Whitepaper

Learning from the data: The impact of battery management trends

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Introduction

The issues associated with battery management, particularly with electric powered construction equipment and aerial work platforms, are significant factors in fleet maintenance costs. Due to this high impact on profitability, the subject is the focus for rental companies and has driven a market for battery "recovery" systems and demand for new and "better" batteries.

Following a decade of limited exploration of the technology, the last few years have finally seen the adoption of telematics in construction rental companies gain traction. As a result we now have access to quantifiable data on machine usage, rather than just abstract theory.

Skyjack looked to this convergence to see what patterns real usage data provided and how it applies to their electric powered lifts. Using an approach involving machine learning applied to aggregated machine data, the goal of the study was identifying the key indicators of in-field behaviors impacting battery management. Skyjack wanted to take those indicators and provide them in a simple and easy to action format.

Skyjack was able to identify operator charging behavior, irrespective of battery type, as a primary factor in machine performance, frequency of battery replacement, and cost of ownership of electric powered machines.

This document details how that study was carried out, the insights that are now understood, and how they have been applied to effective new digital products which interact with Skyjack's latest smart aerial work platforms to provide a lower cost of ownership.

To summarize the questions addressed in this paper:

1. How do we reliably detect battery management issues in powered lifts?
2. What are the real world trends for battery treatment in the field (on work sites)?
3. How is this impacting the life of batteries, machine performance, cost of ownership?
4. How does this data become a solution for the rental industry?

Industry Application

There are several conditions that make the ability to measure and manage the treatment of lead acid battery packs in construction equipment a pressing concern for the industry.

1. There is a move towards electric powered construction machines for various reasons. Large segments of construction fleets are already electric powered.
2. With electric powered machines, a primary driver of cost of ownership becomes, battery back maintenance.
3. In order to lower costs and increase profitability, advances need to made in the longevity, and general condition of battery packs.

4. Lead acid battery packs are the standard battery pack type in construction equipment, are exceptionally recyclable, and have potential to attain much longer life than the current industry average when managed properly.

5. Even as we see the slow adoption of lithium and other alternative battery materials, the bulk of electric machines already in the field continue to use lead-acid batteries.

Baseline Analysis

A key starting point was being able to accurately and efficiently identify the baseline data on a voltage curve. Being able to identify when an electric powertrain isn't active allows resources (processing power/cellular transmission) to be dedicated to analyzing meaningful events. Lifts are stationary far more often than they are moving, so removing that uninteresting data has a big return.

A first reaction to the voltage data might be that it's clear that baseline is where it flattens out (Figure 1: Baseline fluctuation). However, when we take a closer look these areas are actually constantly fluctuating with decay of the battery charge, temperature etc.

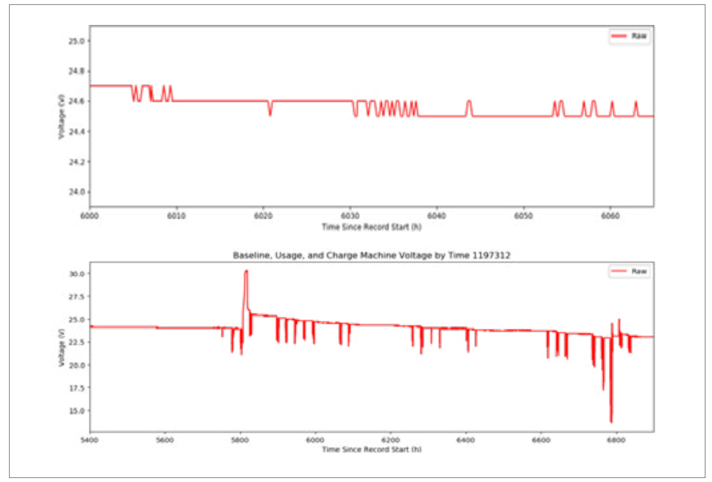


Figure 1: Baseline fluctuation

The amount of data – in this study 84 million data points – is what makes these problems interesting. It's not difficult (not even a little bit) to look at a single voltage graph and identify charge, baseline, and activity segments.

