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Incremental Degradation Estimation Method for Online Assessment of Battery Operation Cost

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***Abstract*—To ensure optimal and economical battery operation, it is necessary to consider its lifetime-limiting aspects, e.g., performance degradation and degradation costs. Battery performance degradation is commonly assessed by offline lifetime models. They are suitable for battery planning and performance monitoring, but cannot be used in real-time operation. Therefore, in this letter, an incremental degradation cost estimation method for optimal battery real-time operation is proposed. It enables battery degradation evaluation for any time resolution and set of operating conditions during the real-time operation.**

***Index Terms*—Battery, rainflow cycle counting, degradation, operation cost, real-time operation.**

I. Introduction

Key performance parameters of the battery, such as energy capacity and power capability, are strongly affected by the battery degradation. The degradation is an irreversible change in the battery material, which is a consequence of the battery usage. Several factors related to the operating condition, such as cycle depth and discharge rate, can strongly influence the degradation rate [1]. In order to plan an optimum operation strategy, the battery degradation needs to be determined. This is usually done by means of the offline lifetime estimation models. The lifetime estimation models typically calculate capacity fade for the input operating conditions, which are defined as finite set of time series data [1].

Normally, the irregular set of operating conditions is translated into equivalent set of simple stress reversals using cycle counting algorithms. Afterwards, the degradation model is used to estimate the capacity fade for each stress level. The physical degradation rate due to different operating conditions can be represented through the degradation cost. This quantity is used to compare the degradation with other performance aspects in the economic domain. This process is suitable for the battery planning and long-term performance monitoring [2], but cannot be implemented for the real-time operation (e.g., 5 minute intervals). The main limitation is that the complete time-series stress profile is not available during real-time operation. Therefore, the cycle counting algorithms cannot estimate the set of stress reversals that contribute to battery degradation.

One approach to overcome aforementioned limitations includes employment of machine learning-based models. For example, in [3], [4], a neural network-based approach is used to determine the battery degradation for the predicted operating conditions in the future. However, machine learning-based models heavily rely on a set of historical data that cover the most aspects of battery operation-induced degradation. If data are not large enough or of a good quality, the predictions of battery degradation can be biased and lead to untrue results. An alternative approach is to simplify the degradation model by making assumptions about the battery operation [5], [6]. For example, in [5], it is assumed that only one cycle per day is made. Moreover, in [6], it is assumed that the hourly profile consists of extrema, and the Rainflow cycle counting can produce information about the degradation. In both cases, the set of stress reversals that contribute to battery degradation can be known in advance, as stress profiles are greatly simplified. However, such assumptions about operating conditions cannot be made in the majority of the battery applications.

Therefore, a new method for battery degradation estimation is proposed in this letter. It overcomes the cycle counting limitations of the conventional methods for real-time application. In fact, it evaluates the increment in the degradation for any two consecutive operating points and for any given operating conditions. Hence, it can be used for variety of the battery applications without restrictions of the operating conditions even before the cycle is formed. Furthermore, the proposed method can be used to find the optimum battery operation

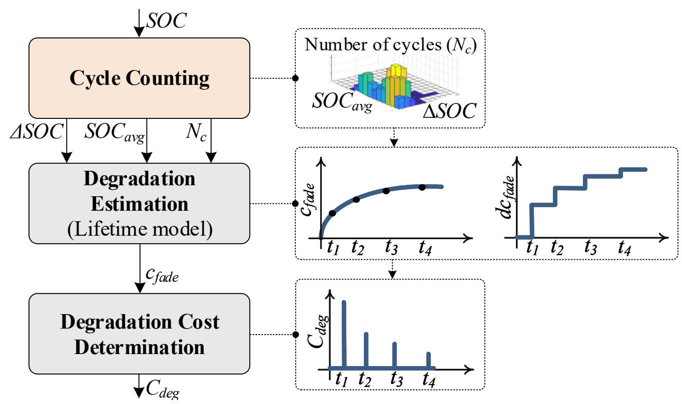

Fig. 1. Procedure for degradation cost assessment. The input is battery state-of-charge SOC (mission profile), the output is battery degradation cost C_{deg}. N_c is the number of cycles for certain cycle depth ΔSOC and average state-of-charge SOC_{avg}. c_{fade} is capacity fade, dc_{fade} is increment in degradation between two time instances, and C_{deg} is degradation cost.

