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An Analysis of Charging Practices and their Impact on Battery Degradation in North American Electric Vehicles Built Between 2010-2020

A Dissertation

Presented to

The College of Graduate and Professional Studies

College of Technology

Indiana State University

Terre Haute, Indiana

In Partial Fulfillment

of the Requirements for the Degree

Doctor of Philosophy (Ph.D.) in Technology Management

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by

Douglas William Edward Ferrier

May 2022

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Keywords: Technology Management, Electric Vehicle, charging, Tesla Supercharger, battery degradation, State of Health, CHAdeMO, CCS, real world, J1772

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ABSTRACT

Electric vehicles (EVs) are emerging as a component of the global solution to combat climate change. However, in North America, particularly in the United States and Canada, the transition away from internal combustion engines (ICE) has been slow. North America faces unique challenges due to its geographical size and population in comparison to other continents. The good news is that EV adoption is increasing within North America. Along with increased EV adoption, governments and public companies are constructing charging infrastructure to support increased consumer EV purchases. Despite increased adoption, many future and current owners throughout North American society have concerns about an electric vehicles' key feature: the battery.

Many EV owners are concerned about the battery's State of Health (SOH) – how to keep batteries healthy and use best practices to keep their range at maximum capacity. SOH is influenced by five key factors: (1) temperature, (2) charge/discharge rate, (3) charge/discharge depth, (4) cyclic charging, and (5) ending State of Charge (SOC). This study primarily focuses on data centered around charging.

This dissertation examines data generated by everyday EV users and uses it to predict how charging habits affect batteries over time. Charging effects include decreasing battery SOH and capacity degradation. Lowering the SOH reduces the battery's viability for continuous use; at approximately 70% SOH the battery is 'typically' deemed End of Life (EoL). The overall range of the EV is affected by capacity degradation; as batteries degrade, the total km (or miles) available decreases. This study uses regression analysis to examine relationships and predictors of SOH, temperature, levels of charging, and SOC. The data collected and analyzed determine best practices for charging batteries at home and abroad for consumers. There were two methods for analyzing data: (1) Using EV generated data (SOH, Charger Type) saved in CSV files via a smartphone application, and (2) Analyzing consumed energy in a large dataset using a segmentation process based on equivalent SOC differences between two points in time. The current study makes use of one of the largest datasets of "real world" data ever collected from EVs in the United States and Canada, with over one million lines. Eighteen models of EVs are used to make comparisons for amounts of degradation over one year. A discussion of how these findings affect EV owners' usage of models from 2010-2020 is included. Multiple recommendations for future studies are provided.

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A special thanks to my dad and mom. My dad was always concerned his children get an education and all three did! Thanks for supporting my undergrad and first graduate degree at ISU – it helped my interest in continuing my schooling. To my mom, I think the "Challice trait" of excelling at public speaking and always looking at the end result has helped me drive forward throughout my education.

To my children, Amy and Justin, I love you lots and hope you go far in school! I did this to show how you can do anything you set your mind too! It took almost six years of hard work. I look forward to reading something you have published in the future.

I would have never made it through my first degree at Indiana State without my grandparents. All four of my grandparents were alive during my first stint at ISU. Both sets of

grandparents were influential in my growth as a person. My grandma Ferrier would be very proud. My grandpa Ferrier was a very bright person working on famous aircraft in Canada and hopefully his intelligence has trickled down to me.

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CHAPTER 1

INTRODUCTION

Climate change is having an effect on the world we live in. Corals are dying in the oceans, smog is covering our cities, and the polar ice caps are melting. Cars and trucks that run on fossil fuels have been polluting our air and water for over a century. With the mass production of electric cars beginning in 2008, a transition away from fossil fuels began. This transition to electric vehicles (EVs) began globally. Norway and the United Kingdom are leading the way in removing Internal Combustion Engine (ICE) vehicles from their roads. In many countries, federal and state governments have provided consumers with incentives to purchase EVs in order to discourage ICE vehicle consumption. EV purchase incentives and a focus on lowering greenhouse gas emissions have resulted in increased EV adoption globally.

EVs are becoming more popular, while ICE sales are decreasing. Global car sales fell by 16% in 2020, but EV sales increased by 41% to around three million vehicles. In 2020, consumers spent approximately $120 billion on EVs (EV sales soared, 2021). The same global vehicle consumption pattern was observed in the United States. Only three of the twelve vehicle manufacturers in the United States increased sales in 2020, including Tesla. Tesla only manufactures electric vehicles. Tesla increased vehicle sales the most compared to the other two manufacturers, Mazda and Volvo, with +20.3 percent versus +.2 percent and +1.8 percent, respectively (Hurd, 2021). This increase in sales is being driven by the popularity of the Tesla Model 3.

Although electric vehicles are becoming more popular, the United States and Canada lag far behind in terms of EV purchasing, as a percentage of the population, when compared to many European countries. The various levels of government in North America including Federal, Provincial, and State, emphasize that they will "catch up" through promotion and infrastructure development. Large-scale EV infrastructure projects developed in many European countries but yet to be implemented in states and provinces across Canada and the United States are one reason for the slow adoption of EVs in North America. As recently as 2019, there were few Level 3 (DC Fast) chargers in western New York state or Southwestern Ontario, Canada, to support EVs on trips of two hours or more. To support longer trips, charging infrastructure must be convenient for consumers in terms of both time, using fast charging, and location. Due to the lack of convenience because of required charging time and an undeveloped charging infrastructure in 2022, ICE vehicles will continue to be consumed at high rates.

Mass Producing EVs

Tesla and Nissan were among the first companies to mass-produce electric vehicles. Tesla began production of the Roadster in 2008. The Roadster is an all-electric sports car that was far beyond anything else marketed by a car company in 2008. One distinguishing feature is its range, which is twice that of previous EVs built before 2008. (Mangram, 2012). When compared to previous EVs, the large range assisted Tesla in gaining popularity in the EV market, ultimately leading to market dominance. Although the general public could purchase a Roadster, the price was more than $80,000 USD ($100,000 CDN), placing it out of reach for the vast majority of consumers. Nissan built the Leaf not long after the Roadster was released. The all-electric Leaf debuted in 2010, but it was not yet ready for mass production. Both electric vehicles, the Nissan Leaf and the Tesla Roadster, were widely available to consumers in 2012 versions. The Leaf charges at Level 3 speeds via a CHAdeMO port and Level 2 using a J1772 connector port. Tesla has a proprietary connector solution for charging at home and its SuperChargers. Since J1772 port chargers are the most commonly used type for public charging, Tesla created an adapter to work with them. The majority of EV charging was done at home using a 120V connection or a proprietary charger for early adopters. The Leaf was a more affordable EV that was available to the general public in the United States in 2010. In 2010, the Leaf was priced at $35,000 USD ($43,000 CDN). These two vehicles from Nissan and Tesla influenced other manufacturers, including Ford, General Motors, Kia, and Hyundai, to become involved in the development of EVs. As of 2019, there were over 82,000 charging stations available to the public (Plugshare.com, 2021).

The Nissan Leaf went into mass production in 2012, despite being available in multiple markets, including the United States, since 2010. Kinoshita et al. (2013) created an article "Newly Developed Lithium-Ion Battery Pack Technology for a Mass-Market Electric Vehicle" where they provide an overview of the Nissan Leaf and its lithium-ion battery pack. Nissan employed all six of the authors. The physical construction of the battery pack and its structure are shown in Figure 1, this includes the BMS (Battery Management System). The BMS is included in EV development to help maintain battery health by monitoring cells. A conclusion from the Kinoshita et al., 2013 article is EVs should develop smaller, lighter, and less expensive battery packs suitable for global mass manufacturing. The newly developed battery pack should scale comparable to vehicle mass-production because it will be an important factor in supporting the widespread diffusion of EVs (Kinoshita et al., 2013). One important omission from the

Kinoshita et al. (2013) article is about how to charge the EV battery pack. Charging is such an important factor in mass deployment because users are not driving an EV in a closed environment. EV battery charging is critical, as discussed by Tomaszewska et al., 2019, Figenbaum, 2019, Yang et al., 2018, and Collin et al., 2019. Weight is an important aspect of an EV, but so is charging. The battery and charging system must be viewed as a process for improved societal acceptance of EVs; this review was overly focused on how the car was mass-produced.

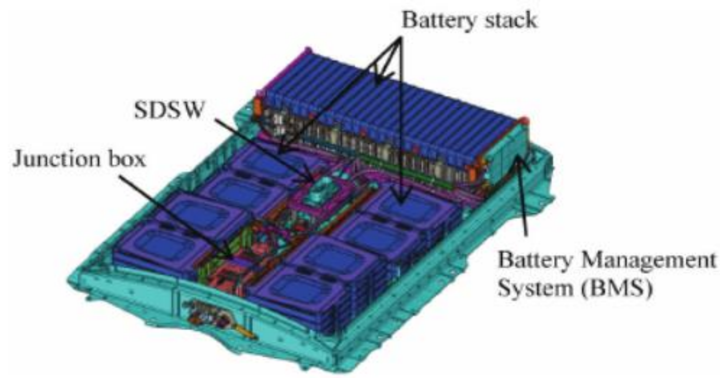

*Figure 1***.** Battery pack configuration for a 2010 Nissan Leaf

Note. Design of a 2010 Nissan Leaf battery pack including BMS. From *Lithium-Ion Batteries in Electric Drive Vehicles* (p. 7), Pesaran, A. (Ed.)., by Kinoshita et al., 2013. Copyright 2016 by SAE International. Reprinted with permission (see Appendix IV).

Charging Basics

A Nissan Leaf EV can charge at approximately eight km (five miles) per hour using a 120V electrical outlet in 20℃ (68˚F) weather. The inconvenience of waiting twelve hours for less than 100 km (62 miles) at home discourages many consumers from adopting an EV, so developing Level 2 and 3 charging infrastructure across North America is critical according to Egbue and Long. Egbue and Long (2012) discovered that barriers to EV adoption included battery range, cost, and charging infrastructure. The ability to drive to work or attend a baseball game and charge while owning an EV needs to become convenient. One group of researchers reviewed studies involving annual EV miles traveled; their findings indicate an increase of 25% or more chargers is required in areas where drivers have access to DC fast charging stations (Yang et al., 2018). Furthermore, researchers offer a suggestion that both safe and fast charging of lithium-ion batteries will lead to successful adoption for EVs (Wandt et al., 2018).

Based on the experiences of the author, how to "properly" charge with Level 2 and 3 chargers is a topic that EV owners frequently discuss at public charging stations. The author has had many EV owners remark about charging to 80 percent SOC with a Level 3 charger because it is the best value and it could cause battery pack damage after that point. What happens when a continuously charged battery reaches 85 percent or 100 percent capacity on a Level 3 charger? There is little research and literature for consumers to discuss the exact charging levels that could degrade their battery over the life of the EV.

There was talk from the Society of Automotive Engineers (SAE) about standardizing a format for charging EVs as early as 2009. For charging EVs, a J1772 connection, as shown in Figure 2 on the right side, was chosen as the standard for North American vehicles. The J1772 choice was motivated primarily by concerns the EVSE could handle three functions: ac-dc rectification, voltage regulation, and a physical coupling usable by the operator (Tuite, 2011). One of the standard's primary functions is to define an interface that an EV owner can use safely, with safety implying both protection from electric shock and protection of the charging electronics and traction battery (Tuite, 2011). J1772 connectors continue to be one of the most used types for charging EVs as of 2020.

Figure 2. Nissan Leaf Level 2 and 3 Charger Ports

Note. The charging ports located at the front of a 2017 Nissan Leaf. The left is the CHAdeMO Level 3 port and right is the Level 2 J1772 port. The left port can only use Level 3 connectors and the right port only Level 2. (Ferrier, 2021)

From 2010 to 2020, electric vehicles in North America were charged in four different ways. This study will employ all four charging methods. Level 1 charging is accomplished by connecting a cable to the EV via a J1772 connector on one end and a standard 120V three-pronged plug on the other. The three-pronged plug is used with a 120V electrical outlet, which can be found in homes and businesses throughout North America. A 240V power supply is connected to an EV via a J1772 connector for Level 2 charging. Level 2 chargers are installed in private homes, malls, businesses, parking lots, and carpools across North America. In most cases, using a Level 2 charger is inexpensive costing around $1.00 - $2.00 US dollars per hour at the time of writing. Level 3 chargers, also known as DC Fast chargers, are most found in commercial buildings or parking lots. DC Fast chargers are powered by a 480V power supply. In North America, three connection ports are used for employing DC Fast chargers – (1) CCS, (2) CHAdeMO, and (3) Tesla V3. Many domestic vehicles, including Ford and GM, use CCS connections. Manufacturers such as Kia, Mitsubishi, and Nissan use CHAdeMO connections. CHAdeMO chargers are also popular in Europe, but not so much in North America. Using a public Level 3 charger usually comes at a per minute cost. The Tesla V3 Supercharger is the third and only proprietary connection. Tesla built their own charging stations across North America. The Superchargers can only be used by Tesla vehicles at the time of writing. Every year, Tesla vehicle owners receive 400 kWh of free power from Superchargers. After owners consume the first 400 kWh, using a Supercharger incurs a fee. All three of these methods will appear in log files created by data loggers or the BMS ECU (as 1,2,3) (Electronic Control Unit). When used with a data logger, Tesla V3 Superchargers appear as Level 3 in log files. Tesla V3 Superchargers have a maximum charge rate of 250 kWh.

Consumers in the United States purchased 244,713 EVs in 2019. (Crider, 2020). Along with the increase in purchases, there has been an increase in charging stations. Figure 3 depicts a starting point, in the United States, of approximately 5,000 public stations in 2012, rising to over 82,000 by 2019. Public charging stations are now available in public places such as department stores and hotels. Customers are taking advantage of opportunities to use public transportation to make their lives easier. Unlike ICE vehicles, however, EV batteries can be negatively impacted by a variety of factors, including charging at various SOC levels (Redondo-Iglesias et al., 2020).

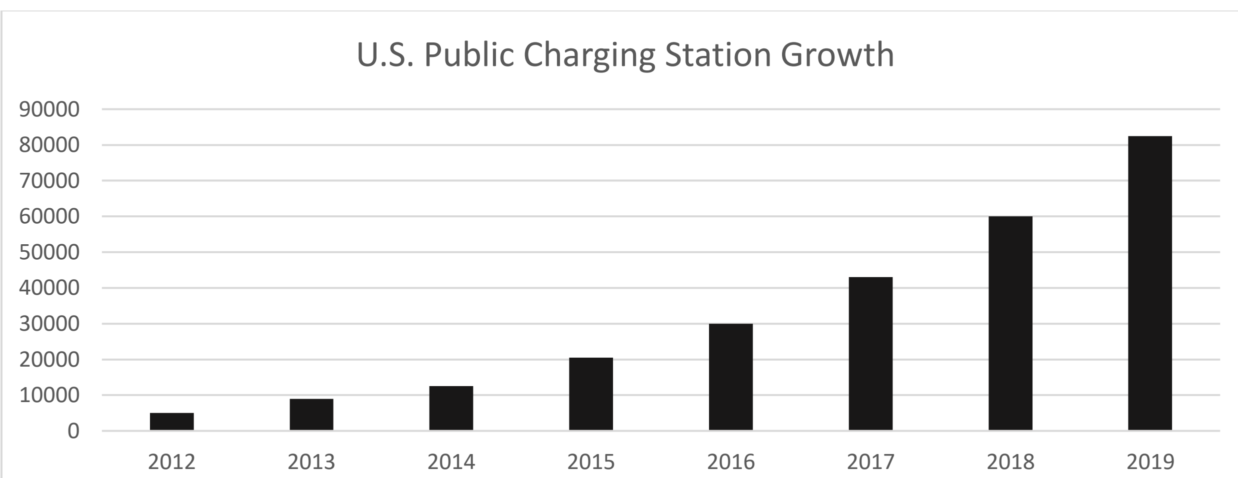

Figure 3. U.S. Public Charging Stations

Note. Plugshare is a smartphone app available to help EV consumers (or potential ones) find charging stations around the world. Data from *Plugshare.com, 2021*.

Big Data Analysis

Big data technologies will be utilized in the current study because they have transformative potential and significant opportunities for various aspects of human life (Jena, 2020). Many businesses use "Big Data" to improve business practices through analytics. What exactly is "Big Data?" The most used definition of big data comes from a Gartner Group revision in 2013: Big data is high-volume, high-velocity, and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation (Sicular, 2013). FleetCarma, part of the Geotab company, created one of the largest EV datasets which included monitoring 1,000 EVs, including PHEVs, across Canada for more than two years. FleetCarma's dataset contains 941,142 lines of data generated by EVs. Combine 941,142 rows by 11 columns to get a total of 10,352,562 data cells. Vehicle Make, Vehicle Model, Province, Start Time, End Time, Charger Energy, Charger Loss, Charging Level, Start Session SOC, End Session SOC, and Charge Location are included in the dataset. This study incorporates a portion of their dataset.

Generating Data from “Spy” Software

The Nissan Leaf and Kia Soul EV are two popular types of EVs purchased by consumers during the study's target years. To learn more about the internal systems and battery packs of both EVs, software developers created smartphone applications. Leaf Spy Professional (Pro) and Kia Soul Spy were developed. Nissan Leaf data will be collected using Leaf Spy Pro and saved in CSV files as reporting logs. Leaf Spy Pro connects to a Nissan Leaf's OBD2 port via a Bluetooth dongle, as shown in Figure 4, to provide data such as battery health (SOH). Kia Soul

Spy owners, like Leaf Spy owners, can use a similar connection, smartphone plus a Bluetooth dongle, to generate and collect data in log files. For an hour trip, the data generated by various Spy Apps is frequently over a thousand lines contained within a single CSV file. A thousand lines of data are spread across 159 columns of data generated by Leaf Spy Pro– this amounts to an accumulation of "Big Data" across a year for just one EV.

Figure 4. Bluetooth Dongle connector for the OBD2 port

Note. A Bluetooth-enabled dongle used for sending data to a smartphone application which interprets and saves EV diagnostics. (Ferrier, 2020)

Other Logged Data

Other EVs, such as the BMW i3, Kia Niro, and Chevrolet Bolt, produce seven or more columns of data in a charging report. Charging reports, like "Spy" log files, are stored in CSV files. The log files contain the following information: Start Date, Duration, Charging Power (Level), Charger Energy (kWh), Charger Loss (kWh), Start SOC (%), and End SOC (%). Unfortunately, no SOH is reported in any of these log files; this will have to be calculated as part of the current study. This study includes all three EVs, the BMW i3, Kia Niro, and Chevrolet Bolt.

Terminology

This dissertation employs several terms. A brief description for such terms is provided below:

Big Data

Big data is high-volume, high-velocity and/or high-variety information assets that demand cost-effective, innovative forms of information processing that enable enhanced insight, decision making, and process automation (Sicular, 2013). Big data can be structured or unstructured.

Electric Vehicle

Acronym: EV or EVs. Vehicles that have no Internal Combustion Engine (ICE) and are powered only by batteries. EVs do not create emissions.

Bluetooth

A short-range technology is used to connect devices to share files or information between them. Bluetooth technology is used with laptops, smartphones, and OBD2 devices such as dongles.

OBD2 Port

Acronym: On-Board Diagnostics. OBD2 ports have been included inside ICE vehicles for years. OBD2 ports can help diagnose car problems via the codes it provides a car scanner; when connected. For electric vehicles, the OBD2 port can be used with a Bluetooth dongle connected to a smartphone application for gathering information about the battery or other car features such as tire pressure.

CSV File

Acronym: Comma Separated Value. A delimited file with fields separated by commas. It is a standard format used with Microsoft products such as MS Excel and MS SharePoint.

Hybrid Vehicle

The big difference between a PHEV and an HEV (Hybrid Electric Vehicle) is how the electric motor is integrated with the combustion engine. HEV batteries are charged either by the combustion engine or by regenerative braking and are not plugged in externally (to a charging station), which limits its electric range (Panday & Bansal, 2014)

BEV

Acronym: Battery Electric Vehicle. A BEV is the original term used to discuss a vehicle solely powered by electric power. BEV was often used around 2014 and 2015. Today, in 2021, the usage is no longer BEV; it has been replaced by EV.

PHEV or Plug-in Hybrid

A Plug-in Hybrid vehicle (PHEV) has both a combustion engine and an electric motor. The electric motor can plug into a charging station which adds range to the vehicle. The electric motor can propel the vehicle independently without help from the combustion engine until battery depletion.

EVSE

Electric Vehicle Supply Equipment. In general, these are all the chargers used with EVs regardless of level.

FCEV

Acronym: Fuel Cell Electric Vehicle. These are vehicles powered by hydrogen.

SOC

Acronym: State of Charge. The amount of current battery level available in the EV. A SOC of 75% means 25% of the total available charge has been used.

SOH

Acronym: State of Health. Battery *SOH* is defined as the difference between the usable capacity and the end-of-life (EoL) capacity (Marra, Træholt, Larsen & Wu, 2010)

J1772 Connection

A standard Level 2 charger uses a J1772 connector consisting of 5 circular inputs. Public charging stations use these connections operating at 6.6 kWh for a dedicated vehicle.

CCS

Acronym: Combined Charging System. These chargers are used by GM, Ford, BMW, and Jaguar. Most chargers provide up to 150 kWh of power – these are classified as Level 3.

CHAdeMO

Acronym: CHArge de MOve, meaning: 'move by charge'. These chargers are used by Mitsubishi, Kia, Porsche, and Nissan EVs. CHAdeMO DC Fast Chargers provide up to 50 kWh of power – these are classified as Level 3.

LiOH

Lithium Hydroxide. Many lithium-ion batteries used in EVs are created using it.

LiCO3

Lithium Carbonate. Many lithium-ion batteries used in EVs are created using it.

Supercharger

A Supercharger is a proprietary charging system used with EVs developed by Tesla. There are two versions currently in use. The pre-2019 versions had a maximum output of 150 kW, but the capped value was 120 kW. Version three (v3) was released in 2019. A v3 Supercharger is capable of charging some of the Model 3s at a rate of 250 kW. Those Tesla vehicles able to use the maximum charging rate will be capable of adding up to 75 miles (120 km) of range in five minutes (O'Kane, 2019).

SEI

Acronym: Solid Electrolyte Interface (SEI). A thin film layer that grows on the anode (negative electrode) within the battery

Significance of the Study

Both the Canadian and US governments are making a concerted effort to accelerate EV adoption to combat climate change. Some provinces and the federal government in Canada provide rebates to encourage adoption. British Columbia, Canada offers $5,000 CDN ($4,000 USD) incentives for new battery electric vehicles, and a $5,000 CDN federal rebate is now available for vehicles under $45,000 CDN ($36,000 USD). (B.C. sets 2040, 2019). President Biden has goals specific to electric vehicles, including working on adding more than 500,000 public electric-vehicle charging stations over the next decade and restoring tax credits to encourage the purchase of electric vehicles (Orr, 2021).

Based on interactions with EV buyers at charging stations, there is typically little discussion from salespeople to new owners on how to recharge the vehicle to keep the battery in a healthy state over long-term ownership or lease. One EV owner who purchased the vehicle in 2021 said he was told to “not charge past 80% at fast chargers” and that’s it. The author has test-driven six EVs from various manufacturers, with only the Tesla salesperson discussing charging due to their proprietary stations. Many EV owners have adopted charging habits based on word of mouth, but there are no precise figures on how each charge affects the battery in short and long-term scenarios. The following study will summarize how charging practices, using log analysis and multiple regression, can predict battery SOH. Furthermore, charger levels from 1–3 and Superchargers will be compared to determine best practices for charging an EV. All data will be representative of "real world" conditions. The current research does not aim to develop or improve a specific technology, but rather to improve the charging process used by EV owners in everyday life. Consumers will benefit from the dissemination of findings because it will provide them with clear and objective information on how to charge their EVs based on quantitative analysis, thereby reducing battery degradation.

This research will benefit the Technology Management profession by expanding our understanding of the technologies used with EVs. For researchers, the application of “real world” data will help in deciphering differences between it and how batteries are used or tested in a lab environment. EV dealerships can use these findings for professional development of salespeople. The efficient use of charging technologies discussed here will eventually benefit society by reducing EV battery disposal in landfills and lowering air pollution by requiring less electricity generation.

Problem Statement

Consumers must understand how to properly charge their EVs; otherwise, battery degradation, resulting in less range, or other battery-related issues may occur over time. Two studies, Jiang, Shi, Zheng, Zuo, Xiao, Chen, Xu and Zhang (2014) and Lu, Han, Li, Hua and Ouyang (2013), discovered that EV batteries operating between 20% and 80% SOC exhibit excellent cycling performance with reduced capacity degradation. Outside of these values had negative consequences, resulting in degradation. In 2021, Chevrolet Bolts are experiencing battery issues because 30% of owners charge them to 100% when a maximum level of 90% is recommended (Nedelea, 2021). Some consumers may recharge to 100% on a Level 2 charger (240V), while others recharge to 90 percent on a Level 3 charger (480V); both options have negative consequences for owners including possible degradation or thermal runaway.

This research will address the problem of charger-related battery degradation in EVs. If the problem of exact battery degradation amounts caused by all levels of EV chargers is not solved, tens of thousands of consumers will charge more frequently than necessary, damaging battery packs over time. Other reasons for resolving this issue include consumers losing money due to inefficient DC Level 3 quick charging, wasting time due to slow charger output, and premature battery pack replacement. Due to general resources used to create and dispose of batteries, early replacement contributes to environmental damage. There is a significant gap in current knowledge about consumer charging techniques between owners who use "real world" EV batteries and researchers' findings from lab experiments—this study aims to close that gap. Addressing this gap will result in proper charging procedures being passed on to consumers via promotion of these findings and follow-up educational activities based on analysis of current EV owners.

Research Questions

The research questions in this study pertain to North American EV owners and those researchers interested in “real world”, not lab-based, studies. Based on this audience, the following questions need answering to provide clarity on the issue of charging EVs and battery degradation:

1) What are the effects of various types of charging (Levels 1-3, SuperChargers) on battery pack degradation for North American EVs built from 2010-2020?
2) Based on data analysis, how can altering charging practices lessen battery degradation in EVs used by North American owners?
3) What is the impact of an above-average battery pack size on the speed of degradation in North American EV models?

4) Out of the North American EV models, what battery packs degrade at the fastest and slowest rates?
5) How much of an impact does temperature have on different levels (1-3, SuperChargers) of charging for North American EVs?

Assumptions

Since early 2017, the author has owned an EV and has charged it in Ontario, New York, and Pennsylvania. The author has met several EV owners at public charging stations and talked about charging. Therefore, based on these discussions, the author has been presented with commonly known charging practices among consumers. Other written discussions about how EV owners charge their EV have occurred through numerous postings, read by the author, on social media.

It is assumed sample data collected represents the EV population owned from 2010 to 2020 in North America because of the large dataset provided by FleetCarma, a third-party EV research company. Due to data privacy concerns, the dataset will not be made available. The FleetCarma study included over 1,000 electric vehicles, including plug-in hybrids (which are excluded from the current study). FleetCarma's study, titled "Results from the World's Largest Electric Vehicle Charging Study," includes 727,000 EV charging events from across Canada (FleetCarma, 2019). It is assumed that the data will be applicable to EVs driven in northern states (the United States) and Canada. Participants used a variety of chargers (FLO, ChargePoint, Sun Country, Electrify America, Tesla, and so on) and Levels 1-3. The data supplied by EV consumers will span multiple months for the same EV, providing a good cross-section of charging activities. Because of groups called Nissan LEAF Owners USA and Canada Nissan

Leaf Owners, it is assumed that many of the social media forums where information about the study is focused had citizens from the United States and Canada.

It is assumed that the data loggers and smartphone applications used in this study are accurate. The data submitted is assumed to be unaltered and correct. The same data will be generated by various smartphones. Bluetooth connections will be used to connect to smartphones. Bluetooth dongles of various types will be used to connect to smartphone applications. All data is generated by the EV. EV owners will send CSV files via e-mail, and it is assumed no manual changes to numbers, SOH, dates, or charger level will be made. Participants will send data with the understanding that precise location information (longitude/latitude) will be removed from the files. It is assumed that people submitting data wanted to help the researcher for altruistic reasons and because of their interest in the EV community.

Limitations

There are limitations to this study. The current study only includes North American EVs from 2010 to 2020; no European model data was requested for manufacturer comparisons. However, European data was requested to help validate the processing of North American EV data. There is no data for the 2008-09 Tesla Roadster or 2021 models. Data on hybrid and plug-in hybrid vehicles is irrelevant to this study and will not be collected. None of the generalized findings will apply to Roadsters from 2008 to 2009, 2021 models, hybrids, or plug-in hybrid battery packs. There are additional limitations to the CSV files submitted by 2010-2015 EV owners because few were sold, consumers did not retain or store their generated data, and few smartphone applications were developed to provide owners insight into the behaviour of their vehicles. Only 67,944 electric vehicles were sold in the U.S. in 2015 (Argonne, 2020). The Leaf Spy smartphone application (for Nissan Leafs) began distribution in 2013.

The location of EVs is limited to Canada and the United States. Since a large dataset is being provided by FleetCarma (part of GeoTab), a Canadian company, most data were from Canada. Due to the large amount of data from Canada, the results may not be applicable to the southern states. The average temperature in Canada is much lower than in southern states such as New Mexico, Florida, Georgia, Arizona, and Texas. The country's data is unbalanced for three reasons: (1) No company or federal government department in the United States has ever conducted a large, comprehensive, multi-year study on EVs like Canada has (via FleetCarma), (2) Participation through social media forums has been minimal by U.S. participants, and (3) The U.S. has been slow to adopt EVs (compared to places such as Quebec, Canada, and British Columbia, Canada) before 2020 which limits the amount of historical data available.

Data collection may be limited. Social media postings were featured in a variety of areas; however, many forum participants did not save or store their historical data, removing some of the randomness from data collection. There are fewer EV groups on Facebook for US owners than for Canadians, limiting access to US data. Those with historical EV data can participate, including those who no longer own one but have saved CSV files. In 2021, all data will be collected. When comparing SOH, not all data from EVs is the same, and alternate calculations are required. Data loggers generate far less data than their smartphone "Spy" software counterparts, leading to more difficult calculations.

Data analysis may be limited around EV models. There may not be enough data retrieved from certain EV models to conduct accurate comparisons to others. In the case of limited EV model data, comparisons will be removed.

CHAPTER 2

LITERATURE REVIEW

There have been many articles written on different topics about EVs and their batteries since the 2000s. Important topics related to EVs include alternatives to charging (battery changing), batteries, temperature, SOH, calendar aging, cycling aging, and DC fast charging. Batteries are the most important part of an EV, so that topic is divided into sub-sections such as lithium plating and basics. This dissertation begins with examining what has occurred in the recent past so mistakes are not repeated, and successes are built upon for future solutions.

Brief History of Battery Packs

EV batteries have changed over the years in terms of size – they are much bigger in 2020 compared to 2010. “Older” EVs such as the 2015 Chevrolet Spark or 2015 Mitsubishi iMiev started with small battery pack sizes of 20 and 16 kWh, respectively. Similarly, the original Nissan Leaf and Tesla Roadster have much smaller batteries than their predecessors. The mass-produced 2012 Leaf uses a 24-kWh battery pack while 2008-2012 Tesla Roadsters employ a 53 kWh. As EVs have matured, so has the size and development of battery packs. Nissan Leaf battery packs moved from 24 kWh to 30 kWh to the current model. 2020 Leafs use a 40-kWh battery pack, and a 2020 Tesla Model X 100D utilizes a 100 kWh. There were no Tesla Roadsters built the last few years, but a new model has been announced for 2022, and it may include a 200-kWh battery which would be the largest available on any EV. Table 1 clearly shows that most EVs built from 2010-2020 use a battery pack of 30 kWh or more, with larger batteries appearing around 2018-2019. Battery size was a factor considered in this study. As size of batteries increase, so have needs to keep charging convenient for consumers. Aside from charging, other alternatives have been tried making EVs more convenient on long-distance trips.

Table 1

Models, manufacturers, battery pack sizes for EVs included in dataset

Make and Model	Year	Battery Pack (kWh)	SOH
Nissan Leaf	2013	24	Leaf Spy
Nissan Leaf	2014	24	Leaf Spy
Nissan Leaf	2016	30	Leaf Spy
Nissan Leaf	2017	30	Leaf Spy
Nissan Leaf	2018	40	Leaf Spy
Nissan Leaf	2019	40	Leaf Spy
Kia Soul	2020	64	Soul Spy
Kia Soul	2019	30	SOH Calculation
Kia Soul	2018	30	SOH Calculation
Kia Soul	2016	27	Soul Spy
Chevrolet Spark	2014	20	SOH Calculation
Chevrolet Spark	2015	19	SOH Calculation
Smart Fortwo Electric Drive	2018	16.5	SOH Calculation
Volkswagen eGolf	2017	35.8	SOH Calculation
Volkswagen eGolf	2018	35.8	SOH Calculation
Volkswagen eGolf	2019	35.8	SOH Calculation

Table 1 *Models, manufacturers, battery pack sizes for EVs included in dataset* (continued).

