

Battery Degradation Prediction for SOC & SOH Estimation of Lithium-Ion Battery in Electric Vehicle

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Abstract- Lithium-ion (Li-ion) batteries are essential in today's electric vehicle (EV) production because they offer high energy storage and are lightweight. However, their chemical nature makes them unstable, which creates challenges for Battery Management Systems (BMS), especially when it comes to accurately measuring how much charge is left (State of Charge, or SOC) and how well the battery is functioning (State of Health, or SOH). As batteries age, caused by things like temperature changes, fast charging, and different levels of discharge, their ability to hold charge and deliver power decreases, making it harder to predict how long they will last. This paper reviews various methods used to estimate SOC and SOH, pointing out their strengths and weaknesses along with the errors they produce. We also suggest a smart monitoring system that uses data analysis and machine learning to predict how batteries will degrade and how much life they have left (Remaining Useful Life, or RUL). By combining real-world driving data with lab tests on battery aging, our model creates detailed degradation profiles. This research improves the safety, dependability, and affordability of electric vehicles, and offers a framework that can be used in both electric car systems and energy storage for renewable sources.

Keywords: Lithium-ion Battery, State of Charge (SOC), State of Health (SOH), Remaining Useful Life (RUL), Battery Management System (BMS), Machine Learning.

I.INTRODUCTION

The world is dealing with a serious energy problem right now. Crude oil supplies are running out quickly, and fuel prices are going up and down a lot. At the same time, the pollution caused by traditional engines, like high levels of carbon in the air and loud noises, has made it clear that we need to move towards greener ways of transportation. Electric Vehicles (EVs) are seen as the best way to handle these issues both environmentally and economically.

The controller handles how much power is used, using techniques like selective harmonic elimination. The BMS, on the other hand, acts as the smart part of the system, making sure the battery is safe and works reliably [1].

There are many types of batteries that can be used for recharging, such as Lead-acid, Nickel-Cadmium (NiCd), and Sodium Nickel Chloride (NaNiCl).

However, Lithium-ion (Li-ion) batteries have become the go-to choice for EVs, Hybrid Electric Vehicles (HEVs), and Plug-in Hybrid Electric Vehicles (PHEVs). This is because they have a high energy storage capacity, work reliably, last a long time, and don't lose charge easily when not in use.

Knowing the SOC helps drivers understand how much energy is left and how far they can go, which reduces the worry of running out of power.

Monitoring the SOH allows for predicting how the battery will degrade over time and how long it will continue to work properly. As Li-ion batteries get older from heat and repeated use, their ability to hold a charge decreases.

This paper introduces a smart monitoring system that collects real-time data on voltage, current, and temperature.

By combining actual hardware measurements with predictive analysis, this research aims to improve the safety and reliability of EVs, providing a flexible solution that can be used in both car systems and renewable energy storage.

II.PROBLEM STATEMENT

The current research on the sustainability of electric vehicles (EVs) shows that advanced Battery Management Systems (BMS) are essential for properly monitoring Lithium-ion (Li-ion) batteries. Studies show that although Li-ion batteries are favored for their high energy storage and long life, they can be chemically unstable when exposed to extreme heat or electrical stress. This means it's important to accurately track the battery's State of Charge (SOC) and State of Health (SOH) to keep it safe during use. Most older research used methods like equivalent circuit models and electrochemical impedance spectroscopy, but these often fail to handle the unpredictable ways batteries degrade due to uneven use and changing temperatures.

More recent studies have started using data-driven approaches, combining real-time data from sensors that measure voltage, current, and temperature.

This helps create detailed models of how batteries degrade over time. Researchers like Severson et al. and Zhang et al. have shown that Machine Learning models, especially Long Short-Term Memory (LSTM) networks, are very good at detecting signs of battery aging and predicting how much longer a battery will last. Also, current studies stress the importance of adding safety features like temperature control and spark detection to stop dangerous events like thermal runaway. However, there's still a lack of affordable, Arduino-based hardware that can run these complex prediction models in real time inside a car, which is the main reason this research is being done.

