Early Faulty Battery Detection in Electric Vehicles Based on Self-Discharge Rate Analysis

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1. Introduction:

As lithium-ion battery technology matures and becomes more affordable, it is extensively used in transportation equipment and energy storage systems. However, even with a minimal percentage, manufacturing defects can still occur, resulting in poor performance and, in rare cases, safety issues. Therefore, it is crucial to continuously monitor battery usage and detect faults early on. This paper introduces a method to detect self-discharging, a leading phenomenon when batteries are failing, using data analytic algorithm on huge amount of run-time data from electric vehicles. The algorithm focuses on long-term trends, enabling the identification of minor self-discharging well in advance before it becomes a serious issue. The experiments were conducted on ten electric vehicles, and the results demonstrate the effectiveness of the method. Three cases of abnormal self-discharging were detected in their early stages, ranging from 20 days to 5 months before they caused system malfunctions. Additionally, the method proposed in this research can be easily adapted for different battery types and applications with simple parameter adjustments.

2. Background Research:

Extensive research has been conducted worldwide on the topic of self-discharge consistency in lithium-ion batteries, given its crucial influence on the longevity and dependability of electric vehicles and energy storage systems. Prof. Pucheng Pei et al. from Tsinghua University proposed two methods for measuring self-discharge of lithium-ion batteries: 1) Static measurement, which involves long-term battery resting to obtain the self-discharge rate and 2) Dynamic measurement method, which involves parameter identification of the battery during dynamic processes. [1] The latter method is more time-efficient, as it accelerates the self-discharge rate by changing experimental temperature and battery state of charge (SOC), so that the measurement parameters can exhibit relatively large changes in a shorter period of time. Furthermore, Dr. Haiyu Liao et al. from School of Mechanical Engineering, Shanghai Jiao Tong University proposed a rapid detection method to characterize self-discharge rate by OCV (Open Circuit Voltage) in a short period, based on the change of OCV during the battery resting process [2]. Bing Xia et al. from San Diego State University presents an innovative fault detection method for short circuits based on the correlation coefficient of voltage curves [3]. The proposed method utilizes the direct voltage measurements from the battery cells, and does not require any additional hardware or effort in modeling during fault detection. To sum up, previous research focuses on self-discharging mechanisms and measurement. In order to minimize the risk and maintenance cost caused by self-discharging, this paper investigates an early self-discharging detection method based on long term battery data analysis.

3. Methods & Procedures

3.1 Data Collection

In electric vehicles, hundreds of batteries are integrated into a single structure called battery pack. In order to monitor the operation of these batteries, a vast amount of data is collected constantly, which include the voltages and temperatures of every single cell, total pack voltage and current, state of charge, state of energy, state of health, and contactor states. The total number of features usually exceeds one thousand.

To analyze the self-discharging behavior of cells, this paper provides an example of an electric vehicle that experienced abnormal self-discharge. The paper collected data on the vehicle's total current, maximum and minimum cell voltages, maximum and minimum cell numbers, maximum and minimum temperatures, and voltage data for all cells during operation from June 2021 to July 2021. The data was then analyzed to determine how the abnormal cell behaved during battery operation. *Figure 1* illustrates the daily changes in the average voltage of all cells in idle state from June 2021 to July 2021. The x-axis represents the date, and the y-axis represents the average voltage. Prior to June 26, the voltage difference between the abnormal (orange) cell and other cells was small, but it gradually increased over time. On July 14, the battery voltage dropped too low, triggering an alarm and stopping vehicle operation. Further investigation revealed that over the course of a month, the cell with the minimum voltage gradually moved from random locations to one particular location, as shown by the orange curve.

