An Overview of Different Approaches for Battery Lifetime Prediction

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Abstract. With the rapid development of renewable energy and the continuous improvement of the power supply reliability, battery energy storage technology has been wildly used in power system. Battery degradation is a nonnegligible issue when battery energy storage system participates in system design and operation strategies optimization. The health assessment and remaining cycle life estimation of battery gradually become a challenge and research hotspot in many engineering areas. In this paper, the battery capacity falling and internal resistance increase are presented on the basis of chemical reactions inside the battery. The general life prediction models are analysed from several aspects. The characteristics of them as well as their application scenarios are discussed in the survey. In addition, a novel weighted Ah ageing model with the introduction of the Ragone curve is proposed to provide a detailed understanding of the ageing processes. A rigorous proof of the mathematical theory about the proposed model is given in the paper.

1. Introduction

Renewable energy sources play an important role in solving the global environmental pollution problems. However, the renewable resources are unsteady and uncontrollable because the output of renewable energy sources vary with the weather and native conditions. Many serious challenges will happen including power system reliability and power quality because of the high penetration of the renewable energy. In recent years, how to compensate the renewable energy fluctuations is studied by lots of researchers. The battery energy storage system has been used in many projects and experiments as an effective method to make much fluctuant renewable energy into the electrical power system peacefully.

At present, the overviews of battery energy storage in the application of the electric power system mainly focus on introducing the characteristics of each type of energy storage battery, the control of the energy storage system and configuration modes and various application fields in power system, etc. However, the battery degradation cost plays a significant role in the cost optimization and dispatch control because extending the battery service life can effectively reduce the battery switching and operation maintenance cost. This paper introduces the battery aging processes caused by the internal chemical reactions and the stress factors which influence the battery lifetime, and then we compare the three battery lifetime prediction approaches. The advantages and disadvantages of them as well as their application scenarios are discussed in the survey. Based on the existing incomplete Ah aging model, a novel weighted Ah ageing model is proposed to provide a precise presentation of the battery degradation processes.
2. Influence factors of battery life

When a battery is used under different conditions, the combination and decomposition reactions of the active material occur all the time. There are many research studies which can prove that in addition to the desired active compound, many other elements existing in the battery give rise to unwanted chemical reactions. This phenomenon can result in the battery capacity reduction and resistance increase.

2.1. Temperature

The battery operates in hotter condition; the chemical reactions are faster and the battery performance will be improved observably. On the other hand, the unwanted reactions are also active when the temperature is higher.

As shown in Figure 1 is a lead-acid battery capacity change curve obtained through the year-round operation at different temperatures. We can see that the battery has a better capacity performance at than the lower temperature, but the high-temperature operation is also accompanied by a short life and significant economic waste.

![Figure 1. Battery capacity degradation at different temperatures](image)

2.2. Depth of discharge (DOD)

When the other operation conditions are determined, the transformation of active chemicals is proportional to the DOD in the process of charging and discharging. Figure 2 shows how the battery cycle life varies with the DOD of a lead-acid battery. Noted that with the higher DOD at which the battery cycles, the battery cycle life goes down obviously.

The throughput ability of the battery determines how long the battery can be used, which is related to the tolerating ability of the battery internal active chemicals. Without considering the effects of additional factors, a battery can experience fixed throughput in its whole life, that is, a 100% DOD charge-discharge cycle is equivalent to two 50% DOD charge-discharge cycles.

![Figure 2. Cycle life versus DOD curve for a lead-acid battery](image)
2.3. Charging and discharging rate
For the lithium battery, how much lithium ions the battery anode material can transport per unit of time has an upper limit. Forcing excessive current into the battery during charging process will cause excess lithium ions to deposit on the surface of the electrode to form the lithium metal layer which is called lithium plating. This unwanted chemical phenomenon is followed by the serious capacity loss and internal impedance growth. On the other hand, too high discharge rate will incur that the chemical conversion process of the active material cannot meet the output of the battery current, resulting in additional harmful chemical reactions and further causing electrode crystal morphological change. Figure 3 shows the change trend of battery capacity at different charge and discharge rates.

![Figure 3. Battery capacity versus number of cycles curve under different rates](image)

3. Battery life prediction approaches
A precise lifetime prediction is almost impossible in the engineering applications for many reasons, such as the simplification of the model and the measuring error caused by the test system that cannot be avoided. This paper regards the approaches as the tools for evaluating economic value of the optimization strategy and improving the renewable energy quality which are not enough superior to be injected to the power system. The empirical-based approaches which are also called the statistics-based approaches do not need the complex parameters and have smaller workload. There are three frequently-used prediction models: physic-chemical ageing approach, event-oriented ageing approach and weighted Ah ageing approach.

