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1 **Quantifying the Impacts of Electric Vehicle Travel Patterns on Battery Lifespan**

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**ABSTRACT**

Electric vehicles (EVs) are a promising alternative to conventional vehicles. Several commercial EVs have already been in the market for a few years. However, greater adoption of EVs still faces several challenges. The concern about lifespan of EV batteries due to degradation is one of them. Lifespan information of populations of EV batteries is still scarce. Understanding the lifespan characteristics of EV batteries is significant for EV adoption, vehicle and/or battery resale market, and battery warranty strategy design. This study quantifies the impacts of EV travel patterns on the battery lifespan. Real-world household vehicle travel information extracted from the National Household Travel Survey (NHTS) of 2009 data. A microscopic traffic simulation model is built for the Indianapolis road network to generate speed profiles. Then, household vehicle travel patterns are obtained by matching the NHTS travel information (such as departure time, distance, travel time, purpose, etc.) with the simulated speed profiles. A semi-empirical battery degradation model is used to predict battery lifespan for a simulated population of vehicle travel patterns based upon the NHTS data. The results indicate that vehicle travel patterns, driving behavior (that is, average speed, speed deviation, etc.), and temperature have significant impacts on EV battery lifespan. The impact of vehicle travel patterns and driving behavior increases with decrease in temperature. For Indianapolis, 10% of batteries have lifespan less than 5.15 years, 50% have less than 7.57 years, and 90% have less than 9.65 years.

## INTRODUCTION

The transportation sector is an important component of energy consumption. It accounts for about 70% of the total oil consumption in the US (1, 2). Conventional vehicles use liquid fossil fuels as their energy sources, and have become the largest contributors to urban air pollution (3). In 2013, greenhouse gas emissions from transportation accounted for about 27% of total U.S. greenhouse gas emissions, making it the second largest contributor of greenhouse gas emissions in the U.S. after the electricity sector (1). With the fluctuation of petroleum prices and the large CO<sub>2</sub> contribution of conventional vehicles, electric vehicles (EVs) have been introduced to the commercial marketplace to provide an alternative. EVs use electric motor for propulsion and have no tailpipe emissions. Since electricity can be generated from renewable energy, EVs have the potential to significantly reduce emissions from transportation sectors as the electricity fuel mix evolves (4–6). EVs can be equipped with regenerative braking system that can further enhance overall fuel efficiency and reduce emissions (7). Therefore, EVs provide large scale experience in electric energy storage that drives innovation. However, the greater adoption of EV still faces several substantial challenges. These include range anxiety (that is, the fear of running out of battery charge before completing the trip), long battery recharging time, scarce availability of charging infrastructure, the potential impact on power grid stability, higher vehicle prices, and concerns about battery such as reduction in lifespan due to degradation and resale value for second use (8–14). In this context, this paper focuses on predicting useful battery lifespan of EVs based on their travel patterns.

The majority of EVs in the market use a Li-ion battery pack with an energy capacity of around 20 kWh. For example, the battery pack energy capacity for the Nissan leaf is 24 kWh, Honda Fit EV is 20 kWh, Ford Focus Electric is 23 kWh, and Smart EV is 17.6 kWh. The energy capacity of a battery pack degrades with time and usage (15–20). As the energy capacity decreases, the vehicle range drops. An oft-stated common criterion is that the battery should be retired from the vehicle application if its capacity has depleted to 70–80% of its original capacity (10, 18, 20). The replacement of a battery pack poses significant cost to vehicle owners, though batteries can be resold and utilized for other applications such as renewable energy storage (11, 21, 22). Under this common battery replacement criteria, well-designed battery warranty strategies will play a crucial role in widespread EV adoption. However, among the current commercialized EVs available in the market, only Nissan Leaf has a battery capacity warranty against degradation from regular use. Under this warranty, Nissan will repair or replace a Leaf's battery within five years or 60,000 miles if it loses more than 30 percent of its energy capacity (23). Therefore, quantifying EV battery lifespan for a large population of EVs is important for vehicle manufacturers, car owners, and battery researchers seeking to support practical applications.

Battery degradation mechanisms are an important consideration to explore EV battery lifespan. Two types of degradation/aging mechanisms are significant: during storage (calendar aging) and during use (cycle aging). Calendar aging is due to side reactions resulting from thermodynamic instability of active materials, while cycle aging results from kinetic effects, such as structural disordering, or concentration gradients. In past work, the total aging effect is considered as the summation of calendar aging and cycle aging, but interactions may occur (20, 24, 25). Battery aging mainly happens at the two electrodes: anode (e.g. graphite) and cathode (e.g. lithium metal oxide). Aging mechanisms occurring at anodes and cathodes are significantly different. Most researchers believe that changes to the Solid Electrolyte Interphase (SEI) due to reactions of the anode with the electrolyte are the major source for aging at the anode (18, 26). Unlike the anode, the cathode can be made using different types of metal oxide materials. Different

materials have quite different effects on battery life, and the mechanisms of capacity fade at the cathode are not completely understood. Moreover, battery aging is induced by various processes and their interactions, and most of them cannot be studied independently (8). Due to the complexity of the Li-ion battery system, some researchers have created semi-empirical battery life models for specific Li-ion battery chemistries based on experimental data (15–17, 27). Thomas et al. built a degradation model and an error model using a statistical method based on experimental data (28).

Using the aforementioned battery life estimation models, some researchers have studied the battery lifespan for EVs/PHEVs (plug-in hybrid electric vehicles). For example, Guenther et al. studied the EV battery lifespan for different charging behaviors and three speed profiles (19). Similarly, other studies (29) applied speed profiles from standard driving cycles, such as Urban Dynamometer Driving Schedule (UDDS), by either repetition or combination. However, the impacts of realistic vehicle travel patterns with detailed speed profiles on battery lifespans for a large population of EVs have not been studied. As shown in our study results, vehicle travel patterns and driving behavior can have significant impacts on battery lifespan. Using speed profiles from standard driving cycles may be useful under a variety of considerations, but they fail to represent the variation in driving behavior and traffic conditions. Hence, using realistic speed profiles that can capture the effects of traffic conditions will enhance the estimation of EV battery lifespan.

This study quantifies EV battery lifespan for a large population of EVs through a semi-empirical battery aging model and a microscopic traffic simulation model. Realistic speed profiles are generated using microscopic traffic simulation model for the Indianapolis road transportation network. Five different temperature scenarios are examined. The results illustrate the impacts of temperature, total distance traveled, average speed and speed deviation on battery lifespan. This will provide insights for policymakers, vehicle manufacturers and researchers to improve battery technology, and design regional strategies to promote EV adoption.

