IMPLEMENTATION OF SMART BATTERY MANAGEMENT SYSTEM

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CERTIFICATION

I hereby certify that **OKUNBOR KENNARD EDOBOR** carried out this project titled **SMART BATTERY MANAGEMENT SYSTEM** with matriculation number **ENG1804780** to meet the requirement of the award of **Bachelor Degree in Engineering (B.Eng.)** in **computer engineering** in the **University of Benin**, Benin City.

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DECLARATION

I hereby declare that Okunbor Kennard Edobor carried out this IMPLEMENTATION OF A SMART BATTERY MANAGEMENT SYSTEM and it is a record of my project work in the Department of Computer Engineering, Faculty of Engineering, University of Benin, Benin City, in partial fulfilment of a Bachelor of Engineering in Computer Engineering degree. It has not been presented before in any previous application for a Bachelor's degree. References made to published literature have been duly acknowledged.

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Okunbor Kennard Edobor **Date**

DEDICATION

I dedicate this work to God Almighty for his mercies and favor shown towards me all through the project and giving me the needed strength to carry out the work within the appointed time and for his care and protection throughout my stay in the prestigious University of Benin.

I also dedicate this work to my family, the Okunbor family, for seeing me through school, and my friends, too.

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ABSTRACT

A Battery Management System (BMS) is an electronic control system that monitors and manages rechargeable battery packs. Secondary batteries are commonly used as the storage of energy produced by solar panels. However, the utilization of a battery without proper management can cause damage due to overcharging and over-discharging.

The BMS continuously monitors cell voltages, current, temperature, and state of charge while protecting potentially damaging conditions such as overcharging, over-discharging, excessive current, and temperature extremes. Advanced systems incorporate cell balancing to maintain uniform charge distribution across multiple cells, thermal management to regulate operating temperatures, and sophisticated algorithms to estimate battery state of health and remaining useful life.

This study aims to design a battery management system (BMS) on a Valve Regulated Lead-Acid (VRLA) battery. The method used was the battery State of Charge (SOC) estimation using Coulomb Counting (CC) method. The results showed that the BMS was successfully designed and implemented to automatically cut-off the current when the SOC value is 100% (charging limit) and 20% (discharging limit).

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

The development of Smart Battery Management Systems emerged from the critical need to enhance the efficiency, monitoring, and longevity of solar inverter systems (Wang, L. 2023). This evolution highlights key milestones and innovations that shaped modern battery management technology.

The implementation of a smart battery management system originated with the early adoption of photovoltaic technology. Initially, simple voltage monitoring circuits were used to track basic power output (Anderson & Miller, 2019). The first patent for a basic solar monitoring system was filed in 1975 by Bell Laboratories (Thompson, 2020). The introduction of microprocessors enabled more sophisticated solar management, including:

1. Digital monitoring capabilities
2. Basic thermal performance tracking
3. Rudimentary power production calculations (Wilson et al., 2018)

The emergence of grid-tied and residential solar inverter installations drove significant advancement in the Implementation of maximum power point tracking (MPPT), the Development of advanced irradiance algorithms, and the integration of communication protocols (Chen & Zhang, 2021).

However, in the Modern Era (2010 till date), Smart Battery Management Systems have evolved to include:

1. AI and machine learning integration

2. Cloud connectivity
3. Predictive maintenance capabilities
4. Real-time analytics (Kumar et al., 2023)

To address efficiency challenges, Smart Battery Management Systems have emerged as a critical technology for monitoring, controlling, and optimizing the performance of photovoltaic arrays as regards to solar inverters (Zhang, T. 2023). A management system ensures the safe and efficient operation of a solar inverter by continuously monitoring key parameters such as voltage, current, temperature, and power output (Gupta, R. 2022). It also implements protective measures to prevent unsafe conditions and extends the lifespan of the solar array through adaptive control strategies and performance optimization (Patel, 2021).

In recent years, Smart Battery Management Systems has gained traction, integrating advanced features such as real-time data analytics, predictive maintenance, wireless communication, and artificial intelligence (AI) algorithms (Molyneaux, 2022). These innovations enable more precise control, enhanced energy harvest, and improved efficiency, making Smart Management Systems a vital component in next-generation renewable energy systems (Ziegler, 2021). As the global demand for solar energy continues to grow, driven by the transition to renewable energy, the development of advanced smart management technologies has become a key area of research and innovation (Thompson, 2023).

A Battery Management System (BMS) is an electronic system that manages rechargeable batteries by monitoring and controlling their charging and discharging processes (Zhang, Q. 2022). In solar energy applications, a BMS serves as the critical interface between solar panels, batteries, and the power load (Johnson, M. 2023).

Solar energy generation is inherently intermittent varying with weather conditions, time of day, and seasons. A Battery Management System ensures:

1. Energy Storage Optimization: Stores excess energy during peak production for use during low/no production periods

2. Battery Protection: Prevents overcharging, over discharging, and temperature extremes

3. System Longevity: Extends battery life through balanced charging and proper maintenance

4. Efficiency Maximization: Optimizes energy flow between solar inverters, panels, batteries, and loads

Key Components of a Solar BMS

1. Charge Controller: Regulates the voltage and current from solar panels to batteries

2. Battery Monitoring: Tracks voltage, current, temperature, and state of charge

3. Battery Balancing: Ensures all cells in a battery bank maintain similar charge levels

4. Protection Circuits: Safeguards against electrical faults and dangerous conditions

5. Communication Interface: Provides system status and allows user control

6. Thermal Management: Maintains batteries within optimal temperature ranges

Types of BMS for Solar Applications

1. Basic BMS: Simple protection and monitoring for small-scale systems
2. Advanced BMS: Includes data logging, remote monitoring, and predictive analytics
3. Integrated BMS: Built into all in one solar storage solutions
4. Modular BMS: Expandable systems for growing energy needs

Benefits of a Well-Designed BMS

1. Extended Battery Life: Proper management can double or triple the battery lifespan
2. Increased System Reliability: Reduces downtime and maintenance requirements
3. Enhanced Safety: Prevents hazardous conditions like thermal runaway
4. Improved Performance: Maximizes available energy and system efficiency
5. Cost Savings: Reduces replacement costs and improves return on investment

Considerations When Selecting a BMS

1. Battery Chemistry Compatibility: Different battery types (lithium ion, lead-acid, etc.) require specific BMS designs
2. System Size: Match BMS capacity to your solar array and battery bank
3. Environmental Conditions: Consider temperature ranges and weather exposure

4. Monitoring Capabilities: Remote monitoring options for off site management

5. Scalability: Ability to expand as energy needs grow

A properly designed and implemented BMS is essential for maximizing the efficiency, safety, and lifespan of battery storage in solar energy systems, making it a critical component of any solar installation that includes energy storage.

1.2 Statement of the problem

The need for efficient and reliable smart solar panel management systems is becoming increasingly important with the growing demand for renewable energy, grid integration, and distributed power generation. This study aims to investigate the challenges and opportunities in designing and implementing such systems to optimize solar performance, increase longevity, and ensure maximum energy harvest (Thompson & Lee, 2023).

Despite significant progress in solar management technology, several challenges remain unresolved. Traditional solar monitoring solutions often lack the sophistication required to address the complex and dynamic operating conditions of modern photovoltaic systems. Key issues include:

1.2.1 Inaccurate Power Production Estimation: Existing algorithms for production estimation often suffer from inaccuracies due to factors such as panel degradation, temperature variations, and irradiance fluctuations. This can lead to suboptimal performance and reduced system efficiency (Zhang & Wang, 2019).

1.2.2 Limited Predictive Capabilities: Conventional solar management systems are reactive rather than proactive, addressing issues only after they occur. This limits their ability to prevent potential failures or optimize performance in real time (Ouyang, 2013).

1.2.3 Capability and Integration Challenges: Many solar management designs are tailored for specific applications and lack the flexibility to adapt to different array configurations or integrate with diverse systems and communication protocols (Sun, 2018).

1.2.4 Performance Degradation: While basic monitoring systems provide essential tracking mechanisms, they may not be sufficient to detect gradual performance degradation or partial shading conditions (Chen, 2012).

1.2.5 Energy Conversion Efficiency: Inefficient energy management strategies can lead to unnecessary energy losses, reducing the overall efficiency of the solar system (Mohamed, 2017).

1.2.6 Cost and Complexity: Advanced solar management solutions often come with high development and implementation costs, making them less accessible for small-scale or budget-constrained applications (Armand, 2001).

