DESIGN AND MODELING OF BATTERY MANAGEMENT SYSTEM FOR ELECTRIC VEHICLE APPLICATIONS

Habtamu Sisay Tegegn

A Thesis submitted to the Department of Mechanical Engineering

School of Mechanical, Chemical and Materials Engineering

Presented in Partial Fulfillment of the Requirements for the Degree of Masters in Automotive Engineering

Office of Graduate Studies

Adama Science and Technology University

February 2024

Adama, Ethiopia

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DECLARATION

I hereby declare that this Master Thesis entitled "**Design and Modeling of Battery Management System for Electric Vehicle Applications**" is my original work. That is, it has not been submitted for the award of any academic degree, diploma, or certificate in any other university. All sources of materials that are used for this thesis have been duly acknowledged through citation.

Habtamu Sisay Tegegn	………………………	…………….
Name of the student	Signature	Date

RECOMMENDATION

I/we, the advisor(s) of this thesis, hereby certify that I/we have read the revised version of the thesis entitled "**Design and Modeling of Battery Management System for Electric Vehicle Applications**" prepared under my/our guidance by Habtamu Sisay Tegegn submitted in partial fulfillment of the requirements for the degree of Masters of Science in Automotive Engineering. Therefore, I/we recommend the submission of revised version of the thesis to the department following the applicable procedures.

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Major Advisor	Signature	Date
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Co-advisor	Signature	Date

APPROVAL

I/we, the advisors of the thesis entitled "**Design and Modeling of Battery Management System for Electric Vehicle Applications**" and developed by Habtamu Sisay Tegegn hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

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Major Advisor	Signature	Date
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Co-advisor	Signature	Date

APPROVAL OF BOARD OF EXAMINERS

We, the undersigned, members of the Board of Examiners of the thesis by Habtamu Sisay Tegegn have read and evaluated the thesis entitled "**Design and Modeling of Battery Management System for Electric Vehicle Applications**" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Automotive Engineering.

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Finally, approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

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ACRONYMS AND ABBREVIATIONS

ADC	-	*Analog-to-Digital Converter*
AKF	-	*Adaptive Kalman Filter*
BMC	-	*Battery Monitoring Circuit*
BML	-	*Battery Management Layer*
BMS	-	*Battery Management System*
CAN	-	*Controller Area Network*
CPU	-	*Central Processing Unit*
EKF	-	*Extended Kalman filter*
FDM	-	*Finite Difference Method*
FEM	-	*Finite Element Method*
FLC	-	*Fuzzy Logic Control*
HAL	-	*Hardware Abstraction Layer*
HEV	-	*Hybrid Electric Vehicle*
ICE	-	*Internal Combustion Engine*
LIN	-	*Local Interconnect Network*
OCV	-	*Open Circuit Voltage*
SOA	-	*Safe Operating Area*
SOC	-	*State of Charge*
SOH	-	*State of Health*
UKF	-	*Unscented Kalman filter*
UT	-	*Unscented Transformation*
VCU	-	*Vehicle Control Unit*

ABSTRACT

The battery management system plays a crucial role in ensuring the safe and efficient operation of electric vehicle batteries. However, accurately measuring the battery's state of charge (SOC) and balancing the battery cells is one of the biggest hurdles. There has been substantial research devoted to the design and modeling of battery management systems (BMSs) tailored for electric vehicles (EVs). Nevertheless, prevailing BMS architectures typically comprise numerous discrete components, highlighting the necessity for novel integrated designs that consolidate multiple functions within a singular unit. As such, in this thesis, a BMS model, developed for electric vehicle applications using MATLAB Simulink based on the specifications of BMW i3 94 Ah battery, was subjected to testing under two distinct scenarios to evaluate its performance. In the first scenario, all battery cells were initialized at 100% SOC, simulating an ideal condition. Conversely, the second scenario involved replicating a more realistic situation where the cells at 100%, 80%, and 74% SOC were selected. The simulation was limited to 4000 seconds to manage computational demand, as the target of the analysis were monitoring of battery state, estimation of state of charge, and cell balancing. The results demonstrated that the model accurately monitored voltage and current in both scenarios, and it effectively estimated the SOC. Additionally, the passive cell balancing circuit performed well in balancing the cells' SOC, taking approximately 25% of the run time to balance the circuit in the second condition. These findings indicate that the model is suitable for monitoring the voltage and current of cells, estimating SOC, and balancing cells.

Keywords*: Balancing, Battery Management System, Monitoring, State of Charge*

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

Electric vehicles (EVs) are vehicles that run on electricity provided by one or more electric motors and a battery or ultracapacitor (Brandl et al., 2012a). The popularity of EVs as a form of transportation is rising as a result of its energy efficiency and environmental friendliness (Hu, 2011). They normally emit no emissions and are more efficient and cleaner than cars that run on gasoline (Barreras, 2017). They are made up of a number of parts that cooperate to create propulsion. The battery, electric motor, power electronics, charging system and battery management system are some of these components. The electric motor, which transforms electrical energy into mechanical energy to move the vehicle, gets its power primarily from the battery. The charging system tops off the battery when it runs short on power, while the power electronics regulate the flow of electricity between the battery and the motor (Kennel et al., 2012).

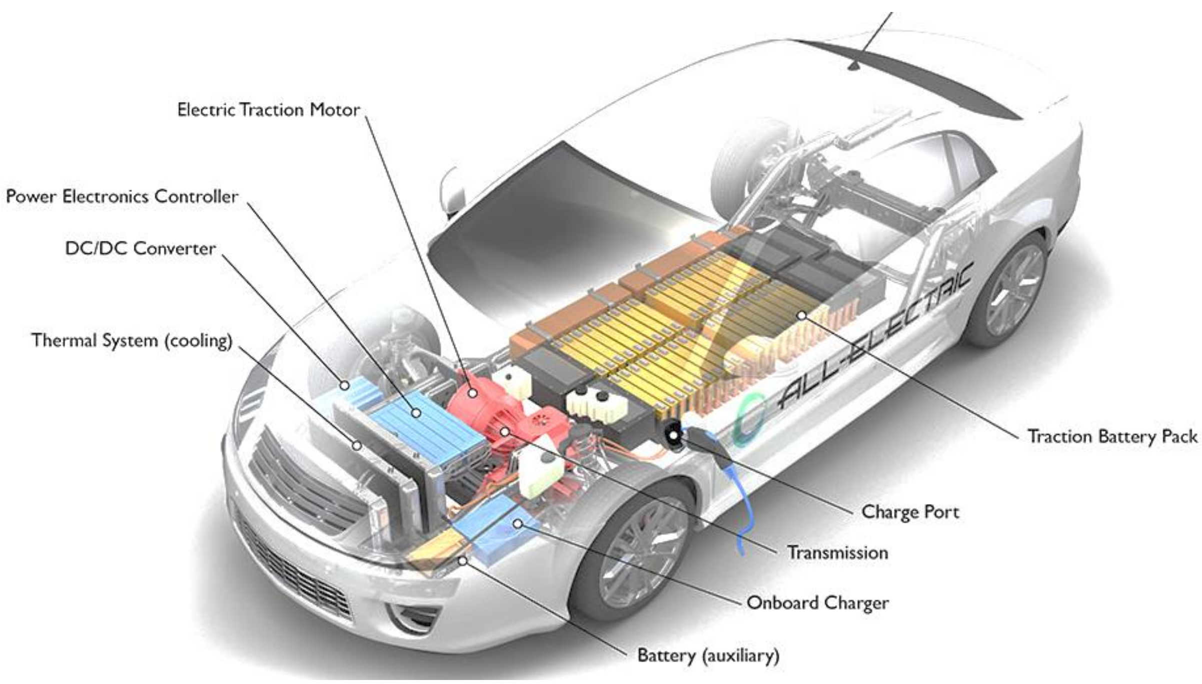

Figure 1.1: Basic components of electric vehicles (US Departments of Energy, 2021)

The battery serves as a crucial element in electric vehicles, storing and supplying the energy necessary to propel the vehicle (Brandl et al., 2012a). Lithium-ion battery, which has a high energy density, lightweight, long lifespan, and fast charging capabilities, is the most common type of battery used in electric vehicles. Another type of electric battery utilized for electric vehicles is the nickel-metal hydride (NiMH) battery, characterized by a lower energy density compared to lithium-ion batteries. However, it has a longer lifespan and it is more environmentally friendly. Lead-acid batteries are also find application in certain electric vehicles, although they exhibit lower energy density and a shorter lifespan when compared to lithium-ion and NiMH batteries (Ali et al., 2019).

Figure 1.2: Lithium-ion battery (Renault Group, 2023)

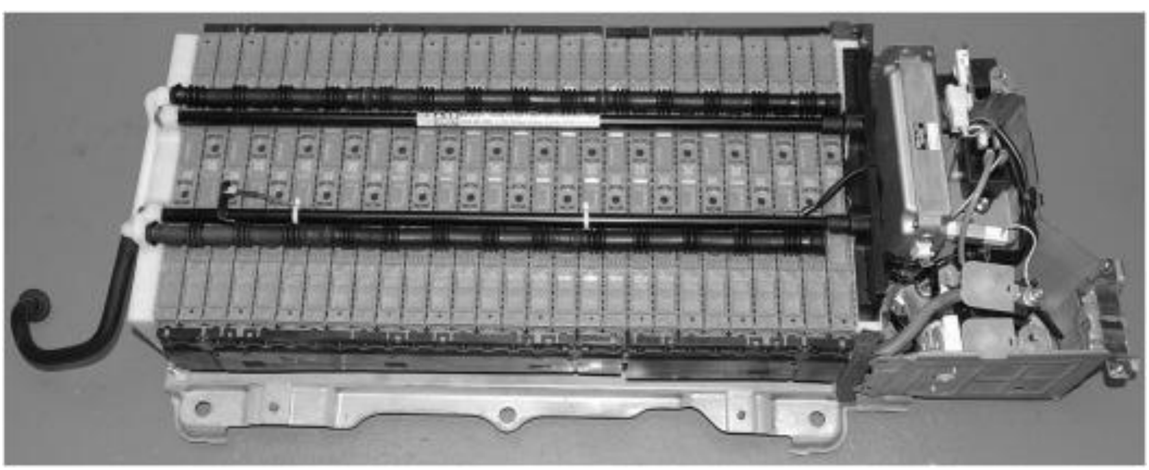

Figure 1.3: Nickel-metal hydride battery (sciencedirect, 2022)

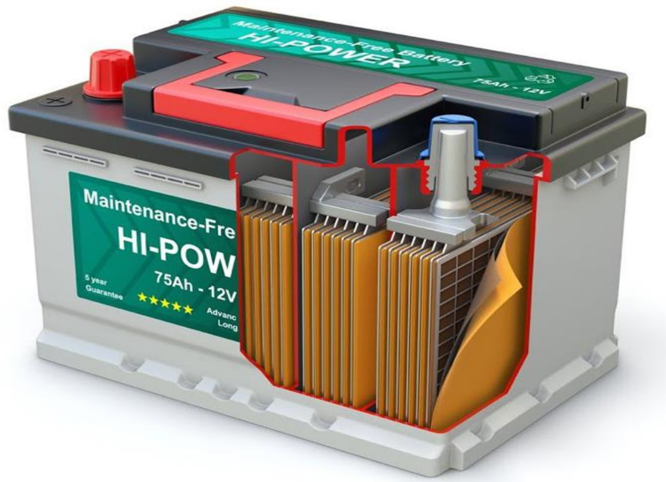

Figure 1.4: Lead-acid batteries (mrpositive, 2022)

The batteries used in EVs are typically rechargeable and consist of multiple individual cells connected in series and parallel configurations (K. Liu et al., 2019). However, the efficient functioning of EVs heavily relies on the performance of their battery systems (Geetha and Subramani, 2017). And, the battery's performance and lifespan can be affected by various factors, such as temperature, charging and discharging rates, and the number of charge cycles (Tie and Tan, 2013). Thus, having a battery management system (BMS) is vital to supervise and manage the battery's performance, ensuring both its safety and reliability (Fanoro et al., 2022).

BMS have evolved to ensure the safe and efficient operation of rechargeable batteries, particularly in applications such as electric vehicles and portable electronics. The first BMS systems were developed in the 1990s to manage nickel-cadmium (NiCd) batteries, which were widely used in portable devices. As lithium-ion (Li-ion) batteries became more prevalent, starting in the 1990s, BMS systems became increasingly sophisticated to handle the unique challenges of these batteries, such as their high energy density and complex charging requirements (Nikhil, 2022). The BMS is responsible for ensuring that the battery operates within safe and efficient limits, preventing damage to the battery and ensuring its long-term health. BMS can be classified into three based on the power source. These are passive, active, and hybrid systems (Florescu et al., 2015).

Electronic components are used by active BMS to actively balance the cells in a battery pack. This is accomplished by transferring charge across cells, either directly or through the use of a switching circuit or by connecting them in parallel. Although active BMS is more expensive than passive BMS, it balances the cells better and increases battery life (Uzair et al., 2021). These systems are more effective at balancing the cells and extending the battery's lifespan. They are applicable in high-performance scenarios, though they come with a greater price tag and the potential to introduce added complexity and weight to the system. (Nikhil, 2022).

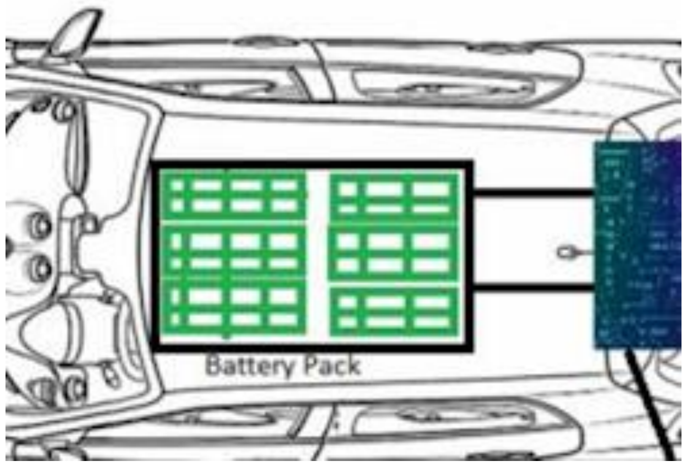

Figure 1.5: Active Battery Management System (Uzair et al., 2021)

Electronic components are not used by passive BMS to balance the cells in a battery pack. Instead, it uses the cells' innate ability to discharge themselves to maintain a stable voltage. Although passive BMS is less expensive than active BMS, it does not balance the cells as well and does not increase battery life as much. The most basic BMS uses resistors to balance the battery cells in passive BMS systems (Uzair et al., 2021). These systems are less expensive, simpler and lighter than active BMS. But, not as effective at balancing the cells and extending the battery's lifespan, and can only be used in low-cost applications (Nikhil, 2022).

Active and passive BMS approaches are used in hybrid BMS. With the effectiveness of active BMS and the affordability of passive BMS, this enables the best of both worlds (Uzair et al., 2021). These systems can be used in a wider range of applications. however, they are more expensive and more complex (Nikhil, 2022).

