

Prediction of lithium-ion battery capacity with metabolic grey model



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ABSTRACT

Given the popularity of Lithium-ion batteries in EVs (electric vehicles), predicting the capacity quickly and accurately throughout a battery's full life-time is still a challenging issue for ensuring the reliability of EVs. This paper proposes an approach in predicting the varied capacity with discharge cycles based on metabolic grey theory and consider issues from two perspectives: 1) three metabolic grey models will be presented, including MGM (metabolic grey model), MREGM (metabolic Residual-error grey model), and MMREGM (metabolic Markov-residual-error grey model); 2) the universality of these models will be explored under different conditions (such as various discharge rates and temperatures). Furthermore, the research findings in this paper demonstrate the excellent performance of the prediction depending on the three models; however, the precision of the MREGM model is inferior compared to the others. Therefore, we have obtained the conclusion in which the MGM model and the MMREGM model have excellent performances in predicting the capacity under a variety of load conditions, even using few data points for modeling. Also, the universality of the metabolic grey prediction theory is verified by predicting the capacity of batteries under different discharge rates and different temperatures.

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1. Introduction

Lithium-ion batteries, as a key component of various technological systems, play an important role in the functional capabilities of many devices. Thus, battery failure causes serious problems such as efficiency reduction, system damage, and even disastrous accidents, especially in electric vehicles and aerospace [1]. An effective technique to monitor batteries can greatly improve system reliability. However, battery performance is restricted to the decline of battery capacity due to aging and energy loss. Capacity is considered as a critical parameter of lithium-ion batteries representing the available energy stored in the fully charged lithium-ion batteries. It is usually used to analyze the SoH (state-of-health) for batteries [2]. Therefore, the prediction of capacity in particular has concerned many researchers [3,4].

Accurate prediction of the capacity variation of batteries has been of great research interest both in the past and at present [5,6]. Many approaches and algorithms have been proposed to predict the capacity, such as the OCV (open-circuit voltage)

method [7–9], coulomb counting method, model-based method, and artificial intelligence method. The OCV estimates the SoC (state of charge) and the capacity with the internal relationship between the OCV relaxation curve and the capacity even if the battery has aged or self-discharged. However, it is not optimal for system online estimation, because of it needs to take a long rest time to reach the battery's steady-state for measuring the OCV. The Coulomb counting method [10] integrates battery discharge current over time to dynamically recalibrate the capacity for estimating the SoH. It only requires the discharge current of batteries inputted; hence, it is suitable for deployment in BMS (battery management systems). However, this method suffers from accumulated error and noise from current sensors. Researchers have also been working on a model-based method to estimate the SoH using a KF (Kalman filter) [11–15]. This method considers a battery as an ECM (equivalent circuit model) to be described by different parameters. However, the method more strongly depends on the accuracy of the model parameters, which is hard to achieve and computationally intensive. To improve the accuracy, noise adaptive measurement models are developed. Artificial intelligence methods (data-driven methods) include fuzzy-logic [16,17], ANNs (artificial neural networks) [18,19] and SVMs (support vector machines) [20,21], which do not require a precise

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model of batteries. With good training, they can be applied to estimate capacity under certain loading conditions. Nevertheless, it is difficult to train and establish a database to cover all the different battery working conditions over a lifetime of a battery, because this process is required to analyze a large amount of test data and is time-consuming for training and processing.

Due to highly nonlinear, time variation of a battery system, it is still a challenge to precisely predict the capacity of a battery. When applying existing methods, there are two problems that need to be overcome: one is that a large amount of data is often required, and the other is that a precise battery model needs to be built to give a good prediction.

In order to predicate the capacity quickly and accurately over the lifetime of a battery, the grey system theory is introduced in this paper, which requires less data and does not depend on accurate parameters of models. The grey system was first developed [22] to tackle uncertainty systems and soon being widely applied in many systems [23–26]. It focuses on the study of problems from uncertain systems that involve small samples and poor information. One of its advantages is that it requires a small amount of data for prediction; thus, it has a significant advantage over conventional statistical approaches. Metabolic grey prediction is one of the main ideas of grey theory, which has recently drawn great attention owing to its performance. It can adjust parameters to new conditions when the metabolic grey prediction is employed in dynamic systems, because it aims to make full use of new information. As the name suggests, the mechanism of metabolic grey lies in that it can remove the oldest data when the newest data is inputted, and keep the same numbers from the data points in forecasting sequences for predicting; consequently, it can track the data fluctuation quickly and enhance the precision of prediction.

