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Integration of sampling based battery state of health estimation method in electric vehicles

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HIGHLIGHTS

- Presentation of a prototype system with full charge discharge cycling capability.
- Presentation of SoH estimation results for systems degraded in the lab.
- Discussion of integration alternatives of the presented method in EVs.
- Simulation model based on presented SoH estimation for a real EV battery system.
- Optimization of number of battery cells to be selected for SoH test.

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ABSTRACT

Battery cost is one of the crucial parameters affecting high deployment of Electric Vehicles (EVs) negatively. Accurate State of Health (SoH) estimation plays an important role in reducing the total ownership cost, availability, and safety of the battery avoiding early disposal of the batteries and decreasing unexpected failures. A circuit design for SoH estimation in a battery system that bases on selected battery cells and its integration to EVs are presented in this paper. A prototype microcontroller has been developed and used for accelerated aging tests for a battery system. The data collected in the lab tests have been utilized to simulate a real EV battery system. Results of accelerated aging tests and simulation have been presented in the paper. The paper also discusses identification of the best number of battery cells to be selected for SoH estimation test. In addition, different application options of the presented approach for EV batteries have been discussed in the paper.

1. Introduction

Battery cost substantially increases the cost of Electric Vehicles (EVs) and it is one of the major obstacles of widely deployment of EVs [1]. Batteries are consumable products with decreasing energy storage capacity. Energy storage capacity loss (i.e., degradation) occurs due to irreversible chemical reactions, formed passive film, and active material dissolution inside the battery during its usage. State of Charge (SoC) is defined as the ratio of available energy stored in the battery at a given time to its energy storage capacity [2], whereas State of Health (SoH) is defined as the ratio of energy storage capacity at a given time to the energy storage capacity in the beginning of the life [3]. Charge/discharge regime, temperature, and depth of charge/discharge are the main parameters affecting SoH degradation speed [4]. The SoH is defined as the ratio of the current energy storage capacity to the initial capacity [5]. SoH identification is a critical process affecting the ownership cost, availability, and safety of the battery. Accurate SoH estimation avoids early disposal of the batteries decreasing the ownership cost and unexpected failures [6,7].

Identification of battery SoH is a challenging problem attracting many studies in recent years. Most of the studies in the literature deal with the cell level SoH estimation methods. However, battery systems used in daily life consist of large number of battery cells. SoH estimation in the system level has not been sufficiently addressed in the literature yet. This paper aims to contribute towards system level battery SoH estimation methodology and its integration within a vehicle.

The paper is organized as follows: Literature review is presented in Section 2. Section 3 presents the SoH estimation methodology and discusses its integration alternatives to vehicles. Section 4 reports results of presented methodology applied on accelerated degradation tests performed in the lab environment.

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The section also involves simulation results for potential integration of the presented method in a sample vehicle. Finally, Section 5 concludes the paper with future work discussion.

2. Literature review

The basic SoH estimation method bases on counting the energy stored and consumed during charge discharge process. This approach is called Coulomb counting (CC) and can be applied in two different ways: CC during test with constant load and CC during daily usage with variable load. The former one requires a discharge process just for the sake of testing. Even though CC during test with controlled constant load may be effective, the time and labor required makes this method unpractical. In the latter one, CC is performed while the system is in use without a distinct test discharge. This approach involves accumulative measurement errors as well as errors due to the dynamic usage profile, even though it is more practical [8,9]. Improvements in the methodology and continuous calibration are needed to identify and correct the errors due to varying usage profile [10–12,8].

SoH estimation studies other than CC can be categorized into two main groups. The first category focuses on identification and modeling of a physical phenomenon that is correlated with SoH and SoC such as Open Current Voltage [13,14], resistance [15], cell skin temperature [16], terminal voltage [17,18], voltage and current curves [3]. In this approach, the relationship between the physical phenomenon and battery SoH is approximated by a model. Equivalent circuit models are examples of modeling the relationship between the internal resistance in a battery and the behavior of the battery in charge and discharge process [19,20]. Ouyang and his colleagues used chemical kinetics to model the battery degradation [21]. The models require measurement of specific parameters to estimate the ones that cannot be measured. Advanced methodologies to measure these parameters may include complex devices such as electrochemical impedance spectroscopy (EIS) equipment. EIS is an advanced technique to identify the effects of chemical reactions in the battery, which may be related to its degradation [22]. The relationship between SoH and EIS measurements at specific frequencies has been proven [23]. The EIS measurement requires special and expensive equipment that increases the cost and complexity of the measurement process [8]. The models used to reflect the relationship between measured parameters and hidden ones (e.g., SoH) are often not satisfactory and cannot clearly reveal SoH effectively. Furthermore, the model may require extensive tuning and calibration leading to practical difficulty.

