

# Battery System Modeling and User Study for Emerging Green-Energy Transportation

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## ABSTRACT

Battery technology is the key bottleneck in many cyber-physical systems (CPS). For green-energy CPS transportation applications, such as hybrid electrical vehicles (HEVs) and plug-in HEVs (PHEVs), the battery system design is mostly based on lithium-ion rechargeable electrochemical battery technology, which is bulky, expensive, unreliable, and is the primary roadblock for PHEV adoption and market penetration. For PHEVs, the battery system performance and lifetime reliability are further affected by various user-dependent effects. Battery system modeling and user study are thus essential for battery system design and optimization.

This paper presents detailed investigation on battery system modeling and user study for emerging PHEVs. The proposed modeling solution can accurately characterize battery system run-time charge-cycle efficiency, and long-term cycle life. In particular, it models battery system capacity variation and fading due to fabrication and run-time aging effects. An embedded monitoring system is designed and deployed in a number of HEVs and PHEVs, which can monitor users' driving behavior and battery usage at real time. Using the proposed modeling and monitoring solutions, we conduct user study to investigate battery system run-time usage, characterize user driving behavior, and study the impact of user driving patterns on battery system run-time charge-cycle efficiency, capacity variation and reliability, and life-cycle economy. This work is the first step in battery system design and optimization for emerging green-energy CPS transportation applications.

## 1. INTRODUCTION

Energy use for transportation represents a pressing challenge, due to the heavy and growing reliance on petroleum and the environmental impacts of emissions from fossil fuel combustion. For instance, over 16 million vehicles are sold in the U.S. every year [12], and most of which use conventional combustion engine. Hybrid electric vehicles (HEVs), which

were first developed in 1900, became widely available since the late 1990s [22], and use both electrical energy storage and power train technologies, have demonstrated the potential for dramatic reductions in petroleum use and vehicle emissions.

Besides a conventional internal combustion engine, an HEV also includes an energy storage system and an electrical motor to offer auxiliary power, which allows to downsize the internal combustion engine, improves user driving experience, and scavenges the energy generated during braking events, thereby improving the fuel efficiency, approximately 30%–45% over a comparable conventional vehicle [8]. Plug-in hybrid electrical vehicles (PHEVs) further advances the HEV technology by offering the function of plug-in recharging electricity from the utility grid. Therefore, PHEVs are able to use electricity as the sole energy source, until the help from the gasoline engine becomes a must. Thus, the PHEV technology can improve fuel efficiency further, e.g., 100 miles per gallon (mpg).

PHEV market penetration, however, has been a great challenge. This is mainly due to the fact that the advances of battery technology, the primary energy storage solution used in (P)HEVs, has not kept pace with the fast growing energy demands. In (P)HEVs, the battery system design is mostly based on the lithium-ion rechargeable electrochemical battery technology, which is bulky, expensive, and unreliable. Fabrication and run-time operation introduce significant variations to the capacity degradation and aging effects to individual battery cells, resulting in serious lifetime reliability concerns of the battery system. As automotive companies typically require a lifetime battery system guarantee, battery storage capacity, cost, and lifetime reliability have become the primary challenges for PHEV adoption and market penetration. The challenges of battery system design are summarized as follows:

- Battery system cost is currently the primary concern of PHEV penetration. For instance, in a 50 mile PHEV, the battery system contains over 1,000 Lithium-ion rechargeable electrochemical battery cells, with a total cost over \$38,000 USD [3]. Battery system cost is in turn affected by the following two parameters, *run-time charge-cycle efficiency* and *long-term cycle life*. The former determines run-time fuel savings, and the latter evaluates the battery system overall lifetime reliability, and long-term financial return. Therefore, ac-

curate battery system modeling is essential to evaluate the feasibility of PHEV technologies.

- Battery system run-time performance and lifetime reliability is directly affected by the run-time usage, which in turn is determined by the user's driving behavior. User-specific run-time driving patterns, e.g., speed, acceleration, road conditions, and traffic conditions, directly affect the battery system usage, current charge and discharge, hence battery system performance and fuel efficiency. In addition, the run-time charge and discharge current generates heat and governs the battery system run-time profile. It is known that, the dominant aging effects, e.g., cell oxidation, are strong function of temperature [2] [5]. Therefore, characterizing user driving behavior is important to understand the battery system usage, i.e., run-time battery system performance and long-term cycle lifetime.

This work investigates the battery system of emerging PHEVs. It first presents a modeling and analysis framework, which can efficiently and accurately characterize the battery system run-time charge-cycle efficiency, and long-term cycle life. A PHEV battery system consists of a large number of battery cells. The overall battery system performance is then constrained by the battery cell with minimal capacity. The proposed modeling tool can model the run-time usage and capacity fading of individual battery cells, thereby accurately characterizing intra-battery system variation and the overall system lifetime. Next, this paper presents an embedded monitoring system, consisting of smart phones carried by drivers, and on-board diagnostics (OBD) devices deployed in HEVs and PHEVs, which can monitor users' driving behavior and battery usage at real time. Using the proposed modeling and monitoring solutions, we conduct user study to investigate battery system run-time usage, characterize user driving behavior, and study the impact of user driving patterns on battery system run-time charge-cycle efficiency, capacity variation and reliability, and life-cycle economy. In summary, this work makes the following contributions.

1. A Battery system modeling and analysis framework to characterize battery system usage, including run-time charge-cycle efficiency and long-term capacity aging, from individual battery cells to the overall battery system. The battery system modeling framework is validated against physical measurements and user studies.
2. An embedded monitoring system for run-time data acquisition of user driving patterns and battery system usage. A set of user studies have been conducted with users with distinct driving behavior under different road conditions.
3. Detailed data analysis to quantitatively characterize user driving patterns, and their impact on battery system run-time performance and lifetime reliability. An analytical economic study is then conducted to investigate battery system lifetime economy and the economic benefit of the emerging green-energy transportation technologies.

The rest of the paper is organized as follows: Section 2 surveys related work. Section 3 introduces the proposed battery system model. Section 4 describes the embedded monitoring system and the user study we have conducted. Section 5 presents the results and analysis of experiments. We conclude in Section 6.

## 2. RELATED WORK

This section summarizes the current status of battery modeling and user driving analysis, and indicates the challenges of system-level battery system modeling and the impacts of user driving effects on battery system performance.

### 2.1 Battery Modeling and Analysis

Driven by portable electronic system design, rechargeable electrochemical battery technologies, in particular, Lithium-ion batteries, have been actively studied in the recent past. Due to the small form factor of portable devices, the battery component used in a portable device only consists of one or a few battery cells. Therefore, most work on battery analysis focuses on individual battery cells.

A variety of empirical and analytical techniques have been developed in the past to understand the battery charge-discharge behavior and lifetime aging effects. Rakhmatov et al. presented a battery lifetime prediction numerical model which closely matches Dualfoil simulation results and experimental measurements [14] [15]. This work, however, ignores the thermal effects, which have significant impact on battery aging (see Section 3). Santhanagopalan et al. [17] developed two empirical electrochemical models to characterize Lithium-ion battery aging process occurred during battery charge-discharge cycles. The battery aging models focus on the cell oxidation process, an dominant battery aging effects [2]. J.Vetter et al. [5] conducted detailed physical analysis of the Lithium-ion batteries electrochemical aging phenomenon, and modeled the aging effects. Peng Rong et al. [13] proposed a battery cell model to estimate battery capacity by considering battery cell cycle aging effects, such as temperature effects and capacity fading. This model considers the impact of temperature and cycle aging on the battery cell state of charge. However, this model configuration requires many physical and empirical parameters (over 15), and is difficult to adopt and calibrate in practise.

