Exploring and Untangling Battery Performance Data

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Abstract

This particular study is part of a larger research performed by VOLTiFiC which evaluated all available battery published data in the secondary battery segment (5-3220AH). The scope of data covers top 10 largest manufacturers of industrial batteries in North America and spans over 1,400 battery models. Nicad, VLA, and VRLA batteries with life designs of 2 - 20 years are evaluated. The majority of batteries are designed for stationary and standby applications with more than 75% advertised as 20 years life.

The findings paint a picture of potential overlooked problems that lie in published battery performance data. While only less than 1% of the data has errors, nearly 10% of the battery models are affected. The distribution of errors in different battery series, types, and across various manufacturers indicates a common theme of inadequate or lack of quality control of battery performance data.

How much data interpolation is considered excessive? Should battery manufacturers be required to disclose when they perform interpolation vs. actual test? What level of measurement accuracy is acceptable for published and battery sizing data? Should 3rd party verification be required for published data? This paper cannot answer all these questions, but first step in answering them is through increased industry knowledge and understanding of confidence levels placed on battery tables and charts. After all, a problem is not really a problem until it's understood.

This paper and subsequent presentation is aimed at laying the groundwork for this much needed discussion to take place. Observations, obstacles, and solutions are being shared with the purpose of improving compliance and application design of batteries.

Detailed comparison of major types of issues, such as incorrect data measurement, data entry, interpolation and publication are examined. A major stumbling block for battery manufacturers is the sheer amount of data that can be produced for each battery model. Some data issues are easily identified with graphical visualization and performing manual quality control. However, in most cases data verification requires computer algorithms and specialized data modeling skills. Once 'bad data' is identified, the solution is trivial. Some require small corrections to sizing applications and published material; some require re-calculating data interpolation and in the extreme cases a repeat of the discharge test.

The extent of issues is sometimes limited to what is published only, while other times the error is consistent with the data in battery manufacturer's sizing application. The occurrence and margin of error is also dependent on data availability, quality and marketing of each battery.

The implications can be significant depending on the application, criticality, design margins and coincidental overlap of errors with actual operating load profiles. Whether you use battery performance data for battery testing or just sizing batteries, it will have different cascading and compounding effects. Examples will be presented in an attempt to empower readers with basic tools to understand what issues exist, and to what extent their systems can be affected.

Introduction

The need to perform battery sizing generally depends on criticalness of the application, size of the load, and reliability requirements of the end user. Mission critical systems such as emergency power back up, protection controls, and safety systems demand battery sizing calculations as a minimum requirement for evaluating/purchasing batteries.

IEEE 485™ and IEEE 1115™ are the most prominent standards in the world for sizing lead acid and Nicad batteries in stationary applications. The calculations in these standards rely on battery performance data provided by battery manufacturers. This means that if one wishes to size (calculate) a battery capacity in terms of percentage or time, data for that battery in the desired time period has to be first made available. In pursuit of developing a universal battery sizing application, we set up a team to collect and analyze all available battery data.

There is currently no specific standard for publishing battery performance data, and data availability is related to application and quality (design life) of the battery among other things.

Before diving deeper, let's make sure we are on the same page on these two important topics:

Design Life

While *design life* is used in this paper to categorize battery quality, a proper way of classifying batteries is actually via warranty period. Design life is often used for marketing purposes with broad understanding of how it can be achieved, whereas warranty period is specific to an application, operating voltage and temperature, charging, and maintenance practices. Warranty period is often proportional to design life but, it can vary depending on the commercial or financial requirements.

Therefore, to make analysis easier, data will be summarized as follows:

Design Life (years) α	Warranty (years)[1]
15 - 20	5 - 7
10 - 12	2 - 3
2 - 6	1 - 1.5

Battery Data

Throughout this paper, the term *battery data* will be used in replace of battery performance data or cell discharge characteristics for ease of reading. This is a reminder for readers not to confuse this with other types of data that is generated and measured with battery monitoring and testing equipment after installation of batteries.

Battery performance data is produced by a controlled capacity discharge test, simulation, or a mixture of both. It is common practice to test one battery model in a series and interpolate (approximate) data for rest of the models in the same series. This is due to the fact that performance data is directly linked to total number of plates per cell in a battery. Number of plates is often the only differentiator in various size models within a single battery series.

[1] Typical full replacement warranty period (excludes any optional or prorated warranty offerings)

Dataset Scope

Now that we have an understanding of why this dataset was collected, let's look at what it includes and what it does not. As mentioned earlier, there is currently no standard for battery data so format and availability of data varies greatly.

Battery cell discharge characteristics data may be presented in tabular or chart format (commonly known as S-curves or Fan curves). Commercial and consumer type batteries generally do not have tabular data readily available, and graphs that are published on product brochures often bear low importance. Due to low accuracy in extracting data from published graphs, any battery model that does not have available tabular data is excluded from this dataset.

