A Novel Model-Based Algorithm for Battery Prognosis

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Abstract: The paper presents an analytical formulation of a damage accumulation law for automotive batteries, derived using curve fitting of experimental data from literature.
The analytical formulation shows the equivalence of the proposed model to the Palmgren-Miner fatigue model used for mechanical components. The proposed model can be used to determine the residual life of automotive batteries and is potentially implementable on-line.

1. INTRODUCTION

The automotive industry is directing its efforts to developing vehicle that are as reliable as possible, while increasing the interval between scheduled maintenance checks. Onboard diagnosis (OBD) plays a crucial role in automatically detecting system failures (loss of functionality) or faults (reduction of functionality), thus reducing the time and effort needed to identify the source of a problem. Prognosis, i.e. the ability to track the degradation of a system and predict its failure, is a further step towards reliability and customer satisfaction.

Due to the increasing importance of the electrical power and storage systems in modern vehicles, especially evident in electric or hybrid electric vehicles, diagnosis and prognosis of electric power systems is the object of intense research and development efforts.

In this article, we focus on prognosis techniques for batteries used in automotive applications, for either conventional vehicles (12 V starter batteries) or electric/hybrid electric vehicles (nickel-metal hydride or lithium-ion). The objective of this work is to derive a model for tracking the state of health of a battery using data collected on board of the vehicle, and predicting the moment in which the battery is not able to deliver its specified performance. Being able to determine this end-of-life condition in advance allows for more efficient preventive maintenance.

Batteries age with usage. Battery aging includes the loss of rated capacity, faster temperature rise during operation, reduced charge acceptance, higher internal resistance, lower voltage, and more frequent self-discharge. In automotive applications, in particular, it is experimentally observed (Chehab et al. [2006]) that the main effects of aging are an increase of the internal resistance and a decrease of the capacity (charge acceptance). The former manifest itself as loss of efficiency and consequent reduction of peak power (a smaller fraction of the chemical power is available at the terminals); the latter reduces the amount of energy that can be stored in and subtracted from the battery. In conventional vehicles using lead acid batteries, the most important effect of battery aging is the loss of the ability to start the engine, due to the fact that the power supplied by an aged battery is not sufficient to crank the engine. In electric and hybrid-electric vehicles, on the other hand, the battery pack has a much higher maximum power, and thus its reduction is not as critical as in a conventional vehicle; however, the decrease in peak power and efficiency reduce the overall efficiency of the vehicle.

The reduction of capacity, and therefore of the amount of energy that can be stored on board, is critical especially for pure electric vehicles and plug-in hybrid electric vehicles, which discharge their batteries very deeply (unlike charge-sustaining hybrids). In these cases, battery aging may imply a substantial reduction of the operating range, or decrease of the gas mileage. By contrast, charge-sustaining HEVs usually operate their batteries in a relatively narrow range of state of charge, using only a fraction (20-40%) of the available energy; therefore, the decrease of the total energy that can be stored in the battery is not critical, until a minimum value is reached.

The objective of this paper is to present a general methodology to derive an analytical aging model for automotive batteries based on experimental results collected on three different kinds of batteries: lead-acid (PbA), nickel-metal hydride (NiMH) and lithium-ion (Li-Ion). Even though the paper focuses on methodology rather than experimental results, published data from several sources are used to propose an aging model.

The paper has the following structure. In Section 2 a description of the main aging parameters affecting the life of automotive batteries is presented. In Section 3 the theoretical framework for aging modeling is introduced; its application to calculate the damage progression of automotive batteries is shown in Section 4 and Section 5.

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2. BATTERY AGING

Several authors (Chehab et al. [2006], Serrao et al. [2005], Wenzl et al. [2005], Dubarry et al. [2007]) in the past have attempted to characterize the process of battery aging, and in particular to quantify the effect that the operating parameters have on battery life.

