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FAST FAULT DIAGNOSIS OF A LITHIUM-ION BATTERY FOR HYBRID ELECTRIC AIRCRAFT

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ABSTRACT

A well-designed battery management system along with a set of voltage and current sensors is required to properly measure and control the battery cell operational variables for Hybrid Electric Aircrafts (HEAs). Some critical functions of the battery including State-Of-Charge (SOC) and State-Of-Health (SOH) estimations, over-current, and over-/under-voltage protections are mainly related to current and voltage sensor measurements. Therefore, in case of battery faults occur in HEA, designing a reliable and robust diagnostic procedure is essential. In this study, for Li-ion batteries, a new and fast fault diagnosis technique via collecting data is proposed. Finally, the effectiveness of the proposed diagnostic method is validated, and the results show how over-charge, over-discharge and sensor faults can be accurately detected.

INTRODUCTION

At present, Lithium-Ion Batteries (LIBs) gained wide application in electronic devices; due to having high energy density, high power density and long life compared with other commonly used batteries [1-7]. However, there may be limitations on the wide application of lithium-ion battery in Electric Vehicles (EVs), because of some issues like safety, durability and cost in large capacity of batteries [8-12]. Many countries increased investments on investigating and utilizing lithium batteries in the EVs and Hybrid Electric Vehicles (HEVs), although some battery faults resulted in some EV accidents in latest years [13, 14]. Lithium-ion batteries must operate within a defined temperature and voltage range which is the safe and reliable operating area; rising above the restrictions of these ranges will result in safety issue or improper performance of batteries [15-18] which need to be addressed using new cooling approaches [19].

In order to guarantee the performance and safety of batteries, the battery management system (BMS) is needed to monitor the battery properties by measuring the voltage, current and temperature values of battery cells [20, 21]. Main functions of BMS include: estimation of parameters and state-of-charge (SOC), fault diagnosis and prognosis; safety control in improper conditions by disconnecting the

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battery pack electrically; cell-balancing by decreasing the cell-to-cell imbalance in voltage and SOC; over-charge or over-discharge prevention by battery protection from over-current, and under-/over-voltage.

Researches have shown the voltage and current measurement are the most essential elements for battery safety due to the quick response and high sensitivity to some main electric faults such as external short circuit, internal short circuit, over charge and over discharge. Since some faults occurring in the battery can result in irreversible and catastrophic damages, it is essential to detect and diagnose any fault occurring in the battery quickly to avoid such conditions [22]. Regarding the fault characteristics, faults can be usually divided into two groups: 1- the serious sudden fault; 2- the gradually increasing fault. Health monitoring and prognosis are the general methods used for the gradually increasing fault [23].

Fault diagnosis methods have been used in the industry in the past, can be categorized in two groups: data-driven and model-based fault diagnosis methods [24-26]. Data-driven method is based on the extensive measurements and the most common drawback of this method is the uncertainty inherent in the system [27]. If uncertainties are not carefully managed during the various steps of the algorithm, they get compounded at each processing step and can raise beyond control in predictions. On the other hand, the application of model based fault diagnosis techniques have been widely utilized for accurate fault diagnosis in LIBs because of their inherent advantages of lower cost and high flexibility [28].

Among many battery modeling techniques published so far, Equivalent Circuit Model (ECM) is popularly applied by circuit designers since it can be easily utilized in circuit simulator [29-31]. An accurate and intuitive equivalent circuit model for lithium-ion battery with two resistor-capacitor (RC) parallel networks has been proposed by [30], as shown in Fig. 1. This ECM model is proven to be accurate and able for predicting current-voltage performance of lithium-ion battery [30].

A multiple-model based fault diagnosis approach was implemented for the lithium-ion battery to diagnose the over-charge and over-discharge with the application of a bank of extended Kalman filters (EKFs) in [32]. The identification of a healthy model, over-charge model and over-discharge model is necessary for this approach, and in each model an EKF is used for state variable estimation. In this method, the major drawback is the large computational demands required for required for running a bank of EKFs.

