Pack-Level Current-Split Estimation for Health Monitoring in Li-Ion Batteries

Haris M. Khalid, *Member, IEEE*, Qadeer Ahmed, *Member, IEEE* Jimmy C.-H. Peng, *Member, IEEE*, and Giorgio Rizzoni, *Fellow, IEEE*

***Abstract*—Due to the complicated structural hierarchy and electrochemical processes, lithium-ion battery packs are often monitored by numerous number of sensors. The performance of a pack is highly dependent on the health of these sensors. However, sensors may encounter faults due to manufacturing defects, external shocks or long exposures to high temperatures. A faulty current sensor in particular, may affect the estimation accuracy of the state-of-charge and state-of-health. This may cause the battery to suffer from charging and aging issues. Therefore, a scheme to monitor health of these sensors has been proposed. The first step is to estimate the current-split among parallel connected cells, followed by diagnosing the health of sensors to improve the overall performance of battery at pack-level. A median-expectation based covariance intersection diagnosis approach (MCIA) is proposed. MCIA evaluates the median of a possible set of values by calculating the covariance of the interconnected cell structure to estimate the current-split. This has been achieved by first deriving the median-based covariance intersection filter-based smoother for predicting the state vector of the current-split among cells. The scheme is further developed from the residuals of these estimates to isolate the faulty sensors. Performance evaluations have been conducted by analyzing sets of real-time measurements collected from Li-ion battery pack used in electric vehicles (EV). Results show that the proposed filter accurately estimated the battery parameters in the presence of temporary and permanent faults.**

***Index Terms*—Battery powered vehicles, battery life issues, covariance intersection, current-split, electric vehicles (EVs), energy management system, estimation, expected value, hybrid electric vehicles, lithium ion (Li-ion) batteries, recursive, renewable energy.**

I. Introduction

EFFECTIVE health monitoring of Li-Ion batteries is crucial for the automotive industry and other energy storage applications. Besides issues related to the internal chemical characteristics of the battery, external physical malfunctions can also deteriorate its performance. For example, from the point of view of system engineering, a battery pack is composed of numerous interconnected subsystems, i.e. battery cells. These subsystems are equipped with voltage, current and temperature sensors, resulting in an on-board complex network composed of hundreds of sensors. Such complex system is controlled by an on-board Battery Management System (BMS) that relies on sensors to achieve the desired performance of the battery pack. BMS is responsible for the State of Charge (SoC) estimation, State of Health (SoH) estimation, thermal management of the pack, voltage equalization, battery current and voltage limits etc. It can be seen that these functions are sensor dependent. Therefore, health monitoring of sensors holds prime significance in the development of the overall pack diagnostics scheme.

This work was developed on the data generated from Center of Automotive Research, The Ohio State University, USA. The experiments were supported by US NSF Grant.

H. M. Khalid and J. C.-H. Peng are with Department of Electrical Engineering and Computer Science, Institute Center for Energy, Masdar Institute of Science and Technology (MI), Masdar City, U.A.E. (e-mail: mkhalid,jpeng@masdar.ac.ae)

Q. Ahmed and G. Rizzoni are with Center for Automotive Research, The Ohio State University (OSU), Columbus, OH 43210 USA (e-mail: ahmed.358,rizzoni.1@osu.edu)

To date, most of the efforts on battery health monitoring are limited to cell level [1–3]. The nonlinear behavior of battery cells connected in series and parallel makes it difficult to develop a reliable diagnostic scheme [4, 5]. Furthermore, the cell to cell variability makes the monitoring task more challenging. The realization of a current-split among the parallel cells is very critical to have a reliable diagnostic scheme [6–8]. The contribution of each sensor at cell level to the pack level can be identified if the current-split information is accessible along with voltage sensor information. Since most of the diagnostics schemes focus at cell level, little effort has been invested to resolve this challenge.

The focus of this paper is on the development of the systematic diagnostics scheme for a battery pack. At first, the impact of the sensors faults on the parameters of the battery have been generated to show the complexity of pack level diagnostic problem. Later on, a current-split estimation scheme has been devised to realize the current flows among the cells connected in parallel. Once all of the information has been made available we then develop residual to diagnose and Isolate the faults. The benefits associated with this approach is that SoC, SoH and capacity false estimation can be avoided and thus BMS can make more intelligent and reliable decisions to deliver the desirable performance. We have analyzed a 2P3S pack with a permanent and intermittent fault to test and validate the algorithm. The main contribution of this paper is to enhance the reliability of Li-ion battery packs. This was accomplished by estimating the current-split between the parallel cells connected in a series circuit, in the presence of temporary and permanent faults. As the faults may have the form of random glitches and spikes, the proposed scheme has been developed based on median filters [9–12].

The paper is organized as follows: The problem is formulated in Section II. In Section III, the implementation and evaluation of the scheme are discussed, and finally conclusions are drawn in Section IV.

II. Proposed Methodology of Current-Split Estimation

An overview of the formulation framework of this section is illustrated in Fig. 1. It summarizes the procedures for estimating the current-split and diagnostics of the battery-pack. Note that only two parallel cells are connected in a module of N number of series are considered here. Each cell is equipped with a current sensor and there is a voltage sensor at module level. The sensors signal are collected via bus for further analysis. The presented configuration is the standard structure used in Li-ion battery packs [5].

