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Accuracy improvement of SOC estimation in lithium-ion batteries

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ABSTRACT

Scheduling Lithium-Ion batteries for energy storage applications in power systems requires an accurate estimate of their state of charge (SOC). The Coulomb counting method is popular in the industry but remains inaccurate.

This paper presents an intelligent technique for the SOC estimation in Lithium-Ion batteries. The model is developed offline using adaptive neuro-fuzzy inference systems (ANFIS). It considers the cell nonlinear characteristics, as supplied by the manufacturer, which provide the relationship between the cell SOC and open-circuit voltage (OCV) at different temperatures. The manufacturer data are used to model the cell characteristics by ANFIS in order to yield the cell SOC at any arbitrary OCV and temperature within the given range. The pack SOC is accordingly estimated.

For the purposes of comparison, the Coulomb counting method is used at the cell level, rather than the pack level, to estimate the SOC of the battery. Laboratory experiments are conducted on a 5.3 kWh battery module where measured SOC is compared to Coulomb counting computations at the cell and pack levels. Results show distinct superiority for the proposed ANFIS technique over the traditional Coulomb counting method.

1. Introduction

In modern power systems with increasing penetration of renewable sources, which are characterized with uncertainty and variability, energy storage becomes a necessity. Besides the basic function of storage and retrieval, energy storage elements play a crucial role in providing ancillary services to the hosting system. Batteries of all technologies represent a key element in many applications such as portable equipment, electric vehicles, satellite components, and power systems. The Lithium-Ion battery is a versatile and promising technology due to the high energy density, low self-discharge rate, and long life cycle as compared to other standard battery types. However, over charging or discharging of Lithium-Ion batteries can cause an irreversible damage to the battery cells which deteriorates performance and shortens lifetime. In addition, in many applications, accurate estimation of the available energy in the battery at a given time instant is imperative for the proper functionality of the whole system. Therefore, a reliable and robust estimation algorithm for the state of charge (SOC) of Lithium-Ion batteries is always sought. The SOC estimation algorithm is normally programmed in the battery management system (BMS), and is typically dependent on monitoring the performance characteristics of the battery.

A large variety of methods of battery SOC estimation is available in the literature [1–27]. The Coulomb counting method relies on the integration of battery current with respect to time to account for the charge added or withdrawn from the battery [1]. Electrochemical impedance spectroscopy can be employed to assess the battery SOC in case the impedance is correlated with the energy in the battery [2]. The open-circuit voltage (OCV) of the battery can be measured during a long rest period, and the relationship between OCV and SOC can be used for SOC estimation [3]. Such fundamental methods of SOC estimation are also combined. In [4], the relationship between battery impedance and SOC is realized and combined with Coulomb counting for SOC estimation. Another combination between Coulomb counting and impedance estimation is presented in [5] for the determination of available capacity in Lithium-Ion batteries. However, the changes to battery current, terminal voltage, and internal impedance are combined to estimate the SOC and remaining capacity of Lithium-Ion batteries [6]. Nevertheless, lack of accuracy is a common feature of these techniques for different reasons not limited to the clear dependency on measurements or estimations of other variables.

More mathematically exhaustive methods for direct SOC estimation depend on several variations of Kalman filter [7–13]. Considering linear [7] and nonlinear [8] electrochemical models,

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an extended Kalman filter is used to supress measurement and process noise, and to eliminate the need to know initial SOC. Therefore, SOC estimation accuracy is enhanced. An adaptive extended Kalman filter is employed to estimate the OCV, which is used in turn to estimate the SOC [9]. In [10], an extended Kalman filter is used to determine the model parameters of the Lithium-Ion battery, and an adaptive extended Kalman filter is used to estimate the SOC. The unscented Kalman filter is proven in [11] to accurately identify nonlinear parameters of Lithium-Ion batteries leading to SOC estimation; an adaptive version of the same filter is also used for the same purpose in [12]. The large computational burden is usually an obstacle for feasible implementation of such methods; it also reflects on the cost of the BMS, and hence, the whole system.

Artificial intelligence is also exploited to estimate the remaining capacity and SOC of Lithium-Ion batteries. Two different architectures of artificial neural networks (ANN) are trained based on data gathered through 480 charge/discharge cycles in order to assess the capacity fade and SOC of commercial Lithium-Ion batteries [13]. In [14], fuzzy logic, neural networks, and genetic algorithms are combined together in a technique for battery SOC estimation. A number of small fuzzy neural networks are merged into a hierarchical learning structure in order to overcome the problem of large number of inputs. Genetic algorithms are used to tune the parameters of the control inputs and ANN weights; whereas, experimental data were used for training [14]. The hierarchical fuzzy neural networks decrease the number of free parameters which appear with traditional ANN, and hence reduce the training time and effort [15]. A combination of ANN and extended Kalman filter is also implemented to estimate the SOC of Lithium-Ion batteries where radial basis function networks [16] and multilayer perceptron networks [17] are both used. The ANN is trained offline on experimental measurements, while the Kalman filter eliminates the data noise. In [18], radial basis function networks are combined with an extended $H\infty$ filter to perform the task of SOC estimation in Lithium-Ion batteries.

