A Comprehensive Study on the Existing Techniques of SOC Estimation of the EVs Battery

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ABSTRACT

Due to the rapid development of Electric vehicles (EVs) day by day as well as the global focus on mitigating the environmental pollution, a large portion of the world is growing interest on EVs. To ensure efficient driving performance, an advanced battery management system is required, incorporating State of Charge (SOC) techniques with high accuracy. SOC is similar to fuel gauge for EVs, which indicates the remaining capacity of battery. Researchers are actively working to develop more advanced method for stable and nearly 100% SOC estimation. Although many SOC estimation techniques have been developed, a significant research gap remains in addressing the limitations related to handling non-linear behaviors, sensor errors, data dependency, and the lack of physical feedback in practical scenarios. The main aim of this article is to review the literature of existing categories and mathematical model of SOC estimation. This paper also describes each method of SOC estimation in details with present drawbacks and positive aspects as well as provides an opinion which methods are best in various conditions.

Keywords: State of Charge (SOC), Electric Vehicles, Battery Management System (BMS), Coulomb Counting Method, Kalman Filter, Deep Learning Model.

1. INTRODUCTION

Currently whole world is concerned due to the use of high number of diesels, gasoline in vehicles which produces tremendous amount of carbon dioxide, sulfur dioxide, nitrogen oxide results in global pollution and fast change of climates. The transportation industry, which is largely concentrated in urban areas, emits more than 20% of total greenhouse gas emissions [1]. Another concerning portion is that, due to the use of high amount of fossil fuels which may lack in recent future [2]. To mitigate these issues, most of the countries are focusing on Electric vehicles (EVs) which is comparatively more environment friendly, and emits very lower amount of greenhouse gas [3]. To power up EVs, generally rechargeable lithium-ion, lead acid and metal-nickel-hydride batteries are so much popular. But these batteries have few drawbacks with several advantages. One of the disadvantages is over charging and over discharging reduce battery life sometimes may damage completely [4]. To solve this problem Battery Management System (BMS) as shown in Fig. 1 is introduced, which enhances battery life. The main function of BMS is to collect raw data of voltage, current, temperature, State of Charge (SOC), State of Health (SOH), State of Power (SOP), protects from over charging, over discharging, overheating and short circuit, cell balancing, and communication with External Control Unit (ECU) [5-8].

In this study, we will only focus on SOC estimation of battery. SOC is mainly responsible to protect the battery from over charging and over discharging. It defines as the ratio of remaining charge to the nominal capacity of the battery. It generally expresses as percentage [9].

$$\text{SOC} = \frac{\text{Current Capacity (Ah)}}{\text{Total Capacity (Ah)}} \times 100\% \qquad (1)$$

For Example, considering a half charged 12V 100 Ah battery,

$$\text{SOC} = \frac{50}{100} \times 100\% = 50\% \qquad (2)$$

Accurate SOC estimation directly affects electric vehicles performance. Due to the parameter uncertainties, SOC estimation is not easy [10, 11]. A lot of research was already done for effectively SOC estimation. Researchers

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estimated SOC through following categories: Direct measurement, Book keeping, Filter based and Data driven. Direct measurement method utilizes physical properties such as voltage and impedance [12]. But it is more applicable during stable state condition of battery as well as is not an effective method. Book keeping method [13] is far better than direct measurement method. But due to the error of initial SOC estimation, Kalman filter family [14-16] is over popular. Few researchers estimated SOC through data driven category such as Neural Network [17], Fuzzy Logic [18], Random Forest [19] etc. But in this case for higher efficiency, enormous data collection is required. This article presents every existing method of SOC estimation. Lastly, the best method for SOC estimation is determined.

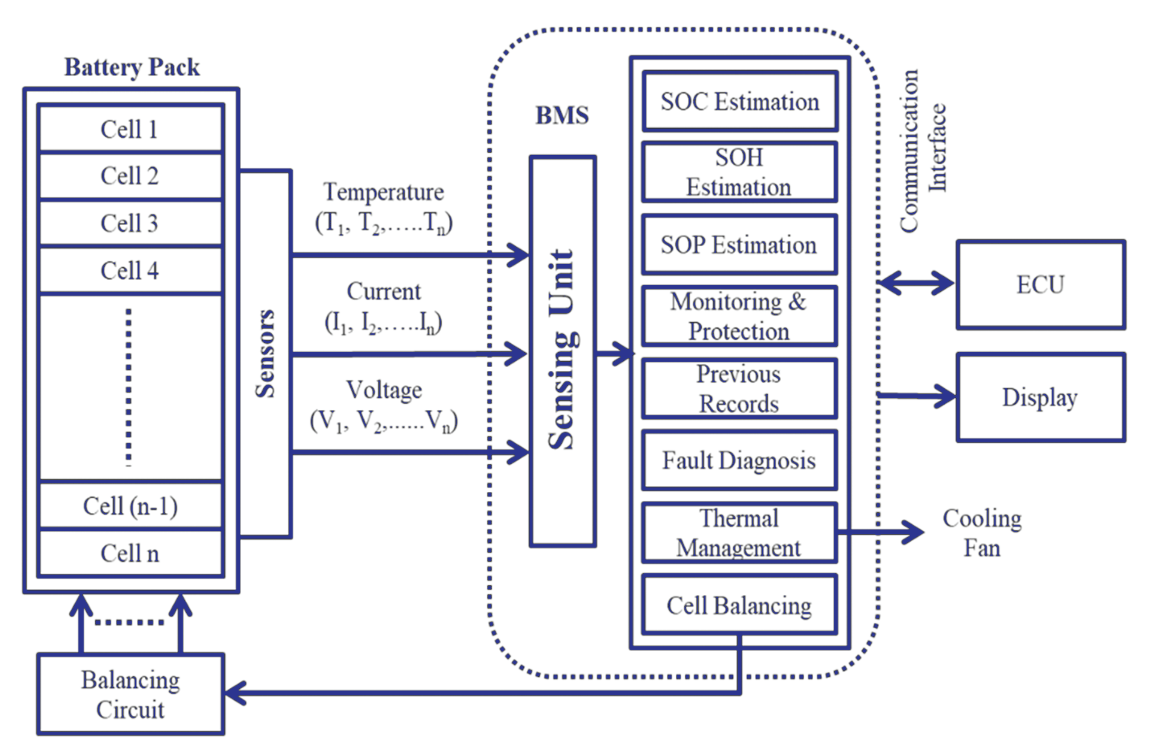

Fig. 1: Simple Block Diagram of Battery Management System

2. BATTERY MODEL

Modeling helps us to understand the battery behavior that will help to improve the system performance and increase the system efficiency. Battery can be modeled to describe the V-I Characteristics, charging status and battery's capacity. It is therefore necessary to create an exact electrical equivalent model that will help to determine the battery efficiency. There are different electrical models which will be discussed and examined along with the benefits and demerits. The mathematical relationship between the elements of Lithium-ion batteries and their V-I characteristics, state of charge (SOC), internal resistance, operating cycles, and self-discharge is depicted in a Lithium-ion battery model. The equivalent circuit model of a Lithium-ion battery is a performance model that uses one or more parallel combinations of resistance, capacitance, and other circuit components to construct an electric circuit to replicate the dynamic properties of Lithium-ion batteries. Time domain analysis is used to produce the most often utilized electrical equivalent models.

The battery model must reflect proper static and dynamic characteristics of the battery for the accurate estimation of SOC.

(a) Rint Battery Model: Rint model (Internal Resistance Model) is a basic equivalent circuit, consists of internal resistance and ideal voltage source. It is also known as 'resistance in series' model. This model design is simple and easy to implement. But it is able to capture some aspects of dynamic behavior of batteries in a limited sense and ignores hysteresis because of the absence of capacitance, which leads an inaccurate SOC estimation [20, 21].

(b) Thevenin Battery Model: Thevenin model which is the combination of a parallel R_pC_p network with Rint model in series. It is also known as Single RC model. It is able to describe the polarization effect of the battery. It has a good controlling capability of dynamic behavior [21]. This model exhibits the abrupt and gradual changes of voltage during charging and discharging.

Polarization Behavior:

$$V_{RC}(t) = V_{RC}(0)e^{\frac{-t}{R_P C_P}} + 1R_P\left(1 - e^{\frac{-t}{R_P C_P}}\right) \tag{3}$$

Dynamic Behavior:

$$V(t) = V_{OC}(SOC) - IR_0 - V_{RC}(t) \tag{4}$$

Here, the series resistance R_0 represents sudden change of resistance and parallel R_pC_p network is used to gradual voltage changes [22]. The C_p partially corrects the hysteresis behavior. Higher the value of C_p, lower the hysteresis behavior.