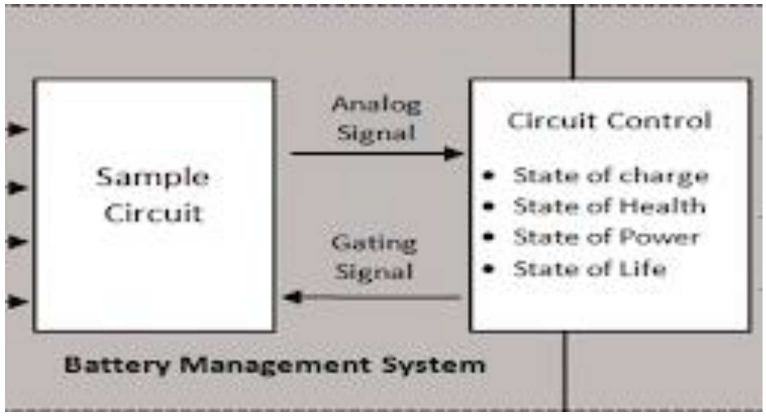

Figure 1.6: Passive Battery Management System (Uzair et al., 2021)

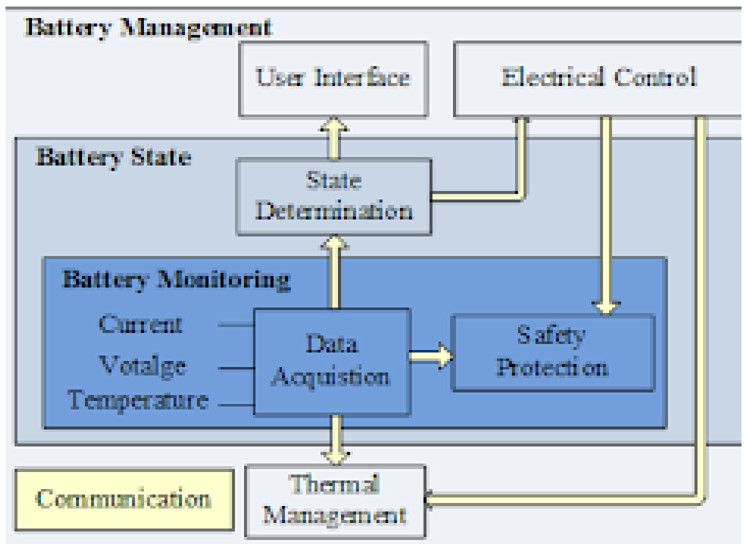

Figure 1.7: Hybrid Battery Management System (Uzair et al., 2021)

In addition, BMS can be classified as centralized, distributed and modular. The centralized BMS has embedded all general functions. It has cell Voltage, Temperature, Series Current sensing, and cell balancing in a single control module, and was widely applied on smaller battery packs for commercial vehicles. Whereas, distributed BMS has a controller for each cell in the battery pack. This allows for more accurate monitoring and balancing of the cells. And, modular BMS is a combination of centralized and distributed BMS. It has a central controller that monitors the overall health of the battery pack, and it has individual controllers for each module in the battery pack (Brandl et al., 2012a).

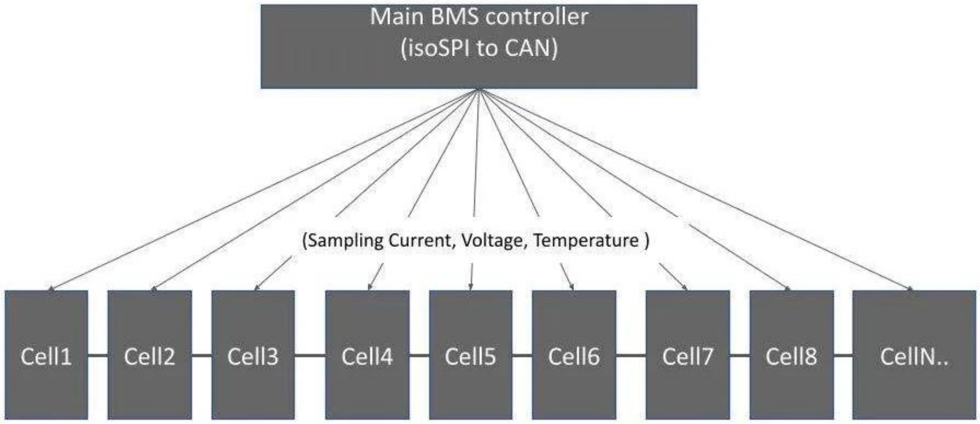

Figure 1.8: Centralized Battery Management System (batterydesign, 2023)

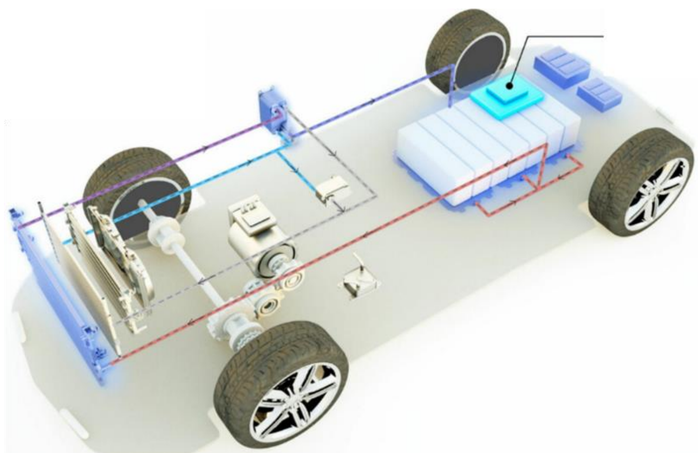

Figure 1.9: Distributed Battery Management System (Marelli, 2022)

Figure 1.10: Modular Battery Management System (hanyu-motor, 2022)

As such, this thesis aims to develop a battery management system model which integrates various functions of battery management system such as battery state monitoring, state of charge estimation, and cell balancing.

1.2. Statements of the Problem

The growing interest in sustainable energy solutions has led to the increasing popularity of EVs. However, the limited range and battery lifespan of EVs remain a significant challenge to their widespread adoption. The BMS plays a crucial role in addressing these challenges and ensuring the safe and efficient operation of EV batteries. The design and modeling of BMS for EV applications is a complex task that requires careful consideration of multiple factors, including the accuracy and complexity of the system, integration with other EV components, and validation procedures. Despite tremendous progress in recent years, a number of obstacles still stand in the way of the BMS's performance and dependability being optimized. Accurately measuring the battery's state of charge (SOC), and cell balancing are the biggest challenges of BMS design. Many scholars have suggested alternative modeling and control approaches for BMS design to overcome these issues. These methods use various algorithms and strategies for SOC estimates, cell balancing, and fault detection. However, existing BMSs are often composed of multiple discrete components. Thus, new integrated BMS designs that combine multiple functions into a single unit are needed. Therefore, this thesis aims to develop a battery management system model which integrates various functions of battery management system such as battery state monitoring, state of charge estimation, and cell balancing.

1.3. Objectives

1.3.1. General Objective

The general objective of this thesis is design and modeling of battery management system for electric vehicle applications.

1.3.2. Specific Objectives

The specific objectives of this thesis are:

- To develop a model for battery state monitoring based on voltage and current sensor of individual battery cells.
- To develop a model for state of charge estimation based on battery state monitoring of individual battery cells.
- To design a cell balancing circuit model based on the estimated state of charge, and
- To integrate monitoring of battery state, estimation of state of charge and cell balancing in to one single unit of Battery Management System.

1.4. Scope of the study

This thesis is dedicated to the design and modeling of a Battery Management System (BMS) with a general focus on integrating functions BMS such as State of Charge (SOC) estimation, cell balancing, and monitoring battery state in electric vehicles. This model is developed using MATLAB software. However. the study does not delve into the implementation details of the system.

1.5. Limitation of the Study

Battery management systems are usually developed specific to the types of batteries used, and specific functions required. As such the model is developed for Li-ion batteries. Thus, the BMS may not perform well for other types of batterie. Moreover, due to computational restricts, the model is not tested for the whole cells of the battery pack. Furthermore, even though, battery state monitoring, state of charge estimation, and cell balancing is included in the BMS model; temperature monitoring is not included in the model.

1.6. Organization of the thesis

The thesis is divided into seven chapters, with the **Chapter One** serving as an introduction, providing background information on electric vehicle batteries, outlining the research objectives and scope, and presenting the structure of the thesis. **Chapter Two** reviews various battery management systems, addressing research gaps and limitations. **Chapter Three** details research materials, tools, and methodologies, along with a visual representation of the thesis's flow. Moreover, it includes the process followed to model the intended BMS. **Chapters Four** compares and discusses the results from the previous chapters, employing charts and figures. Finally, **Chapter Five** offer conclusions and recommendations based on the findings, alongside a list of references and supplementary appendices.

CHAPTER TWO

LITERATURE REVIEW

Battery management systems (BMS) play a crucial role in ensuring the secure and effective functioning of batteries across diverse applications. Researchers have conducted extensive work on the design and modeling of BMS, including state of charge (SoC) estimation, voltage monitoring, current monitoring, thermal management, and cell balancing of batteries.

Designing a BMS for EVs is a critical task that ensures the safety, efficiency, and longevity of battery pack of the vehicle. Several design considerations must be taken into account, including current and voltage monitoring, estimation techniques of charge and discharge, protection mechanisms, equalization techniques, and thermal management strategies (Balasingam et al., 2020).

A BMS is a sophisticated electronic system that monitors and controls various aspects of a battery (Rahman et al., 2017). This arrangement facilitates the provision of a specific range of voltage and current for a predetermined duration, catering to anticipated load scenarios (Ali et al., 2019; Han et al., 2017). It does this by measuring the current, voltage, SoC, and temperature of each cell in the pack, and then using this information to ensure that the battery is operated within its safe operating limits (Habib et al., 2023). It is a critical component in electric energy storage systems as it plays a vital role in ensuring the safe and reliable operation of batteries. It acts as an intelligent interface between the battery pack and the user, enhancing the overall performance and efficiency of the battery system (Lipu et al., 2021).

A BMS's primary purpose is to regulate and safeguard the battery cells in a pack to extend their life and performance (Deepika et al., 2021). It guarantees the batteries are operated within safe operating parameters, guards against overcharging, and upholds ideal charging and discharging conditions (Li et al., 2021). A further benefit of BMS is that it enables precise SoC calculations, guaranteeing that the battery's energy availability is properly tracked and managed. Additionally, it is in charge of controlling the voltage, temperature, and cell balance (Uzair et al., 2021).

2.1. Battery Technologies for Electric Vehicles

The rising popularity of electric vehicles (EVs) is attributed to their environmental advantages and the lower costs associated with their operation (Buccolini et al., 2016). The choice of battery technology for EVs is crucial, as it directly affects the vehicle's range, performance, and cost. The BMS needs to be customized to meet the distinct demands of the battery chemistry and application, taking into account variables such as temperature sensitivity and voltage regulation (Brandl et al., 2012a). Various battery compositions, such as nickel-metal hydride, lithium-ion, and lead-acid, come with their respective pros and cons, encompassing factors like cost, energy density, lifespan, and safety considerations (Lu et al., 2013).

2.1.1. Lithium-ion (Li-ion) Batteries

Electric vehicles often utilize lithium-ion batteries due to their elevated energy density, extended cycle life, and minimal self-discharge rate (Lu et al., 2013). These batteries provide a great power density, allowing for quick acceleration and regenerative braking. Moreover, their light weight and excellent power-to-weight ratio make them suitable for EVs (Renault Group, 2023). Despite being more costly than other battery technologies, Li-ion batteries stand out for their superior energy density and extended lifespan. Therefore, due to their superior performance and durability, they are the preferred choice for EVs (Habib et al., 2023).

2.1.2. Nickel-metal Hydride (NiMH) Batteries

NiMH batteries, while less prevalent in modern EVs, have been extensively utilized in HEVs for a significant period of time. They offer better thermal stability and lower manufacturing costs compared to lithium-ion batteries (sciencedirect, 2022). However, NiMH batteries have lower energy density and are more susceptible to memory effects (Hannan et al., 2012). Despite these drawbacks, they still find application in some HEVs due to their affordability and higher safety compared to Li-ion batteries (Serpi and Porru, 2019). On the whole, NiMH batteries tend to be more cost-effective and have a longer operational lifespan than Li-ion batteries. However, they do come with the drawback of having lower energy density and a shorter overall lifespan (hanyu-motor, 2022).

2.1.3. Lead-acid Batteries

Lead-acid batteries stand out as the most economical choice. Nevertheless, they come with the trade-off of having the shortest lifespan and the lowest energy density (mrpositive, 2022). Despite being the oldest and most well-established technology, lead-acid batteries are unsuitable for electric vehicles (EVs) due to their low energy density and limited lifespan (K. Liu et al., 2019). Nevertheless, they continue to be employed in certain internal combustion engine (ICE) vehicles for starting and lighting functions. In summary, lead-acid batteries are cost-effective but lag behind in terms of energy density and lifespan compared to other battery technologies (Geetha and Subramani, 2017).

2.1.4. Solid-state Batteries

Solid-state batteries represent a promising emerging technology, providing increased energy density, quicker charging, and enhanced safety in comparison to lithium-ion batteries (K. Liu et al., 2019). They have garnered significant attention due to their ability to overcome some of the limitations of traditional Li-ion batteries (Tie and Tan, 2013). However, solid-state batteries are still in the research and development phase and are not yet widely used in EVs (Nikhil, 2022).

2.1.5. Sodium-ion (Na-ion) Batteries

Sodium-ion batteries stand out as a promising and innovative technology, providing high energy density and cost-effectiveness when compared to lithium-ion batteries. Despite these advantages, sodium-ion batteries are still undergoing research and development and have not yet been extensively employed in electric vehicles (EVs) (Guo et al., 2020).

2.1.6. Lithium-Sulfur (Li-S) Batteries

Lithium-sulfur (Li-S) batteries, an advancing technology, display potential in achieving superior energy density compared to lithium-ion batteries. This potential could lead to a significant increase in the driving range of electric vehicles (EVs). Challenges such as shorter cycle life and sensitivity to operating temperatures are being addressed by researchers (Guo et al., 2020).

2.2. Design of the Battery Management System hardware

The Battery Management System (BMS) is composed of different functional units that collaborate to monitor and regulate various aspects of the battery's performance. These units are interconnected with the batteries and other electronic parts of the vehicle, enabling control from external sources like the grid or charging stations (E. V. Kumar et al., 2022). By incorporating components such as battery monitoring circuits, cell balancing circuits, safety protection circuits, power electronics, and communication interfaces, the BMS ensures optimal performance, extends battery life, and enhances the overall driving experience of electric vehicles (Buccolini et al., 2016).

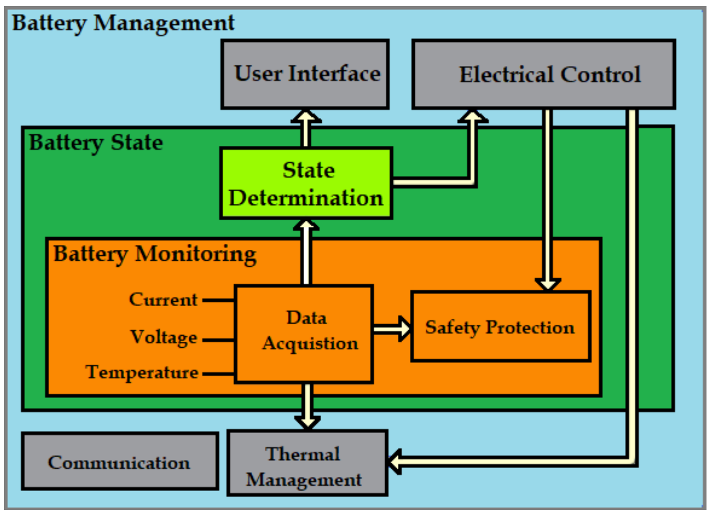

Figure 2.1: Hardware layout of Battery management system (E. V. Kumar et al., 2022)

2.2.1. Estimation of State of Charge

A crucial requirement for a Battery Management System (BMS) is the precise monitoring of the State of Charge (SoC) of the battery pack (Qiang et al., 2006). SoC represents the proportion of the battery's remaining charge in relation to its rated or maximum capacity (Buccolini et al., 2016), denoting the residual charge available compared to the nominal capacity specified by the manufacturer (Bhovi et al., 2021). This metric is influenced by factors such as temperature, battery lifespan, and discharge rate (Jeyashree and Kumar, 2021). The State of Charge of the battery can be defined as (Nikhil, 2022):

$$SOC = \frac{Q_t}{Q_n} \qquad \text{Equation 2.1}$$

Where:

- SOC is battery's the state of charge,
- Q_t is the remaining capacity of the battery, and
- Q_n is the nominal or maximum capacity of the battery.

