Electric Vehicle Battery Modelling Methods Based on State of Charge– Review

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Abstract

Battery behavior prognostic is an important concern in most of the applications especially in electric vehicles which are using lithium ion batteries. Battery performance estimation methods will improve the life span by preventing over-discharge and overcharge, yielding increased battery life. It allows the battery user to make out the available energy in the battery stack. Therefore an accurate, easy to use battery model should be established to estimate the battery parameters. In this paper five important lithium-ion battery models such as Empirical, Equivalent circuit, Electro chemical, Reduced-order and Data driven models are discussed based on the State of charge estimation and compared along with their advantages and disadvantages. Battery model parameters are obtained by using Electro-chemical Impedance Spectroscopy (EIS) test and the implementation details are presented.

Keywords: Battery model, Electric Vehicle (EV), Battery Management System (BMS), Lithium-ion (Li-ion) battery, State of Charge (SoC).
1 Introduction

In the recent years, Li-ion batteries are the most advanced energy storage device compared to other batteries due to their low self-discharge, high energy density, compactness, no memory effect and low maintenance. The cost of the Li-ion batteries are also declining which makes the lithium based batteries the best choice for electric vehicles application [1]. Due to these Li-ion batteries have drawn the attention of automobile makers and researchers to focus on various battery modeling.

For safe and efficient operation of the Li-ion battery stack exact calculation of battery SoC is important [2]. Battery SoC measurement during real-time is a challenging task [3] and more research is happening in this area. Many SoC methods are discussed and classified. Four important battery SoC estimation methods are classified as [4-7]: Coulomb counting based, Look-up table based, Data driven and Model based methods. Look up table method is based on the correlation between SoC and Open Circuit Voltage (OCV), it takes more time to measure the battery OCV. Since, the battery needs a lot of rest time to measure accurate OCV, it is only applicable to the research laboratory. Coulomb counting method measures SoC by integrating the battery current, its SoC measurement is inaccurate due to current measurement error. So, it’s opted to work with other methods, e.g. model based methods. Data driven methods are based on battery sample data. It can achieve better results based on their advanced high fidelity machine learning algorithm. Model based methods uses a set of non-linear equations and adaptive filters (Kalman filter, sliding mode observer) to find the battery internal state. Since the lithium ion batteries exhibit the nonlinear characteristics, choosing the accurate battery model is a difficult task [8]. The lithium ion model selection is based on the nature of the application and the system design [9]. This review paper emphasizes the data driven and model based approaches based on the current SoC estimation techniques.

This paper is structured as follows: The section 2 describes about the structure and working principle of lithium ion cell. Section 3, 4 explain about the detailed modeling methods of lithium ion cell and model based methods. Section 5 represents data driven models. Comparison of modeling methods are discussed in section 6. Battery testing methods to find out the parameters of the battery models are explained in section 7.
2 Lithium-ion Cell Structure

Fig. 1. Li-ion Cell Composition [10]

Fig. 1 shows the lithium ion cell composition. Each cell has four important components electrodes (Anode and Cathode), electrolyte and separator. For charging and discharging, reduction–oxidation process happens in the positive (cathode) and negative (anode) electrode in which the electrolyte is typically a lithium salt dissolved in an organic solvent. The separator is a porous membrane separating the anode and cathode electrically as well as symmetrically. It allows only Li+ ions to migrate inside the cell between electrodes [10].

During discharge the cell supplies current to the outside circuit. Oxidation takes place in the anode

\[ x \cdot Li \cdot C_6 \rightarrow x \cdot e^- + x \cdot Li^+ + x \cdot C_6 \]  

(1)

Reduction takes place in the cathode

\[ x \cdot e^- + Li_xCoO_2 + x \cdot Li^+ \rightarrow LiCoO_2 \]  

(2)

For example, if the anode is made from graphite and cathode is made from lithium cobalt oxide (LiCoO₂) during charging the Li-ion (Li⁺) moves from the positive electrode and reaches the negative electrode through the electrolyte. The same way electrons (e⁻) moves from positive electrode to the negative electrode through the outer circuit. The Li⁺ accumulates between the layers of graphite.

