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DESIGN AND DEVELOPMENT OF A REAL-TIME BATTERY MANAGEMENT SYSTEM WITH SOC AND SOH ESTIMATION FOR LITHIUM-ION BATTERY PACKS

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Abstract: The growing use of lithium-ion batteries in electric vehicles, renewable energy systems, and portable electronics has increased the need for efficient Battery Management Systems (BMS). Lithium-ion batteries are highly sensitive to voltage, current, and temperature variations, which can affect performance, safety, and lifespan. Hence, accurate monitoring and estimation of battery parameters are essential for safe and reliable operation. This project presents the design and development of a real-time Battery Management System for lithium-ion batteries with State of Charge (SOC) and State of Health (SOH) estimation using the Extended Kalman Filter (EKF). The system continuously monitors battery voltage, current, and temperature using a voltage sensor, INA219 current sensor, and Dallas DS18B20 temperature sensor interfaced with an Arduino Uno microcontroller. The EKF algorithm is implemented to estimate SOC accurately under dynamic conditions. Compared to conventional methods such as Coulomb counting and voltage-based estimation, EKF reduces errors caused by sensor noise, drift, and nonlinear battery behavior. SOH is determined based on battery capacity degradation, which helps analyze battery aging and health condition. To ensure battery safety, MOSFETs are used to control charging and discharging operations. The system automatically disconnects the battery during abnormal conditions such as overvoltage, undervoltage. A DC motor is used as a load to simulate discharge conditions. The measured and estimated parameters are stored in an SQLite database and displayed through a Flask-based web dashboard for real-time monitoring and visualization. Experimental results show that the developed system provides stable SOC and SOH estimation, reliable monitoring, and improved battery safety. The proposed system is cost- effective, scalable, and suitable for battery management applications in electric vehicles and renewable energy storage systems

Index Terms – Battery Model, State of Charge, State of Health, Kalman Filter, Battery Management System.

I. INTRODUCTION

The rapid growth of modern technology has significantly increased the demand for efficient and reliable energy storage systems. Among the various battery technologies available today, lithium-ion batteries have become the preferred choice for numerous applications such as electric vehicles, renewable energy storage systems, portable electronics, and industrial backup systems. Their popularity is mainly due to advantages such as high energy density, lightweight structure, low self-discharge rate, and longer cycle life compared to conventional battery technologies.

Despite these advantages, lithium-ion batteries are highly sensitive to operating conditions such as voltage, current, and temperature. Improper charging, deep discharge, excessive current flow, or abnormal temperature conditions can negatively affect battery performance, reduce lifespan, and create safety hazards such as overheating or thermal runaway. Therefore, efficient monitoring and management of lithium-ion batteries are essential to ensure safety, reliability, and optimal performance. A Battery Management System (BMS) is an electronic system designed to monitor, control, and protect batteries during operation. The primary functions of a BMS include monitoring battery voltage, current, and temperature, estimating battery states, controlling charging and discharging, and protecting the battery from unsafe conditions. Among battery states, State of Charge (SOC) and State of Health (SOH) are two critical parameters.

State of Charge represents the available capacity of the battery as a percentage of its full charge capacity. Accurate SOC estimation is essential to determine the remaining battery energy and avoid unexpected shutdowns. State of Health indicates the condition of the battery relative to its ideal state and reflects battery aging, degradation, and remaining useful life. Traditional SOC estimation methods include Coulomb counting and Open Circuit Voltage (OCV)-based methods. Coulomb counting calculates SOC by integrating battery current over time, but small sensor errors accumulate, causing drift and inaccurate results. OCV methods require the battery to remain at rest for accurate measurement, which is not suitable for real- time applications.

Battery behavior is nonlinear and affected by factors such as load conditions, temperature variations, and aging. These challenges make traditional estimation techniques less reliable. Therefore, advanced estimation algorithms are required for accurate real-time battery state estimation.

This paper focuses on the design and development of a real-time Battery Management System capable of monitoring battery parameters and estimating SOC and SOH using the Extended Kalman Filter (EKF). The EKF is widely used for nonlinear systems and provides accurate state estimation by combining system modeling with real-time measurements. The proposed system integrates hardware and software components. The hardware system includes an Arduino Uno microcontroller, voltage sensor, INA219 current sensor, Dallas DS18B20 temperature sensor, MOSFET switches, LCD display, and DC motor as load. The software system implements the EKF algorithm for SOC estimation and calculates SOH based on battery degradation. The voltage sensor continuously measures battery voltage, while the INA219 sensor monitors charging and discharging current. The DS18B20 sensor measures battery temperature to ensure safe operation. The Arduino processes sensor data and performs monitoring functions. MOSFETs are used to control charging and discharging circuits, enabling automatic protection during unsafe conditions such as overvoltage, undervoltage, overcurrent, and high temperature. A DC motor is connected as a load to simulate practical battery discharge conditions. This allows evaluation of battery performance under varying load conditions. The measured data and estimated parameters are displayed on a 16×2 LCD for local monitoring.

