Efficient On-Board Health Monitoring for Multicell Lithium-Ion Battery Systems Using Gaussian Process Clustering

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***Abstract*—Accurately monitoring health condition of individual lithium-ion (Li-ion) cells such as state of charge (SOC) and state of health (SOH) in multicell batteries is crucial to build high-performance and safety-critical battery systems. However, this involves considerable computational burden to embedded battery management systems (BMSs), as number of battery cells increases. This paper proposes an efficient on-board health monitoring method for multicell Li-ion battery systems consisting of large number of cells using the proposed Gaussian process clustering. The Gaussian process clustering method first preprocesses all cell voltages using Z-score standardization and classifies a normal cell cluster and an abnormal cell cluster using outlier scoring vector. Then, a representative of the normal cell cluster and abnormal cells are carefully monitored using the threads of a condition monitoring algorithm. Instead of using cell-based method for all cells in a pack, the proposed method can significantly reduce the computation cost for onboard implementation. We show the usefulness of the proposed health monitoring algorithm through simulation results.**

Keywords—Battery management system (BMS), battery condition monitoring, fault diagnosis, gaussian process clustering, lithium-ion battery

I. Introduction

Lithium-ion (Li-ion) batteries are excellent power source and energy storage devices due to high power and energy density, low maintenance requirement, low self-discharge, and no memory effect [1]. Therefore, multicell Li-ion batteries consisting of a large number of cells have pervasively used in electric vehicles (EVs) [2] and grid-tied energy storage systems for electric power distribution systems [3]. Moreover, it is anticipated that the large-scale multicell Li-ion battery technologies are needed for the future generation of large transport aircraft [4] and electric ships [5]. However, there are critical concerns regarding the safety, reliability, and performance degradation of the Li-ion batteries [6] and the overall cost of the battery system is still high. A properly designed battery management systems (BMSs) are required to ensure their safety, reliability, optimal performance, and cost-effectiveness [7]. A key mission of state-of-the-art BMS is cell-level condition monitoring and fault diagnosis for Li-ion batteries [8]. An excellent summary of the condition monitoring and fault diagnosis algorithms for Li-ion batteries may be found in [9].

Condition monitoring involves tracking changes in parameter such as cell resistance and cell capacity and operational states such as cell state of charge (SOC, i.e., quantifying available battery capacity) and cell state of health (SOH, i.e., quantifying the battery aging and wear) [10]. In general, the model-based condition monitoring methods have been proposed to estimate parameters an states simultaneously (e.g., a dual extended KF (EKF) [11], a dual sigma-point KF (SPKF) [12], dual sliding mode observer (SMO) [13]). Although the model-based condition monitoring algorithms can provide relatively accurate estimation, their computational complexity is still high. This will be a significant challenge to the embedded BMSs as the number of battery cells increases. For example, if a pack include 96 cells that requires eight 12-cell monitoring ICs [14] and 96 threads of cell-level condition monitoring algorithms should be sequentially executed in an embedded system.

Fault diagnosis for battery cells is also a critical technique that detects (potentially) faulty cell and identifies types of faults [15]. 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 the estimated parameters and/or evaluate residuals from the model-based condition monitoring algorithm, which are used for battery fault indicators. Model-free methods include signal processing-based methods that extract fault symptoms

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from battery data by using signal processing methods (e.g., discrete Fourier transform, wavelet transform [16], and Shannon Entropy [17]) and knowledge-based methods use artificial intelligence techniques [15] (e.g., fuzzy logic and artificial neural network).

To minimize such computational burden of the health monitoring algorithm in the embedded BMS (for N cells to be monitored), several methods have been proposed. An SOC polling method [18] polls cells sequentially and updates simple N Coulomb-counting SOC estimators using an EKF. An SOC and SOH compensation method [10] executes periodically to compensate N Coulomb-counting and capacities using an adaptive SMO and a two-point method with a certain interval during operation or during a long relaxation period of the battery cell. However, they may need to wait a long time to compensate all cells. Bar-delta filtering method [19] has been proposed to estimate cell SOC and SOH values of a battery pack using a Bar filter (i.e., multi-state SPKF) and N delta filters (i.e., single-state SPKFs and/or single-state DEKF) that compensate SOC and SOH of cell simultaneously, which takes advantage of similar states among pack cells. Although this method may require only slightly more computation than for a single cell. However, the computation cost of the SPKFs will be still high in the embedded systems.