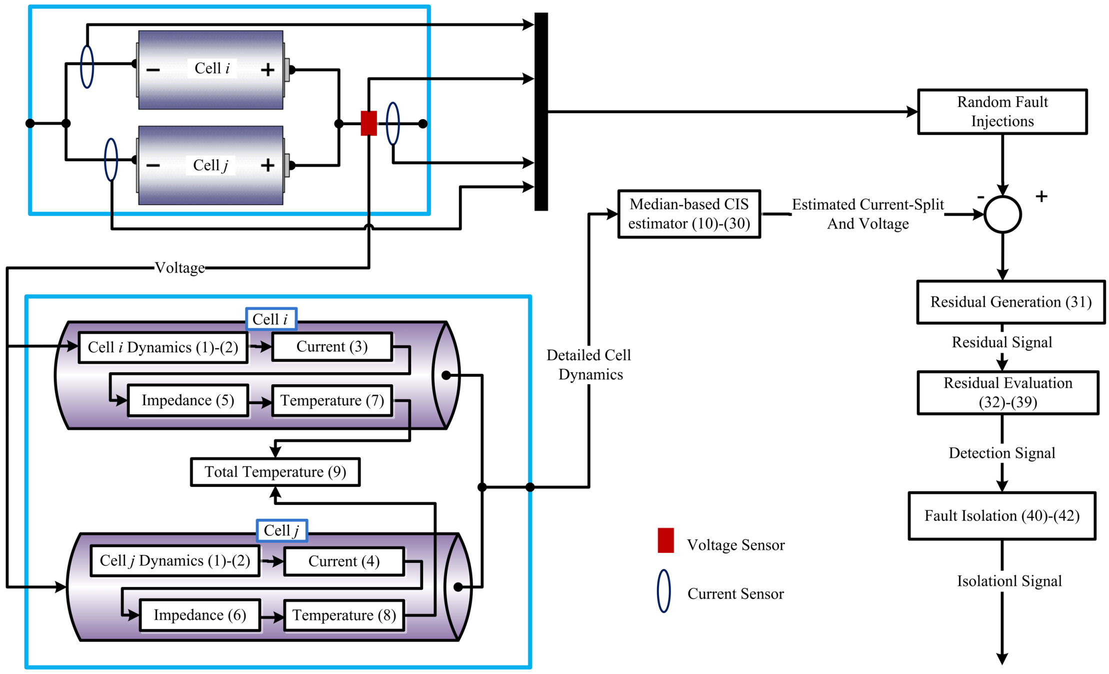

Fig. 1. Proposed MCIA scheme for pack-level health diagnosis

A. *Battery Pack State Model and Conductivity Relationships*

Consider a discrete-time dynamical model of a battery-pack involving Cells i and j connected in parallel with a voltage supply to N number of in-series connections. It can be represented by a state difference equation and an observation model at time-instant t as:

$$I_{t+1}^{ij} = F_t^{ij} I_t^{ij} + \frac{\alpha_t^{ij}}{2}(\Gamma_t^i + \Gamma_t^j) + \beta_t^{ij}(z_t^i + z_t^j) + G_t^{ij} w_t^{ij} \quad (1)$$

$$y_t^{ij} = H_t^{ij} F_t^{ij} I_t^{ij} + \nu_t^{ij} \quad (2)$$

where superscript ij presents the fused form of cells i and j. The $I_0^{ij} \in \mathbf{R}^r$ is the initial condition of the state of current, and $F_t^{ij} \in \mathbf{R}^{r \times r}$ is a model matrix of the state response of current, such that it depends on the covariates. Meanwhile, $\alpha_t^{ij} \in \mathbf{R}^{r \times r}$ is the transition matrix of temperatures $\Gamma_t^i \in \mathbf{R}^r$ and $\Gamma_t^j \in \mathbf{R}^r$ of Cell i and Cell j, respectively. $\beta_t^{ij} \in \mathbf{R}^{r \times r}$ is the impedance transition matrix of impedances $z_t^i \in \mathbf{R}^r$ and $z_t^j \in \mathbf{R}^r$, respectively. Also, $G_t^{ij} \in \mathbf{R}^{r \times r}$ is the noise transition matrix, which can be defined as a probability vector. Its elements are non-negative real numbers and sum to 1. $w_t^{ij} \in \mathbf{R}^r$ is the random process noise, t is the time instant, where $t = 0, 1, ..., T$, and T refers to the number of time instants. In the observation model of (2), $y_t^{ij} \in \mathbf{R}^p$ is the observation output of state of current, p is the number of simultaneous observations for estimation made at time instant t, $H_t^{ij} \in \mathbf{R}^{p \times r}$ is the observation matrix of current state, I_t^{ij} is the current state matrix, and $\nu_t^{ij} \in \mathbf{R}^p$ is the observation noise. Note in (1), the state of current I^{ij} is calculated at time $t+1$, where it is evolved from its prior state at time t.

The noises w_t and ν_t have been assumed initially uncorrelated zero-median white Gaussian based on [12]. Once the observation model is extracted from the measurements of the battery pack, the relation between different parameters of the battery collected from sensors are formulated by considering cells as conducting bodies only. Therefore, the known parameters of parallel cells connected in a series string are: the string voltages, temperature and current.

At the time instant t, I_t^i is the current of Cell i. This can be represented as the difference between input voltage $V_{1,t}^{ij}$ and output voltage $V_{2,t}^{ij}$ to the parallel connected cells:

$$I_t^i = \frac{V_{1,t}^{ij} - V_{2,t}^{ij}}{z_t^i} \quad (3)$$

Similarly, I_t^j is the individual reading from the current sensor at Cell j, and is defined as:

$$I_t^j = \frac{V_{1,t}^{ij} - V_{2,t}^{ij}}{z_t^j} \quad (4)$$

Also, impedances z_t^i and z_t^j for cell i and j are:

$$z_t^i = z_t^{i^0} + \left[1 + \alpha_t^{ij}(\Gamma_t^i - \Gamma_t^{i^0})\right], \quad (5)$$

$$z_t^j = z_t^{j^0} + \left[1 + \alpha_t^{ij}(\Gamma_t^j - \Gamma_t^{j^0})\right] \quad (6)$$