In addition to hardware monitoring, the system includes backend support for data storage and visualization. Battery parameters and estimated values are transmitted through serial communication and stored in an SQLite database. A Flask-based web server is developed to display battery information in real time through a web dashboard.

The web dashboard provides visualization of voltage, current, temperature, SOC, and SOH, allowing live monitoring and historical analysis. This feature improves accessibility and makes the system suitable for intelligent battery management applications.

The implementation of EKF significantly improves estimation accuracy compared to conventional methods. By combining prediction and correction steps, EKF minimizes estimation errors caused by sensor noise, model uncertainties, and nonlinear battery behavior. This project contributes to safer battery operation, improved performance, and extended battery lifespan. It also demonstrates a cost-effective and scalable Battery Management System suitable for electric vehicles, renewable energy systems, and smart energy applications.

II. Literature Survey

The paper [1] proposed and developed Extended Kalman Filter based reliable and robust solution for real-time SOC estimation in lithium-ion battery systems. The algorithm demonstrated stable performance under nonlinear operating conditions and varying load profiles. This paper strongly supports the use of EKF for real-time SOC estimation and forms an important basis for the proposed battery monitoring system. [1].

The authors of the paper [2] proposed an improved fractional-order Extended Kalman Filter for State of Charge estimation of lithium-ion batteries. These models capture diffusion effects and dynamic responses of batteries more effectively. Compared to conventional EKF, the proposed method showed superior accuracy under nonlinear and dynamic conditions. This paper highlighted the importance of model accuracy and demonstrates further advancements in EKF-based battery estimation.

The paper [3] introduces a hybrid State of Charge (SOC) estimation technique that combines the Adaptive Extended Kalman Filter (AEKF) with an Artificial Neural Network (ANN). The authors concluded that combining EKF with intelligent algorithms such as neural networks can significantly enhance battery state estimation performance. This paper highlights modern research trends in battery management systems and validates the Extended Kalman Filter as a fundamental component in advanced battery estimation techniques.

The paper [4] presents a comparison of multiple battery State of Charge (SOC) estimation algorithms based on factors such as computational complexity, memory requirements, execution time, and estimation accuracy.

The study analyzed various SOC estimation techniques including Coulomb Counting, Open Circuit Voltage (OCV) method, Artificial Neural Networks, and the Extended Kalman Filter (EKF). Based on the obtained results, the authors concluded that the Extended Kalman Filter provides the best trade-off between estimation accuracy and hardware resource requirements for embedded Battery Management Systems.

The authors of paper [5] paper evaluated different equivalent circuit models used for lithium-ion battery State of Charge (SOC) estimation using the Extended Kalman Filter (EKF). The authors compared the performance of first-order RC and second-order RC equivalent circuit models to determine which model provides better SOC estimation accuracy. The authors concluded that higher-order equivalent circuit models can considerably improve SOC estimation performance in lithium-ion battery systems. The paper also highlighted the importance of accurate battery modeling in Extended Kalman Filter-based estimation techniques and emphasizes that proper model selection is essential for achieving reliable battery management performance.

The paper [6] proposed an Adaptive Extended Kalman Filter (AEKF) technique for online State of Charge (SOC) estimation of lithium-ion batteries. The authors developed an improved battery model capable of representing nonlinear battery behavior more accurately under varying operating conditions. The authors concluded that the Adaptive Extended Kalman Filter is highly suitable for real-time battery monitoring and advanced Battery Management System applications due to its enhanced accuracy and adaptability. The paper further validates the importance and effectiveness of EKF-based techniques in modern lithium-ion battery estimation systems.

From the literature survey, it is observed that traditional battery estimation methods are not sufficient for accurate real-time monitoring because of sensor errors, parameter drift, and nonlinear battery behavior. The Extended Kalman Filter provides improved estimation accuracy, robustness, and real-time capability for State of Charge estimation. Recent research studies indicate that EKF-based techniques are widely adopted in Battery Management Systems and continue to be reliable solutions for lithium-ion battery monitoring applications. Therefore, this paper adopts the Extended Kalman Filter for accurate real-time SOC estimation and State of Health (SOH) analysis.

III. LITHIUM-ION BATTERY CHARACTERISTICS

Lithium-ion batteries are widely used due to their:

- High energy density
- Long cycle life
- Lightweight design
- Low self-discharge rate
- High efficiency

Battery performance changes continuously during operation. Important battery characteristics include:

3.1 Terminal voltage

Battery voltage changes according to:

- SOC
- Load current
- Internal resistance
- Temperature

3.2 Battery Current

Battery current determines charging and discharging rate.