It is when we need to scale that analysis beyond the capability of human ability – 84 million data points in a short time – that there is a challenge.

Efficiency is also key. There is limited processing power in a telematics unit, and identifying when to analyze and transmit is a critical capability to actually building solutions. The requirement was to develop an algorithm that could successfully identify the different features of charging data with high accuracy, which requires effectively understanding and interpreting all of the edge cases.

For this purpose, it is necessary to consider how a telematics device "sees" in terms of live data. Think about driving down the highway versus looking at map. Since the data is captured as it happens, the algorithm cannot zoom out and look at the voltage curve. That is why Skyjack looked to engineer the algorithm to determine baseline activity by looking at only a handful of data points at a time.

This approach resulted in the ability to identify baseline data dynamically with high accuracy. This analysis also uncovered interesting features of the data that will help us focus computational power in future versions of **ELEVATE** on more interesting problems. The simplest example of this is understanding that over 50% of all data transmitted by a standard telematics device is baseline data. That means there is significant resources to be directed to other tasks.

Algorithm Development

The Skyjack algorithm is "lossless" in the sense that although it can detect and ignore large portions of uninteresting baseline data, it never discards an important data feature.

If we look at the the top-right graph (Figure 2-A: Baseline detector tuned for lower specificity), it represents an earlier version where there was a loss of interesting data for increased performance.

Some data was incorrectly being mischaracterized as not useful. Since then, subsequent versions of the algorithm have been tuned for greater specificity (Figure 2-B: Baseline detector tuned for higher specificity), to make sure that while performance and efficiency remain high, useful data is kept.

Some of the most important insights that can be delivered through this approach are those around charging behaviors of electric powered lifts.

Charging frequency and length of charge, along with time spent at extremely low charge, are all key drivers of cost of ownership for electric powered lifts, leading to premature and unplanned battery replacement.

Being able to reliably detect poor charging behavior and present that information quickly to Skyjack electric scissor owners and operators has the potential to greatly reduce the costs associated with battery replacement, as well as help to quickly diagnose and resolve service issues around battery pack performance.

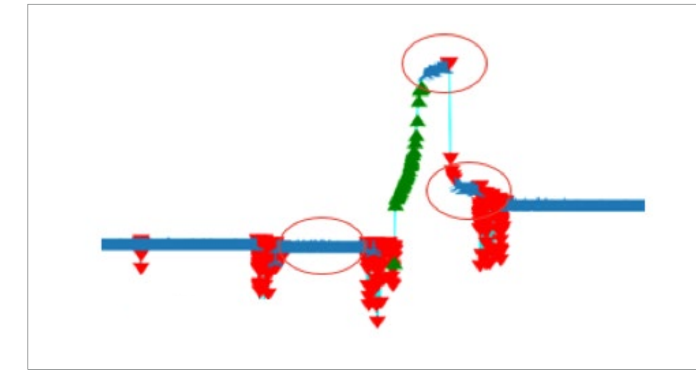


Figure 2-A: Baseline detector tuned for lower specificity

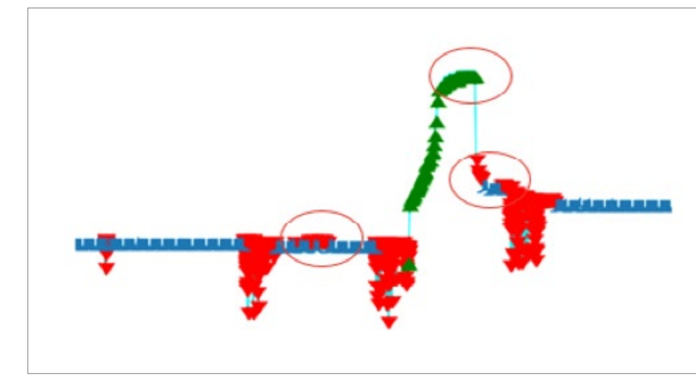


Figure 2-B: Baseline detector tuned for higher specificity

Therefore, it is critical that the algorithm reliably detects charging patterns in the data.

