Outlier Mining-Based Fault Diagnosis for Multicell Lithium-Ion Batteries Using a Low-Priced Microcontroller

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***Abstract*—Fault diagnosis for lithium-ion batteries involves detecting faulty cells and identifying types of faults. It is crucial to build safety-critical battery systems, which has not been fully integrated in conventional battery management systems. This paper proposes a novel data mining-based real-time fault diagnosis for multicell lithium-ion batteries using a microcontroller. The proposed fault diagnosis algorithm includes: 1) a model-based battery condition monitoring algorithm that estimates physical model parameters and operational states and 2) an outlier detection algorithm that detects abnormal battery cells based on the outcomes of the condition monitoring and identifies the types of faults such as internally shorted cells and anomaly aged cells. The proposed fault diagnosis method is implemented in a low-priced microcontroller and validated by experiments in a multicell battery simulation testbed.**

Keywords—Battery management system; fault diagnosis; internal short circuit battery, lithium-ion battery, outlier mining

I. Introduction

Lithium-ion (Li-ion) batteries are excellent power sources and energy storage devices due to high power density, energy density, low maintenance requirement, low self-discharge, and no memory effect [1]. Therefore, Li-ion have gained widespread use in applications ranging from portable electronics devices to energy storage systems for electric vehicles [2] and power grids [3]. However, safety and reliability are still of concern in using Li-ion batteries due to the existence of manufacturing defects, abuse operation, and the aging process [4].

The faults in a battery system include sensor fault, communication fault, cell fault, loose connection (causing arc fault), insulation fault, etc. Among them, battery cell faults include mild faults (e.g., an aged dead cell due to aging process) and incipient faults (e.g., an internally shorted cell due to latent defects built into the cell during manufacturing and inadequate design or operation [5]). Specifically, early detection of an internal short circuit that is internal micro short circuit condition in a battery cell can prevent thermal runaway that occurs a fire and an explosion, and thus ensures battery safety [6].

Fault diagnosis for battery cell is a critical technique that detects faulty cells and identifies types of faults [5]. A variety of fault diagnosis methods have been developed, which, in general, can be classified into two categories: model-based methods and model-free (or called data-driven) methods. Model-based methods utilize a model (e.g., electrochemical models [7] and electrical circuit models [8]-[10]) and estimate parameters and/or evaluate residuals which are used for battery fault indicators. Model-free methods include signal processing-based methods that extract fault symptoms from battery data by using signal processing methods (e.g., discrete Fourier transform, wavelet transform [11], and Shannon Entropy [12]) and knowledge-based methods use artificial intelligence techniques [5] (e.g., fuzzy logic and artificial neural network).

This paper proposes a new outlier mining-based fault diagnosis algorithm for multicell Li-ion batteries. The proposed fault diagnosis algorithm systematically incorporates a model-based battery condition monitoring algorithm estimating physical model parameters into the proposed outlier detection algorithm. Hence the proposed algorithm detects abnormal battery cells based on the outcomes of the condition monitoring and identifies faulty cells. The proposed algorithm is implemented in a microcontroller and validated by experiments in a multicell battery cell simulation testbed for nine Li-ion battery cells.

II. Proposed Fault Diagnosis Algorithm for Multicell Batteries

The proposed outlier mining-based fault diagnosis algorithm for multicell batteries are a set of a condition monitoring algorithm and an outlier detector, as shown in Fig 1. In this paper, the hybrid filter (HF)-based condition monitoring algorithm [13] is applied.

A. A Real-Time Battery Model

Fig. 1 illustrates a real-time battery model. *VOC* (i.e., instantaneous OCV) comprises two parts, as shown in Fig. 2.

