

Model-Based Parameter Identification of Healthy and Aged Li-ion Batteries for Electric Vehicle Applications

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ABSTRACT

Electric vehicles are receiving considerable attention because they offer a more efficient and sustainable transportation alternative compared to conventional fossil-fuel powered vehicles. Since the battery pack represents the primary energy storage component in an electric vehicle powertrain, it requires accurate monitoring and control. In order to effectively estimate the battery pack critical parameters such as the battery state of charge (SOC), state of health (SOH), and remaining capacity, a high-fidelity battery model is needed as part of a robust SOC estimation strategy. As the battery degrades, model parameters significantly change, and this model needs to account for all operating conditions throughout the battery's lifespan. For effective battery management system design, it is critical that the physical model adapts to parameter changes due to aging.

In this paper, we present an effective method for offline battery model parameter estimation at various battery states of health. An equivalent circuit with one voltage source, one resistance in series, and several RC pairs modeled the battery charging and discharging dynamics throughout the lifespan of the battery. Accelerated aging tests using real-world driving cycles simulated battery usage. Three lithium nickel-manganese-cobalt oxide (LiNiMnCoO₂) cells were tested at temperatures between 35°C and 40°C, with interruptions at every 5% capacity degradation to run reference performance tests for tracking changes in the battery model parameters. The equivalent circuit-based model was validated using real-world driving cycles. The parameter estimation procedure resulted in an efficient model that keeps track of the battery evolution as it ages.

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INTRODUCTION

During the last several years, hybrid electric vehicles (HEVs) and battery electric vehicles (BEVs) have received considerable attention due to their efficiency and sustainability [1]. Batteries, a component of

paramount importance for these types of vehicles, require accurate real-time monitoring and control in order to avoid any overcharge or over discharge conditions that shorten their lifespan and impact safety.



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The battery management system (BMS) is responsible for monitoring the battery state-of-charge (SOC), state-of-health (SOH), state-of-power (SOP), and remaining useful life [2]. The BMS also performs thermal management, cell balancing, and attempts to avoid battery overcharge or under-discharge that might affect driver safety and shorten battery life. The battery SOC, SOH, and SOP are three key variables used in battery condition monitoring and energy management. Since electric vehicles have been on the market for a relatively short period of time, possible battery malfunction or severe fires would result in loss of market share and in a move away from electric vehicles. Therefore, an adaptive BMS is necessary to account for degradation in performance that might affect vehicle drivability and range of operation.

The performance and safety of HEVs and BEVs are highly dependent on the accurate and immediate assessment of the SOC, which is the amount of charge available for use by the vehicle at any time. The range, fuel economy, and other critical calculated performance criteria rely greatly on the SOC. Consequently, accurately estimating the SOC will ultimately improve both vehicle safety and customer satisfaction. The SOH is often related to the loss of rated capacity. When the capacity reduces to 80% of the beginning of life capacity, the battery is considered to have reached its end of life. Cycling and calendar aging cause the battery to lose its capacity.

Battery models are typically classified as one of the following: equivalent circuit-based models, behavioral models, or electrochemical models. **Equivalent circuit-based models** use basic RC circuit elements such as resistors and capacitors to model battery dynamics. Equivalent circuit-based models are simple, computationally efficient, and can be easily implemented onboard a BMS. **Behavioral models** are empirical and utilize various functions to model battery dynamics. In [3], Plett introduced a series of behavioral models, namely: the combined model, the simple model, the zero-state hysteresis model, the one-state hysteresis model, and the enhanced self-correcting model. These models can be easily optimized and they account for Ohmic losses, hysteresis, and polarization time constants. **Electrochemical models** utilize partial differential equations to model lithium intercalation inside the electrolyte and both electrodes. Since electrochemical models provide a physical insight of the battery chemistry, they are favored in SOH estimation and in tracking battery degradation. However, in general, electrochemical models have numerous parameters that are hard to set, are relatively complex, and require more computational power. Therefore, for their application in real-time BMS, these models need to be simplified and reduced to an appropriate level of dynamic significance [3].