Various versions of adaptive neuro-fuzzy inference systems (ANFIS) have been implemented in the literature in the context of battery SOC estimation [19–25]. All such techniques operate at the pack level rather than the cell level; in addition, none of them considers the cell characteristics as supplied by the manufacturer. Since ANFIS is well known to suffer from the curse of dimensionality, large number of inputs is likely to hinder the estimation performance [20,21,23]. Some methods rely on the value of the internal resistance of the battery which requires either a measuring instrument or an accurate estimator [22] and [24]. Extensive experimentation is sometimes required to obtain the ANFIS training dataset [21] and [24]. The technique presented in [25] updates the SOC value, which requires a good guess to start and suffers from long idle periods.

Several automatic control theorems are utilized to develop algorithms for the estimation of battery SOC. A proportional integral (PI) observer is developed to estimate the SOC in Lithium-Ion battery based on the resistive capacitive (RC) electrochemical model of the battery [26]. After the nonlinear battery model is linearized, an adaptive geometric observer could establish the exponential stability of the error dynamics and parameter estimation [27]; the geometric observer is applied to estimate the SOC of Lithium-Ion batteries. In [28], another observer is designed to include the nonlinear relationship between SOC and OCV, and to observe the RC model of the battery leading to SOC estimation. Using linear matrix inequality (LMI), a robust H_∞ filter is developed for the estimation of SOC in Lithium-Ion batteries [29]. Lyapunov theory assures the stability of an adaptive observer used for the estimation of SOC in Lithium-Ion batteries with no need for *a priori* knowledge of the model parameters [30]. Under extreme operating conditions of the battery, estimation techniques based on control theory are expected to face technical difficulties including poor stability and lack of accuracy.

An online SOC estimation technique is proposed by predicting the terminal voltage of the Lithium-Ion battery as a result of an impulse response test [31]. A fast particle filtering algorithm is employed for real-time estimation of SOC and discharge time in Lithium-Ion batteries [32]. The mapping between SOC and OCV is found most critical in estimating battery SOC; accordingly, an adaptive estimation algorithm is developed and experimentally tested on Lithium-Ion batteries [33]. Battery aging is accounted for in SOC estimation by comparing the capacity error with Coulomb counting and look-up Table methods [34]. Conclusively, it appears that the available SOC estimation techniques are either inaccurate or computationally exhaustive. The literature obviously lacks an SOC estimation method which is simple, accurate, and easy to implement.

This paper presents an estimation technique for SOC in Lithium-Ion batteries centred on adaptive neuro-fuzzy inference systems (ANFIS) modeling of cell characteristics. Based on the manufacturer data of Lithium-Ion cells, an ANFIS model is offline trained and developed to yield the cell SOC at any given temperature and OCV within the training range. The cell SOC is estimated while the battery is at rest, and the Coulomb counting approach is adopted at the cell level. The cell SOC is evaluated again at the following rest condition of the battery in order to eliminate the effect of error accumulation during Coulomb counting. The cell SOC is used to estimate the energy available in the cell, which is added up to find the pack energy and SOC.

The traditional Coulomb counting method is preferred by most BMS manufacturers due to its simplicity and ease of implementation; however, the method is inaccurate since it assumes all cells work at the same voltage and temperature. Nevertheless, the proposed technique accounts for the difference in cell voltages and temperatures, and yields more accurate estimation for the battery SOC. The technique could be easily implemented on an 8-bit microcontroller since it is basically dependent on a fuzzy model [35–37]. As compared to SOC techniques available in the literature, the proposed method has the following advantages:

1. The discrepancy on cell voltages and temperatures is taken into account.
2. Cells are modeled based on the manufacturer supplied characteristics.
3. Simplicity and straightforwardness due to reliance on Coulomb counting.
4. The routine is easy to implement, and is not mathematically exhaustive.
5. No extra sensors or measurements are required.
6. SOC estimation is noticeably improved compared to traditional Coulomb counting.

2. Problem statement

The traditional Coulomb counting technique for battery SOC estimation is preferred by most BMS manufacturers due to its simplicity and ease of implementation. However, the technique is inaccurate because of a number of reasons, of which the assumption that all cells are balanced is of utmost effect. In reality, battery cells usually have different levels of voltage and temperature, under all modes of operation, which makes their individual SOC vary. The manufacturer typically supplies the relationship between cell SOC and OCV at different temperatures based on prototype laboratory testing. Such characteristics assure that SOCs of individual cells vary as the cell OCV and/or working temperature differ.