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Battery Power Prediction for Protecting Droop Cells from Over-discharging

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Abstract: The estimation of battery parameters and states at both battery pack and cell levels are studied using the extended Kalman filter (EKF). The estimation results are evaluated with Chevy BOLT electric vehicle data. The cell level estimation when applying EKF is more challenging and an appropriate scaling of cell parameters is required, due to the fact that the current and voltage values of a cell are quite different in magnitude. This estimation study also shows that the cell-level parameter estimation can provide important health information to a battery management system (BMS) for diagnostics and prognostics. The cell-level estimates are then used to predict the voltage limited battery pack power available to a vehicle when a weak cell or droop cell occurs. This power limit can avoid over-discharging a droop cell and protect it from further damage.

Keywords: Battery management system, extended Kalman filter, state estimation.

1. INTRODUCTION

The current design of battery packs used in electric vehicles are comprised of cells connected in parallel and in series. This arrangement escalates the cell voltage and energy capacity to meet the power requirement. The role of the BMS becomes indispensable for controlling the charging and discharging of the cells in a safe and optimized manner according to the battery electrochemical characteristics and the motor load requirements. During operations, the battery pack status exhibits short and long-term changes at all levels. Therefore, the functionality of the BMS depends on an accurate estimate of key battery system parameters.

The electrochemical status of the battery is continually changing with battery temperature, load current, state of charge (SOC), and aging conditions. All impact battery safety, life span, and performances, including customer on-board indicators of SOC, power and battery remaining energy and battery health. This requires a robust BMS design that can monitor battery status by estimating its corresponding model parameters in real-time. Current battery model parameter estimation methods fall mainly into three categories: the Luenberger-type observer method (Hu, 2010), Lin (2012), the sliding-model observer method (Kim, 2006), (Klein, 2013), and Kalman filter method (Plett, 2004), (Rauh, 2013). Among these methods, the extended Kalman filter (EKF) stands out due to its intrinsic prediction-correction mechanism which makes the filter insensitive to modeling error and measurement noises. However, the EKF estimation stability is impacted by the non-linearity of a battery system and battery current excitation. To guarantee the estimation stability in the BMS application, the parameter boundaries and gradient limits are imposed (GM, 2016), and calibrating these values require experiences.

For production application, battery parameter estimation at the pack level using EKF is a matured technology. However, limited studies have been done for EKF implementation in battery cell-level parameter estimations, e.g. (Zhang, 2021). The individual cells that comprise the battery pack will exhibit mismatches in capacity, self-discharge rate and impedance over time. These mismatches among cells can lead to limiting the total usable energy and the power delivered by the battery pack. Most BMS designs treat the battery system as a lumped battery model, which lacks performance impact of each individual cell state of health.

To further enhance the BMS capability to achieve better safety and longer life, this paper studied how to estimate battery pack available power without violating cell voltage and current limits. This limit could be violated without proper power limit estimation when a cell ages or a malfunction cell occurs. The presented method for power estimation considering a cell SOH status shall avoid over-discharging a droop cell below its voltage limit, which could further damage the cell or leads to a thermal event. The state estimation of both battery pack and cells using EKF are applied to identify both battery pack and cell models, which are used to estimated fault tolerant battery power for the purpose of safe vehicle torque arbitration.

2. BATTERY EQUIVALENT CIRCUIT MODEL

2.1 Pack-level Model

A battery model characterizes the relationship between the terminal voltage and current value of a single battery pack, as shown in Fig. 1, with three resistors, two capacitors, and an open-circuit voltage with hysteresis compensation. The ohmic resister, R_{ohmic}, represents the internal resistance modeling heat loss during charging and discharging. The resistor and capacitor pairs, i.e. $R_{ct1}||C_{cdl1}$ and $R_{ct2}||C_{cdl2}$,

