Performance Validation of Electric Vehicle's Battery Management System under state of charge estimation for lithium-ion Battery

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***Abstract* – Electric Vehicles (EVs) have gained substantial attention in the recent years, since they are an efficient, sustainable and zero-carbon emitting means of transportation as compared to the conventional fossil-fuel powered vehicles. As EVs are becoming popular, the use of Lithium-ion (Li-Ion) batteries is exponentially increasing due to its good charge/discharge performance, high energy and current density and optimum power support. For safe operation of battery, precise estimation of the State of Charge (SOC) is necessary. SOC determines the residual charge accumulated in the battery and how further it can operate under specific conditions. This paper uses the Thevenin-equivalent circuit theory to model the transient behaviour of the Li-Ion battery and the SOC is evaluated using Coulomb counting and Extended Kalman Filter (EKF) methods. First, the battery is mathematically modelled and then the estimation is done via Coulomb counting and EKF in MATLAB/Simulink. A comparison of these two methods indicate that the SOC evaluation of the battery using EKF is more precise than Coulomb counting. The results show that the error is reduced by 1% when implemented via EKF.**

Keywords – Electric Vehicles (EVs), Battery Management System (BMS), lithium-ion batteries, State of Charge (SOC), Extended Kalman filter (EKF), coulomb counting.

I. INTRODUCTION

The continuous depletion of fossil fuels and the increasing environmental concerns have led to the exponential growth of technological development in the fields of Electric Vehicles (EVs). Due to this growing demand for clean energy, EVs manufacturers have drastically shifted from conventional fossil fuel to electrified vehicles. In order to make renewable energy technologies more sustainable, storage plays a vital role. Thus, the battery storage acts as an integral part of renewable energy as it balances its variability issues and stabilizes the frequency and voltage. For various applications, comprising short and long-term power provision, Multiple energy storage techniques such as flywheels, pumped-hydro storage etc. are used [1].

Lithium-ion (Li-Ion) batteries plays a significant role in EV's and are thus required to be accurately monitored and controlled. Despite the advantages of Li-Ion batteries, they also have certain drawbacks. To ensure the safe operation, improved driving ranges, optimized power management strategy, prolonged service life and decreased cost of the batteries, a Battery Management System (BMS) is needed. Crucial functions of the BMS are to evaluate State of Charge (SOC), capacity, state of function (SOF) and State of Health (SOH). However, the major task of battery management system (BMS) is SOC estimation. SOC indicates the available capacity of the battery that can be extracted and is used to prevent it from deep charging/discharging and to operate the battery in such a way that aging effects are reduced [2]–[9].

Various online SOC estimation methods for batteries have been deployed over the past few years that are categorized as; direct measurement and model-based method. The open circuit voltage and Coulomb counting method is considered in direct measurement method. These methods are widely used in BMS for EVs application, as they offer fast computational speed and less complexity. However, both these methods have certain limitations. In open circuit voltage method, the battery should be cut-off from the external circuitry to measure the open circuit voltage and it requires long relaxation times. The Coulomb counting method requires an accurate initial SOC value and it greatly depend on the performance of the current sensors. However, the critical disadvantage of this method is that it is an open-loop estimation and error may be large due to disturbances and uncertainties [10], [11].

Recent studies on SOC estimation focus on model-based methods with improved accuracy. These include Kalman filter, Extended Kalman Filter (EKF), fuzzy logic and neural networks. Kalman filter provides an efficient computational recursive method through a linear filtering to evaluate the SOC. However, the accurate SOC estimation of a battery remains challenging due to highly non-linear and complex electrochemical reactions in the battery and also because with aging, the battery characteristics change [12].

A more robust algorithm is thus needed to estimate the instantaneous charge available in the lithium-ion cell. The EKF technique, which is a non-linear estimator, has been deployed as one of the practical solutions to enhance the accuracy of SOC estimation.

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II. BATTERY MODELING

The purpose of modelling a battery is to obtain its internal parameters by using its external parameters and establish the mathematical model. Internal state variables such as SOC, internal resistance and electromotive force are calculated based on the external variables i.e. battery current, voltage and temperature. Research in the field of electric vehicle simulation, as well as in the estimation of batteries SOC is significantly increasing. The growing interest in this field thus requires the enhancement of battery model's accuracy, especially those concerning Li-Ion batteries. For this purpose, two types of models are used i.e. electrochemical and electrical models among which, electrical models are widely used.