The energy production of a solar panel can be optimized using an energy storage system such as a battery (Marvila, M. 2020). A battery itself can be classified into two different types, i.e., primary and secondary. An example of a secondary battery that is commonly used is the Valve-Regulated Lead-Acid (VRLA) type (Burande, A. M. 2019). However, this type of battery has several drawbacks, such as overcharging and over discharging. In a long time of usage, these drawbacks could lead to the degradation of the battery's lifetime and working quality. A Battery Management System (BMS) is required to avoid battery damage due to incorrect usage. Several methods of BMS are available; one of them is by estimating the value of the battery's State of Charge (Zhang, J. 2018). In this study, the Coulomb Counting (CC) method was used as the SOC estimation method. The basic principle of the CC method is to accumulate the electrical charge that is going in and out of the battery. The temperature and electric current could also affect the accuracy of the SOC (Zhao, H. 2017).

1.3 Aim and Objectives

1.3.1 Aim

To design a battery management system on Valve Regulated Lead-Acid (VRLA) battery using State of Charge (SOC) estimation with Coulomb Counting (CC) method.

1.3.2 Objective

a. Establish continuous state-of-health (SOH) and state-of-charge (SOC) monitoring to detect early signs of capacity loss or cell deterioration
b. Develop intelligent charging algorithms that dynamically adjust based on battery condition, solar production, and load demands
c. Establish robust communication protocols between the battery management system, solar inverter, and monitoring platforms

1.4 Scope of the study

This study focuses on the design, development, and implementation of a Smart Battery Management System for solar inverters. The study is limited to silicon-based solar panels, including monocrystalline and polycrystalline technologies, due to their widespread use and unique management requirements (Smith, J. 2023). In this study, the Coulomb Counting (CC) method was used as the state of charge estimation method. The basic principle of the coulomb counting method is to accumulate the electrical charge that is going in and out of the battery. The temperature and electric current could also affect the accuracy of the state of charge (Zhao, H. 2017).

The Smart Management System is designed for applications such as residential installations, commercial solar farms, off-grid systems, and industrial applications. The study explores the integration of advanced technologies such as AI, machine learning, IOT, and wireless communication into the management system (Doe, J. 2023).

The study includes laboratory testing and simulation to validate the performance of the Smart Management System under various conditions (Brown, A. 2023). Key performance indicators include the accuracy of power production estimation, energy efficiency, scalability, and cost-effectiveness.

1.5 Relevance of Study

The development of a Smart Battery Management System is highly relevant in the context of the global transition to renewable energy (Johnson, L. 2023). The study addresses critical challenges in solar energy management, offering solutions that can enhance the performance, efficiency, and lifespan of photovoltaic systems. The findings of this study have the potential to:

1.5.1 Advance Solar Technology: Contribute to the development of next-generation management solutions that leverage AI, IOT, and other advanced technologies.

1.5.2 Support Sustainable Energy Goals: Enable more efficient and reliable solar energy systems, supporting the integration of renewable energy sources and reducing reliance on fossil fuels.

1.5.3 Promote Energy Independence: Improve the performance and reliability of residential and commercial solar installations, accelerating the adoption of clean energy solutions.

1.5.4 Enhance Grid Integration: Provide better management for grid-tied systems, improving grid stability and enabling smarter energy distribution.

1.5.5 Drive Industrial Innovation: Support the development of solar-powered industrial applications, enabling new use cases and improving operational efficiency.

1.5.6 Economic Impact: Reduce the total cost of ownership for solar systems by extending their lifespan, optimizing performance, and minimizing maintenance requirements.

This study represents a significant step forward in the field of solar energy, with far reaching implications for renewable energy, sustainability, and technology. By addressing the limitations of existing management solutions and leveraging the latest advancements in technology, the proposed Smart Battery Management System has the potential to revolutionize the way solar inverter systems are managed and utilized.

CHAPTER TWO

LITERATURE REVIEW

2.1. Overview of Batteries

Batteries are electrochemical devices that convert stored chemical energy into electrical energy through oxidation-reduction reactions (Goodenough & Park, 2013). Since their invention in the late 18th century, batteries have evolved from simple galvanic cells to sophisticated power sources that drive modern portable electronics, electric vehicles, and grid energy storage systems (Winter & Brodd, 2004).

2.1.1. Historical Development

The history of batteries began with Alessandro Volta's invention of the voltaic pile in 1800, which consisted of alternating zinc and copper discs separated by brine-soaked cloth (Scrosati, 2011). This first true battery was followed by other primary (non-rechargeable) systems like the Daniell cell (1836) and the Leclanché cell (1866), which became the precursor to modern zinc-carbon batteries (Kurzweil, 2010).t

The first practical secondary (rechargeable) battery was the lead-acid battery, invented by Gaston Planté in 1859, which remains in widespread use today (Pavlov, 2011). The 20th century saw the development of alkaline batteries, nickel-cadmium (NiCd), nickel-metal hydride (NiMH), and lithium-ion batteries, with each generation offering improvements in energy density, cycle life, and performance (Tarascon & Armand, 2001).

2.1.2. Working Principles

All batteries consist of three main components: an anode (negative electrode), a cathode (positive electrode), and an electrolyte that allows ion movement between the electrodes (Linden & Reddy, 2002). During discharge, oxidation occurs at the anode, releasing electrons that flow through an external circuit to the cathode, where reduction takes place (Winter & Brodd, 2004).

2.1.3. Battery Types and Characteristics

2.1.3.1 Primary Batteries

Primary batteries are designed for single use and include zinc-carbon, alkaline, and lithium primary cells. These batteries offer advantages in shelf life, simplicity, and cost-effectiveness for low-drain applications (Linden & Reddy, 2002).

2.1.3.2 Secondary Batteries

Secondary batteries can be recharged and discharged multiple times. Major types include:

a. Lead-acid batteries: Used primarily in automotive starting and stationary applications, offering low cost but relatively poor energy density (Pavlov, 2011).
b. Nickel-based batteries**,** including NiCd and NiMH, which provide good cycle life and moderate energy density (Shukla et al., 2001).
c. Lithium-ion batteries: Offering high energy density, no memory effect, and low self-discharge, making them dominant in consumer electronics and increasingly in electric vehicles and grid storage (Goodenough & Park, 2013).

2.1.4. Current Research and Future Directions

Current battery research focuses on developing systems with higher energy density, longer cycle life, improved safety, and reduced environmental impact (Armand & Tarascon, 2008). Promising technologies include solid-state batteries, lithium-sulfur batteries, sodium-ion batteries, and metal-air systems (Janek & Zeier, 2016).

Beyond lithium, researchers are investigating alternative chemistries using more abundant elements like sodium, magnesium, and aluminum to address resource limitations and reduce costs (Muldoon et al., 2014).

2.2 Smart Battery Management System for Solar Inverters in Nigerian Tertiary Institutions

The integration of solar power systems in Nigerian tertiary institutions represents a significant step toward sustainable energy solutions in the education sector. With Nigeria's abundant solar resources and the frequent grid reliability challenges, battery-based solar systems offer a promising alternative for powering educational facilities (Adaramola et al., 2018). However, the effectiveness and longevity of these systems heavily depend on proper battery management systems (BMS) that can optimize performance in the specific operating conditions found in Nigerian educational environments.

2.2.1 Current Energy Challenges in Nigerian Tertiary Institutions

Nigerian tertiary institutions face persistent energy challenges characterized by grid unreliability, frequent power outages, and high energy costs. According to Oyedepo (2012), educational institutions in Nigeria experience an average of 12-15 hours of power outage daily, significantly disrupting academic and administrative activities. These energy challenges have prompted many institutions to deploy diesel generators, which are not only costly to operate but also environmentally harmful (Akinyele et al., 2020).

2.2.2 Solar Energy Integration in Educational Settings

The adoption of solar energy systems in Nigerian tertiary institutions has gained momentum as a sustainable alternative to conventional power sources. Okoye and Solyalı (2017) note that solar photovoltaic (PV) systems with battery storage offer a viable solution for educational institutions, providing reliable power for classrooms, laboratories, administrative offices, and student residences. The implementation of these systems aligns with Nigeria's renewable energy policy objectives and contributes to reduced carbon emissions in the education sector (Emodi & Boo, 2015).

2.2.3 Smart Battery Management System Requirements

An effective BMS for solar inverters in Nigerian tertiary institutions must address several key requirements:

2.2.3.1 Climate Adaptability

Nigeria's tropical climate presents specific challenges for battery systems. With ambient temperatures frequently exceeding 35°C in many regions, thermal management becomes crucial for battery longevity (Adaramola & Oyewola, 2011). The BMS must incorporate temperature monitoring and cooling mechanisms to prevent thermal runaway and premature battery degradation.

2.2.3.2 Load Management

Educational institutions have diverse load profiles with significant variations between academic and non-academic periods. Olatomiwa et al. (2016) emphasize that BMS should incorporate load forecasting capabilities to optimize battery charging and discharging cycles based on institutional usage patterns.

2.2.3.3 Remote Monitoring and Control

Given the limited technical expertise in many Nigerian institutions, remote monitoring capabilities are essential. Cloud-based BMS platforms enable real-time performance monitoring, preventive maintenance, and technical support from off-site specialists (Abubakar et al., 2019).