## METHODOLOGY

A multi-paradigm modeling approach provides the flexibility to study the lifespan characteristics of a population of EVs. It enables different systems to be simulated with the most suitable modeling methods. Population behavior for a transportation network is addressed using building blocks, each of which represents a relevant set of phenomena. By building up these blocks together, the whole system can be simulated and investigated in a holistic manner. This paper considers four different building blocks: a microscopic traffic network simulation model which provides realistic drive cycles of vehicles, an EV energy consumption model which provides power demand results for different drive cycles, a battery circuit model which converts power demands to current flows, and a semi-empirical battery degradation model which simulates battery lifespan based on current flows and temperature.

Using the microscopic traffic network simulation model, vehicle trips from the National Household Travel Survey (NHTS) of 2009 data are matched with simulated drive cycles that reflect traffic conditions. The drive cycle data is then fed into the EV energy consumption model to compute power profiles. The power profiles are used as inputs to the battery circuit model to obtain battery current data. In the end, the battery current data is fed into the battery aging model to simulate EV battery life. FIGURE 1 shows a simplified flowchart of the methodology framework.

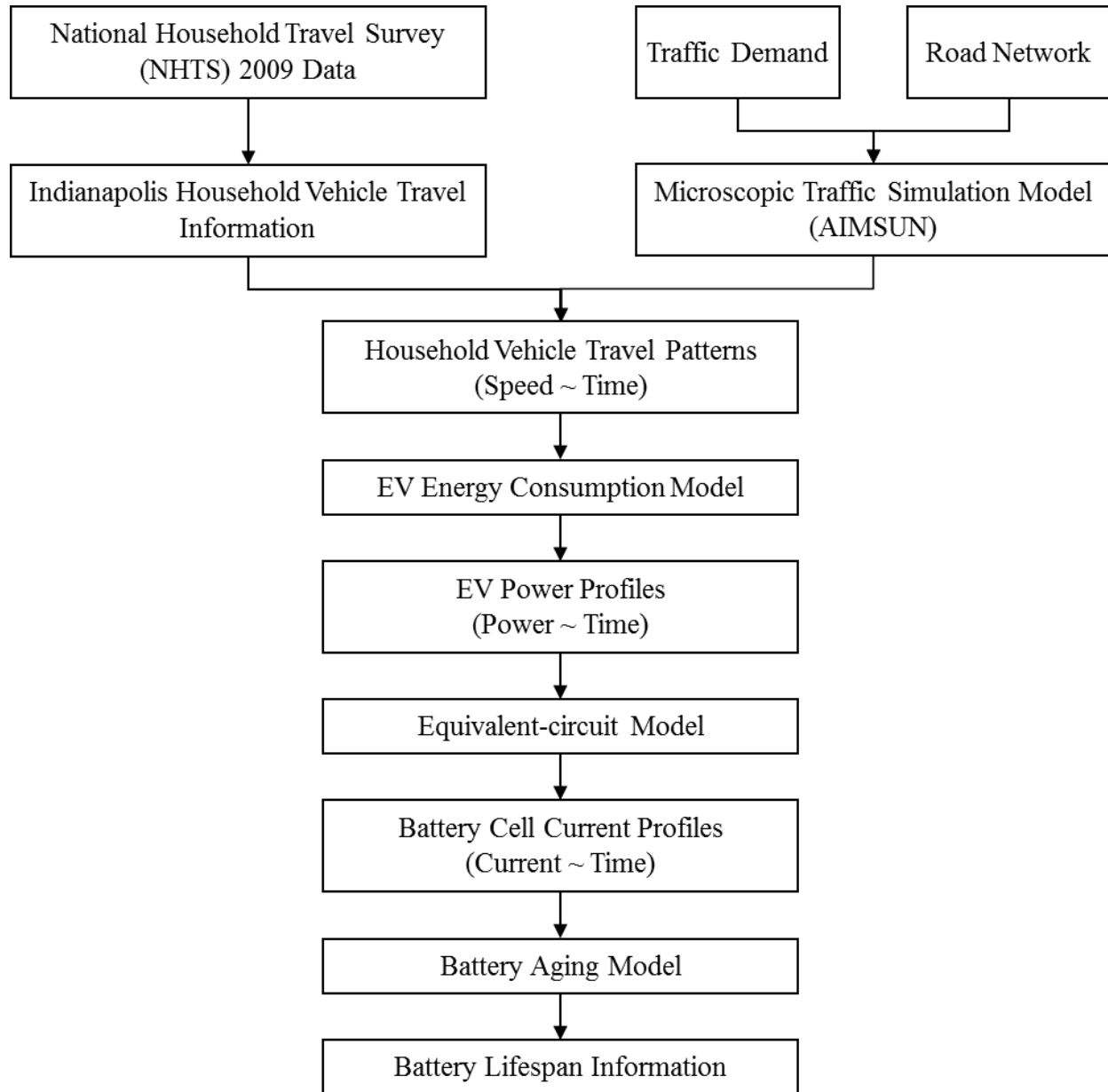


**FIGURE 1 Conceptual flowchart.**

### Household Vehicle Travel Patterns

For EVs, travel distance, travel speed, and vehicle acceleration and deceleration all impact battery lifespan. In this study, real-world household vehicle travel information is extracted from the NHTS data. The NHTS data provides daily trip profiles of 150,147 random households across the United States (22). Among the 150,147 households, 4,350 are from the state of Indiana. This study extracts all of the 2,832 samples which are from Indianapolis urban and suburban areas to represent Indianapolis households. Considering the range of EVs, only samples with daily travel distance less than or equal to 80 miles are selected, resulting in 2,306 (about 81% of 2,832) representative samples of household vehicles. The data includes car type, trip start and end time, trip distance, trip origin and destination, etc.; however, there is no information related to vehicles' speed profiles.

In order to get speed profiles, a microscopic traffic network simulation model is built for the city of Indianapolis. This model is used to generate realistic microscopic speed profiles with 1-sec time resolution. The speed profiles are then matched with each vehicle trip from the NHTS data based on trip characteristics to obtain the household vehicle travel patterns.

Traffic simulation techniques are commonly used to capture the interactions between vehicles as well as between vehicles and infrastructure at a microscopic level. A microscopic simulation model employs various models such as car-following, lane-changing, route choice, etc. to mimic real-world conditions. In this study, detailed speed profiles of vehicles are required to compute the battery lifespan of EVs. The traffic network simulation software AIMSUN is used to generate realistic drive-cycles of the vehicles at the microscopic level (30, 31). A detailed road network of Indianapolis is built in AIMSUN. The network contains all the freeways, most of the urban roads and some minor roads as shown in FIGURE 2. The traffic is simulated for a 24-hour period with discrete 15-minute interval origin-destination (O-D) demand matrices. The traffic demand level is calibrated based on the NHTS data for the state of Indiana.