Data is gathered from manufacturers with manufacturing and/or distribution plants in North America or battery models that are primarily advertised for use and sale in North America. There are battery models that are no longer available for sale, but are still included since their published date is within advertised design life. The dataset does not include any data pertaining to sales activities therefore, quantity of battery models sold and their current operational state is unknown.

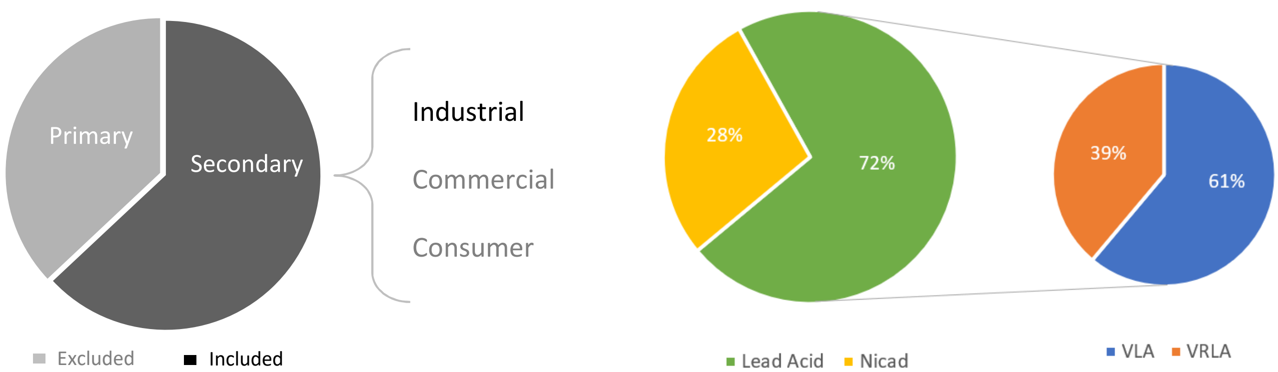


Figure 1: Scope of data showing battery market segment, chemistry and type

While there are some models that are used in nonstationary applications, the majority are designed and advertised for stationary applications. They are all part of the secondary battery segment with range of design life and capacities shown in Figure 2.

Sizing standards allow for a factor to be applied in calculations to adjust for variation of expected temperatures as a function of time (known as Temperature Correction Factor). This allows manufacturers to publish data at a specific temperature and designers to apply correction factor during sizing at minimum operating temperature (most conservative). The temperature specified for most of the data is based on 25℃ or 77℉. There are few models (~ 1%) however, that are advertised at 20℃ (European based).

The standards do not provide a similar factor to adjust for variations in end of discharge voltage or different discharge rates. Manufacturers choose what end of voltage and what time periods to make the data available for. Often, this is derived from target market, application of use, and previous history of sale. There are currently no standards or enforcements of such practices. Subsequently the minimum amount of data that is required for sales in a specific application is tested and published.

Industrial type batteries designed for critical applications are most likely to have available data. These higher quality batteries also come in larger capacity packages, so it's no surprise that batteries with larger capacities and longer design life dominate the dataset.

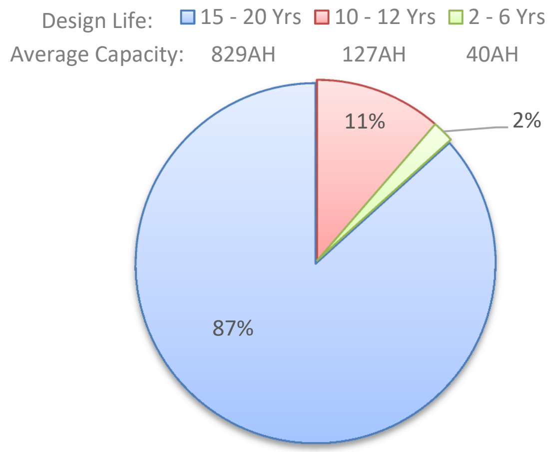


Figure 2: Distribution of data vs. capacity & design life

Data Extraction

The dataset collected for this study is from tabular data formats only. These tables are either from published literature on battery manufacturer's websites or via spreadsheets received directly from battery manufacturers engineering department. Data extraction was performed by a combination of automatic computer algorithms (similar to ones used in web search indexing) and manual verification. For quality control, published data was cross referenced with data used in the battery manufacture's sizing application. This verification was performed in batches and based on the existence and accessibility of the sizing application.