Instruments specifically designed for the task can directly monitor battery parameters like temperature and voltage. While parameters such as temperature and voltage can be directly observed using suitable instruments, SoC is a dynamic state parameter that undergoes continuous changes over time. Consequently, there is currently no dedicated sensor for accurately measuring SoC, making its calculation challenging (Nikhil, 2022). Consequently, various mathematical and analytical approaches have been formulated and are presently in use, as illustrated in *Figure 2.2*. The most common methods are discussed below.

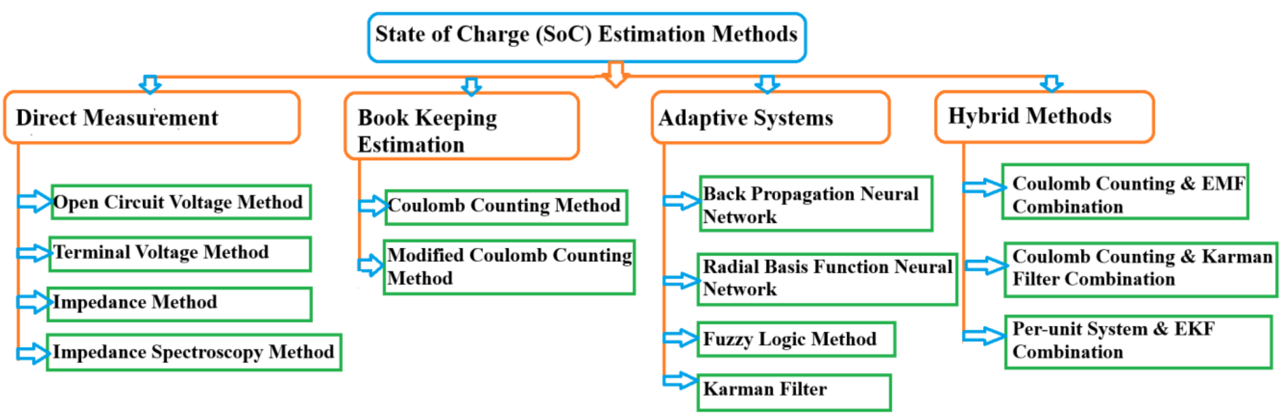

Figure 2.2: Methods of estimating state of charge of electric vehicle battery

The Open Circuit Voltage (OCV) technique stands out as one of the commonly employed methods for approximating the SoC in electric vehicle batteries. This method relies on the correlation between the battery's voltage and its SoC. The open circuit voltage is the voltage across the battery terminals when it is at rest without any load. This voltage is influenced by the internal chemical reactions occurring during battery discharge or charging. By gauging the battery's OCV and comparing it to a predefined voltage vs. SoC curve, the BMS can estimate the battery's SoC. This approach is relatively straightforward, cost-effective, and offers reasonable accuracy in determining the battery's state of charge (Stefano, 2022).

When batteries undergo disconnection from loads for over two hours, the OCV method, which is based on the OCV of the batteries, becomes proportionate to the SOC. However, this prolonged disconnection period may prove impractical for battery implementation (Nikhil, 2022). In contrast to lead-acid batteries, the relationship between the OCV and SOC of a Li-ion battery is not linear. However, this method poses practical challenges because it requires measuring OCV, rendering SOC estimation unavailable during battery charging or discharging, making it unsuitable for real-time applications. Additionally, the OCV-SOC relationship varies among cells, leading to unacceptable errors. Issues may arise with certain cell chemistries, particularly in lithium batteries, which demonstrate minimal voltage changes over most of the charge/discharge cycle (Stefano, 2022).

The OCV technique stands out as one of the commonly employed methods for approximating the SoC in electric vehicle batteries (Stefano, 2022). The OCV method relies on estimating the connection between OCV and SOC. The charge-voltage curve, which is non-linear, exhibits significant variations based on factors like the battery type, operating conditions, and temperature, including the battery's lifespan. For lead-acid batteries, there is an approximately linear correlation between the SOC and the OCV, as outlined by (Nikhil, 2022):

$$V_{oc}(t) = a_o + a_1 + SOC(t) \qquad \text{Equation 2.2}$$

Where:

- $V_{oc}(t)$ is the open circuit voltage,
- $SOC(t)$ is the state of charge of the battery,
- a_1 is the terminal voltage of the battery when SoC = 100%, and
- a_o is the terminal voltage of the battery when SoC = 0%.

(Shrivastava et al., 2022) introduced an all-encompassing co-estimation approach for lithium-ion battery parameters such as SOC, state of energy, state of power, maximum available capacity, and maximum available energy. By accounting for the interdependencies among these variables, their method facilitates a more precise evaluation of the battery's current capacity, energy content, power capability, and maximum available resources. This comprehensive co-estimation technique has the potential to significantly enhance the efficiency and reliability of battery management systems, enabling improved utilization and control of lithium-ion batteries across various applications.

To implement the Coulomb Counting Method, the BMS continuously measures the current flowing into or out of the battery using precision current sensors. The BMS computes the overall charge exchanged with the battery by integrating the measured current over time. This cumulative charge is then compared to the battery's rated capacity to estimate the state of charge (Stefano, 2022). However, it's important to note that the Coulomb Counting Method requires accurate current measurement and precise integration to avoid errors (Brandl et al., 2012b). Additionally, it may suffer from inaccuracies over time due to factors such as cell aging, changes in battery chemistry, and variations in temperature (Lennon, 2019).

$$SOC(t) = SOC(t_o) + \frac{I(t)}{Q_n}\Delta t \qquad \text{Equation 2.3}$$

Where:

- $SOC(t)$ is battery's state of charge,
- $SOC(t_o)$ is previously calculated state of charge,
- $I(t)$ is the discharging current,
- Q_n is the nominal capacity, and
- Δt is the change in time.

The Modified Coulomb counting method is an innovative approach designed to enhance the traditional Coulomb counting method by incorporating the corrected current, as defined in *Equation 2.5*. This corrected current is directly proportional to the discharging current, establishing a quadratic relationship between the corrected current and the battery discharging current (Nikhil, 2022).

$$SOC(t) = SOC(t_o) + \frac{I_c(t)}{Q_n}\Delta t \qquad \text{Equation 2.4}$$

$$I_c(t) = k_2 I(t)^2 + k_1 I(t) + k_o \qquad \text{Equation 2.5}$$

Where:

- $SOC(t)$ is the battery's state of charge,
- $SOC(t_o)$ is previously calculated state of charge,
- $I_c(t)$ is the corrected current,
- $I(t)$ is the discharging current,
- Q_n is the nominal capacity,
- k_2, k_1 and k_o are the experimental data constants, and
- Δt is the change in time.

Several experimental findings demonstrate that, in terms of accuracy, the modified Coulomb counting approach surpasses the traditional Coulomb counting method (Nikhil, 2022).

The Kalman filter effectively minimizes uncertainty by predicting and subsequently correcting the cell status estimation. The crucial component in this method involves a feedback network responsible for executing the correction. As depicted in *Figure 2.3*, the output of the actual system (y) is compared with the model prediction ($\hat{y}$). This outcome is then utilized to adjust the model by applying the gain (K) if the error between the prediction and the actual estimation is deemed significant. Following a specific transient period, the estimation converges to the state of the real system (Stefano, 2022).

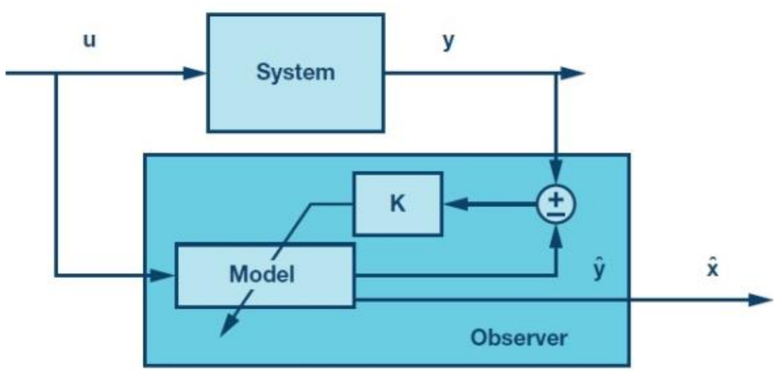

Figure 2.3: Schematic of Kalman filter method (Stefano, 2022)

There are two widely recognized variants of the Kalman filter: the extended Kalman filter (EKF) and the unscented Kalman filter (UKF). The EKF serves as a nonlinear system adaptation of the Kalman filter, involving the linearization of functions based on their mean and covariance. The estimation process comprises two phases. Initially, the time is updated to estimate the states, constituting the a priori estimate. This stage utilizes states from the previous iteration, an input signal sample, and the process covariance matrix as input signals. The second phase involves updating the measurement through feedback, known as the a posteriori estimate and denoted by the carat symbol. It utilizes discrepancies in calculating the output signal to refine the a priori prediction of the states (Bhovi et al., 2021; Nikhil, 2022).

On the contrary, the Unscented Kalman Filter (UKF), in contrast to the Extended Kalman Filter (EKF), doesn't linearize state-space equations. Instead, it employs a nonlinear Unscented Transformation (UT). This method involves repeatedly computing and updating the mean and error covariance to generate sigma points for states. All these sigma points are then passed through nonlinear model functions, offering an a priori estimation of the states and output signal. The mean and covariance of these variables are determined based on their statistics (Bhovi et al., 2021; Nikhil, 2022). The implementation of the Kalman filter has proven to be an accurate method for estimating State of Charge (SoC) in Li-ion Battery Packs. However, its high complexity and computational cost make it challenging to implement on standard microcontrollers (Stefano, 2022).

(Wu et al., 2022) developed a collaborative estimation strategy for State of Charge (SOC) and state of health in lithium-ion batteries, employing an electrochemical model. The approach integrates an equivalent circuit model and an extended Kalman filter for real-time SOC estimation. The electrochemical model incorporated in the scheme accurately represents the characteristics of actual batteries, forecasting their performance across diverse conditions.

(Bai et al., 2022) introduced an adaptive dual extended Kalman filter for SOC estimation of lithium-ion batteries under varying temperature conditions. The proposed algorithm provides a more robust and reliable estimation of SOC, which is crucial for battery management systems and optimizing battery performance in various working conditions.

(X. Liu et al., 2022) created a data-driven State of Charge (SOC) estimation technique for lithium-ion batteries, utilizing a Bayesian information criterion. This method is tailored for estimating the SOC of a battery, employing battery data and measuring parameters such as current, voltage, and temperature. The approach is anticipated to be an online, real-time method characterized by low computational complexity and high accuracy. The proposed method is deemed effective, providing accurate estimations of battery SOC.

(Zhang et al., 2022) suggested a method for estimating the state of charge (SoC) in lithium-ion batteries utilizing an unscented Kalman filter (UKF) and a long short-term memory (LSTM) neural network. The UKF was employed to assess the initial SoC based on measured voltage and current data. Subsequently, the estimated SoC value underwent further refinement using the LSTM neural network, known for its robust nonlinear fitting capabilities. This methodology holds promise for enhancing the functionality of battery management systems, facilitating improved monitoring and control of battery state across diverse applications.

(Lee et al., 2008) proposed a state-of-charge (SOC) and capacity estimation method for lithium-ion batteries using a new open-circuit voltage versus state-of-charge. The OCV method is one of the common techniques for estimating the SoC of lithium-ion batteries. However, the voltage at the battery terminals changes very slightly over a wide operating range, making it difficult to estimate the SoC with good precision. The method involved measuring the OCV at different states of charge and using these measurements to create a more accurate OCV versus SoC curve. This new curve allowed for a more precise estimation of the battery's SoC during operation, enabling better monitoring and management of the battery's performance and capacity.

2.2.3. Battery monitoring circuit

The battery monitoring circuit (BMC) is a critical component within the BMS of an electric vehicle. It provides essential information about the battery pack's condition, contributing to the safe and efficient operation of the electric vehicle (E. V. Kumar et al., 2022). The BMC is typically designed using a combination of sensors, analog circuits, and a microcontroller (Uzair et al., 2021). The BMC stablishes a connection with the battery pack using a set of wires that are associated with voltage, current, and temperature sensors, along with the BMS microcontroller (Sen and Kar, 2009). Its crucial function in ensuring the safety and efficiency of the battery pack positions it as an essential element within the BMS (Rahimi-eichi et al., 2013).

Voltage Acquisition

One crucial responsibility of the BMS is to precisely monitor the voltage of each individual battery cell in an electric vehicle. Several methods, such as voltage divider circuits and differential amplifier circuits, can be employed to obtain the voltage readings of EV battery cells. Voltage dividers use resistors to measure voltage, while differential amplifiers amplify the voltage difference between two inputs. The choice of method depends on factors like accuracy requirements, cost, and size constraints (Lelie et al., 2018).

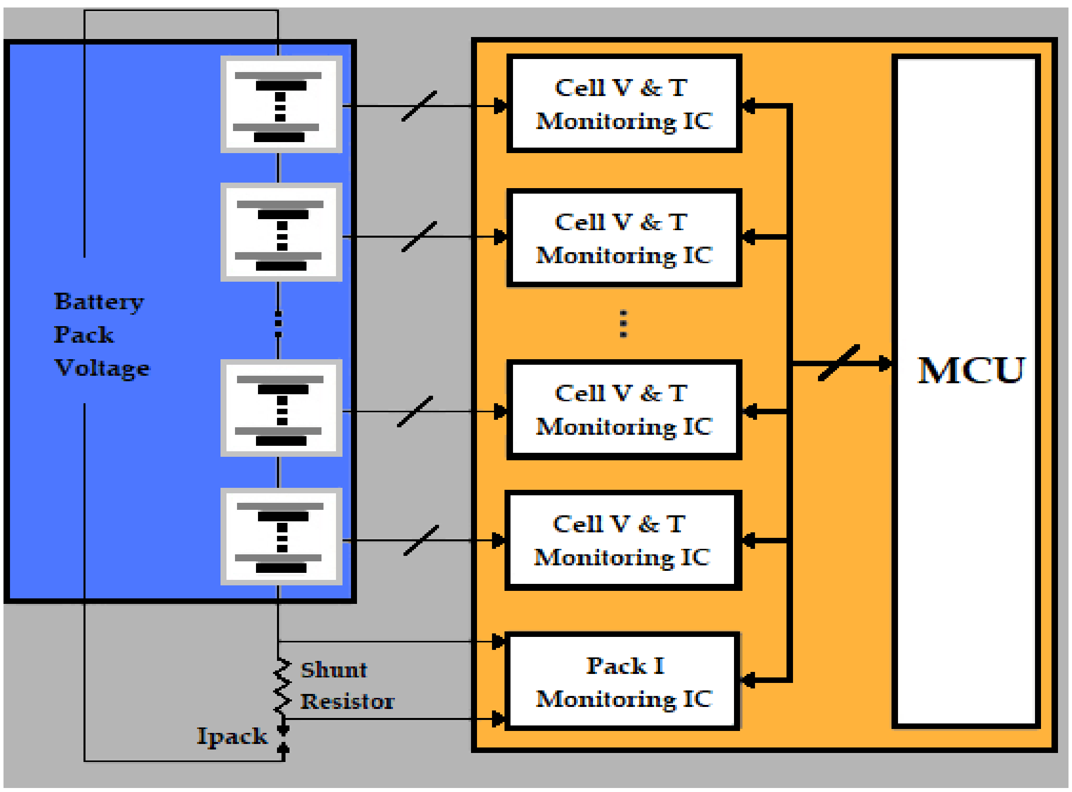

Figure 2.4: Typical Battery monitoring circuit of BMS (A. Raj, 2018)

Voltage sensors measure the voltage of each battery cell, while current sensors measure the current flowing into or out of each cell. The analog circuits convert the sensor signals into digital signals that can be processed by the microcontroller. The microcontroller collects the data from the analog circuits, calculates the SoC and SoH of the battery pack, and monitors for any hazards, taking necessary corrective actions (E. V. Kumar et al., 2022).