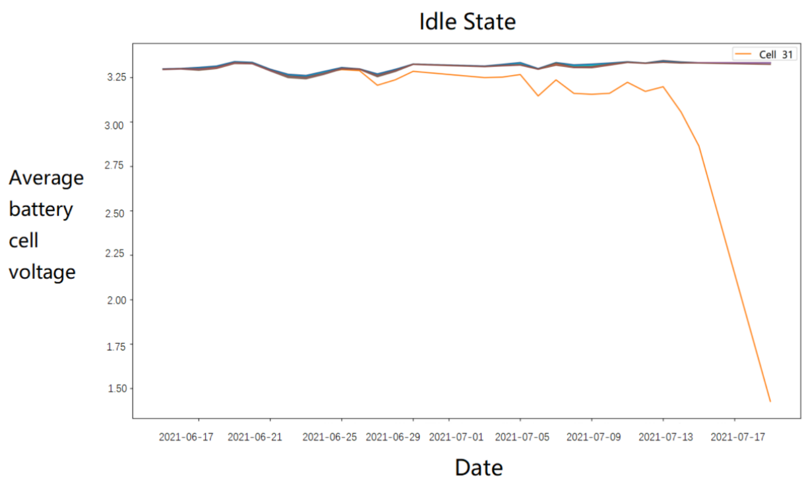

Fig. 1 Average Battery Cell Voltage in Idle State.

From the above investigation, it is clear that not all the data features are necessary. Battery cell voltage and total current are the primary features needed, well explained by the physics behind self-discharging. A typical voltage distribution during a three-day battery usage is illustrated in *Figure 2,* which is consistent with the normal operation range of LFP batteries.

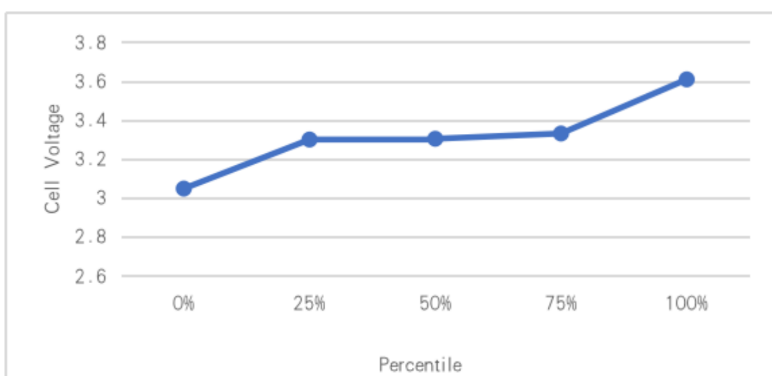

Fig. 2 Battery Cell Voltage Distribution

This paper aims to detect battery cells with abnormal self-discharge rates as early as possible. In the very early stage, the abnormality is too little to tell. However, based on long-term running data, even though the abnormality is small in its absolute value, it could exhibit a more observable trend of value changes over time like in *Figure 1.* Therefore, data becomes the most crucial input in this research, where a minimum of one month of data is used during the development of the initial version of the algorithm.

3.2 Models and algorithms

Figure 3 depicts the overall algorithm flow, which consists of five major steps. As described in Sec.2.1, cell voltages, total current and their timestamps during vehicle operation are chosen as features for subsequent analysis. The data frequency is 5 seconds per frame, which is equivalent to 17280 frames of data per day; the cell voltage is accurate to 1mv. Total current is accurate to 10mA.

To ensure the accuracy of the study, this paper first clean the data with following steps:

1. Fill with 0 if the data is missing;
2. Delete the data row whose cell voltage is not in the range of [0,5];
3. Delete the data row whose current value is not in the range of [-1000, 1000];

The current within [-5,5] ampere is classified as idle state; otherwise active state. Between two consecutive active states, there is one complete idle state. Two idle states are said to be continuous, if the difference between the finishing of the first idle state and the beginning of the second idle state is less than 10 seconds, or 2 frames of data.

As for detect digressive cells, this study will select the data segment with a single idle state that lasts more than 2 hours, delete the first 10 minutes' of data from the beginning of the idle state, and divide the idle state data into 10 minutes chunks, and then calculate the average and the medium of all cell voltages in each chunk.

Clustering is then performed according to the average and the medium cell voltages at each chunk to identify outliers. When a cell is identified as an outlier more than 7 times, it is considered to be an abnormal outlier cell. Afterwards, one will calculate the slope of the average voltage of the abnormal cell at two adjacent chunks. When more than 6 slopes are negative and a linear fitting is performed on the average voltages of all chunks, and the slope of the fitting line is also negative, then the cell is confirmed to be a digressive cell.