This paper proposes an efficient on-board condition monitoring and fault diagnosis method for multicell Li-ion battery systems consisting of large number of series-connected cells using the proposed Gaussian process clustering. The Gaussian process clustering utilizes Gaussian distribution probability characteristics of battery cell voltage data to cluster cells into two groups: 1) a normal cell cluster by taking advantage of similarity of cell states among pack cells [19]; and 2) an abnormal (or outlier) cell cluster by detecting dissimilarity of abnormal cells among pack cells. Then, a representative of the normal cell cluster with the lowest and abnormal cells are carefully monitored. As a result, the number of cells to be monitored can be significantly reduced. Finally, 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 simulation results validate that the proposed Gaussian process method can dramatically reduce the computation for onboard health monitoring solution compared to the cell-based method for multicell Li-ion batteries.

II. The Proposed Cloud-Based Health Monitoring Platform

Fig. 1 shows the block diagram of the proposed efficient on-board condition monitoring and fault diagnosis method using the proposed Gaussian process clustering. In this paper, the hybrid filter (HF)-based condition monitoring algorithm [20] and outlier mining-based battery fault diagnosis algorithm [21] are applied.

A. Gaussian Process Clustering

The distribution of cell voltages V in the battery pack are assumed to be Gaussian distribution with mean m and standard deviation σ as followings:

$$f(V) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{(V-m)^2}{2\sigma^2}\right) \tag{1}$$

This means most of healthy cells/normal cells will have similar voltage characteristic (i.e., high probability of observation); while unhealthy cells/abnormal condition cells will have anomalous voltage characteristics (i.e., low probability of observation) among pack cells. The Gaussian process clustering that includes three main steps: Step1. Cell voltage data preprocessing using Z-score standardization [22];

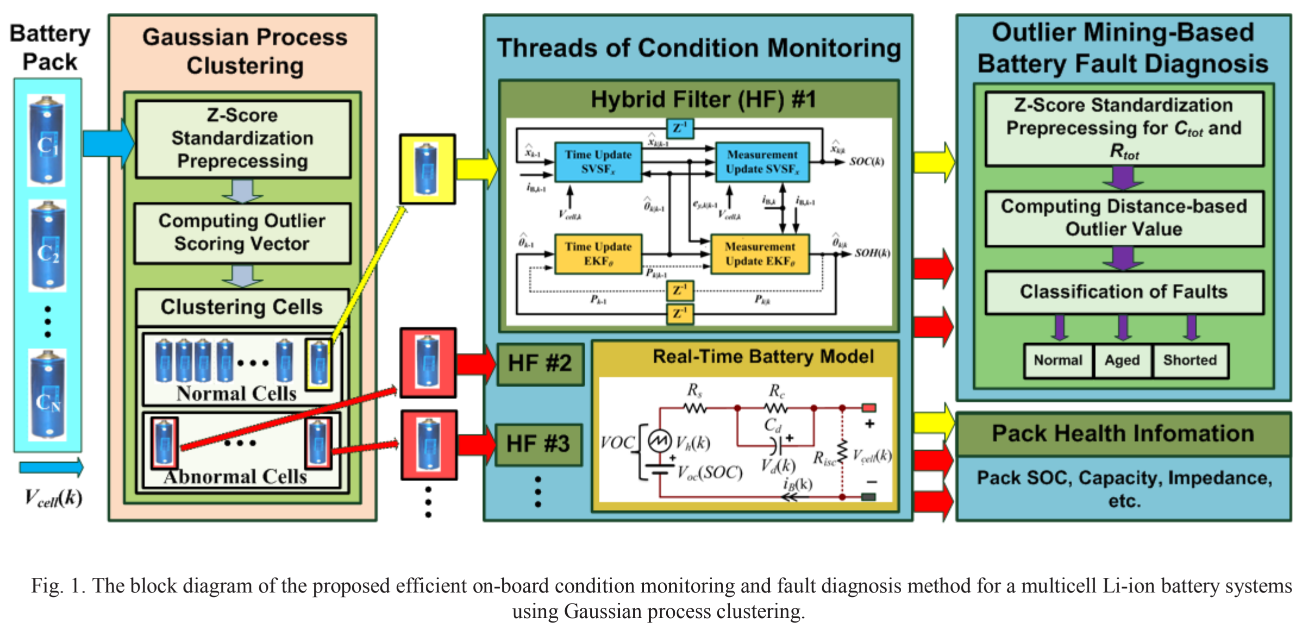


Fig. 1. The block diagram of the proposed efficient on-board condition monitoring and fault diagnosis method for a multicell Li-ion battery systems using Gaussian process clustering.

