A Novel Algorithm to Integrate Battery Cyclic and Calendar Agings Within a Single Framework

S. Ali Pourmousavi, Babak Asghari, Ratnesh K. Sharma

***Abstract*— *Cyclic* and *Calendar* agings are the two primary sources of degradation in a battery. An accurate battery degradation model can only be achieved when both processes are considered. In this paper, a novel framework is proposed to integrate *Cyclic* and *Calendar* aging processes. The proposed framework is able to accommodate different individual *Cyclic* and *Calendar* aging models only with slight modifications. It also can work conveniently as a universal degradation framework in different applications, such as large-scale battery storage systems in microgrids (MGs) and electric vehicles (EVs).**

I. INTRODUCTION

Recently, different battery technologies have attracted lots of attention from power system industry and car manufacturers for large integration. In power system industry, batteries are expected to grow in capacity to an unprecedented level for different applications such as frequency regulation, voltage support, peak shaving, increasing renewable penetration, and microgrid (MG) applications. For instance, batteries are recognized to be an inevitable tool for safe and secure operation of MGs, especially during islanded operation. Although different battery technologies (such as Li-Ion) show significant price reduction in the past few years, they are still considered as the most expensive part of the system, whether a MG or electric vehicle (EV). Since batteries of any technology will gradually lose initial capacity and power capability, their optimal operation (by accounting for their degradation) becomes an important factor for successful and economic utilization of these devices in different applications. Typically, battery operation is controlled via battery management system (BMS) or energy management system (EMS) in EVs and power system applications. Either case, utilizing a powerful battery degradation model in BMS/EMS can improve battery operation.

Battery capacity degradation is a complicated nonlinear phenomenon which is caused by two different aging processes, namely *Cyclic* and *Calendar* aging. The *Cyclic* aging, as the name suggests, occurs due to battery charge and discharge activities over the course of its lifetime. It is well-known that a battery will be directly affected by charge/discharge characteristics such as average state-of-charge (SOC), SOC deviation, charge and discharge rates, and energy throughput. The *Calendar* aging, on the other hand, takes place when battery remains idle. It is known to be a function of storage SOC (i.e., battery SOC at the beginning of the idle period) and its duration. In MG and EV applications, a battery will experience both type of degradation on a daily basis. Therefore, a battery capacity degradation model integrating the two aging processes can potentially increase the accuracy of estimation.

In the past couple of years, significant research work have been reported on battery degradation modeling caused by cyclic activities, e.g. [1]–[12]. Few other research papers focused on the *Calendar* aging separate from *Cyclic* aging, e.g., [13]–[15]. However, to the best of our knowledge, very few research papers addressed integration of the two aging processes within the same framework. In [16], a battery degradation model is proposed considering *Cyclic* and *Calendar* aging together based on actual EV data. First issue with this method is that a linear relation among different parameters is hypothesized which is not adequate for battery degradation modeling. The nonlinearity of this phenomenon is even more significant in large-scale storage applications where batteries are expected to work until they reach to 65% of their nominal capacity, instead of 80% typical expectation in other applications such as EVs. So, a nonlinear model can potentially increase the accuracy of estimation, particularly for MGs and grid-scale applications. Since both *Cyclic* and *Calendar* aging models are put together in a single function in [16], it can be realized that the proposed method is not flexible in terms of accommodating more complicated and nonlinear individual degradation models. Additionally, the proposed method does not consider the impact of one aging on the other one, i.e., the interactive terms.

To fill this gap in research, an innovative approach is proposed in this paper to accommodate *Cyclic* and *Calendar* agings in a single framework. The proposed framework decouples *Cyclic* from *Calendar* aging so that any individual *Cyclic* and *Calendar* aging models can be employed. It is also computationally inexpensive and fast for online applications. The proposed approach starts with extracting required data for individual *Cyclic* and *Calendar* aging models. Then, battery capacity degradation will be estimated for each aging processes separately for a hypothetical battery lifetime. After checking the stability of the estimated values, final integration will be made among individual *Cyclic* and *Calendar* estimated values. Eventually, a curve fitting will be carried out on the final integrated values to achieve battery degradation function with respect to battery W.h throughput.

