IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Analysis Of State Of Charge (Soc) And State Of Health (Soh) In Battery Management System

[1]Hrishikesh Kadu, [2]Niranjan Gurav, [3]Janhavi Tingare, [4]Varad Gaikwad

Department of Mechanical Engineering,
Savitribai Phule Pune University, Pune, India

Abstract: **Lithium-ion batteries are widely used in various applications, and it's crucial to manage them effectively to ensure performance and safety. A battery management system (BMS) is necessary to accomplish this task. In electric vehicles, the BMS plays a critical role since the battery pack stores a significant amount of energy. The BMS monitors battery characteristics, estimates the state of charge (SoC) using different methods, and balances cells. To estimate SoC, Coulomb Counting, Extended Kalman Filters, and Unscented Kalman Filters are commonly used. The estimates from these algorithms are compared to ensure accurate SoC estimation. Overall, the BMS is a crucial component in ensuring dependable operation and prolonging battery performance**

Index Terms - Electric Vehicle (EV), State-of-Charge (SOC), Unscented Kalman Filter (UKF), Extended Kalman Filter (EKF), Battery Pack Current, Coulomb Counting (CC), State-of- Health (SOH), Battery Management System (BMS), Cell balancing.

I. Introduction:

The use of batteries for electric transportation and portability has increased significantly worldwide, requiring high-quality standards for battery performance.[7] The Battery Management System (BMS) is crucial for maintaining optimal battery performance, ensuring safe operation, and managing various aspects of battery function, including charging, discharging, temperature monitoring, cell balancing, and fault detection. A BMS typically includes a microcontroller unit (MCU), analog-to-digital converter (ADC), battery cell balancing circuit, and communication interface. The MCU collects data from the battery cells through the ADC and performs control algorithms to maintain the battery within safe operating limits. The balancing circuit ensures that each cell is charged and discharged equally to prevent any individual cell from overcharging or over-discharging.

The direct calculation of state of charge (SoC) is unreliable due to nonlinearity, temperature, and time-dependent properties of the battery. Therefore, numerous methods have been developed to estimate SoC, and researchers are continuously developing new approaches. SoC, cell balancing, and charge limit calculation are important indicators of battery function and pack capabilities. Maintaining battery health and optimal performance requires attention to these critical factors. In addition to state of charge, the state of health (SoH) is another critical metric for battery management. SoH estimates the remaining useful life of the battery pack, enabling proactive maintenance and replacement planning. Various factors affect battery SoH, including usage patterns, charging and discharging rates, and temperature. Battery modelling is an essential tool for predicting SoH and other battery performance metrics accurately. Modelling techniques range from empirical models that use experimental data to physics-based models that simulate the electrochemical processes in batteries. Accurate battery modelling enables the optimization of BMS control algorithms for improved battery performance, safety, and longevity.

II. Methodology:

The project aims to achieve success by ensuring that each component plays its designated role. For the Battery Management System (BMS), it is broken down into three parts, as depicted in the figure, with the first part focusing on modelling the battery to define its characteristics. The second part involves estimating the State of Charge (SOC) and State of Health (SOH) using different methods. To ensure longevity and minimize errors caused by high temperatures, the BMS was designed and simulated. This simulated design led to a lower degradation rate and longer lifespan for the battery, ultimately resulting in better performance. The simulation was conducted using MATLAB to model and analyze the entire process.

Battery management system		
Battery Modelling	SOC and SOH Estimation	Thermal Management

1. Installation of a commercial BMS on a 48V, 110Ah, 3kWh Lithium-Ion battery pack.
2. Individual cells were tested in laboratory under controlled temperature and charge/discharge conditions.
3. The parameters of an Equivalent Electrical Circuit (EEC) were estimated based on the experimental data fitting using a MATLAB model and estimation software.