The most basic form of battery discharge characteristics is presented by constant discharge current (Amps) or power (watts) per cell (or unit) of battery. This data is specified at a standard temperature (i.e., 25℃), end of discharge voltage, and time. A typical table for a battery model may look as follows:

End of Discharge Voltage	Time													
	1 min	15 min	30 min	1 Hr	2 Hr	3 Hr	4 Hr	5 Hr	6 Hr	7 Hr	8 Hr	10 Hr	12 Hr	24 Hr
1.81 VPC	244	177	129	82	53	40	32	27	23	21	19	15	13	7.6
1.80 VPC	253	181	132	83	54	40	32	27	24	21	19	16	14	7.7
1.78 VPC	267	189	136	85	55	41	33	27	24	21	19	16	14	7.7
1.75 VPC	283	199	142	87	56	41	33	28	24	22	19	16	14	7.7

Table 1: Constant discharge current (Amps) for an example battery model at 25℃

A typical lead acid battery model may have 2-12 voltage data sets listed, ranging from 1 min to 24 hours. These data points are not provided in a similar manner. Some are scattered, some are concentrated in batches and some are evenly distributed. Out of 1440 minutes in 24 hours, a battery model may only have 12-20 data points per each end of discharge voltage.

Challenges that arise from extracting this data are due to inconsistencies across battery models. These include varying end of discharge voltages, time periods and number of data points. Data is often prioritized to showcase the full range of capacities that the battery that has to offer. Subsequently, regions of available data do not often overlap with the most rapidly changing part of the battery discharge characteristics. Any data point that is missing can be obtained through approximation or interpolation, but for this particular study this was omitted. This allows us to examine only the data that is produced and published by manufacturers and not introduce any errors due to approximation. In a way, the more data that is available, the more it will be extracted and scrutinized.

Error Identification

It is difficult to fully validate any data without first understanding the process that battery manufacturers use to obtain them in the first place. The process typically begins with performing capacity discharge tests in a controlled environment with carefully selected constant loads. This produces a baseline for battery manufacturer to use in order to interpolate and approximate data for a whole range of end voltages. It is common practice to perform this type of vigorous testing on one model with a predefined number of plates and use the results to produce data for remaining models in the series. This is due to high costs associated with testing and subsequent analysis. It should be noted that data is never advertised in raw format. It goes through several rounds of conversions and data cleansing, which all produce their own margin of errors. Battery manufacturers may also add a statistical factor on top of the actual test results to allow for process variations during production.

There are no standards or regulations for these procedures, so it's costly to create a standardized test and repeat the measurements. Even if we could finance the expenditure, the likelihood of repeating the exact same test configuration is next to impossible.

So, we will take a different approach. Rather than validating the dataset against what the manufacturer has tested or even what the battery can output, we test the data against itself. We will validate the dataset relative to itself based on underlying physics and chemistry fundamentals:

I. A battery discharged to a higher end of discharge voltage (EOD) should not produce more current in the same time period than one discharged to a lower EOD.

II. A battery with a lower number of identical plates should not produce more current in the same time period and EOD.

III. The discharge characteristics of any battery should always have a negative slope. In other words, the ampacity of the battery while discharging should always decrease as time increases.

These simple rules apply to all battery types and chemistries and will enable us to create some basic error checking algorithms discussed below. This allows us to look at the dataset in one snapshot and assess its health in a very general and aggregated fashion.

One easy method to check the first rule is to compare data from different end of discharge voltages and repeat for each battery. This is illustrated in Figure 3. This type of error could occur at any time period listed.

The battery will fail this test for any one or more data points that this error occurs at.

