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State-of-Charge Evaluation for Real-Time Monitoring and Evaluation of Lithium-Ion Battery Performance

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Abstract

Nowadays, lithium-ion batteries have been garnered significant attention as the primary energy source for energy storage devices within the renewable energy sector. Key concerns surrounding the utilization of lithium-ion batteries include ensuring satisfactory design lifespan and safe operation. Consequently, there's been a practical need for battery management. Responding to this demand, various battery state indicators have seen widespread implementation. Among the battery state indicators, accurate state-of-charge (SOC) estimation is an essential requirement for many situations where Li-Ion batteries (LiBs) are used. The effectiveness of a Battery Management System (BMS) safeguards the battery against deep discharging and over-charging to maximize its lifespan. This paper conducts state of charge (SOC) evaluation of a Li-ion battery module (12V, 13 Ah lithium titanate oxide (LTO) battery) for battery management systems (BMS) in energy storage systems (ESSs).

A. Introduction

Environmental concerns and the depletion of fossil fuel resources are driving the transition from traditional fossil fuels to renewable energy sources [1,2]. With their decreasing costs, extended lifespan, and high power and energy densities, lithium-ion batteries (LIBs) have emerged as the primary power source for most electric vehicles (EVs) [3–5]. The global adoption of EVs is projected to surpass 300 million by 2030, necessitating a corresponding increase in the installed capacity of LIBs to approximately 3000 GWh [3]. Given the voltage and capacity constraints of individual cells, the construction of battery packs comprising numerous cells in parallel or series configurations is commonly used to meet the demands of high-power and high-energy applications [8,9]. Effective management of these large-scale battery packs, necessitates the implementation of advanced Battery Management Systems (BMS) to ensure their safe and efficient operation through control, monitoring, and optimization processes [10].

As a crucial function within Battery Management Systems (BMS), state estimation serves as a vital monitoring tool for power systems. This process involves estimating various key parameters of the battery, including the state-of-charge (SOC) [11]. Given the inherent limitations in directly measuring internal battery states, such as voltage, current, and temperature, estimation techniques rely on indirect signals. However, the complex nature of electrochemical reactions within batteries results in nonlinear relationships between internal states and external signals, particularly evident under challenging operational conditions [9]. Furthermore, battery degradation over time poses a significant challenge to the reliability of state estimation, complicating the task further. Hence, achieving accurate state estimation remains a considerable technical hurdle, especially considering the evolving performance characteristics of batteries with aging. Ensuring stable and precise estimation throughout the battery's lifecycle necessitates innovative approaches and rigorous methodologies [12].

The state estimation technology applied to lithium-ion batteries constitutes a fundamental aspect of Battery Management Systems (BMS), particularly in the context of ensuring the functionality and safety of batteries for energy storage systems (ESSs). This paper offers a comprehensive review of the current state, technical hurdles, and lithium-ion battery state of charge (SOC) estimation. The findings of this research serve as a valuable resource for battery state of charge (SOC) estimation in battery management systems.

The evaluation of State of Charge (SOC) plays a pivotal role in the real-time monitoring and evaluation of lithium-ion battery performance. SOC serves as a key indicator of the remaining energy stored within the battery, providing critical insights into its current operational status. Real-time monitoring systems continuously track SOC levels, allowing for precise management of energy usage and enabling timely interventions to optimize battery performance. By integrating SOC evaluation into monitoring frameworks, operators can effectively monitor battery health, anticipate potential issues such as overcharging or deep discharging, and ensure optimal utilization of battery capacity. This close relationship between SOC evaluation and real-time monitoring enables proactive maintenance strategies, enhances battery reliability, and prolongs overall battery lifespan in various applications, ranging from portable electronics to electric vehicles and renewable energy storage systems.

B. Approaches to State Estimation

Battery State of Charge (SOC) is typically characterized as the percentage of the battery's present remaining capacity in relation to its rated capacity, usually at a particular discharge rate [2]. This value is expressed as:

$$SOC = Q/C\_N \times 100\% \quad (1)$$

In the standard charging and discharging process, the state of charge (SOC) of a battery is determined by the ratio between the current remaining battery capacity (Q) and its rated capacity (CN). At the point of complete discharge, when the battery is entirely depleted, the SOC is recorded as 0. Conversely, when the battery reaches full charge, the SOC is indicated as 100%.

The state of charge (SOC) of a battery serves as a foundational element for various other state estimations, and it is subject to the influence of multiple factors. These factors include the rate of charging and discharging, the number of charge-discharge cycles, ambient temperature conditions, and the aging process of the battery [7].