Limited work has considered battery system modeling targeting clean-energy transportation. Recent studies by National Renewable Energy Laboratory [21] and Argonne National Laboratory [10] discussed the battery system model using the equivalent circuit method to capture the battery run-time charge-discharge cycle behavior. These battery system models assume homogenous conditions within a battery system, and ignore inter-cell capacity variation and heterogeneous thermal effects. As a result, these models are unable to capture the intra-battery system heterogeneities, and the impact on battery system run-time performance and long-term life cycle.

### 2.2 User Driving Studies

Driving analysis has drawn significant attention in the past, as user driving patterns directly affect traffic conditions, fuel usage, and the corresponding CO<sub>2</sub> emissions and environmental impact. The East-West Gateway Coordinating

Council was among the first to utilize GPS instrument in user driving analysis [11]. In the 2002 St. Louis Regional Travel and Congestion Survey, GPS devices were used to investigate trip acquisition for a subset of the survey participants. Lin et al. [7] collected vehicle data (speed and acceleration) in three cities to study the driving behavior. In this work, speed and acceleration intensity and duration were considered to characterize various driving cycles in three cities. From July 2001 to June 2003, Bor Yann Liaw collected data from a fleet of 15 Hyundai Santa Fe electric SUVs operated in Oahu, Hawaii. These data were collected by deployed on-board data acquisition system [6]. He proposed to use “Driving Pulse” [6] to segment trips and apply fuzzy logic rules to set the boundaries for driving pattern recognition. In 2004, United States Environmental Protection Agency conducted a mobile source emission factors research in Kansas City [16], including 5-summer day and 5-winter day per driver vehicles and 60 drivers were involved to study the CO<sub>2</sub> emissions and environmental impact.

Recently, user driving studies began to consider hybrid vehicle technologies. In 2007, Gonder et al. [4] used the real-world driving cycles from St. Louis Regional Travel and Congestion Survey [11] to simulate the energy consumption, battery system performance and operating characteristics of PHEVs. Moawad et al. studied hybrid vehicle performance under electrical dominant mode and blended mode compared against the conventional internal combustion engine vehicles [9]. They also evaluated the control strategies and their impact on energy usage. The drive cycles data they used are measured by the U.S. EPA [16].

### 2.3 Challenges of Battery System Modeling & User Driving Studies

The past studies highlight a number of challenges of battery system modeling and investigating the impacts of user driving behavior on battery system performance.

1. Within (P)HEVs, the battery system consists of numerous battery cells, organized in complex topologies. In order to understand the overall battery system run-time performance and lifetime reliability, battery system modeling requires accurate and fast characterization of all the battery cells, as well as inter-cell interactions. More specifically, within a (P)HEV battery system, the run-time usage and aging effects are heterogeneous, which directly affects the battery system performance and reliability. Existing work however, either focused on analyzing individual battery cell, or assuming homogeneous battery conditions, is not suitable for large-scale battery systems.
2. User driving behavior has direct impact on (P)HEV battery system run-time performance and lifetime reliability. User driving pattern analysis is thus essential for accurate battery system modeling and analysis. Most recent work on user driving analysis focused on conventional internal combustion engine vehicles. User driving characteristics with direct impact on battery system, e.g., acceleration, were mostly ignored in the existing study. Data acquisition is another concern. GPS and accelerometer data are noisy. Data accuracy

was largely ignored in the past studies. Furthermore, due to the technology limitation, data acquisition in the past studies required complex and bulky equipments, e.g., both intrusive and inconvenient to the participants, resulting in serious limitations to the scope of the studies. User privacy concerns were largely ignored in the existing studies.

## 3. BATTERY SYSTEM MODELING

This section presents system-level modeling and analysis techniques targeting (P)HEV battery systems.

The battery systems in (P)HEVs are mainly based on Lithium-Ion rechargeable electrochemical battery technology, which is bulky, expensive, unreliable, and potentially dangerous. They have become a primary barrier to (P)HEV adoption and market penetration. The operation of PHEV and HEV batteries are further affected by various user and environment dependent effects. Accurate battery system modeling is thus essential for understanding (P)HEV battery system performance, lifetime reliability, as well as the corresponding fuel usage, and environmental impacts.

We propose to conduct battery system modeling and analysis. Our goal is accurate and comprehensive characterization of the battery system performance, including both run-time charge-cycle efficiency, and long-term cycle life as a function of the aging effects. The proposed battery system modeling, combined with user driving behavior modeling (see Section 4), will further enable accurate characterization of the impact of user driving patterns on battery system run-time performance and life-cycle economy.

### 3.1 (P)HEV Battery System Overview

As illustrated in Figure 1, a (P)HEV battery system consists of a large number of electrochemical battery cells (e.g., 100s–1000s), connected in parallel and/or serial, providing sufficiently high output voltage and driving current. A (P)HEV battery system is typically characterized using the following design metrics.

- **Energy capacity:** determines the maximum available energy that can be provided by the battery system to a vehicle within a battery charging cycle, hence the duration that the vehicle can operate in the electric mode and the corresponding fuel saving potentials. Compared against other electrochemical storage technologies, such as Nickel-metal-hydride, Lithium-ion offers superb energy storage density (Wh/kg or Wh/L), hence higher total energy capacity under the same weight and form factor constraints, and thus have become the mainstream battery solution in emerging PHEVs.
- **Peak power:** determines the maximum instantaneous power (W/kg or W/L) that can be delivered by the battery system to the vehicle. Note that, energy capacity and peak power are two distinct performance measures. Energy battery cells optimized for energy storage capacity and power battery cells optimized for peak power have been developed in the past. In this work, we propose to integrate both energy cells and

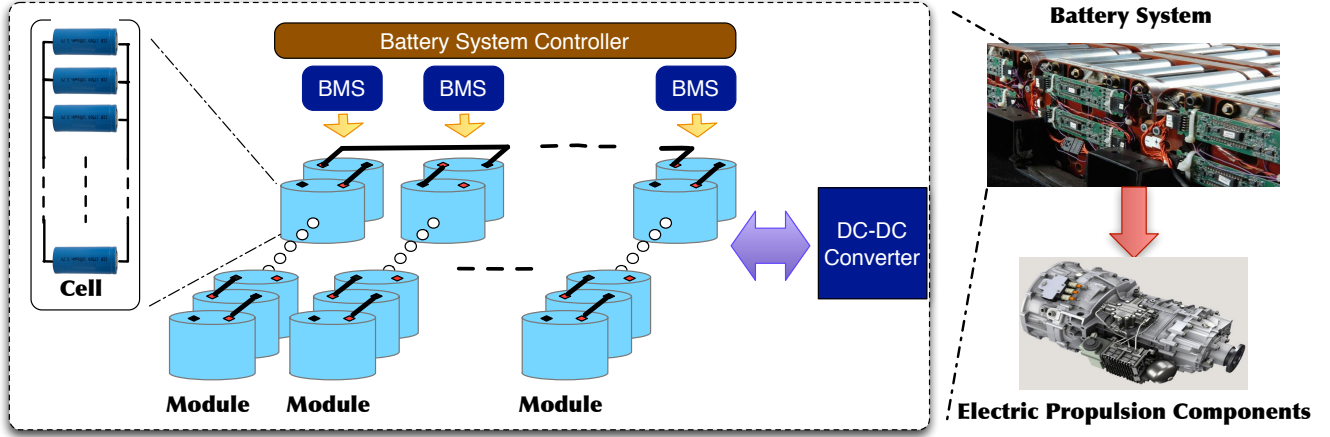


Figure 1: (P)HEV battery system architecture.

power cells in battery system design, thereby optimizing both energy capacity and peak power characteristics of the battery system.