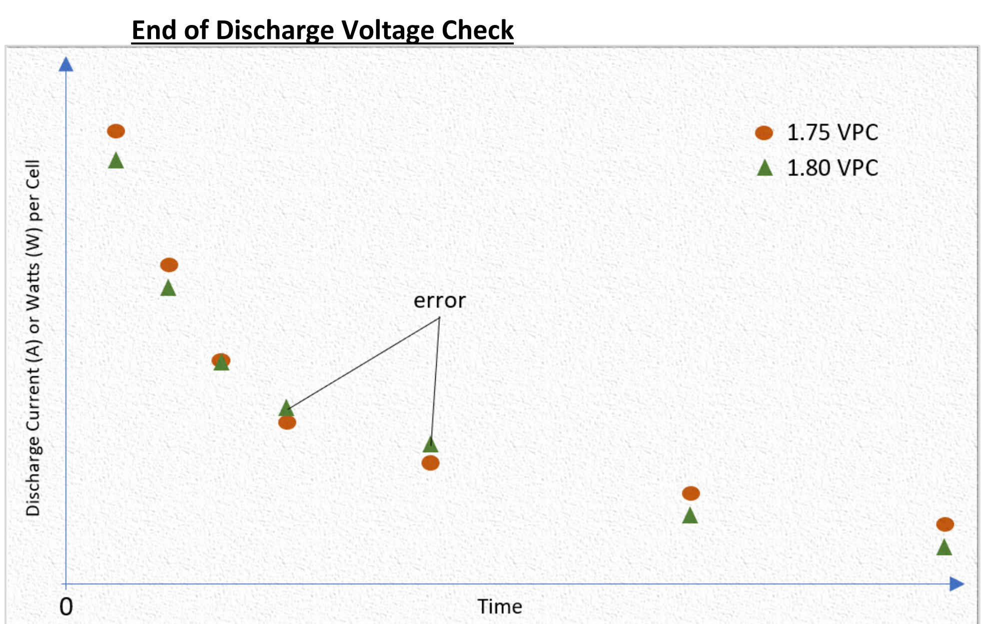


Figure 3: Error Check Algorithm based on EOD

Plate Consistency Check

In order to validate rule II, we compare data for batteries with different numbers of identical plates.

The battery fails this test if any data point has this error occur at the same EOD and time.

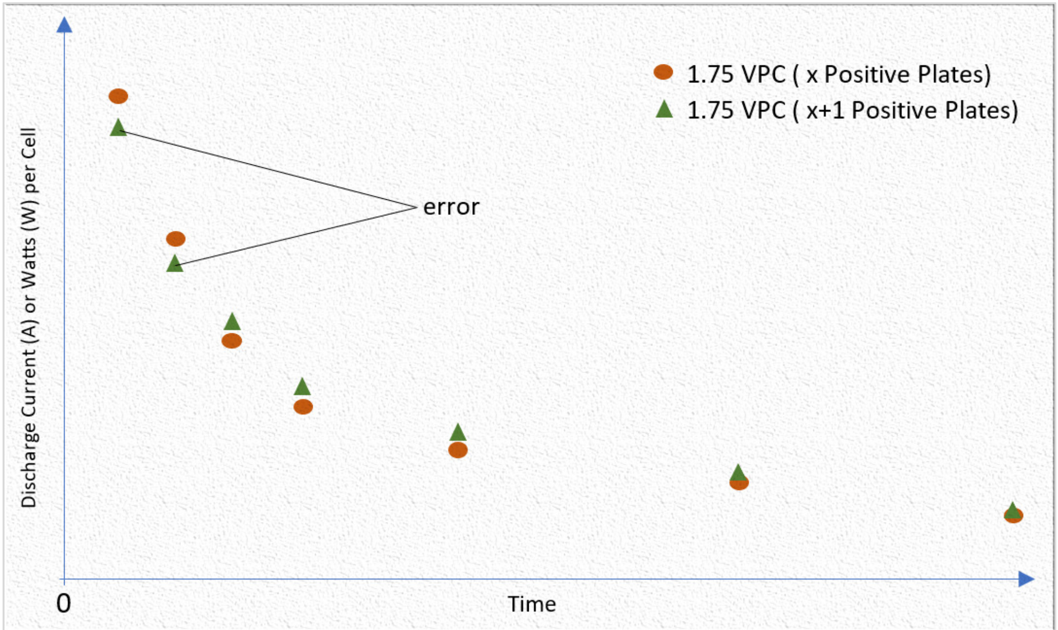


Figure 4: Error Check Algorithm based on # of identical plates

Discharge Characteristics Check

A quick way of checking the last rule is to sequentially compare data points as time increases.

If any data point is higher than the previous, then it is identified as an error.

This is a very basic function as shown in Figure 5, and it will only partially check the last rule.