In many cases, the definition of the battery life is given in terms of the number of charge/discharge cycles that it can sustain before its capacity drops to 80% of the original value (IEEE SCC 29 [1997]). This definition is meaningful only in cases in which a unique cycle is used throughout the battery life. Drouilhet and Johnson [1997] used Ah counting as a unit of measurement for battery life, assuming that a battery can supply a given amount of charge during its entire life. In this way, there is no need to define a specific cycle as a unit of reference. This is the method used in the present article.

In general battery aging is a complex process, resulting from the interaction of several variables, or aging factors. Among them, the most significant in automotive application can be identified as follows:

- operating temperature;
- depth of discharge (amount of charge drawn from a battery during a given cycle);
- battery current.

Higher values of the three factors lead to faster battery aging. Depending on the specific application, other aging factors can be identified: for example, the time between complete recharges (Wenzl et al. [2005]), which is not meaningful in automotive batteries that are never charged completely during normal operating conditions. Overcharging and over-discharging (exceeding voltage limits) can also be very harmful to a battery, as it is remaining at very high or low state of charge (Wenzl et al. [2005]). However, if the battery is monitored by a voltage control system, these events will not take place during normal operation.

The definition of end-of-life is arbitrary, and depends on the specific application. As mentioned, one possible definition of end-of-life corresponds to the condition in which the capacity becomes 80% of the value it had in the new battery. However, aging can compromise the battery usability in other ways, for example, as explained earlier, reducing peak power. In this work, 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. The deterioration of these parameters is represented by using an aging model as described in the following sections.

3. APPROACH TO AGING MODELING

A generic dynamic system subject to aging can be described by

$$\begin{cases} \dot{x} = f(\vartheta, x, u) \\ \dot{\vartheta} = \varepsilon g(\vartheta, p) \\ y = Cx + Du + v \end{cases} \tag{1}$$

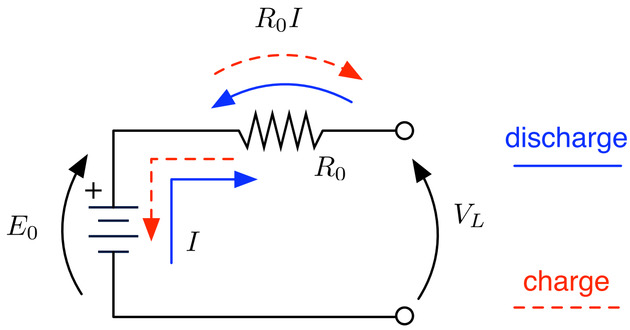

Fig. 1. Zero order circuit model of a battery

where:

$x \in \mathbb{R}^n$ is the set of state variables associated with the fast dynamics of the system;

$\vartheta \in \mathbb{R}^m$ is the set of *damage variables*, i.e. the system parameters that change with the age of the system;

ε is a positive scalar ($\varepsilon \ll 1$) that represents the fact that the dynamics of the damage variables are much slower than the system dynamics, so that the value of the parameters ϑ can be considered constant when dealing with the system dynamic equation $\dot{x} = f(\vartheta, x, u)$;

$u \in \mathbb{R}^l$ is the set of external inputs acting on the system;

$p \in \mathbb{R}^k$ is the set of *aging factors* which have an effect on the aging of the system. p can be composed of states, inputs and/or external parameters;

$y \in \mathbb{R}^j$ is the set of system outputs, dependent on the constant matrices C and D and on the measurement error v.

The dynamic variation of ϑ is assumed to be much slower than the main system dynamics, so that the value of the parameters ϑ can be considered constant when dealing with the system dynamic equation $\dot{x} = f(\vartheta, x, u)$.

The main issue in finding an aging model of the system is the formulation of the aging equation $\dot{\vartheta} = \varepsilon g(\vartheta, p)$, which expresses the parameter variation due to the aging. The rest of this paper focuses on the proposal of such formulation for the case of electrochemical batteries used in electric and hybrid electric vehicles. In particular, the damage variables and aging factors will be identified and described in Section 4, and a form for the function $g(\vartheta, p)$ will be proposed in Section 5, based on the analysis of experimental results.