Note in (5)–(6), the standard relation between impedance and temperature is considered for Cell i and Cell j according to [13]. In addition, the terms $z_t^{i^0}$ and $z_t^{j^0}$ are the standard values of impedance at room temperature $\Gamma_t^{i^0}$ and $\Gamma_t^{j^0}$, respectively. α_t^{ij} is the transition matrix of temperature at Cells i and j. To have an explicit expression for the temperature, (5) can be expressed for temperature Γ_t^i of Cell i as:

$$\Gamma_t^i = \frac{z_t^i}{\alpha_t^{ij} z_t^{i^0}} - \frac{1}{\alpha_t^{ij}} + \Gamma_t^{i^0} \quad (7)$$

Similarly, temperature Γ_t^j of Cell j is:

$$\Gamma_t^j = \frac{z_t^j}{\alpha_t^{ij} z_t^{j^0}} - \frac{1}{\alpha_t^{ij}} + \Gamma_t^{j^0} \quad (8)$$

Since Γ_t^{ij} is assumed to be the average value of temperature for Cells i and j. Therefore, the general relation between battery parameters can be represented as:

$$\Gamma_t^{ij}=\frac{z_t^i z_t^{j^0}+z_t^j z_t^{i^0}-2z_t^{i^0}z_t^{j^0}}{2\alpha_t^{ij}z_t^{i^0}z_t^{j^0}}+\frac{\alpha_t^{ij}\Gamma_t^{i^0}z_t^{i^0}z_t^{j^0}+\alpha_t^{ij}\Gamma_t^{j^0}z_t^{i^0}z_t^{j^0}}{\alpha_t^{ij}z_t^{i^0}z_t^{j^0}} \quad (9)$$

Once the dynamic relationships between battery parameters are determined, the current-split estimation is calculated.

B. Current-State Prediction using Median-Based Covariance Intersection Filter

Based on the formulated system and observation models, the median-based covariance intersection filter can then be derived for the current-split to enhance the estimation in the presence of outliers and small sample size. This required some additional properties of the median expectation, which have been considered from [12]. Suppose the estimated state at time-instant t for the time-sequence T is $\hat{I}_{t|t}^{ij}$. Given the information of (2) and time-sequence $T-1$, the state prediction of current can be defined linearly with a conditional probability as:

$$\hat{I}_{t|t-1}^{ij}=\mathbf{E}_{\mu_{1/2}}[I_t^{ij}|y_{T-1}^{ij}]=F_t^{ij}\arg\min_{I^{ij}}[I_{t-1}^{ij}-\mu_{1/2,t-1}] + \frac{\alpha_t^{ij}}{2}(\Gamma_t^i+\Gamma_t^j)+\beta_t^{ij}(z_t^i+z_t^j) \quad (10)$$

Note the process noise is assumed to have a zero median. Taking the difference between (1) and (10) gives:

$$I_t^{ij}-\hat{I}_{t|t-1}^{ij}=F_t^{ij}(I_{t-1}^{ij}-\arg\min_{I^{ij}}[I_{t-1}^{ij}-\mu_{\frac{1}{2},t-1}])+G_t^{ij}w_t^{ij} \quad (11)$$

Here $I_t^{ij}-\hat{I}_{t|t-1}^{ij}$ is equal to the covariance matrix $P_{I,t|t-1}^{ij}$ as followed by standard KF. Taking the median-based expected value for (11) gives:

$$P_{I,t|t-1}^{ij}=F_t^{ij}P_{\mu_{1/2,t-1|t-1}}^{ij}F_t^{ij^T}+G_t^{ij}Q_t^{ij}G_t^{ij^T} \quad (12)$$

The measurement updated equations for the estimated state $\hat{I}_t^{ij}$ and the covariance matrix $P_{I,t}^{ij}$ have been derived from the first principles based on (10) to (12). However, the derived covariance matrix assumes that both cells have the same impedance, operating temperature, and other cell dynamics. This leads to the motivation to consider the problem for battery pack with dynamic in-cell variations. Variations in the individual cells are primarily due to its total capacity, internal resistance, and the initial value of SOC. These factors give the reason to derive a covariance matrix that can represent the dynamical situation of current-split estimation. Let $P_{I,t|t}^i$ be the conservative covariance estimate of cell i, such that $P_{I,t|t}^i \geq \mathbf{E}_{\mu_{1/2}}\big[\big(\mu_{1/2,t|t}^i-\mathbf{E}_{\mu_{1/2,t|t}}(I_{t|t}^{ij})\big)\big(\mu_{1/2,t|t}-\mathbf{E}_{\mu_{1/2,t|t}}(I_{t|t}^{ij})\big)^{'}\big]$, where $\mu_{1/2,t|t}^i$ is the median vector for current at cell i. Note to achieve convergence, the estimated covariance of Cell i $P_{I,t|t}^i$ is always an over-estimate of the expected squared difference between the true median of the unknown distribution function of Cell i $\mu_{1/2}^i$, and its estimate $\arg\min[I_{t-1}^i-\mu_{1/2,t-1}^i]$. The proposed solution is to assign a weight ω to calculate the current-split among the parallel connection. This weight is then computed in order to determine the trace of current-split and assigns an estimate value to the individual current estimates $\hat{I}_{t|t}^i$ and $\hat{I}_{t|t}^j$ respectively.

