BATTERY AGING, DIAGNOSIS, AND PROGNOSIS OF LEAD-ACID BATTERIES FOR AUTOMOTIVE APPLICATION

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New battery technologies have been emerging into today’s market and frequenting headlines; however, the lead-acid battery overwhelmingly remains the most common automotive battery. Because of this, lead-acid batteries represent a large cost for the automobile manufacturer. If the lead-acid battery’s health can be appropriately diagnosed and its remaining life predicted, significant costs could be reduced. Additionally, if implemented onboard the vehicle, this could represent an added convenience to the vehicle owner. They could be notified of eminent battery failure and replace or recharge their battery before it ever fails. This thesis aims at developing an onboard diagnostic and prognostic algorithm to assess and predict battery life for the automotive application.

The algorithm utilizes a method called amp-hour counting, or Coulomb counting, along with a set of diagnostic tests to determine the battery’s health onboard the vehicle. Once the health is determined, a life prediction is provided. This algorithm is developed through experimental aging of batteries through representative duty cycles. It is then validated through two ‘near death’ batteries by comparing the available battery energy until failure with the prediction from the algorithm.
To Amanda and my family
ACKNOWLEDGEMENTS

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CHAPTER 1
INTRODUCTION

Although lead-acid batteries seem archaic because there are so many emerging battery technologies today, just consider this; nearly every automobile bought, sold, and manufactured today contains a lead-acid battery. For the large auto-companies, this represents an enormous investment. With the more and more popular bumper-to-bumper warranties offered by these companies, the car battery represents an even greater cost. This research aims at developing a diagnostic and prognostic algorithm to determine battery state of health and predict battery failure onboard the vehicle. If battery health can be monitored and its mechanisms for failure identified, not only could this information save the auto-manufacturers considerable costs, but it would also provide convenience for the consumer. The operator of the vehicle could be notified before failure of the battery, which introduces another selling point for the auto-manufacturer.

In order to make this a reality, we have created a methodology for battery aging diagnosis and prognosis. Figure 1.1 shows the process as a flow chart. The red path is the project objective where on-board diagnosis and prognosis of the battery will provide a life prediction. The gray path is the experimental path to make it all possible.
Let us move through the gray path. To develop an onboard diagnostic and prognostic algorithm for automotive starter battery life prediction, we first investigated real-world driving battery current data. This data set is decomposed into a set of basis cycles, which are applied to new automotive starter batteries in a manner to accelerate the aging processes. Laboratory experiments are conducted to assess the battery aging, and the results from those tests identify the factors that have a significant affect on battery aging. The battery aging results and these severity factors generate a cumulative aging model that can map battery life based on cycling characteristics. In real-world application, this
means that any discharge of the battery can be appropriately analyzed to proportionally reduce the battery’s life. The laboratory tests that show the most potential and practicality for onboard application are considered for onboard diagnostics. This set of diagnostic tests and the cumulative aging model are input into the prognostic algorithm, and a life prediction is generated for the battery.

1.1 CONTRIBUTIONS

The results obtained from this research provide the first set of results for a prognostic algorithm of battery aging being developed at the Center for Automotive Research (CAR) at The Ohio State University [1]. Although this research is largely focused on the automotive starter battery application, the methodology can be replicated for any battery for any application.

The three years conducting this research has generated much knowledge for battery aging and battery aging procedures. In fact, these results have helped jump-start a large initiative at CAR for battery research of hybrid electric vehicle batteries, especially Lithium-Ion. A proposal to develop a Center for Excellence is being considered where CAR will collaborate with other research facilities, universities, and industry partners to bring better technology to the market faster.

This thesis represents a complete summary and description of a multi-year lead-acid battery project sponsored by General Motors. To date, there are nine reports submitted to General Motors Research and Development discussing the results of this project [2,3,4,5,6,7,8,9,10,11]. Additionally, an undergraduate thesis has also been written that discusses the very early stages of this project [12]. A separate Masters thesis by Chris Suozzo has also been written over some of the results obtained through this research project [13]. Throughout this thesis, these reports will be referenced for the reader to
obtain more details than what will be presented.

1.2 **Organization**

This thesis will move through the process flow chart in Figure 1.1. Each chapter introduction highlights a portion of this flow chart so that the reader can identify where we are within the process. Chapter 2, however, is a background review of lead-acid batteries and is not contained within the process flow chart. It discusses the basics of lead-acid batteries: their performance, operation, chemical processes, and general aging. This section is meant to provide the reader with a foundation of knowledge for the lead-acid battery.

From there we will move forward with the research project through the process flow chart. Chapter 3 is essentially the start of the flow chart where we discuss the real-world driving data, which is decomposed into a set of basis cycles. Chapter 4 discusses the laboratory diagnostics used to assess the aging of the battery as it is repetitively cycled with the basis cycles. Chapter 5 diverges slightly from the process flow chart. This chapter describes the experimental set-up that is used to cycle the batteries and conduct the aging diagnostic tests. Chapter 6 presents the results of the battery aging, which will be used to develop the aging model and prognostic algorithm in Chapter 7. Chapter 8 is a validation of the prognostic algorithm and aging model from Chapter 7, and Chapter 9 is the summary and conclusion for the research project and thesis. This chapter will also contain recommendations for future work and work that is currently being conducted at CAR.
CHAPTER 2

BACKGROUND

Lead-Acid batteries are the oldest rechargeable batteries in existence. The rechargeable lead-acid battery was invented by French physicist Gaston Planté in 1859. It is speculated that the battery may be much older than this. Some believe that this lead-acid chemistry was used by the Egyptians to electroplate antimony onto copper over 4300 years ago [14].

Even with the new high energy density batteries such as Nickel Metal Hydride and Lithium Ion emerging into commercial markets, lead-acid batteries still dominate in automobiles and large uninterruptible power supply systems. This is the case for several reasons. One, the lead-acid battery is inexpensive and simple to manufacture. Two, it has one of the lowest self-discharge rates of all rechargeable battery systems. Three, it has no ‘memory’. And four, it is capable of very high discharge rates. These advantages, however, come with a price. The lead-acid battery is limited by very low energy density, and the lead content and sulfuric acid electrolyte are not environmentally friendly [14].

2.1 BATTERY CHARACTERISTICS

Batteries are characterized by certain specifications. Likewise, certain terms are used to explain battery operation. These specifications and terms are defined below, and will be used throughout this thesis.

- **Capacity**: The amount of energy the battery can deliver under specific conditions. This is represented in amp-hours (Ah), which means the battery can
provide energy at a rated amount of amps for a certain amount of time. A 50Ah battery can deliver 50 amps for 1 hour or 5 amps for 10 hours, etc.

- **State of Charge (SOC):** The state of charge is a measure of the amount of energy remaining in the battery. It is often displayed as a percent of the battery’s nominal capacity. A 50Ah battery at 50% SOC has 25Ah available for use.

- **Depth of Discharge (DOD):** The opposite of the state of charge. The depth of discharge is the amount of energy removed from the battery, or the amount of replaceable energy. It is also measured as a percent of nominal capacity.

- **State of Health (SOH):** The state of health of a battery is a gauge of the battery’s condition and ability to perform as compared to a new battery. This can also be described as the battery’s age. Most research defines state of health as a percent of the battery’s rated capacity.

- **Specific Energy:** The amount of energy contained within a particular amount of mass. It is expressed as a ratio of energy capability to mass, Wh/kg.

- **Specific Power:** The amount of power contained within a specified amount of mass. It is expressed as a ratio of power capability to mass, W/kg.

- **Calendar Life:** The length of time the battery is able to provide the energy for acceptable performance.

- **Cycle Life:** The number of cycles the battery is able to undergo with acceptable performance.

- **Impedance:** The impedance of a battery is a measurement of its voltage-current relationship as a function of frequency and other variables, such as temperature and SOC. Batteries have energy losses during operation, and these losses may be simply represented as a resistance. It is important to understand that the impedance of a battery is a nonlinear, state-dependent quantity.
• **Power**: The power of the battery is generalized through its ability to provide current. The more powerful the battery, the higher the current it is able to provide.

• **C-rate**: The C-rate of a battery describes the current magnitude provided or given to the battery. A 50Ah battery has a C-rate of 50 amps. If the battery is discharging at 2C, it is discharging at 100A. The C-rate is only a characteristic of the battery through its capacity. It is used to compare different applications with different battery capacities. An application that discharges a 10Ah battery at 1A has the same C-rate (C/10) and therefore the same effect as a 100Ah battery discharged at 10A.

Every battery has different advantages and disadvantages that can often be described based on these characteristics.

### 2.2 Battery Operation

The battery’s primary function is to store energy. This energy is in the form of a voltage potential. Charge separation between the electrodes provides a potential that can give rise to a current flow in the presence of a load. During operation, chemical reactions occur inside the battery at the surface of the electrodes. These reactions are called oxidation-reduction or ‘red-ox’ reactions. The reactions are most simply described as a transfer of electrons, which provide the ability to create electricity. An advantage of chemical (secondary) batteries is their ability to replenish their energy. When the chemical reaction is reversed between the two electrodes, energy can be returned to the battery.

All chemical batteries have the same basic components. Inside each chemical battery there exists four main components.
• **Anode**: The anode is the negative electrode that provides the electrons.

• **Cathode**: The cathode is the positive electrode that collects the electrons.

• **Electrolyte**: The electrolyte is the conductor between the electrodes. It provides the means for electron transfer between the positive and negative electrodes.

• **Separator**: The separator is the medium that prevents transfer of electrons while the battery is at rest. For some batteries, the electrolyte and separator are the same.

The lead-acid battery consists of a lead dioxide cathode and a lead anode. The electrolyte is a sulfuric acid solution. The chemical reactions that occur within this battery are summarized in Table 2.1 [15] and shown in Figure 2.1 [16].

| Positive Electrode: | PbO$_2$ + 4H$^+$ + 2e$^-$ → Pb$^{2+}$ + 2H$_2$O |
|                     | Pb$^{2+}$ + SO$_4^{2-}$ → PbSO$_4$ |

| Negative Electrode: | Pb → Pb$^{2+}$ + 2e$^{-}$ |
|                     | Pb$^{2+}$ + SO$_4^{2-}$ → PbSO$_4$ |

| Full Cell Reaction: | PbO$_2$ + Pb + 2H$_2$SO$_4$ ⇌ 2PbSO$_4$ + 2H$_2$O |
2.2.1 DISCHARGE PERFORMANCE

An ideal battery would provide a flat (constant) voltage during its entire discharge, thus providing the same power output for a constant load demand. Battery energy comes from the voltage difference between the two electrodes. As the battery discharges, these electrodes change in composition, and therefore the voltage between the electrodes changes as well.

As the lead-acid battery discharges, there is an initial drop and partial recovery in voltage known as the coup-de-fouet. Thereafter, the voltage gradually decreases with time. Towards the end of the discharge, as the state of charge of the battery reaches very low
values, the voltage declines very rapidly, which many call the ‘knee’ of the profile. Figure 2.2 shows a typical discharge of a lead-acid battery [17].

![Graph showing discharge profile of a lead-acid battery](image)

**Figure 2.2: Typical Discharge of Lead-Acid Battery**

The discharge profile of these batteries is also dependent on temperature and discharge rate. As the temperature changes, the performance of the battery will also change. Figure 2.3 [17] and Figure 2.4 [18] provide examples of discharge performance at different temperatures. As the temperature decreases, the capacity of the battery decreases. This is easily described through the Arrhenius law, which states that endothermic reactions occur faster in the presence of heat. Placing a battery in a cold environment will therefore reduce the rate of reactions, thus reducing its efficiency.
The discharge rate of the battery affects the voltage curve in a similar fashion. As the discharge rate increases, the voltage curve shifts downward. Figure 2.5 shows this relationship [17].
2.2.2 The Peukert Effect

For lead-acid batteries there is a non-linear relationship with the discharge rate and capacity known as the Peukert effect. The lead-acid battery encounters the Peukert effect more profoundly with higher discharge rates. For example, if one discharges the lead-acid battery at 1C, it will actually take less than 1 hour to discharge completely. Generally, one has to discharge at as low as C/200 in order to accurately calculate the battery’s rated capacity. Table 2.2 provides some example discharge results of a lead-acid battery and its nonlinearity due to the Peukert effect [14].
Table 2.2: Estimated Discharge Time of a 10Ah Lead-Acid Battery

<table>
<thead>
<tr>
<th>Discharge current</th>
<th>C-Rate</th>
<th>Discharge time</th>
<th>End of discharge</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.5A</td>
<td>0.05C</td>
<td>20h</td>
<td>1.75V/cell</td>
</tr>
<tr>
<td>0.1A</td>
<td>0.1C</td>
<td>10h</td>
<td>1.75V/cell</td>
</tr>
<tr>
<td>2A</td>
<td>0.2C</td>
<td>5h</td>
<td>1.70V/cell</td>
</tr>
<tr>
<td>2.8A</td>
<td>0.28C</td>
<td>3h</td>
<td>1.64V/cell</td>
</tr>
<tr>
<td>6A</td>
<td>0.6C</td>
<td>1h</td>
<td>1.55V/cell</td>
</tr>
<tr>
<td>10A</td>
<td>1C</td>
<td>0.5h</td>
<td>1.40V/cell</td>
</tr>
</tbody>
</table>

The Peukert effect can be portrayed through an equation relating available capacity and discharge current. It is most commonly modeled as an allometric function or exponentiation where each battery type has its own Peukert constants to be inserted into the equation. Lead-Acid batteries generally have a Peukert number around 1.1-1.4 [14]. The closer the number is to 1, the less the Peukert effect on the battery. Equation (2.1) shows this relationship.

Peukert’s Equation

\[ Q = I^n \cdot t \]  \hspace{2cm} (2.1)

\( Q \) is the capacity from a C/200 discharge, \( I \) is the discharge current, and \( n \) is the Peukert exponent. \( t \) is the time for a complete discharge at the current \( I \). The equation quantifies how the apparent capacity of the battery decreases disproportionately to a discharge rate increase. For more information on the Peukert effect, consult reference [19].
The equation can also be used to describe battery efficiency. A value close to one indicates efficient battery performance with little loss due to discharge rate differences. If one considers the loss of efficiency to be modeled as a resistor, a battery with a value close to one will have a lower resistance resulting in less energy loss. Figure 2.6 shows the Peukert effect on discharge and capacity [14]. The voltage curves can clearly be seen shifting downward due to the increased discharge rate. Because of the Peukert effect, the 1C discharge does not take one full hour to completely discharge the battery. It only takes about half-an-hour.

Figure 2.6: Peukert Effect on Lead-Acid

2.2.3 **Coup-de-fouet**
The initial dip that occurs in the lead-acid battery’s discharge is called the *coup-de-fouet*. The *coup-de-fouet* is roughly translated in English to ‘crack-the-whip.’ It loosely describes the phenomenon that occurs within lead-acid batteries. It usually occurs when the battery is on a long-term float charge and then suddenly demanded a discharge current [20]. A float charge, also known as a trickle charge, is very common with
operating lead-acid batteries. It is a charging technique that keeps the lead-acid battery continually full of charge by charging it at the same rate at which the battery self-discharges. The battery voltage will drop as expected, but will actually recover and increase after the initial drop. This leads to defining the trough voltage (or peak voltage), the minimum voltage of the initial drop, and the plateau voltage, the maximum voltage of the following increase in voltage. After this phenomenon the battery will discharge and its voltage will decrease as expected.

The best explanation for the *coup-de-fouet* is based on the generation of lead sulfate. The discharge process converts lead dioxide into lead sulfate. This chemical reaction is better facilitated when the lead sulfate molecule is already present. In other words, during the initial moments of discharge, the reaction is slightly less efficient than when the lead sulfate molecules are created [20]. Thus, an initial voltage drop is seen in the discharge, and then it recovers as the chemical reaction becomes more efficient with the generation of lead sulfate. It is important to understand the *coup-de-fouet* of the lead-acid battery cannot be completely explained. The above explanation is the generally excepted version. There are instances, however, that disprove the above explanation. As of today, the exact physio-chemical reason for the *coup-de-fouet* of lead-acid batteries is unknown. Figure 2.7 shows the *coup-de-fouet* region of the discharge [20].
The *coup-de-fouet* also occurs at the onset of a charging current of a fully discharged battery. Figure 2.8 shows the coup-de fouet during charging [20].
2.2.4  Surface Charge
Surface charge is simply the build-up of charge on the surface of the electrode as the battery either charges or discharges. For research that deals with rapid dynamic testing, surface charge can be quite cumbersome. It has the ability to make a ‘good’ battery appear bad, and a ‘bad’ battery appear good through open circuit voltage measurement [15]. If one measures the voltage of the battery directly after a charge, then the voltage will appear very high and possibly above ‘overvoltage’ criteria. This is because of the charge build-up on the electrode. It is recommended to wait at least 4-12 hours for the charge build-up to diffuse, and then measure the open circuit voltage. Additionally, the higher the charge or discharge rate, the larger the surface charge.

Some battery researchers like to describe the coup-de-fouet using a surface charge analogy. During float charging, there is a substantial amount of surface charge on the electrodes. Once a load is applied and the battery switches from charging to discharging, the easily accessible surface charge is quickly displaced causing the sudden voltage drop. In continuation with the discharge the charge within the electrodes must be accessed which is not as easy as removing built-up surface charge [21].

2.2.5  State of Charge and Open Circuit Voltage
Whenever battery experiments are conducted, it is very important to determine the battery’s SOC. Without identifying the battery’s SOC, one cannot properly assess battery performance. This is to say that an aged battery can perform similar to a new battery at a low SOC. In order to properly assess the age or health of the battery, the SOC needs to be estimated.

The battery’s SOC can be accurately estimated from its open circuit voltage, $V_{oc}$, if the surface charge is allowed to diffuse. Our own research has shown that if the battery is at
rest for at least 4 hours, most of the surface charge will diffuse and an estimate of the battery’s SOC can be made. For precise measurement of the battery’s SOC, the battery needs to be at rest (open circuit) for 12 hours. Figure 2.9 provides the SOC-Voc map that is used in this thesis [12]. It is created by partially discharging the battery in steps and then repeating the process through charging. There is an apparent hysteresis involved with this mapping that most research finds for all battery SOC estimation. This is why it is important to rest the battery. The hysteresis is removed if the battery is rested.

Figure 2.9: SOC vs. Voc

2.3 Abusive Operation

The lead-acid battery is well known for its tolerance of abusive conditions. For instance, the lead acid battery can tolerate a wider range of temperatures than most secondary
batteries [14]. However, certain operating conditions will abuse the battery and seriously reduce its performance. This section discusses the operating conditions that can significantly reduce the battery’s life and even cause catastrophic failure.

2.3.1 *OVERCHARGE*

The lead-acid battery can become overcharged if too much charge is forced into the battery. Since the lead-acid battery has such a long history, there are some basic, almost foolproof, methods for charging the battery. One method, which is often used by commercial battery chargers, is a multi-stage charge method that initially controls the charge current, and then switches to control the charging voltage. At first the battery will rapidly charge with a high current until it reaches a specified voltage, then the charger will switch to a controlled voltage and the battery will slowly charge the rest of the way. Figure 2.10 depicts this process [14]. For many applications the battery will then remain at this fixed voltage indefinitely. This process is called float charging and is often used for back-up power systems. The battery will always be fully charged whenever the back-up power might be needed.
Another method involves just the use of a power supply. One can charge a lead-acid battery with a constant voltage or constant current. The charge is turned off when some predefined threshold is reached. Sometimes it is a temperature threshold, or a voltage threshold, etc. These processes must be monitored carefully to prevent overcharging of the battery. Other processes include pulse charge methods which some believe reduce the amount of cell corrosion during charging, but the effectiveness has not been widely accepted [14]. With any charge method, the threshold limits are there to prevent overcharging.

Overcharging for a lead-acid battery comes in two forms, current and voltage. If either of the two is too high, overcharging will occur.
A byproduct of overcharging is heat generation. The energy that is trying to be forced into an already full battery is released through heat. Manufacturers will specify their recommended charge procedure. High temperatures from the excess heat will accelerate the physical failure modes of the battery such as grid corrosion and gassing or venting of oxygen [14]. These physical failure modes are discussed in the Physical Failure Modes section 2.3.4.

2.3.2 Overdischarge
The opposite of overcharge is overdischarge. This occurs when too much energy is removed from the battery resulting in a very low battery voltage. The lead-acid battery should be limited at a specified voltage to terminate a discharge to prevent cell damage. Regular operating conditions generally place this limit at 1.75V/cell [14]. Thus, for a regular 12V six-cell battery, a discharge should terminate at 10.5V. Going beyond this limit will begin to overdischarge the battery. Such abuse can cause cell reversal or even short-circuiting of the battery. These are other physical failure modes that are discussed in more detail in subsequent sections.

2.3.3 Float Voltage Variation
Variation of the float voltage is closely related to overcharging. If the float voltage is too high and charging occurs at a faster rate than the self-discharge of the battery, then overcharging occurs. Additionally, if the float charge is below the rate of self-discharge, then this is known as undercharging and can also damage the battery. Undercharging can lead to sulfation, which is discussed in the next section.
2.3.4 *Physical Failure Modes*

When we discuss the physical failure modes of the battery, we are describing the actual physio-chemical processes that lead to failure. These are different from the energy and power failure modes that are discussed in the Battery Aging section. The energy (or capacity) and power failure modes are failures based on the performance of the battery within a certain application. The physical failure modes generated within the battery cause the failure modes associated with battery performance.