Make and Model	Year	Battery Pack (kWh)	SOH
Mitsubishi i-MiEV	2015	16	SOH Calculation
Mitsubishi i-MiEV	2016	16	SOH Calculation
Hyundai Niro	2019	64	SOH Calculation
Hyundai Ioniq	2017	28	SOH Calculation
BMW i3	2019	42	SOH Calculation
BMW i3	2018	33.2	SOH Calculation
Chevrolet Bolt	2017	60	SOH Calculation
Chevrolet Bolt	2018	60	SOH Calculation
Tesla Model S P85D	2016	85	SOH Calculation
Tesla Model S	2016	75	SOH Calculation
Tesla Model S	2017	75	SOH Calculation
Tesla Model S 90D	2016	90	SOH Calculation
Telsa Model S P90D	2016	90	SOH Calculation
Tesla Model S 100D	2018	100	SOH Calculation
Tesla Model X P90D	2018	90	SOH Calculation
Tesla Model X 100D	2019	100	SOH Calculation
Tesla Model X 75D	2016	75	SOH Calculation
Tesla Model X P90D	2016	90	SOH Calculation
Tesla Model X P100D	2017	100	SOH Calculation
Tesla Model 3	2019	50	SOH Calculation
Ford Focus EV	2017	33.5	SOH Calculation

Battery Changing/Swapping

Battery changing or swapping stations were one of the first ideas to add convenience for EV owners. Experts wanted to implement these stations to remove long charging times by EVs (Mak, Rong & Shen, 2013). One of the first studies was entirely theoretical and created based on Israel. Mass adoption of EVs had yet to take place when the Mak et al. (2013) study was completed. There were two crucial parts to their study: (1) a proposed plan for battery changing stations, and (2) battery standardization as an option to help implement changing stations. There were two challenging aspects to their research – (1) Developing a battery changing station infrastructure is a costly pursuit when different battery packs exist from various manufacturers, and (2) Israel is quite small compared to many other countries such as the United States and scaling up needs additional planning. However, a positive aspect of swapping stations is battery charging completed by experts instead of consumers, possibly lessening degradation. Battery standardization, in the marketplace, did not occur in Europe or North America (as we know in 2021), making it difficult to employ battery swapping stations. Mak et al. (2013) never implemented their theoretical solution with EVs.

Battery swapping is mentioned by Sun, Li, Wang & Li (2019) as an alternative to charging and one of the most time-saving methods for consumers. After the battery is swapped, then charging is completed by people at the swap station. Similar to Mak et al. (2013), challenges using this system are noted as standardization of EV battery packs, recognition by consumers of this alternative, and how to measure SOH of various battery packs accurately. One item not mentioned under the Battery Swap Station (BSS) model is the role of battery SOH in swapping the batteries for equality. For example, if a 2017 Nissan Leaf swaps its battery for a full capacity version previously in a 2016 model, the SOH may be lower and therefore provide less range than the previous model. BSS appears impractical due to SOH issues. However, battery swapping stations were eventually tried by the Better Place company in Israel (Sun et al., 2019).

A review by researchers discusses Better Place's plan to create battery changing stations at gas stations across Israel; approximately 100 were planned (Naor et al., 2015). Better Place tried to get around recharging EV batteries in public areas by employing battery swapping. In 2015, Naor's group tested the Better Place business model (Naor et al., 2015). Better Place worked with the car manufacturer Renault-Nissan and had completed some research in 2009. Better Place used the idea of separating the battery from the EV and leasing the batteries. By separating the battery, which is expensive, from the EV, it makes them more affordable. Better Place battery changing stations were created and used instead of 'typical' EV charging stations used in 2021. Their solution was developed to increase adoption and remove the inconvenience of extended charging times during long trips. Less battery degradation would happen because no Level 3 chargers would be utilized. Charging EV batteries could be completed on Level 1 or 2 chargers after business hours. It was found that keeping spare battery inventories of different batteries is expensive. Unfortunately, Better Place went bankrupt, which illustrates the difficulty in developing battery charging alternatives. Israel is a small country in geographical size compared to Canada and the United States, so implementing battery changing stations would be more challenging in North America due to large distances between stations. The battery changing/swapping system does not appear to be a viable solution to reduce battery degradation with EVs in 2021, especially with all different battery and EV configurations available to consumers.

Battery Basics

EVs use different types of lithium-ion batteries in their vehicles. Nissan Leafs, BMW i3s, and Chevrolet Bolts use lithium-manganese oxide (LMO) batteries (Yang, Xie, Deng, Yuan & Argonne National Lab, 2018; Hannan, Hoque, Hussain, Yusof & Ker, 2018). Tesla uses Lithium Nickel Cobalt Aluminum Oxide (NCA) for their popular Model 3 (Bower, 2018). Both Smart Fortwo and Tesla Roadsters (2008-2010) use Lithium Cobalt Oxide (LiCoO2) batteries (Buchmann, 2011). Smart Fortwo, Leafs, BMW i3, and Bolt data was included in this study. Battery cells operate at an average of 3.7 V. Battery characteristics play an essential role in lessening degradation; this was determined during a manufacturer comparison within this study.

Generally, most manufacturers consider the End of Life (EoL) for a battery to be 70% of its original SOH, representing nine bars (in a Nissan Leaf, see Figure 5) or under on the battery capacity level bar gauge. Information gathered in one study by Yang et al. (2018) calculated EV battery EoL ranged between 5.2 years in Florida and 13.3 years in Alaska under current EV driving conditions in each state. The elevated ambient temperature in Florida impacts SOH, as noted below, thereby increasing EoL. Researchers calculated initial charging–discharging efficiency of the EV battery is 98%, decreasing at different rates annually in different states (Yang et al., 2018). The current study uses SOH to determine the level of battery degradation.

Figure 5. 2017 Nissan Leaf bar gauge

*Note. S*howing 10 of 12 bars indicating battery degradation (Ferrier, 2021)

Lithium Plating

One of the key reasons for analyzing and predicting battery degradation from charging is the after-effects. One of the central effects on the battery can be lithium plating. Reducing lithium plating is imperative to keeping a healthy battery. Lithium-ion batteries that undergo fast charging can increase the risk of a lithium plating reaction and deteriorate battery cells (Yang & Wang, 2018; Tomaszewska, Chu, Feng, O'Kane, Liu, Chen, Ji, Endler, Li, Liu, Li, Zheng, Vetterlein, Gao, Du, Parkes, Ouyang, Marinescu, Offer & Wu, 2019). Plating reduces the porosity within the battery cell causing positive feedback and nonlinear reduction in useable capacity (Tomaszewska et al., 2019). Deteriorating cells through a reduction in capacity can lead to reduced EV range.

All lithium-ion batteries have a cathode, known as the positive electrode, and anode, the negative electrode. A lithium deposit, known as plating, along the negative electrode lessens the porosity within the battery cell. The anode electrode is often made of graphite because it reacts well with lithium ions in the electrolyte solution. Cathodes are often formed of lithium metal oxide. The electrolytes composition varies based on the choice of electrode materials but is typically composed of a mixture of lithium salts (e.g., LiPF6) and an organic solvent (e.g., diethyl carbonate) to allow for ion transfer (Miao et al., 2019). Graphite electrodes can develop lithium plating.

There are different ways lithium-ion batteries can be aged, and the effect of those aging mechanisms is essential to examine for solutions to plating (Broussely et al., 2005). Back in 2005, lithium carbonate was predominately used for the creation of lithium-ion batteries. In one experiment, lithium deposits were found after cycling batteries in the lab. Broussely et al. (2005) applied both 40°C (104° F), and 60°C (140° F) temperatures, while in storage, to lithium-ion batteries, and lithium loss was analyzed. Lithium loss was more predominant in battery samples where higher temperatures were applied. The current study will review higher temperatures in battery packs when charging EVs, although the amounts differ based on the type of charging. Similar findings occurred in a study conducted by Yang et al. (2018), who found capacity issues with batteries in warmer states. Broussely et al. (2005) found that moderate temperatures, like those in northern American states or Canadian provinces, applied to lithium-ion batteries during storage over time will not affect the capacity. Although lithium-ion batteries were used in the study by Yang et al. (2018), EV batteries and their mass production did not happen for several years after 2005. However, the results do apply to the current study because EVs from 2010-2020 can experience plating under higher recharging temperatures, similar to lab findings.

Researchers in 2018 examined ways to avoid lithium plating with lithium-ion batteries (Yang, Zhang, Ge, Wang & EC Power LLC, 2018). As previously noted, electrodes in batteries are often made of graphite – this is where plating occurs. A new solution was sought to create a cell structure that can be actively controlled, thereby removing lithium plating under ambient temperatures. Temperature plays a vital role in lithium plating, as past researchers discovered (Broussely et al., 2005; Tomaszewska et al., 2019). The Arrhenius law significantly affects fast charging (Level 3) and lithium plating because chemical reactions slow down as temperatures are lowered. It takes a much longer time for an EV on a DC Fast charger at -5°C (23° F) than +5°C (41° F) because of the Arrhenius law. Researchers desired to eliminate the lithium plating due to the extra time spent on the DC Fast charger because of the cold (Yang et al., 2018). Heating the batteries before charging would reduce the time spent on a DC Fast charger – this can be achieved by using nickel foils (through a switch) in the battery cells. Using this process with temperatures between -40°C (-40°F) and 45°C (113°F) was found to remove chances of lithium plating. Temperatures above 45°C (113°F) increase the SEI (film), thereby reducing battery capacity; this needs to be avoided. This EV battery heating strategy was not employed from 2010-2020 by anyone other than Tesla.

Tesla revealed a new technology to address charging issues while in ‘cold’ weather with their Model 3. Known as “on-route battery warmup”, a Model 3 heats the battery to the ideal temperature for charging when the driver begins to route the vehicle towards a Supercharger station, it can reduce charge times by 25 percent (Martinez, 2019). The SEI film should be reduced during this process too. The current study seeks to find the effects of different charging options, and based on Yang et al., 2018 findings, it can be expected that those using DC fast chargers in cold weather should experience lithium plating, thereby reducing battery SOH. However, Tesla Model 3 cars (which are included in the current study) may have less degradation because of the battery warmup feature – it will need to be compared to other EVs to see if this is true.

Konz, McShane & McCloskey (2020) looked at the onset of lithium plating with various levels of SOC during DC fast charging. Lab testing involved charging batteries to SOC: 30%, 40%, 50%, 60%, 70%, 80%. Charging to various SOC levels for lithium-ion batteries, as shown in Figure 7, is different from the “real world” charging of EVs. Most “real world” charging at home involves going to 100%. However, adding 50% of power to a starting SOC of 30% is very common for EV owners, especially when using public Level 3 chargers (30% + 50% = 80%). Their research findings indicate an increased SOC cut-off resulted in lowering the capacity of batteries that were tested (Konz et al., 2020). Another result was lithium plating being stripped at higher rates during discharging at a lower SOC. For example, a 50% SOC showed 72% stripping efficiency compared to 65% SOC having only 50%. Consumers use Level 3 chargers to achieve

80% SOC (during most charging sessions), so very little plating would be stripped in most cases. Even with stripping, there is a lithium plating effect as shown in Figure 6.

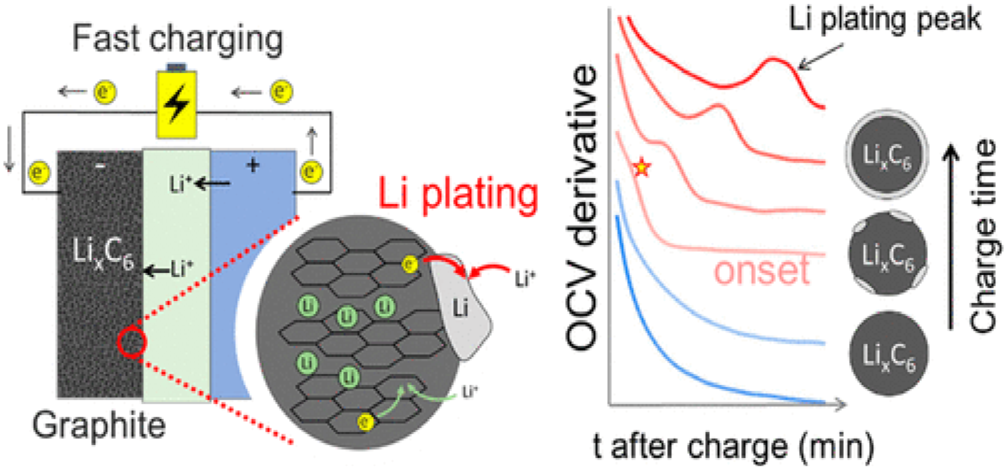

Figure 6. Lithium plating on the graphite anode in a battery

Note. How DC fast charging affects a battery to create lithium plating. From *ACS Energy Letters* (p. 1750), by Konz et al., 2020. Copyright 2020 by American Chemical Society. Reprinted with permission.

Consumers need to learn about lithium plating to negate its effects and extend the life of their EV battery. Consumers want to get the most range from their EV, and plating can reduce it. EV owners keeping the battery healthy for the long term helps increase the value of their investment. It appears there is a correlation between DC Fast chargers, lithium plating, and temperature.

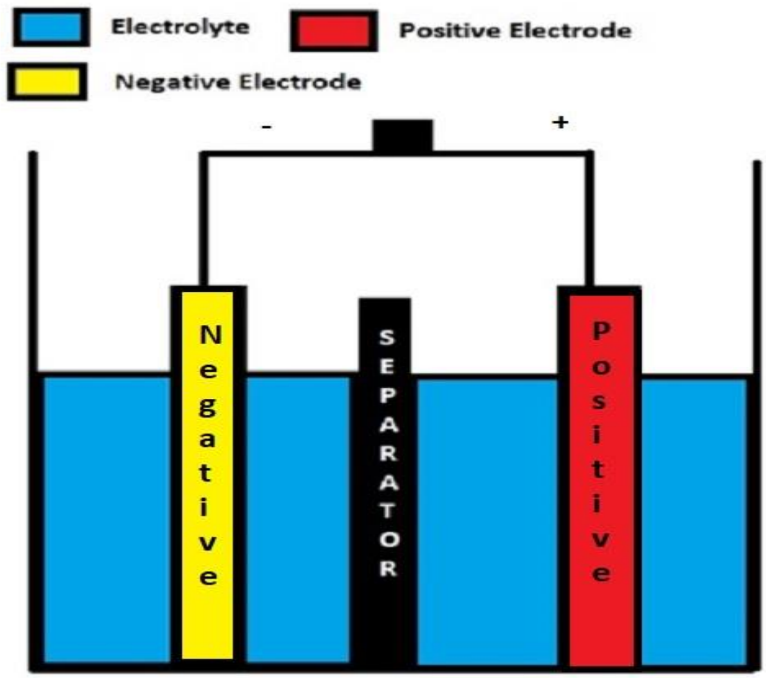

Figure 7. Lithium-ion battery setup

Note. A basic lithium-ion battery diagram with each of the electrodes showing. Current flows from positive to negative when discharging and negative to positive when charging.

Temperature Influence

Temperature is one of the key influencers of battery health in an EV. Multiple studies starting in 2015 examined the effects of temperature on lithium-ion batteries. A report by (Leng, Tan & Pecht, 2015; Chen, He, Li & Chen, 2019) had results showing lithium-ion batteries increasing their capacity in the short-term when temperature increased, but in the long-term battery degradation happened at a faster rate. For example, one study showed degradation at 45°C (113°F) for 900 cycles increased nearly 20% compared to that at 25°C, or 77°F (Chen et al., 2019). The Ferrier and Appiah-Kubi (2020) study involving weight and EVs showed a heating source applied to the battery pack improved range, but added to degradation. One of the Leng et al. (2015) findings, tied to increasing temperature, is a film that develops in the battery cell. A solid electrolyte interface (SEI) film is created which lowers the batteries' reaction rate, thereby decreasing the capacity in the long term (Leng et al., 2015).

SEI is a significant concept for EV batteries because lithium ions need unimpeded movement across the interface for optimized functioning. The interface (in the case of SEI development) is where the negative electrode, as shown in Figure 8, interacts with the electrolyte solution. Battery degradation is mainly caused by the growth of SEI film on the negative surface, as seen in Figure 8, of the battery in the early stage of aging (Chen et al., 2019). Ions move from positive to negative while discharging (traveling) or negative to positive when charging. If a film develops across the interface, it makes the ions' movement more difficult resulting in loss of capacity. EVs need to keep a high battery capacity to optimize their range.

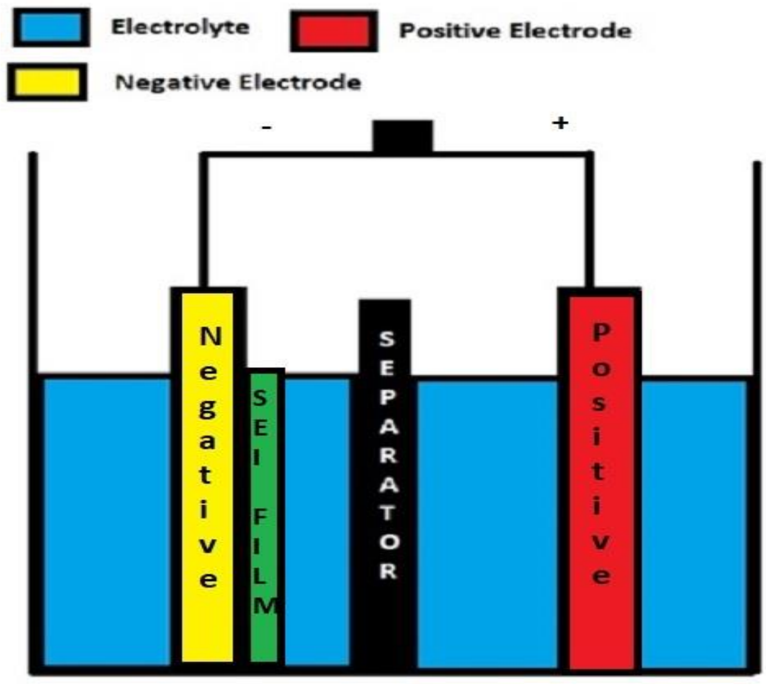

Figure 8. Lithium-ion battery with SEI film

Note. Increasing temperature in lithium-ion batteries causes an SEI film to develop on the negative electrode (often made of graphite)

Shirk and Wishart (2015) did a comparison study with four 2012 Nissan Leafs' over a total of 50,000 miles (approximately 80,000 kms) under the same ambient temperature in Phoenix, Arizona. The comparison study relates to the current topic since they used similar vehicles, Nissan Leafs, and had data loggers attached to all vehicles. The large dataset from FleetCarma included in the present study used data loggers. Part of the Shirk and Wishart (2015) study used public roadways for testing; this scenario was used in the current research. Two of the EVs used Level 2 charging, and the other two were exclusively Level 3. The study used Controller Area Network (CAN) data, including EV speed, battery-pack current, voltage, temperature, and SOC. A discovery was that battery packs on EVs using Level 3 (DC Fast) chargers were 2.1°C hotter (3.78° F) on average than Level 2 packs after each morning drive (Shirk & Wishart, 2015). At the end of charging, findings included EVs charged on Level 3 were 4.9°C (8.82°F) warmer than those on Level 2 chargers. Findings included Level 3 charged vehicles having less battery capacity under all three conditions (lab, track, road). Level 3 EVs had 3.5%, 8.8%, and 6.7% less capacity; respectively. The conclusion from the Shirk and Wishart (2015) study was that greater losses in battery capacity were observed for the fast charged vehicles (Level 3), though the difference compared to the Level 2 charged vehicles was small in comparison to the overall capacity loss. The present study should demonstrate similar results for EVs regularly using Level 3 chargers.

Opposite to the Shirk and Wishart (2015) study, which used one central location, the study from (Yang et al., 2018) took information from multiple U.S. locations where the ambient temperatures were much different. Part of the study by Yang et al., 2018 examined how the environment impacted EV battery degradation in the United States, including Hawaii and Alaska. 2013 Nissan Leafs (24 kWh battery pack) were used for the Yang et al., 2018 study—the same size battery pack and composition, lithium-manganese oxide (LMO), is included in the current study and Shirk and Wishart (2015) study. Does the size of the battery play a role in degradation? This was examined in the current study. The prediction for battery degradation to the 70% level ranged between 5.2 years in Florida to 13.3 years in Alaska under current EV driving conditions (Yang et al., 2018). Although an actual EV battery was used in the Yang et al. (2018) study, all predictions were made in a lab using COMSOL Multiphysics and MATLAB software. The current study uses all “real world” data, none from the lab, and most vehicles from Canada which has much cooler ambient temperatures than Florida.

The third section in the Collin, Miao, Yokochi, Enjeti & von Jouanne (2019) article has findings and discussion topics that directly apply to the current study. They discuss battery SOH and factors affecting it, including (1) Temperature, (2) Charge/Discharge Rate, (3) Charge/Discharge Depth, and (4) How to extend the life of lithium-ion batteries. Higher temperatures within the battery pack can lead to overheating. Overheating is caused by EV charging using a high current (up to 50 kWh CHAdeMO/150 kWh CCS/150 kWh Tesla Supercharger), which stresses the battery (Miao et al., 2019). Overheating affects the performance of lithium-ion batteries and leads to possible “thermal runaway” (Collin et al., 2019; Miao et al., 2019; Leng et al., 2015; Martinez, 2019). Collin et al. (2019) defines “thermal runaway” as one cell heating up and causing a chain reaction leading to a possible fire. There are three parts to thermal runaway as shown in Figure 9. The BMS (Battery Management System) helps monitor and control the battery’s temperature, so a fire is avoided in stage 3 of Figure 9. A BMS is present in all EVs. The BMS can (1) protect the EV from safety hazards such as fire and shock (Collin et al., 2019; Zhao, Zhang, Liu & Gu, 2015); (2) maintain an optimal operating environment (30-40°C or 86-104°F), SOC, depth of discharge (DOD), SOH, charge/ discharge power and assist with battery cell balancing for the enhancement of battery life and efficiency (Haiying, Long, Jianhua, Shuanquan & Feng, 2011), and (3) accurately predicting the remaining driving distance that the battery can support. In addition to the BMS, EVs use thermal management systems to maintain a regular battery temperature. An EV can use both cooling and heating systems, depending on the climate, which leads to the prevention of performance degradation (Collin et al., 2019).

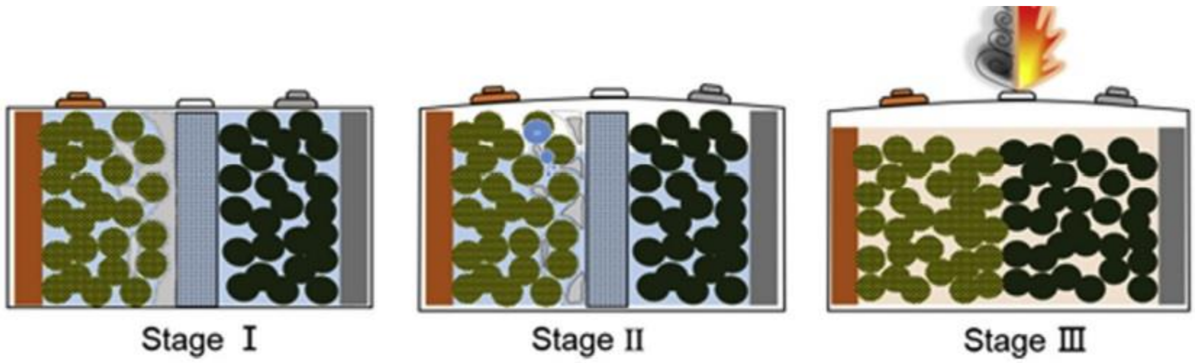

Figure 9. Chain reactions of the thermal runaway process in fast charged batteries

Note. The three stages of how thermal runaway occurs in fast-charged batteries. From *ECS Meeting Abstracts* (p. 585), by Li, Y., Feng, X., Ren, D., Ouyang, M., & Lu, L, 2019. Copyright 2019 by IOP Publishing. Reprinted with Permission.

A review paper from Zhao et al. (2015) details heat generation, management of it, and running batteries above average operating temperatures. Zhao et al. (2015) mention three types of EVs using lithium-ion batteries: Nissan Leaf, Tesla Model S, and BMW i3. All three of these EVs are included in the present study. EVs have TMS (Thermal Management Systems), which deal with maintaining proper heat dissipation outside the battery. The heating of a battery pack in an EV could cause multiple problems related to degradation, so it must be managed. TMS has different ways to cool batteries, including air, liquid, PCM (Phase Change Material), and heat pipe cooling. Each manufacturer uses a different type of TMS which may contribute to varying amounts of battery degradation—comparisons of manufacturers was included in the present study. Researchers Zhao et al. (2015) acknowledge that without proper thermal management, the heat accumulated may overheat the battery, resulting in shortened lifespan, reduced capacity, power with cycling, and even “thermal runaway” in some extreme conditions. Reduced capacity means less range which presents a challenge to older EVs with smaller battery packs or those operating in colder climates. It appears heat generation needs management within EVs and manufacturers require comparisons of battery degradation to note possible enhancements in future TMS.

Calendar Aging

One type of battery aging common to EVs is Calendar Aging. Calendar Aging is capacity loss due to a combination of SOC, aging time, and ambient temperature. Calendar capacity loss occurs during battery energy storage and is mainly caused by battery self-discharge and side reactions (Yang, Xie, Deng, Yuan, & Argonne National Lab, 2018). It is calculated using a modified Arrhenius-form empirical equation. The Arrhenius law was originally used to model the dependence of a reaction rate with temperature (Redondo-Iglesias, Venet & Pelissier, 2020). Reaction rates accelerate as temperature increases. The Arrhenius law applies to EV batteries because different locations have various ambient temperatures that affect the lithium-ion battery over time.

Both calendar and cycling data were examined in the Yang et al. (2018) study. Yang et al. (2018) found the top five states for calendar (battery) loss were Florida, Texas, Hawaii, Louisiana, and Mississippi. These calendar losses can be attributed to the “hot” weather in each of these states. Southern states ‘typically’ have warmer temperatures than their northern counterparts. A majority of current study participants were based in northern states and provinces. Studies from Figenbaum (2020), Yang et al. (2018), and Chen et al. (2019) used temperature as an independent variable within their studies. Researchers Chen et al. (2019) investigated how temperature affected a lithium-ion battery over time. There were three temperatures used to test how the SOC was affected after 30 days: 25°C (77°F), 45°C (113°F), and 60°C (140°F) – this is an example of calendar aging. The results were consistent across all three temperatures – calendar aging of batteries affects them negatively when the ambient temperature is warm. Calendar aging will play a role in the current study because historical data for EVs was generated and stored over months or years.

A novel data-driven battery health monitoring algorithm for usage in fleet management systems was developed by Nuhic, Bergdolt, Spier, Buchholz & Dietmayer (2018). There were two core portions to the study: (1) Testing and simulating with batch modeling, which approximates the capacity degradation trend the best (Nuhic et al., 2018), and (2) the incremental model, which looks at adjusting the degradation on-board while in operation. The study is essential because they tried different mathematical models to predict capacity degradation. They used a battery from a Mercedes Hybrid to test battery cells under various conditions- Smart Fortwo EVs from Mercedes are included in the current study. A prognosis for the current state of battery health was attempted to help in creating the algorithm. Their critique of other studies is that most of the accomplished investigations are based on very uniform tests, batteries are cycled only at one or a few values of SOC, temperature, and DODs (Depth of Discharges), so that the obtained approaches are at least not validated for an application in real-world dynamical situations (Nuhic et al., 2018). The current study has data from a wide range of temperatures, hundreds of cycling events, and SOC. Charging procedures are not noted in the Nuhic et al. (2018) study. As shown, 200 days of calendar aging are shown in Figure 10. A “real world” environment was tested on their hybrid battery—for example, 55% SOC and 15°C or 59° F.

Their predictions of battery aging over time were accurate. Unfortunately, their life-cycle investigations on single cells are not practical for daily use EVs. The current study incorporates "real world" data, so this model cannot be applied to it since it is lab-based.

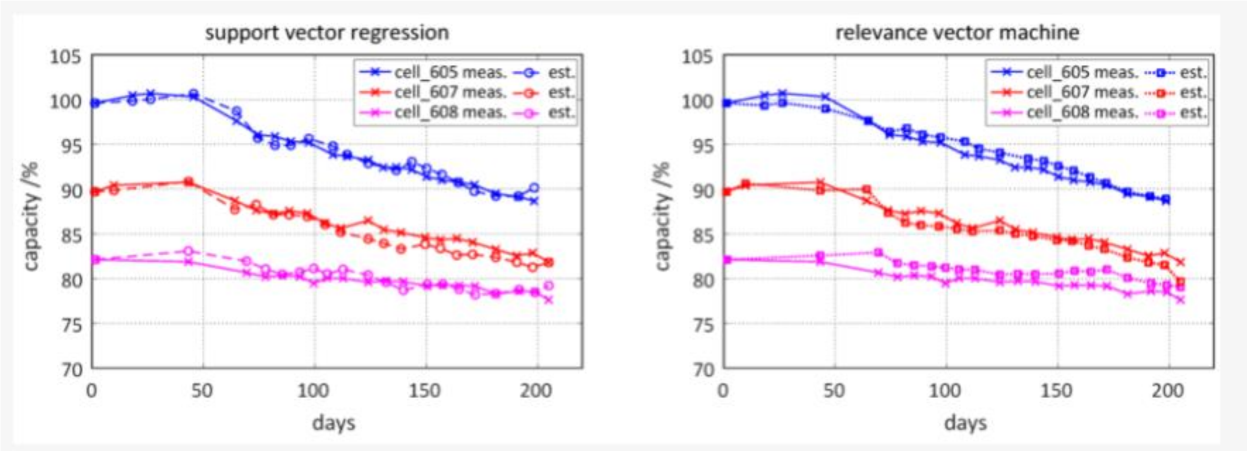

Figure 10. Incremental model results

Note. The initial batch model is updated iteratively on the same data set containing different cells of SOH. Both support vector regression and relevance vector machine models are shown. From *World Electric Vehicle Journal* (p. 16), by Nuhic et al., 2018, Copyright 2018 by MDPI. Reprinted with permission.

Cycling Aging

Cycling Aging is very relevant to the current study because the prediction of battery degradation is influenced by the number of charging/discharging cycles and how driving is conducted. Many studies reviewed include battery cycling in the lab. The cycling process in the lab assumes that conditions remain the same, which is not the case for EV batteries used by consumers. However, lab studies help provide a baseline for "real world" trials.

The cycling of batteries is influenced by many factors such as temperature, charge/ discharge current, charging cut-off voltage, and discharging cut-off voltage plus charging methods (Lin, Tang & Wang, 2015). Chen et al. (2019) used 900 cycles to test degradation (see

Figure 11) under three scenarios (a) different temperatures, (b) under different DOD and (c) at different discharge rates. A 900-cycle test would approximate three years of "real world" driving where people would use their EV to commute to work daily. DOD and discharge rate were not found as influential compared to temperature. The combination of higher temperature and more cycling had the most degradation—this result can be expected in the current study. When testing involved cycling, (Broussely et al., 2005; Redondo-Iglesias et al., 2020; Tomaszewska et al., 2019) large lithium metal deposits (lithium plating) which caused a rapid capacity decay, also known as capacity fading. Capacity fading, as shown in Figure 11 below, is from the Chen et al. (2019) study.

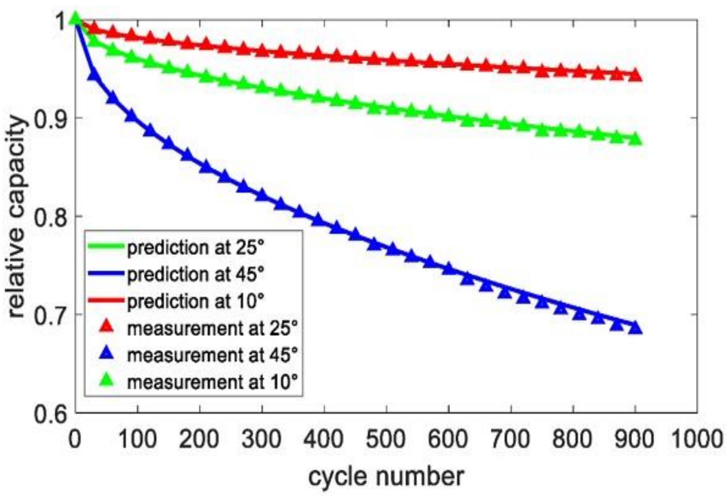

Figure 11. Cycles and capacity of the battery

Note. Relative capacity of the battery based on the amount of cycling. The prediction and actual measurement are shown. From *Energies* (p. 8), by Chen et al., 2019, Copyright 2019 by MDPI. Reprinted with permission.

Chen et al. (2019) looked at multiple factors affecting batteries' degradation, including calendar and cyclic aging. Cycling was considered in the current study since each charge and discharge is accounted for in logged files for an EV. Factors Chen et al. (2019) examined were temperature, SOC, and depth of discharge. The experiment took place in a lab. According to

Chen et al. (2019) and Tomaszewska et al. (2019), battery degradation through cycling is mainly caused by the growth of the SEI film on the negative surface of the battery in the early stage of aging. Findings indicate that the rate of discharge only has a minimal effect on the capacity of a battery. Temperature is a key to helping predict capacity loss and should be incorporated into future regression analysis calculations. Battery temperature is perhaps the most influential factor on the impact of capacity loss, as it affects the growth of SEI film.

