Battery Performance Monitoring and Optimal Observation

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ABSTRACT
Battery Modeling is required to improve the efficiency and reliability of the battery. The Lithium-ion batteries are widely used as a power source for several applications. An accurate battery model and model parameters help in the estimation of the state of charge and state of health. However, battery parameters are variable and depend on several factors such as Temperature, cycle lifetime, the state of charge and depth of discharge and age. By taking account of the characteristics of battery the paper includes circuit oriented model approach of lithium-ion battery. The model characteristics are dependent and linear with respect to the battery's state of charge. This paper presents a state of charge estimation of lithium ion battery using Kalman filter. Rather than other methods, Kalman filter provides weighted average between the measured value and predicted value. Thus the battery modeling helps to improve the performance of Photovoltaic module and other applications

Keywords
Battery Modeling, Lithium-ion battery, Kalman filter, State Of charge(SOC), Sum Square Error(SSE).

1. INTRODUCTION
As lithium is the lightest of all metals and provides greatest electrochemical potential and largest specific energy per weight. Hence lithium ion battery provides extraordinary high energy density [1], Because of its rechargeable nature, Lithium-ion batteries are common in home electronics as well as other applications such as electric vehicle and communication base stations.

It is possible to design battery equivalent circuit using a different model such as electrochemical model which provides accurate results but it is very complex in nature. Another one is the mathematical model but this model is not applicable for all battery cells and does not provide the accurate electrochemical process in the cells. Another model is electric circuit model where model behavior is represented in electrical circuit form and provides good accuracy. Thus in this paper, we will discuss electrical equivalent circuit model [2]. When considering the short term behavior of a battery it includes voltage response, the useable capacity, and determination of the SOC. When considering long-term behavior it includes capacity and power fading of the cells.

State of charge (SOC) and state of discharge defines the life time of the battery [3]. Soc generally expresses in percentage. In this paper, SOC is expressed on the scale of 0 to1. SOC of Lithium battery is the percentage of its total energy capacity that is still available to discharge.

A Battery management system (BMS) is required to keep the battery within a safe operating window and to ensure a long cycle life [4]. Thus proper modeling is a major function of the Battery Management System. Further, in automotive applications such as electric vehicles and photovoltaic array modeling, batteries need very precise control of the charge for efficient and safe management of the energy flows. The SOC estimation must be accurate under all vehicle operating condition. High temperatures and strenuous load profiles can cause cell aging.

Extensive research has been carried out for estimation of charging rate and discharging rate of batteries, such as Coulomb counting [5], fuzzy logic[6], neural network [7], voltage delay method and extended Kalman filter [8].

Coulomb counting is used for the estimation of charging rate of the battery. It integrates the current with respect to time. However, some limitations are still there in coulomb counting. The voltage delay method is another method for charging rate estimation. Discharge curve is used to plot the voltage versus SOC characteristics. Due to the effect of external agents like temperature on the battery, the voltage is significantly affected. The neural network is another approach for SOC estimation but a large amount of calculation makes it very complex. Fuzzy logic is also used for battery charging rate estimation but it is hard to develop a model from a fuzzy system. It requires fine tuning and simulation before the operation.

In this paper, Kalman filter is applied to estimate battery SOC. Electrochemical behavior of the battery is represented in differential equation form. A second order battery equivalent circuit is chosen to establish state space equation for lithium- ion battery. A relation is defined between VOC and SOC. Kalman filter is applied for battery modeling. This paper contributes in getting better results in terms of experimental results and simulation results.

