**Smart SOC estimation for Lithium-Ion batteries in Hybrid Energy Storage for EVs**

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**Abstract.** The critical aspect of battery management systems (BMS) is the state of charge (SOC) in electric vehicles (EV), the accurate estimation of the state of charge directly influences range estimation, energy efficiency, and battery longevity. Soc represents the amount of available charge in a battery relative to its full capacity. While the battery cells is nonlinear dynamics, the electrochemical complexities of lithium iron phosphate (LFP) SOC cannot be measured directly and must be estimated using sophisticated algorithms. The estimation technique integrates an equivalent circuit model (ECM) with parameter tuning and an unscented Kalman filter (UKF). The demands of the battery management and optimized state of charge demands is increasing the increasing use of electric vehicles. The SOC estimation approach for LI battery in a hybrid energy storage system that integrates superconducting magnetic energy storage with a battery system. In a real-time application, ensuring that improved the battery life cycle and efficiency. SOC effective Electric vehicles and battery management system. This paper refers to the SOC estimation using an unscented Kalman filter combined with an equivalent circuit model. The aim is accuracy in SOC estimation.

**Keywords:** Battery management systems, electric vehicles, state of charge, Kalman filter, equivalent circuit model.

**INTRODUCTION**

In recent years, the increasing demand for Electric Vehicles in the automotive field has guided the demand for efficient and unfailing battery management systems [1]. Lithium-Ion batteries (LiBs) are the preferred choice for electric vehicles because Lithium-Ion batteries have long cycle life, high energy density and efficiency [2]. The state of Charge states how much energy is present in the battery, but accurately determining the remaining energy is technically difficult. The SOC of the battery monitors remaining capacity, which causes a harmful situation like over charging or deep discharging and also extends the battery’s lifespan and adjusts its performance across various power management scenarios [3]. Estimating the SOC of a Lithium-Ion battery is possible, but doing this operation is not easy due to the non-linear and unpredictable way the battery behaves, along with external factors like temperature changes and repeated charging and discharging cycles, which make it difficult to achieve highly precise SOC measurements [4].

At the time of combining lithium-ion batteries with Superconducting Magnetic Energy Storage in a Hybrid Energy Storage System, it is difficult to manage and coordinating the power delivery between these two individual technologies [5]. Current research on SOC estimation primarily focuses on methods such as coulomb counting, open circuit voltage .equivalent circuit models with kalman filter to improved accuracy. A new method to more accurately estimate the SOC of a battery for hybrid energy storage, its combination of fuzzy sliding mode system to minimize the errors improve real-time adaptability, charging and discharging time, extend the life span of batteries used in electric vehicles [6]. There we are using for SOC estimation electrochemical models, equivalent circuit models and data-driven techniques. For handling the system uncertainties, the EKF and UKF methods [7]. These methods rely heavily on model accuracy and can struggle with parameter variability. Nowadays deep learning techniques such as LSTM and Artificial neural networks are capturing complex battery dynamics. This paper studies charging techniques, including CC-CV, pulse charging, and multistage charging [8]. Optimization techniques like fuzzy logic and temperature-based charging remain underexplored. This study contributes by comparing CC-CV and CT-CV techniques, emphasizing temperature regulation.

Various SOC estimation methods have been explored like coulomb counting, voltage-based, and kalman filter-based approaches [9]. SOH estimation is a greater challenge for battery degradation as it is nonlinear and dependent on multiple factors like c-rate and temperature [10]. This paper is based on a hardware module for SOC/SOH estimation and the need for real time efficiency and accuracy. UPS configurations mean AC-to-DC and DC-to-AC convert stages, leading to energy losses [11]. The DC UPS solution reduces power conversion losses. For battery monitoring using Coulomb counting-based SOC estimation methods. This study integrates real-time SOC estimation with a DC UPS system to enhance power reliability. The SOC estimation methods like coulomb counting and OCV based estimation are used for limited by error accumulation and reliance on predefined battery characteristics [9]. Here, we use Kalman filter methods for battery SOC and SOH by integrating battery models with real-time measurements. For the longevity of lithium-ion batteries and optical performance in electric vehicles using SOC.