Voltage monitoring plays a crucial role in BMS to ensure the safe and optimal operation of batteries. (Ashok et al., 2022) conducted a study on voltage monitoring techniques for battery cells. They proposed a multi-level voltage monitoring approach that utilized advanced signal processing techniques to detect abnormalities and prevent voltage imbalances in battery packs.

(Wang et al., 2011) proposed a novel BMS design that incorporates a high-precision voltage monitoring algorithm based on an extended Kalman filter. The algorithm effectively estimates the battery voltage taking into account the internal resistance of the battery and temperature variations.

(Deepika et al., 2021) developed a BMS architecture that utilizes a distributed voltage monitoring system. This system comprises multiple voltage sensors strategically placed across the battery pack to accurately monitor individual cell voltages and detect any imbalances or abnormalities. The architecture is based on a decentralized approach, where each cell in the battery pack is monitored individually. This approach ensures that any imbalances in the battery pack are detected early, preventing potential safety hazards and improving the overall performance and lifespan of the battery pack.

(Serpi and Porru, 2019) focused on the modeling of battery voltage behavior under varying load conditions. By employing neural network techniques, the researcher developed a predictive model that accurately estimates the battery voltage based on load profiles, enabling more accurate voltage monitoring. The use of neural networks in battery modeling has been shown to be effective in various applications. As an illustration, a deep neural network model was created to forecast the remaining lifespan of a battery with a mean absolute percentage error of 6.46%, utilizing data from just a single testing cycle (Li et al., 2021).

(Hannan et al., 2012) explored the use of impedance spectroscopy for voltage monitoring in BMS. By analyzing the impedance response of the battery, the researcher developed a model that accurately estimates the battery voltage and detects any deviations from expected behavior. It involves applying an AC signal with stepwise changed frequency to the battery and analyzing its response. The impedance response provides valuable information about the battery's internal processes, such as diffusion phenomena and charge transfer resistance. The use of impedance spectroscopy for voltage monitoring allows for real-time monitoring of the battery's state. Impedance spectroscopy can be integrated into BMS as embedded real-time electrochemical impedance spectroscopy or power line communications. These approaches enable efficient and scalable battery monitoring systems that can be applied to different types of batteries and applications.

(Lipu et al., 2021) proposed a BMS design that incorporates a voltage monitoring algorithm based on the SOC estimation. By considering the battery's SOC, the algorithm effectively predicts the battery voltage and ensures accurate voltage monitoring during charging and discharging cycles. The proposed algorithm uses SOC estimation to predict battery voltage. The algorithm is based on an improved extended Kalman filter.

(K. Liu et al., 2019) explored the use of machine learning techniques for voltage monitoring in BMS. By training a neural network model using historical battery voltage data, the researcher developed an intelligent monitoring system capable of accurately predicting battery voltage in real-time. Machine learning methods offer a more efficient alternative for battery monitoring and management, enabling faster and more accurate predictions of battery performance (Lipu et al., 2021). Yet, the intricate electrochemical processes governing battery performance frequently result in physics-based models that demand significant computational resources, making them impractical for real-time applications (Li et al., 2021).

Current Acquisition

The Battery Management System (BMS) oversees the charging and discharging processes of electric vehicle batteries, ensuring their safety and optimal performance. To achieve this, current sensors are employed to measure the flow of current into and out of the battery pack. These sensors are commonly positioned in series with the battery pack to provide precise measurements of the current traversing through it (Uzair et al., 2021). A common method for acquiring the current of EV battery cells is by using a shunt resistor. This low resistance resistor is positioned in series with the battery pack, and the voltage across it, which is proportional to the current, is measured by the BMS controller using an analog-to-digital converter (ADC) (Lelie et al., 2018).

A Hall effect sensor can be utilized as an alternative method for measuring the current flowing through EV battery cells. This sensor monitors the magnetic field produced by a conductor, like a battery cell, while current flows through it. A Hall effect sensor is used to measure current by placing it close to the battery cell and detecting the magnetic field it produces (Lelie et al., 2018; Lipu et al., 2021).

In a study by (Kennel et al., 2012), a Hall effect current sensor was proposed for current monitoring in BMS. Their work involved integrating Hall effect sensors within the battery pack to measure the magnetic field generated by the current flow, enabling non-invasive and accurate current monitoring.

(Sen and Kar, 2009) conducted a study on the use of shunt resistors for current monitoring in BMS. Their work involved designing precise measurement circuits that utilize shunt resistors to measure the voltage drop across the resistors, providing an accurate estimation of the current flowing through the battery. Shunt-based current sensing offers simplicity, low cost, excellent linearity, and accuracy. However, there are some disadvantages to using shunt resistors for current sensing, such as heat dissipation and lack of isolation (Fanoro et al., 2022).

In a study by (Lelie et al., 2018), they developed a high-precision current monitoring system using a combination of Hall effect sensors and advanced data analysis techniques. The system was designed to provide accurate and reliable current measurements for BMS used in electric vehicles applications. The Hall effect sensors used in the system are designed to operate over a wide common-mode voltage and temperature range, providing lower-drift isolated current sensing. The combination of Hall effect sensors and advanced data analysis techniques offers several advantages over traditional current sensing methods, including improved accuracy, reliability, and reduced system complexity.

(Hauser and Kuhn, 2016) proposed a novel approach to current monitoring using impedance spectroscopy. Their research involved analyzing the frequency response of the battery pack to estimate the internal impedance, which is directly related to the current flow, enabling real-time current monitoring. The use of impedance spectroscopy for current monitoring in BMS offers several advantages over traditional current sensing methods. It provides a non-invasive and real-time monitoring solution, allowing for more accurate and reliable current measurements.

In a study on intelligent current monitoring, (Ali et al., 2019) explored the use of machine learning (ML) algorithms to predict and estimate battery currents based on historical data and system parameters. The method was shown to be able to accurately estimate the current flowing into and out of a battery pack even when the battery is operating under dynamic conditions.

2.2.4. Cell balancing circuit

The cell balancing circuit is responsible for equalizing the voltage levels across each individual battery cell within the pack, optimizing the efficiency and longevity of the battery pack (Geetha and Subramani, 2017). It is typically connected to the battery pack through a series of wires (E. V. Kumar et al., 2022). It monitors the voltage levels of each battery cell and takes corrective action if any cell is found to be imbalanced (Han et al., 2017). This can involve either dissipating the excess energy or redistributing it to the other cells, depending on the type of balancing technique used (Kennel et al., 2012). By maintaining the voltage levels of the battery cells at an equal level, the cell balancing circuit helps to ensure the safe and efficient operation of the battery pack, optimizing its performance and extending its overall lifespan (A. Raj, 2019).

Because the voltage and capacity of an individual battery cell are inherently low, using single batteries in practical applications like electric vehicles is not widespread. In such applications, a considerable number of battery cells are connected in series and parallel to create a battery string. However, it's crucial to note that no two battery cells are identical. Variations may arise in factors such as internal resistance, degradation level, nominal capacity, ambient temperature, and more. The chemicals within the cells, their initial charge capacities, and external impacts also frequently differ (Bhovi et al., 2021). These inherent disparities among the cells in a battery string can result in imbalance, leading to various issues. Maintaining battery balancing is of utmost importance to sustain performance (Jeyashree and Kumar, 2021).

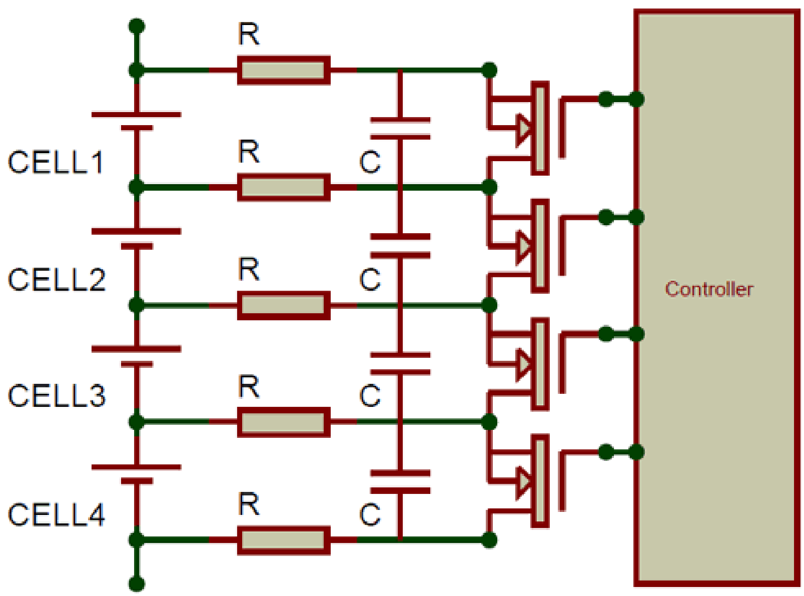

Figure 2.5: Typical Cell balancing circuit of BMS (A. Raj, 2019)

Due to differences in the speed of charge-discharge cycles and the overall lifespan, the state-of-charge among battery cells may become uneven. Variations in the charging and discharging speeds of imbalanced cells lead to discrepancies in the battery voltage and capacity of cells connected in series within the battery pack. These variations are the primary contributors to reduced cell capacity and overall battery life. To address this energy imbalance among cells, a supplementary cell balancing circuit is essential within the battery management system (Brandl et al., 2012a). *Figure 2.6* illustrates various methods that can be employed to balance the cells in the battery pack. The most common methods are discussed below.

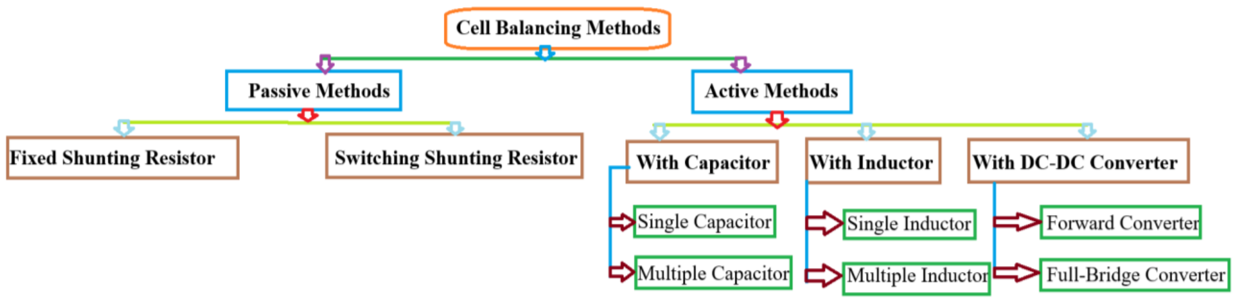

Figure 2.6: Methods of cell balancing of electric vehicle battery

There are various cell balancing techniques and circuit designs used in BMSs. One common approach is passive balancing, which uses resistors to equalize the voltage levels of the battery cells. When a cell reaches its maximum voltage, the excess energy is dissipated through the resistor, allowing the other cells to catch up (A. Raj, 2019). Another approach is active balancing, which uses additional components such as capacitors, inductors, or auxiliary batteries to redistribute the energy between the cells. Active balancing is typically faster and more efficient than passive balancing, but it can also be more complex and costly to implement. The choice of balancing technique depends on factors such as the size and capacity of the battery pack, cost considerations, and desired performance (E. V. Kumar et al., 2022).

An active cell-balancing circuit typically incorporates energy-transfer devices such as capacitors, inductors, or transformers to ensure energy equilibrium among cells within the battery pack. In comparison to passive cell-balancing circuits, the active counterpart is more efficient and requires less time to balance individual cells. However, it comes with a higher cost and demands sophisticated system control algorithms for effective cell balancing. The active cell-balancing approach involves the transfer of charge between cells using inductive or capacitive charge shuttling. While this method has proven to be effective in directing energy where it is needed, it mandates the addition of extra components to the system, contributing to an increase in overall costs (Jeyashree and Kumar, 2021; Nikhil, 2022).

(Hauser and Kuhn, 2016) proposed a novel cell balancing algorithm based on genetic algorithms that optimized the balancing process, considering various factors such as cell aging and capacity degradation. The algorithm developed had monitoring and identification of unbalanced cells, consideration of cell state, statistical analysis for cell selection, optimal balancing time, and genetic algorithms. The research demonstrated improved efficiency and longevity of battery packs.

(A. Raj, 2019) introduced a novel cell balancing approach employing a passive equalization circuit. This method equalizes the state of charge among cells by dissipating energy from cells with higher state of charge (SOC) to balance all cells. The effectiveness of this method in balancing the voltage of cells within a battery pack was demonstrated to surpass that of traditional methods. Passive cell balancing is notably uncomplicated and proves advantageous in scenarios where cost and size are significant constraints.

(Aatabi, 2022) developed an innovative cell balancing technique employing a switched capacitor circuit. This capacitance-based balancing method utilizes capacitors as the energy carrier, coupled with a switching device to transfer energy between cells. The circuit is intricately designed to facilitate energy transfer among cells using capacitors and switches, under the control of a microcontroller. The suggested approach is anticipated to be both cost-effective and efficient compared to traditional methods, presenting a promising solution for cell balancing within battery packs.

(Uzair et al., 2021) proposed a new cell balancing method based on a machine learning algorithm. The suggested technique relies on a hierarchical optimal approach, substantially minimizing the computational load and enhancing the feasibility of implementing the cell equalizing algorithm in real-time. Through simulation analysis, the proposed method demonstrated superior performance in voltage management compared to traditional methods.

Passive Cell Balancing is considered more reliable and requires fewer components compared to alternative equalization circuits. The passive approach involves redirecting excess energy from certain cells through a primarily dissipative channel. This bypass operation is simpler and more straightforward than active balancing methods, contributing to the overall cost-effectiveness of the system, whether it's integrated or external. However, it's important to note that this approach results in a reduced lifespan for the battery, and during discharge, its efficiency is compromised as the surplus energy is dissipated as heat (Jeyashree and Kumar, 2021; Nikhil, 2022). Thus, passive cell balancing is used for this model.

