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State of Charge Estimation Techniques for Lithium-ION Batteries Used in Electric Vehicle Applications

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Abstract: Lithium-ion battery packs constitute an important part of Electric vehicles. The usage of Lithium-ion based chemistries as the source of energy has various advantages like high efficiency, high energy density, high specific energy, longevity among others. However, the management of lithium-ion battery packs require a Battery Management System (BMS). The BMS deals with functions like safety, prevention of abusive usage of battery pack, overcharging & over-discharging protection, cell balancing and others. One of the prominent features of the BMS is the estimation of State of charge (SOC). SOC is like a fuel gauge in automobile, it indicates how much more the battery can be used before charging it again. SOC is also required for other functions of BMS like State of Health (SOH) tracking, Range calculation, power & energy availability calculations. However, there is no means of measuring it directly (at least not on-board a vehicle) or estimating it easily. Various techniques should be used to estimate SOC indirectly. This paper starts from classical techniques that have existed since long time and reviews some of the modern & developing methods for SOC estimation. It contains a brief review about most of these SOC estimation methods, thus highlighting the methodology, advantages & disadvantages of each of these techniques. A brief review of other developing SOC estimation techniques is also provided.

Keywords: State of Charge, SOC, Lithium-ion battery packs, Electric vehicles, Kalman Filter.

I. INTRODUCTION

The world today is inclining more towards Electric Vehicles (EV) as issues like Climate change, increasing oil prices, depleting resources continue to cast a gloom over the future of mankind. The push to search for an alternative to Internal Combustion Engine (ICE) vehicles is increasing from both manufacturer’s and consumer’s end. The quest for an alternative to fossil fuel powered ICE vehicles has led us to the development of technologies like Electric Vehicles, Hydrogen vehicles and others. Electric Vehicles have been posed as the most efficient alternative. The development of Electric vehicles has been accelerated recently due to the increased demand for an alternative. Apart from switching to a cleaner source, EVs provide consumers with wide range of attractions pushing them more to take that step towards EVs. From autonomous driving to smart features, EVs can cater to the consumer of the future. In spite of these advantages, there have been certain bottlenecks for EV industry. High cost, Range anxiety, long charging time have been a few ones to name[2].

At the beginning of the 20th century, EVs constituted a significant part of the automobiles that were on road. Back then, EVs were powered by Lead acid and other primitive cell chemistries. They were an attractive choice for many, as they didn’t emit smoke and they were much smoother compared to combustion engine vehicles. As the demand for longer range and affordable vehicles increased, they eventually paved the way for ICE vehicles that were manufactured on large scale. Now again as the concerns of Global warming, fluctuating oil prices, exhaustion of fossil fuels start to worry the future of mankind, EVs have been positioned as an alternative to ICE vehicles. To cater to the energy demands of EVs, Lithium based cell chemistries have been used for battery packs. The Nissan Altra EV was the first production lithium-ion battery EV introduced in 1997. Lithium-ion battery cells have high efficiency, high energy density, longer life compared to others which makes them a perfect choice for EV batteries. There are various types of lithium-based cell chemistries like lithium cobalt oxide (LCO), lithium iron phosphate (LFP), lithium manganese oxide (LMO), lithium nickel manganese cobalt oxide (NMC), lithium nickel cobalt aluminum oxide (NCA), and lithium titanate oxide (LTO) and others. Because of the high efficiency of lithium ion-based cell chemistries, they should be handled with extreme care. Overcharging a lithium-ion battery even little beyond the permissible range can lead to explosion. Because of the reactive elements present, the explosion makes things even worse.

For proper management of lithium-ion battery packs, we have an embedded system called Battery Management System (BMS) [1]. The main functions of the BMS include protection of the user, safe operating of lithium-ion battery pack, prevention of abusive usage of lithium battery pack, overcharging & over discharging protection [3].
One of the primary functions of BMS include estimation of State of Charge (SOC) of lithium-ion battery pack. The SOC of a lithium-ion battery pack indicates how much capacity of the battery pack is left since its fully charged state and when the battery needs to be recharged. The SOC of a lithium-ion battery pack can neither be measured directly nor estimated directly. The SOC has to be estimated indirectly by measuring various other parameters [12]. Several techniques have been used since long time for the SOC estimation. This paper starts from these classical estimation techniques and moves to modern techniques that are being used currently. The SOC estimation is complicated by the high accuracy requirements, presence of noise, limited computation power and other factors [13]. This paper highlights the principle behind each of these techniques and provides a brief account of these methods. It also provides advantages & disadvantages of each of these techniques and builds upon from one technique to the next.

