Lithium-ion Battery State of Health Estimation Using Ah-V Characterization

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Abstract

The battery state of health (SOH) is a measure of the battery's ability to store and deliver electrical energy. Typical SOH methods characterize either the battery power or energy. In this paper, new SOH estimation methods are investigated based on the battery energy represented by the Ampere-hour throughput (Ah). The methods utilize characteristics of the Ah to estimate the battery capacity or the useable energy for state of health estimation. Three new methods are presented and compared. The simulation results indicate the effectiveness of the methods for state of health estimation.

1. Introduction

Battery diagnostic and prognostic methods are important to maintain proper battery operation. Battery damage occurs due to a number of reasons, such as over-charging and over-depleting the battery. Also, battery operation is dynamic and its performance varies significantly with age. An important aspect of battery diagnostics is the battery state of health (SOH) which is a qualitative measure of the battery's ability to store energy and deliver power. Battery diagnostics track the degradation of battery's performance to estimate battery SOH. There are two common methods to calculate the battery SOH. One method uses the battery impedance, or equivalently the battery power, to determine the battery SOH. The SOH using the impedance, R, can be calculated using Eq. (1).

$$SOH = \left(\frac{R_i}{R_0}\right) * 100 \quad [\%] \tag{1}$$

where R_i is the i^{th} impedance measurement in time and R_0 is the initial value. In the other method, the battery capacity, C, is used to determine the battery SOH as given in Eq. (2).

$$SOH = \left(\frac{C_i}{C_0}\right) * 100 \quad [\%] \tag{2}$$

where C_i is the i^{th} capacitance measurement in time and C_0 is the initial value. There are many studies that have researched the degradation of the battery as it ages (Zhang, 2011). As the battery ages, the battery's performance degradation is related to changes in the battery chemistry. First, the growth of a solid electrolyte interface (SEI) layer reduces the electrical efficiency of the battery. This contributes to an increase of the high-frequency resistance of the battery, reducing the maximum power output of the battery (Troltzsch, 2006). Considerable loss of battery power will result in ineffective vehicle operation or vehicle failure, i.e. vehicle inoperation. Second, the battery capacity degrades as the battery ages (Liaw, 2005). Capacity degradation results from several factors, such as loss of bonding sites in the active material and loss of active Lithium-ions. Considerable loss of battery capacity will result ineffective battery operation and reduced vehicle range.

There have been several attempts to estimate the battery SOH using the battery impedance or the battery capacity. Haifeng et al (2009) defined SOH as a function of the battery's high-frequency resistance. Using a Kalman Filter, the authors estimated the battery resistance to estimate the battery SOH. Also, Kim (2010) developed a technique to estimate the battery capacity for SOH estimation. The author implements a dual-sliding mode observer to estimate battery capacity fade.

Although there has been much progress in the area of SOH estimation, it is still uncertain and still requires research to develop new and more accurate methods. The research presented in this paper investigates new methods which are based on the battery energy storage capability to estimate the battery SOH. The Ampere-hour throughput (Ah) is the current throughput by the battery and represents the energy that is delivered or stored by the battery. The battery terminal voltage and open-circuit voltage varies with the battery state of charge. The Ampere-hour throughput can be related as a function of the battery terminal or open-circuit voltage, i.e. Ah-V. The methods presented in this paper capitalize on unique characteristics of the Ah-V function as the battery ages to estimate the battery SOH.

2. PROBLEM FORMULATION

As stated above, there are two main methods used to estimate the battery state of health (SOH). One method is based on the battery impedance and the other based on the battery capacity. For this paper, the battery capacity is used as the baseline method for SOH calculation. The battery capacity is especially important to electric vehicles (EV) and plug-in hybrid electric vehicles (PHEV) due to the range constraint of the battery. In this section, the problem of SOH estimation will be discussed and the basis for a practical method for online SOH estimation.