Step 2. Computing outlier scoring vector; and Step 3. Clustering cells into two groups: a normal cell cluster by taking advantage of similarity of cell states among pack cells with low outlier matrix values [19]; and 2) an abnormal (or outlier) cell cluster by detecting dissimilarity of abnormal cells with large outlier matrix values.

Step 1. Cell voltage data preprocessing using Z-score standardization: This step converters the Gaussian distribution (m,σ) of $V(k)$ at discrete time index k to Standard Normal distribution function with m = 0 and σ = 1 using Z-score standardization. New variable $Z_{V,i}$ for Cell i is computed as:

$$
\begin{aligned}
Z_{V,i}(k) &= \frac{V_{cell,i}(k) - avg(V(k))}{std(V(k))}, \\
V(k) &= (V_{cell,1}(k), \cdots, V_{cell,N}(k))^T, \quad i = 1, \cdots, N
\end{aligned}
\tag{2}
$$

where i is cell number; the sampled cell voltage of cell i $V_{cell,i}(k)$; $avg(\cdot)$ and $std(\cdot)$ represents the m and σ standard deviation of the cell voltages, respectively. The corresponding probability of the random variable $Z_{V,i}(k)$ will be easily acquired by using the standard normal distribution function, as shown in Fig 2.

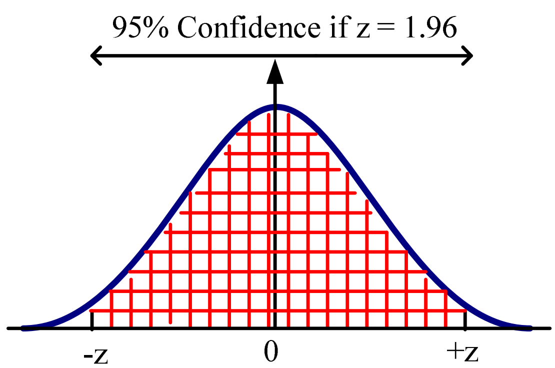


Fig. 2. Standard normal distribution.

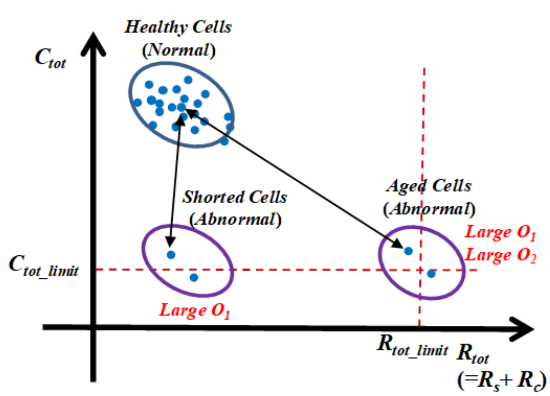


Fig. 3. Clustering analysis of healthy (normal) cells, shorted (abnormal) cells, anomaly aged (abnormal) cells.

Step 2. Computing outlier scoring vector: According to designed confidence (e.g., 95% of confidence: 5% are considered as outlier values when z is 1.96, as illustrated in Fig. 2), an outlier score $D_{V,i}$ for Cell i is made by comparing $|Z_{V,i}(k)|$ with z = 1.96 in a certain time period (L).

$$
\begin{cases}
D_{V,i}(k) = D_{V,i}(k-1) + 1/L, & if\ |Z_{V,i}(k)| \geq z \\
D_{V,i}(k) = D_{V,i}(k-1), & if\ |Z_{V,i}(k)| < z
\end{cases}
\tag{3}
$$

where $D_{V,i}(0) = 0$ at k = 0 and $0 \leq D_{V,i} \leq 1$. A variable sliding window can be used for online/real-time applications. The length of the sliding window L can be adjusted depending on the excitation level of the battery pack current $i_B(k)$ and sampling time.

