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Article

Large-Scale Battery System Development and User-Specific Driving Behavior Analysis for Emerging Electric-Drive Vehicles

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Abstract: Emerging green-energy transportation, such as hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs), has a great potential for reduction of fuel consumption and greenhouse emissions. The lithium-ion battery system used in these vehicles, however, is bulky, expensive and unreliable, and has been the primary roadblock for transportation electrification. Meanwhile, few studies have considered user-specific driving behavior and its significant impact on (P)HEV fuel efficiency, battery system lifetime, and the environment. This paper presents a detailed investigation of battery system modeling and real-world user-specific driving behavior analysis for emerging electric-drive vehicles. The proposed model is fast to compute and accurate for analyzing battery system run-time and long-term cycle life with a focus on temperature dependent battery system capacity fading and variation. The proposed solution is validated against physical measurement using real-world user driving studies, and has been adopted to facilitate battery system design and optimization. Using the collected real-world hybrid vehicle and run-time driving data, we have also conducted detailed analytical studies of users' specific driving patterns and their impacts on hybrid vehicle electric energy and fuel efficiency. This work provides a solid foundation for future energy control with emerging electric-drive applications.

Keywords: battery system; user-specific driving pattern; hybrid vehicle; aging effect

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. During the past years, more than 16 million vehicles have been sold in the U.S. each year [1], accounting for 70% of petroleum consumption and over one third of greenhouse gas emissions. Studies have shown that major reductions in greenhouse gas emissions and the ever-growing dependence on foreign oil can be accomplished by transportation electrification [2,3]. Over the years, active market penetration of hybrid electric vehicles (HEVs) [4], e.g., Toyota Prius and Ford Escape, has been observed. Meanwhile, plug-in hybrid electric vehicles (PHEVs) and pure electric vehicles (EVs) will become market-ready in as early as 2011. The benefits of these electric-drive vehicles are clear—if (P)HEVs are charged from renewable electricity sources, fuel use can be substantially reduced by not using the engine, *i.e.*, operating in an electric mode, and fuel economy can be significantly improved by allowing the internal combustion engine to operate efficiently. Furthermore, (P)HEVs can provide energy storage for smart power grid, balancing energy delivery over peak and off-peak periods, hence further benefiting the energy sector and reducing the impact on the environment.

However, several technical challenges must be addressed before (P)HEVs become beneficial both economically and environmentally. Among (P)HEV technical challenges, large-scale battery system, as a primary energy storage system, has been singled out as a potential show stopper [5,6]. This is mainly due to the fact that advances of energy storage technologies have not kept pace with the fast-growing energy demands. Lithium-ion rechargeable electrochemical battery, which has been adopted for most large-scale battery system designs in PHEVs, is bulky, unreliable and expensive. Since automotive companies typically require a lifetime battery system guarantee, the cost, energy capacity, and limited cycle life of battery system have become the primary challenges for (P)HEV market penetration.

(P)HEV operation is also heavily affected by users' run-time driving behaviors. User-specific driving patterns are dynamic and differ substantially among drivers [7,8], which in turn affect vehicle fuel efficiency and battery system usage. However, accurate acquisition and characterization of user-centric real-time driving patterns have been a challenge. To date, little is known about the relationships between user driving behavior and (P)HEV battery system energy usage. In fact, for hybrid vehicles, in particular PHEVs, the notion of a driving cycle needs to be redefined to encompass when and how PHEV batteries are charged, as they provide an electrical outlet to recharge the batteries from the electrical grid, use increased battery capacity, and use a different strategy to manage the state-of-charge. Without knowledge of possible use patterns of (P)HEVs "in the wild", it is impossible to determine their impact on pollution and energy consumption.

1.1. Related Work

Due to its characteristics such as high-energy density and high-power capability, lithium-ion battery has become an essential power source for portable mobile electronic devices. Previous research on battery modeling has focused on single battery cell. Rakhmatov *et al.* presented a numerical model for battery cell lifetime prediction, which strongly depended on the current discharge profile and did not consider thermal effect [9,10]. Peled *et al.* proposed a model which focused on the cell oxidation process, the dominant aging effect [11]. Peng *et al.* proposed a battery cell model to capture battery capacity degradation due to aging and pointed out the thermal effects [12]. Recently, lithium-ion battery has attracted the attention of the automotive industry for applications in hybrid electric vehicles (HEV) or plug-in hybrid electric vehicles (PHEV) [13]. There has been limited work in large-scale battery system modeling. Recent studies by the National Renewable Energy Laboratory (NREL) [14] and Argonne National Laboratory (ANL) [15] discussed battery system modeling using the equivalent circuit method to capture the battery runtime charge–discharge cycle behavior. However, these battery system models ignored inter-cell capacity variation and heterogeneous thermal effects. The battery system model developed by Dubarry *et al.* also used equivalent circuit method for real-time estimation of battery system performance [16]. It ignored heterogeneous cell-to-cell thermal effects, and did not provide any explanation of the electrochemical reactions. As a result, the battery system run-time performance, long-term cycle life, and capacity fading effect are not accurately characterized.

For user-specific energy consumption analysis, existing studies on vehicle fuel economy are typically tested or modeled by a "typical" driving profile [17] with standard cycles, ignoring the diverse driving patterns of different users, which strongly influence vehicle energy consumption [7,18]. Furthermore, the transferability of standard driving patterns observed for conventional vehicles to (P)HEVs is unknown. The CarTel monitoring system developed by Hull *et al.* used both on-board and external sensors in the automotive context to analyze commute time, Wi-Fi deployment, and automotive diagnostics [19]. Our work differs from these monitoring tools and energy economy analysis. We focus on the impacts of user-specific driving patterns on the battery system of emerging electric-drive vehicles. With accurate battery system modeling and user-specific driving pattern analysis, our work enables an in-depth understanding of hybrid vehicles impacts on energy consumption.

1.2. Our Contributions

The goal of this work is to bridge the information gap between (P)HEV energy consumption and user-specific driving behaviors. We focus on large-scale battery system modeling for emerging (P)HEV applications and analyze the energy economy for user-specific driving patterns. We first present the system model and energy economy analysis, which characterize the battery system run-time charge cycle efficiency and long-term cycle life time. The proposed large-scale battery system tool is validated against physical measurements in real-world user driving studies. The energy economy analysis using real-world user-centric driving patterns and battery system modeling provide a better understanding of how user-specific driving behavior affects (P)HEV battery system usage, fuel efficiency, and environment. In summary, this work makes the following contributions.

1. The proposed large-scale battery system development tool models the run-time charge-cycle usage and long-term capacity fading of individual battery cells (e.g., thermal and depth-of-discharge dependent aging effects). Considering variation effects among a number of individual battery cells, a unified frequency-domain technique for battery system electric and thermal analysis is adopted in the system design, supporting year-level battery long-term cycle life analysis via second-level accurate run-time performance analysis. To the best of our knowledge, this is the first study investigating large-scale battery system modeling that considers the major run-time charge-cycle usage and long-term capacity degradation effects.

2. The proposed personalized mobile monitoring system design and deployment emphasize transparent services for ease of deployment and low-power design. It enables comprehensive data acquisition of user driving patterns, such as speed and acceleration, as well as (P)HEV energy usage and run-time performance. A series of user studies have been conducted, covering diverse driving behaviors under different road and traffic conditions. Using the real-world sensing data, we analyze user-specific driving behaviors and their impacts on (P)HEV energy consumption, battery system usage, and energy economy.