The State of Health (SOH) estimation performed by the Battery Management System (BMS) is crucial for the efficient operation of batteries in electrode production and manufacturing processes. Currently, SOH of batteries is determined by factors such as battery capacity, charge status, and internal resistance. Various definitions of SOH have been proposed, considering these aspects [5–7]. In this study, SOH is defined based on the proportionality between the current maximum capacity that can be stored and the rated capacity of the battery [2], expressed by the following equation:

$$SOH = C\_aged/C\_rated \times 100\% \quad (2)$$

where Caged is the maximum battery capacity that the battery can currently store and Crated is the battery’s rated capacity.

State-of-power (SOP) is typically defined by its peak power capacity. This refers to the maximum power that a battery can either absorb or discharge within a given time frame, constrained by factors such as voltage, current, and state of charge (SOC). In the context of electric vehicle (EV) operation, the Battery Management System (BMS) continuously updates the SOP in real-time. This enables assessment of whether the battery can effectively fulfill power requirements during instances such as vehicle acceleration or uphill driving [3]. SOP serves as a crucial indicator of the battery's ability to accept or deliver energy swiftly without breaching predetermined design constraints.

State of Energy (SOE) denotes the remaining energy stored within the battery [10], correlating with both the battery's discharge capacity and its voltage during discharge. In contrast to State of Charge (SOC), SOE is particularly relevant for estimating the driving range of electric vehicles (EVs) [6]. SOE is categorized into two distinct types. The first type defines SOE as the Theoretical Residual Energy (TRE) of the battery, while the second type defines SOE as the Residual Discharge Energy (RDE) of the battery [9]. TRE signifies the energy that can be released when the battery is discharged to SOC = 0 with minimal discharge current. On the other hand, RDE represents the energy that the battery can deliver when discharged to the cutoff voltage under specific load conditions and ambient temperatures.

The task of battery state estimation holds significant importance within its management system. The state of charge serves as a crucial indicator of the battery's energy level following periods of use or extended periods of inactivity, providing insights into battery life expectancy or remaining usage time. Additionally, the state parameters reflect the operational conditions of the battery during its use [12]. Various estimation methods are employed to assess the battery state under different operating conditions. Prior to state estimation, the state parameters are defined, encompassing state of charge, state of energy, state of power, state of health, and remaining useful life. Subsequently, the primary factors influencing the state are analyzed, along with algorithm fusion and comparison. Parameter measurement technology is then integrated into the analysis of balancing control theory and temperature regulation. In terms of estimation method analysis, foundational techniques such as open-circuit voltage and ampere hour integral are examined. Various methods for state estimation of a rechargeable battery are described in Table 1.

Table 1. Methods for State Estimation of a Rechargeable Battery

No.	State Estimation	Methods	
1	SOC Estimation	1. Impedance method	
		2. Discharge test method	
		3. Ampere-hour (AH) method	
		4. Open circuit voltage (OCV) method	
		5. SOC estimation method based on equivalent circuit model (ECM)	
		6. SOC estimation based on an electro-chemical model	
		7. SOC estimation based on the black box model	
2	SOH Estimation	1. Model driven method	i. Empirical Model
			ii. Semi-Empirical Model
			iii. Mechanism Model
		2. Data driven method	
3	SOP Estimation	1. Characteristic mapping method	
		2. Experimental method	
		3. Limiting conditions method.	
4	SOE Estimation	1. Direct calculation method	
		2. Power integration method	
		3. Model-based filtering method	
		4. OCV method	
		5. Machine learning method	
		6. Joint estimation method	
		7. Prediction-based method	

C. Research Method

The structure of the proposed simulation model is illustrated in Figure 1. There are six subsystems that represent the battery cells. As shown in figure 1, six battery cells (2V, 13Ah lithium titanate oxide (LTO) battery) are connected in series to form a battery module (12V, 13Ah lithium titanate oxide (LTO) battery).

In this model, the value of SOC is managed to stop when it falls to 5%. 2-D lookup tables are used to characterize the required parameters of the battery.