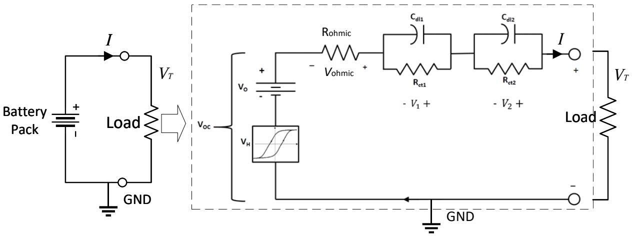

Fig. 1. Equivalent circuit model of a lithium-ion battery

simulate the internal electrochemical charge-transfer and diffusion phenomenon. The voltage source, V_O, simulates the battery open-circuit voltage, which depends on the battery SOC and temperature. The hysteresis polarization effect on battery voltage is modeled (in a standard production software) by the component of V_H. Through a hybrid pulse power characterization (HPPC) test, those parameters can be characterized at different SOC levels and temperature conditions.

2.2 Cell-level Model

The pack-level model is often used for predicting overall energy storage and battery performance. When considering the diagnosis of battery performance relating to the electrochemical process in each cell, their internal properties are more important, which are affected by physical structure, temperature distribution, unbalance between cells, aging, etc. Therefore, a cell-level model can provide more detailed and relevant information for a BMS. Monitoring the health of individual cells is critical in order to prognose and protect a battery pack health, to limit the maximum charging/discharging current and predict accurate SOC, to extend the life of a battery pack.

The cell-level behaviors provide detailed information of a battery pack. The SOC of each cell may differs from others. The aging status among cell-level parameters could be used for prognosis and prediction of the pack life-cycle or driving range. Since a failure in a battery cell would limit total pack energy efficiency, once diagnosed, the relevant module should be maintained or replaced.

The pack-level and cell-level battery equivalent circuit model share the similar model structure as shown in Fig. 1 and the cell-level model governing equation can be written as follows:

$$
\begin{aligned}
V_{T\_cell} &= V_O + V_H + R_{ohmic} I_t \\
&+ R_{ct1}(1 - e^{\frac{-\delta t}{R_{ct1} C_{dl1}}}) I_{t-\delta t} + e^{\frac{-\delta t}{R_{ct1} C_{dl1}}} (V_1)_{t-\delta t} \\
&+ R_{ct2}(1 - e^{\frac{-\delta t}{R_{ct2} C_{dl2}}}) I_{t-\delta t} + e^{\frac{-\delta t}{R_{ct2} C_{dl2}}} (V_2)_{t-\delta t}
\end{aligned} \tag{1}
$$

where, subscript t and δt represent time t and the sampling time respectively. The equivalent circuit model (ECM) has nonlinearities in terms of current input and terminal voltage output. The second order charge-transfer and diffusion follow exponential functions, and the hysteresis has nonlinear character. All the parameters in the model are correlated to battery temperature in a nonlinear form. For simplicity, these nonlinear relationships are not explicitly modeled in equation (1) and they are represented by lookup tables. But the nonlinear phenomena challenge battery parameter estimation.

3. BATTERY STATE ESTIMATION USING EXTENDED KALMAN FILTER (EKF)

The battery parameters are subjected to external environment temperature, operation load, and internal material aging from lithium plating, heat transfer, cell structure deformation and other factors. The purpose of the BMS is to protect the battery pack and maintain the best performance according to the electrochemical character in every cell. When serious malfunction happens, BMS should derate battery pack power to avoid catastrophic failure. To provide this functionality in the BMS, the extended Kalman filter is utilized to identify the battery parameters in real-time.

3.1 Extended Kalman Filter

Some interesting variables are not directly measurable, such as $V_O, V_H, V_{ohmic}, V_1, V_2$, etc. They can only be observed through an observer, like EKF. Only the terminal current, $I(k)$, terminal voltage, $V_T(k)$ and temperature, $T(k)$ of the battery model in equation (1) are measurable. The EKF uses the measurable variables to estimate the interesting internal states. The real-time battery current, terminal voltage and temperature also contain measurement noises. The battery parameter estimation is an iterative process, starting from the initial measurements $I(0)$, $V_T(0)$ and $T(0)$.

