Connection Failure Detection for Lithium-ion Batteries Based on DBSCAN-Projection Method

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Abstract

This paper presents a connection failure detection for a Lithium-ion battery pack when no external vibrations exist. First, the gradient correction method is employed to identify the overall ohmic resistance, which is the summation of the internal and external (contact) resistance. Second, the battery state of health (SOH) is estimated with incremental capacity analysis (ICA) - based method. Third, Density-Based Spatial Clustering of Applications with Noise (DBSCAN) method is applied to diagnose the connection failure by matching the calculated resistance with the estimated SOH. Finally, a linear projection is applied to reduce the method sensitivity to the testing conditions such as different state of charge (SOC). Experiments show that the proposed method can identify the location of the connection failure well in real time.

Keywords: Lithium-ion batteries, connection failure, DBSCAN, state of health estimation, gradient correction

1. Introduction

Occasional connect failure caused by the loose connection between the connecting piece and the pole presents a major problem to the safety of energy storage systems (ESS). Such a failure may lead to battery overheating, burning, and even an explosion \cite{1}. Therefore, it is necessary to monitor and diagnose the connections in a battery pack.

The existing methods for connection failure detection are mainly entropy-based. In Ref \cite{2}, the sample entropy was proposed to study the connection failure of electric vehicles. Shannon entropy and discrete time wavelet method was proposed to diagnose faults in Ref \cite{3}. Modified Shannon entropy was applied to detect faults with a vehicle big-data platform \cite{4}. In Ref \cite{5}, Shannon entropy was combined with the battery equivalent circuit model to distinguish the faults in the increase of the internal and external resistance, as the maintenance cost and methods for these two faults are different.

There are two remaining issues for the above-stated methods: 1) They are designed for vehicle applications with the existence of external vibrations, and 2) the thresholds in these methods have to be tuned, and they cannot provide the confidence of the diagnosis result.

To address these problems, a DBSCAN-projection based method is proposed. The basic idea is that if the overall ohmic resistance (including the internal and external resistance) of a battery is far away from the resistance suggested by its SOH, connection failure is likely to happen. Following this idea, we propose to use an online gradient correction method to extract the overall resistance. In the same time, the battery’s SOH is estimated through an ICA-based method. Then, the DBSCAN is applied to match the SOH with the impedance to diagnose the connection failure. To minimize the influence of factors such as SOC, a linear projection is proposed as the fourth step. The certainty of the diagnosis can also be obtained from the linear projection. The proposed method adds knowledge to connection failure diagnosis for systems without external vibrations.

2. Methodology

Due to the limited paper length, we first summarize the proposed method in Figure 1-(a) and then introduce the details of it.

2.1 Thevenin model and gradient corrections

A Thevenin model \cite{6} shown in Figure 1-(b) is used to model the battery.
resistance and external contact resistance are included. \( C_p \) is the equivalent polarization capacitance, and \( R_p \) is the equivalent polarization resistance, \( U_0 \) is the voltage across the \( C_p \), \( U_0 \) is the voltage across the \( R_0 \), and \( U_{oc} \) is the open circuit voltage (OCV) of the battery. Further, we can denote \( \Delta t \) as the sampling time, \( k \) as the step index, and \( t = R_p C_p \) as the time constant. Then, we can define

\[
\begin{align*}
\alpha_1 &= \exp(-\Delta t / \tau) \\
\alpha_2 &= -R_0 \\
\alpha_3 &= \exp(-\Delta t / \tau) - [1 - \exp(-\Delta t / \tau)] \cdot R_p
\end{align*}
\]  

(1)

Assuming \( \partial U_{oc} / \partial t \approx 0 \) following Ref [7], the Thevenin model can be rewritten as [6]:

\[
Y_k = U_{t,k} = \phi(k) \cdot \Theta(k) = \begin{bmatrix} U_{t,1} & I_{d,1} & I_{d,1} \end{bmatrix} \begin{bmatrix} 1 - \alpha_1 U_{oc,k} & \alpha_1 & \alpha_2 & \alpha_3 \end{bmatrix}^T
\]

(2)

The basic idea of the gradient correction (GC) method is that we should update our estimations so that the error gradient decreases with each step. Therefore, the updating law of the GC method could be given as [8]:

\[
\hat{\Theta}_k = \hat{\Theta}_{k-1} + G \cdot I \cdot (Y_k - \phi(k) \cdot \hat{\Theta}_{k-1})
\]

(3)

where \( G \) is the gain of the gradient correction.