The battery capacity degrades over the life of the battery and varies with temperature. As the battery ages, irreversible losses reduce the amount of energy that can be stored and delivered. Also, over-charging and over-depleting the battery also cause the battery capacity to be reduced further. Determining the battery's state of health (SOH) provides a qualitative measure of its ability to function properly. The battery SOH can be calculated based on capacity measurements from the capacity test shown in Figure 1. The capacity test cycles the battery through constant current charge and discharge profiles. The battery is initially discharged to achieve 0% SOC, ie the terminal voltage is 2.5 V. The battery is charged to 100% SOC, i.e. the terminal voltage is 4.15V. These values are values are defined by the battery manufacturer. The

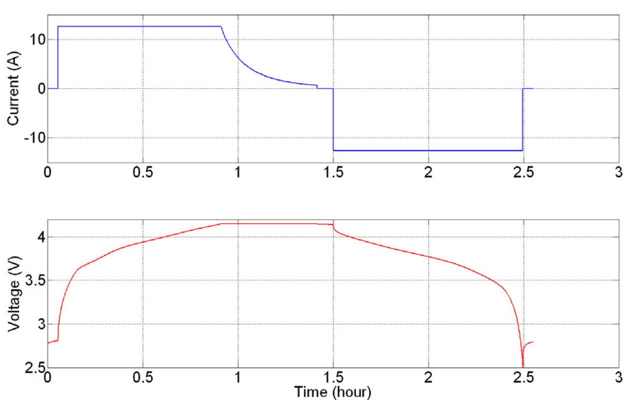

Figure 1. Measured terminal battery current and voltage during capacity test

As the battery ages, battery capacity slowly degrades as shown in Figure 2. The figure shows the measured capacity for three battery data sets. The battery for each data set was subject to capacity tests, performance tests, and accelerated ageing. The capacity test, shown in Figure 1, for the battery in each data set was conducted at 25 °C and was repeated to obtain an average capacity value. The performance tests included Charge Rate, Hybrid Pulse Power Characterication (HPPC), Charge Depleting (EV mode), and Charge Sustaining battery current profiles. During the performance tests, the temperature of the battery for each data set, Data Set 1, Data Set 2, and Data Set 3, was maintained at 20, 30, and 40 °C, respectively. Each battery then underwent accelerated aging at 35 °C. The battery voltage rails, i.e. lower and upper operating voltage limits, were set at 2.5 and 4.15 V, which spans the nonlinear battery operating range. The terminal current and voltage were measured during all tests.

The battery SOH is calculated using the measured battery capacity, as given in Eq. (2) where C_i is the measured capacity of the ith ageing iteration. The battery SOH over time is shown in Figure 3. The SOH is an indication of the battery health over the age of the battery. As the battery continues to age, the capacity will degrade further. At some point, the SOH will indicate that the battery is unhealthy, meaning the battery is unable to store and deliver energy for proper vehicle operation. In an ideal scenario, the battery capacity would be readily available to provide an accurate estimation of the battery SOH. However, in practical vehicle operation, this is not the case. In this context, new methods must be developed which can accurately estimate the battery SOH using online algorithms with the available battery data during vehicle operation.

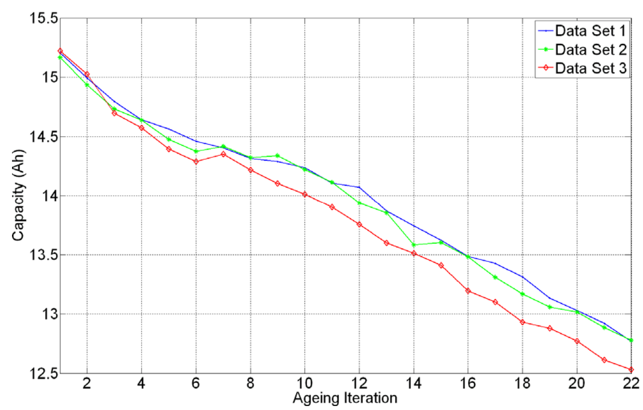

Figure 2. Battery capacity over time.