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The first part, denoted by $V_{oc}(SOC)$, represents an equilibrium OCV, which is used to bridge the SOC to the cell average OCV. The second part V_h is the hysteresis voltage capturing the hysteresis effect of the OCV. The RC circuit models the I-V characteristics and the transient response of the battery cell. Particularly, the series resistance R_s characterizes the charge/discharge energy losses of the cell; the charge transfer resistance R_c and the double layer capacitance C_d characterize the short-term diffusion voltage V_d of the cell; V_{cell} represents the terminal voltage of the cell. A discrete-time state-space version of the electrical circuit with hysteresis battery model was applied and is expressed as follows

$$x(k+1)=\begin{bmatrix}1 & 0 & 0\\ 0 & \alpha & 0\\ 0 & 0 & H\end{bmatrix}x(k)+\begin{bmatrix}\dfrac{-\eta T_s}{C_{tot}} & 0\\ \beta & 0\\ 0 & (H-1)\end{bmatrix}\begin{bmatrix}i_B(k)\\ sign(i_B(k))\end{bmatrix} \quad (1)$$

$$y(k)=V_{cell}(k)=V_{oc}(SOC(k)-V_d-R_s i_B(k)+V_{h\max}v_h(k) \quad (2)$$

$$V_{oc}(SOC)=a_0\exp(-a_1 SOC)+a_2+a_3 SOC - a_4 SOC^2+a_5 SOC^3 \quad (3)$$

where $x(k+1) = [SOC(k+1), V_d(k+1), v_h(k+1)]^T$ is the state, k is the time index, $V_{cell}(k)$ is the measured cell terminal voltage, η is the Coulomb efficiency (assuming $\eta = 1$); C_{tot} denotes the total capacity of the cell, T_s is the sampling period; $i_B(k)$ is the instantaneous current of the cell (i_B is positive if the cell is operated in the discharge mode); V_{hmax} is the maximum hysteresis voltage; $\alpha = \exp(-T_s/\tau)$ with $\tau = R_c{\cdot}C_d$; $\beta = R_c(1-\alpha)$; $sign(\cdot)$ is the sign function; and $H(i_B)$=$\exp(-\rho|i_B|T_s)$, where ρ is the hysteresis parameter representing the convergence rate; and a_j (j = 0, ···, 5) are the coefficients used to parameterize the OCV curve. C_{tot} can be replaced with $C_{\max}$ denoting the maximum capacity of the battery . However, the use of C_{tot} is advantageous since it is independent of ambient temperature and will be used as a good indicator of state of health [14]. In the case of simulating a shorted cell, a short circuit resistor R_{isc} [10] will be included, as shown in Fig. 1.

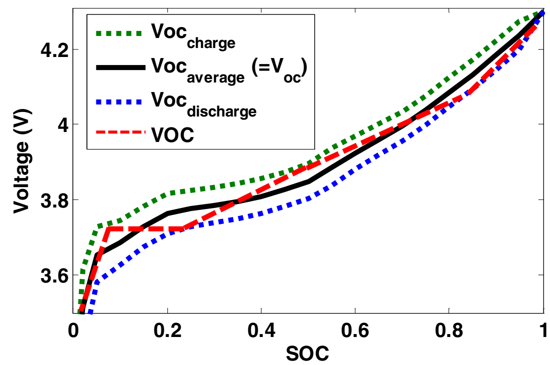


Fig. 2. OCV curves.

B. HF-Based Conditon Monitoring

The HF-based online condition monitoring algorithm, as shown in Fig 1, consists of two cooperating filters: an EKF-based parameter estimator and an SVSF-based SOC estimator. The procedure of the HF algorithm is summarized in Table I. Based on the prior information, the algorithm is initialized by choosing the best guesses of the battery parameters θ_0 (= [α, β, $1/C_{tot}$, R_s, ρ, V_{hmax}]), state x_0 and tuning parameters P_0, Q, R, γ, and Ψ. At each time interval (e.g., T_s = 1 second), the time update and measurement update are consecutively executed from two filters simultaneously. Interested readers are referred to [13] for details.