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in real-time, as it evaluates battery degradation cost at all times. This can help to reduce the extra degradation, which is normally result of battery operation without considered cost of degradation. For example, certain operating conditions cause accumulation of battery degradation, but result with minor benefits for the users (e.g., performance, service provision, economic) when battery is utilized [7]. Such operating conditions can be avoided if battery operation is decided as the optimum of the benefits it provides and the degradation it causes. Hence, the proposed method can be used to extend battery lifetime and increase its profitability in long-term.

II. Conventional Degradation Cost Assessment

The conventional offline degradation cost estimation method consists of three main parts, as shown in Fig. 1, and it is elaborated in the following.

A. Cycle Counting

The input to the procedure is the state-of-charge SOC profile. It is a dynamic finite set time series stress profile of the battery, which is dependent on the operating conditions. Rainflow counting is an example of the cycle counting algorithm that is commonly used to determine the number of cycles with certain cycle depth ΔSOC and average SOC_{avg} [8]. Its working principle is based on the evaluation of four successive local extrema which define three consecutive ranges. If the middle range is smaller than the first and the last range, a full cycle is made. The two extrema defining the middle range are discarded and the remaining local extrema are connected to create a new range. Then, the next local extrema is added to the newly created range. If the full cycle condition is not fulfilled, the new extrema is considered and the evaluation procedure is repeated. The process of counting the full cycles is terminated once the last local extrema is reached. The remaining local extrema define a half cycle [8]. Therefore, to obtain the complete set of reversals, the starting and ending points are necessary. In [9], a method to overcome this limitation is presented. The algorithm provides information after each cycle is formed. In that case, the time series data that define a single cycle is sufficient. However, the main limitation is that the degradation information is not available before or after a cycle is formed. This limits its usage, as in certain applications, a substantial time can pass before the two cycles are formed.

B. Capacity Fade Estimation

The capacity fade needs to be estimated for the characteristic operating conditions of depth-of-discharge and average state-of-charge $(\Delta SOC, SOC_{avg})$. A model extensively tested in [10] and employed in [11] on practical scenario is chosen. It represents a degradation model for Lithium Manganese Cobalt Oxide batteries defined as [11]:

$$c_{fade} = a_{cyc} \cdot (N_{eq}(\Delta SOC, SOC_{avg}))^{b_{cyc}} \qquad (1)$$

where N_{eq} is number of equivalent full cycles for given ΔSOC and SOC_{avg}. a_{cyc} and b_{cyc} are cycle ageing parameters, where a_{cyc} is a function of SOC_{avg} and ΔSOC:

$$a_{cyc} = \frac{1}{\left(K_{SOC_{avg}} \cdot a_w \cdot \Delta SOC^{b_w}\right)^{b_{cyc}}} \qquad (2)$$

where $a_w \cdot \Delta SOC^{b_w}$ represents the maximum theoretically achievable number of cycles that can be determined by means of Whöler function. $K_{SOC_{avg}}$ is an acceleration factor which accounts for increase in the physical degradation for SOC_{avg} values close to the upper and lower SOC boundary. Contrary to a_{cyc} parameter which is depended of input SOC, b_{cyc} is a battery-specific constant which defines early ageing rate. It value is between 0 and 1, where the values closer to 0, reflect a more pronounced degradation at the beginning-of-life.

C. Degradation Cost Determination

The degradation cost C_{deg} is defined as the percentage of the battery capital cost C_{cap}, which is equivalent to the increment in degradation dc_{fade} [12]:

$$C_{deg} = C_{cap} \cdot dc_{fade} \qquad (3)$$

The increment in degradation dc_{fade} is a difference in the capacity fade obtained with (1) at two time instances. For input SOC mission profile, it represents the difference between the initial capacity fade and the one that is a result of the operating conditions for which the degradation is determined. In case of Online Rainflow cycle counting [9], it represents the difference between two consecutive cycles. In both cases, dc_{fade} cannot be known until at least one cycle is formed.