(c) PNGV Battery Model: It is a nonlinear equivalent circuit model, which is preferred over Thevenin model

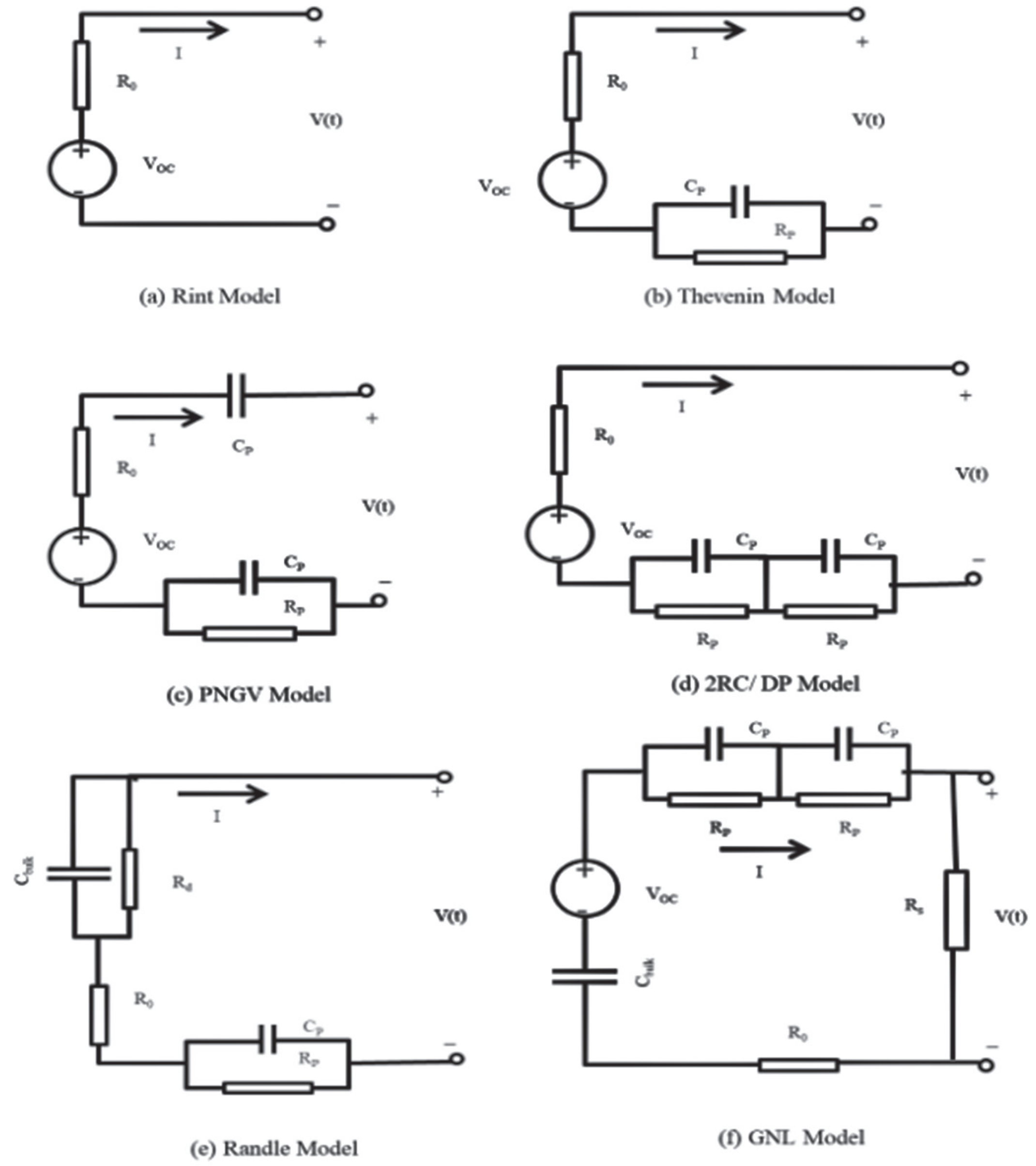

Fig. 2: Battery Model

because it represents the complex battery dynamic behavior more accurately [20, 23]. PNGV model is the combination of Thevenin model and a bulk capacitor which is shown in Fig. 4. The bulk capacitor provides long-term charge storage effects, improving SOC estimation [21]. During transient phase, PNGV model can determine voltage at various SOC. This model is also able to capture both slow and fast dynamic response, which make it more applicable for hybrid electric vehicles. Another improved version of PNGV battery model is proposed, in which an extra parallel R_PC_P network is added in series with conventional PNGV model, to describe the cell polarization more accurately. Also, this improved version of PNGV model provides more accuracy than other models [24].

(d) Dual-polarization Battery Model: Dual-polarization (DP) model is more preferred for online SOC estimation [25]. This model is the improve version of Thevenin model. An extra parallel R_PC_P network is connected in series with the first R_PC_P network as shown in Fig. 5. To capture electrochemical polarization and slow diffusion and relaxation effects as well as higher accuracy 2RC is generally used over Thevenin model [21, 26]. Because of the higher-order RC model (3RC, 4RC etc.) calculation is comparatively complex, 2RC model is used more for battery SOC estimation, despite the slightly lower precision.

(e) Randle Battery Model: The Randle battery model is a mathematical representation which primarily focuses on battery impedance and electrochemical behavior. The battery or power source isn't directly included with this equivalent circuit unlike previously mentioned battery models. The Randle model is shown in Fig. 2(e), where capacitive charge storage C_{bulk} represents SOC indicator, a high valued self-discharge resistance R_d is connected with C_{bulk} in parallel, parallel R_PC_P network indicates small time-constant electrochemical transitions, and R_0 is the internal resistance. The impedance of the battery is obtained through the Electrochemical Impedance Spectroscopy and based on the impedance value; all components of this equivalent circuit are chosen. This model was developed by targeting lead acid batteries [27]. The design of this model is pretty similar to Thevenin model but its accuracy to estimate SOC is comparatively lower. To analyze multiple transient responses, a large number of parallel R_PC_P networks can be added in series with the model [20, 28].

(f) GNL Battery Model: The GNL model contains the characteristics of Rint model, Thevenin model and PNGV model. Comparing other models, the battery SOC estimation accuracy, performance of charging and discharging process are higher of this model. But due to the high complexity in calculation and parameter selection, this model is not popular for real time SOC estimation [20, 29, 30].

3. SOC MEASUREMENT METHODS

3.1 Direct Measurement Methods

Based on the physical attributes of batteries, Direct Measurement Methods are classified as following categories-

(a) Open Circuit Voltage Method: Open Circuit Voltage (OCV) method refers to measure the potential difference across the two terminals of power source or circuit when no current flows. This method is more applicable when there is a direct relationship between open circuit voltage and SOC.

Mathematically, open circuit voltage,

$$V_{OC}(t) = a \times SOC(t) + V_0 \tag{5}$$

Where, V_0 is the lowest possible OCV, when SOC is 0% and is the slop, which represents the change of OCV with respect to SOC. This linearity is generally observed in lead acid battery [31]. But all batteries don't follow linearity such as lithium-ion batteries [32]. Also, this method gives reliable output when the battery is in stable state. To reach in equilibrium state, sometimes battery takes long time around two hours. It is impossible to wait for this long duration practically to SOC estimation [13]. Another demerit is the OCV method is heavily influence by the cell ambient temperature [33].

(b) Terminal Voltage Method: Terminal voltage method which considers internal resistance (R_{int}) during discharging. Due to the internal resistance, it differs from the OCV method [31].

Mathematically, terminal voltage,

$$V_t = V_{OC}(t) + IR_{int} \tag{6}$$

According to equation 5, OCV is proportional to SOC, similarly terminal voltage is approximately proportional to SOC. The main disadvantage is that due to sudden drop of battery voltage at the end of discharge the inaccuracy of terminal voltage is higher [34]. The output terminal voltage is also affected by temperature and to get the proper output, the system must be in equilibrium state.

(c) Impedance Method: The impedance is measured through the ratio of voltage and current, which represents the capacity of battery. This method has high accuracy to estimate SOC at the end of discharging. But it is difficult to get correct internal impedance due to its milliohm range value. The impedance parameters are not identical, this is why this method is preferred for SOC estimation [13].

(d) Electrochemical Impedance Spectroscopy Method: According to the authors [35], the main principle of this method is to excite the steady state electrochemical system by using a small amplitude AC signal and measures the impedance spectroscopy through the ratio of fluctuating voltage and current. This impedance is generally used to estimate SOC indirectly [31].

3.2 Book-Keeping Method

Book-keeping is known as coulomb counting method. Coulomb counting is one of the easiest ways to estimate SOC which is shown in Fig. 3. In this case SOC is determined through the combination of initial value of SOC and the integration of current which flows in or out of the battery [36]. The charging and discharging state of battery is defined through the direction of the current.