The physical failure modes associated with the lead-acid battery are very similar to other modes found in many other electrochemical cells. These physical failure modes can be the result of abusive operation, but some occur naturally through normal operation. In fact, battery aging is often the result of a combination of these failure modes. Even after abusive operation, some of the faults can be removed and the health of the battery restored; they do not necessarily cause immediate and total failure. The main physical modes of failure for the lead-acid battery are provided in Table 2.3 along with their resulting performance loss characteristics.
Table 2.3: Physical Failure Modes

<table>
<thead>
<tr>
<th>Physical Failure Modes</th>
<th>Performance Lost</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 Corrosion of Battery Components</td>
<td>Capacity</td>
</tr>
<tr>
<td>2 Loss of Water in the Electrolyte</td>
<td>Power</td>
</tr>
<tr>
<td>(Dryout)</td>
<td></td>
</tr>
<tr>
<td>3 Loss of Active Material</td>
<td>Capacity</td>
</tr>
<tr>
<td>4 Sulfation</td>
<td>Mostly Power, some Capacity</td>
</tr>
<tr>
<td>5 Cell Reversal</td>
<td>Catastrophic Failure</td>
</tr>
<tr>
<td>6 High Self Discharge/ Shorted Cells</td>
<td>Capacity</td>
</tr>
<tr>
<td>7 Hydration</td>
<td></td>
</tr>
<tr>
<td>8 Thermal Runaway</td>
<td>Catastrophic Failure</td>
</tr>
</tbody>
</table>

Corrosion of the positive grid contributes to most battery degradation. This failure mode takes place through normal operating conditions, but will accelerate if the battery is operated in abusive conditions such as high temperature and overcharging. Corrosion can also occur at the negative strap, but this is rare. Corrosion of the negative strap occurs in absorbed glass mat VRLA batteries (see the Yuasa Battery section 8.2 for more information about VRLA batteries). The negative strap is often not immersed in the electrolyte and is therefore exposed to a hydrogen environment in the void space above the negative plates. Since the negative plates are often depolarized, the negative strap can corrode and fracture causing premature failure of the battery. Some manufacturing processes now wrap the negative strap in absorbed glass matt to prevent corrosion of the negative strap. Corrosion of the battery components leads to loss of capacity because the build up of corrosion reduces the mass available for the active material to interact with the electrolyte [22].

Loss of water in the electrolyte generally has the same effect for lead-acid batteries as it does for most other chemical batteries. It reduces the conduction of the chemical
reactions, which manifests as an increase in internal resistance. Since the electrolyte content plays a large role in the reactions inside the lead-acid battery, it can also account for a small loss of capacity. If the battery undergoes venting, then there will be less water in the electrolyte. Water loss can also occur by diffusion through the plastic battery casing. Vented lead-acid batteries can be accessed to restore the water supply in the electrolyte, but VRLA batteries cannot be refilled. Many call this failure mode starved electrolyte since it is ‘starved’ of water. The corrosion process will also reduce the amount of water in the electrolyte since it is used in the corrosion process. Although some capacity loss might be noticeable with the loss of water, it will largely cause power loss [14].

Loss of active material on the positive electrode will accelerate the loss of capacity. This generally occurs in overcharging, when excessive gassing may knock active material off a partially corroded positive plate [14]. Within the automotive application, the vibrations of the car can knock active material off the electrode surface. Grid corrosion is essentially lost active material as well since the active material has changed composition and is rendered unusable.

Sulfation occurs naturally through the discharge process and is broken down through the charge process. If the battery undergoes abusive conditions, sulfation can become permanent. Higher discharge rates also increase the growth of sulfation [14]. Operating at high temperatures, leaving the battery on a low state of charge, or simply at open circuit for extended periods will increase sulfation. It is generally not a problem unless it crystallizes into an inactive form, which cannot be re-broken through charging. Permanent crystallization is possible in any circumstance in which sulfation occurs. Sulfation will lead to the loss of capacity and loss of power. The capacity is lost basically due to the loss of active material trapped within the sulfation crystals. Sulfation itself
acts as a layer upon the electrode surface increasing the battery resistance causing loss of power [21].

*Cell reversal* is very rare with lead-acid batteries since they are generally very tolerant of abusive operation, but it is still possible. Cell reversal could happen through a very abusive overdischarge process, but mostly occurs if the cells inside the battery do not match. A weak cell will discharge more quickly and could cause reversal if discharged too low [22].

*High self-discharge* is not common in lead-acid batteries because they remain to be one of the least self-discharging batteries available. A lead-acid battery self-discharges at a rate of approximately 5% a month, which is much slower than the nickel-based and lithium technologies. Repeated deep cycling of the battery will increase the rate of self-discharge. A high self-discharge is a form of capacity loss. Other failure modes, like crystalline formation due to sulfation that mars the separator, can cause high self-discharge and in extreme cases a short circuit. Additionally, if the negative strap corrodes and falls over the top of the separator and connects to the positive plate, then it will result in an electrical short circuit [14].

*Hydration* is the process of lead compounds from the plates dissolving in the water of a discharged cell to form lead hydrate, which is then deposited in the separators. This will cause multiple short circuits between the plates. Hydration is caused by overdischarging or leaving the battery in a discharged condition for an extended period of time [23]. This results in yet another form of capacity loss.

*Thermal Runaway* is the process where the battery destroys itself through internal heat generation. This can occurs through overcharging. The battery naturally heats up
through charging since the reaction is exothermic. If the float charge is set too high, more current is needed to keep the float voltage at the set level as the battery charges. The additional current will then provide more gas generation, which results in more heat generation as the gas undergoes the recombination process. The battery temperature will continue to increase, eventually destroying itself by overheating. A thermal runaway sequence is presented in Figure 2.11 [22].

This can also happen if the battery is charged through constant current charging without any voltage threshold limit. As current continues to be forced through the battery, building up more and more charge, the voltage increases. The charge that cannot be contained within the battery is then transmitted out as heat. The temperature will continue to rise, and the battery will overheat causing catastrophic failure. It is for these reasons that limits for charging must be appropriately set and monitored.
2.4 Battery Aging

An ideal battery is theoretically capable of infinite life. If one is able to continually replace and store all the energy previously used, then the battery will never fail. However, as it is known all too well, batteries eventually die. There are two general aging fault modes (or aging mechanisms) for batteries. They can either slowly loose their capacity eventually becoming unable to provide the energy that is needed to run an operation for the time needed (known as energy or capacity loss), or slowly loose their power capability eventually becoming incapable of providing the power to run the operation (known as power loss). Through repeated cycles of charging and discharging, there are small and permanent damages that cause the battery to never regain its original capabilities. These small damages are a combination of the physical failure modes previously described. This is called battery aging.

Research has been done to relate the aging characteristics of the battery to actual physical failure mechanisms inside of the battery, like how grid corrosion of lead-acid batteries causes energy loss. For our research purposes, we care more about the broader picture. We want to study battery aging, which is often a combination of all the failure modes, physical and performance based. We care more about whether or not the battery is suffering from power loss than whether or not the power loss is caused by loss of water in the electrolyte or sulfation. This section provides a description of battery aging through the two performance-based fault modes.

To describe the two aging fault modes, let us imagine the battery as a tank filled with three imaginary elements. The first element is the water inside the water tank, which would relate to the available charge or useable energy in the battery, or SOC. The second element is the empty space that can be refilled. This relates to the batteries DOD. The last element is an unusable section in the form of rocks. This constitutes the accumulated
aging of the battery. Figure 2.12 shows this qualitative relationship [14].

![Figure 2.12: Water Tank with 3 Sections](image)

If the aging mechanism that dominates the degradation of the battery is capacity loss, then one should imagine a water tank slowly being refilled with more and more unusable rock content. If the aging mechanism that dominates the degradation of the battery is power loss, then one should imagine a water tank that cannot deliver as high a flow as before. Figure 2.13 below illustrates both energy and power loss through the water tank analogy [14].

![Figure 2.13: Water Tanks with Aging Failure Modes](image)

Left: Energy Loss (High Rock Content-Low Available Energy)  
Right: Power Loss (High Internal Resistance-Low Power)
Capacity loss can also come in the form of an elevated self-discharge. As a battery is cycled over time, the self-discharge of the battery can increase. Imagine a water tank with holes in its sides decreasing the available water inside the tank. Figure 2.14 shows a water tank with high self-discharge [14].

![Figure 2.14: Water Tank with Self-Discharge for Loss of Capacity](image)

These two fault modes are all too common for automotive batteries. A power failure is encountered when the battery cannot start the engine. However, if the engine is jumped with another vehicle’s battery, then all operations while the vehicle is operating will act as normal. This indicates that the battery has enough energy to maintain the on-board electronics system of the vehicle, but cannot supply enough current, or power, to start the engine.

A capacity failure is observed when the battery can start the vehicle, but nearly all the electronics in the vehicle once the car has started will not operate. This is because the battery does not have enough energy remaining after starting the engine to act as the necessary buffer to the alternator for the electronics system. (More about the operation of the automotive starter battery can be found in the Battery Cycles chapter.) These fault modes are presented separately for help in understanding the differences between power failure and capacity failure for an automotive starter battery. It is important to understand that these fault modes can develop and occur at the same time.
The lead-acid battery is destined to wear out even under ideal operating conditions. There is no guarantee to how long the battery will be able to perform acceptably under any conditions.

All battery aging is generally characterized through loss of capacity or loss of power. Loss of power is not as heavily considered for lead-acid batteries since they are designed to provide energy for high power applications. Most research focuses on the loss of capacity of a battery, since for most applications this is often encountered first. For most research, a battery is assumed at the end of its life when it drops below 80% of its rated capacity.

Ideal performance of the lead-acid battery can actually operate higher than its rated capacity for a portion of its life. Figure 2.15 describes the ideal battery life for a lead-acid battery [22].

![Ideal Battery Life](image)

**Figure 2.15: Ideal Battery Life**
This thesis investigates beyond the 80% end-of-life criteria. We will see how the battery life evolves well past 80% of the battery’s rated capacity. The purpose of this is due to the fact that within an automotive application, batteries can live well past the 80% threshold without any noticeable degradation in performance.

2.5 Aging Factors

Whenever a battery is used it is subjected to certain conditions, which can have an effect on the battery aging process. There are certain characteristics of the loading (or cycling) conditions that can increase the rate at which the battery will age. They are the DOD, SOC, discharge rate, and operating temperature. This section will describe how these aging factors affect battery life.

2.5.1 Depth of Discharge

In general, the automotive battery is not designed for deep cycling purposes. In fact, as seen in Figure 2.16, the flooded lead-acid battery is likely to only provide a couple hundred cycles with a deep discharge [23]. As the DOD increases, the cycle life of the battery decreases.
2.5.2 STATE OF CHARGE
When we say that the SOC of the battery can affect battery life, we are describing the battery’s nominal SOC. (The nominal SOC for this thesis means the SOC of the battery at the beginning of a cycle.) In general, if a battery is cycled at a lower SOC, it will contribute more to aging than a higher nominal SOC with the same cycle. This is to say that if a battery is cycled around an SOC of 75%, then it will have more life reduction than a battery operated around 100% SOC. This general description comes with one catch. If the cycle has a variable DOD, then there may be no aging differences with the nominal SOC. For instance, a full discharge from a 100% SOC battery will not have any difference to a full discharge from 75% SOC. Here the respective DOD’s are 100% and 75%. While the difference in DOD will cause a difference in life, the nominal SOC will not.
The SOC aging factor for lead-acid batteries is conceptually similar to battery memory in Nickel Cadmium batteries. Battery memory describes how the battery forgets its available capacity. If a Nickel Cadmium battery is not fully discharged occasionally, then it will lose capacity effectively creating a false bottom. For lead-acid batteries, if the battery is never fully charged during its operation, it will lead to permanent sulfation. There are effectively unused portions within the lead grid structure that will cause increased sulfation growth, which can significantly reduce the battery’s life. An occasional full charge of the battery will nearly eliminate this problem.

2.5.3 Temperature
The operating temperature becomes an aging factor primarily because it can increase the effects of the physical failure modes. High temperatures facilitate the corrosion process, thus increasing the degradation of the battery components [14]. Figure 2.17 shows how temperature can reduce the life of the battery [22].

![Figure 2.17: Temperature Effect on Expected Life](image)

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2.5.4 Discharge Rate
There is little available research that has looked into the direct relationship of discharge rate and cycle life for the lead-acid battery, or for many other batteries either. It is known that the discharge rate will increase sulfation in the battery as well as increase the generation of a few other physical failure modes [14]. It is easily suspected that the discharge rate will age the battery much like that of DOD. A larger discharge rate will stress the battery more, much like the larger DOD stresses the battery more. Therefore, we expect that a higher discharge rate will reduce battery life.

2.6 Causes of Normal Aging
Even if the battery is operated under ideal conditions, it will eventually fail. As the battery is used, any combination of the physical failure modes can amass, and the battery will suffer in performance through capacity loss and power loss. For most applications, the main cause of battery performance degradation and ultimate failure is loss of capacity. For the lead-acid battery, the predominant physical failure mode is grid corrosion, which is why the loss of capacity is often considered the only aging mechanism. This thesis has presented battery aging through two fault modes because of the application we are studying. An automotive battery will often fail in power before it fails in capacity. Therefore, we must consider both in our research.

2.7 Experimental Battery
Now that we have discussed all the important characteristics of lead-acid batteries, we can begin to discuss our experimental aging plan. This plan is highly dependent upon the duty cycles that will be chosen for experimental aging. The characteristics of these cycles are dependent upon the experimental battery. For instance, if a cycle demands a full discharge of the battery, the time to run the cycle will depend on the battery’s capacity. Additionally, if the cycle’s current is specified in C-rate, this is also dependent
on the battery’s rated capacity. If the battery’s rated capacity is very large, then our electronic equipment may not be able to supply the high current. The duty cycles we used for experimental aging are described in detail in the Battery Cycles chapter.

The battery we chose for experimental aging is an Exide 60 Premium flooded battery shown in Figure 2.18 [24]. This battery has a reasonable rated capacity of 60Ah. This value should work well for our electronic equipment and cycle requirements. The battery specifications can be found in Table 2.4 [24].

![Exide Battery](image)

Figure 2.18: Exide Battery

Table 2.4: Exide Battery Specifications

<table>
<thead>
<tr>
<th>Exide Battery</th>
<th>Battery Group</th>
<th>Capacity</th>
<th>CCA (0°F)</th>
<th>CA (32°F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Value</td>
<td>75</td>
<td>60Ah</td>
<td>630A</td>
<td>785A</td>
</tr>
</tbody>
</table>
CHAPTER 3
BATTERY CYCLES

This chapter reviews the typical operating conditions for the lead-acid automotive starter battery. These conditions have significant effect on the battery’s slow degradation and ultimate failure. A qualitative approach is taken to identify the cyclic conditions that contribute most towards battery aging. These conditions and characteristics are developed into a set of basis cycles used to experimentally age a set of batteries.

3.1 VEHICLE OPERATION WITH RESPECT TO THE AUTOMOTIVE STARTER BATTERY

The automotive starter battery has two main purposes. They are to start the engine and buffer the alternator. The typical lead-acid battery does very well in this setting. In fact,
compared to other battery technologies, lead-acid still remains the best battery for this system because of its high power capability and tolerance to abusive conditions.

The first loading type the battery encounters is starting the engine. It takes a large amount of power to start an engine. There are many inertial and frictional forces that must be overcome. A large current is needed to supply enough power to energize the system. The lead-acid battery is very successful in providing this large power requirement.

Once the vehicle is on and operating, the alternator supplies the energy and power for the on-board electronics. However, alternators are rated to certain current and power limits. If the electronic load demand exceeds those limits, the current must be supplied from the battery. This is the second loading type the battery encounters. Additionally, the alternator does not accept large transient loads very well. For instance, when the air conditioner inside the car is turned on, a moderate transient load is demanded to start the air conditioner. These transient load demands are also provided by the automotive battery. It is for this reason that the battery is said to act as a buffer to the alternator. It limits, or filters, the load demands on the alternator.

The last loading type the battery encounters is when the engine is off, and the alternator is not generating a voltage potential. Any load demands from the operator must be powered directly from the battery.

Based on this description, we can clearly see three distinct types of loading on a typical lead-acid automotive starter battery. First, we have the Cranking load. This describes the engine starting, high-power, requirement of the battery. Second is what we call the Normal driving load. This consists of all the transient load demands of the battery while
the engine is on. Lastly, we have the **Engine-off** load, which of course describes all the loads on the battery while the engine is off. The combination of these load types encompasses the entire loading range of conventional automotive battery application.

### 3.2 Duty Cycles

The next step is to create duty cycles representing the three load demands of the battery. These three duty cycles generate the basis cycle set since the combination of the three can recreate any loading type the automotive battery can encounter. They will be called the Power cycle, the Normal driving cycle, and the Energy cycle respectively. These duty cycles will be repetitively applied to several batteries in order to experimentally simulate battery aging. The results will provide us with the information for identifying which loading type reduces battery life the most.

As we begin to identify our aging plan with the three duty cycles, we must consider three requirements that affect the duty cycles. First, the aging must be representative of our application. We guarantee this by applying the three representative cycles.

Second, the aging must be accelerated in some fashion in order to speed up the process. This is an important step because a typical car battery under real-conditions will last over five years. There are several ways of accomplishing this by simply utilizing any of the known relationships with the four aging factors and life reduction. We must force a shorter battery life in order to generate results for this project. We accomplish this by increasing the typical DOD, increasing the discharge rate, and operating at a high temperature (45°C). This, however, is a give-and-take relationship. Increasing these factors causes the cycles to be less representative, but it is necessary in order to expedite the aging processes and generate results in a reasonable time frame.
Finally, the duty cycles must identify any differences between the aging factors and any relationship to either of the two aging mechanisms (energy loss or power loss). Since this is one of the first battery aging projects at CAR, we would like to identify which of the aging factors contribute more to battery aging, and whether or not certain aging factors generate energy or power loss more profoundly. This last requirement can only be accomplished through a systematic series of aging experiments that properly control the aging factors. To do this, many batteries need to be experimentally tested, which takes too long. The cycles we chose should give us an indication of which aging factor is more severe.

Fortunately, the three duty cycles provide all of these requirements for our aging plan. They are representative of actual loading for automotive applications, and they inherently test the differences between the aging factors. The **Power** cycle is a high-powered discharge (high discharge rate), with a very small equivalent DOD that represents the Cranking load. The **Normal Driving** cycle is a low-power (small discharge rate), low DOD discharge type with transient behavior that represents the Normal driving load. The **Energy** cycle is in general a very low-power discharge but with reasonably constant and small current load demands that represents the Engine-off load. To accelerate the aging process, the Energy cycle will also be a full discharge. Notice that the Energy and Power cycles are practically opposite each other between DOD and discharge rate with respect to automotive applications. The Normal Driving cycle is effectively somewhere in-between.

The following sections provide detailed descriptions of the three duty cycles that will be applied to batteries for aging research.
3.3 Normal Driving Cycle

The Normal driving cycle is intended to represent the loads encountered while the engine is on. In general, the battery is in constant voltage charging mode while the engine is on. An alternator’s voltage regulator usually sets the battery’s voltage slightly above 14V, which is a moderate voltage for charging the lead-acid battery. A Normal driving cycle would largely consist of constant voltage charging with the transient loads demanded by the onboard electronics randomly interrupting the charging.

We need to determine the magnitudes of these transient loads in order to create a duty cycle for this loading type. Therefore, we set up an onboard data acquisition system to determine the loading of the battery while the engine is on. In order to collect battery data from a real vehicle during operation, a portable data acquisition system is created. Using an inductive current sensor, a voltage divider, a Dell laptop, and a National Instruments DAQ box, a data acquisition system is easily installed on the vehicle.

The system is powered by an inverter through the car’s cigarette lighter port. Additionally, the inductive current sensor is supplied a ±15V source through a voltage regulator and the inverter.

The battery current and voltage are recorded for approximately two months generating a data set of 39 recorded trips. The data is sampled at 1kHz with some sets sampled at 10kHz. They are filtered using a fifth order chebyshev filter with a cut-off frequency of 5Hz and the \texttt{filtfilt} command in Matlab. This command uses the chebyshev filter to filter the data forwards and backwards to remove any delay induced by the filtering.

One of the 39 recorded trips is shown in Figure 3.2. Included in the figure is a green line that shows the zero current. Within the figure a positive current is charging current. The
dashed green line is a 20A discharge current level. This is placed on the figure to help show if the discharge transients peak above 20A.

Let us look more closely at the first 360 seconds of this data where there are a few more significant discharge events. Figure 3.3 provides this plot.

Figure 3.2: Real Driving Data
We can clearly see the discharge events from the voltage plot. Whenever the voltage of the battery drops steadily, we have encountered a more continuous load. Whenever the voltage drop is more of a spike, the load is one of the fast transient loads.

Within Figure 3.3 there is a large voltage change at the very beginning of the plot. This is the cranking event. The cranking current for a typical automobile is usually around 800-900A. Our current sensor is only rated to 100A and cannot properly record this discharge event. Figure 3.4 identifies the cranking event within the current plot.
Recall that we have already identified the cranking event as its own representative cycle. Anything after cranking while the engine is on should be considered for the Normal driving cycle. We will therefore investigate the loading of the battery after the cranking event, which includes the charging after the cranking occurs. Figure 3.5 shows what is excluded from consideration for the Normal driving cycle.

![Figure 3.4: Cranking Event](image)

![Figure 3.5: Excluding the Cranking Event](image)
From these figures we can see that the current rarely breeches the 20A discharge threshold. Without any currents above 20A, it is likely that a Normal driving cycle will not have any significant impact on battery aging.

