SOC prediction of Lithium-Ion Battery using Extended Kalman Filter

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Abstract—solar energy is become more eminent source of energy among renewable energy sources in order to overcome power shortfall. Energy Storage is also an important subject of renewable power generation, Lithium-Ion (Li-Ion) battery is preferred choice among all batteries due to some advantages, e.g. comparatively better charging and discharging performance, high energy and charge density, and more favorable power support. Battery safety and reliability are ensured usually by battery management system (BMS). Among various parameters in a BMS, State of Charge (SOC) of Li-Ion cells is a key indicator which represents the ratio of the stored energy in the battery to the total energy that the battery can contain. In this paper, state of the art SOC estimation using Ampere-hour (Ah) counting and Extended Kalman filter (EKF) methods have been presented. First, EKF for estimating SOC of Li-Ion battery is mathematically designed. Then electrical battery model is implemented using Ah counting and EKF in MATLAB/Simulink. A comparison of the two methods is given which indicates that the SOC evaluation of the battery using EKF is more accurate than Ah counting method. The error observed from the results of EKF is less than 1%.

Keywords—Solar Power; Lithium-ion Batteries (Li-Ion); State of Charge (SOC); Extended Kalman Filter (EKF); Ampere-hour Counting (Ah counting);

1. Introduction

The continuous depletion of fossil fuels and the increasing environmental concern, importance of fuel saving and the unavailability of power has led to an extensive use of renewable energy sources. Due to this growing demand for clean energy, solar panel manufacturers have dramatically expanded in the recent years. In order to make renewable energy technologies more efficient, storage plays a vital role. Battery storage is an integral part of renewable energy as it balances the variable characteristics of renewable energy, stabilizes frequency and voltage and increases its penetration. For various applications, including short-term and long-term power support, different types of energy storage techniques such as flywheels and battery chemistries are used [1]. The choice of Lithium-ion (Li-Ion) batteries for renewable energy applications being an effective option for storage has been proved to more beneficial option. Despite the advantages of lithium-ion batteries, they also have certain drawbacks. To ensure the safe operation, improved driving range, optimized power management strategy, prolonged service life and decreased cost of the batteries, a management of battery is of very importance. The key function of BMS includes estimate State of Charge (SOC), State of Health (SOH), to estimate capacity and state of function (SOF). However, the major task of battery management system (BMS) is State of Charge prediction. It indicates the future capacity of the charge which can be drawn out from battery and can be used to stop it from going into deep charging or discharging and can easily be operated in a conditions that aging factor of battery can be reduced as possible [2].

Various SOC online prediction and estimation techniques for lithium ion batteries have been developed over the past years that are categorized in two categories which are direct method and model based techniques. The direct method is then further categorized in ampere-hour method and open circuit voltage method. These methods are widely used in BMS for solar applications as they are fast in computations and easy to use. However, both methods face certain limitations. In open circuit voltage method, the battery should be isolated from the exterior circuitry to measure the voltage of open circuit and it requires long resting period of the battery. The ampere-hour counting method requires accurate initial SOC value and it greatly relies on the performance of the current sensors. However, the critical disadvantage of this method is that it is open-loop estimation and may have a large accumulation of error due to disturbances and uncertainties [3].

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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 compound electrical and chemical reactions of the battery and also due to aging, the behavior and characteristics of battery changes [4].

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

2. Battery Modelling

The main aim of modelling a litihm ion battery is to obtain it's external electrical characteristics, internal state variables and to establish the mathematical model. Then state variables (internal) like SOC, battery's internal resistance and internal voltage 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 battery modelling, two types of models are used i.e. electrochemical models and electrical models. Electrical models are widely used for modelling Li-Ion batteries.

2.1 Electrical equalent circuit model

Electrical equivalent circuit models consist of combination of capacitors, resistors and voltage sources. These model the battery's dynamic behaviour [5]. 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. The battery model is consists of SOC controlled OPC (open circuit voltage), an base resistance RO and some Rc blocks accounting for the polarization concentration and polarization activation. RO, R1, R2, C1, C2 represents dynamic response and battery's capacity.