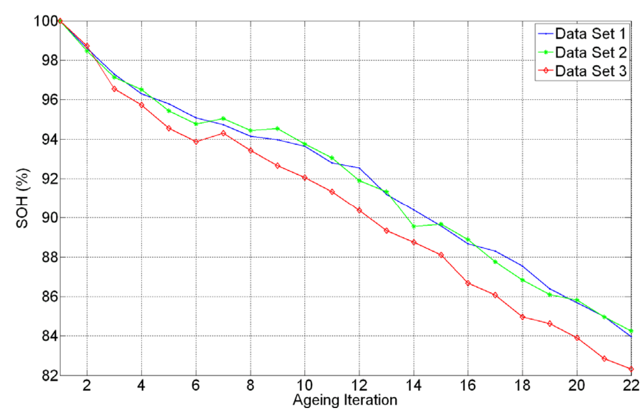

Figure 3. Battery state of health over time using battery capacity value

The battery capacity is the Ampere-hour throughput between the voltage rails of 2.5 and 4.15 V and is measured using the capacity test. However, during vehicle battery operation, the voltage rails are restricted to a smaller voltage range to maintain linear operating behavior and to protect the battery from damage due to over-charging and over-depletion. The relationship between the voltage rails and battery operation is illustrated in Figure 4. The Ampere-hour throughput between the restricted voltage rails is the useable energy during vehicle operation. A distinction is made between the terms "battery capacity" and "useable energy". The "battery capacity" is the total Ampere-hour throughput between the voltage rails of 2.5-4.15 V. The "useable energy" is the Ampere-hour throughput between the restricted voltage rails of 3.4-4 V.

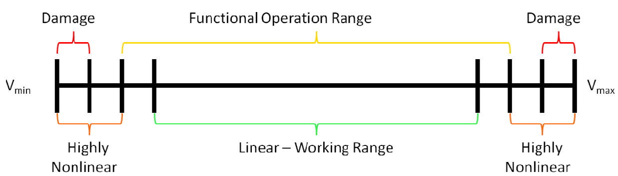

Figure 4. Illustration of the relationship between battery voltage rails and operating behavior

During vehicle battery operation, the voltage rails are restricted and the battery capacity cannot be measured. This inhibits the ability to calculate the battery SOH using the battery capacity. However, online methods can be developed which can provide accurate estimation of the battery SOH using characteristics of the relationship between the Ampere-hour throughput and voltage, i.e. Ah-V, which varies with the age of the battery.

In this study, constant current charge and discharge profiles are used to generate the Ah-V function, using the terminal voltage and open-circuit voltage. Although online constant current profiles will be limited, this study will illustrate that the Ah-V profiles can reflect battery ageing. In particular, the Ah-V profile using open-circuit voltage is not subject to battery loads and may be used to provide Ah-V profiles which can be used to estimate the battery SOH.

Onboard sensors measure the battery terminal voltage and current. The Ampere-hour throughput is the integrated current over time and represents the energy delivered or stored by the battery. The Ah can then be related as a function of the battery terminal voltage or the open-circuit voltage. Although the open-circuit voltage cannot be measured online, several studies have shown that the open-circuit voltage can be accurately estimated using filtering techniques.

In Figure 5, Ah is shown as a function of voltage as the battery ages, i.e. the test iteration number (Itr). For each iteration, the battery was cycled through a capacity test, which comprised of a constant current charge and discharge cycle. The terminal voltage was measured and the open-circuit voltage was estimated offline. The figure shows that the Ah-V function, based on the measured terminal voltage or the estimated open-circuit voltage, gradually changes as the battery is aged. Similar results are seen for Data Set 2 and Data Set 3 but are not shown here. The upper most profiles are generated from constant current discharge. The lower most profiles are generated from constant current charge cycles. The middle profiles are Ah-V profiles generated using measured open-circuit voltage values. Several methods, presented in the next section, are developed which characterize the variations in the Ah-V function to estimate the battery SOH.

The Ah-V profile will be investigated to develop practical methods for SOH estimation. The Ah-V profiles are readily available though onboard sensors and algorithms. Although the current will fluctuate during vehicle operation, constant current charging operation may be available during vehicle battery recharging in EV and PHEV. Also, it is possible to implement an onboard filter to generate Ah-V discharge profiles. The Ah-V using the open-circuit voltage, however, is readily available given onboard estimation algorithms.

The following section will present several methods which utilize the characteristics of the Ah-V profile to estimate the battery SOH. The results will be compared to the battery SOH calculated using the measured battery capacity.