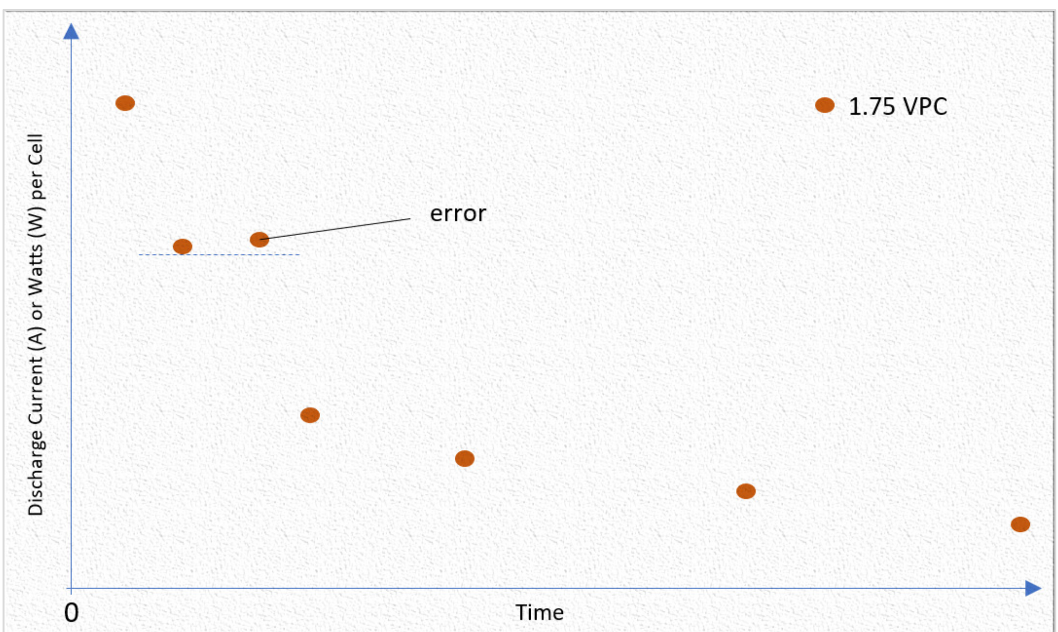


Figure 5: Error Check Algorithm based on discharge characteristics (BASIC)

An ideal algorithm would first apply regression models to approximate where each point should appear and then perform comparison. This more advanced method is illustrated in Figure 6 with an orange dashed line shown as regressed data.

This method does produce inaccuracies due to approximation. Therefore, we will only include results from the basic version of this algorithm and exclude any results from the more advanced one.

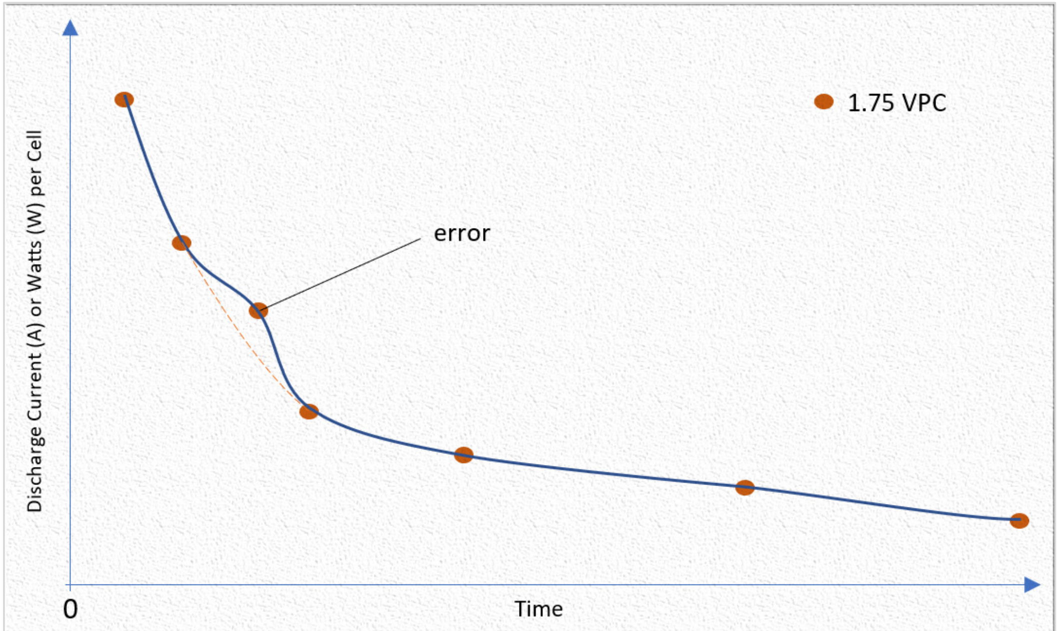


Figure 6: Error Check Algorithm based on discharge characteristics (ADVANCED) not included in results

Results

Before we look at the results of performing the preceding error checks on the dataset, it is important to note that error identification cannot always point to a single cause or source of error. For example in our first algorithm, while 1.80VPC is marked as the one with errors, there is no evidence that the 1.75VDC is not the one with incorrect data. In a way, the moment we observe a single error in a battery model, we lose confidence in all of the entire data from that battery model. Similarly, whenever a battery model fails the second test, we lose confidence in the entire dataset from that battery series.

This type of brief error checking does provide some basic level of quality assurance however, and can be used as a guide in order to narrow down the list of potential causes. For example, when there is a single error in battery data, it is usually a typo that persisted through publication. When there is a repeating pattern of errors in battery models within a single series, it usually points to human errors in later stages of publication such as manipulating data for brochures (ie. sorting, filtering, and extraction). When there are errors identified in discharge characteristics of the battery, it usually points to bad interpolation algorithms or faulty data acquisition from discharge tests. As such, any direct conclusion drawn from these results without further investigation should be avoided. Also note that these results are being shared for the purpose of increasing awareness around battery data issues with focus on existence and type of errors rather than cause or margin of the error. If a battery passes these error checks, its data accuracy still remains uncertain and would require further validation.