The digressive cells identified in the previous step usually cause increasing pack voltage differences. If the pack voltage differences rise at positive rates and the digressive cells' voltages decrease faster than a certain speed (0.25mV/s), then the digressive cells are confirmed to be abnormal self-discharging cells.

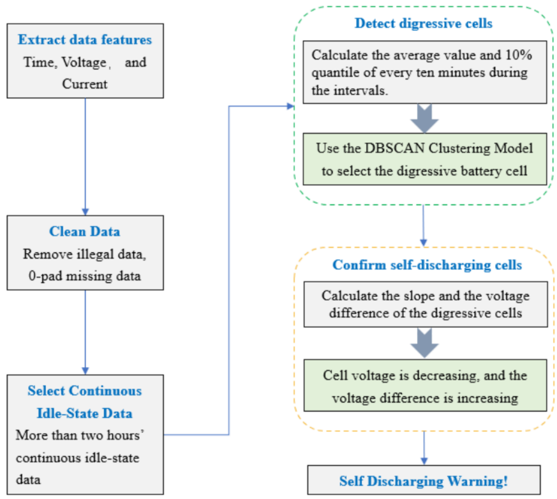

Fig. 3 Self-Discharging Detection Algorithm

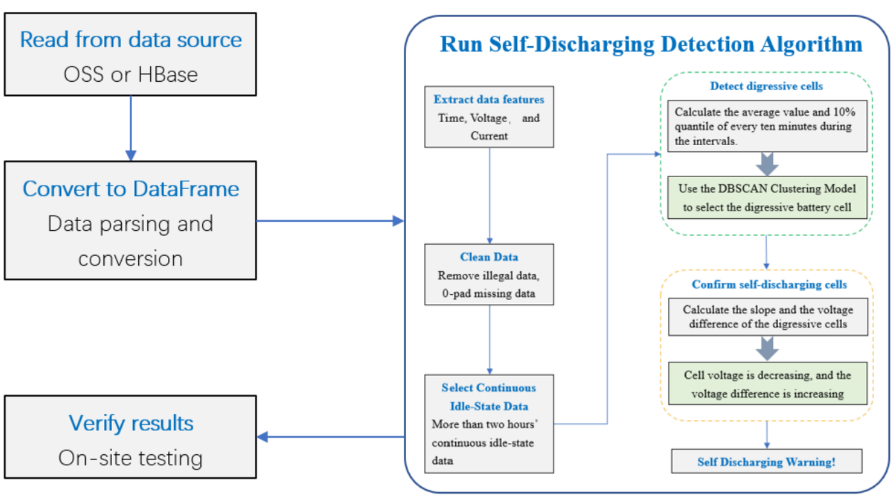

Fig. 4 Evaluation Framework

4. Results & Discussion

4.1 Evaluation Framework

This research is focused on analyzing data to detect self-discharging cells in electric vehicles. To confirm the effectiveness of the algorithm, an evaluation framework has been designed, as shown in *Figure 4*. Electric vehicle data is collected and stored in either file-based storage services or databases. To feed the algorithm, data must be read out first from these sources, which is done by an external data reader. Once the data is read into memory, it is extracted and reassembled into the Data Frame structure, which is highly compact, efficient, and easy to process. The algorithm is developed using *Python 3.8*, as are the data reader and format converter used in the previous steps. It is important to note that each self-discharging cell needs to be confirmed by on-site testing, not only for the purpose of this research, but also as a safety precaution measure. Cell self-discharging usually gets worse over time and may cause fire. Once the on-site testing results are obtained, one can confirm the effectiveness of the algorithm or adjust certain thresholds if necessary due to false positive results.

4.2 Evaluation Result

In this research, about one-month long data from 10 different vehicles was evaluated, and three anomalies with no false positive were found. The first case has been mentioned in *Figure 1*. In the following, more internal steps will be shown to better illustrate how the algorithm works.