All of the data sets are investigated for their peak currents after excluding the cranking event and the immediate charging after the cranking event. The current amplitude at every millisecond is placed into a histogram in Figure 3.6.

![Figure 3.6: Real Driving Current Histogram](image)

We can see here that the overwhelming majority of current during normal driving is actually no current at all or a charging current of 1A. In nearly two months of testing, only 27 millisecond instances occurred where the battery current is at 40A discharging. On the charging side, only 39 millisecond instances occurred at 45A.
Figure 3.7 provides the probability density of the real driving current. It is not quite gaussian since its mean is at 0.6221A. The standard deviation of the data is 2.132A.

![Probability Density of Real Driving](image)

**Figure 3.7: Probability Density of Real Driving**

The data confirms that the battery is doing little else in the electric power generating system than constant voltage charging. Aging a battery with a cycle of this nature would be useless since there are no significant load demands to stress and age the battery.

To verify this assessment we can look at the SOC change during the battery operation. We use the same data in Figure 3.2 to calculate the battery SOC in Figure 3.8 and a zoomed in plot in Figure 3.9.
Figure 3.8: Real Driving SOC

Figure 3.9: Real Driving SOC Zoomed In
The SOC is slowly increasing due to the small charging current present during normal driving. This confirms the fact that there are little aging factors present during normal driving. Without any significant aging factors, we can eliminate the Normal driving cycle from the list of aging cycles for experimentation.

3.3.1 **Normal Driving Cycle Decomposition**

Let us look even closer at the driving data. Recall that we are trying to generate a basis set of cycles of which any loading type encountered by an automotive battery could be created through a combination of the basis cycles. Now that we have ruled out the Normal driving cycle as a part of this basis set, will the Energy and Power cycles be able to complete the basis set?

Once again we will use Figure 3.3 as a representative data set for all the recorded data sets (excluding cranking of course). The set contains some very distinct features that resemble the Power cycle and Energy cycle. For instance all the transient loads resemble a cranking event, but smaller in magnitude. Figure 3.10 identifies those similar events.

![Figure 3.10: Load Transients during Real-Driving](image-url)
If the cranking event is scaled down, it would imitate these load transients very closely.

Next, it is important to identify the smaller, more constant, load demands on the battery during driving. Figure 3.11 identifies these load demands. They resemble the Energy cycle due to their constant demand in nature, just on a smaller scale.

Figure 3.11: Nearly Constant Load Demands during Real-Driving

Based on the data sets, we can clearly see that the normal driving is simply a combination of small-scale cranking and continuous discharge events. The Power and Energy cycles are designed to represent cranking and continuous discharges respectively. Therefore, a Normal driving cycle could be generated through a combination of the Power and Energy cycles, which means that the Power and Energy cycles satisfy our basis set.

3.4 Energy Cycle

The Energy cycle is meant to represent typical engine-off discharges while also accelerating the aging of the battery. This cycle is a complete discharge of a 75% SOC battery through constant current loading, and a replacement of charge through constant current charging. Figure 3.12 shows the Energy cycle.
For a 60Ah battery, the discharge current (positive on Figure 3.12) is 30 Amps and the charge current is 10 Amps. As the battery discharges the cut-off for the discharge is a battery voltage of 10.5V. The cut-off for the charging current is a battery voltage of 14V. These values are imposed to keep the battery from overdischarging and overcharging. The 14V threshold also keeps the battery at a nominal 75% SOC. Figure 3.13 provides a plot of the SOC traversed by the Energy cycle.
No matter if the battery is new or old, the voltage cut-offs ensure a constant SOC path. The battery will always cycle from 75% SOC to 0% SOC and back.

Many research projects involving battery aging utilize cycles very similar to the Energy cycle. Applying a cycle of this nature is easily accomplished with little requirements from electronic equipment. Likewise, adjustment of any of the aging mechanisms is quite simple. In fact, most manufacturers apply cycles similar to the Energy cycle when they provide data on battery cycle life versus DOD.

While the Energy cycle is representative of a portion of the real-driving loads of the automotive starter battery, it is highly representative of the real-driving load demands of a wide range of other vehicular applications. For instance, large city transit busses and golf carts encounter operating cycles where they are repeated deep discharges of a nearly fully charged battery. Certain military vehicles operate in the same manner. Many military vehicles must drive to remote locations. Once they are in location and the engine is off, the battery must provide power to any number of surveillance and/or communicative devices onboard the vehicle. In summary, there are many applications that consist entirely of deep repetitive discharges of a battery making the Energy cycle very common for battery research.

3.5 **Power Cycle**

The Power cycle is intended to represent the cranking load of a vehicle while accelerating the aging of the battery. The battery is discharged through repeated pulses of high current and then recharged at constant current. Figure 3.14 provides a visual depiction of the Power cycle.
There are a total of 40, 5 second, high current pulses. The battery is recharged in the same fashion as the Energy cycle. The pulses, however, are not controlled by an electric load and are hence not a pure current sink. Rather, they are simply current loads through a small resistance connected to the battery. This means that the discharge pulses are not constant in amplitude. In fact for a new battery, they peak around 400A, and as the battery loses charge, the final few pulses usually peak around 300A. For an ‘aged’ battery, the pulses peak at 400A for the first few pulses, and then peak at around 100A for the last few pulses. This is due to the fact that the DOD is not constant between the ‘aged’ and new batteries. The timing of the pulses remains constant throughout the aging experiments. As the battery loses capacity, the pulses will remove more charge. Therefore, the DOD of the pulses grows as the battery ages. This means that the SOC of the battery is lower at the end of the discharge pulses. Figure 3.15 shows the SOC traversed with the Power cycle for a new and old battery.
Figure 3.16 shows a closer look at the SOC changes for a few pulses near the beginning of the cycle. For an ‘aged’ battery the change in SOC is greater for the pulse than the new battery.
3.6 Duty Cycle Summary

There are two duty cycles that generate a basis cycle set for the automotive application. They are the Power and Energy cycles. Aging batteries through these cycles allows for accelerated aging while representing real operation as well as providing the opportunity to investigate the differences between two of the aging factors.

Table 3.1: Cycle Characteristics

<table>
<thead>
<tr>
<th>Cycle</th>
<th>DOD</th>
<th>I</th>
<th>T</th>
<th>SOC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy</td>
<td>75%</td>
<td>30A cont.</td>
<td>45°C</td>
<td>75%</td>
</tr>
<tr>
<td>Power</td>
<td>30%-50%</td>
<td>400A peak</td>
<td>45°C</td>
<td>75%</td>
</tr>
</tbody>
</table>

Each cycle is applied at an operating temperature of 45°C. Approximately every two weeks, the cycling is halted, and aging diagnostic tests are applied to the battery. These tests are described in the next chapter, Aging Diagnosis. They are the metrics for estimating the battery’s state of health.
CHAPTER 4
AGING DIAGNOSIS

We understand that the battery ages through either energy loss or power loss, but how do we track its aging? In order to track the battery’s aging, or estimate its health, we must measure parameters that are directly related to the two aging failure modes. A battery suffers from energy loss when its capacity decreases; therefore one aging parameter that must be measured is the battery’s capacity. When the battery suffers from power loss, the battery has a larger internal resistance. Therefore, we must develop tests to measure the battery’s internal resistance.

This section describes the sets of tests that can be used to directly measure and estimate the battery’s capacity and internal resistance. The tests are broken into two groups. The first group is the capacity estimation group, and the second is the resistance estimation group. Within these two groups, we must also discuss which tests could be conducted on-board the vehicle since this research aims at on-board diagnosis and prognosis of the battery. For our research, all of these diagnostic tests are conducted with a rested battery at room temperature.
4.1 **Battery Capacity**

The battery’s capacity is often the best indicator of the battery’s age or health. In fact, most researchers define battery aging as simply the loss of capacity. We must consider aging for an automotive starter battery to include power failure since many batteries within this application will fail through this aging failure mode.

In any case, the battery’s capacity remains the most reliable and consistent estimate on the battery’s health. There are several tests that can be applied to measure and estimate the battery’s capacity.
4.1.1 **Capacity Test**

Measuring battery capacity is well understood and easily accomplished for most applications and remains as the industry standard for measuring battery capacity. The battery is simply brought to full charge, and then discharged at a low rate (to avoid the Peukert effect) for a full discharge. A procedure like this for a typical automotive starter battery could take several days depending on the battery type. An example capacity test result is shown in Figure 4.2. A detailed procedure of the capacity test can be found in the Appendix.

![Capacity Test Graph](image)

**Figure 4.2: Capacity Test**

For lead-acid batteries, the discharge rate is usually no greater than C/20, and the cut-off voltage is 1.75V/cell (10.5V). The capacity test should be conducted at room temperature and the procedure for stabilizing a battery at a specific temperature can be found in the Appendix.
The calculation of the battery’s capacity becomes quite simple. It is the amount of time for a full discharge, \( t \) (in hours), multiplied by the discharge rate, \( I \). Equation (4.1) is the capacity calculation.

<table>
<thead>
<tr>
<th>Capacity Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q = I \cdot t )</td>
</tr>
</tbody>
</table>

A test of this nature cannot be conducted in a conventional vehicle. Therefore, another diagnostic test must be investigated to determine whether or not it can estimate the battery’s capacity onboard the vehicle.

4.1.2 **Coup-de-fouet Test**

The importance of the *coup-de-fouet* for this report is that other research has shown a direct relationship with estimating battery capacity. Both the trough voltage and the plateau voltage are linearly related with capacity loss. Figure 4.3 shows the results from reference [25].
Reference [26] found similar results. Figure 4.4 provides an example of their results.

If a *coup-de-fouet* test can be applied onboard the vehicle, then assessing health, and even predicting life, could prove to be very simple due to the linear relationship. But this is
not the only useful result from the research done by [25] and [26]. They also found linear relationships between trough voltage and operating temperature, and discharge rate. This means that the discharge rate and temperature effects can be removed for estimating the capacity loss. Figure 4.5 and Figure 4.6 show the linear relationships of discharge rate and temperature effect on trough and plateau voltages of the coup-de-fouet [25, 26].

Figure 4.5: Effect of Discharge Rate on Coup-de-fouet

Figure 4.6: Effect of Temperature on Coup-de-fouet
The results found by these research groups present remarkable potential for the "coup-de-fouet"’s use in estimating battery capacity onboard the vehicle. The linear effects of both temperature and discharge rate would make an onboard diagnostic much easier to apply. However, there are certain characteristics that must be tested and proved before this relationship can be applied for prognosis and diagnosis in the vehicle. First, the "coup-de-fouet" is confirmed for batteries that are fully charged and float charged. Inside the vehicle, the battery is never at full charge and is only constant voltage charged while the vehicle is operating. Results from this research have shown the "coup-de-fouet" in batteries below full charge after prolonged periods of rest. Figure 4.7 shows results from other researchers on the effects of the rest period on trough voltage [20]. These results are from batteries at 100% SOC, but not on float charging.

![Figure 4.7: Rest Period with Coup-de-fouet](image)

A longer rest period results in a more profound trough voltage. One must be careful, however, to not rest the battery too long, which could effectively change the SOC due to
In summary, the *coup-de-fouet* is affected by discharge rate, temperature, SOC, and rest period. Research has identified some of these effects. More research is needed to study how lower SOC’s affect these relationships, since an automotive battery is never at full charge. If these relationships carry over to lower SOC’s, then a *coup-de-fouet* diagnostic test would prove to be very beneficial for onboard diagnosis and prognosis.

4.1.3 *RESERVE CAPACITY TEST*

This capacity diagnostic is developed here at CAR using the results from the Energy cycling data (which will be presented in the Aging Results section). This diagnostic uses the slope of the voltage discharge curve to estimate the battery’s remaining capacity. Using Peukert’s relationship, the battery’s capacity can be calculated. For more information about the development of our Reserve Capacity test, please see reference [13]

Figure 4.8 shows a typical result for our Reserve Capacity test. The testing load must be around the magnitude of a C/2 discharge.
The resulting slope of this test then gets compared to the values in Figure 4.9. The amp-hours remaining values provide the amount of energy the battery will be able to provide if the C/2 discharge is maintained for a full discharge (hence the name Reserve Capacity test).
To calculate the battery’s capacity, we must use the amp-hours remaining result with the Peukert relationship from Equation (2.1).

Before we can use this equation, we must first calculate the time for a full discharge, $t$, at the discharge rate, $I$. This calculation uses the amp-hours remaining result from the Reserve Capacity test and the battery’s initial SOC at the beginning of the test (as determined from the battery’s $V_{oc}$ from Figure 2.9). Equation (4.2) shows how to calculate the discharge time $t$.

| Discharge Time Calculation
| $t = \frac{t_{test} + \frac{Ah_{rem}}{I}}{SOC}$ | (4.2) |

Figure 4.9: Amp-hours Remaining
This time value is then input into Equation (2.1, along with the current. The resulting value is an estimate on the battery’s capacity.

This test could be extremely useful on-board the vehicle since it does not need a full discharge of the battery. All that is required is a constant discharge of around 200 seconds from a rested battery. This can easily be accomplished within the vehicle by turning on an electronic load like the rear defrost with the engine-off after the vehicle has been resting for more than four hours.

4.2 Battery Resistance

Since most automotive starter battery’s experience power failure first, the battery resistance becomes the most important parameter in predicting actual battery failure. The following tests provide measurements and estimates on the battery’s resistance.

4.2.1 Engine Cranking

The Cranking test is one of the simplest of all the resistance measurement techniques. When a battery is used to start an engine, the engine’s inductance demands a large instantaneous current from the battery. The battery’s response to this load demand provides a simple resistance calculation by dividing the change in battery voltage with the change in current over that very small time period. Figure 4.10 provides an example cranking test [13].
To calculate the battery resistance from the Cranking test we use Equation (4.3).

Cranking Resistance Calculation

\[
R_{cr} = \frac{\Delta V}{\Delta I} = \frac{V_0 - V_{min}}{I_0 - I_{max}}
\]  

(4.3)

This test can be conducted every time the car is started. All the equipment is already in the vehicle. We would need, however, the capabilities to have a high sampling rate for a few seconds in order to capture the peak current and voltage.
4.2.2 **ELECTROCHEMICAL IMPEDANCE SPECTROSCOPY**

Electrochemical Impedance Spectroscopy (EIS) provides the means for both internal resistance measurement and battery modeling. This process uses a very small sinusoidal voltage input to determine the battery’s impedance through a large frequency range by measuring its current response. References [12] and [27] provide more detailed information on the EIS tests. An example result of the EIS test is shown in Figure 4.11.

![Nyquist Plot of EIS Test](image)

**Figure 4.11: Nyquist Plot of EIS Test**

The EIS software allows for battery modeling from the EIS results. The example data set in Figure 4.11 resulted in a 3rd Order Randle Model for the battery. This model is the fit result within Figure 4.11, and is shown in Figure 4.12.
This software can process nearly any electrical model. Several different models are analyzed with the EIS data and those results can be found in reference [12].

For strictly power loss purposes, this research focuses on the high frequency results of the EIS test. We specifically look at the resistance at high frequency, which in the model is $R_0$. These results are usually very close to the results obtained from other resistance estimation techniques like cranking. Plus, the high frequency resistance seems to be the most consistent aging parameter from the EIS battery modeling results.

This test however, will be impractical to apply onboard the vehicle. Even if only a few frequencies are applied in the vehicle, the electronic equipment needed for good results are very expensive and would not be installed in a typical vehicle any time in the near future.

4.2.3 \textit{Equivalent Circuit Parameter Estimation}

Much like what is done internally from the EIS software, we can conduct our own battery circuit modeling, only this time from a different input. This alternative input is known as a step input. We apply approximately a 5A step input to the battery, and use its voltage response for equivalent circuit parameter modeling. A first order model has been found
to represent the battery response quite well. Figure 4.13 shows an example result of one of the equivalent circuit parameter estimation tests applied to the battery [13]. More information about the step test can be found in references [12] and [13].

![Figure 4.13: Current Input and Voltage Output with Fitted Model Result](image)

An $n^{th}$ Order Randle Model is shown in Figure 4.14. Multiple models are examined using the step response data and these results are discussed in reference [13]. Recall that the EIS results showed a 3$^{rd}$ order Randle Model is sufficient for capturing the entire spectrum in Figure 4.11. For this diagnostic, only a 1$^{st}$ Order model is needed. The need for a higher order model with the EIS test already indicates that these two tests do not correlate.
The resistances found through this means do not correlate well with the resistances found from EIS or cranking. This is most likely due to the difference in input. This input does not excite the same high frequencies as the EIS and cranking tests, which leads to different resistance results. In any case, the frequencies excited are not the most important aspect. We want a consistent measurement with age to provide life prediction. If the step test provides very consistent results with respect to the battery’s aging, then we can consider this a useful test. References [12] and [13] provide more details about the step test.

A test of this nature would not be that difficult to reproduce inside the vehicle. In fact, the battery already undergoes many step-like loads during operation. Any one of these loads could be analyzed and modeled within an algorithm to estimate a battery resistance.

4.2.4 **Milliohmimeter**

The Milliohmimeter is a simple resistance measurement that operates similar to the EIS test with one exception: the milliohm meter only measures the resistance at a frequency of 1kHz. The results from this measurement essentially replicate the results from the cranking test and the EIS test (at 1kHz of course). This test requires an expensive piece of equipment so it cannot be conducted on-board the vehicle, but for laboratory testing, it remains the easiest and fastest way to measure the battery’s internal resistance.
CHAPTER 5
BATTERY CYCLERS AND TESTING EQUIPMENT

This section of the thesis describes the experimental set-up and equipment used to cycle the batteries with the two duty cycles described in the Battery Cycles chapter. It also describes the equipment used for the aging diagnostic tests needed to assess battery life. Instructions for operating all of the test benches can be found in the Appendix.

5.1 TEST BENCH DESCRIPTION FOR BATTERY CYCLING

There are two separate test benches used for battery cycling. These cyclers are used to repetitively cycle the battery to induce accelerated aging. Both cyclers contain separate data acquisition systems, which are operated through a Matlab visual interface (VI) [28].

The battery temperature, voltage and current are all recorded using the data acquisition system. The battery is cycled using a load and a power supply. The load is different for each cycler. The Energy cycle requires a controllable electronic load so that a continuous discharge can be applied to the battery. The Power cycle uses resistors to apply the high current battery discharge. The equipment for each bench is specified in the following sections. A general schematic for both benches is shown in Figure 5.1.
5.1.1 **ENERGY CYCLE TEST BENCH**

The Energy cycle demands a long slow discharge of the battery. The specified discharge current is around C/2, which means one discharge will take approximately 1.5 hours. After the discharge, a charging current of C/6 is used to replace the charge. This means that one cycle of aging will take approximately 6 hours with a new, fully charged battery.

The Energy cycle is operated manually, while the data acquisition system records all the battery data. To begin the cycle, a current of 30A is set for the electronic load. Once the battery voltage reaches 10.5V, which can be seen through the real-time Matlab VI, the electronic load is turned off. At this point, the battery is fully discharged and charging begins. The power supply is set at constant 10A charging. The fuse is switched connecting the battery to the power supply. Once the battery reaches 14V, the power supply is turned off and the fuse is switched back. This process is repeated continuously until the aging diagnostics are applied.
Table 5.1 summarizes the components that make up this test bench.

Table 5.1: System Components for Energy Test

<table>
<thead>
<tr>
<th>Components</th>
<th>Model/Make</th>
<th>Usage Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Electronic Programmable Load</td>
<td>Agilent N3301A</td>
<td>Load Current</td>
</tr>
<tr>
<td>Power Supply</td>
<td>40V/40A Sorenson DHP Series</td>
<td>Supply Current</td>
</tr>
<tr>
<td>DAQ card</td>
<td>NI SCXI-1000</td>
<td>DAQ system</td>
</tr>
<tr>
<td>Desktop PC</td>
<td>Dell</td>
<td></td>
</tr>
<tr>
<td>Current sensor</td>
<td>Honeywell 225A Sensor</td>
<td>Record Current</td>
</tr>
<tr>
<td>Voltage Sensor</td>
<td>Voltage Divider (1:2)</td>
<td>Record Voltage</td>
</tr>
<tr>
<td>Thermocouples</td>
<td>Omega SA1XL-K-72-SRTC</td>
<td>Battery temperature monitoring</td>
</tr>
<tr>
<td>Temperature chamber</td>
<td>Cincinnati Sub-zero CTH-27-2-2-H-AC</td>
<td>Battery temperature control</td>
</tr>
<tr>
<td>Software</td>
<td>Matlab</td>
<td>Interface and Analysis</td>
</tr>
</tbody>
</table>

5.1.2 **Power Cycle Test Bench**

The Power cycle demands high, short discharge rates with the replacement of charge at the end of the cycle. The desired current for this test is essentially the maximum current the battery can provide. A set of high-power resistors is placed in parallel connection to provide the smallest resistance possible. A fully charged new battery will discharge for five seconds just under 500A with these resistors. The resistors used can be viewed in Figure 5.2.
The Power cycle, however, will start at an initial 75% SOC. The peak current draw through the resistors is then around 400A. This discharge is repeated 40 times, and then the battery is recharged. The last few pulse discharges usually peak at around 300A for a new battery and 100A for an old battery. This is due to the lower SOC and therefore lower voltage potential across the resistors. To replace the charge, we once again charge at 10A with a cut-off voltage limit of 14V. The time to conduct the pulse discharges and replace the charge is estimated to be less than one hour.