The rest of the paper is organized as follows. Section 2 motivates the proposed research. Section 3 presents our battery system model design and analysis. Section 4 describes the impact of user driving behavior on (P)HEV energy consumption and shows the energy economy analysis. We conclude in Section 5.

2. Motivations and Rationale

This section gives an overview of battery system technologies for emerging electric-drive vehicles, then discusses system-level large-scale Lithium-ion battery system design and user-specific energy economy analysis challenges.

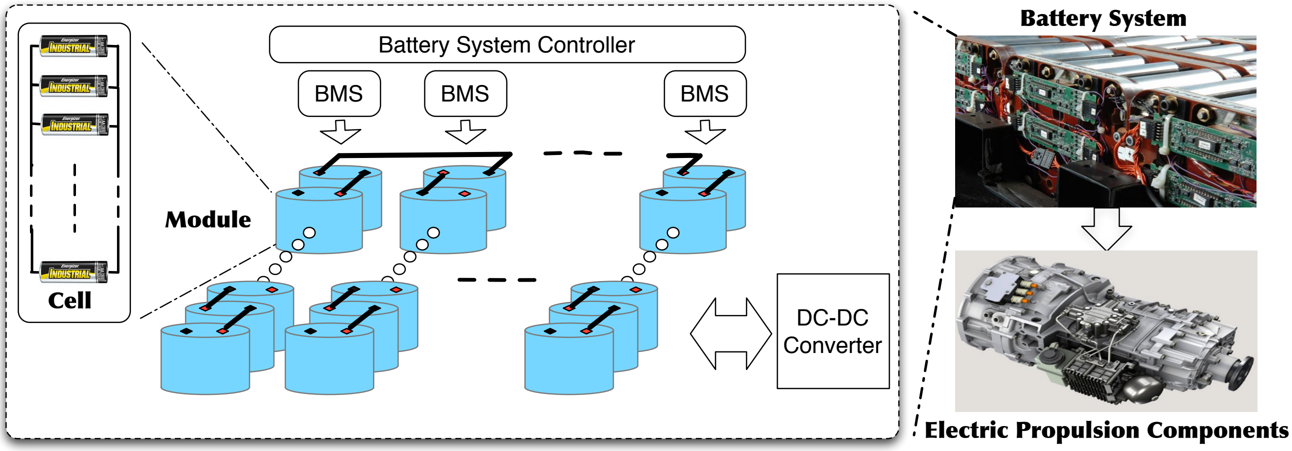
2.1. Battery System Overview

Figure 1 illustrates a block diagram of a battery system connected to electric-drive propulsion components. Due to the chemistry specifics, a single battery cell's voltage, current, and energy storage capacity are relatively low. Hence, a (P)HEV battery system consists of a large number of rechargeable energy storage units (e.g., 1000), connected in parallel and series to provide sufficiently high energy storage capacity to electric-drive vehicles.

2.2. Battery System Design Challenges

As automotive companies typically require a battery system lifetime guarantee (e.g., 10–15 years), battery system cost, energy capacity, and cycle life have become the primary challenges for PHEV market penetration. Our work is motivated by the following challenges of battery system design and real-world transportation energy analysis.

Figure 1. Battery system architecture for electric-drive vehicles.



- *Battery system cost*. Consider the recently developed Toyota Prius PHEVs. Each vehicle has a large-scale energy storage system containing over 500 Lithium-ion electrochemical battery cells with a total cost of over $35,000 [20] for 50-mile electric mode driving. Battery system cost is strongly correlated with user-specific driving behavior, run-time charge-cycle efficiency, and long-term lifetime reliability. Thus, accurate large-scale battery system modeling and development are essential for (P)HEV applications.

- *Battery system run-time performance*. User-specific run-time driving behavior results in different (P)HEV operations. Those vehicle operations directly affect the battery system run-time charging–discharging efficiency and run-time energy usage. For instance, frequent slowing down and speeding up of a vehicle can trigger intensive battery system usage, which causes electrochemical battery self-heating and accelerates battery system long-term capacity degradation. Therefore, it is important to characterize user-specific driving behavior, determine its relationship with battery system usage, and design the large-scale battery system accordingly.

- *Battery system long-term lifetime reliability*. Based on the literature [11], temperature and depth-of-discharge are two factors with key impact on the battery aging effect and long-term lifetime reliability. A large-scale battery system's reliability and performance are limited by its weakest cells, which can incur severe system performance penalties, as well as reliability and safety concerns. Heterogeneous run-time usage, various ambient environment, battery cells' manufacture variation, and system mismatch problem, which lead to significant degradations and variations among individual battery cells, are the deep roots of battery system lifetime reliability crisis. Figure 2 shows the capacity degradation measurement results we obtained from 30 Lithium-ion battery modules in a PHEV. Over 40% capacity variation is observed among these modules due to aging. Hence, it is of particular importance to build an accurate battery system long-term lifetime model.

- *User-specific driving behavior*. People drive their vehicles very differently, and with diverse road and traffic conditions. These run-time user-specific driving behaviors have a significant impact on PHEV battery system run-time charge-cycle efficiency and long-term cycle lifetime. For instance, some aggressive driving behaviors, such as frequently slowing down or speeding up the vehicle, lead to intensive battery system charge and discharge. Such intensive run-time usage causes significant battery self-heating and accelerates temperature-dependent aging effects, leading to battery long-term capacity degradation. Using the proposed battery system model (Section 3), Figure 3 shows the estimated battery system long-term capacity degradation based on six different users' daily commute driving profiles. It demonstrates that users' driving patterns can significantly impact battery system long-term cycle life. Without knowledge of user-specific driving pattern, it is impossible to accurately model the run-time and long-term effects of a large-scale battery system.

Figure 2. Aging-induced capacity degradation of 30 PHEV battery modules.

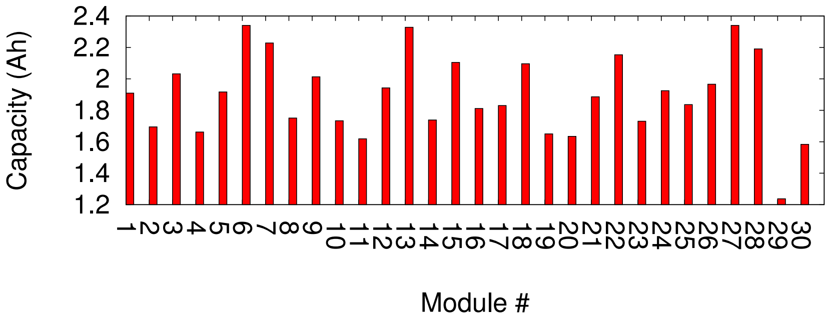
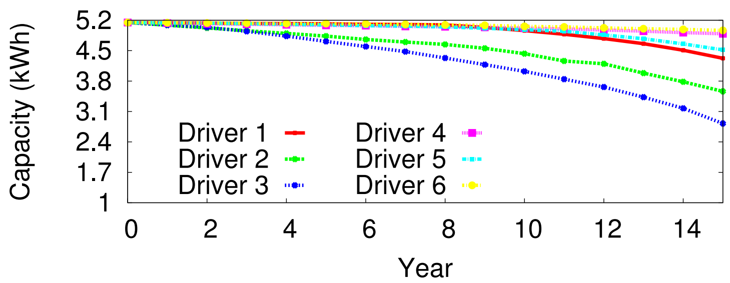


Figure 3. Expected battery system long-term aging based on six different driving profiles.