Rest of the paper is organized as follows. In Section II, the proposed integration framework is introduced from a general perspective. Then, different parts of the proposed framework is described in detail in Section III following up with an example. Finally, the paper is concluded in Section IV.

S. Ali Pourmousavi (email: s.pourmousavi@nec-labs.com), Babak Asghari (email: babak@nec-labs.com), and Ratnesh K. Sharma (email: ratnesh@nec-labs.com) are with Energy Management Department at NEC Laboratories America, Inc., Cupertino, 95014 USA.

II. The Proposed Integration Framework

In an individual *Cyclic* or *Calendar* aging model, single degradation process is considered neglecting the aging occurred by the other process. In addition, the impact of one process is ignored on the other one. It consequently reduces the accuracy of battery capacity estimation. To overcome this issue, a novel framework is proposed in this paper to integrate individual *Cyclic* and *Calendar* aging estimation. It accounts for mutual impact of one process towards another. Furthermore, the proposed framework can accommodate any individual *Cyclic* and *Calendar* aging models. In this framework, individual models will be used to generate primary battery capacity estimation without accounting for the impact of other aging process. Then, a procedure will combine the individual primary estimated values accounting for their mutual impacts. A unique combined degradation model will be created for any given battery charge/discharge profile, as the input parameter. As a result, the proposed framework should be repeated when a new charge/discharge profile is available. Bear in mind that this paper introduces an innovative approach to integrate *Cyclic* and *Calendar* aging within the same framework. So individual *Cyclic* and *Calendar* aging models are not discussed here. Additionally, the proposed framework is developed for single cell battery operation. This way, it provides an opportunity to estimate and track battery degradation for individual cell instead of the whole stack of battery. It further increases the flexibility, scalability, and accuracy of the estimation. It also comply with the real-world application where individual cells are not homogeneously degrading in a stack.

Prior to explaining the procedure, it is worthwhile to highlight couple of premises which the model is built upon, as follows:

- **Premise 1:** The idea is developed based on the fact that *Cyclic* aging happens when battery is under either charge or discharge while *Calendar* aging occurs when battery remains idle. This way, two processes do not occur simultaneously.
- **Premise 2:** It is assumed that the *Cyclic* and *Calendar* agings can be superimposed. The only interactive parameters between the two processes are battery storage SOC (in *Calendar* aging model) and battery estimated capacity (used to estimate individual *Cyclic* and *Calendar* agings) which is also affected by battery operation in the past.

An overview of the proposed framework is shown in Fig. 1. Similar to any other battery degradation model, charge/discharge profile of the battery is required. Since the framework is designed for cyclic operation, at least one day worth of data is expected at the input. In addition, individual *Cyclic* and *Calendar* aging models should be provided for the proposed framework.

As it can be seen from Fig. 1, the procedure starts with ”Pre-Processing Unit” which extracts required data from the given charge/discharge profile. Then, primary *Cyclic* and *Calendar* aging values will be estimated in ”Primary Estimation Unit” for the given profile, using provided individual *Cyclic* and *Calendar* aging models. After processing the results in ”Post-Processing Unit”, final estimation considering both *Cyclic* and *Calendar* aging will be made in ”Final Estimation” unit. Fig. 2 shows the proposed framework in detail.

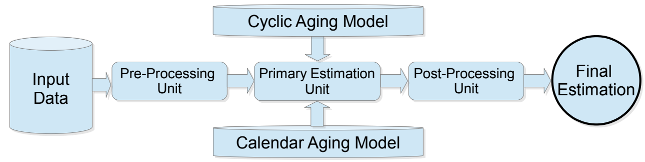

Fig. 1. A general flowchart of the proposed integrated model.

III. Integration Procedure

In this section, different parts of the proposed framework, shown in Fig. 1, will be explained in detail based on Fig. 2. The procedure will start from receiving data and individual *Cyclic* and *Calendar* aging models, and will end with final loop integration.

