Dynamic Deep Cycling Testing

The Use of Dynamic Deep Cycling Testing to Predict Battery State-of-Health in Outside Plant Environments

A Technical Paper prepared for SCTE by

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1. Introduction

Battery health is critical to the reliability of the outside plant network for cable internet providers. Unfortunately, the health of a battery is continuously being degraded due to use, environment, abuse, and many other known and unknown factors. This makes the change in battery performance variable and difficult to predict, with a battery's calendar age an ineffective method to determine performance. Although discharge events can be tracked readily, the challenge is that the vast majority of outages result in partial battery discharges, with power restored at inconsistent and variable times. To address this challenge, Comcast set out to use a partial discharge analysis to determine the state-of-health (SoH) for each battery powering the over 250 thousand outside plant power supplies in its network. SoH is defined here as the percentage capacity (or runtime) a battery can deliver as compared to its new or original rating. This was done without removing the battery from the site, without the need for any external equipment, without the need to visit the site, and without ever having the downstream load unprotected.

Previously, the replacement approach for power supply batteries was based on the calendar age of the battery. This did not account for the many factors that may have degraded the battery prematurely. As such, it may have resulted in the early replacement of batteries in good health or the delay in removing batteries in poor health, which translates directly to a false sense of reliability. The absence of a view into battery health made capital planning more difficult, as battery attributes (model, count, age, etc.) were the only information available to justify replacement. By providing a health score for batteries, long-range capital planning can focus on the true condition of batteries rather than their calendar age. This view into asset condition allows for the most effective use of resources by targeting the locations of greatest need. Views into future years' battery replacement quantities are much more predictable using current battery health metrics and their degradation rate.

The replacement of the batteries of greatest need also significantly improves the reliability of the outside plant powering network. Power supplies can withstand commercial power interruptions more effectively when poor performing batteries are identified and replaced. Improved power supply reliability directly impacts customers who may have a backup generator available or may continue to have commercial power during isolated power outages. Providing front line maintenance technicians with a view into each battery's SoH promotes an effective, efficient, and proactive maintenance strategy for power supply battery replacements.

A SoH assessment was accomplished by developing a unique algorithm used to predict the performance of outside plant batteries when subjected to a controlled, partial discharge event, specific to the power supply's unique load. In this way, Comcast will be improving the reliability of the outside plant network by advancing beyond a calendar age replacement cycle. Access to this information aids in the continued effort to improve infrastructure reliability. The use of a dynamic deep cycle battery discharge test with a prediction of the battery state-of-health will continue to improve Comcast's best-in-class powering network.

2. Background

2.1. Identification of the Proposed Solution

In traditional power backup applications to the utility grid, batteries are continuously on standby, ready to be discharged when utility power fails. In today's Hybrid-Fiber Coax network, these batteries are primarily valve-regulated lead-acid batteries, which have an underlying chemistry whereby the SoH is impacted over time by various influences including charge/discharge cycles, temperature, time and other factors. Partial discharge events are common, where power is restored at completely inconsistent and variable times before the battery has been completely depleted. In contrast, full discharge events (where a battery is fully depleted) are undesirable. If a full outage continues to the point of depleting a battery, the site then fails and customers experience a service interruption as the outside plant equipment necessary for delivering services is no longer powered. In summary, backup batteries are designed to accommodate numerous partial discharges but are oversized and configured such that full discharges are uncommon by design.

The goal of the proposed algorithm is to determine the SoH of a battery which can be used for battery replacement planning to ensure optimal uptime during the discharge. The existing methods for the SoH determination in literature can be divided into two categories [1]:

1. Determining the SoH in a laboratory by changing effective parameters, such as temperature, in a wide range.
2. Determining the SoH using the AC impedances and conductance measurements.

Pascoe and Anbuky have proposed a model for Valve Regulated Lead Acid (VRLA) batteries based on the discharge rate, ambient temperature, charge rate, initial state-of-charge (SoC), and SoH degradation [2]. This model was further developed in different operating conditions by Jossen [3]. These methods, and others similar to them are admittedly effective, but require external equipment, as well as the removal of batteries for testing, leaving the load unprotected. As an indirect process, two methods using the Alternating Current (AC) conductance and impedance have been proposed for assessing the SoH of VRLA batteries. These methods are less accurate and are most effective in identifying outliers, i.e., the failed battery in a battery bank [4, 5]. In short, there was no accurate method uncovered that could assess a battery's SoH without performing offline checks or using external equipment.

