

Battery Managment System Based on Active Balancing

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Battery Management System Based on Active

Balancing

By

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Project submitted as part of the requirements for
the award of MSc in Software Engineering

September 2023

DECLARATION

I, Minglong Li declare that I am the sole author of this Project; that all references cited have been consulted; that I have conducted all work of which this is a record, and that the finished work lies within the prescribed word limits.

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Date : 09/12/23

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Abstract

The Battery Management System (BMS) is responsible for monitoring battery status, protecting the battery, controlling charging and discharging processes, balancing battery cell voltages, and recording data. Battery balancing technology plays a vital role in the BMS, ensuring the equalization of individual cell voltages within the battery pack, thereby extending battery life and improving system performance. Estimation of the State of Charge (SOC) and State of Energy (SOE) of the battery pack provides valuable guidance for estimating remaining available time and designing energy management systems. This paper focuses on the following research aspects related to battery management systems:

1. Study of lithium battery pack balancing topologies: Addressing the issue of reduced efficiency in traditional balancing circuits as the number of individual cells in a series-connected battery pack increases, this research analyzes balancing topologies based on energy transfer paths and various active balancing schemes using different energy transfer media. It implements a non-dissipative balancing topology for series-connected battery packs based on bidirectional flyback converters. The advantages and disadvantages of different balancing variables and their computational complexity are examined. To alleviate the impact of battery internal resistance and polarization reactions on terminal voltage, the paper proposes estimating the open-circuit voltage of the battery as a balancing variable using a first-order equivalent circuit model. The estimation of the capacity difference between different individual cells is calculated based on the estimated open-circuit voltage to determine the end of balancing.

2. Research on SOC and SOE estimation methods for battery packs: Considering the computational challenges for battery management systems with limited computing resources to calculate the SOC/SOE of all individual cells within the battery pack, this study proposes a representative cell selection method based on the Ohmic resistance. By treating the battery pack as a large battery, the problem of high computational complexity for input voltage calculations is mitigated. The state of the battery pack is

represented by the state of the individual cell with the highest internal resistance, and offline parameter identification is performed. To address the issue of significant estimation errors caused by the inability of the Extended Kalman Filter to update the measurement noise matrix and state noise matrix online, an adaptive Kalman filter is designed to estimate the SOC and SOE of the representative cell, achieving state updates for the battery pack.

3. Design of a battery management system based on active balancing: The system employs the BQ769x0 series dedicated battery management chip to monitor individual cell information within the battery pack. An active balancing topology for the battery pack is implemented using bidirectional flyback converters, with active balancing control achieved through the LTC3300. The estimated open-circuit voltage of the individual cell obtained from the first-order equivalent circuit model is used in conjunction with an adaptive Kalman filter to estimate the SOC and SOE of the battery pack. The STM32 microcontroller issues commands for charging, discharging, and protection of the battery pack based on the collected information, thereby enabling battery pack balancing control

Keywords: Battery Management System, Active Balancing, State Estimation.

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Chapter 1: Introduction

1.1 Background and Significance of the Study

According to the World Energy Statistics Yearbook 2022, renewable energy generation, primarily dominated by wind power and photovoltaic (PV) power, continued to experience strong growth in 2021 due to economic recovery. The renewable energy generation reached 3657.2 terawatt-hours (TWh), with wind power and PV power contributing 10.2% to global electricity generation, surpassing the contribution of nuclear energy. China has seen the largest increase in renewable energy, remaining the main driving force behind the growth of PV and wind power globally, accounting for 36% and 39.79% of the total new capacity added worldwide, respectively. According to the overview of development and consumption published on the State Grid's New Energy Cloud website, as of December 2022, China's total installed capacity of new energy reached 79,937 megawatt-hours (MWh), with an additional capacity of 12,635 MWh added in the same year, an 18.77% increase compared to the previous year. In the power structure of 2022, solar power and wind power accounted for a combined total of 758 million kilowatt-hours (kWh), making up 29.14% of the total.

Battery Energy Storage Systems (BESS) are energy storage systems that use batteries to store electrical energy. Compared to other storage methods, BESS offers advantages such as high flexibility, high energy storage efficiency, strong reliability, low cost, and environmental friendliness ^[1]. BESS finds wide applications in various systems, often used to integrate renewable energy generation into the grid, enhancing grid reliability and stability. BESS can be categorized as either standalone systems or grid-connected systems ^[2]. In standalone systems, BESS is connected to renewable energy generation devices like solar panels or wind turbines, providing power to loads or storing excess energy for later use. In grid-connected systems, BESS is connected to the utility grid, supplying power during peak demand periods or storing surplus energy during off-peak periods, facilitating load leveling. Various types of batteries are used

in BESS, including lead-acid batteries, nickel-cadmium batteries, and flow batteries [3]. Among energy storage systems, the lithium-ion battery is the most frequently utilized type.

Due to the limitations of individual energy storage batteries, battery storage systems typically involve a large number of batteries connected in series and parallel to meet the voltage level, capacity, and power requirements of the deployed system [4]. Individual batteries within a battery pack may exhibit inconsistent characteristics, such as different battery capacities, internal resistances, and aging rates, due to variations in production, operating environments, and operating conditions. These inconsistencies can impact the lifespan of the battery pack. To fully utilize the capacity of the batteries, a battery management system is employed to perform balancing operations on the battery pack, improving its capacity utilization and prolonging its lifespan.

A battery management system (BMS) governs real-time parameters of battery modules and manages charging, discharging, and other protective operations related to the battery pack, such as fuse protection. In addition to mitigating the inconsistency among individual batteries through balancing circuits to improve energy utilization, the battery management system is obligated to accurately estimating state parameters such as State of Charge (SOC) and State of Energy (SOE). Accurate estimation of these state parameters is crucial for ensuring the safe operation of the battery within its limits and predicting its remaining lifespan. A well-designed and properly functioning BMS holds the duty of the battery's health, protects it from detrimental operating conditions, and optimizes its performance [5].

1.2 Current Research Status

1.2.1 Research Status in Battery Management Systems

In the field of energy storage, lithium-ion battery energy storage technology is widely applied. The BMS is an essential component of a lithium-ion battery energy storage system, responsible for monitoring and managing each individual cell within the battery pack to ensure optimal performance. The requirements for battery system safety management are illustrated in Figure 1-1. In addition to the basic functions of

measuring battery voltage, temperature, and total current flowing through the battery pack, the BMS must also provide functions such as state estimation, fault diagnosis, and balancing^[6]. The main research directions of BMS in domestic and international studies currently include: improving the acquisition accuracy and reducing power consumption of the management chip^[7], optimization of state estimation algorithms^[8], battery model research^[9], battery pack balancing research^[10], thermal management of battery packs^[11], and cloud-based intelligent battery management systems^[12].

Lithium-ion batteries are influenced by different environments and operating conditions, building battery models can better understand battery behavior and performance^[13]. Commonly used lithium-ion battery models include electrochemical models^[14], neural network models^[15], and equivalent circuit models^[16]. Electrochemical models describe the chemical reactions occurring inside the battery, as well as the movement of electrons and ions within the battery, using physical and mathematical equations. They are suitable for various types of lithium-ion batteries. Electrochemical models can accurately describe the dynamic behavior and performance of lithium-ion batteries, but they are highly complex and require high costs and time for development. Based on the "black box" approach, neural networks can accurately predict battery parameters such as capacity, lifespan, and state to adapt to different environments and usage conditions, but they also require high costs and time for development. Equivalent circuit models for lithium-ion batteries use circuit elements such as voltage sources, resistors, and RC networks to describe the voltage-current characteristics and transient behavior of batteries while consuming relatively fewer computational resources. Commonly used equivalent circuit models include the Rint model, Thevenin model, PNGV model, second-order RC model, and fractional-order equivalent circuit models. Complex equivalent circuit models provide better descriptions of battery characteristics but require more computational resources.

1.2.2 Research Status in Battery Pack Balancing Methods

Battery pack balancing methods can be categorized into dissipative balancing techniques and transfer-based balancing methods, according to the energy transfer approach. Dissipative balancing techniques utilize passive components such as

resistors to dissipate energy and achieve balancing among individual cells in the battery pack. This technique can be further divided into fixed shunt resistors and switchable shunt resistors methods. Xu et al. ^[18] proposed an improved passive balancing method based on a model, which eliminates the discharge resistors in the balancing circuit. Instead, it generates pulse width modulation (PWM) signals through a balancing controller to control metal-oxide-semiconductor field-effect transistors (MOSFETs) for variable and controllable balancing currents. This balancing approach can achieve a maximum balancing current of 10A, which is significantly higher than traditional passive balancing methods and most active balancing methods, while also being more cost-effective than traditional passive balancing methods. This method can quickly reduce the cell inconsistency in the battery pack. However, it still relies on dissipative energy transfer, resulting in significant energy losses, and the high current of passive balancing leads to noticeable temperature rise in the batteries.

As a non-dissipative balancing method, active balancing refers to the transfer of energy through energy storage elements to reduce the imbalance in the battery pack. Based on different energy transfer components, active balancing can be classified into five types of balancing topologies: capacitors ^{[19][20]}, inductors ^[21], power converters ^[22], bypass cells ^[25], and transformers ^[29].

Capacitor-based battery balancing utilizes the energy storage characteristics of capacitors, using them as energy transfer carriers to regulate the switches based on voltage differences and achieve energy flow between batteries. Singirikonda et al. ^[19] proposed an optimized active cell voltage balancing method based on a closed-loop switch-capacitor structure. It enables the shortest path for energy transfer between batteries in the battery pack, thereby improving voltage balancing, speed, overall efficiency, and reducing the cost of the battery pack. Jiang Ze ^[25] used an improved switch array to select the individual cells that require balancing. By combining a DC-DC converter with energy storage capacitors, energy transfer between individual cells in the battery pack is realized, avoiding the issue of decreased balancing effectiveness due to reduced voltage differences in the late stages of balancing. When combined with the designed dual-threshold balancing control strategy based on end-cell voltages, efficient balancing of the battery pack can be achieved.

Inductor-based battery balancing utilizes the non-sudden change characteristic of

inductor current to enable energy transfer between batteries. Noh et al. ^[22] designed a power converter-based balancing method for both intra-pack and inter-pack balancing, enabling energy transfer paths between the battery pack and individual cells. By combining the SOC grading balancing control method for battery energy storage systems, SOC balancing can be achieved within the battery pack.

DC-DC converter-based battery balancing methods are referred to as converter-based balancing. Wang et al. ^[27] designed a bidirectional DC-DC circuit to transfer battery energy and adaptively adjust the duty cycle based on the charge state difference in the battery pack. This ensures stable balancing currents and resolves the issue of decreased balancing current due to diminishing SOC differences among individual cells in the late stages of balancing. Wu et al. ^[28] proposed a balancing topology based on a combination of a Cuk balancer and dual-layer selector switches, enabling energy transfer between any two batteries. By employing segmented balancing methods based on voltage and SOC as balancing variables and utilizing fuzzy logic control to dynamically adjust balancing currents, balancing time and energy losses can be reduced, resulting in effective balancing.

Transformer-based battery balancing methods, compared to methods using capacitors, inductors, and DC-DC components, offer advantages such as efficiency, reliability, stability, and flexibility. Transformer-based balancing belongs to isolated balancing, where transformers serve as energy transfer carriers, transferring energy between two windings. Liu et al. ^[30] proposed a parallel transformer-based charging balancer that enhances the scalability of the balancer and is not limited by multi-winding transformers. It adaptively adjusts the duty cycle based on the charge state difference in the battery pack to maintain stable balancing currents and overcome the issue of reduced balancing current due to diminishing SOC differences among individual cells in the late stages of balancing. Park et al. ^[31] designed a multi-winding transformer-based balancing topology, utilizing voltage balancing operations with auxiliary circuits to satisfy the allowable charging/discharging currents of battery cells even with small magnetizing inductance. This approach offers high flexibility, low cost, and enables balancing within the battery pack as well as inter-pack balancing.