Table 5.2 summarizes the components used in the Power Test bench.
Table 5.2: System Components for Power Test

<table>
<thead>
<tr>
<th>Components</th>
<th>Model/Make</th>
<th>Usage Notes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impedance Load</td>
<td>N/A - see above</td>
<td>Resistive Load</td>
</tr>
<tr>
<td>Power Supply</td>
<td>10W 50V/200A PowerTen</td>
<td>Supply Current</td>
</tr>
<tr>
<td>DAQ card</td>
<td>NI SCXI-1000</td>
<td>DAQ system</td>
</tr>
<tr>
<td>Desktop PC</td>
<td>Dell</td>
<td></td>
</tr>
<tr>
<td>Current sensor</td>
<td>LEM Hall Effect 500A</td>
<td>Record Current</td>
</tr>
<tr>
<td>Voltage Sensor</td>
<td>Voltage Divider (1:2)</td>
<td>Record Voltage</td>
</tr>
<tr>
<td>Thermocouples</td>
<td>Omega SA1XL-K-72-SRTC</td>
<td>Battery temperature monitoring</td>
</tr>
<tr>
<td>Temperature chamber</td>
<td>Cincinnati Sub-zero CTH-27-2-2-H-AC</td>
<td>Battery temperature control</td>
</tr>
<tr>
<td>Software</td>
<td>Matlab</td>
<td>Interface and Analysis</td>
</tr>
</tbody>
</table>

5.2 Test Bench Description for Aging Diagnosis
The test benches used for aging assessment come in a variety of equipmental set-ups. Some of the diagnostics simply re-use the Energy cycling test bench. For instance, a capacity test is conducted using the Energy cycling test bench. All that it requires is a constant current discharge to 10.5V. Other diagnostics have their own stand-alone systems like the EIS test. The following sections provide details for all the aging diagnostic test benches that do not use the Energy cycling test bench.

5.2.1 Engine Cranking Test Bench
To conduct a cranking test, we need an engine and a data acquisition system capable of high sampling rates. The engine used for this test is a 2-liter Diesel Engine (IVECO
industrial engine) that is mounted in a test cell area at CAR. This engine is concurrently being utilized for exhaust and emissions testing in another project. The advantage of using this engine for the cranking tests is the fact that it will demand a high current from the battery, and it is always kept at room temperature.

Three variables are recorded for this test: the battery current, the battery voltage, and the engine RPM. The battery current is measured from a Fluke current clamp rated at 1000A with a resolution of 1mV/A. The battery voltage is divided in half by a voltage divider and sent directly to a NI Data Acquisition card. The engine RPM is estimated from the ECU of the engine. A Dell Laptop equipped with LabView and a NI DAQCard-1200 is used to sample and record the signals. Figure 5.3 provides a diagram of the set-up.

In the middle of the aging experiments the cranking test engine is moved to a different test cell that is actually close enough to the battery aging test benches that a laptop is no
longer needed. After this move occurred, the NI-DAQ equipment and laptop are replaced with the Energy cycle’s equipment. The current clamp is still used to measure the battery current, but all the signals are sent to the DAQ system of the Energy cycle test bench instead of the portable laptop system described in Figure 5.3.

5.2.2 **EIS Test Equipment**

To conduct an EIS test, the battery is connected to the EIS Solartron. This is a stand-alone unit that comes with software that provides a graphical user interface for both running the test and processing the results. The software is called ZView and ZPlot. The EIS Solartron is shown in Figure 5.4.

![Figure 5.4: EIS Solartron](image)

To run an EIS test the battery is connected to the Solartron, and the test is begun using the ZPlot software. The ZView software displays the results and allows for battery
5.2.3 **MILLIOHMETER**

The Milliohmmeter is an Agilent 4338B. This electronic machine measures the battery’s resistance to a 1kHz voltage signal. It is shown in Figure 5.5. The Milliohmmeter comes with several sets of test leads and an Agilent 16143B mating cable. These are contained within the Agilent 16338A Test Lead Set case.

![Figure 5.5: Agilent Milliohmmeter](image)

To measure the resistance with the Milliohmmeter, the proper leads are connected to the Milliohmmeter and then contacted the leads to the battery terminals. The resistance will be displayed on the Milliohmmeter display.
5.3 Software

The software for the Energy cycle and the Power cycle test benches are designed by B.J. Yurkovich, a Computer Science and Engineering student at the Center for Automotive Research [28]. There are two sets of Matlab VI’s for the two test benches. The first is a simple data acquisition VI for the Energy cycle and the charge portion of the Power cycle. The second is a data acquisition VI that includes a controller. The controller portion simply opens or closes the relay switch to a user specified time profile. This connects and disconnects the battery to the resistors according to the specified time profile.

The program, dubbed ‘DAQ Collector’ receives the signals from the voltage divider, the current sensor and the conditioned thermocouples. The program also allows the user to specify a channel that can be plotted in real-time. Additionally, the program allows for the user to specify the sampling rate and the scaling of the channels. Figure 5.6 provides a view of the interface for the program.
The Power cycle test bench utilizes the same program for data acquisition of the charge portion of the cycle, but this bench is semi-automated for the discharge portion. A contactor is needed to accurately time the pulse discharges. The program used for the pulse discharges sends a user-determined time sequence that specifies when the contactor should connect and disconnect to the resistors to the battery: completing the circuit, allowing for the battery to discharge. When the battery undergoes the charging regime, the same program as in the Energy cycle is utilized. Figure 5.7 shows the VI of the Power cycle control and acquisition for discharging.
Figure 5.7: MatLab VI for Power Cycle Discharges
CHAPTER 6
AGING CYCLING RESULTS

This chapter will provide the results of the aging experiments. As the battery ages, its performance suffers. A simple look at the cycle results will show the effects of battery aging.

Aging assessment tests (diagnostics) are conducted between certain cycles. These test are our means for measuring battery aging. This section provides the results of all the diagnostic tests. The results, however, will be presented in terms of amp-hours and not cycles.

Figure 6.1: Battery Aging
The overall objective of the project is onboard diagnosis and prognosis of the battery life. Therefore, these results are investigated for trends and indications of battery life that can be used for prediction. Each result set will be discussed for its practicality and potential for use within a prognostic algorithm onboard a vehicle.

6.1 Cycling Performance with Aging

Battery aging is the given name for battery performance degradation. Without using any of the aging metrics we have discussed in the Aging Diagnostics chapter (capacity decrease, and resistance increase), we can clearly see performance loss when we compare cycle results. This section provides some general comparisons between a new battery and an ‘aged’ battery under the two aging cycles. It is a slight diversion from the organization of this thesis, but it is a good example of the consequences of battery aging.

Table 6.1, Table 6.2, and Figure 6.2 through Figure 6.5 provide some cycle results for the Energy and Power cycles respectively showing the performance degradation due to aging. The ‘aged’ battery shown in the figures and in the tables is simply the same battery, just after many cycles have been applied.

<table>
<thead>
<tr>
<th>Cycle Characteristics</th>
<th>New Battery</th>
<th>Aged Battery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah Discharged</td>
<td>31</td>
<td>9</td>
</tr>
<tr>
<td>DOD (%)</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>Time for one cycle (sec)</td>
<td>4000</td>
<td>1100</td>
</tr>
</tbody>
</table>
With Figure 6.2 and Figure 6.3 we can clearly see the change in performance of the battery under the Energy cycle. First of all, the time to run a cycle has decreased to basically one fourth of the original time length. This is an expected result of capacity
A reduced capacity would cause a shorter discharge and charge time along with a smaller amount of discharged amp-hours.

**Table 6.2: Power Cycle Performance Comparison**

<table>
<thead>
<tr>
<th>Cycle Characteristics</th>
<th>New Battery</th>
<th>Aged Battery</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah Discharged</td>
<td>19</td>
<td>12</td>
</tr>
<tr>
<td>DOD (%)</td>
<td>30</td>
<td>50</td>
</tr>
<tr>
<td>Voltage minimum (V)</td>
<td>6</td>
<td>2</td>
</tr>
<tr>
<td>Current Peak Range (A)</td>
<td>400-300</td>
<td>400-100</td>
</tr>
</tbody>
</table>

**Figure 6.4: Power Cycle Performance Comparison - Current**
Figure 6.4 and Figure 6.5 show how the Power cycle performance suffers from aging. A new battery can handle the cycle quite well with little performance difference until the last ten pulses. An aged battery could only handle the cycle properly until the third cycle after which the voltage drop and current drop is significant. The voltage of the battery is very low towards the end of the cycle and even lower for the aged battery, which limits the amount of current the battery can provide across the resistors. As the internal resistance of the battery increases, its ability to provide the high current is lost. Additionally, as the capacity of the battery is reduced, the cycle removes more and more charge. This means near the end of the pulses, the SOC is lower as the battery ages, which makes it even more difficult to provide current across the resistors.

Now that we have presented the effects of battery aging, we will discuss the results of the diagnostic tests that are our metrics for measuring and tracking battery aging.
6.2 LIFE VERSUS AMP-HOURS

Typically, research on this topic presents the results based on cycle life. The aging parameters for our research are presented with respect to amp-hours discharged instead of cycles for two reasons. First, by defining life in terms of amp-hours, we attempt to ignore the affects of current magnitude and DOD. Providing the results against cycle count carries with it the distinct cycle characteristics. A cycle must be described through both current magnitude and DOD, whereas an amp-hour needs not to distinguish the two. It inherently combines the current magnitude and DOD. For instance, it may be entirely possible that a 60Ah discharge from a small current and high DOD has the same amount of life reduction as a 60Ah discharge from a high current and small DOD. Figure 6.6 shows the transformation from cycle life to amp-hour life.

The second reason for presenting life in amp-hours has to do with the prognostic algorithm strategy. We rely heavily on an Ah-counting approach, and therefore need battery life in terms of amp-hours. This is described more in the Battery Life Prognosis.
chapter.

As the following results will show, there is limited success in defining life in amp-hours versus life in cycles for neglecting the current and DOD effects. This is to say that we still see differences between the two cycle results, which means the DOD and current magnitude cannot be ignored even when amp-hours are used. However, the second reason for using amp-hours instead of cycles, which deals with the prognostic strategy, is the main reason we present battery life as a function of amp-hours discharged.

6.3 Capacity Results

This section presents the results of the capacity diagnostics discussed in the Aging Diagnostics chapter. Not all of the diagnostics are used during cycling. We only provide the results for the capacity test and the coup-de-fouet diagnostic. The reserve capacity results are discussed in reference [13]. Both the reserve capacity results and the coup-de-fouet results are obtained directly from the battery cycling of the Energy cycle. The capacity test results are for both battery cycles.

6.3.1 Capacity Test Results

The following are the results of the capacity tests for both batteries subjected to the two aging cycles. Recall that the battery subjected to the Energy cycle is dubbed battery N1, and the Power cycle’s battery is battery N2.

Figure 6.7 is a plot of the capacity test results for the Energy cycle with a cubic fitting of the data. It is found that a cubic polynomial can fit the data quite well. This polynomial effectively ‘maps’ the life of the battery in terms of capacity under the Energy cycle. The parameters for the cubic fitting are provided in Table 6.3.
Figure 6.7: Energy Cycle Capacity Results

Table 6.3: Energy Cycle Capacity Fitting

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>( f(x) = a_0 + a_1x + a_2x^2 + a_3x^3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>57.71</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>-0.02679</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>9.241x10^{-6}</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>-1.396x10^{-9}</td>
</tr>
</tbody>
</table>

Figure 6.8 is a plot of the capacity test results for the Power cycle with a cubic fitting whose parameters are listed in Table 6.4. Once again, a cubic polynomial is found to fit the data. This means that battery life with respect to battery capacity within the automotive application can be ‘mapped’ with cubic polynomials.
Both test results are fit with cubic polynomials in an attempt to identify a trend with aging. The results for battery N1 show a very good fitting whereas the results for battery N2 are not as good but still quite reasonable. Since battery N1 had longer life, more data
points are available for the cubic fitting which is another reason for the better fit result. Battery N2 failed very abruptly making it difficult to fit a polynomial into the data set. Plus, there are not very many points to fit with the polynomial. These are the main reasons that would affect the fitting result and cause a lower $R^2$ value.

Let us compare the two result sets as in Figure 6.9.

![Figure 6.9: Capacity Results Comparison](image)

Here we can see that the two ‘life paths’ converge at the same capacity. This is significant for development of an aging model that identifies SOH. Based on these results, one can argue that only one model is needed for half the battery’s life. If life beyond 50% of the battery life is not needed, then a simplified aging model can be used. The major cycle differences can be ignored since the amount of amp-hours discharged to reach 50% capacity is the same.

90
For our application, however, we do care about the battery life past 50% capacity. Therefore, the significant differences in life from each cycle must be considered. Let us now normalize the axis of the result figures. This way we can investigate the life path shape with respect to the two cycles.

![Normalized Capacity Decrease Graph](image)

**Figure 6.10: Normalized Results**

Table 6.5 and Table 6.6 provide the fitting parameters for the normalized curves.
Table 6.5: Normalized Energy Cycle Fitting

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>( f(x) = a_0 + a_1x + a_2x^2 + a_3x^3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>0.9584</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>-1.772</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>2.434</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>-1.464</td>
</tr>
</tbody>
</table>

Table 6.6: Normalized Power Cycle Fitting

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>( f(x) = a_0 + a_1x + a_2x^2 + a_3x^3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>1.001</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>-2.128</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>3.849</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>-2.507</td>
</tr>
</tbody>
</table>

Here we can see that the life paths are quite similar and even converge near zero capacity. This result set shows us the path for capacity loss under automotive application. Remember that the two cycles effectively bracket the extremes of cycling within the automotive cycle. The Energy cycle will provide the longest life, whereas the Power cycle will cause the shortest life. Figure 6.11 has removed the testing result data points for easy visualization of the capacity loss path for an automotive battery.
For implementation within an algorithm, it makes little sense to define zero capacity beyond 1 Ah/Total Ah. Let us use the cubic fitting results to superimpose one more point on the capacity map so that we may force zero capacity to meet at 100% of the total amp-hours. This is shown in Figure 6.12.
It is this mapping that can be used within an algorithm to identify capacity loss with respect to amp-hours discharged.

Table 6.7 and Table 6.8 provide the fitting parameters for the results with the forced x-intercept. Notice that these parameters are practically identical to the previous set. This means that we have not altered the fittings with the forced x-intercept. We have merely re-defined the total life in amp-hours so that the battery will have zero capacity at the total life.
Table 6.7: Normalized Energy Cycle Fitting plus x-intercept

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>( f(x) = a_0 + a_1x + a_2x^2 + a_3x^3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>0.9584</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>-1.955</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>2.964</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>-1.968</td>
</tr>
</tbody>
</table>

Table 6.8: Normalized Power Cycle Fitting plus x-intercept

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>( f(x) = a_0 + a_1x + a_2x^2 + a_3x^3 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( a_0 )</td>
<td>1.001</td>
</tr>
<tr>
<td>( a_1 )</td>
<td>-2.326</td>
</tr>
<tr>
<td>( a_2 )</td>
<td>4.600</td>
</tr>
<tr>
<td>( a_3 )</td>
<td>-3.275</td>
</tr>
</tbody>
</table>

6.3.2 COUP-DE-FOUET RESULTS
The coup-de-fouet phenomenon for this research project was not initially considered. It was not until we began finding coup-de-fouets within our cycles and tests (all conducted at less than full charge) that we began to consider its use as a diagnostic. The coup-de-fouet has reportedly only occurred at full charge of the battery. As these results will show, we found coup-de-fouets at lower SOC’s when the battery had been rested overnight.

This section provides the results of the trough voltages during the Energy cycling. Not every Energy cycle is included because only the cycles that began the day (for an overnight rest period) contained coup-de-fouets. As discussed in the Aging Diagnostics
section, the *coup-de-fouet* occurs at the onset of a discharge. Figure 6.13 identifies where we found *coup-de-fouets* within the Energy cycle.

![Figure 6.13: Coup-de-fouet location](image)

Figure 6.13: *Coup-de-fouet location*

Figure 6.14 provides an example of the *coup-de-fouet* seen at the onset of the Energy cycle.

![Figure 6.14: Energy cycle’s coup-de-fouet](image)

Figure 6.14: *Energy cycle’s coup-de-fouet*
All of the identifiable coup-de-fouets are grouped and plotted with respect to the battery’s capacity in Figure 6.15.

![Coup-de-fouet Results](image)

**Figure 6.15: Coup-de-fouet Results**

It is clear that we do not have a very good trend with capacity loss as other researchers have found. But recall that our data set is not all at the exact same SOC. Rather, our data points are around 75% SOC but they are not perfect. This raises the question as to whether or not this creates (what we will call) ‘SOC error’ (or trough error). Figure 6.16 depicts this point.
We can try to remove the SOC error by restricting our data set to those *coup-de-fouets* that are almost exactly 75% SOC. However, this is not the only known source of error. It is shown by Chris Suozzo that our aggressive charging protocols before a capacity test actually increased battery life [13]. When we use this information for the *coup-de-fouet*, we need to look at the data sets as if they are piecewise sets. Each partition begins and ends when a capacity test is applied.

This means that we have two known sources of error. First is the SOC error. Second is the ‘capacity test error.’ To remove these sources of error, we must restrict our data set to results within a specific SOC range. Additionally, we must partition this data set based on capacity tests. For instance, before Energy cycle 234 and after Energy cycle 258, capacity tests are applied. This means that our capacity test partition lies between cycles 234 and 258. We will restrict this data set to those cycles that began within our specific SOC range. Within this data set, three cycles fell within our extremely tight SOC range. Their results are shown in Figure 6.17.

![Figure 6.16: SOC error for coup-de-fouet](image)
Each partition contains a fitting of the test results within the tight SOC range. These fittings are used to determine the trough voltage difference between the fit result and the other data points outside of our SOC range. Doing this provides us with an approximation for how the SOC affects our trough voltage. Figure 6.18 shows the results for trough voltage and SOC error. Another fitting is applied to this data set. It is this fit result that allows us to attempt to remove SOC error from the *coup-de-fouet* results.
Once again a line fits the data reasonably well with only a few outliers at the lower SOC’s, but we still have the expected trend. Higher SOC’s cause higher trough voltages and lower SOC’s cause the opposite. Let us use this relationship within all of our partitions to remove SOC error. Figure 6.19 and Figure 6.20 are examples of two ‘adjusted’ partitions (removed SOC error).
Figure 6.19: Adjusted Partition (cycles 29-35)

Figure 6.20: Adjusted Partition (cycles 51-76)
For many of our partitions, the data sets resulted in a slightly better fitting. Each ‘adjusted’ partition is fit with another line. These lines represent the theoretical result for the *coup-de-fouet*. It is these fittings that represent the trough voltage if there had been no SOC error or capacity test error. It is as if the cycling is continuous without pauses for diagnostic tests.

Let us know put all the theoretical results into one plot. For example, the first partition will begin at its original point, and the following data points within that partition will follow the partition’s theoretical linear fitting. The next partition will begin at an adjusted point based on their own theoretical linear fitting. This is effectively comparing all the slopes of the partitions. If all the partitions begin to resemble one line, then we could claim that the *coup-de-fouet* results have been removed of all the known error.

![Theoretical Coup-de-fouet Results](image)

*Figure 6.21: Theoretical Coup-de-fouet Results*
When the entire data set has been removed of SOC error and capacity test error, we get a decent trend with aging. Please note that we are not suggesting that we use these results as our diagnostic test onboard the vehicle. Too much manipulation has been done to the data. We simply tried to remove all of the known errors within our data set. Additional research needs to be conducted to utilize the coup-de-fouet as a health assessment. We are merely suggesting here that there is potential for this diagnostic.

We can also look at the coup-de-fouets during the capacity tests. Here we do not have either the SOC error or the capacity test error since these tests are done at full charge and during the capacity test after the aggressive charging.

<table>
<thead>
<tr>
<th>Capacity Test</th>
<th>Trough Voltage</th>
<th>Rest Period (hr)</th>
<th>Capacity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.352</td>
<td>12</td>
<td>1.00</td>
</tr>
<tr>
<td>9</td>
<td>12.71</td>
<td>4</td>
<td>0.49</td>
</tr>
<tr>
<td>10</td>
<td>12.745</td>
<td>4</td>
<td>0.46</td>
</tr>
<tr>
<td>11</td>
<td>12.678</td>
<td>4</td>
<td>0.41</td>
</tr>
<tr>
<td>12</td>
<td>12.778</td>
<td>4</td>
<td>0.39</td>
</tr>
<tr>
<td>13</td>
<td>12.787</td>
<td>4</td>
<td>0.37</td>
</tr>
<tr>
<td>14</td>
<td>12.817</td>
<td>4</td>
<td>0.34</td>
</tr>
<tr>
<td>15</td>
<td>12.827</td>
<td>4</td>
<td>0.29</td>
</tr>
<tr>
<td>16</td>
<td>12.866</td>
<td>4</td>
<td>0.22</td>
</tr>
</tbody>
</table>
Figure 6.22: Energy cycle’s capacity test *coup-de-fouets*

Table 6.10: *Coup-de-fouet* during Power cycle capacity tests

<table>
<thead>
<tr>
<th>Capacity Test</th>
<th>Trough Voltage</th>
<th>Rest Period (hr)</th>
<th>Capacity (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>12.332</td>
<td>12</td>
<td>1.00</td>
</tr>
<tr>
<td>4</td>
<td>12.787</td>
<td>1</td>
<td>0.70</td>
</tr>
<tr>
<td>5</td>
<td>12.787</td>
<td>1</td>
<td>0.57</td>
</tr>
<tr>
<td>6</td>
<td>12.728</td>
<td>4</td>
<td>0.50</td>
</tr>
<tr>
<td>7</td>
<td>12.7</td>
<td>4</td>
<td>0.46</td>
</tr>
<tr>
<td>8</td>
<td>12.77</td>
<td>4</td>
<td>0.47</td>
</tr>
</tbody>
</table>
Not all the capacity tests provided a discernible *coup-de-fouet*. This is because the resting time is only four hours after the charging is stopped. A longer resting time could have provided more *coup-de-fouet* results. The Energy cycle results, however, have a nice linear fitting. The Power cycle results do not. Both results, however, have the opposite trend than expected. The trough voltage is expected to decrease with age. Here, they increase. This may be due to the inconsistencies of the rest period. For instance, the first capacity test rested for approximately 12 hours while the others are around 4 hours. Other research has shown that the longer the rest period, the lower the trough voltage (see Figure 4.7). A proper testing protocol is needed to verify whether or not the *coup-de-fouet* can be used for this application.
Recall that the \textit{coup-de-fouet} was not initially considered for testing during this research project. Therefore, we did not develop any testing protocol to properly investigate the \textit{coup-de-fouet}. Through both the cycling results and the capacity tests we cannot conclude that this diagnostic could be used onboard the vehicle, however, we believe that under proper testing protocols it could be studied appropriately, and its usefulness for onboard diagnosis determined. For now, we can only claim that the \textit{coup-de-fouet} has potential as an onboard SOH diagnostic.