3. Large-Scale Battery System Modeling Development

This section presents system-level modeling and analysis techniques targeting large-scale lithium-ion battery systems. Since the basic electrochemical battery cell model requires a large number of parameters, it is hardly recommended for large-scale battery system modeling. Instead, a high-level battery cell model, which still captures the key electrochemical properties, is used as building blocks to construct the entire large-scale battery system model. As illustrated in Figure 1, the battery system for each electric-drive vehicle consists of a large number of lithium-ion electrochemical battery cells (e.g., 1000), connected in parallel and series, providing output voltage, driving current, and energy storage capacity to the vehicle. Battery system performance is measured by run-time charge-cycle efficiency and long-term cycle life. Our goal is to develop a system model and analysis framework for fast and accurate characterization of these design metrics. The primary challenges of battery system modeling are summarized as follows:

- Battery system performance is affected by various electrochemical effects. For instance, battery system long-term cycle life is affected by various aging effects, which in turn are influenced by run-time thermal effects and depth of discharge. All these factors must be carefully considered during battery system modeling and analysis.
- Computational complexity is a primary challenge for large-scale battery system modeling. Since each (P)HEV battery system contains a large number of battery cells and the system's performance depends on the weakest battery cell, it is essential that we model the run-time behavior of individual cells accurately. Run-time battery system usage changes from second to second, and the long-term aging effects vary from months to years. Accurate and fast modeling of a battery system over such a large time span is challenging. Battery system modeling is further complicated by thermal analysis, which is known to have high computational complexity.

3.1. Battery Electrochemical Mechanisms

Each lithium-ion battery system contains a large number of battery cells as the atomic energy storage unit. Each battery cell is composed of an anode (e.g., graphite LiC_6), a cathode (e.g., $LiCoO_2$ and $LiMn_2O_4$), and an electrolyte (e.g., lithium salt water). The electrolyte separates the two electrodes and provides a mechanism for the transfer of charge between them. Pursuant to battery run-time usage, such as charging and discharging process, a series of electrochemical reactions occur in the battery. During battery discharging, the Li^+ de-intercalate from the cathodeand form at the anode surface through a highly conductive electrolyte solution. On the other hand, the free electrons generated from the anode flow through the external circuit towards the cathode. As discharging proceeds, more and more reaction sites become unavailable, eventually leading to a state of complete discharge. The charging process is the reverse process.

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

A battery system comprised of N energy storage units is typically organized as an $N = M \times W$ array. Every W battery cells are connected in parallel, forming a battery module supporting high current. These M battery modules are connected in series, providing high output voltage. In the entire large-scale battery system, the weakest module and cell constrain the whole battery system performance. Therefore, the battery system run-time charge capacity $C(t)$, and charge status $SOC(t)$ (State-of-Charge), during a run-time user driving cycle (started at t_0) can be described as follows

$$C(t) = M \cdot \min_{1 \le i \le M} \{c_i(t)\}, \ \ SOC(t) = C(t)/C(t_0) \tag{1}$$

$$c_i(t) = \sum_{j=1}^{W} \left(\int_{t_0}^{t} i_{i,j}(t) \cdot v_{i,j}(t) \cdot dt + c_{i,j}(t_0) \cdot \omega_{i,j}(t) \right) \tag{2}$$

where $c_i(t)$ and $c_{i,j}(t)$ are the run-time charge capacity of battery module i, and battery cell (i, j), respectively; $i_{i,j}(t)$ and $v_{i,j}(t)$ are the run-time current and output voltage of battery cell (i, j) respectively. $\omega_{i,j}(t)$ models the long-term capacity storage efficiency of battery cell (i, j) due to long-term aging, which is represented in Equation 5.

For each individual lithium-ion energy storage unit i, we capture the primary electrochemical properties, such as long-term aging effect. Recent studies have identified several aging effects, including self-discharge, electrolyte decomposition, and cell oxidation [11,21]. In this paper, we consider the most significant effect—cell oxidation, which leads to a film (called solid-electrolyte interphase) grown on the electrode, increasing battery internal resistance and reducing battery long-term capacity. Considering battery aging effects, a lithium-ion energy-storage unit i's output voltage follows

$$V_{out_i}(t) = Voc_i(t) - (\eta_{sa_i} - \eta_{sc_i}) - (\eta_{ohma_i} - \eta_{ohmc_i}) - (\eta_{diffa_i} - \eta_{diffc_i}) \tag{3}$$

where Voc_i is unit i's open-circuit voltage, η_{sa_i} (η_{sc_i}), η_{ohma_i} (η_{ohmc_i}), and η_{diffa_i} (η_{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 equation above can be further simplified as follows [12]

$$V_{out_i}(t) = Voc_i(t) - i_i(t) \times r_i(t) - \lambda_i \ln(1 - \xi_i(t)\omega_i(t)^{\kappa_i(t)}) \tag{4}$$

where $r_i(t)$ is the battery cell internal resistance, λ_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 the Arrhenius temperature dependence equation [22]. $\omega_i(t)$ models long-term aging, which follows

$$\omega_i(t) = \left\{ \frac{1}{\xi_i(t)} \left[1 - \exp\left(\frac{i_i(t) \times r_i(t) - (Voc_i(t) - V_{c_i})}{\lambda_i} \right) \right] \right\}^{\frac{1}{\kappa_i(t)}} \tag{5}$$

where V_{c_i} is the cutoff voltage.

Lithium-ion battery aging effects, in particular the cell oxidation process, are affected by various parameters such as charge–discharge current, depth of discharge, and temperature. Among these, temperature-dependency is a primary effect [12]. During a run-time charge–discharge cycle, the aging process is further accelerated by battery internal heating. When the battery system is idle, the aging process is determined by the ambient temperature. Specifically, both r_i and Voc_i are strongly correlated with temperature according to our previous study [23]. r_i and Voc_i can be described as follows

$$\frac{dr_i(t)}{dt} = k \cdot n_c \cdot \exp(\frac{-E_{active}}{T_i(t)} + \varphi) \tag{6}$$

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

Voc_i is also a function of temperature. Following the Nernst equation [22], we have

$$\frac{dVoc_i(t)}{dt} = -\frac{R_c \cdot T_i(t)}{n_e \cdot F_c} \ln Q_i(t) \tag{7}$$

where n_e is the number of electrons transferred, F_c is Faraday's constant, R_c is a constant, and $Q_i(t)$ represents the electrolyte equilibrium concentration, which is a function of the depth of discharge based on our previous work [23]. Overall, the aging-induced lithium-ion capacity fading has exponential temperature dependency.

3.3. Large-Scale Battery System Modeling

A (P)HEV battery system consists of a large number of energy storage units. As shown in Section 2, manufacturing tolerance, heterogeneous run-time usage and environment (in particular thermal) effects lead to significant degradation and variations among energy-storage units. Accurate system-level modeling of battery system 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 a battery system consisting of N energy storage units and their connectivity information, the battery system run-time charge status is modeled as follows

$$\mathbf{C}'_{e[N\times N]}(t) = \mathbf{K}_{[N\times N]} \times I(t) + \mathbf{C}_{e[N\times N]}(t_0) \times \mathbf{\Omega}'_{[N\times N]}(t) \tag{8}$$

where matrix $\mathbf{C}_{e[N\times N]}(t)$ 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, which is a function of $\mathbf{C}_{e[N\times N]}(t)$.

The equation above allows us to characterize the battery system run-time efficiency and long-term aging 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

$$\mathbf{C}_{t[N\times N]} \cdot \mathbf{T}'_{[N\times 1]}(t) = \mathbf{G}_{[N\times N]} \cdot \mathbf{T}_{[N\times 1]}(t) + \mathbf{P}_{[N\times 1]}(t) \tag{9}$$

where matrix $\mathbf{C}_{t[N\times N]}$ 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.

