

Battery Degradation Prediction and Life Estimation

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Abstract - With more devices depending on batteries, there's a growing need to check their performance and ensure they stay safe. Over time, batteries can degrade because of things like heat, high electricity use, and frequent charging and discharging. This can make them less effective and even dangerous. This project introduces a system that helps predict how much a battery will wear out and how long it will still work. The system keeps track of voltage, current, and temperature to determine how much charge is left (SOC) and how healthy the battery is (SOH). It can spot problems early and guess how well the battery will perform in the future, which helps it last longer and work more reliably. It also has a feature that detects sparks, which improves safety by turning on a cooling fan when the battery gets too hot. The system uses a small computer chip to provide up-to-date information about the battery's condition. It's an affordable and dependable solution that can be used in many places where batteries are important.

Keywords: Battery Degradation, State of Charge (SOC), State of Health (SOH), Battery Monitoring System, Spark Detection, Cooling Fan Safety Mechanism, Real-Time Monitoring, Embedded System.

1. INTRODUCTION

As we rely more on battery-powered devices, it's important to make sure batteries work well, last long, and stay safe. Batteries in electric cars, solar or wind energy storage systems, and backup power systems gradually lose their ability to hold a charge over time. This happens due to factors like regular charging and discharging, temperature changes, high current flow, and incorrect usage. This decline in performance leads to lower efficiency, faster wear and tear, and can even cause risks like overheating or system failures. To address these issues, this project introduces a system that

can predict battery degradation and estimate how long it will last. It continuously monitors key factors like voltage, current, and temperature in real time. Using this data, it calculates important values such as State of Charge (SOC) and State of Health (SOH), which help evaluate how well the battery is working and detect any unusual behavior early. To add another layer of safety, the system also includes a way to detect sparks and automatically activates a cooling fan when needed to prevent overheating and reduce the risk of problems. This system offers a reliable, cost-effective, and efficient way to improve battery performance, extend their lifespan, and ensure they are used safely.

2. LITERATURE SURVEY

Battery degradation prediction and remaining useful life (RUL) estimation are very important for electric vehicles because battery capacity decreases and internal resistance increases due to heat and repeated charging and discharging [1], [2]. Many studies have looked at how lithium-ion batteries age and degrade, using both physics-based and empirical models [10], [14]. Traditional methods like equivalent circuit models and Kalman filter techniques are often used to estimate state of charge (SOC) and state of health (SOH), but they need careful parameter settings and do not work well when conditions change [8], [9], [13].

To fix these issues, data-driven and deep learning methods have been widely studied.

Models based on LSTM and CNN have proven effective at understanding complex battery degradation patterns and improving RUL predictions [11], [15]. Recent research also shows that data from the early cycles of a battery can be used to predict its life much earlier [5], [12]. More advanced models, such as ATCNN-BiLSTM and diffusion-based models, have performed better than traditional machine learning methods [3], [4], [6].

3. PROBLEM STATEMENT

Battery-powered systems are widely used in modern technology, but batteries gradually lose their efficiency because of temperature changes, high current usage, and frequent charging and discharging. Most existing monitoring systems only track voltage levels, which doesn't fully explain how well a battery is functioning or how long it might last. Additionally, many systems lack effective ways to prevent overheating or other unsafe conditions. Because of these issues, there is a need for a low-cost, real-time battery monitoring system that can accurately show how much charge is left in a battery (State of Charge) and how healthy it is (State of Health). The system should also include automatic safety features to improve reliability and make it safer to use.