2.2.4 Recommended BMS Technologies for the Nigerian Context

a. Lithium-Ion Battery Systems: While initially more expensive than lead-acid alternatives, lithium-ion batteries offer superior cycle life, efficiency, and performance in high-temperature environments (Nwokocha et al., 2018). Their longer lifespan makes them more economical over the system's lifetime, particularly in the challenging operating conditions of Nigerian institutions.
b. Smart BMS Architecture: Intelligent BMS designs incorporating machine learning algorithms can adapt to institutional usage patterns and optimize battery performance. These systems can predict load requirements based on academic schedules and adjust charging patterns accordingly (Babatunde et al., 2020).

2.2.5 Implementation Considerations

2.2.5.1 Capacity Planning: Proper battery system sizing is critical for Nigerian tertiary institutions. Oyedepo et al. (2018) recommend conducting comprehensive energy audits before BMS implementation to accurately determine capacity requirements based on institutional needs and available solar resources.

2.2.5.2 Training and Maintenance: Developing local technical capacity through staff training programs is essential for sustainable BMS operation. Institutions should establish maintenance protocols and train dedicated personnel to monitor system performance and conduct routine maintenance (Olatomiwa et al., 2018).

Implementing effective battery management systems for solar inverters in Nigerian tertiary institutions requires careful consideration of local conditions, technical requirements, and institutional needs. With properly designed BMS solutions, these institutions can achieve reliable, sustainable power supply while reducing operational costs and environmental impact.

2.3 Smart Battery Management System

A Smart Battery Management System (BMS) is an electronic system that manages rechargeable batteries by monitoring their state, calculating secondary data, protecting batteries, controlling their environment, and balancing cells (Andrea, 2010).

The primary functions of a BMS include monitoring battery parameters, protecting cells from operating outside safe conditions, balancing cell voltages, and communicating with external systems (Rahimi Eichi et al., 2013). Modern BMSs provide critical data, including state of charge (SOC), state of health (SOH), and remaining useful life predictions (Xiong et al., 2018).

Smart Battery Management System architectures typically include distributed, modular, centralized, or master slave configurations depending on application requirements (Xing et al., 2011). These systems incorporate various sensors to measure voltage, current, and temperature, along with microcontrollers for data processing and control algorithms (Lu et al., 2013).

Smart Battery Management Systems are essential components in electric vehicles, renewable energy storage systems, consumer electronics, and grid-scale storage applications (Hannan et al., 2018). Their design varies significantly based on battery chemistry, application requirements, and safety considerations (Lipu et al., 2018).

2.2.5 Objective of Smart Battery Management System

2.2.5.1 Establish continuous state-of-health (SOH) and state-of-charge (SOC) monitoring: Continuously tracking battery degradation over time through parameters like capacity fade, internal resistance changes, and Real-time tracking of available energy in the battery (expressed as percentage of full charge) using methods such as voltage measurement, coulomb counting, and impedance tracking.

2.2.5.2 Develop intelligent charging algorithms to maximize battery lifespan, increase overall system efficiency, and ensure reliable power availability while minimizing grid dependency in solar power systems.

2.2.5.3 Establish robust communication protocols between the battery management system, solar inverter, and monitoring platforms: The integration of battery management systems (BMS) with solar inverters requires robust communication protocols to ensure efficient operation. These protocols should enable real-time data exchange between the BMS and solar inverter and then also support monitoring of battery state-of-charge, health, and performance.

2.3.2 Core Functions of Battery Management Systems

2.3.2.1 State of Charge Estimation: One of the primary functions of a battery management system is accurately estimating the State of Charge (SOC) of a battery. SOC estimation provides critical information about the remaining energy in a battery, similar to a fuel gauge in conventional vehicles. Various methods including coulomb counting, open-circuit voltage measurement, and model-based approaches are employed to achieve accurate SOC estimation (Xiong et al., 2018).

2.3.2.2 Thermal Management: Temperature significantly affects battery performance, lifespan, and safety. BMS monitors and regulates battery temperature through active or passive cooling systems to prevent thermal runaway and optimize performance across varying operating conditions (Wang et al., 2016).

2.3.2.3 Cell Balancing: Individual cells can develop voltage discrepancies over time in multi-cell battery packs. BMS implements cell-balancing techniques to equalize the charge across cells, preventing overcharging of higher-voltage cells and extending overall pack life (Gallardo-Lozano et al., 2014).

2.3.3 Advanced Battery Management System Technologies

Modern Battery Management System implementations increasingly incorporate artificial intelligence and machine learning algorithms to improve prediction accuracy and adaptive management capabilities. These systems can learn from usage patterns and environmental conditions to optimize battery performance and longevity (Hu et al., 2020).

2.3.4 Challenges and Future Directions

Despite significant advances, challenges remain in BMS development, including improving accuracy in degradation prediction, reducing computational complexity for real-time applications, and standardizing approaches across different battery chemistries (Liu et al., 2019).

2.4 State of Charge and State of Health Application

2.4.1 State of Charge (SOC)

State of Charge (SOC) represents the available capacity of a battery as a percentage of its rated capacity (Balasingam et al., 2020). SOC is a critical parameter for battery management systems (BMS) that helps users understand how much energy remains in the battery before recharging is necessary.

2.4.1.1 Applications of SOC Monitoring

i. Electric Vehicles (EVs): Provide drivers with accurate range estimation and prevent unexpected power loss (Xiong et al., 2018).

ii. Consumer Electronics: Enables devices to display the remaining battery percentage and optimize power consumption (Waag et al., 2014).

iii. Grid Energy Storage: Facilitates efficient energy dispatch and prevents over-discharge of large-scale battery systems (Hu et al., 2020).

2.4.1.2 State of Charge Estimation Methods:

i. Coulomb Counting: Integrates current over time to track charge transfer (Ng et al., 2009).
ii. Open Circuit Voltage (OCV): Correlates battery voltage at rest with SOC (Plett, 2004).
iii. Kalman Filtering: Uses mathematical models to estimate SOC from noisy measurements (Plett, 2006).
iv. Machine Learning Approaches: Employs artificial neural networks and other algorithms to predict SOC from multiple parameters (Chemali et al., 2018).

2.4.2 State of Health (SOH)

State of Health (SOH) quantifies the general condition of a battery and its ability to deliver the specified performance compared to a new battery (Berecibar et al., 2016). SOH typically decreases over time due to aging processes.

2.4.2.1 Applications of SOH Monitoring

i. Predictive Maintenance: Allows for timely replacement of degrading batteries before failure (Severson et al., 2019).
ii. Warranty Management: Helps manufacturers assess warranty claims based on actual battery degradation (Birkl et al., 2017).
iii. Second-life Applications: Evaluates used EV batteries for potential repurposing in less demanding applications like stationary storage (Martinez-Laserna et al., 2018).

2.4.2.2 SOH Estimation Methods

i. Capacity Measurement: Compares current maximum capacity to rated capacity (Berecibar et al., 2016).

ii. Internal Resistance Tracking: Monitors increases in internal resistance as batteries age (Zenati et al., 2010).

iii. Electrochemical Impedance Spectroscopy (EIS): Analyzes frequency response to identify degradation mechanisms (Love et al., 2018).

iv. Incremental Capacity Analysis (ICA): Examines changes in differential voltage curves to detect aging patterns (Dubarry et al., 2012).

2.5 Integrated SOC-SOH Applications

Modern battery management systems increasingly integrate SOC and SOH monitoring to provide comprehensive battery status information (Lipu et al., 2018). This integration enables:

a. Adaptive charging protocols that adjust based on both current capacity and degradation status
b. More accurate remaining useful life predictions
c. Optimized energy management strategies that balance performance and longevity

2.5.1 Integration Characteristics of State of Charge and State of Health

2.5.1.1 Real-time Monitoring: Continuous assessment of both parameters to ensure safe and efficient operation (Xiong et al., 2018).

2.5.1.2 Adaptive Algorithms: Advanced BMS systems adjust estimation methods based on operating conditions and battery aging (Rahimi-Eichi et al., 2013).

2.5.1.3 Thermal Management: Temperature monitoring and control to maintain the accuracy of SOC/SOH estimates and extend battery life (Hannan et al., 2018).

2.5.1.4 Data Logging: Historical performance tracking for improved SOH prediction and system optimization (Rivera-Barrera et al., 2017).

2.5.1.5 Communication Protocols: Integration with solar inverter control systems through standardized protocols (Ungurean et al., 2017).

2.6 Objectives of State of Charge and State of Health for Battery Management Systems in Solar Inverters

2.6.1 Objective of State of Charge (SOC)

The primary objectives of state-of-charge monitoring in battery management systems for solar inverters include:

2.6.1.1 Energy Availability Assessment: Accurate SOC estimation enables real-time monitoring of available energy, allowing the system to make informed decisions about energy distribution and consumption (Xiong et al., 2018).