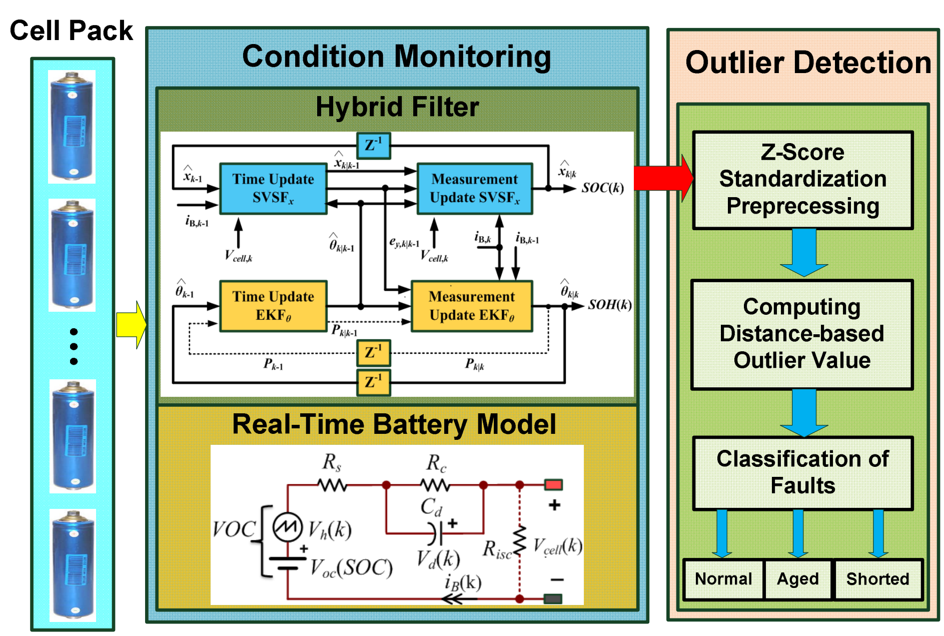


Fig. 1. The black diagram of the proposed outlier mining-based fault diagnosis method for multicell Li-ion batteries.

TABLE I. THE HYBRID FILTER-BASED CONDTION MONITORING ALGORITHM

State-space models:

$x_{k+1} = f(x_k, i_B(k), \theta_k)$ and $\theta_{k+1} = \theta_{k+1} + r_k$

$y_k = h(x_k, i_B(k), \theta_k)$ $d_k = h(x_k, i_B(k), \theta_k) + e_k$

$\cong C_k^x x_{k|k}$

1: algorithm initialization. set k=0, T_s, θ_0, x_0;
   set tuning parameters P_0, Q, R, γ, and Ψ;

2: **repeat**

3: $k \leftarrow k + 1$

4: read new data $V_{cell}(k)$ and $i_B(k)$

5: time update for the EKF$_\theta$

$$\hat{\theta}_{k|k-1} = \hat{\theta}_{k-1|k-1}$$

$$P_{k|k-1} = P_{k-1} + Q$$

6: time update for the SVSF$_x$

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1}, i_B(k-1), \hat{\theta}_{k|k-1})$$

7: measurement update for the SVSF$_x$

$$e_{y,k|k-1} = y_k - h(\hat{x}_{k|k-1}, i_B(k), \hat{\theta}_{k|k-1})$$

$$K_k^x = (C_k^x)^{-1}(|e_{y,k|k-1}| + \gamma |e_{y,k-1}|) \circ sat(e_{y,k|k-1}, \Psi)$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k^x$$

$$e_{y,k|k} = y_k - h(\hat{x}_{k|k}, i_B(k), \hat{\theta}_{k|k-1})$$

$$e_{y,k-1} = e_{y,k|k}$$

8: measurement update for the EKF$_\theta$

$$K_k^\theta = P_{k|k-1}(C_k^\theta)^T [C_k^\theta P_{k|k-1}(C_k^\theta)^T + R]^{-1}$$

$$\hat{\theta}_{k|k} = \hat{\theta}_{k|k-1} + K_k^\theta e_{y,k|k-1}$$

$$P_{k|k} = (I_6 - K_k^\theta C_k^\theta) P_{k|k-1}$$

9: map θ to the battery model parameters.