Figure 7 shows the distribution of errors based on chemistry and type. Each box represents a battery model that failed the error checks. The smallest box (bottom right corner) is equivalent to 1 error, the largest box (top left corner) has 1,089 errors.

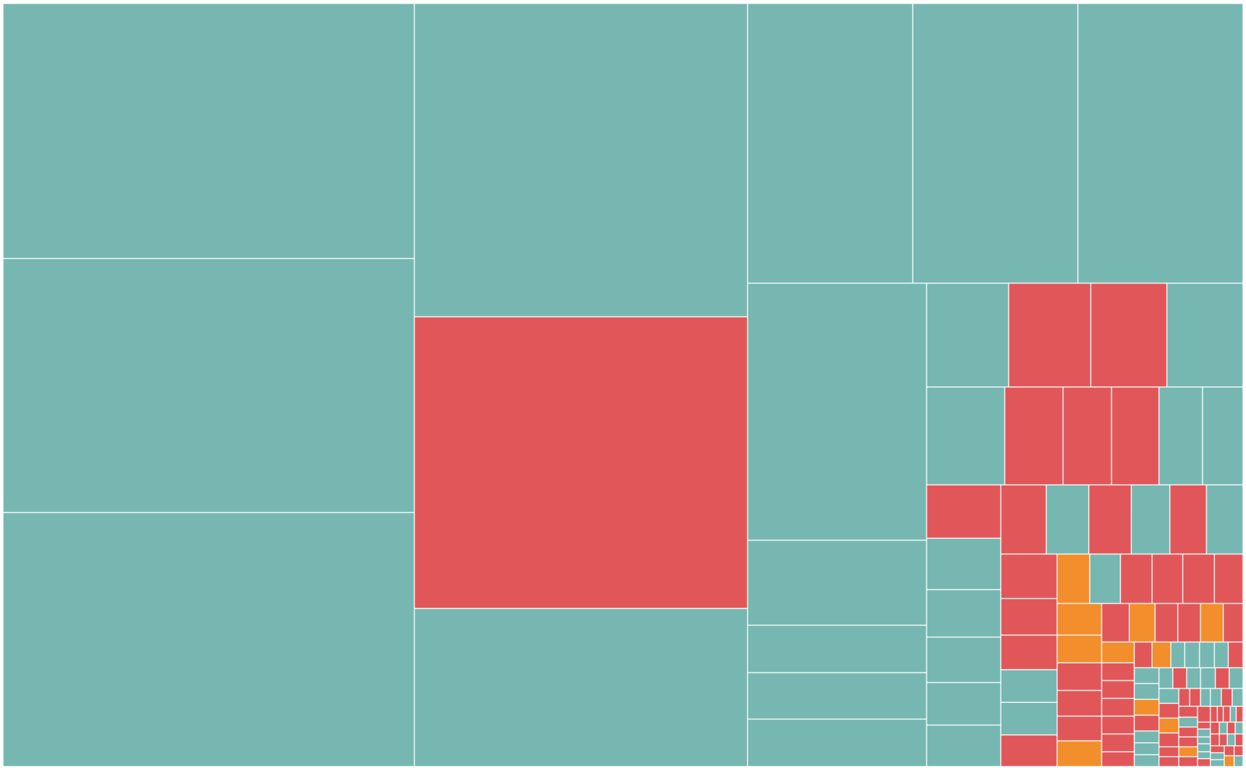
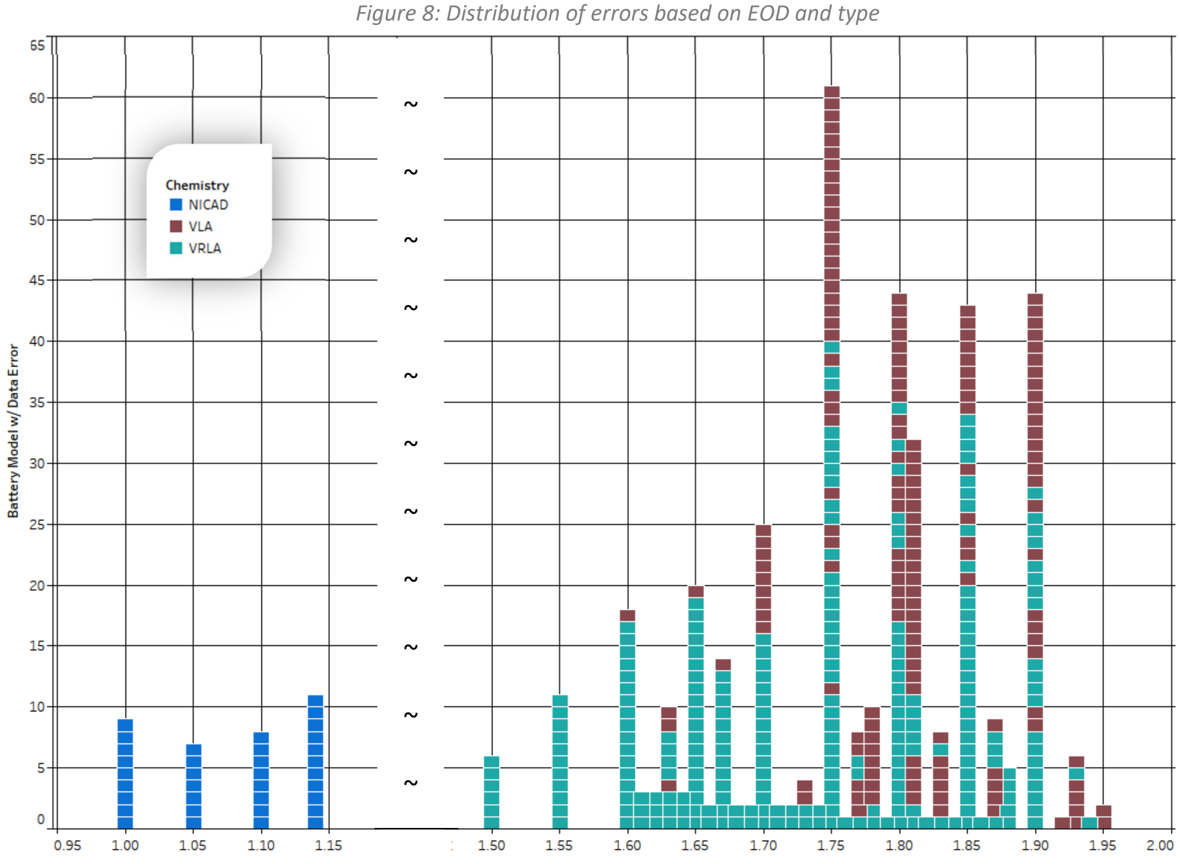