II. DEFINITION of STATE of CHARGE (SOC)

In ad-hoc terms, State of charge (SOC) tells us how much more a Li-ion battery can be discharged before it should be charged again. SOC is like a fuel gauge in an automobile. We define the State of charge (SOC) to be 100% when the battery is in a fully charged state and 0% when it is fully discharged. In other cases, it is a unit-less quantity between 0% & 100%.
The first quantification [1] of SOC tries to express State of charge in relation to the Lithium-ion concentration in electrodes. This arises from the fact that the Lithium ion concentration in negative electrode of the battery is high when the battery is fully charged (which is defined to be at 100% SOC) whereas the concentration of Lithium ions in negative electrode is low when the battery is fully discharged (which is defined to be 0% SOC).We proceed by defining maximum theoretical concentration of Lithium ion in negative electrode as a_{max} and the average concentration of Lithium ion at time t in the negative electrode as $a_{avg,t}$. Then the present Lithium stoichiometry which can be thought of as SOC for that electrode can be defined as

$$c_t = \left(\frac{a_{avg,t}}{a_{max}}\right) * 100\%$$

Then the cell SOC can be defined as

$$SOC[t] = \left(\frac{c_t^{neg} - c_{0\%}^{neg}}{c_{100\%}^{neg} - c_{100\%}^{neg}}\right) * 100\%$$

where,
$c_{0\%}^{neg}$ indicates the stoichiometry obtained from Li-ion concentration in negative electrode when the cell is fully discharged.
$c_{100\%}^{neg}$ indicates the stoichiometry obtained from Li-ion concentration in negative electrode when the cell is fully charged.
Another definition of SOC [2] takes into account of the battery capacity measured at various instances. Here, SOC is defined as the ratio of the remaining battery capacity at time ’t’ to the total capacity of the battery available from fully charged state under the given conditions like C-rate, temperature etc.

$$SOC[t] = \left(\frac{Q_c}{Q}\right) * 100\%$$

where,
Q_c indicates the residual or remaining battery capacity at time ’t’.
Q indicates the Total Battery capacity.

Although both of these definitions of SOC look good theoretically, problems arise when we apply them to calculate SOC in practice. In the first case, it is almost always impossible to determine the Lithium-ion concentration in the electrodes of each cell in a battery pack. In the second case, the definition of battery capacity is not consistent. This leads to a problem with estimation of SOC directly. Hence various indirect methods are used for estimation of SOC.

III. SOC ESTIMATION METHODS

A. Coulomb Counting Method

Coulomb Counting which is also known as Ampere-hour counting is one of the earliest and easiest methods available for SOC estimation. This based method relies on measurement of current over the entire cycle of charging and discharging the battery.

$$SOC[t]=SOC[0]-\frac{T}{C_n}\int_0^t (n*I(t)-S_d)*dt$$

where, SOC[0] is the battery initial SOC, I(t) is the current at time t, T is the sampling period, C_n is the nominal capacity of the battery, n is the columbic efficiency, and S_d is the self- discharging rate.
The advantages of this method in estimating SOC mainly arises from its simplicity. This simplicity leads to easier implementation, low power consumption and low computation on a BMS. The only measurement that is to be done is that of Electric current and hence the sensor dynamics are also reduced. Despite the advantages the Coulomb counting method is seldom used in larger applications like EVs or Grid storage applications. The reason for this is the uncertainty associated with various parameters. The current ‘I(t)’ can never be measured to the required accuracy because of the presence of sensor noise, biasing current and other non-linearity associated. Further, the capacity and self-discharge rates vary with time as the battery ages. Also, the initial SOC is not known at all times. These disadvantages pose a serious problem for the implementation of Coulomb counting method. However various researches are focused on to modifying and even combining the Coulomb counting method with other methods[14].

B. Open Circuit Voltage (OCV) method

The Open Circuit Voltage (OCV) method used to estimate SOC relies on the fact that the Open circuit voltage of Li-ion cells is directly correlated to the SOC of the cell under given temperature and rate of discharge. This has been experimentally well-established fact and forms the basis of this method. For a typical NMC type of Li-ion cell at 25^o Celsius, the open circuit voltage starts from 4.2V when the cell is fully charged (defined as 100% SOC) and reduces to about 3.2V when the cell is fully discharged (defined as 0% SOC) at 1C rate. The OCV method relies on experimental methods to obtain the required data for variation of OCV as SOC is varied for different cell chemistry at different temperature[9]. The data points obtained are then curve fitted using optimal techniques to obtain the characteristic curves for OCV vs. SOC.
OCV[t]=f(SOC[t])