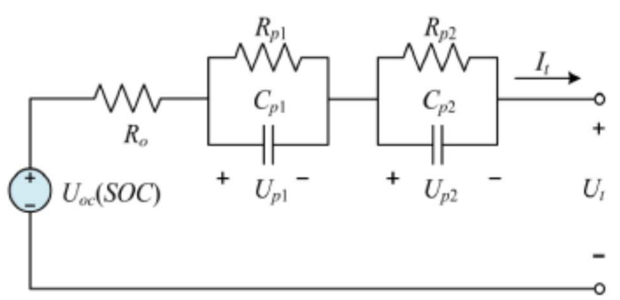

Figure 1: Mathematical model of dual polarized Li-ion cell

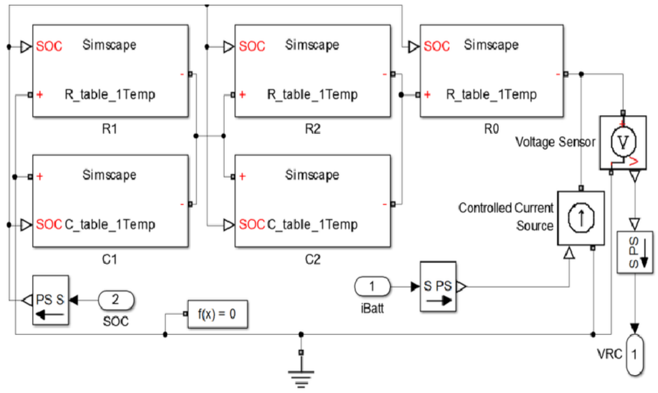

Figure 2: Simscape model of Dual polarized Li-ion cell

The adaptive behavior of above circuit is given by the following equations:

$$\frac{dU_1}{dt} = \frac{iBatt}{C_1} - \frac{U_1}{R_1C_1} \quad (1)$$

$$\frac{dU_2}{dt} = \frac{iBatt}{C_2} - \frac{U_1}{R_2C_2} \quad (2)$$

$$\frac{dsoc}{dt} = \eta \times \frac{iBatt}{Q} \quad (3)$$

The output equation of the DP model according to circuit is given by:

$$y = Em - U_1 - U_2 - R_o \times iBatt \quad (4)$$

3. SOC Estimation Method

SOC estimation of lithium batteries can be done through many methods. Some of them explained below are worked more in research paradigm.

3.1 Ampere Hours computing technique

This is most common and simple technique to obtain a state of charge's accurate status of battery, and is characterized by the following equation.

$$SOC(t) = SOC(t-1) + \int_0^t \frac{iBatt}{cBatt} . dt \quad (5)$$

Where SOC (t) is battery state of charge at time t, SOC (t-1) is battery initial state of charge, iBatt is charge discharge current and cBatt is capacity of the battery.

In Ah counting, SOC variation is estimated by integrating the battery's current over time by battery's capacity. Accurate SOC is estimated if the initial SOC is relatively precise. However, it has several disadvantages such that it is highly important to have an accurate initial estimation of SOC because it cannot get the precise initial SOC automatically. Due to integration of current, even small errors in current measurement lead to large drift in SOC estimation over time. Constant battery capacity is considered and the effects of ageing, current dependencies and temperature changes are not taken into consideration.

3.2 Extended Kalman Filter

EKF is a widely used state evaluation method for non-linear dynamical systems. This filter provides an efficient computational recursive method through a linearization process for state estimation. EKF can be described by equ (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 state or process equation, where the $xk+1$ is state vector which includes SOC, uk is system control input and $f(xk, uk)$ is the non-linear state transition function. Equation (7) is the output or measurement equation which contains measurement function (xk, uk). The process noise wk and the measurement noise vk are assumed to be Gaussian white noise with zero mean Q and covariance R in order to reduce the problem of noise characterization [5].

3.2.1 Extended Kalman filter algorithm

EKF uses a dual stage predictor-corrector algorithm. Firstly, the projection of the most recent state estimation and the estimation of error covariance forward in time is done to calculate a predicted estimate of the states at present time. Second is to correct the predicted state estimate by incorporating the most current process measurement to generate an updated state estimate. 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:

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

(3) Correction:

$$\begin{cases} K_k = P_{k|k-1}C_k^T(C_kP_{K|K-1}C_K^T + R_K \\ \hat{X}_{k|k} = \hat{X}_{k|k-1} + K_k[y_k - g(\hat{X}_{k|k-1}, u_k)] \\ P_{k|k} = (1 - K_kC_k)P_{K|K-1} \end{cases} \quad (9)$$

3.2.2 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.