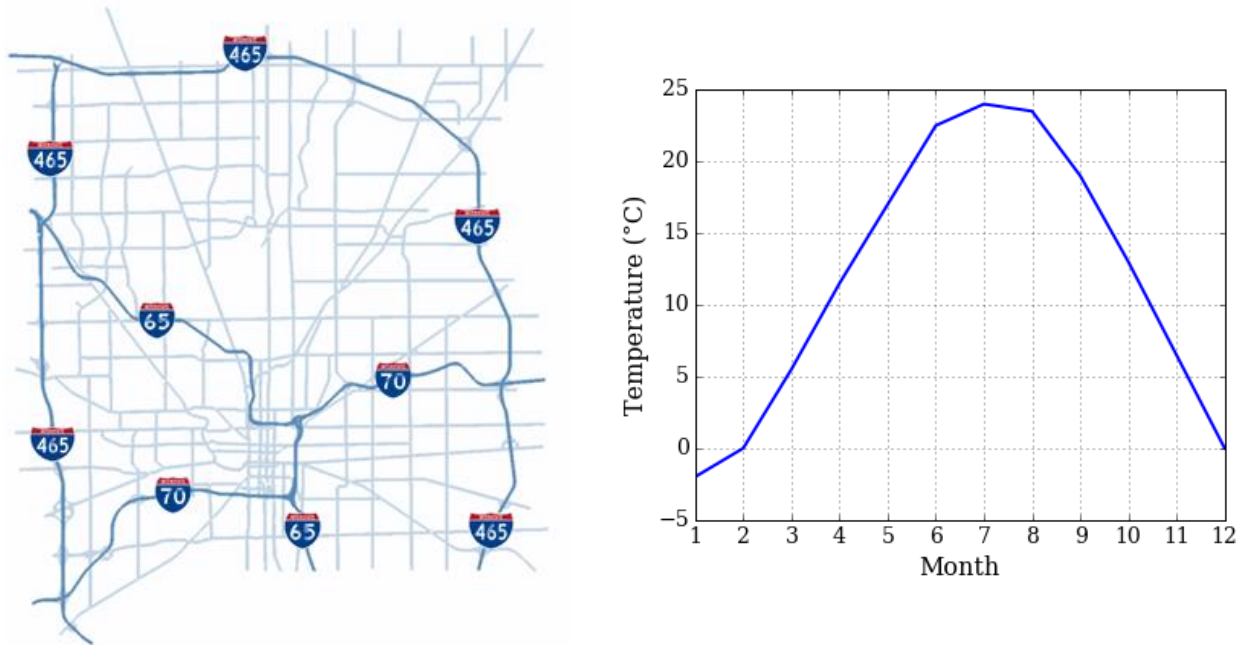


**FIGURE 2 Indianapolis road network and monthly average temperature.**

In AIMSUN, vehicles are assigned to specific routes based on distance and road-type. The trip data for each vehicle from the 2306 samples is obtained by matching to a specific trip in the network based on the trip departure time, trip distance, trip purpose, and freeway route indicator. The trip departure time and trip distance are the primary parameters used for matching. From these, the trip end time will be determined automatically as the drive cycle is generated by the network. The trip purpose is used to assign route towards the downtown area or the sub-urban area, and the freeway route indicator is used to check whether the trip uses the freeway. The drive-cycle data from AIMSUN is gathered for specific vehicles that match the trip profiles from NHTS data based on the above criteria. The first plot in FIGURE 3 shows an example of the vehicle drive cycle information.

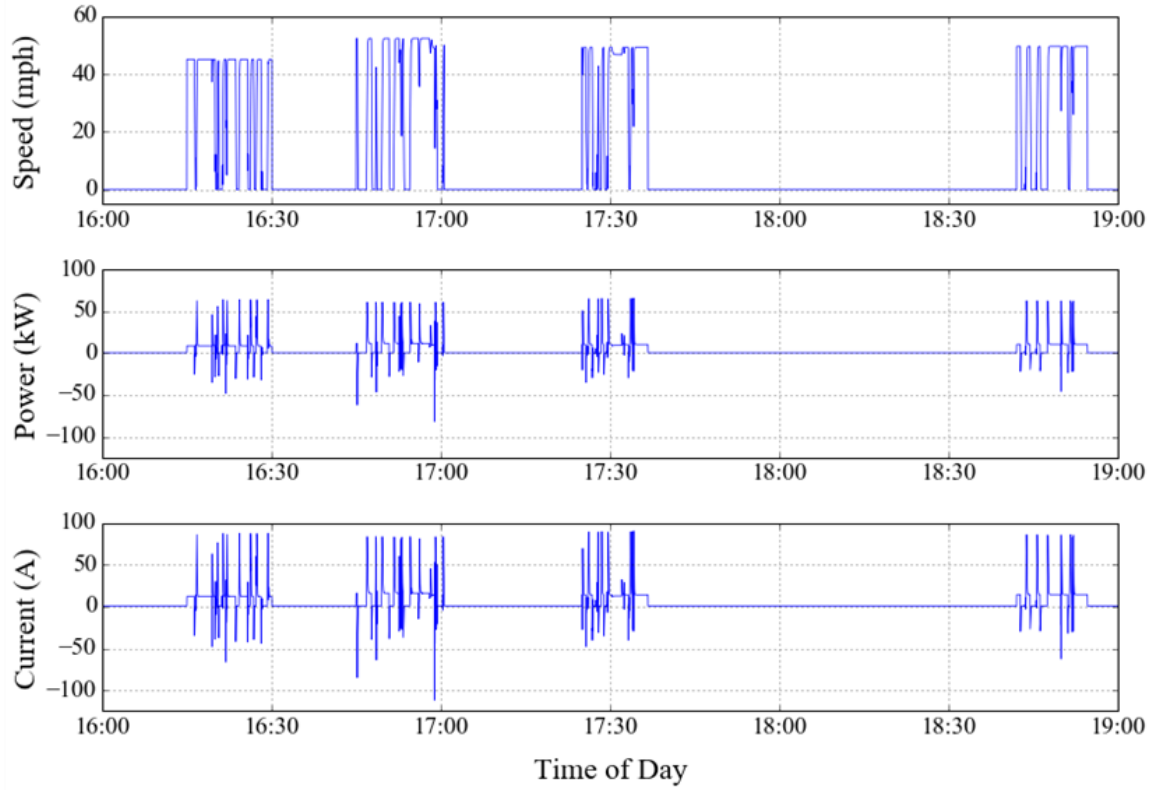


**FIGURE 3 Speed profile of a sample vehicle and its corresponding battery power profile and current profile.**

### Electric Vehicle Energy Consumption Model

EV energy consumption depends significantly on the microscopic drive cycle data. There are several models and simulation tools available that can simulate EV energy consumptions based on the drive cycle data. For example, ADVISOR (32, 33) and Autonomie (34) can simulate an EV's power profile, MPGe (mile per gasoline equivalent), state of charge (SOC) profile, etc. for any given drive cycle. These tools simulate the detailed performance of the power train/propulsion systems, and hence are computationally expensive. Van Haaren presented a physical model to compute energy consumption of EVs (35) and estimated the model parameters based on the Tesla Roadster data published by Straubel (36). This approach is used because: (i) the model illustrates the relationship between speed profile and EV energy consumption; and (ii) the computational runtime is significantly less as compared to packages like ADVISOR that simulates detailed vehicle dynamics that are not needed for this study.

