Pakistan Journal of Engineering and Technology
ISSN (Print): 2664-2042; ISSN (Online): 2664-2050
Received: 2025-02-26
Accepted: 2023-06-07
https://doi.org/10.51846/vol8iss1pp1-13

PAKJET
Pakistan Journal of Engineering & Technology

Article

Advanced Battery Management for Electric Vehicles: Charge Monitoring and Fire Security

Romaisa Shamshad Khan [1], Abdul Aziz [2,*], Rehan Babar [3], Kashif Abbas [4], Nusri Elahi [5], and Muhammad Abdullah [6]

1 Department of Electrical Engineering, NFC Institute of Engineering and Technology Multan, Pakistan
2 Department of Electrical Engineering, CECOS University of IT and Emerging Science, Peshawar, KPK, Pakistan
3 Department of Electrical Engineering, The Islamia University of Bahawalpur, Bahawalpur 63100, Pakistan
4 Department of Renewable Energy Systems Engineering, University of Engineering and Technology, Lahore, Pakistan
5 Department of Electrical Engineering, University of Engineering and Technology, Peshawar, KPK, Pakistan
6 School of Energy Science and Environment, Southeast University, Nanjing China
* Correspondence: Abdul Aziz (abdulamiruet@gmail.com)

Abstract: A thorough study presented in this paper focuses on the design and development of a cutting-edge Battery Management System for Electric Vehicles (EV-BMS). This paper examines the centrality of BMS in prolonging and protecting the valuable life of the lithium-ion battery pack in EVs. What follows focuses on some of the most critical questions, including SOC and SOH estimation, thermal regulation, and fire suppression. The architecture of the proposed EV-BMS integrates advanced estimation methods for superior accuracy in the estimation process, real-time data updates, and the integration of machine learning concepts into the battery control process. The study also presents an outline of countermeasures that can reduce the liability of battery fires, including the optimization of heat dissipation systems, sensors for detecting the onset of fire, and fire extinguishing systems. Additionally, comprehensive simulations and experiments confirm the reliability and usefulness of the proposed EV-BMS structure in optimizing the performance and safety of lithium-ion battery packs in electric vehicles. In total, this research enhances transportation safety and efficiency, particularly by minimizing the risks of fatal accidents and air pollution that affect the entire world and contribute to the prevention of climate change.

Keywords: Electric Vehicles (EV-BMS), SOC and SOH Estimation, Fatal Accidents, Air Pollution

1. Introduction

Electric vehicles (EVs) are leading the global automotive industry's steady transition to sustainable and environmentally friendly modes of transportation. Because high-capacity lithium-ion batteries power their electric drive systems, EVs are more energy-efficient than traditional internal combustion engine cars. These battery architectures must function safely and efficiently to ensure that electric vehicles (EVs) are widely accepted and utilized [1].

This extended proposal showcases the development of an advanced, comprehensive EV battery management system (BMS) featuring Charge Screen and Fire Security. There are further goals: establishing a thorough, modernized structure that would simultaneously improve customer awareness, security, and satisfaction with several aspects of electric vehicle batteries [2, 3]. Here are some of the critical issues. A robust Battery Management System (BMS) is essential to fully leverage the capabilities of electric vehicle (EV) batteries. Among these parameters, the state of charge (SOC), state of health (SOH), voltage, current, and temperature of the battery are some of the key parameters that are often monitored. The BMS reduces the complexity of early diagnosis of disappointments and ensures that the temperature is gradually controlled, allowing each battery cell to function optimally [4]. Another benefit found in the interfaces involves remote checking of the charging handles through persuasive charge checking by EV owners. Real-time observation is most effective in enhancing charges' efficiency, successfully avoiding contact with cheating, and reducing other factors such as control taxes and lattice requests while making preparations to minimize charging costs and framework push [5]. As more electric vehicles utilize high-capacity lithium-ion batteries, the risk of battery-related fires is increasing concern. This project aims to make driving an electric vehicle (EV) more efficient and comfortable while ensuring the battery management system's (BMS) safety, reliability, and longevity. This remarkable project integrates state-of-the-art BMS advances, fire prevention systems, and charge-checking capabilities into a single, coordinated system, pushing the boundaries of electric car security and performance [6, 7]. Regarding the methodology, testing, and use strategies that will be applied to create this hi-tech EV BMS with Charge Screen and Fire Security, we will conduct a thorough literature review to examine the current state of research and industry advancements in these areas. We will illustrate how the project will impact the EV showcase and practical mobility [8].

Our advanced battery management system features diagnostic tools that identify and resolve issues promptly, preventing significant failure situations in electric vehicles.

Our proactive system protects the vehicle from problems and extends the battery's lifespan, building user trust in vehicle reliability. Our plans include setting up a charging method that senses user activities and battery conditions to find the perfect charging speed. Our system will enable batteries to charge faster, reducing power bills and helping the planet. The system allows users to adjust their device settings while viewing current battery power information, thereby strengthening their connection with their vehicle. The project puts electric vehicle technology ahead by engineering safety features that help customers utilize their vehicles more effectively. The improvement project will enhance electric vehicle technology and provide a better user experience, enabling electric vehicles to gain worldwide market acceptance. Our BMS upgrade includes machine learning algorithms reviewing vehicle operation data to improve functionality. These systems will study how vehicles interact with driving conditions to estimate battery degradation rates and design more efficient performance outputs. Our system's advanced predictive analytics provide drivers with helpful information to better care for their cars and achieve optimal operational results. Our system utilizes modern protection features that quickly detect and respond to battery shorts and high temperatures, preventing accidents and ensuring rider safety. Our system utilizes automatic safety protocols and an emergency response system to respond promptly in high-risk scenarios. It will detect and handle battery cell short circuits by isolating the affected area while cooling systems engage as needed. As part of our EV support program, we will develop technology to connect our battery management system with electric grid networks seamlessly. The system can match vehicle charging needs with grid power availability, generating energy savings through efficient usage and making the power network more stable while lowering expenses. Our work advances electric vehicle technology beyond its current limitations to enhance driving comfort and promote sustainability by reducing carbon emissions. To build a sustainable electric mobility path, we take a complete approach.

2. Literature Review

In 1965, the battery model proposed by Clarence M. Shepherd to explain discharge processes for different cells, based on specific variables such as discharge time and current density, was introduced for cells using minimal experimental data [9, 10]. The model comprehensively described cell characteristics, including charge, capability, power growth, and experimental limitations. It was based on key assumptions: the anode and/or cathode contained porous active materials, the electrolyte resistance remained constant during discharge, and the polarization increased linearly with the current density of the active material [11]. The Shepherd model is shown in Fig. 1.

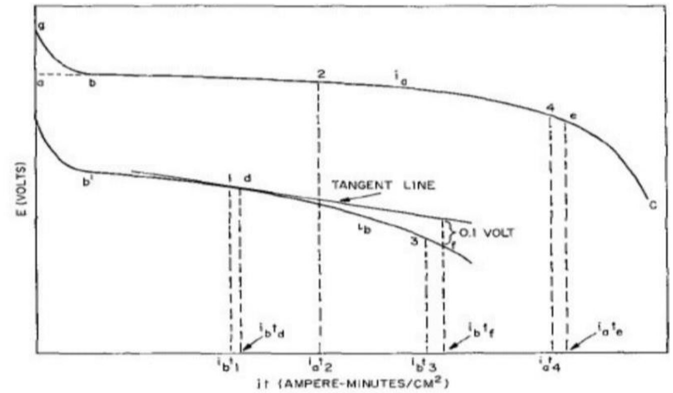

Figure 1. Shepherd model.

The Tremblay model, designed by Olivier Tremblay, simplifies battery analysis using dynamic simulation software. It focuses on the State of Charge (SOC) to avoid algebraic loop issues and represents battery chemistries with internal resistance in series with a regulated voltage source. This model is helpful as parameters can be derived from discharge curves. Compared to experimental and electrochemical models, it provides a better explanation of electrical properties and battery behavior, including internal resistance and voltage. Tremblay addressed issues like algebraic loops and instability in earlier models, improving accuracy and reliability by adding a term to capture nonlinear voltage behavior [12].

