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A new method of accelerated life testing based on the Grey System Theory for a model-based lithium-ion battery life evaluation system

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HIGHLIGHTS

- Present a new method for accelerating battery life test.
- Establish a residual grey model combining the aging law to describe the battery life trend.
- Predict the battery cycle life with a small number of testing samples.

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ABSTRACT

The lack of data samples is the main difficulty for the lifetime study of a lithium-ion battery, especially for a model-based evaluation system. To determine the mapping relationship between the battery fading law and the different external factors, the testing of batteries should be implemented to the greatest extent possible. As a result, performing a battery lifetime study has become a notably time-consuming undertaking.

Without reducing the number of testing items pre-specified within the test matrices of an accelerated life testing schedule, a grey model that can be used to predict the cycle numbers that result in the specific life ending index is established in this paper. No aging mechanism is required for this model, which is exclusively a data-driven method obtained from a small quantity of actual testing data. For higher accuracy, a specific smoothing method is introduced, and the error between the predicted value and the actual value is also modeled using the same method.

By the verification of a phosphate iron lithium-ion battery and a manganese oxide lithium-ion battery, this grey model demonstrated its ability to reduce the required number of cycles for the operational mode of various electric vehicles.

1. Introduction

The evaluation of the lifetime of a lithium-ion battery is an important issue for the development and expansion of the use of Electric Vehicles (EVs). An effective evaluation system can not only diagnose the causes of battery failure and potential danger, thereby ensuring the vehicle's security, but also regulate the use of an EV to extend the battery life and reduce the relative cost of the battery.

According to the objectives of the assessment, the current battery life evaluation systems mainly include the actual life testing under typical working conditions and a model-based method of evaluation.

The primary purpose of the actual life tests is to assess whether the battery can meet the requirements of the typical vehicle applications. For example, the FreedomCAR program has proposed that the battery life of up to 15 years and 300,000 cycle numbers within a shallow State of Charge (SoC) window be the goal for Hybrid Electric Vehicle (HEV) applications. In anticipation of such battery performance, many similar testing specifications and processing methods of experimental data have been developed worldwide [1]. Although this type of application-driven evaluation approach can provide a reference for battery selection and vehicle design, it is difficult to

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estimate the State of Health (SoH) of a battery in use, which is more reliant on the model-based evaluation methods.

For the model-based evaluation approaches, the primary methods are the aging mechanism model, the semi-empirical model and the data-driven model. Various other models have emerged in some available instances. Based on the porous electrode theory, Ramadass et al. have developed a first principles capacity fading model for a lithium-ion battery in Ref. [2], and a commercial simulation tool has been developed by COMSOL 3.5 based on this model. Models based on a similar mechanism have also been developed in Refs. [3–5]. This type of model is primarily based on the principles of the particle transportation process and the reaction process, which were generalized by John Newman's team in Refs. [6,7]. The core of this type of model is the establishment of the variation law of the specific internal or external eigen-parameters during the entire aging process, which is obtained from some simulation work or from numerous accelerated life testing results under various working conditions. Those degradation laws are also the basis of the empirical and semi-empirical lifetime model. Among such models, Bloom et al. [8] characterized the power degradation law of a lithium-ion battery with the power function of the time of use, and their fitting result of the exponent of time approached 0.5. Thereafter, John Wang et al. [9] introduced this type of model structure into the modeling of the capacity fading. Thomas et al. in Ref. [10] and Wright et al. in Ref. [11] reported that such an empirical model can be used to predict the cycle life under the variable stress conditions and the calendar aging conditions. This type of empirical or semi-empirical lifetime model is concise compared with the mechanism model and has become highly feasible for use in EV applications. However, the unknown parameters, such as the weight factor of each external factor, still rely on a huge number of accelerated life testing results. Additionally, the inherent inconsistency between the same type and the same batch of batteries determine the necessity to repeat the same testing cycle several times. Compared with these two types of lifetime models, it is even more necessary to accumulate sufficient experimental testing results for the data-driven evaluation method. The data-driven model is generally based on the statistical method, which relies on a good probability distribution. Thus, whether it is established by the adaptive filtering method [12] or the Monte Carlo simulation method [13,14], these approaches all require sufficient data sets as their modeling basis. As long as these data sets can at least cover the dynamic range of the battery life characteristic, the data-driven models can possess high credibility in their use for lifetime evaluation for a lithium-ion battery. The larger the dynamic range of the sample data that can be covered, the higher is the accuracy of the prediction model that can be obtained. Thus, it is necessary to study accelerated life testing procedure used to obtain the performance data samples when the model-based evaluation method is used.

