

Estimation of Battery State of Charge by Simulation Study

¹Sai Ngaunn Hseng, ²Wunna Swe, ³Nang Saw Yuzana Kyaing

¹Student, ²Professor, ³Professor

¹Electrical Power Engineering Department,

¹Mandalay Technological University, Mandalay, Myanmar

Email – ¹moungsaii@gmail.com, ²wunnaswe@mtu.edu.mm, ³nansawyusana@gmail.com

Abstract: Battery has been well-known to use as an energy storage system in off-grid photovoltaic system. This paper presents the real time estimation of State of Charge of a battery using a hybrid technique. The technique described in this paper employs: Coulomb Counting Method, Electrical Circuit Model and Mathematical Model based on Peukert Law to estimate the parameters of SOC. The paper presents the method of estimating the internal resistance of the battery to determine the open-circuit voltage and describes how to estimate the State of Charge from the selected battery. In this paper, Lead acid battery which has 12 V and 7.5 Ah capacities will apply to analyse the SOC condition. Then, compare the result of SOC by estimating with Coulomb Counting Method and combined SOC for constant load and variable loads. The proposed technique simulated using MATLAB/Simulink and results were presented with necessary tables and graphs. The simulated value of SOC based on Coulomb Counting Method was 41.87%.

Key Words: State-of-Charge, Battery Internal Resistance, Discharging Current, Open Circuit Voltage.

1. INTRODUCTION:

Batteries are very important and widely used electrochemical energy storage devices. Lithium-Ion (Li-Ion), Lithium-Polymer (Li-Po) and Lead-acid batteries are high energy and high capacity batteries used in variety of application such that photovoltaic systems, wind energy system and electric vehicles etc. There is a need for a model capable to describe the battery behavior with a variation of battery conditions such as SOC, temperature, current rates, loading conditions static or dynamic and its applications [1,2].

There are several ways to estimate the state of charge of a battery [3]. So far, the most common method for state of charge measurement is Coulomb Counting Method. But it has problems such as initial value error and accumulated errors. If the measured current has some error, long run integration will bring unpredictable deviation of SOC and results in overcharging or over discharging of battery. Therefore, battery must be reliable, able to deliver the required power and energy based on the demand. To ensure the efficient use of battery, a continuous vigil on its parameters such as State of Charge (SOC) is necessary. Since these parameters not only determines remaining capacity of the battery but also reflect its performance, thus the estimation of is extremely important [4].

The efficient operation and management of battery based systems become very critical if proper estimation of SOC not done. This situation can very well expect in the electric car application and may result in dire consequences due to depletion of the battery pack [5]. The estimation of SOC of any battery is extremely important in ensuring the efficient delivery of energy to use in off-grid/ micro-grid, consumer electronics so on and so forth. In this paper, battery state of charge estimation is executed for the selected lead acid battery by using Matlab/Simulink.

2. LITERATURE REVIEW:

Since the batteries are most commonly used for storing the energy in various applications, it is necessary that its behavioral study is important during charging and discharging cycle, which requires an appropriate model. S.M. Mousavi G. et al [6], have presented an over view of several electrical battery models. The Thevenin models have a good transient response in a significant SOC and in a constant V_{oc} ; however, DC response and the battery run time predictions are not adequately carried out. The effects of temperature and SOC variation have not been considered in this model. Lluís Farre, et al [7] has designed a microcontroller base Ampere hour meter to estimate the SOC of Lead-Acid batteries. Meter is designed based on the mathematical (Peukert law) model of a battery. On a similar ground Noshin Omar et al [8] proposed a method based on Peukert law with modifications to estimate the available capacity of the lithium ion batteries.

The various existing methods of estimating SOC has been detailed in the review of literature. These methods have certain draw backs. For example, Coulombs Counting Method [4,5] suffers due to unknown initial SOC, effect of temperature and battery discharge current. It has been observed that the Peukert law can be used to other batteries such as Li-ion, Ni-MH with modifications. In order to mitigate the accuracy issue, a hybrid model consisting of Coulomb Counting Method, Electrical Circuit Model and Mathematical Model has been proposed.