1.2.3 Research Status in SOC and SOE estimation

SOC describes the current charge status of the battery pack, indicating the percentage of remaining charge compared to the rated capacity. On the other hand, SOE provides a more accurate understanding of the actual available total energy in the battery pack. By combining both parameters, a more comprehensive understanding of the battery pack's state can be achieved, enabling better utilization and management of the battery pack, thereby improving system reliability and efficiency.

The definition of SOE can be represented by Equation (1-1) ^[32], and the definition of SOC is given by Equation (1-2).

$$SOE = \frac{E_e}{E_{bat}} = (SOE_0 - \int_0^t \frac{\eta * U_{bat} * I}{E_{bat}} dt) \quad (1-1)$$

$$SOC = \frac{C_e}{C_{bat}} = (SOC_0 - \int_0^t \frac{\eta * I}{C_{bat}} dt) \quad (1-2)$$

In the equations: E_{bat} represents the rated energy of the battery; E_e stands for the remaining dischargeable energy; I refers to the operating current; U_{bat} represents the terminal voltage of the battery; η refers to the Coulomb efficiency; C_{bat} denotes the rated capacity of the battery; C_e represents the remaining dischargeable energy.

The estimation methods for SOC and SOE can be categorized into three types: integral methods, data-driven methods, and model-based observer methods ^[34]. The power integration method is a widely used approach for estimating the energy state of lithium-ion batteries. Similar to the ampere-hour integration method, the power integration method directly estimates the battery's SOC based on the energy state definition. By integrating the battery's input or output power over a specific time period, this method determines the power added to or consumed by the battery, thereby providing information about the actual remaining energy. The accuracy of the initial SOC value greatly affects the precision of the power integration method. Additionally, the open-loop characteristic of the integral method leads to accumulating estimation errors, resulting in inaccurate estimates.

Data-driven methods for energy state estimation include fuzzy control ^[23], neural

networks ^[35], and other approaches. Data-driven methods offer the advantage of directly estimating the state parameters of lithium-ion batteries using experimental data, without the need for battery modeling. Additionally, this method effectively addresses nonlinearity issues in battery models. However, the effectiveness of models trained with data-driven methods largely depends on the training samples. Different datasets can only yield good state parameter estimates under specific operating conditions, indicating poor generalization capabilities of this method. Data-driven methods require a large amount of training data and often have high computational time.

In the trade-off between estimation accuracy and complexity, model-based SOC and SOE estimation methods have been extensively explored. Improved algorithms based on Kalman filtering are commonly used for energy state estimation. Plett et al. ^[36] first introduced the Kalman filter algorithm into battery SOC estimation. However, lithium-ion batteries are typical nonlinear systems, making the linear Kalman filter algorithm less ideal. Chen et al. ^[37] employed the square root unscented Kalman filter algorithm to estimate SOE, achieving estimation errors within 2% under dynamic conditions.

The relationship between State of Energy (SOE) and State of Charge (SOC) in lithium-ion batteries is positively correlated ^[39]. Zheng et al. ^[40] conducted discharge experiments on batteries under different temperatures, discharge or charge current rates, and varying degrees of battery aging. The results demonstrated that the relationship between battery SOE and SOC exhibits good stability under different operating conditions and battery aging levels. The fitting function accurately matches the true relationship between SOE and SOC. Utilizing the experimentally fitted relationship between SOC and SOE for joint estimation of SOC and SOE in battery packs can reduce computational complexity, but it requires more experimental calibration of the SOC-SOE relationship curve.

Shrivastava Prashant et al. ^[42] used a multi-timescale bidirectional extended Kalman filter for joint estimation of SOC and SOE. They achieved estimation errors below 1% when considering dynamic load distribution at three different temperatures. Lai et al. ^[43] estimated the battery's SOC using the extended Kalman filter algorithm and updated the battery capacity online based on the battery's SOC estimate using the Ordinary Least Square (OLS) algorithm combined with Coulomb counting. They then

estimated the battery's SOE using the unscented Kalman filter algorithm. Experimental verification showed that the estimation errors for State of Health (SOH) and SOE were both less than 4%, achieving good estimation accuracy. However, this method relies on the SOC estimate obtained using the extended Kalman filter.

The specific battery within a battery pack can effectively represent the dynamics of the entire pack. By monitoring the selected representative battery online, the computational cost can be significantly reduced if these batteries can accurately reflect the pack's dynamics over a relatively long period of time. Zhang et al. ^[44] proposed selecting the battery with the highest terminal voltage during charging as the representative battery and the battery with the lowest terminal voltage during discharging as the representative battery, and then updating the pack's State of Charge (SOC). Zhou et al. ^[45] used the Thevenin equivalent circuit model and calculated the open-circuit voltage of the individual battery cells based on the collected current and terminal voltage values, combined with the offline obtained internal resistance values of the cells. The quasi-open-circuit voltage was then used to select the representative battery for the battery pack. By adding a simple calculation, the quasi-open-circuit voltage can more accurately reflect the SOC distribution of individual cells within the pack, leading to better estimation accuracy for the battery pack. However, due to uneven thermal distribution and increasing cell inconsistency, the terminal voltage or quasi-open-circuit voltage may not accurately reflect the SOC level of the battery pack, resulting in the selected representative battery failing to represent the pack's state. Zhang et al. ^[46] proposed selecting the representative battery for the pack based on the internal resistance values. When the internal resistance differences among the cells are small, the representative battery is chosen as the one with the highest internal resistance for state estimation. When there is a significant difference in internal resistance within the pack, the weighted average of the SOE values of the battery cell with the highest and lowest internal resistances is used as the pack's SOE.

In battery management systems, due to limited computational resources at the terminal, it is not feasible to implement complex state estimation algorithms. Therefore, using Kalman filters based on representative batteries can achieve SOC/SOE estimation for the battery pack, providing real-time estimation with high accuracy.

Chapter 2: Research on Battery Pack SOC and SOE Estimation Methods

Lithium-ion batteries are a type of chemical reaction-based battery. By establishing a mathematical model for lithium-ion batteries, the physical and chemical behavior of the batteries can be described, enabling better prediction of battery states and a more accurate understanding of their status and remaining lifespan. This, in turn, allows for the optimization of battery usage and control strategies.

In Chapter 1, through an analysis of existing individual battery models, considering model accuracy and the limited computational resources of battery management systems, this paper adopts a first-order RC circuit model as the foundation. Based on edge-terminal coordination, a battery pack model is designed using a representative battery cell. Additionally, an adaptive extended Kalman filter algorithm is utilized to design an SOC and SOE estimation algorithm for the battery pack. This algorithm enables the estimation of the SOC and SOE of the battery pack.

2.1 Lithium Battery Modeling and Experimental Testing

2.1.1 Lithium Battery Equivalent Circuit Models

Compared to electrochemical battery models, equivalent circuit models strike a balance between computational complexity and simulation accuracy while offering higher practicality. Therefore, this paper selects a first-order RC equivalent circuit model to simulate the characteristics of the battery. The schematic of the first-order equivalent circuit model is shown in Figure 2-1. The electrical characteristic equations are described by Equation (2-1) and Equation (2-2), where R_o represents the ohmic resistance, R_p represents the polarization resistance, C_p represents the polarization capacitance, U_{bat} represents the output voltage of the battery, U_{ocv} represents the open circuit voltage of the lithium-ion battery, and I represents the current flowing through the battery. In this paper, the discharge current is defined as positive, while the charging

current is defined as negative.

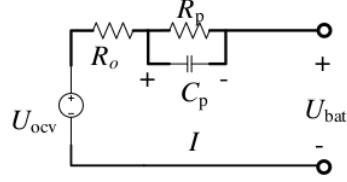


Figure 2-1: First-Order RC Equivalent Circuit

$$\text{Model} \quad U_{bat} = U_{ocv}(SOC) - R_o I - U_p \quad (2-1)$$

$$\frac{dU_p}{dt} = \left(\frac{1}{C_p}\right)I - \left(\frac{1}{R_p C_p}\right)U_p \quad (2-2)$$

2.1.2 Battery OCV-SOC Testing

Estimation of SOC and SOE for lithium-ion batteries requires the battery's model parameters. Therefore, after establishing the battery model, it is imperative to perform charge and discharge experiments and identify the capacitance and resistance parameters of the model based on the collected battery data. The open circuit voltage (OCV) of a lithium-ion battery is an important indicator of its current discharge capacity. Therefore, determining the OCV-SOC curve is instrumental in estimating the initial state of charge for lithium batteries. For lithium-ion batteries that have been adequately rested, their open circuit voltage can be approximated as the terminal voltage. Based on the characteristics of the battery system, there is a specific functional relationship between the open circuit voltage and the state of charge. Therefore, under the assumption of sufficient rest for the lithium-ion battery, the open circuit voltage-state of charge curve can be calibrated by measuring the battery's terminal voltage. In this paper, the test battery used is the INR18650/35V lithium-ion battery produced by EnerDel, and its parameter information is shown in Table 2-1.

Table 2-1: Battery Parameter Information

Battery Parameter Category	Parameter Information	Battery Parameter Category	Parameter Information
Rated Capacity	3500mAh	Maximum Continuous Current	3C
Nominal Voltage	3.6V	Dimensions	18mm*65mm
Operating Voltage Range	4.2~2.5V	Weight	48±2g
Operating temperature range	-20~60°C	Energy Density	263Wh/kg

In this paper, constant current pulse discharge experiments were conducted on the battery at an ambient temperature of 20°C. Each discharge involved 10% of the battery's rated capacity, resulting in a 10% decrease in SOC. After each discharge, the battery was allowed to rest for one hour, during which the changes in current and voltage were recorded. The specific testing steps were as follows:

(1) According to the datasheet, the charging of lithium batteries follows a charging method that involves a constant current, which is followed by a constant voltage. At the beginning of the charging process, a constant current of 0.68A was applied to the battery until the charging voltage went to 4.2V. Subsequently, the charging operation persisted in a mode of constant voltage, maintaining the voltage at 4.2V, until the charging current decreased to 20mA, indicating the end of the charging process. After charging, the battery was left to rest for 12 hours at an ambient temperature of 20°C.

(2) The battery pack was subjected to constant current pulse discharge using a DC electronic load. The current was set to 0.5C (1.75A), and the discharge time was 12 minutes, resulting in a 10% decrease in SOC. The battery's output current and voltage data were recorded during the discharge process.

(3) The battery was left to rest for 1 hour at room temperature, and the voltage value during the rest period was recorded.

(4) Steps (2) and (3) were repeated until the battery was discharged to the cutoff voltage of 2.5V.

The complete variation of the battery's output current and voltage during the

constant current pulse discharge experiment is shown in Figure 2-2. The corresponding relationship between the battery's open circuit voltage and SOC is presented in Table 2-2.