- **Cost:** The total cost of the battery system is contributed by both the energy storage units and the power electronics control components. Battery system cost has been the primary challenge of the (P)HEV adoption and market penetration. For instance, the battery system in a 50-mile PHEV contains over 1,000 Lithium-ion battery cells, with the total cost over \$38,000.
- **Safety:** Electrochemical battery cells contain hazardous chemical content. In particular, Lithium-ion battery is chemically unstable under high temperature, which may cause outgassing and risk of fire from damage or heating. Safety is another important design issue.
- **Lifetime:** The battery system lifetime is characterized as long-term cycle life, i.e., the total number of charge-discharge cycles before the battery system capacity permanently degrades below certain threshold. (P)HEV imposes stringent lifetime constraint to battery systems. For instance, Automotive vendors typically targets a 15-year battery system life guarantee with maximum allowed 20% capacity degradation.

## 3.2 Run-Time Charge-Cycle and Long-Term Cycle Life Analysis

This section focuses on modeling and analysis of the run-time charge-cycle performance and aging-induced battery capacity fading effects.

A battery cell is the atomic energy storage unit, which consists of a cathode and an anode embedded in electrolyte. Battery run-time usage, i.e., charge and discharge, is a result of a series of electrical-chemical reactions – the anode receives or releases electrons during charge and discharge. The performance of battery cell can be characterized using the following two metrics, run-time charge-cycle efficiency and long-term cycle life. The former metric models battery run-time usage or energy delivery. The later metric models battery lifetime reliability due to run-time aging effects.

### 3.2.1 Run-Time Charge and Discharge Cycle Analysis

The run-time charge status,  $SOC_i$ , of battery cell  $i$ , during a run-time driving cycle, is defined as follows:

$$SOC(t) = \frac{1}{\sum_{i=1}^N c_i(t_0)} \sum_{i=1}^N \left( \int_{t_0}^t \frac{1}{\alpha_i(t)} \times v_i(t) i_i(t) \cdot dt + c_i(t_0) \cdot \omega_i(t) \right), \quad (1)$$

where  $c_i(t_0)$  is the fully charged capacity of energy storage unit  $i$  at  $t_0$ ;  $i_i(t)$ ,  $v_i(t)$  and  $\alpha_i(t)$ , are unit  $i$ 's run-time current, voltage, and the corresponding DC-DC converter efficiency.  $\omega(t)$  models long-term aging or capacity fading, which will be explained next.

### 3.2.2 Battery Cell Long-Term Capacity Aging Effect

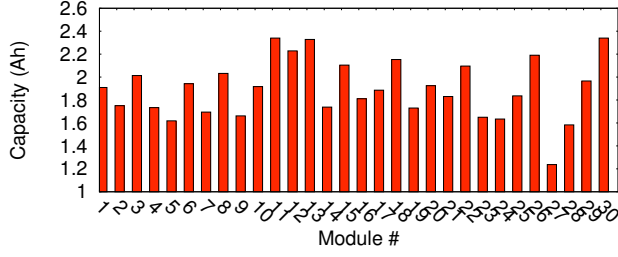
Capacity fading is a known effect that affects Lithium-Ion rechargeable battery. Battery capacity fading is caused by several aging effects, including self-discharge, electrolyte decomposition, and cell oxidation [2] [5]. Among these, cell oxidation is most significant, which leads to a film (called solid-electrolyte interphase) grown on the electrode and increase battery internal resistance, and thereby reducing battery capacity.

$$V_{out_i}(t) = Voc_i(t) - (\eta_{sa_i} - \eta_{sc_i}) - (\eta_{ohma_i} - \eta_{ohmc_i}) - (\eta_{diffa_i} - \eta_{diffc_i}), \quad (2)$$

where  $Voc_i$  is unit  $i$ 's open-circuit voltage,  $\eta_{sa_i}$  ( $\eta_{sc_i}$ ),  $\eta_{ohma_i}$  ( $\eta_{ohmc_i}$ ), and  $\eta_{diffa_i}$  ( $\eta_{diffc_i}$ ), are the surface overpotential, ohm overpotential, and concentration overpotential of unit  $i$ 's anode (cathode), respectively. Surface overpotential is due to electrochemical reaction between the electrodes surface and the electrolyte. Ohm overpotential and concentration overpotential are due to ion migration and diffusion in the electrolyte. The above equation can be further simplified as follows:

$$V_{out_i}(t) = Voc_i(t) - i_i(t) \times r_{internal_i}(t) - \lambda_i \ln(1 - \xi_i(t) \omega_i(t)^{\kappa_i(t)}), \quad (3)$$

where  $r_{internal_i}(t)$  is the battery cell internal resistance,  $\lambda_i$  is an experimentally determined constant.  $\xi_i(t)$  and  $\kappa_i(t)$  denote the temperature dependence of the diffusion coefficient of the active material, which can be obtained using



**Figure 2: Aging of 30 battery modules.**

the Arrhenium temperature dependence equation [?].  $\omega_i(t)$  models long-term aging, which follows:

$$\omega_i(t) = \left\{ \frac{1}{\xi_i(t)} \left[ 1 - \exp\left( \frac{i_i(t) \times r_{internal_i}(t) - (Voc_i(t) - V_{cutoff_i})}{\lambda_i} \right) \right] \right\}^{\frac{1}{\kappa_i(t)}} (4)$$

Recent study has shown that, the oxidation process has strong temperature dependency [13]. When the battery system is idle, the aging process is determined by the ambient temperature. During run-time charge–discharge cycle, the aging process is further accelerated due to the battery self-heating effects. More specifically, both  $r_{internal}$  and  $Voc$  are temperature dependent, as follows:

$$\frac{dr_{internal}(t)}{dt} = k \cdot n_c \cdot e^{-\frac{E_{active}}{T(t)} + \varphi}, \quad (5)$$

where  $T(t)$  is the run-time battery temperature profile.  $k$  and  $n_c$  are constant values.  $E_{active}$  is the activation energy, and  $\varphi = \frac{E_{active}}{T_{ref}}$ , and  $T_{ref}$  is the reference temperature.

In addition,  $Voc$  is also a function of a temperature. Following the Nernst equation, we have,

$$\frac{dVoc(t)}{dt} = -\frac{R_{coefficient} \cdot Temperature(t)}{n_e \cdot F_{coefficient}} \ln Q \quad (6)$$

where  $n_e$  is number of electrons transferred,  $F_{coefficient}$  is a Faraday’s constant,  $R_{coefficient}$  and  $Q$  are constant values.

### 3.3 Battery System Architecture Model

A (P)HEV battery system consists of a large number of energy-storage units. Manufacturing tolerance, and heterogeneous run-time usage and environment, in particular, thermal effects, lead to significant degradation and variations among energy-storage units. Figure 2 shows the capacity fading measurement results we conducted on 30 Lithium-Ion battery system modules in a PHEV. It shows that, over 40% capacity variation is observed among the 30 modules. As the overall system capacity in conventional battery system is determined by the weakest cell, the heterogeneous aging effects seriously affect battery system long-term cycle life. Accurate battery system system-level modeling is thus essential.

