ABSTRACT

RAHIMI-EICHI, HABIBALLAH. Online Adaptive Battery Parameters Identification, and State of Charge (SOC) and State of Health (SOH) Co-estimation. (Under the direction of Mo-Yuen Chow).

Real-time estimation of the state of charge (SOC) and state of health (SOH) of the battery is a crucial need in the growing fields of electric vehicles (EV) and smart grid applications. The accuracy of the estimation algorithm directly depends on the accuracy of the model used to describe the characteristics of the battery. Considering a resistance-capacitance (RC) equivalent circuit to model the battery dynamics, we use a piecewise linear approximation with varying coefficients to describe the inherently nonlinear relationship between the open circuit voltage (VOC) and the SOC of the battery. We also propose a novel battery hysteresis effect dynamics model that provides a compact and accurate description of a family of the battery VOC-SOC trajectories over a large operating range of electric vehicles. The battery hysteresis loops are modeled as responses to a Linear Time-Invariant (LTI) four-state system with various initial conditions. Experimental validations demonstrate that the proposed model can provide accurate descriptions of the battery hysteresis loops. The proposed hysteresis effect modeling method can be used as the basis for the VOC-based battery SOC estimation. However, we still use the experimental OCV-SOC look-up table in the SOC estimation algorithm due to the availability of the experimental results and the need for more accuracy. Several experimental test results on different lithium-ion batteries show that battery parameters including internal resistance and relaxation effect vary with the SOC, charging/discharging rates, temperature and ageing effect. We use sensitivity analyzes to evaluate the effect of the changes in the battery parameters on the battery model by investigating the terminal voltage variation due to the changes in the parameters.
Accordingly, adaptive parameters/SOC co-estimation is proposed to accurately estimate the 
SOC of the battery. In this algorithm, the moving window Least Squares (LS) parameter 
identification technique is used to identify the battery parameters. The parameters are 
continuously updated to accurately represent all of the battery’s static and 
dynamic characteristics. Since the SOC is one of the states of the battery model, an observer 
is designed based on the updating model to estimate the SOC of the battery. Both simulated 
and experimental data indicate that updating the parameters of the battery model during SOC 
estimation is a key to increase the accuracy of the estimation and avoid unnecessary 
compensation for uncertainties. Moreover, the internal resistance and the full capacity of the 
battery are two important factors to estimate the SOH of the battery by predicting the 
remaining useful life and end of life. Therefore, since we have already identified the internal 
resistance, first we show that the parameters identification and SOC estimation results are not 
dependent on the correct approximation of the full capacity. Afterwards, we develop 
parameters/SOC/Capacity co-estimation algorithm in which using another observer is 
designed on top of the parameters/SOC co-estimation algorithm that uses the estimated SOC 
to estimate the actual capacity of the battery.
Online Adaptive Battery Parameters Identification, and State of Charge (SOC) and State of Health (SOH) Co-Estimation

by
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A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Electrical Engineering

Raleigh, North Carolina

2014

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DEDICATION

To my wife, Maryam, and my parents for all their support and love
BIOGRAPHY

I was born in Isfahan, a beautiful and historical city in the central part of Iran. I earned my Bachelor degree in Electrical Engineering with specialty in Control and Automation from Isfahan University of Technology, a high ranking university of my hometown in engineering area, in 2001. Afterwards, joining the graduate Control engineering program at Khaje-Nasir University of Technology in Tehran, I wrote my Master thesis on “Composite Quantitative Feedback Theory (QFT) controller design for flexible joint robots”; and graduated in 2004. After graduation, I worked as a research assistant in University of Isfahan, and several other research centers in my hometown, on different applications of control and automation including control design and instrumentation. After joining NC State University in Fall 2009, I joined the Advanced Diagnosis, Automation, and Control (ADAC) lab as a Research Assistant with focusing on online battery modeling, and state of charge (SOC) and state of health (SOH) estimation especially in electric vehicles and smart grid applications. I have been serving as a secretary of the Energy Storage Technical Committee (ES-TC) at IEEE Industrial Electronics Society from 2012; and published several journal, magazine and conference papers inside and outside the society on battery monitoring subjects.
ACKNOWLEDGMENTS

First and foremost, I would like to thank my PhD advisor, Professor Mo-Yuen Chow, for all his advices during my PhD program about different issues, from analyzing and problem solving skills to research ethics. I really enjoyed fruitful meetings and discussions with him and the group to enhance my research and presentation skills and deliver a quality research results. I am also thankful to all Advanced Diagnosis, Automation and Control (ADAC) lab members for their generous help and inputs during group discussions to improve the quality of my work.

Also I would like to thank Future Renewable Electric Energy Delivery and Management (FREEDM) Systems Center for the financial support of my project during PhD program. Moreover, Samsung Advanced Institute of Technology (SAIT) partially supported my project; and I had fruitful discussion with Dr. Tae-Jung Yeo and Dr. Paul Barom Jeon from SAIT during their visits and through emails.

I am also grateful to my internal committee members Dr. Srdjan Lukic and Dr. Aranya Chakrabortty for their feedbacks and careful reviews of my research milestones. Especially, I want to extend my deep appreciation to Dr. Yahya Fathi who accepted to be the graduate representative in my committee; and all the things I learned from him as a dedicated teacher and researcher, and an amazing human being.

I thank all my friends who have helped me through my school years. Last but not least, I want to thank my parents and parents-in-law for all their support and unconditional
love. I would like to thank my wife, Maryam, who has always been supportive, encouraging and patient to me.
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CHAPTER 1: INTRODUCTION*

* This chapter is a combination of the following published articles and book chapters:


Introduction

With the rapidly evolving technology of smart grid and Electric Vehicles (EVs), battery as the most prominent energy storage device, attracts a significant amount of attention. The very recent discussions about the performance of the lithium-Ion batteries in the Boeing 787 has confirmed so far that, while battery technology is growing very fast to develop cells with higher power and energy densities, it is equally important to improve the performance of the battery management systems (BMS) to provide safe, reliable and cost-efficient solution. The specific characteristics and needs of smart grid as well as electric vehicles such as deep charge/discharge protection and accurate State of Charge (SOC) and State of Health (SOH) estimation intensify the need for more efficient BMS. The BMS should contain accurate algorithms to measure and estimate functional status of the battery and at the same time be equipped with state-of-the-art mechanisms to protect the battery from hazardous and inefficient operating conditions.

I. The Need for Energy Storage in Smart Grid and EVs

The smart grid and EV are two of the growing technologies that need advanced infrastructure and components to emerge. Energy storage as one of the major components in the smart grid and EVs needs to satisfy several power and energy density criteria based on the characteristics of the application. For different applications including short term and long term power support various types of energy storage from flywheels to numerous battery chemistries are employed.
Twenty-nine states in the US have issued the Renewable Portfolio Standards (RPS) that mandate 15%-30% renewable electricity sales by 2025 [1]. Because of this push toward green energy, solar and wind power generation are coming to the forefront as the primary sources of renewable electricity production for the electric utility grid. It is a well-known fact that energy storage is a crucial element in the integration of renewable energy into the grid especially due to the intermittent nature of renewable energy generation. In addition, it is accepted that oil reserves are going to be exhausted in a few decades; 2057 is estimated to be the oil depletion year [2]. This has led to the penetration of battery-powered electric vehicles into the market. Energy storage has thus emerged as a top concern for the future smart grid and EVs. Below after a brief introduction to these applications, we will discuss the energy storage needs for them.

The smart grid is a concept involving an electricity grid that delivers electric energy using communications, control, and computer technology for lower cost with higher reliability [3]. The US Department of Energy has defined several features for a smart grid including active consumer participation, accommodating all generation and storage options, and enabling new products, services, and markets. Depending on the major requirement, the smart grid applications can be categorized into power and energy applications. Power applications such as frequency/area regulation, voltage support, electric service reliability, power quality, etc. require short bursts of high power output that could last from few seconds to a few minutes. Energy storage devices such as Flywheel, lithium-ion (Li-ion), and advanced lead-acid (Pb-acid) batteries are identified [4] as the potential solutions for these applications. On the other
side, energy applications such as energy time-shift, load following, distributed energy storage, and renewable energy integration require a large amount of energy storage that could be discharged for a longer period of time (i.e., from several minutes to several hours). Sodium-sulphur (Na-S), flow battery, and Li-ion have been identified as potential energy storage devices for energy applications [5].

EVs are the main components of the future advanced transportation system. To better introduce the EVs in the market they are categorized into three types: hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs), and pure or battery electric vehicles (BEVs). While HEVs and PHEVs utilize battery energy storage along with an internal combustion engine (ICE), BEVs purely employ rechargeable batteries to power the electric motors for propulsion. The two driving forces for the penetration of EVs in the world market are (1) to reduce/eliminate harmful gas emissions (e.g., carbon monoxide (CO), and carbon-dioxide (CO₂)) and (2) to reduce the energy dependence on oil for transportation [5]. While there are several advantages to using EVs, such as home charging, excellent acceleration, zero emissions, independence from fuel use, etc., electric batteries are heavier than gasoline and take a long time to recharge, making them less attractive in terms of vehicle range and refueling than gas-powered conventional vehicles.

In order to compete with the existing market, several factors need to be taken into consideration in the design and usage of electric batteries. The United States Advanced Battery Consortium (USABC) has set several medium- and long-term goals for advanced
batteries in EVs. Some of the parameters of interest for USABC are cost (dollars per kilowatt-hour, or $/kWh), power density (watts per liter, or W/L), specific power (watts per kilogram, or W/kg), specific regenerative power (W/kg), energy density (watt-hours per liter, or Wh/L), life (years), cycle life (cycles), operating environment (degrees Celsius, or °C), etc. Some of the batteries that have been used for EVs are nickel-cadmium (NiCad), nickel-metal-hydride (NiMH), lithium-iron phosphate (Li-FePO4) and lithium-polymer (Li-Po). Due to the high energy and power density requirements, the research is also moving toward ultra-capacitors [4] and metal air batteries, such as zinc/air (Zn/air), lithium/air (Li/air), etc.

II. Battery Technology in Electric Vehicles

Rechargeable batteries are the most important energy storage devices in the electric vehicles. In the battery cells, the chemical energy transforms to the electric energy during discharge mode, and vice versa during charge mode. Several battery cells are connected in series in a battery module to support the sufficient operating voltage of the vehicle, and several battery modules are connected in parallel in a battery pack to provide enough power to supply the vehicle. Batteries with different chemistries and technologies have been manufactured to supply electric energy in vehicles applications.

Lead-acid batteries are the traditional solutions in conventional vehicles that provide starting-lighting-ignition energy. In this type of battery, the electrolyte is a diluted sulfuric acid that separates the lead-based electrodes. The overcharge of this battery causes hydrogen release, and water shortage in the electrolyte. That is why refilling the distilled water in the
electrolyte is needed to maintain the battery cell. In Valve-Regulated Lead Acid (VRLA) batteries, since hydrogen and oxygen are allowed to recombine and produce water, they are maintenance-free sealed batteries. Although the low cost of these batteries makes them desirable in many applications, the lead material that is used in assembly of them causes two major disadvantages that gradually reduces the usage: The lead material not only increases the environmental pollution of the lead acid batteries but also decreases the energy and power density both in volume and weight that is a key factor in choosing the proper energy storage for EV applications.

The Nickel Cadmium (NiCad) and Nickel Metal Hydride (NiMH) batteries became very popular as the small size energy storage of the first generation portable electronic devices. The larger size batteries of these types were used in the automotive market for supplying electric vehicles because of better energy and power densities compared to lead-acid ones. The shorter life cycle, toxicity of Cadmium, and lower energy density of NiCad batteries compared to NiMH was the reason to replace them by NiMH batteries. Although NiMH batteries benefit from good safety and tolerance to misuses, the high self-discharge rate and the emergence of Lithium-ion (Li-ion) batteries have determined a gradual substitution of NiMH batteries with Li-ion ones in EVs and many other applications.

The Li-Ion technology with providing much higher power and energy density has dominated the portable electronic device market including laptop, notebook and smartphone. It is also the most promising technology to achieve the determined goals in the EV market. Different
versions of the li-ion based batteries with different materials for anode; cathode and electrolyte have been proposed by chemical research with the purpose of extending their life, improving safety, and reducing material costs. While LiCoO$_2$ batteries have dominated the market, replacing the Cobalt with Nickel-Manganese-Cobalt (NMC) or Nickel-Cobalt-Aluminum (NCA) in other variants has provided batteries with higher capacity in spite of a lesser safety and higher cost. LiFePO$_4$ is known as the most promising chemistry for the EV market. Although it has a lower volumetric density compared to the other Li-Ion batteries, the lower cost and higher safety are two important factors to make it a good candidate for EVs. However, Li-ion batteries suffer from a low voltage stability region, risk of flammability, and detrimental environmental effects [5]. Current research in Li-ion batteries focuses on extending their life, improving safety, and reducing material costs. Moreover, the mismatch of the battery cells has a significant effect on the battery pack performance. Therefore, a monitoring and management system that controls the temperature, the voltage and the charge of each cell which is a part of the battery management system (BMS) is a necessary component of the EV energy storage. Table 1 summarizes the comparison of different battery chemistries from the materials in the structures, advantages, and disadvantages point of view [6]. Also, Figure 1 compares the power density and energy density of different battery chemistries [4], [7].
Table 1: Comparison of different battery chemistries

<table>
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<th>Disadvantages</th>
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<td><strong>Lead Acid</strong></td>
<td>Pb-based electrodes, diluted sulfuric acid electrolyte</td>
<td>Low cost, Tolerant to overcharge, Maintenance free in VRLA version</td>
<td>Not Environmental friendly, Low power and energy density</td>
</tr>
<tr>
<td><strong>NiCad</strong></td>
<td>Electrodes Nickel hydroxide (Ni(OH)$_2$) and cadmium (Cd) electrode, Potassium-hydroxide (KOH) electrolyte</td>
<td>High power and energy density High charge/discharge rate</td>
<td>Toxicity of Cadmium, Shorter life cycle and lower energy density compared to NiMH</td>
</tr>
<tr>
<td><strong>NiMH</strong></td>
<td>Nickel-hydroxide and Hydrogen absorbing alloys electrodes, Potassium-hydroxide (KOH) electrolyte</td>
<td>Good safety and tolerance to misuses, Environmentally friendly, Long cycle life (&gt;3000)</td>
<td>High self-discharge rate, Lower energy and power density compared to Li-ion batteries</td>
</tr>
<tr>
<td><strong>LiCoO$_2$</strong></td>
<td>Carbon and Lithium Cobalt dioxide electrodes, Lithium Salts electrolyte</td>
<td>Very high power and energy density, High cell voltage</td>
<td>Low safety, Easy thermal runaway, High cost</td>
</tr>
<tr>
<td><strong>NMC</strong></td>
<td>Carbon and Lithium Manganese compound electrodes, Lithium Salts electrolyte</td>
<td>High capacity, High power and energy density</td>
<td>Less safety, High cost</td>
</tr>
<tr>
<td><strong>LiFePO$_4$</strong></td>
<td>Carbon and Lithium Iron Phosphate</td>
<td>More safety and lower cost compared to the other Li-ion batteries,</td>
<td>Lower volumetric density compared to the other Li-Ion batteries</td>
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III. Battery Management System (BMS) and its features

Beside the growth of the battery technology, the BMS is a key element to make the utilization of the battery in the smart grid and EVs safe, reliable and efficient. The BMS not only controls the operational conditions of the battery to prolong its life and guarantee its safety but also provides accurate estimation of the SOC and SOH for the energy management modules in the smart grid and EV. To fulfill these tasks a BMS has several features to control and monitor the operational state of the battery at different battery cell, battery module and battery pack levels.

Although the battery technology is growing very fast to provide practical solutions to the EV industry, the progress in technology and material cannot guarantee the safety, reliability
and cost efficiency of the battery operation in electric vehicles. That is why battery management system (BMS) in an electric vehicle fulfills most of the responsibilities of the energy management system, or at least provides necessary platform to apply a smart energy management. A battery management system (BMS) not only provides accurate estimations of the battery status to the driver and the EMS, it also actively controls the functions of the storage device to maximize its life, efficiency and safety [8].

Figure 2 shows a block diagram explaining the function of the BMS in monitoring the battery and providing necessary estimations to the smart grid and EVs. In this figure:

1. The data acquisition (DAQ) module collects the battery data including current, voltage and temperature at proper sampling frequency and precision.

2. The collected data is sent to the state estimation algorithm module that includes online parameters identification module and a state observer. In this module, considering a simple model for the battery dynamics the parameters of the battery are identified using the input/output data. Afterward, the updated parameters of the battery model are fed to a state observer to estimate the SOC, SOH and State of Life (SOL) of the battery. Since the state observer is designed based on the state-space model of the battery, online identification and updating of the model parameters enhances the accuracy of the estimation. The SOC, SOH and SOL are the information that the monitoring and management system in the smart grid and the EV need to know about the battery to perform efficiently.
The smart grid diagram in figure 2 shows a distributed control and energy management among distributed resources, loads and energy storages in a typical power network in the smart grid. In this network, each component of the grid collaborates with the others to manage the available energy based on the local information and the information from the neighbors.

The electric vehicle diagram shows the power allocation of a large scale EV parking deck to different charging stations based on the state of the batteries and customers preference. The EMS module in the parking deck maximizes the satisfaction factor of the customers without exceeding the power constraints. The customer satisfaction is
evaluated by the SOC of the vehicle battery at the arriving and depicting times and the budget preferences of the customers.

In electric vehicles specifically one of the major concerns for battery packs is safety. The battery as well as the occupants of the vehicles should be protected against any fire/shock hazard [8]. Prediction accuracy of remaining distance is also equally important since battery is the only source of energy for the vehicle. Furthermore, these vehicles will be traveling a long distance which will involve deep discharges of up to 80% or more, thus it is crucial to have proper battery protection during deep charge and discharge. A battery pack in an EV can contain 10-100 cells arranged in series and parallel combinations to deliver the required energy and power density [9]. In this scenario thermal management for maintaining optimal operating environment (30-40°C) can also highly increase the efficiency of the battery.

Most of the electronic control that is built around these batteries consists of protection circuits [10] against high and low voltages. These simple control units that only monitor current and voltage can be classified as protection units rather than a BMS. Thus, we need a thorough and accurate BMS that can predict the state of charge, state of health, remaining useful life, etc. in order to increase the efficiency and the safety of the battery. As demonstrated in figure 3, a BMS includes seven key features that can be divided into two hardware and software main categories:
BMS Hardware Features:

i. Cell-level Measurement

Gathering the current, voltage and temperature of each individual cell in the vehicle’s battery pack is the premise to fulfill the BMS roles. Requirements on voltage and current measurements vary according to the type of the battery technology. LiFePO4 chemistry is the most challenging in terms of voltage accuracy, because the open circuit voltage (OCV) versus the SOC curve is very flat between 20% and 80% of the SOC, which is the typical operating range of the battery. A reliable SOC estimation requires a cell voltage measurement as accurate as 1 millivolt (mV) to 2mV. Other types of the Li-ion chemistry, such as Li-Po, Li-titanate (Li2TiO3), and Li-mangan (Li-Mn), are less challenging in terms
of voltage measurement accuracy. A typical accuracy of around 5mV can be achieved by many commercial multi-cell battery monitor integrated circuits (ICs).

Current measurements must also be carried out with high accuracy. The battery current represents the major input of any SOC algorithm, where it is integrated over time to estimate the variation of charge stored. Ideally, the integration operation (i.e., Coulomb-counting) requires that the current sensor is offset-free over the working temperature range and time. In other more sophisticated SOC algorithms, the battery current is usually fed to a dynamic cell model together with the measured cell voltage. Therefore, the measurements of the battery current and the voltage of each cell must be performed at the same time. A typical accuracy target for the current measurement is about 0.5% to 1%, whereas the measuring range depends on the application and can be up to 450 amperes (A) in an EV. Automotive applications also demand compliance with the International Organization for Standardization (ISO) 26262 functional safety standard (i.e., “Road vehicles - Functional safety”). In particular, the BMS design should meet the Automotive Safety Integrity Level (ASIL) C/D safety integrity levels.

ii. Safety and Protection

One of the main functions of the BMS is to ensure the safety of the battery and protect it from operating at conditions that are harmful to the battery and the users. Hazardous conditions are mostly due to the chemical characteristics of the battery. The limitations corresponding to these situations include deep charging of the battery when the voltage is below a certain percent; overcharging of the battery when it is fully charged; and charging or
discharging the battery with a C-rate that is higher than the safe level for the battery chemistry. Operating temperature, which is determined by both the electrochemical reactions inside the battery and the environmental conditions of the application, is an equally important element in the safety of the battery, especially in case of Li-ion batteries. The BMS sets safety limits to protect the battery from working beyond the safe temperature range, which is, for example, 0°C to 60°C for charging and -20°C to 60°C for storage and discharging of a Li-ion battery. The last but not least safety factor for Li-ion batteries is related to mechanical over-stress including vibration, shock and drop that can easily lead to thermal runaway, vent, and flame.