Commercial and academic studies [13, 14] on BMS hardware systems have been conducted. The BMS for electric vehicles is in the infancy stage. Off-the-shelf BMSs are available from some manufacturers. However, additional options may become available shortly. Commercially, simpler BMSs for smaller batteries are available from Chinese manufacturers. These BMSs are not for large lithium-ion packs. Major manufacturers offer high-quality BMSs that are not available to the general public. Low-cost, compact BMSs from European and American manufacturers are scarce. Analog BMSs cost $16 per cell for distributed systems and $2 per cell for protection. Higher-end digital Battery Management Systems (BMSs) with additional functionalities are used in electric cars. In low-power applications, integrated circuits are used to develop simple Battery Management Systems (BMSs). Electric vehicle battery management is more complex and expensive [15]. Some systems focus on monitoring without safety features, and cell balancing is often addressed. A CAN bus-based Battery Management System (BMS) is illustrated in Fig. 2 for electric vehicles, which connects to the vehicle controller and monitors battery data [16]. A fault-tolerant, battery-protecting BMS design with innovative battery modules is noted, though it wasn't specified for lithium-ion batteries [17, 18]. The digital lithium-ion BMS using the TMS320LF2407A DSP is cost-prohibitive due to the high price of the DSP [19].

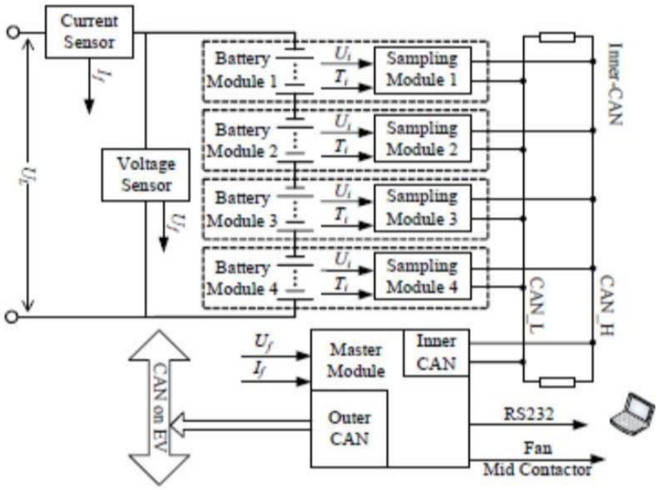

Figure 2. BMS structure on CAN-bus.

The principles of BMS based on DSP are shown in Fig. 3.

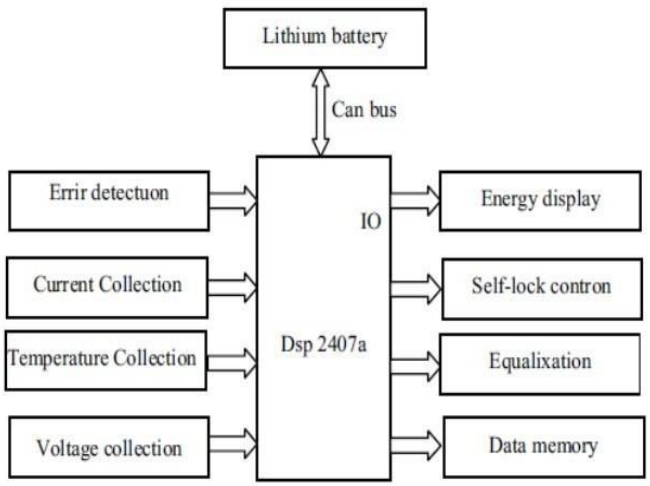

Figure 3. Principle of BMS based on DSP.

3. Materials and Methods

3.1. Working Principle of Electric Vehicle

Electric vehicles (EVs), shown in Fig. 4, are powered by one or more electric motors, utilizing an electric motor pack to store energy instead of an internal combustion engine (ICE) which burns fuel [20]. Electric vehicles (EVs) offer several advantages, including reduced reliance on fossil fuels, quieter operation, and lower emissions [21]. Electric motors are more efficient than internal combustion engines (ICEs), resulting in lower operational costs. As the world pursues a cleaner and more sustainable future, the potential of EVs is rapidly increasing, with governments incentivizing their adoption and automakers expanding EV offerings [22]. Despite their benefits, EVs face challenges, such as internal cell films affecting thermal performance. Excessive heating can cause battery fires when heat interacts with fuel.

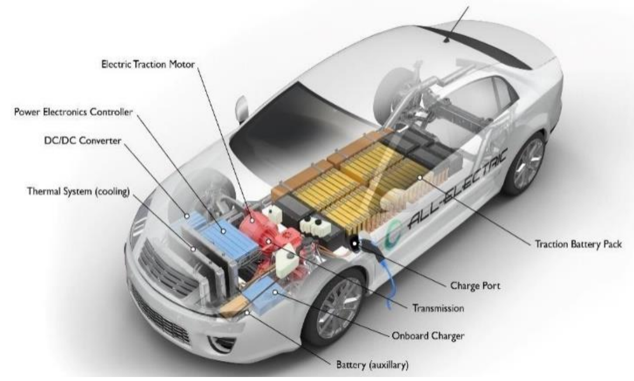

Figure 4. Electric vehicle.

A Battery Management System (BMS) manages rechargeable batteries in electric vehicles (EVs) and oversees the charging, discharging, and monitoring of the battery's condition to prevent damage from overcharging or overheating [23].

A BMS includes components such as Li-ion batteries, as shown in Fig. 5, LCDs, push buttons, voltage and current meters, and thermometers. The system is often designed with a 3S lithium-ion battery, ensuring proper charging and safety. The BMS regulates voltage and current during charging, displays the battery voltage, and disconnects power when the battery is fully charged. It monitors current consumption and adjusts charging or discharging rates to maintain optimal battery temperatures [24].

The BMS safeguards batteries by reducing or halting charging when overheating occurs and increasing charging rates if the battery is too cold. This ensures efficient operation, enhances safety, and extends battery lifespan, making the BMS an essential part of EV systems [25].

The 1990s saw the development of lithium-ion batteries to meet the demand for lightweight, rechargeable cells for flexible electronics [26]. Initially used in cameras and multifunctional phones, they are now powering tools, large-scale energy storage systems, and vehicles. With high energy density and numerous discharge cycles, lithium-ion batteries are key for electric vehicles and flexible phones, surpassing traditional battery chemistries in various ways.

Figure 5. Lithium-ion batteries.

The BMS description differs depending on the procedure. BMS, in the broadest way, refers to an operating system that monitors, controls, and optimizes the operation of one or more battery modules inside an energy storage system [27]. The BMS can determine how to remove a module or modules from the system in abnormal conditions. Battery performance is enhanced in applications when the proper safety measures are included [28]. To achieve optimal coverage, control, and battery power efficiency, battery life is also a key consideration. BMS serves in power system operations. BMS is used in machine operations to manage energy in different system interfaces and safeguard the system from threats that appear visually appealing. BMS is composed of various functional building elements. The BMS's functional blocks are linked to batteries and every other component of the organized system, including distributed batteries, regulators, and grids. Sufficient armature, well-functioning blocks, and sophisticated electronics can all help prolong the system's battery life. Upon request, several commercial Building Management Systems (BMSs) are provided [29]. For example, NUVATION Energy offers a UL 1973-recognized, durable, modular, and versatile Building Management System (BMS) for fixed and mobile energy storage operations. The Battery Management System design is illustrated in Fig. 6.

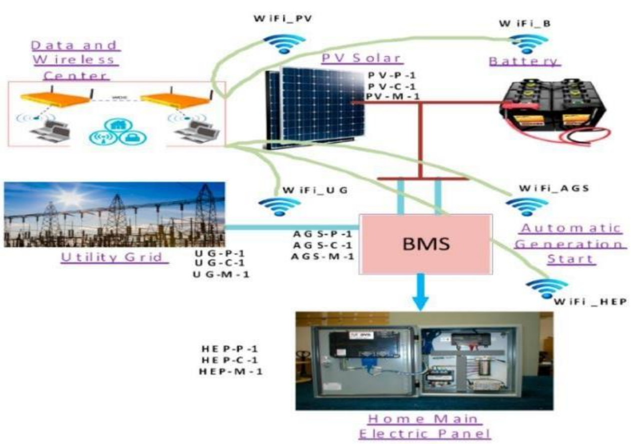

Figure 6. Battery management system.

