

Operating Batteries at the Limit - Safely and Profitably

Identification of Weak Cell Blocks in Electric Aircraft Battery Packs

Robert Masse Shrilakshmi Bonageri Daniel E. Shea

NASA Aerospace Battery Workshop November 2023



© 2023 Astrolabe Analytics, Inc. All Rights Reserved.



Outline

- 1. Astrolabe Overview
- 2. Problem Statement
- з. Approach
- 4. Algorithm Development
- 5. Results and Discussion
- 6. Conclusions and Future Work



About Astrolabe

Established

2018

Based in Seattle, WA



Electrifying the unthinkable by enabling batteries to go beyond using Data Driven Battery Health and Performance Modeling.

Multiple commercial projects pertaining to eVTOL, drone, and ground assets

\$2.3M in non-dilutive funding



Facts

Mission & Technology

Funding

Relevant Professional Memberships and Partners





High Level Problem Motivation

Electric aviation represents a new arena for battery engineering and development

Less mature and requires higher safety and performance regulations than automotive

Batteries are a looming certification challenge for electric aviation hopefuls

> Elan Head, The Air Current (2022)

Certification Basis Under Development



eVTOL very demanding on batteries +1MW of power for take off and landing

Astrolabe eVTOL Analytics System

Astrolabe eVTOL Analytics System

Specific Problem - Weak Cell Block Identification

Problem

Weak cell blocks will **hurt overall pack-level safety** and performance. Low OCV at the end of flight indicates broken bond wires or imbalanced cell blocks (inter alia).

Goal

Accurately identify weak cells faster than status quo (~30min into flight test)

Specific Problem - Implications

Weak cell ID useful input for **RUE/RUL** estimation

Rationally downselect to a manageable set of cells (out of ~10,000)

The **SOC for the weakest cell** may be **appreciably lower** than the average SOC of the pack

© 2023 Astrolabe Analytics, Inc. All Rights Reserved.

Weak Cell Block Identification

Solution

Outlier detection algorithm employed with features derived from voltage data to identify weakest cell blocks in battery pack

- 1
- First step towards the **development of standards** for measuring remaining useful energy (RUE) and remaining useful life (RUL)
- 2
- Considers first **5 minutes of data** (or less) and compares favorably against status quo

Validated against battery flight test data from **two different battery pack** manufacturers

Pack Characteristics

Manufacturer 1

- 1 pack = 14 modules in series
- 1 module = 14 cell blocks in series
- 1 cell block = 16 cells in parallel
- 1 pack = 196s16p

Manufacturer 2

- 1 pack = 8 modules in series
- 1 module = 16 cell blocks in series
- 1 cell block = 34 cells in parallel
- 1 pack = 128s 34p

Input Data

Manufacturer 1

The first **300 seconds** of voltage data

Manufacturer 2

The first **200 seconds** of voltage data

Defining Weak Cells

Low OCV at the end of flight indicates broken bond wires or imbalanced cell blocks (inter alia)

Cells with the lowest open circuit voltage at the end of the flight test are weak cells in a pack

Outlier Detection

The open circuit voltage for weak cells is **noticeably lesser than the median value** and thus they can be considered as outliers

Feature Engineering

Two features produced the most accurate results for 300s of input data

Maximum Voltage

The (standardized) maximum voltage for each cell group in a pack.

(Standardized) Trapezoidal integral of voltage for each cell group in a pack. MFG 1

Feature Engineering

The features were standardized by removing the mean and scaling to unit variance.

The standard score (z) of a sample (x) is calculated as shown right, where μ is the mean of the training samples and σ is the standard deviation of the training samples.

$$z=rac{x-\mu}{\sigma}$$

 $\mu=$ Mean
 $\sigma=$ Standard Deviation

Local Outlier Factor

Local Outlier Factor is a **density-based** outlier detection algorithm. The following parameters were used to detect the weak cells:

n_neighbors: 35

Finds the n nearest neighbors of a point and returns the distance to each point (Nearest neighbor search)

contamination: 0.15

The amount of contamination of the data set, i.e., the proportion of outliers in the data set. When fitting this is used to define the threshold on the scores of the samples.