Cycling degradation is impacted by SOC and ΔSOC (Chen et al., 2019; Lin et al., 2015; Redondo-Iglesias et al., 2020). Cycling at very low and at very high levels of SOC (0% to 20% and 80% to 100%) caused respectively the slowest and the fastest degradations (Redondo-Iglesias et al., 2020). Fast charging to a cut-off of 80% (SOC) is often regarded as a best practice (see DC Fast Charging section) because of degradation. Based on Redondo-Iglesias et al. (2020) findings, continually charging after 80% SOC would create faster battery degradation which is to be avoided. Cycling numbers and SOC are available in reported numbers (log files) within this study; these were used to help predict degradation.

Longer distances can explain cycling losses traveled from point to point. The top five states with cycling losses include Mississippi, Maryland, Indiana, Maine, and North Dakota (Yang et al., 2018). For example, in Indiana, many live-in rural areas that travel “long” distances to the nearest city for goods. Traveling to those cities may involve an extra charging period going to or from the destination. During a long trip with an EV, cycling occurs more often with smaller battery pack sizes (2012 Nissan Leaf, 2015 iMiev, 2015 Chevrolet Spark, etc…). It can be expected in the current study that cycling will occur in large numbers because some participant vehicles have smaller battery packs and drive within the Canadian prairies, like North Dakota’s environment.

Lin, Tang & Wang (2015) discuss a power-law concerning batteries and cycles. The power-law relates battery capacity loss to the number of cycles a battery has undergone. However, the power-law and battery capacity discussions are not specifically aligned with EVs because those cycles are not consistent from day to day. All reviewed articles were written before 2012—years before substantial data had been gathered on EVs. The current study will examine cycles and how they potentially impact capacity loss.

State of Health (SOH)

SOH is an essential factor in the current study, so various methods used to obtain it were examined. The battery SOH is how a person determines the current capacity for the battery. A new EV starts with a 100% SOH. There is degradation to EV batteries over time and the SOH expresses how much has occurred. When buying a used EV, SOH should determine the price and how long the vehicle will last. SOH has been calculated several ways over the past twenty years and is featured in many smartphone applications that connect to the EV. However, the SOH calculation cannot be conducted through direct measurements (Noura, Boulon & Jemeï, 2020). Therefore, obtaining a complete battery SOH diagnosis compatible with EV applications is still a significant challenge (Lin et al., 2015).

Semanjski & Gautama (2016) studied the SOH of batteries and car sharing in Europe. The study looked at data generated by users using Level 2 and 3 charging stations and sensors included in the EV. Level 2 and 3 data was used for prediction in the current study. Mitsubishi iMievs were used in their study, they are included in the current one too. iMievs have a 16 kWh battery; 14.2 kWh is usable, according to Semanjski and Gautama (2016). Other sources say the usable battery is 14.5 kWh (EVExpert.EU, 2021). With conflicting data, the calculation of SOH for various models needs to be cross-referenced with manufacturer specifications making it challenging to apply on a wide range of EVs in the "real world." A SOH calculation (see below) was derived from detailed EV and charging station transaction data to forecast the EV battery *SOH* for two identical EVs shared under different practices. The calculated numbers are accurate but charging station data may be difficult to obtain due to privacy concerns, making this calculation not applicable to the current study. SOH calculation derived from EV and charging station transaction data:

SOH = Total net energy supplied by the battery / Battery capacity at 100% SOH * (SoC_1 – SoC_2)

(Semanjski & Gautama, 2016)

Lin, Tang, & Wang (2015) used five different approaches to SOH estimation for lithium-ion batteries including, (1) Spectroscopy and electrochemical techniques, (2) Circuit-based models, (3) Semi-empirical based models, (4) Analytical models, and (5) Statistical approach. Many of these models require numerous data before analysis can be completed; data is not always available for EV researchers. Spectroscopy is not useful for analyzing EV batteries in the "real world" because of practicality. Circuit-based models work with practical applications and can be used with EVs. Semi-empirical models use temperature and cycles. The cycling assumes that conditions remain the same, which is not the case for EV batteries used by "real world" consumers. Temperatures fluctuate in everyday life, and different types of charging are used with EVs; therefore, conditions differ, and semi-empirical models should not be used with EVs outside the lab. The coulomb counting method is introduced for the Analytical modes and Statistical approach; it uses an electrical current "over time" calculation. However, the BMS does not provide the consumers with current information. Gismero, Schaltz & Stroe (2020) developed a method for calculating SOH via coulomb counting (see below). SOC and OCV (open circuit voltage) are used in the calculation; they do not have a linear relationship. The SOH method is estimated by evaluating the accumulated charge between two different SOC (ΔSOC = starting minus ending) using a recursive least squares (RLS) solution (Gismero et al., 2020). The ΔSOC and RLS method is a good starting point. A variation of this method using charger energy instead of SOC was employed within this study. All tests were completed in the lab. The calculation they use for SOC = Q_{rem} / Q_{act} - Q_{rem} is the remaining capacity, and Q_{act} is the actual capacity when full. The capacity is based on a point in time plus the Current Rate (C-Rate) and temperature. *I* in this model is battery current. *dt* represents “over time.” SOC or SOH is present in all files created by data loggers or smartphone applications; there is no need for manual SOC calculations in the current study. The actual capacity would need to be measured or tracked (due to the previous degradation) before each charge or journey, not practical for “real world” measurements. Figure 12 shows SOC calculations (as per Gismero et al., 2020):

$q = \int_{t0}^{t} I_b \, dt$

$SOC_t = SOC_{t0} + q / Q_{act}$

$Q_{est} = q / \Delta SOC$

$\Delta SOC = SOC_t^{\ OCVupdate} - SOC_{t0}^{\ OCVupdate}$

Figure 12. Coulomb Counting Calculations

Wang, Zeng, Guo & Qin (2019) are referenced for the circuit-based models because they determined that battery SOH can be estimated by constant current-constant voltage (CC-CV). Wang et al. (2019) took a more practical approach to determine SOH because impedance and capacity are difficult to calculate in a “real world” EV. An EV discharges at varying currents, and the battery does not fully discharge, vastly different than how lithium-ion batteries are tested in the lab. In the lab, batteries can be fully discharged without repercussion. Wang et al. (2019)

say the failure to discharge fully does affect the charging process. Since the current study will use battery data from EVs in the "real world", the CC-CV approach is not practical.

Huang et al. (2017) created a new and different SOH estimation model that no longer needs to find the number of charges that a battery has undertaken in the past. Lithium cobalt oxide ($LiCoO_2$) batteries were used for their experiment, which is excellent because Smart Fortwo EVs (Mercedes-Benz) and Tesla Roadsters use them. Like most tests on batteries in the past, a lab was used. Huang et al. (2017) say that their model is to help monitor a battery in use (real-time), and a full discharge should not occur. Removing the full discharge requirement represents a more accurate method to measure EV batteries. According to Huang et al. (2017), their new model is essential because the cycle number is no longer needed; it is often unavailable with real-time applications. For this experiment, our data will have the number of cycles over an extended period. They used a SOH regression model for a specific SOC level that translates to SOH(%) = $A \cdot (1/V') + B$ (a linear equation). The A and B example uses a 70% SOC because it is common. *A* and *B* are regression coefficients to be determined. The study proposed a new parameter called the *unit time voltage drop* $V' = \Delta V / \Delta t$ (Huang et al., 2017). The ΔV is the voltage drop in the discharging process. The new model accurately predicted SOH using 900 or more cycles. The correlation was $R^2 > 0.983$ for three of four batteries, with an anomaly occurring in the fourth due to early cycles showing battery resistance. The Huang et al. (2017) model appears to be a good method to estimate SOH for batteries removed from EVs for testing or recycling, but not "real world" measurements.

As technology has grown more sophisticated, so have the means to test a battery SOH. Noura et al. (2020) completed a comprehensive review on battery SOH estimation methods. They divide the estimation methods into three areas: Experimental, Model-based, and Machine

Learning methods. As noted, many practical ways to find battery SOH involve work in the lab- this cannot be applied to "real life" scenarios involving ownership of an EV. Experimental methods for the SOH will, therefore, not be applied in the current study. There are a few Model-based methods; common ones listed are Kalman-based filters, Least squared-based filters, and Electrochemical models (EM). Machine Learning methods include Support Vector Regression Algorithm (SVR), Fuzzy Logic, and Neural Networks. The Machine Learning methods for obtaining SOH have two drawbacks (1) They depend heavily on the quality, the diversity, and the quantity of the training data used, and (2) All require a high-performance controller (Noura et al., 2020). Machine Learning methods will not be used due to the drawbacks. EIS (Electrochemical Impedance Spectroscopy) is used by Noura et al. (2020) within multiple machine learning experiments including one with a lead-acid battery—this method will not work with an EV battery pack because EVs do not utilize no lead-acid batteries. The conclusion is that Model-based methods are the most practical for use with EVs. As previously noted, a variation of the Recursive Least Squared method appears valid for EV-generated data.

The Xu, Wang, Lind & Zhang (2021) study is the most promising for applying their methods to the current study. They attempted something vastly different than previous studies involving EVs because "real world" driving data was used. The discrete incremental capacity is calculated and used to predict a battery SOH at a specific time. Mileage between two points is used. One drawback, voltage information is needed for calculations. Data was used from nine cars with a prediction value of 100,000 km or more. Nine SOH graphs were created, one for each car, with all having slight variations in their outcomes. Conclusions are much different with "real world" data than from the lab! The findings demonstrate there is not a linear relationship as the mileage increases, there is fluctuation based on temperature, driving habits, and charging (Xu et al., 2021). Since findings fluctuated based on temperature and charging, the current study expects to see similar results. Some negative consequences of using this method include the time required for the segmentation of data. However, segmentation may be an appropriate approach for the current study because of field data generated by an EV. The example from Xu et al. (2021) was completed with a small number of cars and may not lend itself to large numbers of vehicles unless automation of the calculations can be applied—this was attempted.

DC Fast Charging

There have been many projects from 2010-2020 to create and implement EV fast-charging infrastructure in North America. Public chargers have been installed at locations such as hotels, malls, carpools, and government offices. Chargers installed in public places are Level 2 or 3. Consumers need to understand how chargers affect batteries, as detailed in Figure 13, in their EVs to make informed decisions for present and future use. A lack of knowledge leads to the question: Does the amount of DC fast charging of batteries contribute to a shortened lifespan and capacity of EVs? Yang et al. (2018) and Tomaszewska et al. (2019) concluded that fast-charging technologies could induce extra degradation in the battery pack if they were regularly used. However, how much degradation? The current study seeks to answer this question.

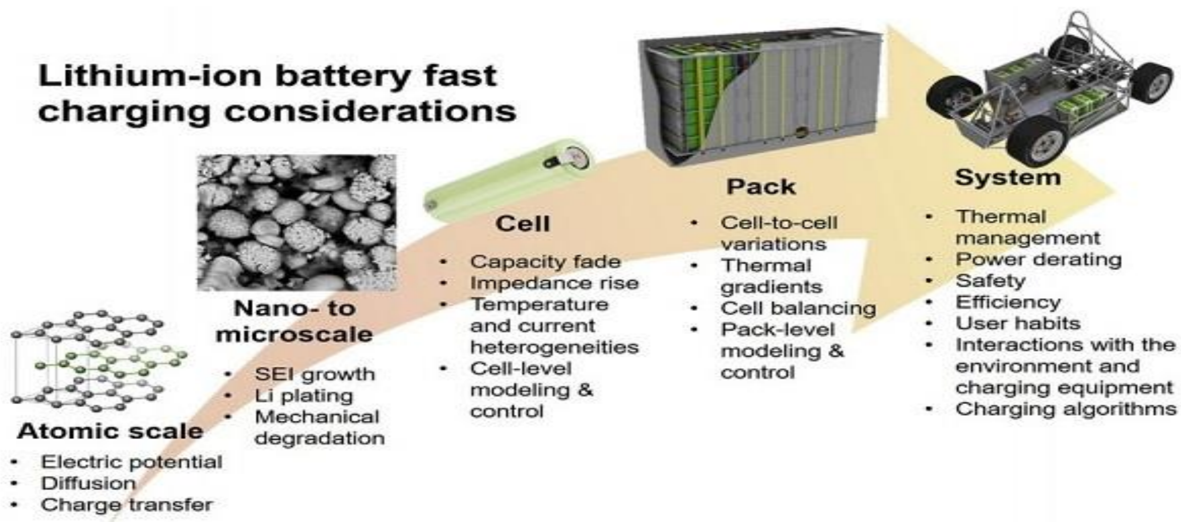

Figure 13. Key factors affecting Li-ion battery fast charging at different length scales

Note. Possible problems related to battery fast charging and available system fixes. From *eTransportation* (p. 2), by Tomaszewska et al, 2019, Copyright 2019 by Elsevier. Reprinted with permission.

Norway was far ahead in the adoption of EVs compared to North America as of 2020. One of the top EV researchers in Norway is Figenbaum. He has produced numerous studies involving EVs. In 2019, he looked at practices of using fast charging in Norway. Data from 2017 was analyzed and used to provide results and conclusions – many of the EVs used in the current study are from 2017. One of the important results discovered in his 2019 study was the average EV fast charging time of 20.5 minutes. The length of time on a fast charger can impact lithium plating and SEI formation as previously shown. According to Figenbaum (2019), users who fast charge beyond 80% SOC are inefficiently charging their vehicles. Figenbaum's statement leads to the questions: (1) Is there an impact on the EV charging to 81%, 85%, or 90%? and (2) If charging is free of cost, does inefficiency matter? Answers to these questions were sought out for the current study. Another recommendation is for charging companies to provide instructions for the efficient use of their fast chargers. Figenbaum (2019) suggests charging stations have an automatic stop at 80% SOC. This automatic stop does have ramifications in colder countries where more than 80% of battery capacity is often needed for travel, especially with older vehicles containing smaller battery packs. An interesting consideration from the 2019 study results was that all Tesla Supercharger data were excluded. However, Tesla vehicles can charge on CHAdeMO networks with an adapter. Therefore, readers of the Figenbaum (2019) study cannot generalize these findings to owners of Tesla vehicles. Tesla vehicles and cold weather will factor into the current study's results.

Another study by Figenbaum (2020) examined Level 3 charging records kept between 2016-2018 in Norway. Norway has a high adoption rate of EVs. The study looked at four different effects of fast charging: (1) Vehicle Effects, (2) User Effects, (3) Climatic Effects, and (4) Network Effects. The study found an average fast charge (Level 3) session lasted 20.5 minutes and provided 9.6 kWh of energy at a power rate of 30.2 kW in 2017 (Figenbaum, 2020). One interesting note is the size of EV batteries being used that averaged 26 kWh, this is smaller than many common battery packs in EVs from model years 2017 and newer. Battery pack size and temperature during charging are two variables that were examined during the current study. One finding was that charging power (or power rate in kWh) consumed between summer and winter months was smaller the longer the charge took. It is common for a Level 3 charger to lower the speed as the battery pack fills up and cold slows down charging speed meaning extended sessions are required. This speed alteration is due to the heating effect of the battery while charging (Figenbaum, 2020). Unfortunately, the heating effect can be detrimental to EV batteries, as discussed in the previous Temperature section. Many of the participants using fast chargers stopped charging around 80% SOC (Figenbaum, 2020); this is not always the case in North America. There is no mention of harming the battery above 80% SOC, but it mentions the common finding that fast chargers will show lower consumption rates than possible, contributing to less efficiency. In addition to the extra time used with lower consumption rates, EV owners paying for charging while moving from a higher starting speed (for example) 36 kWh to 18 kWh (after time) creates an inefficient scenario. Both Figenbaum (2020) and Figenbaum (2019) studies took place in Norway, where winter temperatures are colder than many locations, such as Washington state or Vancouver, British Columbia, taking part in the current study. Many of the findings, including battery pack size and Level 3 charging time, can be compared to current study results.

The research group Collin et al. (2019) included a full review of impacts to batteries used with EVs and fast charging (DC Fast – Level 3). The discharge section reviews why Level 3 chargers (ultra-fast or DC Fast) can impact an EV. The fast-charging of EVs produces even greater amounts of heat, thereby damaging the battery SOH (Collin et al., 2019). The section concludes with an essential statement for EV consumers – it is recommended to use ultra-fast chargers only when necessary (Collin et al., 2019). The current study will predict the level of degradation occurring when using DC fast charging with different EVs.

Sun et al. (2019) created an article that is a comprehensive review on EVs, including information on batteries, motors, infrastructure, and emerging technologies. All EVs mentioned as using lithium-ion batteries, in the battery section, were utilized in this study, including the Nissan Leaf, various Tesla vehicles, and BMW i3. They discuss the reason for two ports on EVs. Level 1 and Level 2 chargers use the smaller J1772 port in conjunction with an onboard AC/DC converter system. Level 3 chargers use larger ports, either CCS or CHAdeMO, with DC/DC converters inside them. As Sun et al. (2019) note, EVs can only store power in their batteries with DC power, so converters need to be used. Another option mentioned is inducive recharging (wireless). No inductive charging stations exist for public use in Ontario, Canada, as of 2020. Level 1 recharging equipment prices are noted as costing $500-800 (Australian Dollars (AUD) /CDN or $386-618 USD), but these chargers ‘usually’ come with a new EV. The price of Level 2 chargers is slightly more costly at $1000-3000 (CDN/AUS or $773-2319 USD). Sun et al. (2019) state that the building of charging infrastructure is a challenge. There are comparisons between countries in Asia and Europe to American projects involved with EV infrastructure.

BYD (Chinese car manufacturer) EVs in Beijing were used by Yang, Tan & Ren (2020) to help predict fast charging behavior. They define a slow charge as a 120V connection and 220V as a fast. A Level 2 charger in North America uses 220V and is not defined as a ‘fast charger’; only Level 3s use DC fast charging technology. There were 130 EVs used in their study. Although this is a reasonable number of subjects, the current study aspires to include over 1000 vehicles. Slow charging was more prominent during the daytime in their study. Slow charging, Level 1, was examined as part of the current study. In the Yang et al. (2020) study, distances traveled during the day were shorter than other times, meaning less cycling. Cycling was examined in terms of the total numbers associated with a vehicle. The following were analyzed and reported as descriptive statistics: start-SOC, time origin, time duration, driving distance, driving speed, day of the week, wind scale, temperature, weather (snow, rain, etc…), and fast charging – yes or no. While dates are recorded in the data, the actual day (Monday, Tuesday, etc.) was not. The day of the week has no impact on the current study. Findings indicate start-SOC, time-origin, travel time duration, driving distance, driving speed, and temperature all have a significant effect on predicting the use of fast charging (Level 2 – 240V). They found that subjects using fast charging one day often followed the next day with the same behavior – if this is the case for the current study, then it could be expected that people using

Level 3 chargers will frequently use them. A binary regression model was used to describe factors that predicted charging behavior, the prediction rate was 89.36%. The current study used regression analysis to help predict battery degradation.

Resistance

Lots of research has been done on batteries and internal resistance. Studies from GeoTab, including FleetCarma, include measuring energy consumption, in kwh, and losses. Hoque, Nurmi, Kumar, Varjonen, Song, Pecht & Tarkoma (2021) examined internal cell resistance and found it is an excellent candidate feature for battery health prediction. Their study looked at three key areas relating to the current study: internal resistance, temperature, and battery capacity. Hoque et al. (2021) had a key finding that during discharging a strong negative correlation implies that the internal resistance of batteries increases as the capacity degrades, their study used room temperature as a gauge. A difference for this study is the battery is charging, not discharging, and temperature does not remain constant for an EV. Battery degradation or lowered SOH will correlate to lower resistance. Higher energy consumption when recharging should occur because of battery degradation and increasing internal resistance as capacity is reached. It is important to compare when ending SOC, or capacity, is reached. FleetCarma data including energy will be analyzed to see if battery degradation has happened. Hx increases with age and degradation because capacity is lessened. The odometer reading was 110,729 km or 68,803.81 miles, lowering the internal resistance to 57.09 percent.

Big Data and EVs Background

Multiple studies involving EVs have used big data to help analyze the characteristics of their travels. Pan, Tian, Tang & Yang (2019) examined data from almost 200,000 connected EVs in Shanghai, and each sends back information regarding battery data, driving data, insulation resistance data, and power consumption. Battery data was obtained for the current study too. Data from the 200,000 EVs was uploaded every 10-20 seconds during 24 hours, thereby creating a large-scale dataset with diverse information. The diverse dataset allowed the researchers to map out and select the best locations to set up EV charging points.

Big data was used with thermal runaway, as discussed earlier, in EVs. A thermal runaway prognosis scheme for battery systems in EVs was proposed based on the big data platform (Hong, Wang & Liu, 2017). Big data was recorded through a centralized management center—similar to data loggers used in the current study but much different than retrieving smartphone application data. Generated data from EVs included battery voltage, cell voltage, battery temperature, ambient temperature, temperature difference, and charge/discharge current. Current charges (SOC) were used within this study to determine starting and ending points for charging. There were aspects to the Jena (2020) study that relate to the current one. Jena, (2020) used big data from social media sources to analyze the sentiment towards EVs. The current study uses social media to gather data from users. Some data was collected from 2016 to 2018 in Jena's study and the current one.

CHAPTER 3

METHODOLOGY

Since this study is based on charging data, the most important part is locating EVs that had historical or recorded information about connecting to an EV charger. The level of charger used, the length of time it was used, the starting and ending SOC values, and the general location must all be included in the data. The section that follows explains how charging data was obtained, who took part, how data was processed, and the experimental design. Before any analysis began, the total data evaluated exceeded one million lines (MS Excel—CSV files).

Participants and Data

All EV data are from North American-based vehicles sold between 2010 and 2020. Any EV from those model year groups was eligible to participate in this study. The study did not include any hybrid or plug-in hybrid vehicles because they have smaller battery packs and gas-powered engines, which have a lower impact on battery packs. North American EVs have a multitude of challenges not found in Europe, including less developed infrastructure, larger areas to travel, and a wide range of temperatures from Florida to Alaska. For an example of less infrastructure development, there is not one Level 2 or 3 charger between Terre Haute, IN and Indianapolis, IN (Plugshare.com, 2021) – a total of 108.54 km or 67 miles. In Europe, Antwerp, Belgium to Rotterdam, Netherlands is 95.6 km or 59.01 miles and has six Level 3 and two Level 2 chargers (Chargemap.com, 2021).

This study relies on four different dataset sources – social media, Internet forums, EV Society of Canada, and the FleetCarma dataset. One reason for using each of these dataset sources is that they are all focused on North American content. Data was gathered from four sources in order to access a wide range of data generated by various makes and models of EVs.

The first source of data was social media connections, such as Facebook groups related to electric vehicles in North America. Data in the form of CSV files was requested from social media group participants; all information was EV generated. CSV files were e-mailed to the author. Each type of EV generates unique data in the CSV columns (See Data Files section below). Jena (2020) observes that social media connections are easily accessible and a low-cost method of data acquisition. Facebook groups included in the data request were: All Things Tesla, Tesla Model 3 Canadian Group, The Canadian Electric Vehicle Owners, Kia Soul EV, Chevy Bolt EV/EUV Owners Group, Nissan Leaf Owners English, Hyundai Kona EV, Nissan Leaf Owners USA, Hoosier Electric Vehicle Association, and Canada Nissan Leaf Owners. On the home page of each EV-related Facebook group, as shown in the above list, information about the study and requests for historical EV data files were posted (see Appendix III for an example). The posting request for EV data files in the social media groups was posted indefinitely, though they were replaced on the home page with newer posts. There were nine people who sent CSV files based on this request. Files sent in were from The Canadian Electric Vehicle Owners, Chevy Bolt EV/EUV Owners, and Canada Nissan Leaf Owners. There was no data sent in from any Tesla-specific groups including All Things Tesla and Tesla Model 3 Canadian Group. Furthermore, no data was received from any U.S-based groups, Kia Soul EV, or Hyundai Kona EV.

A second set of data requests consisted of postings on two forums - https://www.mykiasoulev.com and https://www.mynissanleaf.com, both requested CSV data from Soul Spy and Nissan Leaf Spy smartphone applications. These two forums were chosen because historical data from the applications used with these EVs could be easily retrieved. The forum postings were conducted on August 31, 2021 and are still visible as of today (November 12, 2021). Only forum members could respond to the posting. Members could respond to the request via the posting or e-mail address provided. No respondents from either forum posting sent in or posted data files.

The third set of data was from members of the EV Society of Canada. Members of the society were sent an email on April 5, 2021 requesting EV-generated data for this study (see Appendix I). Also, anyone who visited the EV Society website after April 5, 2021 could view the news item sent out in the email about the study, it is visible at https://evsociety.ca/ev-data-wanted-for-research-project. In addition, data were sought from people associated with the EV society through personal connections of the Vice-President. The VP spoke with his connections about the study. There were three people from Europe, connected to the VP, who sent data files – these were used as part of the validation process. The VP of the EV Society sent in historical data files from his two personal EVs. I, the author, am a member of the EV Society, added in data files from my 2017 Nissan Leaf. There was a total of six people who sent in data from the EV Society. One person connected to the EV Society sent in data from Europe that was unusable due to lack of information contained within the CSV file.

A total of 15 people sent in data to take part in this study. There were nine from social media groups, six from the EV Society, and zero from the forums. One person sending in data from a 2016 Kia Soul EV was not included, see below for further details. The person from

Europe with improper data that could not be analyzed was excluded. FleetCarma data was used, but hybrid data inside the dataset was not included for analysis.

As previously stated, FleetCarma provided the fourth dataset from its "Charge the North" study. FleetCarma files are in CSV format. Data collection for their study began on June 14, 2017. There dataset includes 941,142 lines of generated data from EVs including hybrids. Only EV data was included in the current study, not hybrid or plug-in hybrid vehicles, so the numbers decreased to 847,410 lines. The data contains Vehicle Make, Vehicle Model, Province, Start Time, End Time, Charger Energy, Charger Loss, Charging Level, Start Session SOC, End Session SOC, and Charge Location. There were multiple reasons why data from this study was requested – a variety of EVs are included, charging data is available, more than a year of data collection exists, and a large number of vehicles took part.

One dataset not included in the FleetCarma study was sent from an owner of a 2016 Kia Soul EV. The Soul EV data was not included in this study because the battery was replaced. The information from the original battery had many null values and atypical results because it was defective. All other vehicles taking part in this study used the original battery pack supplied by the manufacturer.

There were 371,239 lines of data not used from the FleetCarma study because they were generated from hybrid models. Apart from hybrid vehicles not used from the FleetCarma dataset, there was one vehicle model removed from this data too: Hyundai Kona EVs. None of the data involving Kona EVs were analyzed due to a recall on them. There were 135 lines of data from two Kona EVs located in Ontario and Quebec, Canada. Model years 2017-2020 have possible battery issues that could lead to fires. For some of the vehicles data available for this study, the vehicle year is unknown and could include 2017-2020 models.

Unfortunately, there were a number of companies across Canada and the United States who have established networks of EV charging stations, but declined to take part in providing data. Charging companies such as FLO were contacted because they have data on customers such as personal information (address, phone number, email), vehicle, charging start time, end time, location, charger number, date, how long it took to charge, how much energy the EV consumed, and cost. Table 2 lists companies that were approached, but declined to participate in this study:

Table 2

Charging companies contacted regarding data

Company Name	Date	Type of Contact (email, phone, app)	Response
FLO	March 9, 2021	email	Thank you for your email. Unfortunately we do not share our data externally for a number of reasons, so we are not in a position to assist you with your research project. We wish you good luck with your project and are sorry we cannot be of any support.
ChargePoint	March 10, 2021	email	Thank you for reaching out. Unfortunately, ChargePoint won’t be able to participate as we do not share this type of information publicly. We do however have a wealth of information on our website and our blogs cover a lot of the trends. I have included links below for your reference
ChargePoint	March 23, 2021	phone	ChargePoint won’t be able to participate as we do not share this type of information
Tesla	March 2021	phone	No response

Table 2 *Charging companies contacted regarding data* (continued).

Company Name	Date	Type of Contact	Response
Tesla	March 10, 2021	email	As it turns out, we are not able to provide this information on any Tesla vehicles, nor do we have the local capability of doing so anywhere at the ground level of our local stores or service centres. Gurjyot has also informed me that you have reached out to press@tesla.com which would be your absolute best avenue for this type of inquiry. I wish you the best in your study, and thank you for supporting our mission to accelerate the world's transition to sustainable energy.
Electrify America	March 2021	phone	We do not have this information at this time. Sorry…
Greenlots	March 16, 2021	email	No response
Sun Country	March 16, 2021	email	No response
Ford	July 12, 2021	email	It took me a while to find the right contacts in the U.S. to ask the question. Unfortunately, the group I spoke to (EV product & engineering team plus internal legal counsel), are not looking to enter into new agreements and share that data externally at this time. I'm sorry I wasn't able to get the response you were hoping for.

Note. Phone and email responses in regard to the study

The collection of data for the current study began in March 2021 with postings in social media groups. Data from any EV was acceptable, but it could not be from a hybrid or plug-in hybrid. An EV generates data during its journeys and charging. All generated data in this study was completed using a data logger or smartphone app. Data loggers are one method of tracking generated data from an EV. The FleetCarma EV study employed data loggers with all the participants. Both data loggers and smartphone apps are connected to the OBD2 port through plugging in directly to it or using a Bluetooth connector, or dongle, with a smartphone app. Data had to include the charging level (1, 2, 3), date, time, province or state, starting SOC, ending SOC, charging time, charger energy, vehicle model, and vehicle make. Since this study is looking into the effects of chargers on battery degradation, the charging level is required. SOC is required to determine where the EV begins and ends the charge, which aids in segmentation (see below). Charging time may impact battery degradation; regression analysis was required to test this. Charger energy aids in detecting degradation because if all other variables are equal, it should remain constant; otherwise, degradation may have occurred; ambient temperature needs to be reviewed. Vehicle model and make are required because manufacturers and battery sizes are compared. The province or state plays a role in determining the ambient temperature. If available, the ambient temperature during the charge was accepted and documented. SOH, Quick Charges (QC), Range, and Total Time to Charge (TTC) are all useful fields. As the dependent variable, SOH is used. The other three useful fields, QC, Range, and TTC can aid in the detection of battery degradation. For example, if the range is consistently deteriorating, this indicates that battery degradation is occurring; if ambient temperature remains the same. All personally identifiable information (PII) was removed from any data collected. The removal of information pertaining to the precise location, latitude and longitude, VIN (Vehicle Identification

Number), and profile name information was part of the data scrubbing process. Pan et al. (2019) collected exact locations, but did not remove it because they were selecting charge points based on it—this is not the case in the current study. All data is kept private and will not be published as part of the study.

Amazon Web Services (AWS) allows users to store their data in relational databases such as Microsoft SQL Server and PostgreSQL. AWS is cloud-based, meaning all services are accessed, and utilized from remote locations. All data from various sources was uploaded and stored in a secured PostgreSQL database at Amazon with a password and user id. The Amazon data center used for this study is located in the eastern United States. No data was stored on a Local Area Network (LAN) within a file server, thus preventing a possible security risk. To ensure security, the HTTPS protocol was used to connect to and access cloud-based data. To access and process data from AWS, the DBeaver SQL client is used from a remote laptop with Windows 10/11 installed.

Data Validation

Although the study is primarily focused on North American vehicles, data from European vehicles was collected to validate findings. The same types of data were gathered – all of it was generated by EVs. Data was gathered from two of the four North American sources, including contacts from the EV Society of Canada and Facebook groups. Leaf Spy Pro data, in CSV file format, from a Nissan Leaf situated in Europe was the same as those Leafs' used in North America thereby showing consistency of collected data. Data gathered from Europe is from the same period in North America – 2010-2020. File formats from EV generated data is the same for European and North American models. Location and VIN number in any files sent from European respondents were scrubbed. The findings were validated by using EU data (on a smaller scale) and replicating the process used to determine battery degradation with North American vehicles. SOH was used with Nissan Leafs and Kia Soul EVs. The segment model was used for other EV battery degradation analysis. Results were analyzed across manufacturers due to similar building processes; however, models differed slightly between Europe and North America. The research questions apply to data from the EU and yielded similar results.

Data Analyzed

All data was converted to CSV or MS Excel file format so that it could be easily imported into a relational database. The DBeaver client version 21.0.2 was used to import data into a cloud-based PostgreSQL Server. SQL statements are used to select data from the tables and export it to result sets. SQL is used to keep track of the number of cycling events for each EV. The export includes the charger type, starting and ending SOC, location (state or province), start and end time, charger energy, and vehicle make/model. The data exported from the database was analyzed using IBM SPSS. Descriptive statistics are created through SPSS. The analysis includes regression testing to predict how various charging levels affect rates of battery degradation. Temperature affects batteries and was required for determining energy consumption or SOH comparisons. Ambient temperatures were obtained through extractions from CSV files or the website timeanddate.com. Timeanddate.com has historical temperature data from countries and cities around the world. Times on the site were matched with logged times from data files to retrieve a high temperature from the site at that specific location. High temperatures were used for consistency. Locations affect temperatures too. This study was very liberal in how it approached using the location of chargers. For example, the GTA, Greater Toronto Area, fell under Toronto when determining temperature, but encompasses all surrounding areas including Pickering, Mississauga, Oakville, and Burlington. Similar inclusions of the surrounding areas were made in regards to Montreal, Vancouver, Calgary, and Fredericton. Keeping a constant location and consistent temperature format leads to more accurate results.

