ARTICLE IN PRESS

Applied Energy xxx (xxxx) xxx–xxx

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

State-of-health estimation for the lithium-ion battery based on support vector regression

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HIGHLIGHTS

- An improved Li-ion battery model is proposed.
- A support vector regression method is employed to estimate the state-of-health.
- The particle swarm optimization is used to optimize the global parameters.
- Comparison with other methods shows the advantage of the proposed method.

ARTICLE INFO

Keywords:
State estimation
Parameter identification
Least square support vector regression
State-of-health

ABSTRACT

Lithium-ion batteries have been widely used in many fields. The state-of-health is necessary and important for battery performance evaluation and lifetime prediction. A reliable state-of-health estimation is essential to help batteries work in a safe and suitable condition. In this paper, a novel state-of-health estimation approach is proposed for lithium-ion batteries based on statistical knowledge. An improved battery model, which combines the open-circuit-voltage modeling and the Thevenin equivalent circuit model, is proposed to improve the model accuracy and study the relation between internal parameters and states of the battery. The joint extended Kalman filter-recursive-least squares algorithm is employed to estimate battery state-of-charge and identify the model parameters and open-circuit-voltage simultaneously. Then a particle swarm optimization-least square support vector regression approach is employed to give a reliable state-of-health estimation result with high accuracy and good generalization ability, where the particle swarm optimization algorithm is used to improve the algorithm ability of global optimization. In order to verify the accuracy of the proposed method, static and dynamic current profile tests are carried out on lithium iron phosphate batteries in different aging levels. The experimental results indicate that the proposed method can present suitability for state-of-health estimation with high accuracy.

1. Introductions

Rechargeable batteries have been highly used nowadays, mostly in electric vehicles and digital products [1]. The main characteristic of the rechargeable batteries is that they can realize the transformation between the electric energy and chemical energy when charging and discharging. There are many kinds of rechargeable batteries, such as lithium-ion batteries, lead-acid batteries, nickel-cadmium batteries, etc. Among these batteries, lithium-ion batteries have gained many people's attention with advantages of high energy density, environmental protection, wide operating temperature range and long cycle life [2–4]. However, in practice, lithium-ion batteries age during cycling and long-term storage. Under these conditions, the state-of-health (SOH) is employed to show the degeneration degree and the current performance of lithium-ion batteries. Hence SOH, which indicates the current maximum capacity of a battery, can be defined as the ratio of current maximum available capacity to the nominal capacity impressed as follows [5]:

$$SOH = \frac{Q_{now}}{Q_{new}} \times 100\% \tag{1}$$

where Q_{now} represents the current maximum available capacity, Q_{new} represents the nominal capacity. When SOH is lower than 80%, we consider the battery totally aged and unserviceable because the capacity degradation data exhibit a trend with exponential decay after

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http://dx.doi.org/10.1016/j.apenergy.2017.08.096
Received 11 March 2017; Received in revised form 16 May 2017; Accepted 11 August 2017
0306-2619/

crossing the 80% threshold [6]. In actual use, the accurate SOH estimation is essential to prevent battery from over-charging and over-discharging and extend the lifespan of the lithium-ion batteries. SOH estimation is a critical process which relates to the availability and safety of batteries [7]. On the other hand, there are many uncertain factors that influence batteries' SOH, like ambient temperature, current profiles and so on, so it is quite difficult to estimate the SOH accurately [8–10].

Extensive studies have been conducted on SOH estimation in recent years, which can be divided into four categories according to the estimation methods: methods based on direct measuring, adaptive estimation methods, degradation-model-based methods and statistical methods. The internal resistance and capacity measurement are a direct ways to obtain the SOH of the battery. Remmlinger et al. [11] considered that the internal resistance was a function of temperature and presented a method to identify the resistance. Tsang et al. [12] analyzed the relationship between the internal direct current resistance and battery capacity. This kind of methods has the advantages of being easy to understand and implement, but the internal resistance and capacity measurement require high accuracy which is difficult to meet in actual operation. Adaptive estimation methods mainly contain Kalman filter based algorithm and adaptive observer. Kalman filter based algorithms, including the extend Kalman filter (EKF) and the unscented Kalman filter (UKF), are effective methods for SOH estimation. Andre et al. [13] proposed a dual Kalman filter method to estimate SOC and SOH concurrently. In Ref. [14], a dual-sliding-mode observer method, which includes a fast speed observer and a slow speed observer, was designed to monitor the internal resistance and capacity in real time. The adaptive methods are frequently-used due to the advantages of high accuracy, simple construction and easy to realize in projects. But this kind of methods is computation-intensive. Another kind of method is based on the modeling of the battery degradation mechanism. Ouyang et al. [15] proposed a capacity degradation model based on mechanics which reflected the number of active material and lithium ion inside the battery. The degradation model based methods have accurate estimation results but are complex and require deep understanding of the electrochemical mechanism. SOH can also be estimated by probabilistic and statistical methods, which are shown in Refs. [16–19]. The probabilistic and statistical methods combine mathematical knowledge with empirical knowledge to construct an empirical or semi-empirical model. The main advantages of this kind of method are that complex electrochemical mechanism is not needed and the method is easy to understand. But it would cost much time to obtain plenty of experimental data. Some intelligence algorithms based on statistical knowledge are also widely used in SOH estimation, including neural network, support vector machine (SVM), Bayesian network [20], etc. The neural network is an effective way to estimate SOH. Eddahech et al. [21] presented a battery model based on EIS, and described a method of SOH monitoring, which used recurrent neural network to predict the deterioration in battery performance. You et al. [22] presented a data-driven approach to estimate SOH based on neural network in a practical environment. Wu et al. [23] estimated SOH through computing some features of the charging curves, and then built a polynomial neural network. Although the neural network method showed high nonlinearity and good self-adaption, a large amount of experimental data were still needed in order to acquire ideal results.