In this study, a new and fast model-based (FMB) fault diagnosis scheme is proposed for a lithium-ion battery cell to detect over-charge, over-discharge and sensors faults in HEA. Moreover, Impedance Spectroscopy (IS) is used to estimate state and parameters of a Li-ion battery in healthy, Over-Discharged (OD) and Over-Charged (OC) conditions, and then verify the cell model with experiment. In contrast to the scheme proposed in [24], the scheme proposed in this paper needs less computational time and is less complicated. Moreover, a generated signal named FMB factor (K) is generated and evaluated by the new method to determines the fault presence. Finally, results show the proposed diagnostic method is effective to detect OC, OD and sensors faults accurately.

BATTERY MODEL

Variant techniques for modeling a lithium-ion battery have been proposed such as electrochemical, experimental, neutral networks, and equivalent circuit modeling [33]. Among these techniques, the ECMs are used mostly because of properly representing the battery dynamics and less computational demands. The third order ECM is applied for this study to balance the model accuracy and computational demands. As shown in Fig. 1, this model contains a battery cell Open Circuit Voltage (OCV), a resistance *R*, and two parallel Resistance-Capacitor (RC) networks.

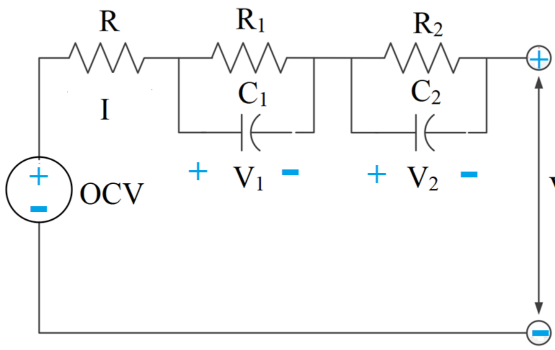

Figure 1. Battery cell electrical model

The interfacial impedance of the battery and the local properties of the electrode are represented by the R_1-C_1 and R_2-C_2 network, respectively. In this paper, the assumptions include: the temperature is constant; the system ageing is not considered in the battery model; and only the voltage source is a function of SOC. The equations applied to illustrate the voltage across the RC networks, and to estimate the SOC and terminal voltage are as following,

$$\dot{V}_1 = -\frac{V_1}{R_1 C_1} + \frac{I}{C_1} \quad (1)$$

$$\dot{V}_2 = -\frac{V_2}{R_2 C_2} + \frac{I}{C_2} \quad (2)$$

$$SOC(t) = SOC(0) + \int_0^t \frac{\eta I(\tau)}{C_n} d\tau \quad (3)$$

$$\eta = \begin{cases} 1, & charging \\ 0.98, & discharging \end{cases}$$

$$V = OCV(SOC) - V_1 - V_2 - R \cdot I \quad (4)$$

Where, I is the battery cell current in Ampere, V is the cell terminal voltage, R represents the ohmic resistance, V_1 and V_2 are the voltage across the two RC parallel network. In eq. (5), SOC(0) is the initial SOC, η representing the coulomb efficiency is assumed to be 1 at charging and 0.98 at discharging, and C_n is the battery cell capacity in Ampere hour.

Therefore, the discrete time form of battery equations using the zero-order hold discretization method will be [34]:

$$V_1(k+1) = \exp(-\Delta t/(R_1C_1)).V_1(k) + R_1 \cdot (1-\exp(-\Delta t/(R_1C_1))) \cdot I(k) \quad (5)$$

$$V_2(k+1) = \exp(-\Delta t/(R_2C_2)).V_2(k) + R_2 \cdot (1-\exp(-\Delta t/(R_2C_2))) \cdot I(k) \quad (6)$$

$$SOC(k+1) = SOC(k) + \int_0^t \frac{\eta I(k)}{C_n} d\tau \quad (7)$$

$$V(k) = OCV(SOC(k)) - V_1(k) - V_2(k) - R \cdot I(k) \quad (8)$$

where, k represents the time index; and Δt is the time interval. And the cell dynamics in discrete time as a nonlinear time invariant system are as following:

$$\begin{cases} x_{k+1} = g(x_k, I_k) + w_k \\ y_k = h(x_k, I_k) + v_k \end{cases} \quad (9)$$

$$g(x_k, I_k) = \begin{bmatrix} V_1(k+1) \\ V_2(k+1) \\ SOC(k+1) \end{bmatrix} \quad (10)$$

$$h(x_k, I_k) = OCV(SOC(k)) - V_1(k) - V_2(k) - R \cdot I(k) \quad (11)$$

here, $h(x_k, I)$ and $g(x_k, I)$ are nonlinear discrete-time state-space model; w_k and v_k are an independent, zero mean, Gaussian process and measurement noise of covariance Q_k and V_k, respectively. The state variables of one battery cell is x_k = [V_1(k) V_2(k) SOC(k)].

Impedance Spectroscopy (IS) results for the selected electrical circuit parameters fitted to the impedance curve for the battery cell in healthy and also under OC and OD condition is shown in Table. 1.

Table 1. DATA of IS

	R	R_1	C_1	R_2	C_2
Healthy	0.127	0.014	0.018	0.008	0.575
OC	0.215	0.530	0.001	0.247	0.009
OD	0.081	0.011	0.191	0.006	3.211

FAST MODEL BASED DIAGNOSIS SCHEME

The block diagram of the proposed diagnostic scheme for the battery is shown in Fig. 2. The basic idea of FMB is that the residuals can be generated

$$K_E = -(V_1 + V_2 + R \cdot I)/I \qquad (12)$$

$$K_M = (V - OCV)/I \qquad (13)$$

through comparing the estimated FMB factor (K_E) of the battery cell in healthy, OC and OD condition with the corresponding measured FMB factor (K_M). 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 K_E matches the output of K_M and makes the mean value of the residual signal zero, then the covariance of that signal evaluated at each sample can be given by [24, 34].

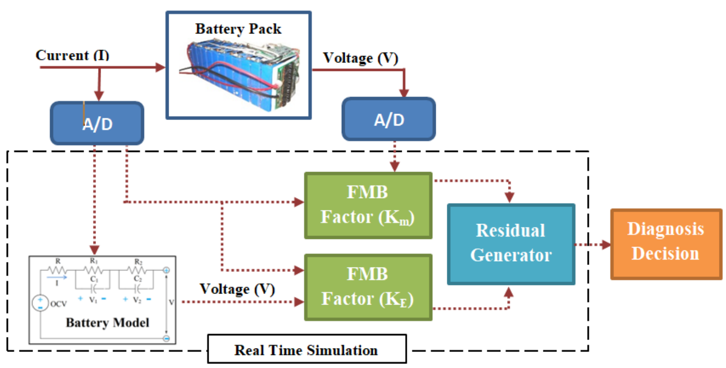

Figure 2. Proposed fault diagnosis method

As shown in Fig. 2, the inputs of the residual generators include K_M calculated by the measured signals (Voltage-Current) and K_E defined by battery model outputs. To detect the fault, the generated residuals will be sent to the diagnosis decision block. In this block, if the corresponding residual cross the predefined threshold, the fault can be isolated based on the detection signals. As depicted in Fig. 3, in this study, there are three residuals for three different conditions considered for the cell (healthy, OC and OD). In order to validate the effectiveness of the proposed fault diagnosis method under different fault scenarios, its simulation is implemented in the Matlab/Simulink.

RESULTS AND DISCUSSION

This paper mainly concentrates on OC, OD and sensors faults in a battery cell through a new method. These faults in a battery cell can be diagnosed by a considerable variation in some parameters that cause sensible changes in the performance of the battery cell. Each of the cell parameters shown in Fig. 1 will illustrate a particular variation when OC and OD fault happens as illustrated in the Table. 1.