We propose to conduct battery system system-level modeling to characterize the overall battery system run-time performance and long-term cycle life. Given an battery system

consisting of  $N$  energy storage units (Lithium-Ion and ultracap cells), and the connectivity information, the battery system run-time charge status is modeled as follows:

$$\begin{aligned} \frac{d\mathbf{C}_{electric[N \times N]}(t)}{dt} &= \mathbf{K}_{[N \times N]} \times \mathcal{A}^{-1}(t) \times I(t) + \\ \mathbf{C}_{electric[N \times N]}(t_0) &\times \frac{d\mathbf{\Omega}_{[N \times N]}(t)}{dt}, \end{aligned} \quad (7)$$

where matrix  $\mathbf{C}_{electric[N \times N]}(t)$  is a diagonal matrix that models the run-time charge capacities of the  $N$  energy-storage units. Matrix  $\mathbf{K}_{[N \times N]}$  models the battery system topology and the corresponding current distribution  $I(t)$  among the  $N$  units. Matrix  $\mathbf{\Omega}_{[N \times N]}$  models the run-time aging of individual units. Matrix  $\mathcal{A}(t)$  models the DC-DC converter efficiency of the  $N$  units.

The equation above allows us to characterize the battery system run-time performance and aging effects by characterizing the charge–discharge current, depth of charge–discharge, process variation of individual units, and thermal effects. Since the aging effects have strong temperature dependency, thermal modeling is critical for battery system system-level modeling. Given the run-time current charge and discharge profile, the battery system run-time thermal profile can be modeled as follows:

$$\mathbf{C}_{heat[N \times N]} \cdot \frac{d\mathbf{T}_{[N \times 1]}(t)}{dt} = \mathbf{G}_{[N \times N]} \cdot \mathbf{T}_{[N \times 1]}(t) + \mathbf{P}_{[N \times 1]}(t), \quad (8)$$

where matrix  $\mathbf{C}_{heat[N \times N]}$  models the heat capacity of the  $N$  units. Matrix  $\mathbf{G}_{[N \times N]}$  models the thermal conductance between adjacent units.  $\mathbf{P}_{[N \times 1]}(t)$  models the run-time power dissipation of individual units.

#### 3.3.1 Frequency-Domain Analysis

Computational complexity is the primary challenge for battery system system-level modeling. A (P)HEV battery system contains a large number of energy storage units. The run-time behavior of individual units must be accurately modeled. The battery system run-time usage changes from second to second, and the long-term aging effects vary from month to month. Accurate and fast modeling of an battery system consisting of a large number of units over such a large time scale range is challenging. battery system modeling is further complicated by thermal analysis, which is essential for accurate battery system cycle life analysis. It is known that thermal analysis has high computational complexity.

To address these challenges, we have develop a unified battery system modeling framework using novel multi-scale frequency-domain analysis techniques.

Using Laplace transformation, Equation 8 follows:

$$\begin{aligned} \mathbf{T}_{[N \times 1]}(s) &= \left( \sum_{i=0}^{q-1} \frac{K_{i[1 \times N]}}{s - p_i} \right) \cdot \left( \frac{\mathbf{P}_{power[N \times 1]}}{s} + \right. \\ &\left. \mathbf{C}_{heat[N \times N]} \cdot T_{[N \times 1]}(0) \right) \end{aligned} \quad (9)$$

where  $p_i$  is the  $i$ th order pole for the circuit,  $K_{i[1 \times N]}$  are the residues for all interested points of all the power numbers.

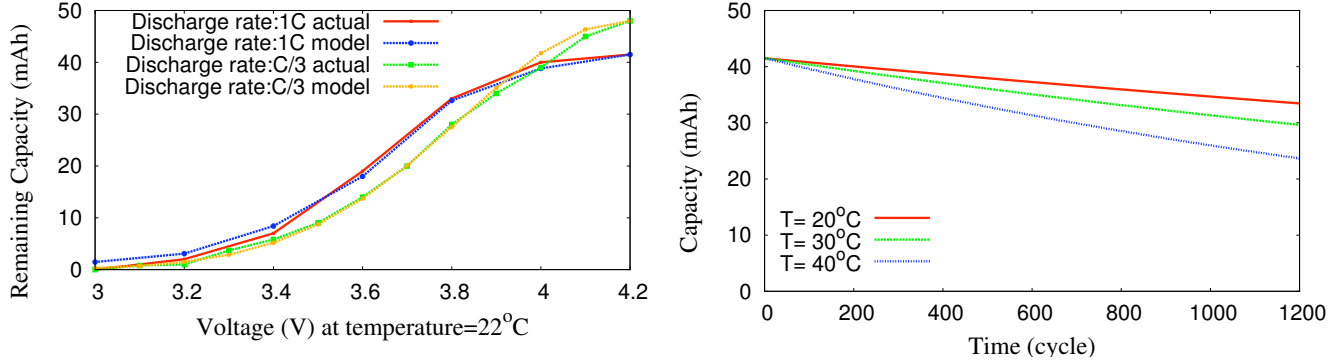


Figure 3: Battery long-term cycle life modeling validation.

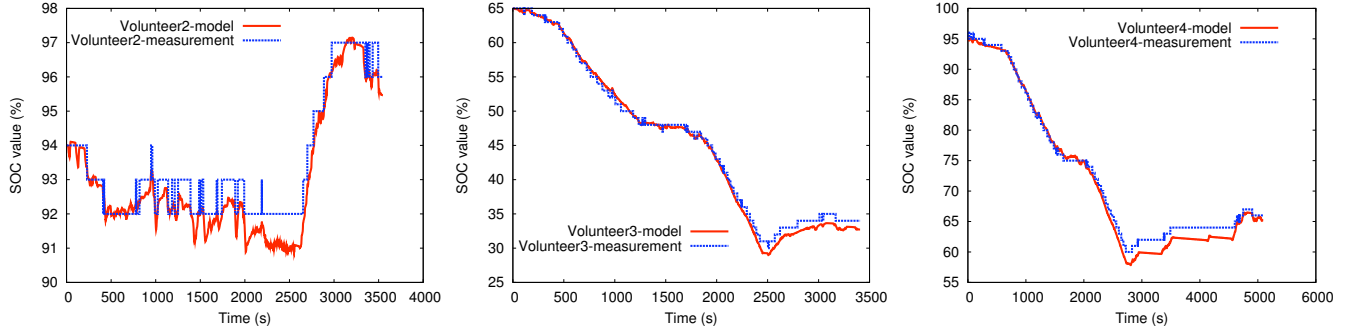


Figure 4: Battery run-time charge-cycle modeling validation.

Next, we have:

$$\begin{bmatrix} -1/p_0 & -1/p_1 & \cdots & -1/p_{q-1} \\ -1/p_0^2 & -1/p_1^2 & \cdots & -1/p_{q-1}^2 \\ \vdots & \vdots & \ddots & \vdots \\ -1/p_0^q & -1/p_1^q & \cdots & -1/p_{q-1}^q \end{bmatrix} \begin{bmatrix} k_{1,j} \\ k_{2,j} \\ \cdots \\ k_{q,j} \end{bmatrix} = \begin{bmatrix} m_{0,j} \\ m_{1,j} \\ \cdots \\ m_{q-1,j} \end{bmatrix} \quad (10)$$

By calculating the poles and residues, we can transfer the frequency-domain to time-domain, hence the temperature function of time domain as:

$$T_i(t) = \sum_{l=1}^q k_l \cdot e^{p_l \cdot t} \cdot (P_{ower_i}(t) + C_{heat} \cdot T_i(0)) \quad (11)$$

Using frequency-domain analysis, battery system's run-time charge-cycle efficiency and long-term cycle life can both be modeled efficiently and accurately.

### 3.4 Battery System Model Evaluation

The proposed battery system model has been validated using real-world measurement results.