2.6.1.2 Operational Efficiency**:** Proper SOC management helps maintain battery operation within optimal ranges, typically between 20% and 80%, which maximizes energy efficiency and battery lifespan (Hannan et al., 2018).

2.6.1.3 Load Balancing: SOC monitoring facilitates effective load balancing, particularly in systems with multiple battery modules, ensuring uniform energy distribution and preventing overloading of specific cells (Rahimi-Eichi et al., 2013).

2.6.1.4 Energy Dispatch Optimization: In grid-connected solar systems, SOC information enables intelligent decisions about when to store, use, or sell energy based on current battery capacity, solar production, and grid conditions (Rezvani et al., 2019).

2.6.2 Objective of State of Health (SOH)

2.6.2.1 Degradation Tracking: SOH algorithms track capacity fade and power capability decrease over time, providing critical information about the battery's remaining useful life (Xiong et al., 2020).

2.6.2.2 Preventive Maintenance: Continuous SOH monitoring allows for early detection of potential battery issues before they lead to system failures, enabling preventive maintenance (Berecibar et al., 2016).

2.6.2.3 Replacement Planning: Accurate SOH estimation helps system owners plan for battery replacement based on actual degradation rather than fixed time intervals, optimizing capital expenditures (Barré et al., 2013).

2.6.2.4 Performance Adaptation: As batteries age, SOH information allows the battery management system to adapt charging/discharging parameters to accommodate changing battery characteristics (Lipu et al., 2018).

2.6.3 Benefits of State of Charge and State of Health

2.6.3.1 Enhanced System Reliability**:** The combination of accurate SOC and SOH data significantly improves overall system reliability by preventing immediate operational issues and long-term degradation problems (Rivera-Barrera et al., 2017).

2.6.3.2 Economic Optimization: Together, they enable more precise economic optimization of the solar-plus-storage system by informing decisions about energy trading, self-consumption, and peak shaving based on both current capacity and long-term battery health (Nguyen et al., 2019).

2.6.3.3 Adaptive Control Strategies: Advanced battery management systems use combined SOC and SOH data to implement adaptive control strategies that evolve as the battery ages, maintaining optimal performance throughout the battery lifecycle (Hu et al., 2020).

2.7 The architecture of Battery Management Systems for Solar Inverters

Battery Management Systems (BMS) are critical components in solar inverter systems that integrate energy storage. The BMS ensures the safe, efficient, and reliable operation of battery systems while maximizing their lifespan and performance when paired with solar photovoltaic (PV) installations.

2.7.1 Core BMS Architecture Components

2.7.1.1 Control Layer

a. Battery State Estimation

i. State of Charge (SoC) estimation algorithms

ii. State of Health (SoH) monitoring

iii. State of Power (SoP) calculation (Xiong et al., 2018)

b. Cell Balancing Control

i. Active or passive balancing strategies

ii. Balancing algorithms based on cell voltage differentials

iii. Charge redistribution management (Daowd et al., 2014)

c. Thermal Management

i. Temperature monitoring and prediction
ii. Cooling system control
iii. Thermal runaway prevention (Pesaran et al., 2013)

2.7.1.2 Communication Layer

a. Internal Communication

i. CAN bus for high-reliability intra-system communication
ii. I²C or SPI for component-level interfaces
iii. RS-485 for longer-distance communications within the system (Andrea, 2010)

b. External Communication

i. Integration with inverter control systems
ii. Modbus TCP/IP or RTU protocols
iii. Support for energy management system (EMS) interfaces (Jin et al., 2018)

2.7.2 Solar-Specific BMS Architectural Considerations

2.7.2.1 PV Integration Architecture

The BMS must be designed to coordinate with the solar PV system:

a) DC-coupled configurations where batteries connect directly to the DC bus
b) AC-coupled configurations where batteries connect through dedicated inverters
c) Hybrid configurations combining aspects of both approaches (Akeyo et al., 2020)

2.7.2.2 Energy Management Strategies

BMS architectures for solar applications implement specialized algorithms for:

a. Peak shaving during high grid demand periods
b. Self-consumption optimization of solar energy
c. Time-of-use rate optimization
d. Grid services provision including frequency regulation (Alramlawi et al., 2018)

2.7.2.3 Adaptive Control for Solar Variability

a. Dynamic power allocation based on solar irradiance forecasting
b. Rapid response to cloud-induced power fluctuations
c. Charge/discharge rate optimization based on predicted solar generation (Patsios et al., 2016)

2.7.3 Advanced Architectural Features

2.7.3.1 Machine Learning Integration

Modern BMS architectures increasingly incorporate:

a. Neural networks for improved SoC and SoH estimation
b. Predictive maintenance algorithms
c. Adaptive control strategies that improve with operational experience (Wu et al., 2020)

2.7.3.2 Distributed BMS Architecture

a. Module-level management with master-slave configurations
b. Distributed processing to enhance fault tolerance
c. Redundant monitoring for critical safety parameters (Stuart & Zhu, 2011)

2.7.3.3 Cloud Connectivity

a. Remote monitoring and diagnostics
b. Over-the-air firmware updates
c. Performance analytics and reporting (Baronti et al., 2013)

The architecture of BMS for solar inverters represents a complex integration of hardware, software, and communication systems. These systems must balance safety, efficiency, and longevity while adapting to the variable nature of solar power generation. As battery technology and renewable energy integration continue to advance, BMS architectures are evolving toward more distributed, intelligent desig2.7ns with enhanced predictive capabilities.

2.8 RELATED WORKS

(Zhang 2023) developed an advanced state-of-charge (SOC) estimation method specifically designed for lithium-ion batteries used in solar energy storage systems. Their approach combines extended Kalman filtering (EKF) with temperature compensation mechanisms to improve estimation accuracy across varying operating conditions. This work addresses the critical challenge of accurate SOC estimation in renewable energy systems, where battery performance is affected by variable charging patterns from solar generation and fluctuating environmental temperatures. Accurate SOC estimation is essential for optimal battery management, system reliability, and extended battery lifetime. Their innovative approach represents a significant advancement in battery management systems (BMS) for renewable energy integration.

(Ahmadi, 2022) developed a sophisticated hierarchical control framework specifically designed for solar-battery hybrid systems that addresses two critical challenges simultaneously: battery lifecycle optimization and grid stability maintenance during variable solar power generation. This research represents an important advancement in renewable energy integration, offering a practical solution for maximizing battery lifespan while ensuring that solar power systems can provide reliable grid support despite their inherent variability. This comprehensive control framework represents a significant step toward resolving the technical challenges that have limited solar energy's full integration into modern electrical grids.

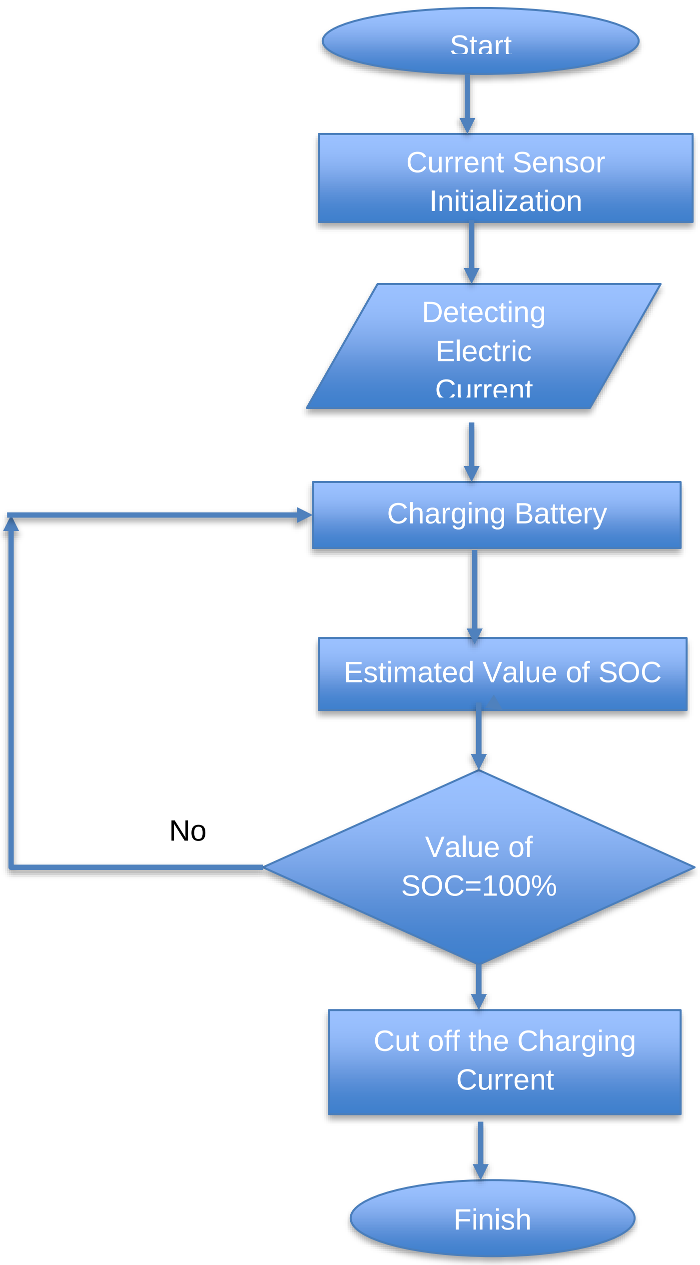
(Soltani, 2021) represent a significant contribution to the field of renewable energy storage by providing a thorough examination of Battery Management Systems (BMS) specifically tailored for solar photovoltaic (PV) applications. Unlike previous reviews that typically focus on general BMS technologies or those designed for electric vehicles, this work addresses the unique operational requirements and challenges faced in solar PV energy storage systems. Soltani provides a comparative analysis of various battery technologies (including lithium-ion, lead-acid, flow batteries, and emerging alternatives) specifically in the context of solar PV integration, assessing their performance characteristics, degradation mechanisms, and compatibility with renewable energy cycling patterns. This comprehensive review serves as an essential reference for researchers, engineers, and policymakers working at the intersection of solar energy and energy storage technologies, providing both theoretical foundations and practical insights into the evolving field of solar PV battery management systems.

