

A review on advanced techniques for state of charge estimation of electric vehicle battery pack

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Abstract— With the raising global temperatures it is recommended for alternative transport options which doesn't generate carbon emission. This can only be achieved by EVs which operate completely on electrical power provided by a battery pack. This battery pack need to be charged using renewable sources for zero carbon foot print. During the charging or discharging of the battery pack the SOC estimation of the battery is very crucial in order to ensure better charging methods for long life of the battery. SOC estimation helps the BMS to control the charge current injection to the battery pack which reduces damages and corrosion to be cells. By avoiding the corrosion, ionization of the electrodes can be mitigated which increases the charge and discharge cycles. With precise SOC estimation different charging techniques can be deployed which reduces the temperature buildup in the battery cells avoiding explosion of the battery pack. In this review paper introduction to different SOC estimation techniques that are employed in the EV battery SOC estimation module is presented. For the analysis same rating battery cell is considered for the SOC estimation with different techniques. These techniques involve traditional, modern and advanced techniques for precise SOC estimation.

Keywords— EV (Electrical Vehicle), SOC (State Of Charge), BMS (Battery Management System).

I. INTRODUCTION

This The pollution in air throughout the globe is majorly caused by the internal combustion (IC) engine vehicles which run on fossil fuels. These IC engine vehicles carbon emissions contribute 70% of environmental pollution in any major country [1]-[5]. These vehicles need to be replaced by modern vehicle technologies which has zero carbon emissions. These vehicles are electric vehicles which use battery packs to run the machine for the driving of the

vehicle. Most of the countries in the world are adopting to EV cars and most researches are done on the battery power management. For efficient power management of the battery pack in the vehicle, advanced techniques need to be used. For extended battery life and long drive range of the vehicle several measuring modules and actuators are included in the vehicle. The voltage and current measuring units are connected to the battery for SOC (State of Charge) and SOH (State of Health) estimation [5]-[9].

The SOC of a battery indicates its remaining capacity as a percentage of its full capacity. In EVs, precise SOC estimation is crucial for reliable performance, efficient energy management, battery longevity, and an enhanced user experience. Since SOC cannot be measured directly, it must be inferred from observable parameters such as voltage, current, and temperature. To improve estimation accuracy, various techniques are employed, including Coulomb counting, open-circuit voltage methods, and advanced model-based approaches like Kalman filters and machine learning algorithms [10] [11] [12]. Accurate SOC estimation prevents harmful overcharging and deep discharge, which can accelerate battery degradation, while also providing drivers with reliable range predictions to minimize range anxiety.

With the rising adoption of electric vehicles, the demand for advanced, real-time SOC estimation methods is increasing. This drives innovation in Battery Management Systems (BMS) and supports the global shift toward sustainable electric mobility. For the estimation of the battery SOC several measurements are considered which include battery voltage, current, and pack internal temperature [13] – [15]. The below figure 1 shows the internal structure of the SOC estimation of battery pack.