$$\hat{I}_{t|t}^{ij}=P_{I,t|t}^{ij}\Big(\omega P_{I,t|t}^{i^{-1}}F_t^{ij}\hat{I}_{t|t}^i+(1-\omega)P_{I,t|t}^{j^{-1}}F_t^{ij}\hat{I}_{t|t}^j\Big) \quad (13)$$

where the difference between $\hat{I}_t^i$ and $\hat{I}_t^j$ can be expressed by δ_t^{ij} as follows:

$$\delta_t^{ij}=\hat{I}_{t|t}^i-\hat{I}_{t|t}^j \quad (14)$$

The expression (14) can be normalized further using median-based expectation operator as:

$$\mathbf{E}_{\mu_{1/2}}[\delta_t^{ij}\delta_t^{ij^{'}}]=\mathbf{E}_{\mu_{1/2}}[\hat{I}_{t|t}^i-I_{t|t}^{ij}-(\hat{I}_{t|t}^j-I_{t|t}^{ij})][\hat{I}_{t|t}^i - I_{t|t}^{ij}-(\hat{I}_{t|t}^j-I_{t|t}^{ij})]^{'}=P_{I,t|t}^i+P_{I,t|t}^j-P_{I,t|t}^{ij}-P_{I,t|t}^{ij^{'}} \quad (15)$$

The term $P_{I,t|t}^{ij}$ refers to the associated covariance of fused current with its estimate $\hat{I}_{t|t}^{ij}$. Also,

$$P_{I,t|t}^{ij}=\mathbf{E}_{\mu_{1/2}}[(\hat{I}_{t|t}^i-I_t^{ij})(\hat{I}_{t|t}^j-I_t^{ij})^{'}] =\mathbf{E}_{\mu_{1/2}}[\tilde{I}_{t|t}^i\tilde{I}_{t|t}^j]=P_{I,t|t}^{ij^{'}} \quad (16)$$

where $P_{I,t|t}^{ij}$ is the correlation between the two current estimates $\hat{I}_t^i$ and $\hat{I}_t^j$, respectively. Also, according to (13), $P_{I,t|t}^{ij}$ can be represented in the form of $P_{I,t|t}^i$ and $P_{I,t|t}^j$ as:

$$P_{I,t|t}^{ij}=\frac{P_{I,t|t}^iP_{I,t|t}^j}{\omega P_{I,t|t}^i+(1-\omega)P_{I,t|t}^j} \quad (17)$$

However, there is a value for the trace of the current-split, which is dependent on variants of the temperature change, voltage fluctuations and external disturbances. Let the current at Cell i I^i consists of a correlated component $I_{\mathcal{C}}^i$ and an uncorrelated component $I_{\mathcal{UC}}^i$ with respect to Cell j, such that $I^i=I_{\mathcal{C}}^i+I_{\mathcal{UC}}^i$, then the estimated covariance matrices for $I_{\mathcal{C}}^i$ and $I_{\mathcal{UC}}^i$ will be $P_{I,\mathcal{C}}^i$ and $P_{I,\mathcal{UC}}^i$ respectively. This gives a new definition of the covariance matrices for Cell i and Cell j as:

$$P_{I,t|t}^i=\frac{P_{I,\mathcal{C},t|t}^i}{\omega}+P_{I,\mathcal{UC},t}^i,\ P_{I,t|t}^j=\frac{P_{I,\mathcal{C},t|t}^j}{1-\omega}+P_{I,\mathcal{UC},t}^j \quad (18)$$

where ω belong to the interval $[0,1]$. Note ω can also be determined by optimizing an objective function in terms of ω, such as the determinant of new covariance [14]. This gives the fused form of covariance matrices for Cell i and j in the form of correlated and uncorrelated current estimate measurements:

$$P_{I,\mathcal{C},t|t}^{ij}=P_{I,t|t}^{ij}-P_{I,\mathcal{UC},t|t}^{ij} \quad (19)$$

$$P_{I,\mathcal{UC},t|t}^{ij}=P_{I,t|t}^{ij}\big(P_{I,t|t}^{i^{-1}}P_{I,\mathcal{UC},t|t}^iP_{I,t|t}^{i^{-1}} + P_{I,t|t}^{j^{-1}}P_{I,\mathcal{UC},t|t}^jP_{I,t|t}^{j^{-1}}\big)P_{I,t|t}^{ij} \quad (20)$$

Considering the correlated and uncorrelated measurements from Cell i and Cell j (18), (13) becomes:

$$\hat{I}_{t|t}^{ij}=P_{I,t|t}^{ij}\Big[\Big(\frac{\omega^2\hat{I}_{t|t}^i}{P_{I,\mathcal{C},t|t}^i+P_{I,\mathcal{UC},t|t}^i}\Big)+\Big(\frac{(1-\omega)^2\hat{I}_{t|t}^j}{P_{I,\mathcal{C},t|t}^j+P_{I,\mathcal{UC},t|t}^j}\Big)\Big] \quad (21)$$

(21) can be further expressed as:

$$\hat{I}_{t|t}^{ij}=\Big(\frac{\omega^2F_{t|t}^{ij}\hat{I}_{t|t}^iP_{I,t|t}^{ij}}{P_{I,\mathcal{C},t|t}^i+P_{I,\mathcal{UC},t|t}^i}\Big)+\Big(\frac{(1-\omega)^2F_{t|t}^{ij}\hat{I}_{t|t}^jP_{I,t|t}^{ij}}{P_{I,\mathcal{C},t|t}^j+P_{I,\mathcal{UC},t|t}^j}\Big) \quad (22)$$

Considering feedback for the update of current-split estimate gives,

$$P_{I,t|t}^{ij^{-1}}\hat{I}_{t|t}^{ij}=-(N-1)P_{I,t|t}^{ij^{-1}}\hat{I}_{t|t}^{ij}+\Big(\frac{\omega^2F_{t|t}^{ij}\hat{I}_{t|t}^{i}P_{t|t}^{ij}}{P_{I,\mathcal{C},t|t}^{i}+P_{I,\mathcal{UC},t|t}^{i}}\Big)+\Big(\frac{(1-\omega)^2F_{t|t}^{ij}\hat{I}_{t|t}^{j}P_{I,t|t}^{ij}}{P_{I,\mathcal{C},t|t}^{j}+P_{I,\mathcal{UC},t|t}^{j}}\Big) \quad (23)$$

where current-split estimate can be iteratively updated at each time-instant t. N is the number of cells, which is 2 for this formulation. This completes the updated measurement equations of the filtering step.

