Journal of Power Sources 268 (2014) 758–764

Contents lists available at ScienceDirect

Journal of Power Sources

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

Short communication

Real-time estimation of lead-acid battery parameters: A dynamic data-driven approach

Yue Li, Zheng Shen, Asok Ray*, Christopher D. Rahn

Department of Mechanical and Nuclear Engineering, Pennsylvania State University, University Park 16802, USA

HIGHLIGHTS

- Estimation of State of charge (SOC) and State of health (SOH) in lead-acid batteries.
- Algorithm development based on symbolic dynamic filtering for feature extraction and k-NN for pattern classification.
- Validation on experimental data.

ARTICLE INFO

Article history:
Received 18 February 2014
Received in revised form
18 June 2014
Accepted 18 June 2014
Available online 7 July 2014

Keywords:
State of charge
State of health
Lead-acid battery
Symbolic dynamic filtering
k-NN regression

ABSTRACT

This short paper presents a recently reported dynamic data-driven method, Symbolic Dynamic Filtering (SDF), for real-time estimation of the state-of-health (SOH) and state-of-charge (SOC) in lead-acid batteries, as an alternative to model-based analysis techniques. In particular, SOC estimation relies on a k-NN regression algorithm while SOH estimation is obtained from the divergence between extracted features. The results show that the proposed data-driven method successfully distinguishes battery voltage responses under different SOC and SOH situations.

1. Introduction

Lead-acid batteries provide low-cost energy storage with high power density and operational safety. Consequently, large lead-acid battery packs are increasingly being used in vehicles, renewable energy applications, power backup systems, and the smart grid. Applications requiring large and dynamic power demands (e.g., plug-in electric vehicles and hybrid locomotives) use real-time estimates of the state of health (SOH) and the state of charge (SOC) to efficiently allocate power and energy within battery packs and between other prime movers such as internal combustion engines. Accurate SOC estimates mitigate the risk of the battery system being over-charged and over-discharged; similarly, reliable SOH estimates enhance preventive maintenance and life cycle cost through recharging or replacement of battery units.

The battery SOC and SOH can be estimated from the available current and voltage measurements at reasonable sampling rates (e.g., ~1 Hz for experiments in this paper) based on a simplified model of the cell electrochemistry. This approach results in estimates that explicitly related to the geometric, material, and electrochemical characteristics of the underlying model. A variety of parameter estimation tools (e.g., system identification, minimum variance, and linear least squares) have been applied to lead-acid [1] and lithium-ion [2] batteries.

This paper proposes a dynamic data-driven approach for SOC and SOH estimation of the lead-acid batteries as an alternative to a model-based approach. The proposed estimation method is built upon the concept of symbolic dynamic filtering (SDF) [3] that has been successfully applied in a variety of physical processes for anomaly detection [4] and pattern recognition [5]. The major advantages of the data-driven parameter estimation method, presented in this short paper, are delineated below.

- The proposed method of battery parameter estimation is capable of real-time execution on in-situ computers (e.g., at sensor nodes of individual batteries).
- There is no requirement for a detailed knowledge of the battery electrochemistry and its internal dynamics.

* Corresponding author.
E-mail addresses: yol5214@psu.edu (Y. Li), zus120@psu.edu (Z. Shen), axr2@psu.edu (A. Ray), cdrahn@psu.edu (C.D. Rahn).

http://dx.doi.org/10.1016/j.jpowsour.2014.06.099
0378-7753/

2. Battery state parameters

This section introduces standard definitions of pertinent battery parameters, at a given ambient temperature [6].

Definition 2.1. (Battery capacity) The capacity $C(t)$ of a battery at time t is its maximum charge (in units of ampere-hours) that can be drawn from its fully charged condition at a rate $C(t)/30$ (in units of amperes).

Definition 2.2. (SOH) Let a new battery be put into service at time t_0. The state of health SOH(t) of the (possibly used) battery at the current time t, where $t \geq t_0$, is defined to be the ratio of the battery capacities at time epochs t and t_0, i.e.,

$$\mathrm{SOH}(t) = \frac{C(t)}{C(t_0)} \quad \forall t \geq t_0 \tag{1}$$

Definition 2.3. (DOD and SOC) Let a battery be fully charged at time t and let $I(\tau)$ be the applied current (in units of amperes) at time τ. Then, depth of discharge (DOD) and state of charge (SOC) at time $t + \Delta t$ are respectively defined as

$$\mathrm{DOD}(t+\Delta t) = \frac{1}{C(t)} \int_t^{t+\Delta t} I(\tau)\mathrm{d}\tau, \Delta t \geq 0 \tag{2}$$

$$\mathrm{SOC}(t+\Delta t) = 1 - \mathrm{DOD}(t+\Delta t), \ \ \Delta t \geq 0 \tag{3}$$

Remark 2.1. It is noted that SOH $\in$ [0,1] and SOC $\in$ [0,1] for all time $t \geq t_0$, where t_0 is the time of putting a new battery into service.

