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Adaptive extended kalman filter based fault detection and isolation for a lithium-ion battery pack

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Abstract

To monitor the battery system, a well-designed battery management system with a set of current and voltage sensors is demanded to properly track the battery properties. It is imperative to design a reliable and robust diagnostic scheme in case of the employed sensors faults occurred. This paper presents a model-based fault diagnosis scheme to detect and isolate the faults of the current and voltage sensors applied in the series battery pack based on an adaptive extended kalman filter, and the robustness of the proposed diagnostic strategy is ensured. The diagnostic scheme is validated in the Matlab/Simulink, and the simulation results show the effectiveness of the proposed strategy in detecting and isolating various fault scenarios using the real-world driving cycles.

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Keywords: Lithium-ion series battery pack; Fault detection and isolation (FDI); adaptive extended kalman filter;

1. Introduction

Lithium-ion batteries are becoming the main energy sources in today's electric vehicle market due to the advantages of high energy and power density, and long lifespan. To monitor the battery system, a well-designed battery management system (BMS) is required to track the battery properties, such as the state-of-charge (SOC), state-of-health (SOH) estimation, and remaining useful life (RUL) estimation [1]. Among these properties, SOC estimation not only plays the role to indicate the remaining useful capacity of the battery pack and to predict the possible driving mileage, but also to prevent the battery pack from over-charge and over-discharge [2]. SOH estimation as another important function of BMS is applied to predict some battery parameters such as capacity and resistance as to inspect the related capacity and power fade of the battery pack respectively [3]. Besides these, RUL estimation is used to predict the remaining useful time from present time to the end of useful life [4]. The estimation accuracies of these above properties are based on the employed sensors, a fault of which is often neglected when design BMS.

This paper proposes a model-based fault diagnosis scheme to detect and isolate the current and voltage sensors fault. In model-based fault diagnosis, the residual generation as an important step can be classified into three kinds of approaches, as observer-based, parameter identification or parity equation approach [5]. In the exciting

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literatures, Marcicki [6] *et al.* proposed an FDI scheme for lithium-ion battery management system using nonlinear parity equation approach, and the limitation is one of the sensors must be considered as healthy. Liu [7] *et al.* proposed a structural analysis based sequential residual generation method, and the basic idea is to generate different set of equations based on the system dynamic, so as to obtain different residuals.

This paper proposes a model-based fault diagnosis scheme for lithium-ion battery pack with three different cells connected in series. The proposed FDI uses an adaptive extended kalman filter (AEKF) to detect and isolate multiple sensors fault, including the bias fault in current and voltage sensors and gain fault in the voltage sensor. The contribution of this work is to present a systematic FDI scheme for the lithium-ion battery system. Besides that, the robustness of the proposed diagnostic strategy is ensured in the case of inaccurate initial SOC value.

The rest of the paper is organized as follows. Section 2 describes the series battery pack modeling, while Section 3 presents the proposed fault diagnosis scheme. The diagnosis results and resulting conclusions are given in Section 4 and 5, respectively.

2. Series battery pack modeling

2.1. Battery pack description

A lithium-ion battery pack is composed of several battery cells connected in series to provide the required voltage and in parallel to satisfy the capacity requirement. The battery pack properties are based on the applied electrical topologies, of which there are three different types including cells connected in series, parallel of and cells connected in series and series of string of cells connected in parallel. Cells of each battery pack have inhomogeneous performances (such as different SOC, capacity and internal resistance) due to the manufacturing inconsistence and different working conditions (such as thermal imbalance) [8]. Thus, cell-to-cell balance is required to handle this uniformity by using the balance methods with active and passive balance control method [9]. The cell SOC will be differed accordingly by using different methods, and passive control method is used due to its low complexity as the main focus of this work is sensors fault diagnosis. Three $LiFePO_4$ cells connected in series with different capacity are considered as shown in Fig. 1 (a), taking three cells with different capacities of 4.1 Ah, 4.3 Ah and 4.5 Ah as an example. The capacity, resistance and SOC of each cell connected in series are denoted by C_i, R_i, and S_i, respectively, i = [1, 2, 3].

