Energy 64 (2014) 953–960

Contents lists available at ScienceDirect

Energy

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

Enhanced sample entropy-based health management of Li-ion battery for electrified vehicles

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ARTICLE INFO

Article history:
Received 26 June 2013
Received in revised form
18 November 2013
Accepted 23 November 2013
Available online 20 December 2013

Keywords:
Health management
Li-ion battery
Electrified vehicle
Sample entropy

ABSTRACT

This paper discusses an ameliorated sample entropy-based capacity estimator for PHM (prognostics and health management) of Li-ion batteries in electrified vehicles. The aging datasets of eight cells with identical chemistry were used. The sample entropy of cell voltage sequence under the well-known HPPC (hybrid pulse power characterization) profile is adopted as the input of the health estimator. The calculated sample entropy and capacity of a reference Li-ion cell (randomly selected from the eight cells) at three different ambient temperatures are employed as the training data to establish the model by using the least-squares optimization. The performance and robustness of the estimator are validated by means of the degradation datasets from the other seven cells. The associated results indicate that the proposed health management strategy has an average relative error of about 2%.

1. Introduction

Electrified vehicles, including BEVs (battery electric vehicles), HEVs (hybrid electric vehicles) and PHEVs (plug-in hybrid electric vehicles), are important ingredients of a clean, efficient, and sustainable transportation system [1–3]. Traction battery packs, as a vital energy source in electrified vehicles, are still the main technological and cost bottlenecks after decades of investigation [4,5]. In order to safely and efficiently utilize battery packs in practice, a reliable and effective BMS (battery management system) is indispensable. One of its main tasks is to provide accurate knowledge of battery internal states, such as SOC (State of Charge) and SOH (State of Health) [6–9]. SOC is a meter of the remaining charge in a battery, resembling a fuel gauge in traditional internal combustion engine-based vehicles [10,11], while SOH characterizes the health status of the battery that is often manifested as capacity loss or power loss [12,13]. The power loss that causes declined vehicle acceleration and braking-regeneration capabilities is not very challenging to depict, because the increasing internal resistance can often be recalibrated using short-term current pulses [14]. In contrast, the capacity loss that induces a reduced vehicle driving range is more difficult to be accurately measured or estimated [15], as the battery packs of electrified vehicles are seldom fully charged or discharged in realistic operations. Moreover, a direct capacity recalibration is often time-consuming, even sometimes impossible, and has an adverse influence on the battery lifecycle. Therefore, it is significant and valuable to develop an accurate and robust capacity estimator for a rapid and reliable battery health management in electrified vehicles. In this study, the battery SOH is thus defined as the ratio of the current capacity to the nominal capacity when the battery is fresh.

Many approaches to estimating the battery capacity are based on a direct analysis of battery capacity with respect to aging cycle. For example, Rezvani et al. made a comparative study of techniques to predict the Li-ion battery capacity [16]. Several black-box modeling methods were applied to establish the prediction models by using a portion of the capacity-cycle data pairs. Then, the prediction models were validated and compared at other different aging cycles. A capacity estimation model based on the Dempster–Shafer theory and Bayesian Monte Carlo methodology was also proposed [17]. In the model, the Dempster–Shafer theory was used to combine sets of the capacity-cycle pairs from multiple cells (training cells) for initializing the model. Given a portion of the capacity-cycle pairs of another cell (validation cell), the Bayesian Monte Carlo methodology was employed to readjust the initial model parameters and to realize the capacity indication at other cycles. To use this category of models, we need to exactly know the aging cycles of the battery. It is, however, quite difficult to know and record the aging cycles in actual

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http://dx.doi.org/10.1016/j.energy.2013.11.061

BMSs, particularly for HEVs. Furthermore, like the model developed in Ref. [17], in order to ensure good robustness against other cells of the same chemistry and the similar aging, certain new capacity values should be added to update the model. Nevertheless, how to attain the new information in practical operations of electrified vehicles is subject to query.

Sample entropy is a useful tool for exploring complexity and predictability of a signal [18]. As the battery fades, the measurable voltage response under the same excitation accordingly alters. This alteration, in terms of complexity and fluctuation, can be properly captured by calculating the sample entropy of the voltage response. As a result, the sample entropy-based approaches were deployed to diagnose the battery capacity. A sample entropy-based health estimator was established for a lead acid battery unit [19]. In this method, the sample entropy values of the measured sequences of voltage and current under a discharging pulse were firstly calculated and then applied to qualitatively analyze the battery health status. This model had an advantage of being simple enough for on-board applications, whereas it was incapable of yielding numerical capacity estimates, i.e., realizing a quantitative analysis. A sample entropy-based capacity estimator for a Li-ion battery was built in Ref. [20]. The sample entropy of the voltage sequence collected in a complete constant-current discharge process was used as the input of the estimator. Despite offering numerical capacity estimates, the input acquirement was enormously costly, thanks to the long-time voltage sequences. Additionally, the full discharge is detrimental to the battery life. Moreover, it is worth pointing out that the estimator was trained and validated using different capacity-sample entropy data pairs over the lifetime of the same Li-ion cell. This modeling/validation scenario based on a single battery is not appropriate to actual BMSs, since the battery has failed, and its capacity estimation is useless. For a more practical scenario, the capacity estimator may be firstly constructed by using the data pairs over the lifetime of a reference battery, and then applied to estimate other batteries from the same batch that undergo a similar fade.