2.2. State-of-Health Algorithm

This paper describes a method to use partial discharge events to predict the SoH of a battery while the battery is in operation. By using a unique combination of measured and derived metrics that are collected only during the initial portion of the battery's discharge, the battery health can be predicted without relying on a total discharge of the battery. Using a thorough knowledge of chemistry and the electrochemistry occurring within the lead-acid battery, critical metrics were selected at very specific timestamps. The timestamps were selected to capture specific modes of known failure and degradation. The metrics of interest are listed below. It is important to note that the same metric taken at different timestamps can reflect different internal mechanisms within the lead-acid chemistry.

- Voltage
- First derivative of voltage
- Second derivative of voltage
- Change in voltage from optimal
- Change in voltage from charge (prior to discharge event)
- Recovery of voltage from discharge to charge (after discharge event)
- First and second derivatives of the recovery voltage

The figure below shows the voltage discharge curves of a set of VRLA batteries as captured by an actual power supply that has switched to battery back-up mode and is using these batteries for backup power. This set of voltage curves indicates a range of battery SoH, with one battery in particular much worse than the others. This is not an unusual situation found in the field. An additional complication is that this site has two sets of batteries connected in parallel to increase the required runtime for that site. This figure shows the primary items of interest in relation to the voltage discharge curve that were considered in the analysis.

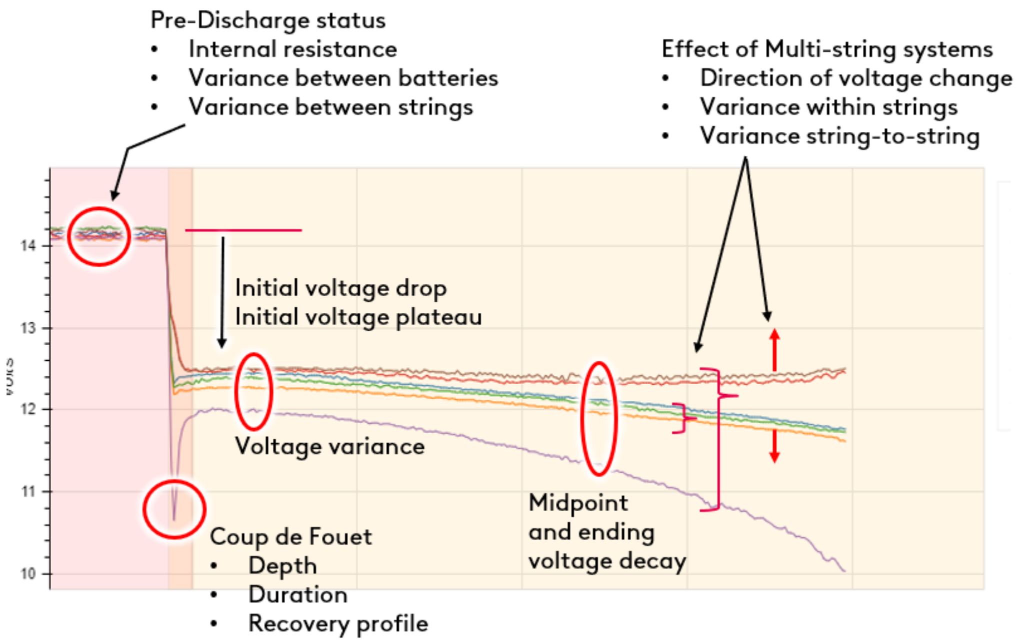

Figure 1 - Points of Interest in Voltage Discharge Curve

In addition to these metrics determined from the voltage curve, there are additional items useful to the predictive algorithm. This includes the following items.

- Temperature
- Number of batteries
- Output load and/or current
- Immediate vs. distant history
- Cycle history – depth, number, accumulated energy
- Charge status – time on recharge, time from last discharge, stability of battery voltage
- Battery information – manufacturer, model, age/install date

An important part of algorithm creation is the correlation of the metric to the electrochemistry of the battery. For example, the battery voltage drop due to the coup-de-fouet (the initial voltage drop seen in lead-acid batteries) is used to indicate the state-of-charge, electrolyte strength, and plate health, primarily the negative plate [6, 7]. Another example is the first derivative of the battery voltage due to the coup-de-fouet. This value is used to indicate the degradation of plate core health, primarily the negative plate and primarily due to cycling. Other metrics and their timestamps were selected because of their correlation to other internal battery mechanisms, such as active material crystal size, positive grid corrosion, negative plate sulfation, and electrolyte purity [8, 9, 10].