Some of the obstacles that the charge curve detector algorithm faced were:

- Identifying the start of a charge curve
- Identifying the end of a charge curve
- Handling split peaks
- Handling voltage plateaus in the charge curve

Identifying Start of Charge

Again, the eye test easily spots when a machine is on charge or not (when the voltage increases), but we run into issues when we go to transfer that common sense to an algorithm that can usefully analyze live data and deliver that information accurately on the fly.

The issue here is the difficulty detecting charge when it immediately followed machine activity (Figure 3: Activity followed by charge). This creates a problem for an algorithm that is simply looking for an increase in voltage for any period of time over the baseline voltage.

When usage data and charge data follow each other closely, early test versions of the algorithm tended to group charge data with activity. Only looking for higher voltages, we end up missing machine activity, and counting it as charging data.

Looking at Figure 4 (Figure 4: Activity within charge curve), there is machine activity (jagged downward spikes in voltage) that is included as part of a charging curve, because it all occurred above the baseline voltage.

The improved algorithm identifies usage activity and uses it to calculate a virtual baseline (If there was no activity, what would the resting voltage be?).

Even when charging and activity follow each other closely important data features are labeled properly. The blue line in Figure 5 (Figure 5: Virtual baseline voltage), this represents a calculated virtual resting voltage.

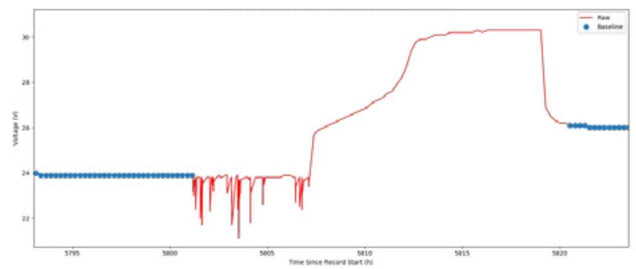


Figure 3: Activity followed by charge

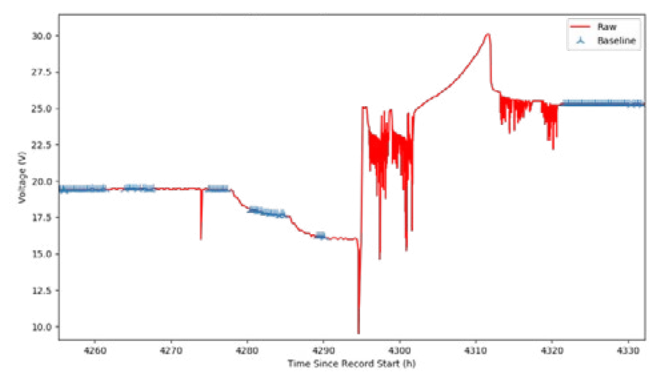


Figure 4: Activity within charge curve

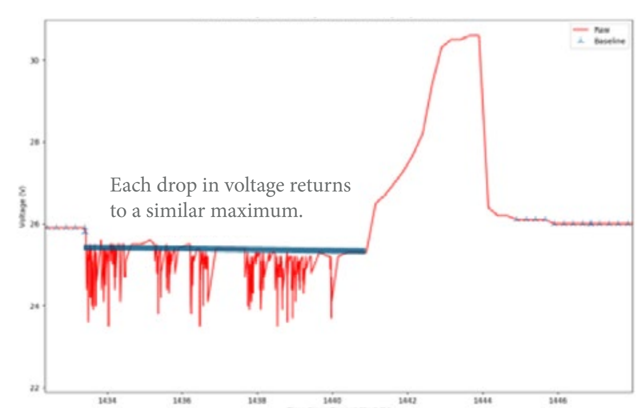


Figure 5: Virtual baseline voltage

Identifying End of Charge

A similar issue had to be worked out for detecting the end of charge cycles. Simply looking for a drop to last known baseline state doesn't succeed due to the time required to return to baseline voltage after a charge (sometimes up to 1 hour), this approach was shown to skew stats as charge heavy. (Figure 6: Misidentified charge activity).