During charging,

$$SOC_t = SOC_0 + \left(\int_0^t \frac{\eta I_{bc}}{C_b} dt \times 100\% \right) \tag{7}$$

During discharging,

$$SOC_t = SOC_0 - \left(\int_0^t \frac{\eta I_{bd}}{C_b} dt \times 100\% \right) \tag{8}$$

To set the value of SOC_0, generally the battery should be full charged, if possible, otherwise based on starting condition SOC_0 is estimated through the test either open circuit or loaded voltage. The SOC is estimated correctly through this method for short term. In the case of long term, due to the lack of self-correction ability, this method is failed to provide proper estimation. With the number of charging and discharging cycle the error of SOC is increased. The researchers Ng et al exhibited that during 5th cycle the error is around 2.2% and this error reaches to 9% after 25th cycle [37]. This is why periodic recalibration is requires for reliable estimation of SOC. Another disadvantage is that this method isn't count the issue of battery capacity due to aging by repeated charging and discharging, internal impedance as well as self-discharge of the battery, which lead an inaccurate SOC. Some groups of researchers already tried to enhance the coulomb counting efficiency. Two groups of researchers [38, 39] considered recalibration and self-discharge correction to enhance coulomb counting which depicts through the flowchart in Fig. 4. When the battery is at open circuit ($I_b = 0$), self-discharging is occurred. Also, due to the over discharge and over charge, internal resistance is varied, which can affect correct SOC estimation. To remove this issue and for the safety of battery recalibration are introduced by them. Another researcher focused on internal resistance of battery and battery aging. To reduce the error of initial value of SOC, they combined open circuit voltage and the potential drop across the internal resistance as shown in equation 9. They also monitor battery capacity that is decreased with charging and discharging cycle.

At k-1 cycle,

$$SOC_{t-1,k} = V_{OC} \pm (I_b \times R_{b,\,k-1}) \times 100\% \tag{9}$$

During Charging,

$$SOC_{tcc,k} = \left(\left(V_{OC} - \left(I_{bc} \times R_{b,k-1} \right) \right) \times 100\% \right) + \left(\int_0^{t_{cc}} \frac{\eta_{k-1} I_{bc}}{C_{b,k-1}} dt \times 100\% \right)$$

$$= \left(\left(V_{OC} - \left(I_{bc} \times R_{b,k-1} \right) \right) \times 100\% \right) + \left(\frac{t_{cc} \eta_{k-1} I_{bc}}{C_{b,k-1}} \times 100\% \right) \tag{10}$$

Similarly at cut-off voltage during discharging,

$$SOC_{tcut\_off,k} = ((V_{OC} + (I_{bd} \times R_{b,k-1})) \times 100\%) - \left(\frac{t_{cut\_off} \eta_{k-1} I_{bd}}{C_{b,k-1}} \times 100\% \right) \tag{11}$$

At the K cycle,

Coulombic efficiency,

$$\eta_k = \frac{t_{cut\_off} I_{bd}}{t_{cc} I_{bc}} \tag{12}$$

The battery capacity for charging,

$$C_{b,k} = \frac{t_{cut\_off} I_{bd}}{SOC_{tcc,k}} \tag{13}$$

The battery capacity for discharging,

$$C_{b,k} = \frac{\left(t_{cut_{off}} I_{bd} \right)^2}{t_{cc} I_{bc} \times SOC_{tcut\_off,k}} = \frac{t_{cut\_off} I_{bd}}{SOC_{tcut\_off,k}} \tag{14}$$

The enhance coulomb counting methods are not completely capable for estimating SOC despite by removing issues of conventional coulomb counting method. These methods are unable to eliminate the sensors errors, which is one of the obstacles to correctly estimate SOC. For this reason, most of the researchers, battery management companies are currently shifting to Kalman filter family or Data driven methods.

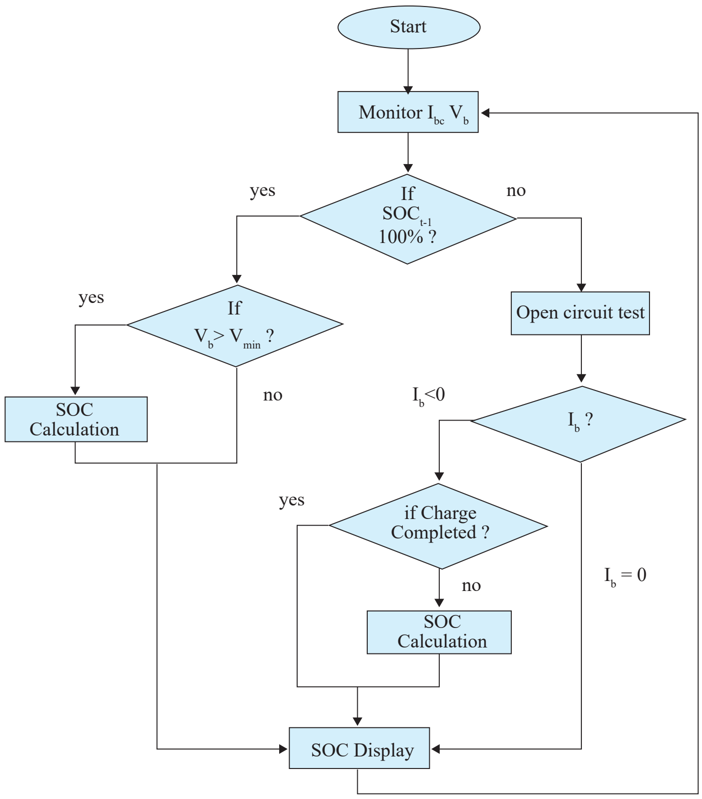

Fig. 3: Flowchart of Conventional Coulomb Counting Method

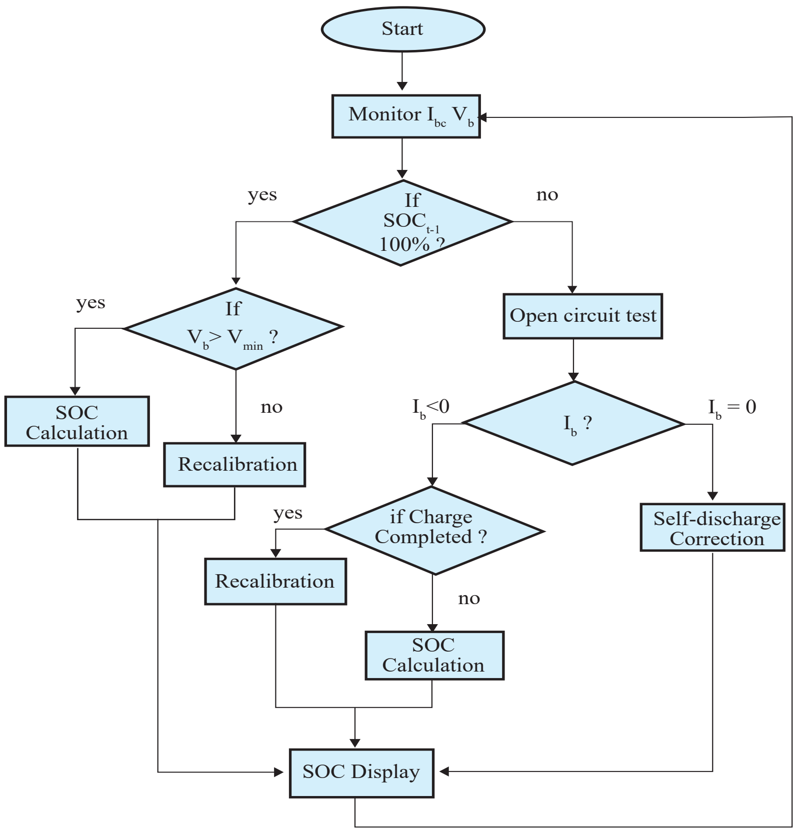

Fig. 4: Flowchart of Enhanced Coulomb Counting Method

3.3 Filter Based Methods

Filter-based methods estimate the state of the system from the perspective of noise elimination. The filter-based approach, which combines a battery model with an iterative process of closed-loop SOC estimation, has been proven to be accurate and real-time achievable due to its low complexity. Compared with the state observer method, the filter-based method the filter-based method has lower computational complexity and is easy to implement online SOC estimation. Moreover, compared to the state observer method, the filter-based method avoids the complicated proof process of the convergence performance. Therefore, the filter-based method is more suitable for the battery SOC estimation.

(a) Kalman Filter: Kalman filter is a recursive estimation technique, which was developed by Rudolf. E Kalman in the 1950s. This method offers real time correction and also has excellent capability to handle noise and work in dynamic conditions capability that makes it more suitable for SOC estimation over coulomb counting method [40]. The summary of Kalman filter algorithm for SOC estimation is given in table I.

Fig. 5 describes the SOC estimation using Kalman filter, where the temperature, current and voltage of battery pack are measured through the sensor. The estimated voltage obtained from the battery model and the difference between estimated voltage and measure voltage are the input of update step where Kalman gain is calculated [41]. As well as in this step, the SOC state is updated using state update equation.

Table I: Summary of Kalman Filter Algorithm for SOC Estimation [42, 43]

Initialization Step	$\hat{x}_0$, P_0
Measurement Step	$z_k - H\hat{x}_k^-$, $H\hat{x}_k^-$
Update Step	$K_k = P_k^- H^T(HP_k^- H^T + R)^{-1}$ $\hat{x}_k = \hat{x}_k^- + K_k(z_k - H\hat{x}_k^-)$ $P_k = P_k^-(I - HK_k)$
Prediction Step	$\hat{x}_k^- = A\hat{x}_{k-1} + Bu_{k-1} + w_k$ $P_k^- = AP_{k-1}A^T + Q$

Here, $\hat{x}_0$ = initial estimated SOC, P_0 = initial error covariance, z_k = measured voltage (Sensor Output), $H\hat{x}_k^-$ = estimated Voltage, $(z_k - H\hat{x}_k^-)$ = residual, K_k = Kalman gain, P_k^- = predicted error covariance, H = measurement matrix, R = measurement noise covariance, $\hat{x}_k^-$ = predicted SOC, P_k = updated error covariance, I = identity matrix, A = state transition matrix, $\hat{x}_{k-1}$ = previous estimated SOC, B = control matrix, u_{k-1} = previous control input (typically indicates battery current), w_k = process noise, P_{k-1} = previous error covariance, Q = process noise covariance.