- Positive current → charging
- Negative current→ discharging

3.3 Battery Temperature

Temperature significantly affects:

- Internal resistance
- Battery efficiency
- Capacity
- Aging rate

3.4 Battery Capacity

Battery capacity represents the total charge storage capability. Unit: Capacity=Ah

3.5 State of Charge (SOC)

State of Charge indicates the remaining battery capacity as a percentage of full capacity. Mathematically:

SOC= Q remaining×100/Q rated

Where:

Q remaining = available battery charge Q rated =nominal battery capacity SOC values:

100% → fully charged

0% → fully discharged

3.6 State of Health (soh)

State of Health indicates battery condition relative to a new battery. It is defined as:

$$SOH=\frac{C\_current}{C\_rated} * 100$$

Where:

C_current =current battery capacity

C_rated = initial battery capacity

SOH helps determine:

- Battery aging
- Remaining useful life
- Replacement requirement

IV. BATTERY MODELING

Battery modeling is an essential part of Battery Management Systems because it provides a mathematical representation of battery behavior under different operating conditions. Accurate battery modeling helps to estimate internal battery states such as State of Charge (SOC) and State of Health (SOH), which cannot be measured directly.

Lithium-ion batteries exhibit nonlinear behavior influenced by voltage, current, temperature, charging/discharging rates, and battery aging. Therefore, battery models are required to represent these characteristics for real-time monitoring and estimation. In this paper, an equivalent circuit model is used to represent lithium-ion battery dynamics. The battery model is integrated with the Extended Kalman Filter for SOC estimation.

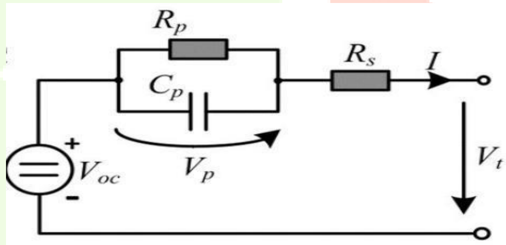

Fig 1. First Order Battery Modelling

The figure 1 shows the first-order battery circuit modelling of a battery used for analyzing battery behavior and SOC estimation. The open-circuit voltage (Voc) represents the battery voltage under no- load conditions, while the series resistor (Rs) represents the internal resistance of the battery. The parallel combination of Rp and Cp models the polarization effect and transient response during charging and discharging. The terminal voltage (Vt) and current (I) represent the output characteristics of the battery under operating conditions. This model represents:

- Instantaneous voltage drop
- Dynamic transient response

4.1 Mathematical Model of battery cell

Battery terminal voltage:

$$V_t = V_{oc} - IR_S - V_p \tag{1}$$

Where:
Vt = terminal voltage
Voc = open circuit voltage
I = battery current
R0 = internal resistance
Vp = polarization voltage

SOC Equation is represented in Eq.2

$$SOC(k+1) = SOC(k) - \frac{I\Delta t}{Q_n} \quad (2)$$

Where:
Qn = nominal capacity
Δt = sampling time

These equations are used by EKF for predictions.

4.2 Importance of Battery Modeling in EKF

Battery modeling is required because EKF needs:

- State equations
- Measurement equations
- Battery model provides:
- Voltage prediction
- Dynamic behavior representation

Benefits of Battery modeling

- Improved SOC accuracy
- Better noise rejection
- Real-time implementation

Without accurate battery modeling:

- Poor estimation
- Higher error

V. EXTENDED KALMAN FILTER (EKF):

Accurate estimation of battery states is one of the most critical functions of a Battery Management System. Parameters such as State of Charge (SOC) and State of Health (SOH) cannot be directly measured using sensors and therefore must be estimated using suitable algorithms.

Among these parameters, State of Charge is particularly important because it indicates the remaining available capacity in the battery. Accurate SOC estimation helps prevent overcharging, deep discharge, battery degradation, and unexpected system shutdown.

Traditional battery state estimation methods such as Coulomb Counting and Open Circuit Voltage methods are simple but suffer from major limitations. Coulomb Counting accumulates errors over time due to sensor drift and current measurement inaccuracies. Open Circuit Voltage methods require the battery to remain at rest for a long duration, making them unsuitable for real-time applications. To overcome these limitations, this project implements the Extended Kalman Filter for real- time SOC estimation.

The Extended Kalman Filter is an extension of the classical Kalman Filter designed for nonlinear systems. It combines mathematical system modeling with real-time sensor measurements to estimate unknown system states recursively.

EKF is widely used in applications such as:

- Battery Management Systems
- Robotics
- Aerospace navigation
- Signal processing
- Autonomous systems

Its ability to provide accurate state estimation under noisy and nonlinear conditions makes it highly suitable for lithium-ion battery applications.

5.1 Kalman Filter overview

The Kalman Filter is a recursive estimation algorithm used for estimating unknown variables in dynamic systems. It was originally developed for linear systems and provides optimal state estimation in the presence of noise and uncertainty.

The Kalman Filter works by combining:

- System model prediction
- Sensor measurements

The filter continuously updates the estimated state by minimizing estimation error. The Kalman Filter operates in two main stages:

- Prediction: The current state is predicted based on the previous state and system model.
- Correction: The predicted state is corrected using measured sensor data. This recursive process improves estimation accuracy continuously. However, the standard Kalman Filter assumes system linearity. Battery systems are nonlinear.
  Hence, the Extended Kalman Filter is used.

