Selection of OCV–SOC Model for Battery Management Systems

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A battery management system (BMS) plays a crucial role to ensure the safety, efficiency, and reliability of a rechargeable Li-ion battery pack. State of charge (SOC) estimation is an important operation within a BMS. Estimated SOC is required in several BMS operations, such as remaining power and mileage estimation, battery capacity estimation, charge termination, and cell balancing. The open circuit voltage (OCV) model needs to be stored within the battery management system for real-time SOC estimation. The selection, storage, and processing of OCV models involve several design constraints.

battery management systems | Li-ion battery | battery model parameter estimation

1. Introduction

Li-ion batteries first entered the commercial market as portable batteries for consumer electronics. Today, the use of battery-operated rechargeable systems is envisioned to be the most promising alternative for hazardous emissions due to the use of fossil fuels [1]. Moreover, passenger electric vehicles will continue to see the dominant use of Li-ion batteries [2]. In recent times, it has become customary to constantly monitor and manage a battery using a battery management system (BMS) [3] to ensures the safe, efficient, and reliable operation of the battery. BMSs are usually made of the following three components: a battery fuel gauge (BFG), an optimal charging algorithm (OCA), and cell balancing circuitry (CBC). The BFG is the most important element of a BMS, and it estimates several important states and parameters of the battery, including the state of charge (SOC). The CBC ensures safety by preventing cell imbalance between batteries in a battery pack. The OCA allows faster charging during usage without affecting the battery's health. It is important to note that accurate SOC estimation by the BFG is crucial for efficient BMS operation, as both CBC and OCA depend on it. Furthermore, the effect of error in the SOC estimation can also lead to compounded problems such as the reduced lifespan of batteries, over-charging/over-discharging, inefficiency, safety, and reliability issues [4]. Thus, research on accurate SOC estimation has intensified over the past decade, and several approaches have been studied for application in BMS.

2. Open-circuit Voltage (OCV) and State of Charge (SOC)

Open-circuit voltage (OCV) is the measure of the electromotive force of the battery. The OCV of a battery is shown to possess a monotonically increasing relationship with the SOC of a battery. Thus, several approaches and models based on the OCV–SOC characterization have been studied for SOC estimation. For this, an OCV–SOC characterization is conducted in a laboratory setting using a scientific-grade battery cycler that is able to maintain precise voltage and current values across the battery terminals. The data collection for the OCV characterization is designed in a way that the effects of the hysteresis and relaxation phenomenons of the battery can be nullified in the obtained OCV model. Depending on the OCV modeling approach, the data collection may also vary. In [5], a slow-rate data collection approach is demonstrated on various existing OCV–SOC models for parameter estimation. In this approach, a fully charged battery is very slowly discharged (typically at a C/30 rate) using a constant current until it becomes empty. Then, it is charged back to full charge using the same amount of constant current. This entire discharge–charge process takes 60 h. Constant current ensures that the capacitances of the equivalent circuit model remain saturated; a very low magnitude of current assures that the hysteresis effect can be approximated as an equivalent resistance. By measuring the voltage and current values during this entire discharge/charge process, the OCV–SOC parameters are obtained. It is preferred that these data are free of measurement noise and bias. High-precision battery cyclers can maintain constant currents with very little variation and can measure and store voltage and current with very little measurement noise.

3. Different OCV Models

Different OCV–SOC models exist in the literature to adequately represent the OCV curve in the entire span of SOC (0–100%). Several reasons can be stated as to why many variations in the parametric expression for different models exist. Each model approximates the OCV curve differently for the lower (≈0–30%) and higher (≈80–100%) ranges of SOC. For example, the OCV–SOC relationship is quite approximately a straight line between 30% and 80% of the SOC. The straight-line model is the most simplistic approach to OCV–SOC characterization, needing just two parameters; however, the accuracy of the model is compromised at very low and very high SOC regions. In order to improve the accuracy of representation, higher-order empirical models utilizing special functions, such as the polynomial [6], trigonometric [7], logarithmic [8][9][10][11], and exponential functions [12][13], are used. The estimated parameters using these special functions often need to be represented up to their *n*th decimal digit for the precise estimation of SOC (for example, in combined+3 model [11], *n* needs to be as high as six to preserve the modeling accuracy). This directly translates to using a large number of bits to completely represent, store, and process these parameters. However, many practical applications (see examples form Texas Instruments [14] and Maxim Integrated [15]) only allow low-bit processing for BFGs, requiring the traditional OCV–SOC parameters to be rounded. Rounding has been shown to significantly alter the model representation, resulting in poor SOC estimation accuracy [16]. To be able to represent the OCV–SOC curve in low-computing environments precisely, tabular models can be used [16]. Finally, variations in battery chemistries are also a driving factor for varied OCV–SOC representations.

4. Selection of OCV–SOC Model

Different OCV–SOC models vary in their formulation, in the methods of estimation of their parameters, and eventually in the resulting SOC estimation error. While accurate SOC estimation is crucial, selecting a model solely based on the accuracy of estimation may not be suitable in many applications. For example, in high-power restrictive medical equipment, such as an implantable cardiac pacemaker, reducing computational complexity is crucial [17], while the accuracy of SOC estimation is also important. In the case of electric vehicles (EV), for example, drivers are found to experience range anxiety [18]. Here, the accuracy of SOC estimation is crucial, and the computational requirement for SOC estimation is not a concern. These examples illustrate that BMS designers need to take multiple constraints before selecting an OCV–SOC model. There needs to be a systematic approach to selecting a particular OCV–SOC model from the numerous models presented in the literature for a specific application.

The selection of the OCV–SOC model in practical situations is based on requirements that are specific to the application. For example, if high SOC estimation accuracy is required, then models with the lowest error metrics will be selected. This would imply that the computational and memory requirements are high. Most practical situations demand more than one constraint in model selection. The Borda count is an intuitive method for combining different selection criteria for a compromised selection. The Borda count was originally a voting method in which each voter gives a complete ranking of all possible alternatives. **Table 1** ranks the OCV models presented based on all the selection criteria discussed.

Table 1. Model selection metrics rankings.

Model	BF	R2	ME	RMSE	AIC	AIC2	FPE	BIC	MDL	KL	CosD	C	SR	Rank
(65)	1	1	1	1	1	1	1	1	1	4	4	4	1	1
(14)	3	3	4	3	3	3	3	3	3	3	1	1	14	2
(6)	2	2	2	2	2	2	2	2	2	13	2	2	13	3
(10)	4	4	3	4	4	4	4	4	4	10	3	3	12	4
(7)	5	5	5	5	6	6	6	6	6	5	5	5	6	5
(5)	6	6	7	6	7	7	7	7	7	11	6	6	10	6
(11)	8	8	9	8	8	8	8	8	8	6	7	7	7	7
(8)	7	7	8	7	5	5	5	5	5	14	14	14	11	8
(4)	9	9	11	9	9	9	9	9	9	8	8	8	5	9
(12)	10	10	10	10	10	10	10	10	10	7	9	9	8	10
(13)	11	11	12	11	11	11	11	11	11	9	10	10	9	11
(15)	12	12	13	12	12	12	12	12	12	12	11	11	3	12
(2)	13	13	14	13	13	13	13	13	13	1	13	13	2	13
(3)	14	14	6	14	14	14	14	14	14	2	12	12	4	14

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