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NUMERICAL CURRENT INTEGRATION WITH INCIDENT OCV OBSERVATION FOR BATTERY STATE-OF-CHARGE ESTIMATION IN PHOTOVOLTAIC SYSTEMS

Faizal Arya Samman*, Khairul Jihadi, Muhammad Arif Fitrayadi Said and Syafaruddin

Department of Electrical Engineering
Universitas Hasanuddin
Jl. Poros Malino Km. 6, Bontomarannu 92171, Gowa, Indonesia
*Corresponding author: faizalas@unhas.ac.id

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Abstract. *This paper presents a new method to estimate the battery state-of-charge (SoC) in photovoltaic (PV) systems using numerical current integration algorithm with incident open circuit voltage (OCV) observation. The proposed methodology is more reliable compared to existing approaches in literature, especially under disconnect conditions. The existing stand-alone coulomb counting method is not robust during power reset of its electronic charger unit as well as during battery disconnection for protections or maintenance. Meanwhile, the traditional OCV charge estimations must isolate battery from the source and the load during OCV measurement, resulting in an incident power discontinuity. Voltage-based estimation itself without OCV measurement is not feasible for charging with ambient energy sources such as solar energy. We propose accordingly the combination of the numerical current integration with an incident OCV observation methods to improve the reliability of the existing battery SoC estimation methods. The experimental results present that the proposed techniques can estimate the battery SoC simply and effectively.*
Keywords: Power electronics, Battery state-of-charge estimation, Coulomb counting, Open-circuit voltage method, Numerical integration

1. **Introduction.** Renewable energy has been an important issue in recent years. Some renewable energy sources are ambient energy sources, i.e., the continuity of their constant availability cannot be predicted. Sunlight for instance as photovoltaic (PV) energy source is only available during daytime. Therefore, a battery system is sometimes needed to store the PV-based electric energy, such that it can be used at night. So far, new batteries with new materials and technologies have been developed. The important specifications of the battery are their ampere-hour capacity over weight ratio, and their life cycle.

Nevertheless, some PV-based power systems are not equipped with a battery, where an automatic transfer switch is used to switch the supply from existing grid, as the electric energy from the PV panels is not available. Some reasons of the battery absence are the high cost and low life cycle. The life cycle of a battery depends on the used technology to develop it (internal aspect) and also on the way to protect it from damage (external aspect). Battery protection can be effectively made when the battery lifetime model can be assessed well that can be used to predict its aging condition [1]. The use of a well-configured cooling system can potentially lengthen the battery lifetime [2]. Furthermore, there are two battery operating conditions that can lower the battery life cycle, namely over-charging and over-discharging or under-voltage discharging. Both operating modes must be avoided to lengthen the battery life cycle.

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In order to operate the batteries outside the aforementioned operating modes, we should be able to detect the signs indicating that the battery will come into the operating modes. To detect the operating condition, its state-of-charge (SoC) must be well estimated. SoC can be defined as the amount of electric charges stored in the battery. Physically, the electric charge (in coulomb) is difficult to measure. The possible parameters that can be measured are voltage, current and in any cases battery temperature. Equation (1) shows the general SoC estimation equation using the OCV method. The estimated battery charge is a function of open-circuit voltage (V_{OC}) measurement. The function can be realized using a look-table or an interpolation function.

$$S_{Ch} = f(V_{OC}) \tag{1}$$

Equation (2) shows the general SoC estimation equation using coulomb counting or ampere counting or current integration. Q_n is the nominal capacity, i.e., the maximum amount of electric charges that can be stored in the battery. $S_{Ch}(t-1)$ is the initial SoC estimation, and $i_B(t)$ is the current flowing to/from the battery.

$$S_{Ch}(t) = S_{Ch}(t-1) + \frac{1}{Q_n}\int_{t_0}^{t} i_B(t)dt \tag{2}$$

Battery SoC estimation using existing stand-alone coulomb counting method [3] is not robust and reliable. When power reset is applied to its electronic charger unit then the coulomb/current integration will disappear from the control program memory. This happens also when the battery is disconnected, and separately charged or discharged, or when the battery is replaced with a new battery with different initial SoC condition.