A. Input Data

Individual *Cyclic* and *Calendar* aging processes require certain input parameters to run. This is specific to each model and can change from one model to another significantly. However, most of the required data can be extracted directly from battery charge/discharge profile. This profile can be given either as battery power or current versus time. Battery charge/discharge profile is typically generated by BMS or EMS in different applications. The given profile will be used to extract required data to run individual *Cyclic* and *Calendar* aging model, as required by the given models.

In addition to input parameters required by individual *Cyclic* and *Calendar* aging models, other parameters might be needed such as latest estimated battery capacity, accumulated W.h throughput, and initial SOC of the battery at the beginning of given profile. Other required parameters specific to individual models (such as ambient temperature, sampling interval (i.e., $W.h_{Interval}$), maximum W.h ($W.h_{max}$) and so on) can also be given in this module.

B. Pre-Processing Unit

As shown in Fig. 2, the proposed procedure starts with extracting required information from given data at the input. Except for specific parameters associated with *Cyclic* and *Calendar* aging models, explained in the previous subsection, other parameters can be extracted directly from given battery charge/discharge profile vs. time. In the rest of this paper, the given charge/discharge profile is assumed to be battery power versus time.

Typically, *Cyclic* aging models utilize parameters such as daily average SOC, SOC deviation, charge and discharge rates, ambient temperature, and W.h throughput. First, SOC values will be calculated for each time stamp based on the initial SOC value and given profile. The average daily SOC will be the arithmetic average of the calculated SOC values. To calculate SOC deviation, SOC values are divided into two categories: 1) values greater than daily average SOC, and 2)

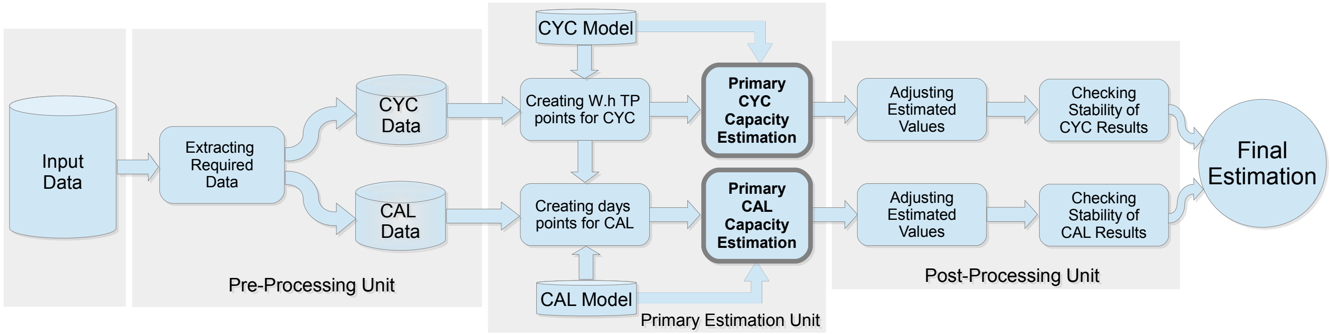

Fig. 2. Detailed flowchart of the battery degradation model integrating *Cyclic* and *Calendar* aging.

values smaller than daily average SOC. The SOC deviation then is the difference between average of the first category and average of the second one. In order to find charge and discharge rates, it is first required to calculate normalized charge/discharge rates for each time step, neglecting idle periods. Normalized rate is calculated as follows:

$$(.)_{rate} = \frac{|P_i| \times \Delta T_i}{C_{prev} \times V_{batt}} \quad (1)$$

where $(.)_{rate}$ can be either C_{rate} or D_{rate} in p.u.; $|P_i|$ is the absolute value of charge or discharge event i in Watt; ΔT_i is the time interval of event i in hour; C_{prev} is the previous estimated capacity of the battery in A.h; and V_{batt} is the battery voltage during the event, or simply the rated voltage. In this study, all values are calculated and reported for a single battery cell. Ultimately, the average charge and discharge rates for the daily profile will be the arithmetic average rates of charge and discharges events throughout the day, respectively. Extracted parameters will be stored in "CYC Data" for later use. Daily W.h throughput of the battery is calculated by:

$$W.h_{TP} = \sum_{i=1}^{N} |P_i| \times \Delta T_i \quad (2)$$

where N is the number of intervals.