A further consideration for this algorithm was the time scale. Discharge events in the field have traditionally been measured in time (hours and minutes) with a minimum runtime depending on the criticality of the downstream equipment. A conventional discharge curve is shown in Figure 2 below.

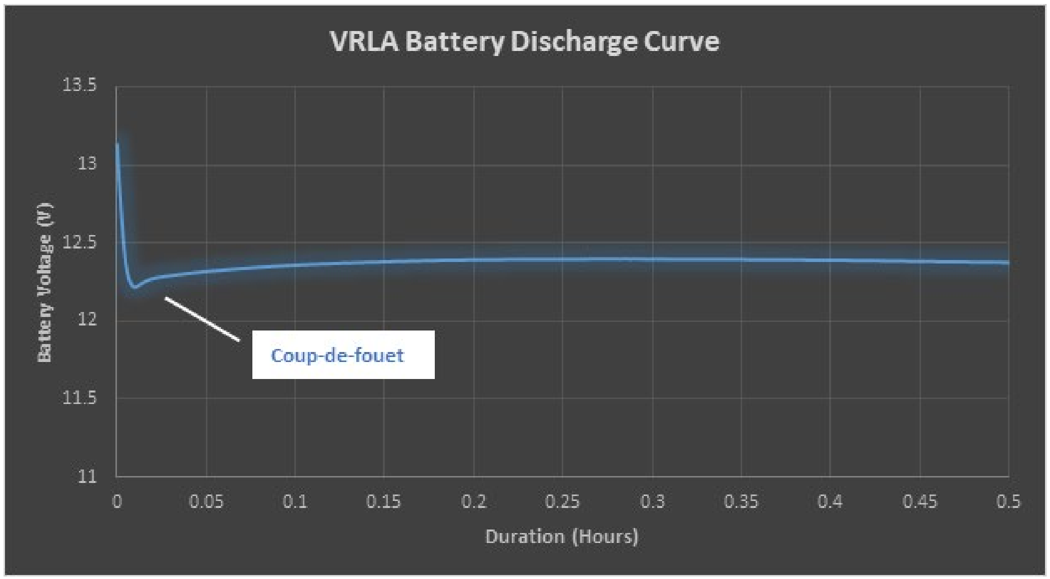

Figure 2 – Coup-de-fouet of a VRLA Battery

However, because the downstream load varies with every power supply, the time value will vary. That is, a five-hour discharge on a *lightly* loaded battery is not the same as a five-hour discharge on a *highly* loaded battery and the voltages are not comparable. To normalize the runtimes due to varying downstream loads, the battery discharge curves were plotted against 'Percent of Original Capacity Removed.' In this way, discharge curves and voltages were made to be directly comparable. An important implication of this is that when a discharge was made to a predetermined percent capacity, the discharge time would vary based on the downstream load on that power supply. In this way, the discharge times for each power supply are dynamic and fully time varying.

3. Data Collection

The dynamic deep cycle testing leverages the ANSI/SCTE 38-4 outside plant power supply management information base (MIB) for measurements. This long-established standard contains all the data points necessary to measure a deep cycle battery test.

The MIB exposes key power supply voltage and configuration information in the psDeviceTable. The MIB reports each battery's voltage in each battery string in the psBatteryTable. Each individual output current is reported in the psOutputTable. The power supply itself must instrument and report all these values.

The data collection interval is key for deep cycle testing. The practical limit for Simple Network Management Protocol (SNMP) data collection in an operational outside plant network is one sample per second. Polling the power supply data at slower than five minutes for these tests reduces the fidelity of the curve fitting and requires longer test periods which then become detrimental to battery health. Collecting the data at intervals between one second and two minutes per sample has been shown to provide sufficient accuracy for the curve fitting.

Another benefit of this dynamic testing is that high-rate data polling does not need to be sustained. Contemporary collection systems may already be capable of ingesting these data points at rates that can be used directly in the curve fits. If not, running higher speed collection for a brief period before the start and after the end of the deep cycle test is sufficient to collect the data necessary to analyze battery health. This allows operators to manage the overall amount of data the polling system retains.