5.2 Extended Kalman Filter

The Extended Kalman Filter (EKF) is a nonlinear version of the conventional Kalman Filter that is widely used for battery state estimation applications. Unlike the standard Kalman Filter, the EKF is capable of handling nonlinear state equations and nonlinear measurement equations, making it more suitable for lithium-ion battery systems that exhibit nonlinear behavior under varying operating conditions. The main concept of the Extended Kalman Filter is based on approximating nonlinear functions using first-order linearization techniques. This linearization is achieved through Taylor series expansion around the current operating point of the system. The Extended Kalman Filter estimates unknown battery states by first predicting battery behavior using mathematical battery models and then correcting those predictions using real-time sensor measurements. By continuously updating the estimated values based on measured data, the EKF improves estimation accuracy and provides robust real-time monitoring performance. Due to its ability to handle nonlinear battery dynamics and measurement uncertainties, the Extended Kalman Filter has become one of the most widely adopted techniques in modern Battery Management Systems for accurate State of Charge and State of Health estimation.

The Extended Kalman Filter (EKF) shown in Fig.2 shows a recursive mathematical algorithm used to provide high-precision estimates of a battery's State of Charge (SoC) and State of Health (SoH) by accounting for non-linear cell behavior. It operates through a continuous cycle of predicting the next battery state based on current and temperature inputs, then correcting those predictions by comparing them against real-time measured voltage. This "prediction-correction" mechanism uses a calculated Kalman Gain to minimize estimation errors, ensuring the system remains accurate even when sensors provide noisy or imperfect data.

5.2.1 Working Principle of EKF

The Extended Kalman Filter works recursively.

At each time step, the algorithm performs prediction followed by correction.

During Prediction previous battery state is used

- Battery model predicts next state
- Real-time voltage measurements are obtained
- Predicted voltage is compared with measured voltage
- The difference between predicted and measured values is called residual error.
- The filter uses this error to correct the predicted SOC.
- This correction improves estimation accuracy.
- The process repeats continuously.

Thus, EKF continuously estimates battery state in real time.

5.2.2 Mathematical Representation of EKF

A nonlinear system is represented by:

State equation*:*

$$x_k = f(x_{k-1}, u_k) + w_k \qquad (3)$$

x_k= state vector

u_k=input vector

w_k=process noise

The state vector represents unknown battery states. In this paper:

- SOC
- polarization voltage are included in the state vector.

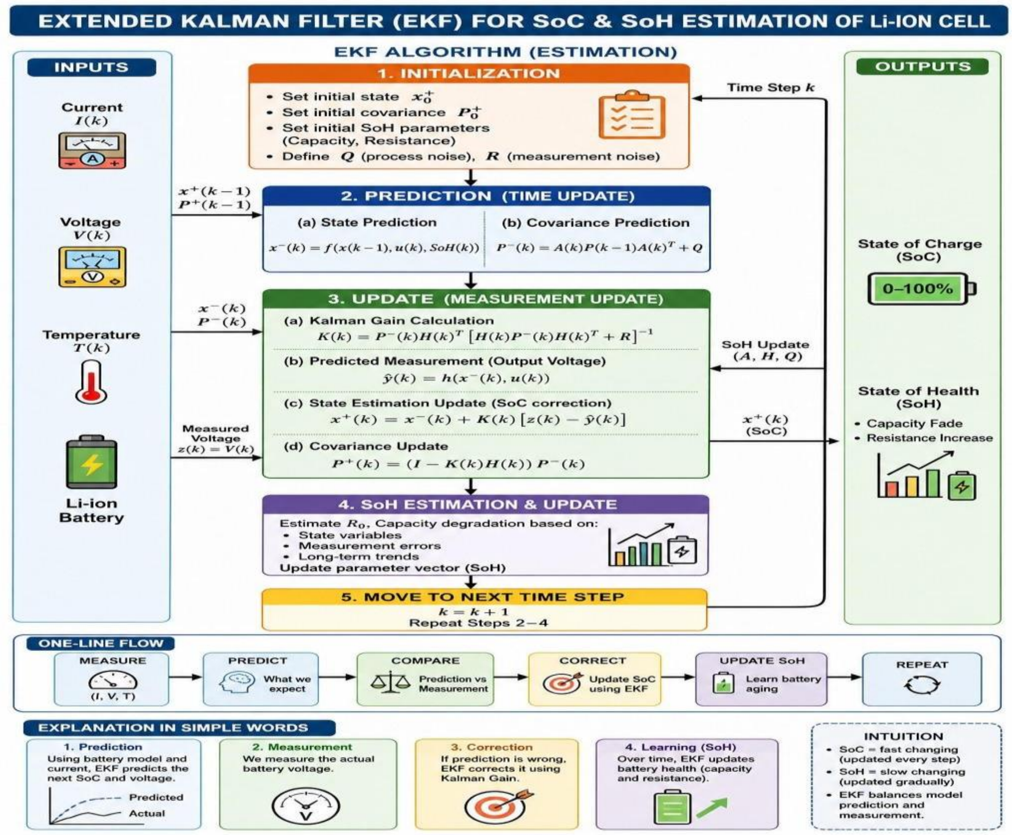

Fig 2. EKF Algorithm

Measurement equation:

$$z_k = h(x_k) + v_k \tag{4}$$

Where:

z_k=measurement vector

v_k=measurement noise

Measured value is terminal voltage The EKF estimates hidden states from measurable parameters.

