A new life estimation method for lithium-ion batteries in plug-in hybrid electric vehicles applications

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Abstract: This paper presents a new approach to life estimation for lithium-ion batteries used in plug-in hybrid electric vehicles (PHEVs) applications. A new framework for battery life estimation is developed which investigates the effects of two primary factors of battery life reduction in PHEVs applications, namely, depth of discharge (DOD) and temperature (Tbatt), under typical driving conditions, driving habits, and average commute time of typical user over a year. This framework, whose development is built upon a weighted ampere-hour throughput model of the battery, is based on the novel concept of severity factor map which captures and quantifies the battery damage caused by different operating conditions. The proposed methodology can be a suitable tool to estimate battery life in terms of miles/year on-board of the vehicle.

Keywords: energy storage systems; plug-in hybrid electric vehicle; PHEV; battery lifetime estimation; battery ageing model.

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1 Introduction

PLUG-IN hybrid electric vehicles (PHEVs) are regarded today as one of the most promising technologies for transportation petroleum displacement and greenhouse gas emission reduction (Markel et al., 2008). The achievement of PHEV energy economy comes not only from the PHEV energy management control strategies implemented on-board of the vehicle, but also from PHEV design and extended energy storage (Tulpule et al., 2009). In this scenario, lithium-ion batteries are starting to play an important role in our mobility because of their advantages over other battery technologies and they are recognised as being best suited for fulfilling the requirements of this vehicle technology (Axen et al., 2008). Their high specific power and energy density content allow overcoming the limitations typical of Ni-MH batteries in meeting the power and energy demands of electric vehicles (EV) and hybrid electric vehicles (HEV) and, in addition, they withstand a wider range of temperatures.

The current battery price of Li-Ion batteries is one of the major disadvantages, though, which prevents PHEV market penetration, as the current cost of lithium-ion batteries is estimated to be about $1,000/kWh, and the long term goal that would facilitate speedy introduction of PHEVs is $250/kWh (Shiau et al., 2009). Economies of scale could definitely reduce the cost of the batteries per kWh, but still this rechargeable energy storage system remains the most expensive component of the vehicle.

Improvements are needed in order to make lithium-ion batteries more competitive, in particular, battery longevity, safety, reliability and lifetime prediction are key issues that need to be addressed fairly soon before assisting to a high market penetration of this technology, as they represent key barriers to commercialisation of PHEVs (Dubarry and Liaw, 2007; Pesaran et al., 2009; Wang et al., 2011).

The problem of understanding how to assess battery life degradation and battery performance during vehicle operation is of primary importance in this context. In particular, the focus of this paper is to address the question: "how can we suitable quantify battery degradation under real-world operating conditions?"

Knowing the battery useful life in automotive applications is crucial in order to guarantee performance and durability of the battery and limit the risks of premature failure. A successful battery lifetime prediction approach requires knowledge of the ageing processes, the factors which determine the ageing itself and their combined effects (Ruddell and Svoboda, n.d.).

Performance degradation affecting electrochemical energy storage systems is due to factors such as current severity (or C-rate), elevate temperature, discharge rate, *DOD*, amount and frequency of overcharge (Wang et al., 2011; Serrao et al., 2005). Moreover, battery ageing can be accelerated by factors from the driver such as combination of cycling, irregular patterns of charge and discharge cycles (Sauer and Wenzl, 2008). Thus, in approaching life estimation methods design, requirements of the driver (power and energy demand) together with other external factors like the temperature distribution within the battery, *DOD* and *SOC* of the battery need to be accounted for.

This paper focuses on developing a novel approach for battery life estimation in PHEV applications. The paper is organised as follows: in Section 2, methods for battery life estimation proposed in the open literature are reviewed. A framework for battery life prediction based on an accumulated ageing model (Serrao et al., 2009) is discussed in Section 3. Within this framework, a weighted Ah-throughput model for life estimation is presented with the new concept of severity factor map. Assessment analysis of the battery life estimation method proposed is discussed in Section 4 for a PHEV case study. Finally, conclusions are given in Sections 5.

2 Review of battery life estimation methods

Two different approaches to battery lifetime estimation and prediction modelling are found in the open literature, namely: *performance-based models* and *weighted ampere-hour (Ah)-throughput model*s. The performance-based models account for the rate of change of battery parameters while the various ageing processes take place. These models are potentially very accurate for making technical and financial decisions. The weighted Ah-throughput models, on the other hand, relate the end of life of a battery to some parameters which can be easily determined, such as Ah-throughput, number of cycles and time since manufacturing. Although these models are inherently limited in their accuracy, they are the only available as planning tools which incorporate battery lifetime features. These two classes of modelling approaches are briefly reviewed in this section.