For a nonlinear system in the following discrete state-space form (Wampler, 2017):

$$
\begin{aligned}
x_k &= f(x_{k-1}, u_k) + w_k, w_k \sim N(0, Q) \\
z_k &= h(x_k, u_k) + v_k, v_k \sim N(0, R)
\end{aligned} \tag{2}
$$

The online estimation begins with an initial condition or pre-measurement state (named as the '*a priori*' in literature), $\hat{x}_k^-$. In the iterative process, $\hat{x}_k^-$ is related to the previous step, $\hat{x}_{k-1}^+$, using the nonlinear system model (2). Then the *a priori* and its covariance propagation can be expressed as following:

$$
\begin{aligned}
\hat{x}_k^- &= f(\hat{x}_{k-1}^+, u_k) \\
P_k^- &= F_k P_{k-1}^+ F_k^T + Q
\end{aligned} \tag{3}
$$

where, $\hat{x}_k^-$ is the *a priori* state estimate for the step k; $\hat{x}_{k-1}^+$ is the *a posteriori* state estimation for step $k-1$; u_k is the input for the step k; f is the nonlinear state-space function; F_k is the Jacobian of f with respect to x; P_k^- is the *a priori* state covariance for step k; P_{k-1}^+ is the *a posteriori* state covariance for step $k-1$; Q is the state process noise covariance estimate. Also, the interested process output can be predicted according to model (2):

$$
\begin{aligned}
\hat{z}_k &= h(\hat{x}_k^-, u_k) \\
y_k &= z_k - \hat{z}_k
\end{aligned} \tag{4}
$$

where, z_k is the measurement of process output for step k; $\hat{z}_k$ is the prediction of process output for step k; y_k is the model error of the estimation; Then the Kalman filter gain is determined by.

$$
\begin{aligned}
K_k &= P_k^- H_k^T S_k^{-1} \\
S_k &= H_k P_k^- H_k^T + R
\end{aligned} \tag{5}
$$

where, S_k is the output model estimate covariance for step k; H_k is the Jacobian of h with respect to x; P_k^- is the *a* *priori* state covariance estimate for step k; R is the output covariance; K_k is the Kalman filter gain. The *a posteriori* state estimate at step k, $\hat{x}_k^+$ is defined by the combination of *a priori* and model error:

$$\begin{aligned} \hat{x}_k^+ &= \hat{x}_k^- + K_k y_k \\ P_k^+ &= (1 - K_k H_k) P_k^- (1 - K_k H_k)^T + K_k R K_k^T \end{aligned} \tag{6}$$

The Kalman filter gain, K_k, is an optimal and unbiased estimation of the process if the process is linear. When the process is nonlinear, like the battery application, the linearized model is used for Kalman filter gain derivation.

3.2 Battery State and Parameter Estimation Using EKF

By extending the state vector x with the parameter vector $\theta = \theta(t)$, the system model becomes (Wampler, 2017):

$$\begin{aligned} \hat{x}_k &= \begin{pmatrix} f(x_{k-1}, u_k) \\ \theta \end{pmatrix} \\ \hat{z}_k &= h(x_{k-1}, u_k) \end{aligned} \tag{7}$$

From the ECM (1), above battery system model equation can be expressed in state-space form as:

$$\begin{aligned} \hat{x}_1[k] &= f_1(x_{k-1}, u_k) = e^{-\frac{\delta t}{R_{ct1} C_{dl1} V_1[k-1]}} + \frac{\delta t}{C_{dl1}} I[k] \\ \hat{x}_2[k] &= f_2(x_{k-1}, u_k) = e^{-\frac{\delta t}{R_{ct2} C_{dl2} V_2[k-1]}} + \frac{\delta t}{C_{dl2}} I[k] \\ \hat{x}_3[k] &= f_3(x_{k-1}, u_k) = R_0[k-1] \\ \hat{x}_4[k] &= f_4(x_{k-1}, u_k) = R_1[k-1] \\ \hat{x}_5[k] &= f_5(x_{k-1}, u_k) = R_2[k-1] \\ \hat{x}_6[k] &= f_6(x_{k-1}, u_k) = C_1[k-1] \\ \hat{x}_7[k] &= f_7(x_{k-1}, u_k) = C_2[k-1] \\ \hat{x}_8[k] &= f_8(x_{k-1}, u_k) = V_{oc}[k-1] \\ \hat{z}[k] &= h(x_{k-1}, u_k) \\ &= k_v V_{oc}[k] + K_v V_1[k] + K_v V_2[k] + K_v \frac{R_0[k]}{K_R} I[k] \end{aligned} \tag{8}$$