Figure 7: Number of errors based on chemistry

VLA batteries typically have twice the amount of data compared to VRLA. That correlates with the fact that most VLA batteries have minute by minute data whereas the majority of 10 year design VRLA batteries have data in batches. To get a better understanding of which EOD data has errors, look at Figure 8. Here, each colored box represents a battery model that has errors.

Figure 8: Distribution of errors based on EOD and type



While there are more battery models that have errors at 1.75VDC and 1.80VDC, these numbers simply correlate with the amount of data that is available in each category. Similarly, the number of Nicad battery models with errors may appear less than lead acid, but that is simply because there are less data available.

There are small areas where errors are more concentrated, but in general they are representing a more random pattern. To better picture this reality, take a look at Figure 9. Here, each box represents a battery model that is included in the dataset. The size of each box represents the AH capacity rating of that respective battery at the 5 hour discharge rate. The largest battery is 3,229 AH and the smallest battery is 5AH. Boxes that are colored red are battery models that have data errors (~ 9.7% of batteries in dataset)

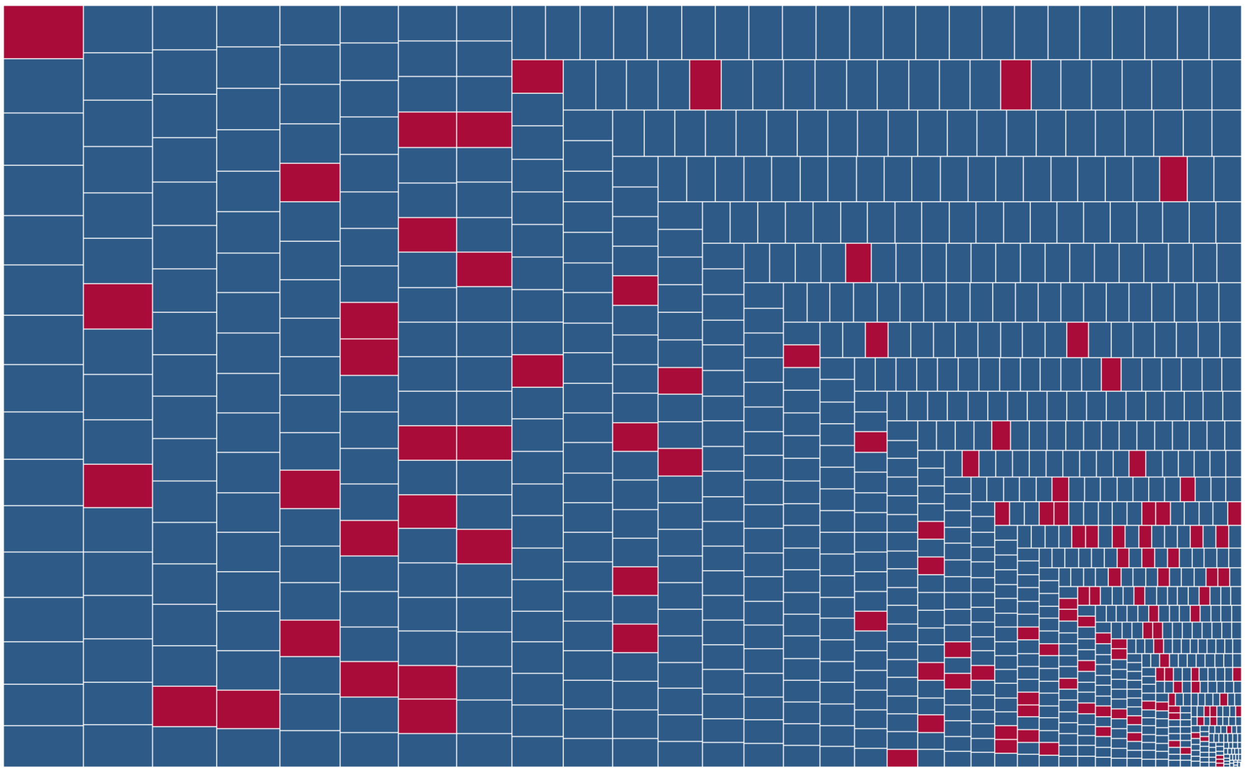


Figure 9: Distribution of errors based on capacity (5 hour rate)

The magnitude of errors and its effects on individual battery systems is outside of the scope of this paper, but we will look at one example as a way of understanding the nature of the ramifications. A typical switchgear power back up system requires an 8 hour discharge profile. If the load profile has 3 load steps (ie. 50A for 5 minutes, 10A for 470 minutes, followed by 50A for 5 minutes), then it can be assumed that 5 data points are required as a minimum to calculate sizing. The number of batteries in existence that can satisfy such a load profile is limited. The list gets even smaller as technical aspects and economics of customer specification often reduces the number of battery solutions, types and sizes. In one extreme but obvious case, we observed a 7% difference between incorrect data and an approximated data calculated based on correct data. As a standard, these systems are oversized with much higher design, aging, and future growth margins. Even if no margin was applied for sizing, the odds of that incorrect data matching the load profile are extremely rare. While that is good news, it should be noted that odds of any battery discharge cycle matching the original designed load profile is also extremely rare.