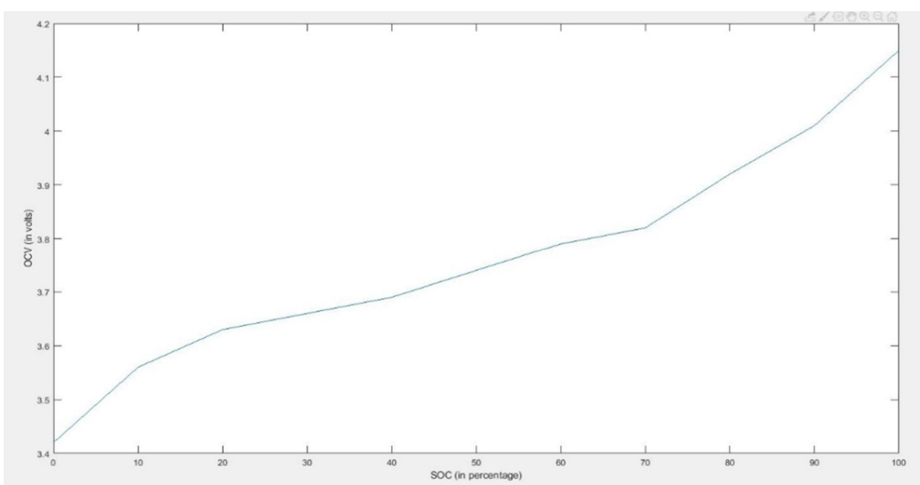

Fig. 1 The above plot shows the result of OCV variation with SOC for a NMC cell.

The advantage of the OCV method is its ease of implementation as the algorithm is simple. The data from the curves are stored in memory as Look up tables. The microprocessor in the BMS must just perform a look-up for the corresponding open circuit voltage it has measured from the cell to know the SOC. Although this seems easy theoretically, there are problems with implementation of OCV method in practice. One of the main reasons being that, the measured voltage is always the terminal voltage and not the OCV of the battery. Further, the OCV vs SOC curves for some Li-ion cell chemistry is so flat that the variation of 0.2V can correspond to 50% SOC variation. Thus, even a small error in OCV measurement can lead to significant errors in SOC estimation. Because of these shortcomings, OCV method is usually used with other methods.

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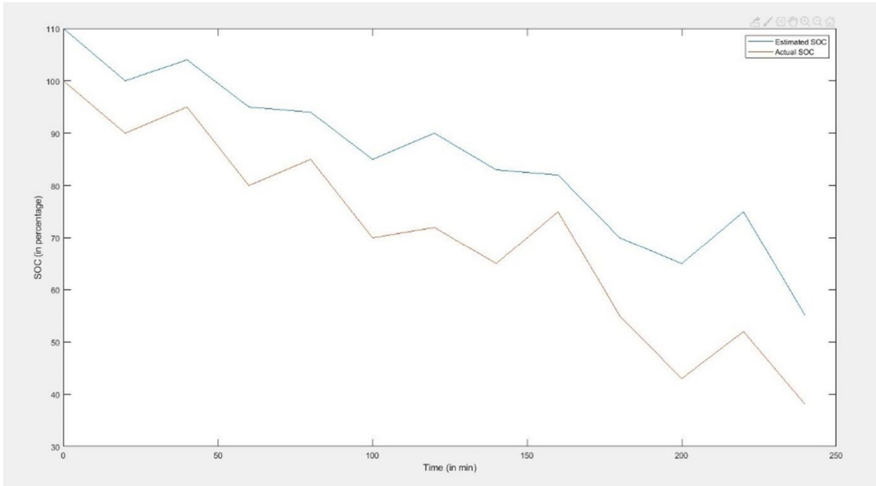

Fig. 2 The above plot shows the variation of SOC when the cell is subjected to test load profile. One plot shows the actual SOC variation of the cell. Another plot shows the SOC as estimated by OCV method.

C. Impedance & Internal Resistance method

This method tries to estimate the SOC based on the relationship between electrical parameters of the Lithium-ion cell like Internal resistance and impedance and its SOC. Like the OCV method, this method also uses experimental data to obtain the correlation between Internal resistance which is obtained from the Cell models like PNGV to SOC. Also, parameters like Impedance variation with SOC may also be used.

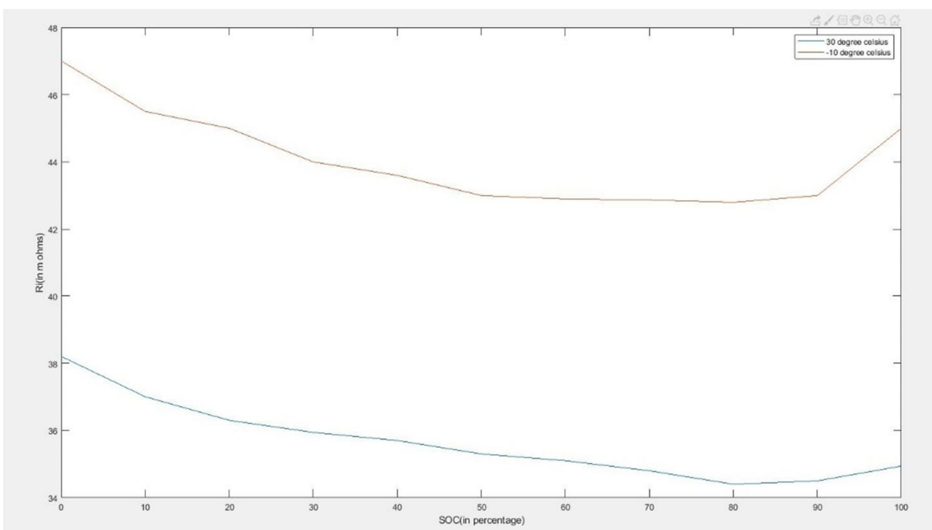

Fig. 3 The above plot shows the variation of Internal resistance of a NMC cell with SOC for two different temperatures.