where, the system states are $x_1 = V_1$, $x_2 = V_2$, and the model parameters extended as states, x_3 through x_8; $x_8 = V_{oc}$ is modeled as a constant, as it changes very slowly withing dynamic response time of battery models. The system output is $z = V_T$. The states are scaled into a domain of same scale for numerical stability consideration.

$$\begin{aligned} R_0 &= k_r R_{ohmic} \\ R_1 &= k_r R_{ct1} \\ R_2 &= k_r R_{ct2} \\ C_1 &= k_c C_{dl1} \\ C_2 &= k_c C_{dl2} \end{aligned} \tag{9}$$

where, the scaling factors k_r, k_c and K_v are adjusted for EKF design.

The nonlinear battery system is linearized with respect to the operating condition state at each step to obtain the Jacobian matrices of the system (7):

$$F_x = \frac{\partial f}{\partial x_k} \tag{10}$$

$$H_x = \frac{\partial h}{\partial x_k} \tag{11}$$

The EKF estimate may diverge if the initial estimates are not sufficiently accurate (Ljung, 1979). To improve the stability of EKF estimation, the parameters' boundaries can be set within physically meaningful limits.

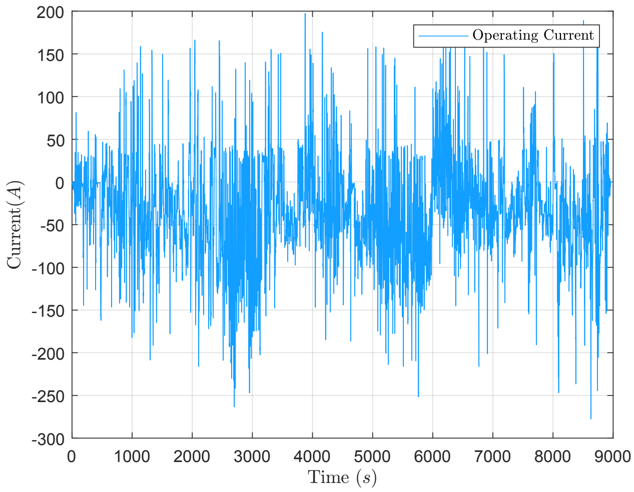

Fig. 2. The test current of the battery pack

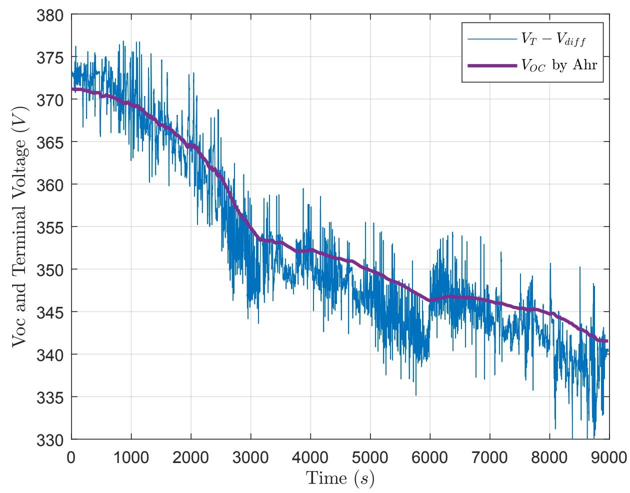

Fig. 3. The terminal voltage and V_{OC} of the battery pack

4. BATTERY PARAMETERS ESTIMATION AND ITS APPLICATION TO BATTERY POWER PREDICTION WITH VOLTAGE LIMIT

In order to evaluate the performance of the EKF algorithm on battery state estimation and failure detection, the EKF algorithm is applied to both experiment pack-level and vehicle cell-level. The battery capacity is 158 Ah (55 kWh).