10: check whether estimated parameters are within the predefined range of values

11: update the internal parameters

12: **until** parameter estimation task ends

C. Outlier Detection for Fault Diagnosis

In this paper, fault diagnosis mainly detects abnormal cells (shorted and anomaly aged cells) that will be faulted very soon, which are more practically useful in the battery systems. Any detectable abnormalities in the measurements (e.g., cell voltage and current) and condition monitoring results (e.g., states SOC, V_c, and V_h, and parameters C_{tot}, R_s, and R_c) will be good indicators of fault diagnosis algorithms. Fig. 3 shows a clustering analysis of healthy cells, shorted cells [10], and aged faulty cells (i.e., almost dead cells) [5] using estimated parameters C_{tot} and R_{tot} (= R_s +R_c). Since the shorted cells and anomaly aged cells have high abnormalities of C_{tot} and R_{tot} compared to those of normal cells, two parameters can be considered as outlier values in this paper.

Outlier detection is a method of data mining and a process of finding data objects with behaviors that are very different from expectation [15]. In this paper, a distance-based outlier detection approach with Z-score standardized preprocessing method is proposed for battery fault diagnosis. The Z-score standardized method is computed by

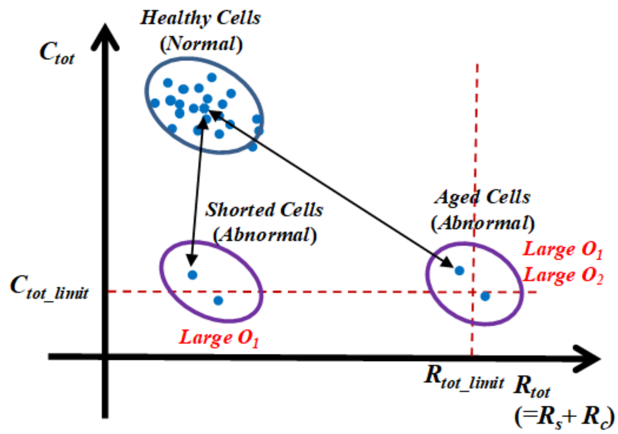


Fig. 3. Clustering analysis of healthy (normal) cells, shorted (abnormal) cells, anomaly aged (abnormal) cells.

$$Z_{1,n} = \frac{C_{tot,n} - avg(C_{tot})}{std(C_{tot})}, \quad Z_{2,n} = \frac{R_{tot,n} - avg(R_{tot})}{std(R_{tot})} \tag{4}$$

where Z_1 and Z_2 are the preprocessed parameters of C_{tot} and R_{tot}, respectively; n is cell number (n = 1, ⋯, N) where N is the number of cells; $avg(\cdot)$ represents the mean of the parameter of all cells; and $std(\cdot)$ is the standard deviation of the parameter.

The distance-based outlier detection method applies Euclidean distance between two points, which develops a flexible distance function and extracts outliers effectively. The outlier values O of the battery is defined as the sum of Euclidean distance among a specific cell n and others (i = 1, …, N).

$$\begin{cases} O(Z_{1,n}) = sum(|Z_{1,n} - Z_{1,i}|), & i = 1, \dots, N \\ O(Z_{2,n}) = sum(|Z_{2,n} - Z_{2,i}|), & i = 1, \dots, N \end{cases} \tag{5}$$

Large outlier values $O(Z_1)$ and $O(Z_1)$ mean the cell tends to be abnormal compared to other cells. If both outlier values $O(Z_1)$ and $O(Z_2)$ of a cell are large, it is classified as an anomaly aged cell, while a shorted cell will only have a large $O(Z_1)$. By this way, it is easy to classify faulted battery cells.

III. VALIDATION

The proposed fault diagnosis method for multicell batteries is implemented and validated by a multicell battery simulation testbed with a low-priced microcontroller for nine cells connected in series, as shown in Fig. 4, where the algorithms are coded in a microcontroller (i.e., Arduino 2560) and a battery emulator (i.e., a Raspberry pi board where the battery cell models are coded) sends the cell data. Once new data received, the microcontroller executes the proposed algorithm.