The assessment of battery status is a crucial aspect of BMS but it is also a weak point. It has a significant impact on the performance of the BMS and is a major concern for EV users who prioritize safety and reliability of the power system. The main worry is the possibility of running out of battery power while driving. Accurate measurement of the battery's SOC, SOH, and SOL has become a critical task for BMSs. This section provides a review of the latest approaches for predicting and estimating the state of the EV battery.[1]

III. Battery Modelling:

Battery modelling is the process of creating a mathematical model or simulation that represents the behavior and characteristics of a battery. This model can be used to predict the performance of the battery in different conditions and environments.

3.1 Battery Calculation:

We have calculated the required capacity of the battery i.e. the A-H rating of the battery.

Motor output power = 4 KW

Maximum RPM of motor = 3000 RPM

Maximum speed of motor = 65 km/m

= 18.05 m/s

Also, we have considered battery to be of 48V

O.P Power/Speed = 4000/65

= 61.538 Wh/Km

To get the AH/Km rating of the battery we divide the above value by voltage

AH/Km = 61.538/48

= 1.28204

Considering a range of 95Km in a single charge for our kart also peaukert's rating for LI-ION battery

= 1.04

Taking efficiency (n) of battery as 80%

AH rating = AH/Km rating x peaukerts rating x n x range

= 1.2820 x 1.04 x 0.8 x 95

= 101.3292 AH

Therefore, according to above calculations, we have selected a battery of <u>110 AH</u> capacity.

Charging time of battery:

= Battery Amph/Charging current (AH/A)

Charging current should be 10% of the A-H rating of the battery, therefore

AH = 110 AH

Charging current for 110 AH battery

= 110 x 10 /100

= 11 A

Charging time of battery = 110/11

= 10 Hrs (Ideal case)

Assuming 40% losses charging time increases by 4hrs, so practical charging time is 14 hrs.

Discharging time:

= Battery AH x Battery voltage /Applied Voltage

= 110 x 48 /4000

= 1.32 Hrs

Assuming 40% losses discharging time comes down to 0.528 hrs.

IV. State of Charge (SoC) Estimation:

State of Charge (SoC) is a critical parameter in Battery Management System (BMS) that indicates the amount of energy stored in a battery at any given time. It is usually expressed as a percentage of the total energy capacity of the battery.[3]SoC is expressed as a percentage and indicates how much longer the battery can operate before it needs to be charged or replaced. Since there is no sensor to directly measure SoC, various mathematical and analytical methods have been developed to estimate it. These methods include Coulomb Counting, Unscented Kalman Filter (UKF), and Extended Kalman Filter (EKF).

4.1 Coulomb Counting Method

Ampere-hour counting and current integration are other names for this procedure. This is also the most frequent method for calculating the SoC. To determine SoC values, it uses battery current data that have been mathematically integrated over time.[5] The remaining capacity is then calculated using the coulomb counting method, which accumulates the charge moved in and out of the battery. The accuracy of this approach is mostly determined on a precise measurement of the battery current and a precise estimate of the initial SoC. The State-of-Charge of a battery may be computed by integrating the charging and discharging currents during the working periods with a known capability, which may be originally determined by the operating parameters. During the charging and discharging processes, heat is lost. In addition to self-discharging, these losses result in accumulated mistakes. These aspects should be considered for a more accurate and exact SoC assessment of the battery. Furthermore, the SoC must be re-calibrated on a regular basis, and the decline of the discharging charge should be taken into account with a more precise estimation. To solve the drawbacks of the coulomb counting approach and increase its estimation accuracy, an upgraded coulomb counting technique has been devised for calculating the SoC. As a result, the SoC estimation becomes more exact and accurate. The proportion of the releasable regarding sustainability to the nominal battery is the state of charge.