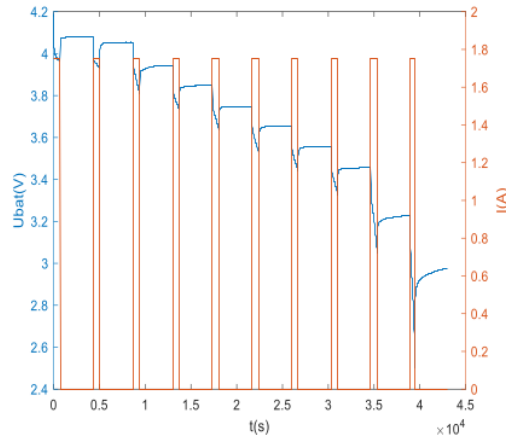


Figure 2-2: Output Voltage and Current Data for Pulse Discharge Experiment

Table 2-2: Corresponding Relationship between Open Circuit Voltage and SOC

SOC	OCV/V	SOC	OCV/V	SOC	OCV/V
0	2.977	0.4	3.656	0.8	4.054
0.1	3.228	0.5	3.749	0.9	4.079
0.2	3.456	0.6	3.850	1.0	4.190
0.3	3.577	0.7	3.943		

The data in Table 2-2 was fitted using a 6th-order curve fitting tool in MATLAB, resulting in the expression for SOC-OCV as shown in Equation (2-3). The fitted OCV-SOC curve is depicted in Figure 2-3.

$$f(SOC) = 42.87 * SOC^6 - 125.8 * SOC^5 + 134.9 * SOC^4 - 62.09 * SOC^3 + 9.162 * SOC^2 + 2.125 * SOC + 2.977 \quad (2-3)$$

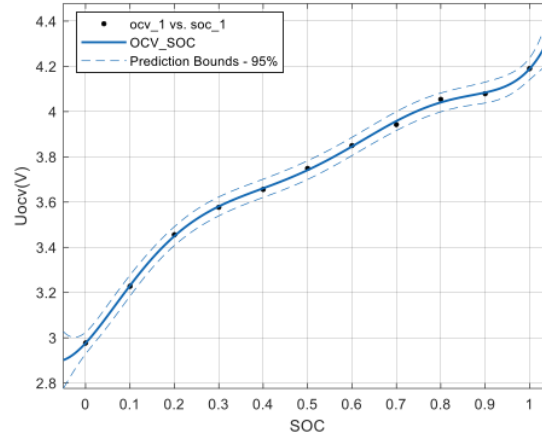


Figure 2-3: OCV-SOC Fitting Curve

The RMSE (Root Mean Square Error) of the fitted OCV-SOC curve is 0.0122, indicating a good fit accuracy. The calculation of RMSE is defined in Equation (2-4).

$$RMSE = \sqrt{\sum_{i=1}^N (\bar{x} - x_i)^2 / N} \quad (2-4)$$

2.1.3 Battery OCV-SOE Testing

The open circuit voltage (OCV) of lithium-ion batteries exhibits a nonlinear relationship with the SOE. To determine the OCV-SOE curve of the battery, experimental measurements can be conducted. This curve provides essential information about the battery's energy state. In this paper, the OCV-SOE curve for the battery is determined through constant power pulse discharge experiments. The process can be outlined with the following specific steps:

(1) According to the battery's datasheet, lithium-ion batteries are charged using a constant current followed by a constant voltage charging method. Initially, the battery is charged at a constant current of 0.68A until the charging voltage reaches 4.2V. Then, the charging continues in constant voltage mode until the charging current drops to 20mA, indicating the end of the charging process. After charging, the battery is left to rest for 12 hours at an ambient temperature of 20°C.

(2) The battery pack is subjected to constant power discharge using a DC electronic load. Since the selected lithium-ion battery has a maximum discharge current limit of 10.2A and a rated voltage of 3.65V, the battery is set to discharge at a constant power of 6.3W for a duration of 12 minutes, resulting in a 10% decrease in SOE.

(3) The battery is left to rest for 1 hour at room temperature, and the voltage value at the end of the rest period is recorded.

(4) Steps (2) and (3) are repeated until the battery is discharged to the cutoff voltage of 2.5V.

The open circuit voltage values of the battery under different SOE conditions are presented in Table 2-3.

Table 2-3 Corresponding Relationship between Open Circuit Voltage and SOE

SOE	OCV/V	SOE	OCV/V	SOE	OCV/V
0.0	2.976	0.4	3.670	0.8	4.041
0.1	3.214	0.5	3.755	0.9	4.094
0.2	3.452	0.6	3.857	1	4.169
0.3	3.583	0.7	3.962		

The OCV-SOE curve of the battery, obtained using the curve fitting tool in MATLAB, is depicted in Figure 2-4. The fitted curve has an RMSE of 0.006388, indicating a good fit accuracy. The expression for OCV-SOE is given by Equation (2-5).

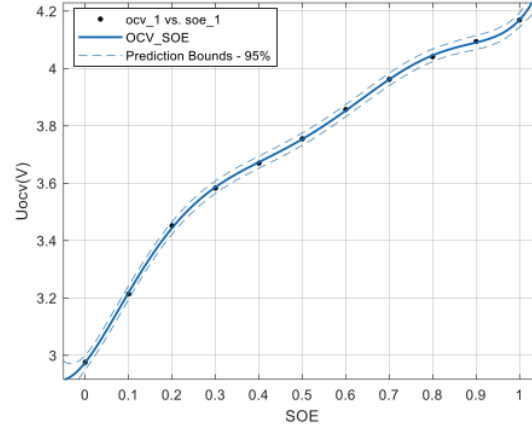


Figure 2-4: OCV-SOE Fitting Curve

$$f(SOE) = 39.08 * SOE^6 - 117.7 * SOE^5 + 130.4 * SOE^4 - 63.01 * SOE^3 + 10.48 * SOE^2 + 1.901 * SOE + 2.975 \quad (2-5)$$

2.2 Model Parameter Identification

2.2.1 Offline Parameter Identification

Offline parameter identification refers to the process of collecting performance data from batteries through static or dynamic experiments conducted outside their actual operation. These data are then used in offline processing methods to identify the parameters of the battery model. Offline parameter identification requires less stringent data acquisition requirements compared to online parameter identification. It also allows for the use of more complex processing methods to improve identification accuracy. However, it requires a certain amount of battery performance data to be collected before offline processing can be performed to obtain the historical parameters of the battery model. As a result, real-time performance is compromised.

To accurately estimate the capacitance and resistance parameters of the first-order equivalent circuit model for lithium-ion batteries, this paper constructs a model in the Simulink environment. Combining with the constant current pulse discharge experimental data of lithium-ion batteries, parameter estimation algorithms are applied

to identify the capacitance and resistance parameters of the first-order equivalent circuit model.

The experimental circuit model for constant current pulse discharge testing is shown in Figure 2-5. The first-order equivalent circuit model for lithium-ion batteries is depicted in Figure 2-5(a). This model incorporates a one-dimensional lookup table, a variable capacitor, a variable resistor, and a controllable voltage source to achieve variable capacitance, resistance, and open circuit voltage. The state of charge (SOC) calculation in the model employs current integration method. The model takes the current, voltage, and time data from the battery pulse discharge experiment as inputs and utilizes the parameter estimation algorithm to fit the battery parameters. The battery discharge model circuit is depicted in Figure 2-5(b), where a controllable constant current source is used to facilitate constant current discharge of the individual cell.

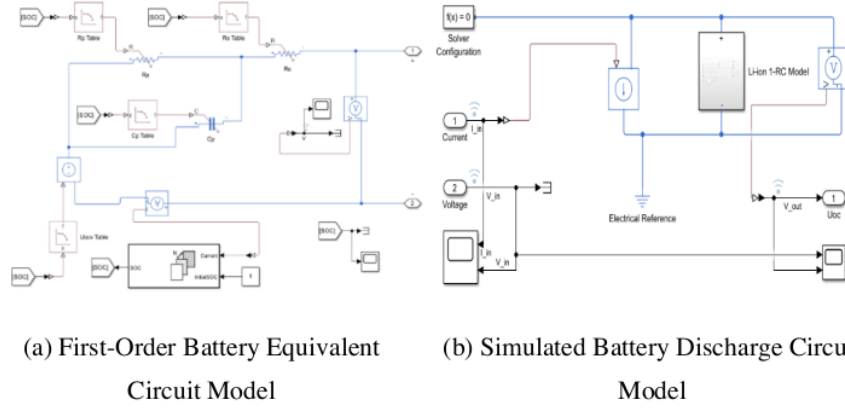


Figure 2-5: Battery Pulse Discharge Experimental Model

In this study, the parameter estimation algorithm is set to nonlinear least squares method, with the fitting algorithm set to trust-region method. The tolerance is set to 0.0001, and the maximum number of iterations is set to 20. The obtained ohmic resistance values from offline identification are shown in Figure 2-6. The obtained polarization parameters from offline identification are shown in Figure 2-7. From Figures 2-6 and 2-7, it can be observed that the capacitance and resistance parameters of the first-order equivalent circuit model remain relatively stable within the SOC range of 0.1 to 0.9. When the battery's SOC exceeds 0.9 or falls below 0.1, more significant

electrochemical reactions occur in the battery. Specifically, when the SOC exceeds 0.9, the positive electrode of the battery experiences loose lithium ion crystals, leading to increased internal resistance and decreased voltage. When the SOC falls below 0.1, the negative electrode of the battery accumulates an excessive number of lithium ions, causing an increase in internal resistance and instability in the electrochemical reactions, resulting in a decrease in voltage. The average values of the model parameters identified within the SOC range of 0.1 to 0.9 are presented in Table 2-4.

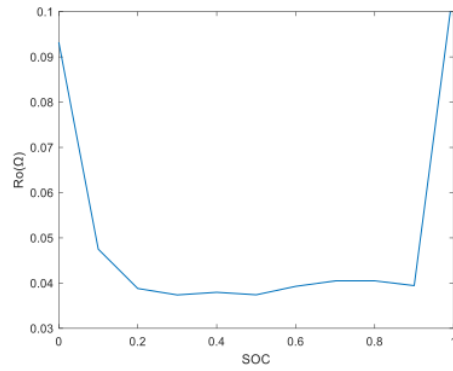
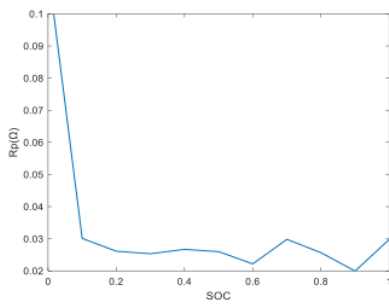
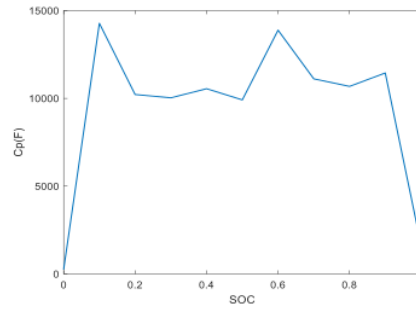


Figure 2-6: Ohmic Resistance Values from Offline Parameter Identification



(a) Polarization Resistance Values from Offline Parameter Identification



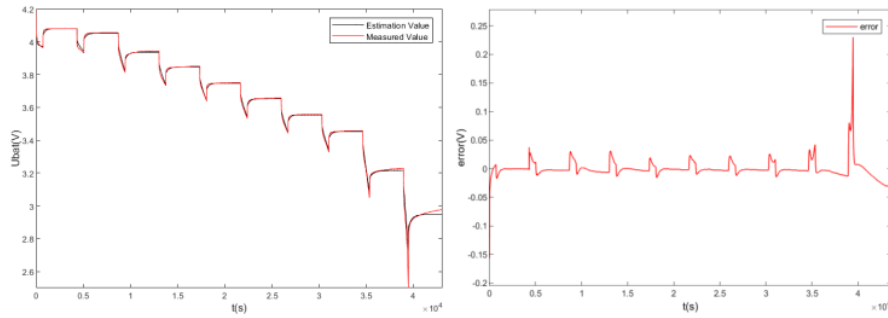
(b) Polarization Capacitance Values from Offline Parameter Identification

Figure 2-7: Polarization Parameters Obtained from Offline Parameter Identification

Table 2-4: Average Parameters from Offline Parameter Identification Model

$R_o(\Omega)$	$R_p(\Omega)$	$C_p(F)$
0.039868	0.025742	11346.42

To confirm the correctness of the parameter identification for the battery pack model, the constant current pulse discharge model and the identified parameters of the first-order equivalent circuit model were used to obtain the model's output voltage. The measured voltage from the constant current pulse discharge experiment for the individual cell and the estimated voltage output from the model are shown in Figure 2-8(a). The error between the estimated voltage and the measured voltage is depicted in Figure 2-8(b). From Figure 2-8(b), it can be observed that the modeled terminal voltage exhibits significant errors during the late stage of discharge, with a maximum absolute error of 0.231V. Overall, the fitting performance of the identification results is considered good.



(a) Variation Curve of Measured and Estimated Values

(b) Error Curve

Figure 2-8: Comparison of Offline Parameter Identification: Estimated Terminal Voltage vs. Measured Voltage

2.3 Battery Pack SOC and SOE Estimation Research

2.3.1 Overview of Kalman Filters

The Kalman filter is a mathematical algorithm employed to estimate the unobserved state of a system using a time series of measurements, and to predict future states. It is widely applied in engineering, control systems, and many other fields. The Kalman filter is a recursive algorithm that combines measurement data with a model of the system being measured using a set of equations. It uses the measured values to estimate the current state of the system and predicts the next state based on this estimate. Then, it compares the prediction with the actual measurement and updates the estimate of the state based on the difference between the prediction and the measurement. The state equation and observation equation of the Kalman filter algorithm are represented by equations (2-6) and (2-7) respectively.