In case 1, the data from the date of 6/10, 6/26 and 7/14 all in 2021 is analyzed. They show the cell voltage clustering result. On 6/10, all cells are in the same cluster (same black color in *Figure 5, left*). They are different by only 1mV, which is also the voltage sensing accuracy. 16 days later, on 6/26, one cell (#31) diverged from the others by 20mV (the black dot vs yellow dots in *Figure 5, middle*). At this point, the algorithm claims this cell is abnormal self-discharging. On 7/14, the diverging cell departed even farther away, by 400mV, from others (*Figure 5*, *right*). Then the local battery management system sent out the alert, and the subsequent on-site testing confirmed the result. Thus, the algorithm detected the anomaly about 20 days in advance.

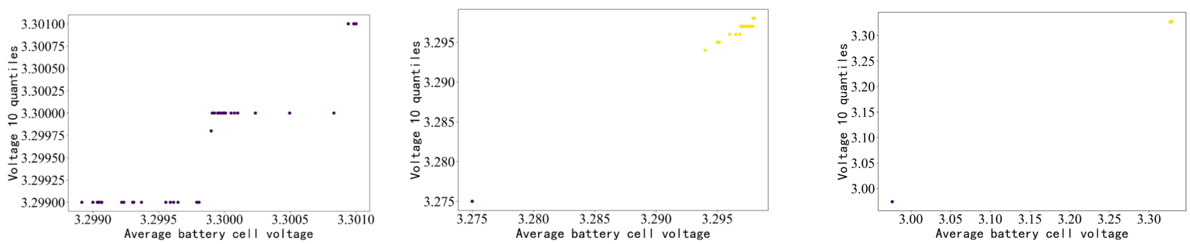

Fig. 5 Cell voltage clustering diagram on 2021-06-10 left), 2021-06-26 (middle) and 2021-07-14 (right).

Now, let's look at the data in different presentations. *Figure 6* and *Figure 7* exhibit the voltage changes over time on 6/26 and 7/14 respectively. The left graph shows the abnormal cell (orange, #31) voltage diverging from others. The upper right graph shows the average voltages in 10-minute chunks. Cell #31 has its voltage moving lower and lower, and the decreasing rate exceeds the detection threshold. As a result, the pack voltage difference (bottom right graph) is increasing higher and higher, also the fitting curve has a positive slope. Therefore, cell #31 is identified as an abnormal self-discharging cell.