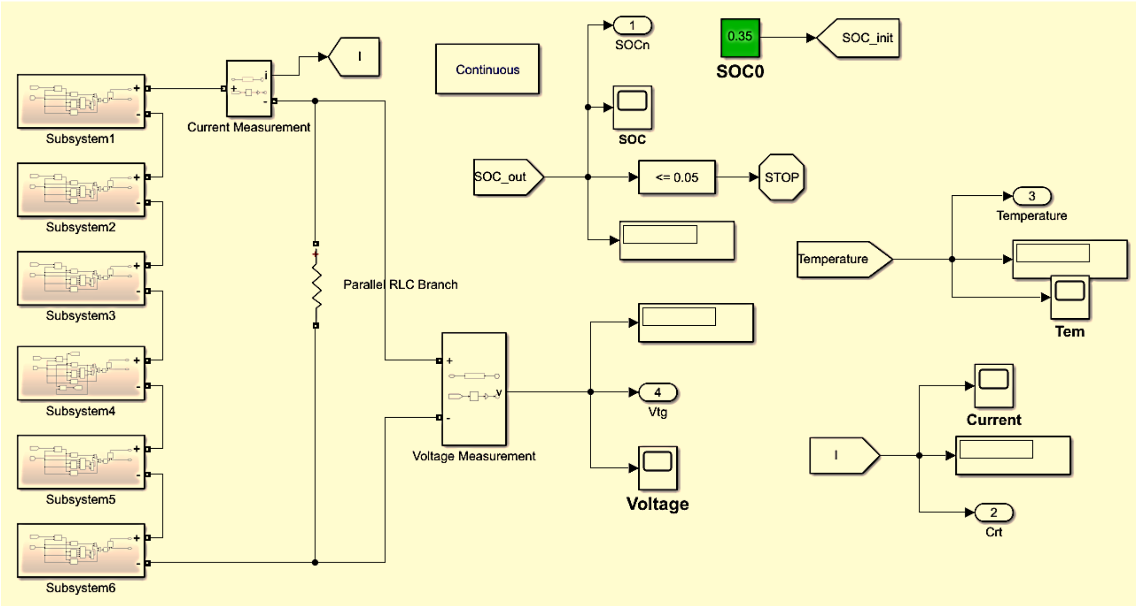


Figure 1. The Proposed Simulation Model

The structure of a subsystem of the proposed simulation model is depicted in Figure 2. A subsystem represents only one battery cell. The OCV, R_1, R_2, C_1, C_2, and R_S values are determined based on the results obtained from pulse discharge testing (PDT) conducted at a temperature of 30°C. Within this subsystem, 2-D lookup tables are employed to characterize the OCV, R_S, and the parameters of RC parallel networks. The quantities of OCV, R_S, and RC parallel networks (R_1, C_1, R_2, and C_2) are treated as variables dependent on both current and state of charge (SOC). The most appropriate values are determined through the utilization of the interpolation-extrapolation lookup method within the 2-D lookup table.

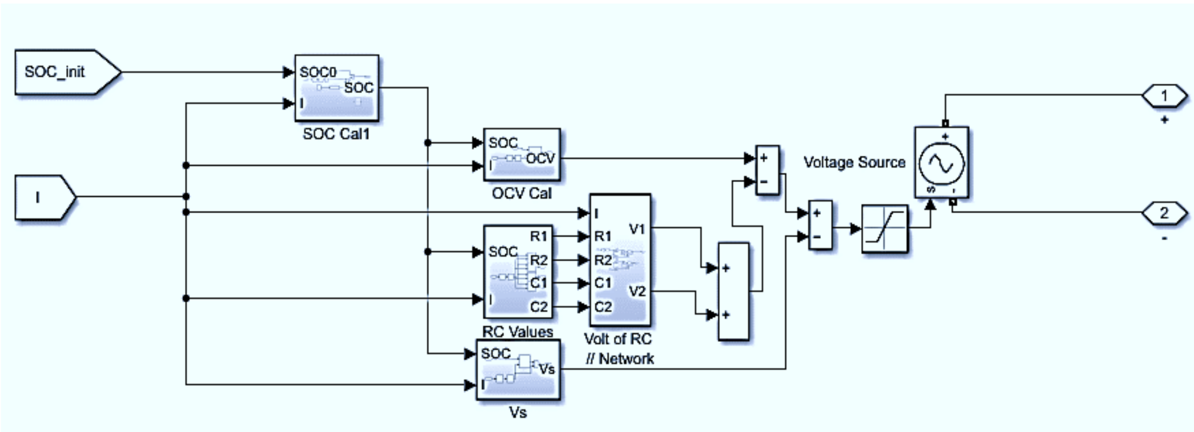


Figure 2. A Subsystem of the Proposed Simulation Model

The structure of an expanded subsystem of the proposed simulation model is shown in Figure 3. An expanded subsystem is composed of five sections; 1. State of Charge (SOC) estimation, 2. Open Circuit Voltage (OCV) evaluation, 3. The

Parameters of RC Parallel Networks, 4. Voltages of RC Parallel Networks Calculation and 5. Voltage Drop from DC Internal Resistance (V_0) Calculation.

