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Decay model of energy storage battery life under multiple influencing factors of grid dispatching

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Abstract. Energy storage batteries work under constantly changing operating conditions such as temperature, depth of discharge, and discharge rate, which will lead to serious energy loss and low utilization rate of the battery, resulting in a sharp attenuation of life, and the battery often fails before the end of its service life. Battery replacement leads to increasing energy storage costs, and in order to ensure the efficient, safe and reliable operation of batteries under complex working conditions of the power grid, effective management of batteries is required. The battery model is the theoretical basis of the management algorithm, and life prediction is the key technology to ensure battery safety. In view of the above practical application requirements, this paper studies the dynamic modeling of energy storage battery life based on multi-parameter information, and the results show that the proposed life model accurately reflects the battery life under multi-parameter information.

1 Introduction

Lithium-ion batteries have the advantages of high energy and power density, low discharge rate and high cycle life, and are an important choice for building microgrid-level energy storage systems. (Battery energy storage system ,BESS) .BESS plays an important role in improving power quality and ensuring the safe and stable operation of microgrids, and the life of the battery needs to be considered to evaluate the value of BESS[1]. At present, it is more important to consider the full life cycle of battery use to analyze the cost of energy storage. However, because the energy storage battery works under constantly changing operating conditions such as temperature, depth of discharge, and discharge rate, it will lead to serious energy loss and low utilization rate of the battery, resulting in a sharp attenuation of life, and the battery often fails before the end of its service life. The replacement of batteries leads to an increasing cost of energy storage, so it is necessary to study the battery life attenuation of energy storage based on different operating conditions [2].

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2 Semi-empirical life decay modeling for lithium-ion batteries

At present, most of the battery life attenuation models of energy storage are based on the irreversible capacity of the battery, and the influence of many factors such as charge-discharge rate, charge-discharge cut-off voltage, temperature and the like on battery capacity is often considered and modelled [3].

The cycle aging and life decay of energy storage batteries are the common results of many factors such as temperature and depth of discharge, as (1):

$$t = t_{on} - t_{DOD} - t_{SOC} - t_T - t_s - t_N \tag{1}$$

The energy storage battery model constructed by Arrhenius equation only under the influence of temperature simulates its temperature dependence on the chemical reaction rate, and obtains the temperature model, as (2):

$$f_T(T) = \exp\left[g_T (T - T_{ref}) \bullet \frac{T_{ref}}{T} \right] \tag{2}$$

In formula: $f_T(T)$ -Lithium-ion battery capacity decay(%);

g_T -Temperature stress coefficient;

T_{ref} -Reference temperature.

2.1 The battery capacity decay model under the influence of multiple factors is considered

Using the solved temperature and multi-stress model to fit the data separately, it is found that there is still a large deviation in the data, which is that the battery life not only depends on the external stress factors, the battery degradation is a nonlinear process relative to the time and stress cycle, so a decay model combining nonlinear components and linear components is proposed, and the role of SEI film is simulated with nonlinear components, and then the impact of battery life on degradation is estimated, and the stress model under different conditions can be obtained by separating the mode[4].As fig1.

Battery life attenuation includes calendar decay and cyclic decay. The rate of calendar decay is determined by the temperature and SOC of the battery, so equation (3) can represent the aging decay model:

$$Q_{cal} = f_1\left(t, \overline{\sigma}, \overline{T_c}\right) \tag{3}$$

Cyclic attenuation refers to the loss of battery life during each charge-discharge cycle, and the loss is affected by factors such as depth of discharge, average SOC of cycles, average battery temperature, charge-discharge duration, and discharge rate, so equation (4) can represent the cyclic decay model.

$$Q_{cyc} = \sum_{i}^{N} n_i f_c\left(\sigma_i, \xi_i, T_i, T_s, C_i\right) \tag{4}$$

There into: N -Number of cycles in actual use; n_i indicates whether the loop i is a full cycle,the rain counting cycle algorithm is adopted.The above equations (3) and (4) are linearly integrated to obtain the attenuation function model Q_{loss} :

$$Q_{loss}\left(t,\xi,\sigma,T_c,T_s,T_i,C\right)=k_1 f_1(t,\overline{\sigma},\overline{T_c})+k_2\sum_{i}^{N} n_i f_c\left(\sigma_i,\xi_i,T_i,T_s,C_i\right) \tag{5}$$

Among them: $k_1+k_2=1$, the rain current counting algorithm can be used to simulate the estimation combined with the actual operation of the battery, which is more suitable for complex battery attenuation model[5].

2.2 Battery life attenuation model based on semi-empirical method

The decay rate of an energy storage battery is not a linear process, and the actual decay rate per cycle $\left(dL/d\left(Cycle\right)\right)$ is expressed as a function of L the linear decay rate over a cycle:

$$\frac{dL}{d\left(Cycle\right)}=\frac{dL}{dN}=f_L^{cyc}\left(L,f_d^{cyc}\right) \tag{6}$$

There into: L -The current life state of the battery is normalized by the ratio of the capacity lost by the battery to the rated capacity.