2.1 Performance-based models

The battery lifetime and the battery end-of-life (EoL) can be expressed as function of different *performance parameters*. These parameters, such as the battery voltage, current, uptake power, *SOC*, etc., can be modelled through various parameterised models (Pesaran et al., 2007). These models, though, suffer in managing the changes in performance values of the battery due to ageing processes (Wenzl, et al., 2005). The performance is usually characterised using battery models, such as:

- electrochemical models
- equivalent circuit models
- analytical models with empirical data fitting
- artificial neural networks.

Electrochemical models provide detailed information on local conditions and performance (e.g., temperature, potential, current, electrolyte concentration etc.). On the other hand, they require specific knowledge of the chemical and physical interactions, e.g., porosity of the active materials, electrolyte volume and density, etc. Because of its intrinsic complexity the computational speed of the simulation is low (Smith et al., 2008).

In *equivalent circuit models* the battery is represented by components of an equivalent electric circuit like voltage and current sources, resistors and capacitors. The ageing process is represented by the change of the values of the equivalent circuit components. This type of models is very common for predicting battery dynamic characteristics (Liaw et al., 2005; Dubarry and Liaw, 2007). A first study of an ageing model for predicting battery life, able to capture the slow variation of model parameters with ageing (and with factors contributing to ageing such as C-rate, *DOD* and temperature) is presented in (Serrao et al., 2009).

In *analytical models,* with empirical data fitting, the lifetime is predicted by means of interpolation and extrapolation from test results and field data, which, in turn, require a lot of data (Rong and Pedram, 2003).

Artificial neural networks have a tremendous potential to discover relationships between inputs (operating conditions) and outputs (ageing processes and performance values). This approach to modelling does not rely on a detailed understanding of the mechanism which link input and output, but measurements are needed to derive the model (Yamazaki et al., 1998; Mukherjee, 2003).

2.2 Weighted Ah-throughput models

The second class of modelling framework for battery lifetime prediction uses models which relate the EoL of a battery to parameters such as Ah-throughput, number of cycles or time since manufacturing. Once a predetermined value of the parameter has been exceeded, the battery is considered to have reached its EoL. The overall Ah-throughput depends on the actual operating conditions. At the cell level, the severity of the charge transfer depends on the current severity relative to the battery size[2] (C-rate), the battery temperature T_{batt} and the *DOD*. The weighted Ah-throughput models are based on the assumption that under particular standard conditions (e.g., given C-rate, T_{batt} and *DOD*) a battery can only achieve a given Ah-throughput until the EoL is reached. For automotive applications a battery is considered reaching its EoL when it shows a capacity loss of 20% or more with respect to the original capacity (Wenzl et al., 2005).

These models account for the fact that deviations from the standard operating conditions (in terms of C-rate, T_{batt}, *DOD*) may increase or decrease the physical Ah-throughput a battery can give and consequently the rate of ageing. A measure of the effective Ah-throughput is given by:

$$Ah_{eff} = \sum w_E \cdot n_E \cdot Ah_E \tag{1}$$

where

Ah_{eff} weigthed Ah-throughput, i.e., effective Ah-throughput that the battery can achieve before reaching its EoL.

E an event is characterised by a particular instance of current load of fixed magnitude under a given temperature, *DOD* and initial *SOC*. It is generated from the discretisation or segmentation of the current signal. The duration of an event, i.e., the step of discretisation, is decided in the implementation phase and can be either fixed or time varying.

w_E weigh or severity associated with an event E.

n_E number of events E.

Ah_E Ah-throughput over an event E.

The battery is considered to fail and reach its EOL when the effective Ah-throughput, as obtained from the model of equation (1), is greater than the total Ah-throughput measured under nominal operating conditions (e.g., discharge/charge at fixed current rate and fixed *DOD*) as provided by the battery manufacturer.

If, from one hand, this type of models represent a good option for the lifetime estimation of batteries in PHEVs because of their easy structure which allows for very high computational speed and adaptation to different battery technologies, on the other hand, the determination of the parameters for the weighting factors remain an issue. In this paper we refer to the weighting factors as severity factors, which are responsible for reduced lifetime. Accurate values of these factors would require extensive data collection, not yet available.

The approach to life estimation presented in this paper is based on the weighted Ah-throughput models. Generally, battery nominal life (20% loss in capacity) is measured by the manufacturers under 100% *DOD* cycles. Cycles with lower *DOD* have minor effects on performance degradation (in terms of 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 (a curve of expected cycle number vs. *DOD* of each cycle is found in (Chan et al., 2001).

Battery life depends on the interaction of operating conditions or severity factors and ageing characteristics and it is, indeed, a highly non-linear process.

At the pack (vehicle) level, the determining factor for pack ageing 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 generalisation to the vehicle level under assumption of all cells equivalent.

Battery requirements differ according to the specific application. High power is needed to provide adequate boost in HEV applications, while power density is less important in PHEV and EV applications due to their larger battery pack. On the other hand, as energy translates into vehicle range, high energy is needed to provide adequate mile range. This is more important for PHEVs and EVs rather than for HEVs. In fact, a HEV battery is operated in charge sustaining mode at intermediate SOC through shallow cycles and only uses a small portion of the available energy. Thus, HEV batteries differ from PHEV and EV batteries, in that they require higher power density than energy density. In this paper, in virtue of the application under consideration, the capacity is considered as the only ageing parameter that effects battery life and thus, life characteristics of the battery are defined based on its residual capacity.