4. PROPOSED METHODOLOGY

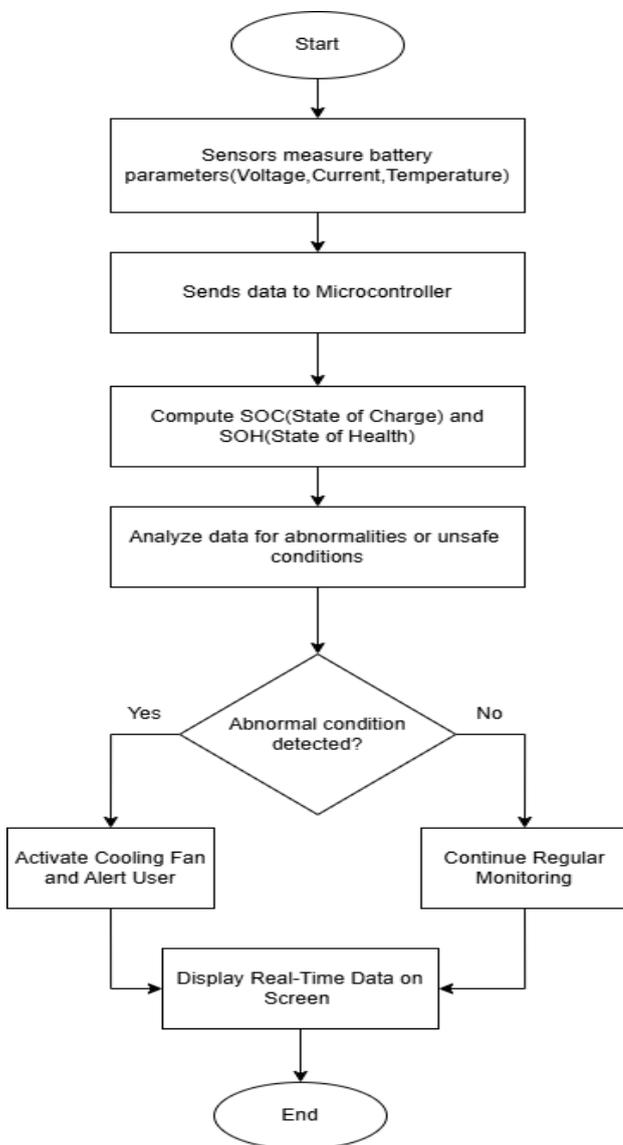


Figure.1 System Flowchart

The Battery Health Monitoring System is designed to track how batteries degrade over time and keep them operating safely. It uses real-time sensing, onboard processing, math based predictions, and safety controls to do this. The system is built using a microcontroller and follows the steps shown in the system flow diagram.

1. Real-Time Data Collection

The system keeps collecting important battery information using sensors:

- Voltage Sensor
- ACS712 Current Sensor
- DHT11 Sensor

The signals from these sensors are converted from analog to digital using a 10-bit ADC, which gives readings from 0 to 1023.

2. Calculating Battery Voltage

The battery voltage is found using the value from the microcontroller's analog-to-digital converter (ADC).

This ADC gives a number between 0 and 1023. The full charge voltage of the battery is considered to be 12.6 volts. The battery voltage is determined from the ADC reading with this formula:

$$V_{battery} = \frac{\text{ADC Value}}{1023} \times 12.6$$

- 12.6 volts is the battery's full charge voltage.
- The ADC has a 10-bit resolution, meaning it can give values from 0 to 1023.

In this case, the ADC value shows the battery voltage that has been measured, and 12.6 volts is the voltage when the battery is completely charged. This formula changes the digital number from the ADC into the real battery voltage.

3. Calculating Battery Current

The battery current is measured with the ACS712 current sensor. When there is no current, the sensor outputs a voltage of 2.5 volts, which is the middle point of the ADC scale, equivalent to a value of 512.

The current is calculated using the ACS712 sensor, which has a 2.5V midpoint.

The formula is:

$$I = \frac{(\text{ADC Value} - 512)}{1023} \times 30$$

- 512 is the midpoint value for the ADC.
 - 30 amps is the highest current the sensor can measure.
- In this equation, 512 shows where the current is zero, and 30 A is the highest current the sensor can measure. When you take away the middle value, the formula finds out how much real current is going 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:

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

Substituting the known values:

$$SOC = \frac{V_{battery} - 10.5}{12.6 - 10.5} \times 100$$

- V_max is 12.6 volts

- V_min is 10.5 volts

SOC is kept within the range of 0% to 100%.

Here, 12.6 volts means the battery is completely charged, and 10.5 volts means it's completely discharged. The state of charge is kept between 0% and 100% to give accurate results.