Calendar aging is affected by the storage SOC, idle time duration, and ambient temperature. Although idle situation can happen multiple times throughout a day with different time duration, its accumulated impact is considered in this study for further simplification. As a result, accumulated daily idle time and average storage SOC will be calculated in "Extracting Required Data" block. Average storage SOC is the arithmetic average SOC of the battery at the beginning of all idle events throughout the day. Derived information will be stored in "CAL Data" module for later use.

C. Primary Estimation Unit

After calculating required information from input data, battery capacity (known as primary battery capacity) will be estimated for *Cyclic* and *Calendar* aging separately, assuming that the parameters will remain the same for battery lifetime. For *Cyclic* aging, battery capacity (i.e., $C_{cyc}^{prim}(i)$) will be estimated for different W.h throughput values while other parameters (which resides in "CYC Data" unit) are kept constant. To do so, a vector of W.h throughput values (i.e., $E_{th}(i)$) will be generated from zero to "maximum W.h throughput" with "W.h throughput interval", which are given as input parameters. For *Calendar* aging, battery capacity (i.e., $C_{cal}^{prim}(i)$) will be estimated based on accumulated shelf time while other parameters, stored in the "CAL Data" module, will remain constant. To combine two sets of capacity estimations, *Calendar* aging will be estimated at the same point in time as of *Cyclic* aging based on $E_{th}(i)$. This way, we will calculate a vector of battery accumulated shelf time (i.e., $T_{idle}(i)$ for primary *Calendar* aging estimation) relative to every W.h throughput value created previously, assuming that the given profile is for a day, as follows:

$$T_{idle}(i) = \frac{E_{th}(i).T_{idle}^{daily}}{24 \times E_{daily}} \quad (3)$$

where $E_{th}(i)$ is the i^{th} W.h throughput value in W.h; T_{idle}^{daily} is the daily idle time of the battery in hour; and E_{daily} is the daily W.h throughput. This part of calculation will be performed in "Creating days points for CAL" block.

Having input parameters ready for primary *Cyclic* and *Calendar* capacity estimation for all W.h throughput and shelf time created previously, it is possible to carry out battery degradation estimation individually. Parameters required for each model (described in Section III-C) is already derived from the given data and reside in "CYC Data" and "CAL Data" modules. Finally, battery capacity for individual *Cyclic* and *Calendar* aging will be calculated in "Parimary CYC Capacity Estimation" and "Parimary CAL Capacity Estimation", separately. So far, one can realized that any individual degradation model can be utilized without any significant changes.

D. Post-Processing Unit

In this unit, one can develop algorithms to check primary estimated values. For instance, battery capacity is supposed to decline after each charge/discharge events (ignoring some special instances), although minuscule. If there is an increase in primary estimated values, it can be fixed before integration. Additionally, individual *Cyclic* and *Calendar* aging models are developed using specific experimental datasets. Sometime, it is possible to use one such model for a battery of different capacity but similar chemistry. This can also be considered in "Adjusting Estimated Values" module. Because

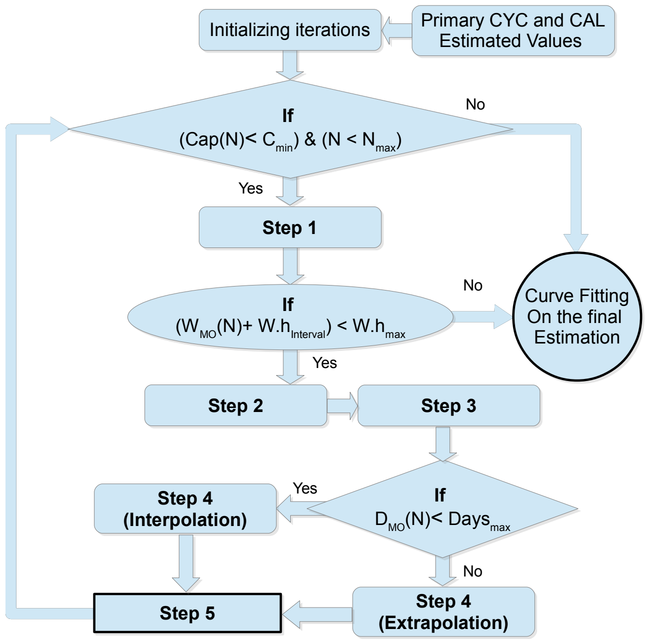

Fig. 3. Detailed schematic diagram of the "Final Integration Loop" of Figure 2.

of the page limit, these algorithms are not discussed in this paper.