4.2 Extended Kalman Filter

The Kalman filter is a method used to estimate a battery's SoC, as well as to determine the inner states of a dynamic system. It is particularly effective for linear systems in the presence of process and measurement noise. The Extended Kalman filter is the nonlinear version of this method, and it linearizes functions using their mean and covariance. The estimation process has two stages: the initial stage involves updating the time to estimate the states, which is referred to as a priori estimate. This stage uses the states from the previous iteration, an input signal sample, and the process covariance matrix as input. The second stage involves updating the measurement using feedback, known as a posteriori estimate, symbolized by the caret symbol. This stage corrects the a priori prediction of the states using the inaccuracies in calculating the output signal.

4.3 Unscented Kalman Filter

The Unscented Kalman filter differs from the EKF in that it does not linearize state-space equations. Instead, it employs a nonlinear Unscented Transformation (UT) to calculate the mean and error covariance, which are then repeatedly updated to generate sigma points for states[5] The sigma points are passed through nonlinear model functions to obtain an a priori estimate of the states and output signal. The mean and covariance of these variables are determined based on their statistics.

V. SOH Estimation:

As the battery capacity is defined as per the values of internal battery resistance. This was predicted using EKF as it has higher estimation rate then UKF. [6] This graph represents the increase in the internal resistance when the battery is used for many life cycles. As multiple uses of the batteries lead to the increase in the internal resistor which makes more heat dissipation and more increase in internal barrier which lead more opposing current factor which is known as internal resistance.

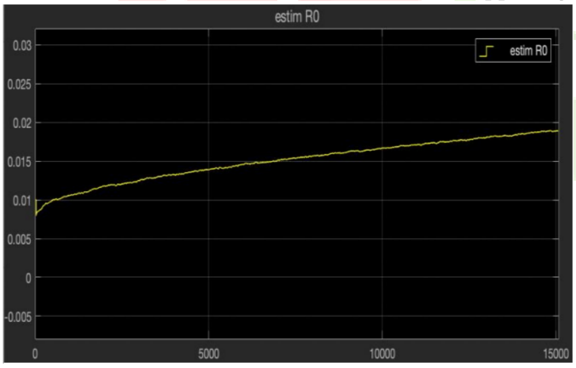

Fig: SOH estimation using EKF

VI. Results and Analysis:

6.1 State of charge (Soc)

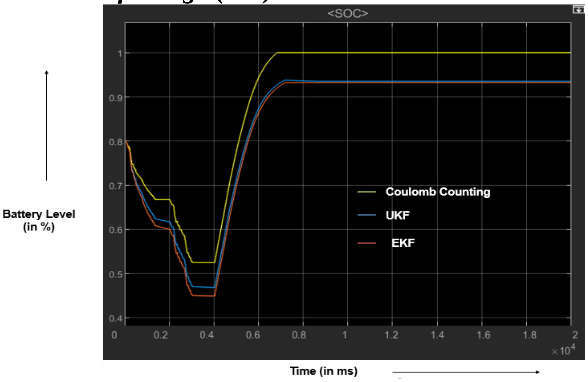

Fig: State of Charge

The graph displays the lines of three distinct SoC methods utilized in our study, represented by yellow, blue, and orange traces for Coulomb Counting, Unscented Kalman filter, and Extended Kalman filter, respectively. At the start of the discharging phase, the SoC of the cells is 80%, and as the BMS state progresses to Standby, the SoC values for the different methods fluctuate.

Sr. No	State	Coulomb Counting	EKF	UKF
1	Beginning of Discharge	80	80	80
2	End of Discharge	51.17	49.12	46.73
3	During Standby	52.65	47.8	43.6
4	Beginning of Charging	60.3	56.5	55.5
5	End of Charging	100	98.62	98.46

Note: All values are in %

Table: Comparison of Soc Estimation Methods Based on BMS States

Based on the table, it can be inferred that the Extended Kalman filter (EKF) is more precise and accurate in estimating SoC compared to the Unscented Kalman filter (UKF), as it can recover from the initial error more effectively.