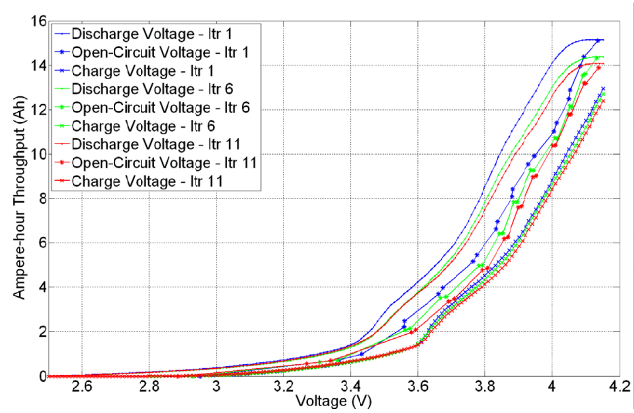

Figure 5. Ah as a function of terminal and open-circuit voltage during constant current charge and discharge cycles for Data Set 1.

3. METHODS

As the battery ages, variations in the battery Ah-V profile can be seen. Several new methods are developed which characterize the variations in the Ah-V profile to estimate the battery state of health (SOH). The methods estimate the battery capacity or useable energy to estimate the battery SOH. Also, the methods presented in this paper can be applied to online vehicle operation. New Ah-V data can be continually input and update the SOH estimation.

3.1 Non-linear Model

As seen in Figure 5, the Ampere-hour throughput is a nonlinear function of the battery terminal and open-circuit voltage between the voltage rails of 2.5 to 4.15 V. The Ah-V function can be modeled using a logistics growth curve, i.e. Richard's curve (Richards, 1959), as given in Eq. (3).

$$F(x) = A + \frac{C}{\{1 + S\exp[-\beta(x - x_o)]\}^{1/s}} \qquad (3)$$

where A = Lower Limit Value, C = Upper Limit Value, S = Symmetry, β = Growth Rate, x_o = Inflection Point.

This equation can be used to model the Ah-V function. The lower limit value, A, is set to zero, assuming that the Ah value is 0 when the battery is completely discharged, i.e. when the measured terminal voltage is 2.5V. The upper limit, C, represents the battery's maximum energy storage potential, i.e. its capacity. Online battery data can be used to fit the model to determine parameter values. New Ah-V data can be used to update the model parameters.

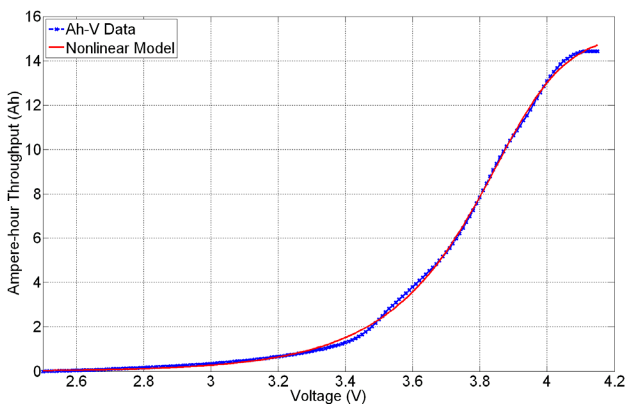

Figure 6. Nonlinear model fit using Ah-V data

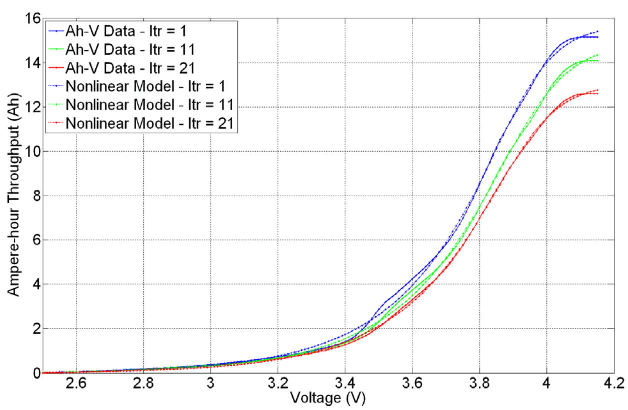

Figure 7. Ah-V data and fitted nonlinear model at different ageing iterations for Data Set 1

The Ah-V profile generate using constant current discharge data has a shape very similar to the logistics curve. Therefore, the Ah-V profile using the terminal voltage during constant current discharge is used to fit the logistics curve using least squares method, shown in . As seen in this figure, the model fits the data relatively well. In addition, the maximum Ampere-hour throughput from the nonlinear model matches the battery capacity well.