In the physical model presented by Van Haaren, the total energy consumption is composed of two parts. One is the energy loss that the vehicle needs to overcome to travel at any given constant speed. The other is the kinetic energy loss (or gain) during acceleration or braking. The first part can be further divided into 4 parts: power loss due to aerodynamics,  $P_{aer}$ , power loss for drive-train,  $P_{dr}$ , power loss for tires,  $P_{rr}$ , and power loss for ancillary systems,  $P_{anc}$ . These power losses are expressed as equations (1)-(4). The definitions and values of the parameters are listed in TABLE 1.

$$P_{aer} = \frac{1}{2} \rho A C_d V^3 \quad (1)$$

$$P_{dr} = \alpha_{dr} V^3 + \beta_{dr} V^2 + \gamma_{dr} V + c_{dr} \quad (2)$$

$$P_{rr} = c_{rr} m g V \quad (3)$$

$$P_{anc} = 1.0 \text{ kW} \quad (4)$$

Kinetic energy of the vehicle includes linear kinetic energy  $E_{lin}$  and rotational kinetic energy  $E_{rot}$ . Typically, rotational kinetic energy is about 5-10% of the linear kinetic energy and hence, is assumed that the total kinetic energy  $E_{kin}$  is 1.05 times the linear kinetic energy. The energy loss during acceleration  $E_{acc}$  and energy recuperation  $E_{dec}$  during braking are illustrated in equations (7)-(8). The total energy consumption for a drive cycle is expressed as equation (9). Using this model, the power versus time profiles are computed for each vehicle trip from the NHTS data. The second plot in FIGURE 3 shows an example of the power profile generated using this model.

$$E_{kin} = E_{lin} + E_{rot} \approx 1.05 * E_{lin} \quad (5)$$

$$E_{lin} = \frac{1}{2} m V^2 \quad (6)$$

$$E_{acc} = \frac{\Delta E_{kin}}{\beta_{eff}} \quad (7)$$

$$E_{dec} = \beta_{rbs} * \Delta E_{kin} \quad (8)$$

$$E_{tot} = E_{acc} + E_{dec} + \int P_{aer} dt + \int P_{dr} dt + \int P_{rr} dt + \int P_{anc} dt \quad (9)$$

**TABLE 1 Parameter definitions and values for EV energy consumption model**

| Parameter     | Definition                           | Value              |
|---------------|--------------------------------------|--------------------|
| $C_d$         | Drag coefficient                     | 0.29               |
| $\rho$        | Air density (kg/m <sup>3</sup> )     | 1.2                |
| $A$           | Vehicle front area (m <sup>2</sup> ) | 2.27               |
| $\alpha_{dr}$ | Drivetrain coefficient 1             | 4*10 <sup>-6</sup> |
| $\beta_{dr}$  | Drivetrain coefficient 2             | 5*10 <sup>-4</sup> |
| $\gamma_{dr}$ | Drivetrain coefficient 3             | 0.0293             |
| $c_{dr}$      | Drivetrain coefficient 4             | 0.375              |
| $c_{rr}$      | Rolling resistance coefficient       | 0.0075             |
| $m$           | Vehicle mass (kg)                    | 1520               |
| $g$           | Gravity (m/s <sup>2</sup> )          | 9.81               |
| $\beta_{eff}$ | Battery to motor efficiency          | 0.85               |
| $\beta_{rbs}$ | Regeneration efficiency              | 0.4                |

### Battery Model

Battery degradation rate is different at different C-rates, so the current profile is needed to simulate battery life. The C-rate is a measure of the rate at which a battery is being discharged. It is defined as the discharge current divided by the theoretical current draw under which the battery would deliver its nominal rated capacity in one hour. A 1C discharge rate would deliver the battery's rated

capacity in 1 hour. A 2C discharge rate implies that it will discharge twice as fast (30 minutes). Thus, battery current profile is required to compute battery degradation. In this study, an equivalent-circuit model for Li-ion battery is implemented as a Simulink block diagram to extract cell current profile using the power profile. The internal resistance and open-circuit voltage of the cell are implemented as 1-D lookup tables based on instantaneous battery state-of-charge. The equivalent-circuit model can be represented by equations (10)-(14). The definition of the parameters used are shown in TABLE 2.

$$V_{cell}(t) = V_{OC}(t) - I_{cell}(t) * R_{int}(t) \quad (10)$$

$$P_{cell}(t) = \frac{P_{batt}(t)}{N_{cell}} = V_{cell}(t) * I_{cell}(t) \quad (11)$$

$$V_{OC}(t) = f(E_{SOC}(t)) \quad (12)$$

$$R_{int}(t) = g(E_{SOC}(t)) \quad (13)$$

$$E_{SOC}(t) = E_{SOC}(0) + \frac{1}{B_{AhCap}} * \int_0^t \frac{I_{cell}(t)}{3600} dt \quad (14)$$

**TABLE 2 Parameter definitions for equivalent-circuit battery model**

| Parameter                      | Definition                                                   |
|--------------------------------|--------------------------------------------------------------|
| $V_{cell}(t)$                  | Cell terminal voltage at time $t$                            |
| $V_{OC}(t)$                    | Cell open-circuit voltage at time $t$                        |
| $I_{cell}(t)$                  | Cell current at time $t$                                     |
| $R_{int}(t)$                   | Cell internal resistance at time $t$                         |
| $P_{cell}(t)$                  | Electrical power out of the cell at time $t$                 |
| $P_{batt}(t)$                  | Electrical power out of the battery pack                     |
| $N_{cell}$                     | Number of cells in the battery pack                          |
| $E_{SOC}(t)$                   | State-of-charge at time $t$                                  |
| $f(E_{SOC}(t)), g(E_{SOC}(t))$ | 1-D lookup tables as function of state-of-charge at time $t$ |
| $B_{AhCap}$                    | Nominal ampere-hour capacity of the cell                     |

### Battery Degradation Model

Battery degradation causes capacity loss and impedance growth during operation and is also a result of storage. Operational degradation is called cycle aging, and storage degradation is called calendar aging. Calendar aging happens regardless of whether the battery is operated or not. It is mainly caused by the Li-ion loss during SEI formation at the graphite anode, and is strongly affected by two parameters: time and temperature (15). Cycle aging only happens when the battery is operating and there is current flow. The total battery energy capacity loss is the summation of these two effects.