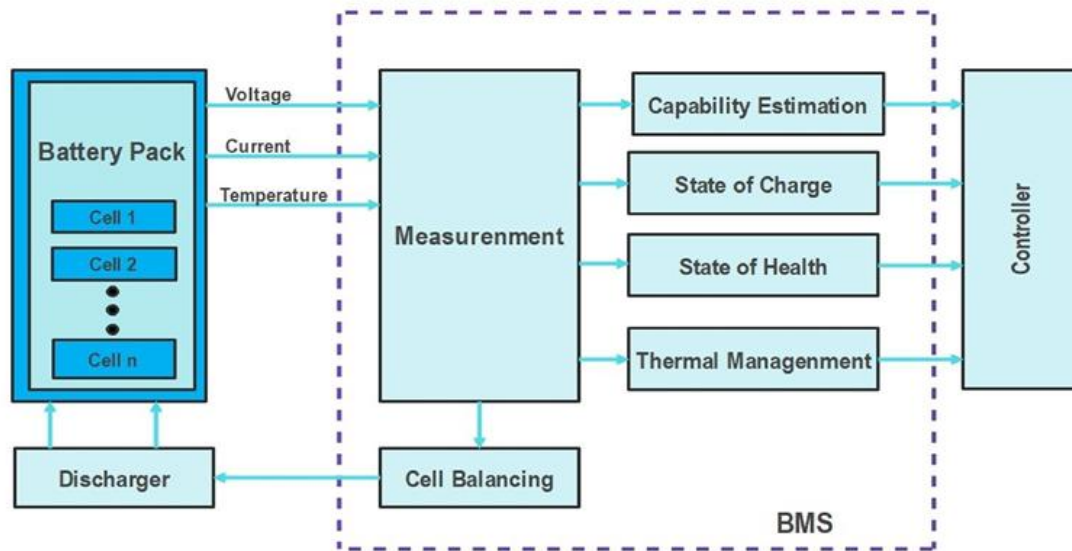


Figure 1: Structure of SOC estimation of battery pack

As observed in figure 1 the SOC estimation of the battery pack helps the controller to control the power circuits for efficient performance of the vehicle. During the charging of the battery pack from the mains, precise estimation of the SOC improves the charging capability of the battery pack [16] – [19]. The SOC estimation helps the drivers know how far they can travel before needing to recharge, reducing range anxiety. Prevents overcharging and deep discharging, both of which can severely damage battery cells and shorten battery life. Ensures optimal battery usage by maintaining operations within safe SOC limits, extending the overall lifespan of the battery. By monitoring battery status accurately, SOC estimation helps avoid dangerous situations like thermal runaway or sudden power loss. Allows for better energy management strategies, leading to more efficient use of the battery during different driving conditions [20] [21]. Enables smart charging systems to optimize charging cycles, improving charging speed and minimizing energy waste.

This paper is arranged in four section which include introduction to the SOC estimation structure in section 1 followed by SOC definition in section 2. The section 3 has the different methods for SOC estimation involving different algorithms. The internal structures and estimation algorithms are mentioned in detail in this section. The final section 4 has the conclusion to the paper followed by references cited.

II. SOC DEFINITION

The SOC of the battery is the ratio of remaining battery current capacity (Q_c) to the capacity available (Q) at specific temperature, discharge or charge ratio [22]. The SOC of the battery can be mathematically defined as

$$SOC_{bat} = \frac{Q_c}{Q} 100\% = 100\% - \frac{Q_c}{Q} \quad (1)$$

In the given expression, the denominator can be changed to rated capacity, cycle capacity or factor capacity which is not specifically defined in any research. In most of the research and software tools the term ‘rated capacity’ is mostly used for determining the SOC of the battery. The rated capacity of the battery pack (Li-ion or Lead Acid) always remains same and the SOC is estimated by subtracting the amount of charge present in the battery pack. The SOC estimated in most of the electric vehicles are calculated by its residual power (Q_c) which is considered at the time of estimation [23] – [25]. Both the numerator and denominator variables are measured in ‘Ah’ (Ampere-Hour) unit. The SOC of the battery varies with different factors inside the pack and also external of the battery. The newly updated SOC mathematical expression with these factors is given as

$$SOC_{bat}(t) = SOC_{t_0} - \int_{t_0}^t \frac{\eta I}{C_n} d\tau \quad (2)$$

Here, $SOC_{bat}(t)$ is the nominal SOC of the battery pack, SOC_{t_0} is the initial SOC of the battery pack, η is the coulomb efficiency depicted as (Q/Q_n). Here, Q is the discharge capacity and Q_n is the charge capacity of the battery. I is the battery current at time τ (in amperes, A). The battery current is considered to be negative during charging and positive during discharge. C_n is the nominal capacity of the battery. SOC indicates the remaining operational time of a battery before recharging is required. As a dynamic measure, it fluctuates in real-time during charging and discharging [26]. Precise SOC estimation is critical for Battery Management Systems (BMS), particularly in applications like electric vehicles, renewable energy storage, and portable electronics.