Computational complexity is the primary challenge for system-level battery system modeling. Given a (P)HEV battery system containing 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 year to year. Accurate and fast modeling of a large-scale battery system over such a large time scale range is challenging. Battery system modeling is further complicated by thermal analysis, which is known to be computationally expensive.

We propose and develop a unified frequency-domain electric and thermal analysis method to enable fast and accurate battery system analysis. The proposed solution builds upon the multi-node moment matching method [24]. Compared with conventional single-point moment matching techniques, such as the AWE method, the multi-node moment matching method offers a number of advantages, including requiring fewer number of moments under the same accuracy constraint, hence higher computation efficiency and better numerical stability.

Equations 8 and 9 are first transformed to the frequency domain as follows

$$sC_e(s) - C_e(0) = \mathbf{K} \cdot I/s - Z/s + \mathbf{Y}C_e(s) \tag{10}$$

and

$$s\mathbf{C}_t T(s) - \mathbf{G} \cdot T(s) = P/s + \mathbf{C}_t \cdot T(0) \tag{11}$$

where $\mathbf{\Omega}$ is described using piece-wise linear approximation of C_e.

The multi-node moment matching method is then applied to calculate the poles and residues, and then transform the two equations back to the time domain. The run-time charge capacity and temperature of each energy storage unit i can then be estimated as follows

$$C_{e_i}(t) = \sum_{l=0}^{q_e-1} X_{e_{i,l}} \cdot e^{p_{e_l} \cdot t} \cdot (\frac{\mathbf{K}}{p_{e_l}} \cdot I(t) - \frac{Z}{p_{e_l}} + C_e(0)) \tag{12}$$

$$T_i(t) = \sum_{l=0}^{q_t-1} X_{t_{i,l}} \cdot e^{p_{t_l} \cdot t} \cdot (\frac{P(t)}{p_{t_l}} + Q) \tag{13}$$

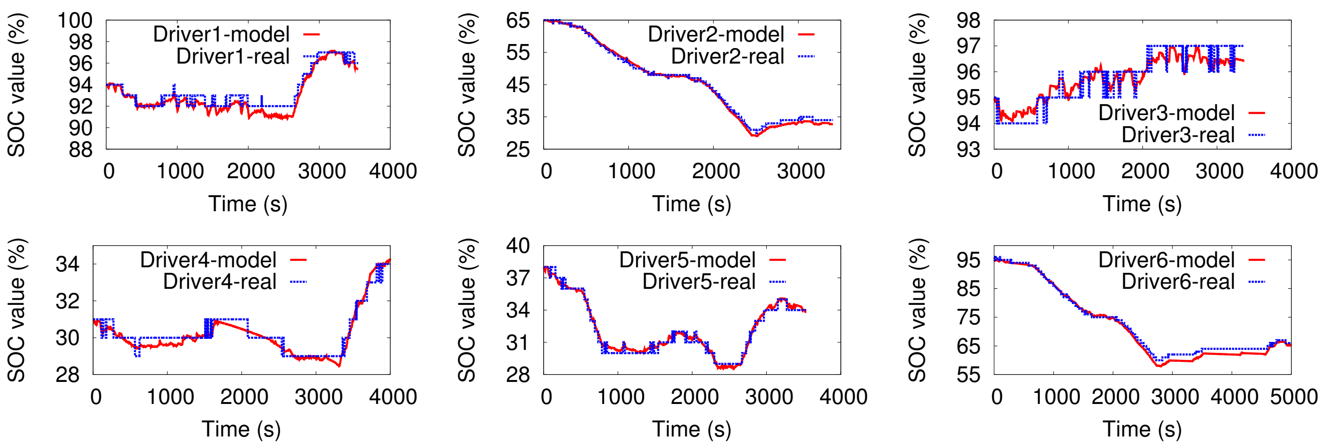
where Z, J and Q are coefficient vectors. q_e and q_t determine the order hence the accuracy of the model. Operated in unison, the above two equations enable a unified electric and thermal analysis to characterize battery system run-time charge-cycle efficiency and long-term cycle life.

3.4. Large-Scale Battery System Validation

In this section, we use the real-world user driving behavior gathered by our mobile sensing system (see Section 4) to evaluate (P)HEV battery system run-time performance and long-term aging effects. We also evaluate the efficiency of large-scale battery system modeling.

- ***Battery System Run-Time Validation*** Based on real-world driving data acquisition, we pick six driving traces and use their current, voltage and temperature information to simulate the SOC at each time point and compare the simulated SOC values to the physically measured values. In this study, the PHEV battery system consists of 1200 lithium-ion battery cells with a total energy capacity of 5.1 kWh. Figure 4 shows that the battery system run-time charge-cycle analysis accurately matches the measurement results of six different users' driving profiles.

Figure 4. Battery system run-time charge-cycle model validation.



- ***Battery Cell Long-Term Aging Effect Validation*** To validate the model of long-term aging effect, we use generalized Sony 18650 cell with 1.8 Ah capacity. We adopt the conventional constant current and constant voltage charge/discharge policy. A direct current of 1 A is used to charge the cell during the constant current part, and the cut-off voltage is set to 4.2 V. Subsequently, the voltage is held constant at 4.2 V till the current drops to 2.0 V. In the validation, we consider three temperature settings: 20 °C, 45 °C, and 55 °C. The simulation results are shown in Figure 5, which are consistent with the measurement results from the literature [25]. As shown in the figure, during the initial cycles, different temperatures have a similar impact on battery aging. As the number of cycles increases, higher battery temperature leads to more significant degradation of battery capacity.

- ***Battery System Modeling Efficiency*** In order to validate the battery system modeling efficiency, we adopt ten daily driving traces with diverse duration to measure the computation time of 15-year battery system lifetime simulation. For the experiment, we assume that during the 15 years, the same trace is repeated daily. As shown in Table 1, the proposed model can simulate 15-year battery system lifetime in less than two minutes, and it scales well as trace duration increases.

Figure 5. Battery cell long-term aging effect validation.

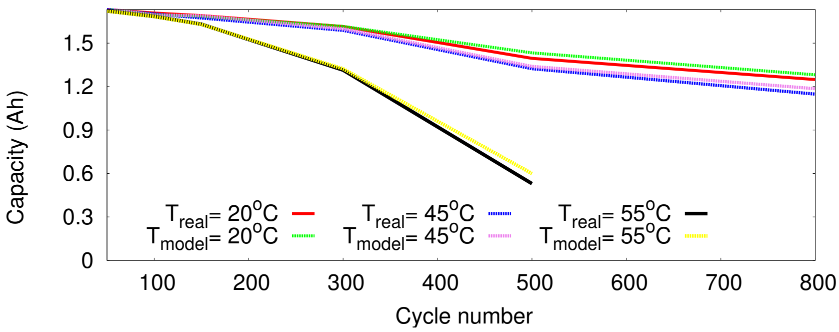


Table 1. Efficiency of 15-Year system lifetime simulation.