$$f(X_k, U_k) = \begin{bmatrix} \frac{iBatt}{C_1} - \frac{U_1}{R_1C_1} \\ \frac{iBatt}{C_2} - \frac{U_1}{R_2C_2} \\ \eta \times \frac{iBatt}{Q} \end{bmatrix} \quad (10)$$

$$g(X_k, U_k) = Em - U_1 - U_2 - R_o \times iBatt \quad (11)$$

For (7) and (8), Taylor series expansion is required to linearize the model. The linearized model is thus described by (13) and (14):

$$f(X_k, U_k) = A_k \times X_k + B_k \times U_k \quad (12)$$

$$g(X_k, U_k) = C_k \times X_k + D_k \times U_k \quad (13)$$

Among these:

$$A = \begin{bmatrix} \frac{-1}{R_1C_1} & 0 & 0 \\ 0 & \frac{-1}{R_1C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix}, B = \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{\eta}{Q} \end{bmatrix}$$

$$C = [-1 \quad -1 \quad E_m], \qquad D = R_o$$

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

$$\begin{bmatrix} \frac{dU_1}{dt} \\ \frac{dU_2}{dt} \\ \frac{dsoc}{dt} \end{bmatrix} = \begin{bmatrix} \frac{-1}{R_1C_1} & 0 & 0 \\ 0 & \frac{-1}{R_1C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} U_1 \\ U_2 \\ SOC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{\eta}{Q} \end{bmatrix} [iBatt] \quad (14)$$

$$U = [-1 \quad -1 \quad E_m] \begin{bmatrix} U_1 \\ U_2 \\ SOC \end{bmatrix} + R_o\,[iBatt] \quad (15)$$

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

$$\begin{bmatrix} \frac{dV_1}{dt} \\ \frac{dV_2}{dt} \\ \frac{dsoc}{dt} \end{bmatrix} = \begin{bmatrix} e^{\frac{-Ts}{R_1C_1}} & 0 & 0 \\ 0 & e^{\frac{-Ts}{R_1C_2}} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} V_1 \\ V_2 \\ SOC \end{bmatrix} + \begin{bmatrix} R_{1,K}\left(1 - e^{\frac{-Ts}{R_1C_1}}\right) \\ R_{2,K}\left(1 - e^{\frac{-Ts}{R_1C_2}}\right) \\ \frac{-\eta}{Cuse \times 3600} \end{bmatrix} [iBatt]$$

(16)

4. Simulation Results

Depending on the analysis and the mathematical description of the battery, SOC estimation based on EKF is more accurate than Ah counting method. Ah counting and EKF methods are developed in MATLAB/Simulink to validate the mathematical model. A model using Ah counting is shown in Fig. 3. It should be noted that models in simulation are considered ideal since no noise is added. A band limited white noise source is added in the model to make the system non-ideal.

Simulation result of Ah counting is shown in the Fig. 4 and the error between SOC of battery and Ah counting is shown in fig.5. From the graphs, this can be observed clearly that there is an increased error between the estimated SOC and the real SOC of the battery.

This is due to the fact that Ah counting method is incapable to correct its error. Ah counting method uses integration of current to estimate the charge and discharge capacitance with respect to time. Thus the measured noises in the current will be added in the process of integration.

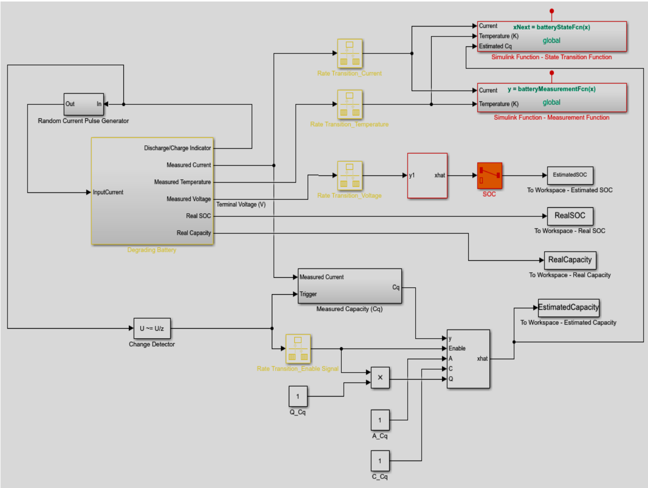

Figure 3: Ampere Hour Counting Simulink model

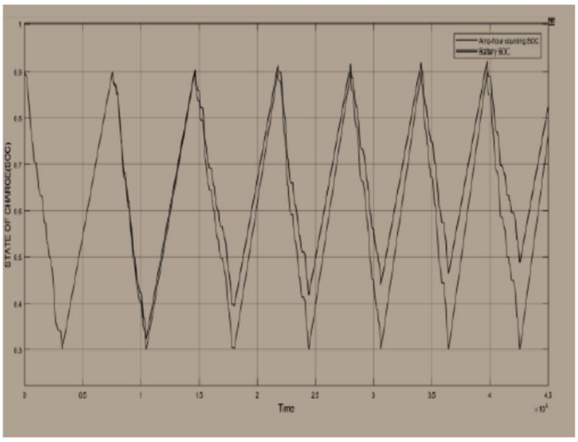

Figure 4: Ampere-hour counting simulation results. Red curve = Real SOC, Blue curve = Estimated