Figure 4 Battery Safety Issues
iii. **Charge Control**

Although the discharge rate of the battery is predetermined by the application in which the battery is being used, the charging rate needs to follow some standard profiles to fully charge the battery in minimum time, maximum efficiency, and less damage to the health of the battery. **Constant Current Constant Voltage (CCCV)** is one of these standard methods in which the battery is charged with a constant current rate before reaching to the upper cut-off voltage. After that the voltage is set constant until the charging current drops below a certain value. Those standard profiles are embedded in the customized charging stations of the particular batteries or general purpose chargers. However, the BMS on the battery pack also needs to have this built-in feature to manage, optimize, and protect the charging profile when the specific charger is not available.

iv. **Thermal Management**

As discussed in the safety features, temperature is an important factor in the operation of a battery. In addition to the safety issue that is defined by the temperature range, the efficiency of the battery is also affected by the ambient temperature because of degradation in capacity and an increase in internal resistance. Therefore, the BMS needs to have the ability to control the temperature of the battery and keep it at the optimal point under different operating conditions. The need to dissipate the heat produced by the battery cells due to electrochemical reactions will be more serious when several cells are compacted in a battery pack. In thermal management heat-transfer analysis is utilized to estimate the distribution of
the heat inside the battery pack, and embed cooling channels to remove the heat using air or liquid.

v. **Cell Balancing**

A multi-cell battery pack consists of several battery cells in parallel and series to provide sufficient operating voltage and capacity to support the EV application. However, if there is a mismatch between the voltage and capacity of the connected battery cells, the entire battery pack’s operation will be limited to the weakest battery cell characteristics. For example, during discharge as soon as the first cell reaches below cut-off voltage, the discharge should be stopped and the charge in the rest of the cells cannot be utilized. This type of mismatch can happen because of the difference between the capacities or the SOCs of the cells. That is why cell-balancing techniques need to be deployed to optimize the performance of the battery pack. The cell-balancing techniques can generally divided into two categories: While passive cell-balancing techniques the extra energy stored in the more highly charged cells is dissipated as heat through a bleeding resistor, in active cell-balancing techniques the extra energy is transferred to the less highly charged cells.

**BMS Software Features**

vi. **State of Charge (SOC) estimation**

SOC is an indicator that represents the available charge stored in the battery compared to the full capacity charge of the battery. An accurate estimation of the SOC is necessary not only for the optimal management of the energy in the EV, but also to protect the battery from
going to the deep discharge or overcharge conditions that are harmful to the battery life and unsafe for the application. Despite the importance of this element, the SOC cannot be measured directly from the battery terminals. That is why algorithms need to be developed to estimate the SOC of the battery pack and the individual cells based on the measured data of each one. Most of the existing SOC estimation algorithms are either non-accurate without considering the dynamics of the battery or so complicated that cannot be implemented online in the electric vehicle’s BMS. Following this section, some efforts to develop online adaptive SOC estimation algorithms that consider the dynamic and operating conditions of the battery will be discussed.

vii. **State of Health (SOH) estimation**

SOH is another important indicator of battery function that can be observed at the cell level or the pack level. SOH predicts the number of times that the battery can be charged and discharged before its life is terminated. This status of the battery is crucial to the EMS to choose strategies to prolong the life and simultaneously do the necessary arrangements to substitute the battery. Again, SOH is not a parameter that can be measured directly from the battery terminals. Furthermore, there is also a need to clearly define SOH. Nowadays, a significant effort is going on to study the SOH of the battery especially for online estimation of the SOH for EV applications. While most of the SOH estimation approaches subjectively define the end of life (EOL) of the battery based on the capacity degradation or/and internal resistance increase thresholds, the application requirements needs to be considered to have an
objective estimation of the remaining useful life (RUL) of the battery. The attempts to develop an application-driven SOH estimation algorithm will be discussed in the following section.

**BMS Architecture**

Architectural choices for implementing a BMS are strictly dependent on the physical structure of the battery. In high-power applications such as the EVs and smart grids, usually 10 to more than 100 high-capacity elementary cells are series-connected to build up the required battery voltage. The overall cell string is usually segmented into smaller modules consisting of several series-connected cells. Thus, the battery can be regarded as being made of three nested layers: the elementary cell, the module, and the pack (i.e., the series of modules). Each layer can serve as an intelligent platform for the effective implementation of a subset of the previously outlined BMS. This general view leads to the BMS hierarchical architecture that is schematically depicted in Figure 5. The innermost layer hosts the Cell Monitoring Units (CMUs), one for each cell in the string. The middle layer consists of the Module Management Units (MMUs), one for each module in which the string has been partitioned. An MMU uses the basic monitoring functions of the CMUs and provides higher-level services to the Pack Management Unit (PMU), which finally supervises the entire battery string. A dedicated and *ad hoc* designed link can be used to connect each CMU to the relevant MMU. A shared galvanic-isolated Controller Area Network (CAN) bus is the preferred choice to implement communication between the MMUs and the PMU. The CAN
bus also embeds the interface between the battery and the other control units of the system hosting the battery.

This hierarchical architecture platform is flexible and scalable, as the BMS functions can be freely distributed and, if redundancy is needed, replicated over all three layers of the platform. A simplified instance of the hierarchical platform consists of only the two outer layers. In such a case, the BMS embeds just an MMU for each module and the PMU. This is a relatively common choice since providing each cell with a dedicated CMU can be expensive. In addition, it may increase the overall self-discharge rate of the battery in a non-negligible way. However, the actual trend is to build up the battery by series-connecting very high capacity cells, instead of groups of parallel-connected cells with lower capacity. Consequently, the cost and power consumption of a CMU may become affordable, when compared to the cost and self-discharge rate of a very high capacity cell. The use of the cell layer can add some benefits to the implementation of the BMS monitoring tasks. The CMU can easily act as a gauge measuring the voltage and the temperature of the related cell [11] to provide redundancy to this key BMS function. In addition, because the embedded CMU can store valuable information, such as the serial number, the lifetime, the number of cycles to be evaluated and stored, into the cell itself. This enables easy tracking of the cell history, thus facilitating the potential use in a second market application of smart grid, when the progressive degradation of its usable capacity makes the cell no longer suitable for an EV. Along with shrinking size and cost, a key point in implementing the CMU is the communication with the MMU. This needs to be isolated because the MMU and the relevant
cells belong to different voltage domains. An interesting approach based on a capacitive coupled link among the cells and the MMU is shown in [12] that avoids the wiring harness with the cells and the MMU[13].

Figure 5 Hierarchical architecture of the BMS
IV. Challenge and state-of-art of related techniques

An extensive research is going on to improve the performance of the BMS to meet the required standards in the smart grid and the EV applications. This research includes developing online algorithms to estimate the SOC and SOH of the battery accurately. Consequently, building a precise model to represent all dynamic and static behavior of the battery is a prerequisite for the state estimation accuracy. The results of the modeling and state estimation in the cell level is a necessary information to perform cell balancing and to increase the efficiency of the battery pack.

Designing BMS for the proper integration of energy storage in both the smart grid and the EV applications has various challenges as well as opportunities. Several national labs and research institutions are working toward developing better BMS. The Advanced Diagnosis, Automation and Control (ADAC) Laboratory at North Carolina State University is working on different aspects and issues of BMSs, especially in the area of SOC and SOH estimation and battery modeling. Figure 6 shows the ADAC Lab experimental platform consisting of a direct current to alternating current (DC-AC) converter, an EV simulator, and a LabVIEW-based Graphical User Interface (GUI). In the following paragraphs, some of the challenges and results in SOC and SOH estimation, battery modeling, and cell-balancing are briefly described.
Battery Modeling

An accurate model representing the characteristics of the battery is essential to the SOC and SOH estimation accuracy. Some researchers have performed rigorous analysis on the modeling of the electrochemical reactions inside the battery [14, 15]. This type of modeling is useful for manufacturers to optimize the design of their batteries; yet it requires a
tremendous amount of computational time and memory to solve detailed partial differential equations of the battery model. On the other hand, some researchers [16] have modeled the battery as a black box with available experimental current-voltage characteristic with given specific applications. Subsequently, statistical modeling or curve fitting approaches are applied to derive a runtime-based model for the battery. The main shortcoming of these models is that they do not consider the dynamics of the battery.

The drawbacks of the aforementioned models lead researchers interested in the dynamic behavior of the battery to develop electrical models. In these models, the battery is represented by an electric circuit with parameters representing some physical phenomena of the battery. The electrical models are divided into two major categories: impedance-based models and Thévenin-based models. The impedance-based models are derived from the frequency domain analysis of the current-voltage behavior of the battery. The Thévenin-based models were proposed when the impedances were substituted by combinations of resistors, capacitors, and inductors to appear more like electrical circuits. In some of the earlier models, a large capacitor is used to represent battery’s electromotive force (EMF). Most of the recently developed models utilize a controlled voltage source to consider the fact that the OCV-SOC relationship is a static nonlinear characteristic of the battery. In practice, experimental look-up tables are used to map OCV to SOC with different curves for charging and discharging cycles to represent the hysteresis effect [17]. Moreover, in the Thévenin-based models, the battery’s relaxation effect, mainly caused by diffusion and a double-layer charging/discharging effect, is modeled by parallel resistor-capacitor (RC) pairs. The number
of RC pairs used is a trade-off between the accuracy and complexities of the model. It is proposed to use two RC pairs to represent both the long-term and short-term relaxation effects [18], and in many studies using one RC pair has shown accurate enough performance [19, 20]. Figure 7 presents a Thévenin-based model with two RC pairs: (1) The internal resistance is related to the resistance of the electrolyte to the propagation of the ions; (2) The
short term relaxation effect is caused by composing the Solid Electrolyte Interface (SEI) at the Anode electrode; (3) The long term relaxation effect is the product of composing Double Layer Capacitance at both Anode and Cathode electrodes; (4) The experimental OCV-SOC curve for a Lithium-Iron Phosphate battery with the hysteresis effect. All parameters in the model are subject to change with different charging/discharging current rate, SOC, temperature and ageing effect. That is the motivation of using an adaptive model with the same structure given in Figure 7 [21], where the parameters are identified and updated on-line.

Cell-Balancing

A good review of various approaches on cell balancing is provided by [36] and is summarized in Table 2. The implementation of passive cell balancing is straightforward, requiring just a controlled switch and a bleeding resistor per cell to dissipate the extra energy stored in the more highly charged cells as heat. The most promising approaches seem to be the Module-to-Cell and the Shared Cell-to-Cell techniques, in which a single DC/DC converter is used to equalize the charge among the cells of a module. Active cell balancing transfers the extra energy to the less highly charged cells. Different active balancing techniques are possible depending on how the energy is redistributed among the cells. However, a really good trade-off between the circuital complexity of the active balancing method and achievable efficiency has to be found to make active balancing competitive against passive equalization. The hardware implementation of the charge-equalizer circuit
Table 2 comparison of the various balancing techniques

<table>
<thead>
<tr>
<th>Balancing technique</th>
<th>Pros</th>
<th>Cons</th>
<th>Related works</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>PASSIVE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Cell-to-Heat</em> (One bleeding resistor and switch per cell)</td>
<td>Very simple Very cheap</td>
<td>0% efficiency Slow (Limited by the maximum allowable dissipated power on board)</td>
<td>[37]</td>
</tr>
<tr>
<td><strong>ACTIVE</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><em>Module-to-Cell</em> (Charge transfer from a battery module to a single cell by means of a galvanic isolated DC/DC converter)</td>
<td>Relatively simple Good efficiency Fast</td>
<td>Switch network High isolation voltage of the DC/DC</td>
<td>[38, 39]</td>
</tr>
<tr>
<td><em>Distributed</em> (Charge transfer from adjacent cells)</td>
<td>Moderate efficiency Moderately fast</td>
<td>Bulky Complex control</td>
<td>[40]</td>
</tr>
<tr>
<td><em>Shared</em> (Charge transfer from cell A to tank, then from tank to cell B)</td>
<td>High efficiency Fast</td>
<td>Switch network</td>
<td>[41, 42]</td>
</tr>
<tr>
<td><em>Cell/Module Bypass</em> (A cell/module disconnection from the current path)</td>
<td>High balancing efficiency Very fast and flexible</td>
<td>High current switches Complex to implement Decrease battery efficiency during operation</td>
<td>[43, 44]</td>
</tr>
</tbody>
</table>

lies in the Module Management Unit, while the overall balancing procedure is usually supervised by the Pack Management Unit, which controls the amount of charge stored in each cell of the package string. Usually, the charge equalizer at the module level can achieve
a very high efficiency up to 90%, in comparison with the 0% efficiency in passive cell balancing.

**SOC Estimation Algorithms**

Several algorithms and approaches have been proposed to estimate the SOC from the battery’s available measurements. Coulomb-counting [22] or Ah-counting is one of the most conventional methods in which a time integral of the terminal current determines the amount of charge released from or stored in the battery and is compared to the full charging capacity. Although easy to implement, this method suffers from the unknown initial value for the SOC, as well as a current sensor error, which accumulates over time because of the integration process. Measuring the open circuit voltage is another approach to calculate the SOC based on the static relationship between the OCV and the SOC. This method is used independently [23] or in combination with Coulomb-counting [24] to increase the accuracy of the SOC estimation. However, due to the long term battery dynamics (to be explained in more details later), obtaining the OCV requires the battery to stay at rest (i.e., no charge or discharge) for a long time (sometimes as long as 8 hours or more). This requirement voids this method for online applications such as EVs. Similarly, Electrochemical Impedance Spectroscopy (EIS) [25] is another tool used to estimate the SOC. The internal impedance of the battery is calculated by applying small current signals with different frequencies to the battery and measuring the corresponding voltage using special EIS analyzer equipment. This process again takes a long time and is only suitable for offline analysis.
Recently, online methods, such as model-based SOC estimation approaches, have been developed and become popular. The dynamics of the battery are modeled as an intrinsically nonlinear system. Various techniques are employed to design observers to monitor the system’s SOC. Ranging from simple observers designed by trial and error, to advanced robust, optimal [26], and recursive techniques, (e.g. Kalman Filters [27] and Sliding Mode observers [28]) have been developed. Although the latter provides more accurate robust results, these methods are all designed based on offline identification of the battery model parameters. The constant parameters for the battery model identified offline contradict the experimental and analytical results of modeling different batteries at different SOCs and various environmental conditions. As shown in [21], some parameters of the battery model change as much as 800% at the same temperature and discharging current rate when the SOC changes between 0% and 100%.

Our proposed method, “battery parameters/SOC co-estimation” depicted in Figure 8 [21, 29], estimates the SOC based on considering a simple battery dynamics model while using an adaptive online parameter-identification algorithm to identify and update the model’s parameters. Subsequently, deploying a piecewise linearized mapping of the OCV-SOC curve, the parameters are continuously updated to accurately represent all of the battery’s static and dynamic characteristics. Since the SOC is one of the states of the battery model, an observer is designed based on the updating model to estimate the SOC of the battery. Both simulated and experimental data indicate that updating the parameters of the
battery model during SOC estimation is a key to increasing the accuracy of the estimation and avoiding unnecessary compensation for uncertainties.

![Battery parameters and SOC co-estimation block diagram](image)

**Figure 8 Battery parameters and SOC co-estimation block diagram**

**SOH Estimation Algorithms**

While the SOC is a well-defined indicator of the amount of available charge left in the battery, the SOH, which is supposed to give a sense about the “health” of the battery, has not been well defined. Most studies consider the following equation to define the SOH of the battery:
Where $Q_R$ is the rated capacity and $Q_{act}$ is the actual capacity of the battery that is degraded due to the cycling effect. The shortcoming of this SOH definition is that it does not put the application of the battery into the account. Let’s use a human health analogy to explain this issue. We cannot define a person’s health without considering the age, history, and activity of the human being. An ordinary healthy person who can run three to four miles a day may not be healthy enough to take part and finish a marathon race with a desirable time period. The situation is the same for batteries; the definition of the battery’s SOH should be strongly tied to the application in which the battery is used, as well as the age and history of its use. Despite the ambiguity in SOH definition, several studies on the microscopic and macroscopic behavior of the battery show some physical facts that can be used to shed some light on this concept:

- Microscopic analysis detects an aging (i.e., fatigue) phenomenon in the battery that can be caused by various mechanisms [30]. From the application’s point of view, aging can be related to two major causes: the calendar life of the battery and the cycling life of the battery.
- Macroscopic representations of aging in the battery are:
  1. The capacity degradation, which is predominantly produced by cycling, and
  2. The internal resistance, which can also be increased by the storage life of the battery [31].
These variations in the battery’s parameters are irreversible and are different from those caused by changes in the operating conditions. Temperature can be used to accelerate the battery life test. Every 10°C increase in the temperature halves the life of the battery cell [32].

Despite knowing all the factors that affect the battery life, finding an appropriate definition for the SOH is still not an easy task. Most studies in this area consider capacity degradation or internal resistance increase or a combination of the two as the measure of the SOH [20, 33]. While the changes in the capacity and the internal resistance are just indicators. They are meaningless without considering the application of the battery. For example, some approaches consider the failure threshold of the battery to be when the capacity is reduced to 80% of its rated value. Some studies have defined more practical indicators, namely the remaining useful life (RUL) and end-of-life (EOL) to predict the lifetime of the battery [34, 35]. Although those studies employ statistical analysis to estimate the RUL and EOL of the batteries mostly in military and aerospace applications, they do not consider the requirements and characteristics of the smart grid or EV applications.

An application-dependent definition of the SOH in the EV and in the smart grid applications is proposed by ADAC at predicting the RUL and EOL. These applications have different requirements of operating power and energy for a given time periods, and with different charging and discharging trends to the battery. It is necessary to take all of these characteristics into consideration in predicting the EOL and RUL of a battery for the specific application.
The future behavior of the vehicle and the smart grid is highly dependent on the stochastic behavior of the users and the operating conditions. Therefore, statistical analysis is needed to predict the EOL and RUL.

The current status of the battery needs to be determined online, by identifying the corresponding parameters (i.e., capacity and internal resistance).

Accurate models for the capacity degradation and internal resistance increase regarding cycling need to be developed. Again statistical analysis is to be used to determine the effect of partial cycling on the battery parameters, compared to the full cycling effect.

Figure 9 shows the steps to be taken to estimate the RUL and EOL of the smart grid and the EV applications.

1. The online parameters identification algorithm estimates the capacity and the internal resistance of the battery while it is being used in the application.
(2) From the capacity degradation and the internal resistance increase models, with the updated online estimations, predict the capacity and the internal resistance of the battery in the future.

(3) Estimate the EOL and RUL of the battery using Monte Carlo Simulation and Bayesian analysis. This prediction is based on the statistical data about the application and the users’ behavior.

V. Conclusion

A smart BMS is crucial in the realization of the smart grid and the escalation of the EV industry. The growth of battery technology to provide higher energy and power density and to reduce the cost cannot be fully utilized without proper BMS circuits and algorithms to monitor and control the battery and to guarantee the safety and reliability of the energy storage devices. Although most of the performance requirements for the BMS in laptop and cell phone applications are already provided, there is still enormous research and development needed to satisfy the standards for EVs and smart grid applications. The field of research includes, but is not limited to, finding an accurate and practical algorithm to estimate the SOC, define proper application-oriented SOH measures to accurately predict the remaining useful life and end of life of the battery, and finding methods to actively balance different cells and modules in the battery pack.
References


CHAPTER 2: MODELING AND ANALYSIS OF BATTERY HYSTERESIS EFFECTS

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Paper published in:

Modeling and Analysis of Battery Hysteresis Effects

Abstract—Battery state estimation is an essential step in providing an optimal management system for the battery. With an accurate relaxation-effect model, the battery’s open circuit voltage (VOC) can be obtained from direct measurements of the terminal voltage and load current. The battery’s state-of-charge (SOC), thereby, can be accurately estimated if a precise model for the VOC-SOC relationship with hysteresis effect is considered.