5. Estimating State of Health (SOH)

The State of Health (SOH) shows how well a battery can hold a charge compared to when it was new. It is calculated 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:

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

Substituting the numerical values:

$$SOH = 100 - \left(\frac{12.6 - V_{battery}}{2.1} \times 20 \right)$$

This method shows how the battery's capacity is decreasing over time.

This equation explains how the battery's ability to hold a charge slowly goes down as the voltage of the battery lowers because of getting older and being used many times.

6. Detecting Abnormal Conditions

The system constantly checks for unsafe conditions.

- Thermal Condition:

If the battery temperature exceeds the safe limit:

$$T > T_{max}$$

$$T_{max} = 50^{\circ}C$$

- Overcurrent Condition:

If the battery current exceeds the allowable limit:

$$I > I_{max}$$

$$I_{max} = 5A$$

Fan ON if $(T > 50) \vee (I > 5)$ This helps protect the battery from overheating and high current stress. If the temperature gets too high or there's too much current, the cooling fan turns on by itself to stop the device from getting too hot and to keep the battery safe from harm.

5. RESULTS AND IMPLEMENTATION

The Arduino-based system gathered data on voltage, current, and temperature in real time to calculate the state of charge (SOC) and state of health (SOH) using models that rely on voltage readings. The voltage graph displays repeating patterns of charging and discharging, along with a non-linear trend showing the battery is degrading over time. The SOC curve shows how the charge level changes with usage, while the SOH graph indicates the slow loss of battery capacity after many charge cycles. The results show the system can accurately estimate SOC and SOH in real time and correctly trigger thermal protection when specific limits are reached.

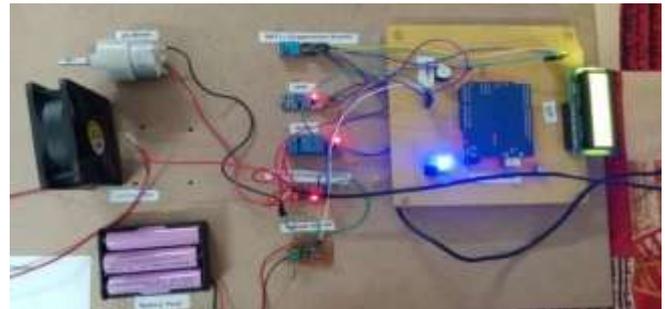


Figure 2. Hardware Setup

The prototype uses an Arduino-based system that has a precise voltage sensor, an ACS712 current sensor, and a DHT11 temperature sensor to gather data quickly and in real time. The system uses built-in calculations to estimate how much charge is left in the battery and how healthy it is. This helps keep track of the battery's performance and how it's changing over time. The processed results are displayed on an LCD screen so you can see the system's status right away. If the temperature or current goes beyond safe limits, a cooling system automatically turns on to stop overheating and electrical problems. The whole setup is an affordable, flexible, and energy-efficient design that offers real-time tracking, predicts how the battery will age, and includes automatic safety features. This makes the battery more reliable, stable, and longer-lasting.