3. GENERAL BACKGROUND:

The most expensive and critical component of off-grid PV system is battery. The performance of the off-grid PV system is directly depended upon the efficient utilization of the battery. SOC describe the remaining capacity, which in turn defines the run time of the system. Estimation of SOC protects the battery by preventing it from deep discharge, and improves the life expectancy. The SOC is defined as equation (1).

$$SOC = \frac{Q_t}{Q_r} \tag{1}$$

Where Q_t is capacity of the battery at time 't' and Q_r is rated capacity of the battery specified by the manufacturer

4. PROPOSED METHOD:

As discussed in the previous sections, the proposed method is a hybrid model, consisting of Coulombs Counting Method [4,9], Electrical Circuit Model [6], and Mathematical Model [7] with corrections. The details of these basic constituent models and the parametric corrections are briefed in proceeding sections along with the estimation of final SOC.

4.1 Coulombs Counting Method

The Coulomb Counting is the most commonly used method of estimating SOC [4,5]. In this method, the measured discharging current is integrated over time to determine the SOC. As given in Equation (2) [5].

$$SOC_t = \left(1 - \frac{1}{Q_r} \int_0^t i_\tau d\tau \right) \times 100\% \tag{2}$$

Where i_τ discharging current. The greatest advantage of this method is that the current can be estimated in real time and hence the SOC.

4.2 Electric Circuit Model

Since battery is used in various applications, an accurate modeling and simulation of a battery are necessary to evaluate the performance. [4,6]. There are various classes of models of which Thevenin-based models are shown in Figure 1[6].

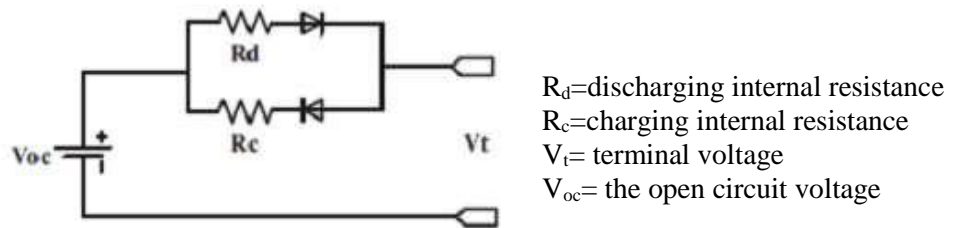


Figure1. Modified Thevenin Battery Model[6]

Considering, the linear part of the battery discharge curve the open circuit voltage of a battery is given by Equation (3).

$$V_{OC} = V_t \pm IR \tag{3}$$

Where: V_{oc} is open circuit voltage or EMF of battery, V_t is terminal voltage; I is discharge/charge current; R is internal resistance of battery either R_d or R_c .

The instantaneous EMF (V_{oc}) and the SOC are given as in Equation (4) [8]:

$$V_{OC} = \alpha SOC \pm V_{min} \quad ; V_{min} \text{ is } 11.4V \text{ for } 12V \text{ nominal battery} \tag{4}$$

SOC can be found by rewriting Equation (4), as in Equation (5) [10].

$$SOC = \frac{V_{oc} - V_{min}}{\alpha} \quad ; \alpha = 0.013V \text{ to } 0.018V \tag{5}$$

4.3 Mathematical Model

Piker Law is the most widely used method to estimate the discharging and charging efficiency of the batteries. Peukert demonstrated that the discharge capacity, discharge current and time are related by an empirical Equation (6) [6].

$$Q_{rl} = i^n \times t \tag{6}$$

; Q_{rl} =released capacity, i =actual Discharge current

Therefore, for all practical purposes, the equation is reformulated [8] and is given by:

$$Q_{rl} = K \times i^{(1-n)} \quad ; K \text{ and } n \text{ are constants} \tag{7}$$

$$K = i_1^n \times t_1 = i_2^n \times t_2; n = \frac{\lg(t_2/t_1)}{\lg(i_1/i_2)} \quad (8) \text{ From Equation}$$

(8), the coefficient of efficiency for a battery can be derived as in Equation (9):

$$\eta_d = i^{(1-n)} \quad (9)$$

Where η_d =Coefficient of efficiency (discharge). The value of ‘n’ varies between 1-1.3. Typically, it is 1.2 [11].