### 2.2 SOH estimation with incremental capacity

The battery’s SOH can be defined as the ratio of actual available capacity to fresh cell capacity. In this paper, we use an interval capacity to evaluate the SOH. Its key idea can be stated as follows [9]:

**The capacity contained in a 50mV interval could reflect the battery’s SOH if the center of this interval is the voltage at which point \( dQ / dV \) reaches its peak**, where \( Q \) stands for the charge. Here, the \( dQ / dV \) curve is also known as the incremental capacity (IC) curve and \( \Delta Q / \Delta V \) is commonly used in discrete time systems.

To implement this estimation, a five-step procedure is provided as follows. First, the battery charging curve is obtained. An example is shown in Figure 2-(a). Second, use the direct \( \Delta Q / \Delta V \) method to calculate the IC value. An example result is provided in Figure 2-(b). Then, the standard Kalman filter is utilized to smooth the obtained signal, and an example result could be found in Figure 2-(c). Next, the voltage corresponding to the IC peak can be extracted, as shown in Figure 2-(d). The extracted voltage is also the center of the 50mV voltage interval. Finally, the capacity contained in the voltage interval can be extracted by integrating the current over time. An example result is shown in Figure 2-(e). For the readers’ convenience, the battery degradation is depicted in Figure 2-(f).

### 2.3 DBSCAN method

DBSCAN is a clustering algorithm that categorizes the target into different groups based on a pre-determined rule [10]. Compared with the other clustering methods such as K-means algorithm [11], it has several important features: 1) the number of categories is online determined, 2) the cluster shape can be arbitrary, and 3) parameters for noise filtering are supported. Before introducing the detailed algorithm, some definitions should be noted first:

- **Distance**: In Euclidean space, we use the two-norm to define the distance between two selected points;
- **\( \varepsilon \)-neighborhood of object \( O \)**: the space with center \( O \) and radius \( \varepsilon \);
- **Neighborhood density of object \( O \)**: the number of the other objects contained in the \( \varepsilon \)-neighborhood of target \( O \);
- **Neighborhood density threshold**: a threshold describing the least number of the neighborhood density, represented by \( \text{MinPts} \) in this paper;
- **Kernel object**: if the neighborhood density of object \( O \) is greater than \( \text{MinPts} \), object \( O \) is a kernel object;
- **Direct density reachable**: if object \( P \) is in the \( \varepsilon \)-neighborhood of kernel object \( Q \), \( P \) and \( Q \) are defined as direct density reachable;
- **Density reachable**: if object \( P \) and \( Q \) are direct density reachable, object \( P \) and \( R \) are also direct density reachable, then \( Q \) and \( R \) are defined as density reachable.
dimensions, namely, the calculated method in Table 1 is suggested to implement the calculate a linear fit (abnormal value of DBSCAN algorithm. This implement has a complexity of projection is designed based on this fact. Its "normal" are always reliable. The proposed linear tuned parameters may also lead to wrong judgments. The DBSCAN method can then be used to operating conditions (e.g., SOC) change, a set of well-

<table>
<thead>
<tr>
<th>Step</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Initialize:</td>
<td>Obtain the unified data set $D$, radius $e$, and neighborhood density threshold $Minpts$; Mark all the objects in $D$ with &quot;unvisited&quot;; Mark all the kernel objects with &quot;kernel&quot;;</td>
</tr>
<tr>
<td>2. Select an object:</td>
<td>If there exist some &quot;unvisited&quot; kernel objects Select an &quot;unvisited&quot; kernel object $P$; Mark $P$ with &quot;visited&quot;; Else Select an &quot;unvisited&quot; object $Q$; Mark $P$ with &quot;visited&quot;;</td>
</tr>
</tbody>
</table>
| 3. Mark the object: | If $P$ is a kernel object Create a new cluster $C$.
If $Q$ is "unvisited"; add $Q$ into $C$; If $Q$ is a kernel object add the objects direct density reachable to $Q$ into $N$; Else Mark $Q$ with "boundary"; |
| 4. Loop: | If all objects in $D$ are "visited" break; Else Goto 2; |

Based on these definitions, we define a cluster obtained through the DBSCAN method as a maximum set, in which the objects are density reachable. The method in Table 1 is suggested to implement the DBSCAN algorithm. This implement has a complexity of $O(n^2)$, where $n$ is the object number [12].

In this paper, the Euclidean space has two dimensions, namely, the calculated $R_0$ and estimated SOH. The rough rule, "when battery SOH drops to 80%, the impedance of a battery is doubled", is suggested to unify the estimated impedance. It can guarantee that the estimated SOH and unified $R_0$ are in the same level of magnitude. The DBSCAN method can then be used to diagnose the connection failure by extracting the abnormal value of $R_0$.