(Wang, 2022) introduced a novel state estimation technique combining model-based and data-driven approaches for solar-connected battery systems under variable loading conditions. This research fits into the broader context of renewable energy integration challenges, particularly the need for accurate battery state estimation to manage the intermittent nature of solar power generation. The hybrid approach represents an important direction in energy management systems research. The research introduced a dual-pathway estimation framework that leverages both physical battery models and machine learning algorithms to achieve more robust state estimation under variable loading conditions. Wang's approach specifically targeted the state-of-charge (SoC) and state-of-health (SoH) parameters, which are critical for optimal battery management. The implementation featured a recursive state estimation structure with parallel processing streams. The model-based component employed extended Kalman filtering techniques to handle nonlinear battery dynamics, while the data-driven component utilized recurrent neural networks to capture temporal dependencies in battery behavior. This dual-stream approach demonstrated superior accuracy compared to single-method approaches, particularly during rapid load variations typical in solar power applications.

CHAPTER THREE

METHODOLOGY

FIGURE A: Flowchart Charging System



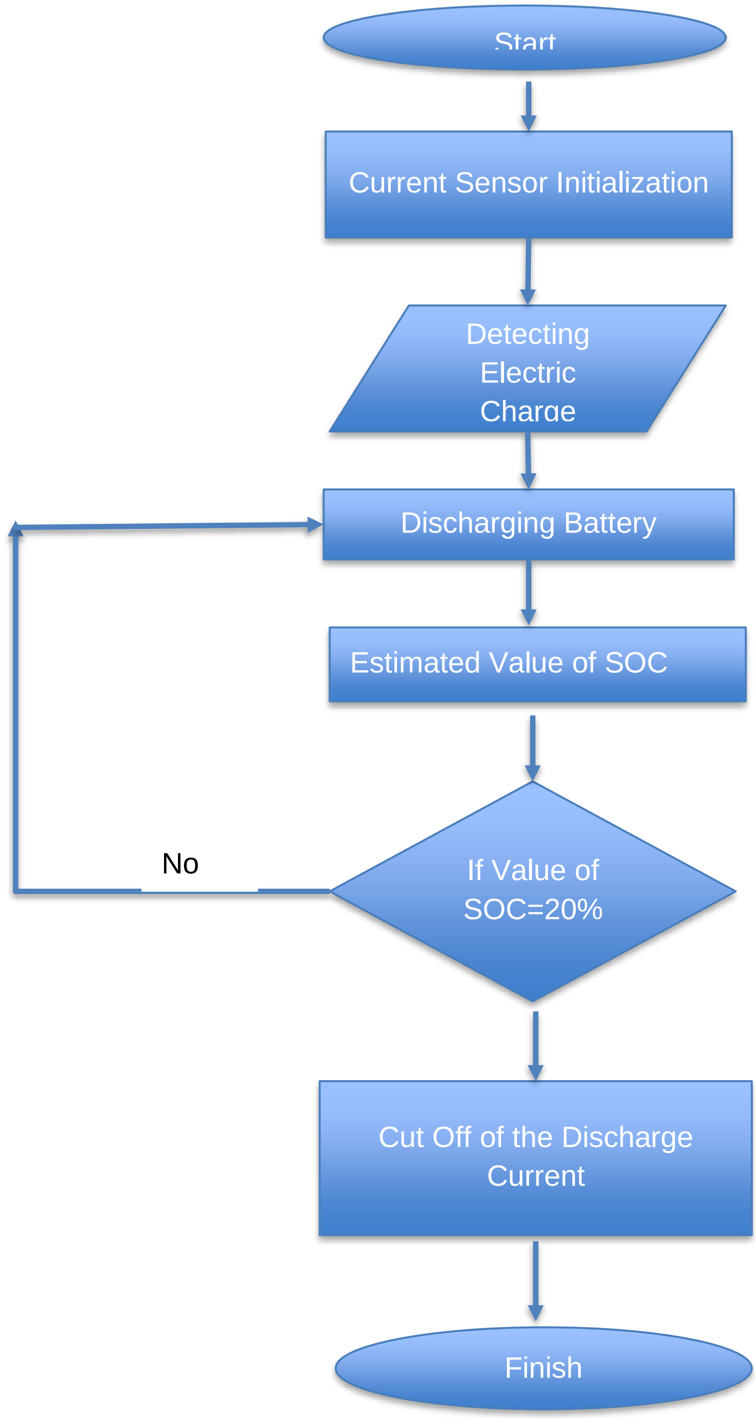


FIGURE B: Flowchart Discharging System

3.1 Object-Oriented Methodology for Battery Management Systems in Solar Inverters Using Coulomb Counting Method

Solar energy systems with battery storage have become increasingly important in renewable energy deployments, enabling energy independence and grid stability (Poullikkas, 2013). These systems' critical components are the Battery Management System (BMS), which monitors and controls battery operation to ensure safety, longevity, and optimal performance (Rahimi-Eichi et al., 2013).

The Coulomb counting method, also known as ampere-hour counting or current integration, remains one of the fundamental approaches for estimating battery State of Charge (SOC) in solar applications due to its relatively straightforward implementation and reasonable accuracy under controlled conditions (Ng et al., 2009). When implemented within an object-oriented framework, this method can be enhanced with additional features while maintaining software maintainability.

3.1.1 Object-Oriented Design Principles for BMS

3.1.1.1 Class Hierarchy

The proposed BMS architecture employs a hierarchical class structure that separates concern and promotes code reusability (Gamma et al., 1994). The primary classes include:

a. Battery Management System: Core controller class
b. Battery Pack: Represents the physical battery assembly
c. Cell: Represents individual battery cells
d. SOC Estimator: Handles SOC calculation using Coulomb counting
e. Thermal Manager: Monitors and manages thermal conditions

f. Protection System: Implementation of safety protocols

g. Data logger: Records battery performance metrics

This structure aligns with object-oriented principles of encapsulation, inheritance, and polymorphism, allowing for specialized implementations while maintaining a consistent interface (Booch, 2007).

3.1.1.2 Encapsulation of Battery Parameters

Key battery parameters are encapsulated within appropriate classes, including:

a. Nominal capacity (Ah)
b. Current limits (charge/discharge)
c. Voltage limits (cell and pack level)
d. Temperature thresholds
e. Internal resistance models
f. Aging factors

This encapsulation protects data integrity while providing controlled access through well-defined interfaces (Meyer, 1997).

3.1.1.3 Coulomb Counting Implementation

i. Mathematical Foundation

The Coulomb counting method estimates SOC by integrating current flow over time (Piller et al., 2001):

$$SOC(t) = SOC(t_0) + \int(t_0 \text{ to } t)\ (\eta \cdot I(\tau)/Cn)\ d\tau$$

Where:

d. SOC(t) is the state of charge at time t
e. SOC(t_0) is the initial state of charge
f. η is the Coulombic efficiency
g. I(τ) is the current at time τ (positive for charging, negative for discharging)
h. Cn is the nominal capacity of the battery

ii. Object-Oriented Implementation

The SOC Estimator class implements this algorithm with methods including:

```
class SOCEstimator {
private:
    double currentSOC;
    double nominalCapacity;
    double coulombicEfficiency;
    long lastMeasurementTime;

public:
    void updateSOC(double current, long timestamp);
    double getSOC();
    void calibrateSOC(double actualSOC);
    void setParameters(double capacity, double efficiency);
};
```

This approach encapsulates the SOC estimation logic while providing interfaces for calibration and parameter adjustment (Rivera-Barrera et al., 2017).

