An Observer-Based Fault Diagnosis in Battery Systems of Hybrid Vehicles

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Abstract

Hybrid electric vehicles (HEVs) currently use Nickel-Metal Hydride (Ni-MH) batteries which have advantages of design flexibility, superior power, environmental acceptability and recyclability, long life, wide-range operating temperature and low cost. No matter how good a battery is, a failure can always occur in a battery leading to serious inconvenience, performance deterioration and costly replacement. Thus, it is desirable to be able to detect the underlying degradation and to predict level of unsatisfactory performance. By using current, voltage and temperature measurements of Ni-MH batteries, they can be modeled so that the internal dynamics of the batteries can be estimated and state of health of the batteries can be predicted for secure and long-life operations. An observer-based fault diagnosis approach is designed to analyze the state of health of the Ni-MH battery system of HEVs in this study. Real-world input data is used to assess the efficiency of the approach in the existence of uncertainties. The possible sensor faults and unexpected parameter deviations are diagnosed efficiently with statistical evaluation of the generated residuals.

1. Introduction

The increasing needs for high energy, power, life-cycle, fuel economy, wide-range operating temperature and environmentally acceptable batteries in electric and hybrid electric vehicles (EVs and HEVs) are the driving forces for rapid growth of Ni-MH batteries. Ni-MH batteries are dominant battery technology for HEV applications by having the best overall performance in the wide-range requirements set by automobile companies [1]. The functionality and reliability of Ni-MH batteries as one of the major energy storage device can be enhanced with fault diagnosis and health monitoring.

Ni-MH batteries are fabricated in sealed maintenance free cells so that it is not possible to have close measurement probes. Hence, the only possible measurements are current and voltage at the poles of the battery. Using these measurements, it is necessary to acquire state of health of a Ni-MH battery system in a HEV in order to prevent serious damage and failures in the battery. In the literature, most of the studies are provided for the fault diagnosis and health monitoring of Li-ion batteries with several methods, including extended Kalman filter, autoregressive moving average model and fuzzy logic, which are summarized in [2]. There are a few studies on state estimation and fault diagnosis of Ni-MH battery systems. A model-based algorithm is developed to estimate battery hysteresis for state of charge estimation in [3]. A model-based fault diagnosis algorithm for Ni-MH battery is used in [4]. A combination of artificial network and fuzzy interface is used to estimate state of charge of Ni-MH batteries in [5]. In this study, an observer-based fault diagnosis methodology is considered for Ni-MH battery systems of the HEVs for fault detection and isolation under noisy measurements. Fault diagnosis of the possible sensor and parameter faults are studied with statistical residual evaluations to minimize false alarms.

The diagnostic algorithm monitors the battery system for any possible faults and malfunctions. It helps in detecting deviations of the battery performance from its normal behavior and also isolates the possible causes for the faults. In practice, output signals of the system under consideration are often directly evaluated and compared with a given threshold [6]. However, such an approach is insufficient in critical processes due to possible masking of faults by control systems, and capability to react only after a relatively large change in the measured variable [7]. If the system is modeled, and the difference between the measurement and its estimation (residual) is obtained, then it is theoretically possible to detect every fault with residual generation [8]. Fig. 1 illustrates the general structure of a fault diagnosis system using model-based methods. The residuals are usually generated from the difference between the predictions of the mathematical models of the process under consideration and the actual process input and outputs in the observer-based methods. Then a residual evaluation subsystem is used to provide fault information by comparing the residuals with their nominal values.

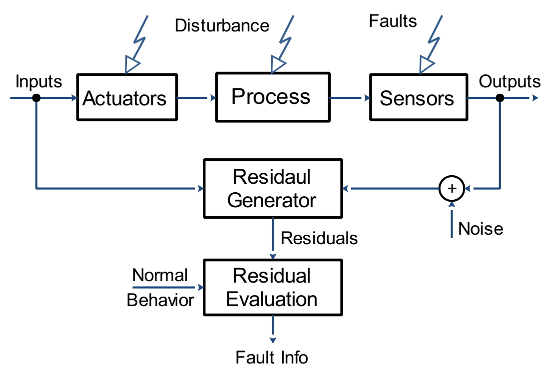

Fig. 1. A general diagram of the model-based fault diagnosis.