**METHODOLOGY**

This study aims to precisely estimate the SOC of a LEP battery cell by utilizing an equivalent circuit model that is carefully tuned through optimisation techniques, and then further refined using an UKF for improved accuracy in real time. In battery-charging applications, both open-loop and closed-loop control methodologies are essential. Open-loop charging functions with a constant current and voltage, while closed-loop charging regulates temperature and voltage consistently. This guarantees efficient and secure charging while averting overheating. The approach employs a PID controller to manage temperature and current. The charging duration is assessed to ascertain the time required for the battery to attain full charge. An initial evaluation of the battery's State of Health and State of Charge is performed prior to commencing the charging procedure.

The assessment of state of charge also depends on open-circuit voltage measurements. When the circuit is open, the voltage attains its peak, rendering it advantageous for initial state of charge estimate. Upon complete battery charge, the mechanism autonomously disengages to avert overcharging and superfluous discharge. An external power source charges the superconducting magnetic energy storage device by transmitting a DC current through a superconducting coil, therefore storing energy. Both charging and discharging coils are essential for effective energy transmission. An approach for State of Charge estimate based on a Sliding Mode Observer is utilized to enhance precision. This approach uses a second-order RC equivalent circuit model to depict battery behavior, with simulations conducted using COMSOL Multiphysics software. A fuzzy sliding mode observer is further incorporated to improve state of charge estimate for electric car batteries. A second-order Thevenin equivalent circuit model is utilized, and the fuzzy sliding mode observer aids in reducing estimate errors, resulting in enhanced battery management reliability.

**SYSTEM DESCRIPTION**

The flowchart shown in Figure 1 shows the optimization of SOC in Lithium – Ion Batteries for electric vehicles. Here Lithium Ion – Battery take as a primary energy source. At the time of battery charging and discharging time some changes is happens in performance. To maintain the issues, SOC is implemented to control the performance. When the battery is very less at that time SOC indicate the ratio (<40%) and DC source will be used. When the battery is overcharged at that time SOC exceeds 80% which help to select the battery to be use. Here energy management system (EMS) also plays a significant role to maintaining power flow among the Lithium – Ion – Battery and motor controller. The bi-directional converter connected as a series connection to regulate the voltage levels. The battery management system (BMS) is monitoring the SOC state and the temperature of batteries and voltage level also. This flowchart shows the advantages of SOC how it control the power consumption generate by supercapacitor and power battery.

**Design Calculation**

The various parameters of the battery calculation are listed below:

(1)

Where, is the current at time K(negative for discharging), is the battery nominal capacity(Ah) is the time step(s).

**A diagram of different colored squares

AI-generated content may be incorrect.**

**FIGURE 1.** SOC model of electrical vehicle.

(2)

(3)

Where, OCV is the open circuit voltage function (nonlinear), is the open internal resistance.

(4)

Where, is the predicted error covariance, is the observation matrix, R is the measurement noise covariance

(5)

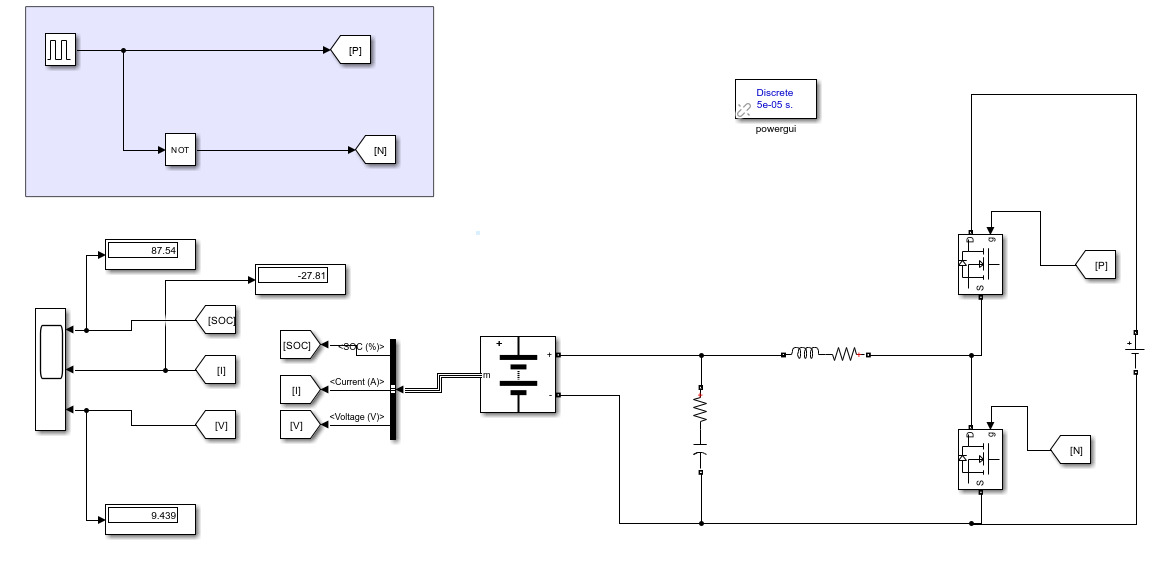
(6)