A. Electrical Equivalent Circuit Models

Electrical equivalent circuit models consist of a combination of capacitors, resistors and voltage sources. These models show the battery's dynamic behaviour [13]. Their accuracy lies in the range of 1-5% and they are accurate enough to be used in real-time simulations due to their low computational intensity.

A second order Thevenin equivalent circuit model named Dual Polarization (DP) is used in this paper and is shown in Fig. 1 and its Simscape model is shown fig. 2. The battery model is composed of SOC controlled open circuit voltage Uoc(SOC), an ohmic resistance R_O and two RC blocks, accounting for the polarization concentration and polarization activation. The parameters R_O, R_{p1}, R_{p2}, C_{p1}, C_{p2} are used to represent battery's dynamic response and capacity.

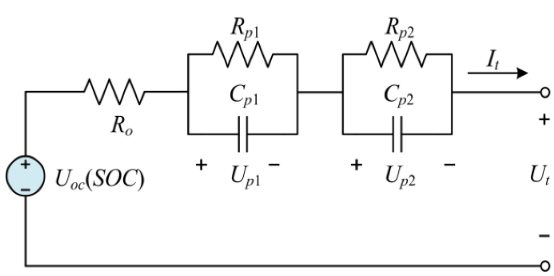

Fig. 1 Mathematical model of dual polarised li-ion cell

The electrical behaviour of the circuit is given by following equations:

$$\frac{dU_{p1}}{dt} = \frac{I_t}{C_{p1}} - \frac{U_{p1}}{R_{p1}C_{p1}} \quad (1)$$

$$\frac{dU_{p2}}{dt} = \frac{I_t}{C_{p2}} - \frac{U_{p2}}{R_{p2}C_{p2}} \quad (2)$$

$$\frac{dSOC}{dt} = \eta \times \frac{I_t}{C_{batt}} \quad (3)$$

The output equation of the DP model according to fig. 1 is:

$$y = Uoc(SOC) - U_{p1} - U_{p2} - R_0 \times I_t \quad (4)$$

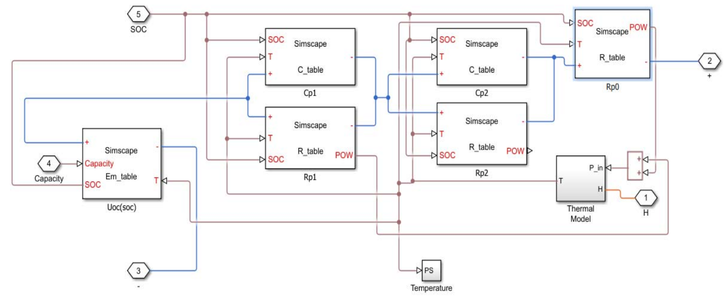

Fig. 2 Simscape model of dual polarised li-ion cell

III. SOC ESTIMATION METHODS

A. Coulomb Counting Method

This is the most general and simplest method to obtain a battery's SOC and is characterized by the following equation.

$$SOC_t = SOC_0 + \int_0^t \frac{I_t}{C_{batt}} . dt \quad (5)$$

Where SOC_t is the state of charge at time *t*, SOC_0 is the initial state of charge, I_t is the charging/discharging current and C_{batt} denotes the capacity of the battery.

In coulomb counting, SOC variation is estimated by integrating the battery's current over time by its capacity. The dilemma of this method however is the accurate estimation of the initial SOC. Due to integration of current in this method, even small errors in measurement lead to large drift in SOC estimation over time. This method considers the battery capacity to be constant and the effects of ageing, current dependencies and temperature changes are not taken into account.