In prior work [4], a battery aging study was conducted using current profiles at fixed C-rates to age the battery, however this did not reflect real-world driving conditions. Electric vehicle batteries are subjected to high transients resulting from vehicle acceleration and regenerative braking. Accordingly, this paper addresses the issue by conducting an aging scenario for a BEV, assuming an average North-American driver. These tests were conducted over a 12-month period and

involved accelerated testing of battery lifetime at temperatures between 35 °C and 40 °C using current profiles from real-world driving cycles, such as the Urban Dynamometer Driving Schedule (UDDS). An equivalent circuit with one voltage source, one resistance in series, and several RC pairs was used to model the battery charging and discharging dynamics throughout the anticipated lifespan of the battery. This model provides a good compromise between model accuracy and simplicity for real-time BMS implementation. A parameter estimation method implemented in MATLAB utilized optimization functions to fit simulation results to experimental data. The parameter estimation procedure clearly showed dependencies of the equivalent circuit model parameters on the battery state of charge and state of life. These dependencies were implemented as lookup tables to be used in simulation.

This paper is organized as follows: First, we describe the electric vehicle model development to generate the current profile required for experimentation. Second, we provide a summary of the aging experiments. Third, we describe the experimental setup used for data collection. Fourth, we focus on the battery model and the identification of equivalent circuit model parameters during the cell's lifespan. Fifth, we discuss the experimental results and the cell changes due to aging. Finally, we outline conclusions and applicability of the proposed method.

ELECTRIC VEHICLE MODEL AND CURRENT GENERATION

This section describes the electric vehicle model used to generate the current profile from the velocity profile of various driving cycles. A mid-size BEV model, as shown in [Figure 1](#), was modified from an existing hybrid vehicle model [5]. The model was developed in Simulink using Simscape library components. At a fully charged state, the driving range of the simulated BEV is approximately 200 km. [Figure 1](#) shows the BEV model consisting of a lithium-ion battery pack, a vehicle speed controller, vehicle dynamic model, electric motor, and DC-DC converter.

Three benchmark driving schedules were considered in this study, namely: a UDDS, a light duty drive cycle for high speed and high load (US06), and a highway fuel economy test (HWFET) [5]. The UDDS driving cycle is used to characterize a city driving condition. Its purpose is to replicate average speed, idle time, and number of stops for an average driver.

The US06 cycle is a high acceleration, aggressive driving cycle, and the HWFET embodies highway driving conditions with speeds below 60 miles per hour [6]. The three above mentioned driving cycles are shown in [Figure 3](#). A summary of these driving cycle characteristics such as distance, time, and average speed is provided in [Table 1](#) [6].

The pack current profiles from these driving cycles are shown in [Figure 3](#). The pack-level current profiles have been scaled down to the cell level while ignoring cell-to-cell balancing.

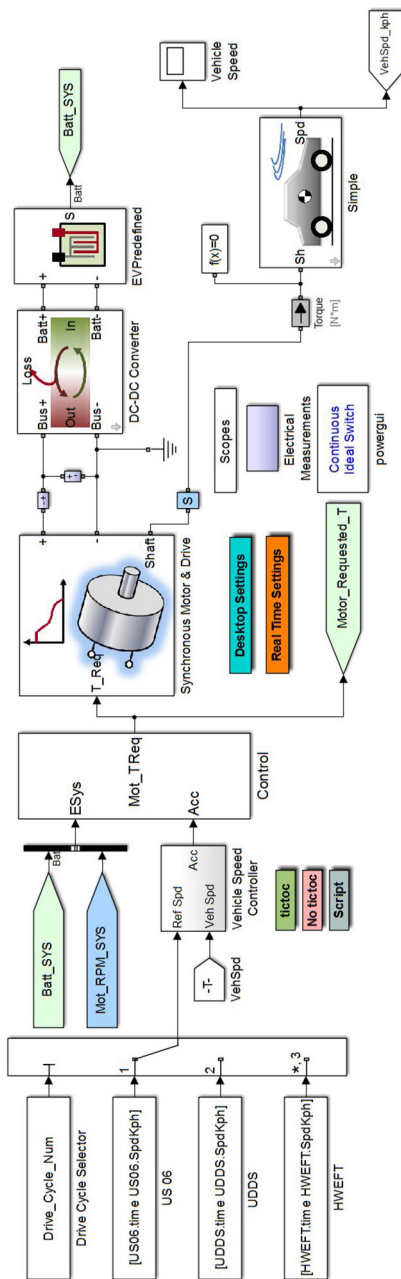


Figure 1. All-electric, mid-size sedan simulation model in Simscape (adopted from [5]).