To improve the initialization procedure, a smoother process has been introduced. It analyzes a sequence of T observations from the previous filter measurements. Here, the time sequence was turned backwards such that $t=T, T-1,\ldots, 0$. This sequence updates the smoothed $a-posteriori$ estimate covariance, $P_{I,t|T}^{ij^S}$. The subscript S denotes the smooth operator. Taking the difference between (22) and (1), and then its update with respect to the state estimate of (22) gives:

$$\begin{aligned}P_{I,t|T}^{S}=&F_t^{ij}f(\tilde{P}_{I,\mu_{1/2},t-1|T}^{i^S})\omega^2P_{I,t|t}^{ij}(P_{I,\mathcal{C},t|t}^{i}+P_{I,\mathcal{UC},t|t}^{i})^{-1}\\&+F_t^{ij}f(\tilde{P}_{\mu_{1/2},t-1|T}^{i^S})(1-\omega)^2P_{t|t}^{ij}(P_{I,\mathcal{C},t|t}^{j}+P_{I,\mathcal{UC},t|t}^{j})^{-1}\\&+\frac{\alpha^{ij}}{2}(\varGamma_t^i+\varGamma_t^j)+\beta_t^{ij}(z_t^i+z_t^j)+G_t^{ij}w_t^{ij}\end{aligned} \quad (24)$$

$$\hat{I}_{t|T}^{ij}=\hat{I}_{t|t-1}^{ij}+P_{I,t|T}^{ij^S} \quad (25)$$

where using definition in [12], $\mathbf{E}_{\mu_{1/2}}(I_t^{ij}-\hat{I}_{t|t-1}^{ij})=f(\tilde{P}_{I,\mu_{1/2,t-1|T}}^{i^S})$. The desired measurement update for the state estimate is $\hat{I}_{t|T}^{ij}$.

The median-based covariance intersection based-smoother will provide estimation of the current-split. To detect the faults in cells, it is required to generate the residuals from the estimated current-split and voltage of each thread.

C. Residual Generation

The residuals of the estimated parameters are generated to detect any variations caused by system-bias and sensor faults. To detect variations of each measurement, expression (22) can be constructed as:

$$\hat{I}_{t|t}^{ij}=\Big(\frac{\omega^2F_{t|t}^{ij}\hat{I}_{t|t}^{i}P_{I,t|t}^{ij}}{P_{I,\mathcal{C},t|t}^{i}+P_{I,\mathcal{UC},t|t}^{i}}\Big)+\Big(\frac{(1-\omega)^2F_{t|t}^{ij}\hat{I}_{t|t}^{j}P_{I,t|t}^{ij}}{P_{I,\mathcal{C},t|t}^{j}+P_{I,\mathcal{UC},t|t}^{j}}\Big)+\xi_{f,t}(y_t^{ij},I_{t|t}^{i},I_{t|t}^{j})+\gamma_t(y_t-\hat{y}_t) \quad (26)$$

where $\xi_{f,t}\in\mathbf{R}$ is a parameter that changes unexpectedly when a fault occurred, γ is the residual weighting matrix that is dependent on the difference between $y_t^{ij}=H_t^{ij}F_t^{ij}I_t^{ij}+\nu_t^{ij}$ and the residual $r_t=\gamma_t(y_t-\hat{y}_t)$.

D. Residual Evaluation using Cross-Covariance

Once the residual is found, evaluations are required to determine the threshold selection for identifying a sensor fault. The residual evaluation is performed by calculating the cross covariance between the nominal and faulty measurements for a threshold region th between 0 and 1. Let $P_{I,t|t}^{ii_f}$ be the cross-covariance between the current at Cell i and faulty cell i_f, respectively. Using median expectation properties from [12] gives:

$$P_{I,t|t}^{ii_f}=\mathbf{E}_{\mu_{1/2}}\Big[I_{t|t}^{i}I_{t|t}^{i_f}-I_{t|t}^{i}\mathbf{E}_{\mu_{1/2}}(I_{t|t}^{i_f})-\mathbf{E}_{\mu_{1/2}}(I_{t|t}^{i})I_{t|t}^{i_f}+\mathbf{E}_{\mu_{1/2}}(I_{t|t}^{i})\mathbf{E}_{\mu_{1/2}}(I_{t|t}^{i_f})\Big] \quad (27)$$

The test statistic $test_{stat}$ has been chosen to be the median value of the cross-covariance between the nominal measurements and the faulty measurements:

$$test_{stat}=\mu_{1/2}(P_{I,t|t}^{ii_f}),\text{ where } test_{stat}=\begin{cases}\leq th\,fault\\ > th\,no\,fault\end{cases} \quad (28)$$

where $0\leq th\leq 1$ is a threshold value. Note (27)-(28) show the computation of the cross-covariance for Cell i. It has also been derived for Cell j accordingly.