#### 3.4.1 Battery Aging Effect Validation

The proposed long-term cycle life modeling is validated against the measurement results of Bellcore's PLION battery [20][1][13]. we evaluate battery cell aging effect as follows:

- *The impact of battery discharge rate:* We consider discharge current at  $\{1C, \frac{1}{3}C\}$ . where  $1C$  defines the battery discharge rate at which the battery will be discharged from full charge to zero in an hour at room temperature. Given the target the battery cell,  $1C$  equals  $42mA$ . This study considers both  $1C$  and  $\frac{1}{3}C$  battery discharge rates. Figure 3 shows that the proposed model can accurately characterize the battery aging effects as a function of the discharge rate.
- *The impact of temperature:* As described in this section, thermal effects have direct impact on battery life. In this study, we consider three different temperature settings, from  $20^\circ C$  to  $40^\circ C$ . The simulation results are shown in Figure 3, which is consistent with the measurement results from the literature. As shown in Figure 3, as the battery temperature increases, battery cell capacity degrades more significantly.

#### 3.4.2 Short-Term Energy Estimation validation

We validate the proposed battery run-time charge cycle modeling by comparing it against the measurement results from user studies.

Figure 4 shows that the battery run-time charge-cycle analysis accurately matches the measurement results of three users' driving profiles using EETrex PHEVs. Overall, six user studies have been conducted, and the other three studies show similar results.

In summary, these studies demonstrate that, the proposed

modeling and analysis framework can accurately characterize the run-time charge-cycle performance and long-term aging effects of battery systems.

#### 4. USER STUDY DESIGN & DEPLOYMENT

This section describes how our user study is designed and conducted. This study targets run-time data collection of user driving behavior and pertinent hybrid vehicle operation information, as needed to investigate user driving patterns, (P)HEV battery system performance, and gasoline usage.

As discussed in Section 2, the user study conducted in Kansas city is one of the largest community based studies. This data set is publicly released for research purposes. It contains speed and gas usage in second by second time granularity, and acceleration can be deduced from the speed information. Using this data set, we have plotted the relationship between user driving behavior and energy use. As shown in Figure 5, vehicle energy use is potentially correlated with user driving behavior. Thus, our proposed study is designed to investigate the following key research questions:

- How does driving behavior differ between hybrid power train, and conventional technologies? How to assess the performance of hybrid power train in real-world contexts?
- How do real-world gasoline, electricity consumption and battery life vary with driving behavior in advanced vehicles?

According to the literature survey, there have been some works in fuel economy testing and modeling for certification and comparison purposes. These works were based on a limited number of driving cycles designed to represent typical profiles of speed and acceleration [19]. Researchers currently use these same cycles in simulation and optimization studies for advanced power train vehicles [18]. However, the standard cycles have been developed based on driving patterns observed from conventional gasoline vehicles; their transferability to advanced vehicles is unknown.

To address this information gap, the primary objective of our user study is to gather significant amount of real-world driving behavior data, so as to (1) model the impact of driving behavior and other factors on battery systems based on the data; and (2) increase drivers' awareness of their economic and environmental implications.

To gather real-time user driving data and energy use information, we leverage both smart phones and on-board diagnostic devices (Figure 6, thus introducing minimal inconvenience to participants. Our data collection system consists of three main components:

1. Vehicle run-time monitoring devices that will collect data generated by the vehicle on-board diagnostics (OBD) system, to gather data in real-time, at a second-by-second time scale. OBD is a term to describe a vehicle's reporting capabilities and the OBD-II specification has been made mandatory for all vehicles sold

in the United States since 1996. Vehicle owners can access information on various vehicle sub-systems via an OBD-II cable. The data gathered in our study include physical battery and gasoline usage data, such as battery current and state-of-charge (SoC).

2. Personal mobile devices, such as smart phones, carried by individual drivers to gather driving patterns and trip information using built-in sensors, such as GPS and accelerometer. These sensors can monitor location, speed and acceleration.
3. A computer server to collect and store monitored information for further analysis and exploration. The data are gathered by the OBD devices and personal mobile devices, then transmitted to the computer server by the personal mobile devices.

Table 1 lists the specific types of information collected during the user study and the corresponding collecting frequency. In terms of battery system profile, related data are monitored under the guidance of the proposed battery system simulator which has been discussed in Section 3. Current, ambient temperature and initial SOC need to be collected at run-time to feed into the simulator. SOC values through the whole trip are also collected for model validation. As for user driving behavior, it can be described by acceleration and speed values. Unlike previous user studies, acceleration is monitored directly by accelerometer to avoid the accuracy issue discussed in Section 2. Other related location information, for instance, latitude, longitude and altitude, are also captured to characterize the trip features, such as road condition, trip length, etc.

Nowadays, mobile smart phones are equipped with multiple functionalities including GPS, WiFi, Bluetooth and accelerometer. Six HTC Hero and Magic smart phones are used in the study. They are all based on the Android OS, which supports a rich sensing framework. A software tool has been developed on the Android platform to automatically capture the information generated by built-in GPS, accelerometer, and from Bluetooth connection with the OBD-II interface. Volunteers were asked to take the smart phones whenever they drive to collect related data. During each trip, volunteers only need to press corresponding buttons to record trip start and end. Timestamped information can be delivered to the computer server automatically for further processing and analysis. The user-friendly GUI of the tool is shown on the right in Figure 6.

In total, six individuals from University of Colorado at Boulder participated in this study. One of them is a graduate student and the other five are faculty members. Two of the participants are female. Two different plug-in hybrid vehicles were used for testing during the user study: one was a Ford Escape and the other was a Toyota Prius. Both of them used custom battery system. Data collection devices were deployed on all of the vehicles. The central picture in Figure 6 illustrates one example of the mobile phone deployment for a vehicle in the study. Two smart phones were used at the same time for each vehicle, so we could compare the gathered data afterwards and analyze data accuracy. Note that in the current setup, the phones need to be fixed on the



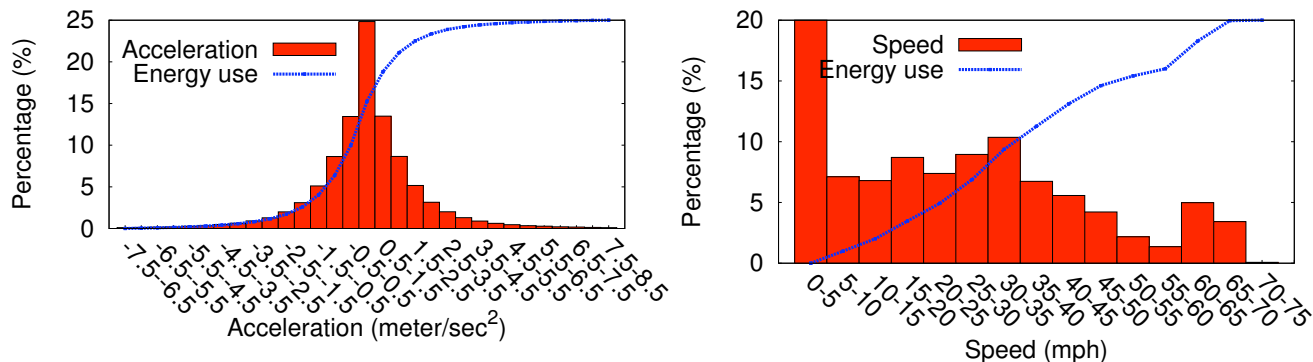


Figure 5: Potential correlation between energy use and driving behavior.



Figure 6: OBD and personal mobile devices deployed in vehicles for real-time monitoring.

windshield inside the car and the screen need to face straight to behind in order to minimize the noise of acceleration. We are in the process of developing the next-generation setup, which will not have this constraint.

## 5. EXPERIMENTAL EVALUATION

The data collected in our user study provide valuable insight into users' driving behavior, as vehicle design, acceleration, speed, and slope are critical factors to determine the required power capabilities of the hybrid vehicle components. In this section, we first conduct quantitatively analysis of user driving behavior, then explore its impact on the energy usage of battery system. We show that, variation of energy usage profile is highly related to the driver' specific driving behavior. Finally, we present the long-term economical analysis for (P)HEV and provide optimization suggestions.