Table 1. Characteristics of UDDS, US06, and HWFET driving schedules, [6].

	Time (sec)	Distance (km / miles)	Average Speed (kph / mph)
UDDS	1,369	12 / 7.45	31.5 / 19.59
US06	596	12.9 / 8.01	77.8 / 48.37
HWFET	765	16.5 / 10.26	77.7 / 48.30

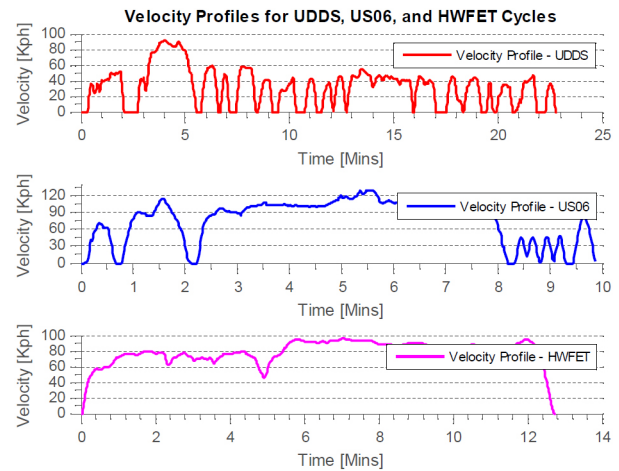


Figure 2. Velocity profiles for the UDDS (upper), US06 (middle), and HWFET (lower) cycles [6]

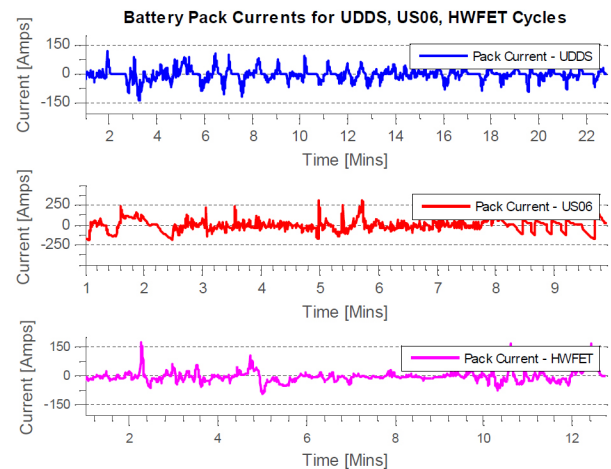


Figure 3. Pack current profiles for the UDDS (upper), US06 (middle), and HWFET (lower) cycles.

AGING STUDY OVERVIEW

Laboratory tests are conducted on battery cells, modules, and packs in order to assess their performance at various states of life and temperature conditions [7]. Data collected during these tests can be used to estimate battery model parameters and validate battery models that are essential for SOC and SOH estimation.

In this paper, two test schedules are considered: Schedule A for Reference Performance Tests (RPTs) and Schedule B for Aging Tests. The RPTs involve a static capacity test at 1C and pulse charge and discharge test. RPTs are conducted every 15 simulated weeks to track degradation in performance as the battery ages. All aging tests were conducted at elevated temperatures (between 35–40°C) to accelerate aging and thus acquire the experimental data in a reduced period of time.

Schedule A - Reference Performance Tests

RPTs capture battery cell baseline performance characteristics such as cell power capability, internal resistance, capacity, and time constants. Tests selected for the study include static capacity and pulse charge and discharge.