To avoid this problem, the SVM/support vector regression (SVR) method is employed. The SVM/SVR can fit the classification/regression problem with less data samples compared with the neural network. This kind of method can transfer the nonlinear problem in a low-dimensional space into the linear problem in a higher-dimensional space. Patil et al. [24] presented a novel multistage SVM based approach. The authors used SVM to classify the battery into four types due to the battery cycle times in the first stage, and selected some features as SVM's inputs. Then they used SVR to estimate battery remaining useful life (RUL) in the second stage. Klass et al. [25] regarded battery capacity and internal resistance as the evaluation indicators of the SOH, and used SVM to estimate the terminal voltage, which showed a good SOH estimation accuracy.

Based on these aforementioned SVM methods, we propose a novel least square support vector regression (LSSVR) based method to estimate the SOH. Compared to the basic SVR method, LSSVR has faster solving speed and simpler solving process. In this paper, a novel state-of-health estimation approach is proposed for lithium-ion batteries based on statistical knowledge. The preparatory work contains modeling and parameter acquisition. An improved battery model, which combines open-circuit-voltage (OCV) modeling and the Thevenin equivalent circuit model, is proposed to improve the model accuracy and study the relation between internal parameters and states of the battery. The joint extended Kalman filter-recursive least squares (EKF-RLS) algorithm is employed to estimate battery state-of-charge (SOC) and identify the model parameters and open-circuit-voltage simultaneously. Then a particle swarm optimization-least square support vector regression (PSO-LSSVR) approach is employed to give a reliable SOH estimation result with high accuracy and good generalization ability. The PSO algorithm is used to improve the algorithm ability of global optimization [26]. The proposed method considers the dynamic performance of batteries. In order to verify the accuracy of the proposed method, static and dynamic current profile tests are carried out on lithium iron phosphate batteries in different aging levels. And the estimation results are compared with the LSSVR method without optimized by PSO and a neural network method showing the superiority of the PSO-LSSVR method. The experimental results indicate that the proposed method can present suitability for SOH estimation with the estimated RMSE less than 2%. In addition, dynamic tests are carried out to verify the robustness of the proposed method.

The structure of the paper is as follows: the preliminary work including battery modeling and parameter identification are given in Section 2. An improved battery model is presented to simulate the battery behavior. The EKF-RLS algorithm is employed to estimate SOC and battery parameters at the same time. The PSO-LSSVR algorithm is introduced in Section 3 to estimate the SOH. In Section 4, experiments including battery capacity tests and several kinds of dynamic tests are conducted to verify the accuracy and robustness of the proposed method. The SOH estimation results are shown and analyzed. Lastly, the conclusions are discussed in Section 5.

2. Li-ion battery model and parameter acquisition

In order to estimate the SOH, the first step is battery modeling. Considering the model accuracy and complexity, an improved battery model is proposed in this section. In addition, the EKF-RLS algorithm is proposed to obtain the battery SOC, model parameters, including OCV, ohmic resistance, polarization resistance and polarization capacitance.

2.1. The improved battery model

An improved battery model is employed in this paper to simulate the electrochemical reaction inside a battery cell. This battery model combines the Thevenin ECM [27] and the OCV model. The Thevenin ECM is one of the most popular models used in the battery's parameter identification and state estimation. However, it is often difficult to obtain the OCV curve in ECMs. Moreover, it always takes a long time to conduct an experiment to get the OCV due to the influence of the battery polarization effect. That's why the OCV modeling is imported here. The OCV is modeled as an empirical function [28] of battery SOC. So like other parameters, the OCV can be seen as a dynamic parameter changing with time. By fitting the parameters of the formula, the OCV-SOC curve is easy to obtain. What's more, the OCV can be estimated with other model parameters at the same time by the parameter identification method shown in Section 2.2, which means the OCV can be obtained through dynamic profiles and the experiment time can be