The primary objective of the Battery Management System (BMS) is to enhance battery lifespan and efficiency in electric vehicles (EVs) through intelligent, adaptive monitoring of battery health, voltage, temperature, and state of charge (SoC). Additionally, the BMS manages thermal operations and ensures safety during charging and driving by providing real-time monitoring through an intuitive interface, allowing EV owners to oversee charging remotely. Fire safety is crucial, with integrated detection and suppression systems in place to mitigate risks. The BMS also utilizes advanced data analytics to optimize battery performance, charge patterns, and preventive maintenance. It supports monitoring key parameters such as cell voltages, pack voltage, current, and temperature to evaluate the depth of discharge (DoD), SoC, and state of health (SoH). These functions help extend battery life while ensuring safe and efficient operation. The BMS also facilitates precise control of charging and discharging, improving energy efficiency and reducing environmental impact. Furthermore, the system safeguards against external factors, manages thermal conditions, and integrates seamlessly with conventional and unconventional energy sources, leveraging IoT for enhanced monitoring and management. Challenges include dependency on model accuracy, high computational costs, and addressing real-world operational factors like uneven terrain and temperature fluctuations. Fig. 7 explains the function of BMS.

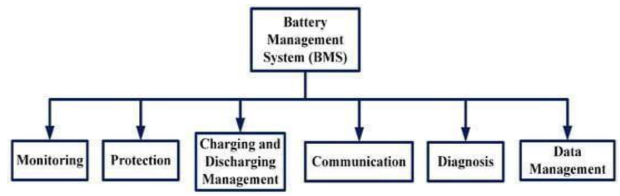

Figure 7. Functions of BMS.

Despite these, the BMS offers significant advantages, including improved battery longevity, protection against damage, and precise SoC tracking. However, its reliance on complex models and training data poses certain limitations.

The current battery model has satisfactory thickness relative to external parameters. The internal chemical reaction is complex and nonlinear, causing terminal voltage to vary non-linearly during charging and discharging rather than exhibiting pure resistance. Polarization increases resistance to charging and discharging, leading to ageing, higher internal resistance, and reduced capacity, causing the state of charge to deviate from reality. Power performance declines from monomers to modules and packs. These factors make it challenging to develop a precise model that accurately represents all battery performance. Various styles are used to simulate properties from different perspectives. Data-driven, equivalent circuit, and electrochemical models are the most common.

The Battery Management System (BMS) of an electric vehicle comprises several critical components that work together to ensure the safe and efficient operation of the car. The microcontroller is a compact integrated circuit that features a CPU, input/output peripherals, and memory, designed to manage embedded applications such as motor and sensor control. It plays a vital role in automation and electronic systems due to its low energy consumption and versatility. The voltage sensor measures the potential difference between two points in the circuit. It converts it into analog or digital signals, providing essential data for the protection and management of electrical networks. Similarly, the current sensor measures the flow of electric current, converting it into signals that help monitor current flow in applications like energy management and motor control, ensuring the safety and efficiency of electronic devices. Temperature sensors monitor environmental temperatures and convert them into proportional signals, which are crucial for regulating conditions in various applications, including industrial processes and vehicle engines. They help ensure that the vehicle operates within optimal temperature ranges, contributing to the safety and longevity of the system. The LCD in the BMS displays real-time data on the battery's voltage, temperature, and charge status, enabling users to monitor the battery pack's health and performance. It shows important information such as the remaining range, charge status, and diagnostic data, ensuring safe operation and enhancing the user experience. The charging circuit regulates the current flowing to the battery during the charging process, preventing overcharging and overheating by controlling voltage, current, and temperature. This system is crucial for maintaining the battery's health and extending its lifespan, directly influencing the vehicle's operating range. Finally, the 3S battery pack, consisting of three cells connected in series, provides a rated voltage of around 11 volts. The BMS constantly monitors each cell's charge and discharge currents, preventing overcharge and ensuring a balance between voltage and energy density, which is essential for the performance of small electric vehicles or larger battery systems. Together, these components form an integrated system that ensures the safe, efficient, and reliable operation of electric vehicles. Fig. 1 illustrates the electric vehicle battery management system model.

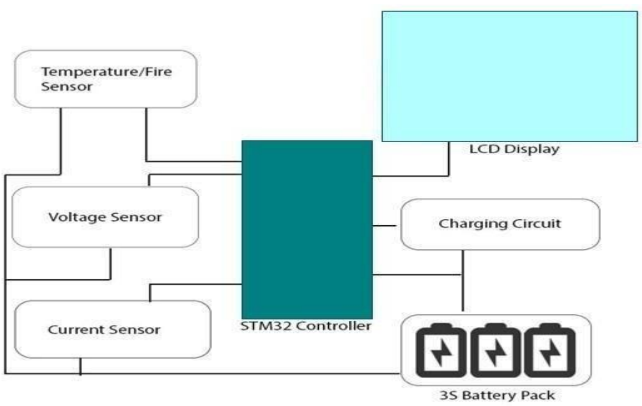

Figure 2. Electric vehicle battery management system model.

This system will be equipped with Li-ion batteries, an LCD screen, push buttons, an LCD charging and checking mechanism, and indicators for voltage, current, and temperature. Thanks to this technology, it actively tracks and protects an EV battery. In this case, a system will be designed to run on a 3S lithium-ion battery for its power needs. The technology will safeguard the battery, prevent mishaps, monitor its condition, and ensure it is recharged safely. The charging and voltage monitoring circuits enable the loading of the 3S battery, typically when the vehicle is on. By anticipating the voltage across the charging circuit, the voltage sensor regulates the current that reaches the battery during charging. Additionally, it features an LCD panel that indicates the battery voltage level. The technology automatically turns off the electricity and shows "Battery fully charged" on the LCD screen when the battery is fully charged. The current sensor tracks and shows the amount of current drawn from the battery when a load is connected. When the battery is being charged or discharged, the temperature sensor monitors the battery's state of charge. The system instantly disconnects the power source, shows the battery temperature, and activates an LCD alert if the temperature deviates from the set parameters. By employing the charging circuitry to monitor the voltage, the voltage sensor controls the current going to the battery during the charging process.

3.2. Cell Monitoring

3.2.1. *Voltage Measurement*

The temperature sensor records the battery's temperature, whether it is charged or discharged. The system immediately turns off the input and output supply, shows the battery's temperature, and sounds an alert through the LCD when it detects a deviation from the standard values. By detecting voltage through the charging circuitry, the voltage sensor regulates the amount of current delivered to the battery during charging.

3.2.2. *Current Monitoring*

The BMS measures the battery's state of charge (SOC) and state of health (SOH) by monitoring the current flowing into and out of the battery pack. It helps prevent overcharging and over-discharging, which can damage the battery.

3.2.3. *Temperature Monitoring*

Continuously monitors battery temperature to ensure it is within safe operating range. Overheating may cause the battery to deteriorate and pose a safety risk; therefore, if the temperature exceeds the threshold, the BMS cools the machine.

3.3. Block Diagram

The block diagram of the electric vehicle BMS is displayed in Fig. 3.

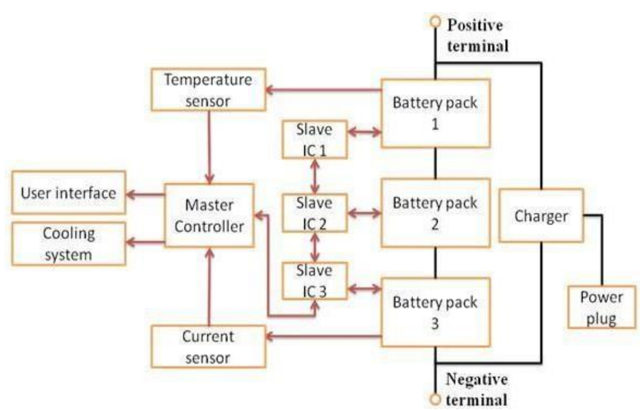

Figure 4. Block diagram of electric vehicle BMS.

The four unused modules were connected once the front chipboard and the majority controller board were interfaced. The TV board was connected to most controller boards via conventional lines and ran on a constant 5V voltage. A temperature sensor was added to this board to measure and link the battery's temperature to the temperature module. Three tiny

Driven markers are used to display the temperature. Temperatures are indicated by green, cowardly, and ruddy lights for moon, medium, and tall, respectively. Additionally, the microcontroller board was attached to the cooling module. Using information from temperature sensors, the central controller controlled the cooling module controller, which operated in three-speed ranges based on temperature. The final module related to this was the one we currently use. The cable that goes to the battery pack now has lobby sensors. Research can be done, and charge and discharge currents can be sent to most controllers.