The traditional OCV-based estimation is not efficient, since the battery must be isolated from the source and the load during OCV measurements. Moreover, the voltage-based estimation, which is implemented without OCV measurement to avoid power discontinuity, is not feasible for charging with ambient energy sources such solar energy.

Based on those problems, a novel approach to estimating battery SoC is proposed in this paper. A numerical current integration is proposed to avoid power discontinuity, and is combined with an incident OCV observation to estimate correctly the initial battery SoC. The OCV is made only incidently when the system power is reset or when the battery is removed for maintenance purpose. As the system power is on or the battery is again on-system-grid after the aforementioned incidents, a single initial SoC estimation using OCV method is made and then followed by the numerical current integration method. The proposed technique can effectively improve the reliability of the existing battery SoC estimation methods.

The remaining parts of the paper are organized in the following sections. Section 2 presents the state of the arts of battery state-of-charge (SoC) estimation methods. Section 3 presents the hardware design and implementation as well as the design concept of the proposed SoC estimation method. The testing results of the hardware are presented in Section 4. Finally, the work is concluded in Section 5.

2. **State of the Arts of Battery State of Charge (SoC).** Table 1 presents the state of the arts of some existing battery SoC estimation methods. The table shows the battery SoC estimation method, the used battery type in the experiment or simulation. The table shows also the used experimental types namely simulation or real hardware test. Although Kalman-based and non-conventional SoC estimation methods, as shown in the table, result in more accurate SoC estimation, it is very complex to implement. As non-conventional method, neural and fuzzy methods require pre-training and prior knowledge about many battery state conditions, before the SoC estimation algorithm is constructed.

TABLE 1. Works related to the battery state-of-charge estimation methods

Ref., year	Battery SoC method	Battery type	Experiment type
[5], 2013	Neural Network (ANFIS)	Lead-Acid	Simulation
[4], 2015	Current Integration + OCV look-up table	NiCd, NiMH, Li-ion, lead-acid	Real hardware test
[6], 2016	OCV	Lead Acid	Simulation
[7], 2016	OCV + Kalman filter	Lead Acid	Simulation
[8], 2017	OCV + Kalman filter	Li-ion	Real hardware test
[9], 2017	H-inf. filter + unscented Kalman filter	Li-ion	Simulation
[10], 2017	Extended Kalman filter	Li-ion	Simulation
[11], 2017	Dual adaptive particle filter	Li-ion	Simulation
[12], 2017	Sliding mode observer	Li-ion	Real hardware test
[13], 2017	Classifier-based selected gain observer	Li-Iron-Phosphate ($LiFePO_4$)	Real hardware test
[14], 2016	Model-based estimation	Li-Iron-Phosphate ($LiFePO_4$)	Real hardware test
[15], 2017	Extended Kalman filter	Li-ion	Simulation
[16], 2017	Ampere Counting + Sliding mode + Fuzzy logic	Lead-Acid	Simulation
[17], 2017	Ampere Counting	not mentioned	Simulation
This paper, 2018	Current Integration + OCV interpolated	Lead-Acid	Real hardware test