This paper proposes a novel battery hysteresis effect dynamics model that provides a compact and accurate description of a family of the battery VOC-SOC trajectories over a large operating range and charging/discharging control strategies such as those used in Plug-in Hybrid Electric Vehicles (PHEVs). The battery hysteresis loops are modeled as responses to a Linear Time-Invariant (LTI) four-state system with various initial conditions. Experimental validations demonstrate that the proposed model can provide accurate descriptions of the battery hysteresis loops. The proposed hysteresis effect modeling method can be used as the basis for the VOC-based battery SOC estimation.

I. Introduction

Today, various fields of research address different challenges about batteries being the most important energy storage devices. A future advanced transportation system via Plug-in Hybrid Electric Vehicles (PHEVs) and Plug-in Electric Vehicles (PEVs) is not feasible without significant improvements in battery technology and battery management systems [1]. Moreover, the battery is a critical component in the infrastructure of the rapidly evolving
smart grid. Since a smart grid is based on distributed energy management and renewable energies as the primary energy providers in a smart grid are intermittent, reliable and efficient energy storage is a prerequisite to guarantee the realization of this technology. In addition to efficiency and reliability that mostly address battery technology, an accurate monitoring of the battery state information is an essential need to control and manage the power of the smart grid. The battery’s state information includes state-of-charge (SOC), state-of-health (SOH), or other state-of functions (SOF). The battery’s SOC, which we consider more deeply in this paper, is defined as the percentage of the capacity left in the battery that can be discharged divided by the battery’s rated capacity.

An accurate estimation of the battery’s SOC has so far been subject of different fields of research: Electrochemical Impedance Spectroscopy (EIS) methods are used to measure the impedance spectra of the battery by applying predefined profiles of current with varying frequencies to the battery. Then, the SOC of the battery is estimated as a function of the battery’s impedance [2, 3]. The other approach to estimating the SOC is to measure the open circuit voltage (VOC) of the battery by putting the battery in a long rest period. Although this method is time-consuming, it can give accurate results since there is a unique relationship between the VOC and the SOC that depends only on the temperature [4]. The other well-known SOC estimation approach is called Coulomb counting (Ah counting). This method simply integrates the input terminal current of the battery and, dividing by the battery’s nominal capacity estimates the SOC. This approach, although easy to implement, suffers from two drawbacks: 1) the initial SOC is rarely known to start estimation; and 2) the cumulative
error prevents this method from providing an accurate estimation. Due to the advantages and disadvantages of the VOC-based and Coulomb-counting estimations, mixed approaches that use a combination of these methods are used to overcome the shortcomings and provide more accurate results [5]. Extended Kalman Filter [6] and sliding mode observer [7, 8] are two accurate approaches to estimate the SOC that consider an resistor-capacitor (RC) equivalent circuit for the battery model. The disadvantages of these methods are that they use complex algorithms and they are hard to implement. With this short survey of SOC estimation approaches, most of the accurate and applicable methods consider a dynamic model for the battery. The more accurate the battery model is, the more precise the SOC estimation we can expect to get from the approach. Therefore, obtaining an accurate battery model that can be used as a dynamic model is key to improving battery monitoring systems.

As is discussed in Section II about battery modeling, hysteresis effect is one of the fundamental elements of battery dynamics. The hysteresis effect shows the different equilibrium voltages to which the battery’s VOC converges, regarding charging or discharging cycles. The extent of the hysteresis effect is different in different types of batteries. The hysteresis effect is extremely significant in Nickel-metal hydride (NiMH) batteries [9]. For Lithium-ion (Li-ion) batteries, the hysteresis effect is not serious, but you still cannot ignore it. Han [10] and Zheng [11] reported their observation of the hysteresis effect in Li-ion batteries and gave a detailed explanation on the generation of hysteresis in Li-ion batteries. Because of the hysteresis effect, the battery’s VOC-SOC function is not a one-to-one mapping, but a family of curves determined by the operating conditions, current rate,
and cycling histories [9, 12]. Without considering the hysteresis effect, all of the estimation approaches based on the VOC-SOC relationship may result in large errors. With a complex cycling history, the battery’s VOC-SOC trajectory can be very complicated, as demonstrated below, lying between the hysteresis major loops. Therefore, it is essential to model the battery hysteresis effect appropriately to build a bridge between the battery’s VOC and SOC. A direct approach in battery hysteresis modeling is to average the major loops and to relate the battery’s VOC with its SOC through the average [13]. As discussed below, this method suffers from a large hysteresis error introduced into the SOC estimation. Windarko and Choi [14] employ the Takacs model in battery hysteresis modeling. This approach is basically an input-output (I/O) mapping of the major loops and minor loops of the hysteresis. Thele, et al. [15] develop a phenomenological approach for the battery’s hysteresis modeling, and this model may lose effectiveness under certain operating conditions when the current changes direction before the minor loop converges with the major loop.

However, for applications such as the Plug-in Hybrid Electric Vehicle (PHEV) with different operating conditions and cycling histories, a dynamic model is the best structure with which to model all the characteristics of the battery. This paper proposes a novel battery hysteresis effect modeling method. The dynamics of the battery’s hysteresis effect is modeled by a linear time-invariant (LTI), four-state, lumped parameter system. The battery’s complicated SOC-VOC trajectory is treated as a response to a four-state system. The motivation behind this modeling method is that the battery’s hysteresis effects are governed by the battery’s dynamics, disregarding whether the hysteresis effects are for the major loop
or the minor loops. As a result, this method provides a compact way to describe complicated
SOC-VOC trajectories. Experimental validations have demonstrated that the proposed method
can accurately model the hysteresis loops of the battery.

In the following sections, Section II presents different characteristics in battery modeling;
Section III demonstrates the existence, extent, and characteristics of the hysteresis effect in a
Li-ion battery using three battery tests; Section IV demonstrates the necessity of battery
hysteresis effect modeling; Section V describes the proposed four-state system modeling
method; Section VI shows the experiment’s validation of proposed method; and Section VII
concludes the paper.

VI. Battery Modeling

Different equivalent circuits have been proposed to model the dynamics of the battery.
Based on the expected accuracy, different components can be added to the model to represent
various characteristics of the battery. However, embedding several components into the model
creates a large amount of complexity and a system with a higher order. Considering the details
in the model becomes a trade-off between accuracy and complexity. The following are some
of the equivalent models for a battery.

Linear Model

A typical battery can easily be modeled by a large capacitor. A capacitor can store a large
amount of electrical energy in the charging mode and release it during the discharging mode.
Since this charging/discharging is a chemical process with electrolyte and inter-phase
resistance, a small resistor is included in series with the capacitor. This small resistor is called the battery’s “internal resistor” and changes with the ambient temperature and the aging effects of the battery. Figure 1 shows a linear model of the battery.

![Linear model of the battery](image)

**Figure 1. Linear model of the battery**

**Relaxation Model**

The relaxation effect is another basic characteristic of the battery that emerges in the charging and discharging cycles. This effect represents the slow convergence of the battery’s VOC to its equilibrium point after hours of relaxation following charging/discharging. The relaxation effect is a phenomenon caused by the double layer charging/discharging [9]. This characteristic is modeled by series-connected parallel RC circuits. Regarding the trade-off between accuracy and complexity, a different number of RC cells can be considered in the equivalent model. Chen et al [16] recommend two RC cells to represent the dynamics of the battery adequately. Figure 2 shows the equivalent circuit for the relaxation model. Another difference between this model and the linear one is that this model has a controlled voltage
source instead of a large capacitance. The voltage source’s value, which represents the electromotive force of the battery, is a function of the SOC.

**Hysteresis Model**

As we discussed above, experimental results show that the VOC-SOC function is not a one-to-one mapping function. As shown in Figure 2, the hysteresis effect causes the discharging curve to stay below the charging curve for the same SOC. The hysteresis in Li-ion batteries is generated due to the thermodynamic entropic effects, mechanical stress, and microscopic distortions within the active electrode materials during Lithium insertion/extraction [9]. Since lithiated and delithiated phases have different lattice constants that cause mechanical stress at the phase barrier, the potential drops inside the individual particles that are switching from charging to discharging [17]. Except for mechanical stress, thermodynamic effects also cause hysteresis in electrode potentials. The battery model that considers the hysteresis effect in the VOC-SOC mapping functions is called the “hysteresis model.” As we discussed earlier, the hysteresis modeling can be as simple as using different look-up tables for charging and discharging cycles; or, regarding the objective of this paper, a dynamic model to represent VOC as an output of a state-space model in which the states are differentially changing via the SOC.
Figure 2. Hysteresis model of the battery

**Combined Model**

Since most of the time a battery contains all of the above properties, a combined model is used to accurately reflect the battery’s characteristics. So, the combined model not only contains the relaxation effect but also includes the hysteresis effect on the VOC of the battery. Figure 3 shows a typical equivalent circuit for the combined model.

Figure 3. Combined equivalent model of a battery cell
VII. Li-ion Battery Hysteresis Effect

In this section, several experiments are designed to investigate quantitatively the characteristics of the hysteresis effect in Li-ion batteries. The battery used in the experiments is the ANR26650 Lithium-Ion battery from A123 Systems. The recommended discharge and charge-cutoff voltages for this battery are 2.0v and 3.8v, respectively and it has a nominal capacity of 2.3Ah. Figure 4 shows the Arbin BT2000 battery testing system that we used to apply the test procedures to the Li-ion cells.

![The Arbin BT2000 battery testing system used](image)

**Charging/Discharging Current-Step Experiment**

This experiment is intended to obtain a quantitative knowledge of the hysteresis effect in Li-ion batteries through a specially designed experiment. Figure 5 shows the current and
voltage measurements from the experiment. The battery is first charged by two 1A current steps and then discharged by another two 1A current steps. There is a one-hour relaxation period following every current step. And the one-hour relaxation is used for the double-layer discharging so that at the end of every one-hour relaxation, the battery voltage is equal to the equivalent point (i.e., the VOC).

Figure 5. Current and voltage measurements from repeated charging/discharging current step test with same capacity step length

Label the battery’s SOC at the end of the first 600As charging as SOC₀ and after the second 600As charging, the battery SOC is SOC₀ + ΔSOC. Then, after the first 600As
discharging, the battery SOC is back to SOC₀. Ignoring the charging/discharging efficiency, at the end of the first 600As charging and at the end of the first 600As discharging, the battery has the same SOC. Without the hysteresis effect, VOC₁ and VOC₂ should also be equal to each other in Figure 5. However, there is a 0.0134v difference between the two VOCs. Figure 6 shows an enlarged view of the battery terminal voltage to describe experimentally the different characteristics of the battery model including internal resistance, the relaxation effect, and the hysteresis effect.

Figure 6. Enlarged view of Figure 5’s voltage measurement
Complete-Cycle Charging/Discharging Current Step Experiment

This test is intended to obtain the hysteresis major loop. Usually, the battery SOC-VOC curves are called hysteresis major loops with complete cycles of SOC and minor loops with partial cycles. Figure 7 shows the current profile used in the test. Initially, the battery is discharged to empty. During the test, we use standard pulses of 1A current steps with a fixed 600 seconds step of charging and -1A current steps with the same 600 seconds step for discharging. Although these steps are sufficient to show the VOC-SOC change properly in the 10% to 90% SOC range, for low SOCs and high SOCs, these steps cannot demonstrate the hysteresis effect accurately. Therefore, we use a 120-second step width for SOC<10% and SOC>90% intervals. In order to obtain the battery’s VOC, the battery is kept at rest for one hour following every charging current step or discharging current step. Then, the terminal voltage of the battery at the end of the 1-hour rest is considered to be a good approximation of the battery’s VOC. The current step is set as low as 1A to minimize heat generation in the battery. The 600As and 120As capacity step width guarantees more than 24 data points on each curve of the major loop.

The time constant of the double-layer charging/ discharging is usually less than one hour. Therefore, the voltage measurement at the end of the 1-hour rest time can be assumed to be a good approximation for VOC. Figure 8 shows the hysteresis major loop of the Li-ion battery obtained from the test. With the same SOC, the battery’s VOC in the charging cycle is higher
Figure 7. Current and voltage measurements from complete-cycle charging/discharging current step test

Figure 8. Li-ion battery’s hysteresis major loop at room temperature
than it is in the discharging cycle. Figure 9 shows the difference between the two curves. Since three local maximums can be found in Figure 9, we divide this curve into three parts:

a) For SOC<10%, the maximum difference is 0.3318v. Since the overall VOC range is from 2v to 3.9v, this difference is considerable because:

\[
\text{difference} = \frac{0.3318}{(3.9-2)} = 17.46\%
\]

b) For 10% <SOC< 90%, the maximum difference is as small as 0.0447v, which is 2.3% of the whole range. Using sensitivity analysis, we show in the next section that even this small difference cannot be neglected.

c) For SOC>90%, the maximum difference is 0.1052v. Using the same formula as in (a), this distance is about 5.5% of the whole range.

Figure 9. The difference between the battery’s VOC in charging and discharging cycles
Partial-Cycle Charging/Discharging Current-Step Experiment

This test is intended to investigate the characteristics of the hysteresis minor loops of the Li-ion battery while the battery undergoes partial cycles. Figure 10 shows the current profile used in the test. Before the test, the battery is fully charged and during the test, the battery is first discharged to 20% SOC by the repeated 1A current steps with the fixed 600As-capacity step length. Then, it is charged to 70% SOC by the repeated 1A current steps and finally discharged to empty by the repeated -1A current steps with the same step length. Again, each current step is followed by a 1-hour relaxation period to reach to the equilibrium voltage.

Figure 10. Current and voltage measurements from the partial-cycle charging/discharging current step test
Figure 11 (a) shows the hysteresis minor loops obtained from the test, and (b) is the partial enlargement view. As in the example shown here, the battery SOC-VOC trajectory can be very complicated with a complicated cycling history. It cannot simply be described by one or two curves but needs a family of curve functions, and the actual VOC-SOC trajectory followed is highly related to the battery’s cycling history.

(a) Hysteresis minor loops

(b) Partially enlarged view

Figure 11. Example of the hysteresis minor loop of the Li-ion battery at room temperature
Two conclusions can be drawn from the test:

(1) Minor loops always lie between the charging and discharging curves of the major loop; and

(2) When the current changes direction, the SOC-VOC trajectory also changes direction and soon converges with the major loop curves with the same direction.

**VIII. Hysteresis Effect Analysis**

According to Figure 9, the maximum distance between the two curves of the hysteresis major loop for 10%<SOC<90%, which is the operating point of the battery, is around 0.045v. This is a small value (2.3%) compared to the full VOC operating range. So, why can this small difference not be ignored? The battery hysteresis effect is modeled for the battery’s SOC estimation. With VOC as the system input and SOC as the system output, the hysteresis error, $e_{hys}$, is defined as:

$$
e_{hys} = \frac{SOC_{charging} - SOC_{discharging}}{SOC_{max} - SOC_{min}} \times 100\%$$

(12)

where $SOC \in [0\%, 100\%]$.

The hysteresis errors of the major loop (Figure 7) are calculated accordingly and shown in Figure 12 (right graph). The left-hand side graph is the same content as in Figure 8 with a coordinate transformation.
From Figure 12, the major loop hysteresis errors may be as large as 31%. Therefore, if we use the midline to estimate the battery’s SOC, it may result in large SOC estimation errors, especially between 10% and 90% SOC, where the battery’s VOC-SOC curves are relatively flat and the battery SOC is quite sensitive to the VOC variation within this range. Thus, it is essential to model the battery VOC-SOC trajectory accurately in order to obtain accurate battery SOC estimation.

Figure 12. Hysteresis errors calculated based on the hysteresis major loop from experiment
The necessity of the battery hysteresis effect modeling can also be explained by the sensitivity analysis of the battery hysteresis major loop. The sensitivity, $S$, is defined as the proportion of the variation in the system output (the battery SOC) explained by the variation in the system input (the battery VOC):

$$S(V_{oc}^n) = \left. \frac{\partial SOC}{\partial V_{oc}} \right|_{V_{oc}^n}$$  \hspace{1cm} (13)

The sensitivity analysis result is shown in Figure 13. Within the input range of $V_{oc} \in [3.2\,V, 3.4\,V]$, the battery’s SOC is highly sensitive to the battery’s VOC whether the battery is following a charging process or a discharging process. In other words, small noises in the battery’s VOC measurement may result in large errors in the battery’s SOC estimation.

Suppose at the 3.353\,V battery’s VOC, there exists 1% of normally distributed measurement noise. In view of the fact that $S|_{V_{oc}=3.353} = 29.8/\mu$, the 1% battery’s VOC measurement noise will be amplified to 29.8% for the battery’s SOC estimation errors. Therefore, because the battery’s SOC is highly sensitive to the battery’s VOC measurement noise, the battery’s hysteresis effect must be modeled to accurately describe the battery’s VOC-SOC trajectory in order to eliminate the high SOC estimation errors introduced by the hysteresis effect.
IX. Hysteresis Effect Modeling

This section introduces the four-state system method proposed to model the battery’s hysteresis effect. The major charging curve is modeled by a four-state system with the following parameters: \( a_1, \ldots, a_4, b_1, \ldots, b_4 \):

\[
\frac{dx}{dSOC} = \begin{bmatrix} a_1 & 0 & 0 & 0 \\ 0 & a_2 & 0 & 0 \\ 0 & 0 & a_3 & 0 \\ 0 & 0 & 0 & a_4 \end{bmatrix} x + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ b_4 \end{bmatrix} u, \tag{14}
\]

\[
V_{OC}(SOC) = [1 \ 1 \ 1 \ 1] x + v_D
\]
where \( v_D \) is the discharge cutoff voltage (i.e., 2.0v). To identify the eight parameters in the LTI system (14), we use conventional curve-fitting techniques for a function with four exponential terms. Each term corresponds to one pair of the \( \{a_k, b_k\} \) parameters. This is due to the fact that the zero-state response to the four-state system (14) is as follows:

\[
V_{OC}(SOC) = \sum_{k=1}^{4} x_k + V_D
\]

\[
= u \sum_{k=1}^{4} b_k \int_{0}^{SOC} e^{a_k(SOC-\tau)} d\tau + v_D
\]  

(15)

The major discharging curve is modeled with the same method, but with different parameters. The major discharging curve is modeled by a four-state system with the parameters: \( a_1^{'}, \ldots, a_4^{'}, b_1^{'}, \ldots, b_4^{'} \):

\[
\frac{dx}{dDOD} = \begin{bmatrix}
a_1' & 0 & 0 & 0 \\
0 & a_2' & 0 & 0 \\
0 & 0 & a_3' & 0 \\
0 & 0 & 0 & a_4'
\end{bmatrix} x + \begin{bmatrix}
b_1' \\
b_2' \\
b_3' \\
b_4'
\end{bmatrix} u
\]  

(16)

\[
V_{OC}(DOD) = [1 \quad 1 \quad 1 \quad 1] x + v_c
\]

where DOD stands for the battery’s depth of discharge:

\[
(DOD = 1 - SOC)
\]  

(17)
and $v_C$ is the charge cutoff voltage (i.e., 3.6v). Again, to obtain the eight parameters in the four-state LTI system (16), we use curve-fitting, considering that the zero-state response of the four-state system (16) is obtained from the following equations:

$$V_{oc}(SOC) = \sum_{k=1}^{4} x'_{k} + v_C$$

$$= u \sum_{k=1}^{4} b'_k \int_0^{DOD} e^{a'_k (DOD-\tau)} d\tau + v_C$$

$$= -u \sum_{k=1}^{4} \frac{b'_k}{a'_k} \left(1 - e^{a'_k (1-SOC)}\right) + v_C \quad (18)$$

Table 1 shows the extracted parameters for both charging and discharging hysteresis dynamic models.
Table 1 Parameters identified for the four-state systems

<table>
<thead>
<tr>
<th></th>
<th>Charging</th>
<th></th>
<th>Discharging</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>a1</td>
<td>-41.9139</td>
<td>a1’</td>
<td>- 75.9468</td>
<td></td>
</tr>
<tr>
<td>b2</td>
<td>48.5209</td>
<td>b1’</td>
<td>17.5694</td>
<td></td>
</tr>
<tr>
<td>a2</td>
<td>-4.2228</td>
<td>a2’</td>
<td>- 3.1574 ×10⁻⁸</td>
<td></td>
</tr>
<tr>
<td>b2</td>
<td>0.7982</td>
<td>b2’</td>
<td>0.1599</td>
<td></td>
</tr>
<tr>
<td>a3</td>
<td>5.3923</td>
<td>a3’</td>
<td>7.6597</td>
<td></td>
</tr>
<tr>
<td>b3</td>
<td>4.9381×10⁻⁴</td>
<td>b3’</td>
<td>3.2652 ×10⁻⁴</td>
<td></td>
</tr>
<tr>
<td>a4</td>
<td>76.3979</td>
<td>a4’</td>
<td>70.3429</td>
<td></td>
</tr>
<tr>
<td>b4</td>
<td>1.2957×10⁻³²</td>
<td>b4’</td>
<td>2.3991 ×10⁻²⁹</td>
<td></td>
</tr>
</tbody>
</table>

X. Experimental Validation

Figures 14 and 15 show the major loop modeling results with the solid red line while the experimental results are demonstrated as blue points.
We use $R^2$ to evaluate how well the model fits.

$$ R^2 = 1 - \frac{SS[E]}{SS[\text{tot}]}, $$

(20)
where, $SS[E]$ is the sum of squares of the modeling residuals, $SS[TOT]$ is the total sum of squares, and:

$$SS[E] = \sum_i (V_{oc_i} - \bar{V}_{oc_i})^2,$$

$$SS[TOT] = \sum_i (V_{oc_i} - \bar{V}_{oc_i})^2,$$

The $R^2$ evaluation of the hysteresis modeling method proposed is listed in Table 2. In general, $R^2 > 0.8$ is considered a good fit in many experimental cases. In Table 2, $R^2 > 0.95$ indicates that the model proposed can well describe the dynamics of the battery’s hysteresis effect.