2.3. Development of the Battery Management System software

The software within the Battery Management System (BMS) oversees the battery's charging and discharging processes, tracks the temperature and voltage of individual cells, and safeguards against overcharging and over-discharging. Additionally, it facilitates precise monitoring, enhancing the capabilities of the cell supervision unit in battery management systems. The software can improve state-of-charge accuracy through high-precision battery monitoring and contribute to reducing vehicle weight by incorporating advanced wireless battery management systems (Chen et al., 2019).

Devising the software architecture for BMS in electric vehicle batteries is an intricate and pivotal undertaking. It entails creating feedback and supervisory control mechanisms to guarantee the safe operation, optimal performance, and extended battery lifespan across varied charge-discharge and environmental conditions. It should prioritize safety features, incorporating fault detection and diagnostic algorithms to identify any abnormalities or malfunctions within the battery pack (Lipu et al., 2021). The BMS software should integrate sophisticated voltage sensing techniques, such as delta voltage measurement or coulomb counting, to continuously monitor each individual cell's voltage and detect any abnormalities or imbalances that may arise, ensuring the battery pack operates within safe limits (Serpi and Porru, 2019).

To ensure the longevity and health of the battery pack, the BMS software should also include SoH monitoring capabilities, tracking the degradation of individual cells over time, detecting any capacity loss or impedance increase. The BMS communicates with other components of the EV, such as the vehicle control unit (VCU) and the driver interface, to provide information about the battery pack status, such as the voltage, SoC, and current. The BMS also receives commands from the VCU, such as to charge or discharge the battery pack at a specific rate (Hauser and Kuhn, 2016).

2.4. Modeling of the BMS behavior

The modeling of BMS behavior is an essential step in understanding how the system operates and how it can be improved (A. Raj, 2018). The modeling process involves several key considerations and can be accomplished using battery simulation software packages or tools like MATLAB and Simulink (Lennon, 2019). One important aspect of BMS modeling is battery characterization. This entails gathering information on diverse battery parameters, including but not limited to internal resistance, capacity, open-circuit voltage, and temperature dependencies. By accurately characterizing the battery, the BMS model can accurately predict its behavior under different operating conditions (P. J. Raj et al., 2020).

The BMS model uses algorithms like Coulomb counting or the Kalman filter to estimate the SOC based on current and voltage measurements. The model takes into account factors like battery aging, self-discharge, and temperature effects to improve the accuracy of the SOC estimation (Dhaigude and Shaikh, 2017). Moreover, SOH monitoring is also incorporated into the BMS model. This involves analyzing degradation mechanisms like capacity fade, impedance growth, and voltage hysteresis to assess the battery's degradation over time. By continuously monitoring the battery's SOH, the BMS can provide valuable information on the battery's remaining useful life and enable proactive maintenance strategies (Baťa and Mikle, 2019).

Modeling and simulation play a role in the design of BMS. They enable designers and engineers to assess the performance of BMS anticipate battery behavior and optimize the parameters of BMS design. In this context it is crucial to consider models, for battery cells and packs within BMS simulation techniques to evaluate BMS performance and the validation of BMS models, through data (Sen and Kar, 2009).

Mathematical models of BMS can be based on electrochemical principles, empirical data, or a combination of both (Szumanowski and Chang, 2008). A commonly employed model is the equivalent-circuit model, which characterizes the battery as an electrical network comprising resistors, capacitors, and current sources (Sen and Kar, 2009). Another approach is the electrochemical model, which describes the battery using differential equations that account for the chemical reactions occurring inside (Serpi and Porru, 2019). Precise and validated models are essential, taking into account both the electrochemical and thermal characteristics of cells and the electrical and mechanical attributes of the battery pack (Szumanowski and Chang, 2008). Battery packs can be modeled using interconnected cells, employing mathematical techniques like network theory to capture electrical and thermal characteristics. These models enable the analysis of factors like cell imbalances and temperature variations on the BMS and electric vehicle performance (Hauser and Kuhn, 2016).

Simulation techniques of BMS allow designers and engineers to assess BMS behavior under various operating conditions, such as charging rates, discharging rates, temperature variations, and SoC. Simulations must consider the electrical, thermal, and mechanical behavior of the BMS and battery pack, accurately predicting parameters like SoC and SoH. (Hannan et al., 2012). By utilizing simulation tools like MATLAB/Simulink, designers can optimize BMS design parameters including control algorithms, sensor placement, and battery pack configuration (Chen et al., 2019). Various numerical and computational methods like the Finite Difference Method (FDM) and Finite Element Method (FEM) simulate the dynamic behavior of the battery system under different operating conditions (Buccolini et al., 2016).

2.5. Research gap

In recent years, there has been substantial research devoted to the design and modeling of battery management systems (BMSs) tailored for electric vehicles (EVs). This effort has yielded significant advancements, particularly in refining BMSs to precisely estimate battery state of charge, monitoring state of battery and execute effective cell balancing procedures. Nevertheless, prevailing BMS architectures typically comprise numerous discrete components, highlighting the necessity for novel integrated designs that consolidate multiple functions within a singular unit.

CHAPTER THREE

MATERIAL AND METHODS

Enhancing the accuracy, reliability, and efficiency, while ensuring the safe and effective functioning of electric vehicle batteries, involves the design and modeling of a battery management system for electric vehicle applications. The methodology for this design and modeling process can be divided into various steps, and the fundamental procedures employed in this research are illustrated in *Figure 3.1*.

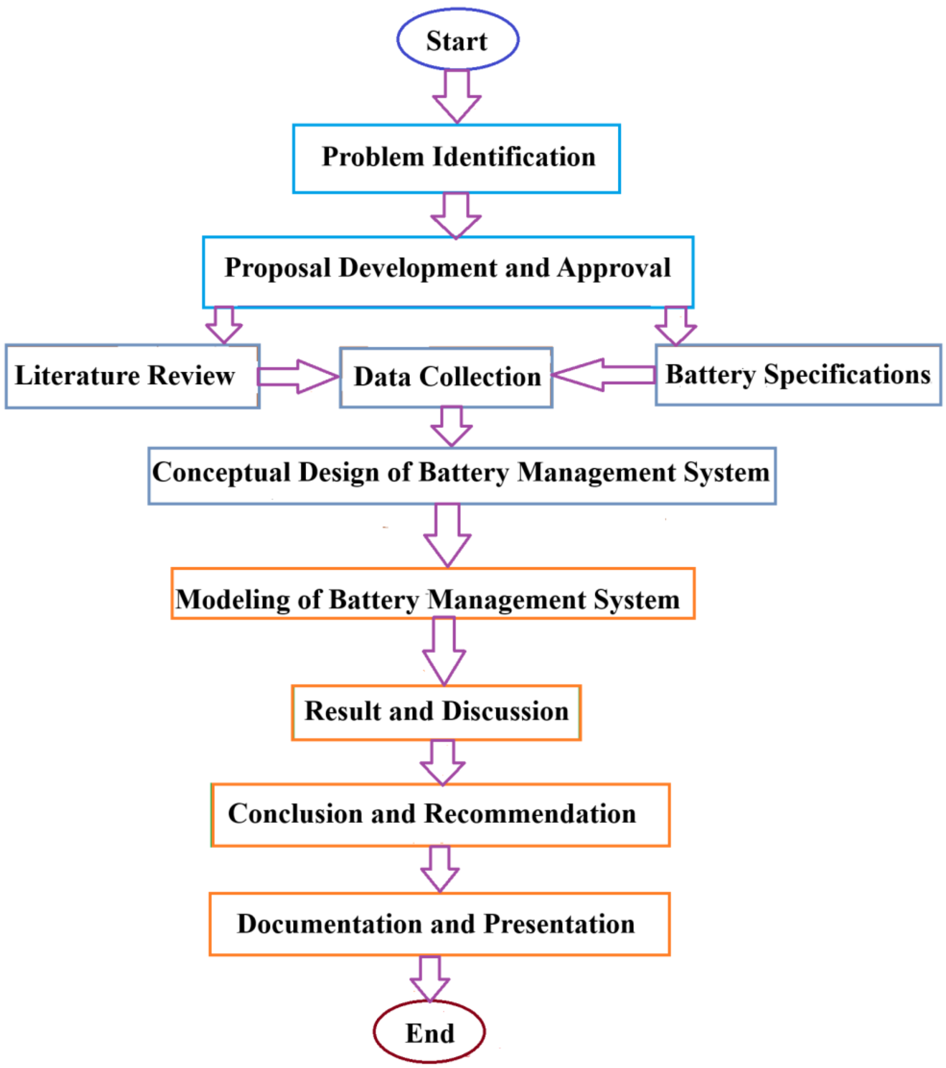

Figure 3.1: A Thesis flowchart

3.1. Research Design

The primary objective of this thesis is to design and model a Battery Management System (BMS) tailored for electric vehicle applications. The study employs a mixed-methods approach, incorporating both quantitative and qualitative data collection methods. The quantitative data survey specifically aims to gather information on electric battery specifications, as well as the power consumption and efficiency of electric vehicles. Therefore, data is collected from the manufacturer of electric vehicle from Li-ion battery. The qualitative data focusing on the methods, approaches and procedures of the BMS modeling is collected through document review. The thesis identified the most feasible battery management system. In addition, it designs and model the most feasible battery management system for electric vehicle applications.

3.2. Data Collection

This thesis adopts a mixed-methods approach for data collection, incorporating two primary methods: document review and gathering data on the specifications of electric vehicle batteries.

3.2.1. Document review

A thorough examination of pertinent literature and documents pertaining to electric vehicles, electric batteries, and Battery Management Systems (BMS) was undertaken. This involved reviewing literature on the components, processes, and procedures involved in designing and modeling BMS for electric vehicle applications. Furthermore, official websites and promotional materials from various electric vehicle manufacturers were consulted. Additionally, the official website of MATLAB software on battery management systems (Mathworks, 2023) was explored to understand the processes involved in designing and modeling BMS. The objective is to gain insights from existing information to inform the research.

3.2.2. Electric Vehicle Battery Specification

To develop and simulate the Battery Management System (BMS) for electric vehicle applications, it is essential to obtain the specifications of the electric vehicle battery. Consequently, details such as the battery's capacity, operating temperature, voltage, and current characteristics are gathered from the manufacturer's website (Electric Vehicle Database, 2020). For this particular thesis, BMW i3 94 Ah battery, shown in *Figure 3.2,* is considered for the modeling of the BMS. The BMW i3 is one of the pioneering EVs in the market, renowned for its innovative design and advanced battery technology, thus making it a prominent candidate for study in the realm of BMS development. Additionally, the widespread adoption of the BMW i3 in the EV sector lends credence to the relevance and applicability of findings derived from studying its battery system. Therefore, the specifications outlined in *Table 3.1* are gathered accordingly.

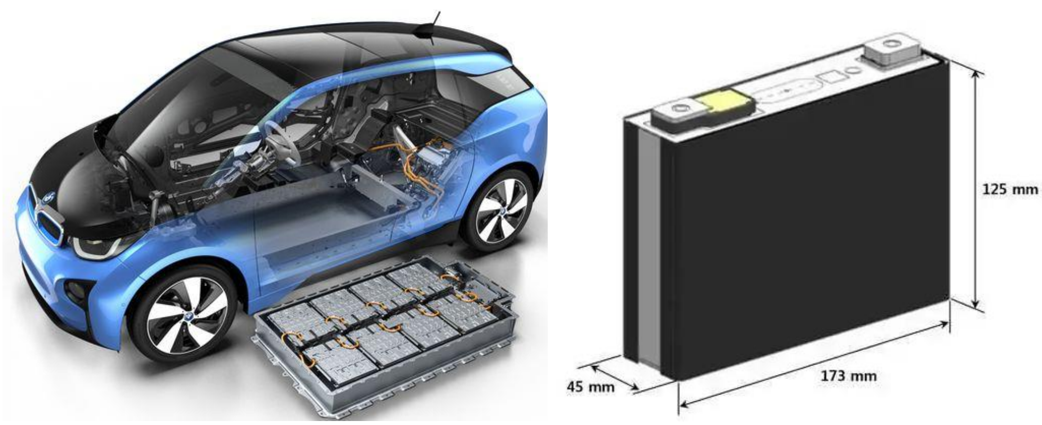

Figure 3.2: The battery selected for analysis (Electric Vehicle Database, 2020)

3.3. Data Analysis

The outcomes of the data collection process primarily encompass two aspects. Firstly, the specifications of the electric vehicle battery are acquired, focusing on essential parameters such as capacity, operating temperature, and voltage-current characteristics. Secondly, data on the performance, power consumption, and general characteristics of the electric vehicle battery are gathered. These two sets of results are meticulously recorded and subjected to thorough analysis.

Table 3.1: Specification of the electric vehicle battery (Electric Vehicle Database, 2020)

S.No.	Parameter	Value
1	Car type	BMW i3 94 Ah battery
2	Type of battery	Lithium – ion
3	Total capacity	33.2 kWh
4	Usable capacity	27.2 kWh
5	Number of cells	96
6	Individual cell voltage	3.68 V
7	Connection of cells	Series
8	Average energy consumption	0.131 kWh/km
9	Charging cycles	4600
10	Charger	Mennekes - IEC 62196
11	Charge Power	7.4 kW AC
12	Charge Time (165 km)	4h30m
13	Architecture	400 V
14	Nominal Voltage	350 V
15	Weight	452 kg
16	Gravimetric energy density	149 Wh/kg
17	Chemistry	NCM 111 (NCM 333)
18	Pack Configuration	96s1p
19	Manufacturer	Samsung SDI

3.4. Software Modeling

After the required specifications of the electric vehicle battery are obtained through data collection, the software modeling of the battery management system was performed using various softwares. There are various softwares that can model the battery management system for electric vehicle applications including MATLAB/Simulink (Mathworks, 2023), Battery Management System Studio (SoftDeluxe, 2020), LabVIEW (LabView, 2021), Orion BMS

(Orion, 2022), and ANSYS (ANSYS, 2022). These software options can help with designing and testing battery management systems, monitoring the state of health of the battery, controlling environmental factors that affect the cell, and balancing the cells to ensure the same voltage across cells. They can also help with monitoring the measured capacity of the battery pack, the internal resistance of individual cells, and the state of charge. Additionally, some software options offer intelligent cell balancing, efficient passive balancing, and field programmable parameters. Among these, MATLAB software is considered for modeling the BMS. Since it provides a comprehensive environment for designing and simulating BMS algorithms, state estimation, and control strategies.

Modeling of battery management system is performed using MATLAB Simulink based on four general steps. These are: Battery pack modeling, monitoring of individual battery cells, Battery cell balancing, and testing the model. The specific procedures adhered to in each modeling step are elaborated upon below.

3.4.1. Battery pack modeling

Battery pack modeling starts with the modeling of the individual cell batteries. Thus, here modeling of the battery cell is performed as shown in *Figure 3.3* and *Figure 3.4* depending on the specification on *Table 3.1*. Simulink implements a generic battery model for most popular battery types.