During discharge, the Li⁺ migrate from the negative electrode and reaches the positive electrode. When the cell is fully discharged all the Li-ions are stored in between the layers of Cobalt and Oxide ion. The lithium ion moves backward and forward between the electrodes as the battery discharges and charges.
3 Classification of Li-ion Battery Modeling

Battery Modeling is to understand the internal cell behavior mathematically with a simple set of equations. Fig.2 represents the various battery modeling methods based on the SoC measurement [11]. Data driven and model based approaches attempt to predict the battery performance and characteristics accurately with the help of complex algorithms with a set of battery data and mathematical equations by integrating several factors [12].

4 Model Based Methods

Model based methods are widely used to find out the SoC, terminal voltage and other battery parameters. It consists of a battery model and a parameter estimation algorithm. Input to the model is generally temperature, current and SoC. Based on the input, the model output voltage is measured and compared with the real battery data. Error in the model output is corrected by tuning the model parameters to obtain better performance.
4.1 Empirical Model

Empirical model also called as mathematical model or black box model, is a simplified model which uses the mathematical approach to obtain the output from the input parameter through transfer functions and not much concerned about the electrochemical phenomenon happening inside the cell. Empirical models are easy to configure and provide quick response, but accuracy is limited. To improve the accuracy it has to be combined with low level models [4]. The empirical models are classified as classical models, enhanced self-correcting model and zero-state hysteresis model.

4.1.1 Classical Model

Classical model is a simplified electrochemical model such as Nernst model, Unnewehr model, Shepherd model and Combination of all. Using simple set of mathematical and polynomial equations, the empirical model describes the non-linear response of the battery compared to other higher order complex battery models. Here, output voltage is expressed as a function of the battery current and the SoC.

The mathematical representation of the classical empirical models are listed in Table 1, where \( E(t) \) is the battery output voltage, \( E_0 \) is the OCV of the battery, \( R_a \) is the Ohmic resistance, \( K_1 \) - \( K_4 \) are constants used for curve fitting, \( i(t) \) is the battery current. Battery current is considered as positive for charging & negative for discharging. \( Q(t) \) represents battery SoC, time index is expressed as \( k \) and \( Y_k \) is the terminal voltage.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Model name</th>
<th>Model output Equation</th>
<th>Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Shepherd model</td>
<td>( E(t) = E_0 - R_a i(t) - \frac{K_1}{Q(t)} )</td>
<td>Continuous discharging real time applications</td>
</tr>
<tr>
<td>2</td>
<td>Unnewehr model</td>
<td>( E(t) = E_0 - R_a i(t) - K_2 Q(t) )</td>
<td>Simple mathematical battery model</td>
</tr>
<tr>
<td>3</td>
<td>Nernst model</td>
<td>( E(t) = E_0 - R_a i(t) + K_3 \ln(Q(t)) + K_4 \ln(1 - Q(t)) )</td>
<td>Best accurate model</td>
</tr>
<tr>
<td>4</td>
<td>Combined model</td>
<td>( Y_k = K_0 - R_i_k \frac{K_1}{Q_k} - K_2 Q_k + K_3 \ln(Q_k) + K_4 \ln(1 - Q_k) )</td>
<td>It includes all the above Characteristics</td>
</tr>
</tbody>
</table>
Based on the performance analysis study Nernst and Unnewehr model confirms better prediction than the Shepherd model. When the estimated terminal voltages of the three models are compared with the actual voltage of the battery Nernst model is reported as the best accurate model since it involves two more constants $K_3$ and $K_4$ to estimate the dynamically changing terminal voltage [13] accurately.

Classical battery models represented in Table 1 consists of voltage sources which is connected with the resistance to model different types of electrochemical batteries. SoC of the battery is considered as a state variable to avoid loop issues [14]. Conventional empirical models are not considering the hysteresis effect of the battery and hence the results are not accurate during the relaxation period [15]. This type of battery models can be easily implemented using dynamic simulation tools like MatLab/Simulink [16].

Combined Model combines Nernst model, Unnewehr model and Shepherd model. By considering additional parameters and chemical reaction happening inside the battery, performance of the combined model can be improved but at the same time implementation complexity is also increased.