Step 3. Clustering cells into two groups: Given maximum number of HF threads (e.g., 5 HFs), the cells that have largest $D_{V,i}$ in descending order will be grouped as an abnormal cell cluster if $D_{V,i} \neq 0$. and the others as normal cells. Instead of monitoring all battery cells, only several cells including a representative of the normal cell cluster and abnormal cells will be carefully monitored using the threads of condition monitoring algorithms. A cell that has the smallest $\Sigma(Z_{V,i}(k))$ will be chosen as a representative cell after performing Step 1 again using on normal cell cluster, which will find an exact median cell among them.

B. Condition Monitoring

A block diagram of the HP-based condition monitoring based on the real-time battery model are shown Fig. 1. The essence of the HF method is to combine the weight EKF for model parameter identification and the state smooth variable structure filter (SVSF) for SOC estimation. When new measurements are available, two filters run concurrently at each time interval: the state EKF estimates states using the current estimated model parameters from the weight EKF; while the weight EKF estimates the model parameters using the current estimated states from the state SVSF.

A discrete-time state-space version of the electrical circuit with hysteresis battery model was developed and is expressed as follows:

$$
x(k+1) = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \alpha & 0 \\ 0 & 0 & H \end{bmatrix} x(k) + \begin{bmatrix} \frac{-\eta T_s}{C_{tot}} & 0 \\ \beta & 0 \\ 0 & (H-1) \end{bmatrix} \begin{bmatrix} i_B(k) \\ sign(i_B(k)) \end{bmatrix}
\tag{4}
$$

$$
V_{cell}(k) = V_{oc}(SOC(k)) - V_d(k) - R_s i_B(k) + V_{h\max} v_h(k)
\tag{5}
$$

$$
\begin{aligned}
V_{oc}(SOC) = {} & a_0 \exp(-a_1 SOC) + a_2 + a_3 SOC \\
& - a_4 SOC^2 + a_5 SOC^3
\end{aligned}
\tag{6}
$$

where $x(k+1) = [SOC(k+1), V_d(k+1), v_h(k+1)]^T$ is the state, η is the Coulomb efficiency (assuming η = 1); 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 ; 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_h is the hysteresis voltage capturing the hysteresis effect of the OCV and V_{hmax} is the maximum hysteresis voltage; $\alpha = \exp(-T_s/\tau)$ with $\tau = R_c{\cdot}C_d$; $\beta = R_c(1\text{-}\alpha)$; $sign(\cdot)$ is the sign function; and $H(i_B)=\exp(-\rho|i_B|T_s)$, where ρ is the hysteresis parameter; and $V_{oc}(SOC)$, represents an equilibrium OCV, a_j (e.g., $j = 0, \cdots, 5$) are the coefficients used to parameterize the OCV curve. In the case of simulating a shorted cell, a short circuit resistor R_{isc} [23] will be included, as shown in Fig. 1. Due to a limited number of pages, HF algorithm is not included. Interested readers are referred to [20] for details.

C. Fault Diagnosis

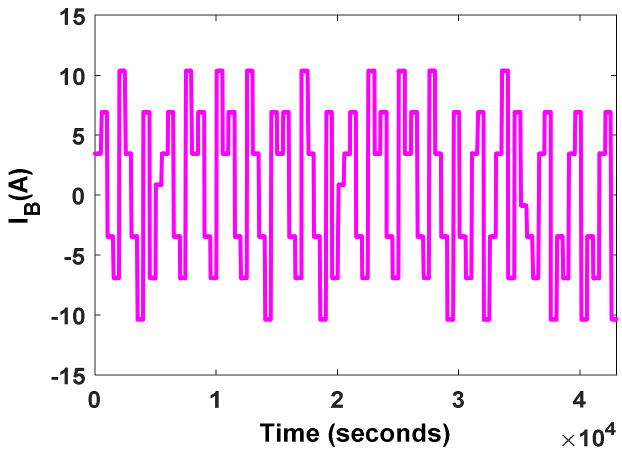
Fault diagnosis mainly detects abnormal cells (shorted and aged cells) that will be faulted very soon, which are more practically useful in the battery systems. Any detectable abnormalities in the measurements (e.g., cell voltage, current, and surface temperature) and condition monitoring results (e.g., 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 [23], and aged faulty cells (i.e., almost dead cells) [15] using estimated parameters C_{tot} and R_{tot} (= R_s + R_c). Since the shorted cells and 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. A distance-based outlier detection approach with Z-score standardized preprocessing method is used for battery fault diagnosis. The Z-score standardized method computes Z_1 and Z_2 are the preprocessed parameters of C_{tot} and R_{tot}, respectively as Step 1. The outlier values O of the battery is defined as the sum of Euclidean distance between a specific cell n ($Z_{1,n}$, $Z_{2,n}$) in the abnormal cell cluster and the representative in the normal cell cluster ($Z_{1,r}$, $Z_{2,r}$).