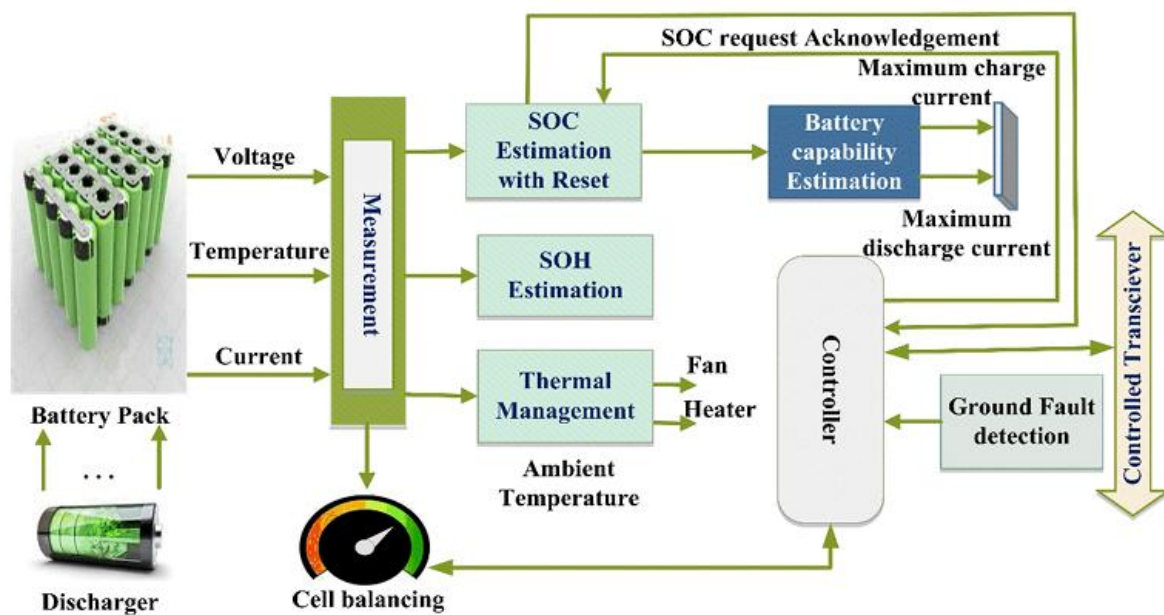


Figure 2: BMS internal structure

The figure 2 BMS is a crucial component in electric vehicles, tasked with monitoring, controlling, and safeguarding the battery pack. As the most valuable and sensitive part of an EV, the battery relies on the BMS to ensure safety, efficiency, performance, and longevity. Ensuring uniform charge/discharge across all cells to prevent weak cells from degrading overall performance or causing failure. Maintaining optimal operating temperatures by regulating cooling/heating systems, preventing degradation and thermal runaway. Tracking usage patterns and degradation to enhance long-term reliability and inform warranty or replacement decisions. By optimizing battery operation, the BMS plays a pivotal role in maximizing both vehicle performance and battery lifespan.

III. SOC ESTIMATION METHODS

Estimating the State of Charge (SOC) accurately is crucial for the safe and efficient operation of battery-powered systems, especially in electric vehicles (EVs), renewable energy storage, and portable electronics. Since SOC cannot be measured directly like voltage or current, various estimation methods are used to determine it indirectly based on measurable parameters and models [27]. Prevents overcharging and over-discharging, which can damage the battery. Enables accurate range prediction in EVs. Improves battery lifespan and system reliability. Supports energy management and thermal control. SOC estimation techniques can be broadly classified into the following categories:

A. Direct Measurement Methods:

Based on voltage or open-circuit voltage (OCV). Simple and fast but not accurate under load or temperature variations. Only effective at rest (no current flow).

B. Coulomb Counting (Ah Counting):

Tracks the current entering and leaving the battery over time. High precision short-term but prone to drift and accumulated error.

C. Model-Based Methods:

Use equivalent circuit models (ECMs) or electrochemical models to relate terminal behavior to SOC. Provide better accuracy and dynamic performance under varying conditions.

D. Data-Driven Methods (Machine Learning):

Use training data and algorithms like neural networks, support vector machines, or random forests. Require historical and real-time data but can adapt to battery aging and nonlinear behavior.

E. Hybrid Methods:

Combine multiple techniques (e.g., Coulomb counting + Kalman filter) for improved accuracy and robustness. Often used in commercial Battery Management Systems (BMS).