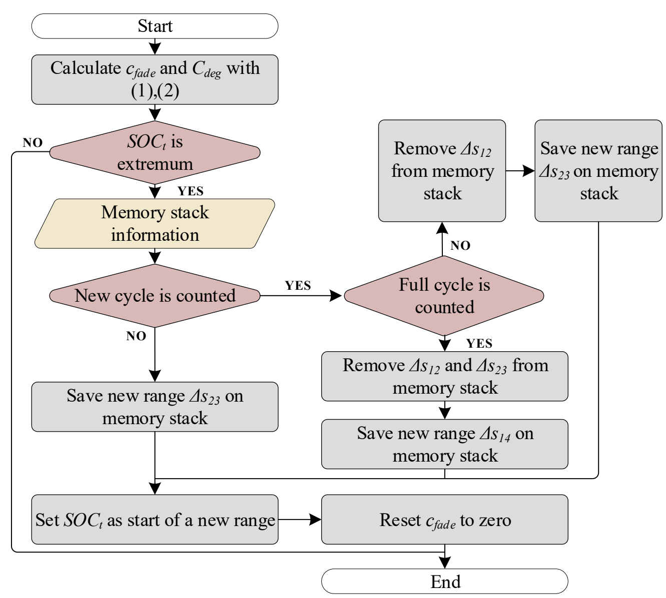

Fig. 2. Working principle of the proposed Incremental degradation cost estimation method. C_{fade} is capacity fade, C_{deg} is degradation cost, SOC is state-of-charge. ΔS_{ij} is a range that is defined by the local extrema S_i and S_j, where $i, j = \{1, 2, 3, 4\}$.

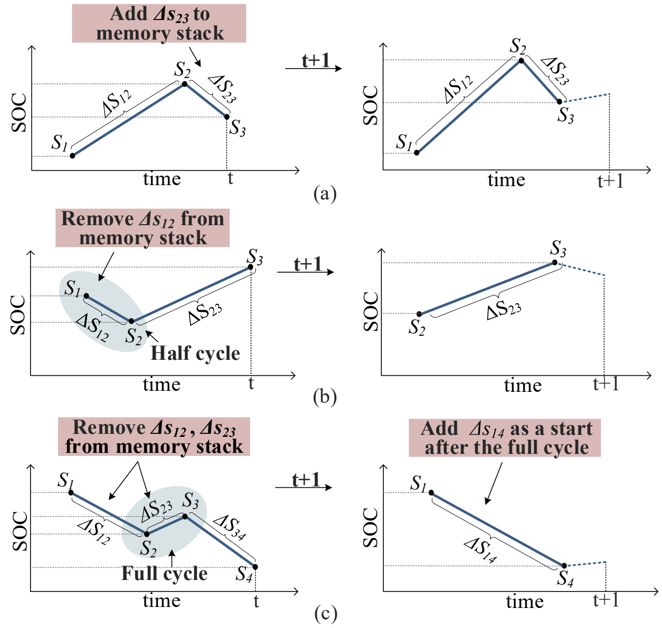

Fig. 3. Working principle of the memory stack shown on the example of two consecutive time instances t and $t+1$ used in the proposed method for incremental degradation cost assessment in case of: (a) No cycles counted, (b) Half a cycle counted, and (c) Full cycle counted. ΔS_{ij} is a range that is defined by the local extrema S_i and S_j, where $i, j = \{1, 2, 3, 4\}$.

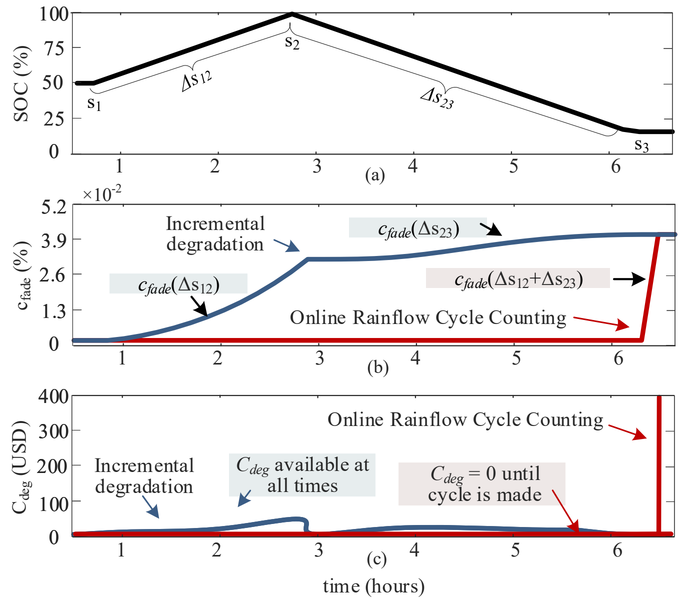

Fig. 4. Validation results: (a) Battery state-of-charge SOC profile, (b) capacity fade c_{fade}, and (c) Degradation cost C_{deg} determined with the Incremental degradation method and Online Rainflow cycle counting method.