4.4 Modifications to CCM

As discussed in previous the SOC estimated using Coulombs Counting Method (CCM) is inaccurate due to unknown initial SOC and cumulative error in current integration. To mitigate this inaccuracy issue, the coefficient of efficiency called a correction factor determined from Peukert Mathematical Model above is applied to the total power and energy released to the load over the entire period. By applying Equation (9) into Equation (2), the modified corrected SOC equation is given by Equation (10).

$$SOC_{tc} = \left(1 - \frac{1}{Q_r} \int_0^{\tau} \eta_d i_{\tau} d\tau \right) \times 100\% \quad (10)$$

Where SOC_{tc} is corrected SOC.

4.5 Estimation of V_{oc} by ECM

As discussed in previous it need to find V_{oc} to estimate the SOC. In the proposed method, V_{oc} is estimated in two ways by internal resistance method and with rest period during discharge of a battery.

4.6 V_{oc} Estimation by Internal Resistance Method

The internal resistance is an unknown element and is the required parameter to determine the open circuit voltage. The IEC 61951-1:2002/2005, internal resistance is found by a method called two-tier DC load and the method is adopted in various works of researchers [11].

The internal resistance is found by using a relation in Equation (11).

$$R = \frac{V_1 - V_2}{I_1 - I_2} \Omega \quad \text{Where, } V_1 I_1 = \text{voltage and current during low current and longer instant of time} \quad (11)$$

$$V_2 I_2 = \text{voltage and current during high current and shorter instant of time}$$

4.7 V_{oc} Estimation with Rest Period during Discharge of a Battery

Here, the battery is subjected to discharge with a particular load pattern shown in Figure 2 with fixed and variable load. For every end of rest period the battery voltage is measured, which represents the open circuit voltage at that instant of time.

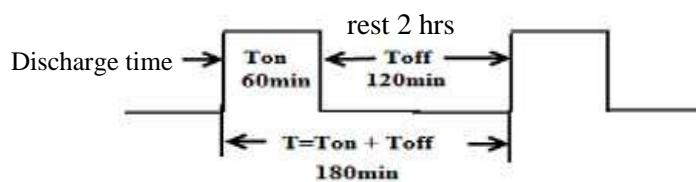


Figure 2. Load Pattern to Estimate V_{oc} [10]

The internal drop of the battery is calculated from the internal resistance and the load current. This drop is given by;

$$V_{ir} = I \times R \quad (12)$$

4.8 Final Estimation SOC of Combination

The estimated state of charge of battery is compared with each other and average of these values is considered to indicate the final SOC.

5. MODELING AND SIMULATION:

5.1 Internal Resistance Estimation-Simulink

The internal resistance of a battery is estimated using a two tier DC load method described in the previous. In this model, two loads are selected such that one draws low current for 10 seconds and the other draws large current for 3 seconds as per IEC 61951-1:2002/2005. The Simulink model of this method is shown in Figure 3.

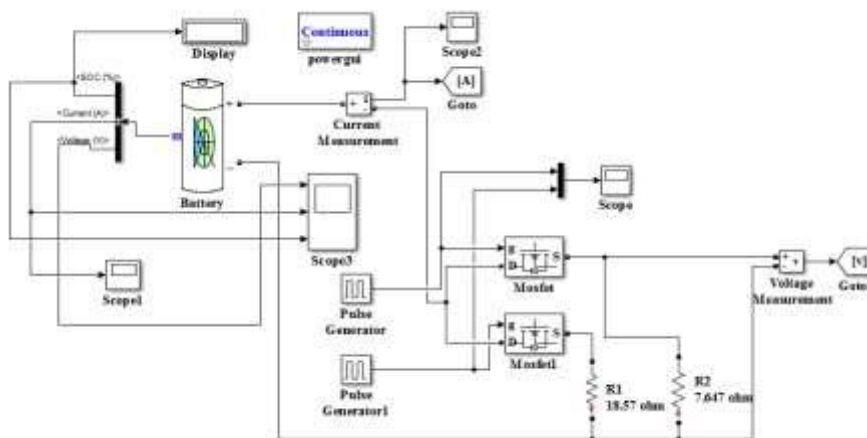


Figure 3. Simulink Model of Internal Resistance Estimation

The simulated waveforms are shown in Figure 4 indicating current, voltage and SOC. And the internal resistance of the battery can be calculated by using these values.