**SIMULATION RESULTS**

The simulation was carried out for the two cases: when battery SOC is greater than 80% and other battery SOC less than 40%. The results are explained below:

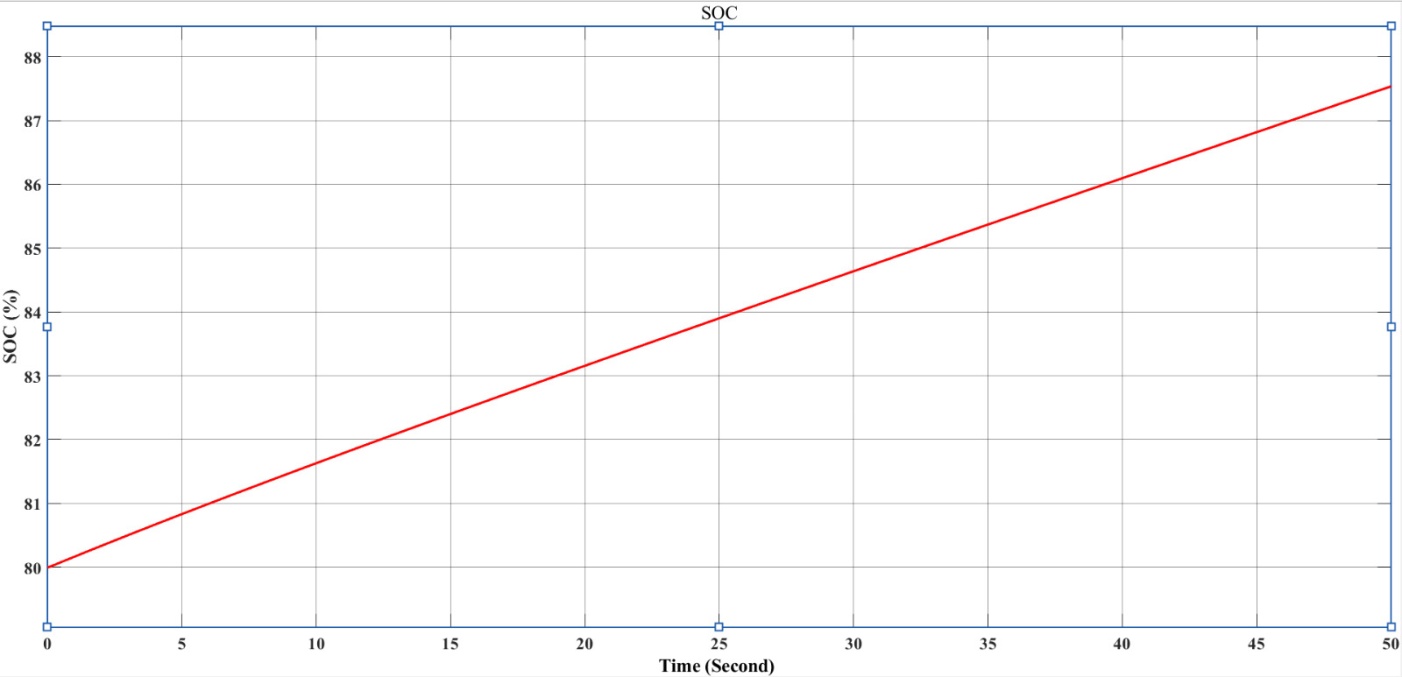
**Case 1: When battery SOC is > 80%**

In this MATLAB/ Simulink model as shown in Figure 2, the PWM generator produces a signal with a 90% ON-time. Power supplies with State of Charge (SOC) at 87.55% from the battery. In display the current reding is showing negative which indicates a discharging state. As two MOSFETs are switching based on the PWM signals the upper switch (P) is on for 90% of duty cycle and the lower switch (N) is on for 10%.