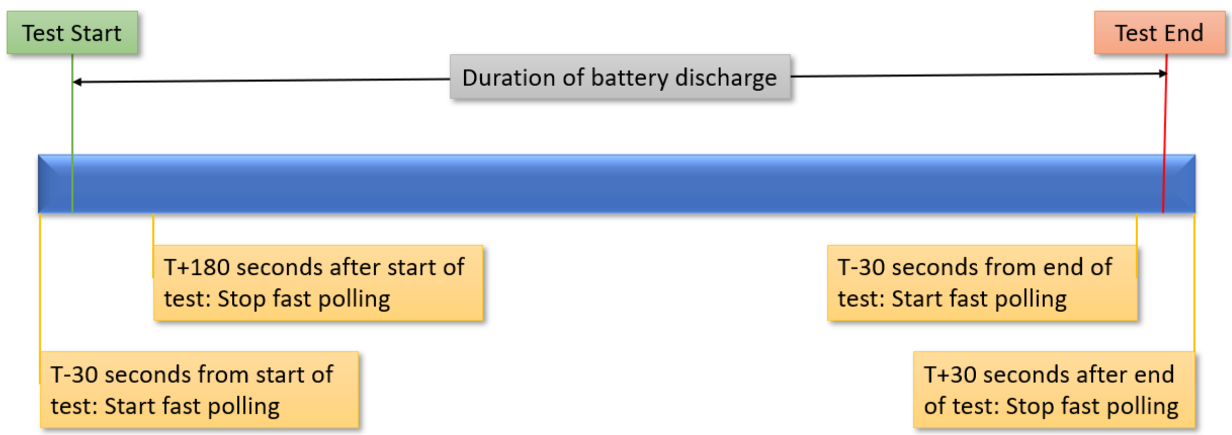

Figure 3 – Collection of Data by Time

By utilizing this well-known SCTE standard, operators can reuse much, if not all of their existing power supply data collection infrastructure to support the deep cycle battery testing analysis.

4. Results

As described in the earlier sections, there are a large combination of metrics that can be selected for a predictive algorithm. For example, the battery's voltage during the discharge is a single metric but can be measured in many ways. It can be recorded at numerous different times, which will represent different chemical actions within the battery. How it deviates from the norm, the magnitude of the change over time and the rate of that change over time can also be measured, as each of these can indicate a completely different mechanism within the battery. High-resolution discharge events were carried out in the lab to determine which metrics were most critical to a SoH prediction.

4.1. Training

A representative set of batteries was recorded under a controlled discharge in the lab for initial training development. The batteries had a SoH range of less than 25% to over 100%. As described previously, the discharges were normalized to a 'Percent of Original Capacity Removed' scale. The voltages were analyzed for the full discharge, down to 100% capacity removed. Additionally, a very high-resolution discharge was run to highlight the voltage curves during the initial 5% of the discharge. Representative curves are shown in the figures below.