4. BATTERY MODELS AND DAMAGE VARIABLES

The simplest circuit model of an electrochemical battery is shown in Figure 1. This is a zero-order model involving two parameters: the open circuit voltage E_0 and the internal resistance R_0, which accounts for ohmic and conductivity losses in the battery. However, even though it does not appear explicitly in the circuit model, the most important battery parameter is the capacity S, i.e. the amount of charge that the battery can hold.

All these parameters are a function of the battery operating conditions (state of charge, temperature, direction of the current) and can vary with the age of the battery. From the aging standpoint, the parameters whose change with age is most noticeable are the internal resistance R_0 (because it affects the power capabilities of the battery) and the capacity S (which affects the amount of charge, and hence of energy, that can be stored in the battery). The internal resistance increases with aging, while the capacity decreases.

However, it can be observed that both the resistance increase and the capacity loss are due to the same underlying physical phenomena. In fact, in lead-acid batteries for example, the degradation of positive active mass causes an increase in electrical resistance at the lead-oxide sites that leads to a loss of capacity, since the resistance of the softened sites increases to a point where they are no longer participate in electrochemical reactions (Suozzo [2008]).

For this reason, only the capacity S is considered as a damage variable: $\vartheta = S$, and the life characteristics of the battery are defined based on its residual capacity. In the rest of this paper, we will use the normalized *damage measure* ξ to express the progression of the aging process. The damage measure is defined as:

$$\xi = \frac{\vartheta_0 - \vartheta}{\vartheta_0 - \vartheta_f} = \frac{S_0 - S}{S_0 - S_f} \tag{2}$$

where $\vartheta_0 = S_0$ is the capacity of a new battery, and $\vartheta_f = S_f$ the capacity of a battery at the end of its life, which is a predefined value. In fact, the end of life is usually defined as the moment in which the capacity becomes 80% of its original value. By definition, the damage measure ξ takes values between 0 (new battery) and 1 (end-of-life battery).

The aging equation $d\vartheta/dt = \dot{\vartheta} = \varepsilon g(\vartheta, p)$ that appears in (1) can be written in terms of ξ and of the number of cycles n rather than ϑ and time, with a simple rescaling of the variables:

$$\frac{d\vartheta}{dt} = \frac{1}{t_c}\frac{d\vartheta}{dn};\ d\vartheta \to d\xi \tag{3}$$

where the first equality is due to the fact that t_c is the duration of each cycle (hence $dn = dt/t_c$) and the second transformation uses the definition (2).

The slope of the curve $\xi(n)$ is

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

and depends on the value of the aging parameters p and the age ξ. It can be used to predict the evolution of battery damage and represents the basis of the aging model proposed in this work. The time evolution of the damage measure, $\xi(t)$, depends also on the duration t_c of each cycle.

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, Juvinall and Marshek [2000]). The rule states that the life of a component under a sequence of variable loads

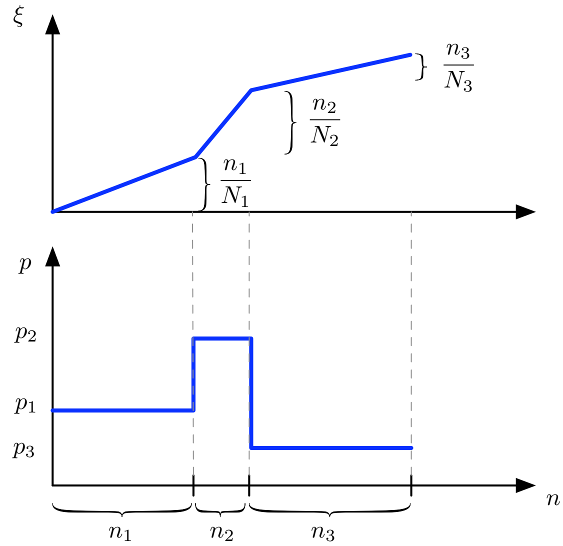

Fig. 2. Graphical representation of the Palmgren-Miner rule, assuming that p represents the intensity of load on a component and that the life is inversely proportional to p