6.4 \textbf{Resistance Results}

This section presents and discusses the results from the resistance diagnostics discussed in the Aging Diagnostics chapter. The diagnostics applied for the two experimentally aged batteries are the cranking test, EIS test, and the step test. Results for the cranking and EIS tests are provided in this section. The results for the step test are provided in reference \cite{13}.

In summary from reference \cite{13}, the step test results showed little discernible trend to identify battery aging through the equivalent circuit parameters. However, there are two parameters that showed somewhat of a reasonable trend for battery aging identification, but only for batteries near end-of-life. Suozzo identified that the capacitance, \(C_1\), and the time constant, \(\tau\), as two parameters within a 1\textsuperscript{st} Order Randle model that could be used for battery health identification near end-of-life.

Also included in this section is a set of results specifically from the Power cycle. We investigate the resistance increase of the battery as the battery is subjected to the Power cycle. This result set is similar to the cranking test in that the resistance is calculated from the change in current and the change in voltage from Equation (4.3).
6.4.1 *EIS and Cranking Results*

The two diagnostics that are consistently applied while the two batteries aged are the EIS and Cranking tests. As the battery ages, the internal resistance increases. Using these two diagnostics, we try to identify a trend or path that the resistance takes towards end-of-life. Included in the result figures are cubic polynomial fittings that are intended to identify this life path for battery resistance. A cubic polynomial is chosen largely based on the expected trend for resistance increase and the results from the capacity tests.

The figures include error bars at each test result. These error bars are calculated from the SOC error during the test. Twice during the battery’s life, a set of tests is applied to investigate the affects of SOC and temperature on battery cranking resistance. This data set provided a means for estimating error based on SOC deviation. These test results are provided in the Appendix.

The results of the Energy cycle resistance measurements are plotted in Figure 6.24, which includes cubic fittings that are specified in Table 6.11. A table of the resistance results can be found in the Appendix.
The Power cycle resistance measurements are plotted in Figure 6.25. The cubic fitting parameters from that figure are provided in Table 6.12. A table of the resistance results can be found in the Appendix.
Both aging cycle results show that the battery tends to be around the five to six milliohm range for most of its life. Just before failure the resistance begins to increase rapidly, and at failure the resistance increases dramatically.

We found similar results for battery resistance as we did for battery capacity. The Energy cycle has a better fitting most likely due to the same reasons discussed in the battery...
capacity results section. The resistance results for the Power cycle, however, are the worst for all the data sets. Because of this, it will be difficult to use ‘life path mapping’ through battery resistance. There is too much scatter within the resistance results. For completeness, we will continue to generate a ‘life path mapping’ with these results in the same manner as the capacity test results.

Figure 6.26 provides both battery results on the same plot. The results clearly show the life differences between the two cycles as seen with the capacity results as well.

These results show that the battery failed whenever the resistance reached above eight milliohms. For prognostic purposes, this can be used as a projected threshold to failure. The closer the resistance gets to eight milliohms, the closer the battery is to failure.
Let us normalize the x-axis of Figure 6.26 so that we may compare the shape of the resistance paths. Figure 6.27 shows us how the resistance will increase with accumulated amp-hours.

![Resistance Increase Comparison](image)

**Figure 6.27: Normalized Resistance results**

Table 6.13 and Table 6.14 provide the fitting parameters from the normalized figure.
### Table 6.13: Normalized Energy Cycle Resistance Fittings

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>$f(x) = a_0 + a_1x + a_2x^2 + a_3x^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_0$ (EIS, Cranking)</td>
<td>5.042, 4.183</td>
</tr>
<tr>
<td>$a_1$ (EIS, Cranking)</td>
<td>6.607, 16.02</td>
</tr>
<tr>
<td>$a_2$ (EIS, Cranking)</td>
<td>-14.07, -40.23</td>
</tr>
<tr>
<td>$a_3$ (EIS, Cranking)</td>
<td>11.6, 29.48</td>
</tr>
</tbody>
</table>

### Table 6.14: Normalized Power Cycle Resistance Fittings

<table>
<thead>
<tr>
<th>Cubic Polynomial</th>
<th>$f(x) = a_0 + a_1x + a_2x^2 + a_3x^3$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_0$ (EIS, Cranking)</td>
<td>4.702, 4.177</td>
</tr>
<tr>
<td>$a_1$ (EIS, Cranking)</td>
<td>7.391, 12.06</td>
</tr>
<tr>
<td>$a_2$ (EIS, Cranking)</td>
<td>-21.30, -26.81</td>
</tr>
<tr>
<td>$a_3$ (EIS, Cranking)</td>
<td>17.21, 17.99</td>
</tr>
</tbody>
</table>

At end-of-life both batteries have reached above the eight milliohm threshold indicating failure. For better visualization, Figure 6.27 has removed the data points so that we can look at the cubic polynomial fittings and what we will call the ‘life path’ through resistance.
Based on our eight milliohm threshold, we can see that the earliest point for expected failure is around 92% of the total life in amp-hours. On the other hand, we might not reach failure until 105% of the total life in amp-hours. This means that failure could occur within a 13% range around the total life in amp-hours. For better visualization, let us highlight the areas where failure can occur in Figure 6.29. We have identified that anything above eight milliohms and beyond 92% of the total life could result in failure.
A life mapping of this nature could be used two different ways. First, if one measured the battery resistance through some onboard diagnostic (like engine cranking), we could try to identify how much life is left in amp-hours. This method is difficult due to the width of the path. If the battery is around six milliohms, then this mapping shows that the battery could be anywhere between 17% and 83% of the total life in amp-hours. This is too wide a margin for prognosis. If the battery is around seven milliohms, the range is narrower, but prognosis would indicate the failure could occur instantly or within 25% of the total life in amp-hours (from 80% to 105%). For the Energy cycle alone, this would be saying that the battery will fail somewhere between 0Ah and 1000Ah. Not a very practical prediction.
The other method for using this map is measuring the amp-hours discharged from the battery instead of measuring the battery resistance. This is the same method discussed with the capacity results. Using this method, we still have the 13% window of failure with respect to the total life in amp-hours. For the Energy cycle, this is an amount of approximately 520Ah. Although it is a smaller window of prediction than the previous method, it is still quite large and not very useful.

Remember that we are basing this mapping off the cubic fitting results. The Power cycle results were not very tightly fit with the cubic polynomial, so we should expect some error, which would generate an even broader prediction for both methods.

Based on these results, we have seen that the battery resistance can fluctuate around five and six milliohms for much of its life. Then the resistance will drastically increase near end-of-life and at failure. More research is needed to narrow this resistance path band so that we can use an Ah-counting technique similar to that discussed with the capacity results. For now, we can only confirm a resistance threshold of eight milliohms for failure. A prognostic algorithm can take this into account when predicting power failure.

6.4.2 **Power Cycle Resistance Results**

Since every cycle of the Power cycle is like a crank of the engine, we can use the cycling results to look closely at the resistance increase. These results are similar to the *coup-de-fouet* results with the Energy cycle, except for resistance, not trough voltage. The first pulse of the Power cycle from each new day of cycling can provide a resistance measurement. The battery is properly rested so the voltage has settled at an identifiable SOC and the drop in voltage is easily obtained. The raw results for this are shown in Figure 6.30.
Although the resistance is increasing, there is not an identifiable trend with aging. As in the *coup-de-fouet* results earlier, these results contain error due to the aggressive charging of the capacity test procedure (capacity test error), and error due to SOC differences (SOC error). This means that these results should be looked at in a piecewise manner since every capacity test had the effect of increasing battery life [13].

Unfortunately, there is simply not enough data to try and remove the SOC error as we did with the *coup-de-fouet* results. We can only investigate removing the capacity test error. This is done in the same fashion as the *coup-de-fouet* results. Partitions are made in between data points that have capacity tests. Each partition is attempted a linear fitting, and the results investigated.
Figure 6.31 provides one of the partitioned data sets (in between capacity tests). Each partitioned set is fit with a line for two reasons. One, it is simple. And two, if the overall resistance results should actually be fit with some curve or polynomial, breaking it up into small enough sections should still allow for linear fittings. In other words, a curve can be represented by a bunch of lines.

![Partitioned Data Set (cycles 70-101)](image)

**Figure 6.31: Partition (cycles 70-101)**

Most of the results show a proper increase in resistance as well as a decent fit result with the line.

In the same fashion as the *coup-de-fouet* results, we can use these partitioned data sets to generate a fictitious data set that contains no ‘capacity test’ error. Figure 6.32 becomes the theoretical data set of resistance results without capacity test error.
These results show that we can get another cubic fitting of the resistance results even with SOC error. A sixth order polynomial fits the data very well. The results also show that if we had not applied the aggressive charging before capacity tests and kept the battery continuously cycling, the battery may have failed significantly faster at around 500Ah discharged. This provides further evidence for Chris Suozzo’s research, which concluded that the charging procedure increased battery life [13]. For our purposes, these results confirm that the resistance increases with aging and increases dramatically near end-of-life.

6.5 Aging Results Summary

The aging results show that the cycle magnitude and DOD cannot be completely ignored since the batteries gave different total life amounts. Up until approximately 50% of the
batteries’ capacity and around 2000Ah discharged, the battery results are quite similar. Therefore, a simplified aging model could be used by neglecting the differences in current magnitude and DOD. Since our research focuses on the entire available life of the battery, these differences cannot be ignored.

A close look at the capacity results for both batteries shows that a cubic polynomial can fit the data. Likewise, a prognostic algorithm could take advantage of these results in order to forecast battery capacity. The resistance results, however, did not have as close a correlation. They seemed to fluctuate as the battery aged, and even the error bars could not account for magnitude of the fluctuations. In any case, these results do show that the battery capacity and resistance are indicators of battery age (one more consistent than the other). If tracked and measured properly, they could be utilized in forecasting battery life in the prognostic algorithm.
CHAPTER 7

BATTERY LIFE PROGNOSIS

This section describes the prognostic algorithm in detail. We use all the experimental aging results to generate a cumulative aging model as shown in Figure 7.1. This model maps battery life based on the cycling conditions. Whenever the battery is discharged, an appropriate amount of life is removed from the battery. This information is input to the prognostic algorithm and with the help of onboard diagnostics a life prediction is provided.

Figure 7.1: Prognostic Algorithm

7.1 DEFINING BATTERY LIFE

The primary objective of the project is to design an algorithm, eventually an
implementable algorithm onboard the vehicle, that is able to estimate the SOH and predict remaining life until failure. The first challenge is to find a suitable way to quantify the life of a battery.

It seems reasonable to assess the life of a battery as a percent of remaining life. A new battery will have a SOH value equal to one (100% of its remaining life) while a value of zero SOH indicates a dead battery.

The prognostic algorithm will attempt to quantify the irreversible damage accumulated within the battery. The variable \( \xi \), called the damage variable, is introduced to quantify the damage inside the battery. The SOH of the battery is simply the reverse of this damage variable as shown in Equation (7.1).

<table>
<thead>
<tr>
<th>Battery State of Health</th>
</tr>
</thead>
<tbody>
<tr>
<td>( SOH = 1 - \xi )</td>
</tr>
</tbody>
</table>

As we know from the Aging Cycling Results chapter, we can characterize the aging of the battery in terms of the variation of two internal parameters: capacity, \( Q \), and resistance, \( R \). The damage accumulated within the battery is therefore due to an increase of the resistance and a loss of capacity. As the capacity of the battery decreases and the internal resistance increases, the damage variable should increase. The damage variable must be defined as some function of the two aging parameters. Equation (7.2) is an average weighting formula to calculate the damage variable.
Battery Damage Variables

\[ \xi = \frac{\alpha_1 \theta_R + \alpha_2 \theta_S}{\alpha_1 + \alpha_2} \]  

(7.2)

\[ \theta_R = \frac{R}{R_f} \]  

(7.3)

\[ \theta_S = 1 - S = 1 - \frac{Q}{Q_0} \]  

(7.4)

Where \( \theta_R \) is the damage component due to the increasing resistance, and \( \theta_S \) is the damage component due to the loss of capacity. The coefficients \( \alpha_i \) are adaptive weighting coefficients to properly weight the overall damage variable according to the major fault mode of the battery. This is to say that if the battery performance is suffering more from power loss, then the damage variable should be weighted more with battery resistance increase. The coefficients \( \alpha_i \) are also adaptive. As the battery ages onboard the vehicle, these coefficients can change based on the predominant failure mode. Figure 7.2 shows the trends for these coefficients.

![Figure 7.2: Trends for the Adaptive Weighted Averaging Coefficients](image)

For now these coefficients are intuitively determined based on the damage component values. However, more battery aging data will allow for systematic identification of these coefficients.
The damage components $\theta_R$ and $\theta_S$ are percents of the allowable damage. For full damage, both values should equal 1 (100% damage). These components are discussed separately in the following sections.

It is important to understand that this definition of battery life is based entirely on our application. Many other applications may not need to consider power failure and therefore do not need to create a damage variable through a weighted average. Since the battery is capable of failing through both fault modes within the automotive application, we must consider both in defining life.

7.1.1 **Damage through Resistance**  
The damage accumulated due to increasing resistance is $\theta_R$. The amount of damage is computed as the ratio between the actual internal resistance $R$ of the battery and the value of the battery’s resistance at the end-of-life, $R_f$. For automotive application under normal driving conditions, the battery will generally fail when the resistance is above $8\,\text{m}\Omega$. Therefore, the $\theta_R$, can be defined in Equation (7.5).

<table>
<thead>
<tr>
<th>Resistance Damage Component</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_R = \frac{R}{8}$</td>
</tr>
</tbody>
</table>

The threshold of $8\,\text{m}\Omega$ is based on experimental results, and it can be different for other applications. This threshold is also slightly premature for failure. Therefore, when implemented onboard the vehicle, the operator will be notified of the eminent battery failure before the battery is expected to fail, which will provide appropriate lead time for replacement or recharge of the battery.
7.1.2 Damage Through Capacity
The damage component, $\theta_{S}$, measures the capacity loss within the battery. This variable is defined in Equation (7.4). $Q$ is the battery’s capacity in amp-hours. $Q_0$ is the battery’s initial or rated capacity. $S$ is the battery’s capacity as a percent of the rated capacity. This damage component is simply the lost capacity of the battery. Most battery applications only need to consider this damage component, which is why SOH is usually defined through battery capacity alone.

7.2 Life Prediction
Now that we have defined a method for considering both power failure and energy failure within the battery’s SOH, we can predict the battery’s remaining life. For the vehicle operator, a life prediction in calendar time or mileage would prove to be the most useful. We can do this through a linear extrapolation of the damage variable as in Equations (7.6) and (7.7).

<table>
<thead>
<tr>
<th>Life Prediction Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>$t_{\text{res}} = \frac{\Delta t}{\Delta \xi} (1 - \xi) = \frac{\Delta t}{\Delta \xi} SOH$</td>
</tr>
<tr>
<td>$\text{miles}_{\text{res}} = \frac{\Delta \text{miles}}{\Delta \xi} (1 - \xi) = \frac{\Delta \text{miles}}{\Delta \xi} SOH$</td>
</tr>
</tbody>
</table>

Where $t_{\text{res}}$ is the residual time for battery life, and $\text{miles}_{\text{res}}$ is the residual miles for battery life. The amount of time it takes, $\Delta t$, to accumulate more damage, $\Delta \xi$, multiplied by the remaining life, $SOH$, will result in the remaining life in time, $t_{\text{res}}$. Here the time or miles variable can be replaced with any desired unit of output. For instance, the Validation chapter uses this formula to predict the battery life in amp-hours remaining instead of...
time or miles.

This is a simple method for prognosis, but it is not unwarranted. Let us consider the assumptions needed for linear extrapolation and the automotive application closely. For linear extrapolation, the conditions in which the data is obtained need to be the same for the data that is forecasted. Patterns must be consistent. For the automotive application, a driver will have a well-defined pattern of driving. Most of the driving will be to-and-from work meaning that the cycling of the battery will be quite similar for most trips. If we investigate a time scale of one day, the variations that a battery might see could be significant. One day could be a regular workday where the car is driven only to and from work. However, another day could be a long road trip to a vacation destination where the vehicle is operated for many hours. While five days out of the week, the driving patterns would be very similar; the other two would be quite different.

Let us now move the time scale back to a week. Now the differences between the workweek and the weekend driving are included within the data set. Week-to-week, there will not be very many deviations from the average week of driving.

What if we consider the weather? Week-to-week, or even day-to-day for that matter, the weather can change significantly. As we have discussed, the operating temperature of the battery is a significant factor in battery aging and, consequently, prognosis. If we continue to move the time scale back further, we will include the weather patterns within the data set. For instance, a time scale of a year will include the seasonal weather patterns in each data set. As in any prognostic method, the more data that is collected, the better the prognostic result. A longer time frame of a year, for instance, will allow for a large data set within the prognostic algorithm. For these reasons, a linear extrapolation can be used as a reasonable method for battery life prediction.
7.3 **AMP-HOUR COUNTING**

We have defined battery life in terms of damage, which is a combination of two fault modes that can occur within the automotive application. But how does this damage variable evolve? To update the damage variable and effectively reduce battery life, we use a method called Ah-counting (a.k.a Coulomb counting).

There are two parts to Ah-counting. First, one needs to define a total amount of amp-hours for battery life. Then, this amount is reduced every time the battery is discharged, and amp-hours are ‘removed’ from the battery. This method provides a rough estimate of the battery’s SOH through a ratio of available or residual amp-hours and the total amount of amp-hours. There are three problems with this approach, however, and they are listed in Table 7.1.

<table>
<thead>
<tr>
<th>Problems</th>
<th>Our Solution</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. How do we define a total life in amp-hours?</td>
<td>Experimental aging results</td>
</tr>
<tr>
<td>2. Not all amp-hours are created equal.</td>
<td>Severity factors</td>
</tr>
<tr>
<td>3. Open loop ‘feed-forward’ approach</td>
<td>Diagnostic feedback</td>
</tr>
</tbody>
</table>

The first problem is the issue of defining battery life. We resolve this problem through our experimental aging results. The two aged batteries allow for direct measurement of battery life in amp-hours. However, this leads to the second problem. These cycles have different cycle conditions and characteristics. These differences mean that not every amp-hour is equal to another. This is to say that one amp-hour discharged under high temperature conditions should reduce the life of the battery more than one amp-hour
discharged at room temperature. We address this problem through the development of a set of severity factors. Whenever the battery is discharged, the cycle characteristics (DOD, I, T, SOC) of the discharge event are factored into the amount of amp-hours of the discharge to appropriately reduce the battery’s life.

The last problem is the fact that subtracting amp-hours from a total amp-hour amount is an open loop system. For better accuracy we need to have some form of feedback to correct the prediction. We can do this through a set of diagnostic tests. If we can apply onboard diagnostics to the battery and directly assess the battery’s SOH, then we can correct our Ah-counting approach by adding or subtracting amp-hours back into the system, which will increase or decrease our life prediction respectively.

7.3.1 **TOTAL AMP-HOUR LIFE**

The results from the aging experiments provide the total amp-hour life amounts as shown in Table 7.2. These amounts are based on the total amount of amp-hours the batteries are able to provide prior to failure. Recall, that the two cycles are essentially the extremes of real driving. Therefore, we have bracketed battery life within the two life amounts based on those cycle characteristics.

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Δ (Total Ah)</th>
<th>Depth of Discharge DOD (%)</th>
<th>Current I (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Cycle</td>
<td><strong>2237.72</strong></td>
<td>30</td>
<td>400</td>
</tr>
<tr>
<td>Energy Cycle</td>
<td><strong>3968.0</strong></td>
<td>75</td>
<td>30</td>
</tr>
</tbody>
</table>

Table 7.2: Total Ah Results
The aging results also provide a mapping of battery capacity with respect to amp-hours. With the map in Figure 6.12 (and re-shown here in Figure 7.3), we can appropriately reduce battery capacity based on amp-hours removed from the battery. It is through this manner that we can update the damage variable. Any time the battery is discharged, the capacity will be proportionally reduced and the capacity damage component will increase. This consequently increases the damage variable, and provides an estimate on battery SOH and life prediction.