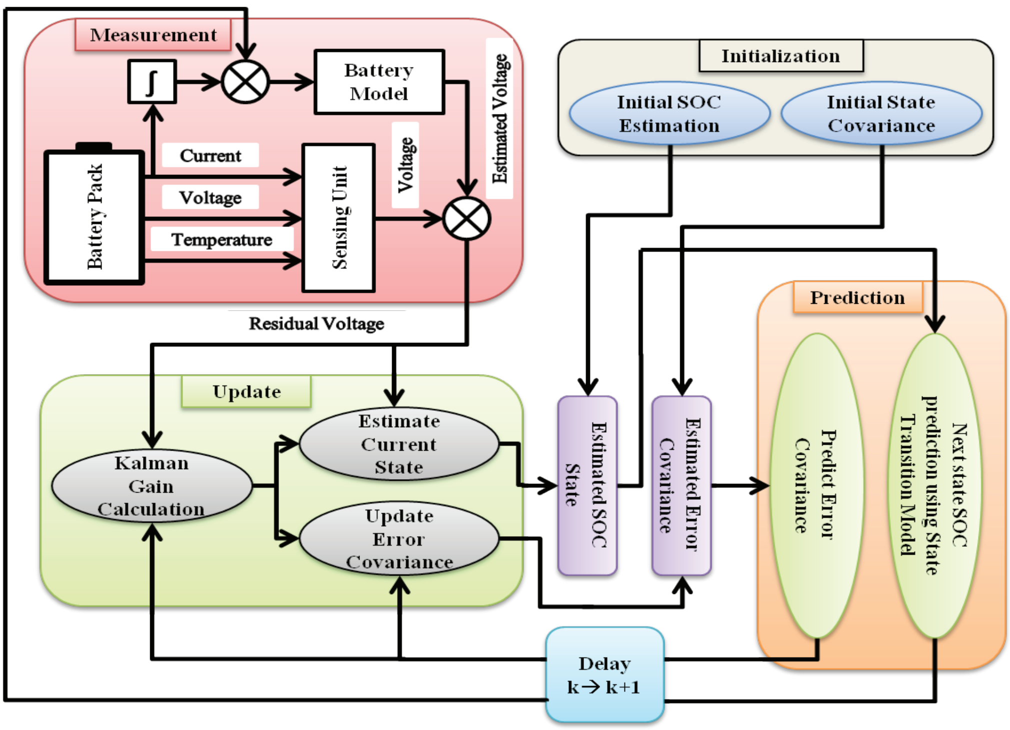

Fig. 5: Flowchart of Kalman Filter

Kalman gain is high when the measurement is more reliable otherwise the value of Kalman gain is poor. If the gain is high, SOC estimation follows the sensor value as shown in equ. 17. On the other hand, if the gain is low, SOC estimation follows the predicted value as shown in equ. 18 [44].

$$\lim_{R\to 0} K_k = \lim_{R\to 0} \mathrm{P}_k^- \mathrm{H}^T(\mathrm{HP}_k^-\mathrm{H}^T + \mathrm{R})^{-1} = H^{-1} \quad (15)$$

$$\lim_{P_k^-\to 0} K_k = \lim_{R\to 0} \mathrm{P}_k^- \mathrm{H}^T(\mathrm{HP}_k^-\mathrm{H}^T + \mathrm{R})^{-1} = 0 \quad (16)$$

$$\lim_{R\to 0} \hat{x}_k = \lim_{R\to 0} \hat{\mathrm{x}}_k^- + \mathrm{K}_k(\mathrm{z}_k - \mathrm{H}\hat{\mathrm{x}}_k^-) = H^{-1}z_k \quad (17)$$

$$\lim_{P_k^-\to 0} \hat{x}_k = \lim_{P_k^-\to 0} \hat{\mathrm{x}}_k^- + \mathrm{K}_k(\mathrm{z}_k - \mathrm{H}\hat{\mathrm{x}}_k^-) = \hat{\mathrm{x}}_k^- \quad (18)$$

The last step is the prediction step, where the SOC is estimated based on the previous SOC using State Transition Model with Gaussian noise and also predicts the error covariance.

But the Kalman filter is applicable for the linear systems [45] in which all noises and errors are strictly Gaussian. In reality, the battery is a non-linear dynamic system. During the driving on high hill, downhill, the SOC of battery wouldn't be linearly changed. Even the noise of battery SOC estimation is non-Gaussian due to the temperature variation, aging effect, sensor inaccuracy etc. As a result, Kalman filter produces an inaccurate Kalman gain which generates wrong estimation of SOC [46].

(b) Extended Kalman Filter (EKF): This filter is introduced to handle the non-linearity of the system. It is the modified version of Kalman filter. Since the battery charging and discharging don't follow the linear behavior, this extended Kalman filter is required to convert into linear behavior through state space model. Then Kalman filter is applied to obtain optimal estimation.

Considering, a state space equation for SOC estimation [47],

$$x_{k+1} = f(x_k, u_k) + w_k \quad (19)$$

Measurement equation,

$$z_k = h(x_k, u_k) + v_k \quad 20)$$

To generate a linear approximation of non-linear function ($f(x_k, u_k)$), first term of Taylor series expansion is utilized [48].

$$f(x_k, u_k) \approx f(\hat{x}_k, \hat{u}_k) + \frac{\partial f}{\partial x_k}\bigg|_{(\hat{x}k,\, \hat{u}k)} (x_k - \hat{x}_k) + \frac{\partial f}{\partial u_k}\bigg|_{(\hat{x}k,\, \hat{u}k)} (u_k - \hat{u}_k) \quad (21)$$

where, $\frac{\partial f}{\partial x_k}\Big|_{(\hat{x}k,\, \hat{u}k)} = A_k =$ Jacobian of f with respect to x_k

$\frac{\partial f}{\partial u_k}\Big|_{(\hat{x}k,\, \hat{u}k)} = B_k =$ Jacobian of f with respect to u_k

$$h(x_k, u_k) \approx h(\hat{x}_k, \hat{u}_k) + \frac{\partial h}{\partial x_k}\bigg|_{(\hat{x}k,\, \hat{u}k)} (x_k - \hat{x}_k) + \frac{\partial h}{\partial u_k}\bigg|_{(\hat{x}k,\, \hat{u}k)} (u_k - \hat{u}_k) \quad (22)$$

where, $\frac{\partial h}{\partial x_k}\Big|_{(\hat{x}k,\, \hat{u}k)} = C_k =$ Jacobian of h with respect to x_k

$\frac{\partial h}{\partial u_k}\Big|_{(\hat{x}k,\, \hat{u}k)} = D_k =$ Jacobian of h with respect to u

Simplifying equation 21 and 22, we get the linear system,

$$x_{k+1} \approx f(\hat{x}_k, \hat{u}_k) + A_k(x_k - \hat{x}_k) + B_k(u_k - \hat{u}_k) + w_k \quad (23)$$

$$z_k \approx h(\hat{x}_k, \hat{u}_k) + C_k(x_k - \hat{x}_k) + D_k(u_k - \hat{u}_k) + v_k \quad (24)$$

Here, x_k = SOC value at time k, u_k = charging and discharging current, w_k = process noise, z_k = battery voltage, v_k = measurement noise, x_{k+1} = predicted SOC.

Now, through the Kalman filtering process more corrected SOC is estimated. But this extended Kalman filter sometimes fails to estimate correct SOC, when the battery plays highly nonlinear behavior.

