Fault Diagnosis of Li-Ion Batteries Using Multiple-Model Adaptive Estimation

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Abstract—In this paper a battery fault detection unit is developed using multiple model adaptive estimation technique. Impedance spectroscopy data from Li-ion cell is used along with the equivalent circuit methodology to construct the battery models. Battery faults such as over charge and over discharge cause significant model parameter variation and can be considered as separate models. Kalman filters are used to estimate the parameters of each model and to generate the residual signal. These residuals are used in the multiple model adaptive estimation technique to detect battery faults. Simulation results show that using this method the stated battery faults can be detected in real-time, thus providing an effective way of diagnosing Li-Ion battery failure.

I. INTRODUCTION

Battery is an important energy storage device used in a range of consumer and industrial applications. Lithium-ion batteries exhibiting higher energy densities than their counterparts [1] and are widely used in numerous applications such as portable devices including hybrid electric vehicle (HEV), and electric vehicles (EV). To derive maximum output from a Li-ion battery without sacrificing safety and or durability, it is essential to accurately predict the state of the battery under all operating conditions. Unchecked faults occurring in the battery can lead to irreversible and under extreme conditions cause catastrophic damages [2, 3]. In order to avoid such conditions it is imperative that any fault occurring in the battery be quickly detected and accurately diagnosed.

Depending on the battery usage, there are different modeling tools, namely, experimental, empirical, equivalent circuit, electrochemical and neural networks [4, 5]. For real-time applications the equivalent circuit model is best suited because of its simpler formulation and good representation of cell dynamics without high computational power demand.

The equivalent circuit model parameters can be extracted from an offline impedance spectrum obtained through the use of Impedance Spectroscopy (IS) technique [6, 7]. IS involves passing a small amplitude of AC current through the Li-ion battery and measuring its AC response. From the known AC input and the measured AC response, the battery impedance is evaluated. The battery impedance is also dependent on the state of charge (SOC) and the temperature [7]. But for this study, these variations are assumed to be small. Also, for simplicity, the non-linear element in the equivalent circuit model, namely Warburg impedance representing the diffusion phenomenon is neglected [8]. The simplified cell model is shown in the Figure 1.

Multiple model adaptive estimation (MMAE) technique is used to detect and identify several fault types. Model-based fault diagnosis requires model-representation of faults to generate residual signals and an evaluation algorithm to extract the information to detect and isolate the fault. In this type of diagnosis, the generation and evaluation of residual signals directly affect the performance of diagnosis [9]. Residual signals are generated by comparing the outputs of the fault models with the simulated output of the system. Mathematical models of faults can be designed to incorporate different system behavior. A model that closely represents the system dynamics considers the effect of noise, shift in parameter values and history of parameter variation.

This study aims at detecting and diagnosing over charge (OC) and over discharge (OD) faults in a Li-ion battery. Both conditions are detrimental to the health of the battery, while over charge can lead to overheating and thus vaporization of active material and hence explosion. Over discharge can short the battery cell [10]. However, these types of failures can be detected before the system reaches the failure condition hence failures can be avoided.

Some of the modern battery systems come with protection circuitry, designed to protect against faults. MMAE for battery fault diagnosis can act parallel with protection circuitry for system redundancy. Some of the battery types have non-resetable fuses, thus rendering the battery useless after a current surge; this can be avoided with MMAE fault detection. In order for the fuse to cut the current, the fault has to have happened, and the circuit has to have experienced the fault to the full extent. A fault diagnosis is more than just an on-off switch; it provides the type of the fault occurring and predicts the changes in the circuit well ahead of time.

II. BATTERY MODELING

The battery cell can be modeled as a third order system using lumped electrical elements like resistors and capacitors. The voltage source is considered as a large capacitor [6, 11]. Each of these circuit elements is a function of SOC and temperature. For this study, we assume the temperature to be constant and only the voltage source to be a function of SOC. Also, the ageing dynamics of the system is not considered in the model. It is important to know that the different fault types occurring in the battery can be modeled to study the effect of system behavior under abnormal conditions. It can also be used in effective control of the battery and to extend the
battery life. The OC failure of battery cell can be attributed to a combination of factors such as excessive temperature along with cell construction and design [12] and can lead to violent thermal runaways. The OD failures are caused due to detrimental copper plating occurring at the negative electrode which can further lead to thermal runaways under severe over-discharge[13]. Distinct parameter variation trend can be observed under both OC and OD failures. The OC and OD faults are modeled as variation in the circuit parameters. The equivalent circuit diagram is shown in Figure 1.