3 A severity factor map-based framework for battery lifetime estimation

Prediction of battery life is achieved through an ageing model which expresses the ageing of the battery in terms of variation of damage variables, i.e., the physical or functional parameters of the battery whose value changes irreversibly because of ageing and modify the behaviour of the system. The approach to ageing modelling presented in Serrao et al. (2009) is briefly reviewed in this section. A generic dynamic system subject to ageing can be described by the following set of dynamics equations:

$$\begin{aligned} \dot{x} &= f(x, \vartheta, u) \\ \dot{\vartheta} &= \varepsilon \cdot g(\vartheta, p) \\ y &= C \cdot x + D \cdot u + v \end{aligned} \tag{2}$$

where

x state variables associated to the fast dynamics

ϑ damage variables associated with slow dynamics

u external inputs

p vector of internal/external ageing factors (including x and u)

y is the set of system outputs, dependent on the constant matrices C and D and on the measurement error v

ε positive scalar (<<1) representing the fact that the dynamics of the damage variables are much slower than the system dynamics

Variation of damage variables (ϑ) implies slow changes in the system behaviour, hence ageing.

To express the progression of the ageing process the normalised damage measure ξ is introduced as:

$$\xi(\vartheta) = \frac{\vartheta_0 - \vartheta}{\vartheta_0 - \vartheta_f} = \frac{S_0 - S}{S_0 - S_f} \tag{3}$$

The damage measure ξ is a scalar index varying between 0 and 1. A value of $\xi = 0$ indicates a new battery ($\vartheta = \vartheta_0$ = known initial value of the ageing parameter) while $\xi = 1$ indicates a 'dead' battery ($\vartheta = \vartheta_f$ = predefined value of the ageing parameter corresponding to battery EoL). Since we are assuming that the capacity is the only ageing parameter, equation (3) is also expressed in terms of the initial (S_0) and final value (S_f) of the capacity S corresponding to a new and EoL battery, respectively. Rewriting the ageing equation $\dot{\vartheta} = \varepsilon \cdot g(\vartheta, p)$ in equation (2) in terms of ξ and the number of cycles n, rather than ϑ and time, (with a simple rescaling of the variables) leads to the equation:

$$\frac{d\xi}{dn} = \varphi(\xi, p) \tag{4}$$

The progression of ageing, i.e., the slope of the curve ξ as given by equation (4), depends on the value of the ageing factors p and the present age ξ.

Equation (4) can be used to predict the evolution of battery damage.

In Serrao et al. (2009), it is shown that, if the capacity evolution is to be predicted, then the progression of ageing, described by the non-linear coupled equation (4) can be expressed as:

$$\frac{d\xi}{dn} = \varphi(\xi, p) = \varphi_1(\xi)\sigma(p) \tag{5}$$

Equation (5) expresses the progression of ageing as a decoupled function of the actual ageing and the actual operating conditions and allows for tracking the progression of ageing if the functions $\varphi_1(\xi)$ and $\sigma(p)$ are known. These two functions are defined as 'ageing factor function' and 'severity factor function', respectively. The ageing factor function is a quantitative measure of the past ageing occurred at the battery at a given moment of its life, while the severity factor function expresses and quantifies the amount of damage due to the operating conditions (or severity factors) such as: T_{batt}, *DOD*, current directionality, C-rate, driving patterns, etc.

In this work, focus is given on the characterisation of the severity factor function $\sigma(p)$ and its use for estimating battery life for PHEV applications. By knowing the map $\sigma(p)$ under different operating conditions, a quantitative assessment of battery performance can be performed and used in the weighted Ah-throughput model previously described by equation (1) for life estimation.

Ongoing research is devoted to develop models to incorporate the life estimation method presented in the paper (in the form of severity factor map) within a prognostics framework. The validation of the severity factor map, as well as the verification of the ageing model framework requires an extensive campaign of experiments which are ongoing at the Center for Automotive Research The Ohio State University (CAR-OSU).

3.1 Severity factor map characterisation for PHEV applications

As mentioned in the Introduction, at the cell level, among the ageing factors that affect the battery life in PHEV applications (Freedom Car Manual, 2008) the two most important considered in this study are:

- battery temperature, T_{batt}
- *DOD*

Notice that, while in HEV applications current C-rate ranges within ±15C, which contribute to significant severity and therefore ageing, the C-rate effect on battery ageing can be neglected in PHEV applications . In fact, being the battery oversized in PHEVs, typical current C-rates range between ±4C. An example of current profile corresponding to a charge-depleting PHEV on a US06 driving cycle is shown in Figure 1, and the statistical distribution of the C-rate is shown in Figure 2.