(c) Unscented Kalman Filter (UKF): Unscented Kalman filter is considered as more advanced in Kalman filter family, which was introduced by Julier and Uhlman in 1997. Like EKF, the UKF doesn't need to consider Jacobian matrix, convert into linearized from non-linear equation, which improves the accuracy of SOC estimation. Previously, researchers used this filter to estimate SOC [30, 42]. According to their research, a small set of sigma points is denoted by x_i, which passes through the non-linear functions and a new mean and covariance are generated. These sigma points actually indicate the uncertain SOC. For example, the actual SOC is 60%, but sigma points will represent variables such as 63%, 59%, 58%, 61%, 60% etc. These points are calculated as-

$$x_i = \hat{x}_{k-1} \pm \sqrt{(n+\lambda)P_{k-1}}, \quad (25)$$

Where, i = 1, 2, ….., 2n

Predicted mean,

$$x_{k|k-1} = \sum_{i=0}^{2n} W_i^m x_i \quad (26)$$

Predicted covariance,

$$P_{k|k-1} = \sum_{i=0}^{2n} W_c^i \left(x_i - \hat{x}_{k|k-1}\right)\left(x_i - \hat{x}_{k|k-1}\right)^T + Q \quad (27)$$

Kalman gain, $K_k = P_{xy}P_y^{-1} = (\sum_{i=0}^{2n} W_c^i\, (x_i - x)(y_i - \hat{y}))\, (\sum_{i=0}^{2n} W_c^i\, (y_i - \hat{y})(y_i - \hat{y})^T) + R)^{-1}$ (28)

Estimated SOC update,

$$\hat{x}_k = \hat{x}_{k|k-1} + K_k(y - \hat{y}_k) \tag{29}$$

Error covariance update,

$$P_k = P_{k|k-1} - K_k P_y K_k^T \tag{30}$$

Here, = previous estimated SOC, = dimension of state, = scaling parameter, = weight for the i^{th} sigma points = cross-covariance matrix, = innovation covariance matrix, = weight for covariance, Q = process noise covariance, R = measurement noise covariance.

But, the accuracy of SOC estimation through this method sometimes affected by initial values and system noise. This is why, Zhou *et. al.* [49] introduced a fading factor and an adaptive adjustment factor to minimize those issues. The modified version of covariance equations is shown below-

$$\text{Modified } P_{k|k-1} = S\sum_{i=0}^{2n} W_c^i \left(x_i - \hat{x}_{k|k-1}\right)\left(x_i - \hat{x}_{k|k-1}\right)^T + Q \tag{31}$$

$$\text{Modified } P_y^{-1} = \frac{1}{\alpha_k}\sum_{i=0}^{2n} W_c^i \left(y_i - \hat{y}\right)\left(y_i - \hat{y}\right)^T) + R \tag{32}$$

$$\text{Modified } P_{xy} = \frac{1}{\alpha_k}\sum_{i=0}^{2n} W_c^i \left(x_i - x\right)\left(y_i - \hat{y}\right)) \tag{33}$$

$$\text{Modified } P_k = \frac{1}{\alpha_k} P_{k|k-1} - K_k P_y K_k^T \tag{34}$$

Here, S is fading factor and is adaptive adjustment factor

3.4 Data Driven Methods

(a) Neural Network: Neural network is a very popular data driven approach for its higher accuracy, capability to handle non-linearity and real time SOC estimation. It consists of three layers- Input layer, Hidden layer, and output layer. Input layer receives real time data from sensors such as voltage (v), current (I), temperature (T) that are obtained from battery. Hidden layer builds a complex relation between input data and estimated SOC. It typically contains 1 to 3 layers. The last one is output layers which represents the estimated SOC. The input layer transmits the input variables with weights and without any computational complexity. On the other hand, the other two layers are responsible for processing the data through activation function [50, 51, 52].

Researchers already used various version of neural network such Back propagation neural network (BPNN), Recurrent neural network (RNN), Convolutional neural network (CNN) to estimate SOC. For example, Shuo Li, S. L. researchers [53] were estimated SOC by using BPNN with input of voltage, current and temperature of battery. BPNN consists of two phases: forward propagation and back propagation. After generating output of SOC through forward propagation and the difference between the output value and actual SOC value, the error is used as feedback to modify the weights and biases between neurons till to get proper SOC output value. Since BPNN has the excellent capability to handle the high non-linearity, this is why another research group [54] used BPNN with duel EKF. Here they used duel EKF to get real time SOC which is justified by the BPNN. And the predicted error by BPNN is combines with the output of dual EFF to estimate correct SOC.

Another version of NN is RNN which is also used to estimate SOC. But RNN is able to remember most recent data due to the vanishing gradient issue. So, the advanced architecture of RNN, LSTM is preferred over traditional RNN, which mitigates the existing problem of RNN [55]. The architecture of LSTM consists of memory cell, and three gates- input gate, output gate, and forget gate. Input gate decides which new input variables such as voltage, current, temperature would be stored in memory cell through sigmoid and tanh activation function. Forget gate uses sigmoid activation function to erase irrelevant old data from memory cell that have less affect to estimate SOC. Based on output forget gate and input gate, memory cell is updated. Finally, the output gate determines output SOC from the memory cell [56]. S. Bockrath, A. R. researchers [57] used LSTM to estimate SOC and compare the accuracy EKF method. In their experiment, they used voltage, current and temperature of lithium-ion battery as input for LSTM NN model and the equivalent circuit model voltage is used as input for EKF model. And during dynamic operation LSTM performs better then EKF to estimate SOC. Another research team [58] used LSTM with extended input and constrained output (EI-LSTM-CO model) during SOC estimation. Due to the highly non-linear behavior of the battery, most machine learning models are failed to figure out the relationship between input variables such as voltage, current, temperature with output SOC during real time operation. This is why, these models are unable to predict SOC properly with new input data. To increase the accuracy, they also used another input, average voltage, which alters more slowly compare to real time variables. Due to use to the extension of input of LSTM, they got less SOC error compare to LSTM-RNN method with various datasets.

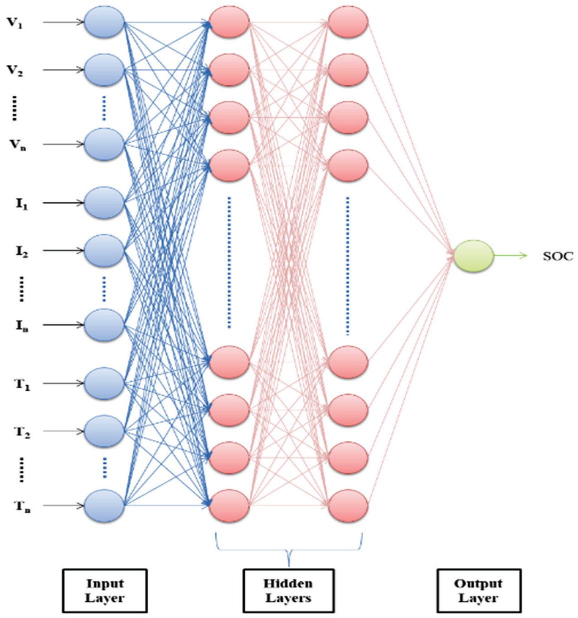

Fig. 6: The structure of Neural Network

Convolutional neural network (CNN) is also is a well-known deep learning method for SOC estimation. The architecture of a CNN consists of several layers, including image input, convolutional, activation, pooling, flatten, dense, and output layers. The image input layer takes the input and passes it into the network. In this case, the inputs are the voltage, current, and temperature of the battery. The conventional layer was used to extract low-level features (trends or sudden changes) from the input data, followed by an activation layer (ReLU) which applies non-linear function to learn complex pattern. The output of activation layer goes to pooling layer to reduce the dimensionality of the data. Then flatten layer converts the feature maps into 1D which used as input of dense layer. In dense layer, the input is multiplied with weight matrix and a bias vector is also added. Finally, the output layer which is a single neuron predicts the SOC value [59]. For checking accuracy, an author group [60] also used loss function layer to calculate the error between actual SOC and predicted SOC. In their experiment, they got a little deviation between true SOC and predicted SOC. XIANGBAO SONG, F. Y.-L. [61] combined CNN with LSTM with the voltage, current, temperature, average voltage and average current of battery as input for increasing accuracy of SOC estimation. The output SOC is fluctuated and has a deviation from the true value of SOC while using only CNN method. But combination of CNN and LSTM, the output SOC is more stable and a very low deviation (2%) from the actual SOC of battery.

(b) Support Vector Machine (SVM): SVM is preferred to estimate state of charge for solving the high non-linearity of the batteries through kernel function as well as its higher accuracy around 98%. SVM is generally used to handle vector problems and vector regression problems. Since, SOC estimation is a regression problem, this is why SVM for regression (SVR) algorithm is used. To estimates SOC through SVR a researcher group used a dataset where battery voltage, current and temperature are used as input to train the SVR model and SOC is used as ground truth to the model. The dataset is randomly divided into 10 equal-sized subsets to efficiently use of data. The basic SVR function to predict SOC is [62]-

$$f(x) = \omega^T \varphi\,(x_i) + b \tag{35}$$

where, function maps the input feature (terminal voltage, current, temperature) into a higher dimensional space to capture the batteries dynamic behavior.