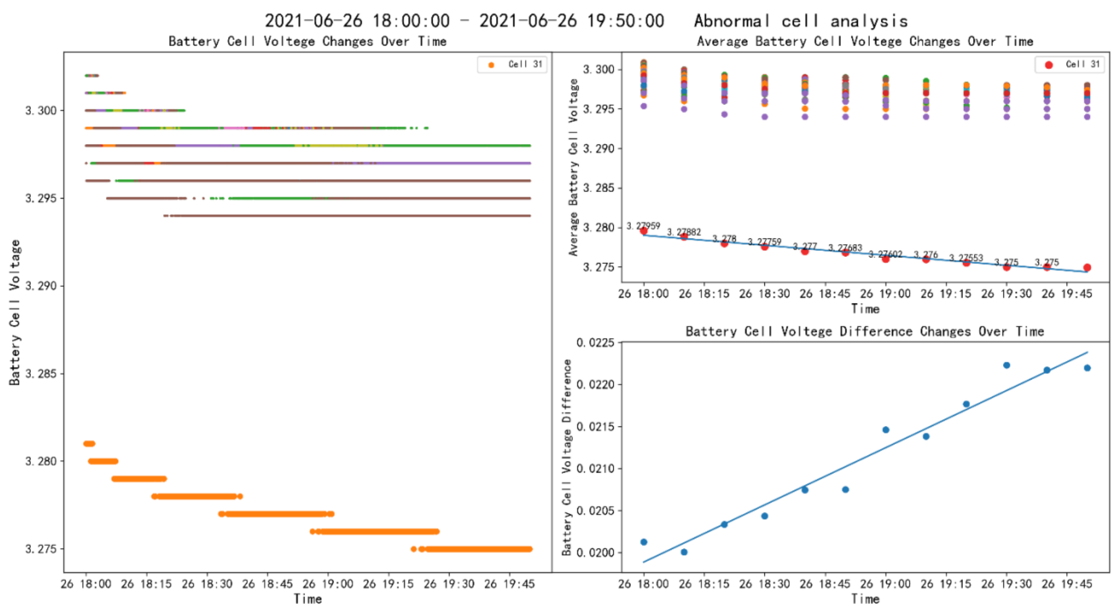

Fig. 6 2021-06-26 Abnormal self-discharging cell voltages

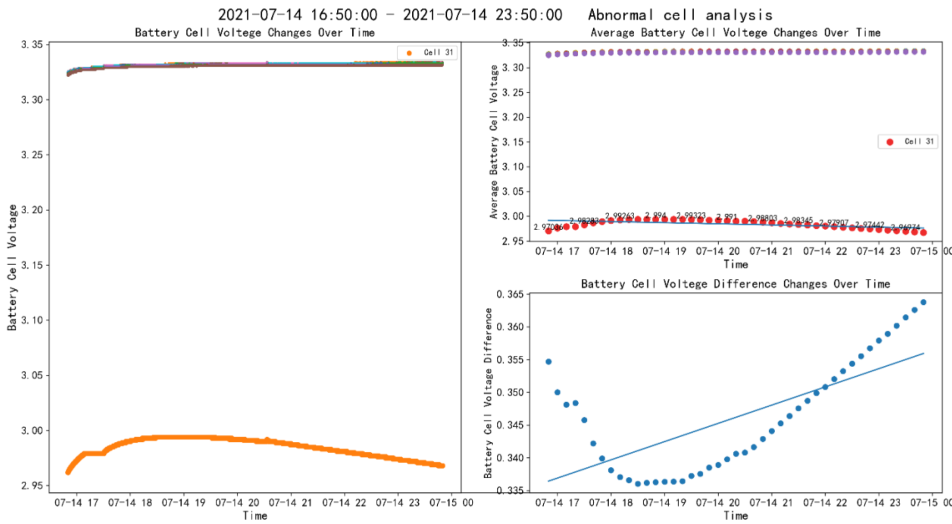

Fig. 7 2021-07-14 Abnormal self-discharging cell voltages

Case 2 and 3 are shown in *Figure 8* and *Figure 9*. Same as the explanation for case 1, a particular cell is identified by its voltage decreasing and further claimed to be abnormal self-discharging. Both were indeed reported by the local battery management systems later. However, the detection algorithm predicts the fault 1.5 months and 5 months earlier respectively before they occurred.