This study uses a semi-empirical model developed by Wang et al. that includes three important experimental parameters: time, temperature, and discharge rate (15). They performed experiments for 1.5 Ah, 18650 cylindrical cells and created a test matrix to measure each cell. The cell has a  $\text{LiMn}_{1/3}\text{Ni}_{1/3}\text{Co}_{1/3} + \text{LiMn}_2\text{O}_4$  (NCM+LMO) cathode and a graphite anode. They modeled both calendar aging and cycle aging using substantial experimental data. The cycle aging model is for a given constant C-rate. In reality, it is not possible for an EV to operate at a constant battery C-rate as the speed of the vehicle and hence, the power drawn from the battery changes with time.

According to their results, under most conditions, the predicted values are within  $\pm 5\%$  capacity loss of the measured values. The model is listed in equations (15)-(17).

$$Q_{loss,total} = Q_{loss,cycle} + Q_{loss,calendar} \quad (15)$$

$$Q_{loss,cycle} = (aT^2 + bT + c) \cdot \exp[(dT + e) \cdot I_{rate}] \cdot Ah_{throughput} \quad (16)$$

$$Q_{loss,calendar} = f \cdot t^{0.5} \cdot \exp\left(\frac{-E_a}{RT}\right) \quad (17)$$

Since the battery current and temperature changes with time, battery energy capacity loss caused by cycle aging and calendar aging are calculated every second. For each second, the current is assumed to be constant, and the instantaneous energy capacity loss  $D_{Q_{loss,cycle}}$  can be expressed as the differential of  $Q_{loss,cycle}$  with time  $t$ . Similarly, at variable temperature, capacity loss results from calendar aging can be expressed as the differential of  $Q_{loss,calendar}$  with time  $t$ . The total energy capacity loss of cycle aging  $\hat{Q}_{loss,cycle}$  and calendar aging  $\hat{Q}_{loss,calendar}$  are computed by summing the respective losses for each second. Note that for constant temperature,  $Q_{loss,calendar}$  and  $\hat{Q}_{loss,calendar}$  are identical. The total battery energy capacity loss  $Q_{loss,total}$  is the sum of cycle aging loss and calendar aging loss, which is updated every day until it is greater than 30%, criteria to retire battery from EV use. The equations (18)-(22) represents the model used in this study. The coefficient values and units are listed in TABLE 3.

$$D_{Q_{loss,cycle}} = (aT^2 + bT + c) \cdot \exp[(dT + e) \cdot I_{rate}] \frac{dAh_{throughput}}{dt} \quad (18)$$

$$\hat{Q}_{loss,cycle} = \sum D_{Q_{loss,cycle}} \quad (19)$$

$$D_{Q_{loss,calendar}} = 0.5f \cdot \exp\left(-\frac{E_a}{RT}\right) \cdot t^{-0.5} \quad (20)$$

$$\hat{Q}_{loss,calendar} = \sum D_{Q_{loss,calendar}} \quad (21)$$

$$Q_{loss,total} = \hat{Q}_{loss,cycle} + \hat{Q}_{loss,calendar} \quad (22)$$

**TABLE 3 Coefficient values and units of the battery degradation model used in this study**

| Coefficient | Value and unit               | Coefficient | Value and unit    |
|-------------|------------------------------|-------------|-------------------|
| $a$         | 8.61E-6, 1/Ah-K <sup>2</sup> | $I_{rate}$  | C-rate            |
| $b$         | -5.125E-3, 1/Ah-K            | $t$         | Days              |
| $c$         | 0.7629, 1/Ah                 | $E_a$       | 24500, J/mole     |
| $d$         | -6.7E-3, 1/K-(C-rate)        | $R$         | 8.314, J/(mole K) |
| $e$         | 2.35, 1/(C-rate)             | $T$         | Temperature (K)   |
| $f$         | 14876, 1/day <sup>0.5</sup>  |             |                   |

### Assumptions and Simulation

In this study, one type of EV, similar to Nissan Leaf with 24 kWh Li-ion battery, is assumed to be used by all of the households. The battery is composed of 44 modules in parallel, where each module has 96 cells in serial, and each cell is 1.5 Ah and 3.75 V. The cell has a NCM+LMO cathode and a graphite anode. Because a NCM+LMO composite cathode presents a good balance of both energy density and power density (15, 37, 38), it is considered as a promising candidate for vehicle applications.

The simulation of battery life in this study is based on the following assumptions. First, the battery is considered unusable in vehicle applications when it has depleted to 70% of its original energy storage capacity. Second, the degradation model is applied to the entire temperature range experienced in Indianapolis (monthly average temperature from  $-2.2^{\circ}\text{C}$  to  $24.1^{\circ}\text{C}$ ). Wang et al. performed experiments at 4 temperatures:  $10^{\circ}\text{C}$ ,  $22^{\circ}\text{C}$ ,  $34^{\circ}\text{C}$ ,  $46^{\circ}\text{C}$ . This study assumes the model still applies at lower (but not extreme) temperatures. Third, this study assumes that EVs are only charged at home with a level 1 (120 V) or level 2 (240 V) charger. Thus, the effects of home charging on battery energy capacity loss can be ignored as level 1 and level 2 charging are both relatively slow. A 24 kWh EV battery takes about 12-13 hours for a full charge on a level 1 charger, and 7-8 hours on a level 2 charger (8), which is equivalent to a  $1/13$  C-rate or  $1/8$  C-rate during charging. At such low C-rates, calendar aging is the dominant element that causes energy capacity loss. The energy capacity loss results from cycle aging at  $1/8$  C-rate at  $20^{\circ}\text{C}$  for 8 hours is: 0.00066%, while the capacity loss results from calendar aging at  $20^{\circ}\text{C}$  for first 8 hours is 0.37% for a new battery, and 0.0056% for a one-year battery. Since capacity loss due to calendar aging, equation (17), is a non-linear function of time, the calendar aging rate decreases with time, and becomes almost linear after one year. Most household vehicle daily trips are within 30 miles, and the energy consumption is less than half of the battery energy capacity and thus, most home charging events are less than 4 hours. Therefore, it is safe to ignore cycle aging effects on battery energy capacity loss during home charging. Fourth, when the EV is in use, regeneration during braking has the same effects on battery energy capacity loss as discharging at the same C-rate.