3.4. Flow Chart

Fig. 5 Shows the flow chart of the electric vehicle BMS.

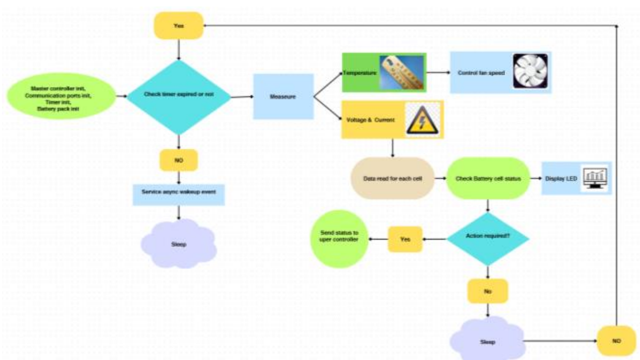

Figure 6. Flow chart of electric vehicle BMS.

The microcontroller had to initialize the peripherals. The second step was to identify and set up the front ICs for assembling the battery stack. The next step was to analyze the voltages, currents, and temperatures of the software to determine the condition of the battery pack and cells. The power management software continuously monitors the battery pack for a "FAIL" scenario by checking the energy pack's strength and cell levels every second. To avoid unfavorable operating conditions for the battery package and the battery cells, the BMS software compared the predetermined values from the datasheet's explanation of the lithium-ion cell characteristics with the actual numbers at runtime. The threshold values were set based on the datasheet's explanation of the lithium-ion cell's characteristics. The cell threshold values were used to deduce the threshold values for the battery pack. The most typical indication of instability was a mismatch in the voltages of the cells, which could be corrected by gradually adjusting the voltage of the cells with higher voltages. It is conventional for this BMS to employ a passive cell-balancing technique based on variations in the cell voltage. Bypass was activated when the cell voltage difference exceeded an individual predefined value in the charging mode.

3.5. Terms Associated with EVs BMS.

3.5.1. State of Charge (SOC)

The SoC is a quantifiable mark of a battery in an EVS BMS. It represents the battery capabilities of an electric vehicle and is expressed as a percentage. From the authors' point of view, the State of Charge (SoC) is calculated by the Battery Management System (BMS) based on voltage, current, temperature, and the battery's historical usage. It is, therefore, essential to estimate the State of Charge (SoC) to define the remaining range and determine the optimal charging and discharging strategies, thereby preventing battery damage from overcharging or deep discharge. Such information may include enabling drivers to navigate the roads more efficiently or use the electric battery system more accurately.

3.5.2. State of Health (SOH)

In an EV BMS context, the SOH reflects the condition and performance capability of the battery pack over a given operational age of the battery. It estimates the extent of deterioration and capacity loss the battery undergoes, depending on its usage and surrounding environment. It constantly checks SOH parameters encompassing internal resistance, voltage response, and charge acceptance. This information also affects the setting of battery utilization time and its maintenance time to avoid compromising the safety of the electric vehicle's power train.

3.6. Estimation of State Charge

The State of Charge (SOC) of a rechargeable battery refers to the amount of charge it holds. Factors such as temperature and discharge rate affect the State of Charge (SOC). A battery's state of charge (SOC) estimates its available charge at any given moment, expressed in probability. The stoner can determine from the SOC how long the battery might last before needing to be recharged or replaced. Due to its non-linearity, SOC needs to be estimated rather than measured. One state parameter that changes stoutly over time is SOC. This has led to the development and operation of numerous acceptable and logical methods. Accordingly, multitudinous pleasing and logical ways have been created and are presently used. As the active material on an electrode wears down, the battery's charge decreases. The suggested SOC estimate ways are:

- ➢ Coulomb Counting
- ➢ Unscented Kalman Filter (UKF)
- ➢ Extended Kalman Filter (EKF).

3.6.1. Coulomb Counting Method

A popular technique for figuring out a battery's State of Charge (SOC) is ampere-hour counting, also known as current integration. Statistical integration of battery current data is employed in this technique to determine State of Charge (SOC) values. The coulomb counting method determines the battery's remaining capacity by monitoring the charge added to and taken from the battery. The accuracy of this method depends on the initial state of charge (SOC) computation and battery charge readings. Integrating the charging and discharging currents during the battery's operating duration yields the battery's charge level. Nevertheless, losses like mistake accumulation and self-discharge are unavoidable in these systems. A thorough SOC assessment requires addressing these factors. The SOC must be updated regularly with a more accurate approximation, considering the discharge charge decreases to increase accuracy. Despite improvements, the Coulomb counting approach still has drawbacks that frequently cause the State of Charge (SOC) to be overestimated throughout the estimation process.

3.6.2. Extended Kalman Filter

The Kalman filter is a technique used to estimate the charge level in a battery and the internal states in a dynamic system. Therefore, it provides a reliable state estimator for linear systems that encounter process and measurement noise. Applying Kalman filters to nonlinear systems produces the Extended Kalman filter, which linearizes a function depending on its significance. There are two stages in the estimation process. The first is the priori estimate, which updates the time to estimate the states. This step is given as an input to the process covariance matrix and a signal sample. The carat symbol represents the posterior estimate's second stage, using an output signal error to refine the a priori state prediction.

3.6.3. Unscented Kalman Filter

Whereas the EKF linearizes state-space equations, the Unscented Kalman sludge does not. However, it employs a nonlinear Unscented Transformation (UT) to generate sigma points for every nation. This involves determining and simplifying the mean and error covariance iteratively. A priori, nonlinear model functions that express all the sigma points are employed to approach the country and affair signals. The means and covariances of the variables are determined from their statistical data.

3.7. SOH Monitoring

The battery's overall condition and capacity to provide performance on par with newly purchased batteries are indicated by the state of health (SOH) rating. A cell's conductance and cell impedance are two parameters that can be used to calculate its specific harmonic number (SOH); both vary dramatically with aging. Cell conductance or impedance measures can be used to estimate SOH. Compared to a fresh battery, the State of Health (SOH) gauges the battery's overall performance and capacity to fulfill performance standards [39]. Battery SOH can be computed using any attribute that changes over time, such as battery conductance or impedance.

3.8. Thermal Management

Cooling System: To maintain the battery cells at their optimal operating temperature, the BMS controls an active cooling system, such as liquid or air cooling. Custom cooling can be achieved by considering variables such as battery size, charge and discharge rates, and ambient temperature. Prevent thermal runaway from getting out of control: If the temperature inside a cell rises rapidly, a thermal burn or a prolonged reaction can damage the cell or even cause a fire. The BMS monitors temperature changes and initiates cooling or insulating mechanisms to alleviate thermal stress. Heating system (cold climates): In cold climates, the BMS can utilize a heating source to warm the battery and maintain an optimal operating temperature. This ensures the cells can deliver acceptable power and capacity despite low ambient temperatures. Temperature balance: Temperature fluctuations in the battery pack can cause the cells to perform unevenly and reduce their overall performance. BMS can adapt sweat by cooling or warming it, ensuring consistent temperature distribution and maximizing cell life and performance. Safe Shutdown: When the battery temperature exceeds the critical threshold, the BMS initiates a safe shutdown procedure to prevent damage or hazards. This may involve disconnecting the battery from the rest of the vehicle's systems and waking the driver or maintenance personnel.

3.9. Cell Balancing

The charge in each cell must be balanced to optimize the energy of the total battery pack. Every BMS demands it because the black of the lowest charge will limit the battery pack's overall energy capacity. Every block requires the same amount of charge to function at maximum energy. The capacity of the battery pack can be determined by utilizing the weakest cell, a balancing pack, and the entire available capacity solely after recharging the balanced battery pack. The charge of the top cells is gradually lowered to match that of the bottom cells, thereby accomplishing passive balancing. Transistors can swap resistors to discharge excess charge. The first method employs a fixed shunt resistor, whereas the second method utilizes an adjustable shunt resistor. Although heat requires energy, proactive counterbalancing appears to be a more advanced approach. In Fig. 7, The Cell Balancing of BMS is shown.