For each ageing iteration, the constant current discharge data is used to generate the Ah-V profile. The Ah-V data is then used to fit the model parameters. shows the Ah-V data and fitted nonlinear model at different ageing iterations. As expected, the fitted nonlinear model is matches the relative shape. In addition, the maximum Ampere-hour throughput is approximately equal to measured battery capacity.

Using the nonlinear model, the estimated battery capacity is defined as the Ampere-hour throughput between the voltage rails of 2.5 and 4.15 V. The estimated battery capacity for each data set over the ageing iteration is shown in .

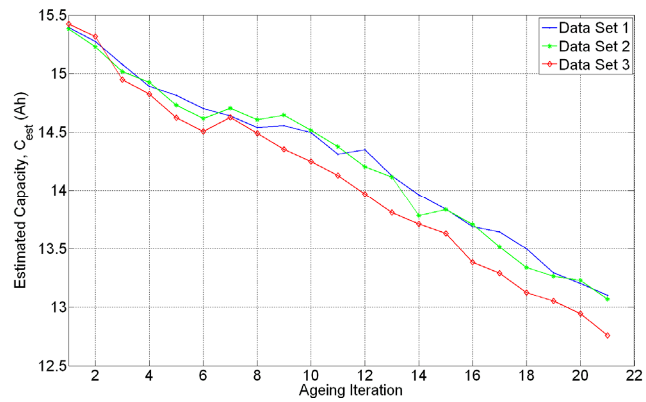

Figure 8. Estimated battery capacity over time

Using the estimated capacity, the estimated battery SOH is calculated using Eq. (4).

$$SOH_{est} = \left(\frac{(C_{est})_i}{(C_{est})_1}\right) * 100 \qquad (4)$$

where the subscripts *1* and *i* indicate the test iteration number. The estimated SOH, SOH_{est}, is compared to the battery SOH in for each data set. In the figure, the label "Battery Data" refers to the SOH calculated using the measured battery capacity. The label "Nonlinear Model" refers to the SOH estimated using the estimated capacity from the nonlinear model. The estimated battery capacity using the fitted nonlinear model provides relatively accurate estimates for the battery SOH.

This method observes the battery behavior over the nonlinear operating region between the voltage rails of 2.5 and 4 V and uses the Ah-V battery data to fit the model parameters. Once the parameters are determined, the estimated capacity can be calculated. However, this method requires the battery to function between the voltage rails of 2.5 and 4.15 V to capture the nonlinear behavior. Ah-V Slope vs Battery Age

As shown above, the battery voltage rails define the working range of battery. In the capacity tests, the voltage rails were defined using manufacture specifications to measure the battery capacity. The Ah-V profile using the

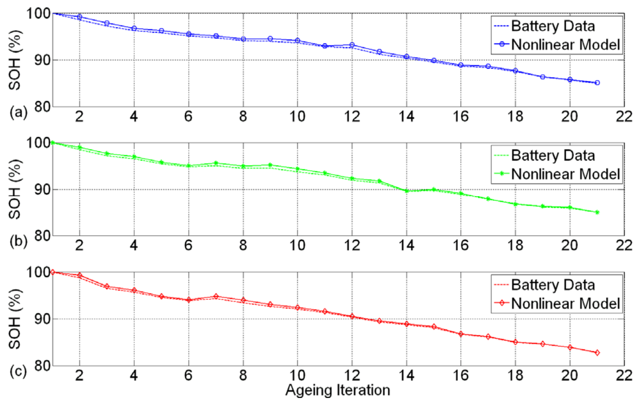

Figure 9. Compare battery SOH to estimated SOH for (a) Data Set 1, (b) Data Set 2, and (c) Data Set 3

voltage rails of 2.5V and 4.15V has a nonlinear profile as seen in Figure 5. However, in electric vehicles, battery voltage rails are restricted to maintain linear operating behavior, i.e.3.4V and 4V. The Ah-V profiles between the restricted voltage rails of 3.4 to 4 V over the age of the battery are shown in . The figure presents three sets of Ah-V profiles at three ageing iterations. The upper three are the Ah-V generated using the terminal voltage during constant current discharge data. The middle three Ah-V profiles use the open-circuit voltage. The lower three are the Ah-V profiles generated using the terminal voltage during constant current charge data.