In this paper, we propose an enhanced sample entropy-based capacity estimator for Li-ion battery health management in electrified vehicles. The proposed estimator effectively overcomes the shortcomings of the two forgoing sample entropy-based models by adding three important original contributions to the related literature. First, the sample entropy of the measured voltage sequence under the HPPC (hybrid pulse power characterization) profile is calculated to be the input of the estimator. Since the HPPC profile only lasts 60 s, the attainment of the input is quite easy and convenient, as well as has negligible harmful effect on the battery lifespan. Further, the HPPC profile comprising a discharging pulse, a rest, and a charging pulse is able to excite the battery better than does a single discharge or charge pulse. Second, the sample entropy

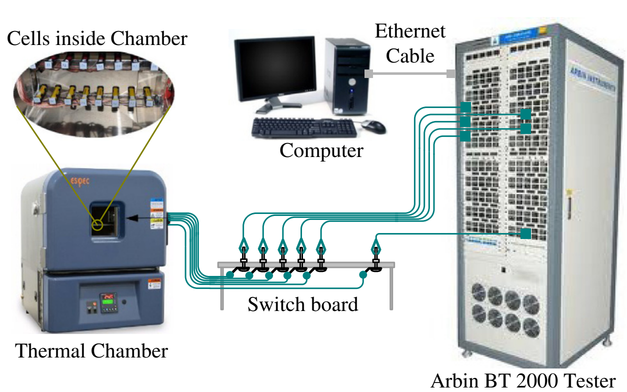

Fig. 1. Configuration of battery test bench [24].

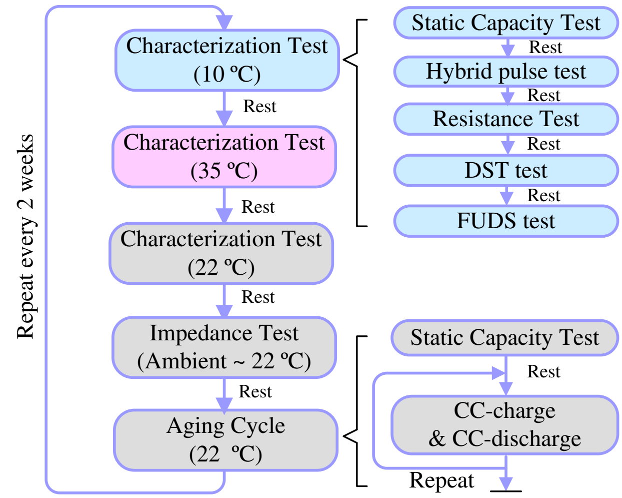

Fig. 2. Flowchart of the test schedules [24].

and capacity of a reference Li-ion battery (arbitrarily selected from eight batteries) at three different temperatures are adopted to train the estimator by nonlinear least-squares optimization. The developed estimator is thus temperature-conscious. Finally, the estimator is applied to predict the capacities of the other seven Li-ion batteries at the three temperatures, so that its performance, usefulness, and robustness can be adequately examined.

The remainder of this paper is structured as follows: the Li-ion battery test is briefly introduced in Section 2; the improved sample entropy-based capacity estimator is elaborated in Section 3; the validation results are elucidated in Section 4 followed by conclusions presented in Section 5.

2. Li-ion battery test

Eight LiNMC (lithium nickel–manganese–cobalt) oxide UR14650P cells from Sanyo were chosen for experimentation in University of Michigan, Ann Arbor, USA. These cells were placed in cell holders (on the top layer) in a thermal chamber and independently tested using 8 channels of the battery tester, as shown in Fig. 1. Note that the same loading profile was applied to the eight cells. The test schedules shown in Fig. 2 were designed to excite and degrade the Li-ion cells. Each

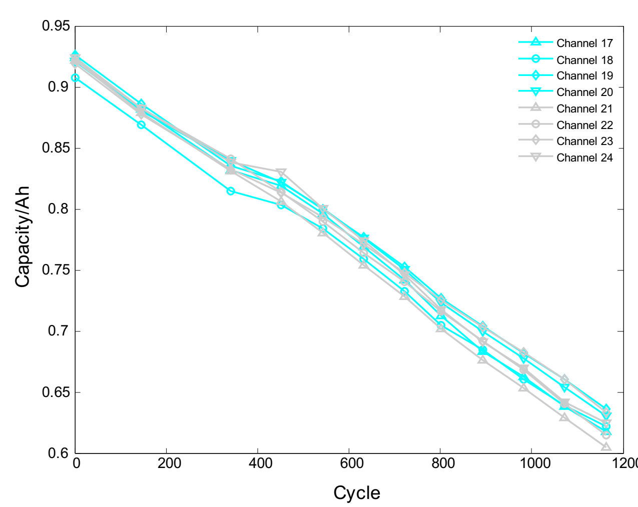

Fig. 3. Capacities of the LiNMC cells at 10 °C.