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1} \quad (2-6)$$

$$z_k = Cx_k + Du_k + v_k \quad (2-7)$$

Where x_{k-1} and x_k represent the state variables of the system at time k and time $k-1$, respectively. u_{k-1} represents the input variable at time $k-1$, and z_k describes the observed output at time k . Additionally, there are system transition matrix A , input control matrix B , observation matrix C , and feedforward matrix D . The system's state noise and measurement noise are denoted as w_k and v_k respectively, both of which are independent Gaussian white noises with Q_k and R_k respectively.

The recursive process of the linear Kalman filter can be divided into two parts: the prediction module and the correction module. The prediction module estimates the state at time k based on the posterior estimate at time $k-1$, obtaining the prior estimate at time k . The correction module utilizes the measurement at time t to correct the estimate obtained from the prediction phase, resulting in the posterior estimate at time t . The update equation for the prediction module is represented by equation (2-8).

$$\begin{cases} x_k^- = Ax_{k-1}^+ + Bu_{k-1} + w_{k-1} \\ P_k^- = A_{k-1} P_{k-1}^+ A_{k-1}^T + Q_{k-1} \end{cases} \quad (2-8)$$

Where x_{k-1}^+ is the posterior estimate at time $k-1$, x_k^- is the prior estimate at time k , P_{k-1}^+ is the posterior estimate covariance matrix at time $k-1$, and P_k^- represents the prior estimate covariance matrix at time k . The correction equation of the Kalman filter can be expressed as equation (2-9).

$$\begin{cases} K_k = \frac{P_{k-1}^+ C_k^T}{C_k P_{k-1}^+ C_k^T + R_k} \\ x_k^+ = x_k^- + K_k (z_k - C_k x_k^- - D u_k) \\ P_k^+ = (I - K_k C_k) P_k^- \end{cases} \quad (2-9)$$

where K_k is the Kalman gain matrix, x_k^+ is the posterior estimate at time k , P_k^+ is the error covariance matrix, and I represents the identity matrix.

2.3.2 Extended Kalman Filters

The Extended Kalman Filter (EKF) is a commonly used filter for state estimation in nonlinear systems. Compared to the Kalman Filter, the EKF linearizes the system by introducing a first-order Taylor expansion in the state transition and observation equations, allowing the linear model of the Kalman Filter to be applicable to nonlinear systems. In the EKF, the state transition equation and observation equation are respectively represented as :

$$x_{k+1} = f(x_k, u_k) + w_k \quad (2-10)$$

$$z_k = h(x_k, u_k) + v_k \quad (2-11)$$

Here, $f(x_k, u_k)$ is the nonlinear function of the system state, and $h(x_k, u_k)$ is the nonlinear observation function of the system. In order to utilize the linear model of the Kalman Filter, the EKF approximates the nonlinear functions $f(\cdot)$ and $h(\cdot)$ at the current state by a first-order Taylor expansion, transforming the nonlinear system into a linear system. This allows for the use of the methods of the linear Kalman Filter in the state update and measurement update steps for estimation.

$$f(x_k, u_k) = f(\hat{x}_k, u_k) + \left(\frac{\partial f(x_k, u_k)}{\partial x_k} \right) \Big|_{x=\hat{x}_k} * (x_k - \hat{x}_k) \quad (2-12)$$

$$h(x_k, u_k) = h(\hat{x}_k, u_k) + \left(\frac{\partial h(x_k, u_k)}{\partial x_k} \right) \Big|_{x=\hat{x}_k} * (x_k - \hat{x}_k) \quad (2-13)$$

Define:

$$\begin{cases} A_k = \frac{\partial f(x_k, u_k)}{\partial x_k} \Big|_{x=\hat{x}_k} \\ C_k = \frac{\partial h(x_k, u_k)}{\partial x_k} \Big|_{x=\hat{x}_k} \end{cases} \quad (2-14)$$

Therefore, the linear expression of the nonlinear system can be written as:

$$x_{k+1} = A_k x_k - A_k \hat{x}_k + f(\hat{x}_k, u_k) + w_k \quad (2-15)$$

$$z_k = C_k x_k - C_k \hat{x}_k + h(\hat{x}_k, u_k) + v_k \quad (2-16)$$

By using equations (2-15) and (2-16) along with the recursive process of the linear Kalman filter, the recursive process of the Extended Kalman Filter can be obtained as shown in Figure 2-9.

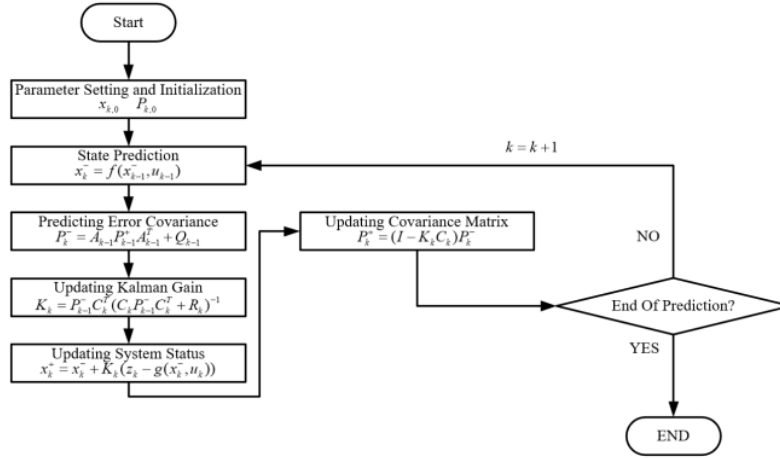


Figure 2-9: Extended Kalman Filter Recursive Process

Due to the fixed values assigned to the observation and state noise during estimation, the linearization approach of the EKF has certain limitations when characterizing the nonlinear dynamics of lithium-ion batteries. The high degree of nonlinearity can result in significant linearization biases, thus affecting estimation accuracy. Furthermore, in practical applications, the dynamics of a battery system can be influenced by external factors such as temperature and vibration, and the statistical characteristics of the noise may be unknown. The noise can persistently change and be unpredictable. Therefore, the EKF estimation algorithm may need to adapt to these uncertainties to achieve accurate state estimation.

One approach to handle the uncertainty in the statistical characteristics of the noise is to use adaptive filtering algorithms, which adjust filter parameters based on observed noise characteristics. Another approach is to employ nonlinear filtering algorithms, such as the Unscented Kalman Filter or Particle Filter, which can handle nonlinear systems and non-Gaussian noise. However, these nonlinear filtering algorithms require more computational resources, which may not be suitable for limited computing resources in microcontrollers. Hence, in this paper, an adaptive filtering algorithm is chosen to handle the uncertainty in the noise statistics.

The adaptive noise covariance matrix is defined to adjust the process and measurement noise in the estimation process based on the variations observed in the data. This enables the noise statistics matrix in the Extended Kalman Filter to adaptively update with the changes in the estimated values, thereby improving estimation accuracy. The update process of the observation matrix and the state transition matrix is shown in Equation (2-17).

$$\begin{cases} e_k = z_k - h(\hat{x}_k, u_k) \\ H_k = \frac{1}{M} \sum_{i=k-M+1}^k e_k e_k^T \\ R_k = H_k - C_k P_k C_k^T \\ Q_k = K_k H_k K_k^T \end{cases} \quad (2-17)$$

Here, M represents the window value, and e_k is the innovation matrix. The recursive process of the Adaptive Kalman Filter is shown in Figure 2-10.

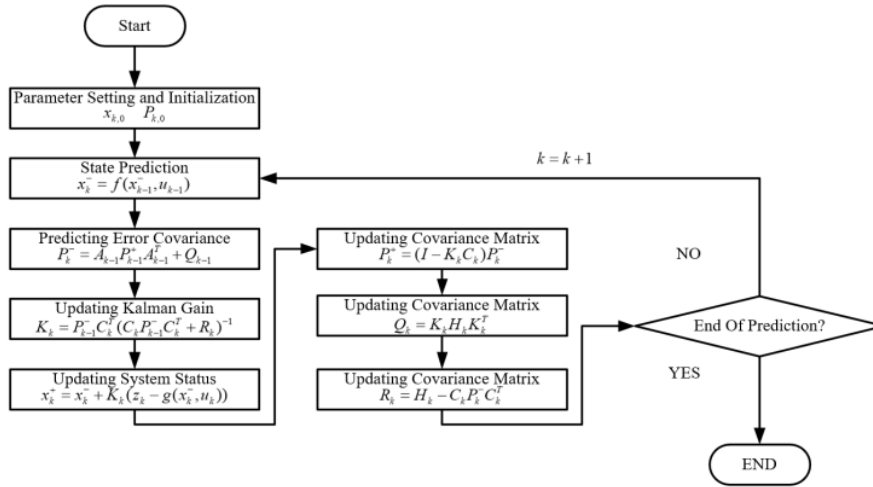


Figure 2-10: Adaptive Extended Kalman Filter Implementation Flowchart

2.3.3 Representative Battery Selection

Due to the low output voltage and limited power of individual batteries, it is common practice to increase the output voltage by connecting them in series or increase the capacity of the battery pack by parallel connection of multiple small-capacity individual batteries. Before serially connecting individual batteries into groups, cell balancing is necessary to ensure that the capacity differences between the individual batteries are kept within a small range.

Assuming that the individual batteries have consistent capacities, during the constant current charging process, when the SOC of the individual batteries in the battery pack is inconsistent, the terminal voltage measured by the BMS can effectively reflect the SOC distribution of different individual batteries after eliminating the differences caused by internal resistance, beyond the voltage plateau region during charging and discharging ^[47]. The charging voltage curve of a battery with a higher internal resistance can be obtained by vertically shifting the charging curve of a battery with a lower internal resistance.

At the same time, the charging current I , battery internal resistance r_1 , and r_0 , and

the difference in charging voltage ΔU satisfy Equation (2-18).

$$r_1 = r_0 + \frac{\Delta U}{I} \quad (2-18)$$

During the battery discharge process, the distribution of individual battery internal resistances can more intuitively reflect the distribution of SOC among the individual batteries. Under the premise of maintaining consistent battery capacity, if the differences in SOC between the individual batteries in the battery pack are small, the terminal voltage of the individual battery with relatively high internal resistance reaches the end voltage of the battery's charge or discharge process first. When there is a large difference in SOC among the individual batteries in the battery pack, the balancing methods introduced in Chapter 3 will be used to keep the SOC differences within a small range. At the same time, the change in battery internal resistance is generally slow, and the update cycle is long. Therefore, this paper selects the value of the battery's internal resistance as a representative of the battery and simplifies the battery pack model to a single battery model in order to reduce computational complexity.

2.3.4 SOC and SOE Estimation Research

Battery management systems need to accurately estimate the SOC and SOE. SOC represents the charge level of the battery, while SOE indicates the watt-hour energy status. Accurate SOE estimation can improve the reliability of remaining power prediction and provide a clear indication of the remaining power supply time. Battery management systems require high-precision SOC/SOE estimation to ensure stable and reliable operation of the system and provide the required energy.