Scatter plots were used to aid in the analysis. To predict battery degradation, all charging levels – Levels 1-3, Supercharger – were used. ANOVA testing was used, as needed, to compare the degradation of vehicle batteries between manufacturers. Any significant findings between manufacturers were subjected to post-hoc analysis, which includes a Scheffe test. A Scheffe test is a good post-hoc test because it can keep the margin of error under control (Tas & Minaz, 2021). To run this test equal variances are required. The Scheffe test determines which pairs of means are significant. The Scheffe test corrects alpha for both complex and simple mean comparisons. Complex mean comparisons involve comparing more than one pair of means simultaneously (Glen, 2016). Battery degradation is based on SOH as a percentage rounded down to two decimal points.

Subjects' information was provided in the form of XLSX, text, or CSV files. CSV files from the same vehicle were merged with Windows 10 using a CMD prompt. A 'copy' command is issued in the same directory as all of the CSV files, followed by the name of the new file, which includes the person's first name and car type. The final CSV file, for example, could be named "bob 2018 Leaf.csv." VINs and exact location information were removed from the merged CSV file. Using the DBeaver client, the merged file was uploaded to the PostgreSQL database. Some CSV files from EVs other than the Nissan Leaf and Kia Soul EV contained information about the type of charger used based on amperage. In order to import the amperage into the database, it was converted to charger Levels 1-3 in a separate column. The amperage from a Level 1 outlet is "typically" 20A, a standard outlet, while a Level 2 outlet is 30A or 40A, and a Level 3 outlet is greater than 40A. A Level 2 ChargePoint charger at home operates on a 40A service.

Data Files

Data files sent in CSV format via e-mail from Facebook group participants contained a minimum seven columns of EV generated data not including SOH or four columns including it. Start Date and Time, Duration, Charging Power or Level, Charger Energy (kWh), Charger Loss (kWh), Starting SOC (%), and Ending SOC (%) are all included in the BMW i3 and Chevrolet Bolt data. Vehicle Make, Vehicle Model, Province, StartTime and Date, EndTime and Date, Charger Energy, Charger Loss, Charging Level, Starting SOC, Ending SOC, and Charge Location are all included in the edited CSV dataset files from FleetCarma. Four columns included in the Kia Soul EV data are Amperage, ChargeTo (SOC), SOH, and Temperature. To include an EV in the study, SOC or SOH data must be present for proper analysis. Facebook group members involving Nissan Leafs sent in CSV files via e-mail. Leaf Spy data generated by various Nissan Leafs contain 156 columns, 96 of them contain Cell Pair (CP) values in millivolts; these were not used or analyzed. The columns used from Leaf Spy data include Date/Time, Odometer, Quick Charges (QC), Level 1 or 2 (L1/L2), Ambient Temperature, SOH shown in Figure 14, Plug State, Charge Mode, Resistance (Hx), and Motor Temperature. A Facebook group member owning a Kia Niro sent in CSV files containing Date and Time, Duration, Trip Distance, Electricity Consumed, Total Energy Consumed, Start SOC, End SOC, Ambient Temperature, Average Speed, and six other columns not used in this study.

Figure 14 depicts the first screen produced by Leaf Spy Professional when used with an Android (operating system) smartphone. The screen displays a number of important items for EV owners and researchers. AHr is a calculated value that indicates how much capacity the battery has – this is unique to the Nissan Leaf. SOH is the percentage of battery health – it always starts at 100 percent when the EV is new. The pack or battery voltage is 353.78V. Hx is the internal resistance of the battery, which begins at 100% for a new battery and decreases with age and charging. As shown in Figure 14, the odometer reading is 110,729 km, lowering the internal resistance to 57.09 percent. QCs are when DC Fast Level 3 chargers are used during a session. L1/L2 represent the total number of Level 1 and Level 2 chargers used with the vehicle; 1831 were used up until the screen capture. The vehicle's SOC at the time the screenshot was taken. The numbers 1 to 96 labelled on the x-axis represent the 96 cell pair voltages, measured in millivolts, in the 2017 Nissan Leaf. Shunts, as shown on the y-axis, are small resistors that can be switched to drain small amounts of energy from one or more of the high voltage battery pack's 96 cells (Pollock, 2018). All data in Figure 14 can be saved in a CSV file for future use.

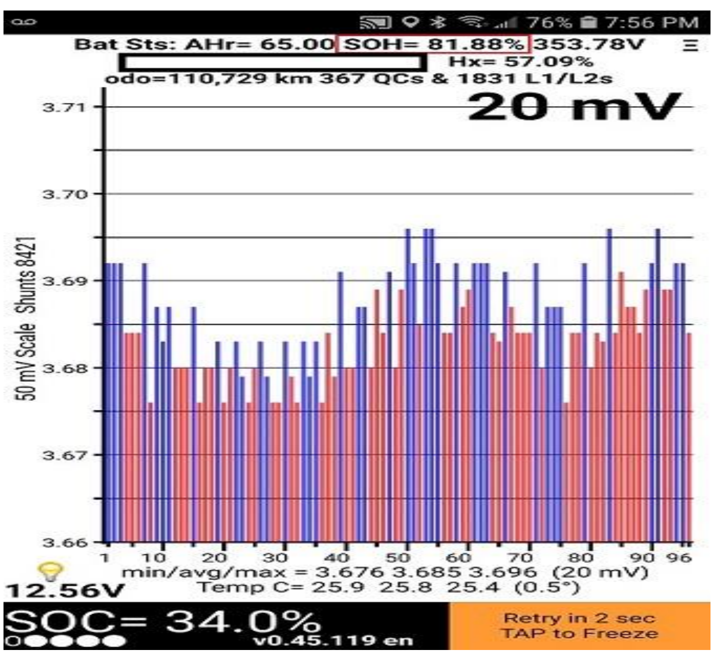

Figure 14. Leaf Spy Professional screen

Note. Leaf Spy Professional application on a smartphone screen as shown on a Samsung A10 with Android 10 Operating System. (Ferrier, 2020)

Experiment Design

The FleetCarma dataset was segmented by vehicle make and model, as well as Starting and Ending SOC. For the same vehicle, the StartSOC or starting SOC and EndSOC or ending SOC values were matched at two different points in time as shown in the highlighted areas of Figure 15. In their study of "real world" EV scenarios, Xu et al. (2021) used a similar segmentation method as shown in Figure 14. Xu et al. (2021) matched the voltage to the charging capacity – applying 322 V multiple times resulted in a different charging capacity value. Similarly, in the current study, two SOC values must match across dates and locations in order to create Charger Energy used comparisons as shown in Figure 15 – these are the segments. A 2018 Volkswagen e-Golf in Quebec, Canada, for example, could begin with a SOC of 67 percent and end with a SOC of 100 percent on December 20, 2018. The matching process necessitates a starting and ending SOC in Quebec with the same vehicle, resulting in the creation of a data segment. Except for Nissan Leafs and Kia Souls (as detailed below), all EV data was segmented the same way because their data includes a calculated SOH used to determine battery degradation.

t_volt/ V	Charging capacity/As	
322	0	
322	0	-12-0=-12As
322	-12	
325	240	0As
326	768.5	1298-768.5=529.5As
326	1298	

Figure 15. 1 Sample segment after voltage precision adjustment

Note. Voltage is shown in the left column. Overall charging capacity is shown in the right column. From *Energy* (p. 8), by Xu et al., 2021, Copyright 2021 by Elsevier. Reprinted with permission.

Table 3 contains values from a dataset that was used to show what happens to an EV during a charging event. The Start and End Time indicate the time and date when the EV began and ended charging. Charger Energy is the amount of energy consumed by the EV during charging, measured in kilowatts. Charger Loss refers to the inefficiency of the charging system, which loses power due to cables, conversion, heat generation, and plugs; it is measured in kilowatts. Conversion references an EV having an onboard converter that takes the AC based energy from a Level 1 or 2 charger and converting it to DC, Direct Current, for storage. Level 3 charging sessions do not have a "Charger Loss" when listed in the log files because the conversion takes place within the charger and sent through large insulated cables to the EV as DC. The Charging Level refers to the type of charger used during the event; for example, a SuperCharger is labelled as a 3 when used with a Tesla. Levels 1-3 are the only ones that are generated. The Start SOC and End SOC are the starting and ending state of charge values for the EV battery in percent format, an End SOC cannot be larger than 100 and Start SOC is never under 0. The first highlighted example shows a Start SOC of 67% and concludes at 100% SOC, a full battery pack.

Table 3

Sample Segment with Matching SOCs

Start Time	End Time	Charger Energy	Charger Loss	Charger Level	StartSOC	EndSOC
12/20/2018 2:40	12/20/2018 4:19	11.474	0.762	2	67.0	100
12/21/2018 2:02	12/21/2018 3:41	11.340	0.776	2	68.5	100
12/21/2018 11:34	12/21/2018 12:15	1.338	1.324	2	100.0	100
12/23/2018 21:38	12/24/2018 1:10	24.176	1.725	2	28.0	99
12/24/2018 11:32	12/24/2018 12:15	2.513	0.302	2	100.0	100
12/25/2018 6:05	12/25/2018 7:38	10.335	0.708	2	71.5	100
12/25/2018 11:32	12/25/2018 12:15	2.538	0.305	2	100.0	100
12/26/2018 4:35	12/26/2018 5:54	8.786	0.606	2	76.0	100
12/27/2018 23:59	12/28/2018 2:06	14.453	1.008	2	59.5	100

Table 3 *Sample Segment with Matching SOCs* (continued).

Start Time	End Time	Charger Energy	Charger Loss	Charger Level	StartSOC	EndSOC
12/28/2018 11:33	12/28/2018 12:14	2.157	0.259	2	100.0	100
12/30/2018 20:23	12/30/2018 22:13	12.503	0.855	2	65.0	100
12/31/2018 11:34	12/31/2018 12:15	2.297	2.296	2	100.0	100
1/1/2019 11:34	1/1/2019 12:15	1.459	0.175	2	100.0	100
1/2/2019 11:32	1/2/2019 12:15	2.543	0.305	2	100.0	100
1/3/2019 11:34	1/3/2019 12:15	2.319	0.278	2	100.0	100
1/4/2019 11:33	1/4/2019 12:14	2.181	0.261	2	100.0	100
1/5/2019 19:38	1/5/2019 22:49	21.780	1.584	2	37.0	100
1/6/2019 21:02	1/6/2019 23:52	19.354	1.383	2	44.0	100
1/7/2019 11:32	1/7/2019 12:15	2.556	0.307	2	100.0	100
1/8/2019 11:34	1/8/2019 12:15	2.273	0.273	2	100.0	100
1/8/2019 21:23	1/8/2019 23:08	11.816	0.807	2	67.0	100

Note. Segment matching on Charger Level, StartSOC, and EndSOC

If the same SOC values occurred on January 8, 2019, then the charging energy was compared. The number of charges or cycles was counted in-between the two dates. Charger energy, in kWh, used is available for all vehicles. A percent is yielded after the first amount of energy consumed, shown in the first date, is divided by the second later date. $Amt_{Needed} = (1 - (Charger\ Energy_{START} / Charger\ Energy_{END})) \times 100$. If the Charger Energy value from a later date is greater than the first, and temperature is negligible, degradation has occurred. According to the findings of the literature review, temperature will influence the energy required to recharge and may cause degradation. The results for the same EV were compared over time to see how much temperature affects the possible degradation while charging—this is known as the Adjusted Degradation (AD). For temperature comparisons, data from the website Timeanddate.com was used, it has temperatures for every major city in Canada and the U.S. While both cold and hot temperatures have an effect on range, colder climates have a greater impact on EVs and their batteries (Argue, 2020). The degradation, in percent, per cycle is calculated by dividing the percent difference, for Charger Energy, by the number of charging cycles from start to finish. Each segment will receive a charger type or types mean score, which was used in SPSS regression testing. SOCDiff, or SOC difference, is shown because it helps determine similar values for comparability.

Table 4

Example of Energy Consumed

EV Model	StartSOC%	EndSOC%	Energy (kwh)	Charger	SOCDiff%
e-Golf	67	100	11.474	2	33
e-Golf	64	100	13.073	2	36
e-Golf	74	100	9.244	2	26

Note. Using Volkswagen eGolf data

SOH for all Nissan Leaf and Kia Soul EV vehicles was extracted from the tables located in the PostgreSQL database – it helps to determine the current health of the battery. Original data from Leafs and Souls was generated through smartphone applications Leaf Spy Professional and Soul Spy. The Nissan Leaf calculates its own SOH through the BMS ECU (Electronic Control Unit), recorded via Leaf Spy Professional. Table 5 is the part of a CSV file generated by a 2017 Nissan Leaf using Leaf Spy Professional. The headings for Table 5 are: QC is Quick Charge (Level 3 charges), L1/L2 are the Level 1 or 2 charges, and SOH for the battery (in percent format).

Table 5

2017 Nissan Leaf data from Leaf Spy Pro with Level 1/2 and QC

QC	L1/L2	SOH
275	1408	85.59
367	1775	83.65
367	1791	83.05

Note. Only provided in this format by Leaf Spy and Soul Spy smartphone applications

The total of charges between changes in SOH can be gathered by counting cycles using a SQL statement. Changes in the SOH following a charging event was noted. Any patterns of degradation, as determined by a lower SOH, can be attributed to charging. Scores for each charger type was analyzed independently for use in SPSS regression testing. Charger types were used in regression testing to help predict battery degradation due to SOH. The temperature, like that of the other EVs in the study, was examined, and data was categorized into four seasons. SOH calculations from Nissan Leafs or Kia Soul EVs do not require charger energy.

CHAPTER 4

RESULTS AND DISCUSSIONS

This study used four resources for gathering data. As previously noted, FleetCarma (via GeoTab) data has 847,410 lines for analysis. Leaf Spy and Soul EV Spy users supplied log files. A total of 87,032 lines were provided by participants using Leaf Spy. Soul EV Spy was used by one participant and 146 lines were analyzed. Members of the EV Society of Canada supplied log files for analysis. Six participants from Facebook Groups called Canadian EV Owners and Nissan Leaf Owners sent in data from their EVs. Unfortunately, only these four sources provided user-submitted data for this study, no users of Internet forums for Nissan Leafs or Kia Soul EVs sent CSV files for analysis. A 2014 Leaf that took part did not have decimal values in the SOH column as part of the CSV file provided.

Charger loss or loss headings are frequently shown starting from Table 19 until the end of FleetCarma data analysis. A Level 1 or Level 2 charger uses Alternating Current (AC) to charge the battery within the EV. Batteries can only store Direct Current (DC) so there is an onboard converter switching AC to DC. The process of switching is not efficient and results in loss of energy, or charger loss. A Level 3 charger uses DC to charge. The process of switching from AC to DC is completed within the charger itself, not the EV. Since DC is used with Level 3 chargers there is no charger loss associated with it.

Internal resistance of the battery is available via the Leaf Spy CSV files. Table 6 below was developed from CSV files created by 2013, 2017, and 2018 Leafs. Hx is the resistance in Leaf Spy tables as a percentage value. The internal resistance of the battery pack increases as the SOH percentage decreases (Pollock, 2018). Internal resistance percentages will show as lower in Leaf Spy data, but represent more resistance. For example, if battery SOH is 80% and Hx is 80%, there is 20% more resistance than when using a new battery. If the battery SOH deteriorates to 75% then Hx will move lower to 75% thus increasing resistance to 25%. As shown with Leaf Resistance Data, there is a moderate-strong correlational relationship between resistance and SOH. Therefore, energy consumed should be higher as degradation increases. A higher Ending SOC (or capacity) will create more resistance and require more energy. There is a large sample of 626,812 lines of data.

Table 6

Leaf Resistance Data

		SOH2	Temp2	Hx
Pearson Correlation	SOH2	1.000	0.000	0.612
	Temp2	0.000	1.000	0.213
	Hx	0.612	0.213	1.000
Sig. (1-tailed)	SOH2	.	0.388	0.000
	Temp2	0.388	.	0.000
	Hx	0.000	0.000	.

Note: all Leaf data from Leaf Spy CSV files (N = 626,812).

A 2013 Leaf employs a 24-kwh battery pack. This study used generated data from a 2013 Leaf including SOH % combined with Quick Charges, L1/L2 charging, and Temperature. A total of 78,970 lines of data were submitted. The battery SOH started measuring at 88.04% and ended at 79.97%, a total degradation of 8.07%. Degradation was measured after 787 days or two years, one month, three weeks, and four days. Pro-rated to per year, there was a degradation of 3.74%.

The first cell using 2013 Leaf data is within Table 7. Table 7 has a segment produced using the same Temperature, number of QC, and identical L1/L2 charges. There is a drop of 0.2% SOH within the first cell. The cell with 85.01%/85.01% happened three days after the initial 85.01% SOH was measured. An additional six L1/L2 charges and one QC happened at this time. At the same time measurements of SOH were taken, the ambient temperature raised 3°C which accounts for why SOH did not reduce via the charging events. The loss of SOH from 84.76% to 84.69% in the first row, second column, shows a difference of 0.07% after one L1/L2 charging event while ambient temperature remained constant at 24.5°C. However, just prior to leveling out to 24.5°C there were entries up to 27°C, while at a cumulative 1,810 L1/L2 charges, before the EV was plugged in. There were twenty days where events were not logged between 84.76% and 84.69%. For the 84.65%/84.61% cell, a reduction in temperature from 24°C to 23°C appears to have temporarily reduced SOH by 0.05%. The drop in SOH by 0.05% based on a reduction of temperature is consistent with earlier findings where a 3°C increase temporarily increased the SOH. The last segmented entry, row four, shows a total of nine additional charging events at L1/L2 resulting in a 0.25% SOH loss. An average of 0.03% SOH loss occurred per L1/L2 charge for row four. In row four, increasing the temperature 2.5°C has not temporarily increased the SOH because of the large number of L1/L2 events that have reduced it. The entry with a sole charging event has created larger differences because of calendar aging.

There are two cells showing an increase in SOH within the 2013 Leaf data, these values are 84.65%/84.67% in the third row, second column, and 84.56%/84.61% in the fourth row, second column, which is unique compared to other cells which have losses. An increase in SOH shows a lack of degradation within the battery pack and is not possible over long periods. Reviewing additional information from the CSV file provides reasoning as to why this irregularity in SOH data occurred. The 12 V battery is registering as NA in the log files. Either a disconnection to the battery terminal occurred or it was low and not registering. Due to a lack of 12 V battery support, disconnection to Leaf Spy from the ODB-II Bluetooth device occurred. Finally, the odometer recording for each of the cells, with an increase, via the logs goes blank from 67,490 to 0 and 67,502 to 0, respectively, which happened at the same time the connection to the 12 V battery was lost. Based on the finding of a disconnected or low battery, the increase of battery health over a long period of time is not applicable.

Table 7

2013 Nissan Leaf data segments

Row	SOH %	QC	L1/L2	Temp	SOH %	QC	L1/L2	Temp
1	85.01	85	1,810	25.0 °C	84.76	85	1,810	27.0°C
	84.81	85	1,810	25.0 °C	84.69	85	1,811	24.5°C
2	84.81	85	1,810	25.0 °C	84.65	85	1,811	24.0°C
	84.76	85	1,810	25.0 °C	84.61	85	1,811	23.0°C
3	84.69	85	1,811	25.0 °C	84.65	85	1,811	24.0°C
	84.56	85	1,813	25.0 °C	84.67	85	1,814	24.0°C
4	84.56	85	1,813	21.5 °C	85.01	84	1,804	21.0°C
	84.31	85	1,822	24.0 °C	85.01	85	1,810	24.0°C

Note: all data from Leaf Spy CSV file.

The 2013 Nissan Leaf had a total of sixteen values from eight segments analyzed to find Pearson Correlations between the dependent variable, SOH, and three independent variables: QC, L1/L2, and Temperature. It had a mean SOH of 84.72% which shows battery degradation had occurred. There was only one change in QCs out of the eight segments, the final cell went from 84 to 85 QCs. There was a mean L1/L2 charging events of 1,811.31. Temperature had a mean score of 24.19°C.

Based on these eight segments in Table 8, a multiple regression was completed on all values. QC and SOH have a moderate negative correlation of -.413 based on these findings. It was expected that as QC increases, SOH will be reduced. It should be noted that only one change in the QC value occurred which accounts for a lower-than-expected correlational value. L1/L2 and SOH have a strong negative correlation at -.822. At -.822, charging of the 2013 Nissan Leaf using a Level 1 or 2 charger shows evidence that charging at lower levels can negatively impact SOH. In addition, SOH can be predicted based on L1/L2 charging. Temperatures occurring while data measurements were made appear to have almost no correlation with SOH in regards to long term degradation. A correlational value of .014 for temperature clearly demonstrates that it cannot help in the prediction of SOH over a long period of time. However, the sample is small for this vehicle with 16 values.

Table 8

2013 Nissan Leaf Segment Correlations

		SOH	QC	L1L2	Temp
Pearson Correlation	SOH	1.000	-0.413	-0.822	0.014
	QC	-0.413	1.000	0.546	0.592
	L1L2	-0.822	0.546	1.000	0.131
	Temp	0.014	0.592	0.131	1.000
Sig. (1-tailed)	SOH	.	0.056	<0.001	0.479
	QC	0.056	.	0.014	0.008
	L1L2	0.000	0.014	.	0.315
	Temp	0.479	0.008	0.315	.

Note: 16 values (N = 16) from the Leaf Spy data segments to create correlations.

Table 9 shows 2014 Nissan Leaf segments. The 2014 Leaf uses a 24-kwh battery pack. Data was recorded in Ontario, Canada. There were two unusual items, compared to other Leaf logs, appearing in the raw data logs: (1) no decimals used for noting SOH, and (2) entries in the QC column of “65535” until an actual QC charging event happened. These logs may have been from an earlier version of Leaf Spy or Leaf Spy Pro.

The Leaf Spy software started recording when there was 10% battery degradation resulting in an SOH of 90%. The 90% occurred after 172 L1/L2 charges and no QCs. A reduction to 89% SOH did not occur until 279 additional L1/L2 charges. At 491 charges, the SOH returned to 90%, this is due to an increase in temperature. A lack of decimals makes it difficult to pinpoint exact fluctuation levels involved in increasing the SOH. SOH never returned to 90% or above after 596 L1/L2 charging events. However, SOH did fluctuate multiple times after 723 charging events. At 727 charges there is an escalation of 1% SOH. A rise in temperature of 5°C explains the temporary increase.

After 733 charging events the SOH stood at 88%. There were only three QC completed on the 2014 Leaf between August 2014 to February 2015. A common occurrence, based on Table 9 data, happened for two days, August 6 to 8, 2014, where the SOH temporarily went up to 89% from 88% after four charges. The change to a temporary higher SOH can be explained by the increase in ambient temperature, it returned to 88% after two days. A similar occurrence happened when the SOH increased from 87% to 88%. There was total battery degradation of 2% after 587 L1/L2 and three QC charging events over six months and eight days in 2014-2015. On a pro-rated basis, this 2014 Leaf had 3.96% degradation, slightly more than the 2013 Leaf. Overall, the 2013 Leaf had an additional 873 L1/L2 and 82 QC charging events compared to the 2014 model. Unfortunately, the 2014 had limited data compared to all other Leafs in this study.

The last row was the final addition to Table 9, it shows ending state after data collecting had finished. Temperature was back into the negative range, same as the first row, first column. Two more QC events and 386 L1/L2 happened with a 2% further degradation. In total, the 2014 Leaf had battery degradation of 8% after five QCs and 2,050 L1/L2 charges, this happened over two years and 361 days or a total of 1,091 days.

Table 9

2014 Nissan Leaf data segments

Row	SOH %	QC	L1/L2	Temp	SOH %	QC	L1/L2	Temp
1	90.00	0	172	-6 °C	90.00	0	491	19 °C
	89.00	0	451	16 °C	89.00	0	596	20 °C
2	88.00	0	723	18 °C	88.00	0	896	18 °C
	89.00	0	727	23 °C	87.00	0	911	11 °C
3	89.00	0	733	22 °C	87.00	1	949	9 °C
	88.00	0	733	22 °C	87.00	3	949	12 °C
4	86.00	3	1,478	8 °C	84.00	3	1,664	27 °C
	85.00	3	1,524	17 °C	82.00	5	2,050	-5 °C

Note: 16 values from the Leaf Spy CSV file.

The 2014 Nissan Leaf had sixteen values from four segments analyzed to find Pearson Correlations. It had a mean battery SOH of 87.38% which shows battery degradation had occurred. Only three QC events occurring within sixteen segments. L1/L2 charging events had a mean value of 940.44. Temperature had a mean score of 14.44°C, substantially lower than 24.19°C generated from the 2013 Leaf.

Table 10 shows multiple regression analysis via SPSS was completed on all values from the four segments created from the 2014 Leaf data. The variable QC has a strong negative correlation of -.897. It was expected QC would be impactful to SOH and it was. Like the 2013 Leaf, L1/L2 and SOH have a strong negative correlation. A negative correlation of -.970 shows charging the 2014 Nissan Leaf using Level 1 or 2 can negatively impact SOH. Based on these findings, a mean L1/L2 of 940.44 charges would create substantial degradation. Like the 2013, SOH can be a good predictor based on L1/L2 charging. One vast difference between 2013 and 2014 data is Temperature. Temperature appears to have a weak correlation to SOH at .239, this was expected over a long period of time such as two years. However, as Temperature rises for a short period, the temporary SOH will rise too. If there are a number of L1/L2 charges followed by a rise in Temperature, as shown in Table 11, row three, column two, then the lowering of SOH will be negated and it will show an increase.

Table 10

2014 Nissan Leaf Segment Correlations

		SOH	QC	L1L2	Temp
Pearson Correlation	SOH	1.000	-0.897	-0.970	0.239
	QC	-0.897	1.000	0.892	-0.358
	L1L2	-0.970	0.892	1.000	-0.133
	Temp	0.239	-0.358	-0.133	1.000
Sig. (1-tailed)	SOH	.	<0.001	<0.001	0.187
	QC	0.000	.	0.000	0.087
	L1L2	0.000	0.000	.	0.311
	Temp	0.187	0.087	0.311	.

Note: sample of 16 (N = 16) used from the data segments to create correlations.

Table 11 shows data from a used 2016 Leaf, the new owner started using Leaf Spy with it. A 2016 Leaf uses a 30-kwh battery pack, 6 kwh larger than the 2013 and 2014 models. Temperatures are listed in Fahrenheit. The first segment from 85.97 SOH to 85.9 SOH had eight L1/L2 charging sessions over two days. Reducing 0.07% over eight sessions is 0.0088% per charging session. In the second cell, first row, moving from 5,832 to 5,834 charges shows an increase in SOH to 85.98%. There were two charging sessions during the increase to 85.98% SOH, meaning the ambient temperature is impactful. The initial measurement of SOH at 85.90% was completed with a temperature of 0.5°C or 33°F. At the time of charging, the temperature moved up to 2.5°C or 36.5°F. The increase of 2°C has temporarily raised the SOH. In the second row, first column, the SOH decreases by 0.18% after twenty L1/L2 charges. The ambient temperature increase of 15.3°F did not override the twenty charging events. A decrease of 0.22% over six days, with the same temperature, occurs with a combination of one QC and seventeen L1/L2 charges. The third row provides consumers evidence that one QC can affect battery SOH in a Leaf. The ambient temperature goes down by 3.3°F, yet the SOH drops by 0.01% after the QC. In the third row, second column, an additional nine L1/L2 charges were added over three days ending at a total of 5,880. Yet the SOH increases 0.12% over the three days. Reduction of ambient temperature by 6.6°F temporarily negates any negative affect of charging. For every °F decrease, the SOH increases 0.02%. Overall, the battery degraded from 85.97% to 85.45%, or 0.52% from February 22 to March 20, 2021, less than one month. Degradation pro-rated over a year would be 6.24%, a result from the high numbers of L1/L2 charging.

Table 11

2016 Nissan Leaf data segments

Row	SOH %	QC	L1/L2	Temp	SOH %	QC	L1/L2	Temp
1	85.97	6	5,819	38.3 °F	85.90	6	5,832	37.4 °F
	85.90	6	5,827	24.8 °F	85.98	6	5,834	36.5 °F
2	85.98	6	5,834	36.5 °F	85.80	6	5,854	50.9 °F
	85.80	6	5,854	51.8 °F	85.58	7	5,871	50.9 °F
3	85.48	7	5,871	58.1 °F	85.47	8	5,871	56.3 °F
	85.47	8	5,871	55.4 °F	85.59	8	5,880	50.9 °F

Note: sample of 16 used from the data segments.

The 2016 Nissan Leaf had twelve values from six segments analyzed to find descriptive statistics and Pearson Correlations. It had a mean SOH value of 85.74% which shows evidence of battery degradation. There were eight QC events analyzed within the segments. A mean number of 5,851.5 L1/L2 charging events occurred, more than seven times the amount from previous 2014 Leaf data. Temperature is in Fahrenheit and had a mean score of 45.65°F or 7.58°C., almost half what the 2014 Leaf registered.

In Table 12, the 2016 Leaf data included more segments and had similar findings to 2014 L1/L2 charging. QCs had a strong negative correlation of -.888. It was expected QCs would be a good predictor of SOH, and it is for a 2016 Leaf. The L1/L2 charging events and SOH have a strong negative correlation. A negative correlation of -.924 shows charging a 2016 Nissan Leaf using Level 1 or 2 chargers can negatively impact SOH. Like a 2013 Leaf, SOH can be predicted based on L1/L2 charging. Temperature appears to have a strong negative correlation to SOH at -.841. Over a long-term period, SOH can be negatively affected by temperature as discussed by Yang et al. (2018).

Table 12

2016 Nissan Leaf Segment Correlations

		SOH	QC	L1L2	Temp
Pearson Correlation	SOH	1.000	-0.888	-0.924	-0.841
	QC	-0.888	1.000	0.836	0.674
	L1L2	-0.924	0.836	1.000	0.876
	Temp	-0.841	0.674	0.876	1.000
Sig. (1-tailed)	SOH	.	<0.001	<0.001	<0.001
	QC	0.000	.	0.000	0.008
	L1L2	0.000	0.000	.	0.000
	Temp	0.000	0.008	0.000	.

Note: sample of 12 (N = 12) used from the data segments for correlations.

A 2017 Nissan Leaf owned by the author of this study was analyzed. The 2017 Leaf employs a 30-kwh battery. Data consists of sixteen rows and two columns created through using Leaf Spy Professional starting in 2019, although the EV model year is 2017. Data was gathered in Ontario, Canada. This EV had more data available for analysis than any other within the study. All charging events were either Level 2 or Level 3. A home charger at L2 was most frequently used. Overall, SOH for the 2017 Nissan Leaf started at 85.06% on November 6, 2019, and finished recording at 77.5% on October 20, 2020, an 11-month and two-week span or 349 days. Pro-rated degradation over a year was 7.53% which is high. A high rate of degradation can be explained by a large number of QCs and charging to 100% SOC. Based on these values, the permanent reduction in SOH per month averaged to 0.66% for this Leaf. The average temperature recorded was 10.49°C. From December 9, 2019, to January 16, 2020, there was some data not evaluated because the EV was either not connected via a smartphone to a cellular network or it was parked for more than a week. There were six temperatures of 87°C or above that were disregarded, either the value was incorrectly saved or was altered to a Fahrenheit value.

The very first cell of 2017 Nissan Leaf data has a constant temperature of 8.5°C and one additional QC from 297 to 298. SOH reduced from 85.06% to 85.01% after the QC, thereby a decrease of 0.05% occurred after one Level 3 charging event. In the second cell, first line, there are an additional 10 QCs and 31 L1/L2 charging events with degradation of 0.11%. However, unlike a constant temperature, it changed by 7°C colder for the SOH measurement of 84.73%. The temperature has altered the measurement of degradation because the value would be 0.50%, not 0.11%, if temperature remained at 8.5°C for ten QCs. The colder temperature has decreased the measured degradation.

The second row, first column, and sixth row, second column of Table 13 show a similar pattern to the 2013 Leaf, the SOH increases instead of showing degradation. For the second row, a substantial increase of 10°C occurred where 85.14% SOH temporarily increased to 85.20%. Temperature began as a minus value and climbed upward which positively impacted the SOH. Similarly, the sixth row, second column SOH went up from 82.21% to 82.24% after one charge and a temperature increase of 2.5°C. The increase of 10°C results in .01% SOH temporarily gained per 1°C. For the sixth row, the 2.5°C temperature increase raised the SOH, a change of 0.03% provides 0.01% per 1°C.