E. Final Estimation

In order to combine individual *Cyclic* and *Calendar* aging values from sub-section III-C, it is required to modify battery operating point for each estimated value, and to re-estimate W.h throughput and accumulated shelf day using interpolation and extrapolation. The reason is simple: each *Cyclic* and *Calendar* aging value of sub-section III-C is estimated when the two aging processes did not have any impact on each other. For instance, when calculating *Cyclic* aging, there was not a notion of *Calendar* aging on initial battery capacity and vice versa. In reality, however, battery experiences idle period (and consequently *Calendar* aging) which its impact should be considered on individual *Cyclic* estimation. This can become more important at higher accumulated W.h throughput values when battery degradation is more nonlinear and faster. Therefore, it is required to modify battery operating point (i.e., actual W.h throughput in *Cyclic* aging, and actual accumulated shelf time in *Calendar* aging) prior to combine them together. To do so, algorithm shown in Fig. 3 is developed, which is detailed flowchart of "Final Integration Loop" module in Fig. 2.

As shown in Fig. 3, the loop starts with primary *Cyclic* and *Calendar* estimated values. Then, number of iteration, N, will be set to two at the beginning and maximum number of iteration, N_{max}, will be set to the number of *Cyclic* estimated values from sub-section III-C. Minimum *Cyclic* battery capacity, C_{min}, will be set to the minimum estimated value in the *Cyclic* primary estimated values of sub-section III-C. The loop will stop when Cap(N) is less than C_{min} or when we reach N_{max}, or when W.h throughout exceeds maximum limit. Cap(N) is the actual battery capacity considering both *Cyclic* and *Calendar* aging. In the first iteration, battery starts fresh. So *Cyclic* and *Calendar* agings will start from the installed battery capacity. Combined battery capacity at each iteration, Cap(N), is the previous combined battery capacity minus individual *Cyclic* and *Calendar* aging values of that iteration. The procedure is divided in to four steps, as shown in Fig. 3:

- **Step 1:** Therefore, calculating new *Cyclic* aging for the next point in W.h throughput vector requires modifying W.h value based on the Cap(N). In other words, actual W.h throughput value does not represent Cap(N) and should be modified. The same rationale can be recognized for *Calendar* aging except that accumulated shelf time should be modified for the combined capacity fade, i.e., Cap(N). In order to calculate new W.h, $W_{\text{MO}}(N)$, a linear interpolation is realized using primary *Cyclic* estimated values. Experimental data analysis showed that the battery capacity changes linearly in short period of time, although it might be nonlinear in long-term analysis.
- **Step 2:** If $W_{\text{MO}}(N) + W.h_{\text{Interval}}$ is less than $W.h_{\text{max}}$ (which is given as a parameter in "CYC Model"), the new W.h throughput value is within the range of experimental data which individual model is trained. The loop will be terminated when it goes outside of the range. Having new W.h throughput value associated with Cap(N), we can calculate the *Cyclic* degradation for the next W.h throughput value which is $W_{\text{MO}}(N) + W.h_{\text{Interval}}$, where $W.h_{\text{Interval}}$ is the interval of W.h throughput fetched as input parameter from "CYC ANN Model" in Fig. 2. Here, new *Cyclic* capacity estimation, $\text{CYC}_{new}(N)$, is calculated using linear interpolation among primary *Cyclic* aging estimated values.
- **Step 3:** When new *Cyclic* degraded capacity is calculated, we compute battery new capacity as a result of *Calendar* degradation for the next interval. Prior to do that and similar to *Cyclic* aging calculation, we need to adjust accumulated shelf time for the new combined degraded capacity, i.e., Cap(N). This can be done by interpolation in the primary *Calendar* estimated values for Cap(N).
- **Step 4:** If the new accumulated shelf time, $D_{\text{MO}}(N)$, in this iteration is less than maximum available storage days in the primary aging estimations, we can carry out interpolation to calculate new *Calendar* aging capacity, i.e., $\text{CAL}_{new}(N)$. Otherwise, as shown in Fig. 3, we need to perform extrapolation. In both cases, a linear operation is preferred because *Calendar* aging in typical ambient temperature (i.e., below $40\,^{\circ}\text{C}$) follows a linear trend. In temperature-controlled environment, batteries' temperature is kept well below $40\,^{\circ}\text{C}$ which further justifies this assumption.