The calculation formulas for battery SOC and SOE can be discretized as shown in Equation (2-19), where T_s represents the sampling interval, and SOC_k and SOC_{k-1} represent the SOC estimation values of the battery at time k and time $k-1$, respectively. C_{bat} represents the rated capacity of the battery. Similarly, SOE_k and SOE_{k-1} represent the SOE estimation values of the battery at time k and time $k-1$, respectively, and E_{bat} represents the rated capacity of the battery.

$$\begin{cases} SOC_k = SOC_{k-1} - \frac{I * T_s}{C_{bat}} \\ SOE_k = SOE_{k-1} - \frac{I * U_{bat} * T_s}{E_{bat}} \end{cases} \quad (2-19)$$

The discrete state equation and discrete observation equation for the battery State of Charge (SOC) estimation system based on filtering can be represented as equations (2-20) and (2-21) respectively. In these equations, U_{bat} represents the terminal voltage of the battery at time k , $U_{1,k}$ and $U_{1,k-1}$ represent the voltages across the RC circuit terminals at time k and time $k-1$ respectively, SOC_k and SOC_{k-1} represent the SOC values of the battery at time k and time $k-1$ respectively, T_s is the sampling time interval of the system, R_o represents the ohmic resistance, R_i represents the polarization resistance, C_i represents the polarization capacitance, C_{bat} represents the rated capacity of the battery, E_{bat} represents the rated energy of the battery, and U_{ocv} represents the open-circuit voltage.

$$\begin{cases} \begin{bmatrix} SOC_k \\ U_{p,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{T_s}{\tau_p}} \end{bmatrix} \begin{bmatrix} SOC_{k-1} \\ U_{p,k-1} \end{bmatrix} + \begin{bmatrix} \frac{-T_s}{C_{bat}} \\ \frac{T_s}{C_p} \end{bmatrix} I_{k-1} \\ U_{bat} = \left[\frac{dU_{ocv}(SOC)}{dSOC} \right]_{k-1} SOC_k - I_k R_o + U_{ocv} \end{cases} \quad (2-20)$$

$$\begin{cases} \begin{bmatrix} SOE_k \\ U_{p,k} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & e^{-\frac{T_s}{\tau_p}} \end{bmatrix} \begin{bmatrix} SOE_{k-1} \\ U_{p,k-1} \end{bmatrix} + \begin{bmatrix} \frac{-U_{bat} T_s}{E_{bat}} \\ \frac{T_s}{C_p} \end{bmatrix} I_{k-1} \\ U_{bat} = \left[\frac{dU_{ocv}(SOE)}{dSOE} \right]_{k-1} SOE_k - I_k R_o + U_{ocv} \end{cases} \quad (2-21)$$

2.4 Experimental Analysis of SOC and SOE Estimation

To validate the estimation accuracy, the SOC and SOE of the battery were verified

under pulse discharge conditions. The initial parameters were set as shown in Table 2-5.

Based on offline parameter identification, the EKF and AEKF algorithms were used to estimate the battery's SOC during the pulse discharge process. The SOC estimation results, including the maximum error, average error, and root mean square error (RMSE), are shown in Figure 2-11 and Table 2-6. It can be observed that there are larger errors in the battery's SOC estimation at the beginning and end of the discharge process. The significant error when SOC is greater than 0.8 is attributed to the issue of initial value setting. From the data in Figure 2-11, it is evident that the AEKF method provides better SOC estimation accuracy than the EKF method under pulse discharge conditions.

Table 2-5: Initial parameter values for EKF and AEKF

	$\hat{\theta}_0$	P_0	Q_0	R_0	M
EKF	$[0.9 \ 0]$	$0.0001 * I_{2*2}$	$0.0000015 * I_{2*2}$	0.01	
AEKF	$[0.9 \ 0]$	$0.0001 * I_{2*2}$			60

Table 2-6: SOC estimation errors of different algorithms under pulse discharge conditions

SOC Estimation	Maximum Absolute	Average Absolute	Root Mean Square
Method	Error	Error	Error
EKF	0.3216	0.0161	0.0329
AEKF	0.1102	0.0109	0.0213

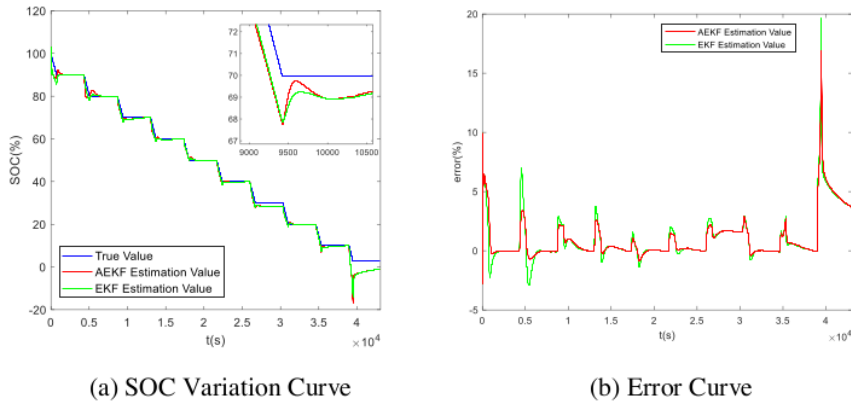


Figure 2-11: SOC Estimation under Pulse Discharge Conditions

To estimate the energy state of the battery, the verification of SOE estimation was conducted under pulse discharge conditions. The SOE estimation of the battery during the pulse discharge process is shown in Figure 2-12(a). The maximum error, average error, and root mean square error (RMSE) of the estimation results are presented in Table 2-12(b). Based on the data in Figure 2-12, it can be observed that the AEKF method provides better accuracy in SOC estimation for the battery under pulse discharge conditions.

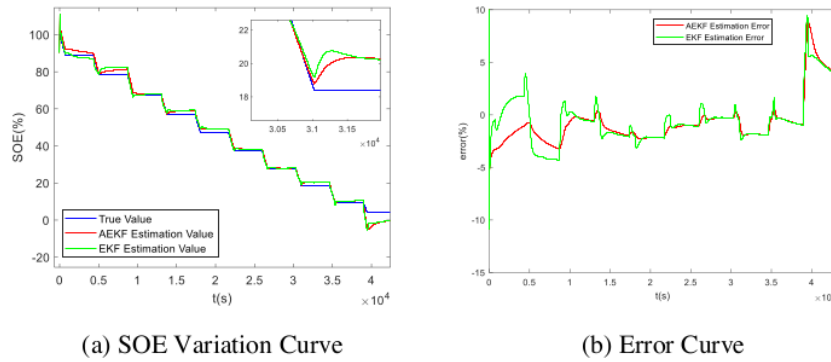


Figure 2-12: SOE Estimation under Pulse Discharge Conditions

Table 2-7: SOE Estimation Errors of Different Algorithms under Pulse Discharge Conditions

SOC Estimation	Maximum Absolute	Average Absolute	Root Mean Square
Method	Error	Error	Error
EKF	0.3216	0.0161	0.0329
AEKF	0.1102	0.0109	0.0213

Chapter 3 Research on Lithium Battery Pack Equalization Method

With the widespread application of lithium-ion batteries in energy storage and mobile devices, battery pack balancing technology has become increasingly important. Imbalances in battery packs can lead to reduced battery life, energy loss, and safety issues. Therefore, lithium-ion battery balancing techniques have become a crucial component of lithium-ion battery management systems. In this section, existing lithium-ion battery balancing methods will be studied from both hardware and software perspectives. An active balancing circuit based on a bidirectional flyback converter will be designed, along with corresponding balancing control strategies, to achieve precise balancing control of the battery pack. This will provide technical support for the long-term stable operation of the battery pack.

3.1 Battery Balancing Technology

To meet the power output requirements of lithium batteries, multiple batteries are typically combined to form a battery pack, either in series to increase voltage or in parallel to increase energy storage capacity. Due to the differences in individual lithium battery characteristics, the cycle life and capacity utilization of the battery pack are usually lower than those of individual batteries. The inconsistencies in lithium-ion batteries mainly manifest as inconsistencies in capacity, state of charge, terminal voltage, internal resistance, and other characteristic parameters, which can be attributed to differences in the production process and battery usage. The balancing function of the battery management system improves the inconsistencies in the battery pack by dynamically adjusting the battery's charging and discharging states.

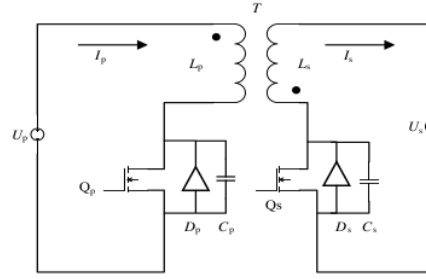
3.2 Battery Pack Balancing Circuit

3.2.1 Active Balancing Topology Design

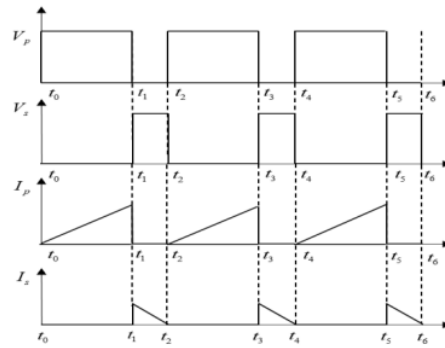
A bidirectional flyback converter is a device that enables bidirectional conversion

between input and output DC power sources. When applied to an active balancing circuit, it transfers energy within the battery by converting electrical energy to magnetic energy, thereby achieving battery pack balancing. This converter has minimal energy losses and high balancing efficiency during the balancing process.

Figure 3-3 illustrates the structure of the bidirectional flyback converter, the drive waveforms of the switching devices transferring energy from individual cells to the battery pack, and the variations in primary and secondary side currents. In the figure, T represents the converter, U_p represents an individual cell, U_s represents the battery pack, L_p and L_s represent the inductance values of the primary and secondary windings of the converter T , respectively. I_p and I_s represent the currents on the primary and secondary sides of the converter, respectively, while Q_p and Q_s denote the switching devices connected to the primary and secondary side of the bidirectional flyback converter.



(a) Structure of the Bidirectional Flyback Converter



(b) Operation Waveforms

Figure 3-1 Structure and Operation Waveforms of the Bidirectional Flyback Converter

In Figure 3-1(b), V_s and V_p represent the drive signals for the switching devices Q_p and Q_s , respectively. $t_0 \sim t_2$ denotes one energy transfer cycle when the switching device Q_p is turned on, and Q_s is turned off. L_p results in charging. During this charging phase, electrical energy is converted into magnetic energy and stored in the converter. The rate of change of the primary current I_p can be expressed by Equation (3-1).

$$\frac{dI_p}{dt} = \frac{U_p}{L_p} \quad (3-1)$$

At time $I_{p,\max}$, the primary current reaches a predetermined peak value and can be represented by Equation (3-2)

$$I_{p,\max} = \frac{U_p}{L_p} * D_t * T_p \quad (3-2)$$

T_p represents the period of the switching device drive signal and D_t stands for the duty cycle. At time t_2 , the switching device Q_p is turned off, Q_s is turned on, allowing the energy stored in the primary winding to be released through the freewheeling path and transferred to the secondary winding. Assuming a ratio of $1/k$ between the primary and secondary windings of the converter, the relationship between the primary current and the secondary current can be expressed by Equation (3-3).

$$I_{s,0} * k = I_{p,\max} \quad (3-3)$$

The decreasing rate of the secondary current I_s can be represented by Equation (3-4)

$$\frac{dI_p}{dt} = -\frac{U_p}{L_p} \quad (3-4)$$

the secondary current I_s can be represented as

$$I_s = I_{s,0} - \frac{U_s}{L_s} (1 - D_t) T_p \quad (3-5)$$

By toggling the switching devices between the on and off states during $t_0 \square t_2$, there is a continuous conversion of electrical energy to magnetic energy and vice versa, facilitating the transfer of energy from individual cells to the battery pack.

The selected flyback converter model for this paper is WURTH-750312504, with an inductance value of $3.46\mu\text{H}$, a turns ratio of 1:1, and a saturation current of 10.2A. The switching devices are driven by a dedicated driver chip, LTC3300-2, which controls the opening and closing of the switches based on the peak current in the windings, enabling energy transfer. Specifically, during energy transfer from the primary to the secondary side of the transformer, the switching device is turned on, and the current gradually increases in the primary winding. LTC3300-2 detects a voltage of 50mV across the shunt resistor connected in series with the primary winding, indicating the desired threshold, and then closes the switching device while opening the other one, facilitating energy transfer. Therefore, different current balancing circuits can be achieved by modifying the shunt resistor value and the saturation current of the converter. In this study, a shunt resistor value of 0.008 and a peak current of 6.25A are designed.

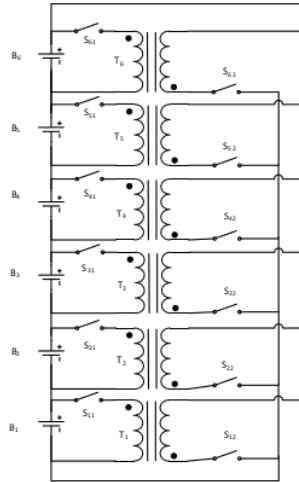


Figure 3-2: Active Balancing Circuit Based on Bidirectional Flyback Converter

3.3 Battery Pack Balancing Strategy

The battery pack balancing strategy consists of two parts: the selection of balancing variables and the design of balancing control strategy. This section first focuses on selecting appropriate balancing variables and optimizing them as a basis for the overall control of the balancing process by the balancing control strategy.