4.1 Pack-level Estimation

The battery test operation includes a running cycle lasting approximately 2.5 hours. The operating current and the terminal voltage are shown in Fig. 2 and Fig. 3. The current data, as the input, has rich excitation for the EKF estimation. The terminal voltage data is used as the system output measurement. During the test, the battery was discharged from about 72% to 25% SOC and the temperature dropped from 29° to 21°C. The referenced V_{oc} value is demonstrated in Fig. 3 as well. The purpose of EKF is to estimate the V_{oc} value and the internal circuit model parameters of resistors and capacitors. From previous descriptions, the calibration parameters, the scaling and parameter boundary limits, must be defined correctly,

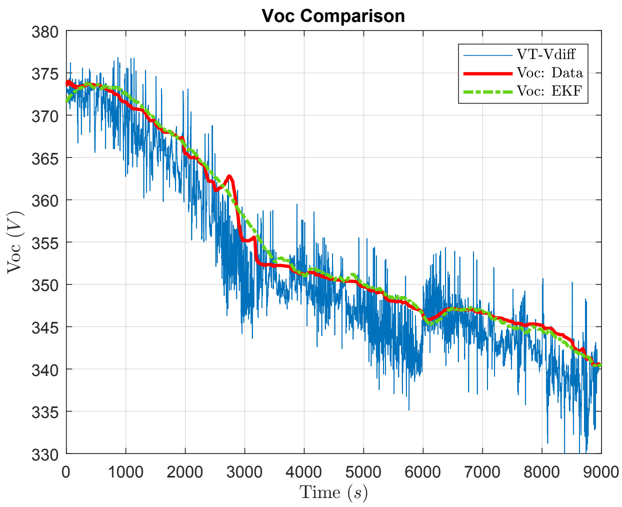

Fig. 4. EKF estimation of open-circuit voltage

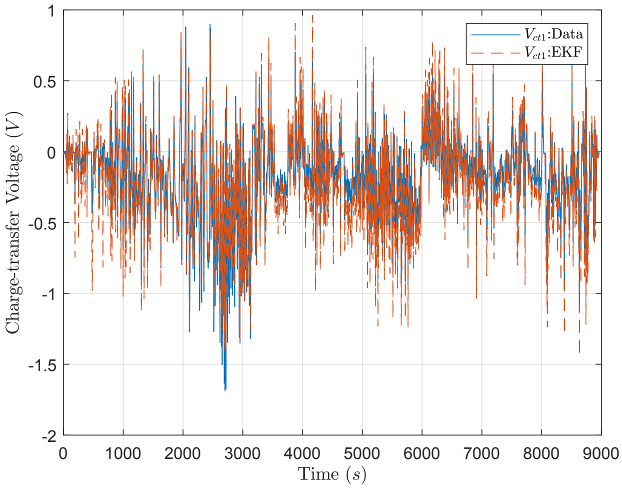

Fig. 5. EKF estimation on charge-transfer voltage

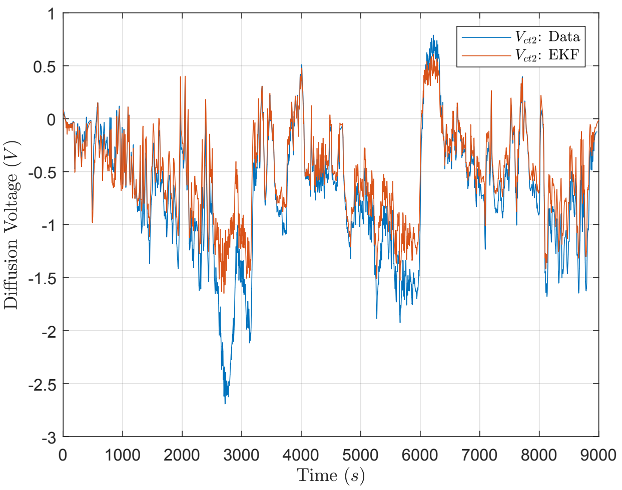

Fig. 6. Estimation on diffusion voltage

as they guarantee EKF estimation stability and keep the model parameter values from diverging.