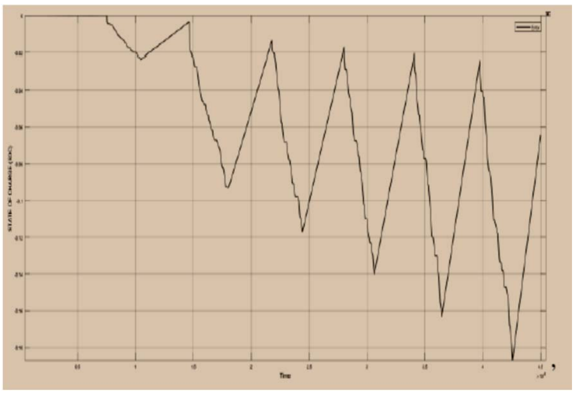

Figure 5: Difference between SOC of Battery and Ampere-hour counting method

For EKF, the integration of current is neglected. EKF performs estimation and regulates the error to minimum. The MATLAB/Simulink model of EKF is shown in Fig. 6 and the simulation results and its difference are shown in Fig. 7.

The results show that SOC evaluation based on EKF is more accurate as compared to the Ah counting method. The estimated SOC curve follows the real SOC curve of the battery closely as can be seen in Fig. 6.

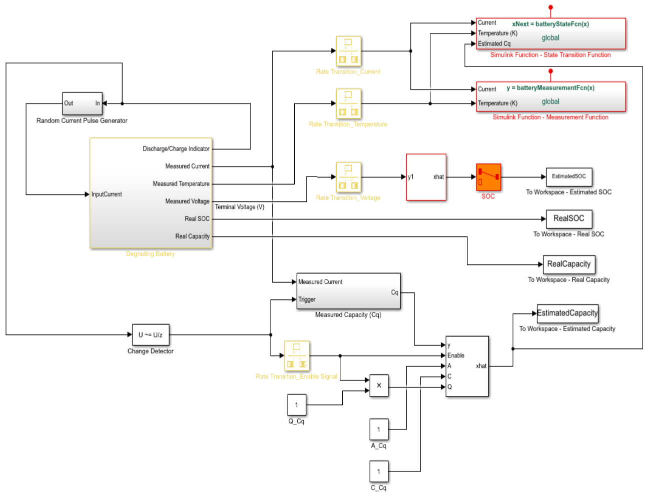

Figure 6: Matlab/ Simulink model of EKF

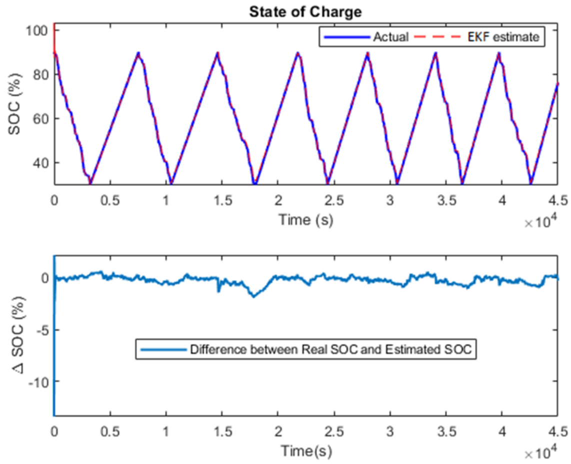

Figure 7: (a) Estimation using EKF (b) Difference between Real SOC and Estimated SOC

5. CONCLUSION

An accurate electrical equivalent network model of a rechargeable lithium cell with thermal dependence is done in the paper and a procedure is established to experimentally identify the model SOC. An Ah integration and EKF techniques for SOC estimation has been developed based on the state space equation of second order Thevenin equivalent circuit model. The design flow of the two techniques is introduced in detail. Simulation results show that the accuracy of EKF is significantly better than Ah integration method. The simulation result of EKF shows an error of less than 1%.

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