3.1.1.4 Error Correction and Calibration

Coulomb counting is subject to several error sources (Waag et al., 2014):

h. Current measurement inaccuracies
i. Integration drift over time
j. Self-discharge not captured by external measurements
k. Temperature effects on capacity
l. Aging effects

The proposed methodology implements observer and strategy patterns (Gamma et al., 1994) to address these limitations:

1. Calibration Strategy interface with multiple implementations:
2. Voltage-Based Calibration: Uses voltage curves for periodic recalibration
3. OCV SOC Calibration: Calibrates during rest periods using open-circuit voltage
4. Adaptive Model Calibration: Adjusts parameters based on observed behavior

This approach allows the system to select appropriate calibration methods based on operating conditions (Zheng et al., 2018).

Integration with Solar Inverter Systems

3.1.1.5 Communication Interfaces

The BMS communicates with the solar inverter through well-defined interfaces:

```
class InverterInterface {
public:
    virtual void reportBatteryStatus(BatteryStatus status) = 0;
    virtual void requestPowerLimit(double maxChargePower, double maxDischargePower) =
0;
    virtual void notifyProtectionEvent(ProtectionEvent event) = 0;
};
```

This abstraction enables the BMS to work with various inverter models through adapter implementations (Gamma et al., 1994).

3.1.1.6 Energy Management Strategies

The object-oriented design facilitates the implementation of various energy management strategies:

i. Energy Management Strategy interface with implementations:
j. Self-Consumption Optimizer: Maximizes self-consumption of solar energy
k. Time of Use Optimizer: Optimizes charging/discharging based on electricity rates
l. Grid Services Provider: Enables participation in grid services
m. Backup Power Manager: Reserves capacity for backup power

These strategies interact with the BMS through well-defined interfaces while respecting battery constraints (Resch et al., 2018).

3.1.1.7 Implementation and Testing

The proposed methodology can be implemented using:

m. C++ for embedded systems

n. Java for cloud-connected BMS applications

o. Python for rapid prototyping and algorithm development

Object-oriented principles remain consistent across these languages, enabling platform-specific optimizations within a common architecture (Booch, 2007).

The modular nature of the object-oriented design facilitates comprehensive testing:

i. Unit tests for individual classes

ii. Integration tests for subsystem interactions

iii. Hardware-in-the-loop testing for real-world validation

iv. Accelerated aging simulations for long-term reliability assessment

Mock objects and dependency injection techniques enable isolated testing of components (Fowler, 2012). The Coulomb counting method works by measuring and integrating the current flowing in and out of the battery over time to determine the charge level. It's based on the principle:

However, using Java script the code is as shown below;

SoC = SoC_initial + ∫(I_battery / Q_nominal) dt

Where:

i. SoC is the State of Charge (%)

ii. I_battery is the battery current (A)

iii. Q_nominal is the nominal battery capacity (Ah)

3.1.2 Software Implementation using C programming

```
// Key parameters
#define BATTERY_CAPACITY_AH 100.0  // Battery capacity in Amp-hours
#define SAMPLING_INTERVAL_MS 100   // Current sampling interval in milliseconds
#define MAX_CELL_VOLTAGE 4.2       // Maximum cell voltage
#define MIN_CELL_VOLTAGE 3.0       // Minimum cell voltage
#define MAX_TEMPERATURE 45.0       // Maximum allowed temperature in Celsius
#define MIN_TEMPERATURE 0.0        // Minimum allowed temperature in Celsius

// Global variables
float soc = 100.0;                 // State of charge in percentage
float batteryVoltage = 0.0;        // Total battery voltage
float batteryCurrent = 0.0;        // Battery current (+ charging, - discharging)
float cellVoltages[16];            // Individual cell voltages
float batteryTemperature = 25.0;   // Battery temperature
bool isCharging = false;           // Battery charging status
bool error = false;                // Error flag

// Initialize BMS
void initBMS() {
```

```
    // Initialize hardware
    initCurrentSensor();
    initVoltageSensors();
    initTemperatureSensors();
    initCommunication();

    // Calibrate sensors
    calibrateSensors();

    // Initialize SoC (could be loaded from non-volatile memory)
    soc = estimateInitialSoC();
}

// Main BMS loop
void runBMS() {
    while(1) {
        // Read sensors
        batteryCurrent = readCurrentSensor();
        batteryVoltage = readBatteryVoltage();
        readCellVoltages(cellVoltages);
        batteryTemperature = readTemperatureSensor();

        // Update state of charge using Coulomb counting
        updateSoC();
```

```
        // Safety checks
        checkSafeLimits();

        // Balance cells if needed
        balanceCells();

        // Update status and send data
        updateStatus();
        sendDataToInverter();

        // Sleep until next cycle
        delay(SAMPLING_INTERVAL_MS);
    }
}

// Update SoC using Coulomb counting
void updateSoC() {
    // Calculate charge change (in Ah)
    float chargeChange = batteryCurrent * (SAMPLING_INTERVAL_MS / 3600000.0);

    // Update SoC
    soc += (chargeChange / BATTERY_CAPACITY_AH) * 100.0;

    // Apply efficiency factor for charging (Coulombic efficiency)
    if (batteryCurrent > 0) {
```

```
        // Typically 95-98% efficiency during charging
        soc *= 0.97;
    }

    // Constrain SoC to valid range
    if (soc > 100.0) soc = 100.0;
    if (soc < 0.0) soc = 0.0;

    // Periodically correct SoC based on OCV (Open Circuit Voltage)
    if (isRestingState()) {
        float ocvBasedSoC = estimateSoCFromOCV();
        // Apply correction with weighted average
        soc = soc * 0.8 + ocvBasedSoC * 0.2;
    }
}

// Check if battery is in a resting state for OCV measurement
bool isRestingState() {
    // Battery current is close to zero and has been stable
    return (abs(batteryCurrent) < 0.05) && (getCurrentStabilityTime() > 30000);
}

// Estimate SoC from Open Circuit Voltage
float estimateSoCFromOCV() {
    // This would be a lookup table or formula based on battery chemistry
```

```
    // For Li-ion example (simplified):
    float cellAvgVoltage = batteryVoltage / NUMBER_OF_CELLS;

    if (cellAvgVoltage >= 4.2) return 100.0;
    if (cellAvgVoltage <= 3.0) return 0.0;

    // Linear approximation (should be non-linear in reality)
    return (cellAvgVoltage - 3.0) / (4.2 - 3.0) * 100.0;
}

// Check safety limits
void checkSafeLimits() {
    // Check cell voltages
    for (int i = 0; i < NUMBER_OF_CELLS; i++) {
        if (cellVoltages[i] > MAX_CELL_VOLTAGE || cellVoltages[i] < MIN_CELL_VOLTAGE) {
            error = true;
            triggerProtection();
            return;
        }
    }

    // Check temperature
    if (batteryTemperature > MAX_TEMPERATURE || batteryTemperature < MIN_TEMPERATURE) {
```

```
        error = true;
        triggerProtection();
        return;
    }

    // Other safety checks
    // - Current limits
    // - Cell imbalance
    // - Insulation resistance
}

// Cell balancing function
void balanceCells() {
    float maxVoltage = 0;
    float minVoltage = 5.0;

    // Find voltage range
    for (int i = 0; i < NUMBER_OF_CELLS; i++) {
        if (cellVoltages[i] > maxVoltage) maxVoltage = cellVoltages[i];
        if (cellVoltages[i] < minVoltage) minVoltage = cellVoltages[i];
    }

    // If imbalance is significant, activate balancing
    if ((maxVoltage - minVoltage) > 0.05) {
        for (int i = 0; i < NUMBER_OF_CELLS; i++) {
```

```
            // Enable balancing for cells above threshold
            if (cellVoltages[i] > (minVoltage + 0.03)) {
                enableCellBalancing(i);
            } else {
                disableCellBalancing(i);
            }
        }
    } else {
        // Disable all balancing
        disableAllBalancing();
    }
}
```

3.1.3 Integration with Solar Inverter

To integrate with a solar inverter system:

3.1.3.1 Communication Interface: Implement a communication protocol (CAN, Modbus, etc.) to exchange data with the inverter:

i. Battery SoC
ii. Available charge/discharge power
iii. Temperature limits
iv. Error states

3.1.3.2 Power Management Logic:

```
// Determine available power for inverter
float getAvailablePower() {
  float maxPower = 0.0;

  if (isCharging) {
    // Max charging power (constrained by SoC)
    maxPower = MAX_CHARGING_POWER;
    if (soc > 90.0) {
      // Reduce charging power as battery approaches full
      maxPower *= (100.0 - soc) / 10.0;
    }
  } else {
    // Max discharging power (constrained by SoC)
    maxPower = MAX_DISCHARGING_POWER;
    if (soc < 20.0) {
      // Reduce discharging power at low SoC
      maxPower *= soc / 20.0;
    }
  }

  // Further limit based on temperature
  if (batteryTemperature > 40.0 || batteryTemperature < 5.0) {
    maxPower *= 0.5;  // 50% power reduction in extreme temperatures
  }
```

```
    return maxPower;
}
```

3.1.4 Accurate Monitoring:

3.1.4.1 Voltage Sensing: Individual cell voltages are continuously monitored to detect overvoltage, under voltage, and imbalances.