In the 82.05% segment, second row, second column it is very clear the SOH degraded from 82.05% from one L2 charge under identical temperatures. There were three days and three charges at L1/L2 where SOH dropped from 82.26% to 82.05%, in the third row, for a total degradation of 0.21%. The 0.21% degradation over three days averages to 0.07% per charging event, this is extremely high compared to previous L1/L2 charging degradation. However, it is a small sample time. A drop of 11°C during three days negatively influenced the SOH value. In the 82.28% cell, third row, a degradation of 0.02% occurred after one L1/L2 charge and a 5°C increase. Based on the 0.02% SOH degradation, the value for row four, 82.26%, having three L1/L2 events, should create a value of 0.06 at 5°C, but this shows 11°C. Taking 0.06 and multiplying the temperature by 2.2 to reach an 11°C difference would result in 0.13% SOH, not 0.21% as shown. A 6°C increase from 5°C to 11°C appears to degrade a battery an additional 0.15% over time or 0.03% per 1°C, twice the increase as the previous example. Therefore, starting above 9°C is more impactful on battery SOH than below 0°C when using an L2 charger. The difference between the 82.26%/82.05% and 82.28%/82.26% cells can be explained by the increase of 5°C in temperature. The 82.34%/82.34% cell shows an increase of one L1/L2 charge, but a reduction in SOH appears to be negated by the lower temperature. This is an important cell because an 0.5°C increase is not altering the measured SOH.

The 83.71%/83.65% segment created from 2017 Leaf data was calculated over the same day. An L2 charging event happened, as did an increase in ambient temperate, resulting in a loss of 0.06% SOH. At .01% per 1°C, a temperature increase of 2°C would account for 0.02% of the 0.06% SOH loss. The 0.036% loss can be attributed to the L2 charging event. This is slightly higher than usual based on other Leafs, but not uncommon.

The sixth row, first column has a constant temperature of 12.5°C and yet a degradation of 0.09% SOH after one L1/L2 charging event. This is the highest single difference for one L1/L2 charge compared to the previous five rows. One part of the explanation is that 82 37% SOH was a temporary value, the previous value only a day before was 82.34%. Based on this information, the degradation of 0.06% for a single charging event, after use, is like past findings with a Nissan Leaf. A value of 0.06% is still high because 20 L2 charges per month would equate to losing 1.2% SOH, this is not the long-term loss as shown above, 0.66% per month. The reduction in SOH from 82.37% to 82.28% happened on the same day, May 14. A total of 93 km was driven this day between 11:14 A.M. and 12:33 P.M. The other part of the explanation centers around a temperature decrease. Temperature decreased 1°C from 13.5°C to 12.5°C during the drive until the next charge, it appears the change negatively effected the SOH. Charging occurred before 11:14 A.M. and after 12:36 P.M. when a 93 km trip was completed, this is when the SOH was measured. The day before, May 13, the EV was charging on an L2 charger. Based on a small amount of time between charges, cyclic charging has not influenced degradation of the battery.

Row seven has 82.17% SOH as a starting value and ends with 82.15%. There were only two L2 charging events plus a temperature decrease of 5.5°C. Based on row eight data the temperature under 10°C should equate to 0.01% per 1°C reduction. It cannot be determined that degradation occurred here because the 0.02% loss is equivalent to impact via temperature.

Row eight shows two segments that add clarity to how temperature impacts SOH. QC and L1/L2 remains constant while SOH increases 0.02% and 0.06% in the first and second cells respectively. The only independent variable changing is temperature. An increase of 4°C in cell one, starting above 0°C, added 0.02% to SOH. This averages out to 0.01% per 2°C raise, or 0.005% per 1°C in temperature. Row eight, second column shows an SOH increase of 0.06% starting at 82.99% and ending 83.05%. A 5°C raise in temperature, above 9°C, averages to 0.012% SOH increase per 1°C. The higher starting temperature in the second column impacts the SOH more as shown by a higher increase per 1°C.

Row ten, column one has a reduction of 0.64% SOH, 82.99% to 82.35%. Five additional L1/L2 charging events happened plus a reduction of 4.5°C. The 4.5°C change occurred right at 9°C, based on row 7 data it should equate to 0.01% per 1°C reduction or 0.05% total. The five charging events equate for 0.59% of degradation or 0.12% per charge, this is extremely high.

Like row ten, row eleven shows a big drop in SOH, a total loss of 0.66% occurred. Taking temperature into account, 0.01% SOH decrease per 1°C occurs. At 5.5°C degrees less from the starting point, a total of 0.07% from an overall 0.66% decrease is accounted for while the other 0.53% is due to sixteen Level 2 charges. Each Level 2 charge averages to a reduction of 0.03% SOH for the battery. If SOH degradation averages to 0.66% per month for this Leaf, then 0.03% equates to 19.87 charges per month which is common and validates these findings.

Row thirteen has two important cells of information—cell one helps calculate impact of temperature and cell two helps define QC degradation. Column one has one L1/L2 charge with a 2°C temperature decrease. A decrease of 0.04% SOH happens after charging. Using 0.01% per 1°C decrease, and SOH loss of 0.02% per L2 charge, same as row fourteen, then a calculation of 0.04% SOH is valid. Column two shows the first additional QC recorded since the third row, it also shows a decrease of 0.2% in SOH. Temperature is at 29°C and 23°C. There are seven new L2 charging events, a reduction of 6°C, plus one QC at .025%. A decrease of .012% per 1°C, based on previous results, accounts for 0.069%. Adding QCs plus seven L2 charges equals a 0.2% SOH reduction. Using the first cell in Table 13, the QC accounts for a 0.05% SOH reduction. Adding QC and temperature equals 0.12% which means 0.08% is created by seven L2 events or 0.01% per charge.

Row fourteen, column two has evidence of battery degradation from charging with a lowered SOH of 0.20%. There was one additional QC, seven L2, and a temperature decrease of

6°C to 23°C. The degradation based on a temperature of 23°C appears to be 0.02% per L2 charge or 0.11% in total. Two QC events represent 0.095% of the overall 0.20% SOH degradation.

Row fifteen, column one has an SOH reduction of 0.06%. Column one has one additional L2 charge and a 5°C increase to 29°C. The starting temperature of 24°C is lower than 29°C from row sixteen, and therefore it represents less than 0.10% degradation. Using the final row value of 0.03% SOH degradation for one L2 charge plus 0.03% accounted for by temperature at 24°C provides consistent results across rows. Lower ambient temperatures create lower degradation values which is consistent in findings from Yang et al. (2018). There was a reduction of 0.26% SOH in row fifteen, column two, it decreased from 81.49% to 81.23% SOH. Based on column one, a temperature of 23°C in column two accounts for less than 0.03% SOH degradation, and the rest is from charging. Two QC events occurred accounting for 0.10% based on previous findings. Temperature plus QCs total a 0.11% SOH decrease. Twenty-four L2 charging events occurred between measurements, a decrease of 0.15% SOH or 0.006% per L2 event.

The final row of Table 13 provides insight into both influence of temperature and Level 2 charging on SOH. Column two is examined first because it provides a rationale behind the obtained numbers in column one. Column two has no additional charges, but a drop of 0.10% SOH occurs as the temperature rises 1°C to 30°C. At 30°C, this is an above average temperature for Ontario, Canada and has impacted the battery health. The original degradation of 0.01% per 1°C does not appear to be valid in the 29-30°C range. If a decline of 0.10% SOH happens around 29°C, then this would apply to column one. Row sixteen, column one has a drop of 0.19% SOH after three L2 charges and increasing the temperature 9°C to 28°C. A 30°C temperature accounts for 0.10% of a total decline at 0.19%, this leaves 0.09% based on three L2 charging events. Using both temperature and charging events creates an average of 0.03% loss per L2 charge at

28°C. Row eleven had similar findings to the final row thereby validating the final value of 0.03% SOH is lost through charging a 2017 Nissan Leaf on a L2 charger during 30°C weather.

Table 13

2017 Nissan Leaf data segments

Row	SOH %	QC	L1/L2	Temp	SOH %	QC	L1/L2	Temp
1	85.06	297	1,519	8.5°C	84.84	336	1,662	3.0°C
	85.01	298	1,519	8.5°C	84.73	346	1,693	-4.0°C
2	85.14	277	1,420	-3.5°C	82.05	367	1,825	11.0°C
	85.20	290	1,453	6.5°C	82.00	367	1,826	11.0°C
3	84.93	332	1,643	2.0°C	82.28	367	1,820	13.0°C
	84.84	336	1,661	5.0°C	82.26	367	1,821	18.0°C
4	83.71	367	1,774	15.5°C	82.34	367	1,817	9.5°C
	83.65	367	1,775	17.5°C	82.34	367	1,818	10.0°C
5	82.26	367	1,822	24.5°C	82.29	367	1,813	3.0°C
	82.05	367	1,825	13.5°C	82.22	367	1,812	4.5°C
6	82.37	367	1,819	12.5°C	82.21	367	1,809	9.5°C
	82.28	367	1,820	12.5°C	82.24	367	1,810	12.0°C
7	82.17	367	1,804	14.0°C	82.33	367	1,800	1.5°C
	82.15	367	1,806	8.5°C	82.14	367	1,803	12.0°C
8	82.22	367	1,811	4.0°C	82.99	367	1,791	10.0°C
	82.24	367	1,811	8.0°C	83.05	367	1,791	15.0°C
9	82.17	367	1,804	11.0°C	83.71	367	1,774	15.5°C
	82.14	367	1,803	11.5°C	83.65	367	1,775	17.5°C
10	82.99	367	1,792	9.5°C	81.96	367	1,828	17.0°C
	82.35	367	1,797	5.0°C	81.92	367	1,830	18.0°C
11	83.71	367	1,774	16.0°C	81.88	367	1,831	19.0°C
	83.05	367	1,790	10.5°C	81.99	367	1,836	20.0°C
13	81.92	367	1,830	21.0°C	81.82	367	1,849	29.0°C
	81.88	367	1,831	19.0°C	81.62	368	1,856	23.0°C
14	81.99	367	1,837	19.0°C	81.43	368	1,861	31.0°C
	81.89	367	1,848	16.0°C	81.33	368	1,861	39.0°C
15	81.88	367	1,848	24.0°C	81.49	372	1,869	24.0°C
	81.82	367	1,849	29.0°C	81.23	374	1,893	23.0°C
16	81.62	368	1,858	19.0°C	81.23	374	1,894	29.0°C
	81.43	368	1,861	28.0°C	81.13	374	1,894	30.0°C

Note: largest CSV file from 2017 Nissan Leaf.

The 2017 Nissan Leaf had sixty-four values from thirty-two segments analyzed to find descriptive statistics. It had a mean battery SOH of 82.54% which shows battery degradation. There was a mean of 360 QC events analyzed within the segments, much higher than other Leafs. A mean of 1,792.47 L1/L2 charging events occurred. Temperature had a mean score of 14.73°C, much higher than the 2016 Leaf.

The 2017 and 2016 Leaf findings for correlation were similar for QC, L1/L2, and Temperature values. A 2016 Leaf uses the same battery pack size as a 2017 Leaf. In Table 14, strong negative correlations were present for all three correlational values. QC and SOH have a negative correlation of -.797 over sixty-four values, this pattern is consistent with previous findings using 2016 data. A strong predictor of SOH is L1/L2 with a negative correlation of -.903. With more values analyzed than previous participants, temperature appears to have a moderate-strong negative correlation with SOH. A -.631 represents a moderate-level negative correlation, slightly less than the 2016 Leaf.

Table 14

2017 Nissan Leaf Segment Correlations

		SOH	QC	L1L2	Temp
Pearson Correlation	SOH	1.000	-0.797	-0.903	-0.631
	QC	-0.797	1.000	0.967	0.461
	L1L2	-0.903	0.967	1.000	0.595
	Temp	-0.631	0.461	0.595	1.000
Sig. (1-tailed)	SOH	.	<0.001	<0.001	<0.001
	QC	0.000	.	0.000	0.000
	L1L2	0.000	0.000	.	0.000
	Temp	0.000	0.000	0.000	.

Note: sample of 64 (N = 64) used from data segments for correlations.

Table 15 provides a summary of findings from above in regards to how temperature is affecting various years of Nissan Leafs. As one would expect, extremes at either end, cold or hot, have an impact on battery degradation. The extreme heat at 27-30°C will degrade the SOH over the long term as Yang et al. (2018) detailed in their study. These findings validate past findings with 0.10% SOH degradation happening during L2 charging sessions. Compared to 30°C, 21°C is 9°C lower and has less impact on the SOH degradation when charging. Similar findings from FleetCarma (2019) have the optimal driving temperature at 21.5°C for an EV. Using Level 3 chargers can have a serious negative impact even at moderate temperatures such as 8.5°C. A 0.05% reduction in SOH can be correlated to using a Level 3 charger. Based on this information, it is best to reduce Level 3 charging to a minimum.

Table 15

Nissan Leafs Charging, Temperature and SOH Degradation Evaluations

Charger Type	Temperature	SOH Degradation
L2	27 - 30°C	0.10%
L2	21 - 23°C	0.012%
L2	9 - 18°C	0.012%
QC/L3	8 - 9°C	0.05%
QC/L3*	13 - 23°C	0.03%

Note: values provided from2017 Nissan Leaf results. * value from 2018 Nissan Leaf

Table 16 has values of a 2018 Nissan Leaf beginning at the start of ownership. All temperatures are shown in Fahrenheit (°F). A temperature of 56.3°F is equivalent to 13.5°C. The 2018 Leaf has a 40-kwh battery, larger than both the 2016, 2017, and 2013 models. SOH started at 99.76% and ended at 85.98% in the CSV file. An overall SOH reduction after 143 QCs and

2,597 L1/L2 charges is 13.78%, this indicates battery degradation happened over 1,052 days or two years, ten months, two weeks, and one day. The yearly pro-rated degradation amount is 4.78%. There were anomalies in the February 2021 data with 2,010 kms missing and multiple cells with “NA” - this data was not analyzed.

The first cell shows an increase of one QC and five additional L1/L2 charges, yet the SOH results are 0.07% less. Based on previous results, one QC for a smaller battery pack can remove 0.05% SOH, but this seems unlikely with the 40-kwh. As 56.3°F or 13.5°C is colder than 21°C, SOH degradation will be less than 0.01% per charge based on previous Leaf findings. At 0.01% per charge for five charges, there should be 0.05% attributed to L1/L2 charging. A QC for 0.03%, or half the impact level on a 30-kwh battery, represents the remainder of the 0.07% SOH degradation. Temperature remains consistent during both measurements negating any impact on SOH.

The first row, second column of Table 16 has an additional eight QCs and 73 L1/L2 charging sessions resulting in an SOH reduction of 0.18%. At 0.05% SOH reduction for a QC, as shown with the 2013 and 2017 Leafs, the total SOH should be reduced by 0.40% which is not feasible. The value of 0.003% per charge from the second row is not feasible for 0.18% degradation; it is slightly less. Therefore, using a larger battery pack than 30-kwh renders a QC less impactful and has a value of less than 0.025%.

The second row, first cell shows an additional four QCs and 59 L1/L2 charging sessions creating a 0.93% SOH decrease. More charging occurred in the first row, column two than the second row, and from these numbers it was expected a larger drop in SOH would occur. However, the SOH drop in the second row is more than triple than the first row, second column. The second row, second column shows a reduction of 0.15% SOH, this happened over 14 days.

Two QC and 27 L1/L2 charging events happened, almost two per day. From June 15 to June 29, 2019, there is a temperature difference of 12.6°F or 7°C. Degradation of 0.025% per event or 0.05% overall can be accounted for through QCs at temperature 13.5°C. A 0.10% SOH change remains unaccounted for, this is due to 27 L1/L2 charges for an average of 0.003% per charge, much less than battery packs 30 kwh and under.

Table 16

2018 Nissan Leaf data segments

Row	SOH %	QC	L1/L2	Temp	SOH %	QC	L1/L2	Temp
1	99.68	1	20	56.3 °F	94.17	33	1,020	56.3 °F
	99.61	2	25	56.3 °F	93.99	41	1,093	56.3 °F
2	93.99	41	1,093	56.3 °F	93.06	45	1,152	56.3 °F
	93.06	45	1,152	56.3 °F	92.91	47	1,179	68.9 °F

Note: limited data was available for this EV.

The 2018 Nissan Leaf had a mean SOH of 95.06% which shows slight battery degradation. There were 47 QC events occurring within eight segments, a small sample size but moderate QC use. A mean of 841.75 L1/L2 charging events occurred. Temperature had a mean of 57.88°F or 14.38°C lower than the 2013, 2016, and 2014 Leafs. A higher SOH happened for this vehicle compared to other Leafs due to size of battery and charging temperature.

Table 17 shows strong correlations except for SOH and Temperature. QC has an extremely strong negative correlation to SOH at -.994. Like the 2013 and 2014 Leafs, L1/L2 and SOH have a strong negative correlation. A strong negative correlation of -.996 shows charging the 2018 Nissan Leaf using a Level 1 or 2 can negatively impact SOH. Like the 2013 and 2014, SOH can be predicted based on L1/L2 charging. Temperature appears to have a weak negative correlation to SOH at -.302, this was expected because there are only four segments and some were matched on temperature.

Table 17

2018 Nissan Leaf Segment Correlations

		SOH	QC	L1L2	Temp
Pearson Correlation	SOH	1.000	-0.994	-0.996	-0.302
	QC	-0.994	1.000	0.992	0.318
	L1L2	-0.996	0.992	1.000	0.268
	Temp	-0.302	0.318	0.268	1.000
Sig. (1-tailed)	SOH	.	<0.001	<0.001	0.233
	QC	0.000	.	0.000	0.221
	L1L2	0.000	0.000	.	0.260
	Temp	0.233	0.221	0.260	.

Note. sample of 8 (N = 8) used from data segment for correlations.

Leaf Comparisons

Descriptive statistics were created for all five Leaf vehicles utilizing Leaf Spy. Statistics are cumulative and not based on segments. An N of 87,032 represents total lines of data processed within the CSV files provided by participants. A mean of 86.18% for SOH shows moderate battery degradation, End of Life (EoL) is defined as 70% SOH and under. The L1/L2 represents the mean number of charges using either a Level 1 or 2 charger. A value of 1,702 for L1/L2 is a large number considering most EVs only have time to charge once per day. The mean for QCs is 245.71, this indicates they make up 14.44% of charging events compared to 85.56% for L1/L2 chargers.

The obtained correlation coefficient, R value, for all Leaf Spy data was R = .783, R Square = .613, Adjusted R Square = .613, and the Standard Error of the Estimate was 1.519. A value of .783 demonstrates a strong predictor relationship between charging events and SOH for Leaf batteries, this takes into account all types of charging used by a Nissan Leaf.

The correlations table for Leafs, Table 18, provides two areas of interest: a Pearson Correlation and Significance between the dependent variable, SOH, and two independents, L1/L2 and QC. A correlation of -.236 for L1/L2 charging displays a weak negative correlation to SOH while a value of -.682 is much stronger for QCs. Temperature shows a weak correlation, approaching moderate, of .345 which explains a temporary raise in SOH for some data.

Table 18

Cumulative Leafs Correlations

		SOH	QC	L1L2	TEMP
Pearson Correlation	SOH	1.000	-0.682	-0.236	0.345
	QC	-0.682	1.000	-0.200	-0.340
	L1L2	-0.236	-0.200	1.000	-0.082
	TEMP	0.345	-0.340	-0.082	1.000
Sig. (1-tailed)	SOH	.	0.000	0.000	0.000
	QC	0.000	.	0.000	0.000
	L1L2	0.000	0.000	.	0.000
	TEMP	0.000	0.000	0.000	.

Note: values from 87,032 (N = 87,032) lines of Leaf data as analyzed in SPSS.

Within the regression analysis, an ANOVA was completed to see if regression variables could provide a good prediction of the dependent variable: SOH. L1/L2, QCs, and Temperature were used as the three predictors of SOH. As the number of L1/L2 and QC charging events increase over the life of the EV, the SOH for the battery decreases indicating degradation. As a whole, L1/L2, QCs, and Temperature provide good predictors of SOH (See Appendix VII). The significance was analyzed using a .95 Confidence Interval.

The information presented in Figure 16 below shows data interaction points between SOH and QC. A linear relation was expected based on previous research. A scatterplot is an excellent way to show linearity. One of the questions to answer is “What are the effects of various types of charging on battery pack degradation on North American EVs?” The scatterplot shows the long-term effect of QCs on Nissan Leafs SOH. Values hug the line of fit as the number of QCs grow. After approximately 300 QCs, SOH has deteriorated to 86%.

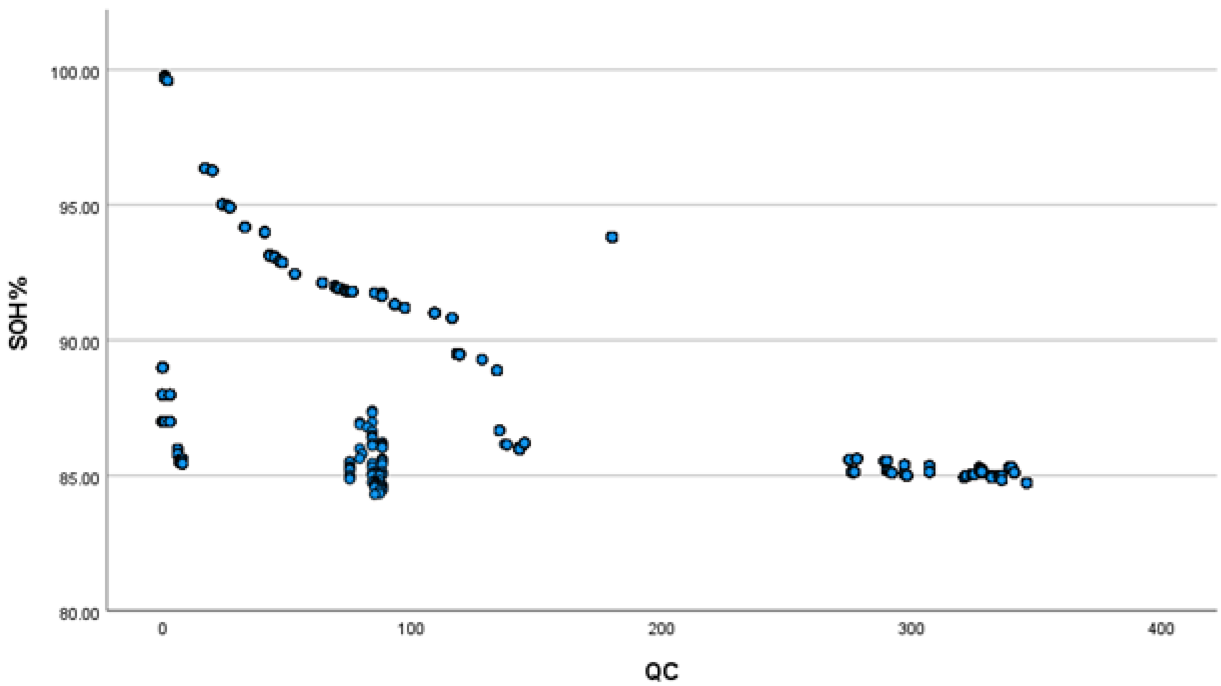

Figure 16. Scatterplot of SOH by QC for Nissan Leafs

Like Figure 16, information presented within the scatterplot of Figure 17 shows data interaction points between SOH and L1/L2 charging for Nissan Leafs. The line of fit has a large congregation of data from 1,500-2,000 L1/L2 charges. SOH will be in the 85-90% range after approximately 1,500 L1/L2 charges. There are outlier values near the 6,000 L1/L2 charging events created by the 2016 Leaf. The 2016 Leaf has a very low number of QCs, mean of 6.67, and it appears to have made a significant difference in keeping a healthy battery. For the 30-kwh battery pack used in 2016 and 2017 Leaf models, there is a negative impact of using a Level 3 charger for quick charging.

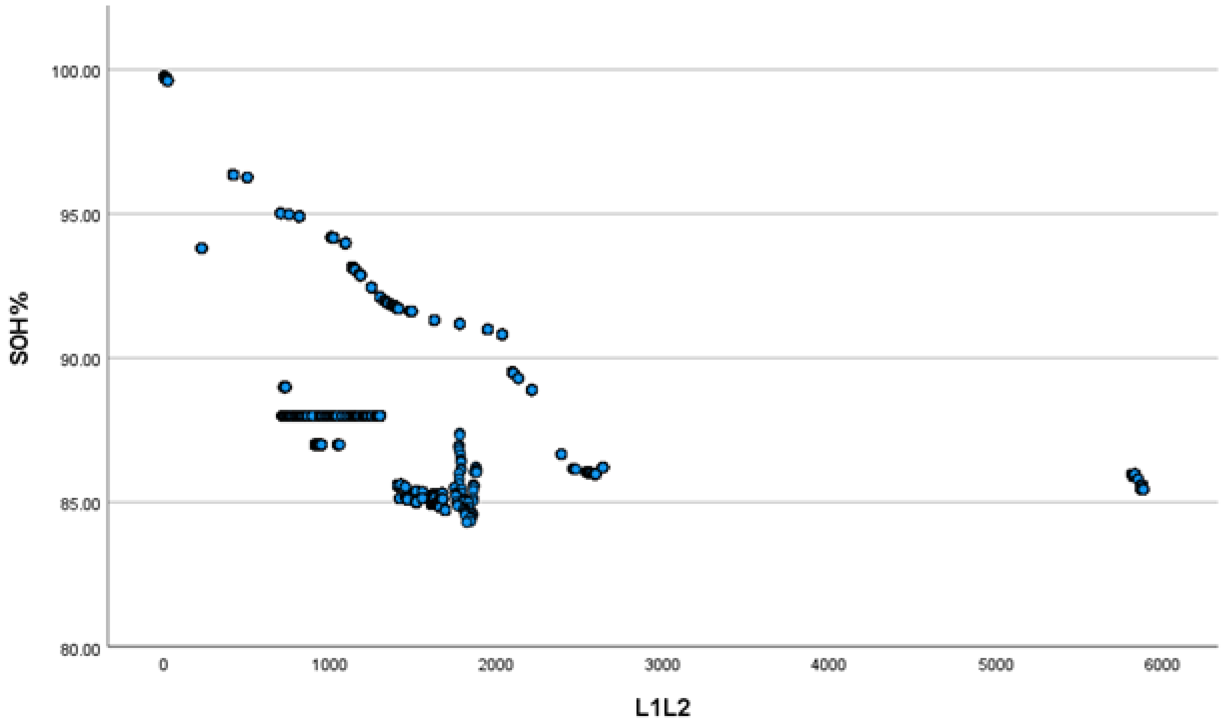

Figure 17. Scatterplot of SOH by L1/L2 for Nissan Leafs

There was data from multiple Nissan Leafs taking part in the FleetCarma study. Leafs from British Columbia, Ontario, Alberta, Manitoba, Nova Scotia, and Quebec took part. The following Leaf data in Table 19 was chosen from Ontario because previously analyzed Leafs using Leaf Spy were from there. Table 19 has one Nissan Leaf using a data logger to see if results are consistent with Leaf Spy generated data.

In segment one, 603 lines were analyzed with a SOC difference of 1% or greater. SOC difference, Charger Level, Starting SOC, and Ending SOC were equivalent. No Level 1 charger was used. Three Level 3 and 600 Level 2 charging events happened. An increase in energy from August 9, 2017 to July 13, 2018 required an additional 0.44 kwh or 2.81%. Pro-rated for one year shows an energy increase of 3.03%.

In segment two, charger level and ending SOC were equivalent because of which SOC difference had to be adjusted for comparisons. At 34.51%, 10.658 kwh becomes 10.695 kwh. An energy increase happened over the year and seven days of 4.08%. Pro-rated for one year the required energy is 4.00% higher. A range of 3.03% – 4.00% appears accurate because only three Level 3 charges occurred. Results are similar to other Nissan Leafs using Leaf Spy and limited Level 3 charges with SOH degradation values of 3.74%, 3.96%, and 4.78%. The 2017 Leaf with excessive Level 3 charging and frequent 100% Ending SOC shows the impact on SOH with the highest value 7.53%.

Table 19

Nissan Leaf Data from Ontario via FleetCarma

StartTime	Energy (kwh)	Loss	Level	Starting-SOC%	Ending-SOC%	SOC-Diff%
8/9/2017 2:00	15.336	1.840	2	50.00	100.00	50.00
7/13/2018 0:00	15.779	2.090	2	50.00	100.00	50.00
7/21/2017 2:00	10.658	0.853	2	65.61	100.00	34.39
7/28/2018 1:26	11.149	1.799	2	65.49	100.00	34.51

A 2017 Chevrolet Bolt employs a 60-kwh battery pack. Data in Table 20 shows battery degradation for a 2017 Chevrolet Bolt over time starting in November 2018 and continuing to March 2021, using a 10.2% capacity increase, for the first five entries. The last two entries show a 15.68% capacity increase. The EV is located in Canada. A total of 1,900 charging events were documented. Of the 1,900, 838 or 44.11% of charging events ended with an SOC above 80%. Of 838, 184 or 21.95% were to a 100% SOC. Charging at this level appears to increase degradation levels based on previous data. Degradation is expected to be higher than in many other EVs due to frequent charging to 100% SOC. There were no Level 3 chargers used at any time.

The energy used for a 10.2% SOC increase in the November 2018-2019 entries are relatively close, a 1.43% decrease occurred from November 2, 2018 to December 6, 2019. Another energy decrease happened comparing November 16, 2019 to December 6, 2019, a total of 4.34% more was required to add 10.2% SOC. Both these small decreases in energy consumed can be explained by a previous charging event. First, on November 2, 2018, a charging event started at 8:29 P.M. for 55 minutes and ended with 71.76% SOC, the next recorded event is shown in Table 20 at 9:28 P.M. There is a four-minute gap with no data which cannot be accurately explained. Second, data from November 15, 2019 shows an 11 hour and 28-minute Level 1 charging event followed by recorded data in Table 20. Many owners, myself the author included, use a combination of chargers to “top up” the range because of time, cost, or access to a faster charger. Moving from one charger to another creates a new line of data in the CSV files. Other data analyzed from July 12, 2020 shows no other charging events occurring the same day, previous to data line creation, or the day before. Like July 12, March 1, 2021, had no previous day charging events. Prior to the 7:40 P.M. charging event on March 1, there was no charging for 1 hour and 48 minutes. There was driving that reduced the SOC by 5.5% during the period of no charging. Based on the sequence of charging and two small decreases in consumed energy after time, these were anomalies and should be treated as such. Other numbers in the segments clearly show battery degradation.

In July 2020 and March 2021, comparative differences to November 2018 data shows 0.81 kwh and 1.86 kwh increases in consumed energy, 11.4% and 22.8% respectively, to reach the same SOC three years earlier. It would be expected, based on Arrhenius Law, that more energy is required at -5.1°C compared to 6.9°C, a difference of 12°C. However, at 28°C in July 2020, the cold weather is no longer a factor and cannot explain the 0.81 kwh difference. A 0.81 kwh or 11.4% difference from November 2, 2018 to July 12, 2020, a total of 21 months and 11 days, is 0.54% kwh per month more energy or a minimum energy increase of 6.51% per year. Charging to 100% SOC has negatively affected the Bolt, even with a larger battery pack. One can see battery degradation has occurred after 1,253 L1/L2 charging events. Similarly, as shown in the Figure 16 scatterplot, Nissan Leaf data clearly shows over 10% SOH degradation after 1,000 L1/L2 charges.

The last two entries of Table 20 are based on an SOC increase of 15.68%. A difference of 0.04 kwh shows temperature has impacted charger loss and possible degradation has occurred over one year, three months, and 16 days. Unfortunately, with a 3.5°C temperature difference it is not possible to calculate exact degradation. The Start-SOC, End-SOC, and SOC-Diff are all equal values using 15.68%. Temperature can be accounted for through additional energy loss via the Level 2 charger. One unique aspect to all CSV data for this 2017 Bolt is no Level 3 charging.

Table 20

2017 Chevrolet Bolt Segmented Data

Date/Time	Level	Energy (kwh)	Loss	Start-SOC%	End-SOC%	SOC-Diff%	Temp
2021-03-01 19:40	2	8.18	2.41	77.25	87.45	10.20	-5.1 °C
2020-07-12 13:07	2	7.13	0.74	50.98	61.18	10.20	28.0 °C
2019-12-06 10:05	2	6.23	0.53	80.39	90.59	10.20	1.7 °C
2019-11-16 11:06	2	5.96	0.46	74.51	84.71	10.20	-5.6 °C
2018-11-02 21:28	2	6.32	0.51	71.76	81.96	10.20	6.9 °C
2021-03-06 10:49	2	10.91	2.74	72.16	87.84	15.68	-3.1 °C
2019-12-21 5:11	2	10.95	2.63	72.16	87.84	15.68	.4 °C

Note: selected segments based on equivalent SOC-Diff scores.

Descriptive statistics developed from analyzing 2017 Chevrolet Bolt data provide an excellent assessment of how the vehicle was treated under “real world” circumstances. A charging report generated by the 2017 Bolt was used and a total of 1,900 lines were analyzed. The starting SOC had a mean score of 71.32% which is much higher than 20%, below this level was found to be harmful to the battery over time as studies in labs have shown by both Jiang et al. (2014) and Lu et al. (2013). A mean ending SOC of 83.82% is above 80% which may add to degradation based on lab research by Jiang et al. (2014) and Lu et al. (2013). Based on charging events above 80%, it was expected that ample degradation would happen, and it did! A minimum energy increase of 6.51% per year occurred with this specific Bolt.