You can see the correction implemented in a later version of the algorithm (Figure 7: Corrected charge activity identification), where the time falling back to resting voltage after charge is not considered active charge time.

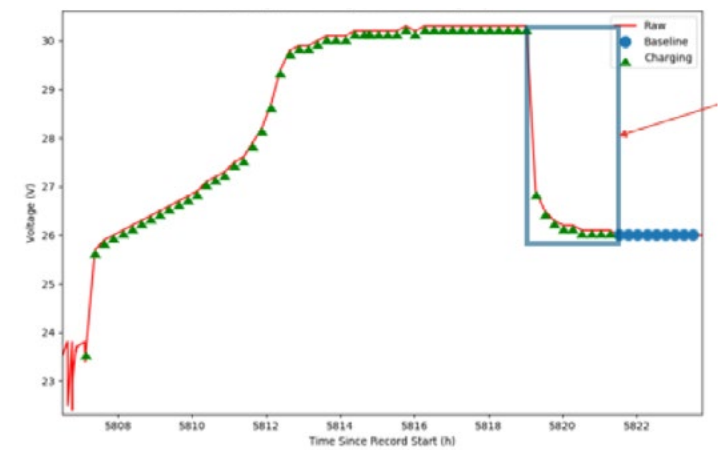


Figure 6: Misidentified charge activity

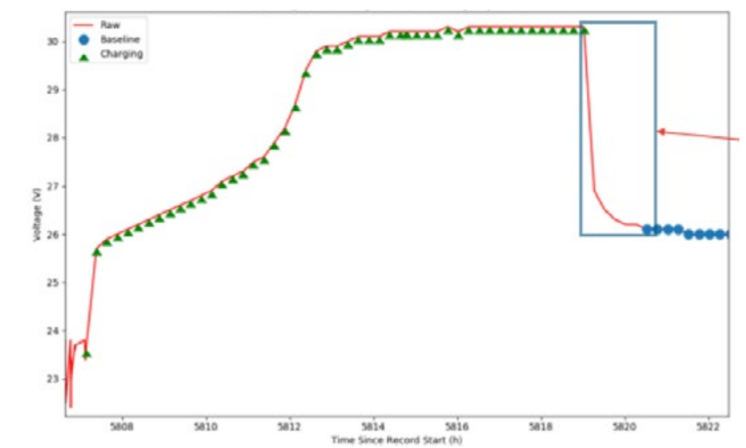


Figure 7: Corrected charge activity identification

Handling Split Peaks

Split charge curves caused by inconsistent power sources proved another challenge. This often occurs on early stage worksites, where generators provide charge power to electric machines.

However, because there was "blinking" on the power circuit that the charger was plugged into (generator delivered power), we see a spiking upward curve, rather than the smooth curve.

The current algorithm looks for split peaks, and identifies the trend in upward movement of voltage from peak to peak – which is labeled as a charge curve from start to finish.

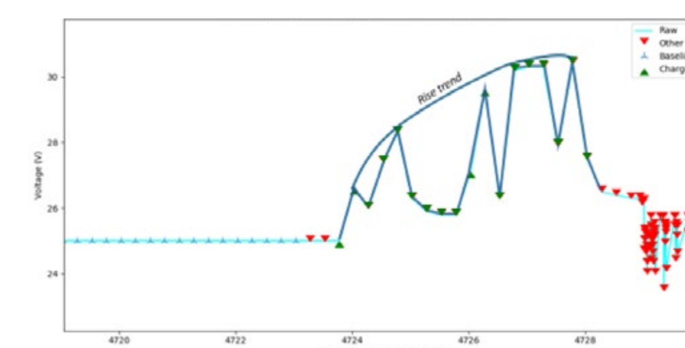
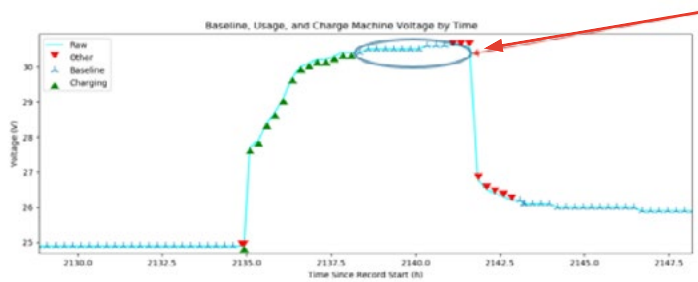