Figure 1 Typical current (c-rate) profile for a PHEV (in charge-depleting mode) during an us06 driving cycle

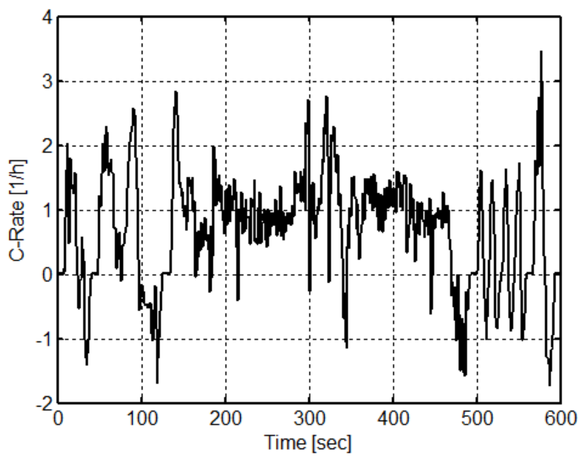
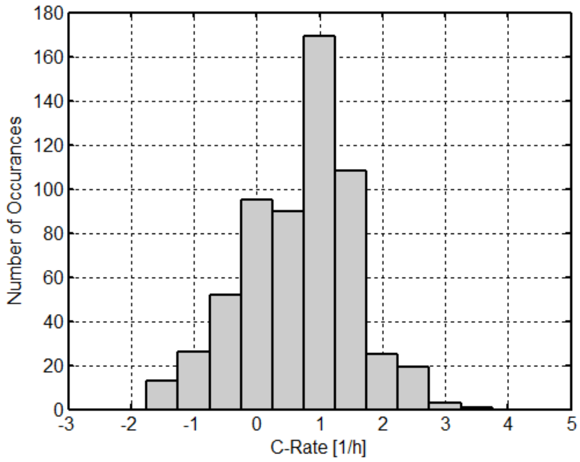


Figure 2 Current (C-rate) statistical distribution for a PHEV (in charge-depleting mode) during an us06 driving cycle



This observation implies that the vector [T_{batt}, DOD] represents the vector p of ageing factors used in the damage accumulation model of equation (6).

Usually, battery manufacturers define battery life with respect to a nominal cycle ($I_n(t)$) with these characteristics: C-rate = 1, DOD = 100%, T_{batt} = 25°C. Thus, battery life is defined as the overall Ah-throughput (in and out charge from 0 to EoL) when the battery is subject to cycle $I_n(t)$:

$$Ah - throughput_{nominal} = \int_0^{EoL} |I_n(t)|\, dt \tag{6}$$

The ageing effects caused to the battery by any other cycle are quantified by the relative severity factor σ when given with respect to the nominal cycle or 'baseline'. In particular, the severity factor σ at a given $DOD = \overline{DOD}$ and $T_{batt} = \overline{T_{batt}}$ is defined as:

$$\sigma\left(\overline{DOD}, \overline{T_{batt}}\right) = \frac{Ah - throughput_{nominal}}{\int_0^{EoL} |I(t)|\, dt} \tag{7}$$

where the quantity $\int_0^{EoL} |I(t)|\, dt$ indicates the overall Ah-throughput corresponding to cycle the battery at current $I(t)$ under conditions $DOD = \overline{DOD}$ and $T_{batt} = \overline{T_{batt}}$. The severity factor represents the relative ageing effect with respect to the baseline given by the nominal cycle. A severity factor σ greater than 1 represents conditions which are more severe than the baseline in terms of ageing.

The determination of the relative severity factors to form the overall severity factor map (namely, the function $\sigma(p)$ in equation (5) on the domain of interest (i.e., DOD and T_{batt}) is typically difficult to obtain and is very dependent on the particular battery chemistry, anode and cathode composition and construction. Furthermore, all information related to ageing characteristics even for a given cell, requires extensive and very lengthy (hence costly) data collection. For the purpose of this paper, a prototypical example of ageing severity factor map was extracted from battery manufacturer data, albeit with considerable difficulty as the tests were not necessarily conducted with our framework in mind. For the purpose of illustration of the methodology, an estimate of the value of severity factor as a function of operating temperature and *DOD* is given based on publically available data (Markel and Simpson, 2006; A123, 2007). This severity factor surface will be referred to as 'estimated' in the remainder of this paper. The topology of this 'estimated' severity factor map, while specific to a particular cell and very lengthy to determine experimentally, is generic enough in its overall shape. On a real vehicle application, though, the actual ageing conditions (wide range of temperature and low state of charge) are different from the ones considered to obtain those data. Hence, the need to carry out a campaign of ageing experiments meant to collect data reflecting actual operations of the battery on the vehicle is unquestionable.