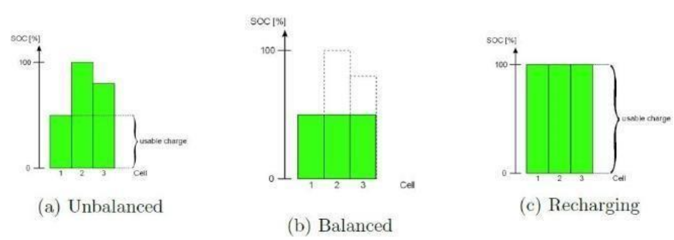

Figure 8. Cell balancing of BMS.

4. Simulation Results

The study's proposed BMS solution comprises two main components: the BMS controller and the battery plant. The battery plant includes an inverter, a charger, a pre-charge circuit, and a six-cell module. In addition, the BMS model is shown in Fig. 9, which has a state machine, a SOC estimate block, a charge limit block, and a cell balancing circuit model. Using the proper sensors, the battery module's properties are collected, including the controller, which accepts input values such as the currents of each cell, cell voltages, temperatures, and the total pack current. Based on these inputs, the controller will decide on the limits of charge in input and output, inform the user about the state of charge (SOC), and instruct the battery plant to balance the cells.

This section discusses cell balance and SOC estimation simulation. Ninety-six lithium cell battery packs are considered for the procedure. This cell design uses the appropriate detectors to uproot each cell's voltage, current, and temperature. On this variant, there is only one visible battery module. Six independent cells connected in sequence make up a single battery module. These modules are designed to enhance system efficiency while simulating various configurations. Every single cell has a separate thermal element that indicates the temperature of each cell.

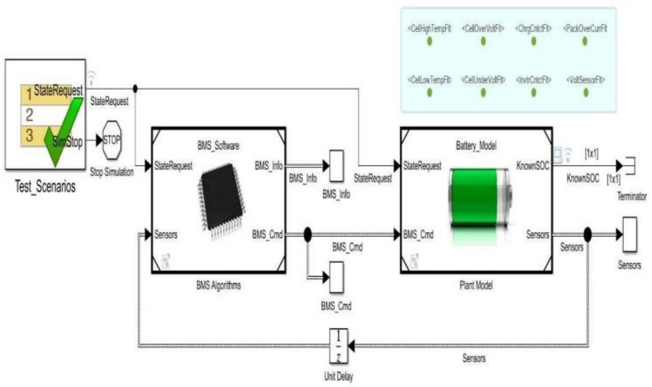

Figure 10. Simulation of electric vehicle BMS model.

This is the system position design within the BMS Algorithm, as shown in Fig. 13. It has the following Blocks: State Machine, SOC Estimation, and Balancing Logic block. The State machine is responsible for enforcing three senses, videlicet:

Driving: Characteristics tell us the response to the different driving conditions

Charging: Response to the EV while Charging

Balancing: Response to the fault options

The SOC estimation is also a crucial block in the BMS algorithm, which helps estimate the battery charging condition, including whether the cells are charging correctly. The balancing sense controls how the battery pack operates while charging to prevent a weak cell from entering the system. Weak cells are introduced into the pack, compromising the SOC and SOH. Test Request Parameters for EV's BMS Simulation are shown in Fig. 11.

Temperature data is captured together with each cell's voltage and current. This reduces the likelihood of trash value and facilitates the straightforward computation of SoC. Three methods are employed to estimate the SOC: the Coulomb Counting System shown in Fig. 15, the Extended Kalman Filter shown in Fig. 16, and the Unscented Kalman Filter. Cell voltages serve as the input for the Kalman Filter, which forecasts State of Charge (SOC) values, factory temperature, and current, all of which are inputs to the Coulomb Counting system. It shows the setup for CC. The primary concern of the Coulomb Counting system is the current leaving the cells to calculate the State of Charge (SOC).

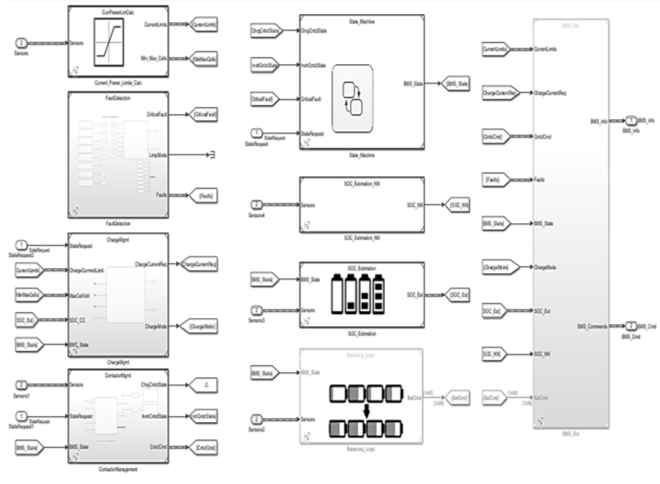

Figure 12. BMS algorithm.

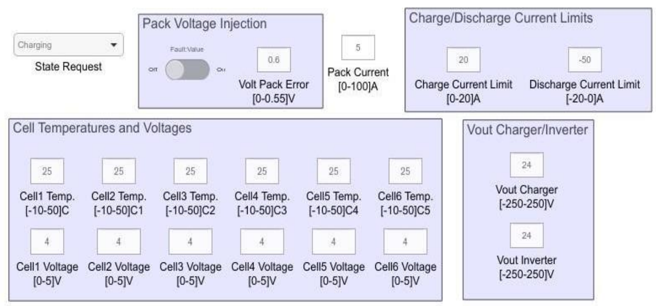

Figure 13. Test request parameters for EV's BMS simulation.

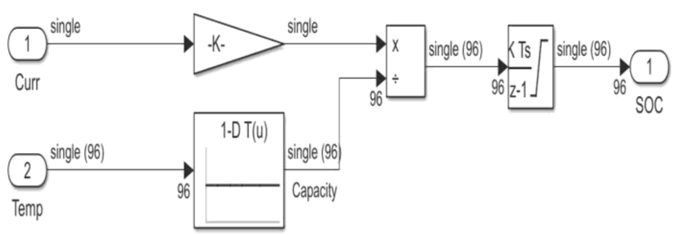

Figure 14. Coulomb counting.

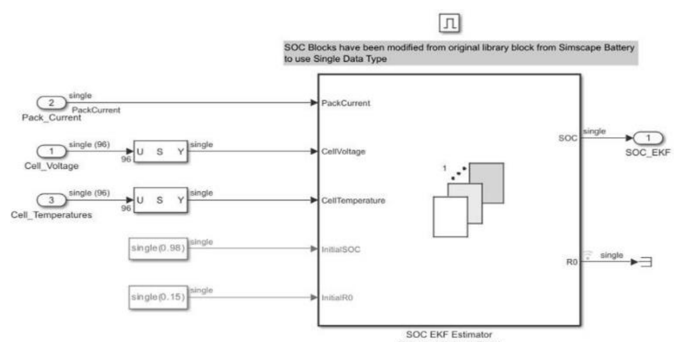

Figure 15. Kalman filter.

After running the BMS model, the battery characteristics were simulated, including cell voltages, cell temperatures, and battery pack.

4.1. Cell Voltages

The voltage of each cell in the pack is constant regardless of operational conditions. The cell voltages displayed in Fig. 16.

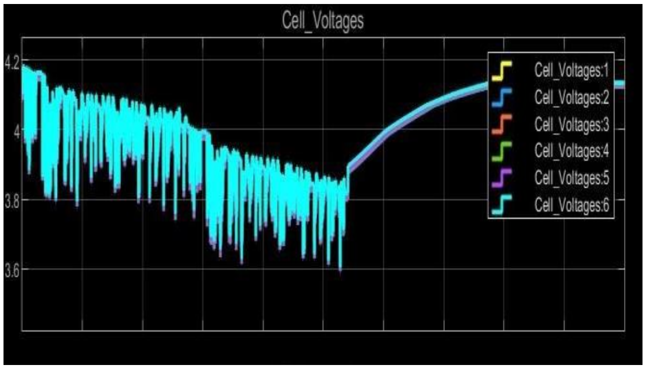

Figure 17. Cell voltages.

However, cell voltage varies due to the in-flow and out-flow of the battery. At the initial phase of simulation, the BMS is set to discharge, and a slight state of charge (SoC) imbalance causes the cell voltages to oscillate. As simulation advances, the SoC imbalance corrects itself, and the voltages converge. The cell voltage of the battery pack decreases gradually from 3.8 V to 3.48 V, whereas the voltage of the backup cell remains constant at 3.6 V during the discharging phase. After the BMS enters the charging phase, the cell voltage begins to increase.