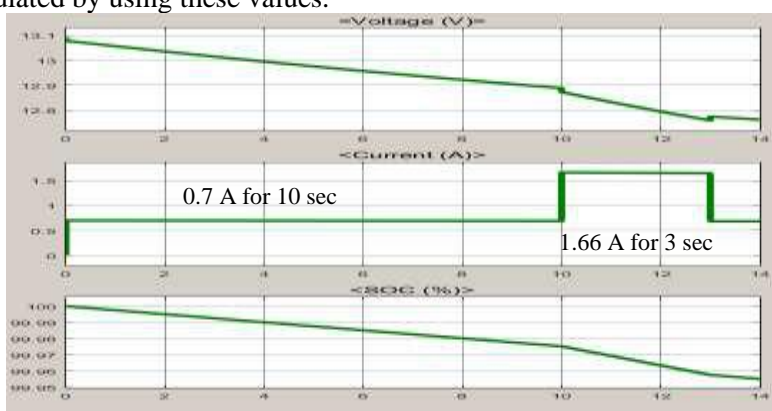


Figure 4. Waveforms of Simulink Model for Internal Resistance Estimation

5.2 Battery Discharge for Constant and Variable Load-Simulink

The battery is discharged for a constant load of 5W LED bulb (28.2Ω load) to estimate the SOC. And the battery is also used to discharge for a variable load of 20Ω , 10Ω and 5Ω to estimate the SOC. With a load pattern described in section, the battery is discharged. And the battery will discharge until the SOC reaches 10% which is decided for the depth of discharge (DOD) 90%. The condition of this SOC is derived from applying logical and relational operators of the Matlab/Simulink. The Simulink model is shown in Figure 5 and in Figure 6 and the corresponding waveforms are described in Figure 7 and in Figure 8.