Trace	**1**	**2**	**3**	**4**	**5**
Daily trip duration (s)	211	516	1202	1470	1598
Computation time (s)	8.6	15.5	37.5	45.3	50.0
Trace	**6**	**7**	**8**	**9**	**10**
Daily trip duration (s)	1717	2140	2571	2894	3536
Computation time (s)	53.5	67.5	81.7	92.0	112.4

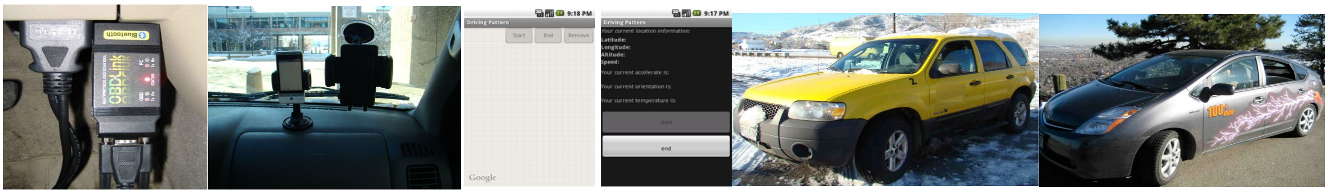
4. Comprehensive Analysis of Driving Behavior and Energy Usage

This section studies how user-specific driving behavior affects battery system performance and gasoline usage. According to a report from fleet owner webinar [26], the fuel economy of a vehicle is the main concern of a driver who wants to save money in his/her daily driving. Ideally, PHEV is an excellent way to achieve this goal. However, PHEV has higher purchasing cost because of the extra battery system and it is still not clear whether the extra money spent for the battery system can be justified by potential energy cost savings. There have been several fuel economy studies which evaluated the benefits by running simulations over certification cycles [27,28]. However, since previous experiments used standard test cycles, they may not represent actual driving behaviors on PHEVs. In this work, we propose a large-scale battery system model which characterizes the dependence of PHEV energy efficiency and wear rate on user-specific driving behavior based on real-world driving studies. By quantifying the benefit or cost of using a PHEV, relative to a conventional internal combustion engine automobile, we enable rational economic decisions about PHEV purchase, which vary from driver to driver.

4.1. *Real-World User Driving Pattern Monitoring System*

In order to acquire real-time user driving pattern information, we leverage both personal smart phones and on-board diagnostic (OBD) sensing devices for real-time monitoring (Figure 6). Our real-time data monitoring system consists of three main components: (1) vehicle run-time monitoring devices that collect driving data from built-in sensors—OBD devices; (2) personal mobile devices, such as smart phones, carried by individual driver to collect detailed driving patterns and trip information using built-in sensors, such as GPS and accelerometer; and (3) a remote computer server to store monitored information for further analysis and exploration.

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



Six different drivers have participated in our study. Two different PHEVs were used in the user study: a converted Ford Escape and a converted Toyota Prius. Both vehicles used custom battery system designed by a clean-energy transportation company [29]. Six smart phones were used in the study. They are all based on the Android OS, which supports a rich sensing framework. The smart phones communicate with the OBD devices via Bluetooth and with the remote computer server via Wi-Fi.

4.2. *Real-World User Driving Behavior Impact Analysis*

To analyze how user-specific driving behavior affects (P)HEV battery system run-time usage and long-term life cycle, we use the real-world user-driving data gathered from the deployed personalized mobile sensing systems and analysis framework.

- ***User-Specific Driving Behavior Analysis*** In (P)HEV applications, the energy usage of large-scale battery system is strongly correlated with users' driving behavior, which differ significantly from one driver to another. Figure 7 shows the heterogeneous routes taken by our six drivers in their regular driving activities. For instance, driver 4 travels more often on highway, while driver 5 spends most of his/her driving time on city roads. These routes vary in road condition with different slope and speed limit. Table 2 compares the driving trips of the six participants. Note that the driving behavior of different users may differ significantly even when the road and traffic conditions are the same. Some drivers drive their vehicles more aggressively than others, e.g., frequently speeding up and slowing down the vehicle. In order to evaluate this phenomenon, we conducted a study in which four drivers drove the same selected route with the same starting time, which eliminates possible variations of road and traffic conditions. Figure 8a–c shows the vehicle speed, acceleration and acceleration change profiles of the four drivers. As can be seen from these figures, the four drivers have similar speed profiles due to the same traffic congestion, stop signs, speed limit, and traffic lights. On the other hand, their driving profiles vary significantly in terms of vehicle acceleration and acceleration change.

Figure 7. Heterogeneous routes driven by the six users in our study.

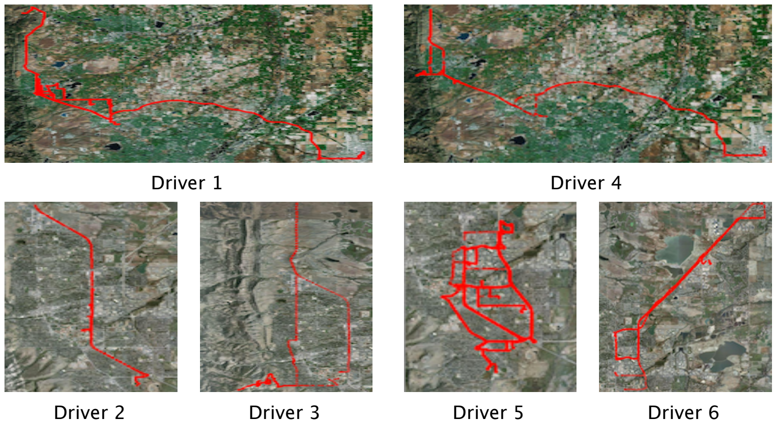
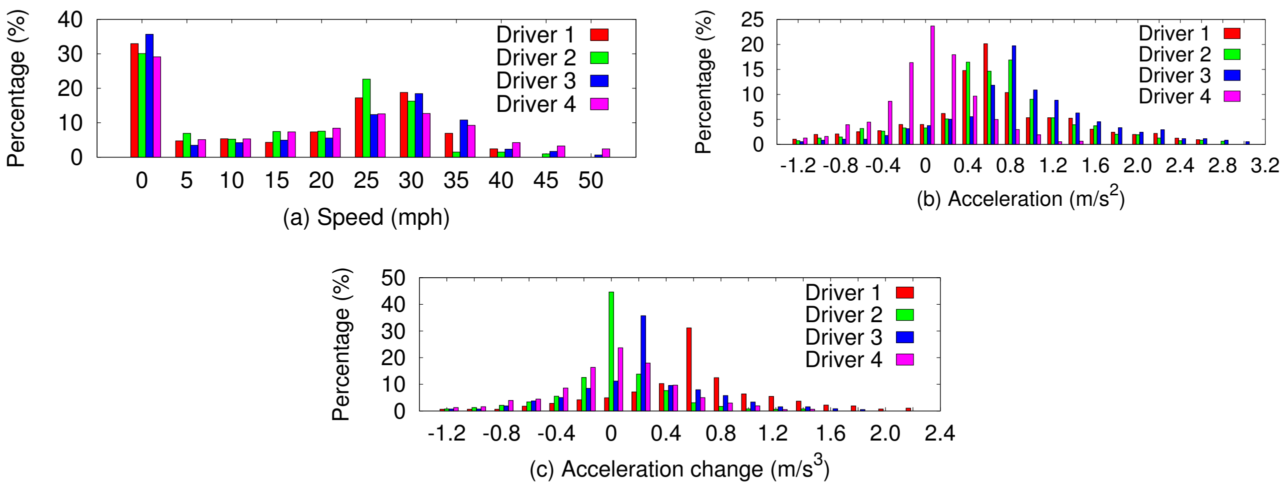


Table 2. Comparison of different participants' driving trips.

