
Reuben Z. Toll
Michael R. Moore

UNIVERSAL SOLUTIONS, INC.
1660 Chambers Road
Aurora, CO  80011
www.universalsolutions.com

Abstract

A general vision of battery capacity prediction as a function of multiple non-invasive measurements is presented. The importance of quantifying the uncertainty of such predictions is underscored. A VRLA cell test group is chosen to develop and examine a detailed functional relationship of capacity with conductance; particular emphasis is placed on the range of 75-105% battery capacity. It is hoped that consolidation of the vast studies conducted throughout the industry will one day lead to a robust battery state of health prediction model with reasonable confidence limits.

1.0 Background & Motivation

Over the last decade, a multitude of significant studies, on a combined population of over 650,000 units, have examined VRLA batteries in operation and established that original 10-20 year product life claims were not realistic. The results indicate that actual service life tends to be in the range of 4-8 years. Overall, similar results were obtained for various manufacturers, different discharge rates, AGM cells, Gel cells, Monoblocks, pre-1994 products, and post-1994 products, with the newer AGM, and particularly Gel, cells on the higher end of the service life range. Also demonstrated in some studies was that capacity begins to decline after as few as 2 years in service for a large enough portion of the product to warrant concern [1][2][3][4][5][15].

In response to shorter than expected service life for VRLA products, the community of users employing the technology immediately turned to methods to estimate the actual state of health at a given point in time. The prospect of incurring another round of significant purchase and deployment costs for battery protection much earlier than expected left many trapped in a compromise of budgets for reliability. The search had begun for accurate and inexpensive methods to ascertain the two most critical aspects of battery health, existing capacity and remaining service life. Understandably, the battery user would like to squeeze every last penny from the units already in service.

2.0 Capacity Prediction

A comprehensive, non-invasive model for predicting battery capacity remains elusive. There are a number of models that have been developed, but the issue is extremely complex; a myriad of variables exist, the technology is constantly evolving, and there are multiple failure modes to consider. It stands to reason that even if each model fails to provide conclusive results individually that combining the most promising approaches could lead to more accurate battery capacity predictions. Statistically, it would be expected that combining unique indices will increase the confidence of the predictions. To accomplish this, the uncertainty must be known for each of the indices must be determined first. A consolidated battery “fuel gauge” approach is not a new idea, but perhaps the timing is now right to draw on the substantial research results which have been obtained industry wide. It is easy to remain apprehensive about quantifying results, but to be truly valuable to the battery user, both the capacity prediction and associated uncertainty must be known. A preliminary vision of such an approach is presented in Table 1.

<table>
<thead>
<tr>
<th>Item</th>
<th>Parameters</th>
<th>Invasive?</th>
<th>Possible Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>A.</td>
<td>Discharge</td>
<td>Yes</td>
<td>Capacity = Actual Time / Published Time</td>
</tr>
<tr>
<td>B.</td>
<td>Temperature</td>
<td>No</td>
<td>N/A</td>
</tr>
<tr>
<td>C.</td>
<td>Float Voltage</td>
<td>No</td>
<td>N/A</td>
</tr>
<tr>
<td>D.</td>
<td>Float Current</td>
<td>No</td>
<td>Capacity = mx + b ± error</td>
</tr>
<tr>
<td>E.</td>
<td>Coup de Fouet [Trough Voltage]</td>
<td>Yes</td>
<td>Capacity = mx + b ± error</td>
</tr>
<tr>
<td>F.</td>
<td>Ohmic</td>
<td>No</td>
<td>Capacity = mx + b ± error</td>
</tr>
</tbody>
</table>

Table 1. Possible VRLA Battery Capacity Prediction Models to be Included in a Combined Parameter Approach

Attempting to tackle each possible measure in all of its complexities is beyond the scope of this study. The
immediate objective is to examine one of the most promising measures and to propose a blueprint for the building blocks of a multiple measure capacity prediction model. An exploration into which parameter to consider first follows.

2.1 Discharge Testing and Definition of Capacity

The most accurate determination of battery state of health is a discharge test because it evaluates how the unit performs under the very condition a back-up battery is designed to accommodate. Derived from discharge results, capacity is defined as the ratio of the actual time a battery can sustain certain load conditions to the expected or designed time under the same conditions. A well recognized criteria for battery degradation is 90% capacity and for failure/replacement is 80% capacity [6]. Unfortunately, discharge testing is costly, time consuming, and most importantly invasive; removal of a battery system from the distribution plant it protects inevitably carries increased risk for service outages.