III. Incremental Degradation Cost Assessment

A. Working Principle

The proposed method determines the degradation in the incremental manner for any two successive points during the real-time operation (e.g., 5 minute intervals). In fact, it provides the information about the true battery degradation cost at all times. The method is implemented as a two-step procedure that is applied to two successive points SOC_t and SOC_{t+1} (input). The first point SOC_t represents the current SOC state. The second point SOC_{t+1} represents the SOC state in the next time instance for which the cost of degradation needs to be determined. In the first step, the increment in degradation $dc_{fade}(\Delta t)$ for the two successive points is determined, as shown in flow chart of the process in Fig. 2. First, the capacity fade $c_{fade}(t+1)$ is calculated with (1)-(2) for the input $\Delta SOC = |SOC_{t+1} - SOC_t|$ and $SOC_{avg} = 0.5 \cdot (SOC_{t+1} + SOC_t)$. Then, the increment in degradation $dc_{fade}(\Delta t)$ is determined by subtracting the capacity fade $c_{fade}(t+1)$ and the known capacity fade from the previous moment $c_{fade}(t)$. The output is degradation cost C_{deg} determined with (3) for the obtained $dc_{fade}(\Delta t)$.

To determine the increment in degradation, it is assumed that the SOC_t is the extremum of the range which forms a half cycle. However, according to the Rainflow cycle counting rules, this information becomes available after three consecutive ranges are formed. The assumption is made, as in the real-time operation, a substantial time can pass until information about the three consecutive ranges is known. To minimize the impact of this assumption on the accuracy of the results, a second step is employed. In this step, the impact of SOC_t point on the formation of cycles is examined. This is done by introducing memory stack, which stores the extrema and range information. The memory stack operates on the base of cycle counting rules. Once it identifies that a half or a full cycle is formed, the actual capacity fade is calculated for a given cycle. This value is then used as a basis for further calculations of the capacity fade in the future. The memory stack considers four cases for which the SOC_t point has different influence on the formation of cycles, as shown in Fig. 3. If the SOC_t is a point between two extrema, no information is stored in the memory stack. If SOC_t is extremum, three cases can be differentiated, where either half or a full cycle are counted or no cycle is formed. This is done by examining the ranges available in the memory stack. In case of three active consecutive extrema, two ranges ΔS_{12} and ΔS_{23} are considered. The Rainflow cycle counting rules outlined in Section II are used to examine the ranges available in the memory stack. If no decision about the new cycle can be made, the information about the two ranges is kept in the memory stack and the three local extrema remain active. If a half cycle is counted, the range information are no longer needed. The range ΔS_{12} is removed from the memory stack, the local extremum S_1 is deactivated, and the subsequent local extremum S_2 is indicated as the start of an active local extremum. To count for a full cycle, three consecutive ranges ΔS_{12}, ΔS_{23} and ΔS_{34} are needed. Once the full cycle is identified, the degradation is determined for a ΔS_{23} range. The information for the three ranges is replaced with a new range ΔS_{14} and the degradation is added to the memory stack.

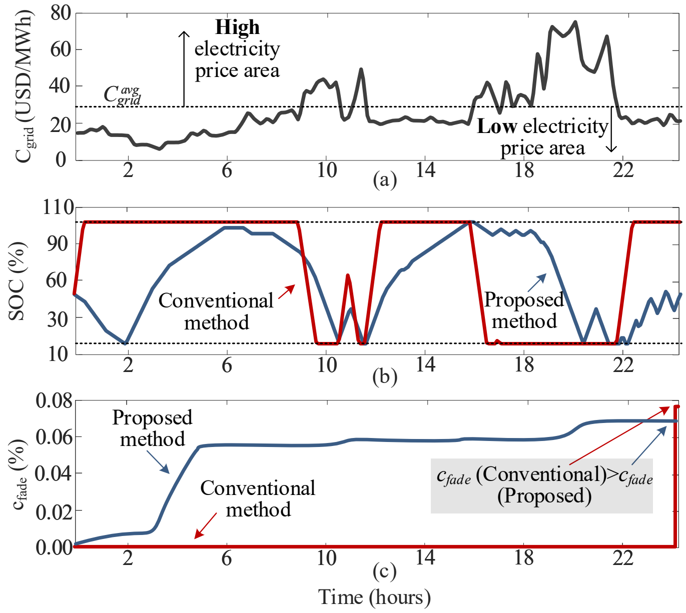

Fig. 5. Validation results: (a) Electricity price profile C_{grid} (c) State-of-charge profile SOC, and (d) Capacity fade c_{fade} for the proposed and the conventional method used for determining the battery operation.