Figure 3. LCD Output Display A



Figure 4. LCD Output Display B

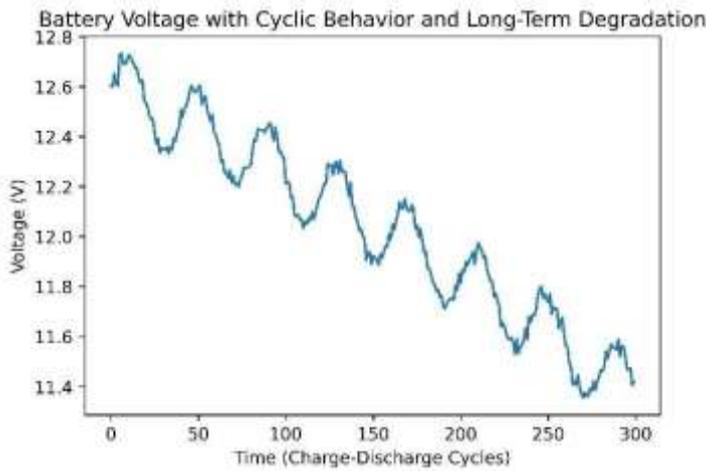


Figure 5. Voltage Degradation Profile Under Cyclic Charge–Discharge Operation

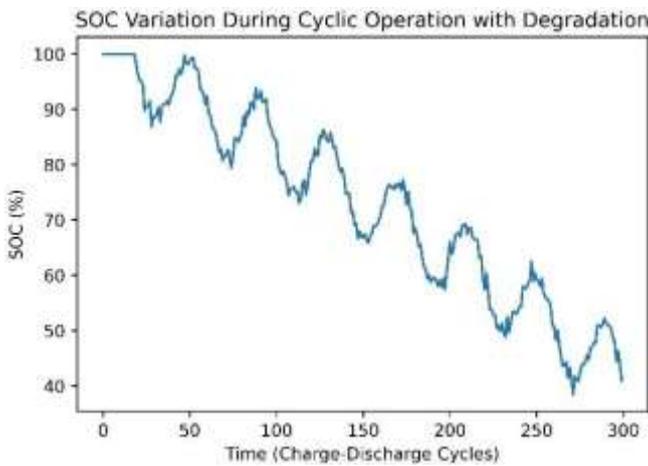


Figure 6. State of Health (SOH) Degradation Trend Across Charge–Discharge Cycles

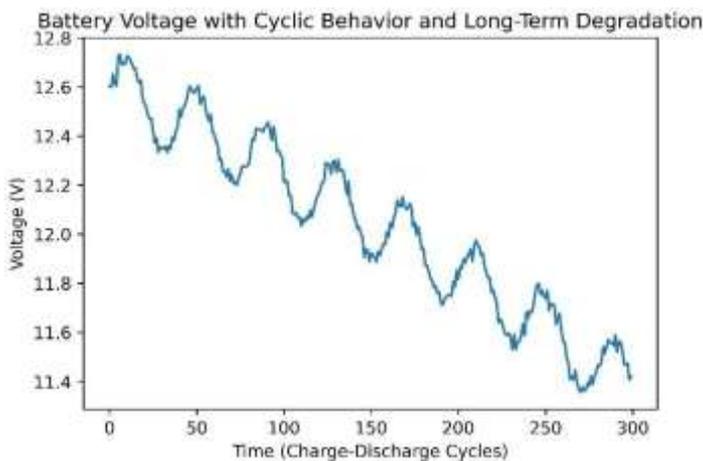


Figure 7. State of Health (SOH) Degradation Trend Across Charge–Discharge Cycles

The experimental observations indicate a gradual decline in terminal voltage over successive cycles, resulting in proportional reduction in SOC and a steady decrease in SOH, thereby validating the degradation estimation model under real-time operating conditions.

TABLE I

Experimental Battery Performance and Degradation Data

Cycle No.	Voltage (V)	Current (A)	Temp (°C)	SOC (%)	SOH (%)
1	12.60	0.12	30	100	100
50	12.05	0.24	35	74	95
100	11.35	0.30	40	40	90
150	10.85	0.38	45	17	85
200	10.60	0.45	48	5	82

6. CONCLUSION

This project shows a system that watches how a battery works and guesses how much it is wearing out by checking things like voltage, current, and temperature all the time. The system gives accurate details about how much charge is left and how healthy the battery is, which helps find problems early and spot any issues. The system also has safety tools like detecting sparks and using an automatic fan to cool things down, which lowers the risk of overheating and makes the setup safer. The system is not too expensive, works well, and is simple to set up, so it can be used in many different places where batteries are used. In general, this system helps batteries last longer, makes using them safer, and improves how well they are managed overall.

7. FUTURE SCOPE

The system can be made better by using advanced AI and machine learning methods to predict battery wear more accurately and estimate how much longer the battery will work. Models like LSTM and a mix of CNN and LSTM can help understand complicated patterns in past battery data. In the future, using AI on devices and in the cloud can allow for real-time tracking and managing many batteries at once. Using AI to find faults and manage heat can also make batteries safer and more dependable. Adding this to mobile or web apps will let people check the batteries from far away and make smart choices.

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