Both experimental data sets have very reasonable cubic fittings representing their decrease in capacity as a function of accumulated amp-hours discharged. For our purposes of on-board prognosis, we can use these curves to estimate the capacity of the battery. Figure 7.4 provides a schematic of this process.
Figure 7.4: Ah-counting Schematic

This schematic demonstrates the process of Ah-counting. Any time the battery is discharged, the amount of amp-hours is determined through integration of the battery current. The battery’s capacity is then reduced based on the amount of amp-hours removed. The capacity damage component is updated which updates the damage variable and provides a SOH estimate. This can then be input into the life prediction Equation (7.6 for an estimate on remaining life.

7.3.2 Aging Severity Factors
Recall the four main cycle characteristics that affect battery aging: temperature, SOC, DOD, and current magnitude. These characteristics are developed into four severity factors, $\sigma_i$, that are applied to the amp-hours in the Ah-counting process. These severity factors are used to appropriately weight the severity of each amp-hour removed from the battery.

<table>
<thead>
<tr>
<th>Number</th>
<th>Cycle Characteristic</th>
<th>Severity Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Temperature</td>
<td>$\sigma_T$</td>
</tr>
<tr>
<td>2</td>
<td>State of Charge</td>
<td>$\sigma_{SOC}$</td>
</tr>
<tr>
<td>3</td>
<td>Depth of Discharge</td>
<td>$\sigma_{DOD}$</td>
</tr>
<tr>
<td>4</td>
<td>Current Magnitude</td>
<td>$\sigma_I$</td>
</tr>
</tbody>
</table>
Figure 7.5 provides a schematic diagram for applying the severity factors to the amp-hours cycled, denoted as $\sigma$.

Many experiments are needed to properly estimate the four severity factors. Unfortunately, we do not have enough time to systematically identify all of these severity factors individually. Presently, we have two experimental results and four factors. This is similar to saying that we have two equations and four unknowns. Therefore, for this prognostic algorithm to move forward, we must intuitively generate two severity factors. Based on our knowledge of battery aging, we estimate the severity factor functions for temperature and SOC. The severity factor for SOC, $\sigma_{SOC}$, is estimated to be a linear relationship with life.

<table>
<thead>
<tr>
<th>SOC Severity Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma_{SOC} = \frac{4}{3} SOC$</td>
</tr>
</tbody>
</table>
Qualitatively, this function represents the effects of SOC and battery life. As the battery is cycled at lower SOC’s, its available life decreases. The baseline is set at 75% SOC which is typical for the nominal SOC within the automotive application. Anything below this baseline will reduce life, and anything above will increase it.

The severity factor for temperature, $\sigma_T$, is estimated to be an exponential relationship.

\[
\sigma_T = 1.01 - 0.78 \left( e^{\frac{-1}{3}(46-T)} \right)
\]  \hspace{1cm} (7.9)
The baseline for this severity factor is 25°C, or room temperature. As the battery is cycled at higher temperatures its available life decreases. However, lower temperatures do not add much to life.

Recall that in the Background chapter a similar figure (Figure 2.17) is introduced. This figure has a slightly different relationship for battery life. Our function spans a wider range of temperatures and therefore needs to be defined differently. In Figure 2.17, the baseline temperature is also room temperature and the temperature in which life is halved is about 94°F (34.4°C). Our baseline is the same temperature, and our life is halved at 44°C (111.2°F). If the relationship in Figure 2.17 had been used, we would have to define a piecewise relationship in order to define the life at lower temperatures. Until we experimentally determine the temperature severity and verify it with Figure 2.17, we will
use Equation (7.9) for simplicity.

Now that we have defined two of the severity factors, we can use our experimental results to incorporate our other severity factors with battery life. For the DOD and current severity factors, we will not define them directly against battery life. We do not have enough data to do this. We can, however, incorporate them within a total amp-hour life equation shown in Equation (7.10).

\[
\Lambda = \sigma_{SOC} \sigma_T \left( a \frac{1}{(DOD)(I)} + b \right) \tag{7.10}
\]

This equation determines the total amp-hour life of the battery based on the cycling characteristics. We use the severity factors we defined to proportionally reduce the amp-hour life based on the SOC and temperature. The other two severity factors are incorporated into this equation as factors on battery life. Using the aging results from the two batteries in Table 7.4, we can identify our two unknowns, \( a \) and \( b \).

<table>
<thead>
<tr>
<th>Set</th>
<th>( \Lambda ) (Ah)</th>
<th>DOD (%)</th>
<th>I (A)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Power Cycle</td>
<td>2000</td>
<td>30</td>
<td>400</td>
</tr>
<tr>
<td>Energy Cycle</td>
<td>4000</td>
<td>75</td>
<td>30</td>
</tr>
</tbody>
</table>
Table 7.5: Ah Life Equation Coefficients

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a$</td>
<td>12350 A²hr</td>
</tr>
<tr>
<td>$b$</td>
<td>5280 Ah</td>
</tr>
</tbody>
</table>

Finally, our life estimator equation becomes…

\[
\Lambda = \left( \frac{4}{3} \text{SOC} \right) \left( 1.01 - 0.78 e^{-\frac{1}{5}(46-T)} \right) \left( \frac{12350}{DOD} \frac{1}{I} + 5280 \right) \tag{7.11}
\]

The four main cycle characteristics can be applied to this equation, and an estimate of life in amp-hours can be calculated. For prognostic purposes, any amount of amp-hours discharged will carry with it these four factors. The total life in amp-hours can be calculated as if the battery is to be continuously cycled to death under those conditions. The actual amount of amp-hours discharged can then be normalized by this value, and appropriately applied to the feed-forward approach as a percent of capacity removed. It is in this manner that we can resolve the problems that all amp-hours are not created equal and define a total amount of amp-hours for battery life.

7.4 Diagnostic Feedback

The Ah-counting method needs some form of correction for accurate life prediction. This section presents a set of diagnostic tests that are found under laboratory conditions that have the highest potential for being implemented onboard the vehicle. This set of diagnostics is listed in Table 7.6.
All of these diagnostic tests are described in the Aging Diagnostics chapter. The diagnostic tests are critical to the prognostic algorithm accuracy for two reasons. First, the only way to update the resistance damage component is through the cranking diagnostic. As of now, there is no analogy to Ah-counting for battery resistance, so we can only track the battery resistance increase for power failure by measuring it directly when the engine is started. Secondly, diagnostics are the method for correcting the open loop Ah-counting approach. Therefore, the diagnostics are critical for the algorithm accuracy.

The other three diagnostic tests provide estimates for the battery capacity. All of these diagnostics can be applied during one onboard test. A controlled discharge of a rested battery will allow for the three capacity estimates through the three diagnostics. Figure 7.8 provides an example of such an onboard test.

<table>
<thead>
<tr>
<th>Diagnostic</th>
<th>Reserve Capacity</th>
<th>Cranking</th>
<th>Coup-de-fouet</th>
<th>Step Response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
<td>( \frac{dV}{dt} ) ( \rightarrow ) ( Ah_{rem} )</td>
<td>( R_{cr} )</td>
<td>( V_T ) (Trough voltage)</td>
<td>( C_1, \ Tau )</td>
</tr>
<tr>
<td>Purpose</td>
<td>( \frac{S}{Ah_{rem}} + S_{SV} )</td>
<td>( \frac{R}{R_{cr} = \Delta V/\Delta t} )</td>
<td>( V_T \rightarrow S_{cdf} )</td>
<td>( C_1, \ Tau \rightarrow S_{rnt} )</td>
</tr>
</tbody>
</table>

1. \( SOC = \frac{1}{(V_{oo})} \)
2. \( t = \frac{(SOC, Ah_{rem}, t_{ref})}{Q_0} \)
3. \( Q_{SV} = \frac{1}{n} \)
4. \( S_{SV} = \frac{Q_{SV}}{Q_0} \)
Waking up the vehicle’s ECU and turning on, for instance, the rear defrost of the car could accomplish a test of this nature. This load will be nearly constant at around 30-45A, which is usually around C/2 for a car battery.

This diagnostic test provides extra estimates for battery capacity. It is these estimates that are fed back into the Ah-counting method to correct for errors. For instance, if the Ah-counting method is estimating a 60% capacity, but the diagnostics estimate 70%, then the algorithm will effectively add amp-hours back into the system and adjust the capacity back to around 70%. This diagnostic feedback closes the loop for our Ah-counting method.
7.4.1 Calculating Capacity

When the diagnostic test depicted in Figure 7.8 is applied onboard the vehicle, it means that there are four estimates for the battery’s capacity when the Ah-counting method is included. The algorithm needs only one estimate of capacity to update the damage variable. We will once again utilize a weighted average to create one capacity value for the battery.

### Capacity Weighted Average

\[
S = \frac{\sum_{i=1}^{4} w_i S_i}{\sum_{i=1}^{4} w_i}
\]

(7.12)

Where \( i \) represents the four capacity estimates: \( S_1 = S_{\text{cyc}} \) (the Ah-counting estimate), \( S_2 = S_{\text{Ry}} \) (the reserve capacity estimate), \( S_3 = S_{\text{cdf}} \) (the coup-de-fouet estimate), and \( S_4 = S_{\text{sr}} \) (the step response estimate).

The weighting coefficients, \( w_i \), are based on a number of conditions. Once again, they are adjustable making the capacity calculation another adaptive weighted averaging. First, we want to weight the capacity value based on the confidence in the diagnostic results. A more reliable diagnostic test should have higher weighting in the calculation. Likewise, a failed diagnostic test should have zero weighting. (A diagnostic test could fail, for example, if the driver interrupts the test by turning on another load.) Second, we want the variables to be adaptable. If one diagnostic is showing a clear and expected trend with aging, we want to increase its weighting. Lastly, we want the weighting of an estimate to increase the closer it gets to end-of-life (with respect to the other estimates). For now, the highest confidence will be placed in the reserve capacity estimate, and then
the Ah-counting estimate, thus making $w_2$ greater than $w_1$.

<table>
<thead>
<tr>
<th>Initial Coefficient Weightings</th>
</tr>
</thead>
<tbody>
<tr>
<td>$w_2 &gt; w_1 &gt;&gt; w_3 = w_4$</td>
</tr>
</tbody>
</table>

(7.13)

7.5 **PROGNOSTIC ALGORITHM**

When the Ah-counting method, diagnostic feedback, and capacity calculator are put together, we have our prognostic algorithm. We predict battery life as the damage variable increases through its two components. Figure 7.9 provides a schematic of the prognostic algorithm.

The temperature, current, and voltage of the battery are collected. For every discharge, the battery capacity is adjusted based on the feed-forward approach. This automatically updates the damage variable through the change in capacity damage component, $\theta_c$. When a successful diagnostic test is completed, the results are combined with the feed-forward approach to adjust not only the damage variable but also correct the feed-forward approach’s capacity value. For now, the only estimate for battery resistance is through a
cranking test conducted onboard the vehicle. With more research, it may be possible to create a similar approach with resistance/amp-hours to our capacity/amp-hours approach. It may also be possible to relate resistance directly to battery capacity and predict and catalog battery life through capacity decrease alone [1]. Until these advancements are made, this algorithm depends upon both the well-defined capacity life curve in Figure 7.3, and the diagnostic tests in order to predict battery life.
CHAPTER 8

VALIDATION

This chapter tests the validity of the prognostic algorithm discussed in the Battery Life Prognosis chapter. A ‘near death’ battery is cycled until failure. The amp-hours are counted and diagnostic tests are applied to provide a life prediction. The algorithm is adjusted to predict remaining life in amp-hours. The validation of the algorithm becomes a comparison of the predicted value versus the physical result.

8.1 DOUGLAS BATTERY

In order to expedite the validation process, we used a ‘near-death’ battery. The aging experiments for the Power and Energy cycles took nearly two years of testing before failure is encountered. Therefore, a battery near its failure point should be used in order to meet the deadlines for this project.

This validation battery is a Douglas manufactured battery found in a BMW automobile. The battery has a rated capacity of 75Ah and a cold cranking ampere (CCA) capability of 650 CCA.
The argument behind a SOH of near-death is due to the fact that the battery has failed twice in its ten-year lifetime. After each failure, the battery was trickle charged using a simple lead-acid battery charger, effectively increasing its useful life. This charging procedure extended the life beyond what a typical consumer’s battery would provide.

The validation strategy is listed in Table 8.1.

<table>
<thead>
<tr>
<th>Steps</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Determine the SOH of the battery using diagnostic tests</td>
</tr>
<tr>
<td>2</td>
<td>Cycle the battery to failure</td>
</tr>
<tr>
<td>3</td>
<td>Compare the algorithm prediction with actual end-of-life result</td>
</tr>
</tbody>
</table>

Unfortunately, this battery is so close to end-of-life, that the cycling portion is never reached. The battery reaches end-of-life immediately following the final diagnostic test. The validation strategy must take the first three steps listed above, and squeeze them into
step one. The first successful set of diagnostic tests is used as both SOH identification and a means of life prediction. The last set of diagnostic tests is considered the ‘cycling’ to failure portion. The validation then becomes a comparison between the amount of amp-hours available from the algorithm prediction and the actual amount of amp-hours provided right before failure.

The diagnostic tests that are used in this validation are the Reserve Capacity diagnostic, and the cranking resistance diagnostic. Since we are conducting this validation within a laboratory setting, we can include EIS and Milliohmometer measurements for extra resistance measurements. These diagnostics combined with the Ah-counting approach generate our prognosis for the Douglas battery.

8.1.1 **Test Results**
Provided in Table 8.2 is the series of diagnostic tests applied to the battery. After these diagnostic tests, two capacity tests, two reserve capacity tests, and one step test, are applied to the battery right before failure. These tests will be considered the ‘cycling’ portion for the validation strategy and are listed in Table 8.3. All tests and discharges are conducted at 25°C.
Each test is listed with its respective abbreviation. The SOC is determined through the Voc-SOC relationship from Figure 2.9. The test results are shown in the final column in both resistance values for the resistance tests and capacity values for the two reserve capacity tests. Every discharge event and diagnostic result will update the damage variable and provide a life prediction.

Table 8.3 provides the ‘cycling’ portion for the validation experiments. These values will provide the comparison of amp-hours between the algorithm output and the actual amp-hours provided. To reiterate, these results come from the diagnostic tests right before failure. Two Capacity tests are applied along with a 6A Step test and two Reserve Capacity tests in between.
Table 8.3: Test Results 2

<table>
<thead>
<tr>
<th>Date</th>
<th>Test</th>
<th>Voc</th>
<th>SOC (%)</th>
<th>Ah's Discharged</th>
</tr>
</thead>
<tbody>
<tr>
<td>22-Oct-08</td>
<td>Capacity part1</td>
<td>12.9</td>
<td>87.96</td>
<td>30.49</td>
</tr>
<tr>
<td>23-Oct-08</td>
<td>Capacity part2</td>
<td>12.32</td>
<td>49.75</td>
<td>18.42</td>
</tr>
<tr>
<td>24-Oct-08</td>
<td>mΩ</td>
<td>12.81</td>
<td>82.03</td>
<td>0</td>
</tr>
<tr>
<td>24-Oct-08</td>
<td>Reserve Capacity</td>
<td>12.76</td>
<td>78.74</td>
<td>4.56</td>
</tr>
<tr>
<td>27-Oct-08</td>
<td>Reserve Capacity</td>
<td>12.51</td>
<td>62.27</td>
<td>5.75</td>
</tr>
<tr>
<td>27-Oct-08</td>
<td>6A step</td>
<td>12.38</td>
<td>53.70</td>
<td>0.02</td>
</tr>
<tr>
<td>27-Oct-08</td>
<td>mΩ</td>
<td>12.40</td>
<td>55.02</td>
<td>0</td>
</tr>
<tr>
<td>29-Oct-08</td>
<td>Capacity</td>
<td>13.2</td>
<td>107.73</td>
<td>49.6</td>
</tr>
<tr>
<td>3-Nov-08</td>
<td>mΩ (death)</td>
<td>10.63</td>
<td>0</td>
<td>0</td>
</tr>
</tbody>
</table>

Total 108.84

This table shows that the ‘cycling’ portion of the validation gave 108.84Ah. Recall that not all amp-hours are equal. The Reserve Capacity tests have higher currents with shallower discharge depths. This means that the 108.84Ah has some small error, but for our purposes, it will remain as a sufficient result.

8.1.2 Algorithm Results
To explain the algorithm fully we will move through each iteration the algorithm must make. Whenever a diagnostic test or discharge event occurs, the algorithm provides a new life prediction. First, we must make an initial assumption for the battery SOH before diagnostic testing. Because our Energy cycle battery failed at around 22% capacity, we will assume that the initial capacity before any diagnostic test is 22%. This value along with a resistance measurement of 4.36mΩ provides us with our initial damage variable.
Recall that for a new battery, the internal resistance should be just above 4.0mΩ. Therefore, a resistance damage component slightly above 50% resembles a new battery. This means that our weighting coefficients are in the 4th quadrant of Figure 7.2, i.e., \( \alpha_1 << \alpha_2 \). If we assume \( \alpha_1 = 0.1 \) and \( \alpha_2 = 5 \), then our damage variable becomes 77.54%. Alternatively, our SOH is 22.46%.

Please note that because of the weighting coefficients, the damage variable is largely made of the capacity component. The results of these initial tests show no signs of failure due to resistance, especially when compared to the capacity component. The next test conducted is another resistance test. Here the resistance increased to 4.91mΩ without any discharge events. This means only the resistance damage component will increase, resulting in a slightly higher damage variable.
We now move to the third row of diagnostic testing. Here a discharge event has occurred so the capacity damage component will increase. Since this discharge resembles the Energy cycle, we will use the Energy cycling results for the feed-forward approach. This will continue to be applied for all subsequent discharges since the majority of the discharges are small in magnitude. First, we must assess the conditions of the discharge. A 5A, 25°C, discharge at 51.06% SOC and approximately a 1.67% DOD results in an amp-hour life of 104110Ah. We use this value to determine how much capacity should be reduced from the initial capacity of 22% through the Ah-counting map. The ratio is very small which effectively does not change the capacity damage component.

<table>
<thead>
<tr>
<th>Second Update: Capacity reduction through Ah-counting</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ \Lambda = \left( \frac{4}{3} .5106 \right) \left( 1.01 - 0.78 \left( e^{\frac{1}{5} \left( \frac{46-25}{0.0167} \right)} \right) \left( \frac{12350}{0.0167(5)} + 5280 \right) \right) = 104110Ah ]</td>
</tr>
<tr>
<td>[ \Delta Ah = \frac{Ah}{\Lambda} = \frac{0.1375}{104110} = 1.32e^{-6} ]</td>
</tr>
<tr>
<td>[ S_{cyc} = f(Ah + \Delta Ah) = 0.2199992 ]</td>
</tr>
<tr>
<td>[ \theta_5 = 1 - 0.2199992 = 0.7800008 ]</td>
</tr>
<tr>
<td>[ \xi = \frac{0.1(0.614) + 5(0.78)}{0.1 + 5} = 0.7767 ]</td>
</tr>
</tbody>
</table>
Since we have accumulated a very small amount of amp-hours with this test with essentially no significant change in life, we will not calculate our prediction of the remaining life in amp-hours yet for it will most certainly be a very large number. Instead we will move on to the next test.

The next test has a slightly larger discharge, but is also a diagnostic test. This means that not only will the $S_{cyc}$ be updated, it will be weighted with the $S_{dr}$ to update the damage variable. Here the conditions for the discharge are 30A and approximately a 13.88% DOD with a slightly lower SOC. The DOD is calculated using the latest value of the battery’s capacity. Following the same procedure we get our third update of the damage variable and our first life prediction.

### Third Update: Capacity reduction through Ah-counting and Reserve Capacity diagnostic

$$\Lambda = \left(\frac{4}{3} \cdot 0.4975\right) \left(1.01 - 0.78 \left(e^{-\frac{1}{5}(46-25)}\right)\right) \left(\frac{12350}{0.1388(30)} + 5280\right) = 5460.3 \text{Ah}$$  \hspace{1cm} (8.11)

$$\Delta Ah = \frac{Ah}{\Lambda} = \frac{2.29}{5460.3} = 4.19e^{-4}$$  \hspace{1cm} (8.12)

$$S_{cyc} = f(Ah + \Delta Ah) = 0.2195$$  \hspace{1cm} (8.13)

$$S = \frac{w_1S_{cyc} + w_2S_{rc}}{w_1 + w_2} = \frac{(1)(0.2195) + (2)(0.1050)}{3} = 0.1432$$  \hspace{1cm} (8.14)

$$\theta_s = 1 - 0.1432 = 0.8568$$  \hspace{1cm} (8.15)

$$\xi = \frac{0.1(0.614) + 5(0.8568)}{0.1 + 5} = 0.8521$$  \hspace{1cm} (8.16)
The capacity damage component grew slightly with this discharge event. Without another resistance diagnostic, we assume resistance is constant when we recalculate the overall damage variable and predict remaining life in amp-hours.

First Life Prediction:

\[
Ah_{res} = \frac{0.1375 + 2.29 \cdot 0.767 (1 - 0.8521)}{0.0767} = 4.68
\]  

Therefore our first prediction is 4.68Ah remaining for the Douglas battery. Now that the algorithm has been shown step by step, we will group together the next two diagnostic tests (the cranking and EIS test respectively). These tests are both measurements for the battery resistance, but the cranking test involves a discharge event. Therefore, we must account for a capacity change due to the discharge event using Ah-counting and the last resistance measurement for our resistance increase. This means both the resistance and capacity damage components will be updated.

