Lithium-ion Batteries Life Estimation for Plug-in Hybrid Electric Vehicles

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Abstract— **This paper deals with life estimation of lithium batteries for plug-in hybrid electric vehicles (PHEVs). An aging model, based on the concept of accumulated charge throughput, has been developed to estimate battery life under "real world" driving cycles (custom driving cycles based on driving statistics). The objective is to determine the "damage" on the life related to each driving pattern to determine equivalent miles/years. Results indicates that Lithium-ion batteries appear to be 10 year/150,000 mile capable, provided that they are not overcharged, nor consistently operated at high temperatures, nor in charge sustaining mode at a very low state of charge.**

Keywords- Lithium-Ion Batteries, Battery Aging, PHEV, Weighted Ah-throughput models,

I. INTRODUCTION

Plug-In Hybrid Electric Vehicles (PHEVs) are receiving a great deal of interest in the United States. Recent improvements in lithium batteries technology are making PHEVs a viable solution to reduce cost, petroleum consumption and emissions in the transportation sector.

To make PHEVs a feasible solution, some issues need to be addresses, such as cost, abuse tolerance, and lifespan of the battery. The current cost of a Li-Ion battery is estimated at about $1000/kWh and the long term goal that would facilitate speedy introduction of PHEVs is $250/kWh. In order to achieve an all electric range (AER) of 30 miles, a PHEV sedan would need about 15kWh of available energy, thus resulting in a $15,000 premium. Economies of scale could definitely reduce the cost per kWh, but the battery clearly represents the most expensive component of the vehicle.

Lithium-ion batteries will play an important role in our mobility because of various advantages over other battery technologies like the high specific energy and the high specific power, which are very important for PHEV applications. In spite of these advantages there are some improvements needed in order to make the lithium-ion technique more competitive in particular in terms of costs and lifetime. The ability to predict the lifetime of batteries is essential for the market introduction of lithium batteries in the plug-in hybrid electric vehicle market. But this key challenge is very complex because in this electrochemical system a number of aging processes take place parallel due to different stress factors which are caused by the varied operation conditions of the battery related to the drivers requirements.

Accurate estimation of batteries life is a great challenge in particular for lithium-ion batteries in traction applications because these batteries experience a very irregular pattern of charge and discharge cycles depending on the driver's driving and recharging habits. The requirements of the driver (power and energy demand) determine the operating conditions of the battery like current and voltage. But also other factors like the temperature distribution within the battery, the depth of discharge (DoD) and the state of charge (SoC) of the battery must be taken into account in the lifetime estimation. These operating conditions determine the stress factors which induce the aging and the rate of aging.

A successful lifetime prediction requires knowledge of the aging processes, the stress factors and their relationships.

II. BATTERY LIFE ESTIMATION

There are two completely different approaches for lifetime estimation: *performance-based models* and *weighted Ah-throughput models* (or cycle counting).

- Performance based models simulate the change of performance values of the battery (e.g. capacity, voltage, current). The End-of-Life (EoL) of the battery is reached when a predetermined particular performance dropped under a threshold value.
- Weighted Ah-throughput models link the End-of-Life of the battery to some parameters which can be determined such as: Ah-throughput, number of cycles or time since manufacturing.

Performance based models

Models which are capable of simulating the change of performance of a battery including aging processes can be distinguished into four groups:
- Electrochemical models
- Equivalent circuit models
- Analytical models with empirical data fitting
- Artificial neural networks (ANN)

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In the following these models and their advantages and disadvantages are shortly discussed.

Electrochemical models provide very detailed information and results on local conditions and performance (e.g. temperature, potential, current, electrolyte concentration etc.). But they require knowledge of the chemical and physical interaction. This type of model is the most complex needing several input information (e.g. porosity of the active materials, electrolyte volume and density, etc.). Because of the complexity of the model the computational speed of simulation is low.

In *Equivalent circuit models* the battery is represented by components of an equivalent circuit like voltage and current sources, resistors, capacitors, inductances. The aging processes are represented by the changes of the values of the equivalent circuit diagram. This type of models is very common for predicting battery dynamic characteristics, but there is no predictive model in the literature which capture the slow variation of model parameter with aging, and with factors contributing to aging such as C-rate, DoD and temperature.

In *analytical models* with empirical data fitting the lifetime is predicted by means of interpolation and extrapolation from test results and field data. For this purpose a lot of data is required. And the question how to investigate a particular effect on battery lifetime such as C-rate, DoD and temperature still remains open.