The paper is organized as follow, section 2 comprises of description of the equivalent circuit model of the battery and simplification of the model. Section 3 comprises of modeling of given circuit model using Kalman filter. Section 4 comprises of Matlab simulation and results. Section 5 comprises of application of battery modeling and section 6 comprises of conclusion

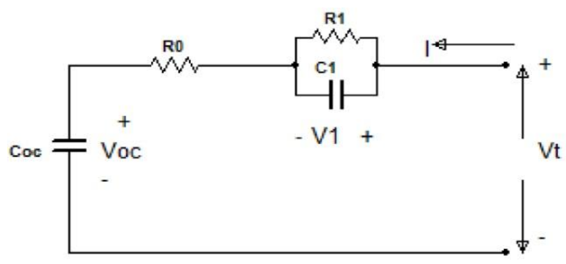

Figure 1: Electrical Equivalent Model of Battery

2. EQUIVALENT CIRCUIT MODEL

A battery cell is an electrochemical system. The battery comprises of three main section namely, a positive electrode, a negative electrode, and separator. A lithium-ion battery is a type of rechargeable battery. The movement of the ion from one electrode to another electrode is a repeated process, which causes charging and discharging of the battery. Due to electrochemical behavior, a case study is required to understand the behavior of batteries to prevent cell aging.

A proper relation needs to be established between electrical equivalent circuit model and electrochemical model. Impedance model helps to set relation between both the models. Impedance model describes electrochemical processes in a cell with the electrical equivalent model.

An equivalent circuit model is build using the common circuit elements. The resulting equivalent circuit model is strong enough to describe the chemical reaction which takes place inside the battery cell. The equivalent circuit model of battery is shown in Fig. 1 [9]. The electrical equivalent circuit model of lithium ion battery consists of capacitance C_{oc} which represents battery storage, voltage across it is given by V_{oc} which represents open circuit voltage, an internal resistance R_o which is an electrolyte resistance and a pair of RC component where R_1 is the resistance at the junction of electrode and electrolyte. It is a charge-transfer resistance. C_1 is the interior capacitance responsible for the charge building in the electrolyte. V_1 is the diffusion voltage which causes degradation in the terminal voltage. From the equivalent circuit model of the lithium ion battery, we will get the following equation

$$V_t = V_{OC} + IR_O + V_1 \tag{1}$$

$$\dot{V}_1 = -\frac{V_1}{R_1 C_1} + \frac{I}{C_1} \tag{2}$$

$$\dot{V}_{OC} = -\frac{I}{C_{OC}} \tag{3}$$

$$Voc = f(Soc) \tag{4}$$

The relation between V_{OC} and S_{OC} is a piecewise linear function,[10] thus it can be taken as

$$V_{OC} = kS_{OC} + d \tag{5}$$

Where k and d are the variable parameters which cannot be zero, but for a given range of SOC as every 10 % rise in SOC it can be considered as almost constant. Thus the above equations describes the battery model, the given system can be written in a state equation form as

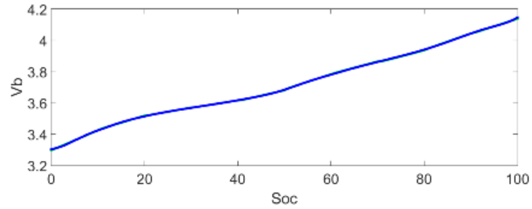

Figure 2: Voc vs. Soc

$$\dot{x} = A_t x + B_t u \tag{6}$$

$$y = C_t x + D_t u \tag{7}$$

For the above system the state variables are defined as

$$x = \begin{bmatrix} V_{oc} \\ V_1 \end{bmatrix} \tag{8}$$

with this state variables, we can define

$$\begin{bmatrix} \dot{V}_{OC} \\ \dot{V}_1 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & \frac{-1}{R_1 C_1} \end{bmatrix} \begin{bmatrix} V_{oc} \\ V_1 \end{bmatrix} + \begin{bmatrix} -\frac{1}{C_{OC}} \\ \frac{1}{C_1} \end{bmatrix} \mathbf{I}$$

$$[V_t] = [1 \quad 1]\begin{bmatrix} V_{oc} \\ V_1 \end{bmatrix} + [R_o]\, \mathbf{I} \tag{9}$$

These are the equations we got as battery model equations in the state matrix form. To solve this set of state equations we are using Kalman Filter. As we have defined a relation between VOC and SOC in equation (4), with the help of experimental values with every 10 % rise in SOC we get a constant value of k and d which we have defined in equation (5).Thus with the help of this values and considering the relation between SOC and VOC we get the plot as shown in Fig 2.