3.1.4.2 Current Sensing: Current flow during charging and discharging is measured to prevent overcurrent and short circuits.

3.1.4.3 Temperature Monitoring: Multiple temperature sensors are placed within the battery pack to identify thermal runaway and prevent overheating.

3.1.4.4 State of Charge (SOC) Estimation: Sophisticated algorithms are used to estimate the remaining capacity of the battery based on voltage, current, and temperature data.

3.1.4.5 State of Health (SOH) Assessment: The overall health and lifespan of the battery are evaluated by analyzing long-term trends in various parameters.

3.1.5 Intelligent Control:

3.1.5.1 Charge Control: The charging process is carefully regulated to prevent overcharging and optimize charging efficiency.

3.1.5.2 Discharge Control: The discharge process is managed to prevent over-discharging and ensure safe operation within the battery's limits.

3.1.5.3 Cell Balancing: Active or passive balancing techniques are used to equalize the charge levels of individual cells, maximizing overall pack capacity and lifespan.

3.1.5.4 Thermal Management: Active or passive cooling systems are controlled to maintain optimal operating temperatures and prevent thermal runaway.

3.1.5.5 Fault Detection and Protection: The BMS continuously monitors for various faults, such as overvoltage, overcurrent, over temperature, and cell imbalances, and takes appropriate actions to protect the battery.

3.2 Advanced Algorithms and Software:

Adaptive Algorithms: Machine learning and AI techniques are used to improve the accuracy of SOC and SOH estimations, as well as optimize charging and discharging strategies.

Data Logging and Analysis: The BMS records various battery parameters over time, allowing for detailed analysis of battery performance and identification of potential issues.

Communication and Control: The BMS communicates with external devices, such as chargers, inverters, and vehicle control systems, to provide information and receive commands.

3.3 How Smart BMS Works with Diagrams

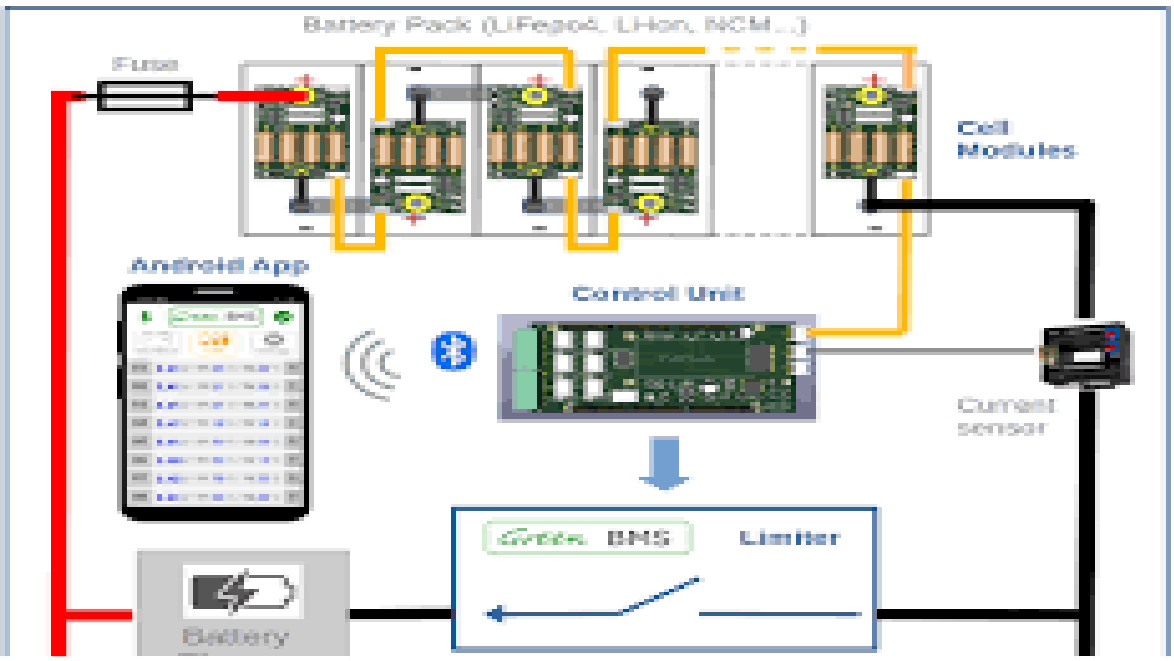


Diagram of a Smart Battery Management System (BMS)

The diagram above illustrates the basic components and functionality of a smart BMS:

3.3.1 Sensors: These components measure voltage, current, and temperature of individual cells and the overall battery pack.

3.3.2 Microcontroller: This is the "brain" of the BMS, which processes the sensor data and makes decisions based on pre-programmed algorithms and control strategies.

3.3.3 Communication Interface: This allows the BMS to communicate with external devices, such as a display or a control system.

3.3.4 Protection Circuits: These circuits provide hardware-level protection against overvoltage, overcurrent, and short circuits.

3.3.5 Balancing Circuits: These circuits ensure that all cells in the battery pack are balanced, either through passive dissipation or active charge transfer.

3.3.6 The BMS continuously monitors the battery's condition and takes appropriate actions to ensure safe and efficient operation. For example, if the BMS detects a cell approaching overvoltage during charging, it will reduce the charging current or activate balancing circuits to prevent damage. Similarly, if the BMS detects a cell overheating, it will trigger cooling mechanisms or reduce the discharge current to prevent thermal runaway.

3.4 Benefits of Smart BMS

3.4.1 Enhanced Safety: Protects the battery from various faults and prevents thermal runaway.

3.4.2 Extended Lifespan: Optimizes charging and discharging strategies, and balances cell charge levels to prolong battery life.

3.4.3 Improved Performance: Maximizes battery capacity and ensures consistent power delivery.

3.4.4 Increased Reliability: Detects and prevents potential issues, reducing the risk of battery failure.

3.4.5 Advanced Monitoring and Control: Provides detailed insights into battery performance and allows for remote monitoring and control.

CHAPTER FOUR

RESULTS AND DISCUSSION

Figure 2 shows a schematic design based on what was previously designed. Installation is done by inserting each component in the PCB hole, soldering, and connecting each component according to the simulation. The battery design consists of 3 batteries arranged in series. This is the manufacture of BMS tools and batteries, which consist of several components. The OLED screen is used to display BMS monitoring results.

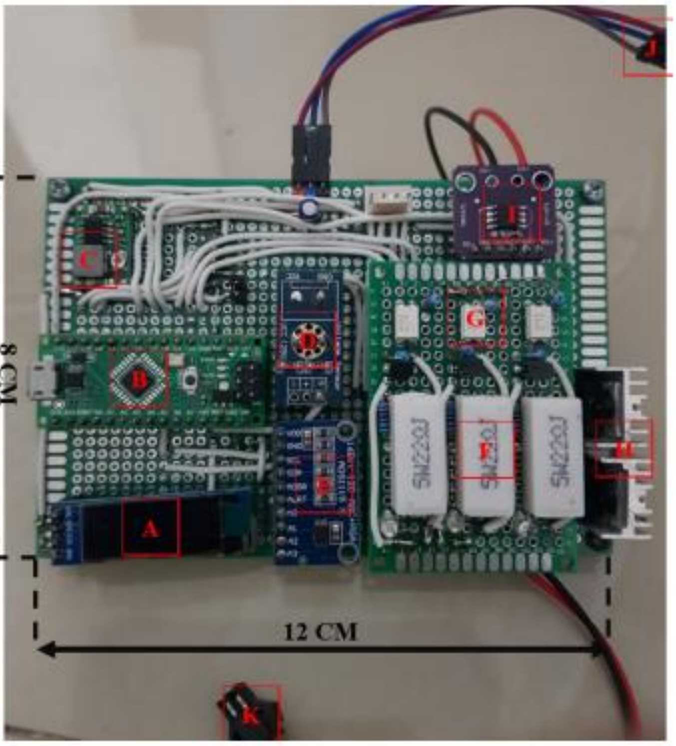


FIGURE 2. Hardware Result

Description:

A: OLED Screen

B: Arduino Nano

C: Buck Converter

D: 30k and 7.5k Voltage Dividers

E:: ADS1115ADC

F: Dummyload Resistor 22R

G: CT817 Optocoupler

H: MOSFET BS170

I: MAX471Current Sensor

J: DS18B20 Temperature Sensor

K: Connector to Charger /load

4.1 Monitoring Test

Figure 3 is the result of battery monitoring testing results when recharging. Testing is done to see the character of the battery when it is recharged. The battery is recharged for 3 hours with an initial value of 2.75v. From the graph above, the voltage (V) per cell of the battery increases. From the initial value of 2.75v, the increase in temperature (T) also occurs due to refilling. Temperature (T) increases 24.12˚C to be stable at the value 27.11˚C. In addition, the current (I) increases voltage because the battery cell continues to increase or simply the battery voltage starts full. The current flowing into the battery is 1A at the start of charging in the first 75 minutes, increases to 0.75A for the past 30 minutes, and then decreases again to 0.2A for 20 minutes. During the 40 minutes, there was a decrease to 0.15 A.