To minimize the prediction error following objective function [63]-

$$\varphi[\omega, b, \varepsilon] = \frac{\|\omega\|^2}{2} + C\sum_{i=1}^{L}(\varepsilon_i^+ + \varepsilon_i^-) \tag{36}$$

The constraints are-

$$\left.\begin{aligned} & y_i - \langle \omega, \varphi\,(x_i) \rangle - b \le \epsilon + \varepsilon_i^+ \text{ (upper bound)} \\ & \langle \omega, \varphi\,(x_i) \rangle + b - y_i \le \epsilon + \varepsilon_i^- \text{(lower bound)} \\ & \varepsilon_i^+, \varepsilon_i^- \ge 0 \end{aligned}\right\} \tag{37}$$

In equation 36, first term reduces overfitting to noisy voltage, current and temperature values and second term ensures the noises or errors are minimized in SOC prediction. The constraint equations 37 represent the estimated SOC stays in an acceptable deviation () from the actual SOC reading. To handle these constraints, Lagrange multipliers are introduced.

$$\varphi[\omega, b, \varepsilon, \alpha_i] = \frac{\|\omega\|^2}{2} + C\sum_{i=1}^{L}(\varepsilon_i^+ + \varepsilon_i^-) - \sum_{i=1}^{N}\alpha_i^+\,(y_i - f(x_i) - \epsilon - \varepsilon_i^+) - \sum_{i=1}^{N}\alpha\alpha_i^-\,(y_i - f(x_i) - \epsilon - \varepsilon_i^-) \tag{38}$$

To handle the non-linearity and establish a linear relationship, RBF kernel comes into play,

$$k(x_i, x_j) = e^{-\frac{\|x_i, x_j\|^2}{2\varphi^2}} \tag{39}$$

For computational efficiency, the dual formulation is introduced instead of primal form. In equ. 36, where the weight , bias , slack variables becomes ineffective for highly non-linear battery variables. This is why, the primal problem is transformed into dual form by applying

Lagrange multipliers which allows kernel function to replace the dot product . The final predicted SOC through SVR function is-

$$f(x) = \sum_{i=1}^{L}(\alpha_i^{+} - \alpha_i^{-})\, K(x_i, x) + b \tag{40}$$

Here, x is the new input data such as voltage, current, temperature.

(c) Fuzzy Logic: Fuzzy logic was developed by Lotfi A. Zadeh in the mid-1960s. It is preferred for SOC estimation because of less mathematical difficulties, well suited for dealing with uncertainties, and provides continuity in SOC values. A simple block diagram of Fuzzy Logic Controller is shown in Fig. 07, which consists of Fuzzification, Decision Rules, Fuzzy Inference, and Defuzzification [64]. Fuzzification block takes voltage, current, temperature, required power etc. as inputs and converts into fuzzy sets (Ex: For voltage fuzzy set would be: “Low,” “Medium,” “High”). Every fuzzy set is connected with membership function. Decision Rules block considers as heart of the controller which consists of if-then rules that represent the relationship between crisp input and output SOC. The Fuzzy Inference is a computational unit that applies fuzzy rules to the fuzzified inputs and the Defuzzification generates the output SOC.

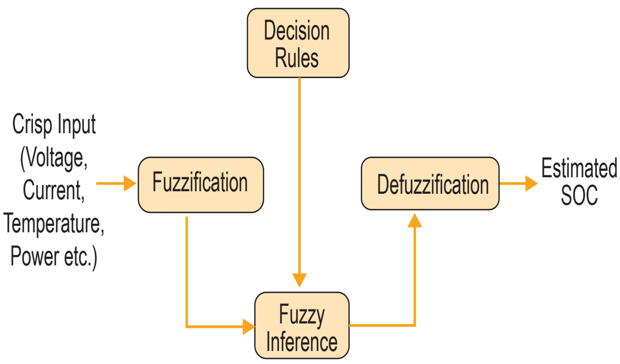

Fig. 7: Block Diagram of Fuzzy Logic Controller

A group of researchers [65] incorporated fuzzy logic into bi-directional equalization circuit to equally charging and discharging of each cell in a battery pack. They used the SOC difference of cells and modules as input of Fuzzification and also set start and stop threshold. Based on the threshold values the SOC equalization process starts and stops. Darsana Saji, P. S. [66] used fuzzy logic with coulomb counting method to enhance the accuracy of SOC estimation. In this case, the input of Fuzzification is SOC which comes from the coulomb counting method. According to their experiment, during charging only using coulomb counting the SOC error is around 13.8% and after incorporating fuzzy logic the SOC estimation error is 3%. Similarly, during discharging, combination of fuzzy logic with coulomb counting method exhibits excellent accuracy.

(d) Random Forest: Random Forest is an ensemble of decision trees. Due to easy implementation and training with small dataset compare to RNN and CNN, first prediction, and lower overfitting risk random forest is preferred for SOC estimation of EVs’ batteries. According to Mohd Herwan Sulaiman, Z. M. [67] random forest follows eight steps during SOC estimation. Firstly, the real time data of voltage, current, battery temperature and ambient temperature are recorded in a single dataset with proper alignment. Secondly, around 87% of data of the dataset are used for training and remaining of them is used for testing. Then the model is configured and the training data are divided into 5 subsets. After that various number (25, 50, 75 and 100) of trees are used for trial with 5 subsets. Based on the trial performance, 25 trees random forest architecture provides more balance accuracy and this architecture is used for model training. Finally, the model is evaluated and analyzed the result. According to the Chuanjiang Li, Z. C. research group [68], random forest regression (type of random forest) provides 0.5% less error compares to BPNN to estimate SOC. Similarly, another research team [69] founds small error to estimate SOC through random forest compare to ANN. But this model is unable to exhibit high performance with large dataset.

The advantages and disadvantages of each category are shown in Table II.

4. DISCUSSION

By reviewing each existing method of SOC estimation, we are clear that SOC estimation has shifted significantly toward data-driven and hybrid methods, as conventional techniques face limitations in real-time accuracy and adaptability. Earlier methods such as Open Circuit Voltage (OCV), Coulomb Counting, and even standard Kalman Filters were useful but often struggled with non-linearity, sensor noise, and battery aging effects. This has led to a growing trend of integrating advanced filtering techniques (like EKF, UKF) with machine learning models for improved estimation accuracy.

Among the most prominent trends is the use of deep learning, particularly LSTM and CNN-LSTM hybrid models, which outperform traditional methods due to their ability to model non-linear dynamic behavior and extract time-dependent features from large datasets. The EI-LSTM-CO model, incorporating extended input and constrained output, has also gained attention for its enhanced accuracy in real-time applications.

Table II: Advantages and Disadvantages for Battery SOC Estimation Methods

Category	Method	Advantage	Disadvantage
Direct Measurement	Open Circuit Voltage	• Simple and easy implementation • Good accuracy and low cost	• Requires long time rest before measure • Gives wrong estimation during operation
	Terminal Voltage	• Simple and easy implementation • Can be used in real time operation	• Sensitive current fluctuation • Output can be affected by internal resistance
	Impedance	• Easy to implement • More accurate estimation than terminal voltage method	• Accuracy is varied with temperature and aging • Difficult to find accurate impedance due to its lower value
	Electrochemical Impedance Spectroscopy	• Higher accuracy	• Requires complex equipment and high cost • Not suitable for real time application • Requires expert knowledge
Book Keeping	Coulomb Counting	• Simple and easy for implementation • Real time monitoring is possible	• Decrease the SOC estimation accuracy due to the error of initial SOC • Self-discharge and sensor errors aren't counted
	Enhance Coulomb Counting	• Higher accuracy compared to conventional coulomb counting method	• Doesn't consider sensor errors • Calibration is required
Filter Based	Kalman Filter (KF)	• Higher accuracy due to considering sensor errors • Comparatively more suitable for real-time operation	• Not suitable for non-linear systems • Due to increase of state variable calculation time increases
	Extended Kalman Filter (EKF)	• Suitable for non-linear system • Good balance between accuracy and complexity	• Complex calculation • Due to increase of state variable calculation time increases • Unable to accurate SOC estimation for highly non-linear systems
	Unscented Kalman Filter (UKF)	• Handles highly non-linear battery system • Lower complex calculation compares to EKF	• Sometimes accuracy is affected by initial values and system noise
Data Driven	Neural Network (NN)	• Handles highly non-linear battery system • Higher accuracy and can improve overtime with more training • Doesn't need to consider electrical and physical changes of battery • Able to estimate in both offline and online	• Needs large dataset • During training high amount computational power is required
	Support Vector Machine (SVM)	• Higher accuracy • Able to work well with small to medium dataset	• Inflexible model • Greatly depends on kernel function
	Fuzzy Logic	• Doesn't require complex mathematical model • Capable to handle uncertainty	• Less accuracy • Performance depends on membership function & rule base
	Random Forest (RF)	• Good accuracy with small dataset • Lower prediction time	• Performance is lower with large dataset

Moreover, researchers are increasingly combining filter-based methods with neural networks to create hybrid models, aiming to reduce errors due to battery aging, environmental variation, and sensor inaccuracies.

Furthermore, SVM model and Random Forest model are trending as fast and efficient alternatives for small to medium datasets, especially where computational resources are limited. These models offer high prediction accuracy with less training time and are favored in embedded battery management systems.

Looking ahead, the research is trending toward hybrid approaches that fuse Enhanced Coulomb Counting techniques with neural networks or Kalman filters to adaptively learn from real-time data while correcting for accumulated errors. In our opinion, combining enhanced Coulomb Counting with CNN-LSTM or EI-LSTM-CO models presents a promising future direction. Such hybrid systems can utilize real-time SOC readings as feedback to continuously optimize the machine learning models, resulting in more robust, adaptive, and highly accurate SOC estimation frameworks suitable for commercial EV applications.