VI. SOFTWARE IMPLEMENTATION

The software system performs data acquisition, processing, SOC estimation, data storage and visualization. The software is divided into:

1.Arduino firmware

2.Backend processing

3.Web Dashboard

The flowchart in Fig.3 illustrates the working procedure of the battery monitoring and SOC estimation system using the Extended Kalman Filter (EKF) algorithm. Initially, the system loads the required libraries, initializes battery model parameters, and establishes serial communication with the Arduino and Flask dashboard. The sensor data such as voltage, current, and temperature are continuously read, validated, and processed to estimate the battery SOC and other states using EKF prediction and correction steps. Finally, the processed data are displayed on the dashboard, stored in files, and the system stops when the stop command is received.

6.1 Arduino Programming

The Arduino microcontroller is responsible for initializing the sensors, reading battery parameters, controlling the LCD display, managing MOSFET operations, and sending serial data to the backend system. Sensor readings are continuously acquired and processed in real time to monitor battery performance accurately. The Arduino transmits the collected battery data to the backend through serial communication for further analysis and monitoring. The firmware is designed to operate in a continuous monitoring loop to ensure uninterrupted battery management and real-time system operation.

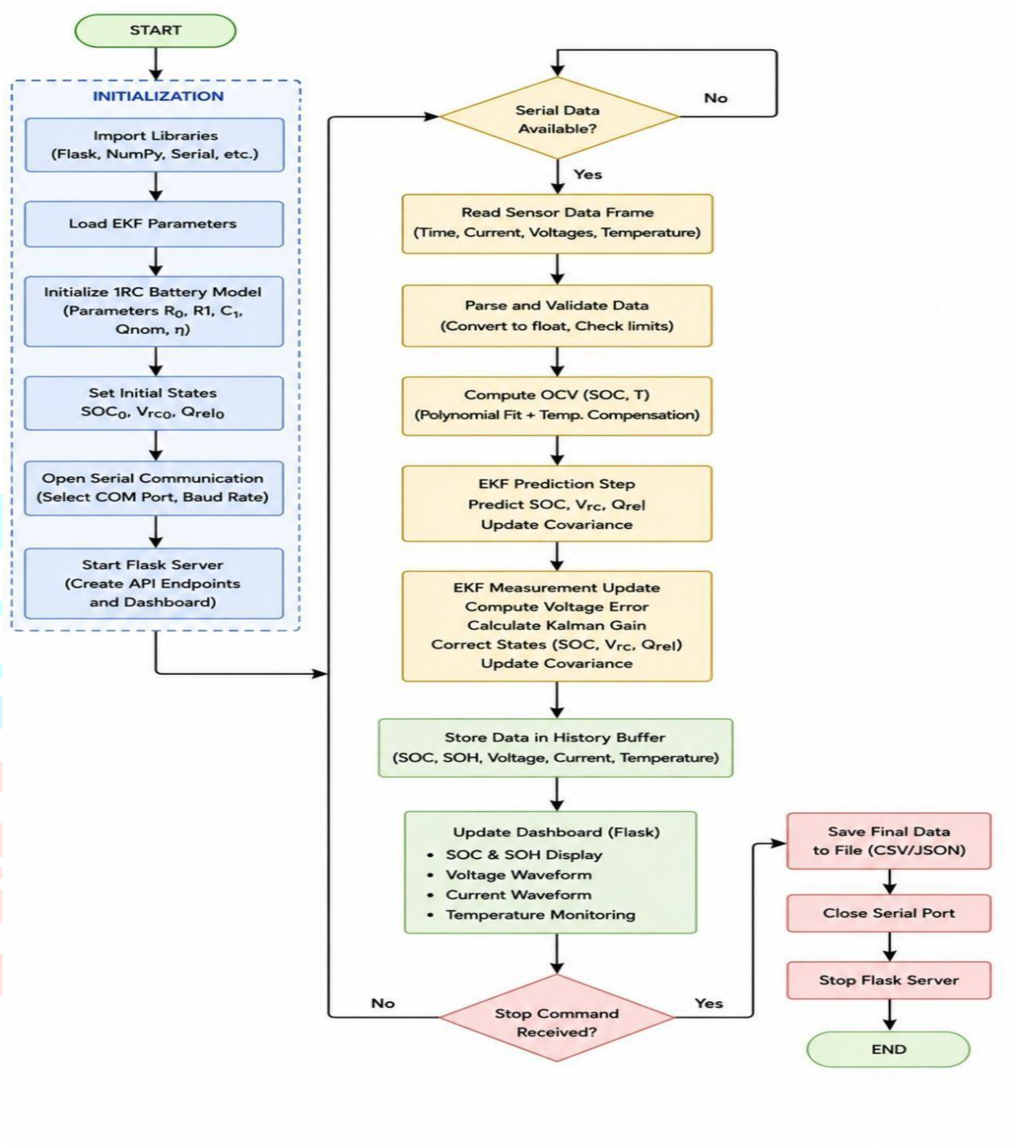

Fig 3. Flowchart of EKF-Based Battery Management System

6.1.1 Extended Kalman Filter Implementation.

The Extended Kalman Filter is implemented in the software system to estimate the battery State of Charge in real time. The algorithm continuously processes battery measurements and updates SOC recursively. The working sequence of the EKF algorithm begins with initialization of the battery state variables and covariance matrices. Initial SOC and battery parameters are assigned before the estimation process begins.

After initialization, the system continuously reads battery voltage, current, and temperature values from the connected sensors. These measured values are used as inputs to the battery model and estimation algorithm. During the prediction step, the EKF predicts the next battery state using the battery mathematical model and previously estimated state values. This predicted state provides an initial estimate of SOC. In the correction step, the measured battery voltage is compared with the predicted battery voltage. The difference between measured and predicted voltage is used to calculate the estimation error.

The Kalman gain is then computed to determine the weighting between predicted values and measured values. Using this gain, the predicted SOC is corrected to obtain a more accurate estimate. The updated SOC value is stored and displayed. The estimation cycle repeats continuously as new sensor measurements become available.

6.1.2 SQLite Database

The backend system uses SQLite as the database for storing battery monitoring data. SQLite is a lightweight relational database management system suitable for embedded and local applications. It does not require a separate server and can be easily integrated with Python and Flask. The database stores all battery parameters along with timestamps. The database stores important battery parameters including battery voltage, battery current, battery temperature, State of Charge (SOC), State of Health (SOH), and date and time information. Each record is automatically inserted into the database whenever new sensor data is received from the monitoring system. The stored data enables historical data analysis, battery trend observation, continuous data logging, and performance analysis for effective battery monitoring. The battery information stored in the database can also be accessed by the Flask web application for real-time visualization and monitoring purposes. SQLite was selected for the proposed system due to its simplicity, low memory usage, portability, and ease of integration with embedded and web-based applications. These features make SQLite highly suitable for the proposed battery monitoring and management system.