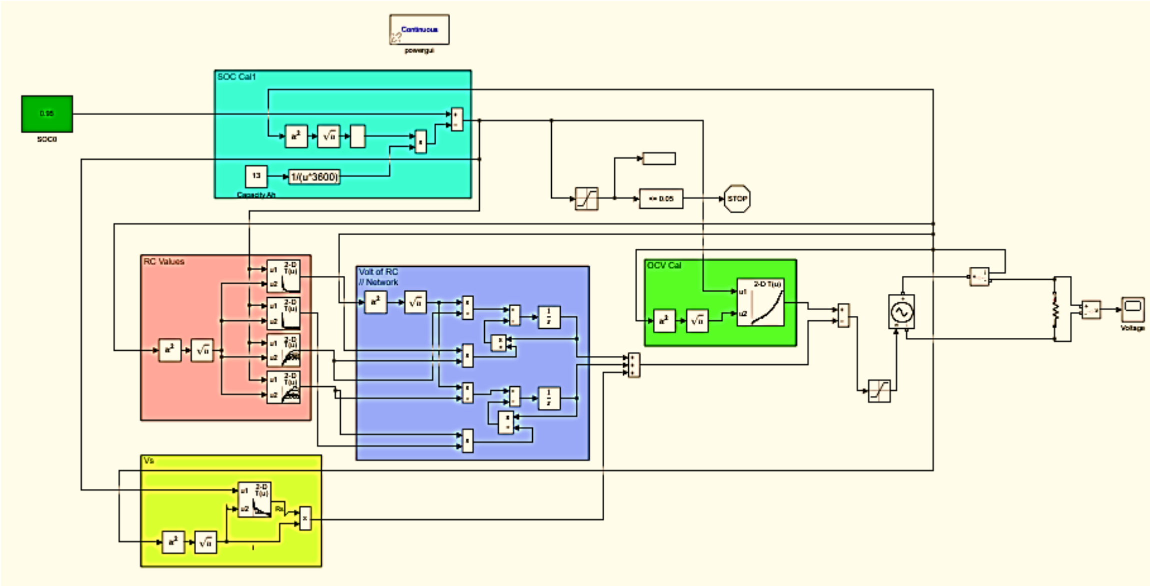


Figure 3. An Expanded Subsystem of the Proposed Simulation Model

The following equation (3) is utilized for the calculation of the State of Charge (SOC) of the battery.

$$SOC_n = SOC_0 - \int (I \times 100)/(\alpha^U \times 3600)\, dt \quad (3)$$

The inputs of the subsystem consist of the current (I) and the initial State of Charge (SOC_0) [4]. The usable capacity (α^U) is adjusted based on the current magnitude. A 2D lookup table is employed to ascertain the impact of capacity on the current of the battery cell.

For the dynamic behaviors of a battery, the proposed construction of a second-order Thevenin equivalent circuit model is depicted in Figure 4.

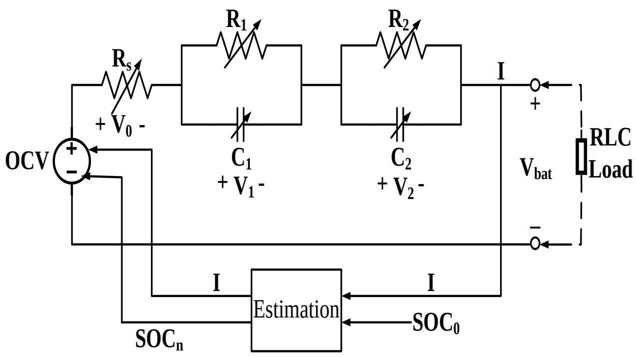


Figure 4. Second Order Thevenin Equivalent Circuit Model

Where, SOC_0 represents the state of charge of a battery at the initial state, and SOC_n denotes the state of charge of the battery in real-time. The current and initial state of charge (SOC) of the battery serve as inputs to the system, with a resistive load connected to the system. Outputs of the system, such as OCV, V_0, V_1, V_2, and V_{bat}, can be estimated using the Simulation Model.

In this paper, the current pulse method is employed to parameterize and develop a model of a 13 Ah lithium titanate oxide battery. The values of R_S, R_1, R_2, C_1, and C_2 are variable and contingent upon the current and State of Charge (SOC) of the battery. The values of current and SOC of the battery fluctuate depending on the types and magnitude of loads [5].

D. Result and Discussion

In this paper, a battery model is developed for a 12V, 13 Ah lithium titanate oxide (LTO) battery module. The structure of the proposed simulation model (initial SOC=95%, Load resistance = 1) is illustrated in Figure 5.