4. CONCLUSION

This article analyzed various methods of battery SOC estimation with battery models and identified higher accuracy approaches. Every researcher has tried to increase the accuracy of the SOC estimation by using various methods, both in the past and even today. Previously, SOC monitoring techniques are inefficient because of their limitations. But current techniques of SOC estimation are offering higher precision, which contributes to battery longer life as well as ensures more reliable vehicle performance. In near future, we will try to build a hybrid model that we previously mentioned, for getting more correct and stable SOC of EVs battery.

REFERENCES

[1] M. Bharathidasan, V. Indragandhi, V. Suresh, M. Jasiński and Z. Leonowicz, "A review on electric vehicle: Technologies, energy trading, and cyber security," Energy Reports, Vol. 8, pp. 9662-9685, 2022.

[2] H. Zhang, W. Na and J. Kim, "State-of-Charge Estimation of the Lithium-Ion Battery Using Neural Network Based on an Improved Thevenin Circuit Model," IEEE Transportation Electrification Conference and Expo, pp. 342-346, 2018.

[3] A. F. Challoob, N. A. B. Rahmat, V. K. A/L Ramachandaramurthy and A. J. Humaidi, "Energy and battery management systems for electrical vehicles: A comprehensive review & recommendations," Energy Exploration & Exploitation, Vol. 42, pp. 341-372, 2024.

[4] P. Kumari, A. K. Singh and N. Kumar, "Electric vehicle battery state-of-charge estimation based on optimized deep learning strategy with varying temperature at different C Rate," Journal of Engineering Research, Vol. 11, pp. 158-163, 2023.

[5] L. Lu, X. Han, J. Li, J. Hua and M. Ouyang, "A review on the key issues for lithium-ion battery management in electric vehicles," Journal of Power Sources, Vol. 226, pp. 272-288, 2013.

[6] J. Meng; M. Ricco; G. Luo; M. Swierczynski; D. Stroe and A. Stroe, "An Overview and Comparison of Online Implementable SOC Estimation Methods for Lithium-Ion Battery," IEEE Transactions on Industry Applications, Vol. 54, pp. 1583-1591, 2018.

[7] S. A. Hasib, S. U. Islam, R. K. Chakrabortty, M. Ryan, D. K. Saha, M. H. Ahamed, S. I. Moyeen, S. K. Das, M. F. Ali, M. R. Islam, Z. Tasneem and F. R. Badal, "A Comprehensive Review of Available Battery Datasets, RUL Prediction Approaches, and Advanced Battery Management," IEEE Access, Vol. 9, pp. 86166-86193, 2021.

[8] L. Buccolini; A. Ricci; C. Scavongelli, G. DeMaso-Gentile, S. Orcioni and M. Conti, "Battery Management System (BMS) simulation environment for electric vehicles," International Conference on Environment and Electrical Engineering, 2016.

[9] C. Truchot, M. Dubarry and B. Y. Liaw, "State-of-charge estimation and uncertainty for lithium-ion battery strings," Applied Energy, Vol. 119, pp. 218-227, 2014.

[10] B. D. Soyoye, I. Bhattacharya, M. V. A. Dhason and T. Banik, "State of Charge and State of Health Estimation in Electric Vehicles: Challenges, Approaches and Future Directions," Batteries, Vol. 11, pp. 1-42, 2025.

[11] B. Zine, H. Bia, A. Benmouna, M. Becherif and M. Iqbal, "Experimentally Validated Coulomb Counting Method for Battery State-of-Charge Estimation under Variable Current Profiles," Energies, Vol. 15, pp. 1-15, 2022.

[12] T. Kunatsa, H. C. Myburgh and A. D. Freitas, "A Review on State-of-Charge Estimation Methods, Energy Storage Technologies and State-of-the-Art Simulators: Recent Developments and Challenges," World Electric Vehicle Journal, Vol. 15, pp. 1-44, 2024.

[13] W.-Y. Chang, "The State of Charge Estimating Methods for Battery: A Review," International Scholarly Research Notices, Vol. 2013, pp. 1-7, 2013.

[14] P. Spagnol, S. Rossi and S. M. Savaresi, "Kalman Filter SoC estimation for Li-Ion batteries," International Conference on Control Applications, pp. 587-592, 2011.

[15] D.-W. Chung and S.-H. Yang, "SOC Estimation of Lithium-Ion Battery Based on Kalman Filter," E3S Web of Conferences, pp. 1-6, 2018.

[16] J. Guo, S. Liu and R. Zhu, "An unscented Kalman filtering method for estimation of state-of-charge of lithium-ion battery," Frontiers in Energy Research, Vol. 10, pp. 1-9, 2023.

[17] D. Wang, J. Lee, M. Kim and I. Lee, "Neural Network-Based State of Charge Estimation Method for Lithium-ion Batteries Based on Temperature," Intelligent Automation & Soft Computing, Vol. 36, No. 2, pp. 2025-2040, 2023.

[18] D. Jiani, L. Zhitao, W. Youyi and W. Changyun, "A Fuzzy Logic-based Model for Li-ion Battery with SOC and Temperature Effect," International Conference on Control & Automation, pp. 1333-1338, 2014.

[19] F. A. Tantri, D. Harjunowibowo, E. R. Dyartanti, M. Nizam, M. R. A. Putra, R. R. MP, T. H, Lim and A. Jamaluddin, "Predictive State of Charge (SoC) Modeling using Machine Learning Algorithms in Lithium-Ion NMC Batteries," Engineering Journal, Vol. 28, No. 9, pp. 1-10, 2024.

[20] N. Li, Y. Zhang, F. He, L. Zhu, X. Zhang, Y. Ma and S. Wang , " Review of lithium-ion battery state of charge estimation," Global Energy Interconnection, Vol. 4, pp. 619-630, 2021.

[21] W. Zhou, Y. Zheng, Z. Pan and Q. Lu, "Review on the Battery Model and SOC Estimation Method," Processes, Vol. 9, pp. 1-23, 2021.

[22] H. He, R. Xiong and J. Fan, " Evaluation of Lithium-Ion Battery Equivalent Circuit Models for State of Charge Estimation by an Experimental Approach," Energies, Vol. 4, pp. 582-598, 2011.

[23] C. Liu, W. Liu, L. Wang, G. Hu, L. Ma and B. Ren, " A new method of modeling and state of charge estimation of the battery," Journal of Power Sources, Vol. 320, pp. 1-12, 2016.

[24] H. Zhou, S. Wang, C. Yu, L. Xia and C. Fernandez, "Research on SOC Estimation for Lithium ion batteries Based on Improved PNGV Equivalence Model and AF-UKF Algorithm," International Journal of Electrochemical Science, Vol. 17, pp. 1-13, 2022.

[25] H. Bouchareb, K. Saqli, N.K. M'sirdi, M. O. Bentaie and A. Naamane, "Sliding Mode Observer Design for Battery State of Charge estimation," International Conference on Renewable Energies for Developing Countries, pp. 1-5, 2020.

[26] B. V. Rajanna and M. K. Kumar, "Comparison of one and two time constant models for lithium ion battery," International Journal of Electrical and Computer Engineering, Vol. 10, No. 1, pp. 670-680, 2020.

[27] S. Nejad, D.T. Gladwin and D.A. Stone, "A systematic review of lumped-parameter equivalent circuit models for real-time estimation of lithium-ion battery states," Journal of Power Sources, Vol. 316, pp. 183-196, 2016.

[28] Q. Chen, J. Jiang, H. Ruan and C. Zhang, "A New Double Sliding Mode Observer for EV Lithium Battery SOC Estimation," Mathematical Problems in Engineering, Vol. 2016, pp. 1-9, 2016.

[29] W. Kai, F. Xiao, P. Jinbo, R. Jun, D. Chongxiong and L. Liwei, " State of Charge (SOC) Estimation of Lithium-ion Battery Based on Adaptive Square Root Unscented Kalman Filter," International Journal of Electrochemical Science, Vol. 15, pp. 9499-9516, 2020.

[30] L. Wang, F. Wang, L. Xu, W. Li, J. Tang and Y. Wang, "SOC estimation of lead–carbon battery based on GAMIUKF algorithm," Scientific Reports, pp. 1-14, 2024.

[31] M. Danko, J. Adamec, M. Taraba and P. Drgona, "Overview of batteries State of Charge estimation methods," International Scientific Conference on Sustainable, Modern and Safe Transport, pp. 186-192, 2019.

[32] M. Coleman, C. K. Lee, C. Zhu and W. G. Hurley, "State-of-Charge Determination From EMF Voltage Estimation: Using Impedance, Terminal Voltage, and Current for Lead-Acid and Lithium-Ion Batteries," IEEE Transactions on Industrial Electronics, Vol. 54, No. 5, pp. 2550-2557, 2007.

[33] S. Jeon, J.-J. Yun and S. Bae, “Comparative Study on the Battery State-of-Charge Estimation Method,” Indian Journal of Science and Technology, Vol. 8, pp. 1-6, 2015.

[34] S. R. C. Geda and M. Sharam, “An overview of SOC estimation in Li-ion batteries with direct measurement methods and coulomb counting,” International Journal of Engineering Applied Sciences and Technology, Vol. 7, pp. 237-242, 2022.