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 , $i = 1, ..., W$ corresponds to the condition:

$$\sum_{i=1}^{W} \frac{n_i}{N(p_i)} = 1, \tag{5}$$

that is, 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. Experimental results collected over the course of the years for basic mechanical components are readily available as tabulated data.

This empirical rule has found wide usage in mechanical fatigue analysis because it is followed with fairly good approximation in many cases of practical relevance. It implies that the order in which the loads are applied is not significant, that their effect is accumulated and that the progression of damage is linear.

An important result tying the Palmgren-Miner rule to the damage accumulation equation (4) was formulated by Todinov [2001]. He proved that the additivity law coming from Palmgren-Miner rule is equivalent to (4) if $\frac{d\xi}{dn}$ can be factorized as product of two independent functions:

$$\frac{d\xi}{dn} = \varphi\left(\xi, p\right) = \varphi_1(\xi) \cdot \varphi_2(p) \tag{6}$$

Therefore, if one assumes that an additivity rule like the Palmgren-Miner rule (5) applies to the case of battery aging, it is possible to simplify the analytical development of the aging model by using the form (6) for the aging function φ. On the other hand, the validity of this assumption must be verified by fitting $\varphi(\xi, p)$ to experimental data and showing that the decomposition (6) is possible, as done in Section 5.

The expression (6) allows for tracking the progression of aging if the functions $\varphi_1(\xi)$ and $\varphi_2(p)$ are known. The two functions can be defined respectively as the age factor and the severity factor, since they account for different effects, and are derived using experimental data collected during aging experiments.

The independent variable n that represents how much the component has been used is commonly identified with a number of cycles. However, the concept of "cycle" is not meaningful in the case of a battery for traction applications, because every charge or discharge event is different. For this reason, the accumulation of age in a battery is expressed using the total ampere-hour throughput, in both charge and discharge, i.e.:

$$n = \int_0^t |I(t)|\, dt. \tag{7}$$

5. AGING MODEL FROM EXPERIMENTAL DATA

The aim of this section is to give an analytical expression of damage progression model (6) using curve fitting of experimental data relative to the three main kinds of batteries used in automotive applications.

While their relative importance can change depending on the battery chemistry, the aging parameters p can be identified with:

- operating temperature, T;
- state of charge SOC, i.e. variation of state of charge during a single charge or discharge event;
- intensity of current I drawn from or flowing into the battery, or – more in general – characteristics of the load profile.

From a qualitative point of view, higher values of these parameters reduce the useful life of the battery.

Using laboratory experiments it is possible to characterize the aging process of a battery, or in other words, determine the quantitative behavior of the damage progression $\frac{d\xi}{dn} = \varphi_1(\xi) \cdot \varphi_2(p)$ as a function of the aging parameters $p = [T, SOC, I]$. In order to derive the damage progression $\frac{d\xi}{dn}$, the curve $\xi(n)$ parameterized in p, is fitted to experimental data.

The data used for for NiMH and PbA batteries was collected in the Battery Laboratory at the Center for Automotive Research of the Ohio State University (Chehab et al. [2006], Suozzo [2008]), while the data for Li-Ion batteries is published by A123Systems.