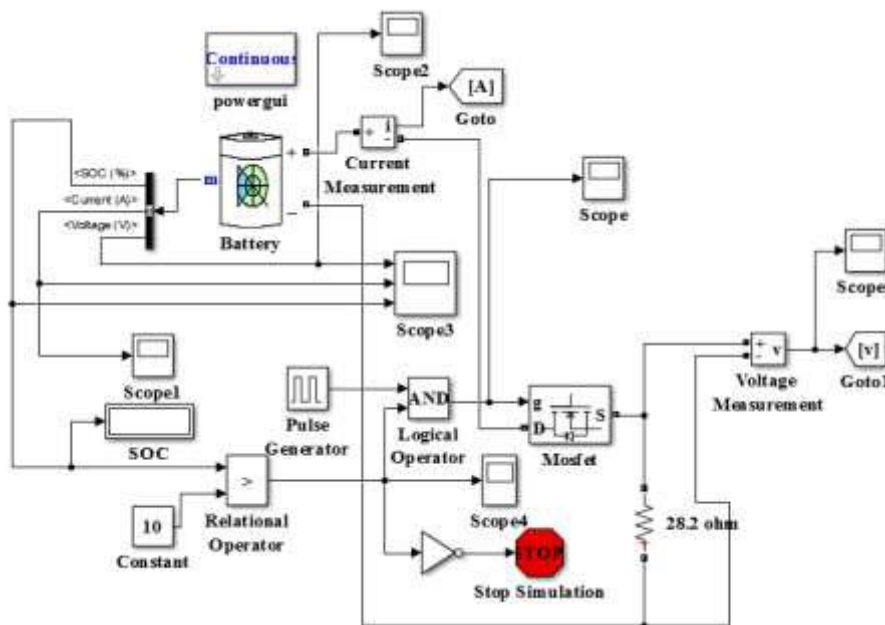


Figure 5. Battery Discharge Model-Constant Load

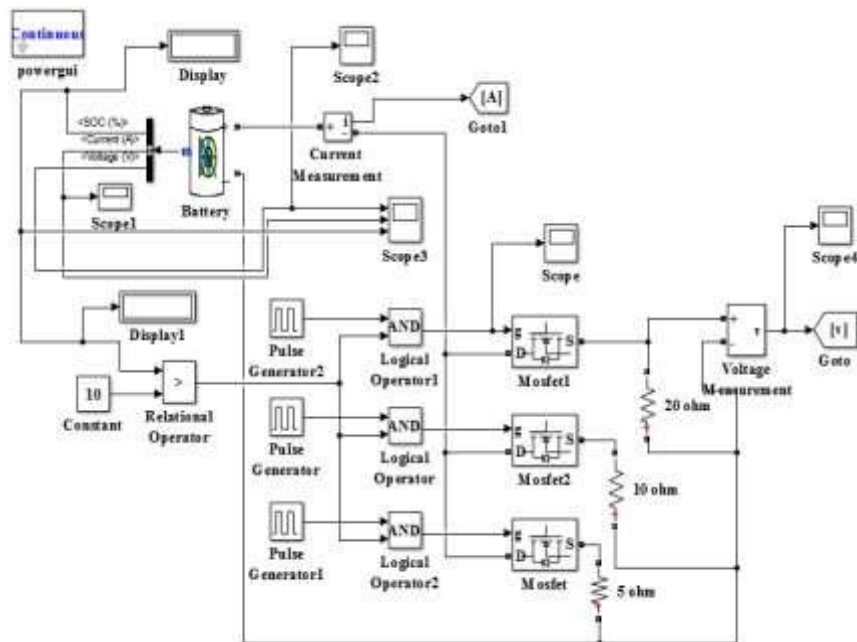


Figure 6. Battery Discharge Model-Variable load

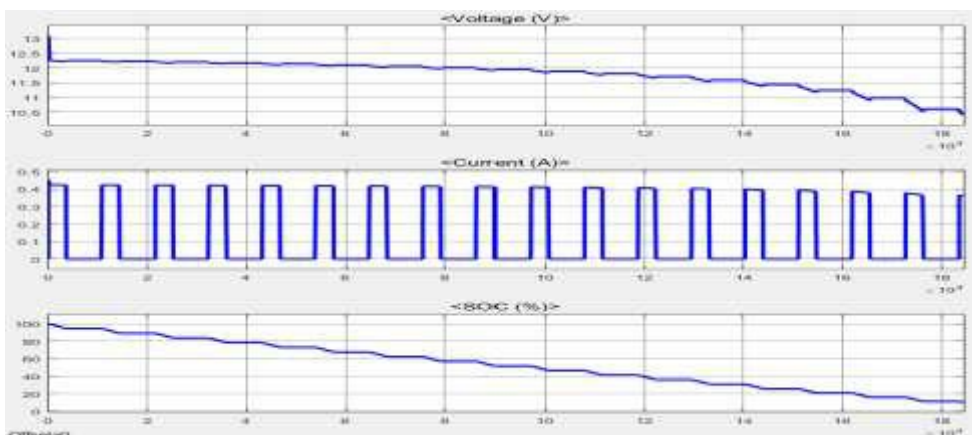


Figure 7. Waveforms for Constant Load

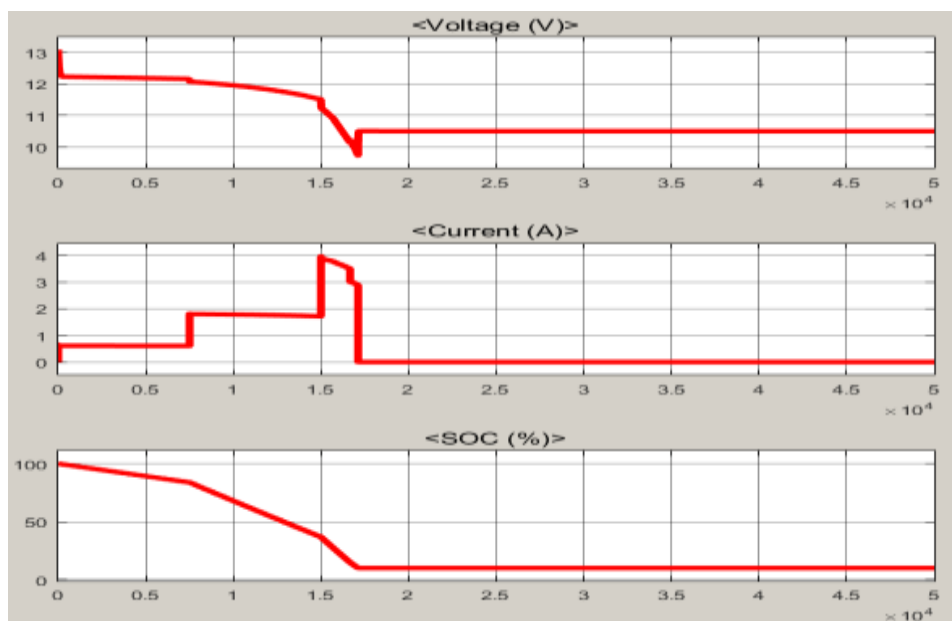


Figure 8. Waveforms for Variable Load

Figure 8 presents about the waveforms of variable load and depend on the current draws at about 0.61 A, 1.71 A and 3 A and the voltage is declined starting at 12.22 V, 10.14 V and until 8 V for the same duration. And the value of SOC is also decreased depend on the current draw high and low until it is reached at about 18%.

6. RESULT AND ANALYSIS:

6.1 Internal Resistance

The internal resistance was estimated by using Equation (11).

Hence, $R_{isim} = 0.217 \Omega$

6.2 V_{oc} Estimation-Constant load

The internal drop of the battery was calculated from the internal resistance and the load current. This drop calculated by Equation (12).

Hence, $V_{irsim} = 0.091 V$

TABLE I. V_{oc} with internal drop by Simulation-Constant load

Battery: 12V,7.5Ah, Load: 28.2 Ω				
Sr. No	V_t (V)	I (A)	V_{oc} (V)	V_{oc} (V) Calculated
1	12.24	0.42	12.25	12.331
2	12.00	0.41	12.01	12.091
3	10.4	0.36	10.41	10.491

6.3 V_{oc} Estimation for Variable load

On the similar lines of V_{oc} estimation for constant load, the variable parametric values were tabulated in Table II corresponding to simulation. Although the value of V_{oc} with internal drop changes the SOC % do not have any impact.

TABLE II. V_{oc} with internal drop by Simulation-Variable load

Battery: 12V,7.5Ah, Load: 20 Ω , 10 Ω ,5 Ω				
Sr. No	V_t (V)	I (A)	V_{oc}	SOC (%)
1	12.22	0.61	12.311	96.5
2	11.52	1.71	11.611	36.5
3	10.14	3.0	10.231	18

6.4 Comparison of SOC from CCM and combined CCM for Constant and Variable load

The total amount of energy released to the load in these 15 cycles is given by:

$E_{sim} = I \times T = 0.42 \times 15 Ah = 6.3 Ah$