Static Capacity Test

The static capacity test measures the battery cell capacity in amperehours at a constant current (CC) discharge rate. This discharge rate, or C-rate, is dictated by the capacity of the battery. For example, a 1Ah battery has a C-rate of 1C when the battery is discharged in one hour, i.e., with a current of 1A. This test provides a baseline for a fresh battery cell capacity. The test procedure follows the constant-current constant-voltage (CCCV) protocol and consists of the following steps [3]:

1. Charge the battery at 1C rate (5.4 A) to the fully charged state in CCCV mode. The battery is fully charged to 4.2 V when the current end point is at 0.02 C (0.108 A).
2. Let the battery rest for one hour in order to allow for voltage and current stabilization.
3. Discharge sequence at a constant current 1C rate until the voltage reaches the battery minimum limit of 2.8 V as recommended by the manufacturer.
4. Let the battery rest with no load for one hour.

Pulse Charge and Discharge Test

The pulse charge and discharge test characterizes the battery voltage response (cell dynamics) at various states of charge and current rates. The test comprises a series of discharge and charge pulses across the full SOC range. The test procedure is summarized as follows:

1. Charge the battery to a fully charged state.
2. Let the battery rest for one hour for voltage and current stabilization [3].
3. Discharge the battery with pulses of 1% of capacity from 100% to 90% SOC at 1C rate and allow for one-hour rest periods between pulses.
4. In the 90% to 10% SOC range, discharge the battery by 5% capacity steps at 1C rate and allow for four hours rest between cycles.
5. In the range between 10% and 0% SOC, discharge the battery by pulses of 1% of capacity at 1C rate while allowing a one-hour rest between cycles.

Schedule B - Aging (Cycle Life) Tests

The purpose of aging tests is to study the process of battery degradation due to multiple charge and discharge cycles [7] mimicking a driver's behavior in real-world driving conditions. The present study combines UDDS, US06, and HWFET driving schedules (Table 2). These tests are defined based on a target velocity profile and its corresponding current profile for an all-electric, midsize sedan vehicle modeled in Simscape.

Schedule B consists of a combination of driving cycles that discharge the battery down to 25% SOC. The test is conducted at elevated temperatures in the range of 35°C - 40°C to accelerate aging. The description of Schedule B for both weekday and weekend is as shown in Figure 4 and Figure 5, respectively [8].

Table 2. Aging Schedule B scenario [8]

Trip	Drive Cycle Combination	Frequency	Description
Work	UDDS _l + US06 _l + UDDS _l + US06 _l	Twice Daily 5 days/week 48 weeks/year	Starting from a fully charged state, a commute from home to work and back with no charge at work
Weekend / Vacation	UDDS _l + HWFET _l + HWFET _l + HWFET _l + UDDS _l + UDDS _l + HWFET _l + HWFET _l + UDDS _l	2 days/week 124 days/year	Starting from a fully charged state, assuming no charging station at the weekend destination