The 'estimated' or postulated severity factor map, $\sigma_{T_{batt},DOD}$ as a function of T_{batt} and *DOD*, is shown in Figure 3. In the rest of the paper, the symbol $\sigma_{T_{batt},DOD}$ indicates the overall severity factor map (Figure 3) while $\sigma(\overline{DOD},\overline{T_{batt}})$ indicates the severity factor value as obtained when the battery is cycled at $DOD = \overline{DOD}$ and $T_{batt} = \overline{T_{batt}}$.

Two regions on the severity factor map are of main interest: a *fringe spot* and a *sweet spot*. If the battery is operating in a *fringe spot* the Ah-throughput will be weighted with a severity factor higher than the severity factor used when the battery is operating in the sweet spot, which, in turn, reflects the more severe operating conditions. In fact, working at high temperature (> 25°C) and wide *DOD* will result in an accelerated ageing of the battery. The severity factor as a function of the *DOD*, parameterised in temperature, is shown in Figure 4.

Figure 3 Severity factor map for PHEV applications

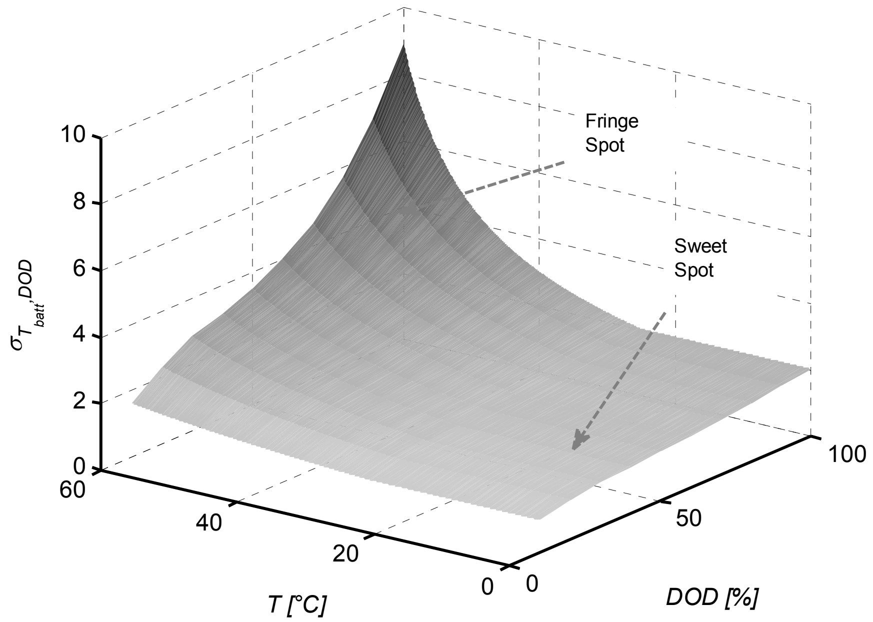
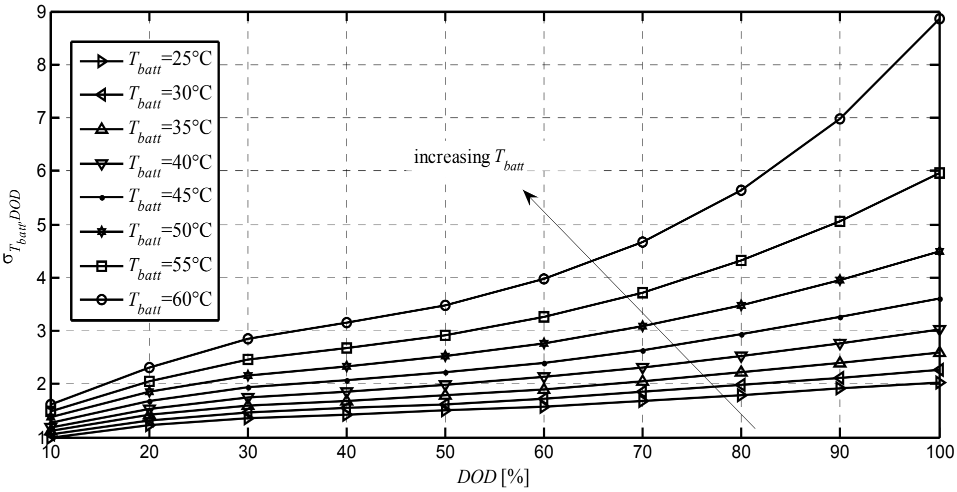


Figure 4 Severity factor as function of *DOD* parameterised with respect to battery temperature



A targeted design of experiments is being conducted to validate the shape of the severity factor map over the battery operating domain. Not only will the verification of the severity factor map through experiments be a valid tool to assess battery life but also it can be used as a guideline to better design PHEV control strategies. In fact, it can be used to investigate the possibility of making the charge sustaining operation happen at lower *SOC* than the one effectively used in vehicle now (typically 30% *SOC*) by looking at what degradation level the battery will be reaching. In general, important insights can be derived from the qualitative behaviour of the severity factor map for more conscious control strategies concerning fuel consumption minimisation as well as battery life extension.