Some alternate methods are implemented to improve the performance accuracy of the conventional combined empirical models. Modified empirical model is proposed by considering the discharge and the charge cycle of the battery separately using shepherd equation [17].

\[
V_{\text{dis}} = E_0 - K_{dr} \left( \frac{Q}{(Q-it)} \right) i^* - R_0 i - K_{dv} \left( \frac{Q}{(Q-it)} \right) it + e^t
\]

\[
V_{\text{ch}} = E_0 - K_{cr} \left( \frac{Q}{(it+\lambda Q)} \right) i^* - R_0 i - K_{cv} \left( \frac{Q}{(Q-it)} \right) it + e^t
\]

Where, $Q$ is battery SoC, $K_{cr}$, $K_{dr}$ are the polarization resistance coefficient at charge and discharge. $K_{cv}$, $K_{dv}$ are the polarization over voltage coefficient at charge and discharge. The $E_0$ term express the interconnection between the SoC and OCV. The filtered current ($i^*$) of the battery shows the dynamic behavior of the battery. Exponential term ($e^t$) emulates the hysteresis phenomenon of the battery. Third term ($R_0 i$) is added with respect to the polarization voltage. The temperature, batteries ageing, capacity fading and self-discharge effects are not considered in this model.

**4.1.2 Zero-State Hysteresis Model**

When the cell is permitted to take rest then the diffusion voltage $V_{oc}$ decays to zero and the model voltage ($V_i$) reaches to zero but this does not
happen in real time. Diffusion voltage change depends on time but the hysteresis voltage \( V_h \) depends on the battery SoC.

![Fig 3 Zero-state hysteresis model](image)

Fig.3 represents the circuit diagram of zero-state hysteresis model. The model equation is described as follows

\[
V_t = V_{oc} (Z_k) - I_k R_0 - M h_k
\]

(5)

Where, \( Z_k \) describes state of charge, \( M \) is a constant coefficient describing the hysteresis level and \( h_k \) describes charging or discharging hysteresis effect. In addition to dynamic hysteresis voltage variation the instantaneous hysteresis voltage variation should also be considered for modeling. The model equation combing the dynamic and instantaneous hysteresis are expressed as follows

\[
V_t = V_{oc} (Z_k) - I_k R_0 - S_k M - M h_k
\]

(6)

Where, \( S_k \) describes the symbol of the current based on charging and discharging.

### 4.1.3. Enhanced Self-Correcting Model

It includes OCV, hysteresis, internal resistance and single parallel RC pair. It can contain more number of RC pairs and all the model parameters should be positive. It describes all dynamic effects.
Fig. 4. ESC model

Fig. 4. shows the circuit diagram of Enhanced self-correcting model. The model equation described as below

$$V_t = V_{oc}(Z_k) - I_k R_0 + S_k M + M h_k - \sum R_j i_{R_j}$$  \hspace{1cm} (7)

4.2. Equivalent Circuit Model (ECM)

The next important battery model is an equivalent-circuit model. EC models are also called as abstract model or grey box model. It’s a widely used battery model for electric vehicle battery management system [18-23]. It’s an alternate way of representing the physical entity. It replaces the complex electrochemical process happening inside the battery to equivalent simple electrical circuit, but it needs look up tables to match with the experimental data. For better accuracy of this model the capacity fading, temperature and aging factor of the battery should be considered.

ECMs are the extensively used battery models for the EV BMS to estimate the dynamic battery characteristics. In order to find out the OCV which is a function of SoC, a cell is charged and discharged to find the battery SoC.

$$SoC = SoC_0 - \frac{\eta}{C} \int I(t) dt$$ \hspace{1cm} (8)

SoC is calculated from equation (8), SoC_0 describes the initial value of SoC, I (t) represents the battery current in Ampere, C describes the total capacity at room temperature, \( \eta \) is Coulomb efficiency usually it’s close to 1 for lithium ion batteries.

EC Model consists of a DC voltage source, resistor-capacitor pair and an internal resistor, which links the input and the output parameters. Compared to mathematical models, EC Models are able to give better insight about the battery and describe the charge and kinetic mass transfer.
characteristics. The Partnership for a New Generation of Vehicles (PNGV) model is now widely used in EV studies.