Artificial neural networks have a tremendous potential to discover relationships between inputs (operating conditions) and outputs (ageing processes and performance values). This model does not rely on a detailed understanding of the mechanism which link input and output, but measurements are necessary in order to conduct this model.

Weighted Ah-throughput models

Weighted Ah-throughput models are based on the assumption that under particular standard conditions (C-rate, temperature, DOD) a battery can achieve an overall Ah-throughput until the end of life (EoL) is reached. This data is usually given by the battery manufacturer and is required for the lifetime estimation with the weighted Ah-throughput model. The impact of a given Ah throughput on the battery lifetime depends on the details of the conditions during this Ah throughput. One important advantage of this model is that it takes into account that deviations from the standard operating conditions (C-rate, DOD) may increase or decrease the physical Ah-throughput and consequently also the rate of aging. The equation for the effective Ah-throughput is given by:

$$Ah_{eff} = \sum w_E \cdot n_E \cdot Ah_E \qquad (1)$$

The sum over all events E consists of Ah_E being the Ah-throughput of an event E, n_E the number of events E and w_E the weighting factor for the event E, which can consider the force of the current of this event or the temperature, or the DOD. There can also be used multiple weighting factors considering different operating conditions (e.g. w_{EI} for the current I, w_{ET} for the temperature and so on). The End of Life of the battery is given once the effective Ah throughput exceeds the total Ah-throughput measured under standard conditions or expressed in an equation:

$$\frac{\sum w_E \cdot n_E \cdot Ah_E}{Ah_{total}} = 1 \qquad (2)$$

This model represents a good option for the lifetime estimation of batteries in PHEVs because of its various advantages. It has an easy basic structure and this allows very high computational speed and can be adapted to different battery technologies. The main issue remains the determination of the parameters for the weighting factors (severity factors). Accurate values would require extensive data collection, not yet available.

III. APPROACH

Most batteries have a nominal cycle life (20% loss in capacity) when doing 100% DoD cycles. Cycles with lower DoD have minor effects on performance degradation (i.e. loss in capacity, increase in resistance), thus resulting in a typical "throughput" type model, where the total number of partial and full cycles are proportionally added together to find out how much of the life has been expended (manufactures publish a curve of expected cycle number vs. depth of discharge of each cycle).

Recent data shows that there is some validity to this, if the battery begins at 100% SoC and is discharged repeatedly to some depth before recharge; given these assumptions, the throughput model is roughly correct (although a bit pessimistic).

A PHEV battery model was developed through a collaborative effort between Ohio State University Center for Automotive Research (OSU-CAR) and General Electric (GE) Global Research. This model is based on the concept of accumulated charge throughput and considers the following input and output.

Input: load duty cycles for batteries based on a typical/predicted usage patterns. One or more typical week/month/year can be identified based on customer driving habits.

Output: life as function of above duty cycles. Number of miles that a battery pack could run within a capacity loss lower than 20%.

The objective is to determine the "damage" on the life related to each driving pattern/ battery load profile; as a final step, the number of cycles is converted into equivalent miles / years.

Battery 'aging' nominally depends on accumulated charge-transfer in/out of the battery (A-h throughput) and the severity

of this charge transfer at each instant. At the cell level, the severity of the charge transfer depends on:
- Current severity relative to battery size (*i.e.,* C-rate)
- Temperature
- DoD/SoC
- Possibly other factors

At the pack (vehicle) level, the determining factor for pack aging and life is going to be the most aged cell, strongly impacted by both electrical cell balancing/BMS and thermal design/management.
Our focus here is on cell level and generalization to the vehicle level under assumption of all cells equivalent.