### 5.1 Driving Behavior Analysis

Figure 7 shows the routes taken by our six drivers in their regular driving activities. These routes vary significantly from driver to driver. For instance, our faculty participants traveled more on highway and city roads, while the student spent most of his driving time between home and points of interest. The routes also vary in road condition, which is primarily represented by slope and speed limit. Table 2 compares the driving trips of the six participants. As shown in the table, users' (daily and total) driving trips vary in both time and distance.

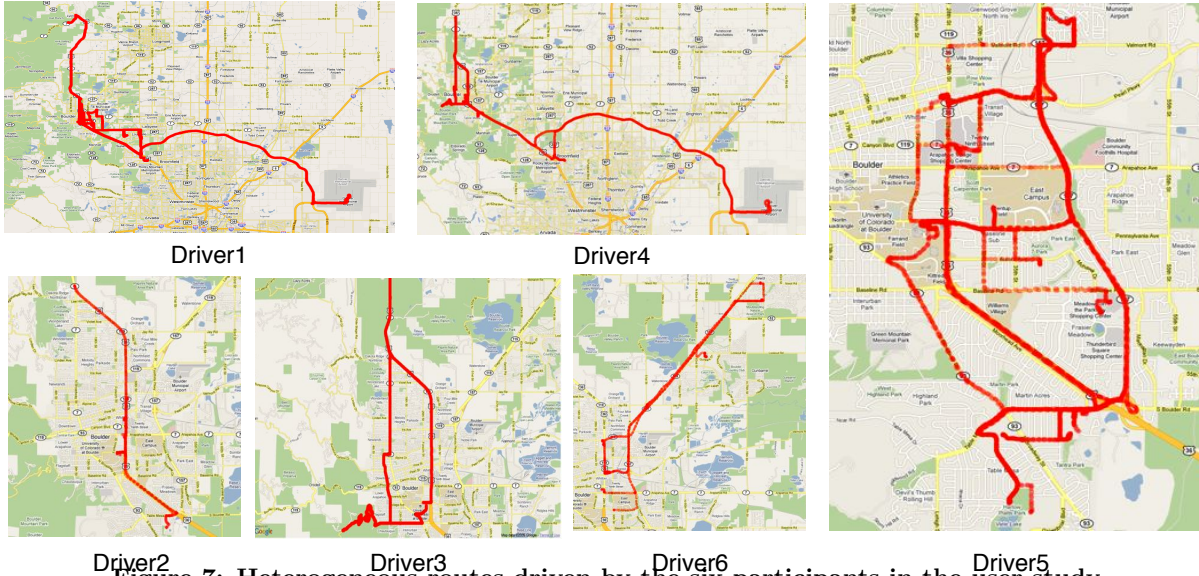
Next, we plot the distribution of each participant's driving behavior as histograms in different measures. Specifically, we compare the distributions of different drivers' trips with

regard to speed, acceleration, slope, and time of day. Figure 8 compares the speed histograms of different drivers. Since different types of road have different speed limits, people who drive mostly on local or city roads (e.g., driver 5) generally have a lower speed profile than people who drive on freeway (e.g., driver 1, 4). A vehicle's movement is directly affected by acceleration, i.e., change in speed in a given amount of time. Here, we consider both the exact value of acceleration and the change frequency of acceleration (change of more than 0.5 meter/sec<sup>2</sup> in our analysis). As shown in Figure 9 and Figure 10, different people drive differently with regard to acceleration. Some drive more aggressively, with higher acceleration values and more acceleration changes, while others drive more smoothly, with lower acceleration values and fewer acceleration changes. Figure 11 shows for each driver the histogram of the slope in his/her trips, measured as rad per minute. While some participants drive mostly on level roads (e.g., driver 5, 6), others also drive in the mountain with more diverse slopes (e.g., driver 2, 3, 4). One other important factor in people's driving behavior is the time of day when they drive. Figure 12 shows the corresponding distributions. The time of day when a person drives depends primarily on his/her professional identity and work schedule. For instance, our faculty participants usually drive in the early morning and late afternoon, while the student drives in late morning and late evening. Time of day when people drive is also related to traffic condition (e.g., morning rush hour), which should be incorporated in user driving behavior analysis.

Based on the driving data we have collected in the user study and the plots above, people's driving behavior differ from

**Table 1: Information Collected from User Study**

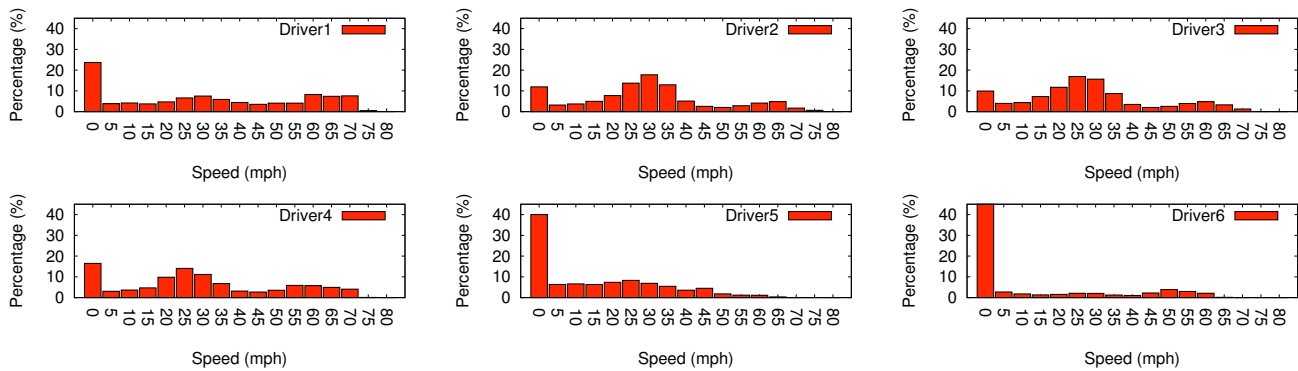
Battery system		User driving behavior	
Type	Frequency(Hz)	Type	Frequency(Hz)
Current	1	Acceleration	3
SOC		Speed	1
Ambient temperature		Location	1
Voltage		Slope	1
Average system temperature		Time	n/a



**Figure 7: Heterogeneous routes driven by the six participants in the user study.**

**Table 2: Comparison of Different Participants' Driving Trips**

	Driver1	Driver2	Driver3	Driver4	Driver5	Driver6
Total time (s)	38,382	26,218	22,188	37,498	38,997	25,249
Total distance (mile)	318.55	177.76	166.53	322.42	168.28	39.93
Total days	14	9	5	9	11	4
Time per day (s)	2,742	2,913	4,438	4,166	3,545	6,312
Distance per day (mile)	22.75	19.75	33.30	35.82	15.30	9.98



**Figure 8: Speed histogram comparison of different drivers' trips.**

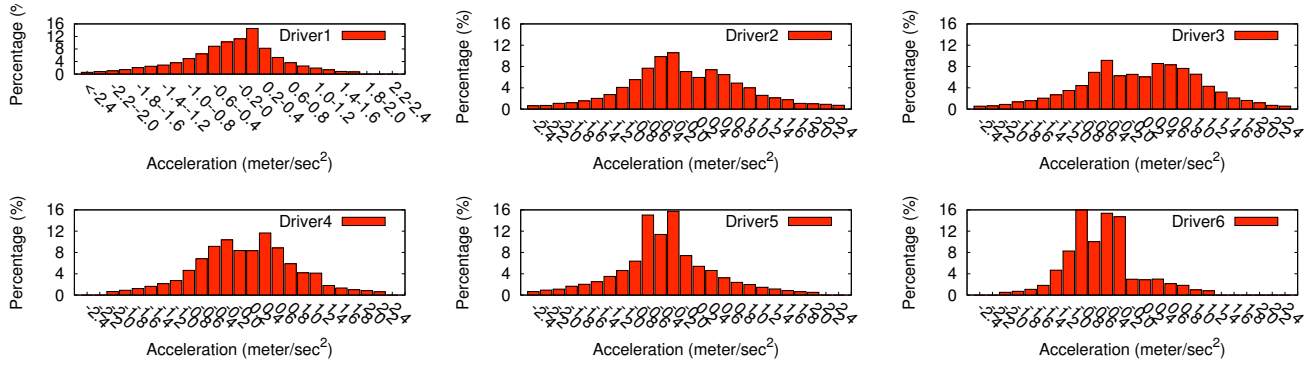


Figure 9: Acceleration histogram comparison of different drivers' trips.