A 2018 Chevrolet Bolt uses the same size battery pack as the 2017 model, 60 kwh. Table 21 data is from a 2018 Chevrolet Bolt having 20 Level 1, 1,185 Level 2, and 52 Level 3 charges. All charging sessions analyzed had an increase of 1% or more SOC%. Including all the charging events, only 20 or 1.59% were to 100% SOC. There was only one charging event to 100% SOC using a Level 3 charger. A total of 949, or 75.5%, charging events occurred with the End SOC higher than 80%. Two 2019 data lines in Table 21 show energy consumption of 0.72 and 0.70 kwh for a battery gain of 10.2% SOC. Increasing energy 10.3% and 9.1% are required for adding 10.2% SOC between the value of 0.7 kwh from October 2019 and two from 2021, 0.78 and 0.77 kwh. For 0.72% in April 2019, there were energy increases of 6.5% and 7.7% compared to the 2021 values of 0.78 and 0.77 kwh. One consistent trend from the data is an increase in energy loss for ending SOC values above 70.2%. As mentioned in the Literature Review, many operators of EVs do not charge past 80% because it is less efficient. These findings support an ending SOC above 87.45% for a minimal gain of 10.2% SOC results in greater energy loss, or less efficiency, during the charging session.

Table 21 is unique because it shows a large amount of loss with a small amount of energy gained by the EV. There are two explanations to the large loss, (1) the Starting SOC value is high, and more losses can occur above 80% SOC due to resistance; and (2) the charger itself is not efficient. Weather does not factor into these results because losses range from 5.81% to 6.85% across summer and winter months.

Table 21

2018 Chevrolet Bolt Segmented Data

Date/Time	Level	Energy (kwh)	Loss	Start-SOC%	End- SOC%	SOC-Diff%
2021-02-13 14:04	2	0.78	6.51	84.31	94.51	10.20
2021-01-28 19:20	2	0.77	6.44	84.31	94.51	10.20
2020-08-17 17:25	2	0.81	6.77	77.25	87.45	10.20
2020-06-15 12:59	2	0.82	6.85	77.25	87.45	10.20
2019-10-25 3:28	2	0.70	5.81	60.00	70.20	10.20
2019-04-29 16:32	2	0.72	5.96	42.35	52.55	10.20

Note: sent in from a participant.

The 2018 Bolt had 542 charging events adding more than 1.00% SOC difference. This specific Bolt had a lot of charging to 100% SOC, 405 events or 74.72%. Using a SOC difference of 10.2%, an Ending SOC of 100% for June 3, 2018, and May 5, 2018, are both higher in loss energy values compared to those charging events ending at an 87.45% SOC. As noted in the literature, EV batteries work best between 20-80% SOC, these results are in line with previous tests completed in the lab. Results suggest starting at 77.25% SOC and charging to 87.45% will take less energy than starting at 89.80% and going to 100%. There were forty charging events above a 1% SOC increase from May 5, 2018, to June 3, 2018.

The segment in Table 22 from December and September 2018 has values charging to 74.11% and 74.90% SOC respectively, not 100%. Using the lesser value of 7.01 kwh from May 2018 and an Ending SOC 100%, the required energy for increasing 32.94% SOC should be 3.23 times or 22.63 kwh. For December 14, 2018, 20.62 kwh is much less energy, an 8.89% decrease, than the equivalent charging to 100% for a 32.94% SOC increase starting at 41.17%. In addition, December is colder than May in Ontario, and based on Arrhenius Law energy consumption should be higher than in May while charging to the same SOC difference. Data shows 8.89% more energy is needed for adding the same amount SOC difference in May if a user charges to

100% compared to 74.11%. Charging practices should change based on this information, less charging to 100% SOC would result in more efficiencies for energy consumption. Charging to 74.11% SOC is a better option for saving money because less energy is required.

Table 22 contains values from a 2018 Chevrolet Bolt situated in Ontario, Canada. The last segment is created from the bottom three values. There are exactly eleven months difference from July 26, 2018 to June 26, 2019, all comparison data is equivalent including Charger Level, Starting SOC, and Ending SOC. Over eleven months, the 2018 Bolt showed an increase of 3.15% which equates to 0.29% per month or 3.44% more energy required per year, much less than the 2017 Bolt. During the same time, 400 L1/L2 charging events happened. No Level 3 charging occurred during the eleven months, and a total of three happened throughout data recording.

Table 22

2018 Chevrolet Bolt from Ontario via FleetCarma

Date/Time	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
5/5/2018 17:38	7.007	0.840	2	89.80	100.00	10.20
6/3/2018 17:02	7.234	0.868	2	89.80	100.00	10.20
6/29/2018 0:41	6.211	0.745	2	77.25	87.45	10.20
8/25/2018 11:38	6.982	0.838	2	77.25	87.45	10.20
12/14/2018 0:01	20.621	2.475	2	41.17	74.11	32.94
9/17/2018 23:01	20.202	2.424	2	43.52	74.90	31.37
7/18/2018 23:02	29.057	3.487	2	54.90	100.00	45.10
7/26/2018 23:02	29.468	3.536	2	54.12	100.00	45.88
6/26/2019 23:00	30.419	3.650	2	54.12	100.00	45.88

After analyzing data from Table 22, there can be good comparisons made between the 2017 and 2018 Chevrolet Bolt, the latter from Ontario using FleetCarma data. Both are using the same sized battery pack and have less than two years of use before data recording began. Based on cyclic charging patterns, the 2017 Bolt would be expected to have more battery degradation, and this is the case. An average of 1.15 charging events happened per day for the 2018 Bolt and 1.56 occurred for the 2017 Bolt. It would require a minimum energy increase of 6.51% per year for the 2017 Bolt whereas the 2018 Bolt required 3.44% more energy per year. The 2018 Bolt had a total of 473 days analyzed with 542 charging events while the 2017 Bolt had 1,216 days and 1,900 charging events. Neither EV used Level 3 chargers often, only three for the 2018 Bolt versus none for the 2017 Bolt.

A 2019 BMW i3 uses a 42.2 kwh battery pack. The BMW i3 in this study was frequently charged to 100% SOC, 71.60% of charging events. No location information was received for this vehicle which disallows temperature influence on calculations. There were 11 Level 1, 83 Level 2, and 11 Level 3 QCs. Energy data from this i3 is only available in integers, no decimals. The first segment uses two different level chargers, so although energy consumption is 2 kwh or 13.34% more after five days, an accurate degradation level cannot be determined.

Table 23 shows three segments, 26.5%, 73.3%, and 75.2%, available from the BMW i3 data based on the SOC difference. The second segment has equivalent SOC differences of 73.3%, yet the energy consumption is higher in the earlier date. It is a small decrease of one kwh from September 21, 2019 compared to January 4, 2020. Two factors could account for the small decrease over time, temperature and rounding. Unfortunately, based on the data, these two factors do not allow for accurate determination of degradation with such a small gap in consumed energy.

The third segment from December 12, 2019 to March 9, 20202 is a good comparison of data because Charger Level, Starting SOC, Ending SOC, and SOC Difference are equivalent. Unfortunately, the timeframe between calculations is minimal. Energy consumption shows an increase of 2 kwh or 6.07% after 87 days, thereby signifying battery degradation. Warmer temperatures in December will impact the level of degradation shown because more energy will be required in March. Using data from this segment combined with the last segment demonstrates a continual pattern of degradation as charging continues.

A fourth segment comparison using data from September 7, 2019 to March 9, 2020, was completed, and it shows the same amount of energy used: 33 kwh. A 4.69% increase in SOC difference happened using equivalent energy for both dates. Results show a loss of 3.70% SOC. A total of 31 charging events happened between September 7, 2019 and March 7, 2020. Based on increased SOC difference comparison, some battery degradation did occur, but energy differences need examining over a longer period of time so definitive values can be determined.

The last segment of Table 23 is from September 2019-2020, a total of 370 days or one year and four days. Energy consumption of 14 kwh created a 32.70% SOC increase in September 2019 whereas one year later it took 15 kwh for a 32.20% SOC increase. From 14 to 15 kwh required a 6.67% increase in power for 1.53% less in SOC. Pro-rated for one year including the higher SOC difference is 6.77%; this amount of degradation is in line with battery packs of the same size. Charger loss is higher on September 11, 2020; the reason is because the EV is charging to a much higher Ending SOC compared to September 7, 2019. Removing the charger loss inequality, due to the higher Ending SOC, would negate the additional energy needed and a 6.67% increase is still required. Based on the higher charger loss when charging to 92% Ending SOC, it is not efficient or advised to charge to 92% SOC or higher with a Level 1 charger.

Table 23

2019 BMW i3 Segmented Data

Date/Time	Level	Energy (kwh)	Loss	Start-SOC%	End-SOC%	SOC-Diff%
9/9/2020 18:15	2	13	1.61	73.50	100.00	26.50
9/14/2020 17:05	1	15	1.82	73.50	100.00	26.50

Table 23 *2019 BMW i3 Segmented Data* (continued).

Date/Time	Level	Energy	Loss	Start/SOC%	End-SOC%	SOC-Diff%
9/21/2019 19:36	2	32	3.84	26.70	100.00	73.30
1/4/2020 5:18	2	31	3.79	26.70	100.00	73.30
12/12/2019 21:36	2	31	3.82	24.80	100.00	75.20
3/9/2020 19:00	2	33	3.96	24.80	100.00	75.20
9/7/2019 18:48	2	33	4.06	21.10	100.00	78.90
9/7/2019 13:45	2	14	1.68	40.30	73.00	32.70
9/11/2020 21:11	1	15	1.82	59.80	92.00	32.20

The first segment examined within data from the lone 2019 Kia Niro EV is shown in Table 24. A 2019 Niro EV uses a 64-kwh battery, larger than most others in this study. There were 462 charging events completed between 2019 and 2021. There were 49 times that the Niro charged to 100% SOC. All charging was done on a Level 2 ChargePoint home charger. Unfortunately, no charger loss was tracked or documented. A value of 10.5% SOC-Diff was common in the data and usable for comparisons. Any charging event with a SOC difference score of zero was removed due to a charge not properly starting and finishing.

Comparing values in the first segment of Table 24 is difficult because of the Starting and Ending SOC. The SOC difference is the same, but the energy consumed to add a 10.5% SOC is vastly different. An energy increase of 2.46 kwh or 26.80% can be partly explained via the starting SOC and ending SOC which are different. As previously mentioned, Jiang et al. (2014) and Lu et al. (2013), discovered that EV batteries operating between 20% and 80% SOC exhibit excellent cycling performance with reduced capacity degradation, this is the case for December 31, 2020 data. However, values of more than 80% had negative consequences in both studies, which explains the additional 2.46 kwh required to reach 100% SOC while adding only 10.5%. Thus, charging to 64% is more energy efficient than to 100%. Consideration for the Starting and Ending level of SOC must be taken into account when comparing data, these are confounding variables for this segment. Energy numbers appear accurate and degradation is occurring, but a better comparison using similar values of Starting SOC and Ending SOC needs completion.

The second segment in Table 24 has a more accurate indication of degradation because it has a constant temperature of 10°C, same SOC difference, equivalent Charger Level, and Ending SOC under 80%. There were twenty-two charging sessions between March 8, 2020 and October 26, 2020. A total of 232 days or seven months, two weeks, and four days happened between measurements. A difference of 0.12 kwh or 1.73% exists between 6.94 kwh and 6.82 kwh, therefore .005% per charge is the required energy to continue charging to a difference of 10.5% SOC over time. Pro-rated for one year, the increase of energy required is 2.72%. The need for added energy at an equivalent temperature provides evidence of battery degradation, but a small amount. A large battery is helping minimize the negative affects of charging to 100% SOC on multiple occasions.

Table 24

2019 Kia Niro EV Segmented Data

Date	Energy (kwh)	Temp	Start-SOC%	End-SOC%	SOC-Diff%	Level
2020-12-31 11:31	6.72	2 °C	53.50	64.00	10.50	2
2021-01-01 11:05	9.18	2 °C	89.50	100.00	10.50	2
2020-03-08 12:59	6.82	10 °C	64.00	74.50	10.50	2
2020-10-26 17:20	6.94	10 °C	44.50	55.00	10.50	2

There was only one 2017/2018 Ioniq in Ontario, Canada taking part in the FleetCarma study. The battery pack in 2017 and 2018 Ioniq models is 28 kwh. There were 84 lines of data where 1% or more SOC difference were analyzed. A total of 27 Level 3 and 17 Level 1 charging events were documented. Data was segmented by equality of SOC Difference and level of charger. All four charging events of Table 25 resulted in an ending SOC of over 90%. The first two dates shown in Table 25, April 13, 2018, and April 20, 2018, create the first segment. Level 2 chargers were used in both segments. March 2018 had similar results to April 2018. Both sets of segmented results show an increase of energy needed to raise the SOC 59.50% and 66.00% respectively. This is evidence of battery degradation considering Temperature and Ending SOC. The temperature was a negligible factor in the first segment because it went higher and based on Arrhenius Law energy should decrease due to warmer climate—it does not. A high temperature of 5°C occurred on April 13, 2018 and 8°C on April 20, 2018 (timeanddate.com, 2018). Both ending SOC values in the first segment are in the 92-99% range, a minimal difference. Energy consumption between April 13, 2018 to April 20, 2018 saw an increase of 0.84 kwh or 4.31%. From March 9 to May 11, 2018 an increase of 0.78 kwh or 3.81% was noted. A 0.50% SOC difference exists between March and May, 2018 data. Neither of these dates had substantial time between measurements, so another segment with further distributed end points was added to see if the previous results were consistent.

The final segment consists of data between 111 days or three months, two weeks, and five days. Charger Level and SOC Difference were consistent. Energy consumption between May 10 to June 29, 2018 saw an increase of 0.36 kwh or 1.69% degradation. Pro-rating a 1.69% rate of degradation creates a yearly value of 5.56%.

Table 25

2018 Ioniq Electric Segmented Data from Ontario via FleetCarma

StartTime	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
4/13/2018 15:00	18.699	1.513	2	33.00	92.50	59.50
4/20/2018 11:00	19.540	1.712	2	40.00	99.50	59.50
3/9/2018 16:53	20.206	1.726	2	34.50	100.00	65.50
5/11/2018 11:08	21.005	1.703	2	25.50	91.50	66.00
3/10/2018 10:00	20.997	1.520	2	27.00	93.50	66.50
6/29/2018 11:20	21.356	1.919	2	26.50	93.00	66.50

There were 146 lines of data generated by a 2020 Kia Soul. No SOH battery degradation occurred as shown in the warning message shown in Figure 18. The warning message occurred because all of the entries in the SOH column show 100%. A combination of Level 1-3 chargers was used to reach 100%. The Kia Soul can charge to a set SOC by configuring it in the console settings. Only 13 of 146, or 8.9%, charging events were completed to 100%. A segment of 109 lines of data shows the EV was charged to a maximum SOC of 80%. Setting the charging value to 80% can partially explain why no degradation occurred.

Warnings
The dependent variable SOH is constant and has been deleted. Statistics cannot be computed.

Figure 18. Warning Message from SPSS

The first Tesla data examined is a Model S located in British Columbia, Canada employing a 85 kwh battery pack. This one particular Tesla had a total of 452 charging events with a minimum increase of 1% SOC, many occurred with a SOC difference increase of 45%. A total of 8 Level 1, 316 Level 2, and 128 Level 3 charging events occurred. Level 3 charges make up 28.32% of all charging.

The Tesla Model S 85 kwh had an increase of .459 kwh or 1.22% more energy required over one month, August to September 2017, to add 45% of battery capacity ending at 90% SOC. This doesn’t include charger loss. A total of thirteen charging events happened over 31 days between August 5 and September 5, 2017, so results indicate it took 0.02 kwh more energy per charging cycle to reach the same SOC Difference of 45%. The high temperature on August 5 was 23°C and on September 5 it was 22°C (Timeanddate.com, 2017). Based on the minor temperature discrepancy, degradation has occurred, but less than 1.22% because of the 1°C decrease. A longer period of time needed to be examined, so November 6, 2017 to November 8, 2018 was used for comparison, as shown below. Energy numbers should rise if battery degradation was happening, but month-to-month changes often happen due to temperature and cannot be representative of the whole year.

The next segment comparison has two differences in data from September 5 compared to November 6, 2017: (1) the much higher temperature of 20°C versus 5°C (Timeanddate.com, 2017), respectively; and (2) location of charger is Home in September and Other in November. As per results from the Nissan Leafs, temperature can affect the battery in different ways. The warmer temperature in September should account for less energy required to charge as per the Arrhenius Law. However, the difference here is location. Chargers at different locations often have different kwh output. Some have 3.3, 6.6, or 7.2 kwh. The output is unknown and is not a good representative of what is happening with the battery pack.

Another segment used for comparison was from November 6, 2017 to November 8, 2018, one year and two days difference, which helps in the estimation of degradation for a single year. An increase of 1.17% of energy was required over the 367 days. As noted, a high of 5°C on November 6, 2017 at 10:30 A.M. happened whereas November 8, 2018 was 5°C at 12:59 A.M. With an identical Temperature, Level of Charger, Charging Location, and SOC Difference, the comparison of the two dates is very good. The Ending SOC is different and will affect the energy consumed, but it should lessen the value. Based on the lower SOC, a 1.17% is the minimum value of degradation over one year.

The value of 1.17% as a minimum level of yearly degradation can be compared to the month-to-month degradation from August to September, 2017. A value of 1.22% degradation for the month appears to not represent a cumulative value, twelve months at 1.22% each, but a steady value for a year. Adjusting for different Ending SOC levels creates a more accurate representation of data from 70% to 90%, these appear to validate the yearly total. Therefore, 1.17% can be modified to 1.22% to create an accurate comparison of 90% Ending SOC for November 2017 to 90% for November 2018.

The last segment in Table 26 is created from three different values using a Level 3 charger, location of “Other”, plus a SOC Difference of 47%. High temperatures on March 13, April 24, and June 13, 2019 were 9°C, 12°C, and 22°C, respectively (Timeanddate.com, 2019). A comparison of March to April, 2019 yields an energy difference of 0.23 kwh or 1.65%. April, 2019 to June, 2019 has a variance of 1.07 kwh or 2.95%. The longest span of comparison is March to June, 2019. This created a difference of 1.30 kwh or 3.58%. For June, 2019, a Starting SOC of 8% is very low as is the Ending SOC of 55%. Using an Ending SOC 55% is efficient and no extra energy is required unlike the March, 2019 and April, 2019 values that charge to 87% and 90%, respectively. A constant progression of degradation is shown within this segment. From previous results, the degradation should be higher than 1.22% which is true for both values. Similar to Nissan Leafs, using a Level 3 charger increases the amount of degradation.

Table 26

Tesla Model S 85 kwh Segmented Data from British Columbia

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%	Location
8/5/2017 9:30	37.233	4.21	2	45	90	45	Home
9/5/2017 22:57	37.692	4.37	2	45	90	45	Home
11/6/2017 10:30	36.975	4.30	2	45	90	45	Other
12/23/2017 11:00	37.424	4.40	2	45	90	45	Home
3/2/2018 10:00	37.703	4.36	2	45	90	45	Home
11/8/2018 0:59	37.412	4.31	2	25	70	45	Other
3/13/2019 23:22	35.145	0.00	3	40	87	47	Other
4/24/2019 21:07	35.374	0.00	3	43	90	47	Other
6/13/2019 5:29	36.447	0.00	3	8	55	47	Other

A total of 539 lines of data were generated by the Tesla Model S 85D found in Table 27. The Tesla resided in British Columbia, Canada employing an 85-kwh battery pack. There were

36 Level 1, 267 Level 2, and 236 Level 3 charging events from July 2017 – 2019, all had a minimum increase of 1% SOC. Of these, 43.78% of the charging events used a Level 3.

In the first two rows of Table 27, all energy consumption was from Level 2 chargers. Based on energy, it took 8.23% more energy in August compared to November, 2017. There were forty charging events between August 31 and November 6, 2017. August in British Columbia is warmer than November and should require less power. Further investigation resulted in finding charger location differences that account for atypical findings in Table 27, these are discussed below.

For the three rows beginning with 21.691 kwh, SOC differences are equivalent and location is identical which makes it excellent for comparisons. None of the Ending SOC values are higher than 90%. The November 27, 2017 energy required for a 26% SOC increase was 21.69 kwh. In comparison, slightly less than one year later, 354 days, on November 16, 2018, it required 21.92 kwh. An increase of 1.03% in energy required from November 2017 to 2018. Pro-rated for one year this is 1.06% of degradation. There were 205 charging events during this time. From November 6, 2017 to December 12, 2018 an energy increase of 5.07% was required for an additional 26% SOC. Temperature had a high of 9°C on November 27, 2017, compared to 11°C on November 16, 2018 and 8°C on December 12, 2018 (Timeanddate.com, 2018). Based on a higher temperature by 2°C on November 16, 2018, the increase of 1.03% should be higher to adjust for temperature equivalency. Similarly, an increase of 5.07% should be slightly decreased for equivalent measurement because it is 1°C less. So, the range of degradation is 1.06%-5.07%.

In the final segment of Table 27, Level 3 charging results were examined. A difference of 0.138 kwh or 0.41% increase in energy was required over one month, January to February, 2019, with 47 charging events in-between. There are two unique aspects to this data—location and temperature. Location is Other in January and Public in February. A problem exists comparing these two values because Level 3 chargers vary immensely in their charging rates, the Tesla could be using a Supercharger at 150 kw or a CHAdeMO (with adapter) at 50 kw. Temperature had a high of 7°C in Vancouver, B.C. on January 25 and 6°C on February 26, 2019 (Timeanddate.com, 2019). Although there appears to be slight degradation of 0.41% over a month, the previous segment with three values is more accurate because of similar locations.

Table 27

Tesla Model S 85D kwh Segmented Data from British Columbia

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%	Location
8/31/2017 19:00	25.084	5.540	2	62	88	26	Other
11/6/2017 16:05	23.021	3.192	2	62	88	26	Public
11/27/2017 15:55	21.691	1.873	2	63	89	26	Public
11/16/2018 19:29	21.915	1.860	2	26	52	26	Public
12/12/2018 17:52	22.848	3.192	2	34	60	26	Public
1/25/2019 16:34	34.091	0.000	3	48	93	45	Other
2/26/2019 15:47	34.229	0.000	3	48	93	45	Public

Results using a 2016/2017 Tesla Model X took place in Alberta, Canada, and all charging involved Level 2 chargers. Prior to these charging events there was one Level 1 charge on August 28, 2017, at 11:46 A.M. with an energy of 0.35 kwh and charger loss of 0.03% to keep a Starting and Ending SOC of 90%. A total of 199 charging events adding 1% SOC or more were examined, this is very low compared to the previous two Teslas having 452 and 539 events. Data may be slightly skewed due to the smaller sample size. The 2016/2017 Tesla Model X base model uses a 75-kwh battery pack. There were one Level 1, 166 Level 2, and 32 Level 3 charging events from July 21, 2017 to September 14, 2018. Level 3 charges made up 16.08% of the overall total, much higher than some EVs such as the 2014 Leaf that saw only five total Level 3 charges. A total of 21 charging sessions ended at 100% SOC. Based on the high percentage of Level 3 charges plus charging to 100%, it was expected that degradation would be higher than many other Tesla vehicles.

The 2016/2017 Tesla Model X had equivalent Starting and Ending SOC values for September 1st and 23rd entries. There was a 33.83% or 5.77 kwh decrease in energy required for a 26% SOC increase. There were nineteen charging events of more than 1 kwh between September 1 and 23, 2017. Based on the large energy decrease required between the two dates, this does not show degradation and requires further explanation. Temperature does not fully explain the results because on September 23, 2017, Calgary, Alberta had a high temperature of 11°C whereas on September 1, 2017 it was 26°C (Timeanddate.com, 2017). A higher temperature should help the flow of energy, based on Arrhenius Law, not reduce it. Both charging events took place at home. One difference in log data is no charging for three days preceding the September 1, 2017 date, but the previous charging was using a Level 1 as discussed above. The car was driven from 90% to 64% SOC after a Level 1 charge. There was a similar incident of SOH increasing after a Level 1 charge with a Nissan Leaf. It appears that moving from a Level 1 to a Level 2 with usage in-between temporarily alters battery measurement.

The second set of results have a 46% and 45% increase in SOC. Location and Ending SOC were equivalent, these were two reasons why the difference in energy consumed between August 2017 and July 2018, 340 days or eleven months and six days between measurements, had an increase of 15.87%. The August, 2017 entry had a SOC difference of 46% which would decrease energy consumed, if taken proportionately, compared to a 45% SOC difference in July, 2018. Pro-rated to 45%, energy of 30.26 kwh would become 29.60 kwh. Pro-rated for one year, the degradation is 19.00%. This extremely high level of degradation is an anomaly and needs explanation. There were 145 charging events of one or more kwh between August 6, 2017 and

July 12, 2018. Six Level 3 and one Level 1 charge were included in the 145 charging events. August 6, 2017 at 11:06 A.M. had a high temperature of 25°C whereas July 12, 2018 at 5:04 A.M. was 22°C (Timeanddate.com, 2018). Temperatures are within 2°C, not enough to alter degradation by a large amount. Three situations are possible to explain the large amount of degradation: (1) a defective data logger, (2) this vehicle is a 2016 model with extensive degradation from previous use, or (3) a defective battery. A further segment needs to be reviewed for clarification.

The segment using August 17, 2017 and 2018 has dates one year apart using the same level charger and Ending SOC. Temperature was 16°C on August 17, 2017 and 19°C on August 17, 2018 (Timeanddate.com, 2018). Energy needs to be pro-rated based on 63% SOC Difference for consistent comparisons. Pro-rated energy is 44.05 kwh. An increase of 9.69% or 6.182 kwh was required to reach 63% SOC Difference one year later thereby indicating battery degradation. This is the highest amount of degradation discovered in the current study. As mentioned, large amounts of Level 3 sessions and charging to an ending SOC of 100% would greatly increase the degradation, or this could be a defective battery.

Another segment in Table 28 starting on July 21, 2017 was added because it clearly shows charging under 80% SOC with a Level 3 charger is more efficient. Temperature was 16°C on July 21, 2017 and -13°C on March 4, 2018. Using a 29°C lower temperature for 3% SOC Difference should require much more energy, but it does not. The independent variable of Starting and Ending SOC are 21% different. The Ending SOC of 80% is a clearly a negative factor because energy increases while temperature remains much higher than the corresponding March, 2018 value.

A final segment in Table 28 was added to confirm the irregular findings for this vehicle. The SOC difference and charger level are equivalent which is why this data was chosen. Sample data from October 2, 2017 and June 1, 2018 have Ending SOC values under 80% which should not raise energy consumption due to increased resistance. An increase of 14.53% or 2.01 kwh has happened over 242 days or seven months, four weeks, and two days. Pro-rating 14.53% degradation over a year is 21.91%, this is an outlier or anomaly compared to all other results due to one, two, or all three situations enumerated above. Another Model X will be examined to confirm these results as an anomaly.

Table 28

2016/2017 Tesla Model X Segmented Data from Alberta

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC %	SOC-Diff%
9/1/2017 3:32	17.055	1.869	2	64	90	26
9/23/2017 2:00	11.286	0.902	2	64	90	26
8/6/2017 11:06	30.264	3.247	2	54	100	46
7/12/2018 5:04	35.969	3.767	2	55	100	45
8/17/2017 2:00	42.604	4.585	2	28	90	62
8/17/2018 2:00	48.786	5.261	2	27	90	63
3/4/2018 2:54	2.264	0.272	3	56	59	3
10/2/2017 18:50	11.819	1.244	2	54	72	18
6/1/2018 18:48	13.828	1.222	2	40	58	18

In Table 29, there are 392 charging events above 1% SOC difference for the second Tesla Model X. British Columbia temperature was 8°C on March 14, 2018 and 8°C on November 29, 2018 (Timeanddate.com, 2019). Many of the charging sessions early on in the data logging process saw Ending SOC around 90% whereas later it was in the 70-79% range. March 14, 2018 charged to 90% SOC which adds.190 kwh, as a minimum, according to Level 3 charging for the previous Model X. Without the adjustment for an increased SOC, an additional 6.06% or 1.35

kwh was required from March 14 to November 29, 2018. It was 260 days or eight months, two weeks, and one day between energy measurements. Pro-rated for a year there was an energy increase of 7.37% required, this is a similar level of degradation to other EV results. Temperature is not a confounding variable because values are equal.

A second segment in Table 29 was completed for a comparison. The Ending SOC was equivalent at 90%. British Columbia temperatures were 15°C on May 29, 2018 and 11°C on October 18, 2018. Without any adjustment for 90% SOC, the second segment starting with May 29, 2018 required an additional 1.46% kwh. Adjusting for ending SOC by adding 0.19 kwh to energy in October, 2018 between May and October, a total of 142 days or four months, two weeks, and five days, an extra 2.73% kwh was required. Pro-rated for a year there was an energy increase of 7.02% needed, this is not adjusted for temperature. Averaging these two segments is 7.19% degradation. Using these segments that contain consistent results invalidates the previous results from the Model X located in Alberta, Canada.

Table 29

2016/2017 Tesla Model X Segmented Data from British Columbia

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
3/14/2018 0:50	20.889	2.442	2	64	90	26
11/29/2018 0:40	22.236	4.424	2	51	77	26
5/29/2018 0:14	14.345	1.719	2	72	90	18
10/18/2018 23:46	14.557	2.202	2	48	66	18

The 2016/2017 Tesla Model S 60D had the smallest battery pack available from Tesla until the Model 3 was introduced. “D” means it is an all-wheel drive vehicle. A 60-kwh battery pack was 10 kwh larger than the 2017 Model 3 standard battery of 50 kwh. As noted in the validation section, a Model 3 LR, like the one participating from Austria, uses a 75-kwh battery pack. There were 696 charging events above 1% SOC Difference between September 10, 2017 and July 31, 2019. No Level 1 charging happened. There were 208 Level 3 and 488 Level 2 charges out of 696 total charges.

A six-month, thirteen-day span between similar charging characteristics is shown in Table 30. The high temperature on October 6, 2018, in Montreal, Quebec was 11°C and for April 19, 2019, it was 13°C (Timeanddate.com, 2019). The small difference between measurements of 0.08 kwh is explainable by the 2°C increase in temperature. Using a 2°C increase, the energy required to charge on a Level 2 charger decreases 0.04 kwh per 1°C increase in temperature. A six-month period, used in the first segment, with a Tesla battery pack of 60 kwh does not show degradation. Like the 2020 Kia Soul which uses a 64-kwh battery, no battery degradation occurred after 146 charging events. Another segment was used to provide an additional sample for clarification.

The second segment in Table 30 was chosen because the Charger Level, Starting SOC, Ending SOC, and SOC Difference. A large gap between dates of measurements is apparent also. It was -5°C on January 29, 2018 and -8°C on January, 6, 2019 (Timeanddate.com, 2019). For a 3°C increase, the energy required to charge on a Level 2 charger decreases by 0.21 kwh per 1°C increase in temperature when starting at -5°C. No battery degradation can be detected, the same results as the first segment.

Table 30

2017/2018 Tesla Model S 60D Segmented Data from Quebec

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
10/6/2018 6:19	37.185	3.380	2	31	90	59
4/19/2019 2:28	37.101	3.444	2	31	90	59
1/29/2018 0:25	34.065	2.962	2	37	90	53
1/6/2019 23:36	33.434	3.144	2	37	90	53

A Smart Fortwo EV from Mercedes-Benz had data for analyzing. The charging events shown in the segment used Level 2 chargers in Ontario, Canada and ended with 100% SOC. There were 421 lines of data with 1% of more SOC Difference which were analyzed. A segment of three was chosen due to similarity including StartSOC, EndSOC, SOCDiff, and Charger Level. There were 58 charging events from February 7, 2018 to March 27, 2018. However, six events were only a 1% increase in SOC during this time. Less energy was required to add 45% SOC, as temperatures increased, over a six-week period from February 7 to March 27, 2018. February 7, 2018 required the most energy while March 27, 2018 used the least amount thereby signifying temperature played a role in required energy. February 8, 2018 at 12 A.M. was -8°C, March 15, 2018 at 2:25 A.M. was -4°C, and March 27, 2018 at 11 P.M. was 4°C (Timeanddate.com, 2018). The charger loss decreased as temperature increased. Using this information, no noticeable degradation can be calculated.

In Table 31, the second segment consisted of values taken 51 days apart. Starting in August 2018, energy was 11.50 kwh and in September 2018 it raised to 11.52 kwh, a 0.17% difference. Pro-rated for one year this would equal 1.18% degradation, with equal temperature data. This increase of energy was required to raise the SOC difference to an identical level of 45%. There were 48 charging events between August 2 and September 22, 2018, with 22 of them showing only a 1% increase through battery charging. August 2, 2018 had a high temperature of 27°C while September 22, 2018 was 16°C (Timeanddate.com, 2018). Based on Arrhenius Law, September, 2018 should require extra energy because the temperature was 11°C lower. September, 2018 required an additional 0.02 kwh compared to August, 2018. Taking an energy difference of 0.17% and dividing by 11°C is .02% per 1°C, very close to the obtained value for a

Nissan Leaf, 0.012%. It’s not possible to determine degradation because of the large temperature gap and reduction of energy consumed 51 days later.