3.3.1 Selection of Balancing Variables

Commonly used balancing variables in battery packs include terminal voltage, open-circuit voltage, state of charge (SOC), and methods combining voltage and SOC. Terminal voltage can be directly measured, providing high accuracy and convenience. However, terminal voltage is greatly influenced by internal parameters (battery capacity, internal resistance) and external environmental factors (current rate, operating temperature, battery aging), making it unable to accurately reflect the internal state of the battery.

Open-circuit voltage has a good nonlinear relationship with SOC, and using it as a balancing variable can achieve good consistency in the remaining capacity of the battery pack. When the battery pack is in a static state, open-circuit voltage can be directly measured with high precision. However, it is not directly obtainable during battery usage.

SOC provides a visual representation of the inconsistency in the charge state of individual cells in the battery pack, making it effective for balancing control. Estimating SOC for each individual cell requires calculations based on parameters such as current, voltage, and temperature of the battery, resulting in significant computational overhead.

Based on the above analysis, this paper selects open-circuit voltage as the balancing variable to achieve consistency in the remaining capacity of the battery pack, avoiding the influence of internal resistance and polarization reactions on terminal voltage.

The open circuit voltage of the battery at this moment can be approximately represented by the formula (3-6) as follows:

$$U_{ocv} = U_{bat} - I * R_o - I * R_p \quad (3-6)$$

U_{ocv} stands for open-circuit voltage, U_{bat} signifies the terminal voltage of the battery, I represents the current flowing through the battery, R_o represents the ohmic resistance of the battery, and R_p represents the polarization resistance of the battery. The values of the ohmic resistance and polarization resistance are determined through offline parameter identification.

3.3.2 Balancing activation threshold

The selection of the balancing activation threshold is an important decision that directly affects the effectiveness of balancing. The relationship between open-circuit voltage (OCV) and state of charge (SOC) of the battery follows a nonlinear function, represented by the OCV-SOC curve denoted as $OCV = g(SOC)$. Let $y = G(x)$ represent the first derivative of the OCV-SOC curve, and Figure 3-3 illustrates the plot of the first derivative curve of the OCV-SOC relationship. The difference in SOC between two individual cells within the battery pack can be expressed by Equation (3-8).

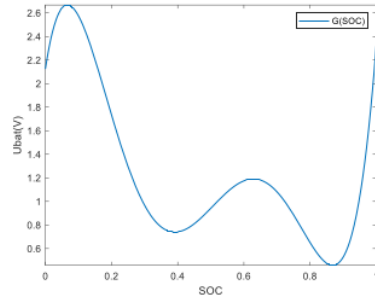


Figure 3-3: The first derivative curve of the OCV-SOC relationship

$$\begin{cases} g(SOC_1) - g(SOC_2) = G(SOC_{\xi}) \times (SOC_1 - SOC_2) \\ SOC_2 < SOC_{\xi} < SOC_1 \end{cases} \quad (3-7)$$

The term SOC_{ξ} in Equation (3-7) can be approximated directly using the OCV-SOC curve obtained from Chapter 2.

$$\Delta SOC = \frac{\Delta OCV}{G(SOC)} \quad (3-8)$$

Since the OCV-SOC curve of the battery pack is nonlinear, the same difference in OCV corresponds to different differences in SOC under different SOC conditions. Based on the OCV-SOC curve discussed in Section 2.1.2, we set ΔOCV to 10mV, 20mV, 30mV, 40mV, and 50mV, respectively, and the corresponding distribution curve of ΔSOC with respect to SOC is shown in Figure 3-4.

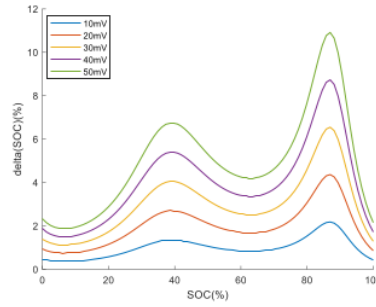


Figure 3-4: Distribution Curve of ΔSOC with respect to SOC

From Figure 3-4, it can be observed that for different SOC values of the battery pack, the same OCV distribution corresponds to different differences in SOC. When ΔOCV is set to 20mV, the maximum ΔSOC is 4.3%. When ΔOCV is set to 10mV, the maximum ΔSOC is less than 1%. However, setting ΔOCV to 10mV significantly increases the number of interrupts called by STM32, which may lead to program freezing. Therefore, this paper designs the balancing activation threshold condition as the range of estimated OCV exceeding 20mV.

3.3.3 Balancing control strategy

The balancing control strategy determines the activation or deactivation of battery pack balancing based on the standard deviation or range of the balancing variable. Let X represent the estimated open-circuit voltage values discussed in Section 3.3.1. The calculations for standard deviation and range are given by Equation (3-9).

$$\begin{cases} X_{avg} = \frac{1}{N} \sum_{i=1}^N X_i \\ \sigma_x = \sqrt{\frac{1}{N} \sum_{i=1}^N (X_i - X_{avg})^2} \quad , \{i, j = 1, 2, \dots, N\} \\ \varepsilon = \max(X_i) - \min(X_j) \end{cases} \quad (3-9)$$

In the above equation, N represents the number of individual cells in the battery pack, X_i represents the estimated open-circuit voltage of the i -th cell acquired by the battery management system, and X_{avg} mean represents the mean estimated open-circuit voltage of the battery pack. σ_x represents the standard deviation of the estimated open-circuit voltage, indicating the dispersion of individual cell's estimated open-circuit voltage within the battery pack. The magnitude of the range, ε , which represents the difference in estimated open-circuit voltage among individual cells within the battery pack, directly reflects the inconsistency of the cells and is often used as a criterion for determining the activation or deactivation of battery pack balancing.

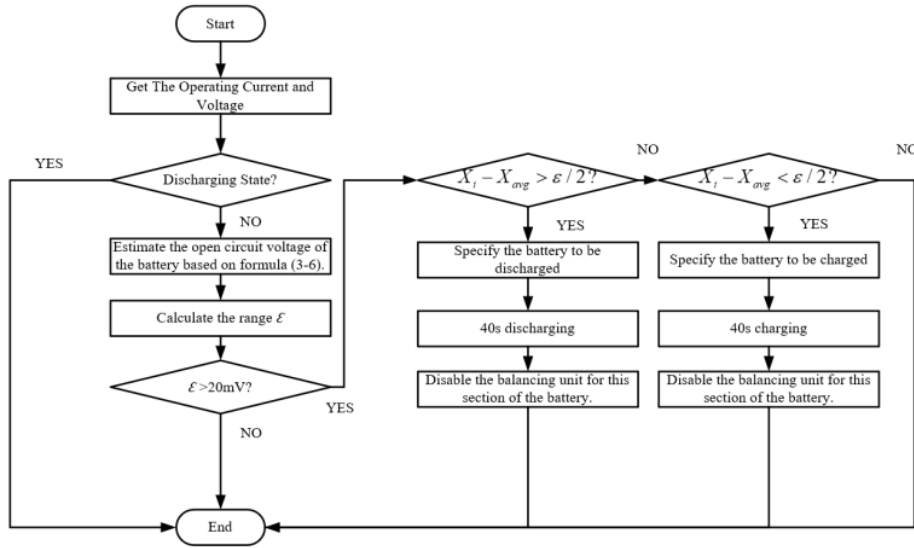


Figure 3-5: Active balancing control strategy based on estimated open circuit voltage.

Chapter 4: Battery Management System Hardware and Software Design

4.1 Overall Design of the Battery Management System

The main functions of the energy storage battery management system designed in this paper revolve around battery pack state monitoring and fault protection. The subsystems include the main controller module, data acquisition module, fault protection module, balancing control module, and communication interface.

The data acquisition module collects voltage, current, and temperature information of individual cells, and monitors the battery pack for abnormal conditions such as overvoltage, undervoltage, overcurrent, and short circuits using the hardware protection functions of the battery management chip. It promptly responds to these conditions and stores the data in internal registers for querying by the main controller. The main controller reads the data from the battery management chip via the data bus and performs preliminary processing of the collected information. With the design of the software protection module, the main controller can issue alarms and execute protective operations in a timely and effective manner in response to faults occurring during the battery pack's operation. Based on the status information of the individual cells in the battery pack and the balancing control strategy, the main controller determines and controls the balancing of the battery pack, reducing the inconsistency among the individual cells. Additionally, using state estimation algorithms, the main controller provides an estimation of the battery pack's state of charge (SOC) and state of energy (SOE) as a reference for the battery pack's remaining runtime.

4.2 Hardware Design of the Battery Management System

4.2.1 MCU and Peripheral Circuits

The main controller is the core of the battery management system, responsible for data interaction with the battery management chip, data calculation, and necessary decision-making processes. Therefore, the main controller chip needs to meet the

Figure 4-2 shows the schematic diagram of the protection circuit. The implementation of the charging and discharging protection circuit switches utilizes power MOSFETs connected in series within the circuit loop. The main controller drives these switches to control the charging and discharging operations. The selected MOSFET model is STB15810, which has a positive temperature coefficient. Multiple MOSFETs are connected in parallel to avoid an increase in the on-resistance of the MOSFETs when the temperature rises. This ensures that the battery management system can accommodate higher operating currents. Since the BQ769x0 integrated circuit includes hardware protection and MOSFET driver circuits, and the main controller also implements software protection, the switching of the STB15810 MOSFET's state is jointly controlled by the battery management chip B1 and the main controller through a logic gate. The STB15810 transistor has a drain-source voltage rating of 100V, a rated current of 110A, and an on-resistance of 3.4 milliohms.

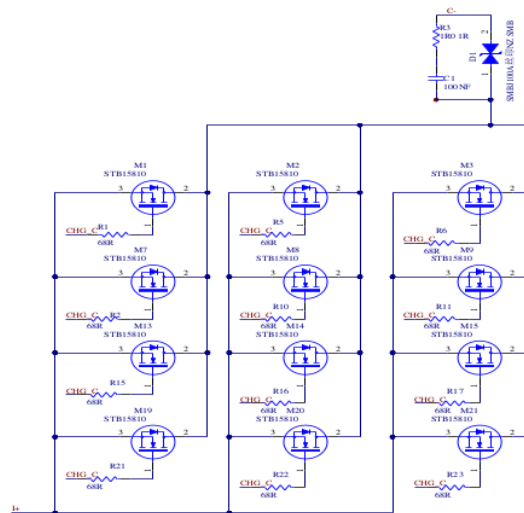


Figure 4-2: Protection Module Circuit Diagram

Figure 4-3 depicts the schematic diagram of the pre-charge/discharge circuit used in the design. Considering the possibility of capacitive loads in the load or charger, direct high-current charging and discharging of the battery pack pose significant safety risks. Therefore, a pre-charge/discharge circuit needs to be designed. The purpose of the pre-charge/discharge circuit is to enable low-current charging and discharging,

limiting the impact of instantaneous capacitor charging/discharging currents when the power supply is connected. This protects the components of the load or charger from damage caused by the momentary short-circuit current of the capacitor. The main controller drives the N-channel power MOSFET NCE0115K to control the pre-charge/discharge control circuit. The NCE0115K transistor has a drain-source voltage rating of 100V, a rated current of 15A, and an on-resistance of 90 milliohms. The circuit is connected to the output of the battery management system and the battery sampling circuit.