$$O(Z_{1,n}) = | Z_{1,n} - Z_{1,r} |, \quad O(Z_{2,n}) = | Z_{2,n} - Z_{2,r} | \qquad (7)$$

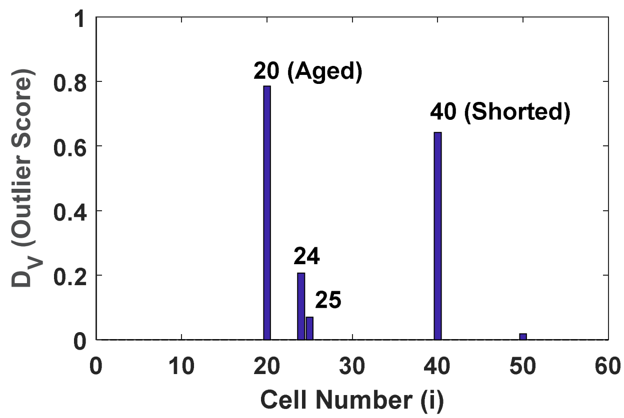
Large outlier values $O(Z_1)$ and $O(Z_2)$ mean the cell tends to be abnormal compared to other cells. If both outlier values $O(Z_1)$ and $O(Z_2)$ of a cell are large, it is classified as an aged cell, while a shorted cell will only have a large $O(Z_1)$. By this way, it is easy to classify faulted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

III. Validation

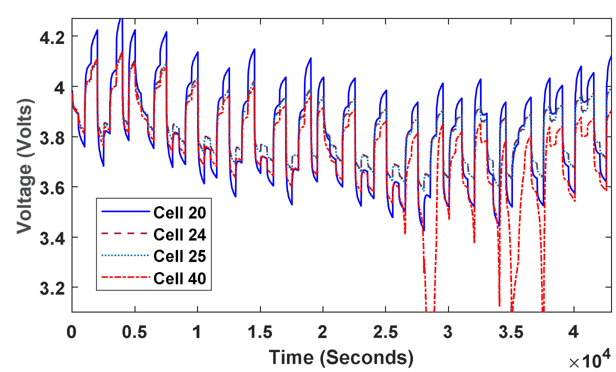
The proposed efficient health monitoring method for 60 multicell batteries connected in series is implemented and validated by numerical simulation. The maximum number of HF threads is set to be 5. The proposed method (1 Gaussian process clustering + 5 HFs + 1 Outlier mining for 5 cells) and the cell-level method (60 HFs + 1 Outlier mining for 60 cells) are implemented in MATLB in a computer with an Intel® Core™ i7-6500U CPU @2.59GHz, 64-bit OS. The 60 battery cell models (Cell 20-anomaly aged cell and Cell 40-shorted cell with R_{isc} = 30 ohm) are operated by a dynamic current profile shown in Fig. 4(a). Fig. 4(b) shows the result of Gaussian process clustering where four cells including Cell 20, Cell 24, Cell 25, and Cell 40 are grouped as an abnormal cell cluster and Cell 21 (the smallest $\Sigma(Z_{V,21}(k) = 0)$ is chosen as a pack representative. Fig. 4(c) and Fig. 4(d) show the voltage responses and SOC estimation errors of Cell 20, Cell 24, Cell 25 and Cell 40, respectively. Figs. 4(d) and 4(e) illustrate the results of outlier values of the total capacities and resistance of the batteries computed from the proposed method using the estimated C_{tot} and R_{tot}. It is observed that