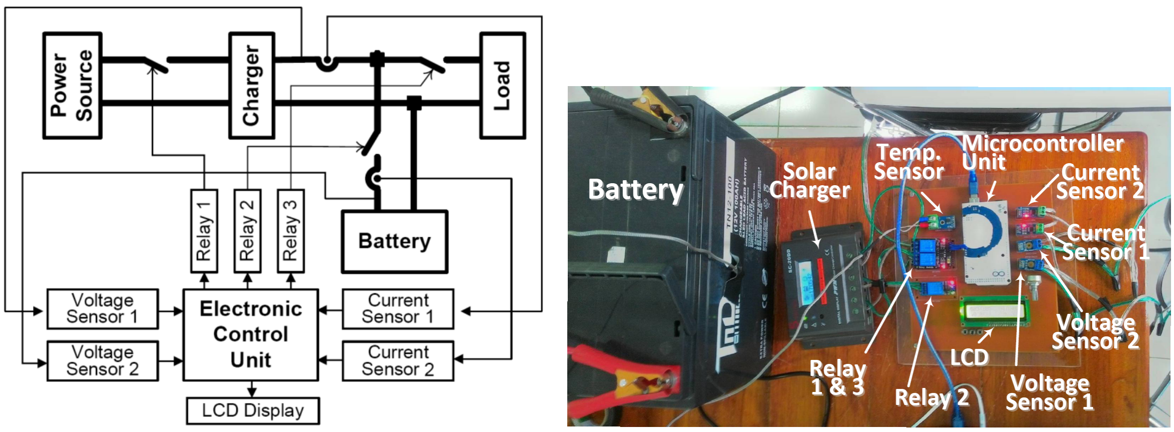
Principally, the battery SoC can be simply estimated from its open-circuit voltage observation. Our proposed method is almost similar to the work in [4] that combines current integration and OCV observation. The difference is that its SoC estimation is made based on a look-up table (LUT) approach, in which the OCV is the table index, while our proposed method uses a simple interpolation equation, in which the OCV is its independent variable and SoC is the dependent variable. The LUT approach has limitation, especially when any OCV data (intermediate OCV point) does not appear in the table.

Our approach, which uses an interpolation equation, is more convenient, where for each OCV point, the estimation can be simply calculated from the interpolation equation. Moreover, when it is implemented on a microcontroller, as the size of the LUT is larger, then its compiled program subroutine will require larger program memory size. The interpolation equation meanwhile will need smaller memory size when its computer program subroutine is compiled and embedded on the microcontroller program memory. Hence, our proposed SoC method contributes to its simplicity in terms of algorithm and computing efficiency, as well as its simplicity to implement.

Other battery SoC estimation methods are presented in Table 1 such as Kalman filter, sliding mode observer, sliding mode fuzzy logic, neural network or artificial neural net adaptive fuzzy inference system (ANFIS), and adaptive particle filter. Principally, all methods are very effective to estimate the battery SoC with certain degree of computing robustness and reliability. However, their computing complexity is higher than our proposed method, leading to higher computing power consumption.

3. Design and Implementation.

3.1. **Hardware.** The block diagram of the testing setup is presented in Figure 1(a). The power line is depicted as bold line in the figure. Three relays are used for system and



(a) Testing diagram (b) Hardware photograph

FIGURE 1. Hardware design and the photograph

battery protection. Relay 1 is used to isolate the power source from the system. Relay 2 is used to isolate the battery from the system, and Relay 3 is used to isolate the load from the system. When the open-circuit voltage of the battery will be measured, the Relay 2 will be open. Voltage and current sensors are used to measure the voltage and current at the charger and battery terminal, respectively. The SoC estimation algorithm is embedded on the electronic control unit. The photograph of the real hardware implementation is shown in Figure 1(b).

3.2. **The proposed SoC estimation method.** In this paper, two battery SoC estimation methods are proposed. The first one is a numerical current integration using Simpson Method with incident OCV observation, which is called NCI Simpson with OCV method. The other one is a numerical current integration using trapezoidal method with incident OCV observation, which is called NCI Trapezoidal with OCV method. The interpolated equation to approximate the battery SoC is shown in Equation (3). The terms $V_{b,\max}$ and $V_{b,\min}$ are the maximum and minimum battery voltages, respectively, and $V_{OC}(t)$ is battery open-circuit voltage observed at the time incident t.

$$S_{Ch}(t) = \frac{V_{OC}(t) - V_{b,\min}}{V_{b,\max} - V_{b,\min}} \tag{3}$$

The Simpson and trapezoidal terms are used to define that the numerical integration of the currents is approached using trapezoidal approximation, as shown in Equation (4) and Simpson approximation, as shown in Equation (5), respectively. The performances of both methods are compared with other methods, namely NCI Simpson and NCI Trapezoidal, both without OCV observation, as well as voltage-based SoC estimation method.