The energy released to the load E_{sim} is equal to

$E_{sim} = \left(\int_0^T i_{\tau} d\tau \right)$
(13)

And, by using Equation (1) (9) and (10), the SOC was estimated and tabulated in Table III. When the battery runs for constant load (28.2), the SOC % is fairly accepted. But after running with variable loads the SOC% appear as negative percentage and the life cycle of battery can reduce as a result.

$SOC = \frac{SOC_1 + \dots + SOC_n}{n}$ (14)

TABLE III. Comparison of SOC from CCM and combined CCM for Constant and Variable load

Sr. No	Load (Ω)	SOC _t	η_d	SOC _{tc}	SOC Combined CCM
1	28.2	16 %	0.692	41.87%	25.94%
2	20	-22%	0.642	15.15%	

3	10	-242%	0.523	-78.86%	
4	5	-500%	0.467	-180.2%	-58.48%

7. CONCLUSION:

The modeling and simulation are carried out using the proposed method and equations of SOC. The proposed hybrid method consisting of coulombs counting, open-circuit voltage and Piker law to estimate the SOC has been the greatest solution. The simulation results carried out using Simulink had counter validity of the proposed SOC estimation technique. The result showed that the correction factor plays great role estimation of SOC. The analysis of simulation results shows clearly that the proposed method is suitable for the real-time estimation of SOC. The simulated value based on Coulomb Counting Method was 41.87% whilst that from proposed method is 25.94 % for constant load. For variable load, SOC were 15.15% -78.86% -180.2% respectively, and the result from proposed method is -58.48%. When SOC is run with combined SOC method and Coulomb Counting Method, there were a difference of 16.48% for constant load and 73.63%, -20.41% and -121.72% for variable load. If the SOC of battery is shown as negative percentage values, it can ruin the life cycle and life time of battery. By using estimation of combined SOC equation, the precious state of charge (SOC) can be obtained.

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