SOC estimation cannot take place directly, the value of Voc at each SOC should be known. A linear plot between VOC and SOC is helpful in determining the state estimation as the plot validates the value of constant k and d which get through the experimental values.

3. KALMAN FILTER

The Kalman Filter can be summed up as an estimator used to recursively obtains a solution for linear optimal filtering [11]. It is a member of a Bayes Filter. It includes the scenario that the next step calculation includes the effect of current state and the previous step calculation includes the effect of current state and the previous state. In other words, the Kalman filter is essentially a set of mathematical equations which provides an efficient recursive method of estimation of the state of the process. It supports estimation of past, present and future [12]. The Kalman filter considers the fact that time instance t can be calculated by considering the effect of time instance t-1. The equations are explained as

$$x_t = A_t x_{t-1} + B_t u_t + w_t \tag{11}$$

Where the notation x_t, B_t and u_t have been explained already in equivalent circuit model and notation A_t is state transition matrix which applies the effect of each system parameter at time t-1 on the system state at time t, and measurement equation of the system can be given as

$$z_t = C_t x_t + v_t \tag{12}$$

Here y_t is a measurement vector and c_t is the transformation matrix. The estimated state vector equation can be given as

$$x_t = A_t\, x_{t-1} + B_t\, u_t + w_t \tag{13}$$

$$x_0 = N(m_0, P_0),\ w_t = N(0, Q_t),\ v_t = N(0, R_t) \tag{14}$$

Where Q_t is the noise covariance matrix associate with the noise control input. R_t covariance matrix of measurement noise. To find the best estimated value one need to minimize the mean square error which is given by

$$P_{t|t-1} = E[(x_t - \hat{X}_{t|t-1})(x_t - \hat{X}_{t|t-1})^T] \tag{15}$$

Where $P_{t|t-1}$ is covariance of the original states. Estimation of next step based on previous is given by

$$\hat{P}_{t|t-1} = A\hat{P}_{t-1|t-1}A^T + Q_t \tag{16}$$

The measurement updated equations are

$$\hat{X}_{t|t} = \hat{X}_{t|t-1} + K_t(z_t C_t(\hat{X}_{t|t-1}) \tag{17}$$

$$\hat{P}_{t|t} = (I - K_t C_t)P_{t|t-1} \tag{18}$$

Where K_t is Kalman gain of the system and it can be given as

$$K_t = P_{t|t-1} H_t^T (H_t P_{t|t-1} H_t^T + R_t)^{-1} \tag{19}$$

4. SIMULATION AND RESULTS

The initial value of SOC is taken as 0.8 and for diffusion voltage (V_1) it is taken as 3.5V. The parameter value used for simulation is given in Table 1 [13]. The sum square error of an estimator measures the average of the squares of the error, that is the difference between the true value and measured value. The difference can be due to the noise in the system or due to insufficient information. Sum square error can be calculated as

$$SSE = \sum (\hat{x}_t - x_t)^2$$

Table 1. Parameter of Equivalent Circuit Model

Parameter	Values
R_o	0.025
R_1	0.08
C_1	3.31
C_b	12100
k	5.38
d	25.21

The SSE is a measure of quality of the estimator. It is always nonnegative value and close to zero. The lesser the SSE, the better will be the estimated value. The simulation is carried out at different value of measurement noise and process parameter noise, to see the effect of noise on SSE.

The process noise and measurement noise variance matrices are given as in table 2. The simulation is taken out in such a