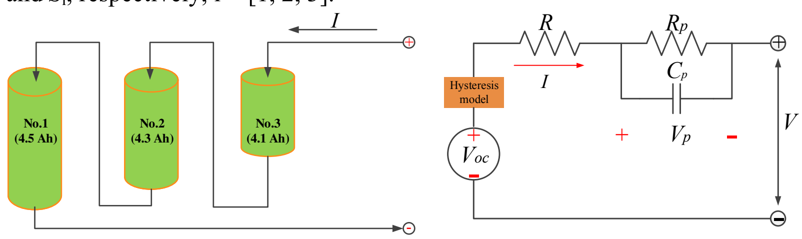

Fig.1. (a) cells connected in series; (b) cell electrical model

2.2. Battery modeling

The electrochemical models and equivalent circuit models are commonly used for the lithium-ion battery to predict the output voltage and SOC. The equivalent circuit model is often applied in the control-oriented battery system, as the electrochemical models are difficult to achieve the state estimation due to the computation complexity of the PDEs structure. The first-order equivalent circuit with hysteresis model is preferred for $LiFePO_4$ battery [10] and will be applied in this work. The model is composed of an open circuit voltage, a hysteresis voltage source, an internal resistance and an RC network, as shown in Fig.1 (b). The dynamic equations used to describe the hysteresis voltage and voltage across the RC network, and to predict the SOC and output voltage are as follows,

$$\dot{V}_p = \frac{I}{C_p} - \frac{V_p}{R_p C_p} \tag{1}$$

$$\dot{h}(t) = -\left|\frac{\eta I(t)\gamma}{C}\right| h(t) + \left|\frac{\eta I(t)\gamma}{C}\right| M(S, \dot{S}) \tag{2}$$

$$\dot{S} = -\frac{\eta I}{C} \tag{3}$$

$$V = V_{oc} - V_p + h(t) - I \cdot R \tag{4}$$

where η is the Coulombic efficiency, C is the battery nominal capacity, I is the outflow current with a positive value at discharge and negative value at charge, V represents the cell terminal voltage, V_{oc} is the battery open circuit voltage (OCV), R is the ohmic resistance, R_p is the equivalent polarization resistance simulating the relaxation effect during charge and discharge process, C_p is the equivalent capacitance, V_p is the voltage across the C_p, $h(t)$ is the hysteresis voltage, γ is a positive constant which tunes the rate of decay, and M is the maximum magnitude of hysteresis voltage which is positive for charge and negative for discharge.

2.3. Considered faults

Hazard analysis for the lithium-ion battery system has been conducted in the previous work to help identify the possible faults and severity, and in this paper, sensors faults including the bias in the current and voltage sensors, and gain fault in the voltage sensor are considered. These faults are taken as an additive fault as the sensor fault model is really difficult to validate in the real industrial application. As BMS required and applied three cells connected in series in this work, there will be one current sensor, and three voltage sensors. It is assumed that only one sensor fault is occurred at a time, and all the parameters are known.

3. Proposed fault diagnosis scheme

Fault diagnosis aims to recognize the faulty behavior of the system components with the sensor measurement signals. In this section, we presents the development of model-based fault diagnosis scheme for the series battery pack based on an adaptive extended kalman filter. The fault signature development and the summary of the applied AEKF are also included in this section.

3.1. AEKF based diagnosis scheme

Fig.2 depicts the block diagram of the proposed diagnostic scheme for the battery pack with three cells connected in series. The basic idea is that the residuals can be generated through comparing the estimated values with the corresponding sensor measurement signals [5].

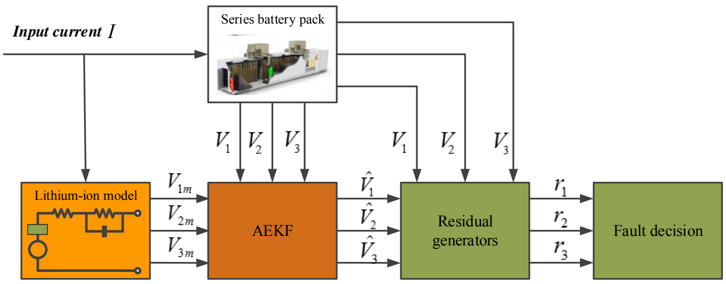

Fig.2. Proposed fault diagnosis scheme

The inputs to the residual generators are the sensor measurement signals and the predicted output using AEKF, and then the generated residuals will be transmitted to fault decision block in which the fault can be detected if the corresponding residual cross the preset alarm threshold, and then can be isolated based on the detection signals. In this work, there are three residuals corresponding to three voltage sensor measurement signals. The final AEKF algorithm is summarized in Table 1 [11,12]. The state variables of one cell is $x = [V_p(t)\ h(t)\ S(t)]^{\mathrm{T}}$.