A lithium-ion battery cell with the rated capacity of 20 Ah and nominal voltage of 4.2 V has been selected for this study. Using Hardware in the Loop (HIL) simulation test the data analysis of the battery can be done in almost real conditions [35-38]. The battery test setup contains a data acquisition system (NI USB-6343), a computer with Labview software for controlling and monitoring, and battery cycler (BioLogic) as shown in Fig. 4. The OCV-SOC of the cell captured from experiment is depicted in Fig. 5.

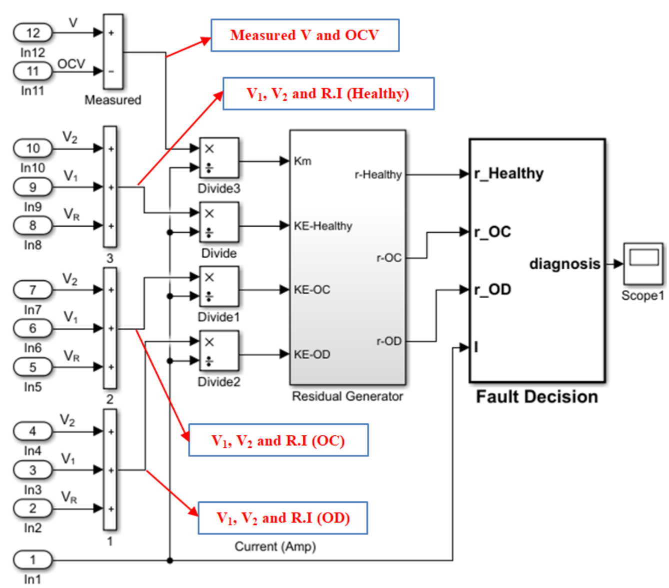

Figure. 3. Simulink Model of FBM Method in MATLAB/Simulink

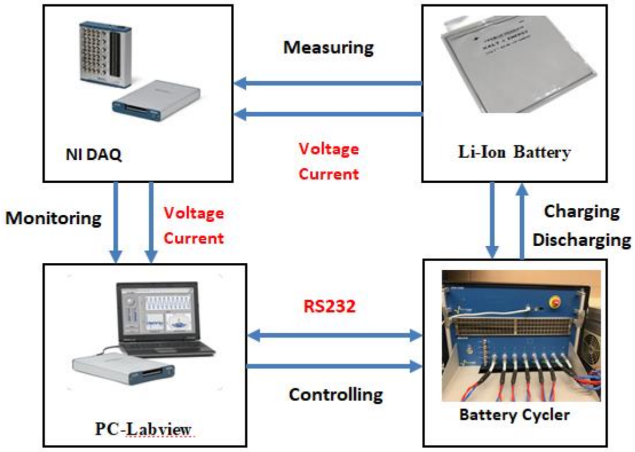

Figure 4. The battery test set up.

In order to simulate the actual driving cycles of electric vehicles, a scaled typical driving cycle, Fig. 6, is applied for the battery as the input current profile. Fig. 7 shows the model validation results under the selected driving cycle; and the battery cell model results in different conditions are depicted in Fig. 8.

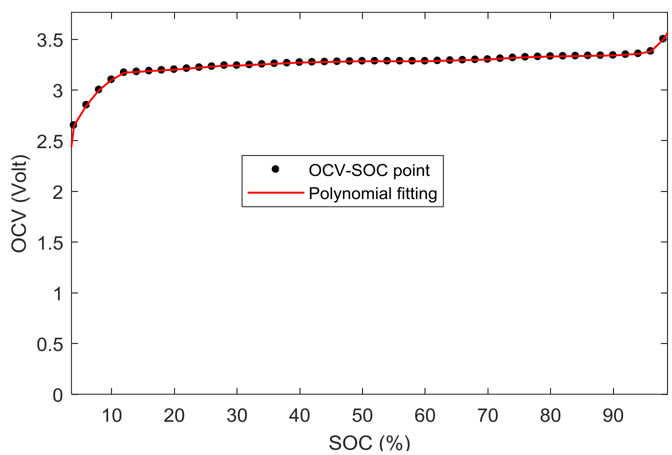

Figure 5. OCV-SOC.