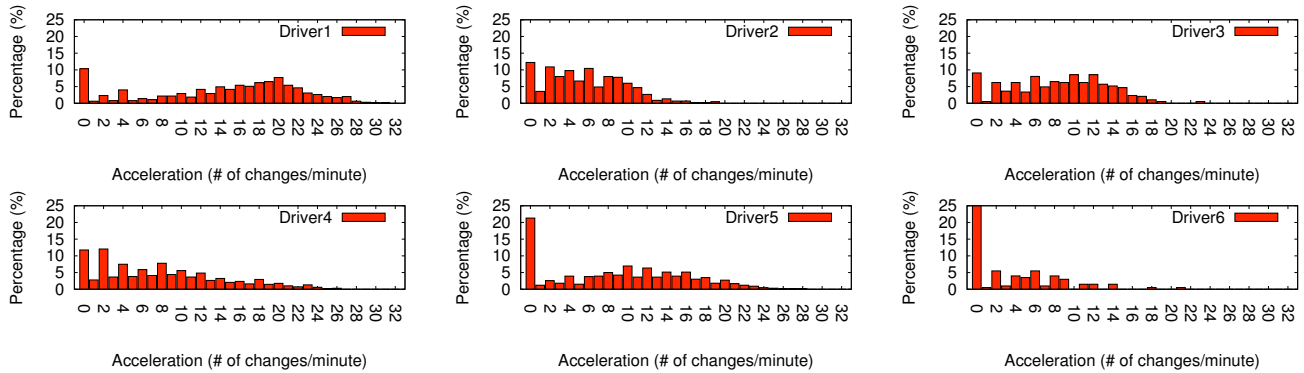


Figure 10: Acceleration change frequency histogram comparison of different drivers' trips.

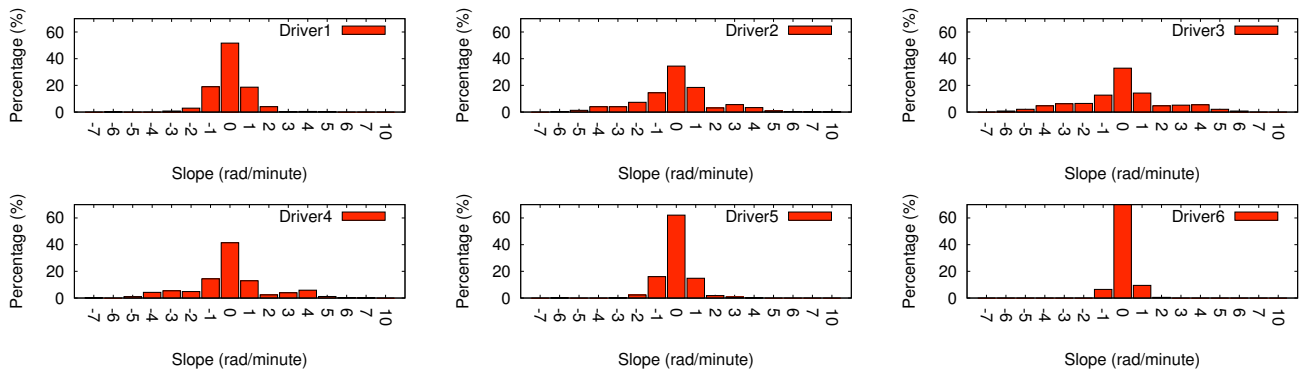


Figure 11: Slope histogram comparison of different drivers' trips.

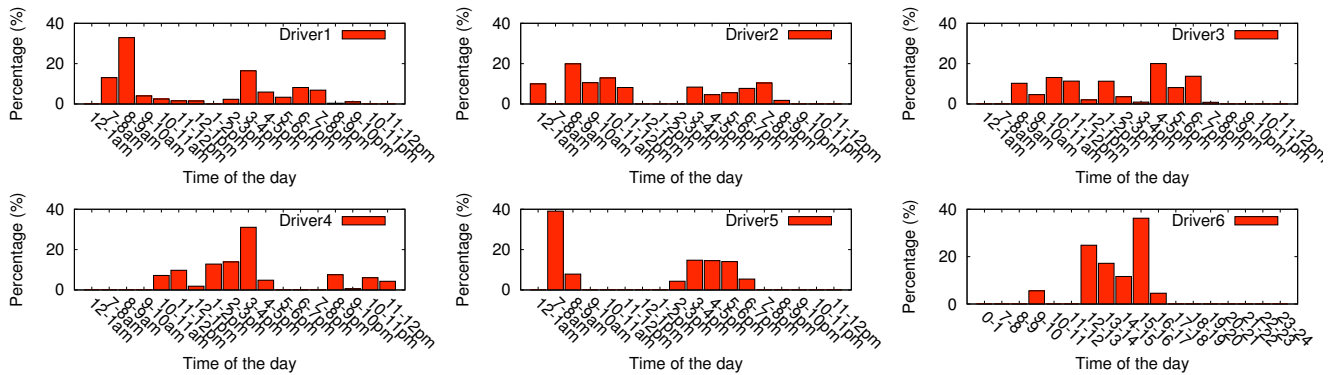


Figure 12: Time of day histogram comparison of different drivers’ trips.

each other significantly. Not only do they vary in speed and acceleration, they also vary in slope and time of day, which are also related to road conditions, traffic conditions, etc. Therefore, to gain a comprehensive understanding of how battery systems perform in real-world scenarios, it is essential that we obtain detailed driving behavior information from individual drivers. In addition, the insights we gain from people’s driving behavior can in turn be utilize in better battery system design and run-time optimization.

## 5.2 Driving Mode Categorization

As shown in the driving behavior analysis, people drive very differently. Such differences in people’s driving behavior in turn affect vehicle battery energy use. To facilitate our analysis of vehicle battery energy use, it is beneficial if we could extract and categorize coherent *driving modes* from people’s driving data, which correlate directly with vehicle battery energy use. Specifically, our goal is to categorize different driving modes using speed, acceleration, and slope information in people’s driving data, which correspond to different current charge–discharge profiles (thus battery system energy use).