2.4 Linear projection method

The clustering result of DBSCAN can be influenced by the selection of $Minpts$ and $e$. Therefore, when the operating conditions (e.g., SOC) change, a set of well-tuned parameters may also lead to wrong judgments. This means that the objects marked with "abnormal" may not represent the battery that is suffering from a connection failure. However, the objects marked with "normal" are always reliable. The proposed linear projection is designed based on this fact. Its implementation is described as follows:

First, select all the cells marked with "kernel" or "boundary", and denote them as "normal"; Second, calculate a linear fit ($y=ax+b$) between SOH and $R_0$ using the "normal" data; Finally, calculate the boundary of the fitting based on the desired confident interval $r$:

$$\text{Boundary}_y = y \pm r \sqrt{s^2 + xSx^T}$$

where $s^2$ is the mean squared error, $r$ depends on the confidence level (0.95 and 0.99 are most commonly used), $S=(x^T x)^{-1}s^2$ is the covariance matrix of the coefficient estimates, where $x=[1]$.

The reasons for a "linear" projection are that 1) many publications have suggested that the battery impedance has a linear relationship with SOH [13], and 2) in general cases, a slave unit in BMS only monitors 12 or 16 cells, and these data may not be sufficient for high-order fitting.

3. Experimental results

The experiments can be categorized into two parts: cyclic aging and DBSCAN algorithm testing. The cyclic aging test was carried out on FST-2000 type batteries with a SUNWAY BTS 4008 tester at room temperature. The constant current rate for charging and discharging was 1C, the cutoff voltages were 4.2V and 2.75V for charging and discharging, respectively, and the cutoff current for constant voltage charging was 0.05C. The results in Figure 2-(e) were obtained from cell #14 after carrying out the cyclic aging test.

### Table 2. SOH (%) of Selected Batteries.

<table>
<thead>
<tr>
<th>No.</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOH</td>
<td>98.1</td>
<td>99.9</td>
<td>97.5</td>
<td>95.6</td>
<td>94.4</td>
<td>94.4</td>
<td>92.9</td>
</tr>
<tr>
<td>No.</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>14</td>
</tr>
<tr>
<td>SOH</td>
<td>93.3</td>
<td>89.2</td>
<td>90.9</td>
<td>89.3</td>
<td>87.7</td>
<td>82.1</td>
<td>79.3</td>
</tr>
</tbody>
</table>

The DBSCAN algorithm testing was carried out using a SUNWAY CE 7001 device under 25°C. Fourteen cells were linked in series with clamp specially designed for 18650 batteries, and cell #06 suffers from a loose connection. The SOH of the selected 14 cells is listed in Table 2. The photo of the experimental platform, stable and loose connections, and the load profile used for testing are provided in Figure 3.

**Figure 3.** Left: Experimental platform; Middle: Example of a stable (top) and loose (bottom) connection; Right: (a): Current profile and (b): Voltage response.

To test the DBSCAN algorithm, the interval capacity should be extracted in the constant current charging phase first. Using the aging model provided in Figure 2-(e), the calculated SOH is shown in Figure 4-(a). With the presence of connection failure, the maximum SOH estimation error can be limited within 3%.

205
The identification result of $R_0$ is provided in Figure 4-(b) (time counts from when the discharging started). The battery impedance can change significantly with time (strictly speaking, SOC). Therefore, we choose two sampling points at 4000s and 8000s to test our DBSCAN-projection algorithm.

From Figure 4-(c) and (d), the relationship between resistance and the SOH can change significantly with SOC. The DBSCAN algorithm does perform differently in these two cases. However, after the linear projection step, only one cell is beyond the confidence region of the linear projection, which is indeed #06. It should be noted that in 4000s, the resistance of battery #06 was the largest among the 14 cells. However, when it came to 8000s, it became the third largest. The proposed method can distinguish the abnormal resistance in both cases, indicating that our result is not a trivial one. By selecting a smaller confident factor, the diagnosis result can also provide an early warning for connection failure.

4. Conclusions

This paper presents a DBSCAN-projection method to detect connection failure of the Lithium-ion battery pack. The idea is to match the battery SOH with the estimated resistance. To avoid circular dependence, the SOH is estimated from the interval capacity method without using resistance information. This method can provide a confident factor of the diagnosis, and it is very suitable for battery pack applications that have no external vibrations, such as the energy storage systems.

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References