To ensure compliance, it is best engineering practice to measure final installed load and recalculate battery sizing based on that instead. In most cases this yields to a smaller than expected load profile which provides additional margin for any data errors. In cases where this yields to a higher than expected load profile, further investigation is necessary as it may lead to shorter back up run time, longer recharge time, and unexpected or unintended drop outs.

Conclusion

The dataset that was examined can be identified as the best of the best in the battery market. These are large batteries in various capacities that are sold and installed in utilities, datacenters and plants all over North America. They are used in some of the most critical applications and have influence in some operation's bottom line. With all the scrutiny that these batteries go through, we can still detect issues with data from all battery manufacturers that are part of the dataset. The exclusion of other battery types such as lithium-ion or flow batteries was not done deliberately; rather it is the outcome of current reality. There are no or very low amounts of information provided by newer types of batteries. What does this mean for other batteries in non-critical applications where they do not necessarily perform battery sizing? There is no standard that covers the amount of data required for a battery to be sold, so the minimum bar in terms of data accuracy, detail, and range is non-existent. Manufacturers are also not required to disclose how they obtain their data. This resonates with batteries that are sold in commercial and consumer markets where end users demand even less data from manufacturers. It is ironic to think that large amounts of resources are spent on capturing, monitoring and trending data produced once a battery is installed, but very little attention is given to original data produced and published by manufacturers. It may be a surprise to some, but the rated capacity which is assigned to represent the quantity of electrical energy in a battery is just a single point in the full spectrum of data that can be produced and measured from that battery.

"Rated capacity which is assigned to represent the quantity of electrical energy in a battery is just a single point in the full spectrum of data that can be produced and measured from that battery."

While battery performance data is important, other attributes such as short circuit capacity, evolution rate, and others are also equally important and should go through a similar form of data quality assurance. Whether this translates to specific standards, regulation, or 3rd party verification of battery data, it depends on how this conversation continues into the future. Will manufacturers who currently dominate the market share in battery data take the lead and develop a path for future battery data requirements or will it be left to consumers and other markets to advance this dialogue?

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