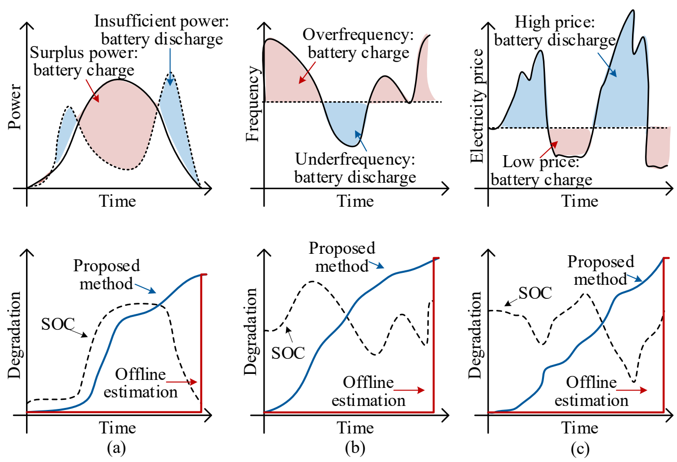

Fig. 6. Illustration of degradation assessment with the proposed method for battery application in: (a) internal load supply in residential photovoltaic applications, (b) participation in frequency regulation, and (c) reduction of electricity bill for large-scale units.

B. Validation

To estimate the degradation with the proposed Incremental degradation method and the Online Rainflow cycle counting method from [9], a SOC profile shown in Fig. 4(a) is used. The profile is obtained by using the battery performance model developed in [13]. The c_{fade} results (Fig. 4(b)) indicate the accuracy of the proposed method, as it yields the same final degradation as the Online Rainflow cycle counting method. The main advantage of the Incremental degradation method over the Online Rainflow cycle counting is that the information about the change in the degradation is available at all times. Therefore, C_{deg} can be evaluated at each time instance, as shown in Fig. 4(c). When the Online Rainflow cycle counting is used, C_{deg} is available at the discrete time instance that corresponds to the time when a cycle is formed. In that case, C_{deg} is zero between cycles, which is not true in a real application. Furthermore, the proposed Incremental degradation method is used to determine the optimal battery operation. The battery operation is decided based on its cost of degradation and price of grid electricity C_{grid} given in Fig. 5(a). This operation is compared with the conventional method, where battery degradation cost is not available at all times. The conventional method minimizes the cost of electricity used without considering the cost of battery degradation during the real-time operation. The SOC and c_{fade} profiles obtained for the two operation strategies are shown in Fig. 5(b),(c). A lower c_{fade} is obtained with the proposed method, which helps to reduce the extra stress by including the degradation cost in an online decision making. On the contrary, when the conventional method is used, the battery charges and discharges more frequently as the grid electricity price changes. This imposes additional degradation, which is not accounted when the degradation cost is known during the operation. Such operation in the long-term results with the accelerated degradation and limits the battery lifetime.

C. Real-Time Implementation and Applications

To perform real-time degradation cost assessment, the proposed method needs to be included in the control or energy management system. It can be used between each two successive operation point updates, where a next operating point is decided based on the evaluated degradation cost. The method is suitable for real-time operation, as it provides information about the degradation even before the cycles are formed. This is illustrated in Fig. 6 on the example of battery application in the internal load supply of photovoltaic residential systems, participation in frequency regulation, and reduction of electricity bill for large-scale units (e.g. data centers). Furthermore, the method can be included with other performance parameters in the optimization process. Hence, its usage can be extended to other applications, where the decision on battery operation is based on cost-benefit evaluation.

IV. Conclusion

This letter has proposed an incremental degradation cost assessment method for a battery. The proposed method overcomes the limitations of the conventional degradation methods for application in the real-time operation. It enables evaluation of the true cost of battery operation, i.e., degradation cost for any chosen time interval. It can be effectively used to assess a true cost of the battery operation at all times.

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