Although this method seems relatively simple, it is difficult to implement in practice for two main reasons. The first one is that the variation of internal resistance with SOC is not static in nature and is more complicated. Hence internal resistance can't be used to estimate SOC. Further, even the Impedance method can't be used because of inability to obtain accurate impedance measurements because of external parameters like noise, temperature etc.

D. Equivalent circuit model (ECM) based SOC estimation

Equivalent circuit models use electrical-circuit analogs to define the behavior of Lithium-ion cell's voltage to variations in input current, temperature, cell cycle and other parameters. ECMs mainly use lumped circuit elements like Resistors, Capacitors & ideal voltage sources to model the electrical characteristics of the battery. A good model should be able to approximate the terminal voltage of a simulated battery with that of an actual battery under any current excitation. Various equivalent cell models have been developed to model the Lithium-ion battery.

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Models such as Rint model, Thevenin model are less complex in nature but are not accurate enough for Electric Vehicle applications. The main problem in these models arises because the characteristics of the Lithium-ion cell cannot be modeled completely by linear elements alone. There are dominant effects like Hysteresis which tends to change the terminal voltage of the battery depending on its history (i.e., whether it was charging or discharging in the immediate past). There also various secondary effects which require attention and can't be neglected while modeling. The Enhanced Self-Correcting (ESC) cell model provides a good approximation for the behavior of Lithium-ion cells and is widely used. The ESC cell model provides mathematical description of effects like hysteresis, Warburg impedance etc., to an acceptable degree of accuracy[5] [7]. The predicted voltage according to the ESC cell model converges to OCV plus hysteresis when the cell rests. The ESC model of a lithium-ion cell is shown below.

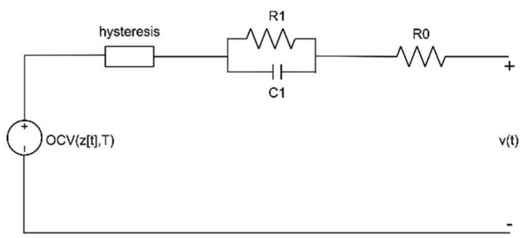

Fig. 4 The above figure shows the ESC cell model of a lithium ion cell.

The above model includes only a single RC pair. But it can be modified to include multiple parallel RC pairs to increase the accuracy of predicted voltage. The current through each RC pair branch (in case of multiple RC pairs) is given by:

$$i_R[k+1] = \begin{bmatrix} T_1 & 0 & \cdots \\ 0 & T_2 & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} i_R[k] + \begin{bmatrix} (1-T_1) \\ (1-T_2) \\ \vdots \end{bmatrix} i[k]$$

$$T_i = e^{(-t/R_i C_i)}$$

The above matrices are denoted as A_{RC} & B_{RC} respectively.
The hysteresis voltages are modeled using a nonlinear hysteresis element.
The state space description of the ESC model is given below.
The state equation is:

$$\begin{bmatrix} z[k+1] \\ i_R[k+1] \\ h[k] \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & A_{RC} & 0 \\ 0 & 0 & A_H[k] \end{bmatrix} \begin{bmatrix} z[k] \\ i_R[k] \\ h[k] \end{bmatrix} + \begin{bmatrix} -n*t/Q & 0 \\ B_{RC} & 0 \\ 0 & A_H[k]-1 \end{bmatrix} \begin{bmatrix} i[k] \\ sgn(i[k]) \end{bmatrix}$$

The output equation is:

$$v[k] = OCV(z[k],T) + M_o s[k] + Mh[k] - \sum_{k=0}^{n} R_i i_{Ri}[k] - R_o i[k]$$

where,
$i_R[k]$ represents current through resistor Ro at time 'k', h[k] represents hysteresis voltage at time 'k', z[k] represents SOC at time 'k', v[k] represents terminal voltage, M_o represents static hysteresis constant, M represents dynamic hysteresis constant, OCV(z[k],T[k]) represents OCV at a particular SOC and temperature, Q represents discharge capacity of cell, n represents coulombic efficiency, R_i & C_i are corresponding R C values of i^{th} branch, Ro is the resistance element in ESC cell model & $A_H[k]$ = exp(-abs(n*i[k]γt/Q)).
The static & dynamic parameters of the model can be obtained by experimental data. The values for Ro, hyst, RC pairs can be obtained by subjecting the cell to various test and obtaining the data from them. The cell is subjected to test profiles that represent the final application demands. Terminal voltage, current, temperature, accumulated ampere-hours are recorded regularly based on the sampling time. A good sampling time considering the cell dynamics would be once per second. The information obtained is then used to tune the parameters of the ESC cell model[8].