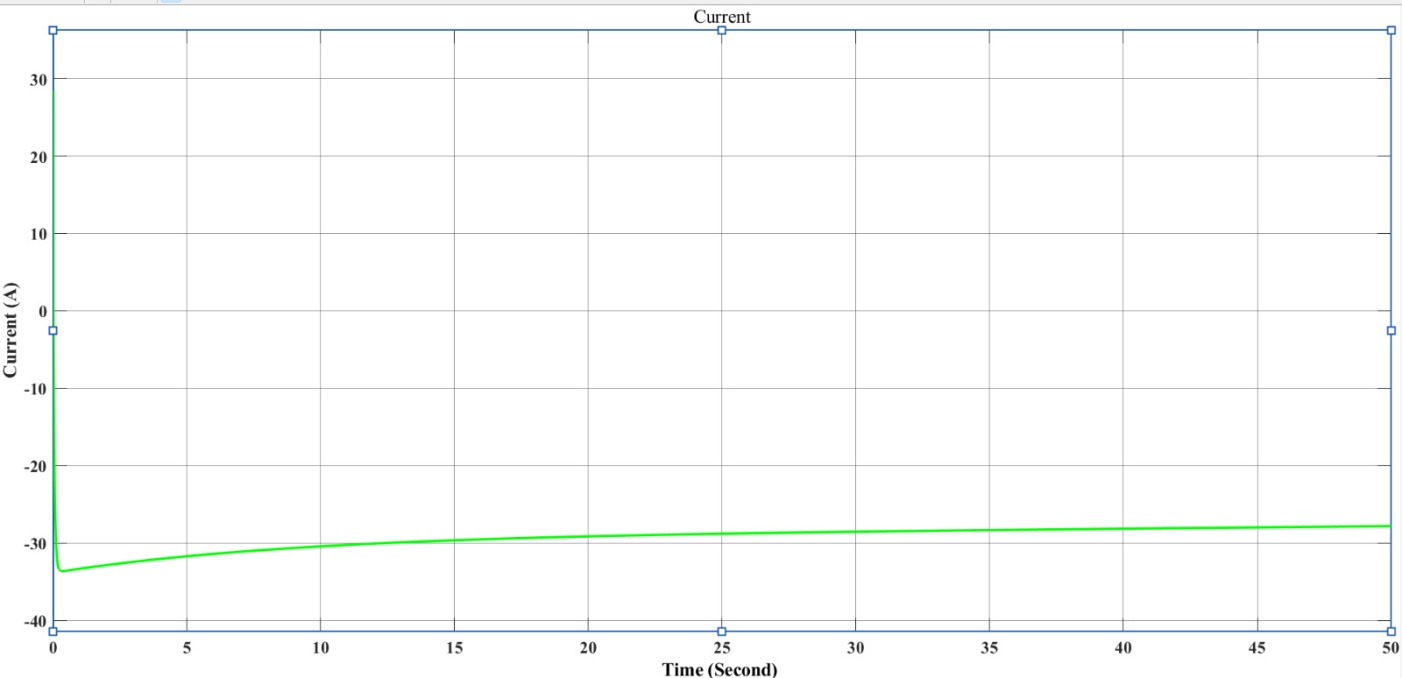


**FIGURE 2.** Simulink model of system with SOC > 80%.

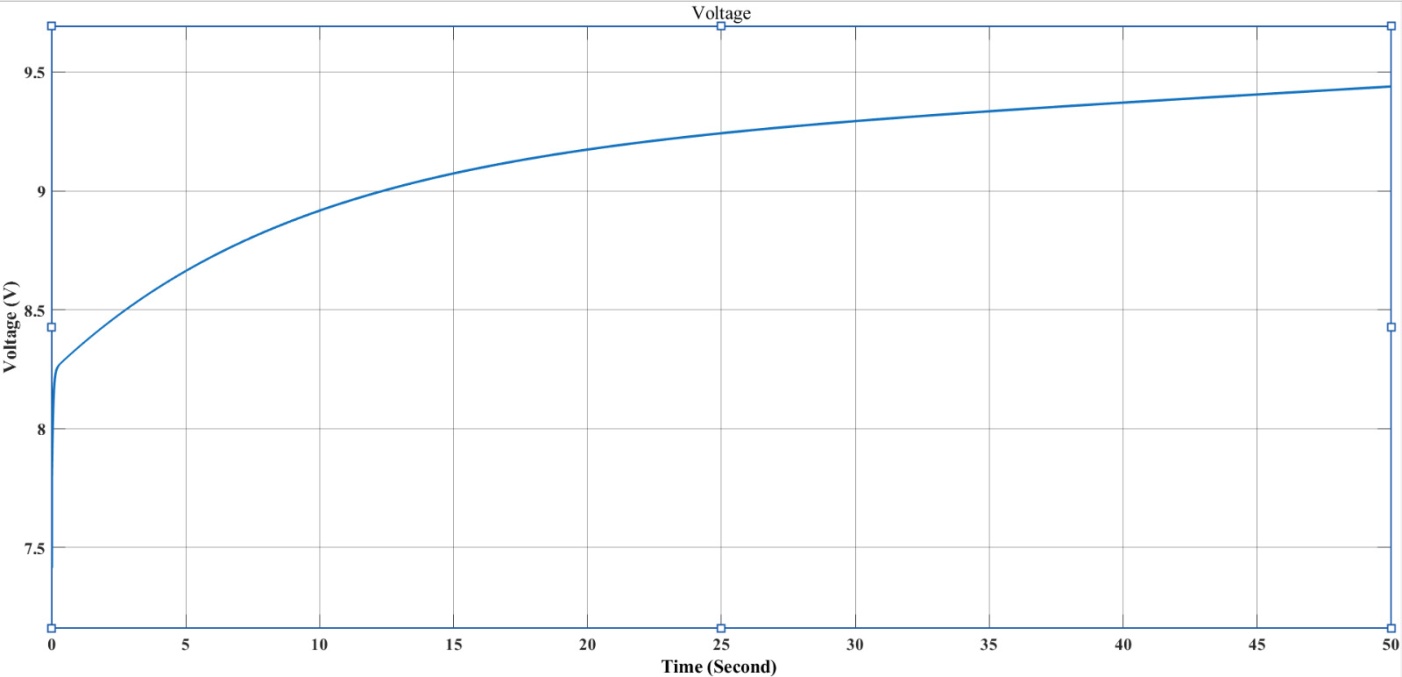
In Figure 3, an increasing SOC percentage over time is shown by the red line. It starts from 80% and reaches around 88-90 % in 50 seconds. This graph indicates the overcharging periods. This indicates that power is being fed back to the battery. In Figure 4, the simulation shows the