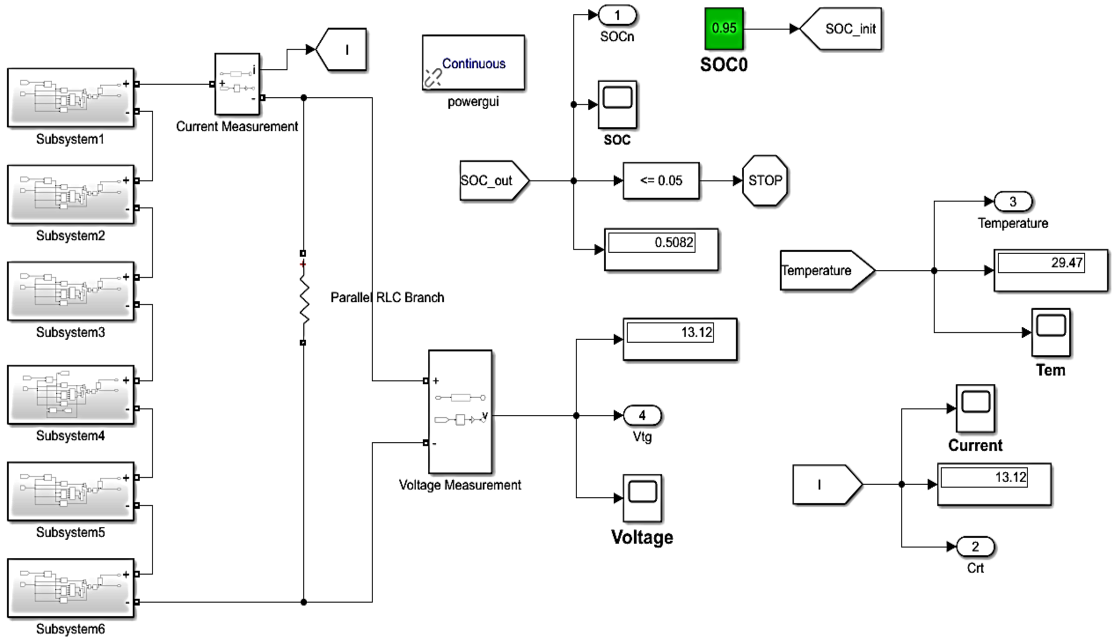
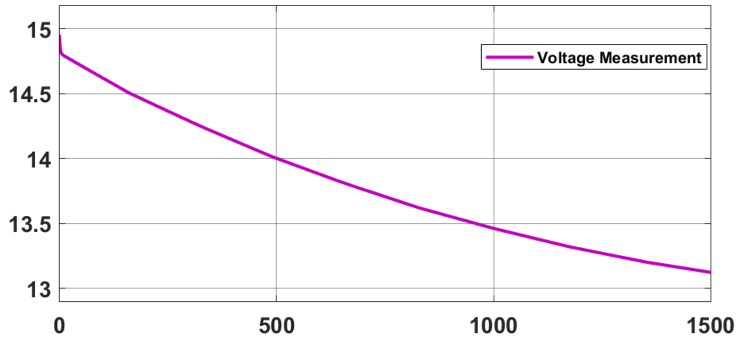
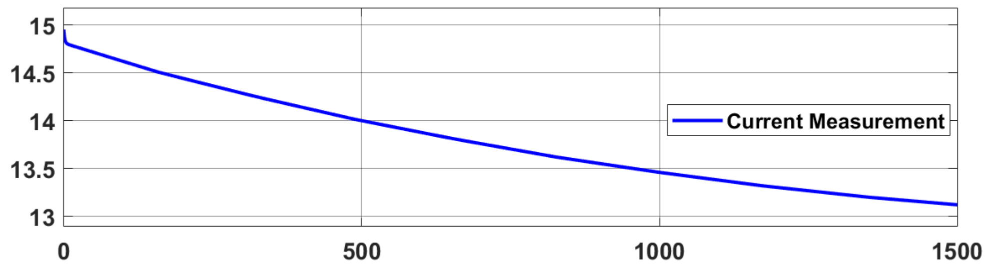


Figure 5. The Proposed Simulation Model for a 12V, 13 Ah lithium titanate oxide (LTO) battery module

By running the MATLAB/simulation shown in figure 5, the result figure 6 can be obtained. For the research, the simulation model depicted in Figure 1 has to run many times by changing the values of SOC and/or load resistance.