This paper is organized as follows: Section 2 provides a background on Ni-MH battery system of HEV. Fault diagnosis strategy is given in Section 3, and application results are given in Section 4. Conclusion of the study is provided in Section 5.

2. Battery System and Modeling

The HEV which combine an internal combustion engine and an electric motor must be supplied by a battery system. The Ni-MH battery plays a significant role in HEV by supplying power to its electric motor and its electrical accessories. This rechargeable battery with mode of constantly charge and discharge has several excellent advantages: flexible cell sizes from 30 mAh - 250 Ah, safe operation at high voltage (+320 V), high volumetric energy and power, maintenance free, excellent thermal properties, environmentally acceptable and recyclable materials, and simple and inexpensive charging and electronic control circuits [1]. The electrochemistry of a Ni-MH battery is given with the following overall reaction of discharge/charge,

$$MH + NiOOH \rightleftharpoons M + Ni(OH)_2 \tag{1}$$

where M is a hydrogen absorbing alloy in the form of AB_5. Many batteries are connected to each other in the form of battery packs to supply high power. As shown in Fig. 2, the battery system consists of Ni-MH battery packs and temperature controller. There are also other electronic systems including rectifier to charge battery and inverter to adjust battery output, but these electronic controllers can be considered separately.

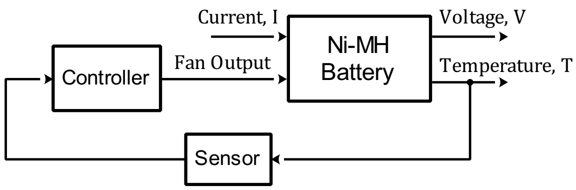

Fig. 2. Schematic diagram of the battery system.

2.1. Battery Model

The electric vehicle batteries have been commonly modeled with two ways: equivalent circuit battery models [9], [10], and electrochemical battery models [11], [12], [13]. Here, we consider an equivalent circuit battery model that is based on current/voltage relations of the Ni-MH battery. Considering battery (load) current as an input, and battery voltage and temperature as outputs, the battery model consists of three sub-models: electrical model, thermal model, and state of charge (SOC) model.

Electrical Model: The most commonly used battery models are ideal model, linear model and Thevenin equivalent model [9]. The Thevenin equivalent model with varying parameters represents a battery with higher accuracy, and thus it is considered in this study. This model is made of electrical values of the open-circuit voltage (E_o), internal resistance (R), capacitance (C_o), and the overvoltage resistance (R_o) [10]. The Thevenin equivalent model of the battery is depicted in Fig. 3.

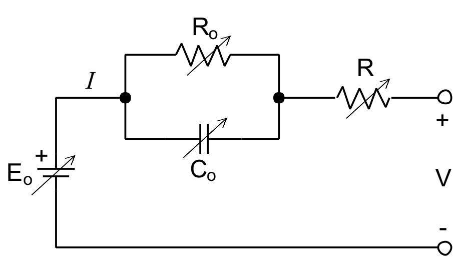

Fig. 3. Battery Thevenin equivalent model.

Using current-voltage relations from Fig. 3, the dynamic electric equations of the circuit are

$$\begin{aligned} \frac{dV_c}{dt} &= -\frac{1}{R_oC_o}V_c + \frac{1}{C_o}I \\ V &= E_o - RI - V_c \end{aligned} \tag{2}$$

where I (in A) is the current at the input, and V (in V) is the output voltage. All the parameters of (2) are functions of battery temperature and SOC, and are usually different in charge and discharge phases.

State of Charge Model: SOC provides information about remaining useful energy and the remaining usable time of the battery, but its measurement is very difficult. While several SOC models have been appeared in the literature [2], [15], one of the most SOC calculation methods is the current integration [2] as given below:

$$S = S_o - \frac{1}{C_n}\int I(t)dt \tag{3}$$

where I (in A) is the battery current, S_o is the initial state of charge, and C_n (in Ah) is the nominal capacity. This approach requires dynamic measurement of the battery current. Practically, a Ni-MH battery for HEV is never fully charged and discharged, and its operating range with respect to SOC is around 40%-80%.