The current practice of SOH estimation includes battery capacity measurement, battery impedance measurement, and coup de fouet methods [7]. Capacity measurement is a slow process as it requires full discharge to SOC = 0 followed by a full charge to SOC = 1. Impedance measurement employs dedicated hardware and/or software to directly measure either DC or AC resistance of the battery [8,9]. The battery impedance also increases as the battery ages and the measured impedance can be correlated to SOH. Coup de fouet [7], [10] is observed in Lead-Acid batteries that have been fully charged, rested, and then pulse discharged. During the first discharge pulse, the voltage dips and then increases and levels off at a plateau voltage, followed by a steady rate of decrease. The voltage dip or undershoot has been empirically shown to be proportional to SOH of the cell [11], [12]. In this work, the capacity measurement method has been used to calibrate the SOH at different stages of battery life.

There are several existing methods for SOC estimation, which include ampere-hour counting, measurements of electrolyte's physical properties, and open-circuit voltage testing. Ampere-hour counting requires an accurate current measurement and the SOC estimate is computed from Definition 2.3. The electrolyte in lead-acid batteries plays an important role in the charge and discharge reactions. The linear relationship between the acid concentration and SOC can be used to determine the latter; similarly, the open circuit voltage varies monotonically with SOC. In this paper, ampere-hour counting has been used to compute the SOC for the experimental work.

3. Symbolization of time series

This section briefly describes the underlying concept of symbolic dynamic filtering (SDF) upon which the proposed data-driven tool of battery parameter estimation is constructed. SDF encodes the behavior of (possibly nonlinear) dynamical systems from the observed time series by symbolization and construction of state machines (i.e., probabilistic finite state automata (PFSA)) [3]. This is followed by computation of the state probability vectors that are representatives of the evolving statistical characteristics of the battery's dynamical system.

Symbolization is achieved by partitioning the time series data into a mutually exclusive and exhaustive set of finitely many segments. In this paper, the maximum-entropy partitioning (MEP) [13] has been adopted to construct the symbol alphabet Σ and to generate symbol sequences, where the information-rich regions of the data set are partitioned finer and those with sparse information are partitioned coarser to maximize the Shannon entropy of the generated symbol sequence from the reference data set. As seen at the upper left hand corner plot of Fig. 1, each segment is labeled by a unique symbol and let Σ denote the alphabet of all these symbols. The segment, visited by the time series plot takes a symbol value from the alphabet Σ. For example, having $\Sigma = \{\alpha,\beta,\gamma,\delta\}$ in Fig. 1, a time-series $x_0x_1x_2\ldots$ generates a sequence of symbols in the symbol space as: $s_0s_1s_2\ldots$, where each s_i, $i = 0,1,2,\ldots$, takes a symbol value from the alphabet Σ. This mapping is called symbolic dynamics as it attributes a (physically admissible) symbol sequence to the dynamical system starting from an initial state. For example, see the symbol sequence at the top right hand corner of Fig. 1.

The core assumption in the SDF analysis for construction of probabilistic finite state automata (PFSA) from symbol sequences is that the symbolic process under both nominal and off-nominal conditions can be approximated as a Markov chain of order D, called the D-Markov machine, where D is a positive integer. While the details of the D-Markov machine construction are given in Refs. [3], [13], the pertinent definitions and their implications are succinctly presented below.

Definition 3.1. (DFSA) A deterministic finite state automaton (DFSA) is a 3-tuple G = (Σ,Q,δ) where:

1) Σ is a non-empty finite set, called the symbol alphabet, with cardinality $|\Sigma|<\infty$;
2) Q is a non-empty finite set, called the set of states, with cardinality $|Q| < \infty$;
3) $\delta{:}Q \times \Sigma \rightarrow Q$ is the state transition map;

and $\Sigma^\star$ is the collection of all finite-length strings with symbols from Σ including the (zero-length) empty string ε, i.e., $|\varepsilon| = 0$.

Remark 3.1. It is noted that Definition 3.1 does not make use of an initial state, because the purpose here is to work in a statistically stationary setting, where no initial state is required as explained by Adenis et al. [14].

Definition 3.2. (PFSA) A probabilistic finite state automaton (PFSA) is constructed upon a DFSA G = (Σ,Q,δ) as a pair $K = (G,\pi)$, i.e., the PFSA K is a 4-tuple $K = (\Sigma, Q,\delta,\pi)$, where:

1) Σ,Q, and δ are the same as in Definition 3.1;
2) $\pi{:}Q \times \Sigma \rightarrow [0,1]$ is the probability morph function that satisfies the condition $\sigma_{\sigma\in\Sigma}\pi(q,\sigma) = 1 \quad \forall q{\in}Q$. Denoting π_{ij} as the probability of occurrence of a symbol $\sigma_j{\in}\Sigma$ at the state $q_i{\in}Q$, the ($|Q| \times \Sigma|$) probability morph matrix is obtained as $\Pi = [\pi_{ij}]$.