4.2. Cell Temperature

In the Fig. 18, cell temperatures are shown. The temperature developed is nearly proportional to the current flowing through it during charging or discharging.

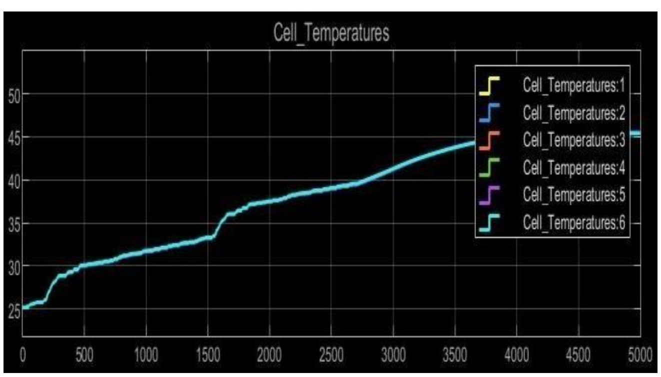

Figure 19. Cell temperatures.

Temperature patterns differ significantly between the coolest and hottest cells within the battery pack. One side of cell one is thermally insulated, so it heats up much more than cell 6. The considerable temperature differential between the edge cells makes active thermal regulation the recommended option.

4.3. Pack Current

The battery cell's maximum resistance is used to compute the current limit. The peak current is shown in Fig. 20.

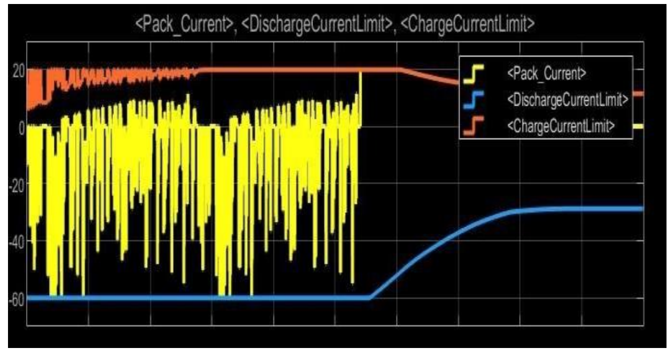

Figure 21. Pack current.

At the beginning of the discharge stage, the current varies between loads. When the device is in standby mode, the graph reaches a value of zero. Later in the charging phase, as the cell voltage approaches its maximum value, the current rises and reaches its peak value. An integrated current-limiting circuit reduces the current to avoid an abrupt spike.

4.4. State of Charge (SOC)

The SOC estimation shown in Fig. 20 for Coulomb Counting appears as a yellow trace. The SOC estimation is a blue and orange trace for the Unscented Kalman Filter and the Extended Kalman Filter methods. Initially, during discharge, the cell's state of charge (SOC) is 80%. During the transition into the standby state, the SOC estimations vary between the estimation techniques utilized for every cell. EKF estimates are, therefore, more accurate and exact. In terms of performance, EKF surpassed UKF after fixing the initial error.

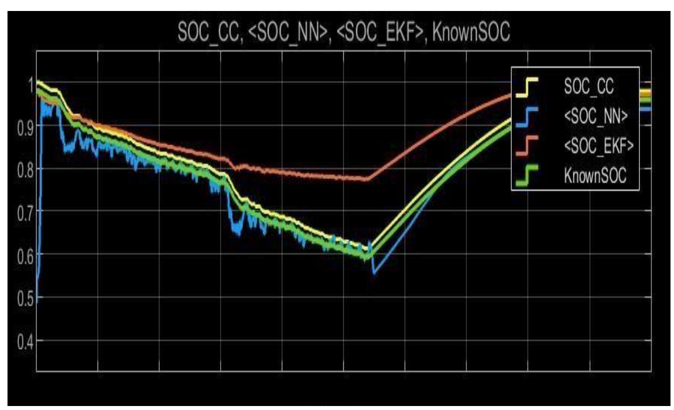

Figure 22. Estimation of SOC.

4.5. Cell Balancing

Cell balancing is one of battery management systems' most critical functions (BMS) functions. The cell balancing and BMS state are shown in Fig. 23 and 22, respectively.

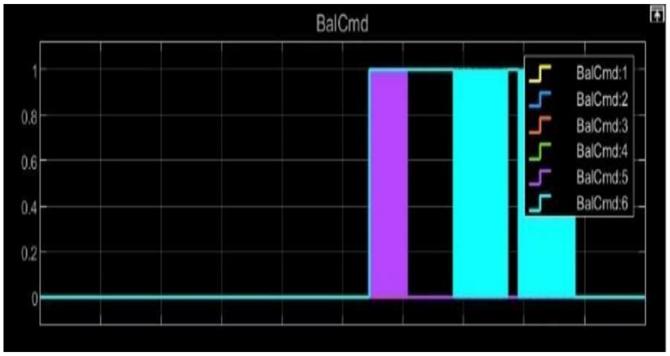

Figure 24. Cell balancing.

The traces of six cells are shown in the graph below.

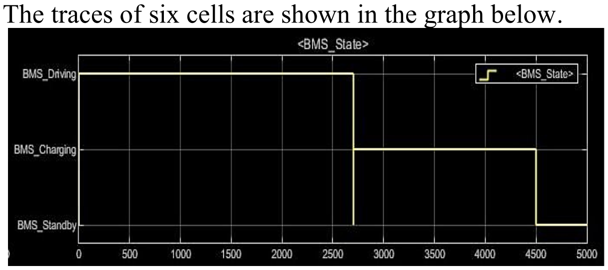

Figure 25. BMS state.

The BMS is fully simulated and divided into three distinct states.

- Discharging
- Standby
- Charging

The Li-ion Cell parameters are shown in Table 1.

Table 1. Constant current and constant voltage charging (Li-ion cell parameters).

Parameter	Value
Battery Model	LP372548
Nominal Capacity	420mAh (0.2C discharge)
Nominal Voltage	3.7V (0.2C discharge)
Charging Voltage	4.2±0.05V
Standard Charge	Method: CC/CV Current: 0.5C Voltage: 4.2V End current: 0.02C
Max. Charge Current	400mA
Max. Discharge Current	800mA
End of discharge Voltage	2.75V
Operating Temperature	Charge: 0˚C – 45˚C Discharge: -20˚C – 60˚C
Storage Temperature	-20˚C – 45˚C (for less than 1 month -20˚C – 35˚C (for less than 6 months)

4.5.1. Uncontrolled Charging with Constant Current Only

With the constant current power source, the voltage had gone high enough to reach the limit of 4.2 V, which was averse to the battery. Constant Current Charging (Current), which is shown in Fig. 26.

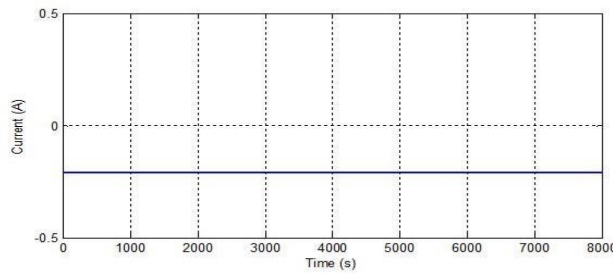

Figure 27. Charging at constant current (voltage).

4.5.2. Charging at Constant Current (Voltage)

The battery charging at a constant current (voltage) with overcharging is shown in Fig. 24.

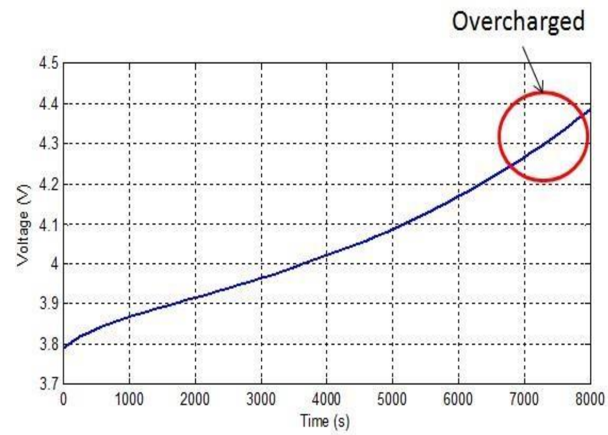

Figure 28. Charging at constant current (voltage).