IV.   APPROACH TO MODELING OF AGING

The age of the battery is expressed in terms of variation of damage variables, i.e. the (physical or functional) parameters of the battery whose value changes irreversibly because of aging and modify the behavior of the system (see [2] for more details). A generic dynamic system subject to aging can be described as:

$$\dot{x} = f(x, \vartheta, u)$$
$$\dot{\vartheta} = \varepsilon \cdot g(\vartheta, p) \qquad (3)$$
$$y = C \cdot x + D \cdot u + v$$

where

$x =$ state variables associated to the fast dynamics

$\vartheta =$ damage variables associated with slow dynamics

$u =$ external inputs

$p =$ vector of internal/external aging factors (including x and u)

$y =$ outputs

Variation of damage variables implies slow changes in the system behavior, hence aging.
In this work the capacity is considered as the only aging parameter that effects battery life and thus, life characteristics of the battery are defined based on its residual capacity. To express the progression of the aging process the normalized damage measure ξ is defined as:

$$\xi(\vartheta) = \frac{\vartheta_0 - \vartheta}{\vartheta_0 - \vartheta_f} = \frac{S_0 - S}{S_0 - S_f} \qquad (4)$$

In practice ξ is a scalar index varying between 0 and 1, where 0 indicates beginning of life and 1 end of life. (S_0 is the capacity of a new battery and S_f is the capacity of a battery at the end of its life). The evolution of the damage variable ϑ is expressed as variation of damage measure ξ as:

$$\frac{d\xi}{dn} = \varphi(\xi, p) \qquad (5)$$

V.   BATTERY MODELS AND DAMAGE VARIABLES

The framework for battery aging is a damage accumulation model borrowed from mechanical fatigue ([1], [2]). In the study of mechanical fatigue the most common approach to modeling the aging of a mechanical component is the use of the Palmgren-Miner rule (see, for example, [3]). The rule states that the life of a component under a sequence of variable loads is reduced each time by a finite fraction. This reduction corresponds to the ratio of the number of cycles spent under the given load condition and the number of cycles that the component would last if subjected to that same load condition for its entire life. In other words, if n_i is the number of cycles spent under the load condition p_i and $N(p_i)$ is the number of cycles that the new component would last if it were cycled under condition p_i until failure, the end-of-life due to a sequence of variable loads $p_i, i = 1 \ldots W$ corresponds to the condition:

$$\sum_{t=1}^{W} \frac{n_i}{N(p_i)} = 1 \qquad (6)$$

i.e., the end-of-life is reached when the cumulative of the fractions of life reduction reaches the unit value. The total life is a function of the loading conditions, and is obtained from experimental data for a wide variety of loads, components, and materials. The equivalence between the Palmgren-Miner, (6) and the damage accumulation model (4), is given if and only if (5) can be factorized as product of two independent functions (see [4]):

$$\frac{d\xi}{dn} = \varphi(\xi, p) = \varphi_1(\xi)\sigma(p) \qquad (7)$$

The expression (7) allows for tracking the progression of aging if the functions $\varphi_1(\xi)$ and $\sigma(p)$ are known. The two functions can be defined respectively as the age factor (how the aging progresses) and the severity factor. The severity factor function depends on the severity occurring to the battery, e.g., temperature, SoC/DoD, current, etc.   It must be mapped using experimental results, since they account for different effects, and are derived using experimental data collected during aging experiments.
In this work, we specifically focus on the characterization of the severity factor function for Li-Ion batteries for PHEV application.

VI.   SEVERITY FACTOR FUNCTION FOR PHEV APPLICATIONS

The main aging factors for PHEV applications can be identified in:
- Temperature
- SoC/DoD

The C-rate effect on aging can be neglected. Typically, the battery is oversized for PHEV applications and therefore typical current C-rates range between ±4C (±2C typical), and hence the currents encountered in such applications do not contribute to any significant severity unlike HEV applications where currents ranging up to ±10 or 15C are experienced. The vector p of aging factors in the aging accumulation model (5) is then given by [T,SOC/DOD].