Driver ID	**1**	**2**	**3**	**4**	**5**	**6**
Total time (s)	43,176	26,218	22,188	37,498	44,615	103,608
Total distance (mile)	366.4	177.8	166.5	322.4	185.6	537.1
Total days	14	9	5	27	11	25
Total trips	26	22	18	37	43	35
Time per day (s)	3084	2913	4438	1388	4056	4144
Distance per day (mile)	26.2	19.8	33.3	11.9	16.9	21.5

Figure 8. Speed and acceleration comparison of four different drivers on the same route.



Based on the analysis above, users' driving behaviors are mainly manifested in the following aspects: acceleration, change of acceleration, slope and speed.

- ***(P)HEV Energy Studies*** This part investigates the impacts of user driving behavior on (P)HEV fuel efficiency and battery system usage. The following studies use the real-world user-driving data gathered from the deployed personalized mobile sensing systems, and the proposed modeling and analysis framework to investigate the impacts of road conditions, as well as user-specific driving patterns.

  1. *Impact of Road Conditions.* Road conditions vary within users' daily trips, which affect user driving patterns and (P)HEV operation. Figure 9 shows the speed and acceleration profiles under three road conditions: city, freeway, and mountain. As shown in this figure, road condition has direct impact on vehicle operation. One key factor is the dynamic elevation change during mountain driving. Freeway driving exhibits the minimal vehicle acceleration, due to the smooth road and traffic conditions. Figure 10 investigates vehicle fuel usage and battery use under different road conditions. In this study, to evaluate the impact on both fuel efficiency and battery system, the PHEV operates in the normal hybrid mode, and the EV mode is disabled. Figure 10a shows the PHEV battery system use. From freeway, city, to mountain driving, the battery system operation becomes increasingly intensive, as more demand from the electric motor (battery discharge) and more braking energy can be harnessed (battery charge). However, the assistance of the battery system does not come for free. Figure 10b estimates the long-term battery capacity loss due to thermal-dependent battery aging effects. It demonstrates that, such intensive battery use causes significant battery self-heating, which accelerates thermal-dependent battery aging effects.

Figure 9. Speed and acceleration comparison under different road conditions.

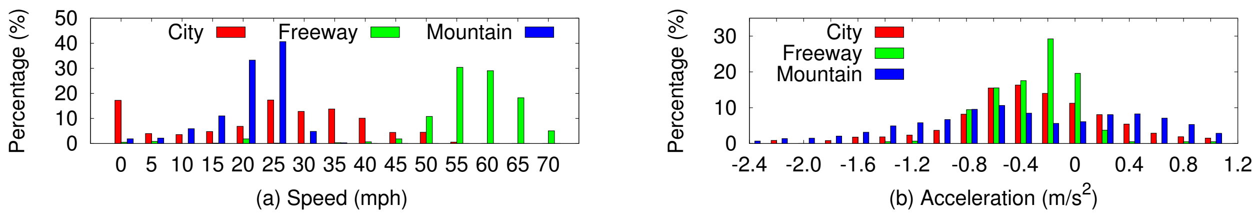
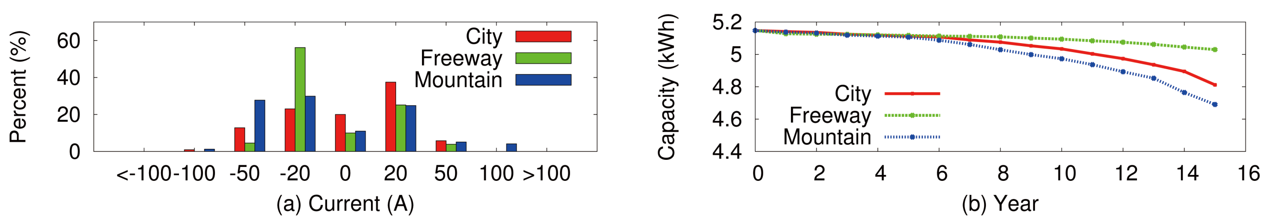


Figure 10. Fuel usage and battery use comparison under different road conditions.



  2. *Impact of User-Specific Driving Patterns.* Driving behavior differs significantly among users, even under the same road and traffic conditions. According to the analysis above, four participants drove along the same selected route with the same starting time, in order to eliminate possible variations of road and traffic conditions. Figure 11 investigates the impact of user-specific driving patterns, which demonstrate the strong correlation between

user-specific driving pattern and vehicle battery system use and capacity degradation. Aggressive driving patterns result in intensive battery system use, causing significant battery life-time aging and capacity loss.

3. *Impact of User-Specific Routes and Driving Patterns.* Different users have different driving patterns, and their routes can be different. Here, we investigate the mixed impact of both routes and driving patterns using six different users' daily driving data. Firstly, Figures 12,13 show the histogram of acceleration, the change frequency of acceleration, speed and slop for different drivers. Based on Figure 12 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 13a compares the speed histograms of different drivers. For instance, driver 5, who drives mostly on city roads, generally has a lower speed profile than people who drive on freeway (e.g., drivers 1 and 4). Figure 13b shows the histograms of slope in different users' trips, measured as rad per minute. As shown in this figure, some people drive mostly on level roads (e.g., drivers 5 and 6), while others also drive in the mountain with more diverse slopes (e.g., drivers 2, 3 and 4).

Figure 11. Battery use and capacity loss comparison of different drivers on the same route.

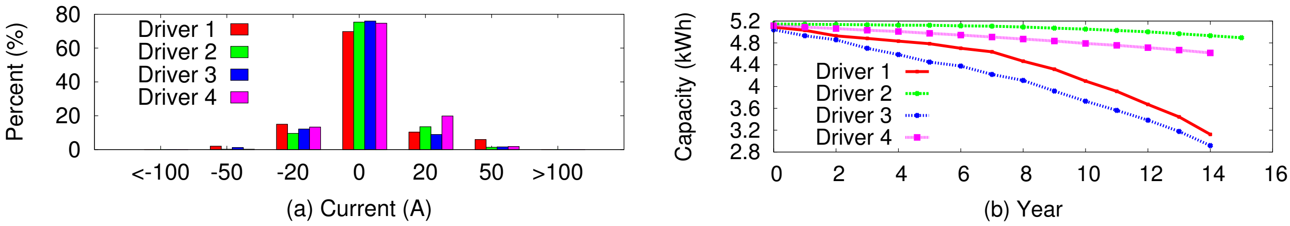


Figure 12. Acceleration (acc.) and Acc. change frequency histogram comparison of different drivers.

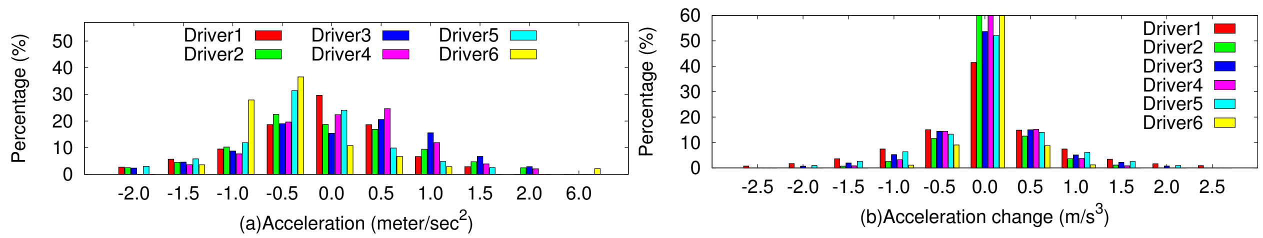
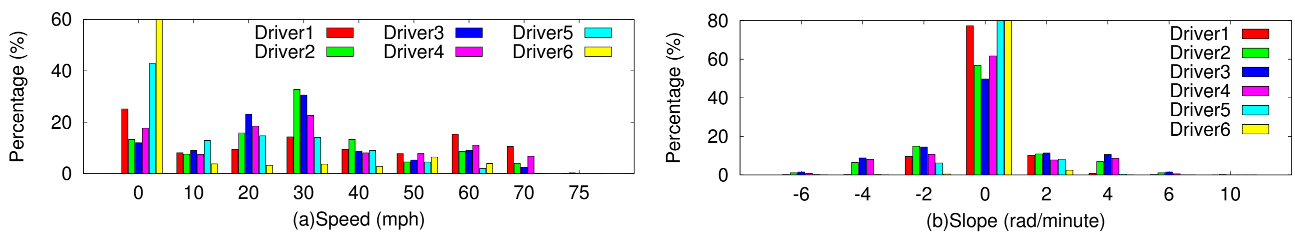


Figure 13. Speed and slope histogram comparison of different drivers.