3.1 Open circuit voltage

The open circuit voltage SOC estimation method is considered to be the first and traditional way of estimating the battery SOC. The SOC of the battery is estimated with respect to the open circuit voltage of the battery when it is disconnected from the load or operating circuit. The relation between the battery open circuit voltage and SOC is expressed as

$$SOC = f(V_{oc}) \quad (3)$$

For generating the above expression, a 'Partnership for a New Generation of Vehicles' (PNGV) battery equivalent circuit need to be developed. The PNGV model has no complex algorithms and control modules for estimating the SOC [28]. The simple circuit of the PNGV model is presented in figure 3.

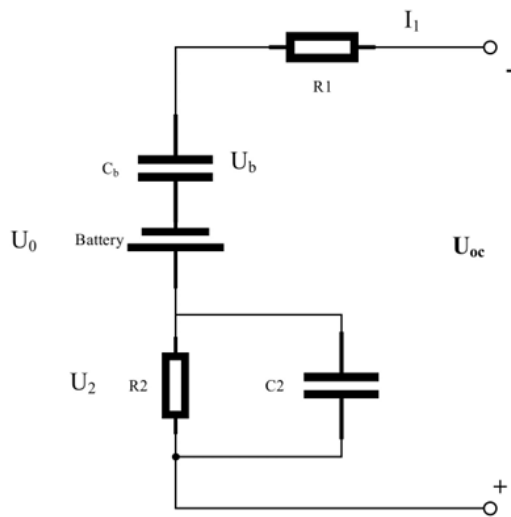
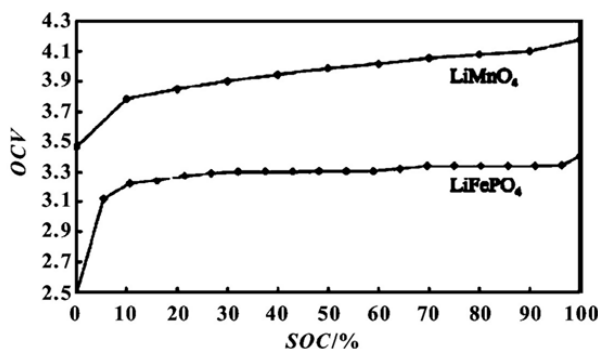


Figure 3: PNGV circuit structure

As presented in above figure the PNGV circuit with battery connected to a extra capacitor C_b in series which defines the open circuit voltage of the battery [29] [30]. When a battery is allowed to rest with no current flow for a sufficient period, its open-circuit voltage (OCV) provides a highly accurate estimate of the state of charge (SOC), as internal polarization effects (voltage drops due to internal resistance) have time to dissipate. Unlike Coulomb counting, which can accumulate errors over time due to inaccuracies in current measurement, OCV does not rely on continuous current sensing and thus avoids drift caused by sensor noise or calibration issues.

Figure 4: OCV vs SOC% for LiFePO₄ and LiMnO₄ batteries

For certain chemistries, such as lead-acid and LiFePO₄, the OCV-SOC relationship is relatively flat but consistent, making OCV a practical method for estimating SOC. In low-load applications like remote controls or smart meters, where batteries often rest between uses, OCV alone is usually sufficient [31].

3.2 Fuzzy based SOC estimation

Fuzzy logic-based SOC estimation is considered to be modern ways of determining the SOC of the battery in complex systems. The Fuzzy logic module comprises of Fuzzification and Defuzzification process for the value generation [32] – [35]. The input to the Fuzzy logic design can be several variables like change in SOC, temperature, discharge or charge current magnitude etc. The output of the Fuzzy logic design for the SOC estimation is much faster and robust compared to conventional methods. The rules

integrated in the Fuzzy module predicts the SOC of the battery with the given parameters to the estimation model. The input variables are set with specific membership functions (MFs) which are arranged in possible ranges as per the minimum and maximum values of the parameter [36] – [38]. The MFs considered for the Fuzzy based SOC estimator with different variables is presented in figure 5.