The determination of the severity factor surface is typically difficult to obtain and is very dependent on the particular battery chemistry, anode and cathode composition, construction. Furthermore, all information related to aging characteristics even for a given cell, requires extensive and very lengthy (hence costly…) data collection. In the context of the methodology described in this paper, two primary types of information is feasible: First, the (very scarce) aging data provided by battery manufacturers, obtained typically under well described, but not necessary relevant PHEV aging protocols; and second, aging data collected at our facility under a variety of proprietary and in-house research protocols. For the purpose of this paper, a prototypical example of aging severity factor was extracted from manufacturer's data, albeit with considerable difficulty as the tests were not necessary conducted with our framework in mind (typically aging is assessed by cycling a cell with 100% depth of discharge at a few temperatures at a set 1C current). Alternatively, we have extracted current, DoD and temperature data from actual vehicles and/or vehicle simulations and develop a methodology to extract statistically representative aging protocols which mimic real life operation. An example of current profile corresponding a charge-depleting PHEV on a US06 driving cycle is shown in Figure 1, and the statistical distribution of current C-rate is shown in Figure 2. One US06 driving profile corresponds in this case to approximately 5% DoD. A synthesized (simplified) current profile is extracted from this data with a statistically similar joint distribution of current level and SoC. For battery aging, this profile is repeated multiple times until a set low SoC limit is reached and the battery is recharged at a prescribed rate (typically 1C for rapid charging). Meanwhile, the cell under aging is subjected a fixed or variable temperature environment.
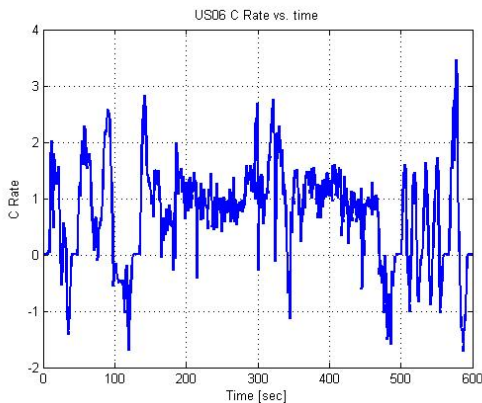

Figure 1 - Typical Current (C-rate) Profile as a Function of Time for a PHEV (in Charge-Depleting Mode) during an Actual Driving Cycle.
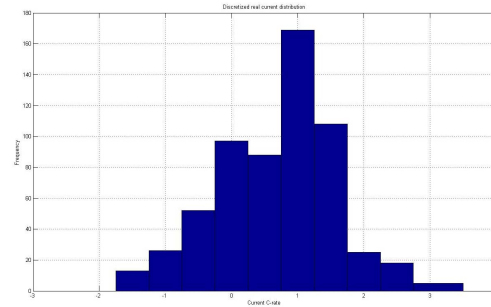

Figure 2 – Typical Current (C-rate) Statistical Distribution for a PHEV (in Charge-Depleting Mode) during an Actual Driving Cycle.

These protocols have been implemented in our battery aging facility, which consist of 12 battery cyclers operated on a 24/7 basis, complete with Peltier junctions or environmental chambers to control the thermal environment.

In this paper, for the purpose of illustration of the methodology, and to not impact on proprietary information, we are limiting ourselves to an estimate of the value of severity factor as function of operating temperature and SoC/DoD based on publically available data. This severity factor surface will be referred to as 'estimated' in the remainder of this paper. The topology of this 'estimated' severity function, while specific to a particular cell and very lengthy to determine experimentally, is generic enough in its overall shape. The 'estimated' severity factor function, σ as a function of T and DoD, is shown in Figure 3.
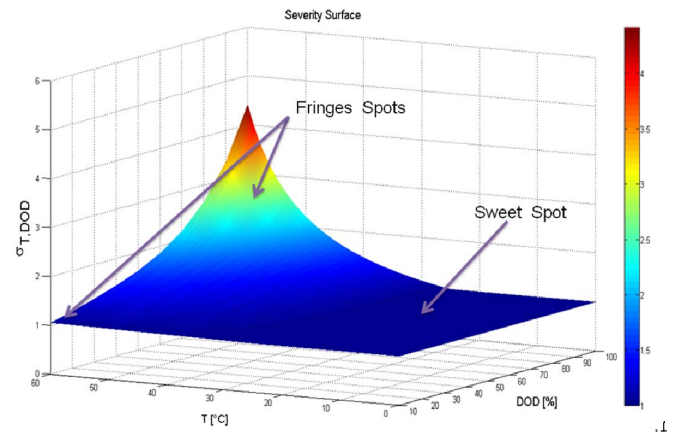

Figure 3 - Severity Factor Map.

The damage accumulation is linked to severity factor parameters, T and DoD, and the postulate is that the map is nominally 1 in the 'sweet spot', increasing rapidly at the 'fringes'. Thus, high temperatures and high DoD will result in higher severity factors which will age the battery faster, while low DoD and low-medium temperature will not affect the severity of the aging, and hence, the A-h discharged and stored into the battery will count all the same.

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While the focus of this methodology is to relate actual vehicle conditions to a damage accumulation model of the aging, the same methodology can be used 'in reverse' to engineer aging studies. This opens up the opportunity for model-based design of aging experiments to experimentally obtain severity maps in an accelerated fashion. This procedure will be described in a separate upcoming paper.