Secondly, in order to analyze the battery system long-term energy usage, we assume that each user drives his/her vehicle for daily commute with the same trip under same road and traffic condition for 15 years. As shown in Figure 14, different people drive differently, thus having different energy demand. Those who drive aggressively have higher acceleration values and more acceleration changes, resulting in higher energy demand. Others who drive more smoothly with lower acceleration values and fewer acceleration changes have lower energy demand. Using the six different users' driving profiles and the proposed large-scale battery system model (Section 3), we obtain the battery system long-term capacity degradation as shown in Figure 3. For instance, some aggressive driving patterns, such as frequent slowing down or speeding up of the vehicle, lead to battery system's intensive charge and discharge operation. Such intensive run-time use makes significant battery self-heating, accelerates temperature-dependent life-time aging effects and capacity loss.

Figure 15a illustrates the thermal distribution in a 15-year battery system for six different drivers. As we can see from this figure, different driving behaviors lead to different long-time thermal distribution in the battery system. Figure 15b demonstrates significant variation of battery system aging among the six drivers, ranging from 14.9% to 74.3%. More importantly, due to the heterogeneous thermal distribution in a battery system, the aging effects vary significantly among the individual battery cells. Strong correlation is demonstrated between user-specific driving pattern and battery system capacity. For instance, driver 3 has the most aggressive driving profile and therefore the worst battery capacity fading effect, while the best battery system performance is achieved under driver 6's driving profile.

Figure 14. Real-time energy demand of different drivers.

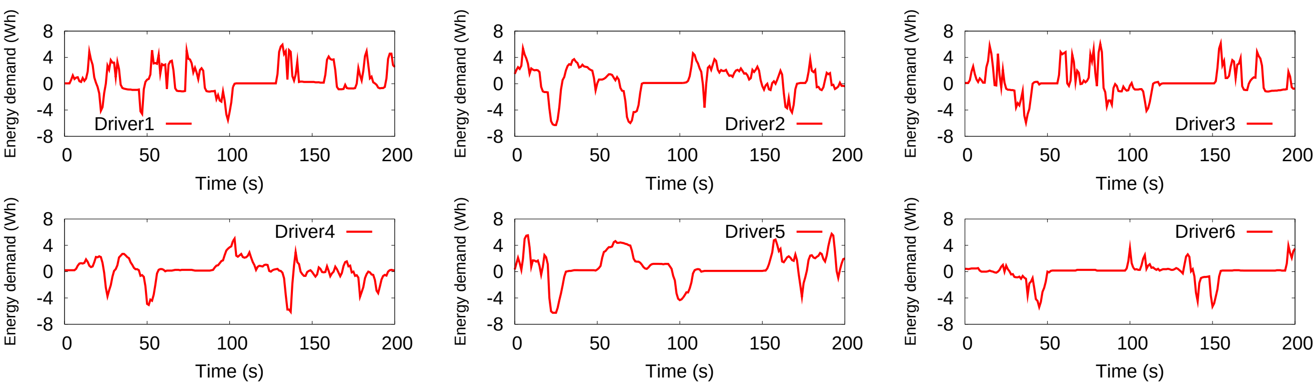
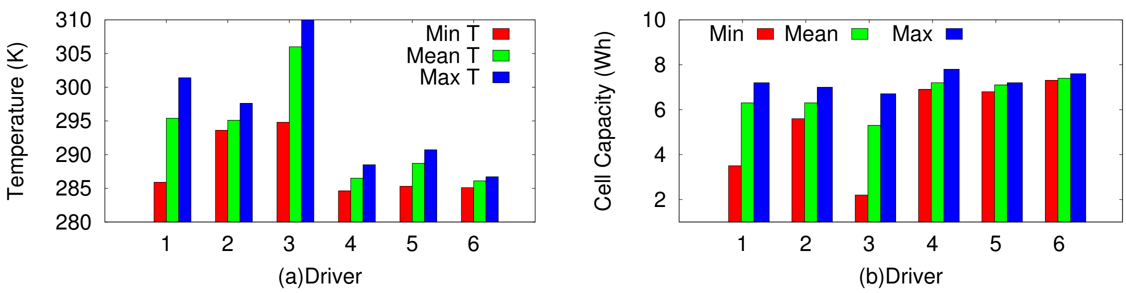


Figure 15. 15-year battery system thermal and capacity distribution of different drivers.



4.3. Energy Economy Analysis

An energy economy analysis of PHEV requires consideration of both fuel consumption and electricity consumption. Here, we adopt a powertrain system analysis tool called PSAT [26]. PSAT is a vehicle-modeling package that can be used to estimate the energy consumption and fuel economy via MATLAB/Simulink. It provides realistic estimation of the energy consumption through wheel torque analysis. The configurations of our hybrid vehicle in PSAT are showed in Table 3.

Table 3. Hybrid vehicle configuration.

Component	**Specifications**
Powertrain	parallel hybrid
Axle	four-wheel drive
Transmission	ECVT (electronically controlled continuously variable transmission)
Engine	2004 US Prius
Single Grear Ratio (torque coupling)	2
Final Drive Ratio	3.8
Frontal Area (m^2)	2.1
Drag Coefficient	0.26
Tire Rolling Resistance	0.007 (plus speed related term)
Wheel Radius (m)	0.317

PHEV's operation mode plays an important role in determining the performance of the vehicle during a trip. In Toyota Prius, there are three different modes [29]:

- *Charge Sustain (CS) mode.* In this mode, Prius acts as a conventional HEV with charge and discharge cycles and try to sustain the SOC level. During a trip, when the driver steps on the gas pedal to cause acceleration, the battery provides necessary auxiliary power. In this case, discharge current is observed. When brakes are applied and the vehicle is decelerating or standing still, battery recharge and charge current are observed, and the current profile is determined primarily by the driving behavior.

- *Charge Deplete (CD) mode.* In this mode, once the vehicle is fully charged, it can be operated almost exclusively (except during hard acceleration) on electric power until its battery state of charge is depleted to a predetermined level, at which time the vehicle's internal combustion engine or fuel component will be engaged.

- *Blended mode.* This is a special charge-deplete mode and usually employed by vehicles, Prius for instance. This is needed when there is not enough electric power to sustain high speed, therefore requiring the help of the internal combustion portion of the powertrain. In Prius, when the speed is less than a preset value, which is considered to be the bottom line of the vehicle speed below which the engine cannot operate steadily, the vehicle will only use electric power no matter what the driving behavior is, while the engine is idling. This is called EV mode by Toyota, which is short for Electric Vehicle mode. This mode is similar to the standard CD mode except for the condition of speed limitation. At higher speed, the internal combustion engine will be used to provide power, while electric power can continued to be used.