4 Case study: preliminary simulation results

In this section, simulation results coming from exploiting the severity factor map to estimate battery longevity using an energy-based model of a hybrid powertrain are presented.

The simulator used in this study, is built upon the energy-based model of Cx-Sim (Tulpule et al., 2010), and adapted to PHEV applications. Table 1 describes the main vehicle characteristics. The vehicle is based on a series-parallel architecture, which includes a diesel engine coupled to a belted starter alternator (BSA) on the front axle and an electric motor (EM) on the rear axle. This configuration allows for a variety of modes such as pure electric drive, electric launch, engine load shifting, motor torque assist, and regenerative braking.

The considered vehicle requires approximately 370 Wh/mile for electric mode in UDDS cycle, thus resulting in about 11 kWh of stored energy required to run 30 miles in AER. To account for battery ageing 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 16 kWh.

Table 1 Basic vehicle modelling parameters

Class	SUV
Mass	2130 kg
Engine	1.9L Diesel
Battery pack	16 kWh (50 Ah × 312V)
Control strategy	Charge depleting-charge sustaining mode

The implemented control strategy is based on charge depleting-charge sustaining energy management policy. In charge depleting mode (or pure electric), the battery is used to drive the vehicle until the electric machine is able to supply required power and the battery *SOC* is greater than the designed lower limit. Once *SOC* reduces below the minimum allowable value (0.3), the vehicle is operated in charge sustaining mode for the remaining of the trip, where an equivalent consumption minimization strategy (ECMS) is implemented (Serrao et al., 2011; Tulpule et al., 2010).

Table 2 Driving and charging events

Driving/charging events	
T1	UDDS+US06 (trip to work after full charge). Initial SOC is 0.95
T1b	US06+UDDS (trip to home after work). Initial SOC is the final SOC of previous trip
T1c	US06+UDDS (trip to home after work). Initial SOC is 0.95
T2	UDDS (errands). Initial SOC is the final SOC of previous trip
T2b	UDDS (errands). Initial SOC is 0.95
T3	UDDS+HWFET+HWFET+HWFET+HWFET+UDDS (this assumes the vehicle is only recharged at the end of the day). Initial SOC is 0.95
C	Charging from SOC 0.25 to 0.95. Charging capability: 6 kW (AC: 220V, 30A; DC: 20A CC/CV)

In order to simulate statistically meaningful scenarios, driving and charging events characteristic of a typical user were used (Table 2) (Sikes et al., 2010) and then combined in a way to compose typical days of driving to reflect common driving habits, and average commute time over a year (Table 3).

Table 3 Typical days

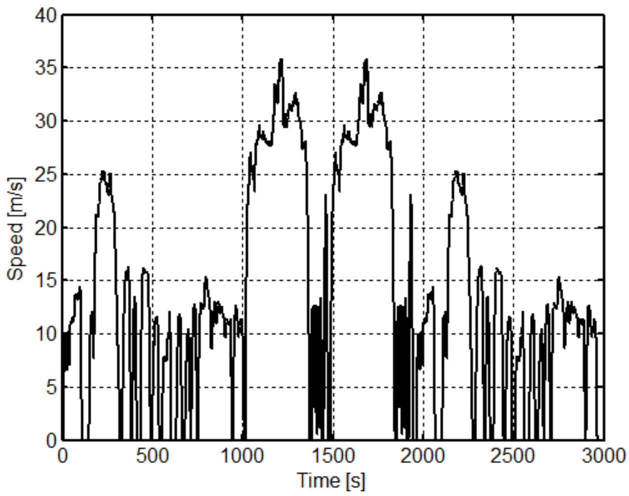
Days	*Combination of events*	*Frequency*
D1a	T1-T1b-T2-C	3 days/week, 48 weeks/year (tot. 144 days/year)
D1b	T1-C-T1c-C-T2b-C	Alternative to D1a
D2a	T1-T1b-C	2 days/week, 48 weeks/year (tot. 96 days/year)
D2b	T1-C-T1c-C	Alternative to D2b
D3	T3-C	2 days/week, 48 weeks/year + 7 days/week, 4 weeks/year (tot. 124 days/year)

Different charging availability is also considered. Two main scenarios have been inspected: controlled charging (once a day, overnight) and uncontrolled charging (charging is possible whenever the vehicle is parked).

Simulation results show that through an 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.

The combination of the described events and typical days results in approximately 15,000 miles/year.

Figure 5 Speed profile of typical day D1a



Note: This profile is the same as D1b (they only differ from the initial soc the battery is discharged from and the charging event).