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After the static and dynamic parameters are determined, the cell model description is complete and can be used to make predictions. This can be used to determine the response of that Li-ion cell to a given stimulus. This method uses experimentally obtained OCV vs SOC curve along with the ESC model to estimate the SOC of the cell. The problem with the OCV method was that the measured voltage was not open circuit voltage but instead terminal voltage. This method tries to obtain the actual open circuit voltage from the measured terminal voltage of the cell using ESC cell model. An example of one such function from a simulation to determine the SOC of the cell for the measured terminal voltage is shown below without the complete description. The function ‘SOCfromOCVtemp ’takes three arguments – voltage, temperature and a structure called model which represents the model of Li-ion cell for which the test was conducted. It returns a value called ‘SOCest ’which is the calculated SOC for that particular temperature. For this method, we give the input to the function as “Terminal voltage + IR drop across internal resistance”. The reason is, this tries to to approximate the terminal voltage to the OCV of the cell by subtracting the voltage drop due to internal resistance. This gives the SOC estimation for that particular voltage. The example run is shown below.

v(t) + i(t)*Ro on “OCV vs SOC” curve

SOCest = SOCfromOCV(v+I*Ro,T,model);

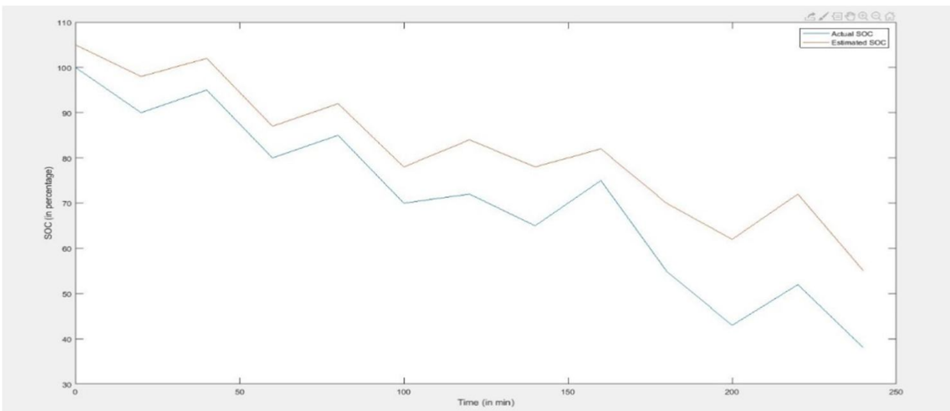

Fig. 5 The above plot shows the variation of SOC when the cell is subjected to test load profile. One plot shows the actual SOC variation of the cell. Another plot shows the SOC as estimated by using ESC cell model.

Although this method provides better results compared to the previous methods used, it still has its own drawbacks. The imperfections in the cell model, drifting of estimated cell parameters, complex nature of hysteresis voltage are a few reasons for its drawbacks. Hence this method can’t be used independently for SOC estimation. However, it provides a good starting point for other SOC estimation techniques that is used in practice today.

E. Using State estimators on ECM

The Modern control theory has many filtering techniques for state estimation like Kalman Filters etc. These techniques provide the required accuracy in spite of effects like hysteresis. Further, these techniques are very robust and hence they provide good results in spite of inaccuracies in the cell model, drifting of parameters and presence of noise. By using these filters along with the ESC model of the lithium-ion cell, we will be able to estimate not only SOC but even other internal states of the cell as well. These states play an important role in other functions of BMS like SOH estimation, power estimation etc. The model-based estimation technique with the additional use of filtering algorithms is showing the below figure.

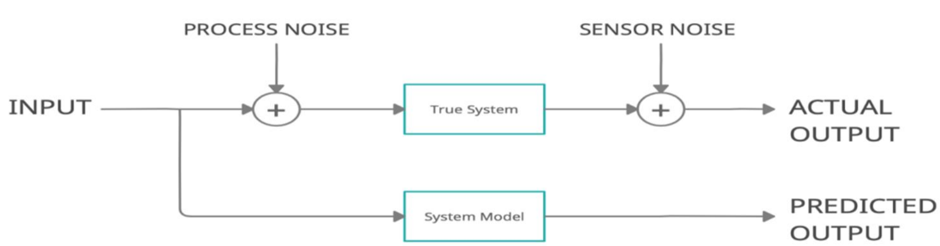

Fig. 6 The above figure shows the block diagram for using filters for SOC Estimation. variation of Internal resistance of a NMC cell with SOC for two different temperatures.

The figure shows two branches through which the input propagates. The first branch is the actual system i.e., the lithium-ion cell. This is designated as 'True System'. The bottom branch is the model of the lithium-ion cell which uses the ESC cell model. The input is the electrical current that it experiences and the output is the corresponding terminal voltage. The uncertainties in measurements due to sensor noise and process noise are also taken into account. The model-based state estimator works by propagating the same input through both the true system and the model of the system. The model produces a prediction of the output which is compared with the actual output. If the two are close, then the model's state estimate is proven to be good. If there is an error between the predicted and measured output, then the state estimate is not up to the mark. In that case, the error is used to make a better state estimate by using a feedback mechanism. This feedback mechanism compares the predicted and actual output and helps in making better decision. All the different types of filtering algorithms fit in a general framework known as Sequential Probabilistic Inference (SPI).
The method of Sequential probabilistic inference begins with a general Non-Linear state space model of the system:

$$x_k=f(x_{k-1},u_{k-1},w_{k-1})$$
$$y_k=h(x_k,u_k,v_k)$$

where, u_k is the measured input signal, x_k is the state of the model, w_k is process noise, v_k is sensor noise and y_k is the output from system.