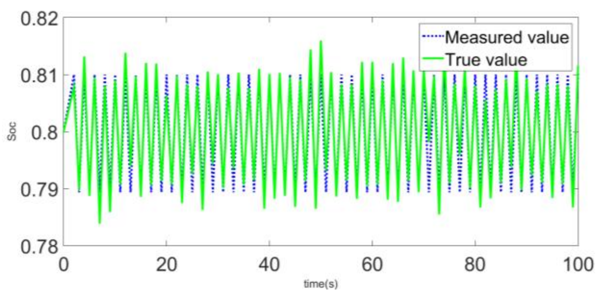

Figure 3: Soc vs. time for case study 1

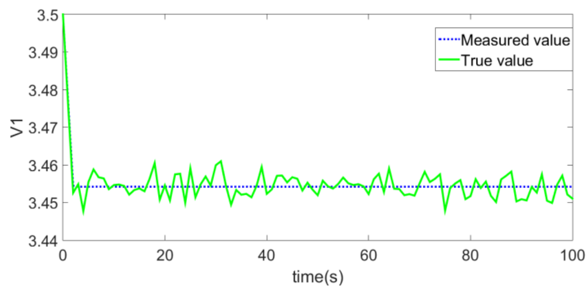

Figure 4: V1 vs. time for case study 1

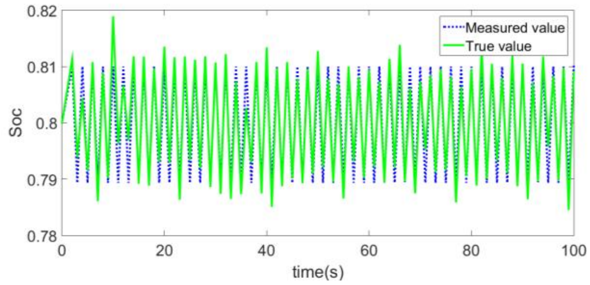

Figure 5: Soc vs. time for case study 2

manner that for three consecutive cases the value of one parameter varied and the value of other two parameters kept constant accordingly. Here, the measurement noise is taken as R, the process parameter noise for the first state is taken as Q_1 and for the second state is taken as Q_2.

The observations are taken for the case study 1 as the $Q1$ is kept as .0025 and $Q2$ is kept as .0025, and value of R is kept as .25. The change in the true value and the measured value is very less in the case of SOC as shown in Fig-3. Similarly the variation is very less in the case of diffusion voltage Fig-4. Thus it results in very less value of SSE and it comes out as 0.014.

In the case study 2, the Q_1 and Q_2 is kept as in case study 1 and R is kept as 1. The variation is very less in the true value and measured value in case of SOC as shown in Fig-5. Similarly the variation is very less in the case of diffusion voltage as shown in Fig-6. Thus it results in very less value of SSE and it comes out as .0015.

In the case study 3, as the value of Q_1 is kept as .0025 and Q_2 is kept as .075, and R is kept as 1. There is a slight variation in the true value and measured value, which can be observed in the case of SOC as shown in Fig-7. Similarly the variation is very random in the case of diffusion voltage as

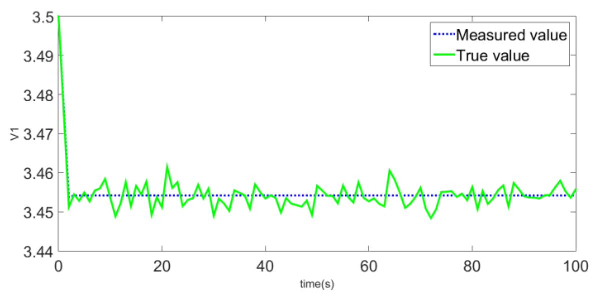

Figure 6: V1 vs. time for case study 2

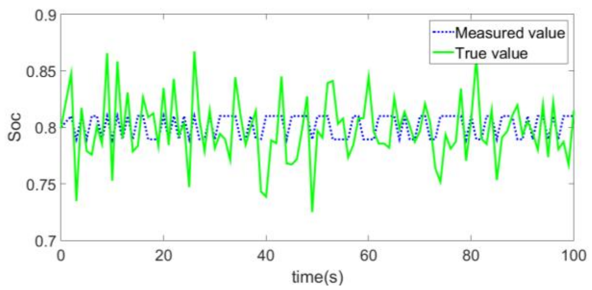

Figure 7: Soc vs. time for case study 3

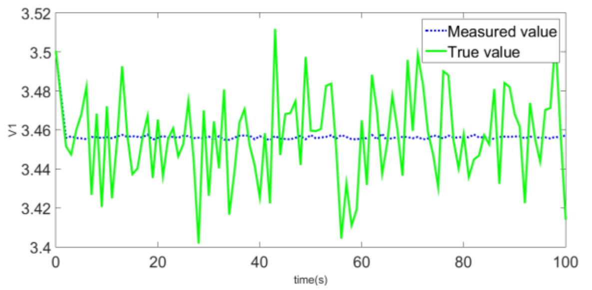

Figure 8 : V1 vs. time for case study 3

as shown in Fig-8. Thus it results in a very high value of SSE and it comes out as 2.