However, the resulting model in Equation (6) cannot simulate the rapid aging phase in the early cycle, and this rapid early decay may be caused by various mechanisms, but the main reason is the formation of solid interface films during the battery cycle. When a new battery starts working, it consumes a certain amount of active lithium ions to form this thin film. When a stable film is formed, the rate at which the film is formed decreases [6]. To model this theory, it is assumed that a certain portion of the battery's active material is consumed during the transient phase to form an SEI film. The rate of formation is inversely proportional to the already formed SEI film and stops at steady state [7].As fig 2.

Let be a portion of the charge capacity irreversibly consumed during SEI film formation. Divide the total normalized battery capacity into two parts: within the SEI section, and the rest decay at a rate proportional to the battery life. Equation (7) SEI formation is modeled, but with a different linear rate, the battery capacity decay is modeled as a double exponential function.as fig 3.

$$L=1-\rho_s esp(-Q_s)-(1-\rho_s)\exp(-Q_{loss}) \tag{7}$$

There into: Q_{loss} --Irreversible capacity decay rate(%); Q_s -Reversible capacity decay rate(%).

The parameters ρ_s depend on the internal design of the battery, and are related to the specific surface area of graphite and the layer formation conditions, generally taking 3% to 8%. Since use and temperature also contribute to the formation of SEI, Q_s is proportional to Q_{loss} (scale factor is φ_s):

The attenuation data shown also reveals the relationship between SOC and calendar life, and its trend of the fitted curve is an exponential model. The first number in the legend indicates the depth of discharge in the battery cycle, so this curve shows the battery capacity attenuation under the influence of different DOD, temperature and discharge[8].

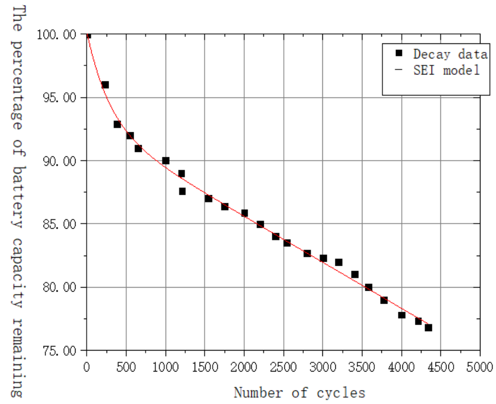

Fig. 1. SEI model fitting result.

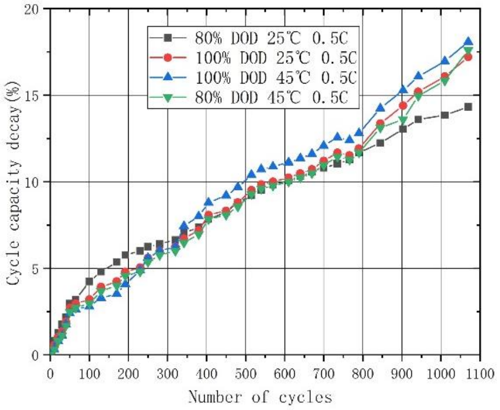

Fig. 2. Cycle capacity decay curve.

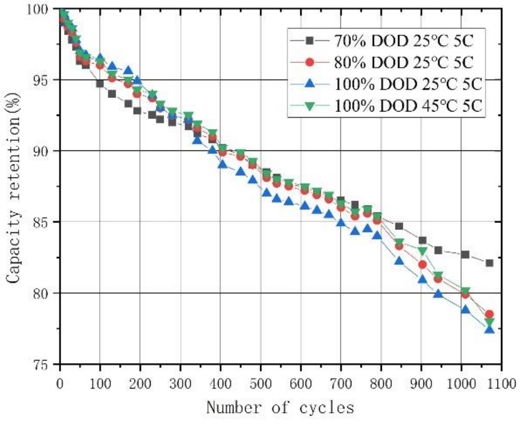

Fig. 3. Battery dynamic test data.

3 Result

Firstly, according to the modeling ideas of single influencing factor model and multi-stress model, a battery life capacity model considering multiple factors is established[9].Secondly, the overall attenuation characteristics of battery capacity are determined based on battery life attenuation experiments, and the results of multi-factor models are evaluated accordingly. The formation mechanism of SEI of lithium-ion batteries was mathematically modeled to solve the problem of inconsistency between the actual decay rate and the model description, and the SEI[10]. Finally, the multi-factor model is substituted into the overall model of SEI to obtain a semi-empirical life attenuation model, and the experimental results show that the model has a high degree of fitting to the attenuation data, and the estimation error of battery life attenuation is kept within 5%.

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