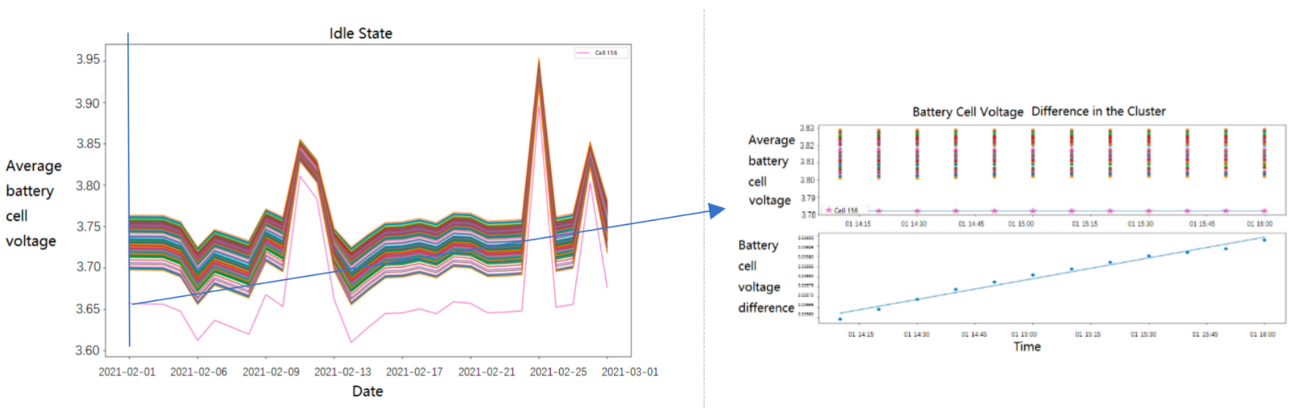

Fig. 8 Case 2: Abnormal self-discharging cell voltages

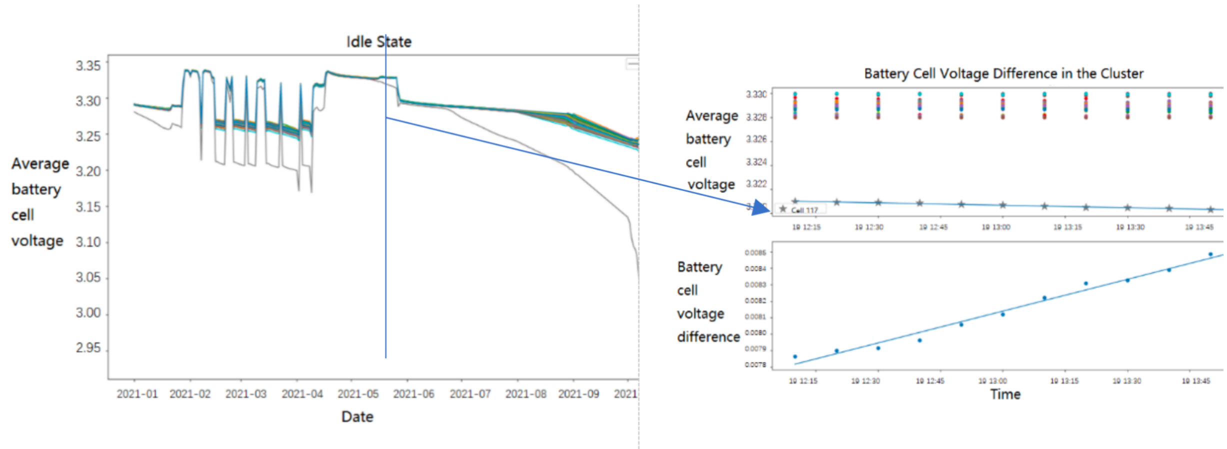

Fig. 9 Case 3: Abnormal self-discharging cell voltages

5. Problems in the Project & Suggestions for Future

Firstly, the idle state requirement for some applications is difficult to satisfy. For instance, frequency regulation applications would have the battery system running constantly. This could be dealt with by relaxing the idle state condition.

Secondly, this research was done on LFP batteries. For NCM batteries, the algorithm detection threshold can be optimized. Because the OCV curve exhibits more monotonicity, it is suspected that the voltages of self-discharging cells drop even more quickly, therefore the algorithm can lower the threshold and detect the faulty cells even earlier.

Finally, more active maintenance actions can be taken to better control the working condition and minimize the chance for self-discharging to occur; if self-discharging happens, remedy with other regular battery management techniques such as balancing should be applied. The last improvement with active actions will make the experimental process much more desirable but needs much deeper research in battery fundamentals.

6. Conclusion

Battery self-discharging is a rare yet harmful phenomenon. No matter how well the battery manufacturing process is optimized, as the total amount of cells delivered quickly skyrockets to billions every year, rare events will surely happen. Therefore, the post monitoring and detecting effort become a must. This paper develops an early self-discharging detection algorithm for lithium-ion batteries. It takes advantage of the battery run-time data already collected by almost all electric vehicles. Even though the fundamental physics principle behind self-charging is straightforward, to be able to detect it far in advance, while the cell behavior is still similar enough to all others, isn't an easy job. Long term data is used to examine the minute trend in the faulty battery's behavior. To verify the effectiveness, month long data from 10 electric vehicles was run through the algorithm, and three self-discharging cases were detected. These results were further confirmed by on-site battery management systems, when the effect of self-charging became large enough to cause negative consequences, which occurred 20 days to 5 months after the algorithm successfully detected them. This time difference enables early preventative maintenance at the lowest cost, and most importantly, eliminates potential safety risks, whose value can never be over exaggerated.

Furthermore, the self-discharging method developed in this paper is not limited to one particular type of battery. Its theoretical principle and the algorithm apply to other types as well. Some popular application areas include NCM (Nickel Manganese Cobalt) batteries, and in the field of passenger cars, logistic vehicles, engineering machinery, energy storage systems, etc.

References:

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[2] Liao, Haiyu, et al. "Research on a fast detection method of self-discharge of lithium battery." Journal of Energy Storage 55 (2022): 105431.

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