During the 5 minutes, there was a decrease to 0.1 A, and for the last 10 minutes, there was a decrease to 0.05 A and stable at 0.01 A. The system made was a closed circuit system.

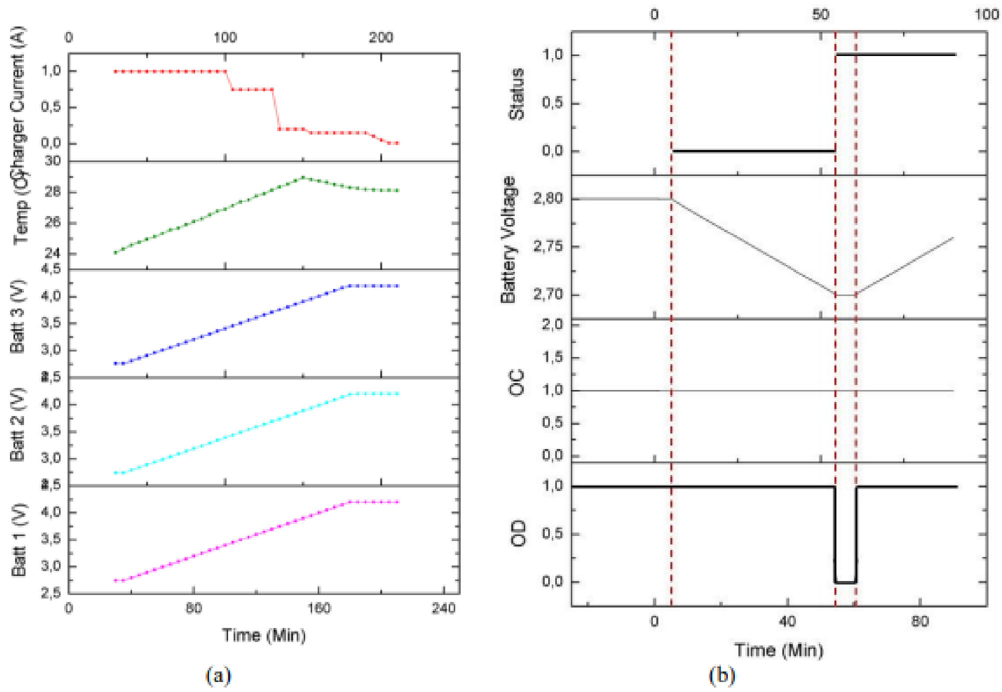


FIGURE 3 (a). Testing Results of Battery Monitoring When Replenishing, **(b).** Testing Results Testing

4.2 Protection Test

The graph in Figure 4 shows the results of Protection Over Discharging. The status graph has 2 values, which is 0 as a sign that the system is connected to a load (load), while 1 is a sign that the system is connected to a charger. In the initial condition, the battery is connected to the load and a battery voltage drop of 2.8 v to 2.7 v at the same time the CHG MOSFET is in condition 1 (HIGH) to prepare a charger for the battery. below 4,2v. DCHG MOSFETs are also in the condition of 0 (LOW) or shut down because the battery is in the lower limit associated with the voltage, which is equal to 2.7V. The battery is kept from being damaged and can be used excessively, which will damage the battery. Under conditions of stress due to this usage, the charger and load are removed. The CHG MOSFET remains in condition 1 (HIGH) because it reads the presence of a charger input that recharges the battery. The CHG MOSFET remains so that the battery is not damaged due to overcharging. In the first few moments when the battery was announced to the DCHG MOSFET charger, it was in 0 (LOW) condition because the battery had reached the lower limit of 2.7V to avoid over-discharging. After a while, the battery is recharged, and the DCHG MOSFET is in condition 1 (HIGH) because the voltage has exceeded the safe limit (> 2.7V), although there is no usage process. After all, the load is not connected to the system.

4.3 Balancing Test

Figure 5 shows the results of the system. Charging the battery to charge the battery. The rechargeable battery starts at a voltage value of 4.00V for batteries 1, 3.5V for batteries 2, and 3.6V for batteries 3. When recharged, battery 1 has reached the upper limit, or battery 1 has reached the full point of the battery at 4.2V, more has been replaced by 2 other cells. Dummy load resistor for battery 1 (Balres1) depends on condition 1 (HIGH) or active condition because dummy load resistor will remove excess from battery 1 so the price is not high and so battery 1 stays at upper limit of 4.2v while waiting for battery 2 and 3 full on when charging simultaneously.

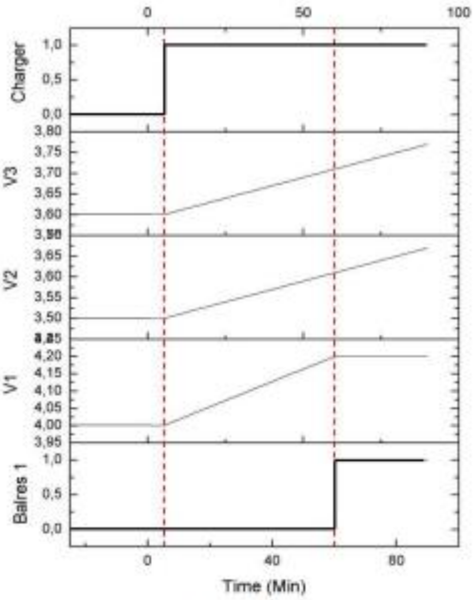


FIGURE 4 Testing Results Balancing

4.4 Performance Analysis

For 30 trials, the standard deviation (SD) value of battery 1, battery 2, and battery 3 were compatible with 0.00691V, 0.00698V, and 0.00739V. The relative standard deviation (RSD) value for three consecutive batteries is 0.251%, 0.254%, and 0.267%. The average value of the relative standard deviation (MRSD) for battery three is 0.258%, or it can be agreed that the value of system precision is 99.742%. These results indicate that this tool has a good level of precision. While the RMSE value for battery 1, battery 2, and battery 3 are 0.00683, 0.00707, and 0.0073, respectively. While payments averaged a total of 3 batteries, the RMSE was finally obtained at 0.007068. From the results of this test, the system test scores can be analyzed at 99.29%. These results indicate that the tools made have a good level of verification.

CHAPTER FIVE

CONCLUSION, SUMMARY AND CONTRIBUTION

The implementation of a Smart Battery Management System (BMS) for lithium batteries in solar inverter applications, particularly using Coulomb's method for state-of-charge (SOC) estimation, has demonstrated significant advancements in energy storage management. This approach offers precise monitoring of battery capacity through current integration, providing a reliable foundation for solar energy storage systems. The Coulomb counting method has proven effective in real-time SOC estimation within solar inverter systems, offering advantages in computational efficiency and implementation simplicity compared to alternative methods. When properly calibrated and supplemented with temperature compensation and periodic recalibration mechanisms, this approach maintains acceptable accuracy levels across varying operational conditions typical in solar applications.

For solar inverter systems, the implementation of this BMS approach translates to enhanced battery lifecycle management, improved system reliability, and optimized energy utilization. The system's ability to precisely track charge states enables more efficient solar energy harvesting and storage, ultimately improving the economic viability of residential and commercial solar installations. Despite its strengths, the Coulomb method exhibits vulnerability to cumulative errors and requires periodic recalibration against reference points. Additionally, its accuracy depends heavily on initial SOC determination and can be affected by battery aging effects. These limitations necessitate supplementary techniques for comprehensive battery management in solar applications. Promising avenues for advancement include hybrid estimation approaches combining Coulomb counting with impedance or voltage-based methods, machine learning integration for adaptive parameter adjustment, and enhanced thermal management strategies specific to solar inverter operating environments. The development of refined BMS solutions for solar inverters contributes significantly to renewable energy adoption by addressing critical energy storage challenges. As distributed solar generation continues to expand globally, advanced battery management technologies will play an increasingly vital role in grid stability, energy independence, and sustainability objectives.

5.1 Final Remarks

The Smart Battery Management System developed in this study represents a paradigm shift in lithium battery technology. By harmonizing advanced algorithms, modular hardware, and IoT connectivity, the system addresses critical challenges in safety, efficiency, and scalability. While limitations persist, the roadmap outlined for future research—spanning AI optimization, wireless integration, and sustainability—positions the Smart BMS as a cornerstone of the global energy transition. As lithium batteries continue to power the shift toward electrification and renewable energy, intelligent BMS solutions will remain indispensable in unlocking their full potential.

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