(a)



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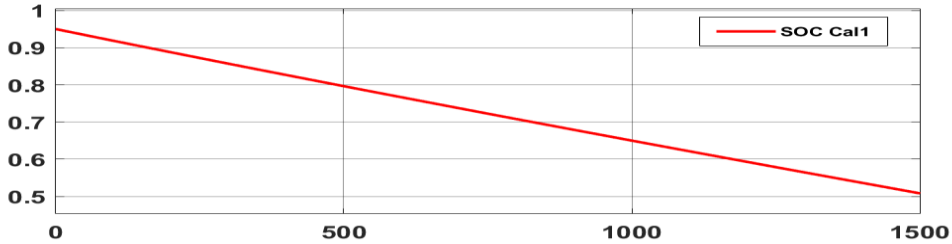
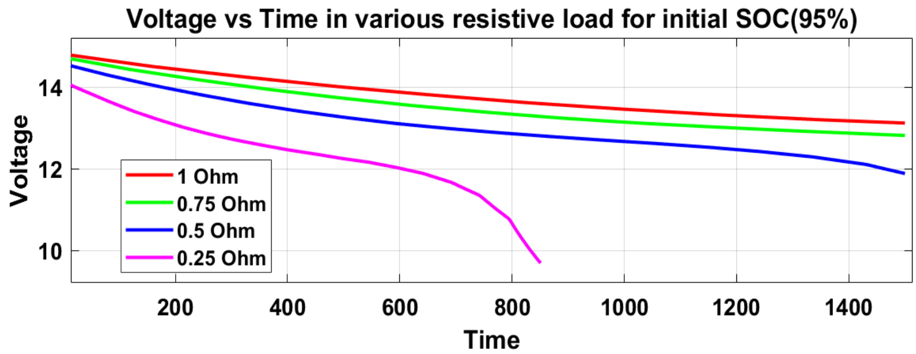


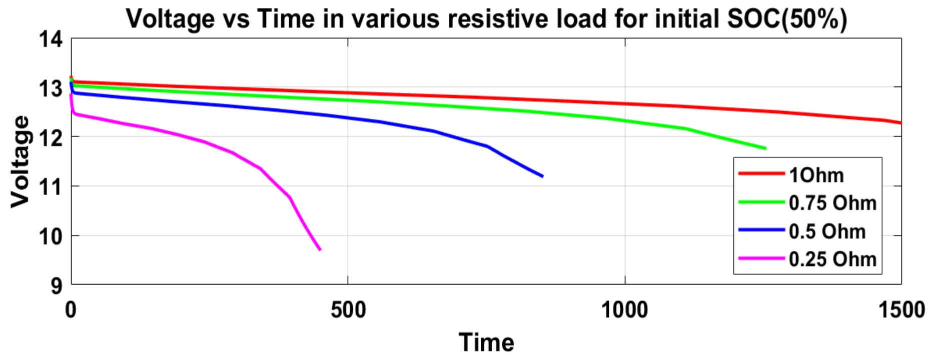
(c)

Figure 6. The result figure of (a) Time vs Voltage (b) Time vs Current (c) Time vs SOC

In this paper, the result values of voltage, current and SOC can be obtained by changing the values of SOC (95%, 50% and 25%) for the values of load resistance (1Ω, 0.75Ω, 0.5Ω and 0.25Ω). The result figures of Voltage vs Time in various resistive load for initial SOC (a)95% (b) 50% (c) 25% are shown in figure 7.



(a)



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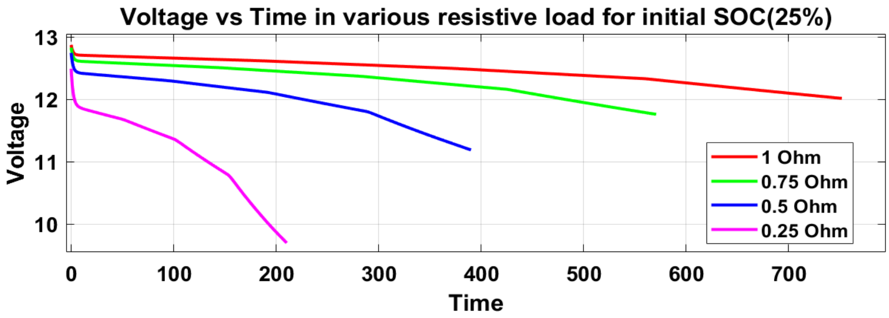
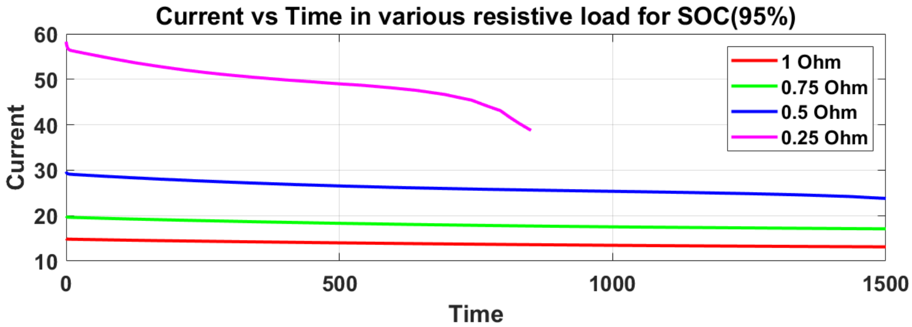