B. Extended Kalman filter (EKF)

EKF is an extensively applied state evaluation method for dynamic systems involving linearity. This filter provides proficient computational recursive method through a linearization process for state estimation. EKF can be described by (6) and (7).

$$x_{k+1} = f(x_k, u_k) + w_k \quad (6)$$

$$y_k = g(x_k, u_k) + v_k \quad (7)$$

Equation (6) is known as the process or state equation, where x_{k+1} represents the state vector, which includes SOC, u_k is system's control input and non-linear state transition function is denoted by $f(x_k, u_k)$. Equation (7) is the output or measurement equation, which contains measurement function $g(x_k, u_k)$. The process noise and the measurement noise w_k and v_k respectively, are presumed to be Gaussian white noise with zero mean and covariance Q and R in order to reduce the problem of noise characterisation [14]–[16].

1) EKF algorithm: EKF uses a dual stage predictor-corrector algorithm. Initially, the projection of the recent state and future error covariance estimation is done to compute the anticipated estimation of the states at present. Secondly, the estimated state is corrected to create an updated state estimate by including the current process measurement. The process of EKF involves the following steps:

(1) Initialization:

Initialize state estimate vector x, error covariance P and noise covariance Q and R.

(2) Prediction:

$$\begin{cases} \hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_{k-1}) \\ P_{k|k-1} = A_{k-1}P_{k-1|k-1}A_{k-1}^{T} + Q_{k-1} \end{cases} \tag{8}$$

(3) Correction:

$$\begin{cases} K_k = P_{k|k-1}C_k^T\left(C_kP_{K|K-1}C_k^T + R_K\right)^{-} \\ \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k\left[y_k - g\left(\hat{x}_{k|k-1}, u_k\right)\right] \\ P_{k|k} = (I - K_KC_K)P_{K|K-1} \end{cases} \tag{9}$$

2) SOC Estimation with EKF: To implement this algorithm in MATLAB, we defined the transition function and measurement function as well as their respective matrices A, B, C and D.

$$f(x_k, u_k) = \begin{bmatrix} \dfrac{I_t}{C_{p1}} - \dfrac{U_{p1}}{R_{p1}C_{p1}} \\ \dfrac{I_t}{C_{p2}} - \dfrac{U_{p2}}{R_{p2}C_{p2}} \\ \eta \times \dfrac{I_t}{C_{batt}} \end{bmatrix} \tag{10}$$

$$g(x_k, u_k) = Uoc(SOC) - U_{P1} - U_{P2} - R_0 \times I_t \tag{11}$$

For (6) and (7), Taylor series expansion is required to linearize the model. The linearized model is thus represented by (12) and (14):

$$f(x_k, u_k) = A_K * x_k + B_k * u_k \tag{12}$$

$$g(x_k, u_k) = C_k * x_k + D_K * u_k \tag{13}$$

Among these:

$$A = \begin{bmatrix} \dfrac{-1}{R_{p1}C_{p1}} & 0 & 0 \\ 0 & \dfrac{-1}{R_{p2}C_{p2}} & 0 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} \dfrac{1}{C_{p1}} \\ \dfrac{1}{C_{p2}} \\ \dfrac{\eta}{C_{batt}} \end{bmatrix}$$

$$C = [-1 \quad -1 \quad Uoc(SOC)], \qquad D = -R_0$$

Equation (12) and (13) can be written in matrix form as follows:

$$\begin{bmatrix} \dfrac{dU_{P1}}{dt} \\ \dfrac{dU_{P2}}{dt} \\ \dfrac{dSOC}{dt} \end{bmatrix} = \begin{bmatrix} \dfrac{-1}{R_{P1}C_{P1}} & 0 & 0 \\ 0 & \dfrac{-1}{R_{P1}C_{P2}} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} U_{P1} \\ U_{P2} \\ SOC \end{bmatrix} + \begin{bmatrix} \dfrac{1}{C_{P1}} \\ \dfrac{1}{C_{P2}} \\ \dfrac{\eta}{C_{batt}} \end{bmatrix} [I_t] \tag{14}$$

$$U_t = [-1 \quad -1 \quad Uoc(SOC)] \begin{bmatrix} U_{p1} \\ U_{p2} \\ SOC \end{bmatrix} - R_0[I_t] \tag{15}$$