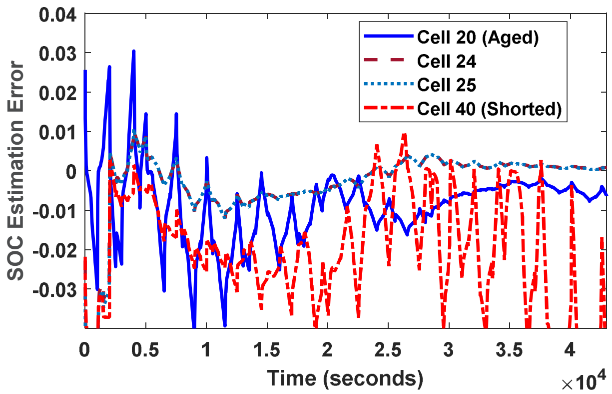
(a)



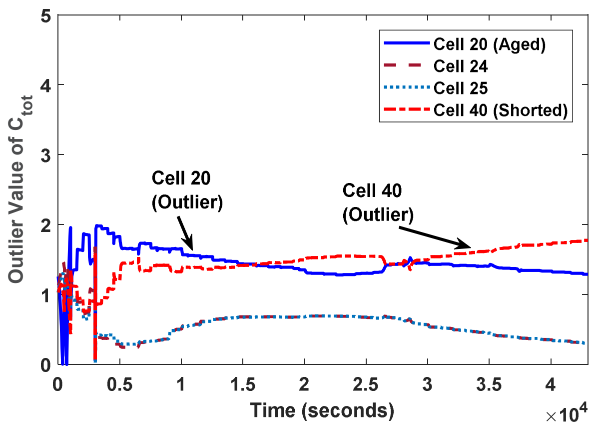
(b)



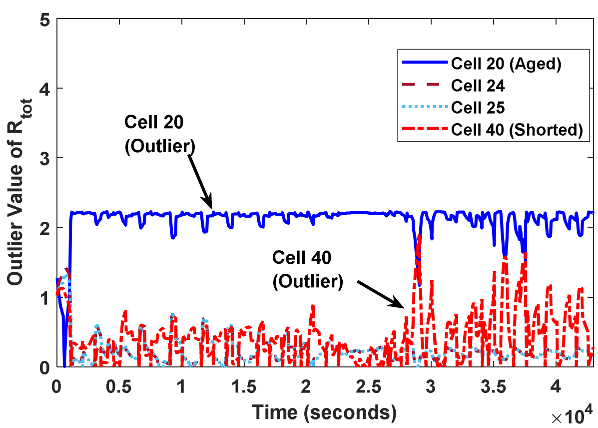
(c)



(d)



(e)



(f)

Fig. 4. The proposed method: (a) input current profile, (b) cell voltages, (c) SOC estimation errors, (d) Gaussian process clustering result, (e) O(Z_1) and (f) O(Z_2).

the aged cell (Cell 20) has significantly large outlier values $O(Z_1)$ and $O(Z_2)$, while the shorted cell (Cell 40) only has a significantly large $O(Z_1)$ and $O(Z_2)$ is oscillated. Table I compares the performance of computational cost using the simulation time on the computer. The results show that the two methods have the similar performance; but the proposed method is about 55 time faster than the cell-based method. Therefore, the proposed method can provide reliable health monitoring results at low computational cost, and thus can be suitable for embedded BMSs for variable applications.

TABLE I: COMPARISON OF SIMULATION TIME IN SECONDS

N = 60 Cells	Proposed method for 5 Cells	Cell-Level Method for 60 Cells
Condition Monitoring	15.78	185.3850
Fault Diagnosis	18.51	1725.2
Gaussian Process Clustering	0.4412	N/A
Total Time	34.7312	1910.6

IV. CONCULUSIONS

This paper proposes an efficient on-board condition monitoring and fault diagnosis method for large number of multicell Li-ion batteries using the proposed Gaussian process clustering. The proposed method is implemented and validated by simulation study. Compared to the cell-based method for all cells in a pack, the proposed method can tremendously deduce the computation cost. Therefore, the proposed will be suitable on-board health monitoring method when a large number of cells are needed to be carefully monitored using the embedded BMSs whose computational recourses are limited. More details of the proposed platform and its opportunities and challenges and more validation results will be provided in the full paper.

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