With the defined initial parameter values, the scaling values, the input current $I(k)$, and the terminal voltage $V_T(k)$, the EKF estimates the open-circuit voltage as displayed in Fig. 4. The estimation result is very close to the reference V_{oc} result from the BMS algorithm in BOLT vehicle integration control module (VICM). From Fig. 5, the fast charge-transfer voltage estimate V_{ct1} is close to the reference data (V_{ct1} and V_{ct2} Data are generated by standard production software VICM). From Fig. 6, the slow charge-transfer voltage V_{ct2} estimate deviates from the reference data with some error, since our calibration of process and measurement noise covaraiances in the models are different from production calibrations.

The Kalman filter gain converges to zero, that means the model-based estimate is accurate and the estimation does not update much from measurements for larger correction. The estimation covariance also converges and has no further significant updates during the iteration process. These results demonstrate the performance of EKF for pack-level estimation.

4.2 Cell-level Estimation

The estimate of battery status at cell-level can provide valuable information for BMS in terms of battery safety protection, power prediction and prognosis in health. One application of monitoring cell status is to prevent over-charging/discharging to protect a weak or malfunctioning cell before it is serviced.

As one example, test conditions are shown from Fig. 7 to Fig. 10. The battery is under driving condition before 3500s and in charging condition between 4500s to 12000s, see Fig. 7. The state of charge was reduced from 82% to 68% during the driving cycle and then was charged to 92% at the end of test. As shown in Fig. 8, one cell has lower terminal voltage, $V_{t\_Cell_2}$ than other healthy cells, e.g. $cell_3$ in the pack. The EKF estimation results for both a nominal and a malfunction cells are listed in Fig. 9 to Fig. 10. The estimated open-circuit voltages indicate that one cell is in normal condition (orange color curve in Fig. 9, which is close to the healthy reference $cell_3$ V_{oc} in blue color) and another one is in abnormal condition (red curve). The abnormal cell (which lost 22% capacity and internal resistance slightly increased) is operated under low SOC status, the energy drains quickly as its terminal voltage drops below the cell voltage limit, i.e. less than 2.7 volt demonstrated in Fig. 8. From Fig. 10, the ohmic resistance of the abnormal cell increased slightly from the normal cell condition. The charge-transfer resistance and diffusion capacitance do not have significant difference.

4.3 Pack Power Estimation

As demonstrated in Fig. 11, when a battery pack is not balanced, the battery power and discharge current are limited by the weakest cell. For a given minimum cell voltage limit, defined by a battery manufacturer, this voltage-limited current and power can be calculated as

$$I(k) = f(V_L), P(k) = V_L \cdot I(k) \tag{12}$$

where $f(V_L)$ is the calculated voltage-limited current from any battery model $f(*)$. As an example, the voltage limited

