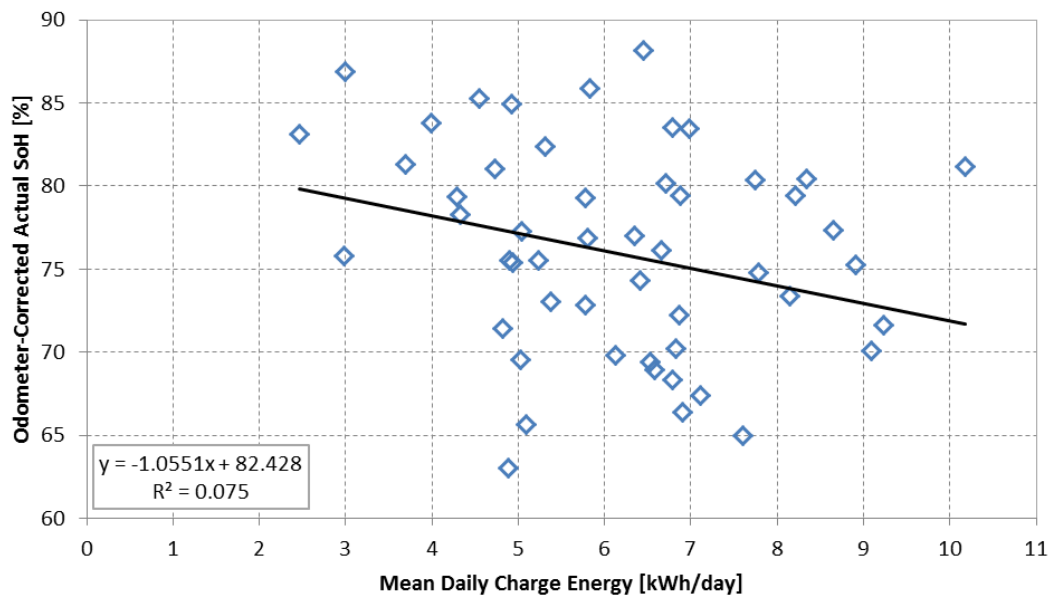


Figure 7: Linear regression fit of battery SoH for 2011-2012 Nissan LEAFs with mean daily charge energy, p-value = 0.0495

A weaker negative correlation also exists between the odometer-corrected actual SoH and the mean daily DoD (Fig.8). The negative correlation accounts for 6.78% of the variation in SoH. This relationship agrees with the results from the dependency on mean daily charge energy because consuming more energy in a

day requires more daily charging to return the battery pack to its original SoC and leads to more degradation.

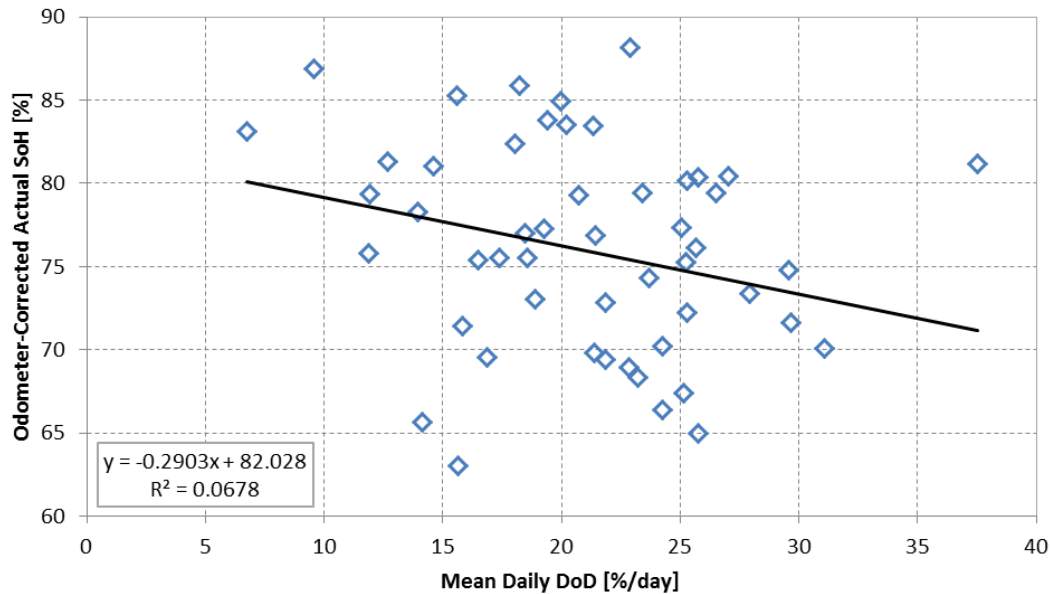


Figure 8: Linear regression fit of battery SoH for 2011-2012 Nissan LEAFs with mean daily DoD, p-value = 0.0623