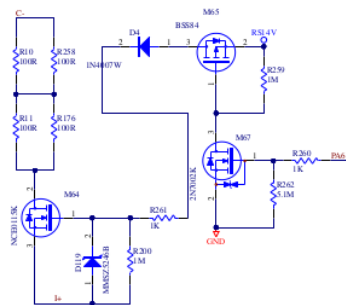


Figure 4-3: Pre-Charge/Discharge Circuit Diagram

4.2.3 Data Acquisition Circuit

The data acquisition module is one of the core circuits in the battery management system. In this design, the module utilizes the BQ76930 acquisition chip produced by Texas Instruments. The BQ76930 is a battery analog front-end acquisition chip capable of handling battery packs with 6 to 10 series cells. It integrates an A/D converter for pure digital readout of battery parameters. This chip ensures a total measurement error of $\pm 20\text{mV}$ within an operating temperature range of 0°C to 60°C . It also features a 16-bit high-precision ADC, which allows accurate current measurement through shunt resistors connected in series with the battery pack's charging and discharging circuit. Temperature measurement can be achieved by connecting specified chip ports to NTC thermistors. Using this integrated battery management chip facilitates high-precision monitoring of battery pack current, voltage, and temperature.

The BQ769x0 series chips integrate internal hardware protection, providing

battery series and utilize 103AT thermistors for detection.

4.2.4 Battery Balancing Circuit

The design of the balancing circuit aims to maximize the utilization of energy in the lithium battery pack and eliminate the inconsistency among individual cells within the battery pack.

The active balancing circuit's balancing unit is designed as shown in Figure 4-5. represents the bidirectional flyback converter. C1-33 and C0-33 connect to the positive and negative terminals, respectively, of the first cell in the battery pack. BOT6-TS connects to the positive terminal of the battery pack. and represent the switch transistors on the primary and secondary sides of the transformer, respectively, with model numbers SIR882DP-T1-GE3 and SIS892DN-T1-GE3. and represent the drive signals for the switch transistors, respectively. and represent the detection pins for the primary and secondary currents.

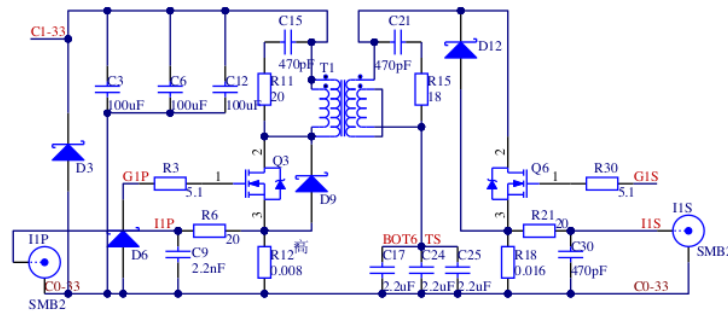


Figure 4-5: Active Balancing Unit Design Circuit

The switches of the active balancing unit are controlled by the LTC3300 driver. The design of the drive circuit is shown in Figure 4-6.

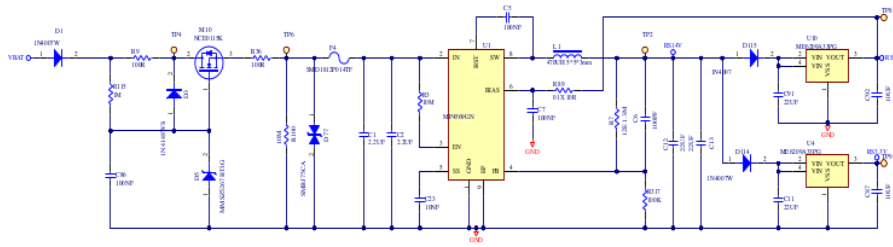


Figure 4-7: System Power Circuit

4.3 Battery Management System Software Design

The implementation of software in the battery management system determines the system's stability. The software design primarily focuses on data acquisition of the battery pack, detection and handling of abnormal battery pack states, state estimation and balancing of the battery pack, and communication functionalities.

4.3.1 Acquisition Module Software Design

The BQ769x0 series battery management chips integrate internal ADC converters for measuring battery voltage, external thermistor resistance value, and battery pack current, converting analog quantities into pure digital values. The software flowchart for the acquisition process of battery voltage, current, and temperature is shown in Figure 4-8.

The main controller reads the SYS_STAT register of the battery management chip via the IIC bus to obtain the current hardware protection status and check if the AD conversion of the sampled values is completed. It then reads the stored count values of the voltage, current, and temperature from the ADC registers and calculates the corresponding voltage/current/temperature values using the calculation formulas. The acquired sample values are checked against predetermined conditions to determine their validity, and the failure flags for voltage/current/temperature are set or cleared accordingly.

Since the chosen battery in this paper operates within the voltage range of 2.5V to 4.2V, the threshold for voltage failure detection is set as below 2.0V or above 4.5V. A thermistor, model 103-AT, is used for temperature measurement, with a temperature

range of -20°C to 120°C. Therefore, the failure threshold for temperature is set as below -20°C or above 120°C. For a series-connected battery pack, if the charging or discharging circuit is disconnected and the current acquisition software program detects a non-zero current value, it is considered a failure in the current sampling.

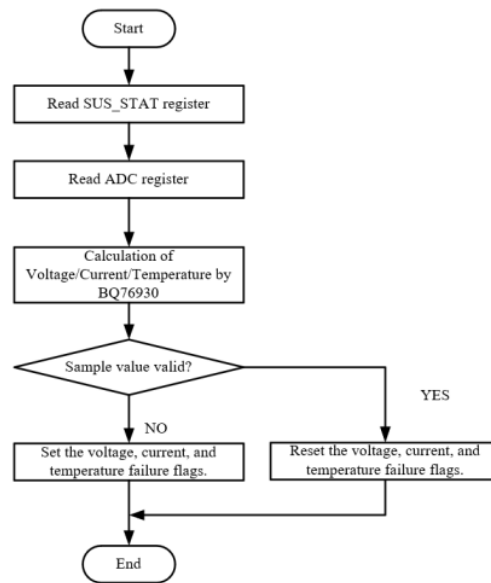


Figure 4-8: Software Flowchart for Acquisition Module

4.3.2 Protection Module Software Design

The process of determining individual cell under-voltage/over-voltage and battery pack under-voltage/over-voltage is similar. Therefore, they are collectively referred to as voltage anomaly detection during the design phase. The flowchart for voltage anomaly detection is shown in Figure 4-9, and the flowchart for voltage anomaly resolution is shown in Figure 4-10. Whether it is for individual cells or the battery pack, if the number of detected under-voltage or over-voltage occurrences exceeds 3, the abnormal state is updated; otherwise, no update is made. The resolution of the voltage anomaly state for the battery pack follows a similar process to entering the anomaly state. If the voltage information is continuously detected below the over-voltage threshold for 3 consecutive times or above the under-voltage threshold for 3

consecutive times, the over-voltage or under-voltage anomaly is resolved. The detection and resolution process for high-temperature and low-temperature anomalies in the charging and discharging environment is structurally consistent with the voltage anomaly detection and resolution process in the software.

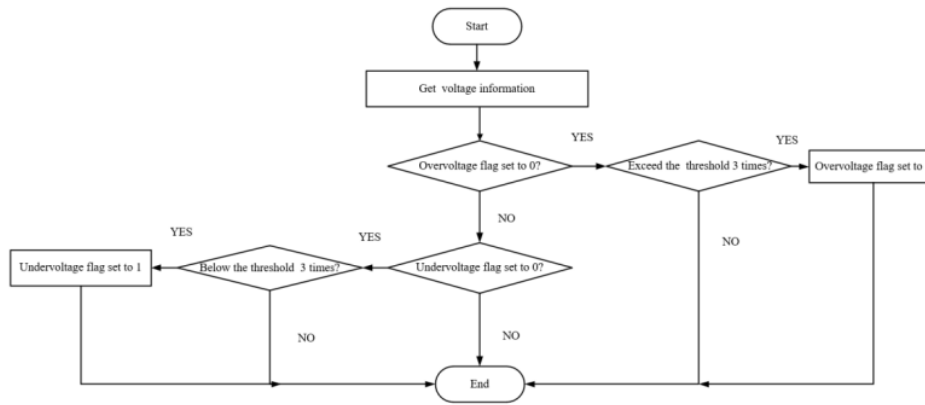


Figure 4-9: Flowchart for Voltage Anomaly Detection

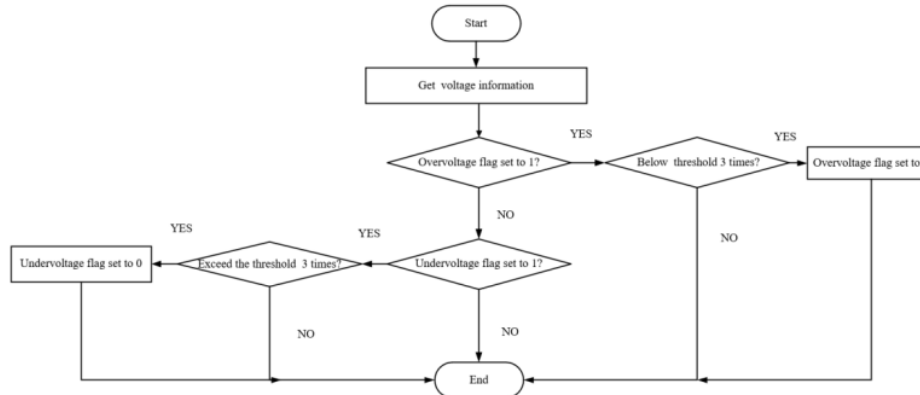


Figure 4-10: Flowchart for Voltage Anomaly Resolution

4.3.3 State Estimation Software Design

The algorithmic flowchart for estimating the State of Charge (SOC) and State of

Energy (SOE) of the battery management system is shown in Figure 4-11. Based on the terminal voltage and current of the representative cell, using matlab to identify the offline parameters. Then, the AEKF algorithm is used to estimate the SOC and SOE. The remaining charging time $Time_{chg}$ and remaining discharging time $Time_{dsg}$ are calculated using Equation (4-1) and Equation (4-2), where SOC_{now} represents the current SOC value, C_{bat} represents the rated capacity of the battery, and I_{chg} , I_{dsg} represent the current charging and discharging currents, respectively.

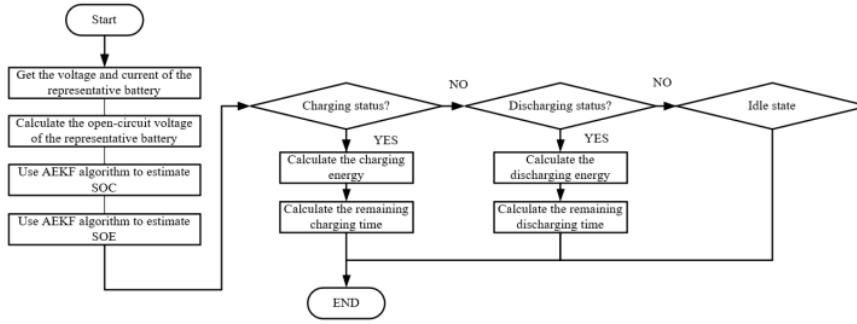


Figure 4-11: Algorithmic Flowchart for Estimation

4.3.4 Balancing Module Software Design

The software implementation of the balancing control, designed based on the active balancing method using LTC3300, is shown in Figure 4-12.

The execution process of active balancing is described as follows: Based on the acquired individual cell voltage values of the battery pack, the software determines whether the individual cell voltages have reached the voltage threshold for balancing activation. In this paper, we designed the criteria for balancing activation as follows: when the SOC of the battery pack is greater than 0.9 and the voltage difference between the individual cell and the minimum voltage exceeds 20mV. If balancing is required, the main controller writes to the balancing control register of LTC3300 to open the balancing switch. The batteries with voltage differences greater than 20mV are discharged, while the batteries with voltage differences lower than 20mV are charged. A balancing period of 40 seconds is executed. Once the balancing period is completed,

the balancing is turned off, and the balancing control for the second group is performed. This process is repeated until all battery voltages are equalized or the charging process is completed, indicating the end of the balancing process.