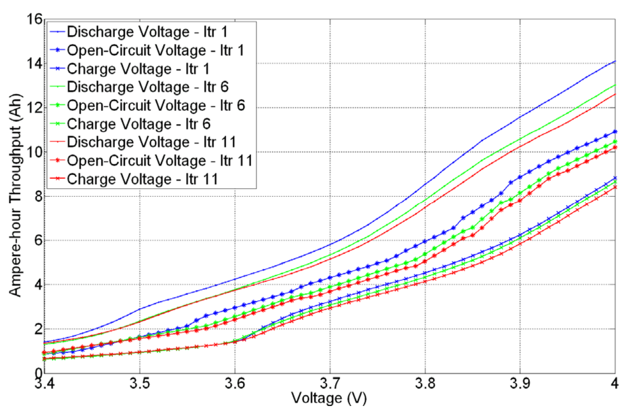

Figure 10. Ah as a function of terminal and open-circuit voltage for constant current charge and discharge over linear battery operation region for Data Set 1

The Ah-V profiles for the terminal and open-circuit voltages are relatively linear and vary with the age of the battery. Specifically, it can be seen that the slope of the Ah-V profiles vary with the battery age. The Ah-V data for the discharge, charge, and open-circuit Ah-V profiles were fitted to a linear model to estimate the Ah-V slope. shows an example of the linear fit of the Ah-V data. The slope, i.e. dAH/dV, of the Ah-V profiles were calculated for each ageing iteration and is shown in . The results show that the slope of the linear fit, for the discharge, charge, and open-circuit voltage Ah-V profiles, is approximately linear over the age of the battery. The linear relationship between the slope of the linear fit to the battery age could be used to estimate the battery SOH from Eq. (4).

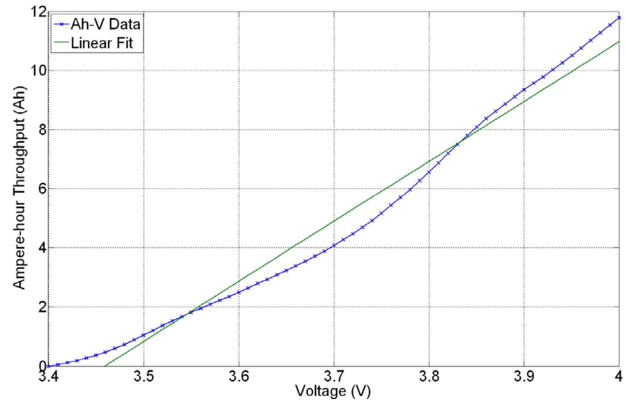

Figure 11. Example of linear fit to Ah-V Data

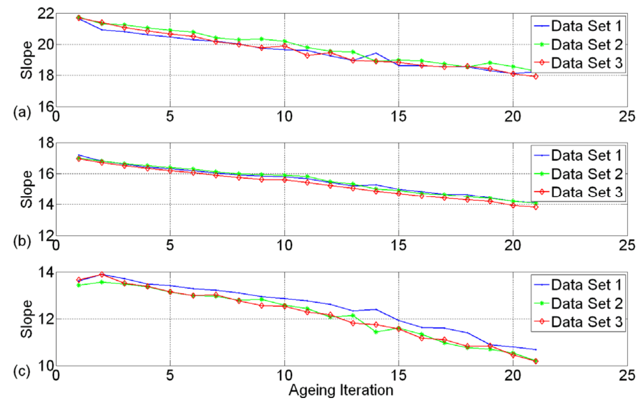

Figure 12. Slope of (a) discharge, (b) open-circuit, and (c) charge Ah-V profile using linear fit over ageing iteration

The slope of the linear fit was related to the battery's measured capacity, shown in Figure 13. The results show that the battery capacity is a linear function of the Ah-V slope. A linear model can be generated to relate the capacity to the slope of the Ah-V function. In this way, online battery data can be used to generate the Ah-V profile and a linear fit can be used to calculate its slope. The slope can then be used to calculate the estimated battery capacity and then estimate the battery SOH.