The conditions for this discharge event will be assumed to be at an average current of 400A, and an approximate DOD of 6.71% from 51.06% SOC. This results in an amp-hour life estimate of 3901.8Ah. The capacity adjustment for this discharge makes \( S_{cyc} \) become 14.29%. Please remember that \( S_{cyc} \) does not start at 21.95% from the last calculation. It starts at the latest capacity value, which is 14.32%.
Fourth Update: Capacity reduction through Ah-counting and Resistance increase

\[
\Lambda = \left( \frac{4}{3} \cdot 0.5106 \right) \left[ 1.01 - 0.78 \left( e^{-\frac{1}{5}(46-25)} \right) \right] \left( \frac{12350}{0.0671 \cdot 400} + 5280 \right) = 3901.8 \text{Ah} \tag{8.18}
\]

\[
\Delta Ah = \frac{Ah}{\Lambda} = \frac{0.72}{3901.8} = 1.85e^{-4} \tag{8.19}
\]

\[
S_{\text{cyc}} = f(Ah + \Delta Ah) = 0.1429 \tag{8.20}
\]

\[
S = 0.1429 \tag{8.21}
\]

\[
\theta_S = 1 - 0.1429 = 0.8571 \tag{8.22}
\]

\[
\theta_R = \frac{6.87}{8} = 0.8588 \tag{8.23}
\]

\[
\xi = \frac{2(0.8588) + 2(0.8571)}{2 + 2} = 0.8579 \tag{8.24}
\]

Notice that the weighting coefficients changed based on the damage component values. Now that the damage component values are practically identical due to the resistance increase, we have weighted them equally.

Second Life Prediction:

\[
Ah_{\text{res}} = \frac{0.1375 + 2.29 + 0.72}{0.0825} (1 - 0.8579) = 5.42 \tag{8.25}
\]
The life prediction increases slightly because there is little change in the damage variable while more amp-hours have been accumulated.

The next diagnostic is once again another reserve capacity test. This discharge event is at a current of 37A, with a 24.5% DOD from a 49.09% SOC. This test also resulted in a $S_{dy}$ of 0.55%. This will drastically change our damage variable and life prediction. We now must change the weighting coefficients for the capacity calculation since the Reserve Capacity result is so low. The $S_{cyc}$ is reduced to 14.23% based on this discharge event.

<table>
<thead>
<tr>
<th>Fifth Update: Capacity reduction through Ah-counting and Reserve Capacity diagnostic</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Lambda = \left( \frac{4}{3} \cdot 1.94 \cdot 10^{-4} \right) \left( 1.01 - 0.78 \cdot e^{\frac{13}{3}(46-25)} \right) \left( \frac{12350}{0.181 \cdot 37} + 5280 \right) = 4654.7 Ah $</td>
</tr>
<tr>
<td>$\Delta Ah = \frac{Ah}{\Lambda} = \frac{1.94}{4654.7} = 4.17 \cdot 10^{-4} $</td>
</tr>
<tr>
<td>$S_{cyc} = f \left( Ah + \Delta Ah \right) = 0.1423 $</td>
</tr>
<tr>
<td>$S = \frac{w_1 S_{cyc} + w_2 S_{rc}}{w_1 + w_2} = \frac{(1)0.1423 + (10)0.0055}{11} = 0.0179 $</td>
</tr>
<tr>
<td>$\theta_s = 1 - 0.1432 = 0.9821 $</td>
</tr>
<tr>
<td>$\xi = \frac{1(0.8588) + 10(0.9821)}{1 + 10} = 0.9709 $</td>
</tr>
</tbody>
</table>
Notice that both the weighting coefficients for the capacity calculation and the damage variable have changed due to the very low Reserve Capacity result.

<table>
<thead>
<tr>
<th>Third Life Prediction:</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Ah_{res} = \frac{0.1375 + 2.29 + 0.72 + 1.94}{0.1955} (1 - 0.9709) = 0.76$</td>
</tr>
</tbody>
</table>

The life remaining prediction is insignificant indicating there is little to no life left within this battery. The Reserve Capacity result of 0.55% has significantly reduced our life prediction.

The final two diagnostic tests are once again resistance measurements. The first is a capacity test that contains a discharge event, and the last is a Milliohmmeter measurement. We will apply these results in the same fashion as the previously grouped diagnostic results of resistance tests. The conditions for this discharge are an average current of 400A and an approximate discharge of 66.2% from an SOC of 58.9%. A DOD larger than the SOC technically means that the battery is overdischarged. These percentages, however, are calculated based on the latest value of the battery’s capacity. This estimate, as in all estimates, will contain some error. Mathematically, it looks like the battery is overdischarging, but the battery may actually be operating properly. These conditions result in an amp-hour life estimate of 4176Ah. The capacity is reduced by the normalized fractional amount, which results in a $S_{cyc}$ of 1.76%. When combined with the last resistance measurement we have our final damage variable value.
Sixth Update: Capacity reduction through Ah-counting and Resistance increase

\[ \Lambda = \left( \frac{4}{3} \cdot 0.5890 \right) \left( 1.01 - 0.78 \left( e^{-\frac{1}{5}(46-25)} \right) \right) \left( \frac{12350}{0.5353 \cdot 400} + 5280 \right) = 4189.8 \text{Ah} \]  \hspace{1cm} (8.33)

\[ \Delta \text{Ah} = \frac{\text{Ah}}{\Lambda} = \frac{0.72}{4189.8} = 1.72e^{-4} \]  \hspace{1cm} (8.34)

\[ S_{\text{cyc}} = f(\text{Ah} + \Delta \text{Ah}) = 0.0176 \]  \hspace{1cm} (8.35)

\[ S = 0.0176 \]  \hspace{1cm} (8.36)

\[ \theta_S = 1 - 0.0176 = 0.9824 \]  \hspace{1cm} (8.37)

\[ \theta_R = \frac{6.96}{8} = 0.87 \]  \hspace{1cm} (8.38)

\[ \xi = \frac{1(0.87) + 10(0.9824)}{1 + 10} = 0.9722 \]  \hspace{1cm} (8.39)

Third Life Prediction:

\[ \text{Ah}_{\text{res}} = \frac{0.1375 + 2.29 + 0.72 + 1.94 + 0.72}{0.1968} (1 - 0.9722) = 0.82 \]  \hspace{1cm} (8.40)

**Table 8.4: Life Prediction Comparison**

<table>
<thead>
<tr>
<th>First Comparison</th>
<th>Prediction</th>
<th>Physical Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah</td>
<td>0.82</td>
<td>108.84</td>
</tr>
</tbody>
</table>
This results in an amp-hour remaining life prediction of 0.82Ah. The battery is physically able to provide 108.84Ah after the final diagnostic test. Therefore, our prediction is on the short side. There are two main reasons for the difference. First, the prognostic algorithm is designed to predict end-of-life before it actually happens, which is largely accomplished through the 8mΩ threshold. This way the consumer will never have to deal with a dead battery. Second, the prediction must follow the linear extrapolation requirements. A linear extrapolation assumes that the future discharge conditions of the battery will be, on average, the same as all the previous discharge conditions. This is not really the case for this validation strategy. Recall that this is a ten year-old battery that had been subjected to changes in temperature through all the seasonal variations, and of real operation, and real driving cycles, etc. The diagnostic tests applied to this battery for validation do not really emulate the average conditions through which this battery has been aged.

This algorithm, however, is not completely invalid. It did predict failure on the short side, as it is designed to do. Likewise, this battery by all indications was very near failure, which this algorithm had predicted with its 0.82Ah prediction. This wide margin between the prediction and the physical result does not necessarily invalidate the algorithm; it is rather a first step at creating a better algorithm.

What if we could remove the two sources of error discussed above for a better comparison? We can remove the pre-failure threshold of 8mΩ by only considering the capacity damage component in the damage variable. If we do this, then we can also remove the linear extrapolation requirements by predicting life through the expansion of our cubic capacity-Ah mapping.
The final capacity result is 1.76%. Using the capacity-Ah map from the Ah-coulomb counting method, we see that the battery is at 99.07% of the total life in amp-hours. If we use the cycle characteristics of the 108.84Ah physical result, we can get a life prediction. Of course, we cannot do this in real life because we do not know the future cycle characteristics. For this comparison we will use the capacity test cycle characteristics since the majority of the 108.84Ah are under those conditions. For a capacity test, the SOC and DOD of the cycle is 100%. The current is 3.3A.

Second Comparison: Using only capacity component

\[
\Lambda = \left( \frac{4}{3} \right) \left( 1.01 - 0.78 \left( e^{-\frac{1}{5}(46-25)} \right) \right) \left( \frac{12350}{(1)(3.3)} + 5280 \right) = 12009 \text{Ah}
\]

\[
\text{Ah}_{rez} = \Lambda (1 - 0.9907) = 12009(1 - 0.9907) = 111.68
\]

Table 8.5: Alternative Comparison

<table>
<thead>
<tr>
<th>Second Comparison</th>
<th>Prediction</th>
<th>Physical Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah</td>
<td>111.68</td>
<td>108.84</td>
</tr>
</tbody>
</table>

This prediction is less than 3% off from the physical result. We could conduct this second comparison because we knew the cycle characteristics of the last cycle, and because of the manner in which this battery failed. If it had not been failing largely through capacity loss, we would not have been able to ignore the resistance component.

Both predictions are dependent on the initial capacity estimate. In a real world application, this would not be a problem because the algorithm would always start at
100% capacity with a new battery. Let us use a different initial capacity of 11%, which is just slightly above the first diagnostic result. If we use all of the same weighting coefficients as we did above, we get a new life prediction of 1.56Ah. By reducing the initial capacity by half, we have effectively increased our life prediction by twice the original amount. If we only look at the capacity-Ah mapping, we get a final capacity value of 1.43%, which translates to a life prediction of 90.07Ah.

<table>
<thead>
<tr>
<th>Third Comparison</th>
<th>Prediction (Ah)</th>
<th>Physical Result (Ah)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Algorithm</td>
<td>1.56</td>
<td>108.84</td>
</tr>
<tr>
<td>Capacity Only</td>
<td>90.07</td>
<td>108.84</td>
</tr>
</tbody>
</table>

For the full algorithm prediction, the prediction improved slightly. The opposite is true for the capacity only prediction.

This is the first set of results for this prognostic algorithm. The full algorithm does as it is designed; but due in part to the validation procedure, the final life prediction is not very accurate with the physical result. When we remove some of the problems involved with the validation procedure, we get a much better life prediction.

More research should be done to tune the weighting coefficients for proper life prediction. Additionally, more data from batteries that are experimentally aged to failure will help generate a more global prognostic algorithm.

At this point, we have investigated predictions using only the capacity life mapping, but what if we did the same for the resistance life mapping in Figure 6.29? The last
resistance measurements showed a battery resistance of 6.96mΩ. Since our resistance mapping has such a wide band, let us provide a range of amp-hours for expected failure. Table 8.7 provides a comparison of the physical result and the predicted range of failure.

Table 8.7: Resistance Prediction

<table>
<thead>
<tr>
<th>Resistance Prediction</th>
<th>Prediction</th>
<th>Physical Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah</td>
<td>Earliest Failure</td>
<td>0</td>
</tr>
<tr>
<td></td>
<td>Latest Failure</td>
<td>2756.07</td>
</tr>
<tr>
<td></td>
<td></td>
<td>108.84</td>
</tr>
</tbody>
</table>

Figure 8.2 shows how these values are obtained. A value of 6.96mΩ can fall within the failure region so the earliest possible failure is 0Ah. The latest possible failure is from the earliest point on the life path to 105% Ah/Total Ah. At 6.96mΩ, the earliest amp-hour ratio is 82%. This means that the latest failure is from 82% to 105% Ah/Total Ah. Based on the cycle characteristics discussed above, this results in an amp-hour prediction of 2756.07Ah.
This prediction range is too wide for a useful life prediction, which is why it is not included within the algorithm. Further testing is needed to narrow the resistance life mapping band so that a more precise prediction can be obtained. This is one of the reasons that the resistance component for damage within the algorithm does not use life mapping like the capacity component, but rather a simple percent difference from the expected failure threshold of 8mΩ.

8.2 Yuasa Battery

A second battery is used for validation of the algorithm, but this battery is not as ‘near death’ as the Douglas battery. This validation battery is a Yuasa manufactured battery found in a Honda Accord. The battery has a rated capacity of 45Ah and a cold cranking
ampere (CCA) capability of 410 CCA. This battery is only 5 years old and failed twice over the previous winter.

This battery is also a sealed lead-acid battery, which makes it different than the other batteries used for this project. This fact may cause problems for the validation since this battery is varies in composition from the regular flooded lead-acid batteries.

A sealed lead-acid battery is also known as a Valve Regulated Lead-Acid (VRLA) battery, which is a better description of its ability. The VRLA battery is designed to recombine the oxygen with the hydrogen and prevent water loss (see 2.3.4 Physical Failure Modes). Only when the battery is under high pressure, will the valves open and the oxygen emitted from the battery. So the battery is not necessarily ‘sealed’. It will allow the venting of gasses under operation. The advantage of maintaining the oxygen is for efficient recharging and to help prevent ‘starving’ of the electrolyte. Likewise, since the valves only open when a certain pressure limit is exceeded, the battery can be mounted in any orientation. This design helps prevent spills and maintenance for the
lead-acid battery. For these reasons, a VRLA battery is also called a ‘Maintenance Free’ battery [29].

They can also be called an Absorbed Glass Mat (AGM) or Gel batteries, both are subsets of VRLA batteries. These nicknames are based on the cell design. Instead of pouring the sulfuric acid electrolyte in between the lead plates found in regular flooded lead-acid batteries, the AGM battery uses a matting of fine glass fibers that absorb the electrolyte. The Gel battery contains a gelatinous electrolyte where the sulfuric acid is mixed with a silica fume to make the electrolyte more of an immobile gel [29].

Because of these design differences, this battery may be difficult for use in validating our algorithm. However, due to the limited availability of ‘near death’ batteries, and the completion date of the project nearing, we decided to test our algorithm on this battery.

With this battery there is no need to readjust the validation strategy from Table 8.1. This battery lived through the preliminary diagnostics and nearly 70 cycles until death. The cycles applied to this battery are described in the following section, Yuasa Validation Cycle.

The diagnostics used for this validation are the Reserve Capacity test and the Milliohmometer. By using only these two diagnostics, it helps expedite the process even further. The Reserve Capacity test can be applied during cycling, which limits the number of times the cycling must be halted for diagnostics, and the Milliohmometer is the easiest and fastest way to measure the battery resistance. These diagnostics along with the Ah-counting method will provide a life prediction through the algorithm in the same manner as the prediction with the Douglas battery.
8.2.1 *Yuasa Validation Cycle*

The cycle used for the Yuasa validation is very similar to the Energy cycle. It is a discharge of 22.5A, which is a C/2 discharge. This is an important specification because it allows us to use the Reserve Capacity test during cycling. The battery is brought to a full discharge by stopping the discharge at a voltage of 10.5V. The SOC of the battery, however, starts at around 86% instead of 75%, so we are effectively applying a nearly full discharge of 86% DOD.

The charging portion of the cycle differs from the Energy cycle. To emulate real driving even further, we use a constant voltage current-limited charging protocol. The power supply for charging is set at 15.5V and limited to 25A. This allows for faster charging of the battery, while representing real driving that much more. The charging is stopped when the current reaches below 2A.

![Figure 8.4: Yuasa Validation Cycle](image)

Lastly, the cycle is also applied at room temperature instead of 45°C. Table 8.8 provides the cycle characteristics for the Yuasa validation cycle.
Table 8.8: Validation Cycle Characteristics

<table>
<thead>
<tr>
<th>Cycle</th>
<th>DOD</th>
<th>I</th>
<th>T</th>
<th>SOC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yuasa Val.</td>
<td>86%</td>
<td>22.5A cont.</td>
<td>25°C</td>
<td>86%</td>
</tr>
</tbody>
</table>

8.2.2 TEST RESULTS
The Yuasa battery lasted through two months of testing before it reached an end-of-life above 8mΩ. The only diagnostics used during the testing are the Reserve Capacity test and the Milliohmmeter. The results of these tests are provided in Figure 8.5 and Figure 8.6. Results from the first few weeks will be used in the algorithm for a life prediction and compared to the physical result in the same fashion as the Douglas battery validation. The accumulated Amp-hours from the testing and cycling are provided in Figure 8.7.

![Reserve Capacity Test Results](image)

Figure 8.5: Reserve Capacity Test Results
The very first Reserve Capacity test resulted in a capacity of 13.9%. After this initial test, the capacity seemed to fluctuate around 22% reaching its lowest value of 11.56% at the 21st day of testing. The algorithm will use all the Reserve Capacity results from this day and prior to generate a life prediction.

The jumps in capacity estimates are likely a result of capacity tests conducted on days 3, 5, 8, 23, 29, 50, and 64. Notice that the capacity results increase on days following the capacity tests. Once again, it seems that the capacity test procedure helps increase battery capacity immediately following the test.

![Milliohmometer Results](image)

**Figure 8.6: Milliohmometer Results**

The Milliohmometer results show how the battery resistance increased throughout the testing period. The battery first reached over the 8mΩ on day 57. Another week of cycling and testing ensued to ensure its end-of-life, and on day 66 the resistance reached
well over the threshold confirming its end-of-life. The resistance measurements from day 22 and prior are used within the algorithm to generate a life prediction. The last measurement before the prediction resulted in 7.02mΩ.

![Graph showing Accumulated Amp-hours](image)

**Figure 8.7: Accumulated Amp-hours**

Figure 8.7 shows the accumulated amp-hours of the testing and cycling. The prediction through the algorithm is made after the 24th day of testing. At the end of this day, the battery is capable of providing 375.29Ah. This value will serve as the physical result for validation.

### 8.2.3 *Algorithm Results*

Based on the results from the Reserve Capacity test and the Milliohmmeter, we can estimate an initial value for our damage components. The highest value of capacity from the Reserve Capacity results is 38%, so we will make this the initial value. In order for
the algorithm to provide a positive life prediction, we need to make sure the initial capacity is equal-to or greater-than all the capacity measurements. The first Milliohmometer test resulted in 6.98mΩ, which will be our initial resistance component.

<table>
<thead>
<tr>
<th>Initial Damage Components</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\theta_R = \frac{6.98}{8} = 0.8725$</td>
</tr>
<tr>
<td>$\theta_s = 1 - 0.38 = 0.62$</td>
</tr>
</tbody>
</table>

The resistance component shows more damage than that of the capacity component and should therefore be weighted higher in calculation of the damage variable. With a weighting ratio of 2:1, the initial damage variable is around 79%, making the SOH of the battery 21%.

<table>
<thead>
<tr>
<th>Initial Damage Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\xi = \frac{2(0.8725) + 1(0.62)}{2 + 1} = 0.7883$</td>
</tr>
</tbody>
</table>

The diagnostic results and the Ah-counting method are used in the same fashion as the Douglas battery validation. After the 24th day of testing, the algorithm provides a prediction of 327.10Ah.

<table>
<thead>
<tr>
<th>First Comparison</th>
<th>Prediction</th>
<th>Physical Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah</td>
<td>327.10</td>
<td>375.29</td>
</tr>
</tbody>
</table>

This prediction is much better than the Douglas battery results. This is due to the fact that this battery accumulated much more Ah during testing before death than the Douglas
battery. So few amp-hours had been accumulated with the Douglas battery with such a large capacity decrease that it forced the prediction to be incredibly small. Here, the Yuasa battery seems to be failing more slowly allowing the algorithm to make a better prediction. Likewise, this battery seems to be failing through a combination of power loss and capacity loss, instead of just capacity loss as with the Douglas battery. This fact makes defining battery life as a combination of capacity and resistance relevant.

Let us look into a prediction through only the capacity component as done with the Douglas battery and under the same reasons. The last capacity estimate before the prediction is 12.53%. This is higher than the Reserve Capacity result because it includes the Ah-counting capacity estimate. This value places the battery life at 92.74% of the total life in amp-hours.

The average cycling conditions for the remaining tests from that day forward are the Yuasa validation cycle characteristics. Using these values, we can calculate the theoretical total life in amp-hours as shown in Equation (8.46 and Equation (8.47).

<table>
<thead>
<tr>
<th>Second Comparison: Using only capacity component</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Lambda = \left( \frac{4}{3} \cdot 0.86 \right) \left( 1.01 - 0.78 \left( e^{-\frac{1}{5^{1.46-25}}} \right) \right) \left( \frac{12350}{0.86 \cdot 22.5} + 5280 \right) = 6774 \text{Ah}$</td>
</tr>
<tr>
<td>$Ah_{res} = \Lambda(1 - 0.9274) = 6774(1 - 0.9274) = 491.79 \text{Ah}$</td>
</tr>
</tbody>
</table>

**Table 8.10: Alternative Comparison**

<table>
<thead>
<tr>
<th>Second Comparison</th>
<th>Prediction</th>
<th>Physical Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah</td>
<td>491.79</td>
<td>375.29</td>
</tr>
</tbody>
</table>
This prediction falls within the same order of magnitude as the full algorithm prediction, but it is not quite as accurate. For the Douglas battery, this prediction is quite accurate. Recall that this battery seems to be failing through both failure modes while the Douglas battery clearly had been failing largely through capacity loss. This is one reason why the capacity component alone prediction is not as close to reality as it is with the Douglas battery.