6.2 Web Dashboard

A web-based dashboard is developed using Flask for real-time monitoring and visualization of battery parameters.The web dashboard acts as the user interface for displaying battery information remotely. The dashboard receives battery data from the backend database and displays:

- Battery voltage
- Battery current
- Temperature
- State of Charge
- State of Health

The web-based dashboard allows users to monitor battery conditions through a browser interface without requiring direct hardware access. The dashboard improves user experience by presenting battery data in an organized, clear, and understandable format for real-time monitoring and analysis. Flask is used as the backend web framework because of its lightweight architecture and easy integration with the SQLite database.The Flask server performs several important tasks including receiving battery data from the monitoring system, fetching stored values from the SQLite database, serving web pages, and continuously updating dashboard information. The dashboard provides real-time visualization as well as historical analysis of battery behavior, enabling users to observe battery performance trends effectively. These features make the proposed system more scalable, efficient, and suitable for advanced smart battery monitoring applications.

VII. RESULTS AND DISCUSSION

This section presents the results obtained from the implementation and testing of the proposed real-time Battery Management System for lithium-ion batteries. The system was tested under different operating conditions to evaluate its ability to measure battery parameters accurately, estimate State of Charge (SOC) and State of Health (SOH), store battery data, and visualize information through a web dashboard.

The developed system integrates hardware sensing, Extended Kalman Filter-based estimation, protection mechanisms, database storage, and web-based monitoring. Experimental observations confirm the proper functioning of each module.

The results obtained from the system are discussed in detail in the following sections.

The hardware setup was tested to verify proper operation of all connected sensors and components.The voltage sensor successfully measured the battery voltage continuously are transmitted readings to the Arduino. The measured voltage values were found to be stable and accurate under both charging and discharging conditions. The INA219 current sensor accurately measured charging and discharging current. During load operation, the current sensor detected variations in current drawn by the DC motor and transmitted the values correctly to the Arduino.

The DS18B20 temperature sensor successfully monitored battery temperature in real time. Temperature readings remained stable during normal operation and responded appropriately to changes in battery temperature.

The LCD display successfully showed real-time battery parameters including voltage, current, temperature, SOC, and SOH. This enabled immediate local monitoring of battery conditions. The MOSFET switching circuit functioned correctly by controlling charging and discharging paths. Protection logic was verified under abnormal conditions such as overvoltage and overcurrent, where the MOSFET successfully disconnected the load or charging path.Overall, hardware testing confirmed reliable operation of sensing, display, and protection modules.