4.5.3. Constant Current Charging (SOC)

The battery constant current charging (SOC) with overcharging is shown in Fig. 25.

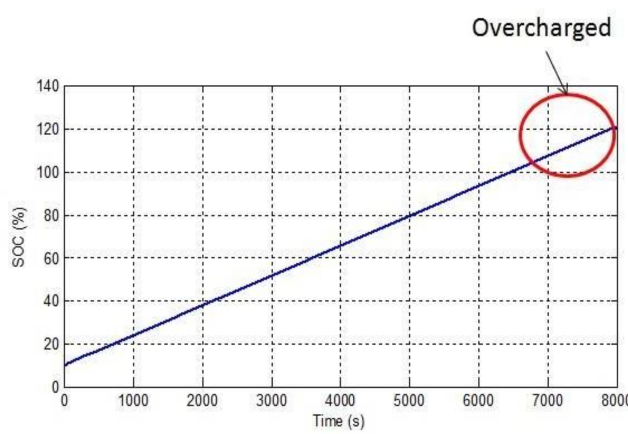

Figure 29. Constant current charging (SOC).

4.6. Uncontrolled Charging with Constant

The amount of current drawn when charged from a constant voltage source surpassed the high current limit of 0.21 A, which was harmful to the battery.

4.6.1. Constant Voltage Charging (Current)

Fig. 26 illustrates the battery charging process with excessive current at a constant voltage.

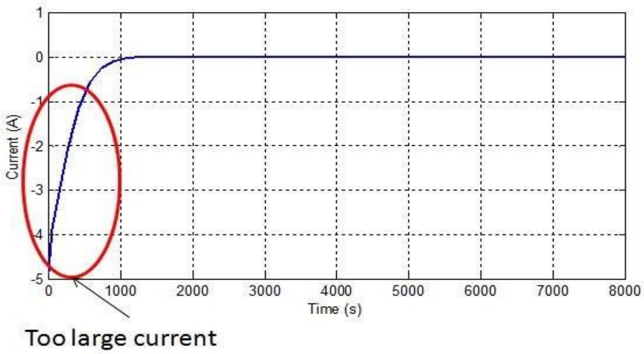

Figure 30. Constant voltage charging (current).

4.6.2. Constant Voltage Charging (Voltage)

Fig. 27 shows the battery's constant voltage charging (voltage).

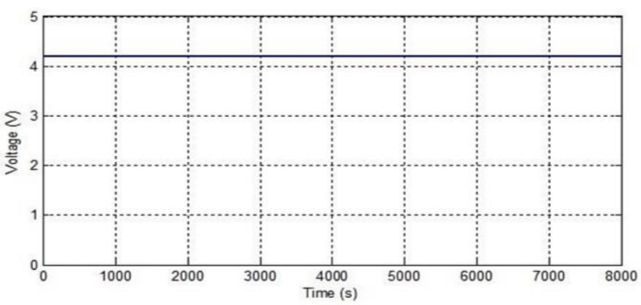

Figure 31. Constant voltage charging (Voltage).

4.6.3. Charging at a Constant Voltage (State of Charge - SOC)

The battery is charged at a constant voltage (SOC) with CC/CV (Current Control/Constant Voltage), as shown in Fig. 28.

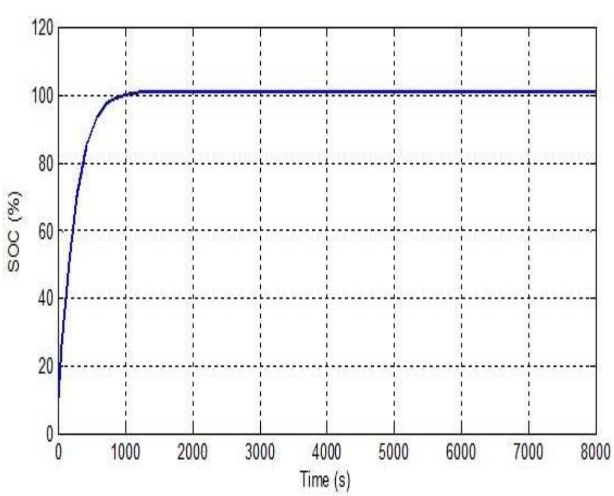

Figure 32. Regulating Charging with CC/CV (Current Control)

4.7. Regulated Charging Using Constant Current/Constant Voltage

Both the voltage and current of the battery were maintained within the SOA when charging with the CC/CV method. It was found that this is the most efficient way of charging the battery. Charging with CC/CV (voltage) is illustrated in the Fig. 33. The battery charging with CC/CV (State of Charge, SOC) is presented in Fig. 30.

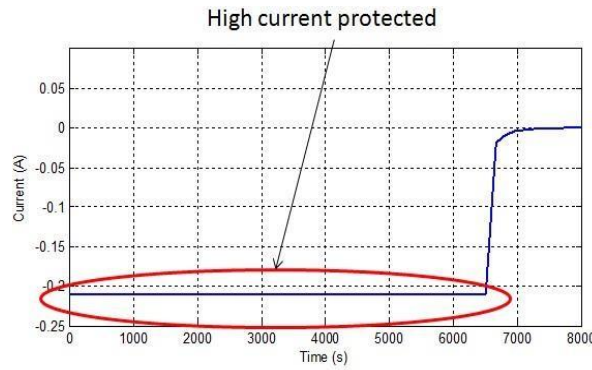

Figure 34. Charging with CC/CV (Voltage).

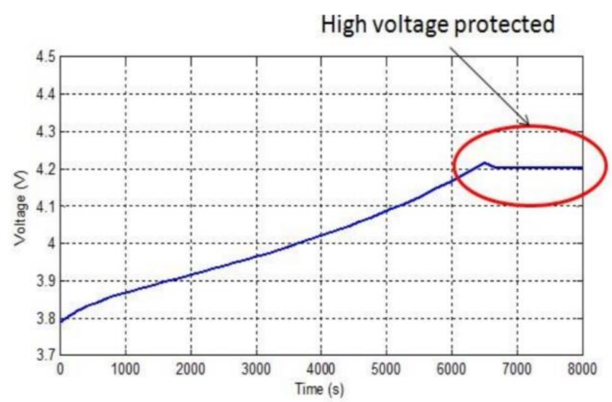

Figure 35. Charging with CC/CV (SOC).

5. Conclusion

The detailed conclusion of the Battery Management System (BMS) study, implemented in MATLAB and visualized through Simulink Scope, emphasizes the methodologies and outcomes of cell voltage, temperature, balance, and State of Charge (SoC) estimations. The study begins by comparing three different estimation techniques, noting that the initial SoC was set at 75%, but adjustments were made to 80% to evaluate the estimators' ability to recover accuracy. The final SoC results showed that the Unscented Kalman Filter (UKF), Extended Kalman Filter (EKF), and Coulomb counting method achieved 100%, 98.74%, and 100%, respectively. Despite the Coulomb counting method achieving a perfect 100%, it's significant to note that this method, being an open-loop current detector system, is prone to accumulating errors, thereby exaggerating the State of Charge (SoC), which should typically never reach a perfect 100%.

The analysis also highlights that the UKF was notably efficient in correcting errors, quickly adjusting to a stable minimum SoC of 48.7% and maintaining it throughout the buffer mode. In contrast, the EKF demonstrated a slower error correction, only managing to recover to a minimum of 47.6%, which suggests a lengthier duration to correct inaccuracies. Despite the slower recovery, the EKF provided more precise estimations over a broader range of SoC values. This attribute is crucial for effective battery management in automotive applications, underscoring the importance of reliable System-on-Chip (SoC) estimations to ensure the battery's optimal operational efficacy and longevity.

The broader market analysis of electric vehicles (EVs) forecasts substantial growth and transformation within the automotive industry. According to a report by Fortune Trade Insights, the global EV market is projected to grow at a compound annual growth rate (CAGR) of 24.3%, increasing from USD 287.36 billion in 2021 to USD 1,318.22 billion by 2028. The Indian EV market is also expected to see a significant rise, with a growth rate of about 44% from 2021 to 2026, propelling its valuation from USD 5 billion to USD 47 billion. These projections are driven by several factors, including technological innovation, supportive regulatory frameworks, and shifts in consumer behaviors toward more sustainable mobility options.