The 'estimated' severity factor map, incorporated in the aging model presented in the previous section, is used to estimate battery life. A case study under "real world" driving cycles is discussed in the next session.

VII. MODELING ASSUMPTIONS

For this study a mid-sedan PHEV30 was selected, thus allowing up to 30 miles of AER (All Electric Range) in UDDS (Urban Dynamometer Driving Schedule) throughout the life of the vehicle.

TABLE 1- BASIC VEHICLE MODELING PARAMETERS.

	Conventional	PHEV-30
Glider Mass (kg)	693	693
Engine/Transmission/Final Drive/Wheels (kg)	441	374
Power Electronics and Electric Machine (kg)	0	44
Energy Storage (kg)	0	124
Fuel Subsystem (kg)	58	48
Total Vehicle Mass (kg)	1192	1283
Total Vehicle Mass w/ 136 kg Cargo (approx. 2 passengers)	1328	1419
Battery Energy (kWh)	-	14
Engine Power (kW)	110	50
Motor Power (kW)	-	55

The considered vehicle requires approximately 260 Wh/mile for electric mode in UDDS cycle, thus resulting in about 7.8 kWh of stored energy required to run 30 miles in AER. To account for battery aging and performance issues, the usable SOC has been assumed in the range 0.25-0.95; starting from this assumption the total storage capacity of the battery needs to be about 11.2 kWh. Annual degradation of the battery capacity has been taken into account by estimating the energy required by each driving pattern and exchanged by the battery both in charge depleting and charge sustaining mode. In order to achieve the desired AER throughout the life of the vehicle (10 years/150,000 miles) part of the battery capacity is preserved and not completely used. Assuming a battery pack sized to keep at least 80% of its original capacity after 150,000 miles, this results in over-sizing the battery pack up to 14 kWh of available energy (300 V, 46.7 Ah) in order to have at least 7.8 kWh of usable power at end of life. These assumptions are probably somewhat conservative.

The EV-mode energy management policy, that is the decision made at the vehicle level to use electric energy exclusively, until the battery has reached a lower acceptable SOC limit, is adopted to maximize fuel economy: independent of trip distance and/or driving patterns, the vehicle runs in pure electric mode (charge depleting) until a set SOC threshold is reached, then the vehicle reverts to parallel, series or dual-mode hybrid operation. Even though this might not result in an optimal power split, its simplicity allows easy and economic implementation on board on today's vehicles without the need of additional devices (e.g. GPS to determine driving cycles in advance). Evaluation of alternative control strategies is currently underway. Refer to [5] and [6] for further details.

In order to simulate "real world" scenarios, custom driving cycles/typical days were identified starting from average driving statistics and well-known cycles.

TABLE 2- DRIVING AND CHARGING EVENTS.

	Description
T1:	UDDS+US06 (trip to work after full charge)
T1b:	US06+UDDS (trip to home after work). Initial SOC is the final SOC of previous trip
T2:	UDDS (errands). Initial SOC is the final SOC of previous trip
T3:	UDDS+HWFET+HWFET+HWFET+HWFET+UDDS (this assumes the vehicle is only recharged at the end of the day)
C1:	Overnight charging after T1b
C2:	Overnight charging after T2
C3:	Overnight charging after T3

The combination of the described events and typical days results in 15,428 miles/year and 3,150 kWh/year of energy needed to recharge the vehicle.

TABLE 3 - SIMULATED TYPICAL DAYS.

	Events	Frequency
D1	T1-T1b-T2-C2	3 days/week, 48 weeks/year (tot. 144 days/year)
D2	T1-T1b-C1	2 days/week, 48 weeks/year (tot. 96 days/year)
D3	T3-C3	2 days/week, 48 weeks/year + 7days/week, 4 weeks/year (tot. 124 days/year)

For a complete analysis it is also important to consider different charging availability, i.e. how often it is possible to recharge the battery. In this paper two main scenarios have been inspected: controlled charging (once a day, overnight) and uncontrolled charging (charging is possible whenever the vehicle is parked).

Clearly through uncontrolled charging a better fuel economy can be achieved, but at the price of reduced battery

life. Other issues are related to the possible overload of the power grid, but this will not be discussed in this paper.