It mainly consists of Two iterative steps:

1) A Prediction step where the optimal estimates of the output, y_k state x_k are predicted. An additional term called Error Covariance matrix is also generated.
2) A Correction step where the predicted output and actual output is used to obtain a final estimate of the state. The error covariance matrix is updated again at the end of this step.

All the filtering techniques discussed below are special cases of this general framework.

a) *Linear Kalman Filter Method:* The Linear Kalman Filter starts with a linear state space model of the lithium ion cell. In this method, the solution of Gaussian SPI is obtained and applied to a specific case where the system dynamics are assumed to be Linear. The Linear state space model of the lithium cell is taken to be:

$$x_k=Ax_{k-1}+Bu_{k-1}+w_{k-1}$$
$$y_k=Cx_k+Du_k+v_k$$

For this model, the Linear Kalman Filter method consists of 6 iterative steps. The first 3 steps are Prediction steps and the next 3 steps are Correction steps. The steps are summarized as:

Initialization step: $\hat{x}_0^+ \ \Sigma_{\tilde{x},0}^+$ [16]

Step 1a: $x_k=A_{k-1}\hat{x}_{k-1}^{+}+B_k u_{k-1}$

Step 1b: $\Sigma_{\tilde{x},k}^- = A_{k-1}\sum_{\tilde{x},k}^{+} A_{k-1}^T+\Sigma_{\tilde{w}}$

Step 1c: $y_k=C\hat{x}_k^-+Du_k$

Step 2a: $\Sigma_{\tilde{x},k}^+ = \Sigma_{\tilde{x},k}^- - L_k\,\Sigma_{\tilde{y},k}\,L_k^T$

Step 2b: $\hat{x}_k^+=\hat{x}_k^-+L_k(y_k-\hat{y}_k)$

Step 2c: $L_k=\Sigma_{\tilde{x},k}^- C_k^T\,[C_k\,\Sigma_{\tilde{x},k}^-\,C_k^T+\Sigma_{\tilde{v}}\,]^{-1}$

[16] Note on notations used:

- $\hat{x}_k^-$ indicates a quantity that is predicted.
- $\hat{x}_k^+$ indicates a quantity that has been estimated.
- Σ_{xy} indicates co-variance matrix between random variable x & y.

The advantage of the Linear Kalman Filter method is that it is robust produces accurate state estimates[10]. But the main shortcoming is that lithium-ion cell models are nonlinear in nature. Hence Linear Kalman Filter based methods are not used in practice.

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b) *Extended Kalman Filter Method:* The main shortcoming of the Linear Kalman Filter method was that it was applicable only to Linear systems whereas the lithium-ion cell has nonlinearity associated with it. The Extended Kalman Filter (EKF) method addresses this issue by approximating the nonlinear system by a linear time varying system. At every time step, the nonlinear system is modelled as a linear system with parameters that are varying. This linear time varying system is then applied to the Kalman filter. The linearised model is obtained using partial derivative and Taylor series expansion.

The Extended Kalman filter starts with a general nonlinear state space model of the lithium cell:

$$x_k=f(x_{k-1},u_{k-1},w_{k-1})$$
$$y_k=h(x_k,u_k,v_k)$$

For this model, the Extended Kalman Filter method consists of 6 iterative steps. The first 3 steps are Prediction steps and the next 3 steps are Correction steps. The steps are summarized as:

Initialization step:

Step 1a: $\hat{x}_k^- = f(x_{k-1}^+, u_{k-1}, \tilde{w}_{k-1})$

Step 1b: $\tilde{x}_k^- = (\hat{A}_{k-1}\tilde{x}_{k-1}^+ + \hat{B}_{k-1}\tilde{w}_{k-1})$

Step 1c: $\hat{y}_k = h(\hat{x}_k^-, u_k, \hat{v}_k)$

Step 2a: $L_k = \Sigma_{\tilde{x},k}^- \hat{C}_k^T [\hat{C}_k \Sigma_{\tilde{x},k}^- C_k^T + \hat{D}_k \Sigma_{\tilde{v}} \hat{D}_k^T]^{-1}$