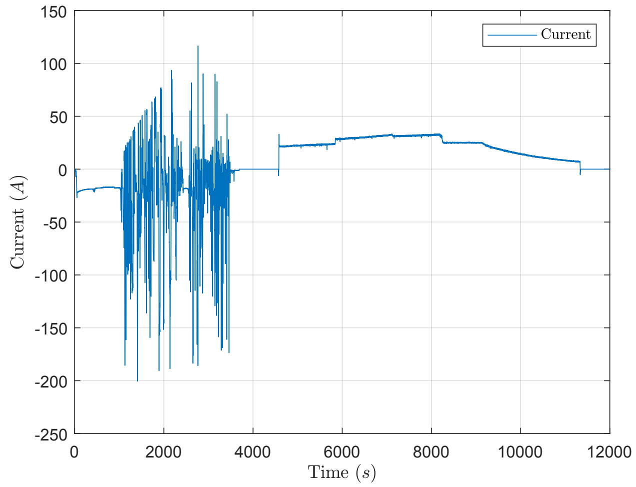

Fig. 7. The current of battery under operation

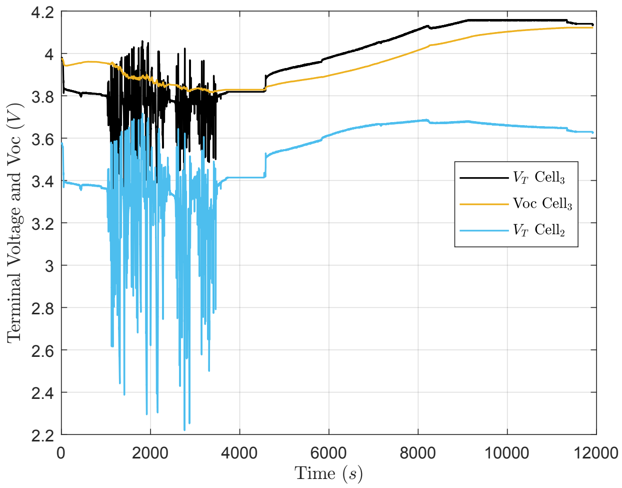

Fig. 8. The terminal voltages and open-circuit voltage of operating battery

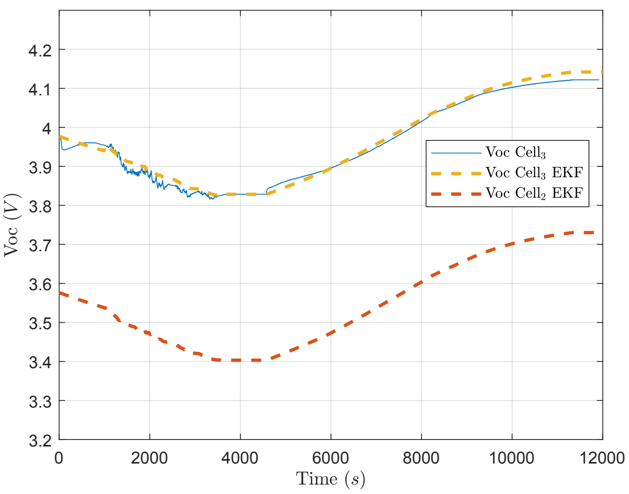

Fig. 9. The comparison between open-circuit voltages of a normal and an abnormal cell

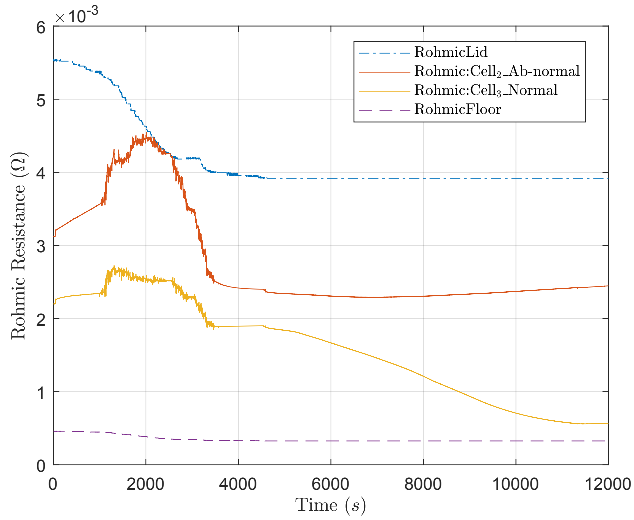

Fig. 10. The estimates of ohmic resistance of normal cell and abnormal cell

current can be calculated from battery equivalent circuit model based on the estimated cell parameters:

$$I(k) = \frac{V_L - V_{OC}^{V_L} - V_1^{V_L} - V_2^{V_L} - V_h^{V_L}}{R_{ohmic} + R_{ct1}(1 - E_1) + R_{ct2}(1 - E_2)} \quad (13)$$