current flow (A) over time. As the SOC is greater than 80%, it indicates the situation is in overcharging mode. So the current is negative which confirms the battery is now in a discharging state. The current starts around -30A to -40A and then starts to increase toward zero over time.



**FIGURE 3.** The SOC waveform (SOC > 80%).



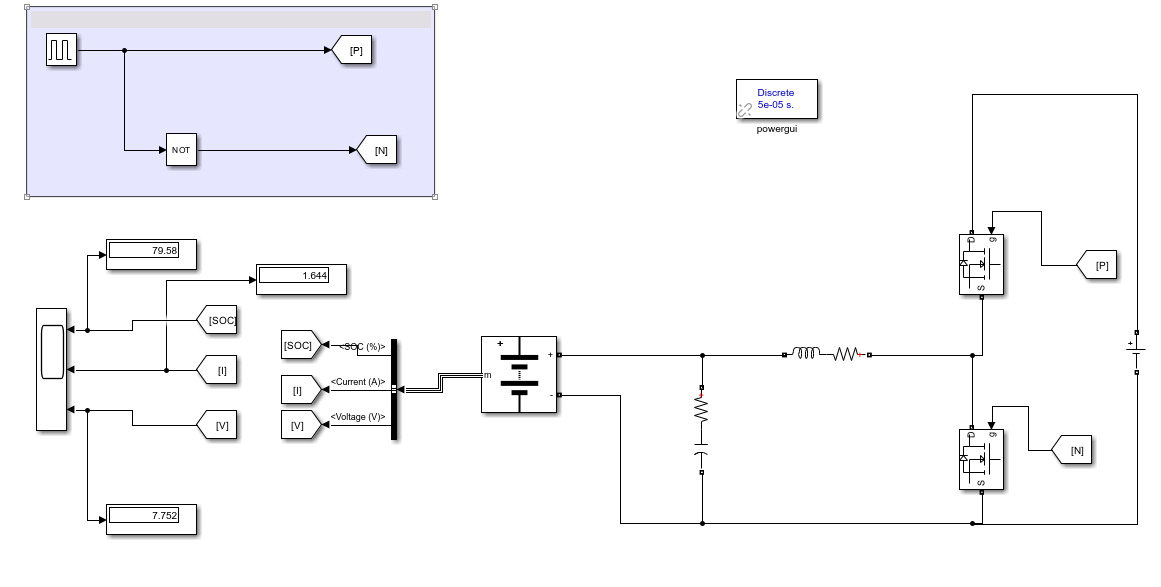
**FIGURE 4.** The current waveform with SOC > 80%.