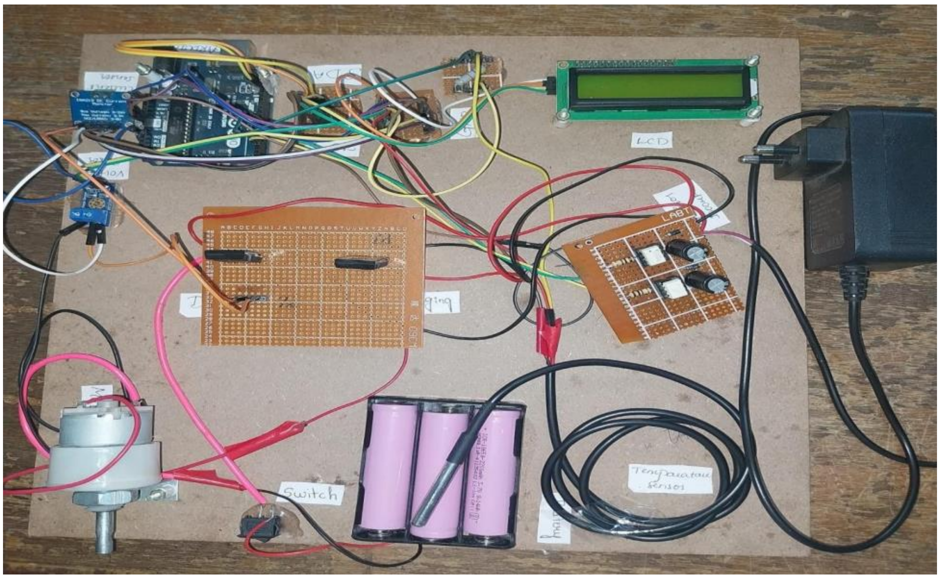

Fig 4 Hardware Setup of BMS

This hardware setup in Fig 4 shows the functions as a battery monitoring system, utilizing an Arduino to interface with current, voltage, and temperature sensors to track real-time data from the Li-ion battery pack. The measured parameters are displayed on the LCD, allowing for the calculation of State of Charge (SoC) and State of Health (SoH) while the battery powers a motor load

The LCD display in Fig 5 shows real-time telemetry from your battery system, showing a terminal voltage ,a constant current and an operating temperature. These parameters are the critical live inputs required for your algorithms to dynamically calculate the battery's current State of Charge and monitor its thermal health.

Fig 5 LCD Display of Voltage, Current and Temperature

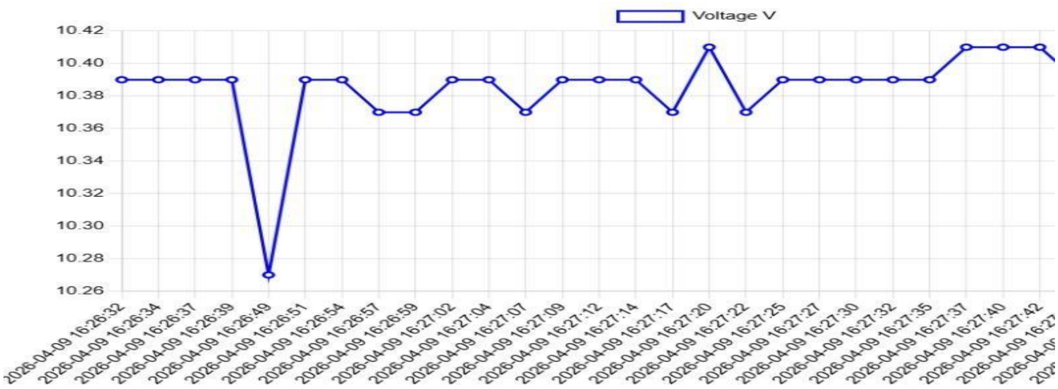

Fig .6 Battery Voltage Graph

The voltage graph in Fig 6 shows a fundamental component of battery analysis, providing the empirical data required to determine the State of Charge (SoC) through voltage-based estimation methods. By monitoring the potential difference over time, the system can map the discharge curve to identify the battery's remaining energy capacity and operational status.

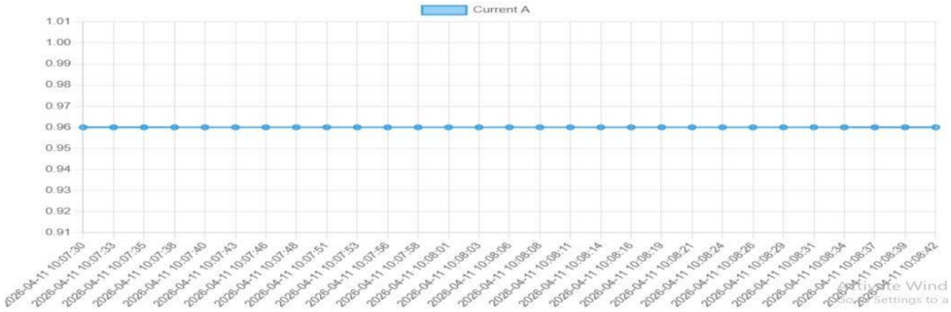

Fig. 7 Battery Current Graph

This graph in Fig.7 depicts a Constant Current (CC) profile of 0.96 A recorded over a 72- second interval, providing a stable baseline for battery modeling. In terms of State of Charge (SoC), this steady flow allows for precise Coulomb Counting, as the linear integration of this constant current directly translates to the capacity removed or added. For your State of Health (SoH) analysis this data is essential for identifying the battery's internal resistance; a steady current without fluctuations indicates a stable electrochemical state and a healthy cell response.