Given a real-world driving trace, the PSAT tool [15] estimates the current operation mode based on driving behavior and battery system capacity state for each year, which is estimated by our large-scale battery system model. After that, We can then calculate fuel and electricity consumption separately.

- ***Energy Economy Modeling.*** To compare the economic implications of purchasing a PHEV or conventional automobile, we conduct an analysis based on the following assumptions. PHEVs and conventional automobiles provide similar transportation utility and average (amortized) maintenance cost [30]. We do not consider the cost of battery replacement because the hybrid battery packs are designed to last for the lifetime of the vehicle, according to Toyota. Since Prius first went on sale in 2000, they have not replaced a single battery for wear and tear [30]. We ignore the impact of inflation, but note that inflation has a similar relative impact on the return of investment for both types of vehicles. We also assume that air pollution is proportional to both gasoline and grid-distributed electricity use, albeit with different factors. We use 12 cents per kWh [31] and \$2.578 per gallon. Table 4 shows the cost breakdown of conventional and hybrid vehicles. We can then calculate the energy usage cost model for conventional vehicle and PHEV according to Equations 14 and 15.

$$ECost_{old-vehicle}(t_i) = ECost_{old-vehicle}(t_{i-1}) + Fuel_{used-gallon} \cdot 2.578 \times 365 \tag{14}$$

$$\begin{aligned} ECost_{PHEV}(t_i) = & ECost_{PHEV}(t_{i-1}) \\ & + (Electric_{used} \times 0.8 \times (0.12/1000) + Fuel_{used-gallon} \cdot 2.578) \times 365 \end{aligned} \tag{15}$$

where $ECost_{old-vehicle}(t_i)$ and $ECost_{PHEV}(t_i)$ are the energy usage cost for conventional vehicle and (P)HEV in the i-th year, respectively. $Fuel_{used-gallon}$ is the cost of fossil fuel usage, and $Electric_{used}$ is the cost of electric usage.

Table 4. Cost breakdown of conventional and hybrid vehicles.

Type	Cost	
	Conventional	**Hybrid**
Purchasing	\$17,245	\$21,881
Electricity	N/A	12 cents per kWh
Gasoline	\$2.578 per gallon	\$2.578 per gallon

- ***Energy Economical Analysis.*** For each driver in our study, we pick the most frequent trip as the driver's representative daily trip. By feeding the trip information into PSAT, the energy consumption of six different drivers is calculated and shown in Table 5.

  Note that the data in Table 5 are calculated under the initial condition that the built-in battery system is brand new. As time goes by, battery system capacity decreases based on the proposed battery system model, and the proportion of fuel usage will increase accordingly. As shown in

Table 5, drivers 1, 2, 3 have similar energy usage profiles, and their fuel ratios are much higher than that of others. For drivers 4, 5 and 6, although their fuel ratios differ from each other, the values are fairly low compared with the first 3 drivers. This trend is in accordance with their respective driving behaviors in these representation trips. Table 6 characterizes the driving behavior for each driver based on his/her corresponding representative trip, and the variance value represents how steadily he/she drove on this trip. Larger variance values represent more aggressive driving, and vice versa. The table shows that drivers 1, 2, 3 have greater variance of acceleration than drivers 4, 5, 6. Driver 6 drove most steadily, resulting in the smallest fuel ratio.

Table 5. Vehicle energy consumption breakdown of six drivers' daily trips.

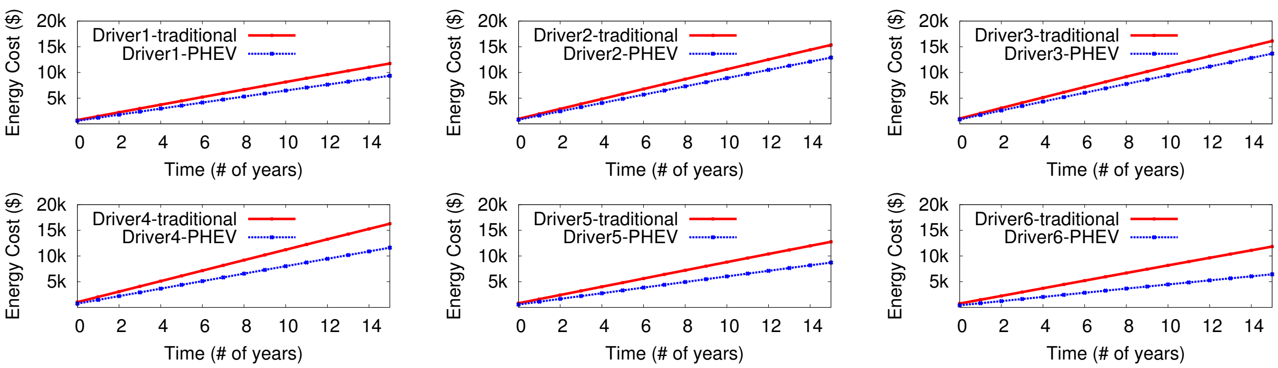
Consumption	Fuel(Wh)	Electrical(Wh)	Total(Wh)	Fuel Ratio	Electricity Ratio
Driver 1	15,298	7298.0	22,696	80.19	19.81
Driver 2	23,155	7419.8	27,057	85.58	14.42
Driver 3	25,125	7525.2	30574.8	86.24	13.76
Driver 4	19,104	13,351	32,455	58.87	41.13
Driver 5	13,656	10,958	24,614	64.73	35.27
Driver 6	8440.3	14,085	22525.3	45.40	54.60

Using the PSAT tool and our proposed battery system model, we can compare the economic impact of purchasing a conventional or hybrid vehicle. We first calculate the 15-year energy cost for both conventional vehicle and PHEV. The overall cost saving is showed in Figure 16. As shown in the figure, the energy cost of conventional vehicle is greater than that of PHEVs, but the extent depends on the driving behavior. For instance, driver 6 has the largest cost saving, while the savings for the first three drivers are much less, This trend matches well with Table 5. Therefore, we can draw the conclusion that the more steadily a person drives, the more saving he/she is able to get.

Table 6. Mean and Variance of Acceleration of Six Different Drivers.

	Driver 1	Driver 2	Driver 3	Driver 4	Driver 5	Driver 6
Mean	0.2901	−0.3762	−0.1462	−0.2718	−0.5153	−0.3849
Variance	0.5638	0.6085	0.7270	0.4683	0.5259	0.1699

Figure 16. Energy economy comparison between conventional vehicle and PHEV.



5. Conclusions

Emerging green-energy transportation has good potentials for reducing fuel consumption and greenhouse gas emissions. Large-scale battery system energy usage and user-specific driving behavior analysis are the key issues for (P)HEV manufacturers and drivers. This article presents a large-scale battery system modeling design and energy economy analysis under different real-world user-specific driving behaviors for emerging (P)HEV applications. We have developed an accurate and fast battery system model which supports short-term energy usage profile analysis, long-term thermal distribution and lifetime estimation, based on heterogeneous real-world user driving behavior. We give a comprehensive energy consumption and fuel economy analysis based on the proposed battery system model and real-world driving behavior. Generally, more smooth driving behaviors are better for electric-drive vehicle lifetime and cost saving. This work is an important step towards large-scale battery system modeling and energy economy analysis for emerging (P)HEV applications, which adequately incorporates and captures the impact of real-world user-specific driving behaviors.

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