**FIGURE 5.** The voltage waveform with SOC > 80%.

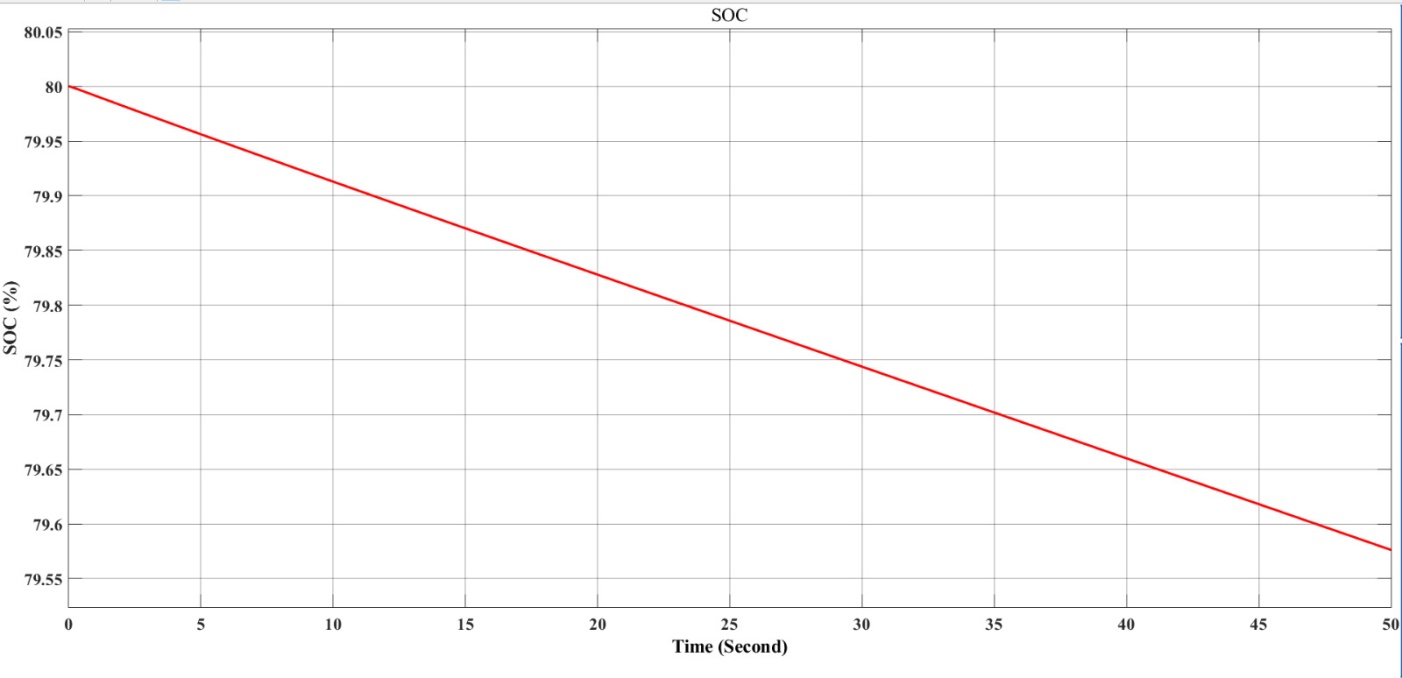
Figure 5 shows the voltage vs time graph. From this graph it is showing that voltage is start from 8 V and gradually increases to 9.55 V over 50 seconds. Which indicates the capacitor is charging over time. That increase shows that the period is in overcharging mode. As we show in the current graph, showed negative values which indicates discharging but it could also go through in regenerative charging mode.