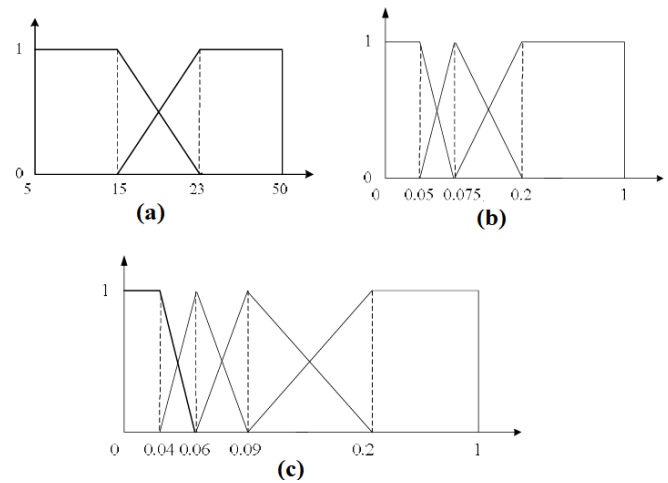


Figure 5: MFs of the considered variable (a) Temperature (b) Change in SOC (c) Output SOC value

The MFs in the variables are arranged in different shapes as per the value sensitivity. The temperature variable has only two MFs which are defined to be low temperature MF and high temperature MF. These two MFs are crossed at nominal temperature range 15 – 23°C. The values beyond 23°C are considered to be high for the battery where the SOC estimation is impacted. In the 'change in SOC' and 'SOC estimated value' there are three MFs and four MFs respectively [39]. The initial and end MFs are trapezoidal type and the middle MFs are triangular type. As the SOC value is sensitive between 4% to 20%, triangular MFs are used for accuracy improvement. Beyond 20% the SOC is almost linear to the temperature and change in SOC, therefore a flat line is sufficed for the SOC. The rule base for the SOC estimation with respect to the MFs is integrated in the Fuzzy module as per the exact value generation [40] – [42].

Once the fuzzy rules are established, the inference process is computationally efficient, making it well-suited for embedded systems such as drones and electric vehicles [43] – [45]. These rules can be derived from battery behaviour observed in laboratory tests or field data. The shape and type of MFs in the fuzzy logic module can be customized based on the specific battery chemistry. Unlike open-circuit voltage (OCV) methods, which require rest periods, fuzzy logic operates in real-time under load. It can also account for asymmetric voltage behaviour during charging and discharging, as seen in batteries like lithium-ion [46]. Overall, fuzzy logic-based state-of-charge (SOC) estimation is ideal for applications that demand real-time performance, robustness to uncertainty, and integration of multiple sensor inputs.

3.3 Kalman filter based SOC estimation

For the estimation of SOC of a battery using 'Kalman Filter' method cannot be used evidently directly. For this method of estimation 'Taylor series' expansion for generative

linearization equation [47] – [50]. And the ‘Extended Kalman Filter’ based modeling is generating linearization equation for non-linear systems like battery SOC estimation. For the EKF based SOC estimation, mathematical model of Li-ion battery is required for the given equivalent diagram of the Li-ion battery in figure 6.

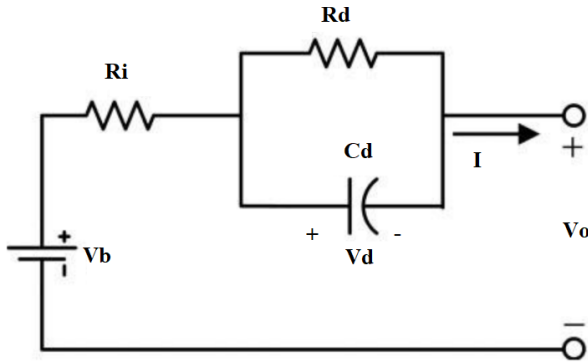


Figure 6: Li-ion battery equivalent circuit

For the above equivalent Li-ion circuit the non-linear mathematical expressions are given as

$$\begin{bmatrix} SOC \\ V_d \end{bmatrix} = \begin{bmatrix} \frac{I}{kC_b} \\ -\frac{I}{R_d C_d} V_d + \frac{1}{C_d} I \end{bmatrix} \quad (4)$$

$$V_o = k * SOC + V_d + IR_i + d \quad (5)$$

Here, V_d is the voltage across the capacitor C_d , C_b is the charge of the battery, R_d is the residual resistance, R_i is the internal resistance, I is the charge or discharge current, k and d are battery coefficients which change as per the temperature and SOC of the battery [51] – [53]. As per the given battery equations (3) and (4) the state space equations are given as