The observations are taken for case study 4 as the Q_1 0.25 and the value of Q_2 and R is same as case 3. The change in the true value and measured value is very less in the case of SOC as shown in Fig-9. Similarly the variation is very less in the case of diffusion voltage as shown in the Fog-10. Thus it results in a very less value of SSE and it comes out as 0.06.

In the case study 5 the Q_1 is kept as .025 and Q_2 and R is same as in the previous case. The variation in the true value and the measured value is significantly low in case of SOC as shown in Fig-11. Similarly the variation is very less in the case of diffusion voltage as shown in Fig -12. Thus it results in very less value of SSE and it comes out as 0.12.

In the case study 6 the Q_1 and R is kept as in the previous case but Q_2 is kept as .075. The irregular change in the true value and measured value can be observed in the case of SOC. Similarly the variation is high for the another state vector. Thus it results in very high value of SSE and it is given as 1.2.

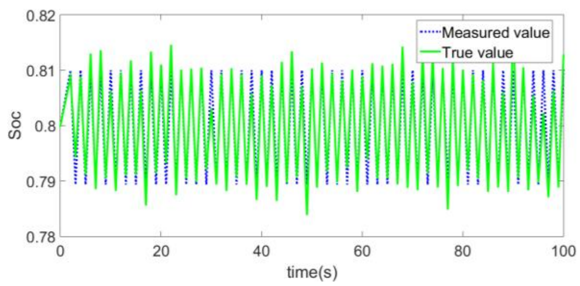

Figure 9 : Soc vs time for case study 4

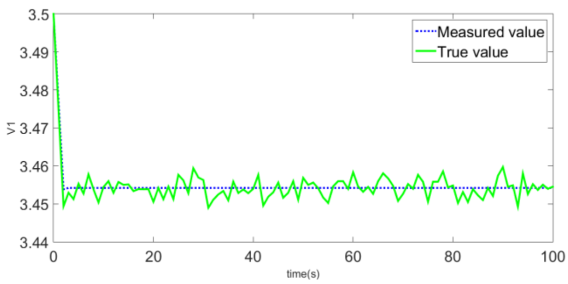

Figure 10 : V1 vs. time for case study 4

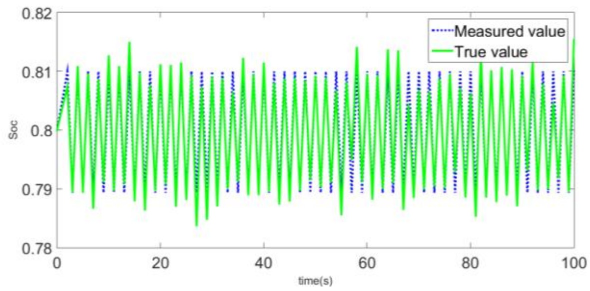

Figure 11: Soc vs. time for case study 5

Thus from this case studies, we can depict that when we set the Measurement noise value between 0.25 and 1, it gives better results. Process parameter noise factor of first state best works between .0025 to .25, and Process parameter noise factor of the second state should be between 0.0025 to .075. The case study depicts that the change in noise value for the second state from .0025 to.075, results in increased SSE. Thus it can be conclude that second state is more sensitive to noise.

The variation of SOC within a range demonstrates low variation in open circuit voltage. Similarly, almost constant variation in diffusion voltage reflects the small internal decay within the battery which results in the desired value of open circuit voltage. It can be inferred from the model that noise plays an important role in the estimator because of the recursive nature of Kalman filter, it can estimate SOC value to some extent of accuracy. A constant current profile leads to oscillating SOC within a range, with a proper value of the parameter noise value, SOC error can be reduced to a certain extent.