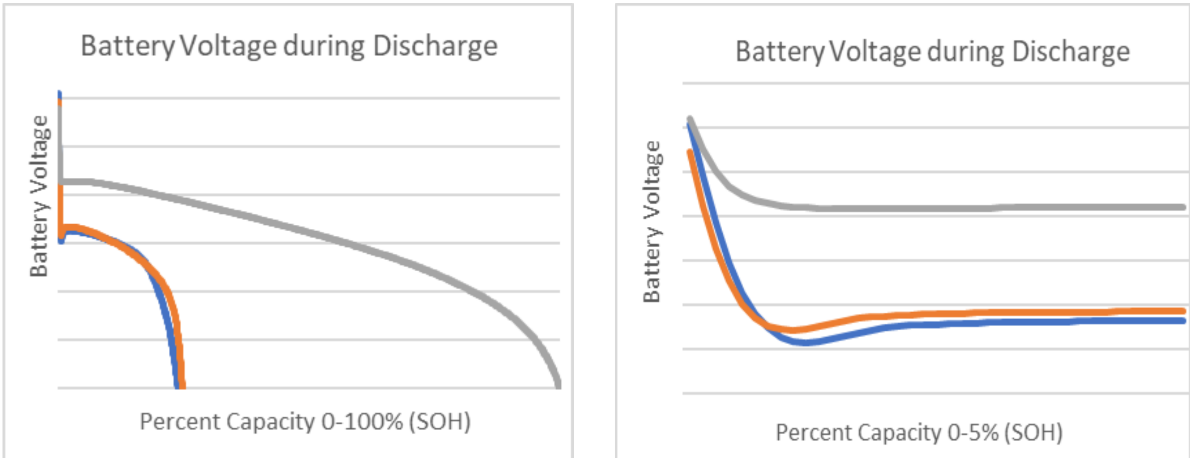

Figure 4 – Battery Voltages During Discharge Testing

Metrics were selected to differentiate the high performing batteries from the low performing batteries using these curves as a basis for ‘good’ vs. ‘bad.’ In particular, the voltage, the deviation of the voltage from an optimal value, its first derivative, and its second derivative, each at selected points throughout these discharge curves were selected. All derivatives were time based. After some review, ten total metrics were selected, and each were normalized to range from 0 to 1, so they would be mathematically comparable. They were then combined using a weighting factor based on experiential knowledge of the lead-acid battery chemistry. The final output of this algorithm provides a predicted state-of-health between 0% and 100% based on four major metric classifications: voltage, voltage deviation from optimal, first derivative of voltage, and second derivative of voltage.

[Normalized **voltage** at selected intervals between 0 and 25%] x [weighting factor(s)] +

[Normalized **voltage deviation from optimal** at selected intervals] x [weighting factor(s)] +

[Normalized **first derivative of voltage** at selected intervals] x [weighting factor(s)] +

[Normalized **second derivative of voltage** at selected interval(s)] x [weighting factor(s)] =

Percentage State-of-Health

4.2. Verification Runs

As a preliminary test of the algorithm, batteries from ten separate field locations were removed from their installations and brought to the lab. They were capacity discharged to determine their actual states-of-health (plotted as ‘Actual’ in the figure below). The algorithm was then run on the initial 25% of each discharge curve of these batteries to determine the prediction vs. the actual SoH (shown as ‘Prediction’ in the figure below). This comparison is shown in the table below and in the scatter plot as shown with the average difference between the predicted and actual less than 13%. Admittedly very small, these preliminary, non-optimized results are extremely promising. It is premature to apply an Analysis of

Variance (ANOVA) analysis to these comparisons because of the sample size, but the f-statistic value and the P-value both strongly indicate that the two sets represent the same group.

Average % difference: 13%

Prediction	Actual
18%	26%
27%	20%
31%	19%
34%	35%
38%	44%
65%	31%
79%	100%
82%	78%
86%	100%
91%	91%

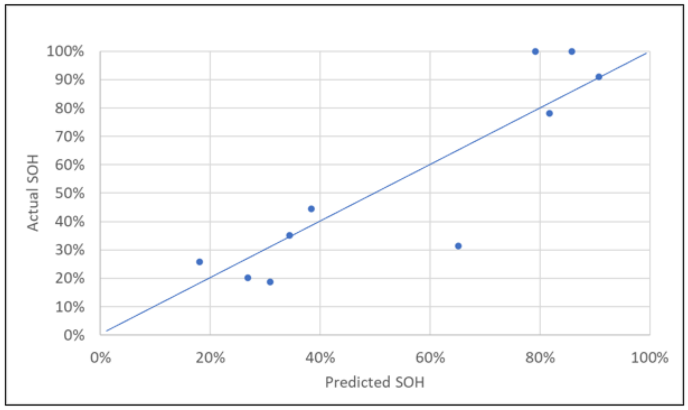

Figure 5 – Dataset from Verification Testing

Several of the battery predictions were well correlated to their actual battery health. However, others displayed prediction variations larger than desired. To better understand this, each separate metric was looked at individually. The ten metrics used are shown as calculated and normalized in the algorithm. When each metric was looked at individually, it is evident that some are better at differentiating between the battery's health condition than others. The differentiation can be affected somewhat by the constants originally selected for the calculation of that metric. A nominal effort was begun to optimize the algorithm by manually adjusting these constants. Also, the same effort was expanded to manually adjust the weighting factor of each metric and the normalizing factor of the compilation of all metrics. The optimization of this algorithm has progressed but is far from complete. This effort appears very promising and will continue in earnest in the next phase of this project when a much larger number of sample sets will be examined.