<table>
<thead>
<tr>
<th></th>
<th>$R^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Major Charging</td>
<td>0.9065</td>
</tr>
<tr>
<td>Major Discharging</td>
<td>0.9922</td>
</tr>
</tbody>
</table>

### XI. Conclusion

In this paper, the battery hysteresis effect is modeled preparing for a future battery’s SOC estimation. A novel hysteresis modeling method is proposed through treating the battery hysteresis loops as the response of a time-invariant four-state system. This proposed method provides a compact and accurate model to describe the battery’s SOC-VOC trajectories with
different battery operating conditions and cycling histories. Experimental validation has

demonstrated that the proposed method can provide an accurate model to describe hysteresis

loops.

**Acknowledgement**

This work is partly supported by the National Science Foundation Award number: EEC-

08212121.
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CHAPTER 3: ADAPTIVE PARAMETER IDENTIFICATION AND
STATE-OF-CHARGE ESTIMATION OF LITHIUM-ION
BATTERIES

Habiballah Rahimi-Eichi  Mo-Yuen Chow

Paper published in:
The proceeding of the 38th Annual Conference on IEEE Industrial
Electronics Society (IECON 2012), Montreal, QC, Canada, 2012
Adaptive Parameter Identification and State-of-Charge Estimation of Lithium-Ion Batteries

Abstract—Estimation of the State of Charge (SOC) is a fundamental need for the battery, which is the most important energy storage in Electric Vehicles (EVs) and the Smart Grid. Regarding those applications, the SOC estimation algorithm is expected to be accurate and easy to implement. In this paper, after considering a resistor-capacitor (RC) circuit-equivalent model for the battery, the nonlinear relationship between the Open Circuit Voltage ($V_{OC}$) and the SOC is described in a look-up table obtained from experimental tests. Assuming piecewise linearity for the $V_{OC}$-SOC curve in small time steps, a parameter identification technique is applied to the real current and voltage data to estimate and update the parameters of the battery at each step. Subsequently, a reduced-order linear observer is designed for this continuously updating model to estimate the SOC as one of the states of the battery system. In designing the observer, a mixture of Coulomb counting and $V_{OC}$ algorithm is combined with the adaptive parameter-updating approach and increases the accuracy to less than 5% error. This paper also investigates the correlation between the SOC estimation error and the observability criterion for the battery model, which is directly related to the slope of the $V_{OC}$-SOC curve.

Index Terms—Battery Parameter Estimation, Parameter Identification, State Observer Design, State-of-Charge, $V_{OC}$-Based SOC Estimation
I. Introduction

Today, the battery is receiving a vast amount of attention as the most important energy storage device in Electric Vehicles (EVs) and the rapidly growing Smart Grid. Different new technologies have been developed to improve the energy and power density of the batteries. Su et al. [1] have presented a survey on the future goals of battery technology and recent achievements toward those goals. While these technologies are bringing considerable diversity to the characteristics and dynamics of the battery, the cost-efficiency and reliability of the battery relies on algorithms to accurately model the battery dynamics and monitor its states while it is in use in a vehicle or grid. The “state” here refers to the battery State-of-Charge (SOC), State-of-Health (SOH), and State-of-Life (SOL), which are very important indicators to consider in optimizing the functionality and life-time of the battery and avoiding permanent damage. The SOC, which we emphasize in this paper, is the percentage of the rated capacity of the battery that the remaining capacity represents.

Among different approaches proposed so far to estimate the SOC, some are based on detailed electrochemical equations in the battery [2]. Despite their accuracy, these methods are hard to implement due to complicated partial differential equations. Similarly, the frequency-based methods that use electro-chemical impedance spectroscopy (EIS) [3] are offline methods and not suitable to be applied to a battery pack while it is in use in a plug-in hybrid electric vehicle (PHEV)/plug-in electric vehicle (PEV). However, other approaches such as Coulomb counting (Ah counting) [4], which can easily be implemented by integrating the battery current, suffer from initial SOC estimation and cumulative error. Estimating the SOC
based on the $V_{OC}$ is another method that can be implemented simply by a look-up table, but an accurate measurement of the $V_{OC}$ is a challenge due to the battery dynamics. To consider these dynamics, a resistor-capacitor (RC) equivalent model has been proposed. To overcome the inaccuracy of the model, adaptive and nonlinear methods, such as an extended Kalman filter [5] and a sliding-mode observer [6], are deployed. Although these complex methods lead to precise and robust results, the implementation of the algorithms is very complicated. Table I provides a comparative list of the aforementioned approaches and compares the advantages and drawbacks of each method.

The method that we use in this paper to estimate the SOC is based on an equivalent RC model of the battery. In addition, we assume that the nonlinear relationship between $V_{OC}$ and SOC can be mapped to several piecewise linear parts with varying parameters. Accordingly, the battery model can be considered as a Linear Time-Varying (LTV) system with current ($i_L$) as the input and terminal voltage ($v_T$) as the output. Afterward, an online adaptive identification algorithm is employed to identify the battery model parameters at each time step. With this continuously updating model, a reduced-order observer is designed to estimate the SOC as one of the states of the system. This type of approach benefits from two advantages of the other methods: 1) Since we use a linear identification method and a linear observer, the algorithm is easy to implement; 2) Continuously updating the parameters of the battery model improves the accuracy of SOC estimation for its updated operating conditions.
<table>
<thead>
<tr>
<th>Approach</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electrochemical approaches</td>
<td>Accurate</td>
<td>Difficult to implement <em>in situ</em></td>
</tr>
<tr>
<td>Ah counting (Coulomb counting)</td>
<td>Easy to implement</td>
<td>1) Dependent on the initial SOC</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2) Not suitable in PEVs with frequent charging/discharging profiles</td>
</tr>
<tr>
<td></td>
<td></td>
<td>due to the need of accurate initial conditions</td>
</tr>
<tr>
<td>Open Circuit Voltage (VOC)</td>
<td>Does not need an algorithm to implement</td>
<td>Needs the battery to be in the resting mode for a long time</td>
</tr>
<tr>
<td>measurement</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extended Kalman filter</td>
<td>1) Accurate</td>
<td>1) Large computational time and memory</td>
</tr>
<tr>
<td></td>
<td>2) Deals with white noise</td>
<td>2) Complicated algorithm to implement</td>
</tr>
<tr>
<td>Sliding-mode observer</td>
<td>1) Accurate</td>
<td>1) Nonlinear</td>
</tr>
<tr>
<td></td>
<td>2) Deals with system-modeling errors</td>
<td>2) Not easy to implement</td>
</tr>
</tbody>
</table>
The remainder of this paper is as follows: In section II, we explain the equivalent RC circuit to model the battery characteristics. In section III, we describe the online identification technique to update the parameters of the model. In section IV, the observer structure to estimate the SOC of the battery is proposed. Section V discusses the results of applying the proposed algorithms to the experimental data and compares the outcomes to the ones obtained from the experiments. Section VI concludes the paper.

II. Battery Modeling

Different equivalent circuits have been proposed to model the dynamics of the battery. Based on the expected accuracy, different components can be added to the model to represent various characteristics of the battery. However, embedding several components into the model creates a large amount of complexity and a system with a higher order. Therefore, considering the details in the model is a trade-off between accuracy and complexity. In the following paragraphs, we describe some of the battery characteristics that are considered in the battery model for this paper.

Linear Model with Internal Resistance

A typical battery can be modeled by a large capacitor. A capacitor can store a large amount of electrical energy in the charging mode and release it in discharging mode. Since this charging/discharging is a chemical process with electrolytes and inter-phase resistance, as
shown in Figure 1, a small resistor, $R$, is considered in series with a capacitor, $Q_R$. This small resistor is called the internal resistor of the battery and changes with the SOC, the ambient temperature, and the aging effect of the battery.

![Figure 1 Battery linear model with internal resistance](image)

**Figure 1 Battery linear model with internal resistance**

**Relaxation Effect**

The relaxation effect is another fundamental characteristic of the battery that emerges in the cycles of charging and discharging. This effect represents the slow convergence of the battery $V_{OC}$ to its equilibrium point after hours of relaxation following charging/discharging. The relaxation effect is a phenomenon caused by the diffusion effect and a double-layer charging/discharging effect [7]. This characteristic is modeled by series-connected parallel RC circuits. Regarding the trade-off between accuracy and complexity, a different number of RC groups can be considered in the equivalent model. Chen et al [7] recommend two RC groups to represent the dynamics of the battery adequately. Between those RC groups, one represents a short-term transient response (on the order of a few seconds) and the other represents a long-term transient response (on the order of minutes or hours). Figure 2 shows
the equivalent circuit for the model that contains the relaxation effect. In this figure, $i_L$ and $v_T$ are the terminal current and voltage, and $Q$ is the rated capacity of the battery.

![Combined battery model with the relaxation effect, internal resistance, and the VOC-SOC function](image)

Figure 2 Combined battery model with the relaxation effect, internal resistance, and the VOC-SOC function

**VOC-SOC Relationship**

Another difference between the model proposed in Figure 2 and the linear one is that the model has a controlled voltage source to include the nonlinear relationship between the $V_{OC}$ and the SOC. This relationship is a static characteristic of a battery under predetermined conditions of temperature and age. To model this nonlinear part of the battery, several nonlinear equations have been proposed [5, 8]. Some of these equations also consider the hysteresis effect of the battery. The hysteresis effect, which is beyond the scope of this paper, causes the discharging curve to stay below the charging curve for the same amount of charge.

Although the proposed models for the $V_{OC}$-SOC function are comprehensive, fitting the experimental $V_{OC}$-SOC curve to the equations results in modeling errors. Therefore, in this paper we utilize a look-up table to represent the $V_{OC}$-SOC relationship. This table can be obtained from a one-time experiment and analyzing method proposed in [9] to rapidly
calculate the $V_{OC}$. The battery used in the experiments is an ANR26650m1A lithium-ion battery from A123 Systems. Figure 3 shows the Arbin BT2000 battery-testing system that we used to perform the experiments, and Figure 4 shows the $V_{OC}$-SOC curve for the charging cycle. To obtain this curve, at the first step the battery is fully charged using the Constant Current-Constant Voltage (CCCV) technique. Then, based on the rated capacity of the battery, 2.3Ah in this case, the battery is continuously discharged to zero SOC with the rate of 1A. Finding the benchmark for the initial SOC, 1A pulse currents are used to charge the battery. Each pulse contains two minutes of charge followed by 15 minutes of rest for SOCs smaller than 10% and larger than 90% and 10 minutes of charge followed by 15 minutes rest for SOCs between 10% and 90%. That is because for small and large SOCs, $V_{OC}$ variation is more significant. With this method, as shown in Figure 4, we obtain about 25 points on the $V_{OC}$-SOC curve for which linear interpolation provides an accurate expression.

Despite the nonlinearity of the $V_{OC}$-SOC curve, since for ordinary charging/discharging current rates the SOC has small variations, the curve can be mapped with a sliding line with a varying slope, $b_1$, and $V_{OC}$ intersection, $b_0$:

$$V_{oc} = f(SOC) = b_1 SOC + b_0 \tag{1}$$

As the next section shows, the adaptive identification algorithm can identify and properly update the mapping parameters at each time step, which is on the order of a couple of seconds.
Figure 3 The Arbin BT2000 battery testing system used

Figure 4 The experimental curve for VOC-SOC

The curve can be described by the equation:

\[ V_{OC} = b_1 \text{SOC} + b_0 \]
State-Space Equations for the Model

To model the battery characteristics, we used the equivalent circuit shown in Figure 5 with one RC group to represent the relaxation effect. Although two RC groups are recommended by [7], there are also several references [6] that state that one RC group structure can provide results accurate enough for a short time-duration (e.g., seconds to minutes) prediction, such as the applications in PHEV and PEV of which our application is one. We chose this simple model to reduce the complexity of the model identification and the parameter extraction. Moreover, as we discussed earlier, the $V_{OC}$ vs. SOC function is mapped to LTV equations in the form of equations (1). If you consider the equivalent circuit for the battery model in Figure 5, the state-space equations can be written as system (2) to represent the battery dynamics. In these equations, the SOC of the battery and the voltage across the RC cell, $V_{RC}$, are selected to be the system-state variables.

![Figure 5 The battery-equivalent circuit](image)
Now, we assume that the terminal current ($i_L$) and voltage ($v_T$) are the only two values that are accessible from system (2). We do not consider the temperature effect and the capacity-fading caused by the aging of the battery. To obtain the estimated SOC as one of the states, the parameters in system (2) need to be identified. We know $Q_R$ to be the nominal capacity of the battery, so we need to estimate $\{b_0, R, C, R_0, b_1, S_{oc}, V_{RC}\}$ as $\{\hat{b}_0, \hat{R}, \hat{C}, \hat{R}_0, \hat{b}_1, \hat{S}_{oc}, \hat{V}_{RC}\}$ using system parameter identification methods and state estimation.

### III. System Parameter Identification

**Least-Squares (LS) and Recursive Least-Squares (RLS) Parameter Identification**

In order to identify the parameters of a linear system, the relationship between the system’s input/output (I/O) samples is described by a standard structure, such as the autoregressive exogenous model (ARX) model [10]:

$$A(q)y(q) = B(q)u(q) + e(q),$$

in which

$$A(q) = 1 + a_1q^{-1} + \cdots + a_nq^{-n},$$

$$B(q) = b_0 + b_1q^{-1} + \cdots + b_mq^{-m},$$
and \( e(q) \) is white noise (zero mean Gaussian noise). Therefore, with this model the output at the present step can be estimated by the I/O values at previous steps. The LS identification approach provides a formula to minimize the LS error between this estimated output value and the real output at the present step. Since the I/O samples are being updated step-by-step while the system is running, a recursive algorithm called RLS can be defined to identify the parameters of the system iteratively. Furthermore, because implementing the RLS algorithm is not easy in a real system and the I/O signal needs to be persistently exciting (PE) [10] at each step, we use the moving-window LS method, which is more practical. In this approach, the I/O data corresponding to a certain number (window) of past steps is used to estimate the parameters. The length of the window depends on the excitation of the input signal to properly reveal the dynamics of the system.

**Battery Parameter Identification**

The parameters of the battery model that need to be estimated are \( \{b_0, R, C, R_0, b_1\} \). Since most of the parameter identification methods use the transfer function of the system to identify the parameters, first we obtain the transfer function form of system (2):

\[
\frac{Y(s) - b_0}{U(s)} = \frac{R_0 s^2 + \left(\frac{b_1}{Q R} + \frac{1}{C R} R_0\right) s + \frac{b_1}{R C Q R}}{s(s + \frac{1}{R C})},
\]

(6)

From transfer function (16) and using bilinear transform \( s \to \frac{2z-1}{T z+1} \) [11], we can get the discrete transfer function of system (2) with sample time \( T \):
where:

\[
\begin{align*}
  c_0 &= \frac{T^2 b_1 + 2QR_0T + 2QRRT + 4QR_0RC + 2b_1RCT}{2QRRT + 4QRRC}, \\
  c_1 &= \frac{T^2 b_1 - 4QR_0RC}{QRRT + 2QRRC}, \\
  c_2 &= \frac{T^2 b_1 - 2QR_0T - 2QRRT + 4QR_0RC - 2b_1RCT}{2QRRT + 4QRRC}, \\
  a_1 &= \frac{-8QRRC}{2QRRT + 4QRRC}, \\
  a_2 &= \frac{-2QR^2 + 4QRRC}{2QRRT + 4QRRC}.
\end{align*}
\]

According to equations (7) and (8a-8e), the time-domain relationship between different samples of I/O is as follows:

\[
y(k) = -a_1 y(k - 1) - a_2 y(k - 2) + b_0 (1 + a_1 + a_2) + c_0 u(k) + c_1 u(k - 1) + c_2 u(k - 2).
\]  

Equations (8d) and (8e) imply that:

\[
1 + a_1 + a_2 = 0,
\]  

which means that the value of \( b_0 \) does not affect the estimation of the current output \( y(k) \) or the other parameters. In other words, \( b_0 \) acts like an output offset that does not influence the I/O dynamic. Thus, we can show that solving equations (8a-8e) gives a unique expression of the battery parameters versus the coefficients of the transfer function (7).
IV. SOC Estimation

After identifying the parameters of the battery, an observer is designed to estimate the SOC, which is one of the states of the model. The observer compares the actual output to the estimated output of the model with the identified parameters. Then, it compensates for the error caused by uncertainties and initial values by giving proper feedback to the states via a designed gain (observer gain). At this stage, the battery parameters \( \{R, C, R_0, b_1\} \) are assumed to be estimated as \( \{\hat{R}, \hat{C}, \hat{R}_0, \hat{b}_1\} \). Moreover, the battery model is represented as a system with equations (11):

\[
\begin{align*}
\dot{x} &= Ax + Bu \\
y &= Cx + Du + b_0
\end{align*}
\]

(11)

in which:
\[ x_1 = S_{OC}, x_2 = V_{RC}, A = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{RC} \end{bmatrix}, B = \begin{bmatrix} 1/Q_R \\ 1/C \end{bmatrix}, C = \begin{bmatrix} b_1 & 1 \end{bmatrix}, D=R_0, u = i_L, \]
\[ y = v_T, x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}. \]

Therefore, the observer can be designed as a system with equations (12):

\[
\begin{align*}
\dot{\hat{x}} &= \hat{A}\hat{x} + \hat{B}u + L(y - \hat{y}) \\
\hat{y} &= \hat{C}\hat{x} + \hat{D}u + b_0
\end{align*}
\]

(12)

in which \( LT = [L_1 \quad L_2] \) is the observer gain vector, and other arguments have the same dimensions as the corresponding arguments in system (11). From equation (12) we can see that even though \( R, C, R_0, \) and \( b_1 \) are estimated accurately, there is no standard method of identifying \( b_0 \). In our recent paper [12], we proposed a piecewise linear approximation for the \( V_{OC}-SOC \) curve. Subsequently, a look-up table has been used to estimate \( b_0 \) based on the identified \( b_1 \). According to the experimental \( V_{OC}-SOC \) curve shown in Figure 4, piecewise
linearization is not an accurate assumption for the ANR26650m1A battery. Therefore, we use another approach here in which a reduced-order observer is designed to estimate the SOC. We can show that with accurate identification of $R$, $C$, and $R_0$, the voltage across the RC group, $V_{RC}$, and the voltage drop on the internal resistance, $R_0i_L$ can properly be estimated without using an observer. That is because the observer is basically used to compensate for the errors caused by initial values or uncertainties and in the case of $V_{RC}$, with negligible uncertainties. We can show that the dynamic of $V_{RC}$ can compensate for the error caused by the initial value in a few pulses. Therefore, as shown in Figure 6, the $V_{OC}$ can be calculated by subtracting $V_{RC}$ and $R_0i_L$ from the terminal voltage, $v_T$. Afterward, using $V_{OC}$ as the output of the reduced-order battery system, the observer equation is:

$$
\dot{S}\hat{OC} = \frac{1}{q_R} i_L + L( f(SOC) - V_{OC} ),
$$

in which $f(SOC)$ is the experimental look-up table for $V_{OC}$-SOC relationship and $L$ is the single-dimension observer gain. This observer structure with a proper gain can compensate the initial value and uncertainty error for SOC estimation.
V. Results and Discussion

To verify the effectiveness and performance of the proposed method, we apply the identification algorithm and consequently the SOC estimation algorithm to the data obtained from actual experiments on the ANR26650m1A lithium-ion battery. This is a nanophosphate lithium-ion battery and can be used in portable high power density devices, grid stabilization energy storage, and commercial truck and bus HEVs. The operating voltage for this battery is 3.0V and the recommended discharge and charge cutoff voltages are 2.0V and 3.8V, respectively. As discussed in section II, the Arbin BT2000 battery testing system (Figure 3) is used to implement and perform the experiments. The initial phase for the pulse-charging experiment that we need for this part is the same as in the previous experiment. The
CCCV process is used to fully charge the battery and check for 100% SOC. After that, the battery is discharged with a constant current rate of 1A to its 15% SOC. Following a long (more than one hour) rest, the battery is charged with sequential pulses of 10 minutes charge with 1A current rate and 10 minutes rest. The testing system logs the battery measured data, which are terminal current, terminal voltage, and the battery surface temperature to the PC with the sample rate of one second and record them in a Microsoft Excel file. Since this paper does not examine the temperature effect on the battery parameters and performance, we import the recorded current and voltage (Figure 7) to MATLAB/SIMULINK to apply the algorithms.