This study simulates 2306 household vehicle samples in Indianapolis. Each vehicle sample follows its unique travel pattern day by day. Five temperature scenarios are analyzed in this study: four constant temperature scenarios ( $10^{\circ}\text{C}$ ,  $15^{\circ}\text{C}$ ,  $20^{\circ}\text{C}$  and  $25^{\circ}\text{C}$ ) and one variable temperature scenario. The monthly average temperatures for Indianapolis are used in variable temperature scenario. FIGURE 2 shows the temperature profile of Indianapolis used in this study.

## RESULTS AND DISCUSSION

The simulation results of EV battery lifespan for different temperature scenarios are presented and discussed in the following paragraphs. Each EV follows its unique speed profile every day. Some EVs may have up to 6 trips every day, while others may have only one trip per day. The impacts of temperature, vehicle travel patterns, and driving behavior are illustrated on battery life distribution to provide a holistic picture of battery lifespan for a large population of EVs.

Temperature affects both calendar aging and cycle aging. FIGURE 4(a) shows the simulated battery life histogram at four constant temperatures. The results indicate that the EV battery lifespan is  $(8.58 \pm 1.80)$  years at  $10^{\circ}\text{C}$ ,  $(7.33 \pm 0.73)$  years at  $15^{\circ}\text{C}$ ,  $(5.73 \pm 0.19)$  years at  $20^{\circ}\text{C}$ , and  $(4.20 \pm 0.06)$  years at  $25^{\circ}\text{C}$ . The EV battery life decreases as temperature increases. At higher temperatures, the battery degrades faster than at lower temperatures. The variation of EV battery life also decreases as temperature increases. This is because at higher temperatures, calendar aging dominates cycle aging as all EVs are at the same environmental temperature, and hence, the effects of vehicle travel patterns and driving behavior diminishes. In reality, temperature will not be constant all year long. The average monthly temperature profile in Indianapolis is used to simulate the EV battery lifespan in the city of Indianapolis. The annual average temperature in Indianapolis is  $11.7^{\circ}\text{C}$ . The simulated EV battery lifespan is  $(7.54 \pm 1.68)$  years. FIGURE 4(b) shows the distribution of battery life in Indianapolis. Although the temperature profile of Indianapolis varies between  $-2.2^{\circ}\text{C}$  to  $24.1^{\circ}\text{C}$ , the simulated result is similar to the scenario of  $10^{\circ}\text{C}$ , and lies between the  $10^{\circ}\text{C}$  and  $15^{\circ}\text{C}$  scenarios (refer FIGURE 4(c)). Therefore, considering consistent vehicle travel

patterns throughout the year, the average annual temperature is reasonable to use as an estimate in computing degradation due to temperature effects. TABLE 4 shows detailed percentile of battery lifespan and EV total travel distance for the five temperature scenarios.

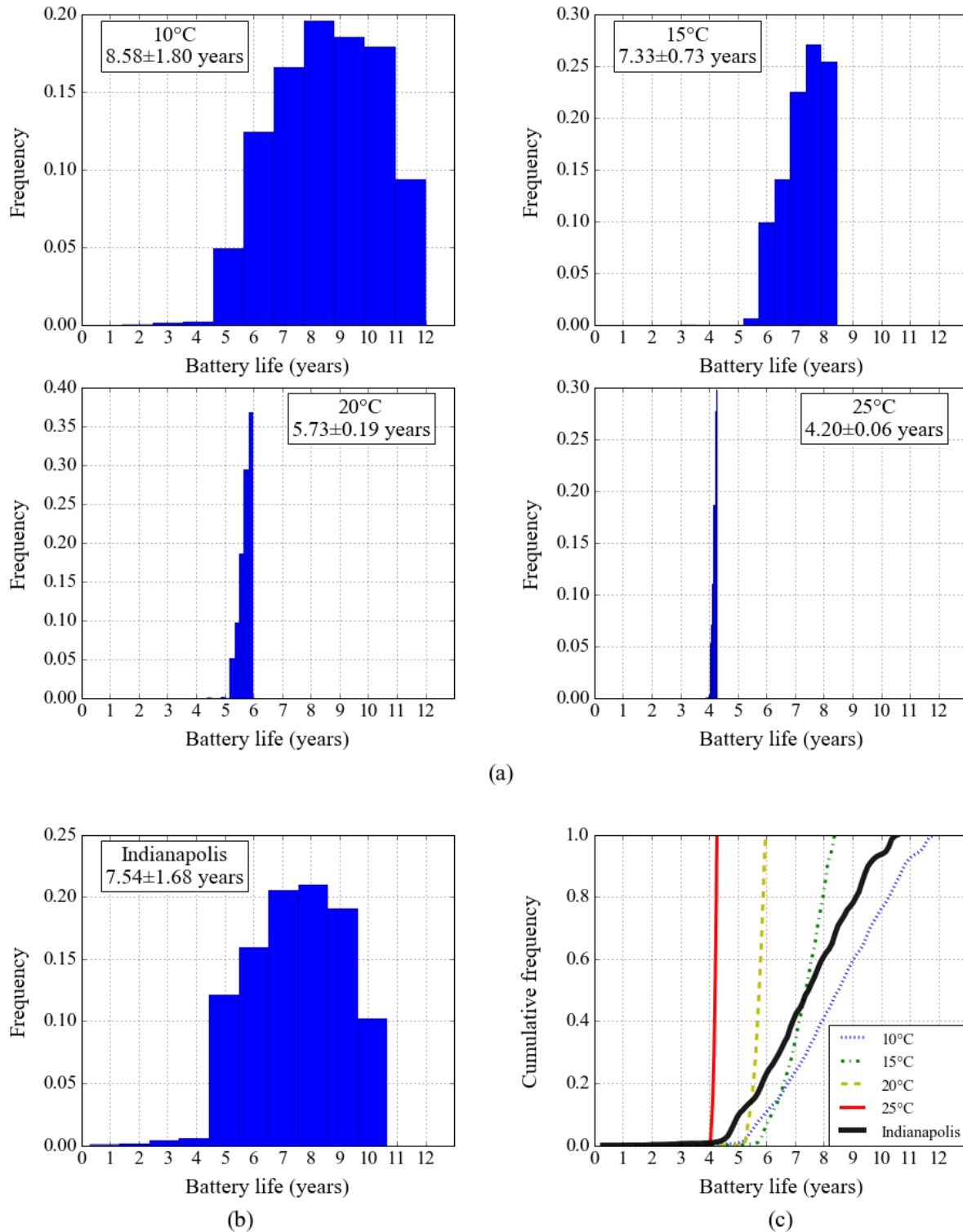


**FIGURE 4 Battery lifespan distribution at: (a) constant temperatures; (b) Indianapolis temperature; (c) cumulative frequency curves for all scenarios.**