EKF can only work in discrete time systems. Therefore, the discretised state space equations are as follow:

$$\begin{bmatrix} \dfrac{dU_{p1}}{dt} \\ \dfrac{dU_{p2}}{dt} \\ \dfrac{dSOC}{dt} \end{bmatrix} = \begin{bmatrix} e^{\frac{-Ts}{R_{p1}C_{p1}}} & 0 & 0 \\ 0 & e^{\frac{-Ts}{R_{p2}C_{p2}}} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} U_{p1} \\ U_{p2} \\ SOC \end{bmatrix} + \begin{bmatrix} R_{1,K}\left(1 - e^{\frac{-Ts}{R_{p1}C_{p1}}}\right) \\ R_{2,k}\left(1 - e^{\frac{-Ts}{R_{p2}C_{p2}}}\right) \\ -\dfrac{\eta}{+C_{batt} * 3600} \end{bmatrix} [I_t] \tag{16}$$

$$U_t = [-1 \quad -1 \quad Uoc(SOC)] \begin{bmatrix} U_{p1} \\ U_{p2} \\ SOC \end{bmatrix} - R_0[I_t] \tag{17}$$

IV. SIMULATION AND RESULTS

Depending on the battery's analysis and the mathematical description, EKF based SOC estimation is more precise than Coulomb counting method. Coulomb counting and EKF methods are implemented in MATLAB/Simulink to validate the mathematical model. Coulomb counting based model is shown in fig. 3. It should be noted that simulation of models in Simulink are ideal. A band-limited white noise source is added in the model to make the system non-ideal. Fig. 4 shows the simulation results of Coulomb counting and fig. 5 shows the error between SOC of battery and Coulomb counting. It can be observed clearly from the graphs, that there is an increased error between the estimated SOC and the real SOC of the battery. This is due to the fact that Coulomb counting method is incapable of self-correction. The charge and discharge capacitance with respect to time is estimated by current integration in this method. Thus, the measured noises will be added in the current because of integration.

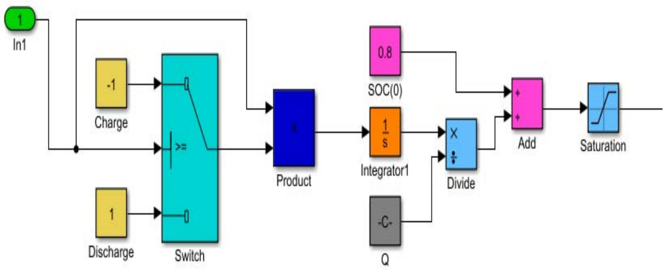

Fig. 3 Coulomb counting Simulink model

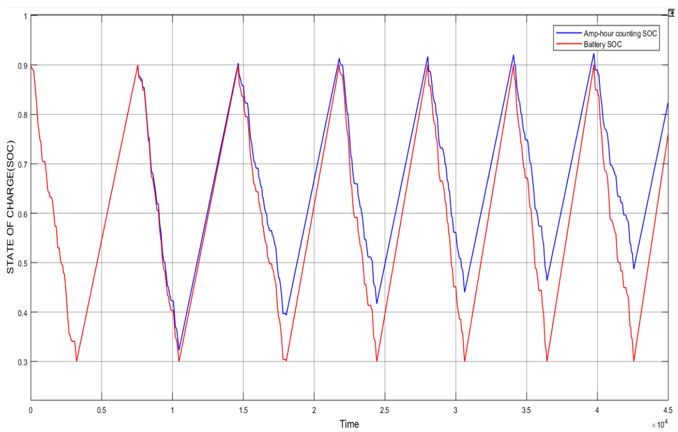

Fig. 4 Simulation results of Coulomb counting. Red curve = Real SOC, Blue curve = Estimated SOC