Let us provide a resistance component only prediction as well. The final resistance measurement before prediction is 7.02mΩ. This results in the smallest amp-hour ratio of 82.96% from the resistance life path mapping in Figure 6.29. Table 8.11 provides the earliest and latest failure predictions based on resistance only.

<table>
<thead>
<tr>
<th>Resistance Prediction</th>
<th>Prediction</th>
<th>Physical Result</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ah</td>
<td>Earliest Failure</td>
<td>Latest Failure</td>
</tr>
<tr>
<td></td>
<td>0</td>
<td>1492.99</td>
</tr>
</tbody>
</table>

Once again, as we expected, the resistance only predictions do not provide useable results. The life path is simply too broad to use as a means of prediction.
CHAPTER 9

CONCLUSION

This chapter summarizes the results of this thesis. It presents the main points that are made and the significance of the results obtained.

9.1 SUMMARY

Two batteries are experimentally aged using two distinct duty cycles that are a basis set for representing real driving. The battery capacity and battery resistance are measured and tracked as the battery ages under these cycles. The resulting data sets allow for the generation of a cumulative aging model that can define battery life in amp-hours based on the discharge conditions.

An algorithm is created that utilizes this model to predict remaining battery life. The algorithm is intended to be implemented onboard the vehicle, and this thesis has listed a variety of diagnostic tests used within the algorithm that have high potential for easy implementation on a vehicle.

For the automotive application, the battery can have two failure modes. The algorithm takes into account the two failure modes by defining life as a combination of battery capacity and battery resistance. From here, a life prediction can be made in time or mileage using linear extrapolation techniques.

The algorithm is tested on two batteries and the results show a reasonable life prediction. More research is needed to tune this algorithm for better accuracy, generate a complete
set of severity factors within the cumulative aging model, and expand the total life
equation to a higher order model.

9.2 Future Work

There are a number of directions that could follow the results of this research project.
First, the project could be continued to develop not only the prognostic method but also
the cumulative aging model. For instance, there is research currently being conducted at
CAR investigating the possibilities for using Kalman filters and particle filters for
prognosis of the battery. This would be a much more accurate method for predicting
battery life than the simple linear extrapolation proposed in this thesis. The only
downside is the amount of data that is needed to generate those kinds of filters. And as
we saw with this research project, generating data for lead-acid battery life research
within the automotive application is not a trivial thing. Many variables need identified
and controlled let alone the time needed to conduct the research.

If more batteries are experimentally aged, then the cumulative aging model could be
broadened to include those results. More ‘life paths’ could be identified and compared
and the total amp-hour life equation could expand and higher order models could be
utilized.

Further research in this manner could also be utilized to tune the algorithm. For instance,
more ‘near-death’ batteries could be used to systematically identify the weighting
coefficients used within the algorithm.

The last suggestion deals with a new duty cycle. Our duty cycles significantly differed
from real driving through charging. If a battery is going to be experimentally aged, a
duty cycle with constant voltage charging should be considered. A proposed duty cycle
is provided in Figure 9.1.

A duty cycle of this form would very closely emulate real driving not only through the discharge events, but also through charging. This duty cycle combines the Power and Energy cycles while accelerating the aging. It would be interesting to see if the results from this duty cycle would fall within the results of the Power and Energy cycles.

Within this research there is also the weakness of conducting capacity tests. Without capacity tests, it is near impossible to accurately measure the battery’s capacity. With the capacity tests, we have seen that it affects battery performance effectively increasing the
battery capacity [13]. It may be possible through more research that the Reserve Capacity test could replace the capacity test. This would allow for more representative results of automotive battery life.

There are quite a few areas within this project that could greatly be advanced with further research. The real hindrance for this kind of work is the extensive time needed just for generating data and results. Even with the limited results obtained within the years of this research, we are fortunate enough to lay the foundation for an implementable onboard diagnostic and prognostic algorithm for lead-acid automotive batteries.
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[21] Dr. Larry Anderson, Emeritus Professor, Chemical Engineering, The Ohio State University, Columbus, OH, 2008.


University, Columbus, OH, 2006.


APPENDIX

A.1 TABLES
This section provides additional tables with results from the aging experiments.

Table A.1: Energy Cycle Capacity Results

<table>
<thead>
<tr>
<th>Cycle Count</th>
<th>Total Ah Discharged</th>
<th>Capacity (Ah)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>60.22</td>
</tr>
<tr>
<td>7</td>
<td>166.24</td>
<td>50.44</td>
</tr>
<tr>
<td>16</td>
<td>333.87</td>
<td>48.33</td>
</tr>
<tr>
<td>27</td>
<td>535.65</td>
<td>42.17</td>
</tr>
<tr>
<td>37</td>
<td>658.15</td>
<td>47.40</td>
</tr>
<tr>
<td>48</td>
<td>814.73</td>
<td>43.67</td>
</tr>
<tr>
<td>83</td>
<td>1217.7</td>
<td>39.17</td>
</tr>
<tr>
<td>116</td>
<td>1516.2</td>
<td>32.23</td>
</tr>
<tr>
<td>141</td>
<td>1856.6</td>
<td>29.40</td>
</tr>
<tr>
<td>167</td>
<td>2200.4</td>
<td>27.40</td>
</tr>
<tr>
<td>198</td>
<td>2582.4</td>
<td>24.84</td>
</tr>
<tr>
<td>229</td>
<td>2855.0</td>
<td>23.73</td>
</tr>
<tr>
<td>258</td>
<td>3117.7</td>
<td>22.14</td>
</tr>
<tr>
<td>301</td>
<td>3376.6</td>
<td>20.58</td>
</tr>
<tr>
<td>362</td>
<td>3635.2</td>
<td>17.72</td>
</tr>
<tr>
<td>435</td>
<td>3968.0</td>
<td>13.03</td>
</tr>
<tr>
<td>435+*</td>
<td>3983.0*</td>
<td>4*</td>
</tr>
</tbody>
</table>

* At failure
### Table A.2: Power Cycle Capacity Results

<table>
<thead>
<tr>
<th>Cycle Count</th>
<th>Total Ah Discharged</th>
<th>Capacity (Ah)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>60.11</td>
</tr>
<tr>
<td>11</td>
<td>204.96</td>
<td>49.30</td>
</tr>
<tr>
<td>21</td>
<td>368.89</td>
<td>44.77</td>
</tr>
<tr>
<td>36</td>
<td>593.97</td>
<td>42.27</td>
</tr>
<tr>
<td>69</td>
<td>1072.7</td>
<td>34.53</td>
</tr>
<tr>
<td>103</td>
<td>1522.9</td>
<td>29.96</td>
</tr>
<tr>
<td>123</td>
<td>1789.6</td>
<td>28.86</td>
</tr>
<tr>
<td>151</td>
<td>2151.9</td>
<td>28.23</td>
</tr>
<tr>
<td>158</td>
<td>2237.7*</td>
<td>4*</td>
</tr>
</tbody>
</table>

* At failure
Table A.3: Energy cycle resistance results

<table>
<thead>
<tr>
<th>Cycle Count</th>
<th>Total Ah Discharged</th>
<th>Cranking (mΩ)</th>
<th>EIS (mΩ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>4.40</td>
<td>5.01</td>
</tr>
<tr>
<td>7</td>
<td>166.24</td>
<td>-</td>
<td>5.25</td>
</tr>
<tr>
<td>16</td>
<td>333.87</td>
<td>-</td>
<td>5.64</td>
</tr>
<tr>
<td>27</td>
<td>535.65</td>
<td>5.29</td>
<td>5.78</td>
</tr>
<tr>
<td>37</td>
<td>658.15</td>
<td>-</td>
<td>5.56</td>
</tr>
<tr>
<td>48</td>
<td>814.73</td>
<td>6.22</td>
<td>5.77</td>
</tr>
<tr>
<td>83</td>
<td>1217.7</td>
<td>5.67</td>
<td>5.65</td>
</tr>
<tr>
<td>116</td>
<td>1516.2</td>
<td>6.22</td>
<td>5.32</td>
</tr>
<tr>
<td>141</td>
<td>1856.6</td>
<td>6.28</td>
<td>7.10</td>
</tr>
<tr>
<td>167</td>
<td>2200.4</td>
<td>5.94</td>
<td>6.13</td>
</tr>
<tr>
<td>198</td>
<td>2582.4</td>
<td>5.45</td>
<td>5.90</td>
</tr>
<tr>
<td>229</td>
<td>2855.0</td>
<td>6.19</td>
<td>6.56</td>
</tr>
<tr>
<td>258</td>
<td>3117.8</td>
<td>6.27</td>
<td>6.27</td>
</tr>
<tr>
<td>301</td>
<td>3376.6</td>
<td>6.61</td>
<td>7.78</td>
</tr>
<tr>
<td>362</td>
<td>3635.2</td>
<td>7.11</td>
<td>7.25</td>
</tr>
<tr>
<td>435</td>
<td>3968.0</td>
<td>9.96*</td>
<td>8.83*</td>
</tr>
</tbody>
</table>
Table A.4: Power cycle resistance results

<table>
<thead>
<tr>
<th>Cycle Count</th>
<th>Total Ah Discharged</th>
<th>Cranking (mΩ)</th>
<th>EIS (mΩ)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>4.37</td>
<td>4.57</td>
</tr>
<tr>
<td>11</td>
<td>204.96</td>
<td>4.64</td>
<td>5.29</td>
</tr>
<tr>
<td>21</td>
<td>368.89</td>
<td>-</td>
<td>5.72</td>
</tr>
<tr>
<td>36</td>
<td>593.97</td>
<td>6.26</td>
<td>5.29</td>
</tr>
<tr>
<td>69</td>
<td>1072.7</td>
<td>5.48</td>
<td>5.09</td>
</tr>
<tr>
<td>103</td>
<td>1522.9</td>
<td>5.51</td>
<td>4.98</td>
</tr>
<tr>
<td>123</td>
<td>1789.6</td>
<td>6.51</td>
<td>6.77</td>
</tr>
<tr>
<td>151</td>
<td>2151.9</td>
<td>5.72</td>
<td>5.77</td>
</tr>
<tr>
<td>158</td>
<td>2237.7</td>
<td>8.29*</td>
<td>9.08*</td>
</tr>
</tbody>
</table>

A.2 Crank Testing at Three SOC’s and Three Temperatures

During the aging experiments, the batteries are crank tested twice under a set of three SOC’s and three temperatures shown in Table A.5.

Table A.5: SOC’s and Temperatures

<table>
<thead>
<tr>
<th>SOC’s</th>
<th>Temperatures</th>
</tr>
</thead>
<tbody>
<tr>
<td>95%</td>
<td>24°C</td>
</tr>
<tr>
<td>75%</td>
<td>-18°C</td>
</tr>
<tr>
<td>65%</td>
<td>-30°C</td>
</tr>
</tbody>
</table>

Both experimentally aged batteries are brought to the above temperatures and SOC’s. A crank test is applied and the results are shown in Table A.6 and Table A.7.
### Table A.6: First Set of Results

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Resistance (mΩ) Battery N1</th>
<th>Resistance (mΩ) Battery N2</th>
</tr>
</thead>
<tbody>
<tr>
<td>24°C</td>
<td>4.06</td>
<td>4.40</td>
</tr>
<tr>
<td>-18°C</td>
<td>5.23</td>
<td>5.69</td>
</tr>
<tr>
<td>-30°C</td>
<td>6.42</td>
<td>7.03</td>
</tr>
</tbody>
</table>

Measurement error estimated at 3-5%

### Different SOC’s

- 95% ~ 13.00Voc
- 75% ~ 12.72Voc
- 65% ~ 12.55Voc

### Table A.7: Second Set of Results

<table>
<thead>
<tr>
<th>Temperature</th>
<th>Resistance (mΩ) Battery N1 116 Cycles</th>
<th>Resistance (mΩ) Battery N2 103 Cycles</th>
</tr>
</thead>
<tbody>
<tr>
<td>45°C</td>
<td>5.32 5.67 6.00 4.59 5.72 5.80</td>
<td></td>
</tr>
<tr>
<td>24°C</td>
<td>5.58 6.10 5.76 5.38 5.40 5.36</td>
<td></td>
</tr>
<tr>
<td>-18°C</td>
<td>6.97 7.53 8.14 7.16 7.38 7.40</td>
<td></td>
</tr>
<tr>
<td>-30°C</td>
<td>8.89 9.30 *12.73 8.72 9.76 *18.3</td>
<td></td>
</tr>
</tbody>
</table>

Measurement error estimated at 3-5%

### Additional Temperature

Not much of a resistance change between hot and room temperatures. Could possibly make it easier for onboard diagnosis of cranking resistance by loosening the temperature restrictions.

### Different SOC’s

- 95% ~ 13.00Voc
- 75% ~ 12.72Voc
- 65% ~ 12.55Voc
It is these results that provide an estimate on the error within the resistance tests. The error listed beneath the tables is based on repeatability tests. The crank tests are repeated on a separate battery and the difference in the results showed approximately a 3%-5% error.

The results also lead us to a more detailed description of battery resistance. The resistance can be described in two parts: a physical resistance, and a chemical resistance. The physical resistance deals with the material resistance within the battery cell. The chemical resistance deals with the Arrhenius law. This law describes how temperature affects chemical reactions. For our case, a higher temperature will help facilitate the endothermic reaction manifesting as a lower battery resistance. Colder temperatures will therefore cause higher resistances. But, if the temperature reaches a certain level, the physical resistance dominates the battery resistance. The chemical reactions are occurring at a fast enough rates that they no longer affect the overall resistance [22].

<table>
<thead>
<tr>
<th>Resistance Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>[ R = R_p + R_c ]</td>
</tr>
</tbody>
</table>

Unfortunately, only two of these sets of cranking tests could be conducted limiting the data needed to continue investigating the battery resistance at different SOC’s and temperatures.

A.3 Testing Procedures
This section discusses the procedures for running certain tests and preparing the battery for testing.
Before any test, the battery must be stabilized at the desired temperature. Below is a set of instructions for stabilizing the battery temperature.

Temperature Stabilization:
1. Place battery in environmental chamber.
2. Soak the battery at 25°C for 24 hours to stabilize at room temperature.
3. If other temperature is desired, soak for additional 16 hours at desired temperature.

If the battery is already at room temperature, then step 2 can be skipped. Instructions for operating the environmental chamber can be found below.

CAR has two environmental chambers that can be used for stabilizing the lead-acid battery temperature. One is a large blue chamber from Jones Refrigeration that has the capabilities of temperature control from -100°F to 300°F. The other is a smaller gray chamber from Test Equity. It is capable of the same temperature range.

Environmental chamber:
Jones Refrigeration – there are instructions posted on the side of this machine
1. Depress CH SEL to display: Select Channel 1.
2. Press RUN/HLT button lighting PROG/HLT light.
3. Press RE STR to get to step 1. Press MODE key to illuminate CHG DATA light. Press CLEAR to erase any previous data for this step. FUNCTION display will display SP.
4. Press ENTER to indicate that this will be a setpoint step. FUNCTION display will display S1.
5. Press Δ or ∇ until desired setpoint value is displayed in the DATA display.
6. Press ENTER to store this value.

7. Press FCTN key repeatedly until SC appears in the FUNCTION display. Press Δ until 0001 appears in the DATA display. Press ENTER. Press ENTER again to go to NX 0002 step.

8. Press FCTN to display NX 0002 in FUNCTION and DATA displays. Press ENTER.

9. The STEP display light should be 02. Press CLEAR to erase any previous data.

10. Press RE-START then RUN/HALT. The PROG END light will illuminate. Press MODE key repeatedly until MNTR DATA light is illuminated. FUNCTION/DATA display will display C1 xxxx indicating current setpoint. ACTUAL display always indicates actual temperature.

Test Equity – this chamber has significantly easier operating instructions

1. Turn on the POWER.

2. Make sure the arrow is at SP1 for setpoint 1.

3. Hit the right arrow to adjust setpoint.

4. Use Δ or V to set desired temperature.

5. Turn on TEMPERATURE to begin controlling temperature at desired setpoint.

Both chambers have the capability of running temperature profiles. To do this, please consult their respective operating manuals.

Once the temperature of the battery is stabilized, the cycling or diagnostic tests can be applied. For our cycles, the battery should be settled at 75% SOC. This is accomplished by setting the battery to a specified \( V_{oc} \), which for these batteries is 12.72V. This should be done at room temperature.
Energy cycle DAQ:
1. Open Matlab on the Energy cycle’s designated computer.
2. In the upper left corner, select DAQ Collector shortcut.
3. Specify the sample rate desired. The lowest rate is 1Hz, and the highest is 5kHz for this computer.
4. Press Load Channel Properties to load the channel scaling.
5. Open FinalEnergyScale.mat within the Session folder. Every so often this scaling should be checked in case of sensor drift.
6. Press Setup and Start to begin collecting data.

Recall, that the crank testing also uses the Energy cycle DAQ. For this test, the channel properties are left un-scaled (no file is loaded). The sample rate is set to 5kHz.

The Power cycle uses the same VI as the Energy cycle for the charging portion of the cycle. The discharging portion includes a controller that commands the relay switch to connect and disconnect the battery to the resistors.

Power cycle DAQ:

Discharging.
1. Open Matlab on the Power cycle’s designated computer.
2. In the upper left corner select Frankenstein Profile Runner.
3. Unless otherwise desired, leave the default sample rate and profile rate. If the profile rate is changed, the time-sequence loaded to control the relay must match the new rate.
4. Select under Battery Specification, Pb Acid (12V).
5. Select Load Channel Properties.
6. Open V_I_T_scales.mat in the Session folder.
7. Select Load Existing Profile.
8. Open PowerCycle40.mat
9. Press Setup and Start to begin collecting data and discharging the battery.

Charging – this is the exact same VI to the Energy cycle DAQ.
   1. Open Matlab on the Power cycle’s designated computer.
   2. In the upper left corner, select Power10 Data Acquisition shortcut.
   3. Input desired sample rate. Lowest is 1Hz, highest is 5kHz.
   4. Select Load Channel Properties.
   5. Open V_I_T_scale.mat in the Session folder.
   6. Press Setup and Start to begin collecting data.

Before a capacity test, for instance, the battery must be fully charged. Below is the procedure used to fully charge the battery.

Charge to 100%SOC:
   1. Stabilize battery at 25°C.
   2. Apply 16V threshold while limiting the current to 25A. Continue for 23 hours.
   3. Apply a C/200 charge current for 1 hour.

Once the battery is fully charged, a capacity test can be conducted.

Capacity Test:
   1. Charge to 100% SOC.
   2. Discharge with C/20 until terminal voltage reaches 10.5V.
   3. Record time taken to reach 10.5V.
4. Do not leave battery at low SOC, recharge to at least 50% SOC.

Usually after the capacity test is done, an EIS test is applied.

**EIS Test:**

1. Stabilize a 75% SOC battery at 25°C.
2. Turn on the Solartron.
3. Connect battery to Solartron leads.
4. Conduct frequency sweep with EIS software

The EIS Solartron comes with its own software to run the machine and conduct a frequency sweep. To run the software, the software key contained on a red flash drive must be inserted in a USB port on the computer.

**EIS Solartron Software (ZView and ZPlot):**

ZPlot runs the EIS test.

1. Open ZPlot.
2. Select the Ctrl E: Sweep Freq tab.
3. Specify the frequency sweep. Most of the EIS data is swept from 1kHz to 0.01Hz. For faster tests, increase the lower frequency limit.
4. Click the ‘Measure Sweep’ icon on the icon bar. It is a white box with one red arch. This will start the test.
5. To open up ZView and watch the data plot as it is acquired, click the icon with the two Z’s in the upper right corner.

ZView plots the data. It can also be used to model the response and fit the data.

1. Open ZView.
2. Open data for plotting by clicking the folder with the Z in it.

3. To create an equivalent circuit, click the icon with the resistor and capacitor.

4. Click the folder to open models. If a new model is desired, go to File, New Model, and generate your new equivalent circuit model. The EIS test’s designated computer contains many saved models that can be used for fitting the data.

5. To input elements into the model, right click the empty model space, and select the elements you would like to input under the New list. This will ask you to select and name the elements.

6. Save the new Model by clicking the floppy disk icon with the three dots below it. This is the Save Model As shortcut.

7. Then go to Model and select Run fit. This will attempt to fit the model within the open data file.

8. To save the model’s data, press the icon in the Equivalent Circuit window with the floppy disk with a Z.

9. To save the model with the parameter values, select the disk with the three dots underneath in the Equivalent Circuit window. This is the Save Model As shortcut.

One of the other resistance diagnostics is the cranking test.

Cranking Test:
1. Stabilize battery at desired temperature.
2. Connect the battery to the engine.
3. Turn on fuel pump and ECU. (powered by separate battery)
4. Begin collecting data. (sample at least 1kHz)
5. Start the engine.
6. Turn off engine.
7. Repeat from step 3 as desired.

The last resistance diagnostic we will discuss is the Milliohmmeter. This measurement device is used largely during the validation phase of the research project.

Milliohmmeter:
1. Stabilize battery to desired SOC and temperature.
2. Connect mating cable and leads to meter.
3. Turn on meter.
4. Place leads on appropriate surface for a short circuit adjustment. Keep connection held.
5. Press the blue button.
6. Press the 4 button (short measurement).
7. Press left arrow twice to select Short Measurement.
8. Press Enter
9. Place leads on both battery terminals for resistance measurement.

All of the instructions for each test and piece of equipment have stand-alone user manuals. If problems occur with the equipment, please seek the user manuals. If the user manual cannot be found within the laboratory area, consult Darrin Orr for a copy of the manual.