Fig. 1. Battery equivalent circuit model

The voltage across the bulk capacitor is given by

$$V_{cb}^{l} = \frac{i_{L}}{C_{b}}, \quad (1)$$

where, $C_{b}$ is the bulk capacitance and $i_{L}$ is the load current of the battery cell.

The ZARC element represents the high frequency depressed semicircle and it occurs if the relaxation time is not single valued[6]. This element consists of a resistance and a constant phase element (CPE) in parallel. The depression factor associated with the CPE is assumed to be equal to unity and valued[6]. This element consists of a resistance and a constant semicircle and it occurs if the relaxation time is not single valued. The ZARC element represents the high frequency depressed semicircle and it occurs if the relaxation time is not single valued. The voltage across the bulk capacitor is given by

$$V_{c} = \frac{V_{c}}{R_{c}} + \frac{i_{L}}{C_{c}}. \quad (2)$$

Low frequency semicircle in the impedance spectra is represented by charge transfer resistance $R_{ct}$ and double layer capacitance $C_{dl}$ elements, $I_{L}$ is the load current and $V_{C}$ is the capacitor voltage. The voltage across the capacitive element $C_{dl}$ is given by

$$V_{C_{dl}} = \frac{-V_{dl}}{R_{ct} C_{dl}} + \frac{i_{L}}{C_{dl}}, \quad (3)$$

and the terminal voltage $V_{o}$ is given by

$$V_{o} = I_{L}R_{b} + V_{C} + V_{C_{dl}} + V_{cb}, \quad (4)$$

where $R_{b}$ is the bulk resistance and $V_{cb}$ is the voltage drop across the bulk resistance. Under no load condition, $V_{cb}$ is the open circuit voltage (OCV). OCV is a function of SOC and temperature [11], which can be found experimentally. For this study we refer the SOC-OCV trend shown in Figure 2 [14]. Although the OCV vs. SOC curve is nonlinear, we assume a linear relationship between SOC and OCV as a first trial. The equation is given by,

$$V_{cb} = k \cdot SOC + d, \quad (5)$$

where $k = \frac{d(OCV)}{d(SOC)}$ is the slope of the line and $d$ is no-charge OCV.

Taking the derivative of (5) with respect to time, the following equation is obtained:

$$\dot{V}_{cb} = k \cdot \dot{SOC}. \quad (6)$$

Substituting (6) in (1) and rearranging, the variation in SOC can be obtained as:

$$SOC = \frac{i_{L}}{kC_{b}}. \quad (7)$$

Rearranging (2), (3), (7) and (4) in state space form,

$$\dot{x}(t) = \begin{bmatrix} A_{n} & B_{n} \end{bmatrix} \begin{bmatrix} x(t) \end{bmatrix} + \begin{bmatrix} d \end{bmatrix}$$

$$y(t) = C_{n} x(t) + D_{n} u(t),$$

can be represented as:

$$\begin{bmatrix} SOC \ V_{C} \ \ V_{C_{dl}} \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \ -\frac{1}{R_{C}} & 0 & 0 \ 0 & 0 & \frac{1}{R_{ct} C_{dl}} \end{bmatrix} \begin{bmatrix} SOC \ V_{C} \ \ V_{C_{dl}} \end{bmatrix} + \begin{bmatrix} 0 \ 0 \ \frac{1}{C_{dl}} \end{bmatrix} \begin{bmatrix} I_{L} \end{bmatrix}. \quad (8)$$

The output voltage can be obtained as:

$$V_{o} = [k \ 1 \ 1] \begin{bmatrix} SOC \\ V_{C} \\ V_{C_{dl}} \end{bmatrix} + [R_{b}] \begin{bmatrix} I_{L} \end{bmatrix} + [d]. \quad (9)$$

In these equations, $A = \begin{bmatrix} 0 & 0 & 0 \\ 0 & \frac{1}{R_{C}} & 0 \\ 0 & 0 & \frac{1}{R_{ct} C_{dl}} \end{bmatrix}$, $B = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{C_{dl}} \end{bmatrix}$, $C = [k \ 1 \ 1]$, $D = [R_{b}]$, $d$ is the disturbance, $x = \begin{bmatrix} SOC \\ V_{C} \\ V_{C_{dl}} \end{bmatrix}$ is the state vector, and terminal voltage $V_{o}$ is the system output.