We looked at the variation of battery capacity with the progression of aging, i.e. at the data points that give the relation $S(n)$. Data for Li-Ion, PbA, and NiMH batteries

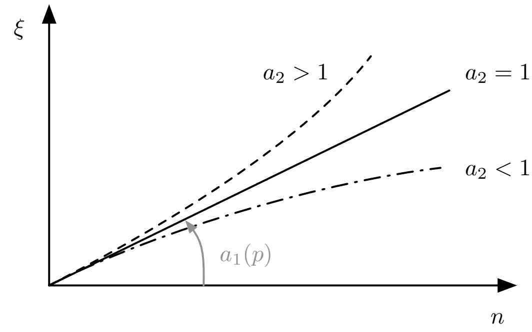

Fig. 3. Different effects of the fitting parameters on damage measure $\xi(n)$

are shown in Figures 4, 5 and 6 respectively. For each chemistry, one or two experiments are present, relative to different operating conditions. Li-Ion batteries are tested under the same cycle, but different temperatures; lead-acid batteries are tested under two different loading cycles, and only one type of cycle is shown for Ni-MH. In all cases, the capacity decreases with the progression of aging. The data have been presented plotting the ratio S/S_0 (S_0 is the value of the capacity at the beginning of life) with respect to the total ampere-hour throughput n, which is easily obtained from the number of cycles and the characteristics of the test cycles, as

$$n = 2 \cdot DOD \cdot S_0 \cdot n_{cycles} \tag{8}$$

where DOD is the depth of discharge of each test cycle (which are supposed to be all identical), and n_{cycles} is the life expressed in number of cycles. The factor 2 is present because we assume as life measurement the amount of Ah extracted or put into the battery, hence both charge and discharge cycles are counted.

The damage measure ξ is calculated according to the definition (2) as:

$$\xi = \frac{S_0 - S}{S_0 - S_f} = \frac{1 - S/S_0}{1 - S_f/S_0} \tag{9}$$

assuming that the capacity at the end of life S_f is a constant for each battery type (corresponding to the lowest final value observed in each family of curves). Figures 7, 8 and 9 show the damage measure points obtained from the data.

All the points are fitted using the same analytical expression:

$$\xi(n) = a_1(p) \cdot n^{a_2} \tag{10}$$

where $a_1(p)$ and a_2 are fitting coefficients. a_2 is a constant for a given battery type/model, while $a_1 = a_1(p)$ is different for each curve, and is used to account for the effects of different loading conditions.

By looking at Figure 3, it can be observed how a_2 is a shape factor, representing the qualitative behavior of the battery aging process, which is reasonable to consider a function only of the battery itself, while $a_1(p)$ is a severity factor, which determines how fast the aging process happens, and therefore it is a function of the loading conditions.

The results of the fitting (10) are shown in Figures 7, 8, and 9. As it can be observed, this expression is adequate

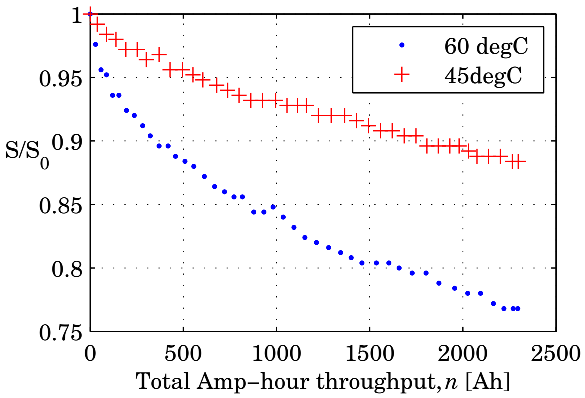

Fig. 4. Variation of battery capacity with progression of cycling, for complete discharge (DOD = 100%), square wave current cycles, I = 2.3 A, at different temperatures. Data referred to Lithium-ion batteries (A123 ANR26650). Source: http://a123systems.textdriven.com.

to fit the progression of aging in all the cases examined here. For each of the figures, a_2 is fixed: effectively, only a_1 is responsible for the difference between curves in the same figure.