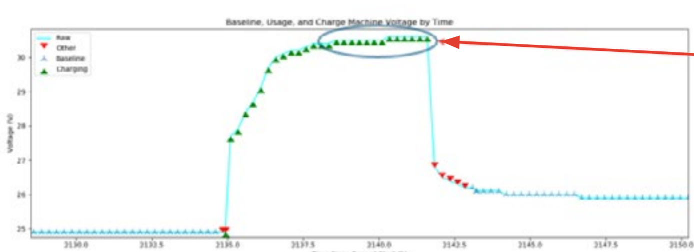
Figure 8: Generator power causing split peaks

Handling Voltage Plateau



Misdiagnosed charge data as baseline due to it leveling out at a high voltage

Figure 9: Mislabeled charge plateau



Completed Charge Improved Algorithm:

To correct the issue, an ad hoc exception was imposed. This allows the voltage plateau to be correctly labeled as part of the charge curve.

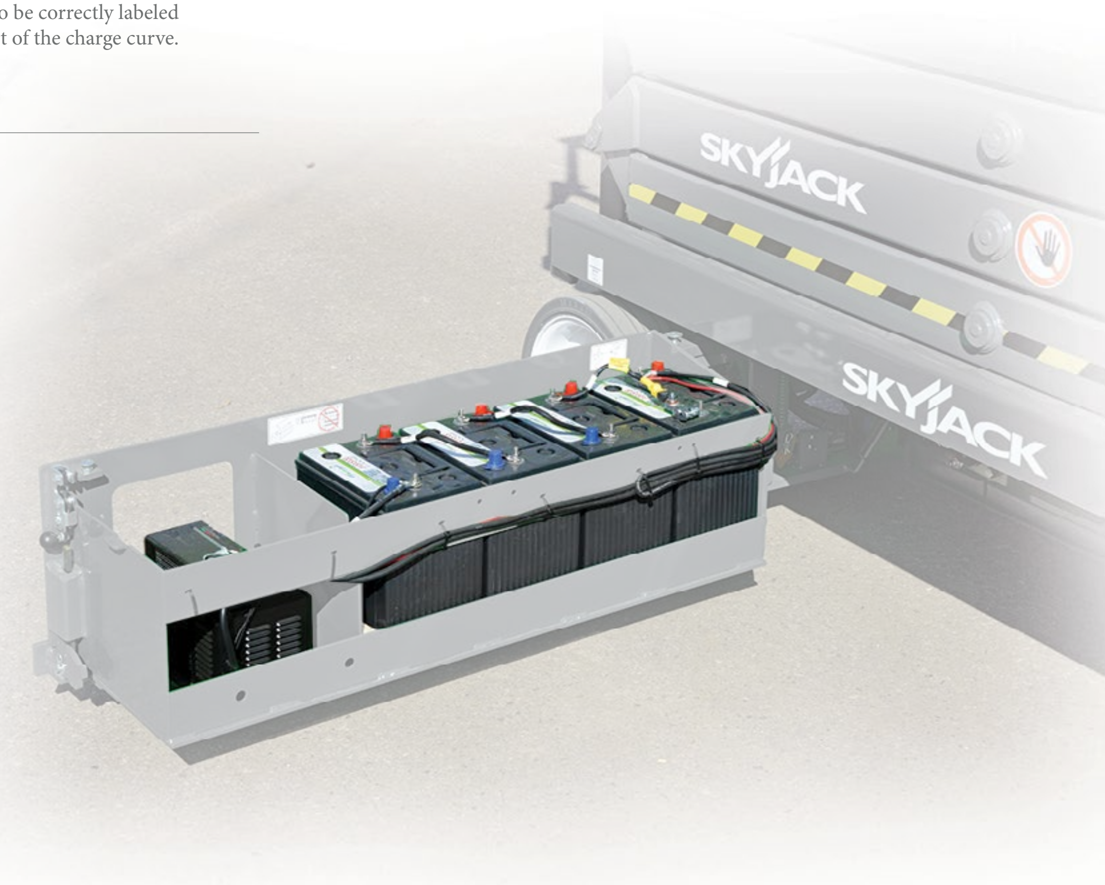
Figure 10: Corrected charge plateau

Another challenge in analysis occurred in analyzing the plateau phase of charge curve. Illustrated in Figure 9 (Figure 9: Mislabeled charge plateau), a section of an extended charge curve flattens out, and would be labeled as as baseline data.

During especially long, full charges this would mislabel significant amounts of charge data.

This represents a simpler problem in identifying labeling issues, however it works as a good example of how subtle adjustments in the analysis can wildly swing results.

With the current algorithm exception handling has been built in to properly this data as “charging” activity (Figure 10: Corrected charge plateau).



The Analysis

Below are some of our initial findings (Figure 11: In-field charging trends), on how often, and for how long, electric scissors are (or are not) being charged. This data is based on a sample of over 1800 machines from across North America, and Europe over 2 years.

We found that the median number of full charges an electric powered scissor lift receives per month is ~1. When a scissor lift is active, it should be charged fully every week at a minimum.

Figure 11: In-field charging trends

Of all the charges applied to an electric scissor lift, 75% can be classified as “opportunity charges”, which are charges less than 2.75 hours.

These charges are not necessarily harmful to battery health, but when they represent such a high number of total charges, this indicates that battery packs are being left at a low state of charge for extended periods of time. This has a direct relation to the permanent reduction of potential amp hours available in a battery pack – an avoidable shortening of the battery pack’s life.

The average time between full charges is 21.5 calendar days. Similar to the median statistic of 1 charge monthly...

...this indicates that batteries are not being charged at anywhere near the required rate or maximum battery life.

The Current Algorithm