3.1. Physic-chemical ageing approach
In this model, the defined deterioration index of battery performance gradually increases with the operating and cycling. When the failure threshold is reached, the battery reaches the end-of-life state and must be replaced. The degradation rate of the battery capacity corresponding to the internal chemical reactions is influenced by many stress factors incorporating charge and discharge rate, DOD and operating temperature.

Alan Millner put forward a new model [1] which could be used to evaluated the battery life at varying conditions, the changing state of charge(SOC), random DOD, application mechanism and temperature. Alan Millner proposed a crack degradation theory quantifying the stress factors effect on the battery cycle and calendar life, such as DOD, SOC and temperature, etc. The experiment results prove the correctness and feasibility of the model. By combining this battery lifetime quantization model with actual data, the power system operation parameters are optimized in [2]. The optimized life-cycle loss is significantly reduced based on the hybrid energy storage coordination control strategy.

In Ref. [3], John Wang accelerated the LiFePO\textsubscript{4} batteries aging process through a series of physical and chemical experiments. The effects of battery life stress factors were investigated and described
through the practical forms. They developed model equations to present the detailed aging extend at four kinds of different charge and discharge power between 15°C and 60°C. The parameters of four models are analysed and fitted in the paper. The battery life model is applicable to the control mode of regular cycle. However, the output power of the battery is fluctuating irregularly in engineering applications, and in every charge-discharge cycle, the rate, depth and time of discharge are varying. To address the issue, Ref. [4] presents the multiple factors polymerization life model in which the whole charge-discharge rates are divided to several intervals and in every interval, all the model parameters are confirmed according to [3] to calculate the corresponding battery loss.

Theoretically, the batteries used on EV (the electric vehicle) could operate at least two years under normal service modes because the performance in the experiments should be good enough to offer 300 and even more life cycles. However, the actual situation gathered by the EV owners does not achieve the prospective result. The explanation is that the actual charge-discharge cycles are too long to ignore the effect of the battery calendar life aging in comparison with the shorter testing time which the accelerated aging cycles go through.

Dai Wang and Jonathan Coignard presented a more complete model [5] to present the battery degradation which is used on the EV and V2G services. They integrated an EV battery thermal model to take the temperature into consideration. This model takes into account the effect of calendar life aging and cycle life aging on capacity degradation and the detailed parameters were acquired by the rigorous scientific experiments and mathematical derivation.

3.2. Event-oriented ageing approach

In this method, a description of the specific event that causes the loss of life is defined. In general, each event has a definiteness of the degree of damage. Monitoring the event status trend during the use of the equipment, accumulate the life attenuation of each event and then get the remaining life of the battery device. The events presented in the aging model are independent of each other and the severity of the recession caused by the same events at different life interval is equivalent. The aging analysis approach is applicable to lead-acid, lithium ion, sodium-sulfur battery and so on.

Ref. [6] proposes the conversion coefficient $\alpha(x)$,

$$\alpha(x) = \frac{N_{BESS(1)}}{N_{BESS(x)}}$$

Where $N_{BESS}(x)$ is the cycle life at the DOD $x$ obtained on the SN curve. During the investigation interval, the number of converted charge-discharge cycles is

$$N'_{BESS} = \sum^n_i \alpha(x_i)$$

Where the number of charge-discharge cycles is $n$, $x_i (1 \leq i \leq n)$ is the DOD of every charge-discharge cycle. When $N'_{BESS} = N_{BESS(1)}$, the battery is on the end-of-life state.

In Ref. [7], the battery control regime decides the recession of battery. A unit degradation model is expressed to give a detailed understanding for the engineering application, as shown in Eq. (3).

$$Loss_i = \frac{1}{N_{BESS(x_i)}}$$

Thus the battery life loss in the investigation time is the sum of all the cycles degradation.

$$Loss = \sum^n_i Loss_i = \sum^n_i \frac{1}{N_{BESS(x_i)}}$$

The rain-flow counting algorithm has been good for dividing the SOC curve to the complete cycles and bringing convenience for succedent calculation. The advantages of event-oriented ageing model are that the calculation is simple and it avoids tedious measurements which are necessary if require the battery internal performance. However, because the rain-flow counting algorithm needs to get the whole running SOC curve to calculate battery life loss, this approach cannot be used to battery life real-time monitoring. In addition, because the model does not take into account charge and discharge rate, calendar life aging and temperature effects, the prediction accuracy cannot be ensured.