VIII. VEHICLE DATA

The Center for Automotive Research at The Ohio State University has launched a new program focused on Plug-in Hybrid Electric Vehicles (PHEVs), Electric Vehicles (EVs) and intelligent charging: SMART@CAR [7]. Several projects are currently underway, ranging from modeling the effects of PHEVs penetration into the energy market to vehicle data collection, etc.

The program is currently in its early phases with the first prototype data acquisition systems operating in vehicles. In order to build up the database, a limited number of vehicles (two or three) will be fitted with acquisition systems and distributed to various affiliates of SMART@CAR. Furthermore, we are currently negotiating with eTec (Electric Transportation Engineering Corporation) a reciprocal agreement that will allow us access to a much more extensive vehicle data base. DOE's Advanced Vehicle Testing Activity (AVTA), INL, and testing partner eTec initiated Plug-in Hybrid Electric Vehicle (PHEV) testing activities during the second half of 2006. The AVTA's PHEV activities include:

- development of the PHEV Integrated Test Plan and Evaluation Program, which is used to conduct accelerated on-road and baseline performance (dynamometer and test track) testing
- testing is being conducted on several PHEV models, with most of the PHEVs from conversion companies. The conversion companies and the base models include: the Hymotion Prius, Hymotion Escape, EnergyCS Prius, Renault Kangoo, HybridsPlus Escape, HybridsPlus Prius, Electrovaya Escape, Green Car Company Prius, and E85 capable Ford Escape
- on-road data collection has started for more than 100 PHEVs already deployed with onboard data loggers being used to capture real-world fleet operations data, including vehicle operations and charging profiles.

These vehicles will be loaned to members of these groups and used for general use – from business trips to picking up kids from school. Each person will have the vehicle for a period of several days to monitor the typical usage patterns of the particular person and then passed on to another test subject. In this way, a limited number of vehicles can be used to generate a database that is statistically representative of a certain segment of the population. Sample data shown in Figure 4 to Figure 8.
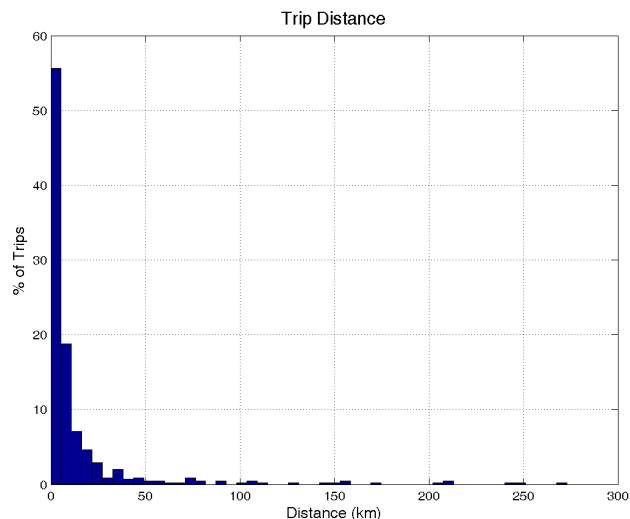

Figure 4 - Trip Distance – Statistical Data.

This task will answer important generic questions related to the fuel efficiency of PHEVs. The calculation of total distance traveled, mean speed, and fuel economy would provide the basis for comparison between the different parameters and also a starting point for comparisons under different conditions. Other calculated values include energy consumed over a trip, during charging, electric range, etc.
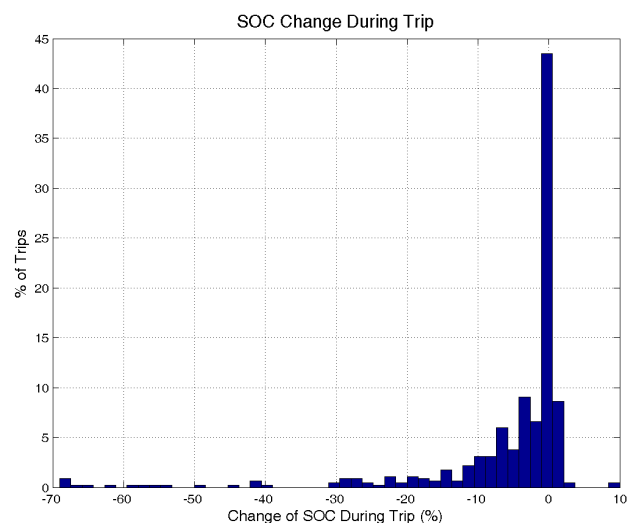