In the segment beginning on October 18, 2018, the Smart Fortwo used 4.07 kwh and on October 31, 2018 it consumed 4.09 kwh. Comparing October 2018 results shows an increase of 0.49% for energy required to add 20% SOC. There were eleven charging events between October 18-31, 2018, with three resulting in an increase of 1% or more. The temperature in Toronto on October 18, 2018 was cool at 8°C for a high while it was much warmer on October 31, 2018 at 14°C (Timeanddate.com, 2018). Location is identical for charging on October 18 and 31, 2018. With a warmer ambient temperature on October 31, energy used to increase SOC 20% should be lower unless there is another factor such as battery degradation. Degradation happened at a minimum value of 0.49% over 13 days because Location, Level, Starting SOC, Ending SOC, and SOC Difference are equivalent. Pro-rated, the degradation would be 13.76% for a year. This is extremely high and needs to be re-examined using additional dates with a larger gap between measurements.

The last segment used dates 76 days apart or two months, two weeks, and one day. Equivalent data including Charger Level, Ending SOC, Starting SOC, and SOC Difference were used for the comparison. The additional energy required to reach 34% SOC difference was 0.12 kwh or 1.74%. Pro-rated for one year, an energy increase of 8.35% was required. Although this is the highest value of degradation, it is only slightly higher than for the 2017 Leaf. No Level 3 charging happened. Other factors have created this large amount of degradation including cyclic charging and using an Ending SOC of 100%. A small battery pack requires frequent charging for daily use. Similar to other EVs, charging to 100% SOC takes extra energy and is not efficient. Based on these results, charging to 100% correlates with higher degradation.

Table 31

Smart Fortwo Electric Drive Segmented Data from Ontario

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
2/7/2018 0:00	8.675	1.041	2	55	100	45
3/15/2018 2:25	8.582	1.030	2	55	100	45
3/27/2018 23:00	7.751	0.930	2	55	100	45
8/2/2018 23:58	11.503	1.380	2	40	100	60
9/22/2018 14:46	11.522	1.383	2	40	100	60
10/18/2018 23:00	4.073	0.489	2	80	100	20
10/31/2018 23:00	4.093	0.491	2	80	100	20
3/3/2018 17:33	6.644	0.797	2	66	100	34
5/18/2018 23:00	6.761	0.811	2	66	100	34

Data from a Volkswagen e-Golf located in Quebec was used, there were 460 lines of charging with a SOC increase of 1% or more. Only 17 Level 3 charging events took place, 3.70%. The first segment starts with 15.79 kwh and ends at 15.59 kwh, a decrease of 1.27% over nine days. The slight decrease in energy is because the SOC difference is 0.5% less on January 22, 2019. There were seven charging events between January 13 and 22, 2019. The temperature in Montreal on January 13 was -8°C for a high while it was much warmer on January 22 at -1°C (Timeanddate.com, 2019). Charging occurred at home on January 13 and January 22. SOC differences of 44.5% and 45.0% combined with a warmer temperature on January 22 does not show degradation.

The next segment was created by taking charges close in time to one another, using the same Level, Starting and Ending SOC value equality, and a SOC Difference of 59.5%. The high temperature for February 1 and 2, 2019, in Montreal was -14°C and -7°C, respectively (Timeanddate.com, 2019). No long-term degradation should happen over one day and one charging session. The importance of this segment is isolating temperature for calculating influence on batteries. A decrease of 0.60 kwh happened with a 7°C increase, this equates to 0.09 kwh per 1°C increase when temperatures ranged from -7°C to -14°C.

The third segment from Table 32 was selected because dates were multiple months apart with the same Starting SOC, Ending SOC Level, Charging Location, and SOC Difference. Energy value comparisons between 19.72 kwh and 20.18 kwh created an increase of 2.26% over 178 days or 5 months, 3 weeks, and 4 days. The temperature was 28°C on September 17, 2018 and 8°C on May 14, 2019 (timeanddate.com, 2019). With positive temperatures at 30°C occurring on September 17, 2018, compared to the second segment analyzed from February 2019, the past findings of 0.09 kwh per 1°C decrease are not valid. The cooler temperatures on May 14, 2019 will cause an increase of energy consumed according to Arrhenius Law, but not 2.26%. A new segment needs to be added to the study to validate if battery degradation has happened.

The final segment in Table 32 was selected to confirm validation occurred with the Volkswagen e-Golf. Selected dates were one year and three days, or 368 days, apart, from June 5, 2018 to June 8, 2019. The same Charger Level, Charging Location, and SOC Difference were used. There were 289 charging events between the two dates. There was a 7.11% increase in energy required from June 2018 to 2019. June 5, 2018 had a high of 14°C while it was 23°C on June 8, 2019 (Timeanddate.com, 2019). Due to an increase in temperature, energy consumed should decrease, but it did not because degradation happened. Using a previous value of 2.26% over 178 days equals 4.67% over 368 days or 4.63% over a year. A range of 4.63-7.11% of battery degradation occurred over 368 days.

Table 32

Volkswagen e-Golf Segmented Data from Quebec

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
1/13/2019 18:40	15.788	1.098	2	55.0	100.0	45.0
1/22/2019 21:08	15.589	1.068	2	55.0	100.0	44.5
2/1/2019 22:26	20.700	1.508	2	40.0	100.0	59.5
2/2/2019 19:02	20.097	1.443	2	40.0	100.0	59.5
9/17/2018 19:49	19.723	1.580	2	42.0	100.0	58.0
5/14/2019 0:37	20.178	1.532	2	42.0	100.0	58.0
6/5/2018 22:39	16.082	1.218	2	31.5	80.0	48.5
6/8/2019 20:26	17.312	1.329	2	51.0	99.5	48.5

A Ford Focus EV from Ontario, Canada created data from 729 charging events between 2017-2019. The first segment in Table 33 involves the Focus using a SOC Difference of 45%. This segment used the most Level 1 charges of participant data analyzed, a mean of 1.33 was calculated. A Level 1 charger was used for 136 charges or 69.74% while a Level 2 charger had 59 charges. There were no Level 3 chargers used during the first segment. A decrease of 0.21% kwh in energy was required for an increase of 45% in SOC. A total of 195 charging events with an increase of at least one kwh happened during the first segment. Toronto, Ontario had a high of 8°C on March 28, 2018, and October 1, 2018, was 12°C (Timeanddate.com, 2018). The difference in temperature provides evidence of why the increase occurred. Degradation is not detectable in this segment.

The last segment in Table 33 used a SOC difference of 58% and a Level 2 charger located at home. There were 100 charging events within the segment. Data was captured three months and one day between May and August, 2018. Temperatures in Toronto on May 18, 2018 and August 19, 2018 were 15°C and 23°C, respectively (Timeanddate.com, 2018). It took an extra 0.20 kwh or 1.11% to increase SOC 58% over 93 days or three months and one day. Pro-rated for one year, the degradation is 4.36%. The 8°C increase in temperature should lower the energy required to increase the SOC. Therefore, degradation of 4.36% is the minimum level because of the influence of temperature on the final calculation.

Table 33

Ford Focus EV Segmented Data from Ontario

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
3/28/2018 21:30	15.916	1.910	1	53	98	45
10/1/2018 22:46	15.884	1.906	1	53	98	45
5/18/2018 7:59	18.233	2.086	2	19	77	58
8/19/2018 16:31	18.437	0.780	2	42	100	58

An ANOVA calculation was completed through regression testing with the Ford Focus EV data using the dependent variable of Energy Consumed, and as independent variables Charger Level and Ending SOC. The regression predictors found significance between energy levels consumed and both independent variables, Ending SOC and Charger Level. Significance for the predictor variables was found at the .001 confidence interval.

The Pearson Correlation between charger energy and charger level is low at .118. As the charger type changes it will not help in the prediction of energy consumed. Since the mean Charger Level approaches 1, the levels of energy are relatively close, making it hard to use for prediction. No Level 3 charging was involved so prediction is limited. Ending SOC is a moderate predictor of charger energy with a correlation of .521. An SOC rising to 100% affects the amount of energy required. Increasing the amount of energy due to a higher Ending SOC is not efficient; the cost will increase using a Level 1 or 2 charger.

Table 34

Ford Focus EV Correlations

		Charger Energy	Charging Level	Ending SOC
Pearson Correlation	Charger Energy	1.000	0.118	0.521
	Charging Level	0.118	1.000	0.107
	Ending SOC	0.521	0.107	1.000
Sig. (1-tailed)	Charger Energy	.	<0.001	<0.001
	Charging Level	0.001	.	0.002
	Ending SOC	0.000	0.002	.

Note: N = 729.

Tesla Model S 90D were represented in data from two different Canadian provinces, Quebec and Alberta. The data from the Quebec-based Tesla shows data from either a 2016 or 2017 using 90 kwh battery; both used the same size battery. Level of Charger, Starting SOC, Ending SOC, and SOC Difference were all equivalent in segment one. A total of 448 charging events of 1% SOC difference or more happened from July 2017 to July 2019. One unique aspect to this EV was the number of Level 1 charges: 25 events. For a large battery of 90 kwh, it would be expected to have a small amount of Level 1 charging due to the extensive time it would take to charge. There were 377 Level 2 charges and 46 Level 3 charges. The high temperature on March 25, 2018 was 4°C and 1°C on November 30, 2018. The energy consumption difference was 2.71%. There was a 250 day span between these two dates. Pro-rated for one year, the energy increase is 3.96%.

Segment two starting with 18.286 shown in Table 35 had a 20% SOC increase while charging. Montreal, Quebec, December 30, 2017, had a high temperature of -18°C whereas it was -10°C on January 1, 2019 (Timeanddate.com, 2019). These results have temperatures 8°C apart. An increase of 0.35 kwh or 1.90% happened over 367 days or 12 months and 2 days. Pro-rated for a year, the energy required was 1.89%. The impact of the 8°C is much more profound on calculating the energy consumption. There is evidence of battery degradation, but it needs to be adjusted based on a lower temperature.

The final entry in Table 35 is from March 15, 2018 to March 4, 2019. There are 354 days or eleven months, two weeks, and three days between data points. March 15, 2018, had a high temperature of 0°C and March 4, 2019 was -6°C, a 6°C difference. An energy increase of 0.40 kwh or 1.29% from March 2018 to March 2019 happened. Pro-rated for one year, the energy required was 1.33%. An Ending SOC of 90% increased the energy consumed due to resistance and the temperature decreased by 6°C thereby further increasing the energy consumed. Using these two variables, it can be assumed the previous value of 1.89% is an accurate measure of degradation over one year.

Table 35

2016/2017 Tesla Model S 90D from Quebec

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
3/25/2018 22:17	38.661	3.373	2	45	90	45
11/30/2018 1:51	39.736	4.963	2	45	90	45
12/30/2017 22:37	18.286	2.741	2	49	69	20
1/1/2019 23:07	18.640	2.340	2	76	96	20
3/15/2018 12:23	31.046	2.637	2	22	58	36
3/4/2019 22:53	31.450	4.020	2	54	90	36

Compared to the Ford Focus EV, the Tesla Model S 90D had much different descriptive statistics. The mean Charging Level of 2.05 was 35.03% higher than the Focus EV, this can be explained through wanting to charge at Level 2 to complete the charging cycle in a “reasonable” timeframe. The large battery pack in a Model S 90D is more than twice the size of a Ford Focus

EV which means longer charging times. Mean charger energy was much higher at 51.36% more. Mean Ending SOC was similar at only 0.91% more in the Tesla Model S 90D.

Regression testing with the Tesla Model S 90D, as referenced in Appendix VII, used a dependent variable of Energy Consumed, while Charger Level and Ending SOC were independent variables. Regression predictors found significance between Energy Levels consumed and both independent variables. Significance for the predictor variables was found at the .001 confidence interval.

The Pearson Correlation between Charger Energy and Charger Level is almost non-existent at .150. Since mean Charger Level is right at 2.05, levels of energy are relatively close making it hard to use for prediction. Ending SOC is a weak predictor of Charger Energy with a correlation of .338, lower than for the Focus EV. The consistent results between a lack of correlation between Charger Energy and Charging Level are evident. The Ending SOC correlation with Charging Energy fluctuates slightly more than Charging Level, this is due to the number of 100% charging events. There are only 29 of 448, or 6.47%, events culminating in 100% SOC.

Table 36

Correlational Data for Tesla Model S 90D

		Charger Energy	Charging Level	Ending SOC
Pearson Correlation	Charger Energy	1.000	0.150	0.338
	Charging Level	0.150	1.000	0.162
	Ending SOC	0.338	0.162	1.000
Sig. (1-tailed)	Charger Energy	.	<0.001	<0.001
	Charging Level	0.001	.	0.000
	Ending SOC	0.000	0.000	.

Note: N = 448.

The Mitsubishi i-MiEV is no longer made, but many are still on the road today. I-MiEVs from New Brunswick, Ontario, Quebec, and British Columbia had data submitted via FleetCarma for this study. There were 11,984 lines of data provided from participants. Both 2016 and 2017 versions of the i-MiEV used 16 kwh batteries, much smaller than most others such as the Nissan Leaf with 24, 30, and 40 kwh battery packs. A total of 203 charging events were examined, each had an increase of 1% SOC or more. A total of 18 Level 1 and 185 Level 2 charges happened. No Level 3 charging occurred. Of the 203 charging events, 74 or 36.45% were to 100% SOC.

Data from the Mitsubishi i-MiEV shows the energy required to increase SOC by 26%. Charging events in 2019 ended at 93.5% and 96% SOC, this can explain some of the additional energy required. There were 46 charging events with more than 1% SOC increase between January 18, 2019 and June 7, 2019. Temperature plays a key factor in reducing the charger loss, there is a vast difference in New Brunswick weather from January to June. With temperature increases, less energy is lost and EA is lowered based on Arrhenius Law. Therefore, battery degradation has occurred—but how much?

The first set of results were inconclusive because of two other important factors: (1) Temperature, and (2) Ending SOC. January 18, 2019 in Fredericton, NB saw a high of -4°C whereas June 7, 2019 was 23°C, a difference of 27°C. Using June 7, 2019, if 6.08 kwh EA is used for a 26% SOC increase, then it takes 1 kwh to change 4.27% SOC. With a SOC increase of 50.5% on June 6, 2019, it requires 1 kwh for a 5.47% SOC change. If no other factors are examined, the energy increase from year-to-year has not occurred which signifies no battery degradation. June 6, 2018 had a high of 18°C while June 7, 2019 saw 23°C. Based on temperature, June 7, 2019 should require less energy to increase SOC per kwh, which it does.

Ending SOC is 2% higher on June 6, 2018, although the Starting SOC value is much lower at 28.5%. Further investigation was needed, so an additional segment with similar data was added.

Comparable data for the last segment was important to reach conclusive results. There were 86 charging events between October 29, 2017 and September 21, 2018. Taking into account the starting SOC was 48.5% in October 2017 and the comparative was 48% in September 2018, the energy used needs to be proportional. The per kwh energy is 5.72% within Starting SOC for October 29, 2017, this results in 8.39 kwh to reach 48% Starting SOC. Ending SOC and Charger Level were equivalent in this segment. October 29, 2017 had a high of 17°C while September 21, 2018 was 16°C, a small 1°C difference. There was almost one year difference, a total of 327 days elapsed between entries. There is a 2.1% difference between the kwh used on October 29, 2017 and September 21, 2018. Using energy results in a definitive increase in kwh being consumed thereby showing battery degradation. For a full year, 365 days, the battery degradation would be 2.32%.

Table 37

Mitsubishi i-MiEV Segmented Data from New Brunswick

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
1/18/2019 16:09	4.230	1.636	2	67.5	93.5	26.0
6/7/2019 13:42	4.647	1.436	2	70.0	96.0	26,0
6/6/2018 19:00	7.464	1.740	2	47.5	98.0	50.5
10/7/2018 15:13	7.838	1.716	2	28.5	79.0	50.5
10/29/2017 19:24	8.474	2.131	2	48.5	100.0	51.5
9/21/2018 18:25	8.560	2.036	2	48/0	100.0	52.0

The i-MiEV had descriptive statistics created to allow for comparisons. Compared to the Ford Focus EV, the mean Charging Level of 1.91% was 0.58% higher. Mean charger energy was very different than the Focus EV, less than half at 5.31 kwh. A smaller battery pack explains less required consumed energy. Mean Ending SOC was 93.22%, 10.45% higher than the Focus EV.

I-MiEV data was tested using SPSS and, like the Focus EV, the dependent variable was Energy Consumed and independent variables were Charger Level and Ending SOC. Regression predictors found significance between energy levels consumed and both independent variables. Same as with the Focus EV, significance for the predictor variables was found at the .001 confidence interval.

Correlational data between Charger Energy and Charger Level shows a very weak relationship at .192 for the i-MiEV. A big difference between the Charger Energy and Ending SOC for the Focus EV compared to the i-MiEV is that there is less than a moderate correlation. There are only two charging sessions where the i-MiEV went below 10% SOC, Starting SOC is high with a mean of 74.17%. A high Starting SOC explains why the correlation is slightly lower than for the Ford.

Table 38

Correlational Data for i-MiEV

		Charger Energy	Charging Level	Ending SOC
Pearson Correlation	Charger Energy	1.000	0.192	0.258
	Charging Level	0.192	1.000	-0.058
	Ending SOC	0.258	-0.058	1.000
Sig. (1-tailed)	Charger Energy	.	0.003	<0.001
	Charging Level	0.003	.	0.207
	Ending SOC	0.000	0.207	.

Note. I-MiEV data from FleetCarma (N = 203).

Other comparable EVs to the i-MiEV were the 2015 and 2016 Chevrolet Spark EV with a 19-kwh battery. No Spark EVs were made in 2017. There were Sparks from Alberta, British Columbia, and Quebec from the FleetCarma dataset. A total of 7,227 lines were submitted. There were three Sparks from Quebec. The second dataset was chosen for the segmentation because it was the largest sample at 1,952 lines. Of these 1,952, 628 lines were used because the charging sessions added a minimum of 1% SOC. All types of chargers were used for multiple sessions including Level 1 – 22, Level 2 – 595, and Level 3 – 11. The Spark was charged to 100% SOC 505 times or 80.41% of the time.

Table 39 has energy values exactly one month apart. The SOC difference, Starting SOC, Ending SOC, and Level are all equivalent in the first segment. On April 27, 2018, Montreal, Quebec had a temperature of 14°C at 4:48 P.M. while on May 5,2018 it was 18°C at 8:02 P.M. (Timeanddate.com, 2018). Based on a slightly higher temperature, the energy charging the Spark would be less based on Arrhenius Law, but this is not true which signals some degradation is present. There is 0.54% more energy used in one month. For one year, the degradation would be 6.48% which is similar to a Nissan Leaf using all three levels of chargers.

The second segment was added to show the impact of charging to 100% SOC compared to a lower value of 64.71%, yet both add 20.39% SOC to the EV. In both 2018 and 2019, April 4 had a high temperature of 1°C for the day. If Temperature, Charger Type, SOC Difference, Start SOC, and Ending SOC were the same, then it would be expected Energy Consumption would be higher one year afterwards due to degradation, but data is not showing that trend. Based on this data, the table clearly shows more energy is consumed, or is less efficient, when charging to 100% with a Level 2 charger versus stopping at 64.71%. It took 20.12% more energy to add 20.39% SOC to the Spark when charging to 100% SOC.

Table 39

Chevrolet Spark EV Segmented Data from Quebec

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
4/27/2018 16:48	5.793	0.695	2	70.98	100.00	29.02
5/27/2018 20:02	5.824	0.699	2	70.98	100.00	29.02
4/8/2018 17:27	4.503	0.540	2	79.61	100.00	20.39
4/8/2019 20:38	3.597	0.432	2	44.31	64.70	20.39

Note. Data from FleetCarma.

Chevrolet Spark data included 628 lines of data that was analyzed to create descriptive statistics for comparisons. The Spark had a higher mean charging level compared to the previously analyzed Focus and i-MiEV data. The Tesla 90D had the highest mean charging level compared to all previously analyzed EVs. For the Spark, a mean Charging Level of 1.98% is 0.7% higher than the i-MiEV. Charger Energy mean is 2.12 kwh higher in the Spark compared to the i-MiEV. Ending SOC mean was extremely high at 95.71%, it is higher than the i-MiEV which had a mean score of 93.22%.

An ANOVA was completed with Chevrolet Spark data within the regression testing. The Spark had consistent results with the Focus, regression predictors found significance between Energy Levels consumed and both independent variables. Significance for the predictor variables was found at the .001 confidence interval. Regression testing with these specific dependent and independent variables is a good way to predict correlations.

Charging Level correlated with Charger Energy was a negative value, but it is an extremely weak correlation at -.052. Ending SOC, similar to the 2017/2018 Kia Soul EV, showed a weak-moderate correlation at .458. Ending SOC correlation is consistent with previous findings demonstrating that charging to 100% is less efficient than 64.71%.

Table 40

Correlational Data for Chevrolet Spark EV

		Charger Energy	Charging Level	Ending SOC
Pearson Correlation	Charger Energy	1.000	-0.052	0.458
	Charging Level	-0.052	1.000	-0.082
	Ending SOC	0.458	-0.082	1.000
Sig. (1-tailed)	Charger Energy	.	0.098	<0.001
	Charging Level	0.098	.	0.020
	Ending SOC	0.000	0.020	.

Note: data from FleetCarma (N = 628).

Kia Soul EVs from Quebec, Ontario, and British Columbia took part in the FleetCarma study. Earlier Kia Soul EV data was gathered from a 2020 model using Soul EV Spy, it shows no battery degradation after 146 charging events. A 2020 Kia Soul EV uses a 64-kwh battery pack. The 2020 Soul was the only Kia Soul EV using the larger 64 kwh battery pack.

Participant data does not specify the Kia Soul model year, but it was from 2018 or 2019 based on times for data collection. Both the 2018 and 2019 used the same sized battery pack of 30 kwh. Interestingly, the 2018/2019 model had only one Level 3 charge out of 85.

There were 85 charging events having a 1% SOC increase or more for a 2018/2019 Kia Soul EV. Of 85 charges, 84 were Level 2 and one was Level 3. The Ending SOC from the 2018/2019 Soul shows charging events beyond 80% multiple times. For comparison, the 2020 Kia Soul EV was never charged past 80% SOC because of a setting available in the vehicle. It took 6.41% more energy on June 27, 2019 to increase SOC 26%. Only four additional charging events occurred between June 21, 2019 and 27, 2019. June 21 had a high temperature of 21°C while on June 27 it was 29°C. Charging to 100% SOC on June 21 should take additional energy, based on previous results and increased resistance, compared to 61.5%. Similarly, the warmer temperature on June 27 should help with reducing energy consumption. Battery degradation can explain the higher energy required during warmer temperatures and charging to a lower SOC. A minimum of 6.41% degradation has occurred for this EV.

The second segment within Table 41 shows two close dates from April 2019, only twelve days apart. It was 0°C on April 9, 2019 in Montreal while on April 21, 2019 it had a high temperature of 16°C (Timeanddate.com, 2019), a large difference with a warmer temperature explains why less energy was required on April 21, 2019. Ten charging events of more than 1% SOC occurred between April 9 and 21. Based on the second segment, no degradation can be determined.

Table 41

2018/2019 Kia Soul EV Segmented Data from Quebec

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
6/21/2019 6:30	9.175	1.222	2	74.0	100.0	26
6/27/2019 21:29	9.803	1.370	2	35.5	61.5	26
4/9/2019 6:20	16.968	2.211	2	53.5	99.5	46
4/21/2019 6:20	16.850	2.259	2	53.5	99.5	46

Note. Data from FleetCarma.

Both Kia Soul EV model years 2018/2019 use a similar sized battery pack to the 2016/2017 Nissan Leafs. Kia did not upgrade the battery pack for the Soul EV until 2020 where it increased to 64 kwh. Nissan increased the battery pack for the 2018 model to 40 kwh, up from the 30 kwh in the 2016/2017 models.

The 2018/2019 Kia Soul EV data had some unique findings compared to previously analyzed EV data. There were only 85 data entries for this specific Soul EV, the Spark had 628 or 543 more lines. Charger Energy mean was 6.86 kwh higher than the Spark. Other than the Tesla Model S 90D, Charging Level mean was highest compared to previous vehicle data used from the FleetCarma study. Ending SOC was lower than the Spark and i-MiEV.

An ANOVA was completed with a 2018/2019 Kia Soul EV having a dependent variable of Energy Consumed via Charger Energy. Charger Level and Ending SOC were independent variables. Using SPSS, regression predictors found significance between Energy Consumed and both independent variables. Like the Focus EV, significance for predictor variables was found at the .001 confidence interval.

This Kia Soul EV had correlational results comparable to the Chevrolet Spark EV. Charging Level correlated with Charging Energy was a negative value, but it is an extremely weak correlation at -.094, the Spark has -.052. Ending SOC was lower than 0.40 resulting in a weak correlation between Charging Energy and Ending SOC of 0.39. Charging Level and Ending SOC had a weak negative correlation at -.320. Overall, there were no strong or moderate correlations associated with 2018/2019 Kia Soul EV data.

Table 42

Correlational Data for a 2018/2019 Kia Soul EV

		Charger Energy	Charging Level	Ending SOC
Pearson Correlation	Charger Energy	1.000	-0.094	0.388
	Charging Level	-0.094	1.000	-0.320
	Ending SOC	0.388	-0.320	1.000
Sig. (1-tailed)	Charger Energy	.	0.195	<0.001
	Charging Level	0.195	.	0.001
	Ending SOC	0.000	0.001	.

Note. FleetCarma data (N = 85).

Validation

Two submissions of data occurred from participants in Europe, a 2017 Hyundai Ioniq and a 2019 Tesla Model 3 LR. North America offered both of these EVs for purchase in the past. A European participant’s data was used for comparisons to validate previous analysis using similar vehicles. One item unique to the Tesla data was the participants use of TeslaFI – it is a smartphone application similar to Leaf Spy Professional. There are future recommendations regarding TeslaFI at the end of this study.

There were 971 lines of data submitted from a participant in Europe who owns a 2017 Hyundai Ioniq. The Ioniq uses a 30-kwh battery pack, of which 28 kwh is usable by the operator, which is similar in size to the 2016-2017 Nissan Leaf. There are no dates listed for data. Data is listed from new to old entries based on the accumulated kilometers. The charger types were converted to the North American equivalents. For example, “keba” is a standard Level 2 charger a person would use at a home or business, any “keba” entries were converted to a “2.” One unique aspect to the European chargers, not found in North America, is the low-speed CCS chargers at 20 kwh. In North America there are usually speeds from 50-150 kwh from CCS chargers. Any CCS connection charges in Europe were converted to Level 3 for analysis.

To compare with data from the North American Ioniq, the SOC difference of 59% was chosen. For the first segment, the exact same starting and ending point were provided along with the same charger. There are two key differences in the data here relating to battery degradation. A difference of 5,357 kms were travelled between the two values of the first segment—this has elements of calendar and cyclic aging. The kwh difference went up over time by 0.1 which shows possible degradation, but temperature has not been accounted for! The final segment uses a same SOC difference, 59%, as the first one, but the kwh increased to reach that identical value. Both the Level 3 and Level 1 charging events, in segment two, have a greater kwh difference than the previous two entries indicating possible degradation. Level 1 charging data from row four occurs before the first row based on the number of kilometers, so degradation is not shown, but the Ending SOC is unique to the Level 1 charge: 99%. As noted previously, charging past 80% is less efficient which explains the extra 0.6 kwh required to achieve a 59% SOC difference.

The final comparison is the only Level 3 charging event shown in Table 43. After 29,626 kms driven, a Level 3 charger was used to reach 76% SOC, up 59% from its starting value. The kwh difference of 17.2 was tied for the highest value analyzed, but no charging occurred after 80%. A difference of 0.7 kwh (17.2 – 16.5 kwh) or 4.07% increase in energy, after 6,641 additional kilometers occurred indicating battery degradation.

Table 43

2017 Hyundai Ioniq Segmented Data from Europe

StartSOC	EndSOC	Startkwh	Endkwh	KMs	SOC-Diff	kwh-Difference	Level
22	81	4787.0	4803.6	28342	59	16.6	2
22	81	3908.5	3925.0	22985	59	16.5	2
17	76	4976.0	4993.2	29626	59	17.2	3
40	99	4617.0	4634.2	27243	59	17.2	1

Note: sent in by a participant.

Table 44 shows the first segment from Table 25 and is used for a comparison to demonstrate validity of data. Both Table 43 and 44 use a SOC difference of 59%. 2017 and 2018 Hyundai Ioniqs employ the same size battery pack—28 kwh usable. Segmented results for Table 44 show an increase of energy needed to raise the SOC 59%, this is evidence of battery degradation. An increase in temperature will lower energy required, this didn’t occur. Similar results happened with 2018 Ioniq data from North America. Table 44 uses the same Charger Levels on April 13 and 20, 2018. Although Temperature is not available, only one week between data points will have a minimal effect. A 4.31% energy increase is shown in Table 44, this is evidence of degradation and is comparable to the 2017 Ioniq from Europe. As noted above, a 4.07% increase in energy occurred indicating battery degradation. A degradation difference of 0.24% between European and North American models can be attributed to Ending SOC differences. Both data lines from the 2018 Ioniq charge past 90% SOC while the Ending SOC of the second and third entry are 81% and 76% respectively. The second and third values were chosen because they have the largest differences in kilometers. As noted above, charging to levels approaching 100% SOC is not efficient and creates a need for added energy. Based on these results, data for the North American Ioniq is consistent and valid.

Table 44

2018 Ioniq Segmented Data from FleetCarma (Canada)

StartTime	Energy (kwh)	Level	Start-SOC%	End-SOC%	SOC-Diff%
4/13/2018 15:00	18.70	2	33	92	59
4/20/2018 11:00	19.54	2	40	99	59

Note: selected for comparison.

Table 45 is part one of two log files generated from TeslaFi that provides valuable insights into what happens with a battery pack inside a Tesla Model 3 Long Range (LR). In addition to Leaf Spy Professional, TeslaFi is very similar to the Soul EV Spy smartphone application. A 75-kwh usable battery is utilized within a 2019 Tesla Model 3 LR. A total of 332 charging events happened between April 9, 2019 and September 10, 2021. Of 332 charges, there were 36 Level 3 charging events which represent 10.84%. A 59% SOC difference is used for analysis. The same starting and ending point of SOC is used for comparisons. Charging time is four minutes less than it was two years prior because the EV cannot add as much range due to battery degradation. The higher temperature in August will reduce the amount of charging time compared to October in Austria. The range decrease is 2.04 km over 17 months from 2019 to 2021 which demonstrates battery degradation, although only a small amount.

Table 45

2019 Tesla Model 3 LR AWD from Austria

Date	Charging Time	from SOC%	to SOC%	SOC Diff	kWh Used	kWh Added	Range Added	Odometer	Charge Number
08-11-2019	4 Hours 5 Min	31	90	59	44.73	43.05	282.76	10,701.67	91
10-06-2021	4 Hours 1 Min	31	90	59	43.87	42.75	280.80	30,642.94	303

This study had Tesla Model 3 SR (Standard Range) data from Quebec, Canada. This is the only one taking part in this study. No charging events occurred using a Level 1 charger or Level 3. All charging was completed on a Level 2 charger. The 2019 Tesla Model 3 LR did use Level 3 charging. There were no 59% SOC difference items within Table 46. A Model 3 LR is a “Long Range” model, different than base Model 3 SR. Although there are no 59% SOC segments, it is possible to generalize from other information found in this study. A Tesla Model 3 SR has a smaller battery pack than an LR. Cyclic degradation will happen faster with the SR versus LR—this happened. The LR from Europe had less degradation than the SR.
Estimated battery degradation of the 2019 Tesla Model 3 LR AWD is shown in Figure 19 below. The blue line indicates the estimated battery range, it descends as time moves forward. A baseline in green is shown to compare other Model 3s using TeslaFI. After 2,807 km of traveling, data suggests a range of approximately 500 km whereas at 35,424 km a capacity of 465 km was available, a 7% decrease over three years or 2.33% per year on average.