Table 1. Summary of the residual sequence based adaptive extended kalman filter

Nonlinear discrete-time state-space model [a]:

$$x_{k+1} = f(x_k, u_k) + w_{k-1} \qquad y_k = g(x_k, u_k) + v_k$$

Definitions

$$A_k = \frac{\partial f(x_k, u_k)}{\partial x_k}\bigg|_{x_k = \hat{x}_k^+, u_k}, \quad C_k = \frac{\partial g(x_k, u_k)}{\partial x_k}\bigg|_{x_k = \hat{x}_k^-}$$

Initialization

For $k = 0$, set

$$x_0^+ = \mathrm{E}\left[x_0\right], \quad P_0^+ = \mathrm{E}\left[\left(x_0 - x_0^+\right)\left(x_0 - x_0^+\right)^{\mathrm{T}}\right]$$

Computation

For $k = 1, 2, \ldots$ compute

State estimate time update: $\hat{x}_k^- = f(x_{k-1}^+, u_{k-1})$

Error covariance time update: $P_k^- = A_{k-1}P_{k-1}^+A_{k-1} + Q_{k-1}$

Kalman gain matrix: $G_k = P_k^- C_k^{\mathrm{T}}\left(C_k P_k^- C_k^{\mathrm{T}} + R_{k-1}\right)^{-1}$

State estimate measurement update: $\hat{x}_k^+ = \hat{x}_k^- + G_k\left[y_k - g(\hat{x}_k^-, u_k)\right]$

Error covariance measurement update: $P_k^+ = \left(\mathrm{I} - G_k C_k\right)P_k^-$

For k >= N, compute

Residual sequence: $v_j = y_k - g(\hat{x}_k^+, u_k)$

Estimated variance-covariance of residual sequence: $\hat{\mu}_k = \frac{1}{N}\sum_{j=k-N+1}^{k} v_j v_j^{\mathrm{T}}$

Process noise matrix update: $Q_k = G_k \hat{\mu}_k G_k^{\mathrm{T}}$

Measurement noise matrix update: $R_k = \hat{\mu}_k + C_k P_k^+ C_k^{\mathrm{T}}$

[a] w_k and v_k are independent, zero-mean, Gaussian noise process of covariance matrices Q_k and R_k, respectively; N is the moving estimation window size.

3.2. Fault signature development

If the current sensor become faulty while the other sensors are healthy, all the residuals are different from zero. On the other hand, if one of the voltage sensor become faulty while the current sensor work properly, then only the corresponding residual will be different from zero. If we define "1" as the residual different from zero and "0" as residual tends to be zero. The fault signature of residuals are summarized in Table 2. The two faults can be isolated uniquely if the signed words formed by the two corresponding columns are different, thus all the four sensors faults can be isolated uniquely in this work.

4. Diagnosis simulation results

The proposed FDI scheme is implemented in the Matlab/Simulink to validate the effectiveness under different fault scenarios. The faulty sensors with different fault modes are specified in Table 3. If the residual exceed the pre-set alarm threshold (denoted in red), the fault alarm will be on, and vice versa. The input current profile plotted in Fig. 3 (a) is Urban Dynamometer Driving Schedule (UDDS) driving cycles, and the OCV of the applied lithium-ion battery obtained from experiment is plotted in Fig. 3(b). Additionally, it is assumed that all the other parameters are known. The initial SOC value is selected to be 20% off from the true value so as to validate the robustness, i.e. the fault diagnosis performance cannot be affected in the case of inaccurate SOC initial value.