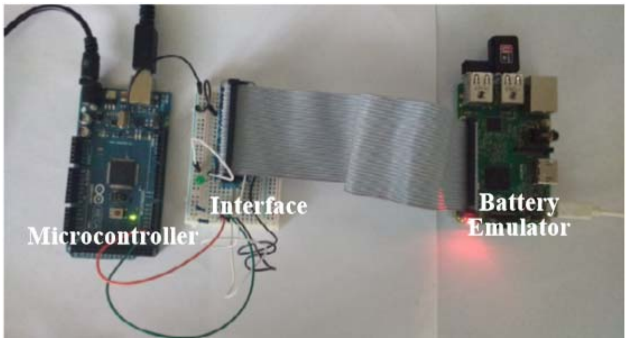
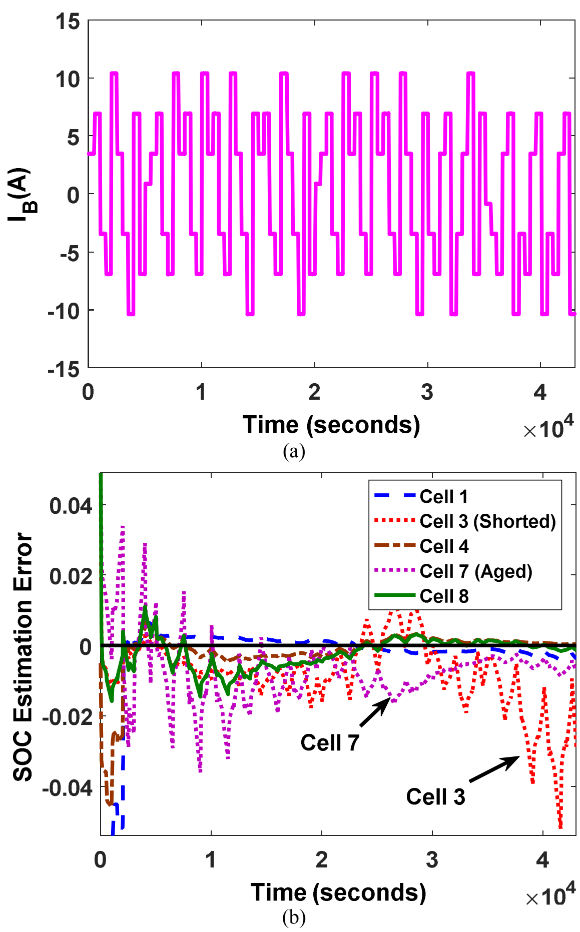


Fig. 4. A multicell battery simulation testbed using a battery emulator, interface, and a low-priced microcontroller.

The battery cell models are operated by a dynamic current profile shown in Fig. 5(a). Figs. 5(b)-(d) show the comparison of true SOCs, total capacities, and total resistances of the Cell 1, Cell 3 (shorted cell), Cell 4, Cell 7 (anomaly aged cell), and Cell 8 with estimated values from the HF algorithm. It has been shown that the estimated values converge to the true values. Figs. 6(a)-(b) illustrate outlier values of the total capacities and resistance of the batteries computed by the