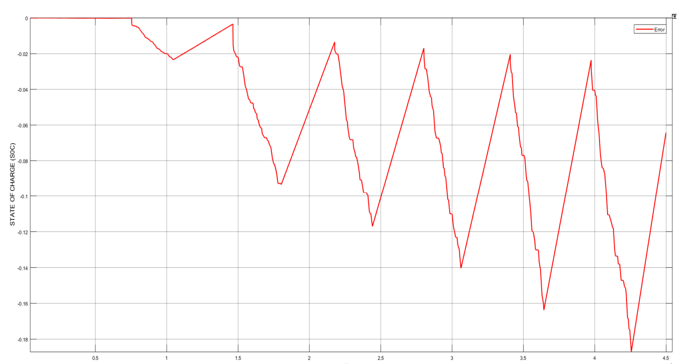

Fig. 5 Difference between SOC of Battery and Coulomb counting method

For EKF, the integration of current is not considered. It performs estimation and minimizes the error. The MATLAB/Simulink model of EKF is shown in fig. 6 and the simulation results with difference are shown in fig. 7 and 8 respectively. The results show that SOC evaluation based on EKF is more accurate as compared to the Coulomb counting method. As shown in fig. 7 real SOC curve is followed by estimated SOC curve.

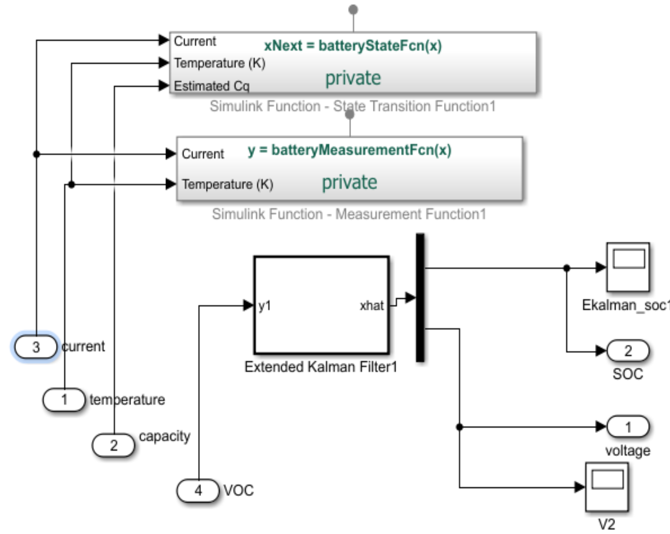

Fig. 6 MATLAB/Simulink model of EKF

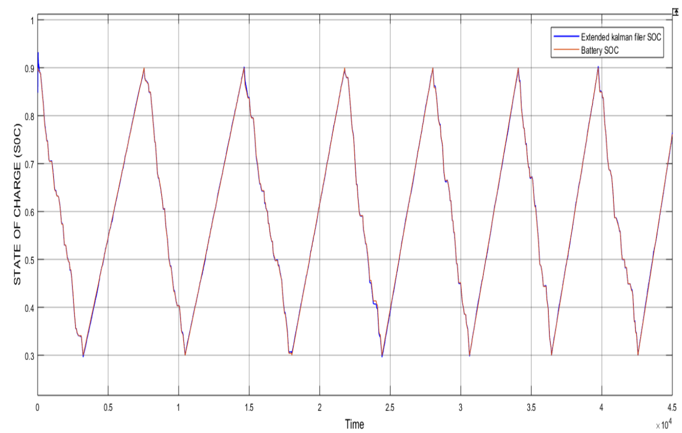

Fig. 7 Simulation results of EKF. Red curve = Real SOC, Blue curve = Estimated SOC

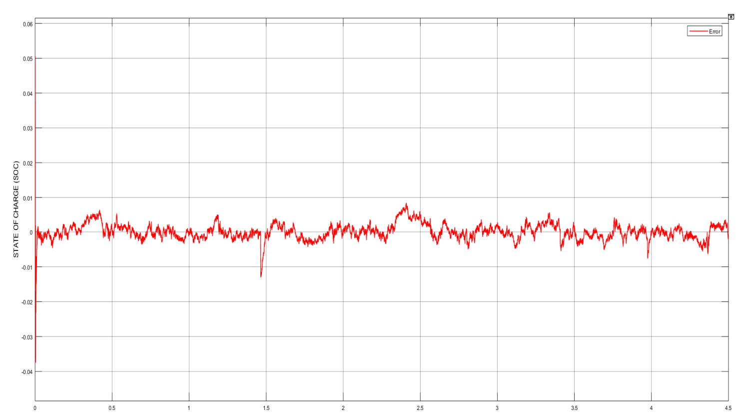

Fig.8 Difference between SOC of battery and EKF method

V. CONCLUSION

An accurate electrical equivalent circuit modelling of a rechargeable lithium-ion cell with thermal dependency is done in the paper and a procedure is established to identify the model's SOC. A Coulomb integration and EKF technique for SOC estimation has been developed using second order Thevenin equivalent circuit based on its state space equations. The design flow of the two techniques is introduced in detail. Simulation results show that the accuracy of EKF is significantly better than Coulomb counting method. The simulation results of EKF shows an error of less than 1%.