Having both *Cyclic* and *Calendar* aging calculated in each iteration for new W.h throughput and new accumulated shelf time, we can calculate the total degraded capacity at the end of current iteration (which equivalently is the beginning of

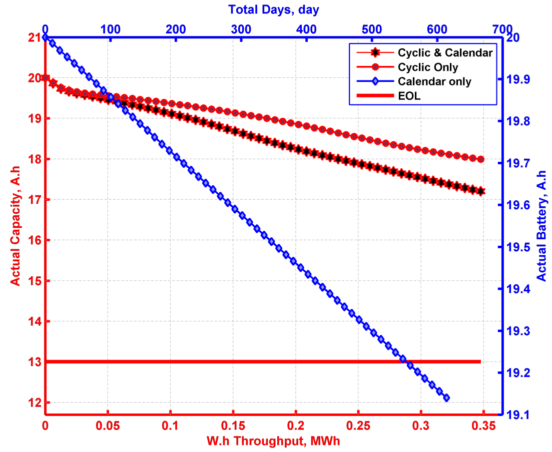

Fig. 4. Sample results of the integration framework with individual *Cyclic* and *Calendar* aging values.

the next iteration, i.e., $N \longrightarrow N+1$), as follows:

$$\text{Cap(N+1)} = \text{CYC}_{new}(N) + (\text{Cap(N)} - \text{CAL}_{new}(N)) \quad (4)$$

where Cap(N+1) will be used as the new battery capacity considering both *Cyclic* and *Calendar* agings at the beginning of the loop in the next iteration. At the end of the loop, we will have combined battery capacity estimation for the given profile from the beginning of the battery lifetime to its end.

Ultimately, combined battery capacity can be expressed as a function of either W.h throughput values or accumulated shelf time. Typically, a second-order polynomial function is adequate fit on the estimated values. However, any other curve fitting models and techniques can be used without changing the proposed framework. Please note that this function is valid only for the given battery charge/discharge profile. Any changes in the battery profile requires repeating the proposed method from the beginning to derive a new function for battery degradation. Since the whole process is automated and very quick, the proposed approach can be utilized for different online and offline applications.

A sample result of the proposed framework is shown in Fig. 4. An arbitrary battery charge/discharge profile is defined where ambient temperature is 23 °C; average SOC and average SOC daily deviation are 0.5 p.u.; average daily charging and discharging rates are 1.0 p.u.; average storage SOC is 0.8 p.u.; and daily cycle is 10. The primary *Cyclic* and *Calendar* values are estimated by neural network models which have been developed and tested at NEC Laboratories America (NECLA). Without loss of generality, this curve is achieved by assuming that battery experiences the same profile until the end of its lifetime. As shown in the figure, *Calendar* aging values change linearly after 650 days, while *Cyclic* estimated values are nonlinear from the beginning. The final combined degradation values are nonlinear, as expected.

IV. CONCLUSIONS

In this paper, a framework is proposed to integrate battery *Cyclic* and *Calendar* aging together. The proposed procedure starts with extracting required information from battery charge/discharge profile for a certain period of time, preferably a day. Then, primary *Cyclic* and *Calendar* estimation will be made based on the extracted information. After adjusting and checking the stability of the primary results, modified values will be utilized in a loop where these two primary estimation will be integrated for final estimation. Ultimately, second-order curve will be fitted on the final estimated values. The proposed approach is flexible, fast, and accurate in terms of integration. Any individual *Cyclic* and *Calendar* aging can be utilized in the proposed framework.