The lumped electrical elements and their associated scalar values represent the model of the battery cell at any given time. Considering different values for the electrical elements $R_{b}$, $R_{C}$, $R_{ct}$ and $C_{dl}$, $n$ distinct models can be obtained each representing a particular condition or health of the battery cell.

This linear time invariant system can be represented in discrete time state space with measurement and system noise as:

$$x[k+1] = \Phi_{n} x[k] + \Gamma_{n} u[k] + G_{n} w_{n}[k], \quad (10)$$

and
\[ z[k] = H_n x[k] + D_n u[k] + v_n[k], \]
where \( x \) is the state variable,
\[ \Phi_n = e^{A T} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{-\frac{T}{\tau}} & 0 \\ 0 & 0 & e^{-\frac{\tau T}{C_d l_d}} \end{bmatrix}, \quad \Gamma_n = \left( \int_0^T e^{A T} d\tau \right) B = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \int_0^T e^{-\frac{\tau T}{C_d l_d}} & 0 \\ 0 & 0 & \int_0^T e^{-\frac{\tau T}{C_d l_d}} \end{bmatrix}, \quad H_n = C , \quad D_n = D \]
are the discrete system matrices, \( u \) is the system input, \( G_n \) is the system noise matrix, \( w_n \) is the input noise with zero mean and variance of
\[ E\{w_n[l]w_n^T[m]\} = \begin{bmatrix} Q, & l = m \\ R, & l \neq m \end{bmatrix}, \]
\( z \) is the measurement vector, and \( v_n \) is the measurement noise, independent from \( w_n \), with zero mean value as
\[ E\{v_n[l]v_n^T[m]\} = \begin{bmatrix} R, & l = m \\ 0, & l \neq m \end{bmatrix}, \]
\( Q = 1e-8 \) and \( R = 1e-8 \) are the process and measurement variance respectively. The process and measurement white Gaussian noise is generated using the polar method [15].

III. MODEL BASED FAULT DIAGNOSIS

The model-based fault diagnosis structure used in this paper is shown in Figure 3. Several models can be designed to accurately represent \( n \) signature faults. The same input signal that drives the actual system is required to excite all models simultaneously. Therefore, each fault-representing model generates an exclusive output. If there is a fault in the system, the actual system’s output will match with the output of one of the faults representing models. Therefore, the difference between their outputs, the residual signal, becomes a zero mean value signal.

![Diagram of fault diagnosis system](image)

Fig.3. Multiple-model residual generation and probability evaluation

The existence of noise in the actual settings results in the fault information loss; therefore, the fault diagnosis becomes insensitive to small parameter variations. Several modeling techniques have been introduced to estimate the output of the fault models in a noisy environment.

In the next section, Kalman filters [16, 17] are introduced and used to generate residual signals. It is essential to note that the proposed fault detection methodology can also use extended Kalman filters (EKF) for generating residual signals when system nonlinearities are considered. This makes MMAE based approach effective on nonlinear system models. The generated residual signals are evaluated in a probability-based approach to indicate the probability of each fault that may have occurred.