Step 2b: $\hat{x}_k^+ = \hat{x}_k^- + L_k(y_k - \hat{y}_k)$

Step 2c: $\Sigma_{\tilde{x},k}^+ = \Sigma_{\tilde{x},k}^- C_k^T - L_k \Sigma_{\tilde{y}k} L_k^T$

where,

$\hat{A}_k = \frac{\partial f(x_k,u_k,w_k)}{\partial x_k} |@ x_k = \hat{x}_k^+$

$\hat{B}_k = \frac{\partial f(x_k,u_k,w_k)}{\partial w_k} |@ w_k = \hat{w}_k^+$

$\hat{C}_k = \frac{\partial h(x_k,u_k,w_k)}{\partial x_k} |@ x_k = \hat{x}_k^-$

$\hat{D}_k = \frac{\partial h(x_k,u_k,w_k)}{\partial v_k} |@ v_k = \hat{v}_k^-$

Although Extended Kalman Filter produces better results than Linear Kalman filter method it has its own shortcomings. One example would be when the system is highly nonlinear in nature. In such a case, the first order Taylor series can't accurately represent the system and this results in linearization error. The error starts accumulating when the voltage exceeds a certain limit which worsens the situation. However, there have been various reaches focused on modifications to this method such as Strong tracking cubature Extended Kalman Filter method (STCEKF) and others [10][12]. The Extended Kalman filter method is preferred mainly because of its less time-consuming nature and accuracy.

c) *Sigma Point Kalman Filter Method:* The Sigma Point Kalman Filter(SPKF) addresses the issue of non-linearity of the lithium ion cell models and provides an accurate SOC estimate. The SPKF approximates the nonlinear system by using statistical and numerical methods. Instead of linearization by using analytic methods as in the case of EKF, the SPKF method uses statistical linearization. The function is evaluated at some points and these evaluations are called samples.

The samples from the input probability density function (pdf) are denoted as' χ' and are called Input sigma points. These points are chosen so as to match the mean and covariance of these points with that of the input random variable to the nonlinear function. These points are then passed individually through the nonlinear function resulting in a set of output sigma points 'y'.

The generated sigma point set can be represented as:

$$\chi=\{\bar{x},\ \bar{x}+\gamma\sqrt{\mathrm{cov}(\tilde{x})},\ \bar{x}-\gamma\sqrt{\mathrm{cov}(\tilde{x})}\}$$

The weighted mean and covariance of these points which is same as that of the random variable 'χ' is given by:

$$\bar{x}=\sum_{i=0}^{p}\alpha_i^{(m)}\chi_i$$

&

$$\mathrm{cov}(\tilde{x})=\sum_{i=0}^{p}\alpha_i^{(c)}(\chi_i-\bar{x})(\chi_i-\bar{x})^T$$

where χ_i is the ith vector member of the set χ, and both $\alpha_i^{(m)}$ and $\alpha_i^{(c)}$ are real scalars where $\alpha_i^{(m)}$ and $\alpha_i^{(c)}$ must both sum to one. The $\alpha_i^{(m)}$ are weighting constants used when computing the mean and the $\alpha_i^{(c)}$ are weighting constants used when computing the covariance.

The weighting constants that are seen in the above equation can be tuned accordingly. Upon application of various numerical methods, various choices of these constants give rise to various methods. The two significant methods are Unscented Kalman Filter(UKF) and the central difference Kalman Filter (CDKF) [15]. The table highlights the choices of tuning parameters for these two methods.

Method	γ	$\alpha_0^{(m)}$	$\alpha_k^{(m)}$	$\alpha_0^{(c)}$	$\alpha_k^{(c)}$
UKF	$\sqrt{L+\gamma}$	$\frac{\lambda}{L+\lambda}$	$\frac{1}{2(L+\lambda)}$	$\frac{\lambda}{(L+\lambda)}+(1-\alpha^2+\beta)$	$\frac{1}{2(L+\lambda)}$
CDKF	h	$\frac{h^2-L}{h^2}$	$1/2h^2$	$\frac{h^2-L}{h^2}$	$1/2h^2$

$\lambda=\alpha^2(L+\kappa)$ with $(10^{-2}\leq\alpha\leq 1)$ & $\kappa\in(0,3-L)$.

$\beta=2$ & $h=\sqrt{3}$ for Gaussian rvs.

#TABLE paramteric#

After this step is completed, the SPKF algorithm starts with a general nonlinear state space model of lithium-ion cell.

$$x_k=f(x_{k-1},u_{k-1},w_{k-1})$$
$$y_k=h(x_k,u_k,v_k)$$

The next step is to obtain the new augmented matrices after obtaining sigma points.

$$x_a^k=\begin{bmatrix}x_k\\ w_k\\ v_{k+1}\end{bmatrix} \ \& \ \Sigma_{\tilde{x}k}^a=\begin{bmatrix}\Sigma_{\tilde{x}k} & 0 & 0\\ 0 & \Sigma_{\tilde{w}} & 0\\ 0 & 0 & \Sigma_{\tilde{v}}\end{bmatrix}$$

$$\chi_{k-1}^{a,+}=\{\hat{x}_{k-1}^{a,+},\ \hat{x}_{k-1}^{a,+}+\gamma\sqrt{\Sigma_{\tilde{x},k-1}^{a,+}},\ \hat{x}_{k-1}^{a,+}-\gamma\sqrt{\Sigma_{\tilde{x},k-1}^{a,+}},\ \}.$$