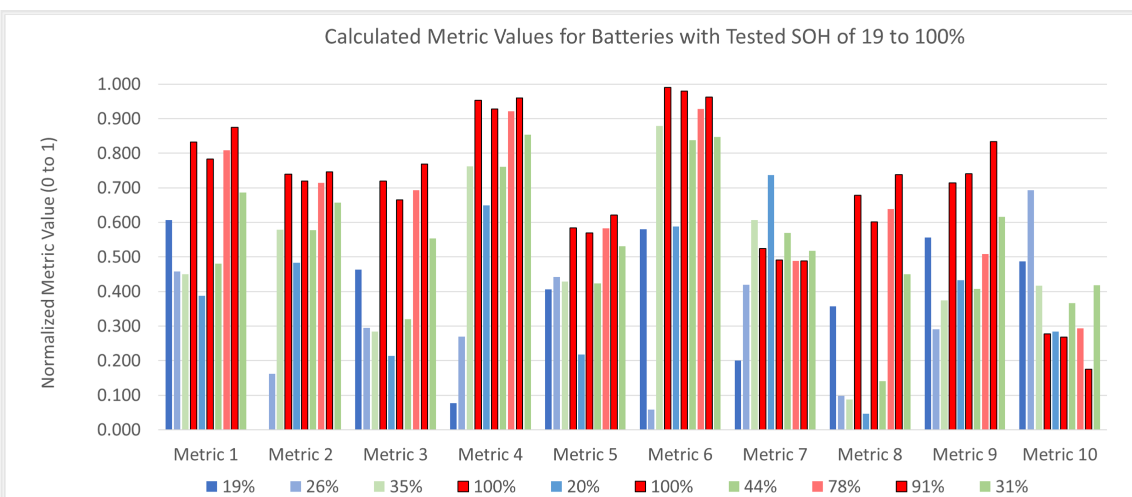

Figure 6 – Calculated Metric Values for Batteries Tested SOH

5. Implementation

This algorithm can be implemented within the Power Supply Notebook (PSNB) so that each battery will generate a health score. The PSNB is an application that manages the inventory and tracks the status of Comcast's outside plant power supplies. There are over 250 thousand power supplies that are managed using the software. Power supplies provide telemetry each minute, reporting of the device status, and select parameters, all of which are displayed within the PSNB. Maintenance tickets can be generated from within the application based on the information available. Incorporating the results from the dynamic deep cycle test of the battery health score into the PSNB application ensures that battery replacements are managed effectively, and the correct power supply maintenance is performed.

Maintenance technicians utilize the PSNB to review power supplies' telemetry and to document maintenance work completed. Importantly to this project, it also allows remote testing of power supplies to ensure their effective operation. This feature will be used to implement a dynamic testing profile based on the algorithm of this work. Within this tool, battery health scores will be initiated, tracked, and recorded, all through the PSNB application. A detailed history of power supply discharge events is also available as a reference and verification method for the resulting battery health score. The real-world power supply performance history and battery health score are imperative in determining maintenance plans for battery replacement.

The ability to view current power supply status, historical events, and the results of the battery testing in one location is critical to the planning process. A poor battery health score will prioritize the power supply in the maintenance plan. The ease of creating maintenance plans is greatly increased by utilizing the battery health score as a key driver, and the ability to access the information for all power supplies in a single location is a key new feature. Additionally, this will enable the tracking of proactive maintenance progress and the monitoring of battery replacements and logged work within the PSNB.

6. Conclusion

The preliminary results presented of the dynamic duration deep cycle testing and algorithm to determine battery health have shown to be extremely promising. By normalizing the discharge data, the downstream load can be utilized to generate battery health values that can be compared directly, despite variations in the downstream loads. The current algorithm developed is applied to only the initial portion of the discharge and a battery health prediction is made. A key characteristic of this method is that only a partial discharge is necessary, and as such, the power supplies are never left unprotected due to a fully depleted battery. Using the Power Supply Notebook to implement the testing capabilities allows for complete integration of the power supply monitoring, maintenance tracking, and battery health ratings in one unified application. The PSNB also allows remote testing of any site with full data collection and access. The use of this functionality is expected to improve the reliability of the outside plant network and the effectiveness of the capital replacement program for the worst performing batteries. It is believed that a dedicated machine learning effort would significantly improve the accuracy of this model and is already planned as a future improvement.

Abbreviations

AC	Alternating current
ANSI	American National Standards Institute
SCTE	Society of Cable Telecommunications Engineers
MIB	Management information base
ANOVA	Analysis of Variance
PSNB	Power Supply Notebook
SoC	State-of-charge
SNMP	Simple Network Management Protocol
SoH	State-of-health
VRLA	Valve Regulated Lead Acid

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