Using current and voltage data as inputs to the identification algorithm described in section III, the parameters of the battery are estimated and shown in Figure 8. The results show that $R_0$, $R$, and $C$ have a slight change for different values of SOC. These changes show that even with an accurate $V_{OC}$-SOC model, a battery model with fixed parameters cannot express the precise dynamic of the real battery. Online identification and updating of the parameters is more effective in enhancing the accuracy, considering the fact that the battery parameters also change with charging/discharging rate, aging, and temperature. Moreover, the last graph in Figure 8 shows the significant change of $b_1$ with an expected SOC because it is basically the slope of the curve in Figure 4. We can see from this graph that although the slope starts from values greater than one, it also goes to very small values (around 0.2) when the $V_{OC}$-SOC relationship in Figure 4 is close to flat.
Since in system (11) the $A$ matrix is already in the canonical form, the observability criterion (index) is defined as non-zero columns for the matrix [13]

$$C_n = C = [1 \ b_1].$$

(14)

Therefore, when $b_1$ is close to zero, the system is in a weak observability condition. The impact of observability on the SOC estimation error can be seen in the results shown in Figures 9 and 10. Figure 9 compares the estimated SOC obtained from our proposed approach to the SOC calculated by Ah counting. The Ah counting method is considered to be a benchmark because in this case the initial SOC is known and, with the smooth charging current, the accumulative error is negligible. We can see in Figure 9 that the estimation error does not exceed 5%, and for some regions it is close to zero. To investigate the reason for a larger error in the time between 3,000 and 7,000 seconds, Figure 10 shows the SOC...
Figure 8 Battery identified parameters
estimation error and on the same plot the identified $b_1$, the slope of $V_{OC}$-SOC curve. We can see from this plot that as soon as the $b_1$ value significantly decreases, the estimation error starts to increase and vice versa.

Figure 9 Comparing the estimated SOC with the Ah-counting SOC results
Figure 10 SOC estimation error and the VOC-SOC slope on the same graph

VI. Conclusion

Online parameter identification and state estimation techniques were applied to lithium-ion battery data to estimate an accurate SOC for the battery. An RC equivalent model for the battery was considered with a nonlinear \( V_{OC} \)-SOC relationship obtained from experimental tests. Approximating the \( V_{OC} \)-SOC curve with a piecewise linear function for small charging intervals, the parameters of the battery model and coefficient of the \( V_{OC} \) vs. SOC function were identified using a common parameter identification approach. A reduced-order observer was designed to estimate the SOC as one of the states of the battery model, while the experimental \( V_{OC} \)-SOC function was used in the observer structure. The algorithms were developed in MATLAB/SIMULINK and the results were verified by comparing them to the
Coulomb counting method as a benchmark. The results indicated that although the estimation error was always less than 5%, there is a direct correlation between the SOC estimation error and the observability criterion for the battery model system. When the observability decreases due to the semi-flat $V_{OC}$-SOC curve or a small slope, the estimation error significantly increases.

**Acknowledgement**

This work is partly supported by the National Science Foundation Award number: EEC-08212121.
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CHAPTER 4: ONLINE ADAPTIVE PARAMETERS IDENTIFICATION AND STATE OF CHARGE CO-ESTIMATION FOR LITHIUM-POLYMER BATTERY CELLS

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Paper published in:
Online Adaptive Parameters Identification and State of Charge Co-Estimation for Lithium-Polymer Battery Cells

Abstract—Real-time estimation of the state of charge (SOC) of the battery is a crucial need in the growing fields of plug-in hybrid electric vehicles (PHEVs) and smart grid applications. The accuracy of the estimation algorithm directly depends on the accuracy of the model used to describe the characteristics of the battery. Considering a resistance-capacitance (RC) equivalent circuit to model the battery dynamics, we use a piecewise linear approximation with varying coefficients to describe the inherently nonlinear relationship between the open circuit voltage ($V_{OC}$) and the SOC of the battery. Several experimental test results on lithium (Li) polymer batteries show that not only do the $V_{OC}$-SOC relationship coefficients vary with the SOC and charging/discharging rates, but the RC parameters vary with them as well. The moving window Least Squares (LS) parameter identification technique was validated by both data obtained from a simulated battery model and experimental data. The necessity of updating the parameters is evaluated using observers with updating and non-updating parameters. Finally, the SOC co-estimation method is compared to the existing well-known SOC estimation approaches in terms of performance and accuracy of estimation.

Index Terms—Battery modeling, open circuit voltage, state of charge estimation, parameter identification, piecewise linearization, observer.
I. Introduction

The battery, as the most prominent energy-storage device, holds promising potential for the realization of the rapidly evolving smart grid concept and electrified transportation systems. Battery technology is growing very quickly to produce cells with higher energy and power densities and to reduce costs. Major developments have been achieved in lithium-ion (Li-ion) battery technology. Among the different flavors of this technology, lithium polymer cells emerge for their very high energy and power densities, making them very attractive for plug-in hybrid electric vehicles (PHEVs) and in general electric-vehicle (EV) use to improve the driving range of an EV. However, the cost-efficiency and reliability of the battery in different applications directly depend on the algorithms applied to perform energy and battery management. The urgent prerequisite of these algorithms for making optimal decisions is to have an accurate estimation of the battery state of charge (SOC) and state of health (SOH).

Among different approaches to estimate the SOC, Coulomb counting (Ah counting) [1] is one of the most conventional ones. However, it suffers from the unknown initial value for the SOC and the accumulated error over time due to the integration process. Although current sensors with high accuracy are available, the error can be caused by different sources such as data acquisition process, noise or Analog to Digital (A/D) resolution with accumulation effect from the integration process. On the other side, measuring the open circuit voltage (\(V_{OC}\)) is another approach that can be used independently [2] or in combination with Coulomb counting [3]. However, this method is inappropriate for online applications, as \(V_{OC}\) measurement requires the battery to be in the relaxation mode for a long time (in the range of hours).
Similarly, electrochemical impedance spectroscopy (EIS), which uses the battery’s internal impedance to estimate the SOC [4], [5], is only suitable for offline applications. That is why observer-based techniques, such as the Kalman filter [6]-[9], the sliding mode [10]-[12], or $H_\infty$ [13], have been developed and have become popular recently to compensate for the over-potential dynamics of the battery and to calculate the SOC based on the estimated $V_{OC}$. Although these techniques use robust recursive tools to consider nonlinearities and uncertainties in the battery model, they are all designed based on an offline identification of the battery model’s parameters. Considering the fixed parameters for the battery model is an assumption that contradicts the experimental and analytical results of modeling different batteries at different SOCs and various environmental conditions. As shown in [14], some parameters of the battery model change as much as 800% without a change in temperature or discharging current rate when the SOC fluctuates between 0% and 100%.

The method we propose here to estimate the SOC is based on considering a simple resistance-capacitance (RC) equivalent circuit to model the battery dynamics while using an adaptive online parameter-identification algorithm to identify and update the model’s parameters as they change. We deploy a piecewise linearized mapping of the $V_{OC}$-SOC curve along with continuously updating the parameters to accurately represent all of the battery’s static and dynamic characteristics. Using this adaptive structure, we design an observer based on the updating model to estimate the SOC as one of the states of the battery model. In this paper, we use simulated and experimental data to assess the accuracy of the parameter-identification algorithm and its ability to track the changes in the parameters. At the same time
we are validating the premise of the battery’s parameter changes regarding different SOCs and different charging/discharging current rates. Moreover, we compare the results from the SOC co-estimation to some of the famous existing algorithms (i.e., the Kalman filter and the sliding-mode observer). Although this algorithm is tailored for parameter identification and SOC estimation in a cell level, it can easily be expanded to be used in battery pack applications. That is because the battery pack consists of several battery cells in parallel or in series and an aggregated model can be used to represent the pack behavior [15], [16].

In the article, Section II describes the modeling of the battery; Section III explains the parameter-identification algorithm and the state observer design; Section IV verifies the efficacy of the identification algorithm to follow the changes in the battery parameters using simulated data; Section V talks about applying the online adaptive parameters/SOC co-estimation approach to the experimental data; Section VI compares the different SOC estimation algorithms with one another; and Section VII concludes the paper.

II. Battery Model

Depending on the required accuracy and the application, different types of models have been developed so far for the battery. Among those models, the RC-equivalent circuit is an effective one to represent the battery’s dynamics. The following subsections describe some of the battery’s characteristics that are considered in the model.

Linear Model with Internal Resistance

A typical rechargeable battery can in first approximation be modeled by a large capacitor that
can store and release electrical energy during charging and discharging cycles. As in any electrochemical process, these charging/discharging cycles encounter a small resistance due to the electrolyte and the inter-phase resistance. This small resistance appears in series with the battery capacitor, Q (internal resistor, $R_0$, in Figure 1). We note that the value of $R_0$ changes with the SOC, the ambient temperature, and the aging effect of the battery.

**Figure 1 Battery model with relaxation effect, internal resistance, and VOC-SOC function**

**Relaxation Effect**

The relaxation effect is another basic characteristic of the battery that appears during and after the charging and discharging cycles. This effect represents the slow convergence of the battery’s terminal voltage to its equilibrium after hours of relaxation following charging/discharging and is modeled by series-connected parallel RC circuits. The number of RC groups is a trade-off between accuracy and complexity. While Chen, et al., [17] recommended two RC groups as the optimal model, there are several references [11], [18], [19] stating that one RC group structure can provide results that are accurate enough for applications, such as PHEVs and PEVs. Temperature effect is another key factor that needs to be considered in the modeling of the battery. Its main manifestation is by the changes in the
parameters of the battery model. As will be described in section III, since the co-estimation approach is based on the online identification of the parameters, the changes in the parameters caused by the temperature effect is embedded in the model, with the online identification of the parameters the effect of temperature on the battery performance.

\textbf{V_{OC}-SOC Relationship}

Despite the simple linear model for the battery in part A of this section, the static relationship between the \( V_{OC} \) and the SOC is intrinsically nonlinear. The nonlinearity of the model increases the complexity of the stability and performance analysis of the estimators. Therefore, considering the \( V_{OC}-SOC \) curve of the Li-polymer battery from experimental results, we show in [14] that it can be divided into eight linear segments, as demonstrated in Figure 2, and
each of them can be described by the following linear equation (1):

\[ V_{oc} = f(SOC) = b_0 + b_1 SOCl. \]  

(1)

Figure 3 describes how the linearized segments have been chosen by extracting the first and the second derivative of the VOC versus the SOC. The spikes in Figure 3(b) show the turning points that separate the piecewise linear regions. Afterward, using the least square (LS) error curve-fitting technique, the best lines to fit the segments are estimated. The values for \( b_0 \) and \( b_1 \) and the goodness of fit evaluation factor, \( R^2 \), are derived and presented in Table 1 for each segment. Detailed rationale and justification of this approach has been described in [14].
### State-Space Equations for the Model

To model the battery’s characteristics, we used an RC-equivalent circuit, like the one in Figure 4, with one RC group to represent the relaxation effect. This simple model reduces the complexity of model identification and parameter extraction.

| Seg.
| Param. | b₀   | b₁   | R²   |
|-------|-------|------|------|------|
| 1     | 3.3046| 1.9702| 0.9991|
| 2     | 3.3861| 1.2348| 0.9997|
| 3     | 3.4299| 1.0337| 0.9945|
| 4     | 3.6407| 0.3389| 0.9933|
| 5     | 3.6479| 0.3014| 0.9667|
| 6     | 3.3746| 0.7604| 0.9979|
| 7     | 3.1981| 0.9892| 0.9998|
| 8     | 3.1442| 1.0509| 0.9999|
Considering the equivalent circuit for the battery model in Figure 4 and equation (1), the state-space equations can be written as a system (2) to represent the battery’s dynamics.

\[
\begin{aligned}
\begin{bmatrix}
\dot{\text{SOC}} \\
\dot{V_{RC}}
\end{bmatrix} &=
\begin{bmatrix}
0 & 0 \\
0 & -\frac{1}{RC}
\end{bmatrix}
\begin{bmatrix}
\text{SOC} \\
V_{RC}
\end{bmatrix} +
\begin{bmatrix}
1/Q_R \\
1/C
\end{bmatrix} I_L \\
V_T &= [b_1 1]\begin{bmatrix}
\text{SOC} \\
V_{RC}
\end{bmatrix} + R_0 I_L + b_0
\end{aligned}
\] (2)

In these equations, the SOC of the battery and the voltage across the RC cell, \(V_{RC}\), are selected to be the system-state variables. We assume that the terminal current (\(I_L\)) and voltage (\(V_T\)) are the only two values that are accessible from outside of the system (2). To obtain the estimated SOC as one of the states, the parameters in the system need to be identified. We assume that \(Q_R\) is the nominal capacity of the battery. So, we need to estimate \(\{b_0, R, C, R_0, b_1, S_{oc}, V_{RC}\}\) as \(\{\hat{b}_0, \hat{R}, \hat{C}, \hat{R}_0, \hat{b}_1, \hat{S}_{oc}, \hat{V}_{RC}\}\) using state estimation and system parameter-identification methods.
III. Parameter Identification and SOC Co-Estimation

Moving Window Least Squares

For online identification of the battery’s parameters, we applied an adaptive parameter-identification algorithm to a linear system. The LS identification approach [20] provides a formula that minimizes the LS error between the estimated output value and the actual output at the present time step. Since the input/output samples are being updated step-by-step while the system is running, the recursive least square (RLS) [20] estimates the parameters of the system iteratively. Because implementing the RLS algorithm is not easy in an actual system and the input/output signal needs to be persistently exciting (PE) [20] at each step, we use the moving window LS method, which is more practical. In this approach, the input/output data corresponding to a certain number (window) of past steps is used to estimate the parameters. The length of the window depends on the excitation of the input signal to properly reveal the dynamics of the system.

Battery Parameter Identification

The parameters of the battery model that need to be estimated are: \{b_0, R, C, R_0, b_1\}. Since most of the parameter-identification methods for linear systems use the transfer function of the system to identify the parameters, first we obtain the transfer function form of the system (2):
From the transfer function (3) and using a bilinear transform \( s \rightarrow \frac{2}{T} \frac{z^{-1}}{z+1} \) [21], we can obtain the discrete transfer function of the system (2) with sample time \( T \), which leads us to the transfer function (4), in which the coefficients are uniquely related to the battery parameters:

\[
\frac{Y(z^{-1}) - b_0}{U(z^{-1})} = \frac{c_0 + c_1 z^{-1} + c_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}}. 
\] (4)

The detailed equations to extract the battery parameters from the coefficients of transfer function (4) can be found in [14]. As shown in [14], despite the fact that the value of \( b_0 \) is not identifiable through this process, it acts like an output offset that does not influence the dynamic between the input and output and enables other parameters to be identified uniquely.

**Observer Design**

After identifying the parameters of the battery, an observer is designed to estimate the SOC, which is one of the states of the model. Assuming that the battery’s parameters \( \{R, C, R_0, b_1, b_0\} \) can be estimated as \( \{\hat{R}, \hat{C}, \hat{R}_0, \hat{b}_1, \hat{b}_0\} \), the battery model is represented as a system with equations (5):

\[
\begin{align*}
\dot{x} &= Ax + Bu \\
y &= Cx + Du + b_0,
\end{align*}
\] (5)
in which, \( x_1 = S_{oc}, x_2 = V_{RC}, A = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{RC} \end{bmatrix}, B = \begin{bmatrix} 1/Q_R \\ 1/C \end{bmatrix}, C = [b_1 \ 1], D = R_0, u = I_L \), 

\( y = V_T, x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \). Therefore, the observer can be designed as a system with these equations (6):

\[
\begin{cases}
\dot{x} = Ax + Bu + L(y - \hat{y}) \\
\hat{y} = C\dot{x} + Du + b_0
\end{cases}
\]  

(6)

in which \( L^T = [L_1 \ L_2] \) is the observer gain vector. To design the observer gain, two methods can be used: the pole placement that we used in [14] and a linear quadratic (LQ) approach, in which an optimal observer is designed to minimize the error and effort. In this method, the \( P \) matrix is calculated by solving the LQ Riccati equation (7),

\[
AP + P^T A - PC^T R^{-1} CP = -Q,
\]

(7)

in which, \( Q \) and \( R \) are arbitrary semi-positive definite and positive definite matrices and the observer gain is obtained from equation (8),

\[
L^T = R^{-1} CP.
\]

Figure 5 shows the block diagram that demonstrates the battery parameters/SOC co-estimation algorithm. In this diagram, the moving window LS is used to identify the
coefficients of the transfer function that represents the battery dynamics. The battery parameters are then extracted from the coefficients and fed to the observer to estimate the SOC of the battery. In this observer, the experimental look-up table is used to present the $V_{OC}$-SOC relationship. Moreover, the LQ approach is employed to calculate the optimal observer gain based on the updated parameters.

IV. Parameter-Identification Simulation Results

To verify the capability of the moving window LS identification algorithm to follow the changes in the battery parameters, we designed a simulation testbed. In this testbed, the input data ($V_T$ and $I_L$) to the identification algorithm is provided by a battery model developed in SIMULINK, instead of actual measurements. The battery model is in the form of an RC-
equivalent circuit similar to the one shown in Figure 4, in which the $V_{OC}$-SOC relationship is described with a look-up table that is obtained from the $V_{OC}$-SOC experimental data measured on a Lithium Polymer battery as shown in Figure 2. We applied the identification algorithm with a linear AutoRegressive with eXogenous input (ARX) structure to the intrinsically nonlinear model of the battery while the other battery parameters, such as $R_0$ and $RC$, change. With this test we make sure that the identified changes in the battery parameters are caused by actual changes in the battery parameters and not by the nonlinearity of the system.