We first consider acceleration and slope using the formula  $(a + g \cdot \sin\theta)$ , where  $a$  is acceleration,  $g$  is gravity, and  $\theta$  is slope. Therefore, this formula measures the combined acceleration by incorporating the acceleration caused by gravity when driving along a sloped road. Using the combined acceleration formula, we classify users’ driving trips into three groups based on how much the combined acceleration has changed: stable, mild, and dynamic, which correspond to small, medium, and large acceleration changes, respectively. The intuition is that how much the acceleration changes affect how much the power demand changes, thus the current profile. In the stable and mild scenarios, the current profile roughly correlates with the acceleration profile; while in the dynamic scenario, the current profile changes quickly and there is less correlation with the acceleration profile. Besides the combined acceleration profile, we also consider the speed profile for each of the acceleration categories, as speed is another factor that affects the current profile. Specifically, for each of the three categories of combined acceleration, we consider three different speed groups: low, medium, and high speed. In addition, we consider the “parked” scenario, when speed equals to zero and there is no acceleration changes.

Therefore, we build up the ten modes to capture the relationship between current profile and acceleration, slope and speed. Table 3 shows how the ten modes are defined, where the boundary values are selected based on our analysis of the six-user driving data set. Given the driving mode categorization, we can then classify each user’s driving traces into the driving modes. Table 4 shows the composition of each user’s driving modes. As shown in the table, the percentage of specific driving modes in the six users’ driving data vary significant, which in turn have very different impact on the battery system.

## 5.3 Short-Term Energy Usage Analysis

Given users’ specific driving behaviors and the composition of driving modes in their driving data, our next step is to evaluate the impact of users’ driving behavior on PHEV battery system energy use. Specifically, we want to construct a mapping from the speed, acceleration, and slope information in users’ driving data to the corresponding PHEV current charge–discharge profile. Our goal is to construct one mapping for each driving mode, as the driving modes vary significantly and their mappings can be very different from each other.

We use a  $k$ -order polynomial regression model to construct a mapping under each driving mode. We choose polynomial regression based on the assumption and general observation that the relationship between current and (speed, acceleration, slope) is roughly polynomial with a relatively low order. Specifically, for each driving mode, we consider the following  $k$ -th order polynomial regression model:

$$I = \sum_{i=0}^k (a_i \cdot S^i + b_i \cdot A^i + c_i \cdot G^i),$$

where  $I, S, A, G$  are the current, speed, acceleration, and grade, respectively; and  $a_i, b_i, c_i (i \in [0, k])$  are the polynomial regression coefficients. In our experiments, we choose  $k = 4$ , which produces regression models with small error. As shown in Table 5, for three different users, using 4-th order polynomial regression, we can achieve 15–18% regression error, which are reasonably good given the relatively short and noisy traces we have for each driver.

## 5.4 Long-Term Energy Usage Analysis

**Table 3: Driving Mode Categorization**

change of acceleration $a + g\sin\theta$ ( $m/s^2$ )	speed (mph)	mode
0	0	1
(0, 0.5]	(0, 20]	2
(0, 0.5]	(20, 50]	3
(0, 0.5]	> 50	4
(0.5, 1.4]	(0, 20]	5
(0.5, 1.4]	(20, 50]	6
(0.5, 1.4]	> 50	7
> 1.4	(0, 20]	8
> 1.4	(20, 50]	9
> 1.4	> 50	10

**Table 5: Regression Error of Three Different Drivers**

Driver	2	3	4
Regression Error	15.23%	18.65%	17.25%

Given users' short-term driving behavior and their corresponding battery energy usage, assuming users' driving behavior do not change (significantly) over a longer period of time, we can then estimate the long-term energy usage. Since the cost of the battery system replacement is very high (over tens of thousands of dollars), the long-term battery system energy usage estimation can be used to determine the cost effectiveness of a PHEV and how to make the best use of the battery system.

Long-term thermal effect analysis is important because the temperature distribution is nonuniform in a large-scale battery system. Usually, we can only measure the maximal and minimal battery temperature, i.e., we cannot obtain detailed thermal distribution information by measurement. In addition, since the individual battery cells have different aging effect at different locations, the battery system thermal distribution analysis is a key problem for battery system long-term energy usage analysis. Specifically, thermal effect of the battery system depends on two factors: *ambient temperature* and *dynamic charging/discharging operations*. Since the dynamic charging/discharging operations have substantial impact on the long-term thermal effect, we incorporate the battery system thermal effect model to capture the thermal distribution of the long-term battery system.

Table 6 shows the estimated thermal distribution (min, max, mean, and variance) in a 15-year battery system for each of the six drivers. As we can see in the table, different driving behaviors lead to different long-time thermal distribution in the battery system.

Table 7 shows the 15-year battery system capacity distribution for the six different drivers. The initial battery system capacity is  $5.096KWh$ . The table shows that the battery system aging varies significantly among the six drivers, ranging from 13.9% to 38.7%. More importantly, due to the heterogeneous thermal distribution in a battery system, the aging effects vary significantly among the individual battery cells.

**Table 4: Composition of Driving Modes in Different Users' Driving Data**

Driver	1	2	3	4	5	6
Mode 1 (%)	20.8	14.5	11.0	18.5	35.0	65.3
Mode 2 (%)	2.9	1.9	1.7	3.3	1.4	2.3
Mode 3 (%)	4.2	5.7	4.4	8.5	6.1	8.0
Mode 4 (%)	9.5	9.7	11.5	7.3	19.9	5.7
Mode 5 (%)	4.1	26.9	13.7	24.7	0.2	2.0
Mode 6 (%)	6.3	23.7	21.1	20.4	5.7	6.3
Mode 7 (%)	22.8	11.6	25.1	6.7	28.4	3.4
Mode 8 (%)	0.8	4.2	3.9	8.2	0.0	1.2
Mode 9 (%)	2.7	1.5	5.9	2.3	0.7	4.5
Mode 10 (%)	26.0	0.3	1.7	0.1	2.6	1.5

## 6. CONCLUSIONS AND FUTURE WORK

User-centric driving pattern and battery system energy usage analysis is critical for PHEV manufacturers, drivers and potential consumers. In this paper, we have developed a large-scale battery system model for PHEVs, which supports short-term energy usage profile analysis, long-term thermal distribution and lifetime estimation, based on heterogeneous real-world user driving behavior. We have developed a real-time user driving data acquisition system and conducted a user study on six participants with diverse driving patterns. Detained evaluation results have show that our batter system model can accurately estimate real-world battery system energy usage; user driving behavior affects battery system usage significantly in both short term and long term. Generally, steadier and smoother driving behaviors are better for electric-drive vehicle lifetime and cost saving.

This work is a first step towards incorporating user driving behavior into the modeling and analysis of battery system energy usage analysis for emerging green-energy transportation. As our future work, we plan to further improve our data acquisition system such that it imposes minimal obstruction or inconvenience on the drivers while collecting real-time vehicle and user driving data with high accuracy. We will also investigate techniques to automatically categorize driving modes and improve the accuracy of the regression model.

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**Table 6: 15-year Battery System Thermal Distribution**

Driver	1	2	3	4	5	6
min temperature( $K$ )	285.92	293.64	294.78	284.55	285.32	285.10
max temperature( $K$ )	301.41	297.64	313.11	288.47	290.67	286.73
mean temperature( $K$ )	295.42	295.10	306.03	286.47	288.67	286.10
variance	20.76	3.04	29.08	1.39	2.48	0.23

**Table 7: 15-Year Battery System Capacity Distribution**

Driver	1	2	3	4	5	6
Decrease percentage (%)	27.14	26.49	38.69	15.93	17.62	13.91
15-year total capacity( $Wh$ )	3712.70	3746.10	3124.40	4284.40	4198.30	4397.20
min capacity( $Wh$ )	3.51	5.59	2.19	6.92	6.80	7.29
max capacity( $Wh$ )	7.16	6.98	6.66	7.80	7.20	7.59
mean capacity( $Wh$ )	6.25	6.31	5.26	7.21	7.07	7.40
variance	1.27	0.18	2.15	0.02	0.07	0.01

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