IV. STATE ESTIMATION AND PROBABILITIES

A. Kalman Filter Design

Kalman filter is used for estimating the states of the linear state space model by minimizing the mean of the squared error. The discrete Kalman filter aims to estimate the state of the system given by (10)-(13). The Kalman estimation equation is given by [17, 18]:
\[ \hat{x}[k+1] = \Phi_n \hat{x}[k] + \Gamma_n u[k] + K_n(z[k] - (H_n \hat{x}[k] + D_n u[k])), \]
where \( \hat{x}[k+1] \) is the estimation of the state variable at time step \( k+1 \), \( \hat{x}[k] \) is the previous estimate, \( K_n \) is the Kalman gain of the \( n^{th} \) model, and \( z[k] \) is the noisy measurement. The Kalman filter gain is recursively obtained by:
\[ K_n = \Phi_n P_n H_n^T (R + H_n P_n H_n^T)^{-1}, \]
where, \( P_n \) is the covariance matrix and is updated by:
\[ P_n = LQ I^T + \Phi_n P_n \Phi_n^T - \Phi_n P_n H_n^T (R + H_n P_n H_n^T)^{-1} H_n P_n \Phi_n^T. \]
The covariance \( P_n \) updates the Kalman gain \( K_n \) recursively. To obtain the residual signal of the model as shown in Figure 3, the estimated output signal from the fault cases is subtracted from the measured output of the system. This is obtained from the following equation:
\[ r_n = z[k] - \hat{y}_n[k], \]
where \( \hat{y}_n[k] \) is the estimated output.

B. Multiple-Model Adaptive Estimation Technique

In the multiple model adaptive estimation (MMAE) technique [16, 17, 19-21], as shown in Figure 3, several models run in parallel while excited with similar input signal as that of the actual system. The differences between the output signals of the individual models and that of the actual system generate residual signals. To evaluate and extract the fault information from the residual signals, an evaluation algorithm should continuously monitor the residual signal variations. If the output of any model matches the output of the actual system and makes the mean value of the residual signal zero, then the covariance of that signal can be computed [16, 17, 20] by:
\[ \psi_n = H_n P_n H_n^T + R. \] (18)

In this paper, probability-based residual signal evaluation was applied to the residual signals. Conditional probability density functions of the \( n^{th} \) model considering the history of measurement \( Z(t_{l-1}) = [z(t_1) \ldots z(t_{l-1})] \) are expressed as [16, 19, 20]:
\[ f_{z(t_l)}(z | \alpha_n, Z_{l-1}) = \beta_n \exp(- \frac{1}{(2\pi)^{l/2} |\psi_n(t_l)|^{1/2}}), \]
where,
\[ \beta_n = \frac{1}{(2\pi)^{l/2} |\psi_n(t_l)|^{1/2}}, \] (20)
\( l=1 \) is the measurement dimension, and
\[ (e) = -\frac{1}{2} \left( r_n T(t) \right) \phi_n - T_n(t), \]  
(21)

where \( r_n \) is the residual signal for the \( n \)th model.

The conditional probability evaluation of the \( n \)th sub-system is given [16, 19, 20] by:

\[ p_n(t) = \frac{f_x(t|x|a|a_{n-1}|z_{n-1})p_n(t_{n-1})}{\sum_{j=1}^{n} f_x(t|x|a|a_{j-1}|z_{j-1})p_j(t_{j-1})}, \]  
(22)

where \( p_j \) is the conditional probability of \( j \)th model \( j = 1, \ldots, n \).

The conditional probability density functions require \textit{a priori} samples to compute the current values and are normalized over a complete sum of conditional probabilities of all systems [16, 19, 20]. The largest conditional probability amongst all can be used as an indicator of fault in the systems. In some applications, where probabilities change rapidly and make the output of the system unpredictable, the output should then be compared with a threshold [17].

V. DESIGN OF EXPERIMENTS

As mentioned earlier, faults in a battery cell can be defined by substantial parameter variations that result in sensible changes in the battery’s operation. This study primarily focuses on over charge (OC) and over discharge (OD) faults in a battery cell. When considering OC and OD battery cell fault types, each of the system parameters such as bulk resistance, ZARC elements, charge transfer resistance and double layer capacitance show a particular trend in parameter variation.

The Li-ion energy storage device selected for this study was A123 18650 LiFePO\(_4\) battery cell [22]. Tables I and II give the impedance spectroscopy results for the 18650 LiFePO\(_4\) battery cell under OC and OD condition respectively. The impedance spectroscopy results are a function of temperature, SOC and ageing. For our study, we neglect the effects of temperature and ageing. The impedance spectroscopy technique involves applying a frequency sweep to the battery system. The frequency sweep usually rides on top of a load current or charging current to capture the impedance data for OD and OC respectively.