To do so, we apply 1 Ampere (A) current pulses with a pulse width of 125 seconds followed by the same amount of resting time to the battery model with a look-up table to represent the actual $V_{OC}$-SOC relationship. At the same time, the battery’s parameters, which are basically $R_0$, $R$, and $C$, change over time according to actual behavior of the battery, as it comes from experiments carried out in similar conditions. Figure 6 shows the simulated terminal voltage of the battery with the corresponding terminal current. Applying the moving LS parameter-identification algorithm to the current and voltage signals as the system’s input and output, the parameters of the battery are estimated online at each simulation time. The main battery parameters (i.e., $R_0$, $RC$, and $R$) are shown in Figure 7 compared to their actual values. The identification results show that the algorithm is able to follow the changes in the parameters accurately after a short transition time. This amount of time is mostly related to the width of the current signal pulses because the algorithm needs to detect a step down or a step up in the input signal window to identify the new parameters. Moreover, some deviations from the actual values after convergence are caused by switching from one $V_{OC}$-SOC linear region to another, and the identification error
is removed afterward. However, Figure 7 shows that we can trust the results of the parameter-
identification algorithm despite the inherent nonlinearity of the battery model, and we can use the
online estimated parameters to examine our models for the changes in the parameters regarding
the SOC, C-rate, and temperature effect.

Figure 6 Current and voltage of the battery model with changing parameters
Figure 7 Parameter-identification results for the nonlinear battery model: the dashed line (--) shows the real parameter from the simulation and the solid line (-) is the identified parameter. The first graph shows $R_0$, the second $R \times C$ and the third $R$.

V. Experimental Results

After testing the parameter-identification algorithm with simulated data, in the next step we applied the algorithm to the experimental battery data, aiming to show the performance under real application conditions. The experimental data was acquired on 1.5 Ah Li-polymer cells (Kokam SLPB723870H4). These cells feature a specific energy density of 150 watt-hours per kilogram (Wh/kg) and can continuously be charged and discharged within the 2.7-volt (V) and 4.2V voltage range with currents up to 3A for charge and 30A for discharge. The experimental
setup, shown in Figure 8, was analogue of the one described in [22], [14] and allowed us to validate the proposed co-estimation algorithm in many battery conditions, controlling the charge/discharging rate, as well as the cell temperature. In Figure 8, starting from the left hand side of the image, we can see the temperature-controlled chamber used to regulate the battery temperature; a power supply and an electronic load which set the charging/discharging current of the battery. All the equipment, as well as the acquisition process, are controlled by a LabVIEW application, whose panel is shown on the screen in the picture.

As a significant example, in Figure 9 we report the current and voltage data of 3 runs of the same pulse-charging test performed at 1 C-rate (i.e. a charging current equal to the capacity value in Ampere) and 25°C. Since these similar data contain different noise and battery chemical conditions, analysis of the identified battery parameters helped us to verify the robustness of the battery parameters identification method and to further validate our conclusions about the changing dynamic of the battery model. Therefore, applying the same identification algorithm to the input and output data, the parameters of the battery i.e. R₀, RC and b₁ are identified. Figure 10 shows the behavior of the estimated parameters versus SOC. We can see from the first graph of Figure 10 that R₀ is, as expected, larger at lower SOCs and it decreases down to 1/8 of the initial value when the battery is fully charged. The changes in RC; and consequently R and C, are more irregular than R₀ due to the fact that RC is more dependent on the chemical reactions of the battery during charge and discharge. Another explanation for this irregularity is that the relaxation effect requires several RC groups to be
accurately modeled. When for a practical application we use just 1 RC group, the estimated value converges to different time constants to provide a better approximation of the actual electrochemical condition. The third graph in Figure 10 reports the estimated $V_{OC}$-SOC slope ($b_1$). Although the slope changes with SOC, the identified value is almost the same for the three tests. This proves the very good repeatability of the static battery behavior represented by the $V_{OC}$-SOC curve.

After identifying the battery parameters, we apply the discrete version of the LQ observer to design the observer to estimate the SOC of the battery. As we demonstrated previously in Figure 2, the $V_{OC}$-SOC relationship function is nonlinear in the structure of the observer, and we used a look-up table that is obtained from experimental data to represent this function. Figure 11 shows how the algorithm is implemented in SIMULINK. The SOC and $V_{RC}$ values
estimated at previous time step are fed back to the algorithm core to estimate the new values. In addition, the SOC is used to find the \( V_{OC} \) through the look-up table. Moreover, identified parameters are injected into the algorithm to update the model continuously. In practical applications, the updating frequency of the parameters depends on the characteristics of the application, including the charging/discharging rate and environmental conditions. Therefore, while we update the parameters at each sample time to observe the details, the updating can be done much less frequently to minimize the computational time and memory needed. The SOC estimation results, shown in Figure 12, demonstrate the performance of the co-estimation algorithm compared to the non-updating LQ observer. Both of the SOC estimation results are compared to the benchmark value for the real SOC, which is obtained from Coulomb counting.

![Figure 9 The current and voltage signals for three pulse-charging tests with the same current rates](image-url)
Figure 10 The identified parameters obtained from three independent tests with the same charging rates: The first graph shows $R_0$ (Ohm), the second RC (s) and the third is $b_0$ (V), the $V_{OC}$-SOC slope. The dashed (---), dotted (...) and the solid graphs show the identification with a known initial SOC and ignoring any sensor errors. The results show that the non-updating observer generates more errors, especially in the region with the lower SOC, than the
updating one. To evaluate the performance of the algorithms, we use 2 norms of the error, namely $\|e\|_2$ and $\|e\|_\infty$ which are defined as follows:

$$\|e\|_2 = \sqrt{\frac{1}{K} \sum_{k=1}^{K} e^2(k)}$$  \hspace{1cm} (9)$$

$$\|e\|_\infty = \max_k |e(k)|.$$  \hspace{1cm} (10)$$

Moreover, we define the convergence time of the estimation as the first time that the estimated SOC enters the 5% error bound compared to the reference SOC.

Figure 11 MATLAB/SIMULIK implementation of the SOC co-estimation observer

Figure 13 demonstrates the $\|e\|_2$ for both approaches and shows that the rate of increase in the norm for the non-updating observer is large from small SOCs, while for the updating observer (co-estimation approach), the increasing rate is small for most of the SOC range. The only region where we see more errors in the estimation of the co-estimation method is between
2000 and 4000 seconds, which corresponds to an SOC between 0.3 and 0.6. This region, as shown in Figure 3(a), is the one with a \( V_{OC} \)-SOC slope of less than 0.5. In [23], we have shown that a small \( V_{OC} \)-SOC slope has a significant influence on the observability of the battery model’s states. Finally, in order to better demonstrate the influence of identifying and updating the battery parameters in the SOC estimation, Table 2 presents the \( \|e\|_2 \), \( \|e\|_{\infty} \) and the convergence time for both cases. As expected, both error indicators are significantly smaller when the parameters are updated in the co-estimation method. In contrast, the convergence time is larger for the co-estimation approach due to the slow convergence of the parameters identification algorithm.

![Figure 12](image.png)

Figure 12 The SOC estimation results with updating (SOC co-estimation) and non-updating observers: The dashed graph (--) is the reference SOC, the dotted line (...) is the SOC estimation for the non-updating LQ observer and the solid graph is the result from the SOC Co-estimation.
Figure 13 The $\|e\|_2$ for updating (dashed (--) line) and non-updating (solid line) observers

Table 2 Comparison of the SOC estimation results for updating and non-updating observers

<table>
<thead>
<tr>
<th></th>
<th>SOC Co-estimation</th>
<th>Non-Updating LQ Observer</th>
</tr>
</thead>
<tbody>
<tr>
<td>$|e|_2$</td>
<td>7.239</td>
<td>16.64</td>
</tr>
<tr>
<td>$|e|_\infty$</td>
<td>0.06395</td>
<td>0.09985</td>
</tr>
<tr>
<td>Convergence Time (s)</td>
<td>60</td>
<td>30</td>
</tr>
</tbody>
</table>
VI. Comparison of SOC Estimation Algorithms

To evaluate the performance and accuracy of the online battery parameters/SOC estimation algorithm, we compare the results to the ones obtained from two of the recently popular algorithms, namely the extended Kalman filter (EKF) and the sliding-mode observer. While both of those algorithms are based on designing an observer for the battery model, the Kalman filter considers the uncertainty of the model as state noise and designs an adaptive filter to minimize the noise effect. EKF is the nonlinear version of the Kalman filter, in which the nonlinear system is linearized at the operating point and an optimal gain is designed based on the linearized model to minimize the noise effect on the state. Similarly, for the sliding-mode observer, a linearized system at the operating point is considered to be the main model for the battery and the nonlinearities in the actual battery are presented as additive uncertainties to the model. Consequently, to design an observer gain for optimal performance of the linearized model, a sliding-mode gain is added to compensate for the uncertainties. The key point for both the EKF and sliding-mode observer is that the observer design is based on a fixed model of the battery, in which the coefficients are obtained from offline identification of the battery’s parameters. Therefore, according to the changes in the battery’s parameters at different SOCs and charging/discharging rates, we expect that the SOC estimation with these algorithms cannot provide accurate results compared to the parameters/SOC co-estimation algorithm.

To compare the performance of these algorithms, we implemented both of them in SIMULINK. Again, for the nonlinear relationship between $V_{OC}$ and the SOC, we used a look-up table in the structure of the observers to increase the accuracy. The SOC estimation results
are demonstrated in Figure 14, in which the results for the sliding-mode observer, EKF, and SOC co-estimation are compared to each other. We can see that the SOC estimation for the EKF is very close to the one in Figure 12 for a non-updating LQ observer. The SOC estimation shows more error from the real SOC when the battery parameters (especially $R_0$) are different from the offline identified parameters. For the sliding-mode observer, the SOC estimation fluctuates around the estimated values that are close to the EKF. Although the fluctuation causes the results to approach the real SOC at some points, most of the time it produces a larger steady-state error. Figure 15, which shows the $\|e\|_2$ of the error for three algorithms, confirms that although the sliding mode gives better results than the EKF for small SOCs (i.e., up to 0.3), the permanent error caused by the fluctuation retards for the larger SOCs. However, the significant difference between the error for the parameters/SOC co-estimation algorithm and the other two algorithms that are based on offline identification of battery parameters implies that online identification and updating the battery parameters are crucial to obtain accurate SOC estimation results. The values for the $\|e\|_2$, $\|e\|_\infty$ and the convergence time, which are demonstrated in Table 3, describe the quantitative differences between the performances of the three algorithms.

Table 3 shows in the $\|e\|_2$, which evaluates the history of the error, the gap between the co-estimation and the other two algorithms with non-updating parameters is meaningful. However, for the $\|e\|_\infty$, which presents the maximum error, the EKF is close to the co-estimation and the sliding mode suffers from a significantly large maximum estimation error because of the fluctuations. According to these results, we can expect that updating the battery
parameters in the structure of the EKF and the sliding-mode observer remarkably improves the performance of those algorithms. Again we can see that the convergence time is larger for the SOC co-estimation algorithm due to the time needed to update the parameters.

Figure 14 Comparison of the SOC estimation results for different algorithms: The dashed graph (--) is the reference SOC, the dotted line (...) is the result from the regular EKF, the dashed-dotted (-.) one is the result from regular sliding mode observer and the solid graph is the SOC co-estimation result.
Figure 15 Comparison of the $l_2$ norm of the errors for different algorithms: The dashed-dotted graph (-.) is the SOC co-estimation result, the dashed (--) one is the result from regular EKF and the solid graph is the result from the regular sliding mode observer.

Table 3 Quantitative comparison of different algorithms

<table>
<thead>
<tr>
<th></th>
<th>SOC Co-estimation</th>
<th>Regular EKF</th>
<th>Regular Sliding</th>
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<td>Convergence Time (s)</td>
<td>60</td>
<td>20</td>
<td>15</td>
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Moreover, to compare the performance of the three algorithms regarding a realistic scenario, we used a typical current profile such as the one represented in figure 16 along with the corresponding voltage profile. This current profile contains both charging and discharging cycles as well as different discharging rates up to 30A (20C) for the same Lithium Polymer battery cell. After applying the three SOC estimation algorithms to the current and voltage data, the estimation results are demonstrated in figure 17. We can see that although the estimation error is larger in this case due to the changes in current value and direction, the SOC co-estimation shows a better performance in estimating the reference SOC value. Table 4 shows the quantitative comparison of the three algorithms’ performance in terms of

![Figure 16 The generic current and voltage profiles](image)
Figure 17 Comparison of the SOC estimation results for generic current profile scenario. The dashed graph (--) is the reference SOC, the dotted line (…) is the result from the regular EKF, the dashed-dotted (-.) one is the result from regular sliding mode observer.

Table 4 Quantitative comparison of algorithms for generic profile scenario

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<th>SOC Co-estimation</th>
<th>Regular EKF</th>
<th>Regular Sliding</th>
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<tr>
<td>$</td>
<td></td>
<td>e</td>
<td></td>
</tr>
<tr>
<td>Convergence Time (s)</td>
<td>60</td>
<td>240</td>
<td>135</td>
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the $\|e\|_2$, $\|e\|_\infty$ and convergence time for the typical profile scenario. Again, the small values for the $\|e\|_2$ and $\|e\|_\infty$ for the SOC co-estimation compared to the other algorithms confirms the need for updating the battery parameters in the observer structure. Moreover, the SOC co-estimation algorithm shows a better performance in term of convergence time in this case. That is because the observers in the non-updating algorithms, i.e. EKF and Sliding Mode, need more time to converge to the correct SOC due to the changes in the current profile while the SOC co-estimation adapts to the changes more quickly.

VII. Conclusion

In order to estimate the SOC of the battery, the RC-equivalent circuit is used to model the dynamics of the battery. Since the parameters of the battery model are functions of the SOC, C-rate, temperature, and aging, all of the parameters are subject to change and need to be identified with a proper frequency during the SOC estimation. Most of the observer-based SOC estimation algorithms proposed so far design the state observer based on a model with fixed parameters that are obtained from offline identification. In this paper, we showed that changing the parameters of the battery needs to be identified and the observer structure updated to provide an accurate SOC estimation. To do that online, the adaptive battery parameters/SOC co-estimation approach was proposed in which a piecewise linear mapping of the $V_{OC}$-SOC function was used to identify the battery parameters and feed them to an optimal observer to estimate the SOC. We verified the performance of the parameter-
identification algorithm by applying it to simulated and experimental data. The necessity of updating the parameters in the observer structure was verified with the results of the experimental data. Moreover, the performance of the SOC co-estimation algorithm was compared to the EKF and sliding-mode observer as two popular SOC estimation approaches. All of the results indicate that updating the parameters of the battery model during SOC estimation is key to increase the accuracy of the estimation and avoid unnecessary compensation for uncertainties.

Acknowledgment

This work is partly supported by the National Science Foundation Award number: EEC-08212121.
References


CHAPTER 5: ADAPTIVE ONLINE BATTERY PARAMETERS/SOC/CAPACITY CO-ESTIMATION

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Paper published in:

The proceeding of Transportation Electrification Conference and Expo (ITEC), IEEE 2013
Adaptive Online Battery Parameters/SOC/Capacity Co-estimation

Abstract—Total capacity is one of the most important parameters to characterize the performance and application of a battery. Although the nominal capacity is provided by the manufacturer, the actual capacity is subject to change with cycling effect, temperature and even storage ageing of the battery. Following our previous publications in which we developed an online adaptive parameters/state of charge (SOC) co-estimation algorithm to identify the parameters of the dynamic model of the battery and accordingly design an observer to estimate the SOC. In this paper, first we show that the parameters identification and SOC estimation results are not dependent on the correct approximation of the capacity. Afterwards, using the estimated SOC, we design another observer to estimate the actual capacity of the battery.

Keywords—Battery, Parameters Identification, SOC estimation, Capacity estimation, SOH

I. Introduction

Advanced battery technology serves electric vehicles industry with employing different chemistries and assembling techniques to provide higher power and energy density. Nonetheless, the mere utilization of these technologies does not guarantee the efficiency, safety and reliability of the battery function. To ensure these features, the battery’s status needs to be accurately monitored and controlled by the algorithms that are designed to
perform battery management system (BMS) [1]. The total capacity is one of the most crucial characteristics of the battery that needs to be monitored. All of the methods that rely on the coulomb counting to estimate the State of Charge (SOC) need to have an accurate estimation of the total capacity. Moreover, the full capacity and its degradation due to ageing is a prominent indicator to determine the State of Health (SOH) of the battery. Other than ageing in the form of cycling or storage ageing, the ambient temperature can also cause capacity fading that makes the total capacity of the battery different from the nominal capacity.

Different methods have been used so far to measure the capacity of the battery. Among those, the most direct one is to count the electrons (coulomb counting) when the fully charged battery is discharged with a small current [2]. This method usually used in cycling tests is time consuming, damaging to the battery and not suitable for online applications. Other practical approaches to estimate the capacity are based on the estimated SOC of the battery. Typically, in these methods the SOC is estimated by an algorithm that is not relied on the coulomb counting; and the capacity of the battery is determined by comparing those results to the coulomb counting formula in the interval between estimations. Considering this general guideline, some of the studies use Extended Kalman Filter (EKF) [3], [4] to estimate the SOC and the capacity simultaneously while some of them use artificial intelligent algorithms [5], [6] to determine the capacity based on the SOC. The main issue of these methods is that since the accuracy of the SOC estimation significantly affects the capacity estimation, the model with non-updating parameters does not provide high resolution SOC estimation. Moreover, while most of the artificial intelligent algorithms are not suitable for online applications,
considering the capacity as a variable state of the battery model in the simultaneous methods makes the model complicated with non-negligible nonlinearity.

In this paper, we use the results from our previous publications [7], [8], [9] on the battery parameters/SOC co-estimation to calculate the capacity. In [7]-[9], we proposed an online adaptive method to identify the parameters of the battery and estimate the SOC by designing an observer with updating parameters. In this paper, we first show that considering the nominal capacity instead of the actual capacity in the battery model does not affect the parameters identification and the SOC estimation results. Therefore, we can use the SOC estimation results as a benchmark to find the actual capacity. As a supplementary result, the identified parameters are valid to be used to perform the battery modeling and for SOH estimation analysis, since we know that the internal resistance is another important factor to estimate the SOH. We then design another observer with the coulomb counting equation to estimate the actual capacity of the battery. After verifying the designed observer with the simulated results, we apply the capacity estimation method to experimental data from a lithium polymer battery. Since the continuously updating structure of the parameters/SOC co-estimation enhances the accuracy of the estimated SOC, the corresponding capacity estimation gives significantly better results.

In the followings, Section II describes the equivalent circuit battery model that is used for SOC and capacity estimation; Section III explains the mathematical analysis of the parameter identification, SOC estimation and the capacity estimation observer. Section IV presents simulation results to support the capacity estimation approach, and section V shows the
results of applying the proposed identification and estimation approach to the experimental data; and Section VI concludes the paper.

II. Battery Model

The model for the battery can be as simple as a large capacitor with the capacity equal to the actual capacity of the battery. Considering the resistance of the battery electrolyte regarding the moving of the ion carriers an internal resistance is added to the capacitance to build the terminal voltage. In addition to those steady state characteristics of the battery, the terminal voltage follows the step changes in the terminal current with a relaxation effect. This effect which shows the transient dynamic of the battery is modeled by several parallel Resistor-Capacitors (RC) pairs. The number of pairs is a trade-off between accuracy and simplicity of the model. Although in some references two pairs are suggested as the optimal number, one pair suffice representing the battery dynamics for electric vehicles in many references.

OCV-SOC relationship

Although in simple models for the battery the relationship between electromotive force (EMF) or Open Circuit Voltage (OCV) of the battery and the current is defined by the
equations of a capacitor, the actual OCV follows a nonlinear relationship with the State of Charge (SOC) of the battery [10]. SOC is the amount of charge remained in the battery compared to the full capacity. The OCV-SOC relationship is a static characteristic of the battery, i.e. it does not change with the current and voltage profile of the battery. However, this curve significantly changes with temperature and ageing.