Local Outlier Factor

Local Outlier Factor is a **density-based** outlier detection algorithm. The following parameters were used to detect the weak cells:

3

p: 1

Parameter for the metric used to calculate distance, p=1 is equivalent to using the Manhattan distance, that is the distance between two points measured along axes at right angles.

In a plane with point p1 at (x1, y1) and point p2 at (x2, y2), it is |x1 - x2| + |y1 - y2|

Algorithm: 'brute'

Algorithm used to compute the nearest neighbors. It is usually used for low dimensional data.

Features used: The feature 'Voltage integral' was used as x-axis data and 'Minimum voltage' was used as y-axis data.

Algorithm Demonstration

18

Repeatability

| Same 3 packs tested 27 times for Manufacturer 2 | Pack type | Number of battery packs | Correct results | Incorrect results | Percent Error |
|--|-----------|-------------------------------|--------------------|----------------------|------------------|
| ID's weak cells with 85% accuracy | Mfg 2 | 81 | 69 | 12 | 14.8% |

Weak Cells are Not Randomly Distributed

30 Tests from Pack 1 from Mfg 2

Considering 5 cells with the lowest final voltage for each test:

- 1 cell appears 63% of the time
- 4 other cells appear
 >30% of the time
- 91 cells never among 5 weakest cells

Reproducibility

| Algorithm achieves |
|--------------------|
| >85% accuracy with |
| both manufacturers |

| Pack type | Number of tests | Correct results | Incorrect results | Percent Error |
|-----------|--------------------|--------------------|----------------------|------------------|
| Mfg 1 | 53 | 46 | 7 | 13.2% |
| Mfg 2 | 81 | 69 | 12 | 14.8% |
| Total: | 134 | 115 | 19 | 14.1% |

Error Analysis

3 categories of errors

Reasoning

The two cell groups with the lowest voltage integral in the outliers are picked as weak cell groups while that is not always the case.

Future Work

What is the optimal set of features and data required to maximize accuracy?

Category 1 Empirical errors in engineered features 5 of 19 total errors

Error Analysis

3 categories of errors

Category 2 Time lag in data logging 3 of 7 errors from Mfg 1

Red circle: Predicted weak cell groups

Error Analysis

3 categories of errors

Category 3

Narrow delta between high and low voltage cells 10 of 19 total errors

Logic to be added

Reproducibility

| Accuracy improves to <5% error after | Pack type | Number of tests | Correct results | Hardware Error | No Weak Cells | Algorithm Empirical Error | Percent Error |
|---|--------------|--------------------|--------------------|-------------------|------------------|---------------------------------|------------------|
| hardware and | Mfg 1 | 53 | 46 | 3 | 2 | 2 | 3.8% |
| including added | Mfg 2 | 81 | 69 | 0 | 8 | 4 | 4.9% |
| logic | Total: | 134 | 115 | 3 | 10 | 6 | 4.4% |

Features Considered

Voltage features most correlated to final voltage

Other features had no or low correlation

Temperature:Resistance:R2 ~ 0.01R2 ~ 0.13

Takeaways

Simple features derived from voltage data at the beginning of the flight can be used to identify weak cells.

6x faster than status quo (5 min vs 30 min)

Algorithm is 85% accurate using data from 2 different battery packs

Can be improved to +95% accuracy after additional error handling logic implemented

Future Work

Answer

What is so special about these features?

Find

Features with maximum predictive power for Minimum timeframe

What is minimum dataset needed, or acceptable tradeoff between speed and accuracy?

Integrate

Embed onto real-time operating system (RTOS) for operational testing

Opportunities

Let's team on proposals or help build your next aerospace battery

Robert Masse <u>robert@astrolabe-analytics.com</u> (920) 698-6028

Questions?

Robert Masse <u>robert@astrolabe-analytics.com</u> (920) 698-6028