The SPKF starts the SOC estimation with the 6 iterative steps. They are as follows:

Step 1a: $\hat{x}_k^-=\sum_{i=0}^{p}\alpha_i^{(m)}\chi_{k,i}^{x,-}$

Step 1b: $\Sigma_{\tilde{x}k}^-=[\chi_k^{x,-}-\hat{x}_k^-][\mathrm{diag}(\alpha^{(c)})][\chi_k^{x,-}-\hat{x}_k^-]^T$

Step 1c: $y_k=\sum_{i=0}^{p}\alpha_i^{(m)}y_{k,i}$

Step 2a: $\Sigma_{\tilde{y},k}=\sum_{i=0}^{p}\alpha_i^{(c)}\left(y_{k,i}-\hat{y}_k\right)(y_{k,i}-\hat{y}_k)^T$; $L_k=\Sigma_{\tilde{x}\tilde{y},k}^-*\Sigma_{\tilde{y},k}^{-1}$

Step 2b: $\hat{x}_k^+=\hat{x}_k^-+L_k(y_k-\hat{y}_k)$

Step2c: $\Sigma_{\tilde{x},k}^+=\Sigma_{\tilde{x},k}^- - L_k\,\Sigma_{\tilde{y},k}\,L_k^T$

The SPKF algorithm is one of the most widely used SOC estimation algorithms for Li-ion batteries in EV sector. The SPKF method meets the high accuracy demands while being robust and having high confidence on its error bounds. The SPKF algorithms are used for state estimation by processors onboard the BMS in a wide range of EVs available today.

F. Other Notable Methods

Other notable methods like Particle filter method and Artificial neural network (ANN) method are also used for SOC estimation. Particle Filter method is based on Monte Carlo simulation technique to approximate the probability density function of random variable [6].

ANN method relies on self-learning techniques and adaptability to a nonlinear model [11]. This method uses data set to train the estimators. There will be at least three layers used here. It can estimate the state even for a highly nonlinear system. But it has a disadvantage of very high computation power & large memory requirement.

Another method which is in development is the usage of Fuzzy Logic for SOC estimation. Further, Adaptive neuro-fuzzy inference systems (ANFIS) methods are proposed for SOC estimation. All these methods have a disadvantage because of high computational power requirement and large memory requirement which makes them difficult to be implemented onboard an EV.

IV. CONCLUSION

Lithium-ion batteries are a bottleneck in EV sector. Improvement in technologies related to lithium battery pack will naturally push the EV sector forward. SOC estimation is an important part of BMS and a challenging one too. SOC estimation is challenging since it has to be estimated indirectly by measuring output and other parameters. This task is complicated even more because of the nonlinear behavior of the lithium-ion cell characteristics. The demand for high accuracy, presence of noise and imperfect cell models only make things worse. This paper reviews various SOC estimation techniques that are used widely.

Coulomb Counting method was the very first estimation method that was introduced. This is a relatively easy method and relied on measurement of current in & out of the battery. But this couldn’t be implemented in practice because of the ambiguities associated with Capacity, sensor noise, parameter drifting and other factors. The techniques like OCV method, Internal resistance method are easy to implement and are less complex. They try to correlate the output voltage or some electrical parameter directly with the SOC since the parameter varies with variation is SOC of the cell. But these techniques are very inaccurate and sometimes produce extremely erroneous and unreliable SOC estimates. The main reason for their failure is not accounting for hysteresis and other secondary effects along with highly noise environment. Because of this, they are seldom used independently in practice.

The advent of modern techniques started with the development of ESC model of lithium-ion cells. This model was used in combination with OCV vs. SOC curves to obtain an estimate of SOC. This method was easy to implement as it performed a lookup from a LUT corresponding to the estimated OCV. Although it produced better results than the previous ones, it was still far from the accuracy needed for EV applications. The drawbacks in this method were due to hysteresis effects, inaccuracy in model, sensor noises and other factors. But this paved the way for other modern techniques. Modern Control techniques like Kalman Filter have been used for SOC estimation. In the methods like Linear Kalman Filter (LKF), Extended Kalman Filter (EKF), Sigma point Kalman Filter (SPKF) probabilistic state inference techniques are used on state space model obtained from ESC model of lithium-ion cells. The methods produce estimates that are more and more accurate as we move from LKF to EKF to SPKF. The SPKF method produces an estimate that is accurate enough for EV applications. Another advantage is that they can be implemented on an embedded system with limited resources. The final section talks about other techniques like Particle Filter method, ANN, Fuzzy Logic method. These techniques are still under development and they can’t be readily applied at this stage onboard an EV.

The SOC estimation algorithms are complex in nature and require significant computational powers for implementation. But the obtained accuracy justifies the cost. SOC estimation is required not only to know the remaining capacity of battery pack but it is also an input to State of Health (SOH) estimation, Range estimation and other important functions of BMS.

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