The graph in Fig. 8 shows the SOC graph successfully estimated SOC continuously based on measured voltage and current values. SOC values updated dynamically according to charging and discharging conditions.During battery discharge, SOC gradually decreased as current was drawn by the DC motor load. During charging, SOC values increased progressively.The estimated SOC values were smooth and stable without sudden fluctuations. Compared to traditional Coulomb Counting methods, the EKF-based estimation showed better stability and reduced drift error. The estimated SOC values were smooth and stable without sudden fluctuations. Compared to traditional Coulomb Counting methods, the EKF-based estimation showed better stability and reduced drift error.The recursive prediction and correction mechanism of EKF effectively compensated for sensor noise and battery nonlinearities.Experimental results confirmed that the EKF algorithm provides reliable and accurate SOC estimation for lithium-ion batteries under dynamic operating conditions

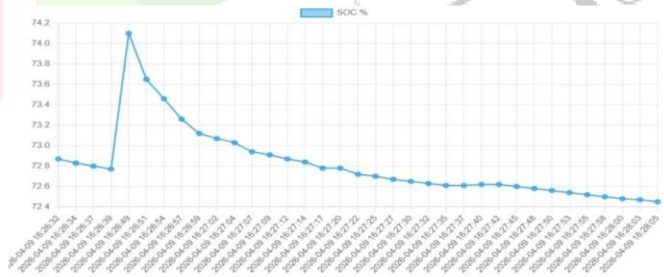

Fig. 8 SOC graph

State of Health was estimated using Extended Kalman Filter. The system successfully calculated SOH values based on current battery capacity relative to rated battery capacity. SOH values reflected battery condition appropriately. Since the test battery was relatively new, the calculated SOH remained close to 100%. As battery aging progresses over repeated charge-discharge cycles, the SOH value is expected to decrease. The implemented SOH calculation provides a simple and effective method for battery health monitoring

Fig. 9 Web Dashboard of BMS

The dashboard in Fig.9 shows the improved accessibility by allowing remote monitoring through a browser interface.The integration between Arduino, backend database, and Flask server functioned successfully. Overall, the dashboard provided an efficient interface for battery monitoring and analysis.

The developed Battery Management System successfully integrates sensing, estimation, protection, storage, and visualization into a single platform. The hardware system accurately measured battery voltage, current, and temperature. The Extended Kalman Filter provided smooth and stable SOC estimation under varying operating conditions. The system effectively reduced estimation errors associated with conventional methods such as Coulomb Counting. The backend system enabled proper data logging and remote monitoring through the web dashboard. The implemented protection mechanisms improved battery safety by disconnecting charging or load paths under unsafe conditions.The results confirm that the proposed system is reliable, scalable, and suitable for intelligent battery monitoring applications.

VIII. CONCLUSION

A real-time Battery Management System for lithium-ion batteries was successfully designed and developed to monitor important battery parameters and estimate battery State of Charge (SOC) and State of Health (SOH).The developed system integrates both hardware and software components for continuous battery monitoring. The hardware section includes voltage sensing, current sensing using INA219, temperature sensing using DS18B20, MOSFET-based protection circuits, LCD display, and Arduino Uno as the central controller. These components work together to measure battery voltage, current, and temperature in real time.The software implementation includes Arduino programming, database storage using SQLite, web-based monitoring using Flask, and State of Charge estimation using the Extended Kalman Filter algorithm. The EKF algorithm was implemented to overcome the limitations of traditional SOC estimation methods such as Coulomb Counting and Open Circuit Voltage methods. The State of Health estimation was performed using battery capacity degradation analysis. The system was able to monitor battery health and provide useful information regarding battery aging and remaining useful life. The results showed that the developed system successfully performed continuous battery monitoring, SOC estimation, SOH calculation, database logging, and web dashboard visualization. The measured voltage, current, and temperature values were stable and reliable. The EKF algorithm provided smooth SOC estimation without sudden fluctuations. The Flask web dashboard enabled remote monitoring of battery parameters and graphical trend visualization. This improved battery safety and operational reliability. Overall, the developed Battery Management System provides an efficient, low-cost, and scalable solution for intelligent lithium-ion battery monitoring applications. The integration of hardware sensing, advanced estimation algorithms, protection mechanisms, and web-based visualization makes the system suitable for real-time battery management applications.

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