**TABLE 4 The percentile of battery lifespan and total travel distances for different temperature scenarios**

|     | Indianapolis  |               | 10°C          |               | 15°C          |               | 20°C          |               | 25°C          |               |
|-----|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|---------------|
|     | Value (years) | Value (miles) | Value (years) | Value (miles) | Value (years) | Value (miles) | Value (years) | Value (miles) | Value (years) | Value (miles) |
| 0   | 0.30          | 1653          | 1.42          | 1845          | 3.01          | 1346          | 4.38          | 967           | 3.88          | 693           |
| 5   | 4.88          | 7612          | 5.62          | 8557          | 5.98          | 6128          | 5.34          | 4368          | 4.08          | 3126          |
| 10  | 5.15          | 14080         | 6.05          | 15937         | 6.23          | 11960         | 5.42          | 8676          | 4.11          | 6232          |
| 15  | 5.67          | 20522         | 6.52          | 23167         | 6.49          | 17738         | 5.51          | 12966         | 4.13          | 9336          |
| 20  | 5.96          | 24057         | 6.86          | 27517         | 6.66          | 21846         | 5.56          | 16210         | 4.15          | 11722         |
| 25  | 6.24          | 28160         | 7.20          | 32299         | 6.83          | 26037         | 5.61          | 19341         | 4.17          | 13968         |
| 30  | 6.57          | 33104         | 7.52          | 37529         | 6.98          | 29413         | 5.65          | 21909         | 4.18          | 15884         |
| 35  | 6.84          | 37303         | 7.79          | 42370         | 7.09          | 34320         | 5.68          | 25692         | 4.19          | 18600         |
| 40  | 7.03          | 41468         | 8.05          | 47277         | 7.21          | 39438         | 5.71          | 29845         | 4.20          | 21658         |
| 45  | 7.33          | 45874         | 8.34          | 52302         | 7.32          | 44586         | 5.74          | 34051         | 4.21          | 24739         |
| 50  | 7.57          | 50940         | 8.62          | 58141         | 7.44          | 49936         | 5.77          | 38548         | 4.22          | 28198         |
| 55  | 7.83          | 55766         | 8.89          | 63756         | 7.54          | 55476         | 5.79          | 43793         | 4.22          | 32193         |
| 60  | 8.04          | 59556         | 9.15          | 68126         | 7.63          | 60685         | 5.82          | 48672         | 4.23          | 35902         |
| 65  | 8.39          | 63527         | 9.51          | 72704         | 7.75          | 66484         | 5.84          | 53664         | 4.24          | 39676         |
| 70  | 8.57          | 68782         | 9.71          | 78730         | 7.82          | 72842         | 5.86          | 58531         | 4.24          | 43029         |
| 75  | 8.88          | 74111         | 10.04         | 85170         | 7.93          | 80160         | 5.88          | 65792         | 4.25          | 48768         |
| 80  | 9.23          | 79197         | 10.37         | 91204         | 8.03          | 88416         | 5.91          | 73454         | 4.26          | 54756         |
| 85  | 9.44          | 85882         | 10.64         | 98854         | 8.11          | 97524         | 5.92          | 81784         | 4.26          | 60833         |
| 90  | 9.65          | 94144         | 10.90         | 108763        | 8.18          | 111200        | 5.94          | 96430         | 4.27          | 73250         |
| 95  | 10.29         | 107729        | 11.49         | 124828        | 8.34          | 131553        | 5.97          | 116933        | 4.28          | 89239         |
| 100 | 10.68         | 146400        | 12.00         | 169360        | 8.46          | 177280        | 6.00          | 156720        | 4.28          | 119280        |

In order to gain insights into the relationship between vehicle travel patterns and battery lifespan, the simulated battery life is plotted against the total travel distance before the battery is depleted to 70% of its original capacity. FIGURE 5(a) shows battery lifespan versus total travel distance at four constant temperatures. The results illustrate that, at lower temperatures the effect of total travel distance is greater than that at higher temperatures. It means that at higher temperatures, battery lifespan is less sensitive to total travel distance. The negative slope indicates that as the EV travels longer, the battery life becomes shorter. The width of the strip shows the variation of battery life resulting from driving behavior such as average speed and speed deviation. As temperature increases, the strip starts shrinking to almost a line, which indicates that the impact of driving behavior at lower temperature is greater than that at higher temperature. Another interesting finding is that after a certain point, the strip becomes almost horizontal, parallel to the x-axis. The horizontal red line provides intuitive information of minimum battery life under regular conditions, which is consistent with TABLE 4. FIGURE 5(b) shows the battery life versus total travel distance in Indianapolis. The results indicate that the impact of driving behavior in Indianapolis is similar to that of constant 10°C, but the battery lifespan is less for similar total travel distance. The horizontal line intersects y-axis at about 4.8 years.