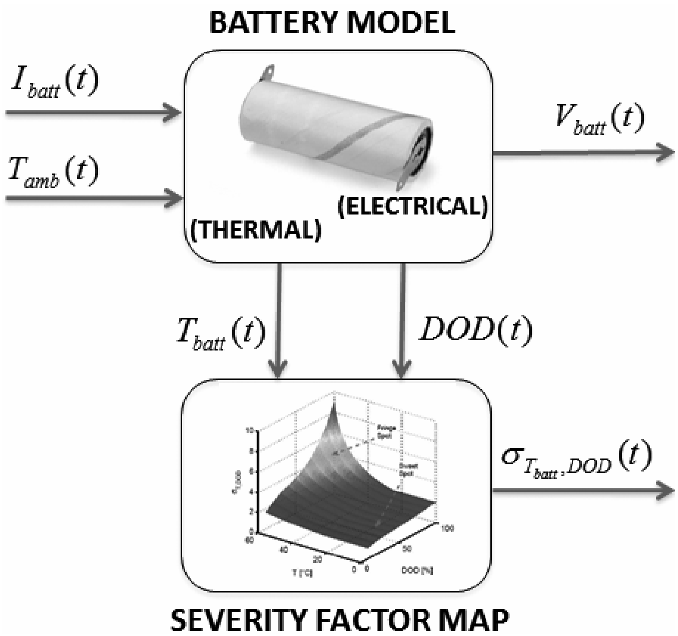
4.1 Weighted Ah-throughput calculation

The approach used to estimate battery life is structured according to the schematic of Figure 6. The battery model used in this study takes the battery current, I_{batt}, over a driving mission and the ambient temperature, T_{amb}, as inputs and gives the battery voltage, V_{batt} and the battery temperature T_{batt} as outputs (Muratori et al., 2011). Then, $\overline{T_{batt}}$ and the $\overline{DOD}$ (derived from the battery model and I_{batt}) are given as inputs to the severity factor map which, once interrogated, returns the value of severity occurring to the battery under those particular conditions. The severity factor value is then used in the accumulated Ah-throughput model through the equation:

$$Ah_{eff} = \int_0^T \sigma\left(\overline{DOD}, \overline{T_{batt}}\right)\left|I_{batt}(t)\right| dt \tag{8}$$

This gives the weighted Ah-throughput or accumulated weighted Ah that the battery has effectively experienced over a trip of length T. From an implementation point of view, the value of the severity factor can be extracted from the map either at each sampling time or over a more meaningful simulation window of seconds or minutes. In this latter case, average values should be used. In this simulation study, a fixed window of two minutes was used to extract the information needed to interrogate the severity factor map.

Figure 6 Schematic of model-based structure for battery life estimation



The battery Ah-throughput or accumulated Ah, given as $Ah = \int_0^T \left|I_{batt}(t)\right| dt)$, is also outputted by the model.

Preliminary simulation results were obtained using the overall battery model (Figure 6) and data (electric power, and battery current) from the PHEV simulator presented earlier under statistically representative common driving/charging scenarios. Table 4 shows the two outputs of the model (Ah-throughput and weighted Ah-throughput) for the series of driving/charging events of Table 2. The average C-rate and the total miles travelled over each events are also given in Table 4.

It is worth observing that the C-rate results in a very shallow severity characteristic over all the events, which subsides the assumption to neglect it as primary ageing factor in this study. The same comparison is then performed over typical days and shown in Table 5.

Table 4 Comparison between Ah and weighted Ah on different driving events

	T1	*T1b*	*T1c*	*T2*	*T2b*	*T3*	*C*
Ah	33.98	6.65	33.98	2.47	9.6	50.62	35.0
Weighted Ah	43.99	10.51	44.55	4.47	9.82	72.11	39.05
Average C-rate [A/Ah]	1.66	0.32	1.66	0.23	0.8	0.68	0.4
Total miles	15.45	15.45	15.45	8.0	8.0	57.0	-

Table 5 Comparison between Ah and weighted Ah on typical days

	D1a	*D1b*	*D2a*	*D2b*	*D3*
Ah	78.1	182.56	75.63	110.63	85.62
Weighted Ah	98.02	215.51	93.55	166.64	111.16
Total miles	38.9	38.9	30.9	30.9	57.0

Figure 7 *SOC* profile (dot-dot) and comparison between Ah-throughput (solid) and weighted Ah-throughput (dashed-dot) for the day D1a (see online version for colours)