$$\int_{t_{n-1}}^{t_n} i_B(t)dt \cong (t_n - t_{n-1})\frac{i_B(t_n) + i_B(t_{n-1})}{2} \tag{4}$$

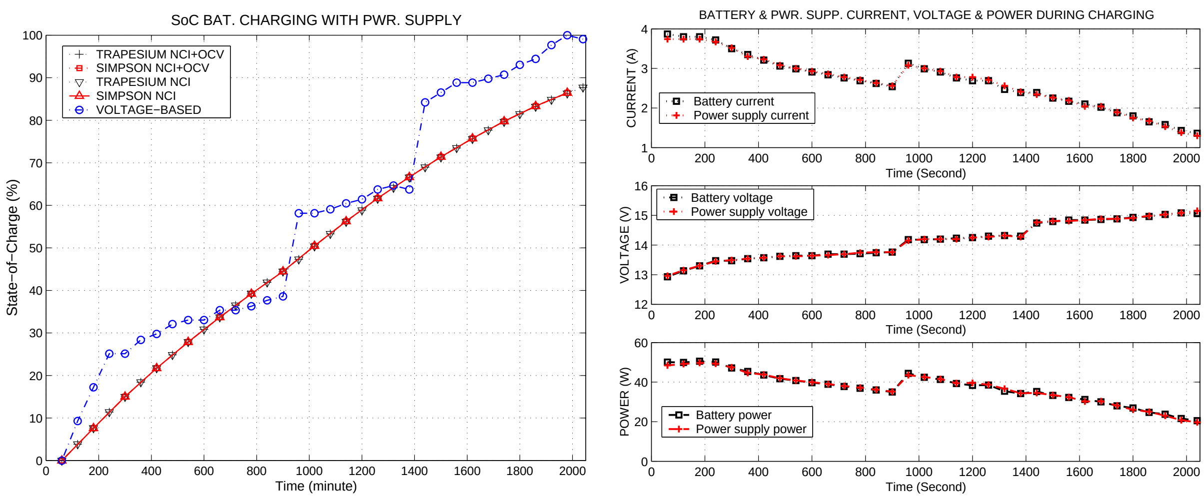
$$\int_{t_{n-2}}^{t_n} i_B(t)dt \cong (t_n - t_{n-2})\frac{i_B(t_n) + 4i_B(t_{n-1}) + i_B(t_{n-2})}{6} \tag{5}$$

Formally, the NCI Trapezoidal with incident OCV method is shown in Equation (6). At initial power on the SoC is estimated using Equation (3). Afterward, namely during normal operation, the SoC is estimated using Equation (4), where in this case, $S_{Ch}(t_{n-1}) = \frac{V_{OC}(t_n) - V_{b,\min}}{V_{b,\max} - V_{b,\min}}$. The formal model of the NCI Simpson with incident OCV method is presented by replacing the sub equation in Equation (6) for normal operation case with Equation (5).

$$S_{Ch}(t_n) = \begin{cases} \dfrac{V_{OC}(t_n) - V_{b,\min}}{V_{b,\max} - V_{b,\min}}; & n = 0 \ (\textit{initial power on}) \\ S_{Ch}(t_{n-1}) + (t_n - t_{n-1})\dfrac{i_B(t_n) + i_B(t_{n-1})}{2}; & n > 0 \ (\textit{normal operation}) \end{cases} \tag{6}$$

4. **Testing Results.** In order to see the performance of the SoC algorithm, then we implement directly the real in-circuit testing. Three testing modes are made, i.e., SoC estimation testing during charging process using electric power sources from power supply and from PV panel, and SoC estimation testing during discharging process.