$$Z = [z_1 \ z_2]^T; \ z_1 = SOC; \ z_2 = V_d \quad (6)$$

$$a(t) = I; \ b(t) = V_o \quad (7)$$

The proposed circuit input is considered to be $a(t)$ which is the current of the battery and the output of the circuit is $b(t)$ which is the output voltage [54] [55]. The updated battery model is expressed as

$$\dot{z} = f(z, a) + w \quad (8)$$

$$y = g(z, a) + v \quad (9)$$

In the given expressions the w and v are the model noise and measurement noise. Here the two functions of the battery are taken as

$$f(z, a) = \begin{bmatrix} \frac{a}{kC_b} \\ -\frac{I}{R_d C_d} z_2 + \frac{1}{C_d} a \end{bmatrix} \quad (10)$$

$$g(z, a) = k z_1 + z_2 + a R_i + d \quad (11)$$

The Tylor series expansion for the non-linear model of the above equation of the battery after linearization are expressed as

$$\delta \dot{z} = A_t \delta z + B_t \delta a + w \quad (12)$$

$$\delta y = C_t \delta z + D_t \delta a + v \quad (13)$$

In the given expressions (11) and (12) the state space variable are given as

$$A_t = \frac{df(z,a)}{dz} | z(t); \ a(t) = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{R_d C_d} \end{bmatrix} \quad (14)$$

$$B_t = \frac{df(z,a)}{da} | z(t); \ a(t) = \begin{bmatrix} \frac{1}{kC_b} \\ \frac{1}{C_d} \end{bmatrix} \quad (15)$$

$$C_t = \frac{dg(z,a)}{dz} | z(t); \ a(t) = [k \ 1] \quad (16)$$

$$D_t = \frac{dg(z,a)}{da} | z(t); \ a(t) = R_i \quad (17)$$

As per the give expressions the internal structure of the Kalman filter design is presented in figure 7.

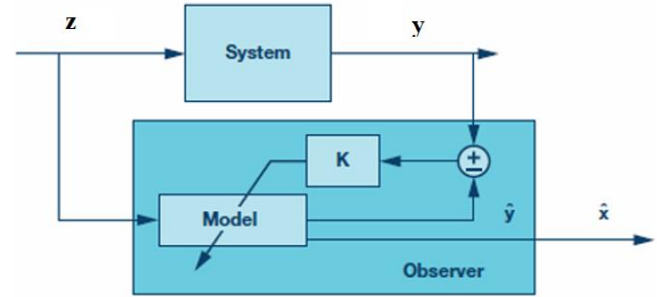


Figure 7: Kalman filter design of the SOC estimation

In the given figure 7 the ‘System’ is the battery pack which has input (z) and output (y) which are considered for the SOC estimation [56]. The variable ‘ K ’ is the tuning factor in the ‘Observer’ module which defines the ‘Kalman Filter’ Model. The model predicts the reference ($\hat{y}$) and the output variable (estimated SOC) $\hat{x}$ [57].

IV. CONCLUSION

SOC estimation is a critical aspect of BMS, impacting the performance, safety, and longevity of batteries. Various methods have been developed to estimate SOC, each with its own advantages and limitations. The choice of SOC estimation method depends on factors such as accuracy requirements, computational constraints, and application-specific needs. Future advancements may focus on adaptive algorithms, improved sensor integration, and AI-driven models to enhance SOC estimation reliability for next-generation battery systems. Thus, ongoing research and technological improvements will continue to refine SOC estimation, ensuring efficient and safe battery operation across various industries. Accurate SOC estimation is fundamental for optimizing battery performance, ensuring safety, and prolonging lifespan in applications ranging from EVs to renewable energy storage. No single SOC estimation method is universally optimal; the selection depends on application requirements, computational resources, and desired precision. As battery technologies evolve, SOC estimation must advance in parallel, embracing AI-driven innovations, improved sensors, and adaptive control strategies. Future research should focus on standardization, scalability, and real-time validation to meet the growing demands of next-generation energy storage systems.

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