2.2 Temperature and Capacity

Temperature is a critical parameter of battery performance. A service temperature increase accelerates the chemical reaction within the cell, increases the available capacity, but ultimately shortens the life [7]. Unfortunately there appears to be little indication that temperature alone correlates significantly with battery capacity. Temperature changes certainly may be a precursor to a problem, but the incorporation of other indices must be combined to verify a battery fault [8]. While temperature may not be an effective indicator of capacity it is an essential quantity to consider when forecasting remaining battery life.

2.3 Float Voltage and Capacity

Float voltage is a measure that has received considerable attention. However, many studies have shown that it has very little ability to accurately predict battery capacity [5][8][9][10].

2.4 Float Current and Capacity

Float, or trickle, current appears to have some correlation with capacity, but has limitations. Since the same current passes through all cells in a given battery system, an inherent difficulty arises when trying to examine the significance of current at a cell level; the best and worst cells in a battery string will experience the same current flow. A thorough study recently examined other logistical difficulties associated with utilizing float current readings. Difficulties obtaining the measurement, appropriate concern thresholds, battery AH size, battery age, and state of charge must all be considered [8].

2.5 Coup De Fouet and Capacity

Encouraging correlations are found between capacity and the initial, highly transient voltage behavior manifested upon application of a load; this phenomena is more commonly referred to as coup de fouet. While measurement of this parameter still requires invasive discharge activity, the time required on discharge to obtain the information is usually on the order of a few minutes rather than a few hours required for a traditional discharge test. Studies have shown reasonably strong linear correlations with either trough voltage or subsequent plateau voltage to capacity. Typically, a lower voltage corresponds to lower battery capacity. There are, however, significant contributions to the results from external operating conditions which detract from knowledge of the condition of the battery itself. Discharge rate, prior time on float charge, and float voltage all have an influence on the results. Some preliminary correction factors have been developed to minimize the effect of these external operating conditions in order to gain a true depiction of the performance of the cell. However, these correction models are still preliminary and under development [11]. Because coup de fouet is a feature of positive limited batteries only, this behavior will not be present for all lead acid batteries [12].

2.6 Ohmic Measurements and Capacity

Perhaps the most robust correlation with capacity has been demonstrated with the ohmic measurements of conductance, impedance, and resistance. As a battery ages, degradation in the internal plates, grids, and connections results in decreased conductance (increased resistance and impedance). This effect has been studied extensively and a strong linear correlation with ohmic measurements and cell capacity is well established [3][7][10][13]. Figure 1 depicts typical behavior of a VRLA cell, examining conductance in particular due to its relative ease of measurement for the battery user.
While the data speak volumes for the obvious linear correlation of capacity and conductance, it is the quality of this correlation that has sparked the most controversy. The high data scatter for higher capacity cells, begs the question of how precisely capacity may be predicted, if at all, using this measure alone. It is with this in mind that a further look into the very nature of the correlation between capacity and conductance is required. For conductance to be one of a combined set of measures used to predict capacity, the uncertainty of resulting predictions must be quantified to understand whether the confidence is palatable to the battery user.

3.0 Test Methods and Sample Description

To further develop and test a functional model for capacity and conductance correlation, a sample of VRLA AGM battery strings currently in operation in various, temperature controlled communications centers was selected. The sample consists of four 533 AH, -48V strings (96 cells) with a service life of 7 years and three 1400 AH, -48V strings (72 cells) with a service life of 2.5 years. The batteries are twenty year class products and represent two different manufacturers. Prior to discharge testing all strings had been on float for a minimum of 72 hours, intercell resistance readings were taken and connections checked for tightness, float voltage was recorded at the cell and string level, and float current was recorded. Additionally, conductance readings were taken while on float since state of charge significantly affects readings. The same Midtronics Micro-Celltron Conductance Tester was used for each measurement, being careful to ensure the probes had direct contact with the cell post lead. Each string was then placed on open circuit and constant current discharge testing was conducted in accordance with IEEE 1188 guidelines [6]. The temperature corrected 3, 4, or 8 hour discharge rate to end voltages of either 1.75 or 1.86 volts per cell was used. Computerized data logging equipment was used to record current and voltage readings every 2 seconds for the first few minutes, every 10 minutes for the majority of the test, and every 1 minute after the voltages began falling quickly. Cell capacity was calculated based on test performance.