Battery State-Space Equivalent model

We model the battery dynamic with an RC equivalent that consists one RC pair as shown in figure 1. Also we use look-up table obtained from experimental data to represent the OCV-SOC relationship. Relying on the fact that the operating point’s moving on the OCV-SOC curve is usually very slow due to the large capacity of the battery compared to the normal C-rates, we consider a piecewise linear relationship between OCV and SOC at the operating point:

\[
V_{OC} = b_0 + b_1 SOC. 
\]  

(1)

With this assumption, system (2) represents the state space equations to describe the dynamic model of the battery. In these equations, the SOC of the battery and the voltage across the RC pair, \(V_{RC}\), are selected to be the system state variables.
Also, we assume that the terminal current ($i_L$) and voltage ($v_T$) are the only two values that are accessible from system (2). To obtain the estimated SOC as one of the states, the parameters in system (2) need to be identified. In our previous works we presupposed that we knew $Q_R$ to be the nominal capacity of the battery and accordingly estimate $\{b_0, R, C, R_0, b_1, S_{oc}, V_{RC}\}$ as $\{\hat{b}_0, \hat{R}, \hat{C}, \hat{R}_0, \hat{b}_1, \hat{S}_{oc}, \hat{V}_{RC}\}$ using system parameter identification methods and state estimation. But as explained, the ageing effect that could be calendar and/or cycling effect could degrade the actual capacity of the battery. In the next section, we will show that keeping the nominal capacity, $Q_R$, instead of the actual capacity, $Q_{act}$, in the equations of the battery will not degrade the identification results of the other parameters.

Figure 1 The battery-equivalent circuit

\[
\begin{align*}
\begin{bmatrix}
S\dot{O}C \\
S_{RC}
\end{bmatrix} &= 
\begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{R_{CL}} \end{bmatrix}
\begin{bmatrix}
S\dot{O}C \\
S_{RC}
\end{bmatrix} + 
\begin{bmatrix}
1/Q_R \\
1/C
\end{bmatrix}
\begin{bmatrix}
1 \\
1
\end{bmatrix}
i_L
\end{align*}
\]

\[
v_T = [b_1 1]
\begin{bmatrix}
S\dot{O}C \\
S_{RC}
\end{bmatrix} + R_0i_L + b_0
\]
III. Mathematical Analysis

Battery Parameter Identification

The parameters of the battery model that need to be estimated are \{b_0, R, C, R_0, b_1\}. Since most of the parameter identification methods use the transfer function of the system to identify the parameters, first we obtain the transfer function form of system (2):

$$
\frac{Y(s)-b_0}{U(s)} = \frac{R_0 s^2 + \left(\frac{b_1}{Q_{act}} + \frac{1}{s} + \frac{R_0}{RC}\right) s + \frac{b_1}{RC Q_{act}}}{s^2 + \frac{1}{RC}} = \frac{b_{00} s^2 + b_{11} s + b_{22}}{s^2 + a_1 s + a_2}.
$$

(3)

From transfer function (3) and using bilinear transform \(s \rightarrow \frac{2z-1}{Tz+1}\), we can get the discrete transfer function of system (2) with sample time \(T\):

$$
\frac{Y(z^{-1})-b_0}{U(z^{-1})} = \frac{c_0 + c_1 z^{-1} + c_2 z^{-2}}{1 + a_1 z^{-1} + a_2 z^{-2}}.
$$

(4)

In order to identify the parameters of a linear system like (4), the relationship between the system’s input/output (I/O) samples is described by a standard structure, such as the autoregressive exogenous model (ARX) model [11]:

$$
A(q) y(q) = B(q) u(q) + e(q),
$$

(5)

where

$$
A(q) = 1 + a_1 q^{-1} + \cdots + a_n q^{-n},
$$

(6)

$$
B(q) = b_0 + b_1 q^{-1} + \cdots + b_m q^{-m},
$$

(7)
and $e(q)$ is white noise (zero mean Gaussian noise). The LS identification approach provides a formula to minimize the Least Square (LS) error between this estimated output value and the real output at the present step. Since the I/O samples are being updated step-by-step while the system is running, a recursive least square (RLS) algorithm can be defined to identify the parameters of the system iteratively. Furthermore, because implementing the RLS algorithm is not easy in a real system and the I/O signal needs to be persistently exciting (PE) [7] at each step, we use the moving-window LS (MWLS) method, which is more practical. In this approach, the I/O data corresponding to a certain number (window) of past steps is used to estimate the parameters. Identifying the coefficients of the discrete transfer function (4), the reverse bilinear transform $\left( z \rightarrow \frac{2+sT}{2-sT} \right)$ is used to find the coefficients of the continuous-time transfer function (3). Therefore, assuming that the coefficients $\{b_{00}, b_{11}, b_{22}, a_{11}, a_{22}\}$ have been identified correctly using the I/O data, we extract the battery parameters from the transfer function (3) coefficients as shown in equations 8-12.

$$R_0 = b_{00}$$  \hspace{1cm} (8)

$$RC = \frac{1}{a_{11}}$$  \hspace{1cm} (9)

$$b_1 = Q_{act} RC b_{22}$$  \hspace{1cm} (10)

$$\frac{1}{c} = b_{11} - \frac{R_0}{RC} - \frac{b_1}{Q_{act}} = b_{11} - \frac{R_0}{RC} - RC b_{22}$$  \hspace{1cm} (11)

$$R = \frac{RC}{c}$$  \hspace{1cm} (12)
While $R_0$ and $RC$ are not dependent on $Q_{act}$ in equations (8) and (9), equation (10) shows that $b_1$ cannot be determined without an accurate approximation of $Q_{act}$. Therefore, if there is a difference between $Q_{act}$ and $Q_R$, the estimation of the $b_1$ will indicate the error. Nonetheless, when we use the non-accurate estimated $b_1$ to estimate $C$ and $R$, as demonstrated in equations (11) and (12), respectively, the $Q_{act}$ is cancelled out and the estimated results do not depend on the $Q_{act}$. To conclude, all the battery parameters except for $b_1$ can be identified uniquely without knowing the actual capacity of the battery. Since we use the OCV-SOC look-up table instead of the identified value of $b_1$ in SOC estimation algorithm, the estimated $b_1$ does not affect the estimation results.

**SOC Estimation**

After identifying the parameters of the battery, an observer is designed to estimate the SOC, which is one of the states of the model. Assuming that the battery’s parameters $\{R, C, R_0, b_1, b_0\}$ can be estimated as $\{\hat{R}, \hat{C}, \hat{R}_0, \hat{b}_1, \hat{b}_0\}$, the battery model is represented as a system with equations (13):

\[
\begin{cases}
\dot{x} = Ax + Bu \\
y = Cx + Du + b_0
\end{cases}
\]  

where, $x_1 = S_{oc}$, $x_2 = V_{RC}$, $A = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{RC} \end{bmatrix}$, $B = \begin{bmatrix} \frac{1}{Q_R} \\ \frac{1}{C} \end{bmatrix}$, $C = [b_1 \ 1]$, $D = R_0$, $u = I_L$, $y = V_T$, $x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$. 
Therefore, the observer can be designed as a system with the equations (14):

\[
\begin{align*}
\dot{\hat{x}} &= A\hat{x} +Bu +L(y - \hat{y}) \\
\hat{y} &= C\hat{x} + Du + b_0
\end{align*}
\]  

(14)

where \(L^T = [L_1\quad L_2]\) is the observer gain vector. We use a linear quadratic (LQ) approach to design an optimal observer that minimizes the error and effort. In this method, the \(P\) matrix is calculated by solving the LQ Riccati equation (15),

\[
AP + P^TA - PC^TR^{-1}CP = -Q
\]

(15)

Where \(Q\) and \(R\) are arbitrary semi-positive definite and positive definite matrices and the observer gain is obtained from equation (16),

\[
L^T = R^{-1}CP.
\]

(16)

Figure 2 shows the block diagram that demonstrates the battery parameters/SOC co-estimation algorithm. All the battery parameters and the observer gain are being updated in the structure. As shown in this figure, we use the OCV-SOC function as a look-up table in the structure of the observer instead of using \(b_0\) and \(b_1\). Therefore, we use \(b_1\) only in designing the observer gain. However, the change in the C matrix caused by different \(b_1\) only affects the optimality of the designed observer from the convergence time and control effort point of view. Moreover, investigating the structure of the observer shows that matrix B also contains the capacity of the battery. If the nominal capacity, \(Q_R\), is used instead of the actual capacity, \(Q_{act}\), to build this matrix, we can show that it does not influence the estimation of the SOC. That is because in this Luenberger type observer, the error between the actual state and the
estimated state, \( e = \hat{x} - x \), the observer error, converges to zero or the observer is asymptotically stable if the matrix \( A-LC \) has all negative eigenvalues. Therefore, the convergence of the observer does not depend on the \( B \) matrix. Later on we will show that the simulation results endorse the fact that considering the nominal capacity instead of the actual capacity in the observer structure does not affect the SOC estimation results.

![Figure 2 Battery parameters/SOC co-estimation block diagram](image)

**Design the battery capacity observer**

After estimating the SOC with the parameters/SOC co-estimation method, we design another observer for a system that contains the coulomb counting equation to estimate the actual capacity of the battery. In this observer, we use this fact that the changes in the SOC of the battery ultimately follow the coulomb counting equation in which the capacity is the actual one:
\[
S\hat{O}C = \frac{1}{Q_{\text{act}}} I.
\] (17)

We showed in the previous section that the estimation of SOC in our method is more based on the OCV of the battery rather than coulomb counting. Therefore, the result of SOC estimation can be used as the measured value to estimate the actual capacity of the battery. We define the following system:

\[
\begin{aligned}
Q(k + 1) &= Q(k) + w(k) \\
SOC(k + 1) &= SOC(k) + \frac{1}{Q(k)} I_L, \\
y(k) &= SOC(k)
\end{aligned}
\] (18)

where \(Q(k)\) is the actual capacity of the battery and \(w(k)\) is a Gaussian Noise. Since one of the states of the system (18), SOC, can be observed directly from the output data, we design a reduced order observer (equation (19)) to estimate the capacity of the battery.

\[
\frac{1}{\hat{Q}(k+1)} = \frac{1}{\hat{Q}(k)} + L (\hat{y}(k) - y(k)),
\] (19)

where \(\hat{Q}(k)\) is the estimated capacity of the battery and \(\hat{y}(k)\) is the estimated output of system (18):

\[
\begin{aligned}
S\hat{O}C(k + 1) &= S\hat{O}C(k) + \frac{1}{\hat{Q}(k)} I_L \\
\hat{y}(k) &= S\hat{O}C(k)
\end{aligned}
\] (20)

Since system (20) is nonlinear, instead of linear analytic design methods we use trial and error approach in this paper to design the observer gain, \(L\). Figure 3 shows the block diagram
that implements the observer described by equation (19) to estimate the battery capacity. As previously explained, y(t) is the output for system (18) which is SOC of the battery.

Figure 3 The battery capacity observer

IV. Simulation Results

To demonstrate the robustness of the identification and SOC estimation results regarding the uncertainties in the full capacity calculation of the battery, we evaluate the results using the input/output data from a nonlinear model of the battery. In this model which has been developed in SIMULINK, we use a look-up table obtained from the experimental data to represent the OCV-SOC function. Also, the battery dynamics are represented by an RC equivalent circuit shown in figure 1 with fixed values for $R_0$, $R$ and $C$. Although those values change with SOC and C-rate in the real system, we keep them fixed in this model to make the verification easier. We obtain the current and voltage data of the model when the capacity of
the battery is dropped by 20% of the nominal capacity, which is the extreme capacity degradation for most of the applications. It is similar to getting the current and voltage of a battery that has lost 20% of its capacity due to the cycling ageing effect. However, in the identification algorithm the nominal capacity is considered as the natural approximation of the full capacity of the battery. Applying the input/output data, demonstrated in figure 4, to the parameters identification algorithm, we compare the identified parameters to the results from an algorithm with the actual full capacity. The identification results for both nominal and actual capacities are demonstrated in figure 5 with a thicker line for nominal capacity to illuminate the difference. Also the dotted lines show the reference value for the parameters that have been used in the simulated model. The first three graphs show that $R_0$, $R$ and $RC$ are

![Figure 4 Current and voltage data obtained from the battery model](image-url)
Figure 5 Comparison of the parameters identification results for the nominal and updated capacity
identified at the same values for both nominal and actual capacities. These parameters are the major updating factors in the SOC co-estimation structure shown in figure 2. On the other side, as expected from equation 10, figure 5 shows that identification of $b_1$ is significantly affected by the assumption about the battery full capacity. However, following the earlier discussion, it does not influence the SOC estimation results because the experimental look-up table is used in the observer structure instead of $b_1$. The simulation results demonstrated in figure 6 confirms that considering the nominal capacity instead of the degraded one does not make any significant difference in the estimation of the SOC. On the contrary, in figure 6 the difference between the estimated SOCs with different full capacity considerations slightly increases for the SOCs between 30% and 60%. This is the area in figure 5 that the difference between the identified $b_1$s is minimum compared to other SOCs. Therefore, we can see again that lack of observability [9] has more negative influence on SOC estimation compared to the full capacity error influence. Afterwards, as shown in figure 7, when the estimated SOC is applied to the observer in figure 3 along with the battery current the parameters/SOC/capacity algorithm is able to accurately estimate the actual capacity of the battery.
Figure 6 Comparison of SOC estimations with nominal and updated capacity

Figure 7 Capacity estimation compared to the actual capacity of the battery
V. Experimental Results

After verifying the performance of the parameters/SOC/capacity co-estimation algorithm using the simulated data, we apply the current and voltage data obtained from the experimental tests on 1.36 Ah lithium-polymer cells (Kokam SLPB723870H4) to estimate the actual capacity of the cells. In this test, we assume that the capacity of the brand new battery is equal to the nominal capacity. Therefore to evaluate the robustness of the algorithm, this time we assume that the full capacity of the battery in the parameters/SOC co-estimation algorithm is considered 20% lower than the nominal capacity. We again compare the results of the parameters/SOC co-estimation algorithm for both nominal and 20% degraded capacity in the algorithm structure. The identified parameters in figure 8 shows that even in the experimental case in which the parameters vary with SOC, the wrong assumption about the full capacity of the battery does not deviate the identification of the main parameters i.e. $R_0$, $R$ and $C$. This figure also shows that $b_1$ is the only parameter that is identified differently for different assumption about the full capacity. But we know that it does not affect the SOC estimation since look-up table is substituted in the algorithm structure. The SOC estimation results demonstrated in figure 9 confirms that considering a wrong value for the capacity does not influence the SOC estimation. Accordingly, we use the estimated SOC results to calculate the actual capacity of the lithium-Polymer battery cell using the online algorithm in figure 3. Figure 10 presents the capacity estimation results compared to the nominal capacity of the battery. This figure shows that although the initial value for the estimated capacity is zero the
Figure 8 Comparison of the parameters identification results for the actual and the degraded capacity on the experimental data
Figure 9 Comparison of SOC estimations with nominal and degraded capacity for the experimental data

Figure 10 Estimated capacity compared to the nominal (actual) capacity for the experimental data
algorithm is able to compensate the initial state error and estimate the full capacity almost accurately before \( t=2000 \)s. The increase in the capacity estimation error between 2000s and 4000s is due to the error in SOC estimation that roots in the observability issue.

VI. Conclusion

Online estimation of the capacity is one of the most important characteristics of the battery. The capacity estimation is crucial to estimate the SOH and predict the end of life of the battery. Following our previous publications on developing an online adaptive parameters/SOC co-estimation algorithm, we developed an algorithm that is able to estimate the actual capacity of the battery using the online SOC estimation results. To do so, we first showed with mathematical analysis that the parameters identification and SOC estimation results does not change with a wrong assumption about the full capacity of the battery. Later, the simulation and experimental results endorsed the analytical conclusions. After that we designed another observer that inputs the battery current and the estimated SOC and estimates the full capacity of the battery. We demonstrated with simulation and experimental data that the algorithm is able to estimate the actual capacity accurately when SOC estimation is accurate and the error occurs due to the weak observability.
Acknowledgement

This work is partially supported by the National Science Foundation Award number: EEC-08212121. Samsung Advance Institute of Technology (SAIT) has also partially supported this research. The authors would like to thank Dr. Federico Baronti, Dr. Gabriele Fantechi, Prof. Roberto Roncella and Prof. Roberto Saletti from the University of Pisa for their support to provide the experimental data.
Reference


CHAPTER 6: SENSITIVITY ANALYSIS OF LITHIUM-ION BATTERY MODEL TO BATTERY PARAMETERS

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Paper published in:

The proceeding of the 39th Annual Conference of the IEEE Industrial Electronics Society (IECON), Vienna, Austria, 2013
Sensitivity Analysis of Lithium-Ion Battery Model to Battery Parameters

Abstract—Different models have been proposed so far to represent the dynamic characteristics of batteries. These models contain a number of parameters and each of them represents an internal characteristic of the battery. Since the battery is an entity that works based on many electrochemical reactions, the battery parameters are subject to change due to different conditions of state of charge (SOC), C-rate, temperature and ageing. Referring to our previous work on online identification of the battery parameters, the change in the parameters even during one charging cycle is an experimental fact at least for many lithium-ion batteries. In this paper, the terminal voltage is used as the output to investigate the effect of changes in the parameters on the battery model. Therefore, we analyze the sensitivity of the model to the parameters and validate the analysis by comparing it with the simulation results. Since the output of the model is one of the main components in estimation of the state of charge (SOC), the sensitivity analysis determines the need to update each of the battery parameters in the SOC estimation structure.

Keywords—Battery modeling, sensitivity, PHEV/PEV, parameter identification
I. Introduction

Developing efficient energy storage devices has attracted worldwide attention in the past decade. With advancements in electrified transportation, Plug-In Hybrid Electric Vehicles (PHEV) and Plug-In Electric Vehicles (PEV) require improved energy storage technologies [1]. Battery technology has been changing rapidly to enhance the storage capabilities of batteries used in PHEVs and PEVS, and thereby advance electrified transportation technology. They are also known to play a vital role in the design of smart grids for efficient energy distribution. However, advanced battery chemistries with higher power and energy densities cannot provide safe and reliable solutions without a smart battery management system (BMS)[2]. A smart BMS in electrical vehicle (EV) and smart grid applications contains several features including cell measurement, cell balancing, thermal management, safety and protection, as well as techniques to estimate the status of the battery. The batteries have certain status information viz. State of Charge (SOC) and State of Health (SOH) [3]. The SOC of a battery is defined as the ratio of the charge left in the battery to the rated capacity of the battery expressed in percentage and the SOH represents the ability of the battery to repeatedly provide its rated capacity over time [4]. In order to meet the requirements, the BMS must have an intelligent algorithm to predict the SOC and SOH accurately. Although, there exist some open loop techniques such as Coulomb counting [5] and open circuit voltage measurement [6], due to the lack of accuracy in online applications, model-based methods are being used extensively these days to consider the dynamics of the
battery. They also use observers to estimate the SOC and SOH. This requires a proper modeling of the battery based on the internal parameters and dynamic characteristics.

Several modeling techniques have been proposed to represent the battery more accurately and to estimate the SOC [7-9] and SOH [4], [7]. Those techniques based on the application and accuracy result in electrochemical models, black box models, statistical based models and electrical models. Electrochemical modeling is based on the chemical reactions that take place inside the battery. Even though, these models are useful to optimize the design of the battery, they are usually computationally intensive on both time and memory to solve partial differential equations [10]. The black box model considers the battery to be a black box system that models it based on the current-voltage characteristics when used in an application. Statistics and curve fitting techniques can be used to develop models for the battery too. However, these techniques are unable to represent the dynamic characteristics of the battery. This drawback is addressed when electrical models viz. impedance based and Thevenin-based models are considered. The impedance-based models are based on the frequency domain response of the battery when a small current signal with varying frequency is applied to the battery. In the Thevenin-based models, the impedances are replaced with capacitors, inductors and resistors. Even though earlier models used to represent the battery as a large capacitor, recent models consider that the OCV and SOC have a non-linear relationship when a controlled voltage source is used. Experimental look up tables are used to relate the measure OCV to the SOC of the battery.
In our previous publications on online adaptive parameters identification and SOC estimation of different lithium ion batteries [11-13], using a Thevenin-based model we showed that the model parameters change under different conditions of SOC, C-rate, temperature and ageing. We also illustrated that ignoring the changes in the parameters with offline identification causes transient and steady-state errors in SOC estimation results. Therefore, it is a need to understand the sensitivity of the battery to variation of the external conditions. To determine this, it is critical to evaluate the sensitivity of the battery model to the changes in the parameters of the battery model. In this paper, the Thevenin-based model with one RC pair to represent the relaxation effect, as it will be explained in the next section, is considered to determine the sensitivity of the battery to its parameters.