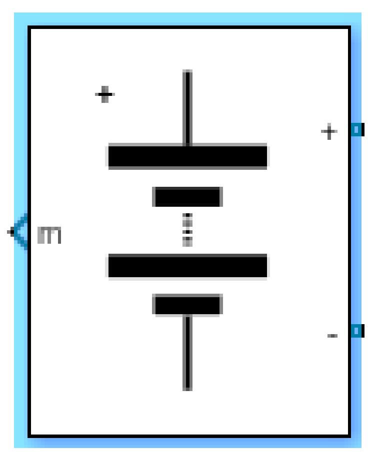

Figure 3.3: Typical battery cell in MATLAB Simulink

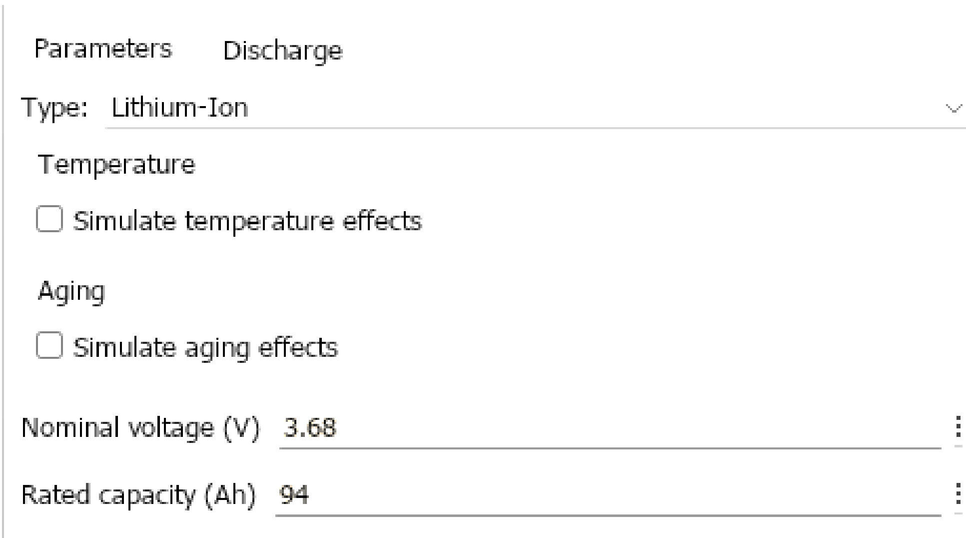

Figure 3.4: Individual cell battery model parameters

Subsequently, a total of ninety-six individual battery cells are linked in a series connection, based on the specification of the vehicle on Table 3.1, to make the whole battery pack of the vehicle, as shown in *Figure 3.5*.

3.4.2. Monitoring of individual battery cells

The Battery Management System possesses the capability to oversee the voltage and current of individual battery cells, as well as the entire battery pack. Furthermore, the system can estimate the state of charge for each battery cell. In this context, a model for monitoring voltage and current and estimating the state of charge for each cell is formulated using two Simulink blocks. These are Scope and Bus selector, as shown in *Figure 3.6*. Bus selector accepts a bus as input which can be created from the battery cells and output from the list, as shown in *Figure 3.7*. In this case the required outputs are voltage, current and SOC. Whereas, Scope is used to simulate the required output parameters provided by the Bus selector.

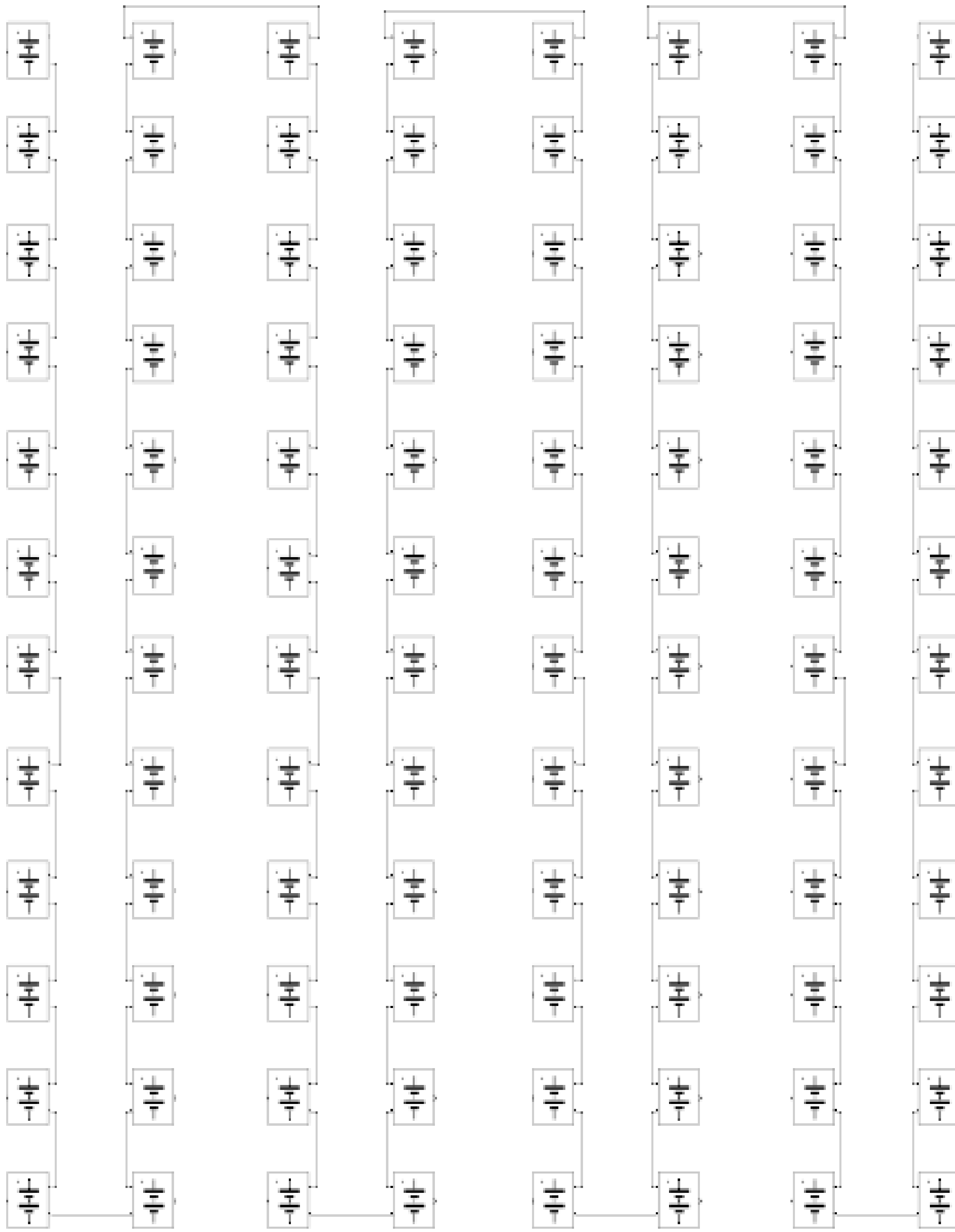

Figure 3.5: Modeling of the Battery Pack in Simulink

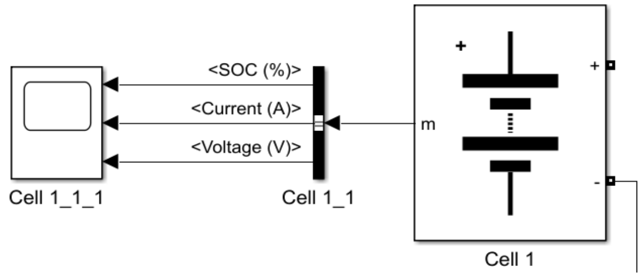

Figure 3.6: Scope, bus selector and battery cell (left to right) in the Simulink model

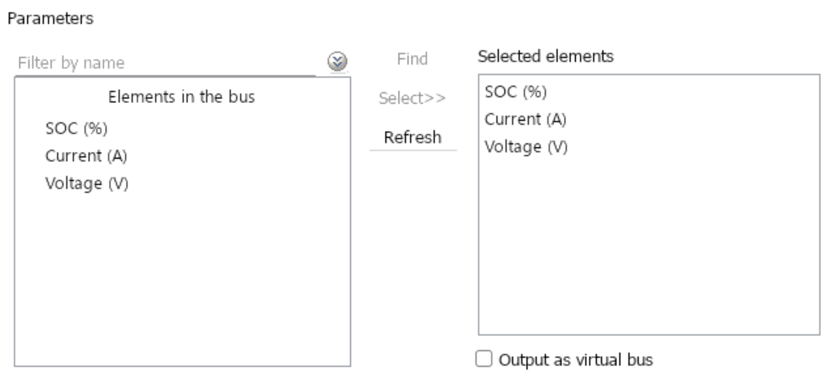

Figure 3.7: Parameter selection for the Bus selector in the Simulink

Afterwards, the monitoring of each individual cell is performed in the battery pack as shown in *Figure 3.8,* following the same procedure as discussed above.

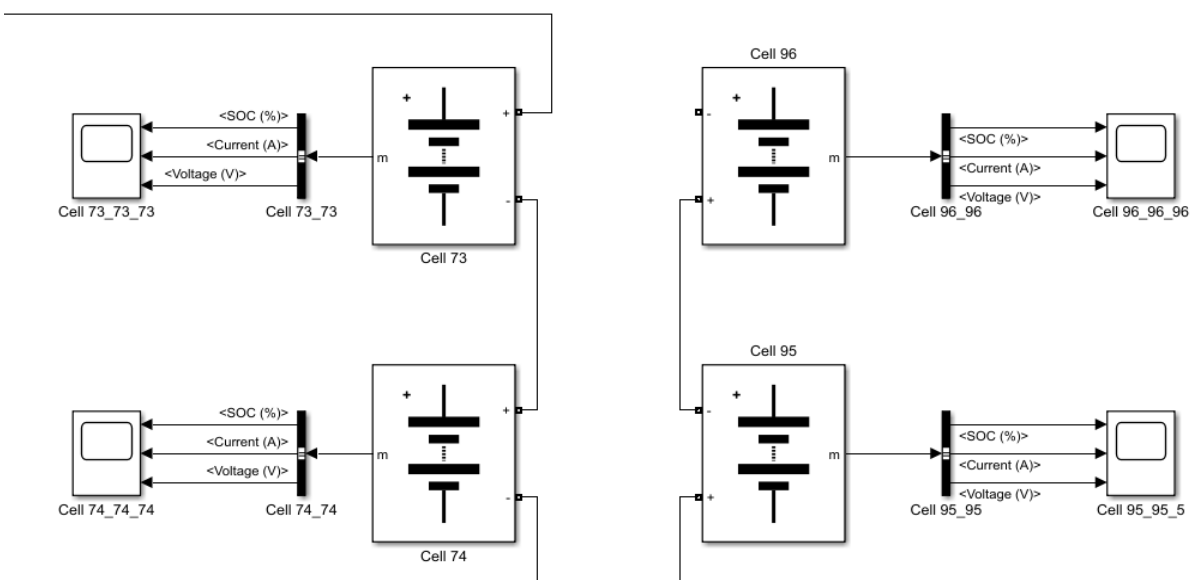

Figure 3.8: Monitoring of each cell in the battery pack

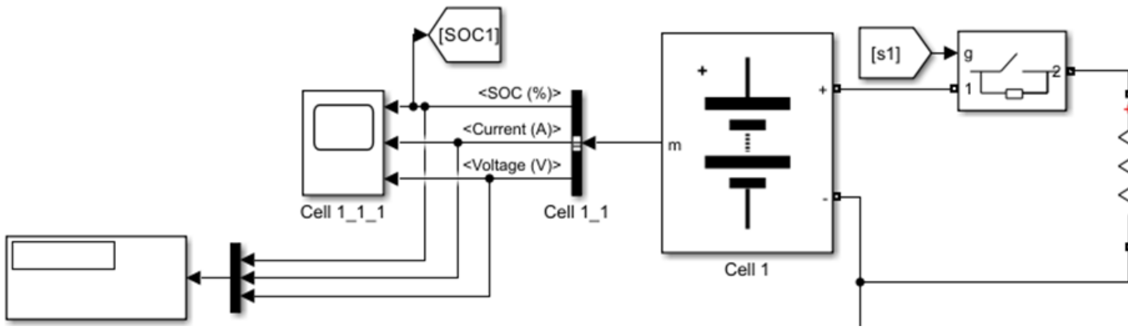

Figure 3.9: Monitoring and balancing of each cell with the display parameter

3.4.3. Battery cell balancing

Cell balancing in the battery management system can be performed in various ways, as discussed in *section 2.2.4*. One of these ways is passive balancing. Here, passive balancing is used to balance the SOC in the battery cell as well as the whole battery pack. Passive cell balancing can be modeled in Simulink using two SimScape blocks. These are Ideal switch and Resistor. Ideal switch, shown in *Figure 3.10*, has two input ports and one output port. It takes the signal from the SOC monitor and send the signal to the resistor to discharge the battery when the certain threshold is reached. The switch is closed by the signal from the monitor only, otherwise it remains open. Whereas, the resistor, shown in *Figure 3.11*, is used in the cell balancing circuit to discharge the battery if and only if the ideal switch is activated by the SOC monitor.

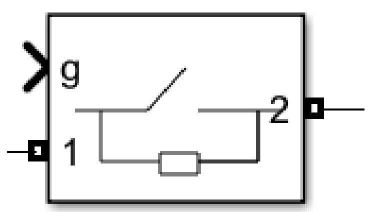

Figure 3.10: Ideal switch for cell balancing in Simulink

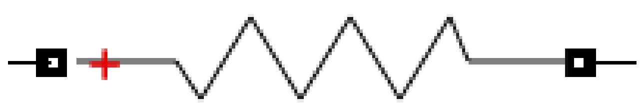

Figure 3.11: Resistor for cell balancing in Simulink

Hence, individual cell, along with the monitoring circuits, can be balanced using passive cell balancing technique as shown in *Figure 3.12*.

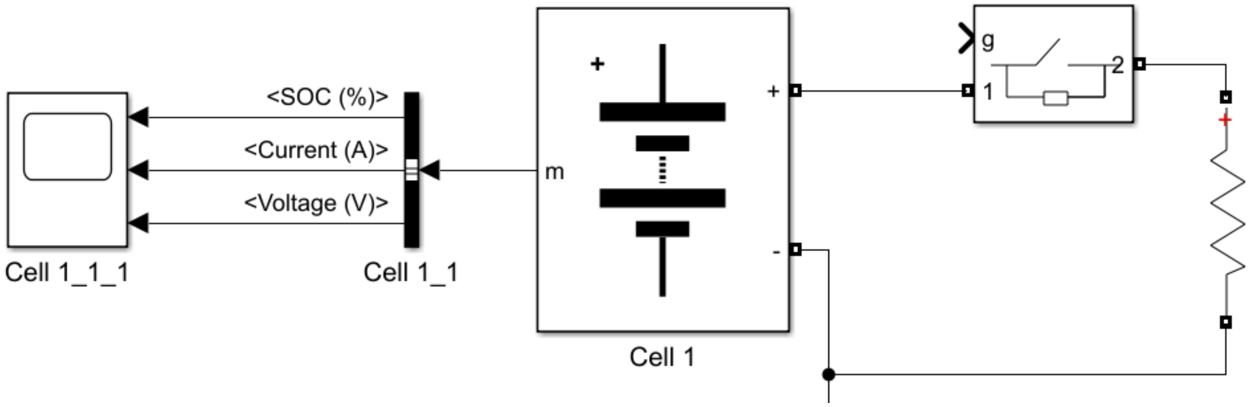

Figure 3.12: Passive cell balancing in Simulink

However, there should be a signal that can activate the ideal switch of the circuit. This signal is created by writing a MATLAB function, shown in *Appendix 1*, that can take input the SOC as input and give the signal to each cell's ideal switches. Then, the block is automatically created providing ports to connect SOC monitoring and ideal switch for each cell of the battery pack. Thus, the function block is connected to theses ports using from and goto block provide by the Simulink, as shown in *Figure 3.13*.