This method does have some drawbacks. The capacity-slope relationship does vary with temperature and with current rate. However, variations are minimized if the open-circuit voltage Ah-V profile is used. This method for capacity estimation is also sensitive to small errors in the slope. Noise and uncertainty in the Ah-V profile will affect the linear fit and will produce inaccurate slope estimation, which will then affect the SOH estimation.

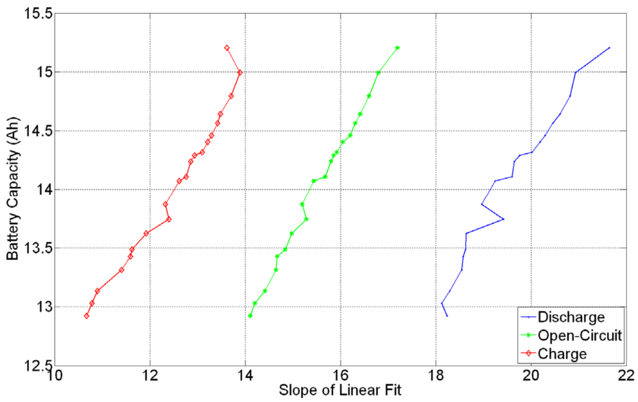

Figure 13. Battery capacity as a function of Ah-V slope over linear battery operating region for Data Set 1

3.2 Estimated Useable Energy Using Quadratic Fit

In the previous section, a linear fit was used to model the Ah-V profile which can then be used to estimate the battery SOH. The major limitation of the previous method is the sensitivity to error, which is largely due to the inaccuracy of the linear fit. The Ah-V data between the voltage rails of 3.4 to 4 V is approximately linear, however, small nonlinearities in the Ah-V function over this region introduce some inaccuracies.

In this method, a quadratic fit is used to model the Ah-V profile. A quadratic model provides a more accurate relationship and will be more tolerant to small errors. Also, the quadratic model can be easily updated to reflect new Ah-V data. This quadratic model can be used to estimate the battery useable energy for SOH estimation. The useable energy is the Ampere-hour throughput between the restricted voltage rails.

The following steps was used to estimate the battery SOH for each ageing iteration.

Step 1: The battery capacity is measured from the capacity tests. The battery capacity of the first ageing iteration is defined as the reference capacity value.

Step 2: The Ah-V profile using the open-circuit voltage is generated between the restricted voltage rails of 3.4 to 4 V.

Step 3: A quadratic fit is generated using the Ah-V data. The quadratic fit is constrained to 0 Ah, i.e. zero useable energy, at the lower voltage rail of 3.4 V. Figure 14 shows an example of the Ah-V profile using the open-circuit voltage and the quadratic fit.

Step 4: The estimated useable energy from the quadratic model is used to estimate the battery SOH using Eq. (5).

$$SOH_{est} = \left(\frac{(Useable\ Energy)_i}{(Useable\ Energy)_1}\right) * 100 \qquad (5)$$

where the subscripts *1* and *i* indicate the test iteration number. A quadratic fit is used to model the Ah-V profile using the battery open-circuit voltage. The Ah-V profile can also be generated using the terminal voltages. However, the Ah-V using the terminal voltages will vary with operating conditions such as temperature and current rate. For clarity, only the Ah-V using the open-circuit voltage is shown. The quadratic model is constrained to 0 Ah, i.e. zero useable energy, at the lower voltage rail of 3.4 V. The Ah-V data, using the open-circuit voltage, and the quadratic fit are shown in Figure 14. The quadratic fit is more accurate than a linear fit.