The second category involves development of advanced computational or statistical methods to estimate SoH using the measured parameters. Examples of these methods include Artificial Neural Networks, Fuzzy Logic, Relevance Vector Machines, Particle Filters [24,25], Support Vector Machines [26], Kalman Filters, *k*-Nearest Neighbor Regression, and Particle Swarm Optimization techniques [1,3,8,26–29]. These methods may integrate the physical models as well as other computational methods to enhance the results. For example, Neural Networks and Kalman Filter have been integrated to remove the dependency to the battery model in [30].

In both categories discussed above, the battery system with multiple battery cells is considered a unique system during charge and discharge. The measurement of physical phenomenon during the SoH test and its processing through computational methods are based on the whole system. A large number of battery cells in a system may lead to discrepancy, inefficiency or impracticality in SoH estimation. Thus, good SoH estimation in the cell level does not guarantee in the system level; a system level analysis for SoH estimation is needed for deployment of SoH estimation methods for large battery systems.

There are studies in the literature regarding the integration of SoH estimation methodology in the EV system. Test procedure development and architecture design for data processing and transfer as well as user interaction have been presented in [31]. Decision making using SoH information and energy management based on SoH information is presented in [32]. Integration of batteries into an EV battery pack has been investigated based on various factors such as packaging, thermal management, assembly and maintenance in [33]. Sampling based testing idea has been presented for system SoH estimation by performing tests on selected battery cells as representative of the whole battery system [34]. Even though a small prototype has been developed to test the presented approach, the cycling tests could have been applied partially due to the cell balancing problems in the battery management system. Thus, the literature lacks a prototype system performing the presented approach using full cycling tests, sufficient degradation test results and analysis of its potential use in the real systems. The contribution of this paper can be summarized as follows:

- Presentation of a prototype system with full charge discharge cycling capability.
- Presentation of SoH estimation results using the developed prototype system from four battery systems, each of which includes 32 battery cells degraded in the lab environment.
- Discussion of integration alternatives of the presented method in EVs.
- Development of a simulation model of a real EV battery system that bases on the presented methodology.
- Analysis of simulation results in optimization of number of battery cells to be selected for test.

3. Methodology

The methodology is discussed in three subsections: A new circuit design for sampled-based SoH estimation technique is presented in the first subsection. Then, integration alternatives of this technique in EVs are given in the second subsection. The third subsection presents a simulation model for a real battery system of a selected EV architecture.

3.1. New circuit design for battery SoH estimation

In the traditional approach all the battery cells are connected to a single output as shown in Fig. 1. The output is obtained with connecting N number of column as parallel, which consists of M number of serially connected battery cells. All the battery cells charge, discharge or be idle together. All estimations regarding SoC (State of Charge) and State of Health (SoH) should be performed based on the single behavior of all battery cells.

Presented circuit design includes two outputs, called main and test as shown in Fig. 2. Each battery cell (shown in circle in the figure) can either connect to the main output or test output depending on the need. Two relays for each battery cell create the cell's ability to be connected with the preferred output. C1 and C2 represent the + and − sides of the battery cell, respectively. C1 is connected to either A1 or B1 and C2 is connected to either A2 or B2. A1 and A2 (B1 and B2) represent the + and − sides of the test (main) output, respectively. The first relay connects C1 (C2) to either A1 or B1 (A2 or B2) through moving the contact. If the contact is pulled by the relay, then C1 (C2) is connected to A1 (A2). If the contact is released, then C1 (C2) is connected to B1 (B2). The battery cells connected to the test output are connected parallel. The battery cells connected to the main output are serially connected in any column. If any cell in a column is connected to the test output, then this cell should be bypassed. The second relay