**TABLE I.**

<table>
<thead>
<tr>
<th>Cycle</th>
<th>( R_s(\Omega) )</th>
<th>( C'(F) )</th>
<th>( R(\Omega) )</th>
<th>( C(\text{F}) )</th>
<th>( R_s(\Omega) )</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.0771</td>
<td>0.0265</td>
<td>0.0156</td>
<td>0.4177</td>
<td>0.0282</td>
</tr>
<tr>
<td>5</td>
<td>0.2433</td>
<td>0.0041</td>
<td>0.0369</td>
<td>0.2463</td>
<td>0.0329</td>
</tr>
<tr>
<td>10</td>
<td>0.1395</td>
<td>0.0018</td>
<td>0.0720</td>
<td>0.1651</td>
<td>0.0376</td>
</tr>
<tr>
<td>12</td>
<td>0.1387</td>
<td>0.0012</td>
<td>0.1429</td>
<td>0.1007</td>
<td>0.0500</td>
</tr>
<tr>
<td>15</td>
<td>0.2865</td>
<td>0.0010</td>
<td>0.2571</td>
<td>0.0589</td>
<td>0.0763</td>
</tr>
<tr>
<td>18</td>
<td>0.1661</td>
<td>0.0007</td>
<td>0.4907</td>
<td>0.0140</td>
<td>0.1833</td>
</tr>
</tbody>
</table>

**TABLE II.**

<table>
<thead>
<tr>
<th>Cycle</th>
<th>( R_s(\Omega) )</th>
<th>( C'(F) )</th>
<th>( R(\Omega) )</th>
<th>( C(\text{F}) )</th>
<th>( R_s(\Omega) )</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.2623</td>
<td>0.0045</td>
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<td>0.0098</td>
</tr>
<tr>
<td>3</td>
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<td>0.2669</td>
<td>0.0055</td>
<td>3.2500</td>
<td>0.0123</td>
</tr>
<tr>
<td>4</td>
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<td>0.4379</td>
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<td>0.2590</td>
<td>0.0054</td>
<td>2.9430</td>
<td>0.0081</td>
</tr>
</tbody>
</table>

Using impedance spectroscopy data, multiple fault representing models can be formulated. The load current applied on the 18650 LiFePO\(_4\) battery cell is based on the UDDS drive cycle for an electric vehicle, obtained using AUTONOMIE [23]. The duration of the cycle considered for the study is 68 seconds as seen in the Figure 4. Battery cells having higher capacity will have higher amplitude of the load current. While the load current profile simulates the actual working condition of the system, the resulting fault probabilities depend more on the zero average residual signal rather than the magnitude of the load current.  

![Fig. 4 Battery cell load current profile](image-url)

![Fig. 5 Simulated battery cell terminal voltage when UDDS load current is applied](image-url)

For successful application of MMAE, there should be sufficient excitation in the system input so that different fault types can be accurately detected and diagnosed. After running numerous simulations the best results were obtained when the load current profile was multiplied by a sine term the current was obtained by:

\[ I_l' = I_l \sin(600 \pi t). \]  
(23)

In addition, the terminal voltage measurement was modified by multiplying with the sine term:

\[ Z' = Z \sin(600 \pi t). \]  
(24)

Each of the models experiences the same input as the modified load current and the modified terminal voltage measurements. Based on these inputs to Kalman filters, the estimated terminal voltage and the residuals are calculated.

VI. DIAGNOSIS PERFORMANCE EVALUATION

A. Fault Diagnosis

To simulate the effectiveness of the fault diagnosis technique, parameter variation is induced in the measurement to represent consecutive fault cases. The simulation is run for total 68 k samples, from which healthy operation is simulated for the first 17 k and last 17 k samples representing identical start and end conditions. This setup helps to check the effectiveness of the algorithm to de-latch itself from a diagnosed fault case [17]. The faults are injected based on the following steps:

The total simulation is divided into four equal parts which occur consecutively:

1. For the first 17 k samples healthy battery cell operation.
2. For 17 k samples OC fault condition.
3. For 17 k samples OD fault condition.
4. For the remaining 17 k samples return to healthy battery cell operation.