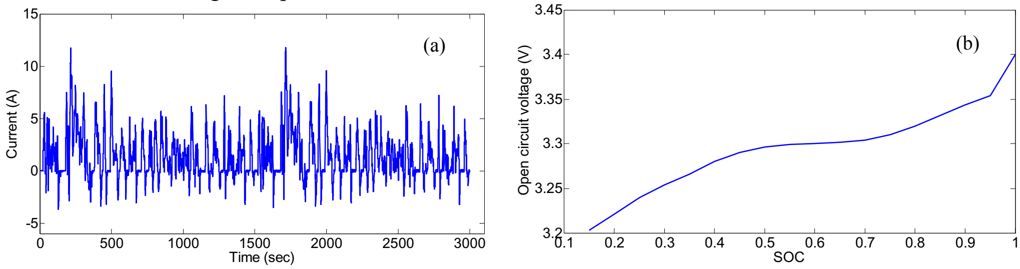

Fig. 3. (a) Input current; (b) open circuit voltage versus state-of-charge

The generated three residuals are plotted in Fig. 4 (a), (b) and (c). It is clear that two faults can be detected in each residual, but the fault can be isolated just from one residual. Based on the fault signature matrix in Table 2, the fault signatures are obtained as plotted in Fig. 4 (d). Also as shown in Table 3, it is concluded that from 600-650s, the current sensor fault is detected; from 1300 to 1350s, the voltage sensor f_{V1} is detected; from 2000 to 2050s, the voltage sensor f_{V2} is detected; from 2500 to 2550s, the voltage sensor f_{V3} is detected. The conclusions matches exactly with the experimental setup, and the validation results shows the effectiveness of the proposed diagnostic scheme. In addition, the fault diagnosis performance is not influenced as see from the residuals.

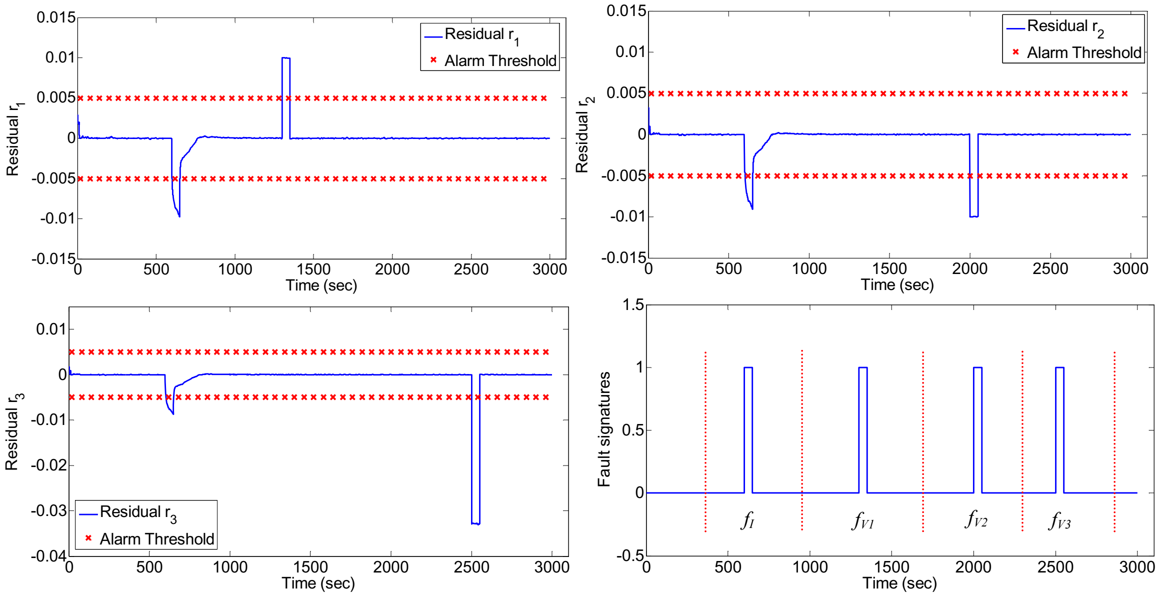

Fig. 4. (a) Residual r_1; (b) Residual r_2; (c) Residual r_3; (d) fault signatures

Table 2. Fault signature matrix

	Faulty I sensor	Faulty V_1 sensor	Faulty V_2 sensor	Faulty V_3 sensor
r_1	1	1	0	0
r_2	1	0	1	0
r_3	1	0	0	1

Table 3. Different sensors fault scenarios

Fault	Time	Type	Specification
f_I	600-650 s	Bias	+1 (A)
f_{V1}	1300-1350 s	Bias	+0.01(V)
f_{V2}	2000-2050 s	Bias	-0.01(V)
f_{V3}	2500-2550 s	Gain fault	-1%

5. Conclusions and future work

This paper presents a systematic method to detect and isolate the current and voltage sensors fault applied in the series lithium-ion battery pack based on an adaptive extended kalman filter. The proposed FDI scheme is capable of detecting and isolating the sensor fault with very small magnitude. The simulation results confirmed the effectiveness of the effectiveness and robustness of the proposed FDI strategy. In the future, the experimental evaluation will be conducted and a more robust FDI scheme will be developed under various disturbances.

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Biography

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