In the following, Section II describes the components of the battery model; Section III explains the mathematical analysis; Section VI evaluates the mathematical analysis with simulation results; Section V concludes the paper.

II. Battery modeling

As described earlier, depending on the required accuracy and the application, different types of models have been developed so far for the battery. Among those models, the RC-equivalent circuit is an effective one to represent the battery’s dynamics. The following subsections describe some of the battery’s characteristics that are considered in the model.

A. Linear Model with Internal Resistance
A typical rechargeable battery can in first approximation be modeled by a large capacitor that can store and release electrical energy during charging and discharging cycles. As in any electrochemical process, these charging/discharging cycles encounter a small resistance due to the electrolyte and the inter-phase resistance. This small resistance appears in series with the battery capacitor, Q. We note that the value of the internal resistance changes with the SOC, the ambient temperature, and the aging effect of the battery.

**Relaxation Effect**

When a battery cycles between charge and discharge modes, the relaxation effect comes into focus. In this effect, the battery’s open circuit voltage ($V_{OC}$) slowly converges to the equilibrium point when it is allowed to relax over a long period of time after the charge or discharge process. Relaxation effect is a result of the diffusion effect and double layer charging/discharging effect [14]. A parallel RC circuit can be used in series with the internal resistance to represent this behavior of the battery. Taking into consideration the trade-off between accuracy and complexity a number of RC circuit models can be used. Figure 1 is the circuit that is considered for the relaxation effect to represent the battery. The controlled voltage source in this model is used to represent the nonlinear relationship between the open circuit voltage and the state of charge. This is a key difference between this model and the linear model.
Figure 1. Combined Battery Model with Relaxation Effect, Internal Resistance and $V_{OC}$ - SOC Function

**$V_{OC}$-SOC Relationship**

Under known conditions of temperature and age, the relationship between the $V_{OC}$ and the SOC is independent of the charging/discharging current. A number of nonlinear equations have been proposed to model the non-linear characteristics of the battery [8]. Hysteresis effect is also considered in some of these equations. The hysteresis effect, which is beyond the scope of this paper, causes the discharging curve to stay below the charging curve for the same SOC [15]. However, the error between those equations and the experimental $V_{OC}$-SOC curve lead us to use the look-up table obtained from experimental data in the model. Figure 2 shows the $V_{OC}$-SOC curve for this lithium-ion battery. Despite the inherent nonlinearity of the $V_{OC}$-SOC curve, since for ordinary charging/discharging
current rates the SOC has small variations, the curve can be mapped with piecewise linearized section with a varying slope, $b_1$ and $V_{OC}$ intersection, $b_0$:

$$V_{oc} = f(SOC) = b_1SOC + b_0$$  \hspace{1cm} (1)

The first and second derivatives of $V_{OC}$ with respect to SOC obtained from the $V_{OC}$ - SOC curve are used to determine the segments to divide the linear regions. These derivatives are displayed in Figures 3 and 4. The threshold level of 0.08 is set by trial and error on the second derivative in figure 4 to find the segments. Figure 5 shows the piecewise linearized mapping of the curve based on the determined segments. We

![Figure 2. Actual $V_{OC}$ - SOC curve for a Lithium-Ion Battery](image)

![Figure 3. The first derivative of $V_{OC}$ versus SOC](image)
can see the high nonlinearity of the curve at SOCs below 5% causes the segments to be very close to each other. However, using the goodness of fit evaluation factor we were able to validate the accuracy of mapping.

**State Space Equation for the Model**

An equivalent circuit like the one described in Figure 6 can be used to model the battery’s characteristics and its relaxation effect. Two RC groups are recommended for an optimal trade-off between complexity of the model and the accuracy [14], however, there are...
references [4], [9], [16] that suggest that just one RC group is sufficient to accurately predict the battery characteristics for EV and smart grid applications. Therefore, this simple model can be used to identify and extract the required parameters. Based on the equivalent circuit model, it is possible to create the state space equations to represent the battery’s dynamics. The voltage across the RC circuit, \( V_{RC} \), and the SOC of the battery are considered as the system state variables.

\[
\begin{align*}
\dot{S}_{oc} &= \left[ \begin{array}{cc} 0 & 0 \\ 0 & -\frac{1}{RC} \end{array} \right] \left[ \begin{array}{c} S_{oc} \\ V_{RC} \end{array} \right] + \left[ \begin{array}{c} 1/Q_R \\ 1/C \end{array} \right] I_L \\
V_T &= [b_1 \ 1] \left[ \begin{array}{c} S_{oc} \\ V_{RC} \end{array} \right] + R_0 I + b_0
\end{align*}
\] (2)

In this paper, the terminal voltage \( (V_T) \) and the terminal current \( (I_L) \) are assumed to be the only values that are measurable from the battery. The effects to temperature and capacity fading caused by the aging of the battery are not considered. The parameters in the system need to be identified in order to estimate the SOC of the battery. Since the nominal capacity
of the battery $Q_R$ is known, \{b_0, R, C, R_0, b_1, \text{SOC}, V_{RC}\} need to be estimated using parameter identification method and state estimation.

## III. Mathematical analysis

In order to analyze the system better, the state space model discussed in the previous section is used. This state space model is converted into a continuous transfer function. A transfer function is defined as the ratio of the Laplace transform of the output of the system to the Laplace transform of the input at zero initial conditions [17]. The transfer function for this system is

$$G(s) = \frac{V_T(s) - b_0}{I_L(s)} = \frac{R_0s^2 + \left(\frac{b_1}{Q_R} + \frac{1}{RCQR}\right)s + \frac{b_1}{RCQR}}{s(s + \frac{1}{RC})}. \quad (3)$$

This transfer function is used to determine the sensitivity of the model to the various internal parameters. Sensitivity of a system to the parameters is defined as the change in the output of the system to a change in the parameter of the system for the same input signal. The sensitivity of the model for a particular parameter is identified by using the partial derivative operation of the transfer function with respect to the parameter under consideration. The sensitivity of the model to the changes in parameter $\alpha$ is given by the partial differentiation of $G(s)$ with respect to $\alpha$ and is denoted as $S^G_\alpha$:

$$S^G_\alpha = \frac{\alpha \frac{\partial G}{\partial \alpha}}{\frac{\partial G}{\partial \alpha}}. \quad (4)$$
The sensitivity of the system for the different parameters, i.e. $R_0$, $R$ and $C$ is calculated using the transfer function (3). The sensitivity of the system to the change in the internal resistance, $R_0$ is given by:

$$S^G_{R_0} = \frac{R_0 \frac{\partial G}{\partial R_0}}{G}.$$  \hspace{1cm} (5)

Since:

$$\frac{\partial G}{\partial R_0} = \frac{RCS^2 + s}{s(RCS + 1)} = 1,$$  \hspace{1cm} (6)

We have:

$$S^G_{R_0} = \frac{R_0RCS^2 + R_0s}{R_0RCS^2 + \left(b_1\frac{R}{Q_R} + R + R_0\right)s + b_1 \frac{1}{Q_R}}.$$  \hspace{1cm} (7)

Equation 6 shows that the ratio of the change in the system to a change in $R_0$ is one. This implies that any change in the internal resistance will directly affect the output of the battery i.e. the terminal voltage, $V_T$. Also, since the sensitivity of the system to the changes in the relaxation resistance, $R$ is given by the equation (8):

$$S^G_R = \frac{R \frac{\partial G}{\partial R}}{G\partial R},$$  \hspace{1cm} (8)

and we have:

$$\frac{\partial G}{\partial R} = \frac{1}{(RCS + 1)^2},$$  \hspace{1cm} (9)

The sensitivity function will be:
The sensitivity of the system to change in the capacitance $C$ is defined by the equation below.

$$S_C^G = \frac{R s}{R_0 R^2 C^2 s^3 + \left(\frac{b_1 R^2 C^2}{q R} + 2 R_0 R C + R^2 C\right) s^2 + \left(\frac{2 b_1 R C}{q R} + R_0 + R\right) s + \frac{b_1}{q R}}.$$  \hspace{1cm} (10)

In order to better analyze the system, the steady state value of the change in the response of the system to changes in the parameter $\alpha$ can be calculated by equation 14:

$$\partial G_{ss\alpha}(s) = \lim_{s \to 0} \frac{\partial G}{\partial \alpha} \times \partial \alpha.$$  \hspace{1cm} (14)

Using equation 14, it is possible to determine the steady state values for the sensitivity of the system to the internal resistance, $R_0$, relaxation resistance $R$ and capacitance $C$ using equations 6, 9 and 12. To do so, the nominal value of these parameters are considered as $R_0=0.011$ Ohms, $R=0.0172$ Ohms and $C=2000$F in the simulation model. These values are related to the parameters of the Lithium Polymer battery that we had reported in previous publications. The amplitude of the step change in each parameter is assumed as 50% of the nominal value that is compatible with experimental results. Therefore, we have:

$$\partial G_{ssR_0}(s) = \lim_{s \to 0} \frac{\partial G}{\partial R_0} \times \partial R_0 = 0.0055,$$  \hspace{1cm} (15)

$$\partial G_{ssR}(s) = \lim_{s \to 0} \frac{\partial G}{\partial R} \times \partial R = 0.0086,$$  \hspace{1cm} (16)
\[
\partial G_{SSC}(s) = \lim_{s \to 0} \frac{\partial G}{\partial C} \times \partial C = 0. \quad (17)
\]

IV. Results and Analysis

Before evaluating the theoretical analysis results with simulation, we use experimental data and online identification results to show the change in the battery parameters due to the SOC and temperature. To do so, we consider Lithium-Iron-Phosphate (LiFePO$_4$) batteries with 10Ah capacity. A constant current constant voltage (CCCV) charging procedure is used to charge the battery completely. The battery is then discharged in pulses at a rate of C/2. Figure 7 shows the discharge current and voltage of the battery at 20°C temperature. The current and voltage data is used to identify the parameters of the battery as described in transfer function (3) or model (2). Figure 8 shows how different parameters of the battery including $R_0$, $RC$ and the $V_{OC}$-SOC slope, $b_1$, change with SOC at the same temperature and same input current. This figure implies that even at the same conditions of temperature and C-rate the internal resistance of the battery, for example, changes from 0.0025 to 0.007 Ohms. In another experiment, similar current and voltage data is obtained at different ambient temperatures and the data is used to identify the battery parameters. Figure 9 shows the identification results for the internal resistance of the battery at different temperatures and at various SOCs. The results show that the internal resistance of the battery significantly decreases with increasing the temperature. The figure shows that this decrease happens at different SOCs. Therefore, these experimental results confirm the change in the parameters
of the battery and justify the need to analyze the sensitivity of the battery model to the changes in the parameters.

Figure 7 Discharging pulsed current and terminal voltage of the battery
Figure 8 Identified battery parameters at different SOCs
In this paper, we consider $R$, $C$ and $R_0$ as the parameters for the sensitivity analysis. To study the sensitivity of the system to a sudden change in one of the parameters the system is given a step change in the parameter at $t=100$ seconds. The system response is plotted with the sensitivity obtained from the simulation of the battery. The output terminal voltage generated by the system for a unit step input of current can be used to analyze the sensitivity of the system as defined in equations below:

$$G(s) = \frac{Y(s) - b_0}{u(s)}$$  \hspace{1cm} (18)

$$G(s) = Y(s) - b_0$$  \hspace{1cm} (19)

$$\Delta G(s) = \Delta Y(s)$$  \hspace{1cm} (20)
Using equation 19, we can establish that the change in the output is equivalent to the change in the system, i.e. the sensitivity of the system.

\[
\Delta G(s) = \Delta V_T(s)
\]  

(21)

To verify the results obtained from equation 20, the systems in equation 5, 8 and 11 are given step inputs with the magnitude of 50\% nominal value of the parameter that was described in the previous section. The response of the systems with the steady state values as mentioned in equations 14, 15 and 16 and the response of the system obtained from system 1 are plotted in figures 10, 11 and 12 along with the error between the responses from theory and simulation. From figure 10, it is observed that the difference in the terminal voltage as predicted by theory and simulation reach the steady state value of 0 within 300 seconds when a step increase of 1000F in the relaxation capacitance $C$ occurred at 100 seconds. Also, the error between the measured and theoretical terminal voltage was calculated to be a maximum of 3mV. Thus the maximum error in the estimation of the change in the terminal voltage for a unit change in capacitance is 3\(\mu\)V/F.

Similarly, from figure 11 the difference in the terminal voltages for theory and simulation for the relaxation resistance reached the calculated steady state value of 0.0086 within 300 seconds for a step increase of 0.0086 in the value of the relaxation resistance that occurred at 100 seconds.
Figure 10 Change in Terminal Voltage to Change in Capacitance $C$

Figure 11 Change in Terminal Voltage to Change in Relaxation Resistance $R$
The internal resistance of the battery, being the most important feature, was analyzed and the difference in the terminal voltages was calculated for a change in the internal resistance of the battery. A step change of 0.0055 in the internal resistance of the battery was given at 100 seconds. The response of the battery to the step change is depicted in figure 12. The change in the terminal voltage follows that of the change in the internal resistance of the battery. The error in the estimation of the change in the terminal voltage according to theory and simulation was found to be 0. From figures 10, 11 and 12, it is also possible to say that the change on terminal voltage as estimated by theory and simulation converge to the steady state values as determined from equations 14, 15 and 16 within a maximum time span of 300 seconds from when the step change was initiated. It was also determined that the response of
the system to a change in the internal resistance $R_0$ of the system is instantaneous and follows
the change in the resistance unlike those of the relaxation resistance and capacitance. Thus
the system is very sensitive to changes in the internal resistance when compared to the
changes observed in the system for changes in the relaxation resistance and capacitance.

V. Conclusion

Thevenin RC equivalent circuit was used to model the dynamics of the battery. Although
the battery model is simple and piecewise linear, the model parameters are not constant. They
change with different conditions of SOC, C-rate, ambient temperature and ageing. The
experimental results were used in this paper to show the changes of the parameters because
of SOC and temperature. The internal resistance has the most significant changes at different
conditions. Following this, sensitivity analysis is used to show the effect of changes in the
parameters on the output of the model. The theoretical analysis shows that the internal
resistance and the relaxation resistance have a steady-state effect with a sensitivity of 1. It
means that any change in either of these values will be reflected in the steady state value of
the terminal voltage. The difference is that for the internal resistance the effect is immediate
while for the relaxation resistance the change is seen as a critically damped second order
system with natural frequency of $1/RC$. The sensitivity of the model to the relaxation
capacitance does not have a steady state component although the transient time is about 300
seconds. Therefore, we can conclude that for applications like electric vehicles with fast
operational dynamics, the battery model is sensitive to all parameters. That is because the transient effect is so slow that it is not dissipated before other changes are applied to the battery. This confirms the need for updating the battery parameters using online identification in the SOC estimation algorithm.
References


CHAPTER 7: CONCLUSION AND FUTURE RESEARCH DIRECTIONS
While advanced battery technology is growing very fast to support the rapidly-evolving technologies such as Smart Grid and Electric Vehicles (EV) with higher power and energy densities, reliability, safety and efficiency of the energy storage performance cannot be guaranteed without a smart battery management system (BMS). Among several hardware and software features of the BMS, there is a crucial need for algorithms to accurately estimate the state of Charge (SOC) and state of health (SOH) of the battery especially in EVs and Smart Grid. In addition to informing the user about the status of the battery, the accurate estimation of the SOC and SOH can be used in the other BMS features such as cell balancing and safety to enhance the performance.

In order to estimate the SOC of the battery, an RC-equivalent circuit is used to model the dynamics of the battery. Although the battery model is simple to implement the model parameters are not constant. They change with different conditions of SOC, C-rate, ambient temperature and ageing. The experimental results were used in this thesis to show the changes of the parameters because of SOC and temperature. The internal resistance has the most significant changes at different conditions. Sensitivity analysis confirms the transient and steady state effect of changes in these parameters on the output of the model. Therefore, since the parameters of the battery model are functions of the SOC, C-rate, temperature, and aging, they need to be identified with a proper frequency during the SOC estimation. Most of the observer-based SOC estimation algorithms proposed so far design the state observer based on a model with fixed parameters that are obtained from offline identification. In this thesis, we showed that changing the parameters of the battery needs to be identified to update
the observer parameters, and provide an accurate SOC estimation. To do that online, the adaptive battery parameters/SOC co-estimation approach was proposed in which a piecewise linear mapping of the $V_{OC}$-SOC function was used to identify the battery parameters and feed them to an optimal observer to estimate the SOC. We verified the performance of the parameter-identification algorithm by applying it to simulated and experimental data. The necessity of updating the parameters in the observer structure was verified with the results of the experimental data. Moreover, the performance of the SOC co-estimation algorithm was compared to the EKF and sliding-mode observer as two popular SOC estimation approaches. All of the results indicate that updating the parameters of the battery model during SOC estimation is key to increase the accuracy of the estimation and avoid unnecessary compensation for uncertainties. Moreover, we tried a reduced-order observer to estimate the SOC for a Lithium Iron-Phosphate (LiFePO$_4$) with a more $V_{OC}$-SOC curve. The results indicated that although the estimation error was always less than 5%, there is a direct correlation between the SOC estimation error and the observability criterion for the battery model system. When the observability decreases due to the semi-flat $V_{OC}$-SOC curve or a small slope, the estimation error significantly increases.

In this thesis, we also proposed a novel battery hysteresis effect model through treating the battery hysteresis loops as the response of a time-invariant four-state system. This proposed method provides a compact and accurate model to describe the battery’s SOC-$V_{OC}$ trajectories with different battery operating conditions and cycling histories. Experimental validation has demonstrated that the proposed method can provide an accurate model to
describe hysteresis loops. However, we still use the experimental OCV-SOC look-up table in our parameters/SOC co-estimation algorithm due to the availability of the experimental results and the need for more accuracy.

Two important parameters to estimate the SOH, i.e. remaining useful life (RUL) and end of life (EOL), are the internal resistance and the full capacity of the battery. The battery ageing causes a significant decrease in the full capacity, and increase in the internal resistance of the battery. The internal resistance of the battery was obtained from the parameters identification process. Following our previous work on developing an online adaptive parameters/SOC co-estimation algorithm, we developed a parameters/SOC/Capacity co-estimation algorithm that is able to estimate the actual capacity of the battery using the online SOC estimation results. To do so, we first showed with mathematical analysis that the parameters identification and SOC estimation results does not change with a wrong assumption about the full capacity of the battery. Later, the simulation and experimental results endorsed the analytical conclusions. After that we designed another observer that inputs the battery current and the estimated SOC and estimates the full capacity of the battery. We demonstrated with simulation and experimental data that the algorithm is able to estimate the actual capacity accurately when SOC estimation is accurate and the error occurs due to the weak observability.

The parameters/SOC/capacity co-estimation algorithm can be utilized in future to estimate the RUL and EOL of the battery. To do that, accurate models for the capacity degradation and internal resistance increase due to the ageing and cycling effect need to be
obtained. Statistical analysis will used to determine the effect of partial cycling on the battery parameters, compared to the full cycling effect. Furthermore, Since different electric vehicles have different requirements of operating power and energy for a given time periods, and with different charging and discharging trends, it is necessary to take all of these characteristics into consideration in predicting the EOL and RUL. Moreover, the future behavior of the vehicle is highly dependent on the stochastic behavior of the drivers and the operating conditions. Therefore, statistical analysis such as Monte Carlo Simulation and Bayesian analysis will be used to predict the future usage and operating conditions.

For the battery modeling, there is still a need to fill the gap between the complicated electrochemical models and the simplified RC equivalent circuits. All the nonlinearities and uncertainties need to be taken into account while developing a model that can be run in real-time for EV and Smart Grid applications.