In order to predict the capacity of a battery quickly and accurately, we propose three metabolism grey prediction models, namely, MGM (metabolic grey model) model, MREGM (metabolic Residual-error grey model) model and MMREGM (metabolic Markov-residual-error grey model) model, which combine three grey models with the metabolism mechanism. We studied the performances of these grey models, for predicting the capacity, and verified their universality via applying them under various discharge rates and temperatures of the batteries.

The remaining parts of this paper are organized as follows: In section 2, the grey systems theory is introduced and some grey models is proposed and illustrated. In section 3, the experiment bench and experiment design for collecting the data from the lithium-ion batteries are demonstrated. In section 4, the results and discussions are presented. Finally, in section 5, some conclusions are provided based on the results.

2. Methodology

2.1. GM model

GM(1,1) is currently one of the most widely used grey prediction models. It essentially is a linear dynamic first-order single sequence prediction model for the discrete form of the differential equation for time series prediction, which can be established by using only four data points. The scheme of proposed method is shown in Fig. 1. The GM(1,1) procedure is expressed as follows [27]:

Step 1: The non-negative historical sequence $X^{(0)}$ is expressed as,

$$X^{(0)} = \{x_{(1)}^{(0)}, x_{(2)}^{(0)}, \dots, x_{(k)}^{(0)}\}, k = 1, 2, \dots, n \quad (1)$$

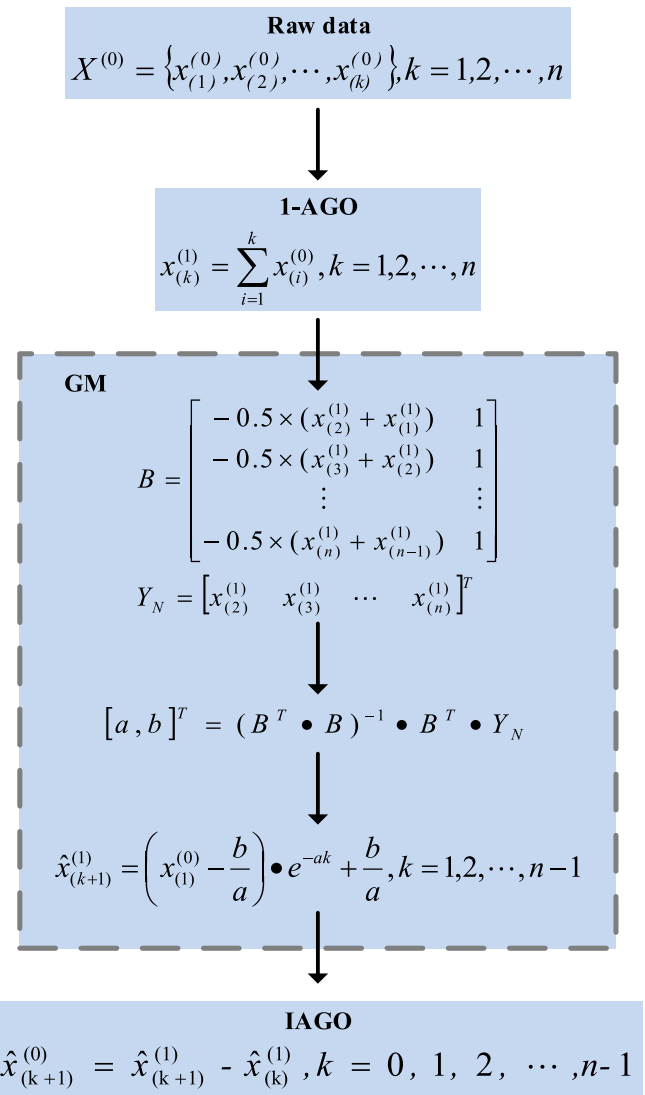


Fig. 1. An implementation flowchart of the GM model.

where $x_{(k)}^{(1)}$ denotes the raw data or actual value of observable variable at time $x_{(k)}^{(1)}$.

Step 2: When this sequence is subjected to the AGO (accumulating generation operation), the following sequence $x_{(k)}^{(1)}$ is acquired. The AGO is expressed as:

$$x_{(k)}^{(1)} = \sum_{i=1}^k x_{(i)}^{(0)}, k = 1, 2, \dots, n \quad (2)$$

Step 3: The whitening grey dynamic model can be acquired by a first order differential equation with coefficient b , where b represents the influence of the external impact on the development of an event.

$$\frac{dx_{(k)}^{(1)}}{dt} + ax_{(k)}^{(1)} = b \quad (3)$$

where $\hat{a} = [a, b]^T$ is a sequence of parameters that can be found as Eq. (4), the $\hat{a}$ is known as the parameters matrix, the a is known as

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