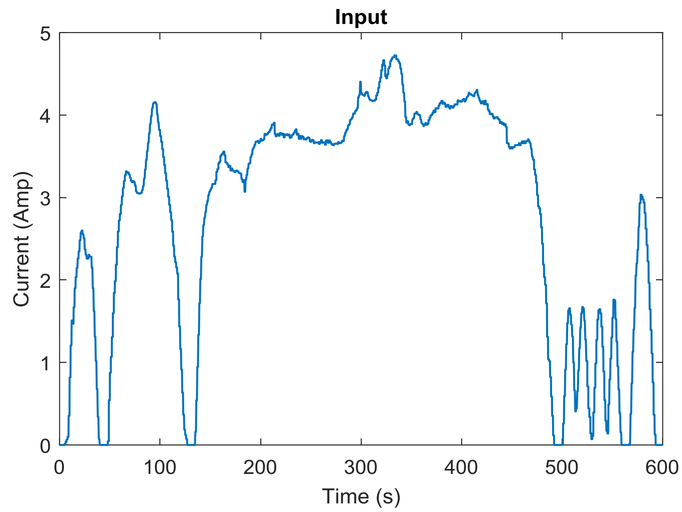

Figure 6. Current profile as input.

The FMB factor K_E results obtained from all models of the battery cell run in healthy and also under OC and OD condition has the value of 0.2609, 0.17, and 0.3131, respectively. In this case study, the impacts of temperature and ageing on spectroscopy results are neglected.

The residuals $r(k)$ can be generated through comparing the estimated K_E factors with the corresponding measured K_E factor. According to the generated residuals, the batteries mode under different condition is determined in Table 2.

$$r(k) = K_M(k) - K_E \tag{14}$$

here r represents the generated residual. If there is no noise in the measuring system, from the three generated residuals (r-healthy, r-OD and r-OC) can be determined in the fault decision section.

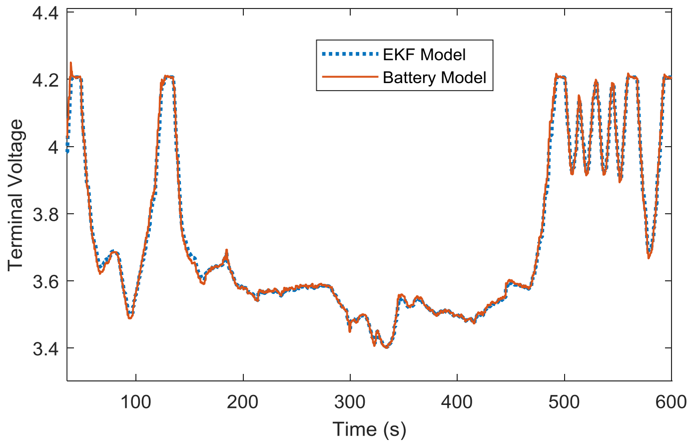

Figure 7. Simulated battery cell terminal voltage

Table 2. Fault index

	Current sensor Fault	Voltage sensor Fault	Over-charge fault	Over-discharge fault	Healthy
R_H	1	1	0	0	1
R_{OC}	1	1	1	0	0
R_{OD}	1	1	0	1	0