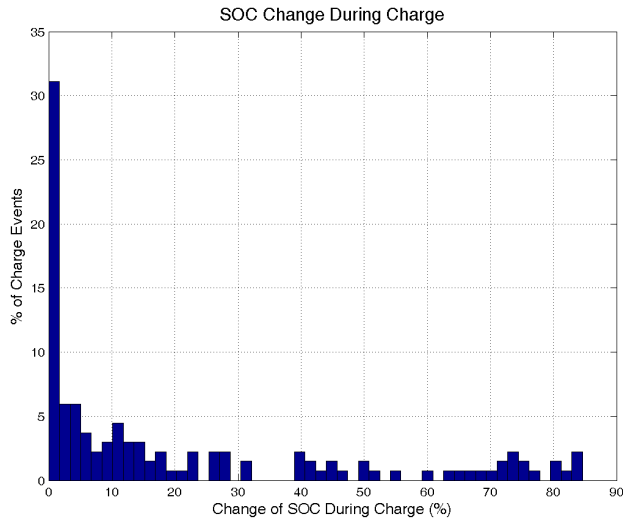Figure 5 - SOC Change During Trip.
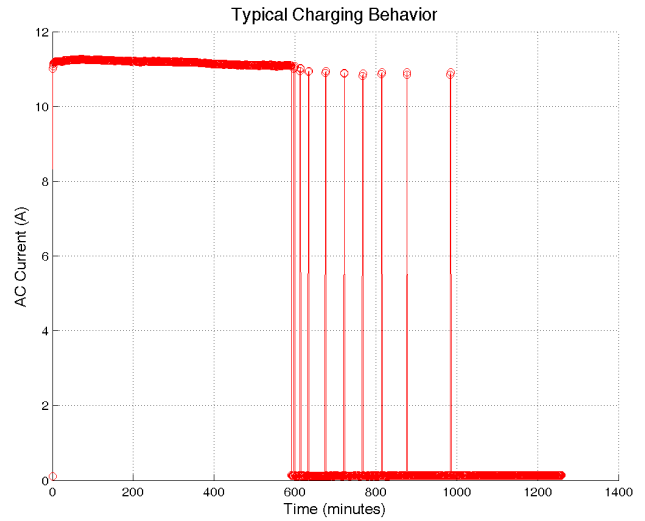
Figure 6 - SOC Change During Charge.

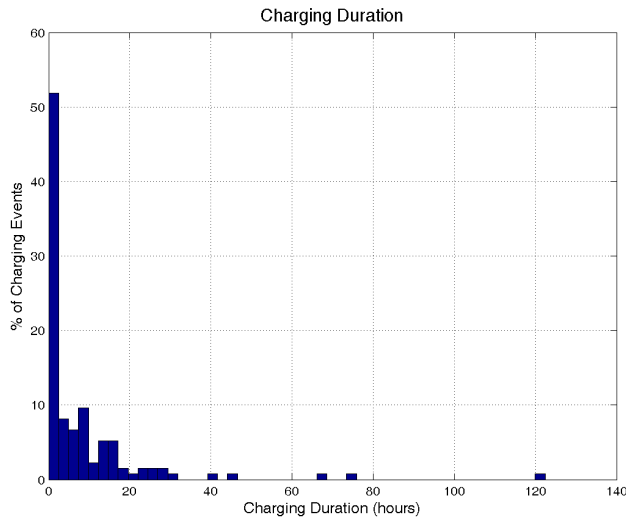Figure 8 - AC Current for a Typical Charging Event.

Figure 7 - Charging Duration.

The investigation will extend beyond the use of simple trip distance information by studying factors related to:

- in-vehicle data, i.e.:
  Vehicle characteristics
  Driving cycles
  Battery pack size (nominal)
  Battery type (conversion kit, battery technology)
  On-board energy (changes over time due to battery aging)

- environment and surroundings, i.e.:
  Operating temperature (weather conditions)
  Geographic characteristics (local analysis)
  Charging availability, charging events (number, duration, …)