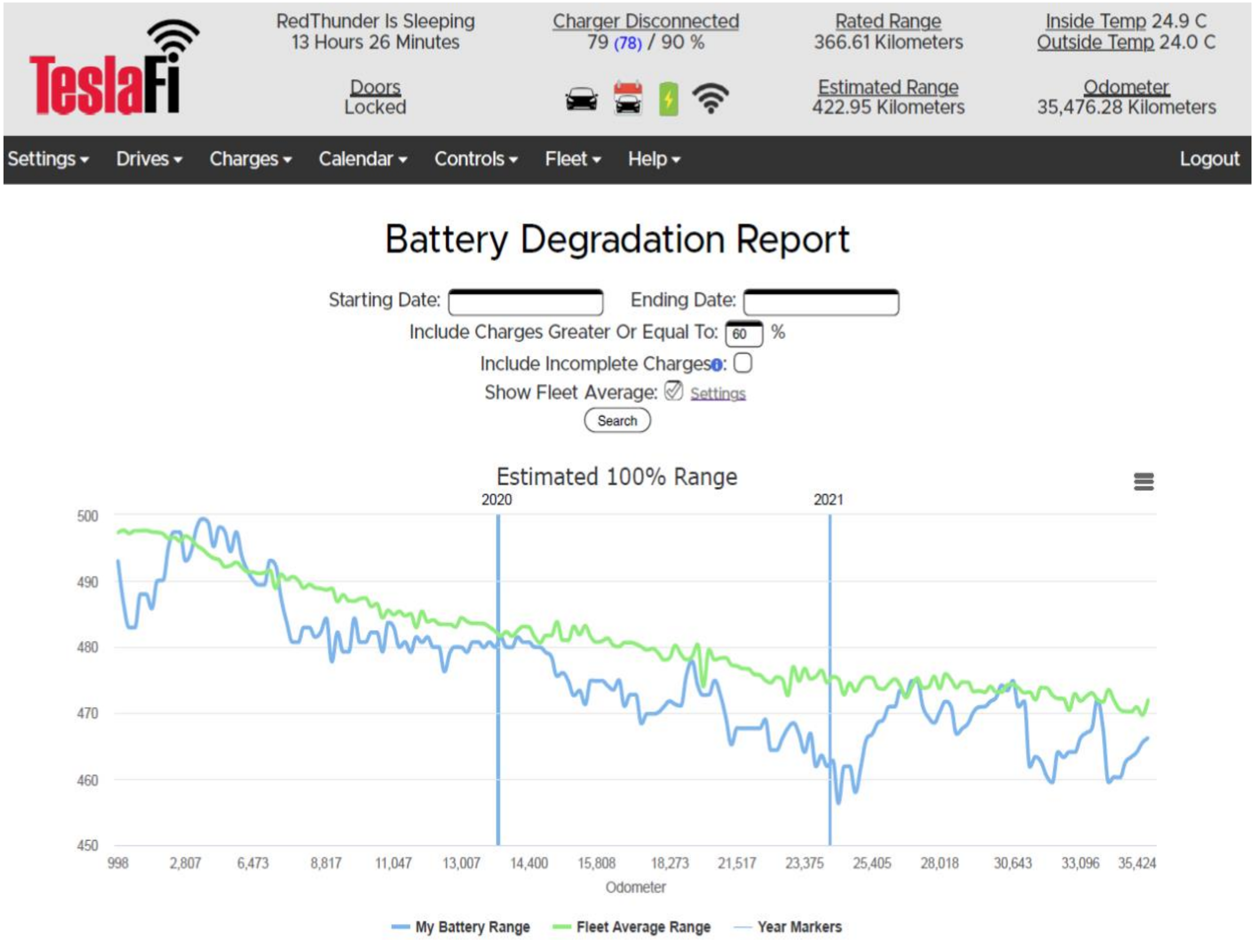

Figure 19. TeslaFI Battery Degradation Report

Note. Sent in from 'Christian' of Austria, generated from his European Tesla Model 3 LR AWD

Data for one Model 3 from Quebec, Canada was available for analysis. There was a delay in the distribution of 2017 Model 3s in Canada which explains the limited amount of them included in this study. The battery size is unknown; but it is not listed as an LR, therefore it is 50 kwh based on the model. Both the 50 and 75 kwh battery packs are bigger than other EVs such as the Nissan Leaf, Ford Focus EV, Kia Soul EV, e-Golf, and Smart Fortwo. There are twenty-eight entries that include a 1% capacity increase for the Tesla Model 3. No charging events occurred using a Level 1 or QC, Level 3, charger during data collection. For these segments, all charging was completed on a Level 2 charger. Four segments were produced having comparable information, and all data is from July 2019.

Initially there were three segments examined to realize if degradation happened. The first segment from July 3 and 5, 2019, have SOC difference increases of 16.07% and 16.80% respectively. An energy increase of 2.53% happened from July 3 to July 5, 2019. Based on the increased SOC difference of 0. 74% (16.80%-16.07%), no noticeable degradation occurred. The other two segments have dates spread apart of 17 and 11 days. A segment from July 4 and 21, 2019, had an exact SOC difference of 5.04%. July 4 had a 2.81 kwh and July 21 required 2.77 kwh EA. A high of 29°C occurred on July 21, 2019, at 10:51 P.M. while July 4, 2019, was 28.5°C at 9:37 P.M. (timeanddate.com, 2019). Examining charging energy, consumption should be higher on July 21 compared to July 4 to show degradation, but this is not the case. The minor discrepancy can be explained by a higher ambient temperature on July 21. Montreal, Quebec had a high temperature of 25°C on July 7 and 28°C on July 18, 2019 (Timeanddate.com, 2019). In the final segment from July 7 to 18, 2019, there were SOC increases of 15.02% and 15.44%; respectively. July 7 had 8.50 kwh consumed and July 18 required 9.22 kwh, an increase of 7.85%. To compare the unique SOC differences, a calculation was required to create comparable units. Using the SOC difference divided by energy creates a percent difference per kwh which is 1.77 for July 7 and 1.67 on July 18, 2019. This does not show any degradation. All values in the first three segments were close in time and no discernable degradation occurred, so a fourth segment was analyzed to see if degradation was present using dates further apart.

A fourth segment was created from July 6 and July 31, 2019, because the location of the chargers was equivalent and differences in time had the greatest comparable information. The high temperature was 28°C on July 31 and 29°C on July 6, 2019 (timeanddate.com, 2019). A percent difference per kwh was created for each date, July 6 had a value of 1.73% and July 31 was 1.74%, a difference of 9.52%. Pro-rating 25 days over a year shows battery degradation at 7.59%, this is excessive for a larger battery of 40+ kwh. This does not appear to be an accurate representation of degradation for a Model 3 SR. An explanation for high degradation such as this is a small sample size and pro-rating based on relatively close dates. Only 28 lines of data were available for analyzing and so generalizability is limited because of the small sample size.

Table 46

2018 Tesla Model 3 Segmented Data from Quebec

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
7/3/2019 14:22	9.344	1.136	2	64.720	80.785	16.065
7/5/2019 22:32	9.586	1.014	2	63.985	80.785	16.800
7/4/2019 21:37	2.811	0.276	2	69.760	74.800	5.040
7/21/2019 22:51	2.771	0.274	2	30.385	35.425	5.040
7/7/2019 14:45	8.498	0.915	2	62.515	77.530	15.015
7/18/2019 16:36	9.221	1.236	2	65.350	80.785	15.435
7/6/2019 18:11	11.391	1.260	2	61.045	80.785	19.740
7/31/2019 22:07	6.570	0.642	2	69.130	80.575	11.445

Note: no Level 3 or Level 1 charging events occurred with any data.

Other than the Model 3 SR, these results are consistent across manufacturers and models which validates minimal degradation in larger 60-75 kwh battery packs found in most Tesla models and newer models from manufacturers such as Kia and Hyundai. The Tesla Model 3 LR had the same range after six months or approximately 6,500 km.

Validation was completed with a third comparison using different sources of data, FleetCarma and Leaf Spy, used with the same model of EV—a Nissan Leaf. This Leaf data from FleetCarma is either a 2016 or a 2017 based on time of data collection. It can be compared with the previously analyzed 2016 Leaf. There were 611 rows analyzed which were over 1% SOC difference. A total of five Level 3, or 0.08%, and 606 Level 2 charging events were completed.

Of the 611, 558, or 91.32%, were completed to 100%. this is extremely high and provides a reason for degradation.

Table 47 has energy values 338 days apart or eleven months and four days. The SOC difference, Starting SOC, Ending SOC, and Charger Level are all equivalent in the first segment. On August 9, 2017, Toronto, Ontario had a temperature of 19°C at 2:00 A.M. while on July 13, 2018 it was 24°C at 12:00 A.M. Based on a slightly higher temperature, energy consumed in July would be decreased based on Arrhenius Law. Therefore, the 2.81% energy increase happened over 338 days. This gives a pro-rated value of 3.03% per year degradation.

To further validate Nissan Leaf data, a second segment was chosen. The level of charger is the same for both values. Measurement of data points were 369 days or one year and four days in-between. SOC difference was slightly different at 20.45% and 20.12%, this needed adjustment for comparisons. An adjusted value of 4.77% is the result of moving to 20.49% SOC difference. On May 26, 2018, Toronto, Ontario had a temperature of 23°C at 2:00 A.M. while on May 30, 2018 it was 21°C at 5:55 P.M. Based on a slightly lower temperature on May 30, 2019, energy consumed on May 30 is lower than the equivalent on May 26, 2018. Energy required 369 days after the initial measurement would be an increase of 5.46%. Pro-rated for one year it is 5.40%. Based on temperature, the lowest value of degradation is 5.40%. Using the previous value of 3.03% over 365 days, the total degradation over 659 days is 5.48%. The two values, 5.40%, and 5.48%, are extremely close to equivalency and rounding adjustments can account for the 0.08% in difference.

The 2016 Nissan Leaf generating data with Leaf Spy utilized Level 3 chargers for 0.136% of charging sessions. Using the FleetCarma 2016/2017 Leaf, there were 0.82% charging events using Level 3 chargers. Based on Level 3 or QC data from other Nissan Leafs within this study, higher degradation didn't occur because of it. The elevated degradation in the 2016/2017 Nissan Leaf is higher due to the number of cyclic charges, thereby validating both numbers. A degradation rate of 5.48% for 606 L1/L2 and five Level 3 charging sessions happened to the 2016/2017 Leaf based on FleetCarma data. The 2016/2017 Leaf charging over 659 days had degradation of 5.48%. A sole participant had 6.24% degradation with their 2016 Leaf. The 2016 Leaf had 67 L1/L2 charging sessions in 26 days or 2.58 charges per day.

Table 47

2016/2017 Nissan Leaf Segmented Data from Ontario via FleetCarma

Start	Energy (kwh)	Loss	Level	Start-SOC%	End-SOC%	SOC-Diff%
8/9/2017 2:00	15.336	1.840	2	50.00	100.00	50.00
7/13/2018 0:00	15.779	2.090	2	50.00	100.00	50.00
5/26/2018 2:00	4.510	0.541	2	39.63	60.12	20.49
5/30/2019 17:55	4.687	0.551	2	65.98	86.10	20.12

Note: evidence of charging to 100% ending SOC.

Manufacturer Comparison

The battery degradation across most manufacturers shows similar results, but Tesla does stand out. For example, the participant 2017 Chevrolet Bolt EV required an energy increase of 6.51% per year, whereas the two 2017 Nissan Leafs required 5.48% and 7.53%. Higher values of degradation can be linked to more Level 3 charges for the smaller-sized batteries under 40 kwh. Volkswagen and Ford had similar degradation results at 4.36% and 4.63%, respectively, both use smaller battery packs.

Tesla has lower levels of degradation compared to competitors. Most of their vehicles had between 1.06% to 3.58%. It was determined that their sample Model 3 SR had irregular results due to a small sample size. The European model used for validation of degradation falls within this range of 1.06% to 3.58% showing valid and consistent results across Tesla models.

Table 48

Manufacturer Comparison of Degradation using Percent

	2013	2014	2016	2017	2018	2019	2020
Nissan Leaf	3.74	3.96	5.48*	5.48*	4.78	4.00*	N/A
Nissan Leaf	N/A	N/A	6.24	7.53	N/A	N/A	N/A
Kia Soul EV	N/A	N/A	N/A	N/A	6.41	N/A	0.00
Kia Niro EV	N/A	N/A	N/A	N/A	N/A	2.72	N/A
Smart Fortwo	N/A	N/A	N/A	8.35*	N/A	N/A	N/A
Tesla S 85	N/A	N/A	N/A	****	N/A	N/A	N/A
Tesla 85D	N/A	N/A	1.06*	N/A	N/A	N/A	N/A
Tesla Model X - AB	N/A	N/A	***	***	N/A	N/A	N/A
Tesla Model X – BC	N/A	N/A	7.19*	N/A	N/A	N/A	N/A
Tesla Model 3	N/A	N/A	N/A	N/A	7.59*	N/A	N/A
Tesla Model 3 LR**	N/A	N/A	N/A	N/A	N/A	2.33	N/A
Tesla Model S 60D	N/A	N/A	N/A	0.00*	N/A	N/A	N/A
Tesla Model S 90D	N/A	N/A	1.89*	N/A	N/A	N/A	N/A
Chevrolet Bolt EV	N/A	N/A	N/A	6.51	3.44	N/A	N/A
Chevrolet Spark EV	N/A	6.48*	N/A	N/A	N/A	N/A	N/A
BMW i3	N/A	N/A	N/A	N/A	N/A	6.77	N/A
Mitsubishi i-MiEV	N/A	N/A	2.32*	N/A	N/A	N/A	N/A
Hyundai Ioniq	N/A	N/A	N/A	4.07**	5.56	N/A	N/A
Ford Focus EV	N/A	N/A	N/A	4.36*	N/A	N/A	N/A
Volkswagen e-Golf	N/A	N/A	N/A	4.63*	N/A	N/A	N/A

Note: per year results developed by Ferrier, 2022.

* Unknown year ** European model *** Invalid Results **** Range from 1.22-3.58%

Another anomaly from Tesla was the Model X. A Tesla Model X from Alberta showed extreme degradation within the range of 9.69 – 19.00%, it appears defective as previously noted.

Summary

The Results and Discussion section provides an in-depth statistical analysis of EV data sent in by participants. The first part used generated data from a smartphone application called Leaf Spy used with Nissan Leafs. There was battery degradation found in all Nissan Leafs. No degradation was found in the 2020 Kia Soul EV or the Tesla Model S 60D. A second part involved analyzing data provided through the FleetCarma study that took place in Canada. Descriptive statistics were included with FleetCarma data for comparison of three key values: Charging Level, Charging Energy, and Ending SOC. Data was validated through the use of European submissions for comparisons. The manufacturer comparison section was completed to answer the question: “Out of the North American EV models, what battery packs degrade at the fastest and slowest rates?”

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

There were many challenges involved within this study, including the collection of historical data, analyzing different content within CSV files, and validating information received from various sources. Some files had no temperature information while others had it in °F Fahrenheit, thereby needing conversion for consistency and comparability. Data generated from a Nissan Leaf or Kia Soul via a smartphone application is much different than a data logger; this needed to be analyzed with different methods. The amount of FleetCarma data was enormous, but the lack of SOH made it difficult to develop meaningful results. However, using the segmentation method was a unique and helpful way to approach comparative data while seeking to explain the degradation through energy consumption over time.

Conclusions

Segmentation as a method for analyzing and comparing results was suitable for this study due to varying data contained within gathered CSV files. After reviewing the results, one challenge was discovering lines of data to create a wide enough segment where degradation would or could happen. One EV only had a month of sample data, a very short period, which made it difficult to detect patterns and degradation—these results were not generalizable to the population. The 2016 Nissan Leaf had battery degradation occur from February 22 to March 20, 2021, less than one month, but data failed to develop long-term patterns because of a shortened timespan within CSV log files. Likewise, the single 2020 Kia Soul EV participating had 146 lines compared to most EVs such as the 2016/2017 Leaf from FleetCarma that had 611 lines. Fortunately, the FleetCarma study had several large datasets available for analysis. Answering questions regarding the effects of charging, it is obvious that L1/L2 and QCs do affect EVs battery degradation over time, but the type of EV also has an impact. For Nissan Leafs, there is a measurable negative impact on battery SOH using a Level 3 CHAdeMO charger for QCs. The 2016 and 2017 Leafs provide evidence that one QC can negatively affect battery SOH in vehicles with smaller battery packs. A combination of high temperatures and L1/L2 charges degrade the battery at faster rates than lower ones. Examining the data shows that owners should charge cars under 24°C or 75.2°F over time to lessen battery degradation.

Research Questions Addressed

Altering charging practices can help an EV charge more efficiently. Charging practices should be altered due to a moderate correlation of charger energy and ending SOC. As ending SOC approaches 100%, the amount of energy is increased disproportionately due to resistance, this is inefficient for charging an EV. The practice of charging to 100% needs to be changed to a reduced level. Even with Level 1 charging on a battery pack of 42.2 kwh, a 92% ending SOC was not energy efficient. A Kia Niro using a Level 2 required additional energy for 100% ending SOC while adding only 10.5% SOC, the same EV charging to 64% SOC did not require extra energy. Charging an EV to 100% is less efficient than 64.706%, but for practical reasons, not all users can reach their destination using a fraction of capacity. Charging to 77% is less than 80% and shows more efficiency than 100%, this is a good value if the required capacity demands it. Ultimately, charging practices need to change so that (1) EV charging is to a minimal ending

SOC% that allows an owner or user to get from point A to point B, and (2) Charging is infrequent as possible to reduce cyclic degradation.

One of the key conclusions is that charging to 100% SOC is not only inefficient, but it is harmful via battery degradation to the EV too. The eGolf and BMW i3 are prime examples of why not to charge to 100% SOC. Only 17 Level 3 charging events for the eGolf took place and there was 6.33% degradation because a majority of charging events ended at 100% SOC. Likewise, the BMW i3 had 71.60% of charging events to 100% SOC resulting in a 6.67% battery degradation. A 2018 Ioniq taking part in the study had fewer 100% ending SOC and less battery degradation. It is recommended to charge less than 100%, even if efficiency is not required from a free EV charger, because over time degradation happens at a higher rate.

Results from all EVs suggests the use of Level 3 chargers should be minimal and limited. Using Level 3 chargers can have a serious negative impact even at moderate temperatures such as 8.5°C or 47.3°F. For pre-2018 Leafs, .05% SOH can be removed through using a Level 3 charger one time. Larger battery packs lessen the effect, but Level 3s are harmful in the long-term. Based on this information, it is best to reduce Level 3 charging to a minimum.

Changing charging practices can have significant impacts on the health of battery packs for users in North America. As shown with the 2020 Kia Soul, which experienced no degradation after 146 charging events, setting the ending SOC to 80%, within the charger or EV, for all types of charging appears to increase battery SOH. 2018 Bolt data found inefficient Level 2 charging above 87.45% SOC. Like North American models, the Ioniq from Europe found charging past 80% is less efficient, which explains extra energy required to achieve the same ending SOC at a lower energy value. These results are consistent and validated using multiple EVs of the same model which means owners or operators of EVs should charge to 80% or lower.

For some newer EVs taking part in the study such as the 2019 Kia Niro EV and 2020 Kia Soul EVs, a digital display provides an ability to change the maximum charging level to various points such as 90%, 80%, 70%, and lower. This feature should be used by owners often to decrease battery degradation through limiting higher ending SOC%. In addition, newer EV models such as the 2019 Kia Niro EV include a smartphone application that allows setting SOC to the desired level. The maximum charging level can be altered for Level 2 and Level 3 chargers. An ability to alter the ending SOC provides help to keep the battery healthier over long-term usage.

An above-average battery pack size, 40-kwh and higher, impacts the speed of degradation in North American EV models. Larger batteries need less charging, and this lessens the degradation rate. Large numbers of cyclic charging used with smaller battery packs introduce degradation. Multiple examples of 40-kwh or higher batteries exist in this study including the 2018 Leaf, 2016/2017 Tesla 90D/85D, and 2020 Kia Soul EV. Comparing the 2017 Leaf using a 30-kwh battery to the 2018 Leaf using a 40-kwh highlights a lessening impact of QCs. A 2018 Leaf has less than a .025% reduction in SOH after a QC whereas the 2017 is between .025% and .05%, both based on temperature. Tesla Models 90D and 85D are all-wheel-drive models using a 90-kwh and 85-kwh battery; respectively, both have large battery packs. Both Tesla models show less than 2% degradation over a year. It doesn’t appear that Tesla makes “better” batteries or has a “superior” BMS system, it’s the larger size that is stopping them from faster degradation compared to their competitors. Another example, the 2020 Kia Soul taking part in the study showed no degradation after 146 charging events, it uses a large 64-kwh battery, this was not the case for its predecessors that used under a 40-kwh and degraded at a quicker rate.

Cyclic charging does negatively impact battery packs over long periods of time. Pre-2018 models of Nissan Leaf, Ford Focus EV, Hyundai Ioniq, Volkswagen eGolf, Mercedes Smart Fortwo, and Chevrolet Spark degrade at faster rates compared to many others because these EVs have small battery packs of less 40-kwh and require frequent charging. A good example of a vehicle with a high level of degradation is the Smart Fortwo from Mercedes. The Smart Fortwo goes through lots of charging sessions due to the small size of its battery and limited range. A degradation rate of 8.352 is higher than all others analyzed because it is more frequently cycled.

There are negative implications associated with temperature and how it applies to EV batteries. The temperature has been discussed throughout this paper because it is correlated with battery SOH and has a major impact on charging EV batteries. This study used multiple regression tests to demonstrate the correlation between temperature and battery health. It is clear that without confounding conditions, such as charging to 100% SOC, SOH declines as temperature increases. A finding from analyzing Leaf data is SOH can temporarily go up with increased temperature, but in the long-term it reflects higher rates of degradation. This finding matches the studies from Leng, Tan & Pecht, 2015 and Chen, He, Li & Chen, 2019 which had results showing lithium-ion batteries increasing their capacity in the short-term when the temperature increased, but in the long-term battery degradation happened at a faster rate. Nissan Leafs' data demonstrate strong negative correlations between SOH and temperature, which can be generalized to other EVs operating 30-kwh and under batteries.

There are positives to how temperature can help charging too. When consuming energy during charging, it takes less when higher temperatures are present. A 2018/2019 Kia Soul EV presented an excellent example where the ambient temperature was greatly increased thereby lowering the energy consumed. Another positive from temperature is an ability to narrowly define degradation rates in conjunction with temperatures. Table 19 clearly shows how temperature can affect L1/L2 and QC charging.

One unexpected occurrence was how previous charging sessions could affect the measurement of data. The author has moved from a Level 1 to Level 2 charger, after a short period of driving, with his 2017 Nissan Leaf in the past. It appears to move from a Level 1 to a Level 2 with usage in-between temporarily alters battery measurement, this happened to two EVs with batteries 50-kwh or over. The 2017 Tesla Model X and 2017 Chevrolet Bolt had Level 1 charging temporarily affect the energy consumed after switching to a Level 2. For the Bolt, Level 1 charging was followed by driving which reduced SOC by 5.5% during the period of no charging. Based on the sequence of charging and two small decreases in consumed energy over time, the process of switching charger types with limited use between should not be completed if an accurate SOH measurement is required. One possible cause of this discrepancy is with the conversion from AC to DC and changing from Level 1 to Level 2, there appears to be a primacy effect, or influence of the first charge on the second; this needs to be investigated in future research.

Future Research

A recommendation for future studies is to use online forums and social media to promote more use of Leaf Spy and Soul Spy to Nissan Leaf and Kia Soul EV owners. Data in the CSV “Spy” files is much more detailed than data loggers, therefore it is much easier to track trends than most other EVs. Integration of a DropBox account into both “Spy” smartphone applications has made it easy to store log files over long periods of time.

Another recommendation is to contact more Tesla owners using TeslaFI in North America to add knowledge about how their EVs are performing over time via the detailed data generated from the application. Although difficult, it would be beneficial to have comparison data from Nissan Leafs and Teslas from years not currently covered, i.e., 2015 Nissan Leaf. As is, there is very limited public information coming from owners and users of Tesla vehicles. It was difficult to find anyone wanting to discuss Tesla data through online channels.

New types of EVs are entering the marketplace this year and next. Replication of this study with newer models would be a good comparison to see if battery technology is advancing. New EV models include the Hyundai Ioniq 5, BMW iX, Cadillac Lyriq, Rivian R1S, Tesla Cybertruck, Mercedes EQS, Nissan Ariya, Fisker Ocean, and Lucid Air. It would be a good idea to get consumers tracking and storing data about these vehicles, from the initial purchase, so that an examination of battery degradation can occur after a year of use. Newer vehicles have the ability to limit charging to a specific percentage such as 70%, 80%, and 90% SOC. A comparison of EVs set at various charging limits would allow for battery degradation analysis for each limit.

New materials are starting to be used in developing batteries for the future. One battery composition started to be employed by Tesla uses LFP or Lithium-Iron-Phosphate (LiFePO4). Many current batteries use Cobalt which can be expensive, LFP is cheaper. Once Tesla or other manufacturers start to mass develop EVs with LFP batteries, a recommendation is to test battery degradation after charging over time with various types of charger levels to replicate this study.

A final idea is to replicate this study with data from newer models, including 2021, 2022, and 2023 versions. Batteries continue to get larger and technology is improving. Various BMS' are being updated to prevent thermal runaway which occurred in many of the 2017-2020 Chevrolet Bolts. It would be a good idea to examine if degradation rates are lower due to technology advancements such as the ability to set charging thresholds.

APPENDIX I

EV data wanted for research project

by Sean Hart | Apr 5, 2021 | EV Society News, News | 0 comments

Do you collect data on your EV?

An EV Society member, Doug Ferrier, is working on a Ph.D. Dissertation project and is looking for EV owners who collect data on their vehicle status such as; charging level, distance travelled, state of health, etc. The research will look at the impact of charging practices on the health of EV batteries over time. Many owners have apps that collect this kind of data (e.g. Leaf Spy, Soul Spy, Tesla app, etc) and Doug is looking for owners willing to share that data to be used for his analysis.

Data from BEVs built between 2010 to 2020 (inclusive) is acceptable. Hybrids and PHEVs are not part of this research. Any personally identifiable information will be removed from any data received (such as names, GPS coordinates, VIN numbers, etc).

If you are interested in participating, please contact Doug Ferrier at: dougfms (AT) msn (DOT) com.

APPENDIX II

My name is Doug Ferrier, I am a Professor and Ph.D. student. I have written a few articles for Automotive Innovations magazine along with a journal article in the American Journal of Vehicle Design. All my articles are on EVs. I am currently working on my dissertation as part of my Ph.D. In addition, there will likely be a journal article and multiple magazine articles created from this study.

I am looking for data from EV-related companies that have kept a history regarding their vehicles (or customers) over a period of time. This data could be from any EV, but it cannot be a hybrid or plug-in hybrid. Data has to include charging level including Superchargers, battery health at the time, charging time, dates, time, quick charges, etc.… I am looking for vehicles from 2010-2020. I have one organization involved as of now - the EV Society of Canada will be providing data as part of this study.

I am looking to accumulate over 1 million lines from combining records of various EVs. This is a "Big Data" project. I am going to be looking at charging practices and how it effects the battery over time – if it does effect the battery. I will be looking at all three levels of chargers plus Superchargers. Here is one more important piece: "Any data gathered will have all personally identifiable information erased from it. Data scrubbing will include removing information related to location (latitude and longitude), VIN (Vehicle Identification Number), and profile name. All data will remain confidential. Data will be stored in a secured location – a password or fingerprint will be required to access it. None of the data will reside on a Local Area Network (LAN)."

Would Tesla have information that fits these criteria? Would you be interested in participating?

I look forward to hearing from you.

Thank you,

Prof. Doug Ferrier, M.S., ITIL., Ph.D. (Candidate)

APPENDIX III

Hello, I am reaching out to EV owners who would be interested in taking part in a university research project. I am an EV owner myself. I am a member of the EV Society of Canada. The study centers around EV batteries. Any type of EVs built between 2010-2020 are eligible. All EV data will be from North American based-vehicles sold during model years 2010-2020. I have already obtained over 350,000 lines of data.

Data collection started in March 2021. I have a few sets of data from Chevy Bolts at this present time. Data can be from any EV, but it cannot be a hybrid or plug-in hybrid (Volts are disqualified). Data from log files created in any app (Leaf Spy, Soul Spy, Tesla app, GM, Ford, etc...) would be very useful. Data should include charging level (Level 1,2,3), dates, time, battery state of health (SOH), charging time, and quick charges. Temperature during the charge will be accepted; if available. Other data will be accepted, but will scrubbed down to only those fields helpful for the study. Any data gathered will have all personally identifiable information erased from it. Data scrubbing will include removing information related to location (latitude and longitude), VIN (Vehicle Identification Number), and profile name. All data will remain confidential. None of the data will reside on a Local Area Network (LAN) within a file server. Data will be stored in the cloud at one of Amazons' data centers in the eastern United States. PostgreSQL will be used to structure the data. The HTTPS protocol will be used to update and access cloud-based data to ensure security.
Please contact me via this group to participate.

Thank you,

Doug Ferrier, M.S., ITIL., Ph.D. (Candidate)

APPENDIX IV

Lithium Ion Batteries in Electric Drive Vehicles (Figure 1)
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APPENDIX V

IRB Notice

Dear Mr. Ferrier,

Thank you for contacting the IRB at Indiana State with an inquiry about the need for IRB oversight for your dissertation research.

You stated that you are collecting data about electronic vehicles and information related to their charging systems. It is possible or even likely that you will collect VIN numbers due to the manner of data collection. The concern is that a VIN number is potentially identifiable and therefore may be the kind of personal information the IRB oversees.

I appreciate your care in thinking about the protection of human subjects. Since a VIN is actually able to be seen in public, it does not seem to the IRB to be the kind of personal information the IRB would need to oversee. In addition, a VIN is unique to a vehicle, not to a person. However likely it is that the VIN would point back to the specific owner of the vehicle, there is no inherent relationship between the VIN and a person's behavior or characteristics.

I therefore do not see any human subjects in your research, meaning the IRB does not need to review your project.

Please be in touch if you have any additional questions.
take care,
Dr. Foster
chair, IRB
Indiana State University

APPENDIX VI

2017 Nissan Leaf S – Leaf Spy Professional Log File

Date/Time	Elv	Speed	Gids	SOC	AHr	12v Bat Amps	Hx	12v Bat Volts	Odo(km)	QC	L1/L2	Ambient	SOH
11/26/2019 20:57:25	88	0	301	941786	677648	0	63.16	12.56	93584	292	1466	8	85.1
11/26/2019 20:57:30	88	0	301	941001	677648	0	63.16	12.56	93584	292	1466	8	85.1

SOC	AHr	Pack Volts	Pack Amps	Max CP mV	Min CP mV	Avg CP mV	CP mV Diff	Judgment Value
649981	680350	380.93	0	3977	3961	3968	16	0
721966	680350	374.98	13.612	3917	3896	3906	21	0

Pack T1 F	Pack T1 C	Pack T2 F	Pack T2 C	Pack T3 F	Pack T3 C	Pack T4 F	Pack T4 C	CP1
70.3	21.3	66.7	19.3	none	none	59.3	15.2	3973
74.7	23.7	71.1	21.7	none	none	63.3	17.4	3903

Motor Pwr(w)	Aux Pwr(100w)	A/C Pwr(250w)	A/C Comp(0.1MPa)	Est Pwr A/C(50w)	Est Pwr Htr(250w)	Plug State	Charge Mode	OBC Out
0	1	12	0	0	12	2	2	2000
0	1	12	0	0	12	2	2	1800

HVolt1	HVolt2	GPS Status	Power SW	BMS	OBC	Debug	Motor Temp	Inverter 2 Temp	Inverter 4 Temp
350.91	393.5	7F	0	0	1	0	40	40	40
350.91	393.5	7F	0	0	1	0	40	40	40

TP-FL	TP-FR	TP-RR	TP-RL
44.75	41.5	42	44
44.25	41.25	41.75	43.5

CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9
3973	3973	3973	-3965	-3965	-3965	3977	-3961	3973
3903	3908	3913	-3905	-3905	-3905	3908	-3901	3913

APPENDIX VII

ANOVA Calculations

Cumulative Leafs ANOVA based on Regression Variables

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	317,905.315	3	105,968.438	45,903.931	.000[b]
	Residual	200,902.648	87028	2.308		
	Total	518,807.963	87031			

Note. a. Dependent Variable: SOH; b. Predictors: (Constant), TEMP, L1L2, QC.

Ford Focus EV ANOVA using Regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	10,882.408	2	5,441.204	137.753	<.001[b]
	Residual	28,676.718	726	39.500		
	Total	39,559.126	728			

Note: a. Dependent Variable: Charger Energy b. Predictors: (Constant), Ending SOC, Charging Level

Tesla Model S 90D ANOVA using Regression

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	24,341.325	2	12,170.662	31.298	<.001[b]
	Residual	173,044.955	445	388.865		
	Total	197,386.280	447			

Note: a. Dependent Variable: Charger Energy; b. Predictors: (Constant), Ending SOC, Charging Level.

I-MiEV Charger Energy ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	324.027	2	162.014	12.317	<.001[b]
	Residual	2630.780	200	13.154		
	Total	2954.807	202			

Note. a. Dependent Variable: Charger Energy; b. Predictors: (Constant), Charging Level, Ending SOC.

Chevrolet Spark EV Charger Energy ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1,535.206	2	767.603	82.842	<.001[b]
	Residual	5,791.177	625	9.266		
	Total	7,326.383	627			

Note. a. Dependent Variable: Charger Energy; b. Predictors: (Constant), Ending SOC, Charging Level.

2018/2019 Kia Soul EV Charger Energy ANOVA

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	977.937	2	488.968	7.334	.001[b]
	Residual	5467.292	82	66.674		
	Total	6445.229	84			

Note. a. Dependent Variable: Charger Energy; b. Predictors: (Constant), Ending SOC, Charging Level.

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