where, the $E_{1,2}$ are the exponential decay coefficients of charge transfer and diffusion; the superscript $(*)^{V_L}$ represents the projected voltages when the battery is operated at the voltage limit. With the cell-level estimation results on this case study and an exemplar voltage limit $V_L = 2.7$(V) for discharging, the estimated limited discharging current is shown in Fig. 12. It can be clearly seen that the actual vehicle load current reached or exceeded the boundary of the allowed current limit, which means the weak cell voltage already hits the threshold limit and has the potential to be damaged if more load were applied. Fig. 11 shows the battery power estimation flow chart. Applying the estimated new load current limit from the droop cell model to the battery pack level model, we can calculate the allowed pack terminal voltage, thus the allowed pack power, which is estimated and shown in Fig. 13. In case there are modeling errors, the estimated available current limit is not precisely estimated, a feedback loop is added to fine tune the torque applied to electric drive-train, such that the terminal voltage of the droop cell will be precisely controlled above the cell voltage limit. This develops a valuable method for the battery management system in vehicle power control while protecting a degraded battery cell from further damaging that in the worst case could leads to potential thermal runaway.

5. CONCLUSIONS

This paper demonstrates the benefits of predicting battery pack level power by using the extended Kalman filter to estimate battery states. The study showed the EKF can identify weak cell parameters in real time, allowing a battery management system to adjust charge/discharge limits accordingly in order to improve battery safety, performance and life expectancy.

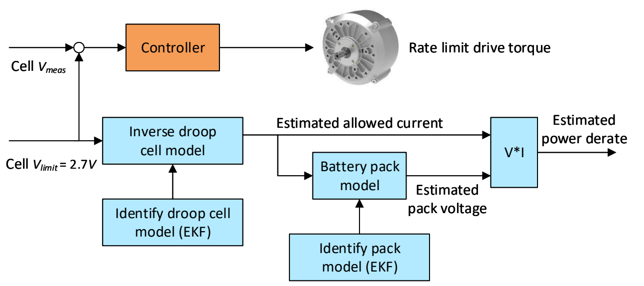

Fig. 11. The power management of battery pack with droop cell

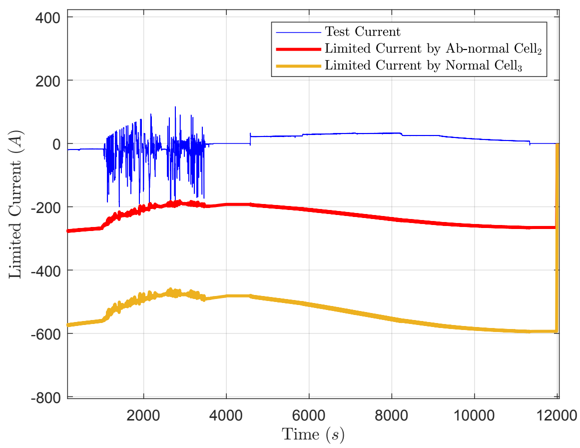

Fig. 12. The limited currents for a specified voltage limit

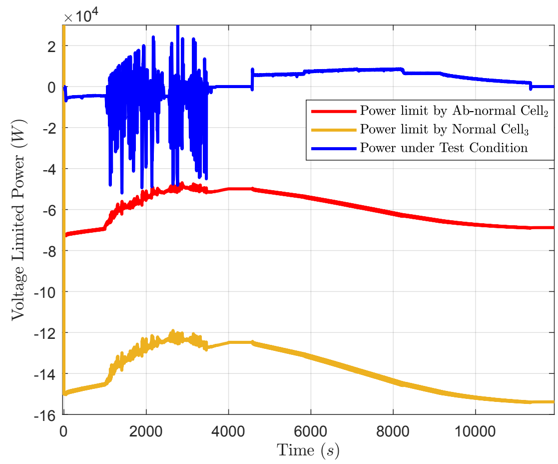

Fig. 13. The limited powers for a specified voltage limit

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