**Case 2: When battery SOC is < 40%**



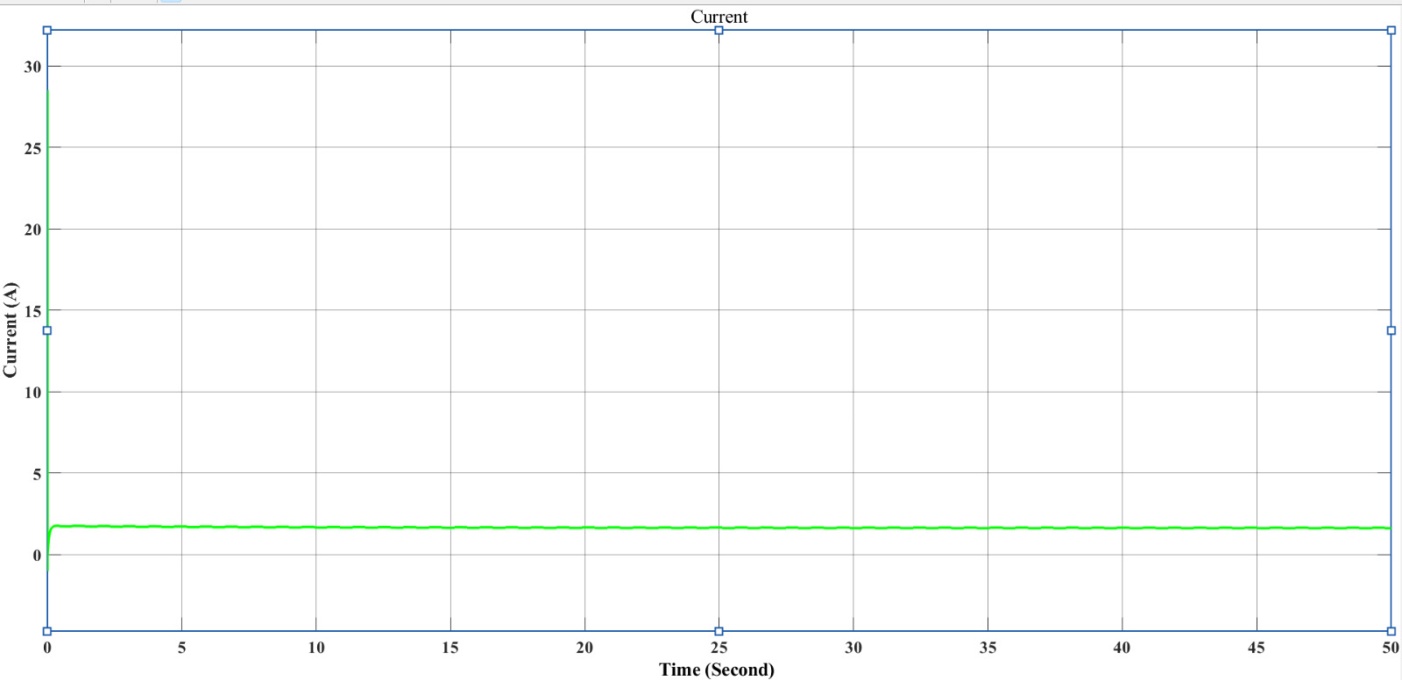
**FIGURE 6.** Simulink model of system with SOC > 80%.

In this MATLAB/ Simulink shown in Figure 6, the PWM generator produces a signal with a 20% ON-time. Power supplies with State of Charge (SOC) at 20% from the battery. In display the current reding is showing positive which indicates a charging state. As two MOSFETs are switching based on the PWM signals, the upper switch (P) is on for 20% of the duty cycle, and the lower switch (N) is on for 10%.