The slope of the curve $\xi(n)$ described with this curve fitting is

$$\frac{d\xi}{dn} = a_1(p) \cdot a_2 \cdot n^{(a_2-1)}. \tag{11}$$

By expressing n as a function of ξ from (10):

$$n = \left(\frac{\xi}{a_1(p)}\right)^{\frac{1}{a_2}} \tag{12}$$

(11) can be written as:

$$\frac{d\xi}{dn} = a_1(p) \cdot a_2 \cdot \left(\frac{\xi}{a_1(p)}\right)^{\frac{a_2-1}{a_2}} = a_1(p)^{\frac{1}{a_2}} \cdot a_2 \xi^{\frac{a_2-1}{a_2}}. \tag{13}$$

As it can be easily seen, the above expression is a product of two terms: one is a function of only p and the other is a function of ξ. Therefore, the curve fitting (11) respects the condition (6). That means that the additivity rule of Palmgren-Miner holds for battery application.

In order to be implemented on a vehicle, (13) must be discretized as follows:

$$\xi_k = \xi_{k-1} + \Delta n_{k-1} \cdot a_1(p_{k-1})^{\frac{1}{a_2}} \cdot a_2 (\xi_{k-1})^{\frac{a_2-1}{a_2}}. \tag{14}$$

where k represents the index of the subsequent updates to the value of the damage measure ξ. Δn_k is the amount of Ah used during the interval $(k-1)-k$. It is assumed that the aging factors p are constant during the same interval. This interval could be defined arbitrarily: for example, it can be taken as any interval in which the aging factors are indeed constant or almost constant, or it can be the interval between a key-on and a key-off events (in the latter case, an average value of the aging factors would be considered).

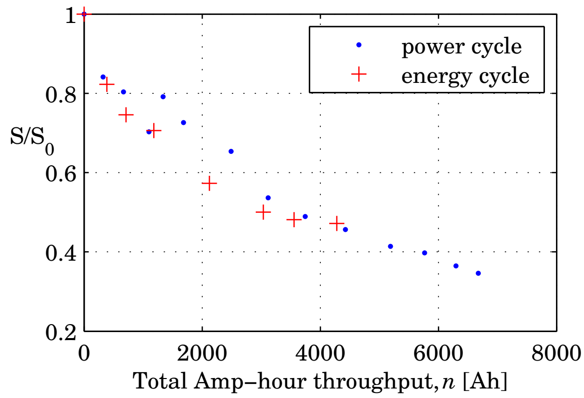

Fig. 5. Variation of battery capacity with cycling (12-V PbA battery), under two different cycles. The power cycle is a sequence of high-current, low duration pulses; the energy cycle is a slow discharge (Suozzo [2008])

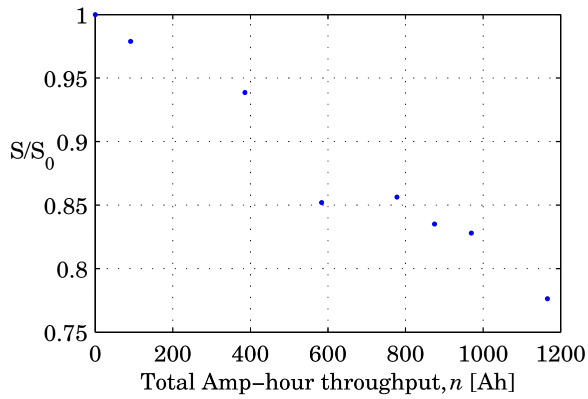

Fig. 6. Variation of battery capacity with cycling (7.2-V NiMH battery), with square wave cycles (15% DOD) (Chehab et al. [2006])

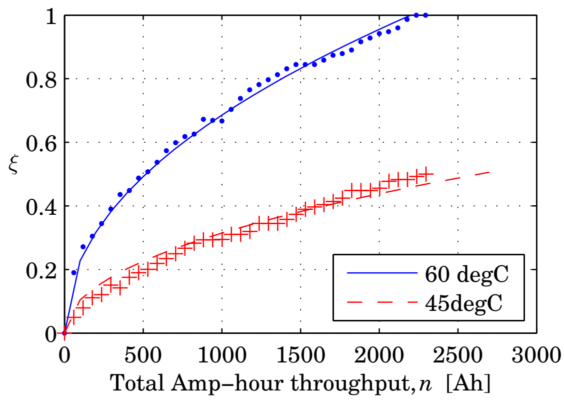

Fig. 7. Damage progression for Li-Ion batteries. The points represent the same data as Figure 4, and the continuous line is the curve fit (10)