[35] Y. Liu, L. Wang, D. Li and K. Wang, “State-of-health estimation of lithium-ion batteries based on electrochemical impedance spectroscopy: a review,” Protection and Control of Modern Power Systems, pp. 1-17, 2023.

[36] K. C. Ndeche and S. O. Ezeonu, “Implementation of Coulomb Counting Method for Estimating the State of Charge of Lithium-Ion Battery,” Physical Science International Journal, Vol. 25, pp. 1-8, 2021.

[37] K. S. Ng, C.-S. Moo, Yi-Ping Chen and Y.-C. Hsieh, “Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries,” Applied Energy, Vol. 86, pp. 1506–1511, 2009.

[38] I. Baccouche, A. Mlayah, S. Jemmali, B. Manai and N. E. B. Amara, “Implementation of a Coulomb counting algorithm for SOC estimation of Li-Ion battery for multimedia applications,” International Multi-Conference on Systems, Signals & Devices, pp. 1-6, 2015.

[39] J. LEE and J. Won, “Enhanced Coulomb Counting Method for SoC and SoH Estimation Based on Coulombic Efficiency,” IEEE Access, Vol. 11, pp. 15449-15459, 2023.

[40] G. Fathoni, S. A. Widayat, P. A. Topan, A. Jalil, A. I. Cahyadi and O. Wahyunggoro, “Comparison of State-of-Charge (SOC) estimation performance based on three popular methods: Coulomb counting, open circuit voltage, and Kalman filter,” International Conference on Automation, Cognitive Science, Optics, Micro Electro-Mechanical System, and Information Technology, pp. 70-74, 2018.

[41] M. U. Ali, A. Zafar, S. H. Nengroo, S. Hussain, M. J. Alvi and H. Kim, “Towards a Smarter Battery Management System for Electric Vehicle Applications: A Critical Review of Lithium-Ion Battery State of Charge Estimation,” Energies, Vol. 12, pp. 1-33, 2019.

[42] P. Shrivastava, T. K. Soon, M. Y. I. B. Idris and S. Mekhilef, “Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries,” Renewable and Sustainable Energy Reviews, Vol. 113, pp. 1-23, 2019.

[43] Z. Zhou and C. Zhang, “An Extended Kalman Filter Design for State-of-Charge Estimation Based on Variational Approach,” **Batteries,** Vol. 9, No. 12, 2023.

[44] J. Yun, Y. Choi, J. Lee, S. Choi and C. Shin, “State-of-Charge Estimation Method for Lithium-Ion Batteries using Extended Kalman Filter with Adaptive Battery Parameters,” IEEE Access, Vol. 11, pp. 90901-90915, 2023.

[45] A. Khalid, S. A. R. Kashif, N. U. Ain, M. Awais, M. A. Smieee, J. E. M. Carreño, J. C. Vasquez, J. M. Guerrero and B. Khan, “Comparison of Kalman Filters for State Estimation Based on Computational Complexity of Li-Ion Cells,” Energies, Vol. 16, pp. 1-20, 2023.

[46] M. A. Akram, P. Liu, M. O. Tahir, W. Ali and Y. Wang, “A State Optimization Model Based on Kalman Filtering and Robust Estimation Theory for Fusion of Multi-Source Information in Highly Non-linear Systems,” Sensors, Vol. 19, pp. 1-22, 2019.

[47] R. Zhang and H. Zhang, “Extended Kalman Filter-Based SOC Estimation for Lithium Battery Packs,” International Conference on Energy Materials and Environment Engineering, pp. 1-4, 2023.

[48] N. A. Windarko, J. Choi and G.-B. Chung, “SOC Estimation of LiPB Batteries using Extended Kalman Filter based on high accuracy electrical model,” International Conference on Power Electronics, pp. 2015-2022, 2011.

[49] H. Zhou, S. Wang, C. Yu, L. Xia and C. Fernandez, “Research on SOC estimation for lithium ion batteries based on improved PNGV equivalence model and AF-UKF algorithm,” International Journal of Electrochemical Science, Vol. 17, pp. 1-14, 2022.

[50] W. He, N. Williard, C. Chen and M. Pecht, “State of charge estimation for Li-ion batteries using neural network modeling and unscented Kalman filter-based error cancellation,” International Journal of Electrical Power & Energy Systems, Vol. 62, pp. 783-791, 2014.

[51] B.-A. Enache and E. Diaconescu, “Estimating a battery SoC using neural networks,” International Symposium on Fundamentals of Electrical Engineering, pp. 1-7, 2014.

[52] M. Ismail, R. Dlyma, A. Elrakaybi, R. Ahmed and S. Habibi, "Battery State of Charge Estimation using Artificial Neural Network," IEEE Transportation Electrification Conference and Expo, pp. 342-349, 2017.

[53] S. Li, S. Li, H. Zhao and Y. An, "Design and implementation of state-of-charge estimation based on back-propagation neural network for smart uninterruptible power system," International Journal of Distributed Sensor Networks, Vol. 15, pp. 1-9, 2019.

[54] L. Xing, L. Ling and X. Wu, "Lithium-ion battery state-of-charge estimation based on a dual extended Kalman filter and BPNN correction," Connection Science, Vol. 34, No. 1, pp. 2332-2363, 2022.

[55] S. Tao, B. Jiang, X. Wei and H. Dai, "A Systematic and Comparative Study of Distinct Recurrent Neural Networks for Lithium-Ion Battery State-of-Charge Estimation in Electric Vehicles," Energies, Vol. 16, pp. 1-17, 2023.

[56] X. Chai, S. Li and F. Liang, "A novel battery SOC estimation method based on random search optimized LSTM neural network," Energy, Vol. 306, pp. 1-13, 2024.

[57] S. Bockrath, A. Rosskopf, S. Koffel, S. Waldhör, K. Srivastava and V.R.H. Lorentz, "State of Charge Estimation using Recurrent Neural Networks with Long Short-Term Memory for Lithium-Ion Batteries," 45th Annual Conference of the IEEE Industrial Electronics Society, pp. 2507-2511, 2019.

[58] J. Chen, Y. Zhang, J. Wu, W. Cheng and Q. Zhu, "SOC estimation for lithium-ion battery using the LSTM-RNN with extended input and constrained output," Energy, pp. 1-14, 2023.

[59] Z. Cui, L. Wang, Q. Li and K. Wang, "A comprehensive review on the state of charge estimation for lithium-ion battery based on neural network," International Journal of Energy Research, Vol. 46, pp. 5423-5440, 2021.

[60] H. S. Bhattacharyya, A. Yadav, A. B. Choudhury and C. K. Chanda, "Convolution Neural Network-Based SOC Estimation of Li-ion Battery in EV Applications," International Conference on Electrical, Electronics, Communication, Computer Technologies and Optimization Techniques, pp. 587-592, 2021.

[61] X. Song, F. Yang, D. Wang and K.-L. Tsui, "Combined CNN-LSTM Network for State-of-Charge Estimation of Lithium-Ion Batteries," IEEE Access, Vol. 7, pp. 88894-88902, 2019.

[62] K. Wei, J. Wu, W. Ma and H. Li, "State of charge prediction for UAVs based on support vector machine," International Symposium on Test Automation and Instrumentation, pp. 9133-9136, 2019.

[63] J. C. Á. Antón, P. J. G. Nieto, F. J. d. C. Juez, F. S. Lasheras, M. G. Vega and M. N. R. Gutiérrez, "Battery state-of-charge estimator using the SVM technique," Applied Mathematical Modelling, Vol. 37, pp. 6244-6253, 2013.

[64] N. Feng, T. Ma and C. Chen, "Fuzzy energy management strategy for hybrid electric vehicles on battery stateofcharge estimation by particle filter," SN Applied Sciences, Vol. 4, No. 256, pp. 1-11, 2022.

[65] Y. Ma, P. Duan, Y. Sun and H. Chen, "Equalization of Lithium-ion Battery Pack based on Fuzzy Logic Control in Electric Vehicle," IEEE Transactions on Industrial Electronics, Vol. 65, pp. 6762-6771, 2018.

[66] D. Saji, P. S. Babu and K Ilango, "SOC Estimation of Lithium Ion Battery using Combined Coulomb Counting and Fuzzy Logic Method," International Conference on Recent Trends on Electronics, Information, Communication & Technology, pp. 948-952, 2019.

[67] M. H. Sulaiman and Z. Mustaffa, "State of charge estimation for electric vehicles using random forest," Green Energy and Intelligent Transportation, Vol. 3, pp. 1-10, 2024.

[68] C. Li, Z. Chen, J. Cui, Y. Wang and F. Zou, "The Lithium-ion Battery State-of-Charge Estimation using Random Forest Regression," Prognostics and System Health Management Conference, pp. 336-339, 2014.

[69] A. Johnson; N. A. Varghese, R. R. Thomas, S. Mathews and R. A. Koshy, "Random Forest Regressor Based SOC Estimation of Li-Ion Battery for Electric Vehicle Applications," International Conference on Power Electronics, Smart Grid, and Renewable Energy, pp. 1-8, 2023.