6.2 BMS State

The Complete simulation of BMS is divided into three states as shown in Fig, they are,

- Discharging
- Standby
- Charging

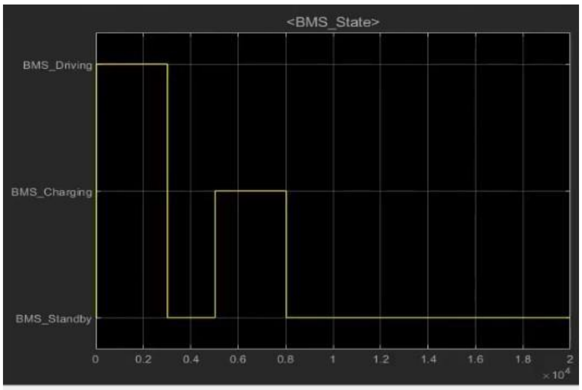

Figure: BMS State

Initially, the BMS enters the discharge state, followed by the standby state, and eventually transitions to the charging state. During the discharge state, nearly all the measured parameters are unstable, while during the standby state, they tend to become zero or low. Subsequently, during the charging state, the graphs show an attempt to achieve a stable state over time.[5]

VII. Conclusion:

MATLAB is used to perform BMS SoC estimation, and the output graphs are simulated in the Simulink Scope viewer to compare three algorithms. The SoC graph shows that the battery pack's initial SoC value is 75%, but the Estimators were initiated at 80% to evaluate their ability to recover. At the end of the charging state, the Coulomb counting, EKF, and UKF estimators reached maximum SoC values of 100%, 98.62%, and 98.46%, respectively. However, practically, SoC cannot reach 100%, and the Coulomb counting method reached 100% due to the accumulation of error from the current sensor, which is an open-loop method. The two versions of the Kalman filter are closed loop and did not reach 100%, eliminating the error.

From the obtained values, it can be observed that UKF recovers from the error much earlier than EKF by dropping to a minimum value of 46.73% and retaining it until standby mode is finished. On the other hand, EKF drops to a minimum value of 49.12%, which takes more time to recover from the error. Therefore, it can be concluded that the Extended Kalman Filter estimates more accurately in the discharging phase, while over a substantially extensive range of SoC values, EKF gives a finer SoC estimation.

VIII. References:

1. Xing Y, Ma EWM, Tsui KL, Pecht M. Battery Management Systems in Electric and Hybrid Vehicles. *Energies*. 2011; 4(11):1840-1857. https://doi.org/10.3390/en4111840

2. Electric Vehicle Wikipedia Page. Available online: http://en.wikipedia.org/wiki/Electric_vehicle

3. Cheng, K.W.E. & Bp, Divakar & Wu, Hongjie & Ding, Kai & Ho, Ho. (2011). Battery-Management System (BMS) and SOC Development for Electrical Vehicles. Vehicular Technology, IEEE Transactions on. 60. 76 - 88. 10.1109/TVT.2010.2089647.

4. Chatzakis, John & Kalaitzakis, Kostas & Voulgaris, Nicholas & Manias, Stefanos. (2003). Designing a new generalized battery management system. Industrial Electronics, IEEE Transactions on. 50. 990 - 999. 10.1109/TIE.2003.817706.

5. Bhovi, Ravi & C, Ranjith & M, Sachin & Bs, Kariyappa. (2021). Modeling and Simulation of Battery Management System (BMS) for Electric Vehicles. Journal of University of Shanghai for Science and Technology. 23. 805-815. 10.51201/JUSST/21/05347.

6. P Chatterjee et al 2021 IOP Conf. Ser.: Mater. Sci. Eng. 1116 012103

7. Piao, Changhao & Wang, Zhaoguang & Cao, Ju & Zhang, Wei & Lu, Sheng. (2015). Lithium-Ion Battery Cell-Balancing Algorithm for Battery Management System Based on Real-Time Outlier Detection. Mathematical Problems in Engineering. 2015. 1-12. 10.1155/2015/168529.