However, in the case of permanent faults, the covariance between the variables must be taken into account. Let I_t^{ij} is dependent on temperature and impedance of Cell i and j, respectively. Additionally, suppose $f_t(I^{ij}(\varGamma^i),I^{ij}(\varGamma^j),I^{ij}(z^i),I^{ij}(z^j))$ is a set of functions that the current-split is dependent on. Considering (1), the combination of all these functions can be expressed as:

$$f_t=\chi I_t^{ij} \quad (29)$$

Let the variance-covariance matrix on I_t^{ij} be denoted by ψ^I:

$$\psi^I=\begin{bmatrix}\sigma^{i2} & \sigma^{ij}\\ \sigma^{ji} & \sigma^{i2}\end{bmatrix}=\begin{bmatrix}\psi^{i^I} & \psi^{ij^I}\\ \psi^{ji^I} & \psi^{j^I}\end{bmatrix} \quad (30)$$

Then, the variance-covariance ψ^f of fault f is given by:

$$\psi^{ij^f}=\chi^i\psi^{ij^I}\chi^j \quad (31)$$

which is the general expression to calculate the fault propagation with impact on the interaction variables. The evaluation output can be treated as a detection signal for fault isolation and location.

E. Fault Isolation using Energy Density

After calculating the current-split estimation, (2) can be represented for each Cell i and j as:

$$y_t^i=H_t^iF_t^iI_t^i+\nu_t^i,\; y_t^j=H_t^jF_t^jI_t^j+\nu_t^j \quad (32)$$

Based on (32), observations of N numbers of cells can be computed. The difference between the predicted output and the observation for Cell i as:

$$\varUpsilon_{t+1}^i=[y_{t+1}^i-\hat{y}_{t+1}^i]=\varSigma_{t=1}^{T}\psi_{t-1}^{'}\theta_t^{I^{(1)}}\varDelta I_t^i+\nu_t^i \quad (33)$$

where the vector $\varUpsilon_{t+1}^i$ is the innovation calculated for Cell i. $\varDelta I_t=I_t^f-I_t$ is the perturbation in I^i ; y_t^i and $y_t^{i^f}$ are the fault-free (nominal) and faulty outputs, respectively. $\theta_t^{i^{(1)}}=\frac{\delta\theta_t}{\delta I_t^i}$, and ψ are the data vector generated from past outputs and past reference inputs of Cell i. The gradient $\theta_t^{i^{(1)}}$ can be estimated by performing a number of offline experiments for Cell i, which consists of perturbing the recognition parameters one at a time. The input-output data from all the perturbed parameter experiments are then used to identify the gradients $\theta_t^{i^{(1)}}$. The outcome can be represented in the form of a density function between the

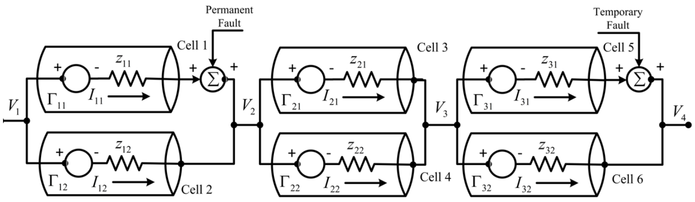

Fig. 2. Li-ion battery pack in-cell setup for current-split estimation for (a) nominal case, (b) with random-noise variance, and (c) with fault-injection

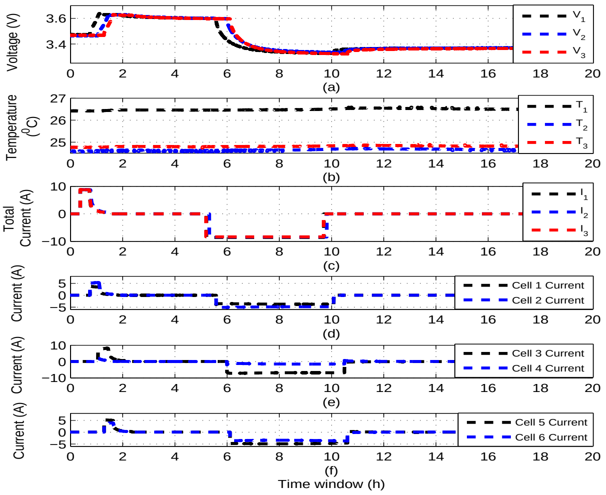

Fig. 3. Measurements of a) total voltage, b) total temperature, c) total current, d) Cell 1 and 2, e) Cell 3 and 4, f) Cell 5 and 6 of Li-ion battery pack

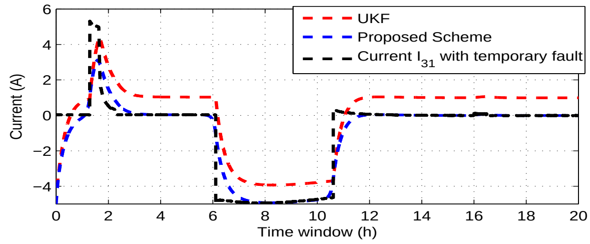

Fig. 4. Test Case I: Comparison of Cell 5 current estimates for temporary fault

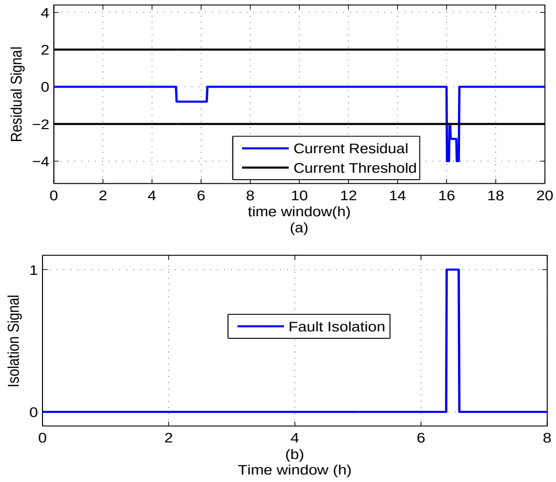

Fig. 5. Test Case I: a) Cell 5 current sensor residual, and b) fault isolation for the temporary fault

faulty data and fault-free data.