Thermal Model: In electric and hybrid vehicles, it is critical to achieve performance and extended life of batteries via thermal management. Suitable modeling for predicting thermal behavior of battery systems in vehicles can also help to improve battery design and development process. Therefore, thermal models for the batteries have been developed based on thermal energy balance of the batteries, and they are coupled with electrochemical or electric models [12], [13]. Based on the electric model and thermal energy balance of the battery, a simple thermal model can be built as

$$\frac{dT}{dt} = \frac{R + R_o}{mc}I^2 - \frac{hA}{mc}(T - T_\infty) \tag{4}$$

where mc (in J/^{o}C) is the effective heat capacity per cell, hA (in J/^{o}C) is the effective heat transfer per cell, and T_∞ (in ^{o}C) is the bulk temperature. The effective heat transfer capacity per cell is given in terms of temperature controller (fan) settings as

$$hA = hA_o(1 + 0.5f_s) \tag{5}$$

where $hA_o = 0.07$ ($J/$°C) for natural convection, and the fan setting f_s depending on the temperature is

$$\begin{cases} f_s = 0 \quad \text{off mode} \quad ; \quad f_s = 2 \quad \text{if} \quad T \geq 35\ \text{°C} \\ f_s = 1 \quad \text{if} \quad T \geq 30\ \text{°C} \quad ; \quad f_s = 3 \quad \text{if} \quad T \geq 40\ \text{°C} \end{cases} \tag{6}$$

2.2. Dynamical Analysis of the Battery Model

The state space form of the battery model can be written by

$$\begin{bmatrix} \dot{V_c} \\ \dot{T} \end{bmatrix} = \begin{bmatrix} -l_1 & 0 \\ 0 & -l_2 \end{bmatrix}\begin{bmatrix} V_c \\ T \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2I \end{bmatrix}I + \begin{bmatrix} 0 \\ l_2 \end{bmatrix}T_\infty \tag{7}$$

where $l_1 = 1/R_oC_o$, $l_2 = hA/mc$, $b_1 = 1/C_o$ and $b_2 = (R + R_o)/mc$. It is obvious from system matrix that both states have distinct and stable eigenvalues with $|\lambda_{V_c}| \gg |\lambda_T|$ since all parameters have positive values and the current and ambient temperature are bounded, i.e. $\sup|I(t)| < I_m$ for $I_m < \infty$ and $\sup|T_\infty(t)| < T_m$ for $T_m < \infty$. These characteristics of the battery model can be used to design an effective observer-based fault diagnosis scheme.

3. Fault Diagnosis in the Battery Systems

The Ni-MH battery system is a complicated system due to its feedback loop and parameter-varying model. The equivalent electrical model parameters of the battery are functions of temperature and SOC, which makes fault detection problem hard. Moreover, the temperature feedback controller can mask the temperature sensor faults so that the detection problem can pose some other challenges.

3.1. Residual Generation

An observer based approach is considered to generate residuals in this study. Based on the system model given in (2)-(6), an observer can be designed by

$$\begin{aligned} \frac{d\hat{V}_c}{dt} &= -\frac{1}{\hat{R}_o\hat{C}_o}\hat{V}_c + \frac{1}{\hat{C}_o}I + k_1(V-\hat{V}) \\ \frac{d\hat{T}}{dt} &= \frac{\hat{R}+\hat{R}_o}{mc}I^2 - \frac{\widehat{hA}}{mc}(\hat{T}-T_\infty) + k_2(T-\hat{T}) \\ \hat{V} &= \hat{E}_o - \hat{R}I - \hat{V}_c \\ \widehat{hA} &= hA_o(1+0.5\hat{f}_s) \end{aligned} \tag{8}$$

where $(\hat{V}_c, \hat{T}, \widehat{hA})$ denotes the estimated values of (V, T, hA) respectively. The observer gains are denoted with k_1 and k_2. These observer gains can always be selected appropriately to bring the initial errors to zero because the battery system is dynamically stable as analyzed in Section 2.2. Since the battery system has two outputs, voltage and temperature, it is possible to detect and isolate single faults in temperature and voltage sensors. More importantly, the possible internal resistance variations can be detected and isolated.