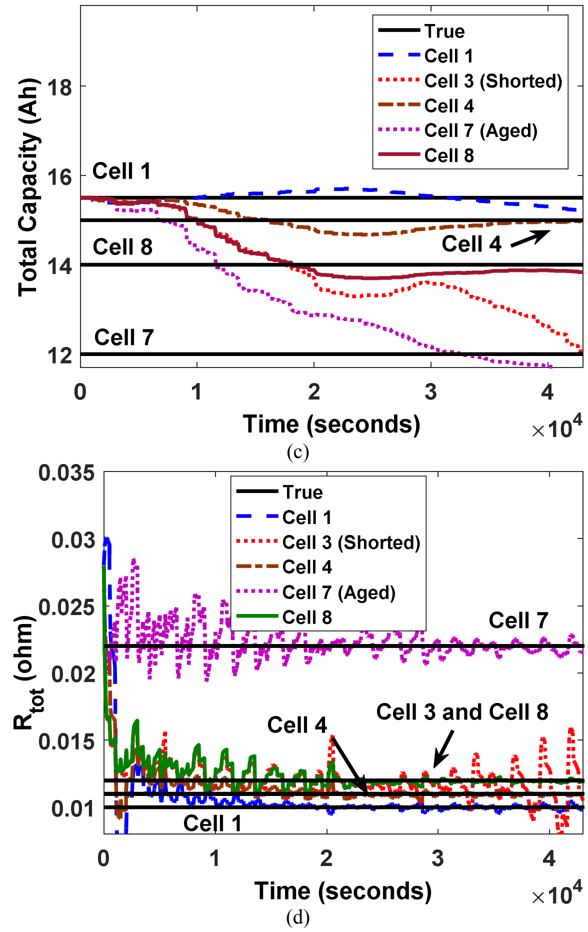
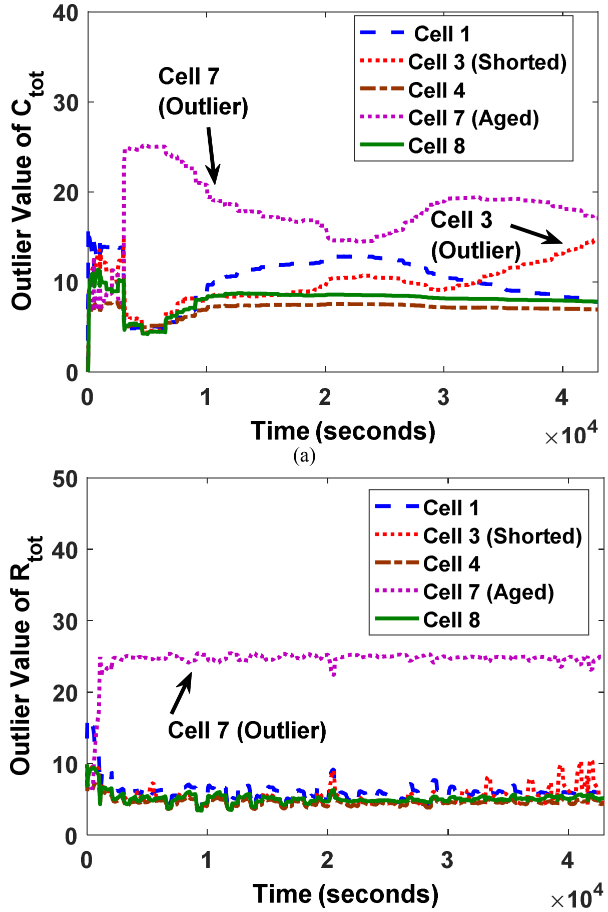


Fig. 5. Comparison of true and estimated values of Cell 1, Cell 3 (internal short), Cell 4, Cell 7 (aged), Cell 8: (a) input current i_B, (b) SOC estimation error, (c) C_{tot}, and (d) R_{tot}.

proposed outlier mining-based fault diagnosis algorithm using the estimated C_{tot} and R_{tot}. The results show that the aged cell (Cell 7) has significantly large outlier values $O(Z_1)$ and $O(Z_2)$, while the shorted cell (Cell 7) only has a significantly large $O(Z_1)$. Therefore, the proposed fault diagnosis algorithm can provide reliable real-time fault conditions of the multicell batteries at relatively low computational cost, and thus can be suitable for real-time embedded BMSs for variable applications.

IV. CONCLUSION

This paper proposes a novel outlier mining-based fault diagnosis algorithm for Li-ion multicell batteries. With the HF-based condition monitoring algorithm, the proposed method has been implemented in a microcontroller validated by using a multicell battery simulation testbed. The proposed model can be applied to any types of Li-ion batteries. Due to low complexity and high accuracy, the proposed method can be used in real-time embedded battery management systems for various applications.



(a) (b)

Fig. 6. Outlier values of the total capacities and resistances of Cell 1, Cell 3 (internal short), Cell 4, Cell 7 (aged), and Cell 8 from the proposed outlier detection-based fault diagnosis algorithm: (a) O(Z_1) and (b) O(Z_2).

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