Figure 3.13: MATLAB function block connecting SOC monitor to Ideal switch

With the same manner, the battery cell blocks are updated, as shown in *Figure 3.14*, to accommodate the signal to the ideal switch from the MATLAB function.

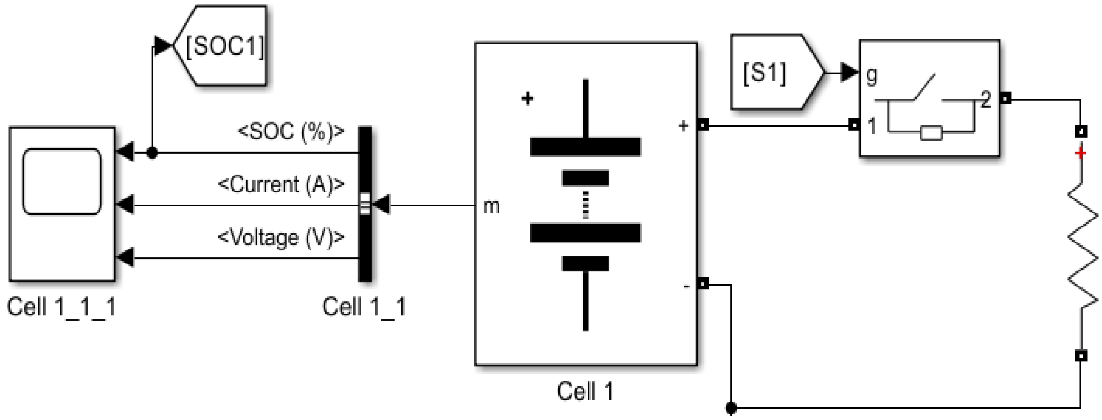

Figure 3.14: Updated battery cell blocks after MATLAB function is included in the modeling

After modeling all the required blocks including the display for the results for the battery management system, the model is now ready for the test run.

3.4.4. Testing

The developed battery management system model underwent testing under two distinct scenarios to evaluate its performance. In the first scenario, the simulation commenced with all battery cells' initial state of charge (SOC) set to 100%, as shown in *Figure 3.15*. This scenario mimics a theoretical ideal condition where all cells are fully charged before discharging. Conversely, the second scenario involved initializing some of the battery cells' SOC at levels below 100%, as illustrated in *Figure 3.16*. This scenario replicates a more realistic situation where the battery pack may contain cells with varying initial SOC levels, possibly due to different charging rates, cell degradation, or other factors. As such, three battery cells at 100%, 80%, and 74% of SOC were selected randomly. Usually, there will be no as much as these differences between cell Soc. However, the test focused on how much it takes to balance the cell if there is as much as these differences. Additionally, to manage computational demand, the simulation was limited to a runtime of 4000 seconds. Since the target of the analysis are monitoring of battery state, estimation of state of charge, and cell balancing, a 4000-second simulation could capture sufficient behavior to draw meaningful conclusions.

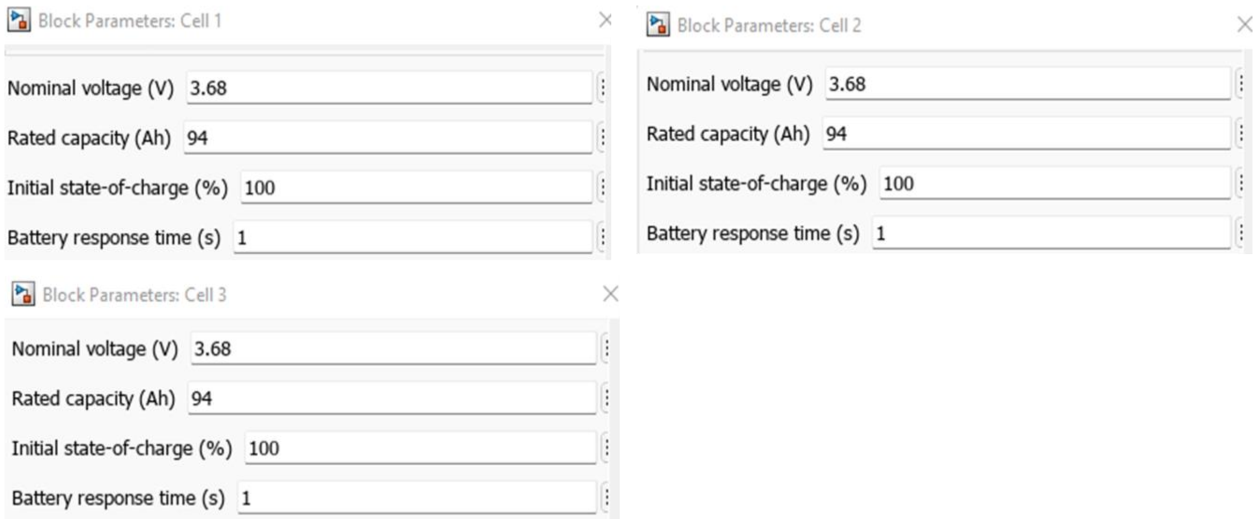

Figure 3.15: Battery cell's SOC variation for testing scenario one

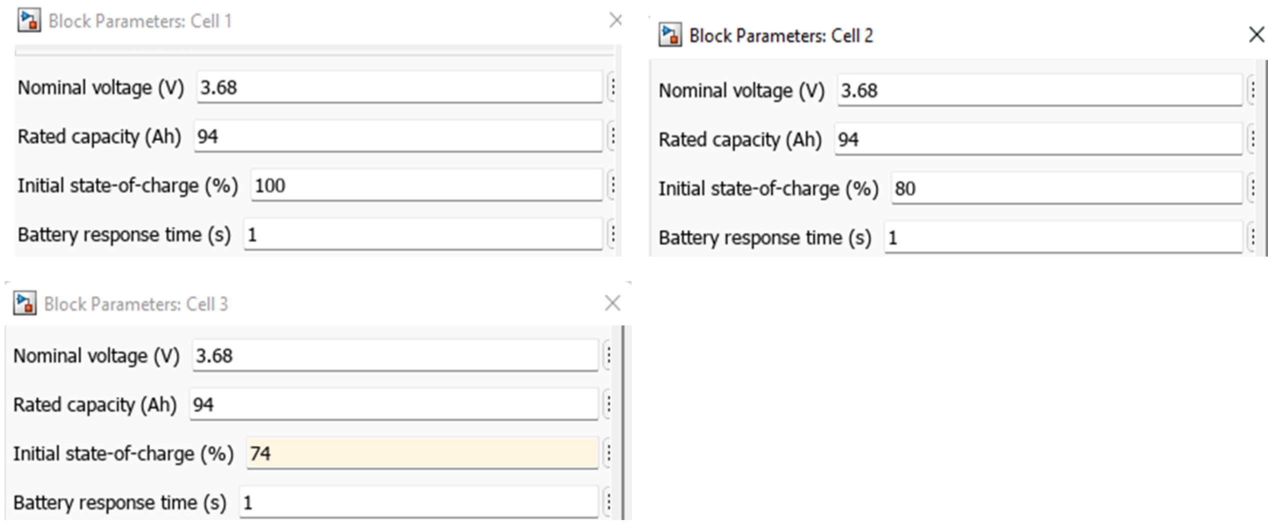

Figure 3.16: Battery cell's SOC variation for testing scenario two

CHAPTER FOUR

RESULTS AND DISCUSSION

The Battery Management System model is created using MATLAB Simulink, specifically tailored to the specifications of the BMW i3 94 Ah battery. This model is constructed and tested within the MATLAB Simulink environment. It includes the battery cell monitoring which includes voltage monitoring and current monitoring. In addition, the model also includes the circuit for state of charge estimation for individual battery cells. Moreover, the passive cell balancing is incorporated into the model to balance the state of the charge (SOC) of each individual cell in the battery pack. From the model various results are obtained.

4.1. Case I – All cells at the same State of Charges

The model is tested for the three cells in the battery pack at the same level of state of charge for 4000 seconds runtime. And, the following results in the form of display and graphs are obtained from the tests.

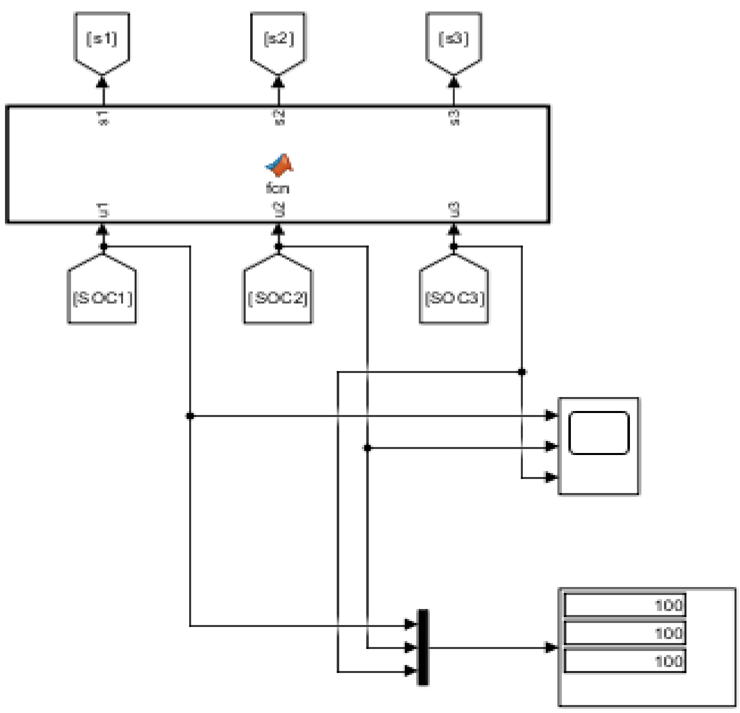

Figure 4.1: Cell balancing circuit for the same state of charges

As shown in *Figure 4.1*, the circuit is designed to ensure that all the battery cells in the system have the same SOC. The cell balancing circuit works by monitoring the SOC of each cell. If a cell's SOC starts to differ from the others, the circuit activates a switch that connects the cell to a resistor. This resistor dissipates energy from the cell, which reduces its SOC. Once the SOC of all the cells is equal, the switch is turned off and the resistor is no longer active.

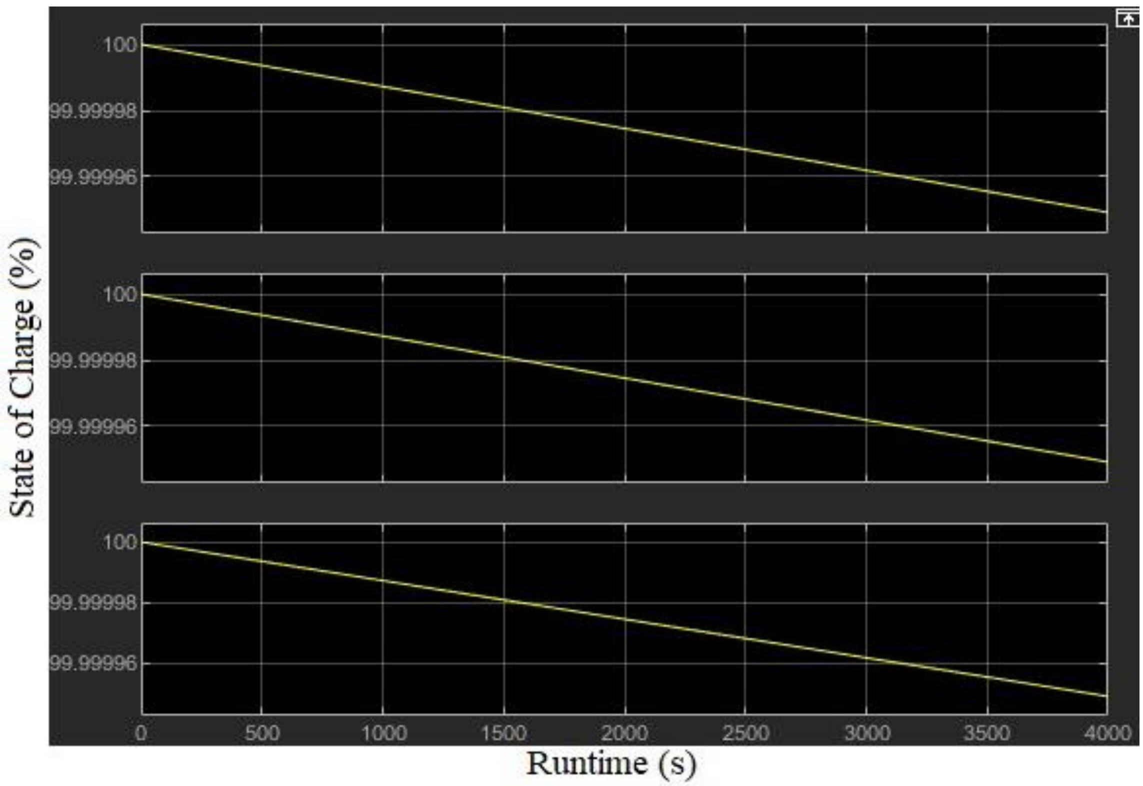

Figure 4.2: SOC graph of Cell balancing circuit for the same state of charges

As shown in *Figure 4.1* and *Figure 4.2*, if the initial state of charge (SOC) of the battery cells are the same, the cell balancing circuit make sure that they stay at the same level of state of charges. That is, the ideal switch of the cell balancing circuit remains open. Thus, the resistor is not activated. Therefore, the cells are discharged when the vehicle runs only with their normal discharge capacities. This is because the cells will naturally discharge at the same rate when the vehicle is running. However, if the cells have different initial SOCs, or if they discharge at different rates due to factors such as manufacturing variations or temperature differences, the cell balancing circuit will need to activate to equalize their SOCs.

As illustrated in *Figure 4.3*, the battery monitoring circuit interfaces with the individual cells of the battery pack. It continuously measures and tracks the current flow in each cell, as well as the voltage across each cell. These measurements are crucial for assessing the battery's health, performance, and remaining capacity. During the discharge process over the designated runtime, the battery monitoring circuit actively collects data and calculates the SOC. This estimation of SOC provides insights into how much energy remains within the battery at any given point during discharge.