It is assumed that only one type of fault can occur in the system at a given point in time. The conditional probability evaluator block evaluates the probability of occurrence of a particular fault. At each time step the probabilities are evaluated to obtain a value between 0 and 1, where 0 means a no fault and 1 means a definite fault. From Figure 6, three probabilities can be observed, where \( p \) represents the probability of healthy operation of the cell while \( p_1 \) and \( p_2 \) indicate the probability of OC and OD fault occurrence respectively.

The OC fault is injected at 17 k, where it can be observed in Figure 6 that the healthy battery operation probability \( p \) reaches zero, indicating the presence of a fault or non-existence of a healthy condition. The fault type is indicated by the probability \( p_1 \) when it changes from 0 to 1, thus indicating an OC fault case. At 34 k probability \( p_2 \) jumps to 1, while \( p_1 \) moves to zero representing an OD fault case. The healthy cell operation is indicated at 51 k when probability \( p \) increased to 1 and both \( p_1 \) and \( p_2 \) are at 0. The injected faults in the system can be accurately detected and diagnosed using MMAE as seen from Figure 6.

**Fig. 6 Conditional probability density evaluated for normal operation, OC and OD faults.**

**B. Experimental Results**

The MMAE results as shown in Figure 6 distinctly represent the parameter variation at 17, 34 and 51 seconds, but some uncertainty can be observed in between the above sample points. This uncertainty or rapid change in probability is intrinsic to the battery cell model and can be corrected when the probabilities are compared with a threshold [17]. Each probability has a unique threshold which is a tradeoff between controlling rapid probability change and losing out on critical fault related information. The corrected probabilities along with uncorrected are shown in the Figure 7. Although majority of the rapidly changing probabilities have been corrected by using a threshold, there are still some areas which represent faulty spikes and dips in the probabilities as indicated in Figure 7.

From Figure 3, it can be seen that the probabilities are evaluated at the conditional probability evaluator block and are dependent on the residual input. Figure 8 shows the plot of OD probabilities along with the OD residual. Each of the spike regions is identified and numbered. The spikes at 13, 20, 30.3, 54, 56 and 60 seconds are attributed to the OD residual reaching near zero as can be seen in Figure 9, which shows the three selected regions from Figure 8.

**Fig. 7 corrected and un-corrected (dashed) conditional probability density evaluated for normal operation, OC and OD faults.**

**Fig.8. OD probability and residual**

**Fig.9. regions of zero OD residuals**

Furthermore, the near zero residual is achieved only when the estimated output of the system is equal to the measured terminal voltage, as represented in (17). This can only be true when there is an OD fault or when the load current reaches zero. Since these spikes are not located in the designed fault regions, they can be positively attributed to zero load current. Under zero load current condition, the terminal voltage of the system represents the open circuit voltage and hence the residual is near zero. Comparing the load current and the OD probability, it can be confirmed from Figure 10 that the spikes in the OD probability are observed at points where the load current is zero.

**Fig.10. OD probability and load current**

One of the suggested solutions to the above problem is achieved by freezing the probabilities whenever the
absolute value of the load current falls below a set point. The results of this technique are represented in Figure 11. This technique of cleaning the fault representing probabilities is effective because it is highly unlikely that a fault will occur when the load current is zero.

From the results it can be observed that MMAE along with Kalman filter can successfully be used for detecting any variation in Li-ion battery cell parameters and thus generating fault probabilities. These probabilities can be further used to diagnose Li-ion battery faults accurately and in real time.

![Fig.11. Cleaned conditional probability density evaluated for normal operation, OC and OD faults](image)

VII. CONCLUSION

This paper applied MMAE technique for fault detection and diagnosis in Li-ion battery cells. Kalman filters were used to estimate the states of the fault models while considering the noise. Fault scenarios of over charge and over discharge were created and simulated to show the effectiveness of the technique. Simulation results show that the proposed method is able to detect the stated battery faults in real-time, thus providing an effective way of diagnosing Li-ion battery failure.

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