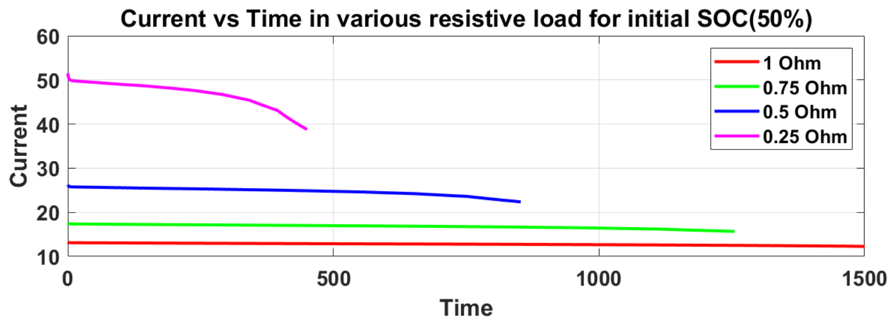
(c)

Figure 7. The result figure of Voltage vs Time in various resistive load for initial SOC (a)95% (b) 50% (c) 25%

By comparing the result figures a, b and c of figure 7, changing the value of voltage can be seen with the values of SOC and load resistance. The result figures of Current vs Time in various resistive load for initial SOC (a)95% (b) 50% (c) 25% are shown in figure 8.



(a)



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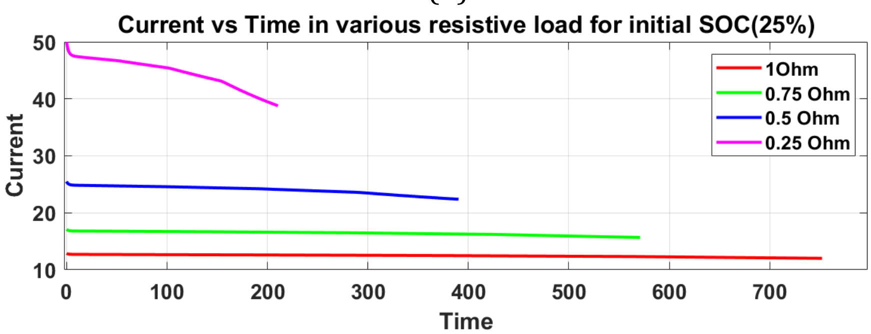

(c)

Figure 8. The result figure of Current vs Time in various resistive load for initial SOC (a)95% (b) 50% (c) 25%

According to the results depicted in Figures a, b, and c in Figure 8, the current value is observed to vary alongside the State of Charge (SOC) and load resistance values. The result figures of SOC vs Time in various resistive load for initial SOC (a)95% (b) 50% (c) 25% are shown in figure 9.