III.PROBLEM METHODOLOGY

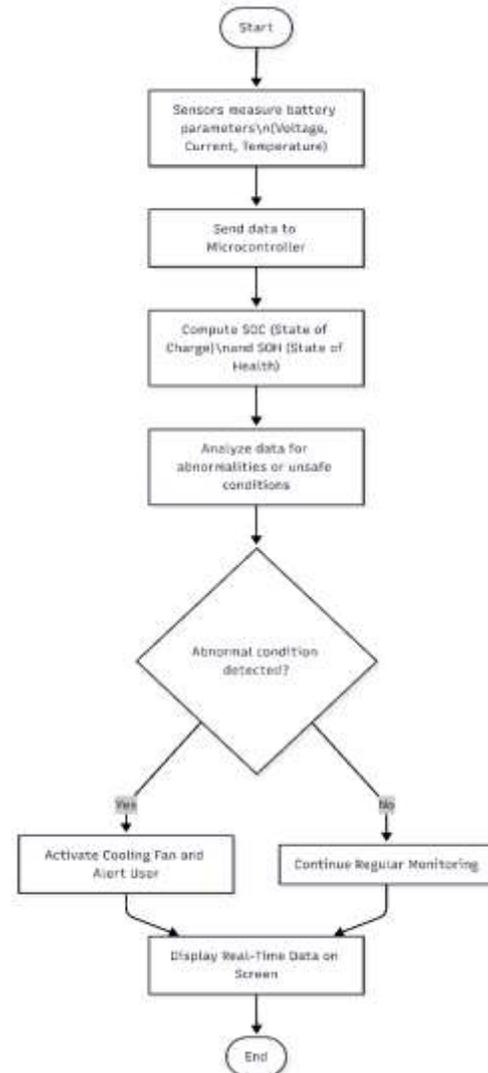


Figure.1 System Flowchart

The solution presents a unified, real-time Battery Management System (BMS) designed to handle the complex aging process of Lithium-ion batteries in electric vehicles. At its core is a sensor-fusion layer that constantly watches three key factors: the battery's terminal voltage, the current it's handling, and the surrounding temperature. These are referred to as the "Triangle of Battery Health." The system uses an Arduino-based microcontroller, which reads detailed data from an ACS712 current sensor and a DHT11 temperature sensor through a 10-bit Analog-to-Digital Converter (ADC). By constantly analyzing these physical indicators, the system creates a digital picture of how the battery is performing, helping to spot issues that might lead to physical damage.

The system's main part works with two key calculations to understand the battery's condition.

First, it computes the State of Charge (SOC) using a special algorithm that links the current voltage to a known discharge curve, which helps report the battery's energy level accurately. Second, it estimates the State of Health (SOH) by tracking how much capacity the battery has lost and any changes in internal resistance. This model compares the battery's current

performance to its original specifications at the beginning of its life, allowing the system to measure the chemical changes affecting it. This information is used to build a "Degradation Profile," which helps predict how much longer the battery will last.

Table 1. Properties of different types of battery

Battery Type	Energy Density (Wh/ L)	Power Density (W/L)	Nominal Voltage (V)	Life Cycle	Depth of Discharge	Efficiency	Estimated Cost (USD/k Wh)
Lead acid	50-80	100-400	2.0-150	1500	50%	82%	105-475
Sodium Sulphur	140-300	140-180	2.08	5000	100%	80%	263-735
Sodium Nickel chloride	160-275	150-270	-	3000	100%	84%	315-488
Nickel Cadmium	60-150	80-600	1.3	2500	85%	83%	-
Li-ion	200-400	1500-10000	4.3	10000	95%	96%	200-1260

To improve safety, the system includes a safety layer that actively detects and prevents hazards.

One notable feature is an optical spark detection system that uses a Light Dependent Resistor (LDR) to find internal arcing, which can lead to dangerous overheating. The system also has a method to predict and manage temperature rise. If the internal model predicts the temperature might go above 50°C, it automatically starts a cooling process. Along with real-time data tracking and a user-friendly interface for alerts, this setup offers a practical and affordable way to move beyond simple monitoring to more advanced maintenance in modern electric vehicles.