REFERENCES

[1] F. Rufus Jr, S. Lee, and A. Thakker, "Health monitoring algorithms for space application batteries," in *Prognostics and Health Management, 2008. PHM 2008. International Conference on*. IEEE, 2008, pp. 1–8.

[2] B. Saha and K. Goebel, "Modeling li-ion battery capacity depletion in a particle filtering framework," in *Proceedings of the annual conference of the prognostics and health management society*, 2009, pp. 1–10.

[3] M. Safari, M. Morcrette, A. Teyssot, and C. Delacourt, "Life-prediction methods for lithium-ion batteries derived from a fatigue approach i. introduction: capacity-loss prediction based on damage accumulation," *Journal of The Electrochemical Society*, vol. 157, no. 6, pp. A713–A720, 2010.

[4] A. Hoke, A. Brissette, D. Maksimović, A. Pratt, and K. Smith, "Electric vehicle charge optimization including effects of lithium-ion battery degradation," in *Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE*. IEEE, 2011, pp. 1–8.

[5] S. Ebbesen, P. Elbert, and L. Guzzella, "Battery state-of-health perceptive energy management for hybrid electric vehicles," *Vehicular Technology, IEEE Transactions on*, vol. 61, no. 7, pp. 2893–2900, 2012.

[6] J. A. M. Penna, C. L. Nascimento, and L. R. Rodrigues, "Health monitoring and remaining useful life estimation of lithium-ion aeronautical batteries," in *Aerospace Conference, 2012 IEEE*. IEEE, 2012, pp. 1–12.

[7] I. Fernández, C. Calvillo, A. Sánchez-Miralles, and J. Boal, "Capacity fade and aging models for electric batteries and optimal charging strategy for electric vehicles," *Energy*, vol. 60, pp. 35–43, 2013.

[8] L. Lam and P. Bauer, "Practical capacity fading model for li-ion battery cells in electric vehicles," *Power Electronics, IEEE Transactions on*, vol. 28, no. 12, pp. 5910–5918, 2013.

[9] X. Wang, N. Balakrishnan, and B. Guo, "Residual life estimation based on a generalized wiener degradation process," *Reliability Engineering & System Safety*, vol. 124, pp. 13–23, 2014.

[10] S. S. G.-H. K. J. N. A. P. K. Smith, E. Wood, "Models for battery reliability and lifetime," National Renewable Energy Laboratory (NREL), Tech. Rep. NREL/CP-5400-57746, March 2014.

[11] A. Cordoba-Arenas, S. Onori, and G. Rizzoni, "A control-oriented lithium-ion battery pack model for plug-in hybrid electric vehicle cycle-life studies and system design with consideration of health management," *Journal of Power Sources*, vol. 279, pp. 791–808, 2015.

[12] A. Cordoba-Arenas, S. Onori, Y. Guezennec, and G. Rizzoni, "Capacity and power fade cycle-life model for plug-in hybrid electric vehicle lithium-ion battery cells containing blended spinel and layered-oxide positive electrodes," *Journal of Power Sources*, vol. 278, pp. 473–483, 2015.

[13] M. Broussely, "Aging mechanism in li ion cells and calendar life predictions," in *Fuel and Energy Abstracts*, vol. 43, no. 4. Elsevier, 2002, p. 260.

[14] Q. Zhang and R. E. White, "Calendar life study of li-ion pouch cells," *Journal of Power Sources*, vol. 173, no. 2, pp. 990–997, 2007.

[15] J. Belt, V. Utgikar, and I. Bloom, "Calendar and phev cycle life aging of high-energy, lithium-ion cells containing blended spinel and layered-oxide cathodes," *Journal of Power Sources*, vol. 196, no. 23, pp. 10 213–10 221, 2011.

[16] A. Barré, F. Suard, M. Gérard, M. Montaru, and D. Riu, "Statistical analysis for understanding and predicting battery degradations in real-life electric vehicle use," *Journal of Power Sources*, vol. 245, pp. 846–856, 2014.