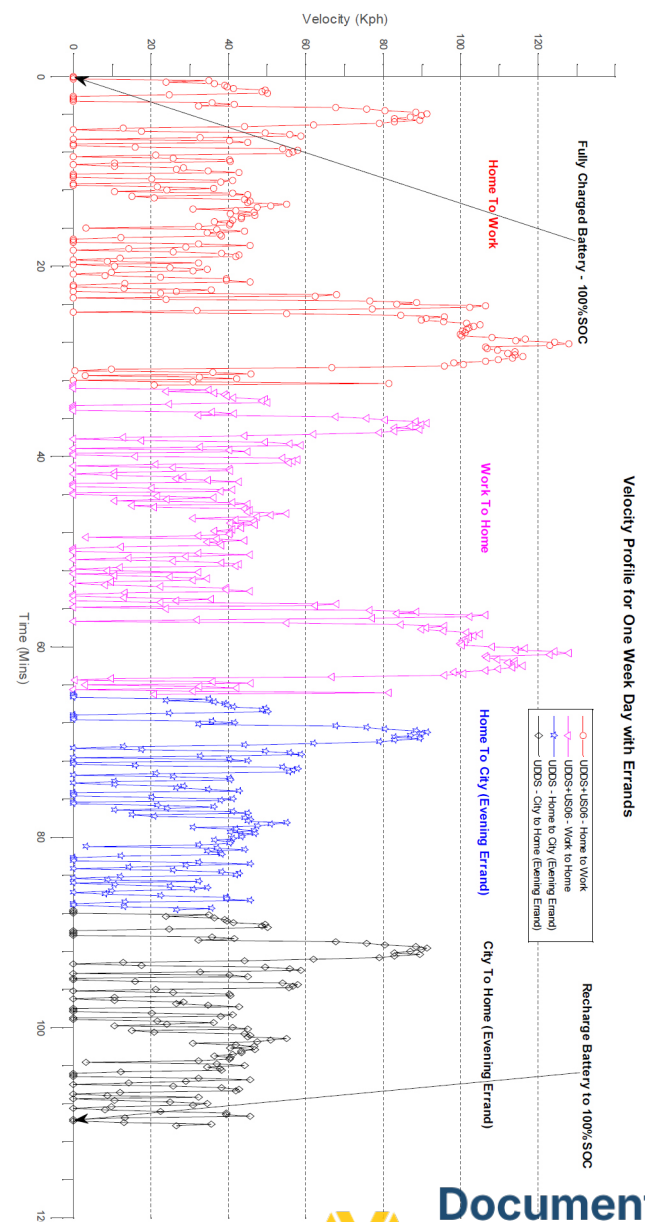


Figure 4. Schedule B: One weekday of driving with errands.

Current profile, voltage, and SOC from one aging week are shown in Figure 6. The SOC varies from 25% to 90% every day. The battery is then fully charged at the end of each day. Current values range from -2C to 2C and voltages from 3.6V to a maximum of 4.2V. Current, SOC, and Voltage for one weekday of driving are shown in Figure 7, and for one weekend of driving are shown in Figure 8.

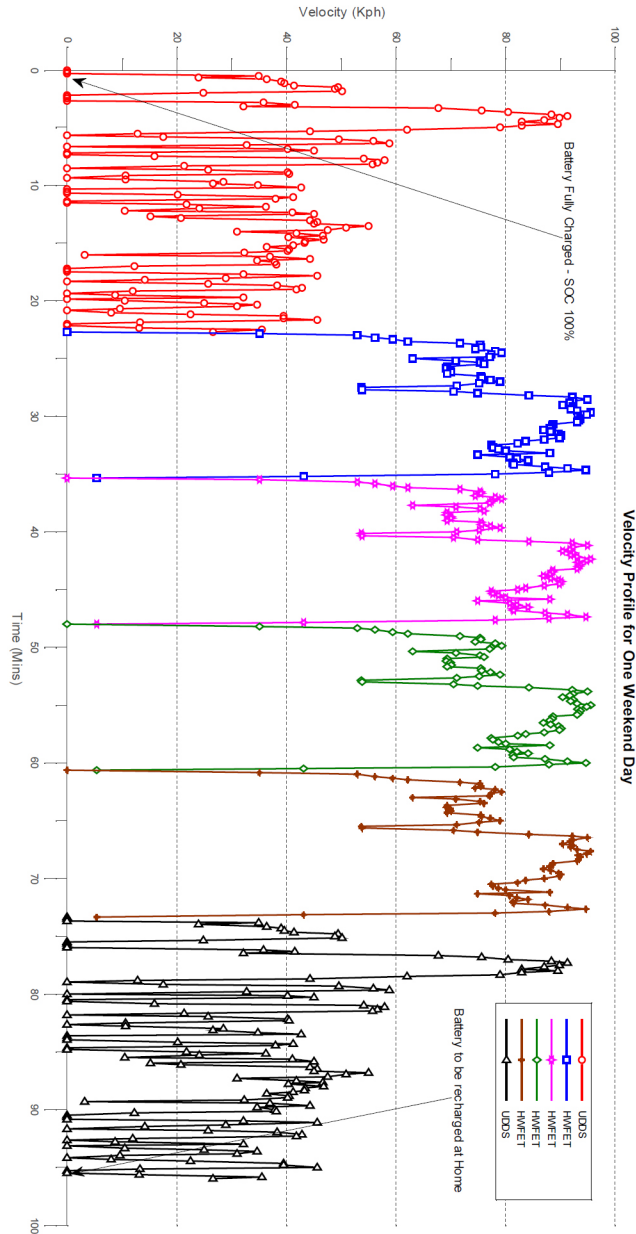


Figure 5. Schedule B: One weekend day driving.