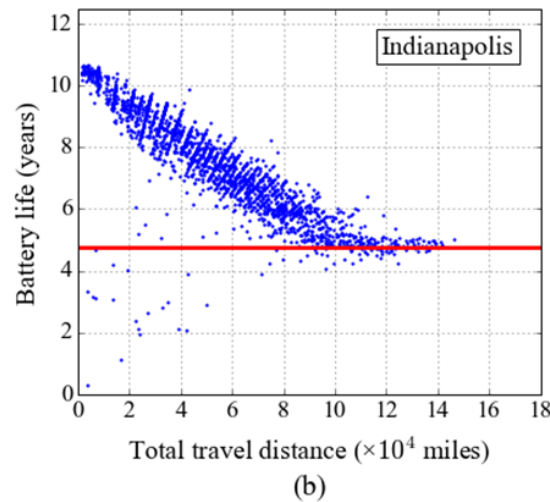
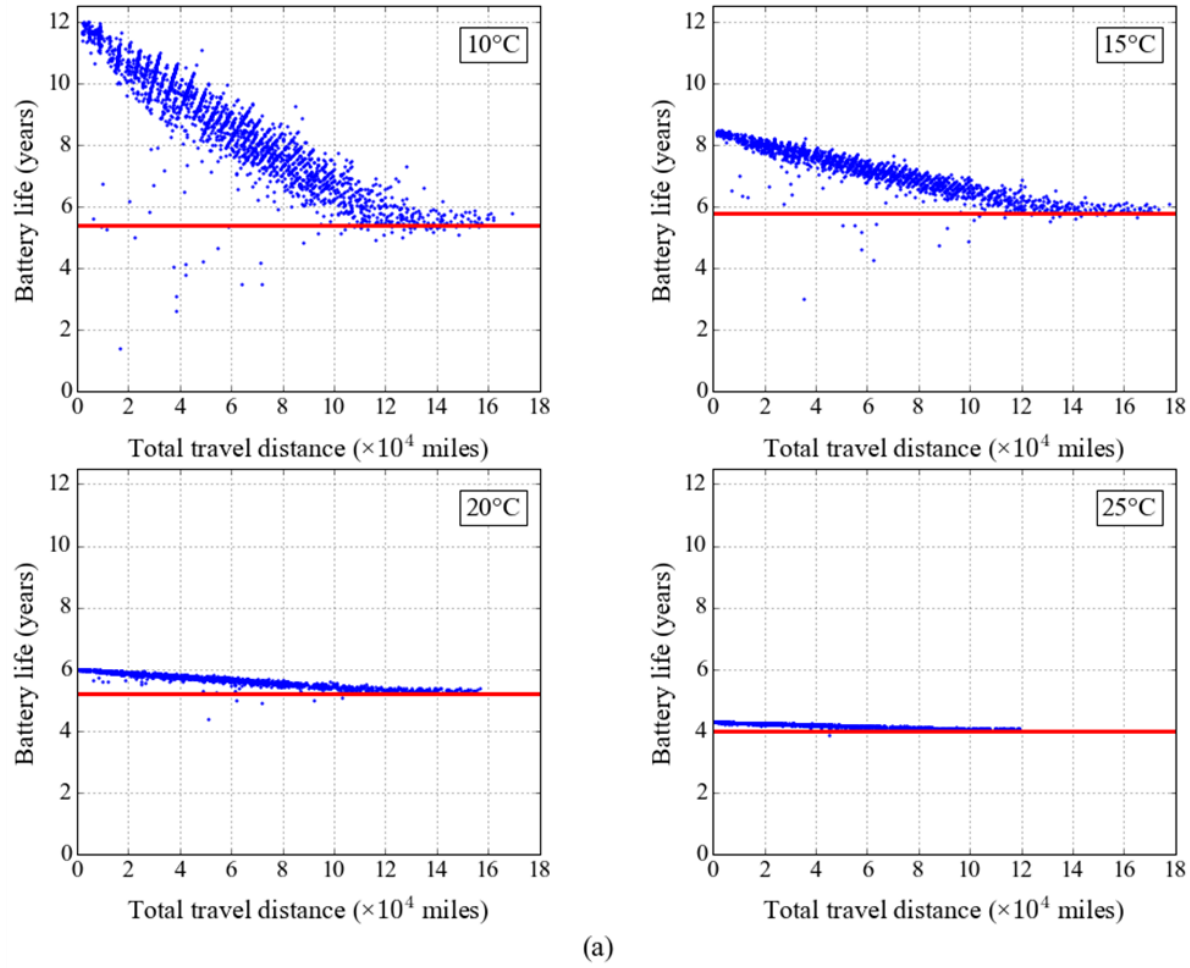


**FIGURE 5 Impact of vehicle travel patterns on battery lifespan at: (a) constant temperatures; (b) Indianapolis temperature.**

The impacts of driving behavior on battery lifespan are illustrated in FIGURE 6. Battery degradation due to cycle aging decreases as the average speed increases and speed deviation

decreases. The average vehicle speed is higher and speed deviation is lower in uncongested traffic conditions. Though power consumption and C-rate are higher at higher constant speeds, at variable speeds, the magnitude of power losses/gains due to change in kinetic energy dominate those of the power losses at constant speed. Due to interactions between average speed and speed deviation, the variation in cycle aging is large.

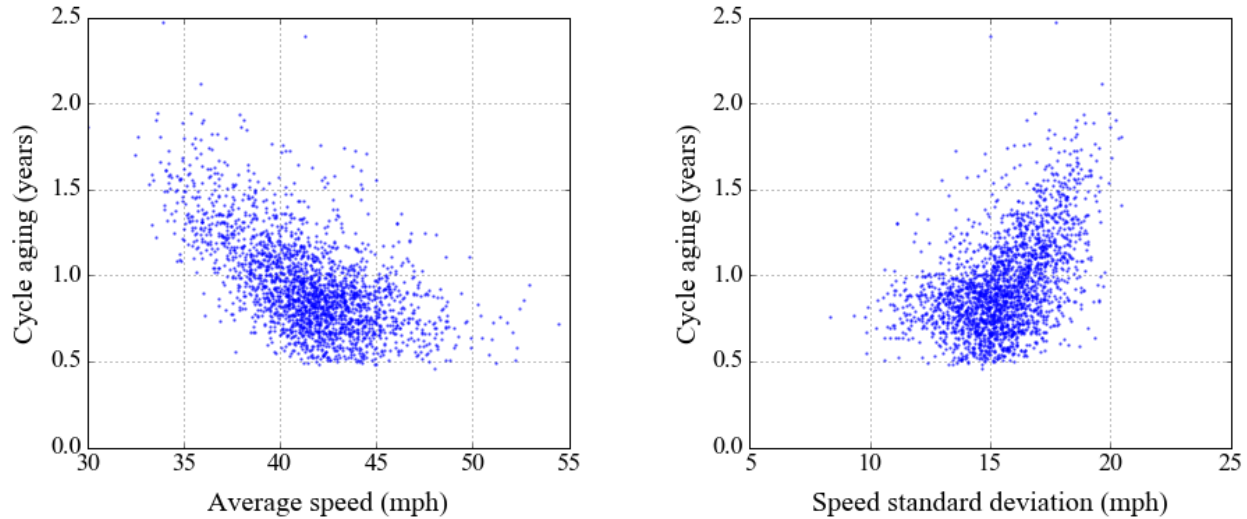


**FIGURE 6 Impact of driving behavior on cycle aging for Indianapolis.**

## CONCLUDING COMMENTS

This study investigates the battery life characteristics of a large population of EVs using a microscopic traffic network simulation model and a semi-empirical battery degradation model. The impacts of temperature, vehicle travel patterns, and driving behavior on EV battery lifespan provide useful information for vehicle owners, policymakers and vehicle manufacturers. The results indicate that temperature has a substantial impact on battery lifespan, and can overshadow the impacts of vehicle travel patterns and driving behavior at high temperatures. The study insights aid vehicle owners to assess the lifetime cost of EV ownership, including maintenance cost, insurance cost and battery resale value, based on their travel needs and geographic location. Since temperature has a significant impact on battery degradation, policymakers and vehicle manufacturers should consider regional temperature conditions while designing strategies like tax credits, battery warranty, etc., to promote EV adoption. Since the impacts of vehicle travel patterns and driving behavior are considerable at lower temperatures, these need to be factored in warranty strategies for colder regions. Vehicle manufacturers should factor the environmental conditions in which the battery will be used, as also vehicle travel patterns and consumer driving behaviors. The data presented in this paper provides a realistic foundation for future work to study the dynamics of EV battery market, and provides insights for battery studies that will impact real-world battery lifespan. Future research should also target improving battery lifespan, and considering regional temperature profiles, vehicle travel patterns and EV driving behaviors.

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