Residuals are acquired with the following features:

$$\begin{aligned} r_V &= V - \hat{V} \\ r_T &= T - \hat{T} \end{aligned} \tag{9}$$

where r_V and r_T are residuals for voltage and temperature measurements, respectively.

3.2. Residual Evaluation

The generated residuals can be evaluated based on some threshold selections. There will always be a trade-off between the avoidance of false alarms and the detection of small faults in the existence of noise and modeling errors. Practically, a fault can be detected only if it causes the residual evaluation function to surpass the threshold, namely [6],

$$|r_i| \geq J_i \tag{10}$$

where r_i is the function of the i'th residual and J_i is the selected threshold for i'th residual function.

A residual evaluation chart is given in Table 1. As seen from the Table 1, all sensor and internal faults can be detected and isolated with the given logic.

Table 1. Fault diagnosis chart

Residuals / **Faults**	Residual 1 $r_V = V - \hat{V}$	Residual 2 $r_T = T - \hat{T}$
Temperature Sensor	0	1
Voltage Sensor	1	0
Resistance Change	1	1

It is well-known that the generated residuals can be disturbed by the measurement noise or disturbance. Hence, a systematical threshold selection should be based on the statistical evaluation of the residuals under the absence of the fault and the presence of the fault. In this study, the thresholds for each residual of measurements are calculated by comparing probability density functions of the residuals for faulty and non-faulty cases. The probability density estimations of voltage residual are illustrated in Fig. 4. The probability density estimation is obtained in the absence of fault and for drift-like intermediate fault (see Fig. 6). A similar case is considered for temperature residual r_T.

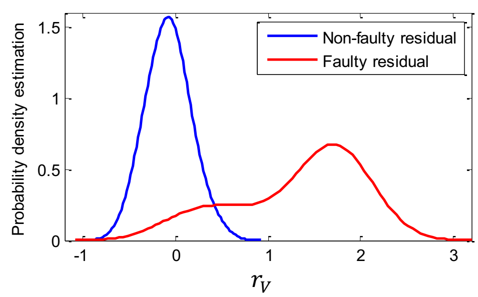

Fig. 4. Probability density estimation for voltage residual.

It is seen from Fig. 4 that especially the standard deviations for faulty and non-faulty cases are completely different in the probability density estimation figures, and probability density estimations for non-faulty cases are similar to Gaussian distribution, so thresholds can be selected based on the means and standard deviations in the fault-free cases. While there is always a trade-off in the selection of thresholds, to avoid false alarms, thresholds for residuals r_V and r_T can be selected as $J_V = \mu_V + 4.4\sigma_V$, and $J_T = \mu_T + 4.4\sigma_T$ where μ is the mean value and σ is the standard deviation of related residuals under fault-free cases. On the other hand, the 4.4σ value can be decreased to have more sensitive fault detections.

4. Numerical Results

The numerical simulation results are acquired with MATLAB/Simulink programs by using experimental current measurements. The data used in this work were acquired as part of the activities of the Center for Automotive Research (CAR) at the Ohio State University. It is assumed that all measurements are exposed to normally distributed measurement noise with a range of $\pm 10\%$ of the measured states. The time responses of the current, voltage and temperature for non-faulty cases are depicted in Fig. 5. The Ni-MH battery has a continuous discharge and charge characteristics, so all other state variables are also having a continuous stochastic fluctuations. This makes fault diagnosis problem difficult since during these fluctuations system parameters are also varying.

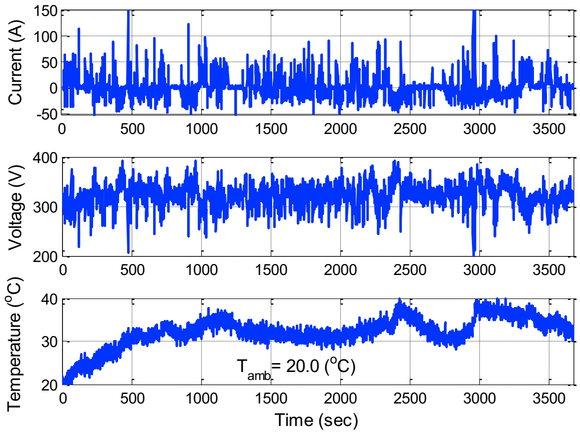

Fig. 5. Time responses of the measured states under normal conditions.