Another weak relationship exists with a negative correlation between the odometer-corrected actual SoH and the mean vehicle speed that accounts for 6.47% of the SoH variation (Fig.9). This trend suggests that the battery experiences more degradation if driven at higher speeds. This is somewhat connected to the mean daily charge energy and mean daily DoD because driving at a higher speed suggests long-distance driving that consumes more energy and thus requires more charging in a given day. Interestingly, it was expected that lower speeds indicative of city driving would lead to more degradation due to the power pulses from accelerations and regenerative braking. However, it appears that the constant power from high-speed driving has a stronger effect on battery degradation than the high-power power pulses from city driving.

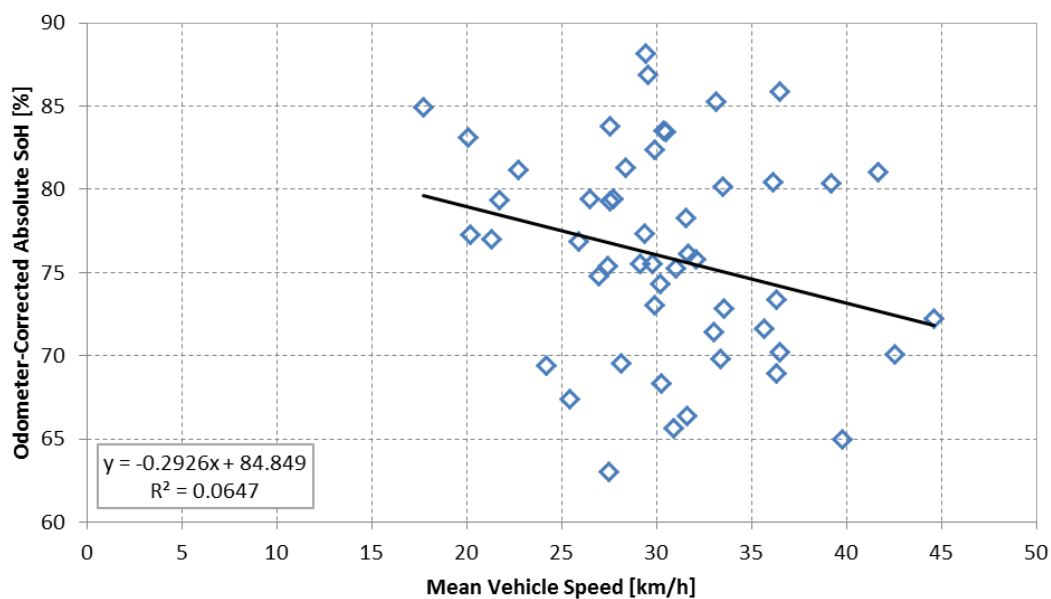


Figure 9: Linear regression fit of battery SoH for 2011-2012 Nissan LEAFs with mean vehicle speed, p-value = 0.0688

4 Conclusions

Collecting up to four years of data on over 900 EVs was made possible by the FleetCarma EV telematics system. Individual EV owners and fleet operators are able to access this data, which includes driving efficiencies, trip and charging logs, charging efficiency, range capabilities, greenhouse gas emissions savings, and battery SoH. Battery SoH is an important metric to monitor because it reveals the seasonal variation and annual decline of energy available to the driver that will directly impact their range.

A review of battery SoH data over time was conducted for the Nissan LEAF, Toyota Prius Plugin, Ford Fusion Energi, and the Ford Focus EV. In addition to showing degradation with time, the analysis revealed a correlation between battery SoH and changing seasonal temperatures for most of the vehicles. Out of all the vehicles included in this analysis, the 2011-2012 Nissan LEAFs contained the largest set of data over the longest period of time with clear degradation and limited seasonal effects; making it an ideal data set for analysing possible degradation factors.

Over 30 possible degradation factors were assessed for their impact on battery SoH of the 2011-2012 Nissan LEAFs. It was determined that driving further distances, operating the vehicle in hotter temperatures, charging the battery pack more in a given day, discharging the battery pack more in a given day, and driving at higher speeds all accelerated battery degradation. The most important result from this analysis is a clear relationship between usage and age; meaning the battery will degrade more as the vehicle is used more. However there was significant noise in the analysis of those five key degradation factors, indicating that battery degradation is a function of many different factors and their complex interactions – no two EV drivers will experience the exact same degradation due to the myriad of factors involved. Fleets or EV owners who are particularly concerned about battery SoH and the associated range reduction implications will likely be best served by monitoring their vehicle's SoH directly using a telematics device.

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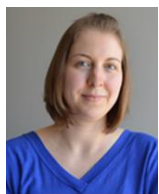
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