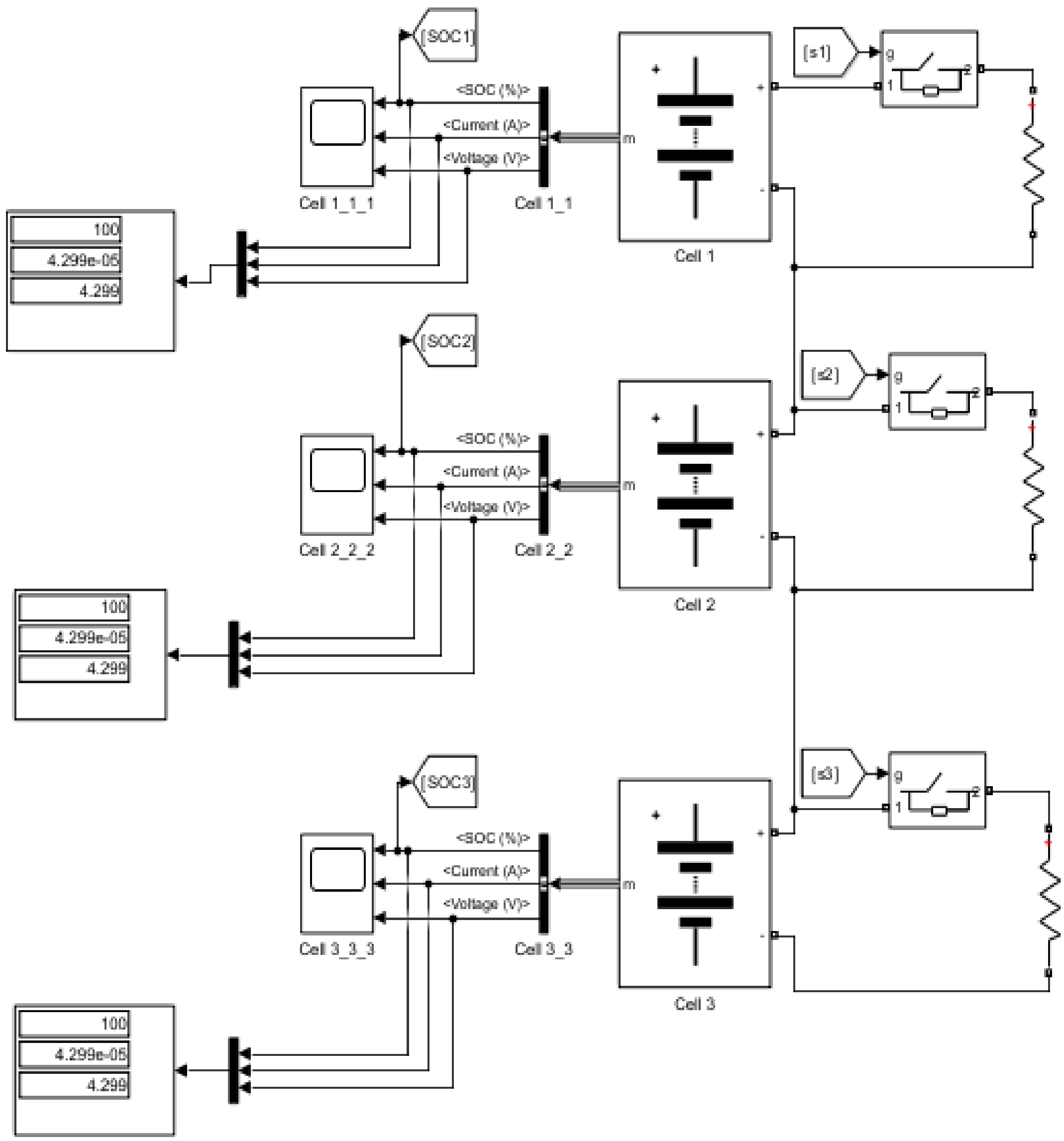

Figure 4.3: Battery monitoring circuit for the same state of charges

Furthermore, the circuit processes the monitored data and presents it in real-time on a display unit. This display could be integrated into the battery system itself or presented on an external interface. Users can conveniently observe parameters such as SOC, current, and voltage, allowing for immediate feedback on the battery's status and performance. By providing real-time monitoring and feedback, the battery monitoring circuit offers a practical solution for evaluating battery behavior during discharge. This information is valuable for ensuring the battery operates within safe limits, optimizing its usage, and diagnosing any potential issues that may arise during operation.

4.2. Case II – All cells at different State of Charges

The model is tested for the three cells in the battery pack at different level of state of charge for 4000 seconds runtime. And, the following results in the form of display and graphs are obtained from the tests. The test is run by considering the first cell, the second cell and the third cell at 100%, 80%, and 74%, respectively.

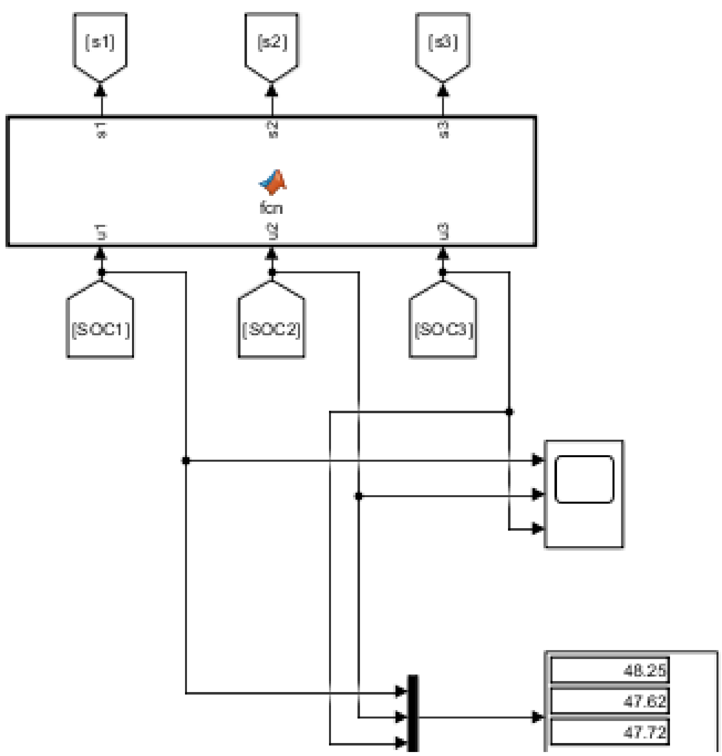

Figure 4.4: Cell balancing circuit for different state of charges at 4000 seconds run time

As shown in *Figure 4.4* and *Figure 4.5****Error! Reference source not found.***, if the initial state of charge (SOC) of the battery cells are different, the cell balancing circuit make sure that they reach approximately same level of state of charges that are at the minimum level. That is, the ideal switch of the cell balancing circuit is closed. Thus, the resistor is not activated. Therefore, the cells with high level of state of charges are discharged quickly to reach the minimum level of state of charges in the battery pack. Hence, it took about 1000 seconds to reach this level. Whereas, the cell with minimum level of state of charge discharges slowly with the normal run.

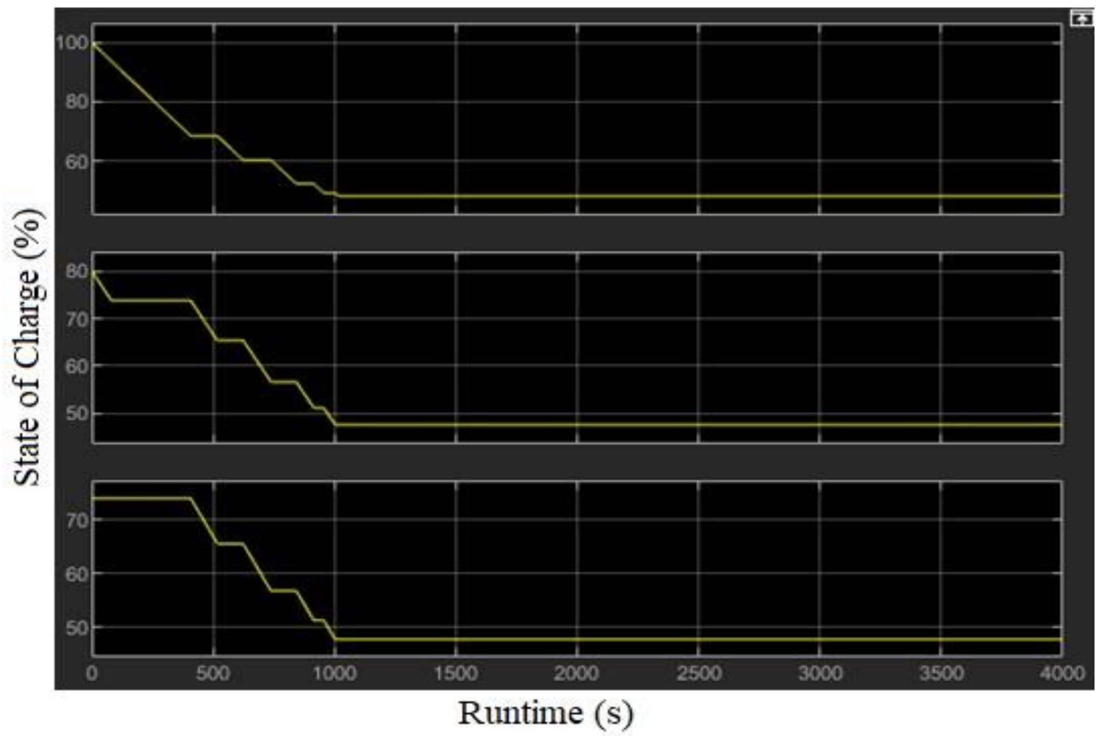

Figure 4.5: SOC graph of Cell balancing circuit for different state of charges at 4000 seconds

As illustrated in *Figure 4.6*, the battery monitoring circuit interfaces with the individual cells of the battery pack. It continuously measures and tracks the current flow in each cell, as well as the voltage across each cell. These measurements are crucial for assessing the battery's health, performance, and remaining capacity. During the discharge process over the designated runtime, the battery monitoring circuit actively collects data and calculates the SOC. This estimation of SOC provides insights into how much energy remains within the battery at any given point during discharge.

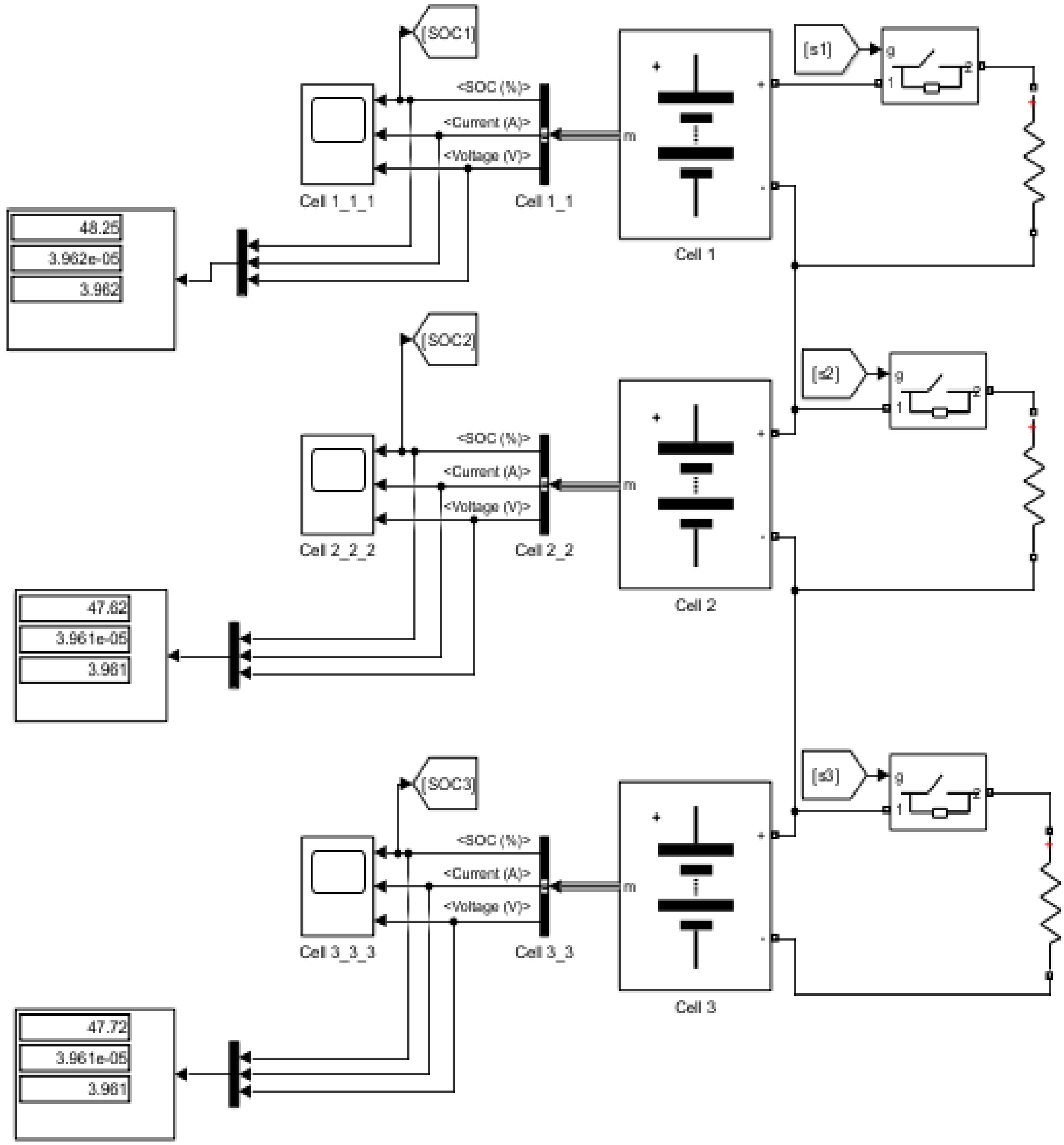

Figure 4.6: Battery monitoring circuit for different state of charges at 4000 seconds run time

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The role of the battery management system is pivotal in ensuring the safe and efficient operation of electric vehicle batteries. However, one of the significant challenges lies in precisely measuring the battery's state of charge and ensuring the balance of the battery cells. To address this, the present paper has formulated a model for a battery management system designed for electric vehicle applications, utilizing the MATLAB Simulink platform. This model is tailored to the specifications of the BMW i3 94 Ah battery and is structured to monitor the current and voltage of battery cells while estimating their state of charge. Additionally, the model incorporates passive cell balancing. Moreover, due to limited computation power, the simulation is performed for three cells of the battery pack by considering two state of charges scenarios and 4000 seconds run time conditions. These are at the same level of state of charges and different level of state of charges.

The results show that, the model performed well both in monitoring voltage and current in both scenarios and both conditions. In addition, the model estimates the state of charges at all test runs. Moreover, the passive cell balancing circuit have performed well in balancing the cells state of charge in both conditions of the second scenario. That is, it took about 25% of the run time to balance the circuit in the second run.

Therefore, it can be concluded that the model is better at monitoring the voltage and the current of the cell as well as the whole battery pack. In addition, the BMS estimation of the state of charge is also great. Moreover, the model has performed well in balancing circuit. Hence, the model can be further tested for the real-world application for electric vehicles.

5.2. Recommendation

The developed model was able to monitor the current and voltage of each battery cell in the battery pack. In addition, the model has the capacity to balance the cell based on the estimated state of charge of the cells. However, due to limited computation power the model is not simulated for the whole cells of the battery pack. In addition, temperature monitoring is not included in the model. Therefore, it is advisable:

- If the high computational power is available, the test should be run for the whole battery pack and for longer run time, and
- The temperature monitoring of the battery cell should be included for further simulation of the model.

5.3. Future Works

The developed model has demonstrated its ability to monitor battery cell voltage and current, estimate SoC, and balance cell states of charge. However, to achieve even better performance, the future works should focus on:

- Increasing the number of simulated battery cells to represent the entire battery pack,
- Extending the simulation run time for more comprehensive testing, and
- Incorporating temperature monitoring into the model for a more realistic representation of the real-world problem.

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APPENDIX

Appendix 1: MATLAB function to activate Ideal Switch

```
function [s1, s2, s3, ... s95, s96] = fcn(u1, u2, u3, ... u95, u96)
u1=int32(u1)
u2=int32(u2)
u3=int32(u3)
...
...
...
u94=int32(u94)
u95=int32(u95)
u96=int32(u96)
if ((u1>u2)||(u1>u3)||(u1>u4)|| ...||(u1>u95)||(u1>u96))
    s1=1;
else
    s1=0;
end
...
...
...
If ((u96>u1)||(u96>u2)||(u96>u3)||...||(u96>u94)||(u96>u95))
    s96=1;
else
    s96=0;
end
```

Appendix 1: MATLAB function to activate Ideal Switch