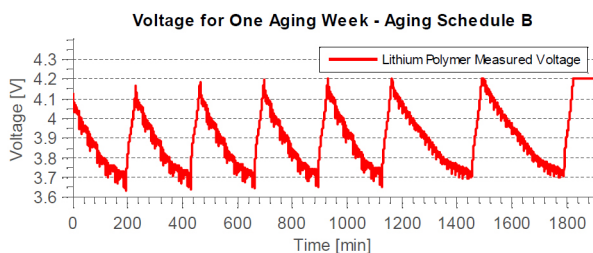


Figure 6.

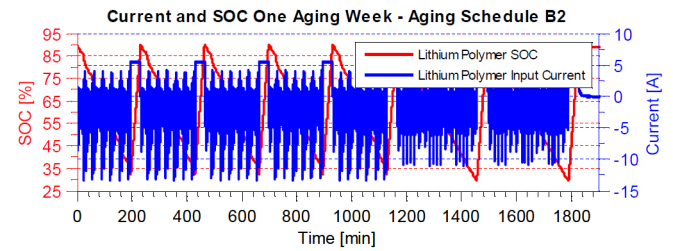


Figure 6. (cont.) Voltage (upper), current, and SOC (lower) for one aging week - Schedule B.

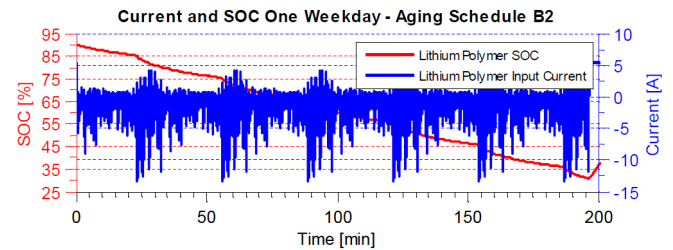
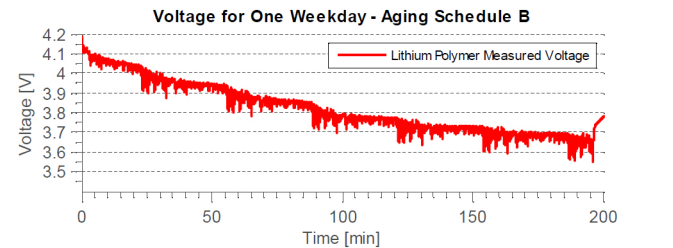


Figure 7. Voltage (upper), current, and SOC (lower) for one weekday - Schedule B.

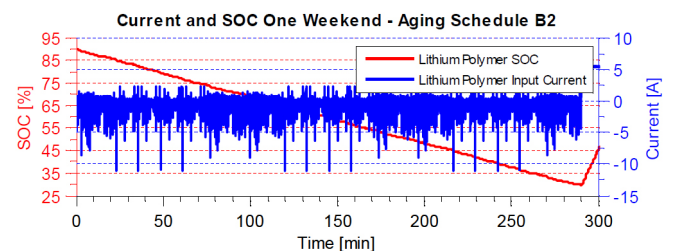
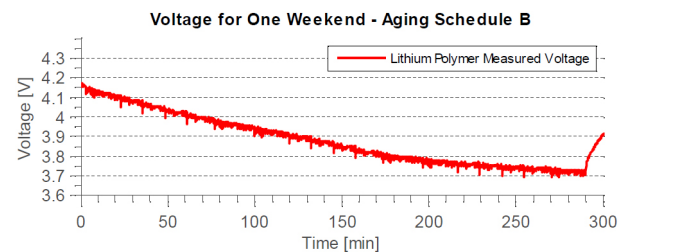


Figure 8. Voltage (upper), current, and SOC (lower) for one weekend - Schedule B.

Experimental Setup

Figure 9, Figure 10, and Figure 11 show the experimental setup utilized for the tests. The setup includes a 3-channel Arbin BT2000 tester, three NMC lithium polymer battery cells, three environmental chambers, an AVL Lynx data acquisition system, and AVL Lynx user interface software. AVL Lynx software is used for setting up the test procedure