Figure 2(a) presents the SoC estimation testing results using the NCI with trapezoidal integration combined with incident OCV method (Trapesium NCI+OCV), the NCI Simpson integration combined with incident OCV method (Simpson NCI+OCV), the NCI with trapezoidal integration method (Trapesium NCI), NCI with Simpson integration method (Simpson NCI) and the voltage-based method during charging process using an electric power source from a power supply. In this test experiment, the charging parameters rates are relatively constant. The Trapesium NCI+OCV, Simpson NCI+OCV, Trapesium NCI and Simpson NCI present similar performance, where the SoC tends to increase linearly. Meanwhile, the voltage-based method presents nonuniform rate of SoC change.

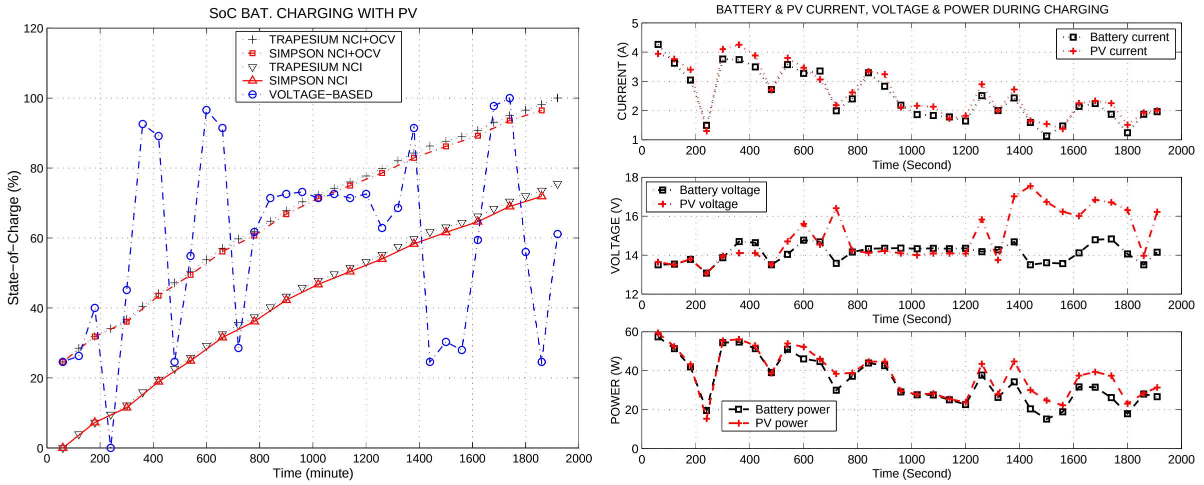


(a) State-of-charge (b) Current, voltage and power

FIGURE 2. Battery's SoC, current, voltage and power measurements during charging process using power supply

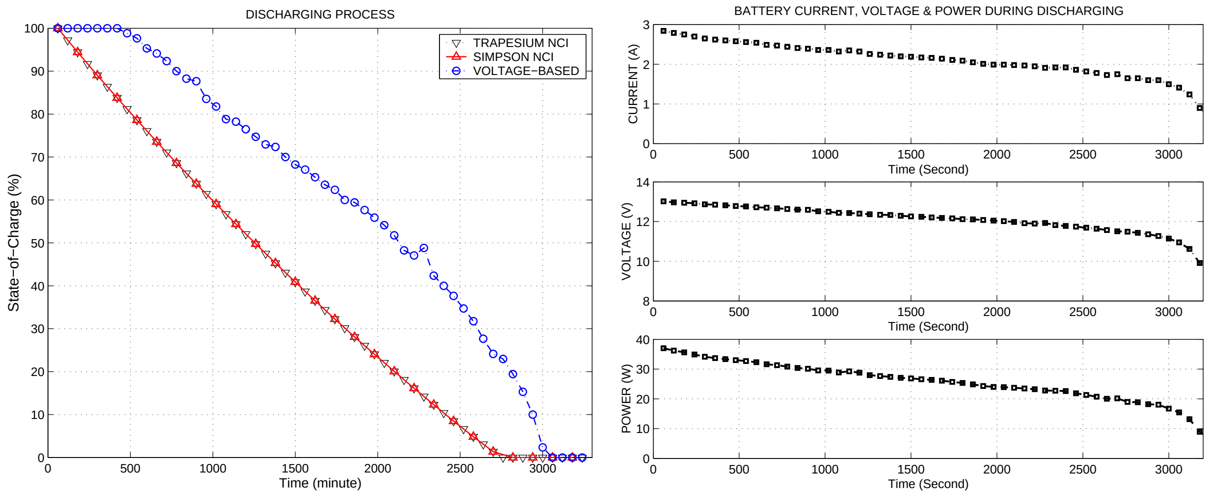
The battery's and power supply's current, voltage and power of the charging process are presented Figure 2(b). As seen from the figure, the charge current tends to be lower as the SoC is increased, while the battery voltage increases linearly. This condition is certainly acceptable, because when the battery is nearly full, the amount of electric charges flowing to the battery will be lower or approach saturating condition. However, the battery terminal voltage will be higher and saturate at any maximum voltage point. In the figure, we can see that the battery voltage approaches 15V steady-point.