REFERNCES

[1] M. A. Hannan, M. S. H. Lipu, A. Hussain, and A. Mohamed, "A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: Challenges and recommendations," *Renew. Sustain. Energy Rev.*, vol. 78, no. May, pp. 834–854, 2017.

[2] R. Xiong, H. He, F. Sun, and K. Zhao, "Online estimation of peak power capability of Li-Ion batteries in EVs by a hardware-in-loop approach," *Energies*, vol. 5, no. 5, pp. 1455–1469, 2012.

[3] Y. Xing, E. W. M. Ma, K. L. Tsui, and M. Pecht, "Battery Management Systems in Electric and Hybrid Vehicles," *Energies*, vol. 4, no. 12, pp. 1840–1857, 2011.

[4] C. Zhang, L. Y. Wang, X. Li, W. Chen, G. G. Yin, and J. Jiang, "Robust and Adaptive Estimation of State of Charge for Lithium-Ion Batteries," *IEEE Trans. Ind. Electron.*, vol. 62, no. 8, pp. 4948–4957, 2015.

[5] X. Hu, S. Li, and Y. Yang, "Advanced Machine Learning Approach for Lithium-Ion Battery State Estimation in EVs," *IEEE Trans. Transp. Electrif.*, vol. 7782, no. c, pp. 1–1, 2015.

[6] R. Xiong, Y. Zhang, H. He, X. Zhou, and M. G. Pecht, "A double-scale, particle-filtering, energy state prediction algorithm for lithium-ion batteries," *IEEE Trans. Ind. Electron.*, vol. 65, no. 2, pp. 1526–1538, 2017.

[7] R. Xiong, Q. Yu, L. Y. Wang, and C. Lin, "A novel method to obtain the open circuit voltage for the state of charge of Li-Ion batteries in EVs by using H infinity filter," *Appl. Energy*, vol. 207, pp. 346–353, 2017.

[8] A. Scacchioli, G. Rizzoni, M. A. Salman, W. Li, S. Onori, and X. Zhang, "Model-based Diagnosis of an Automotive Electric Power Generation and Storage System.," *IEEE Trans. Syst. Man Cybern.*, vol. 44, no. 1, pp. 72–85, 2014.

[9] L. Lu, X. Han, J. Li, J. Hua, and M. Ouyang, "A review on the key issues for lithium-ion battery management in EVs," *J. Power Sources*, vol. 226, pp. 272–288, 2013.

[10] R. Xiong, J. Tian, H. Mu, and C. Wang, "A systematic model-based degradation behavior recognition and health monitoring method for lithium-ion batteries," *Appl. Energy*, vol. 207, pp. 372–383, 2017.

[11] S. Rodrigues, N. Munichandraiah, and A. K. Shukla, "Review of state-of-charge indication of batteries by means of a.c. impedance measurements," *J. Power Sources*, vol. 87, no. 1, pp. 12–20, 2000.

[12] X. Hu, F. Sun, and Y. Zou, "Comparison between two model-based algorithms for Li-ion battery SOC estimation in EVs," *Simul. Model. Pract. Theory*, vol. 34, no. 5, pp. 1–11, 2013.

[13] H. He, R. Xiong, and J. Fan, "Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach," *Energies*, vol. 4, no. 4, pp. 582–598, 2011.

[14] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs - Part 1. Background," *J. Power Sources*, vol. 134, no. 2, pp. 252–261, 2004.

[15] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs - Part 2. Modeling and identification," *J. Power Sources*, vol. 134, no. 2, pp. 262–276, 2004.

[16] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs - Part 3. State and parameter estimation," *J. Power Sources*, vol. 134, no. 2, pp. 277–292, 2004.