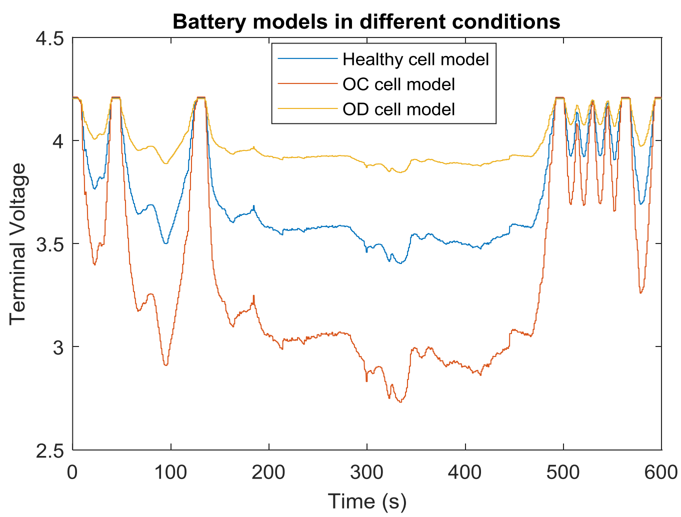

Figure 8. The battery cell model results in different conditions

The residual generator outputs are depicted in Fig. 9-11. As shown in these figures, from 90 (s) to 100 (s), a OC fault happened; between 290 (s) to 310 (s), the OD fault is detected; from 490 (s) to 510 (s), the current sensor fault occurred and between 690 (s) to 710 (s), voltage sensor fault happened. It is clear that using the generated residuals, in the fault decision section, these faults can be detected and isolated. The validation results present the effectiveness of the FMB fault diagnosis method.

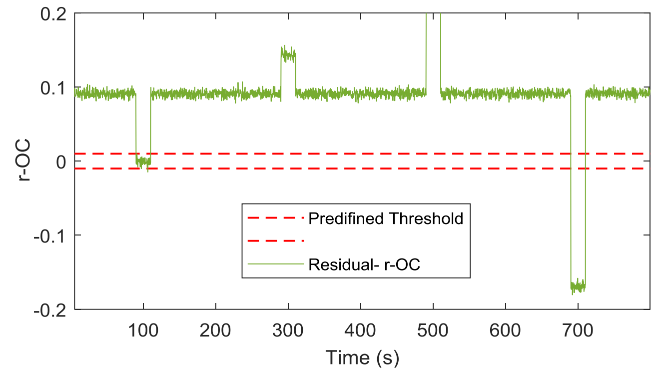

Figure 9. Residual r-OC

CONCLUSIONS AND FUTURE WORK

In this study, a new and fast method is proposed to detect and isolate the OC and OD faults and sensors faults occur in LIBs pack based on some predefined factors which gained from the battery models in healthy, over-charged and over-discharged conditions.

The effectiveness of the proposed method is confirmed by validation results. In contrast to the method proposed in [24], this scheme needs less computational time and is less complicated.

In HEAs application in which more than 10000 battery cells may be used, the processing time allocated to fault diagnosis of each battery cell is important. Therefore, FBM is effective method in order to reduce the processing time.

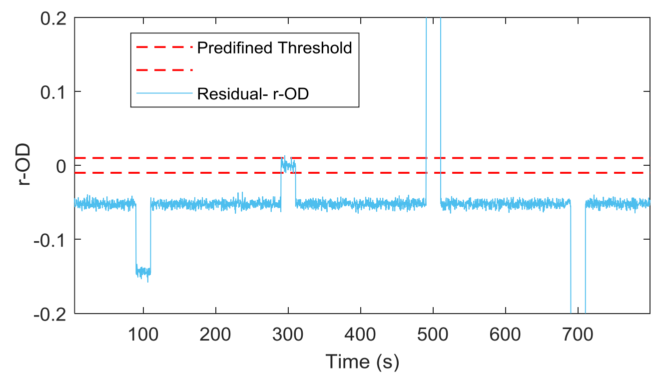

Figure 10. Residual r-OD

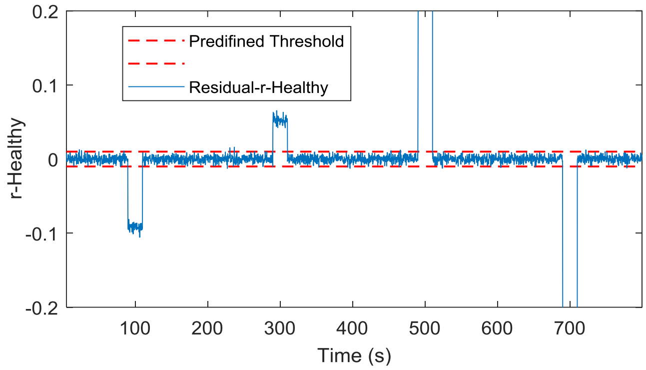

Figure 11. Residual r-Healthy

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