4.0 Test Results and Correlation Model

4.1 Capacity Prediction Model Using Conductance

Conductance is well accepted as an excellent trending tool for trending the capacity of a cell over time by comparing previous readings. To expand beyond trending and address capacity prediction raises questions of effectiveness. Because the test group includes different products with different nominal conductance values, measurements were normalized using a baseline to facilitate comparison of the results. For the purpose of this study, the Midtronics published conductance was used as the baseline, but there are a variety of approaches for obtaining such a value when an average value was not established at the start of service life [13]. A conductance decline of 20-30% from baseline value is typically considered cause for concern and an indicator that cell performance may be declining quickly [6]. In recognition that most battery users are concerned about capacity in the acceptable range of performance, approximately 75-105%, a prediction model will be developed using test data from that same range. Unfortunately, this range is exactly where the data scatter is highest. The full range of capacity and conductance data may indeed generate what appears to be a tighter fit to the data, but when assessing uncertainty of the prediction it may lead to underestimation.
4.2 Prediction Model Development and Uncertainty

Clearly the results for the test strings depicted in Figure 2 do not appear to be very well approximated by a straight line. A statistical analysis of the results enables a quantification of exactly how much uncertainty is associated with such an approximation for capacity [14].

When a linear regression, a.k.a. least squares fit, is applied to a data set, the resulting line minimizes the difference between the data and the line itself to produce a “best fit.” Applying this approach to capacity and conductance generates a line with the equation:

\[
\frac{N}{\Delta} \sum_{i=1}^{N} \text{Cond}_i \text{Cap}_i - \left( \sum_{i=1}^{N} \text{Cond}_i \right) \sum_{i=1}^{N} \text{Cap}_i
\]

The slope and intercept of the line, \(m\) and \(b\) respectively, are defined as follows:

\[
m = \frac{\sum_{i=1}^{N} \text{Cond}_i \text{Cap}_i - \sum_{i=1}^{N} \text{Cond}_i \sum_{i=1}^{N} \text{Cap}_i}{\Delta}
\]

\[
b = 38.336, \text{ for test strings 2-7}
\]

Where, \(\Delta\) is a convenient abbreviation:

\[
\Delta = N \sum_{i=1}^{N} (\text{Cond}_i)^2 - \left( \sum_{i=1}^{N} \text{Cond}_i \right)^2
\]

\[
\Delta = 36821, \text{ for test strings 2-7}
\]

The spread of the capacity “measurements” can be obtained using the standard deviation:

\[
\sigma_{\text{cap}} = \sqrt{\frac{1}{N-2} \sum_{i=1}^{N} \left( \text{Cap}_i - \left( \sum_{i=1}^{N} \text{Cap}_i \right) / N \right)^2}
\]

\[
\sigma_{\text{cap}} = 5.494, \text{ for test strings 2-7}
\]

This standard deviation for the capacity measurements is not the same as the uncertainty in a predicted capacity using the line equation. Rather, it is a representation of the spread in the observed capacity measurements only. To find uncertainty in predictions of capacity for any given conductance input to the line equation, the uncertainty of each argument in the equation must be accounted for. The one standard deviation uncertainty in the slope and intercept of the line, \(m\) and \(b\), is then given by:

\[
\sigma_m = 0.1833, \text{ for test strings 2-7}
\]

\[
\sigma_b = 15.472, \text{ for test strings 2-7}
\]

Employing the basic rule for propagation of random error, the uncertainty in a functional prediction of capacity from conductance may finally be obtained. The slope and intercept values must be treated as variables since they have large uncertainties and are not true “constants.”

\[
\frac{1}{\sigma_m^2} \left( \sum_{i=1}^{N} \text{Cond}_i \right)^2 - \left( \sum_{i=1}^{N} \text{Cond}_i \right) \sum_{i=1}^{N} \text{Cap}_i
\]

The error in the conductance readings is assumed to be randomly distributed and small. This uncertainty is therefore dwarfed in comparison with the large uncertainty of the constants \(m\) and \(b\) due to data scatter. Repeatability of conductance measurements has been demonstrated to be on the order of ± 5% using similar test equipment to that used measuring the test strings [N]. Also recognizing that the arguments are added in quadrature, this uncertainty is further reduced and accordingly neglected. The assumption is further justified by the fact that conductance measurements have been shown to have little variance with temperature under normal operating conditions such as those experienced by the test strings [R].