III. Implementation and Evaluation

To validate the proposed methodology, evaluations have been exhaustively conducted on a Li-ion battery-pack under different operating conditions. The experiments were conducted at the battery laboratory of the Center for Automotive Research (CAR) [15]. They are based on the guidelines in the test manual issued by United States Department of Energy battery [16, 17]. Two test cases are presented in this paper. Each test case is dependent on the setup of parallel cells connected in a string of series configuration as shown in Fig. 2. The online values of all the cells connected in this structure are plotted in Fig. 3. It comprises of the sampled current given to cells, individual current of each cell for testing and verifying the estimation scheme, and the corresponding voltage profile as well as the temperature during the battery charging/discharging operation. Test Case I examined the temporary fault shown in Fig. 2 with effect on Cell 5. The proposed method is referenced with the mainstream technique of Unscented Kalman filter (UKF) [18]. Meanwhile, Test Case II considers a current-split estimation in the presence of an injected permanent fault in Cell 1. The focus of this paper is to estimate the current-split followed by the voltage.

A. Test Case I: Current-split Estimation under a Temporary Fault

The objective of this test case is to examine the estimation capacity of the proposed scheme in the presence of a temporary fault. This fault has been generated in the form of a glitch in the current profile at 16.0-16.5 hour as shown in Fig. 4. It has no impact on other parameters of the circuit. The dynamics of voltage are captured well by the regular UKF. However, it was not able to estimate the fault thoroughly. UKF may have suffered as it considers a Gaussian-noise uniformity in the model profile, which is not the case here. Furthermore, the fault detection has been made by calculating cross-covariance between the fault-free and fault profile of the Cell 5. The threshold selected for current was ± 2. Referring to Fig.5(a), the fault was detected using the threshold selection by the cross-covariance approach. As observed in Fig.5(a), there was a wiggle at 5.0-6.2 hour, which correlates to the dynamics of the real-time data. However, this could be mistaken as faults if an inappropriate threshold is selected. Fault isolation can be seen from Fig.5(b). The operator can clearly analyze that the fault is occurred in Cell 5.

B. Test Case II: Current-split Estimation with Permanent Fault

This test case has been generated to evaluate the performance of the proposed filter in the presence of a permanent fault. Cell 1 was short circuited at 8.0-10.0 hour. The current profile of the shorted cell can be seen in Fig.6(a). This results in a high electrical leakage among the cells and the circuit. This also impacts other parameters of the circuit as seen from the current profile of Cell 3 in Fig.6(b) and voltage profile of V_3 in Fig.6(c). From these figures, UKF is not able to estimate the kinks and outliers accurately in the current and voltage profiles.

Once the estimation accuracy has been achieved, the residuals were generated. Referring to Fig.7(a), the short circuit has been detected using the threshold selection by the cross-

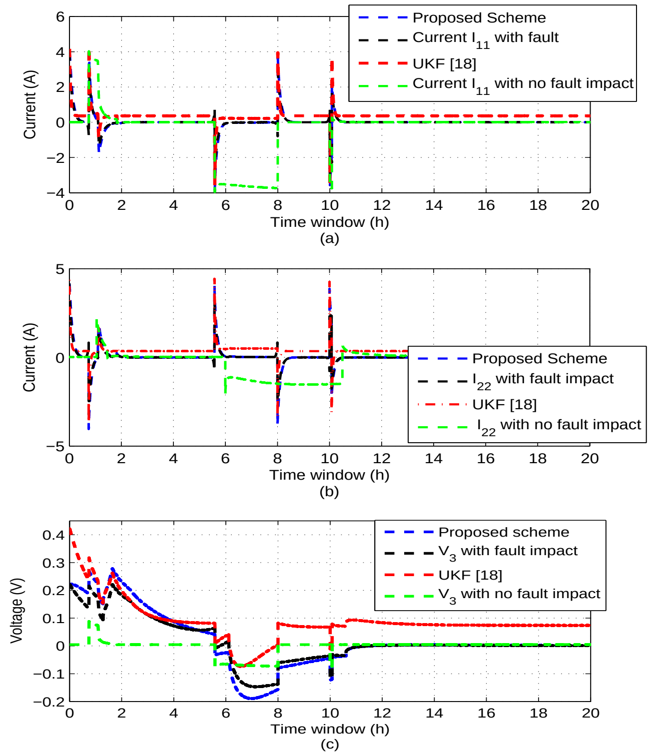

Fig. 6. Test Case II: Comparison of a) Cell 1 current estimates for permanent fault, b) Cell 3 current estimates for permanent fault, c) voltage V_3 impact estimate for permanent fault

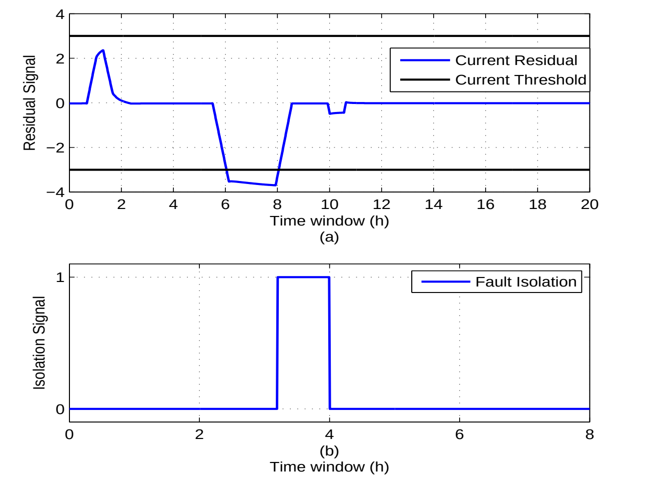

Fig. 7. Test Case II: a) Cell 1 current sensor residual, b) fault isolation for the permanent fault

covariance function. The selected threshold is ± 3. As observed in Fig. 7(a), some wiggles in the residual are seen at 1.0-2.0 hour and 10.1-11.2 hour. These wiggles correlates well with the actual dynamics in the real-time data. However, they can also be mistaken as faults if an inappropriate threshold is selected. In this case, the threshold selection algorithm is good enough to detect the fault while avoiding false alarms. Subsequently, an accurate detection signal is generated for the fault isolation. Fault isolation and localization can be seen from Fig.7(b). The operator can clearly analyze that the fault is occurred in Cell 1.