In capacity fading, for example, the primary task of the cycle life testing process for the model-based lifetime evaluation method is recording the actual capacity at different life state until the pre-specified ending indicator, such as 80% of the initial capacity, is achieved. With the high quality material now being developed for a lithium-ion battery, the data acquisition of battery performance degradation has become an increasingly time-consuming process. Even if accelerated lifetime testing is used, the complete testing matrices containing generally accepted external factors, such as discharge rate, DoD and temperature, should be pre-specified [8–10,15]. Additionally, to determine the relationship between the external factors and the attenuation law, the testing matrices should measure more battery degradation characteristics. Thus, it is more reasonable to shorten the cycle numbers for each testing item than to reducing the number of testing items in the testing matrices. To obtain the approximate numbers of cycles using a small amount of experimental data, there are two primary issues that must be solved: one is the small number of lifetime testing samples, and the other is the complicated coupling between the effects of the external impact factors and the degradation results.

To solve these two problems, a new accelerated method for model-based evaluation system is presented in this study, which can be used to predict the cycles resulting in the pre-specified life-ending indicators and thus shorten the testing numbers correspondingly. Based on this model, no testing item is abandoned, and only a number of testing samples over a relative small cycle range are required. The entire method is still a data-driven method in nature, while also having the ability to predict the battery performance degradation law for any specific working condition; however, this method is not a battery lifetime model because the parameters in the prediction model change for different working conditions. Another feature is the method of experimental data smoothing in our study, which also refers to some general recognized cycle life model structure.

As for the battery performance degradation, the mechanism of the external impact factors is indefinite, but the fading trend of the performance caused by these external factors is determined. This type of system can be called a “grey causes and white results” system, which can be described by Grey System Theory [16,17]. Our study is just based on the Grey Model (GM) established by Julong Deng. The GM exhibits high accuracy even if the number of testing samples is very small. Thus, the GM method is proper for solving the issues being confronted in the accelerated lifetime testing.

The remaining parts of the paper are organized as follows. In first section, a detailed introduction of the testing sample, protocol and contents is presented. Next, we analyze the characteristics of a battery life system to translate this system into the grey system, while concurrently introducing the GM. Combining the GM system and the battery lifetime degradation law, a residual GM (1, 1) model based on the battery aging mechanism is subsequently established. Next, the verification of this model by predicting the characteristics of a manganese oxide lithium-ion battery and a phosphate iron lithium-ion battery is presented in detail. Finally, we provide a number of conclusions based on the results of our study.

2. Experiment

The battery cells used in our study include two typical types of lithium-ion batteries, i.e., a high-power manganese oxide lithium-ion battery and a phosphate iron lithium-ion battery; the detailed information of both of these batteries is listed in Table 1. Additionally, the testing facilities are tabulated in Table 2, and the testing bench is described in Fig. 1.

In our study, we designed the multi-factor testing matrices as listed in Refs. [8,9] for the manganese oxide lithium-ion battery, which can be considered as simulating the conditions of a Battery Electric Vehicle (BEV) in driving mode, and the testing items are sufficient for creating a cycle life model as described in Refs. [8–11].

Table 1
Specification of the testing samples.

Manganese oxide lithium-ion battery		Phosphate iron lithium-ion battery	
Parameters	Value	Parameters	Value
Rated capacity (Ah)	8	Rated capacity (Ah)	8
Rated voltage (V)	3.7	Rated voltage (V)	3.2
Charge cut-off voltage (V)	4.2	Charge cut-off voltage (V)	3.7
Discharge cut-off voltage (V)	2.7	Discharge cut-off voltage (V)	2.5
Maximum pulse charge/discharge rate (C)	25 (20 s)	Maximum pulse charge/discharge rate (C)	25 (20 s)