Technological advancements play a crucial role in this growth, as evidenced by a decade-long investment totaling $400 billion to nurture the sectors of shared, electrified, and autonomous transportation. The investment demonstrates a robust commitment from industry stakeholders to push the boundaries of what is technologically feasible, enabling electric and conventional vehicles to coexist more harmoniously. Additionally, regulatory frameworks across various regions have played a crucial role in promoting the adoption of electric vehicles (EVs). For instance, policies in India aim for EVs to account for 25% of total vehicle sales by 2024 and 30% of light-duty vehicles by 2030. These ambitious targets are supported by offering consumers flexible alternatives such as e-bike rentals, which not only cater to the demand for personal mobility solutions but also help reduce urban congestion and environmental impact. Consumer behavior has also shifted significantly, with an increasing number of individuals adopting electric vehicles (EVs) as a long-term transportation solution. However, challenges persist, particularly regarding the battery capacity and the availability of charging infrastructure. These issues underscore the pressing need for ongoing innovation in battery technology and the strategic deployment of charging stations to ensure that EVs can meet range and convenience expectations comparable to those of internal combustion engine vehicles. The combined influence of technological, regulatory, and consumer behavior factors indicates a vibrant future for the EV market. However, ongoing efforts in innovation, policymaking, and market adaptation are essential for this potential to be fully realized. The electric vehicle industry is not just contributing to a more sustainable automotive sector. Still, it is also setting new standards for what consumers can expect from their transportation solutions in terms of efficiency, sustainability, and innovation.

Funding: This research received no external funding.

Data Availability Statement: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethical Statement: This research adheres to the ethical guidelines established by the Committee on Publication Ethics (COPE). All procedures and methodologies used in this study comply with COPE standards, ensuring transparency, integrity, and respect for all participants involved.

References

[1] V. Chandran, C. Patil, A. Karthick, D. Ganeshaperumal, R. Rahim, and A. Ghosh, "State of charge estimation of lithium-ion battery for electric vehicles using machine learning algorithms," *World Electr. Veh. J.*, vol. 12, p. 38, 2021.

[2] T. Duraisamy and D. Kaliyaperumal, "Machine learning-based optimal cell balancing mechanism for electric vehicle battery management system," *IEEE Access*, vol. 9, pp. 132846–132861, 2021.

[3] R. Xiong, Q. Yu, W. Shen, C. Lin, and F. Sun, "A sensor fault diagnosis method for a lithium-ion battery pack in electric vehicles," *IEEE Trans. Power Electron.*, vol. 34, pp. 9709–9718, 2019.

[4] M. H. Lipu, M. Hannan, T. F. Karim, A. Hussain, M. H. M. Saad, A. Ayob, S. Miah, and T. I. Mahlia, "Intelligent algorithms and control strategies for battery management systems in electric vehicles: Progress, challenges, and future outlook," *J. Clean. Prod.*, vol. 292, p. 126044, 2021.

[5] T. Kang, S. Park, P.-Y. Lee, I.-H. Cho, K. Yoo, and J. Kim, "Thermal analysis of a parallel-configured battery pack (1S18P) using 21700 cells for a battery-powered train," *Electronics*, vol. 9, p. 447, 2020.

[6] M. Uzair, G. Abbas, and S. Hosain, "Characteristics of battery management systems of electric vehicles with consideration of the active and passive cell balancing process," *World Electric Vehicle Journal*, vol. 12, no. 3, p. 120, 2021.

[7] H. Lee, J. Park, and J. Kim, "Incremental capacity curve peak points-based regression analysis for the state-of-health prediction of a retired $LiNiCoAlO_2$ series/parallel configured battery pack," *Electronics*, vol. 8, p. 1118, 2019.

[8] J. Xu, "Accurate estimation of SOC of the power battery pack based on Kalman filter," M.S. thesis, Hangzhou Dianzi Univ., Hangzhou, China, 2009.

[9] X. Liu, X. Deng, Y. He, X. Zheng, and G. Zeng, "A dynamic state-of-charge estimation method for electric vehicle lithium-ion batteries," *Energies*, vol. 13, p. 121, Dec. 2019.

[10] M. Ali, A. Zafar, S. Nengroo, S. Hussain, M. Alvi, and H.-J. Kim, "Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation," *Energies*, vol. 12, p. 446, Jan. 2019.

[11] T. Xiao, X. Shi, B. Zhou, and X. Wang, "Comparative study of EKF and UKF for SOC estimation of lithium-ion batteries," in *2019 IEEE Innovative Smart Grid Technol. - Asia (ISGT Asia)*, 2019, pp. 1570–1575.

[12] Z. B. Omariba, L. Zhang, and D. Sun, "Review of battery cell balancing methodologies for optimizing battery pack performance in electric vehicles," *IEEE Access*, vol. 7, pp. 129335–129352, 2019.

[13] M. Khalid, S. S. Sheikh, A. K. Janjua, and H. A. Khalid, "Performance validation of electric vehicle's battery management system under a state of charge estimation for lithium-ion battery," in *2018 Int. Conf. Comput., Electron. Electr. Eng. (ICE Cube)*, 2018, pp. 1–5.

[14] M. Daowd, N. Omar, P. Van Den Bossche, and J. Van Mierlo, "Passive and active battery balancing comparison based on MATLAB simulation," in *2011 IEEE Veh. Power Propuls. Conf.*, 2011, pp. 1–7.

[15] C. M. Shepherd, "Design of primary and secondary cells—Part 2. An equation describing battery discharge," *J. Electrochem. Soc.*, vol. 112, pp. 657–664, July 1965.

[16] O. Tremblay and L.-A. Dessaint, "Experimental validation of a battery dynamic model for EV applications," *World Electr. Veh. J.*, vol. 3, 2009.
[17] B. Beenish, S. Summaira, and A. Ahmad, "Optimization of microgrid energy cost with electric vehicles and demand response," *Pak. J. Eng. Technol.*, vol. 6, no. 1, pp. 57–62, 2023.
[18] M. Corno and G. Pozzato, "Active adaptive battery aging management for electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 69, no. 1, pp. 258–269, 2020.
[19] F. Tariq and T. Mahmood, "Modeling and analysis of voltage source-based battery energy storage system in microgrid to improve power quality," *Pak. J. Eng. Technol.*, vol. 4, no. 4, pp. 29–34, 2021.
[20] T. Wei, "Estimating the SOC of lithium-ion batteries for electric vehicles based on the decline model," M.S. thesis, Jiangsu Univ., Zhenjiang, China, 2020.
[21] W. Retzlaff, "On board battery diagnostic and charge equalizing system (BADICHEQ)," in *Proc. 11th Int. Electric Vehicle Symp.*, vol. 2, Sept. 1992, pp. 20.03/1–20.03/12.
[22] N. Kutkut, D. Divan, and D. Novotny, "Charge equalization for series-connected battery strings," *IEEE Trans. Ind. Appl.*, vol. 31, no. 3, pp. 562–568, May/June 1995.
[23] N. Kutkut, D. Divan, and D. Novotny, "Design considerations for charge equalization on an electric vehicle battery system," *IEEE Trans. Ind. Appl.*, vol. 35, no. 1, pp. 28–35, Jan./Feb. 1999.
[24] J. Chatzakis, K. Kalaitzakis, N. C. Voulgaris, and S. N. Manias, "Designing a new generalized battery management system," in *Proc. IEEE*, 2003.
[25] H. Zhang, Y. Sun, D. Shenping, and Y. Wang, "Full-digital lithium battery protection and charging system based on DSP," in *Proc. 27th Chinese Control Conf.*, 2008.
[26] H. Ren, Y. Zhao, S. Chen, and T. Wang, "Design and implementation of a battery management system with active charge balance based on the SOC and SOH online estimation," *Energy*, vol. 166, Oct. 2018.
[27] K. W. E. Cheng, B. P. Divakar, H. Wu, K. Ding, and H. F. Ho, "Battery-management system (BMS) and SOC development for electric vehicles," *IEEE Trans. Veh. Technol.*, vol. 60, no. 1, pp. 76–88, 2011.
[28] B. Kumar, N. Khare, and P. K. Chaturvedi, "Advanced battery management system using MATLAB/Simulink," in *2015 IEEE Int. Telecommun. Energy Conf. (INTELEC)*, 2015, pp. 1–6.
[29] B. Balasingam, M. Ahmed, and K. Pattipati, "Battery management systems—challenges and some solutions," *Energies*, vol. 13, p. 2825, Jun. 2020.