Three different faults are considered as seen in Table 1. Fig. 6 illustrates a voltage sensor fault and the generated residual r_V. It is seen that once the voltage sensor fault occurs, it is immediately detected and isolated via residual surpassing the threshold J_V.

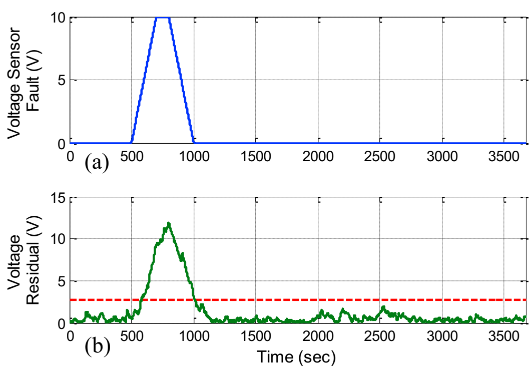

Fig. 6. Injected voltage sensor fault and generated voltage residual.

A temperature sensor fault and its detection via temperature residual are depicted in Fig. 7. Once the fault occurs, as seen in Fig.7b, the residual follows the sensor fault and exceeds the threshold J_T.

An unexpected deviation in the internal resistance as a parameter fault is shown in Fig. 8. A small and drift-like deviation in the resistance results in alarms in voltage (Fig. 8b) and temperature (Fig. 8c) residuals. Since internal resistance deviation gives information about the inner dynamics of the battery pack, such diagnosis of parameter fault is an important aspect of the diagnosis method in terms of efficiency and usability.

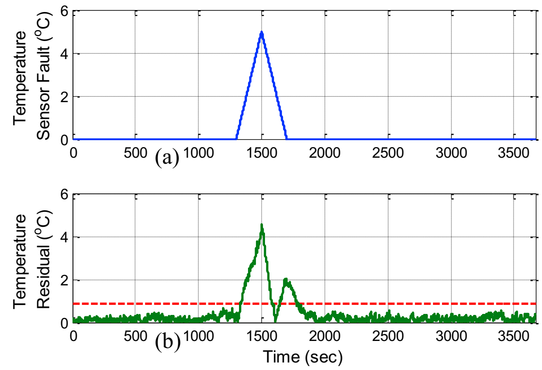

Fig. 7. Injected temperature sensor fault and generated temperature residual.

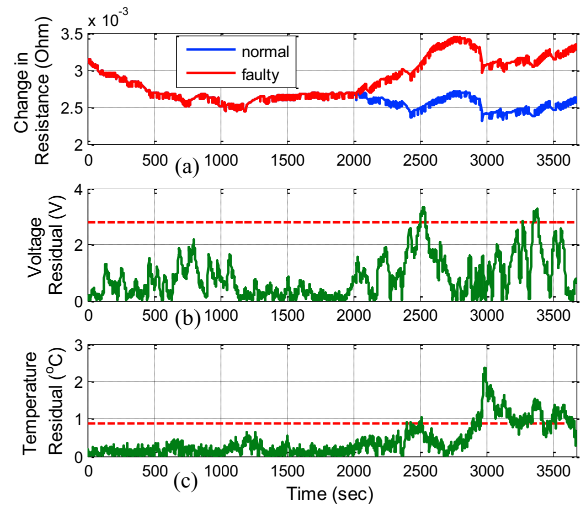

Fig. 8. Resistance deviation and its diagnosis with voltage and temperature residuals.

5. Conclusion

An observer-based fault diagnosis approach is designed for state of health monitoring of batteries of HEVs. All possible sensor faults and unexpected resistance deviation are efficiently detected and isolated in the presence of parameter uncertainties. Since it is not possible to observe what happens inside the battery pack, detection of unexpected internal resistance variations that gives information inner dynamics like corrosion is especially an important result.

6. Acknowledgement

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