Figure 3(a) presents the SoC estimation using the five SoC estimation methods mentioned in the previous subsection during charging process with electric power source from a PV panel. In this experimental test, a non-empty battery is used, or the battery has been charged about 22% before the testing is started. As the results, the Trapesium NCI+OCV and the Simpson NCI+OCV show the same correct SoC computation. The Trapesium NCI and Simpson NCI meanwhile start computation from zero SoC, because



(a) State-of-charge (b) Current, voltage and power

FIGURE 3. Battery's SoC, current, voltage and power measurements during charging process using PV panel



(a) State-of-charge (b) Current, voltage and power

FIGURE 4. Battery's SoC, current, voltage and power measurements during discharging process

SoC computing algorithm makes numerical current integration directly without measuring firstly the open circuit voltage of the battery. Hence, they missed the initial SoC value.

In this experiment test setup, the charging parameters rates are variably different depending on the climate condition that affects the power converted by the PV panel. The battery's and power supply's current, voltage and power of the charging process are presented Figure 3(b).

Figure 4(a) presents the SoC estimation during discharging process using the NCI with trapezoidal method, the NCI with Simpson method and the voltage-based method. As shown in the figure the NCI with Trapezoidal method and the NCI with Simpson method show the same estimation values, i.e., a curve that is almost linear. The SoC curve of the voltage-based method presents meanwhile deviation from the curve given by the NCI methods. Following the electric charge reduction in the battery, then the current, voltage and power curves tend to decrease to a certain value as shown in Figure 4(b).

5. **Conclusion.** This paper has presented the battery SoC estimation method that combines incident OCV observation and numerical current integration (NCI). To integrate current flow from/to battery, the discrete-time numerical integration methods are used. Voltage-based SoC estimation (without open-circuit measurement) is not suitable especially for charging process using ambient energy sources, since the battery voltage changes variably or randomly overtime.

OCV measurements for SoC estimation will isolate battery from the system resulting in power discontinuity during the open-circuit measurements. Therefore, in our method, the OCV observation is seldom made, i.e., only after battery replacement or initial power on, which are rare cases in real application run. Meanwhile, operating the NCI method alone is not reliable in a few cases. Therefore, combining the NCI and the OCV method, as presented in this paper, results in a more reliable SoC estimation.

The performance of the NCI Trapezoidal + OCV method and the NCI Simpson + OCV method is the same. However, the former is better in terms of its lower computing cost due to its simpler approximation equation.

In the future, the battery SoC estimation will be integrated with a battery protection mechanism in the single electronic control unit. The concept of *Internet-of-Things* for the battery SoC observation by users will also be applied. The user can receive online information about the battery state, including some warnings when the corresponding automatic battery protection does not work properly. Hence, the users can hand over a manual protection via Internet or a mobile application to secure the battery life cycle.

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