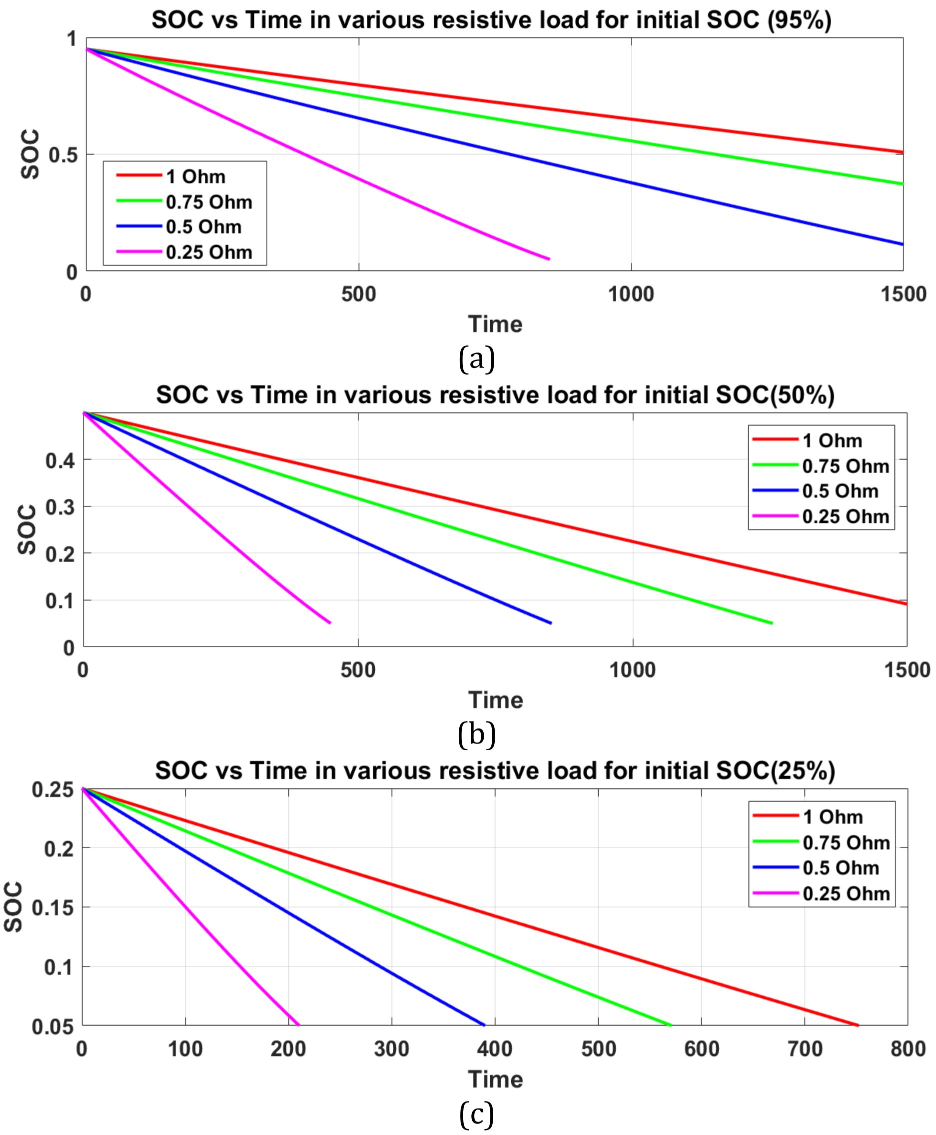

Figure 9. The result figure of SOC vs Time in various resistive load for initial SOC (a)95% (b) 50% (c) 25%

According to the results depicted in Figures a, b, and c in Figure 9, the State of Charge (SOC) value is observed to vary with the load resistance values. As depicted in Figures 6, 7, 8, and 9, the test results demonstrate the battery output voltages, currents, and real-time State of Charge (SOC). In this paper, simulation tests were conducted for a model of a 12V, 13 Ah lithium titanate oxide (LTO) battery module. According to the results, two distinct scenarios can be discerned in relation to a battery under varying loads:

1. Large resistive load: In this scenario, when a large resistive load is applied to the battery, the State of Charge (SOC), open-circuit voltage (VOC), and

battery voltage (Vbat) will be high, while the current of the battery will be low. This is because the load draws less current from the battery, allowing the voltage to remain high. The SOC reflects the remaining capacity of the battery, which would be high because less current is being drawn.

2. Low resistive load: Conversely, when a low resistive load is applied to the battery, the SOC, VOC, and Vbat will be low, while the current of the battery will be high. With a lower load, more current is drawn from the battery, which reduces the voltage. As a result, the SOC decreases because more of the battery's capacity is being utilized.

These behaviors are typical of battery systems and are governed by the principles of electrochemistry and Ohm's law.

The proposed simulation model demonstrates accuracy in real-time monitoring and evaluation of lithium-ion battery performance. While initially designed for a 12V, 13 Ah lithium titanate oxide (LTO) battery module, this model's versatility allows for scalability through series and/or parallel connection of battery cells to form larger battery modules or packs. Satisfactory simulation tests and results can be obtained by adjusting the values of SOC or the size, type, or connection configuration of loads for various purposes.

Furthermore, the applicability of this proposed battery model extends beyond lithium titanate oxide batteries to encompass other battery types, including various types of Li-ion batteries, Nickel-cadmium batteries, Nickel Metal Hydride batteries, Alkaline batteries, and lead–acid batteries. This adaptability underscores the model's potential utility across diverse battery technologies and applications, thereby contributing to advancements in battery research, development, and performance optimization.

E. Conclusion

In conclusion, the accurate evaluation of State-of-Charge (SOC) plays a critical role in real-time monitoring and evaluation of lithium-ion battery performance. Precise SOC estimation is essential for optimizing the utilization of battery capacity, ensuring efficient energy management, and prolonging battery life. By accurately monitoring SOC, potential risks such as overcharging or over-discharging can be mitigated, enhancing both the safety and reliability of lithium-ion battery systems. Furthermore, accurate SOC evaluation facilitates the development of advanced battery management systems (BMS) and enables informed decision-making for optimal battery operation. Continued research and development in SOC estimation techniques are essential to further improve the performance and reliability of lithium-ion batteries across various applications, including electric vehicles, renewable energy storage systems, and portable electronics.

F. Acknowledgment

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