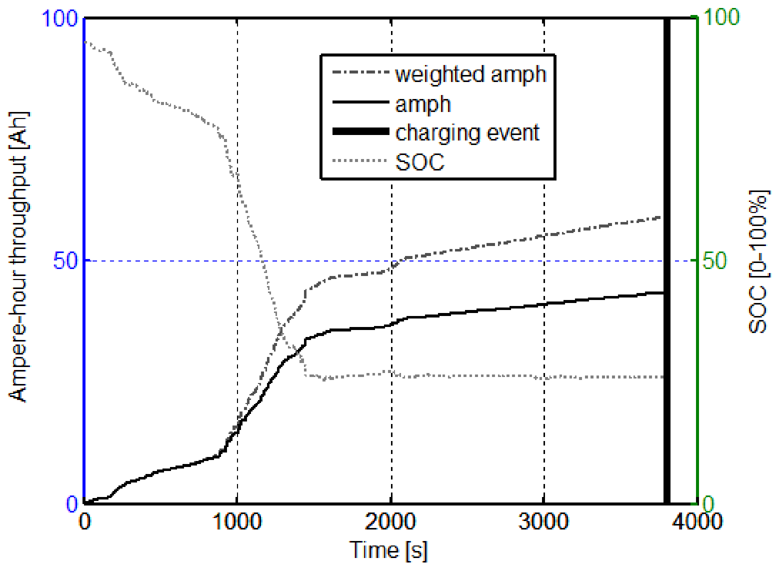
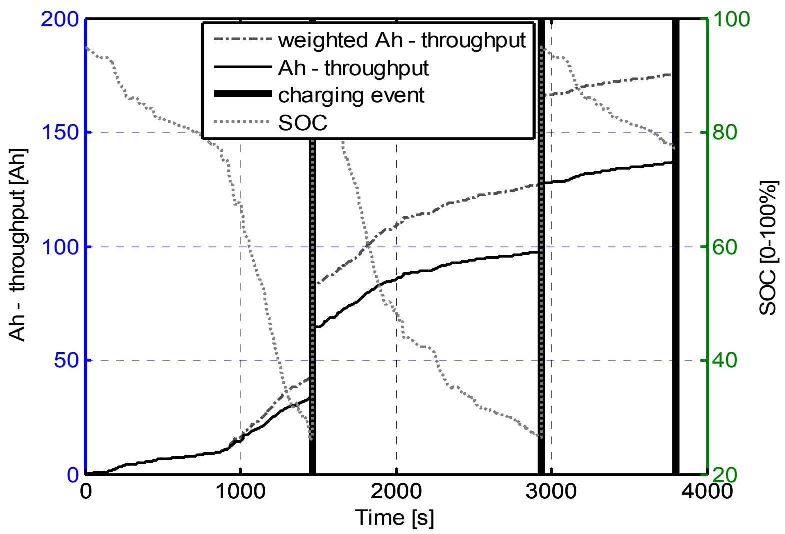


Figure 8 *SOC* profile (dot-dot) and comparison between Ah-throughput (solid) and weighted Ah-throughput (dashed-dot) for a typical day D1b (see online version for colours)



Results showing the difference between accumulated Ah and accumulated weighted Ah are in Figure 7 and Figure 8. In Figure 7 it is shown a charge depleting-charge sustaining behaviour, which results in a battery *DOD* of 0.65 for more than half of the cycle, while in the case shown in Figure 8 the vehicle never operates in charge sustaining due to the repeated charges.

Results show that there are significant differences between accumulated Ah and accumulated weighted Ah as a result of accounting for the cycle severity through the severity factor map, which considerably adjust the life battery expectation as a function of different usage patterns.

Table 6 Expected life example

	Uncontrolled charging (charge at home/work)	*Controlled charging (charge only at home)*
Ah	47,526	29,124
Weighted Ah	60,814	36,879
Total miles	15,636	
Total miles in electric	12,243	6,458
% miles in pure electric mode	78.3	41.3
Nominal capacity (Ah)	50	
Expected cycle life at 100% DOD ±1C	2,500	
Estimated life (years)	8.34	13.76

The expected cycle life and estimated battery life are also assessed under two different charging scenarios as reported in Table 6. This case shows how different charging strategies (either controlled or uncontrolled), which would result in different *DOD* experienced in pure electric mode (the ability to charge the battery more frequently ensure lower excursion in the *SOC*) leads to considerably different expectation of battery life.

5 Conclusions

This paper has presented a novel framework to estimate life of Li-ion batteries in PHEV applications. The new concept of severity factor map has been introduced which is used to quantify the damage occurring to the battery under different driving scenarios, charging availability and usage patterns. Starting from data provided by battery manufacturer, the severity factor map has been designed and quantitatively postulated. This tool, framed within a battery model, is used to give an estimate of battery life in terms of effective Ah-throughput experienced by the battery when used in every day driving scenarios. Preliminary simulation results have shown that different battery usages, corresponding to different driving scenarios and charging events, have a different impact on battery life. Uncontrolled and widely available charging infrastructure would lead to better fuel economy (more miles in EV mode), but at the price of a strongly reduced life (results show a reduction of about 40% in terms of calendar life). The approach described in this paper is fairly generic and has the potential to be applicable to any classes of vehicles, with a fairly simple battery model, as long as the ambient temperature and the battery current are measured on-board of the vehicle. Ageing experiments are currently underway to calibrate the severity factor map, through cycles representative of real driving characteristics.

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Notes

1 Piefrancesco Spagnol has conducted this work while he was a Visiting Scholar at Center for Automotive Research at The Ohio State University.

2 The C-rate is a measure defined as the ratio of the current (in A) to the nominal charge capacity (in Ah): C-rate= I/S where S is the battery capacity.