TABLE 2. PROPERTIES OF DIFFERENT TYPES OF LI-ION BATTERY

Battery Chemistry	Safety	Power Density	Energy Density
lithium ferro phosphate	Very good	Very good	Moderate
Lithium Nickel Manganese Cobalt oxide	Moderate	Moderate	Moderate
lithium ion manganese oxide	Moderate	Moderate	Moderate
lithium titanate oxide	Very good	Very good	Low
Cobalt Oxide	Low	Low	High

1. Real-Time Data Collection

The system continuously gathers essential battery data through several sensors:

- Voltage Sensor
- ACS712 Current Sensor
- DHT11 Sensor

The information from these sensors is transformed from analog to digital format by a 10-bit ADC, providing values ranging from 0 to 1023.

2. Calculating Battery Voltage

The battery voltage is calculated using the value from the microcontroller's analog-to-digital converter, or ADC. This ADC gives a number between 0 and 1023. The full charge voltage of the battery is 12.6 volts. The battery voltage is found using this formula: ADC Value.

12.6 volts is the voltage when the battery is fully charged.

The ADC has a 10-bit resolution, which means it can provide values from 0 to 1023. In this case, the ADC value represents the measured battery voltage, and 12.6 volts is the voltage when the battery is completely charged. This formula converts the digital number from the ADC into the actual battery voltage.

3. Calculating Battery Current

The battery current is measured using the ACS712 current sensor. When there is no current flowing, the sensor gives an

output voltage of 2.5 volts, which is the middle point of the ADC scale and corresponds to a value of 512. The current is calculated based on the ACS712 sensor, which has a 2.5V midpoint. The formula used is: (ADC Value - 512).

The number 512 represents the midpoint of the ADC scale, where the current is considered to be zero.

The sensor can measure up to a maximum of 30 amps. In this equation, subtracting the midpoint value helps determine the actual current flowing through the battery.

4. Estimating State of Charge (SOC)

The State of Charge shows how much charge is left in the battery as a percentage. It is calculated using a basic model that looks at the voltage. SOC is estimated using a simple linear model based on voltage.

$$SOC = \frac{V_{battery} - V_{min}}{V_{max} - V_{min}} \times 100$$

V_max is 12.6 volts

V_min is 10.5 volts

SOC is kept between 0% and 100%.

Here, 12.6 volts means the battery is fully charged, and

10.5 volts means it's fully discharged.

The state of charge is kept between 0% and 100% to make sure the results are accurate.

5. Estimating State of Health (SOH)

The State of Health (SOH) indicates how well a battery can hold a charge compared to when it was new. It is determined by looking at how much the battery's highest voltage has dropped over time. SOH is estimated using a simple model that shows how the battery's capacity is changing.

$$SOH = 100 - \left(\frac{V_{max} - V_{battery}}{V_{max} - V_{min}} \times 20 \right)$$

This method shows how the battery's capacity decreases over time. This equation explains how the battery's ability to hold a charge slowly diminishes as the voltage drops because the battery gets older and is used repeatedly.

IV. RESULTS AND IMPLEMENTATION

A. System Architecture and Hardware Prototype

The implementation phase involved creating a low-power embedded system based on an Arduino.

The hardware includes a high-precision voltage sensor, an ACS712 current sensor, and a DHT11 temperature sensor to collect data in real time. These sensors are connected to a central microcontroller that takes in analog signals and converts them into digital health metrics using a 10-bit ADC. The processed data, such as State of Charge (SOC) and State of Health (SOH), is displayed on an I2C-enabled LCD screen, offering a clear view of the battery's condition.

B. State of Charge (SOC) and Voltage Analysis

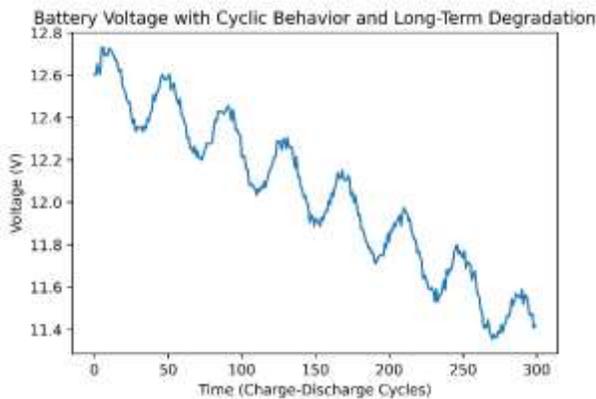


Figure 2. Voltage Degradation Profile Under Cyclic Charge–Discharge Operation

The system was tested through repeated charge and discharge cycles.