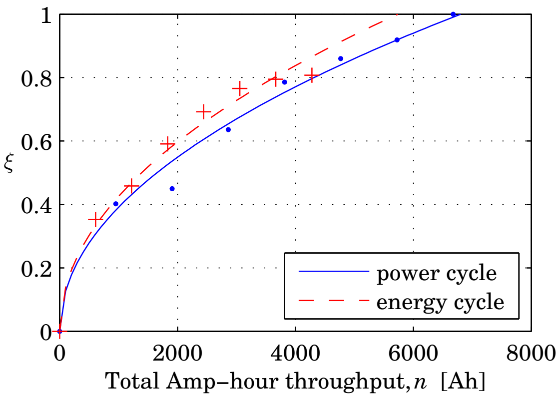

Fig. 8. Damage progression for PbA batteries. The points represent the same data as Figure 5, and the continuous line is the curve fit (10)

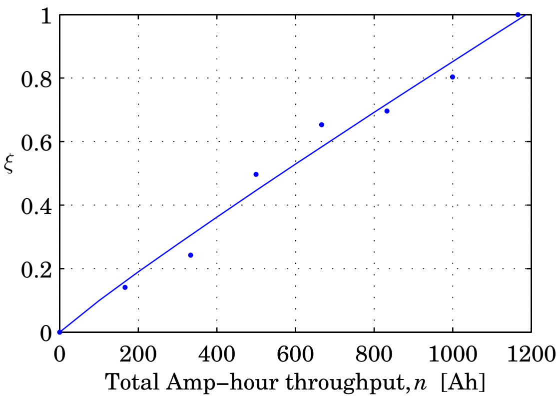

Fig. 9. Damage progression for NiMH batteries. The points represent the same data as Figure 6, and the continuous line is the curve fit (10)

6. IMPLEMENTATION

The advantage of (14) is that it lends itself to online implementation for estimating the current age of the battery and estimating its remaining useful life, since it offers a direct relation between the age of the battery and the aging parameters at the instant $k-1$, and the age at the next instant k. Using a forecast of future loading conditions (for example, on the basis of past operating conditions), the evolution of the damage can be predicted.

However, several issues need to be addressed for a successful implementation of the proposed aging model.

First, for a given battery, comprehensive maps of the coefficient $a_1(p)$ must be obtained from experiments, as a function of the loading parameters p. a_2 is determined from the same experiments, but it is constant for a given battery. These experiments are very time-consuming and thus there is very little data currently available, at least in the open literature.

If the maps are available, the remaining issue is the integration of (14) on board of the vehicle for the entire battery life. In fact, modelling errors and approximations make the integration process subject to unavoidable errors, which should be corrected by appropriately resetting the accumulated value of the damage ξ_k. In order to do this, an independent assessment of battery damage (i.e. a measurement of its capacity) must be available on board, but at this point this is not possible. Finding alternative methods to assess the current damage level (even at infrequent intervals) is then necessary for realistic implementation of the proposed model.

7. CONCLUSION

An analytical aging model for batteries used in automotive applications has been presented, starting from experimental data and curve fitting. The validity of an additive damage accumulation law like the Palmgren-Miner rule used in mechanical fatigue modeling has been proved assuming the validity of the curve fitting approach, and a directly implementable damage progression law has been derived. Open issues regarding the effective implementation of the proposed model are the need for a large amount of experimental data, and the fact that the simple integration of the damage accumulation law may not be reliable without a method to assess periodically the current value of the damage measure ξ.

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