As a result of this study and development process, Skyjack have created an algorithm that handles a wide variety of real world charging and activity patterns.

The Skyjack algorithm is able to quickly digest data as it comes from the machine and label it with high accuracy, while maintaining performance and efficiency that allows delivery of data in real time through **ELEVATE** digital products.

The Conclusion

The construction rental industry average for lead acid battery life is sitting between 1.5 and 2.5 years. As an industry, we're often presented with bright and shiny products, like new battery technologies or battery recovery methods, which miss the greatest opportunity to reduce cost of ownership for electric powered machines.

The more time a battery spends in a low state of charge with the lead cathode sulphated, the greater the chance that the sulphate crystalizes, permanently reducing the storage potential of the battery.

There are ways to try and dissolve the crystalized lead-sulphate with specialized overcharging. However, those methods may lead to a shorter life for the battery and quicker replacement cycle still.

These processes might solve a short-term problem, but will never lead to a longer battery life, because they are destroying critical battery materials.

In the Skyjack analysis, we found that every month 5% of the machines we looked at were left in extremely low state of charge for 15 continuous days. In fact, 441 individual machines out of the 1,800 had spent at least one 15-day period in an extremely low state of charge.

With proper battery treatment, battery lifetime can be extended to four years. That is 200% of your current average battery pack life (Figure 12: Charging Vs Battery pack life).

Knowing the relationship between poor charging habits and shorter time to battery replacement, this study exposes an opportunity to reduce the frequency of battery replacement for electric scissors in our industry, if we can action it.

Regardless of battery type, brand, or region, batteries are not being charged properly. What is keeping rental companies from that 200% battery life and the attached greater profitability? Industry behavior. New technology alone is not the solution – **we need better practices.**

The key to realizing that potential savings is providing involved personnel with access to the data. How do I notify the contractor, the subcontractor, or the operator that a machine needs to be charged? How do I find out about poor battery care as a fleet manager, service manager, or rental desk staff?