IV. Conclusions

The proposed MCIA-based current-split estimation has been effectively demonstrated to estimate current-split in the presence of sensor faults. The median-expectation property of the scheme helped to correctly estimate the profile of parameters in the presence of permanent and temporary faults. The covariance intersection has been incorporated in the filter to enhance the performance of the filter. Furthermore, cross-covariance between the fault-free and faulty cells are supported by calculating the energy density function in the fault isolation. In the future, an adaptive scheme to estimate the current-split of cells and fault propagation analysis will be proposed. This will benefit the cell-balancing control of each individual cell and improve the service life of the battery-pack.

References

[1] Z. Liu, Q. Ahmed, G. Rizzoni, and H. He, “Fault detection and isolation for li-ion battery system using structural analysis and sequential residual generation,” *Proc. ASME 2014 Dynamic Sys. Ctrl. Conf.*, pp. 1–10, Oct. 2014.

[2] W. Chen, W. Chen, M. Saif, M. Li, and H. Wu, “Simultaneous fault isolation and estimation of li-ion batteries via synthesized design of luenberger and learning observers,” *IEEE Trans. Control Syst. Technol.*, vol. 22, no. 1, pp. 290–298, Jan. 2014.

[3] A. Sidhu, A. Izadian, and S. Anwar, “Adaptive nonlinear model-based fault diagnosis of li-ion batteries,” *IEEE Trans. Ind. Electron.*, vol. 62, no. 2, pp. 1002–1011, Feb. 2015.

[4] Y. Hu, S. Yurkovich, Y. Guezennec, and B. J. Yurkovich, ”Electro -thermal battery model identification for automotive applications,” *J. Power Sources*, vol. 196, no. 1, pp. 449 -457, Jan. 2011.

[5] A. C.-Arenas, S. Onori, G. Rizzoni, “A control-oriented lithium-ion battery pack model for plug-in hybrid electric vehicle cycle-life studies and system design with consideration of health management,” *J. Power Sources*, vol. 279, pp. 791–808, Apr. 2015.

[6] K. S. Ng, C.-S. Moo, Y.-P. Chen, and Y-C. Hsieh, “Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries,” *Appl. Energy*, vol. 86, no. 9, pp. 1506–1511, Sep. 2009.

[7] H. Dai, X. Wei, Z. Sun, J. Wang, and W. Gu, “Online cell SOC estimation of Li-ion battery packs using a dual time-scale Kalman filtering for EV applications,” *Appl. Energy*, vol. 95, pp. 227–37, Jul. 2012.

[8] J. Wang, Z. Sun, X. Wei, and H. Dai, “Study on the uneven cells problem of the power battery pack in the automotive application by ECM,” *Phys. Procedia Part B*, vol. 24, Part-B, pp. 984–96, 2012.

[9] H. Cardot, P. Cenac, P., and M. Chaouch, “Stochastic approximation to the multivariate and the functional median,” *Compstat 2010*, Physica Verlag, Springer, pp. 421–428, 2010.

[10] S. Stigler, “Studies in the history of probability and statistics XXXII: Laplace, Fisher and the discovery of the concept of sufficiency,” *Biometrika*, vol. 60, no. 3, pp. 439–445, Dec. 1973.

[11] M. Stanislav, “Geometric median and robust estimation in banach spaces,” pp. 1–28, *arXiv: math.ST/1308.1334*.

[12] H. M. Khalid, Q. Ahmed and J. C.-H. Peng, “Health monitoring of Li-ion battery systems: A median expectation-based diagnosis approach (MEDA),” *IEEE Trans. Transp. Elec.*, vol. 1, no. 1, pp. 94–105, Jun. 2015.

[13] “Standard handbook for electrical engineers,” by H. W. Beaty (Editor), and D. G. Fink (Editor), Aug. 2012.

[14] S. J. Julier, and J. K. Uhlmann, “General decentralized data fusion with covariance intersection (CI),” in *Hdbook. Data Fus.*, D. Hall and J. Linas, Eds. Boca Raton, FL, USA: CRC Press, 2001, ch. 12.

[15] Y. Hu, S. Yurkovich, Y. Guezennec, and B. J. Yurkovich, “Electro-thermal battery model identification for automotive applications,” *J. Power Sour.*, vol. 196, no. 1, pp. 449-457, Jan. 2011.

[16] J. Marcicki, M. Canova, M., A. T. Conlisk, and G. Rizzoni, “Design and parametrization analysis of a reduced-order electrochemical model of graphite/$LiFePO_4$ cells for SOC/SOH estimation,” *Jour. Power Sour.*, vol. 237, pp, 310-324, Sep. 2013.

[17] “Battery test manual for Plug-In hybrid electric vehicles,” *U.S. Dept. Ener. Vehicle Tech. Program*, Revision 0, Mar. 2008.

[18] H. Hea, R. Xiong, and J. Peng, “Real-time estimation of battery state-of-charge with unscented Kalman filter and RTOS μCOS-II platform,” *Applied Energy*, vol. 162, pp. 1410–1418, 2016.