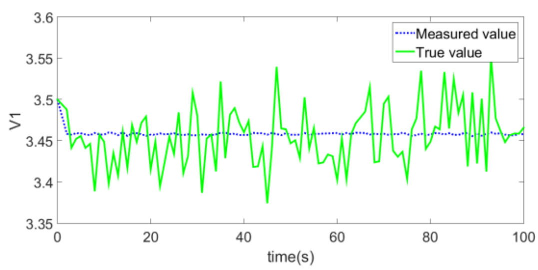

Figure 12: V1 vs. time for case study 5

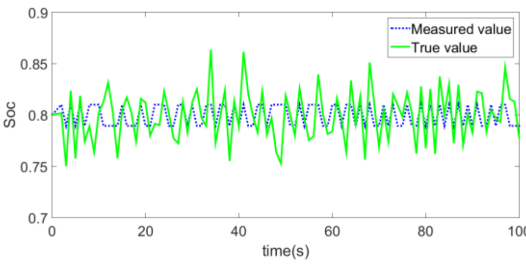

Figure 13 : Soc vs. time for case study 6

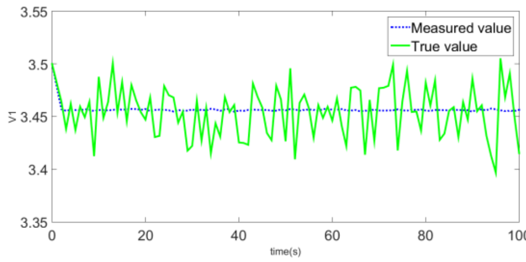

Figure 14: V1 vs. time for case study 6

Table 2. Values used for simulation

Case Study	R	Q1	Q2	SSE
1	.25	.0025	.0025	.0014
2	1	.0025	.0025	.0015
3	1	.25	.075	2
4	1	.25	.025	.06
5	1	.025	.025	.12
6	1	.025	.075	1.2

5. PHOTOVOLTAIC ARRAY MODELING

There are several applications of battery modeling: Photovoltaic array modeling is one of the example, as shown in Fig-15. The maximum power point is extracted from the PV module. Perturb and Observe and Incremental Conductance are several methods for MPP tracking. The obtained maximum power is applied to the boost converter so that power characteristics of the PV module can be matched with the battery characteristics. The output power from the boost converter is applied to the charge controller. The charge Controller and the battery SOC play an important role. The linear relation between SOC and VOC as given in equation no. 5, defines the dependency of open circuit voltage on SOC. Thus recursively estimated SOC value is detected by the charge controller on some instant of time.

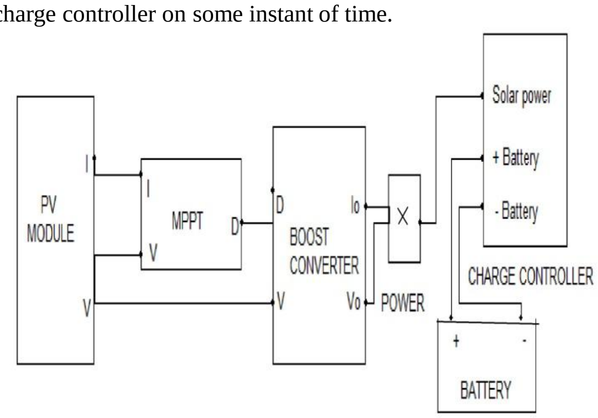

Figure 15 : Battery Storage Modeling of PV panel

According to the SOC at a particular instance, what amount of power should be given to battery is decided by the charge controller. The charge controller and battery leads to an intelligent system and improves performance.

6. CONCLUSION

In this paper, the electrical equivalent model of the battery is applied to Kalman filter for the state of charge estimation of the battery. Linear set of state equation is derived for the formulation of Kalman filter. The experimental values are used to find out the dependent model parameter and later that parameter is used to find the state estimation of the model. The MATLAB simulation is carried out at a constant current profile. From the different result, we can conclude that different noise affects the estimated SOC value and sum square error value. However, Kalman filter can deal efficiently and reasonably with the limitation of SOC estimation, and bound the sum squared error within range.

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