Reducing further:
The final desired result, a function predicting cell capacity and associated uncertainty from a given conductance can be summarized as follows in Equation 1:

\[
\text{Cap} = 0.6921 \times \text{Cond} + 38.336 \pm \sqrt{[(\text{Cond} \times 0.1833)^2 + 15.472^2]}
\]

Equation 1. Capacity Prediction Model Developed from Test Strings 2-7

Figure 3 displays the predicted results from Equation 1 based upon arbitrary conductance input values; the results are superimposed on the original test data, being careful to limit predictions to the 75-105% range of applicability. All test data points are within the calculated range of uncertainty as expected.

4.3 Prediction Model Interpretation

The uncertainty given in Equation 1 is the one standard deviation value. Consulting a normal distribution table, this corresponds to only 68% confidence that any given capacity prediction will be within the uncertainty range. For example, for a baseline conductance input of 70% the resultant capacity prediction is 87% ± 20%. Doubling the uncertainty to obtain the two standard deviation spread would yield confidence of 95.4%, but this corresponds to an uncertainty of ± 40% capacity. This uncertainty range is entirely too large for the model to produce useful capacity predictions; it encompasses the entire range of battery performance, from healthy (≈100%) to failed (80%). Uncertainty ranges in considerable excess of 100% capacity can be rejected since it is unlikely that a battery would actually demonstrate such behavior.

4.4 Prediction Model Analysis and Applicability

It should be noted that Equation 1 applies only to the data considered, test strings 2-7, and does not apply to other situations. Conductance varies with capacity for all failure modes except short circuits so this model may not accurately predict cell capacity when this condition is present [3][7]. The approach used to develop the model is applicable to all batteries where a linear relationship may still be anticipated. Many of the laborious calculations required to develop the model are reduced to a few minutes work with the aid of spreadsheet software.

Predicted capacity results demonstrated in Figure 3 are in general accord with the what would be expected based on past studies [7][10][13]. Development of the model utilized test data of cells in the 75-105% capacity range because this is the same range where capacity prediction is most beneficial. However, the very large data scatter in this range magnifies the uncertainty values. Just as considering the entire range of capacity may lead to underestimation of uncertainty, perhaps the benefit of more linear data lower down the capacity and conductance correlation line would have helped to anchor the slope of the line. How much of the full range of capacity and conductance measurements to consider when developing a prediction model is a critical question to address. Referring again to Figure 1, future re-examination of the model for a slightly expanded capacity range may prove beneficial.

5.0 Conclusions

1. A preliminary vision of a VRLA battery capacity prediction model using multiple non-invasive measurements is presented. To predict capacity with confidence, both the functional relationship to capacity and the uncertainty must be known for each contributing measurement.

2. A mathematical method to quantitatively predict battery capacity and associated uncertainty as a function of conductance measurements is outlined. Confidence values for different uncertainty ranges are given.

3. Capacity predictions derived from a 6 string VRLA AGM test group include an unreasonable amount of uncertainty to accurately predict capacity from conductance measurements; the entire acceptable range of battery performance, 80+% capacity, is encompassed by the uncertainty window. The model concentrates on the typical acceptable service range of about 75-105% capacity. A more robust test group would have been preferred to facilitate better predictions.

4. The approach used to develop the capacity prediction model based upon conductance measurements is applicable to other linearly related measurements. A model specific to a battery type, battery age, or any desired distinguishing feature for that matter, may be developed by choosing the test group appropriately.
5. Accurate and consistent measurements and baseline values are critical to obtain valid predictions.

6.0 Recommendations for Future Work

1. Expand the capacity and conductance correlation model to include more data and a slightly broader range of concentration. Results drawing on a broader sample will help determine if prediction uncertainty may be significantly reduced.

2. Develop quantifiable battery capacity prediction models based upon other non-invasive measurements. Consolidate individual models into one comprehensive model.

3. Approach battery remaining life prediction models in a similar manner to that proposed for capacity prediction. A complete battery state of health prediction will need to consider both elements.

4. Ultimately, results from a battery state of health prediction model could be incorporated into a monitoring algorithm to provide the battery user real time visibility of potential problems.

Acknowledgements

The authors would like to acknowledge and thank the following people for their significant contributions to this study:

Mr. Curtis Ashton of Qwest Communications for his contribution of test data and his perspective on the final results.

The Power Technicians of Qwest Communications, especially Mr. Hal Johns and Mr. John House, for their assistance in obtaining test data.

Professor Michael Dubson of the University of Colorado Physics Department for his assistance in the development of statistical and error propagation models.

References