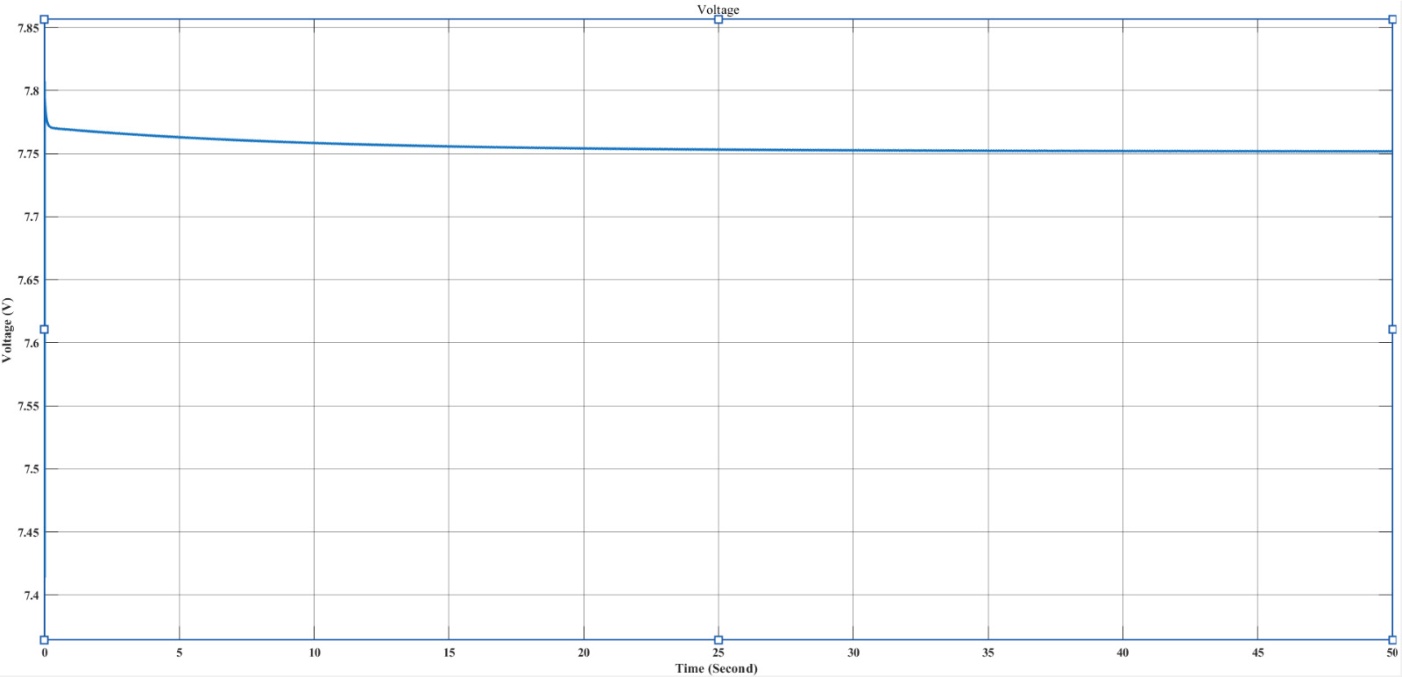
**FIGURE 7.** The current waveform with SOC < 40%.

Figure 7 represents the State of charge in percentage, ranging from approximately 49.94% to 50%. The SOC is decreasing in time, indicating the battery or energy storage system is discharging. The Li-ion battery is discharged (SOC<40%), which can reduce the lifespan of the battery. We have focused on the battery SOC, which is above 50%. If it’s going to be 20-10%, the system may shut down.



**FIGURE 8.** The current waveform with SOC < 40%.

Figure 8 shows the current waveform when SOC is < 40%. It indicates the battery is discharged and need charging. The current situation remains constant in the period. The battery behavior is controlled manner, means load is constant. If the current is stable, the system is lower soc well without overloading. It indicates the charge for the battery.



**FIGURE 9.** The voltage waveform with SOC < 40%.

In this simulation results shown in Figure 9, time battery going to discharge, one at time its slow and steady, which indicate the system is operating normally. When the SOC <40%, the battery does not drop suddenly. It has some capacity left. When discharge is at the minimum voltage threshold, The BMS cuts off the power and protects the battery.

**CONCLUSION**

The power grading approach depends upon the optimized integration scheme to extend battery lifetime by restricting discharge cycles and upper limit current. Superconducting Magnetic storage and the optimal discharge algorithm for Li-battery. In an EV hybrid energy storage system featuring an integration approach for a reasonable switch and battery. And using the Unscented Kalman filter for the SOC estimation. An Extended Kalman filter for internal resistance estimation is derived.

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