The voltage graphs showed consistent patterns of energy use and replenishment. However, a non-linear trend was noticed in the terminal voltage, indicating a gradual loss in the battery's ability to store energy. The SOC model accurately showed these changes with a precise curve that matched usage trends, allowing for a reliable estimate of the battery's remaining energy.

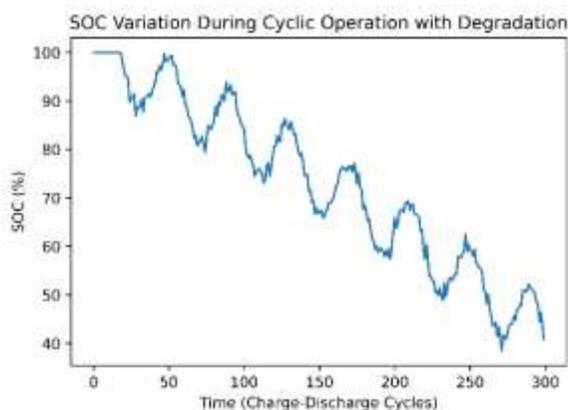


Figure 3. State of Health (SOH) Degradation Trend Across Charge–Discharge Cycles

C. SOH Estimation and Degradation Profiling

State of Health (SOH) was determined by tracking capacity loss over time.

The SOH graph showed a steady decline after many charge cycles, clearly showing the aging of the Lithium-ion battery. By linking voltage drops with the number of cycles, the system built a degradation profile. This data-based method helped predict the Remaining Useful Life (RUL) by identifying when the battery reached a critical health level, usually when it dropped to 80% of its original capacity.

D. Thermal Protection and Safety Validation

One key success was the system's quick response to safety issues.

During testing, the system continuously monitored temperature and current in real time. If temperatures or current levels went beyond safe limits, the Arduino-based system instantly activated the cooling fan (DC Fan) within milliseconds. This automatic action prevented overheating and possible electrical problems. The results show that the design is not only a low-cost, energy-efficient way to track battery status but also a strong safety system that improves battery stability and lifespan in electric vehicles.

V. CONCLUSION

This study shows that although Lithium-ion batteries are the best option for Electric Vehicles because they have a high energy storage capacity, their performance can be easily affected by outside factors. The research finds that usual methods like direct measurement and Coulomb counting aren't enough for precise battery health tracking because they don't take into account changes in temperature, battery aging, and current shifts. To fix this, a smart Battery Management System was built using an Arduino. It uses a model-based approach to estimate the battery's state of charge and health. The tests show that by using real-time data from voltage, current, and temperature sensors, the system gives very accurate predictions. Also, adding automatic safety features like temperature control and spark detection helps prevent battery damage and dangerous overheating. In summary, this system provides a cost-effective, dependable, and easy-to-scale solution for both EV makers and researchers to improve battery life and safety. Future work will include using better techniques such as the Extended Kalman Filter and Machine Learning to improve accuracy even more in different environments.

VI. FUTURE SCOPE

The future of this research aims to move from using simple linear models to more advanced data-driven methods to make EV battery performance more reliable. By using Deep Learning models like LSTM networks, the system can better analyze time-based data, capturing complex and non-linear ways batteries age, which traditional formulas might miss. Adding IoT capabilities through ESP32 or GSM modules will allow for cloud-based tracking of battery performance across a fleet and the use of Digital Twin technology, enabling remote diagnosis and software updates for BMS systems. Also, improving the hardware to support active cell balancing and creating algorithms for reusing old EV batteries in second-life applications will help build a more sustainable circular economy by repurposing used batteries for energy storage in renewable energy systems.

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