3.3. Weighted Ah ageing approach
This approach is based on the assumption that a battery throughput is a fixed value from the manufacture to the moment of scrapping. As an improvement of Ah aging approach, the weighted Ah aging model considers the different effects on the battery life damage for the equal throughput at different conditions (DOD, charge and discharge rate, and battery temperature), so it is necessary to add weighted coefficients to the Ah aging model. When the effective throughput exceeds the threshold value, the battery must be replaced.

The overall Ah throughput is calculated by taking the average of varying throughput under different DOD, and because the same throughput at different SOC levels has a various impact on the battery life loss, the weight loss model is established based on the engineering experience. [8] But this model does not introduce the life damage caused by the arbitrary rates. The NREL (National Renewable Energy Laboratory) battery life model in Ref. [9] states that the battery can release fixed energy at rated discharge power and rated DOD, which is called the total effective discharge. When the cumulative effective discharge energy is equal to the total effective discharge, the battery life is terminated. NREL experiments confirmed the lead-acid battery operating characteristics of different DOD and discharge rates. The model is used by Ref. [10] and [11] as an auxiliary tool for dispatch strategy and energy storage capacity optimization. However, the battery life prediction model has the following shortcomings:

- The NREL model’s conversion parameters cannot guarantee that the total effective discharge is fixed when a battery operates at varying discharge rates and DOD.
- Subsequent experiments show that battery life damage caused by the arbitrary charging process cannot be ignored, thus the total effective throughput should be considered.

Based on the NREL battery life prediction model, select the proper conversion parameters to ensure the total effective throughput constant and deal with the issue how the charge and discharge rate affect the battery lifetime by the insert of Ragone curve.

- To determine the impact of DOD on battery life, we propose performing a best fit for battery cycle life which is available from the product manual.

\[
L_A = L_R \left( \frac{D_A}{D_R} \right)^{u_0} e^{u_1(1-D_A/D_R)} \quad (5)
\]

Having found the equation parameters, the effective discharge throughput will be acquired by rearranging the equations. And the substitution \( \frac{d_{\text{eff}}(D_A)}{D_R C_R} = \frac{L_A}{L_R} \) is of the essence. Now

\[
2L_A \cdot d_{\text{eff}}(D_A) = 2L_A D_R C_R \quad (6)
\]

2L_R D_R C_R is the total effective throughput which is a constant value for a particular battery. Where \( L_A \) is the number of life cycles at arbitrary DOD \( D_A \), \( L_R \) is the number of life cycles at rated DOD \( D_R \), \( d_{\text{eff}}(D_A) \) is the efficient throughput of one charge or discharge cycle at the DOD \( D_A \), \( D_A \) is the actual DOD, \( u_0, u_1 \) are the parameters of the equation.

- Ragone curve [12] describes the relationship between the power density and the energy density of the battery and the best working point which is the useful tool for evaluating the battery performance. According to the Ragone curve, we can get the actual capacity at any charge and discharge rate. Therefore, no one can deny the fact that as the rate grows, the effective throughput will rise, and the relationship between them are described as the following.

\[
\frac{d_R}{d_{\text{actual}}} = \frac{C_R}{C_A} \quad (7)
\]

\( d_R \) is the battery throughput at the rated charge-discharge power, \( d_{\text{actual}} \) is the battery throughput at the actual charge-discharge power, \( C_A \) is the actual capacity of the battery which can be calculated from the battery Ragone curve.

- We use the throughput of two regular cycles to get the actual throughput of the various cycles from the random beginning SOC to the random ending SOC. For example, if the battery is charged from 30% SOC to 70% SOC in the operation interval, the life loss because of the charge process can be expressed as \( d_{\text{eff}} = \left| d_{\text{eff}}(0.7) - d_{\text{eff}}(0.3) \right| \). If all the above charge-
discharge events happen during the study and test time $T$. the specific life time $L_{time}$ of the battery with the specified battery operation regime can be obtained through the function:

$$L_{time} = \frac{2L_{0}D_{R}C_{R}}{\sum D_{eff}}T$$

(8)

4. Conclusions

When the battery energy storage system works as a buffer to make the renewable energy power smooth, the complex physical and chemical reactions happen all the time in the battery. It is almost impossible to analyse the relevance between the battery degradation and the various operation conditions accurately. The above three common battery life prediction models mainly participate in the battery capacity and operational strategy optimization because of the fast calculation speed and simple model parameters. Three prediction models are based on different theoretical principles, but all of them are possible to describe the effect of different stress factors on the battery degradation. The proposed weighted Ah ageing approach is more precise but also needs to be tested in practical applications. Note that the designer should combine the characteristics of optimization goals and forecasting methods with the measured data to determine the appropriate auxiliary prediction model.

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