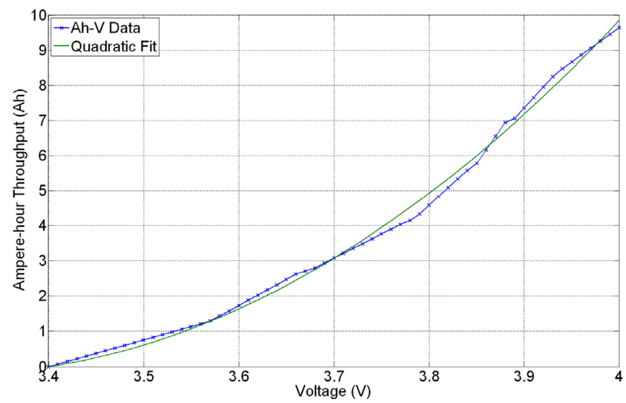

Figure 14. Example of quadratic fit of the Ah-V using the open-circuit voltage over linear operating region

The estimated useable energy is calculated using the quadratic model and is shown in over the battery ageing iteration.

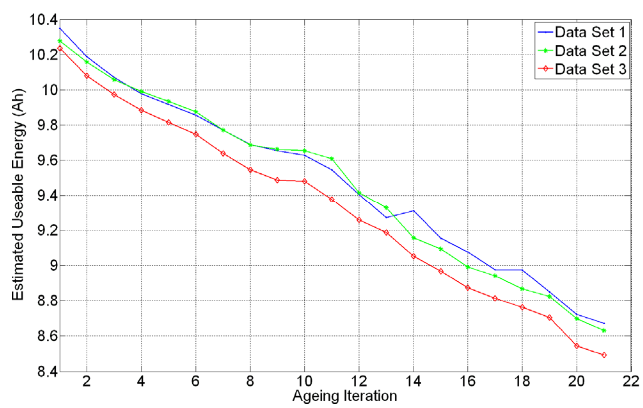

Figure 15. Estimated useable energy calculated from quadratic model of Ah-V

The battery SOH is calculated based on the useable energy determined from the data and quadratic fit of the Ah-V function between the restricted voltage rails of 3.4 to 4 V. The estimated SOH using the useable energy is compared the SOH calculated from battery capacity values are shown in Figure 16 for each battery data set. The SOH using the quadratic fit matches the SOH calculated using the numerical results well. Also, the figure includes the calculated SOH using the measured battery capacity. The figure shows that the SOH calculated based on the quadratic model also match well.

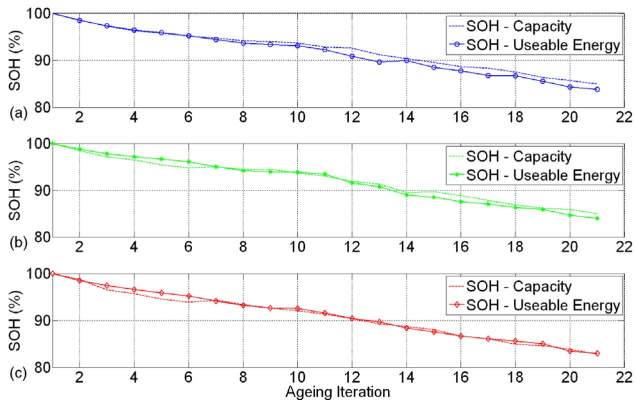

Figure 16. Battery SOH using battery capacity estimated useable energy for (a) Data Set 1, (b) Data Set 2, and (c) Data Set 3

The results from this method show that the battery SOH can be accurately estimated using a quadratic model of the Ah-V. The quadratic model is used to estimate the useable energy over the restricted voltage rails of 3.4 to 4 V which is then used estimate the battery SOH. The estimated SOH matches the battery SOH well. This method can be applied to battery vehicle operation.

4. CONCLUSIONS

Several new methods for capacity estimation were developed and investigated. Each method has a potential to provide capacity estimation for SOH evaluation. The first method models the linear and nonlinear regions of the Ah-V curve using Richard's equation. This method requires a high degree of training effort. The slope of the Ah-V curve was correlated to the battery capacity. This is a relatively simplistic method that provides a linear relationship between the slope and the battery capacity. This method is sensitive to small errors and requires complete charge and discharge cycles to maintain accuracy. The last method uses a quadratic fit to model the Ah-V function. Using the open-circuit voltage, a reliable estimation of the battery useable energy can be used to estimate the battery SOH. This results of this method match well to the SOH calculated using battery capacity values.

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