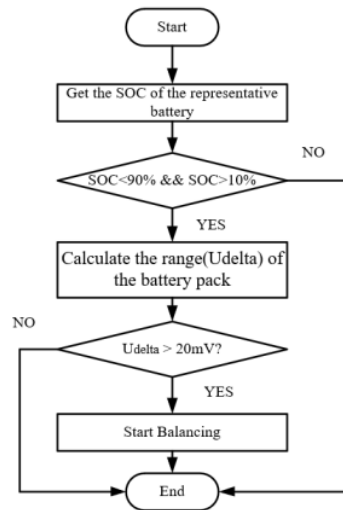


Figure 4-12: Active Balancing Execution Process

Chapter 5: System Functional Testing

5.1 Test Platform Setup

The test platform was constructed based on laboratory equipment, as shown in Figure 5-1. The experimental test battery consists of a battery pack composed of 12 series-connected 18650 batteries, with the model number INR18650/35V. On the left side is the active balancing board based on LTC3300, which is divided into two parts: BOT6 and TOP6. It manages the balancing of a 12-cell battery pack. The top right corner features a BMS acquisition board, with an embedded STM32 serving as the main controller for the entire system. The BQ76930 handles the battery sampling. Due to the relatively high resistance of the selected balancing wires in the experiment, the balancing current lines of the balancing board are separated from the sampling lines of the BMS and the battery pack externally. This separation aims to minimize the impact of balancing current and sampling wire resistance on individual cell voltage measurements.

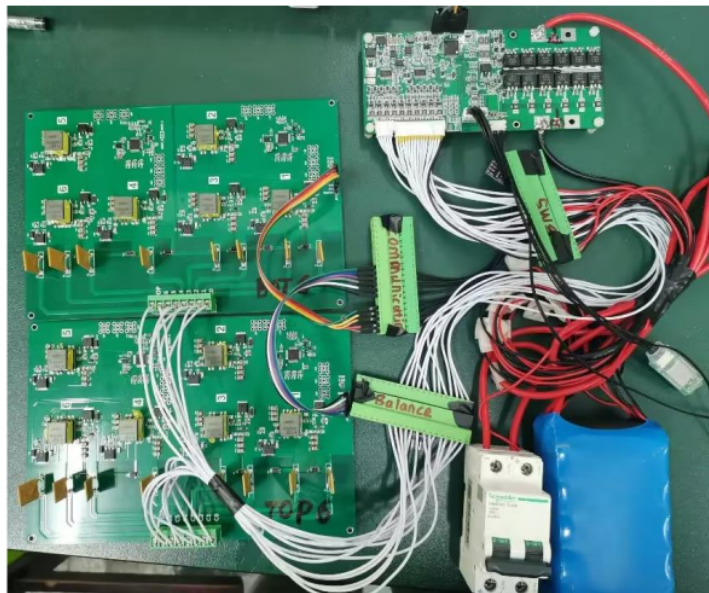


Figure 5-1 Experimental Platform

5.2 System Function Testing

5.2.1 Data Acquisition Function Testing

The BMS collects the voltage of each individual cell in the battery pack, monitors and analyzes it, and implements functions such as state monitoring, state of charge estimation, health condition detection, and charge/discharge control, thereby ensuring the normal operation and extended lifespan of the battery system. Table 5-1 shows the comparison between the measured values of individual cell voltage acquired by the battery management system during the initial series connection of the battery pack and the actual values. It can be observed that the absolute error of the measured individual cell voltage is less than 3%, with a maximum error of 9mV, indicating excellent voltage acquisition accuracy.

Table 5-1: Voltage Acquisition Test Data

Number	Measured Value (V)	Actual Value (V)	Relative Error (%)
1	3.440	3.431	0.26%
2	3.440	3.432	0.23%
3	3.441	3.432	0.26%
4	3.440	3.432	0.23%
5	3.443	3.433	0.29%
6	3.442	3.433	0.26%
7	3.442	3.432	0.29%
8	3.442	3.432	0.29%
9	3.441	3.432	0.26%
10	3.442	3.432	0.29%
11	3.442	3.432	0.29%
12	3.438	3.431	0.20%

The current information of the battery pack is crucial for state estimation and circuit protection parameters. In this study, a constant current discharge was performed on the battery pack using an electronic load, and the current sampling values of the battery management system were recorded and compared with the actual values. The

test data is presented in Table 5-2. From Table 5-2, it can be observed that the relative error of current acquisition is less than 3%, indicating good accuracy in current sampling testing.

The battery management system has three temperature probes, two for measuring the temperature of the battery pack and one for testing the temperature of the acquisition board. Temperature sampling data was recorded at room temperature, and the results are shown in Table 5-3. The temperature acquisition error of the battery management system is less than $\pm 5^{\circ}\text{C}$, meeting the design requirements.

Table 5-2: Current Acquisition Test Data

Number	Measured Value (A)	Actual Value (A)	Relative Error (%)
1	0.5	0.51	2%
2	1.0	0.99	-1%
3	1.5	1.51	1%
4	2.0	2.03	1%
5	2.5	2.58	3%

Table 5-3: Temperature Acquisition Test Data

Number	Measured Value ($^{\circ}\text{C}$)	Actual Value ($^{\circ}\text{C}$)	Error($^{\circ}\text{C}$)
1	22.0	24.0	-2
2	23.0	24.0	-1
3	23.0	24.0	-1

5.2.2 State Estimation Function Testing

For the testing of the state estimation function, constant current charging and constant current discharging of the battery pack were conducted using an electronic load. According to the battery manual requirements, the battery pack was charged with a current of 0.68A until it was fully charged, considering the battery pack's State of Charge (SOC) as 100%. A constant current discharge of 3A was performed on the battery using the electronic load, and the changes in ampere-hour energy of the battery during the discharge process were recorded and compared with the estimated SOC changes of the battery. Additionally, the discharge watt-hour energy recorded by the

electronic load was compared with the actual State of Energy (SOE) changes of the battery during the discharge process. The current and voltage variations during the discharge process are shown in Figure 5-2.

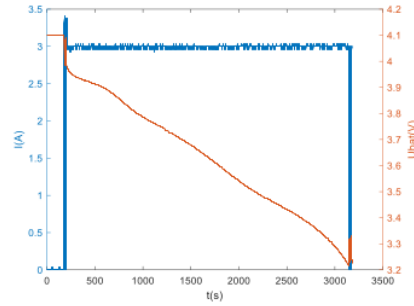
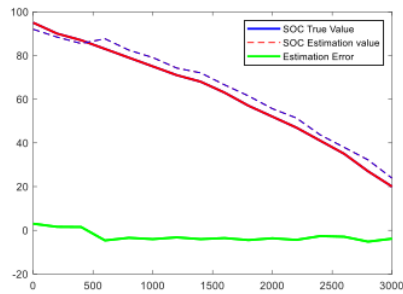
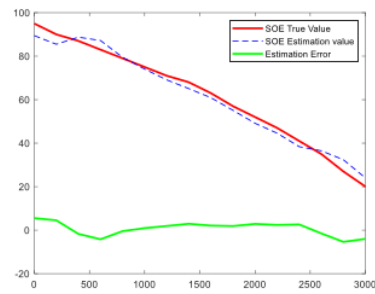


Figure 5-2: Current and Voltage Variation during 3A Constant Current Discharge Process

The results of the state estimation during the constant current discharge process are illustrated in Figure 5-3. Figure 5-3(a) shows the SOC estimation values, actual values, and estimation errors. From the figure, it can be observed that the maximum SOC estimation error is 5.1%, indicating a good estimation accuracy during the constant current discharge process. Figure 5-3(b) presents the estimated SOE of the battery during the discharge process and the corresponding estimation error. The maximum SOE estimation error is 6%.



(a) SOC Estimation Results



(b) SOE Estimation Results

Figure 5-3: State Estimation Results during Constant Current Discharge Process

5.2.3 Battery Balancing Function Testing

Before the balancing process, the battery management system relies on the edge communication function to identify the internal resistance parameters of individual cells within the battery pack, which are used for balancing control. The identified results are shown in Table 5-4. From the data in Table 5-4, it can be observed that the tested batteries have minimal internal resistance differences.

Table 5-4: Internal Resistance Parameters of Batteries Before Balancing

Number	Internal Resistance (Ω)	Number	Internal Resistance (Ω)
1	0.068	7	0.068
2	0.063	8	0.061
3	0.065	9	0.063
4	0.062	10	0.062
5	0.064	11	0.064
6	0.065	12	0.065

Before starting the equalization function test, a differential treatment is performed on the 12 batteries. During the charging process, the charging voltage is set to 50.4V, and the charging current is 1.5A. The comparison of terminal voltages before and after the equalization function test, as well as the variation of terminal voltages during the equalization process, are shown in Figure 5-13. From Figure 5-13(a), it can be observed that before the equalization starts, the maximum difference in terminal voltage of the battery pack is 229mV, with a standard deviation of 0.0635. After the equalization is completed, the maximum difference in terminal voltage of the battery pack is 26mV, with a standard deviation of 0.0094. During the equalization process, the overall terminal voltage of the battery pack increases due to charging. The equalization circuit and control strategy collaborate to successfully reduce the inconsistency of terminal voltage in the battery pack.

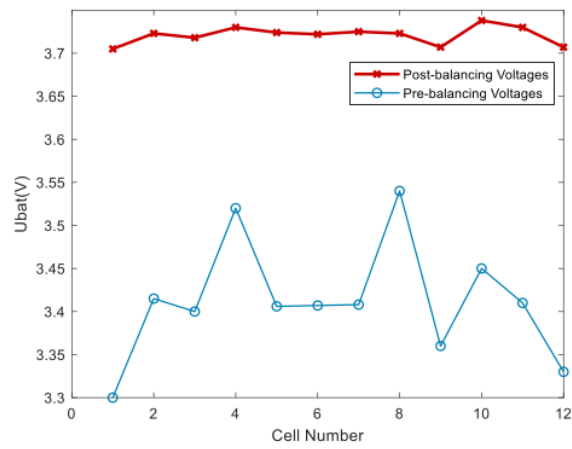


Figure 5-4: Voltage values before and after balancing.

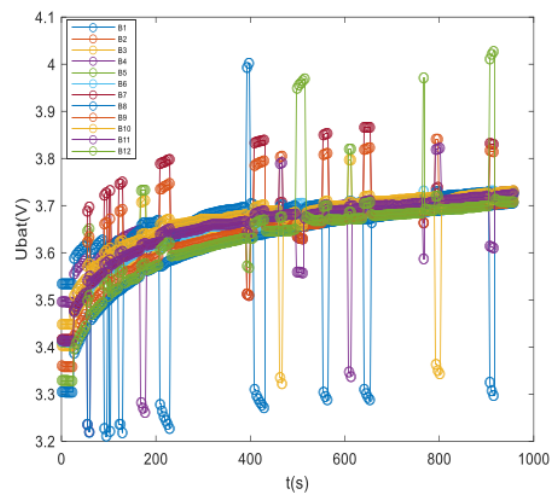


Figure 5-5: Voltage variation at the battery terminals during the balancing process.

Chapter 6: Conclusion

This paper focuses on the research of battery pack balancing topologies and the estimation of SOC and state of energy (SOE) of the battery pack. The main research contributions are summarized as follows:

1. Research on battery pack balancing topologies: This study investigates and analyzes battery pack balancing topologies. Considering the slow balancing speed of existing passive balancing methods for battery packs in multiple series configurations, a non-dissipative balancing topology based on a bidirectional flyback converter is implemented in this paper. This topology enables fast balancing of multiple batteries within the battery pack.

2. Offline parameter identification is performed for all battery parameters within the battery pack, and the battery with the highest internal resistance is selected as the representative battery. An adaptive extended Kalman filter (AEKF) is employed to estimate the SOC and SOE of the representative battery. Due to the limited computational capabilities of the STM32, the SOC representative battery is considered as a representative value for the battery pack. This method calculates the battery's open-circuit voltage based on the terminal voltage, Ohmic resistance, and polarization resistance, then determines the activation of balancing based on the estimated open-circuit voltage.

3. Design of battery management system based on active balancing: The STM32 microcontroller is utilized to drive the BQ769x0 series battery management chip for monitoring battery information within the battery pack. Additionally, the STM32 drives the LTC3300 active balancing chip to perform balancing on the battery pack. The validation results confirm that the designed battery management system achieves satisfactory performance in terms of accuracy in current, voltage, and temperature measurements, state estimation precision, and balancing effectiveness.

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GRADEMARK REPORT

FINAL GRADE

GENERAL COMMENTS

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