IX.   RESULTS AND FUTURE WORK

To achieve 10 year/150,000 mile life, certain abuses must be avoided.   For example, the battery must not be overcharged; therefore, a safety margin of 5% capacity is used in this study and operation above the 95% state of charge (SoC) is avoided.
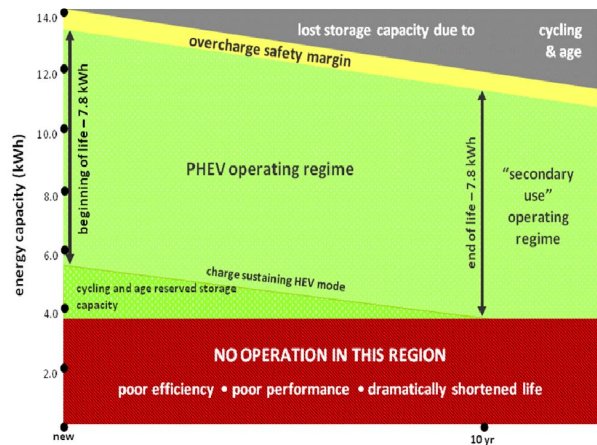

Figure 9 - Battery operating regime for PHEV applications.

If lithium ion cells are discharged or operated at a level lower than ~25% SoC, their efficiency and performance is degraded, plus significant heating and aging will occur.   To avoid this occurrence, a "No operation region" has been established in this study and the batteries will not be operated below 25% SoC.

To achieve 10 year/150,000 mile life of the energy storage system, the PHEV batteries configured in this study are in fact

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oversized. The PHEV required a Li-ion battery pack with a total energy capacity of ~14 kWh. The actual amount of energy used from the battery pack to achieve 30 miles AER is 7.8 kWh.

Studies are currently underway to consider the effects on battery aging of temperature and operating SOC.

Temperature Effects. Testing activities have been conducted at CAR to analyze the effects of temperature on lithium batteries performance. Collected data will be used to estimate severity factors as function of operating temperatures. Such factors are used to estimate battery life at different temperature levels.

Operating SOC Effects. Ideally, testing activities are required to evaluate the effects of different SOC operating points on battery aging. However, testing activities to estimate severity factors as function of SOC operating range would require years of lab tests. CAR is currently collecting data for aging purposes, but these activities represent long term goal and will not be completed in the next future.

In this study we postulate severity factors vs. SOC operating range. This allows to estimate aging effects of operating batteries at SOC lower than 25% or higher than 95%. Giving up these safety margins will result in unpredictable and shortened battery life. This estimation is based on literature data (if available) and (limited) available data collected at CAR battery aging lab.

Increasing the usable energy from batteries could help reducing battery size, thus costs. Automotive OEMs are interested in find ways to reduce cost of batteries. In fact, battery cost is the single largest impediment to large scale commercialization of PHEVs. The aim of this analysis is to assess the pros and cons of using more energy from batteries, thus reducing battery size.

Another approach is not to reduce battery size, but just use more energy. This allows better fuel economy at the price of life reduction. This study aims to understand the optimal trade-off.

X. CONCLUSIONS

This paper describes a damage accumulation model for the battery aging under vehicular operation. It is build on the concept that damage is accumulated with every charge transfer in or out of the battery (bi-directional A-h counting), modulated by a severity factor associated with the (local) conditions of this charge transfer. Li-ion battery, like many other chemistries, exhibit a 'sweet spot' where A-h in or out of the battery contribute equally to the accumulation of damage. However, the 'edges' of this sweet spots depend on C-rate, DoD and temperatures encountered, and the severity surface topology tend to rise rather quickly at those edges. Hence, it is critical to assess and quantify the topology of this surface for proper design, proper battery sizing (hence cost and weight) and powertrain control, so as to minimize the damage

accumulation and lengthen the life of the vehicle. While the methodology described in this paper is fairly generic and applicable to many classes of vehicles, it is highly critical for estimating the life of PHEVs as these vehicles, unlike HEVs, typically strive to maximize the all-electric driving range (AER) and hence will operate the battery for at least part of their life near the margins of the severity factor maps.

Currently available data for Li-ion batteries (albeit based on very incomplete severity factor maps) coupled with AER Battery cycle life data analysis indicates that present lithium ion battery technologies appear to be 10 year/150,000 mile capable, provided that they are not overcharged, nor consistently operated at high temperatures, nor in charge sustaining mode at a very low SOC. Significant gains in life prediction, vehicle design, sizing and control, cost reduction as well as on-board diagnostics/prognostics can be derived form the methodology described here. Furthermore, the methodology can be used to perform model-based design of experiments to significantly shorten aging experiments while preserving

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