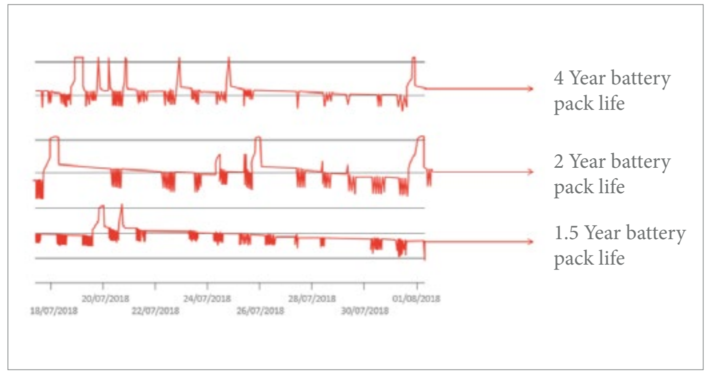


Figure 12: Charging Vs Battery pack life

Actionable Insights

Since the inception of the **ELEVATE** telematics package, Skyjack have focused on actionable insights. The findings of this study have given focus to two new Skyjack digital products. **ELEVATE BMS** (Battery Management System), a battery management algorithm integrated into all of the software for Skyjack's **ELEVATE** telematics solution.

The data being created by the BMS algorithm is available to all relevant users of telematics on Skyjack machines.

Skyjack has incorporated BMS into the new **ELEVATE Live** product, which provides live battery data to the operator, to encourage better charging behavior on the worksite (Figures 13 & 15: ELEVATE Live).

Figure 13: ELEVATE Live

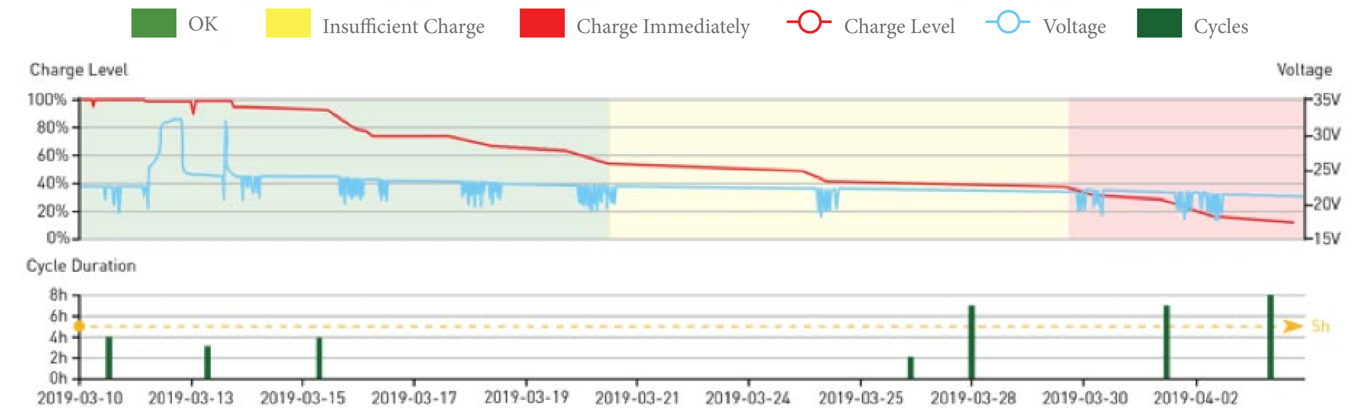


Figure 14: BMS dashboard

Figure 15: ELEVATE Live

For service technicians, rental desk staff, and fleet managers, the BMS algorithm feeds into a robust fleet-wide and deep machine analysis (Figure 14: BMS dashboard), providing easy-to-access charge history and current life (remaining potential amp hours).

The BMS feature goes so far as to provide a metric that Skyjack has labeled "battery care".

"Battery care" trending in the green is headed towards a full potential battery pack life (3-4 years); a machine in the yellow is trending towards the industry average (1.5-2.5 years); and a machine in the red is trending towards an exceptionally short battery life.

This tool provides the metric to manage an electric fleet towards much greater efficiency, much lower cost of ownership, and significantly improved profitability. □