The choice of the ECM is greatly based on the battery cell chemistry. So there is no standard method for all the cells and at the same time the model has to apply appropriate approach for the estimation of the battery parameter. The Fig.5 represents the individual components of the battery cell.

![Equivalent circuit elements representing cell components](image)

In the ECM, the resistor indicates the internal resistance of the electrolyte; electrodes, separator and the current collectors etc. The parallel RC network with different time constants reflects the double layer, charge transfer effect and as well as diffusion process taking place inside the electrolyte and electrodes. The Thevenin model, Rint model, PNGV model is common in the ECMs literature.

### 4.2.1 Rint Model

It is a basic ECM and it reflects only the steady-state behavior of the battery as shown in Fig.6. If the requirement is not concerned about dynamic characterization of the battery then this model is preferred. The battery OCV is derived from the battery SoC.

![Rint Model](image)
The model voltage is expressed as follows

\[ V_t = V_{oc} - I_b R_0 \]  \hspace{1cm} (9)

\( V_t \) refers to the output voltage, \( V_{oc} \) describes the OCV, \( I_b \) represents the battery discharge current and \( R_0 \) indicates the battery internal resistance.

### 4.2.2 Thevenin Model

Thevenin model is also called as resistor-capacitor ECM. The dynamic behavior of the battery is not taken care by the Rint model. To overcome the disadvantage of Rint model, this model uses a RC network along with internal resistance. The RC network is added to characterize the transient behavior of the battery. The value of the RC pair can be determined from hybrid pulse power characterization test (HPPC). The number of RC branches vary based on the type of application.

The output voltage equation of the model which is described in Fig.7 is expressed as follows

\[ V_t = V_{oc} - I_b R_0 - V_1 \]  \hspace{1cm} (10)

\( V_1 \) refers to voltage drop across the parallel RC, \( C_1 \) indicates the double layer capacitance and \( R_1 \) indicates the charge transfer resistance.

### Table 2 Different application of ECM [25]

<table>
<thead>
<tr>
<th>S.No</th>
<th>Model name</th>
<th>Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Simple model</td>
<td>High voltage grid integration</td>
</tr>
<tr>
<td>2</td>
<td>1RC,2RC</td>
<td>Smart grid integration</td>
</tr>
<tr>
<td>3</td>
<td>3RC,4RC,5RC,1RCPE</td>
<td>E-mobility</td>
</tr>
<tr>
<td>4</td>
<td>2RCPE,3RCPE</td>
<td>Diagnosis</td>
</tr>
</tbody>
</table>

Table 2 describes the different application of ECMs. The single R model is not suitable to describe the transient characteristics of the cell but it
explains the static characteristics. It is applicable for grid integration. One RC model explains the charge transfer characteristics while the two RC includes the diffusion process too. Both are suitable for smart grid integration applications. Three RC and higher order RC models along with Constant Phase changing Element (CPE) are used in electric mobility for better accuracy. RC models along with CPE are used in diagnosis tools.

4.2.3 PNGV Model

PNGV model is obtained by adding the additional capacitance in the Thevenin model. The capacitance describes the changes occurring in the electromotive force. Fig.8 represents the circuit diagram of PNGV model.

![PNGV Model](image)

The PNGV model output voltage is expressed as follows

\[ V_t = V_{oc} - I_b \cdot R_0 \cdot V_1 \cdot V_{bc} \]  

(11)

\( V_{bc} \) refers drop across the bulk capacitance. The PNGV model shows better accuracy compare to other two models. By adding more RC network in the model the accuracy increases but at the same time it increases the circuit complexity also. For Li-ion battery SoC measurement, ECMs with one RC and two RC networks are mostly used.

4.2.4. Improved Models

4.2.4.1 DP model

An improved Thevenin Model [28] is obtained by adding one more RC network to Thevenin. \( R_{ep}, C_{ep} \) indicate the electrochemical polarization resistance, capacitance and \( R_{cp}, C_{cp} \) indicate the concentration polarization resistance and capacitance are used to explain the dynamic behavior during discharging or charging as shown in Fig.9.
4.2.4.2 Extended Thevenin model

In the extended Thevenin Model as discussed in section 4.2.2, more RC networks are added to increase the accuracy of the model [27] such as

- 1RC model
- 2RC model
- 3RC model

![Fig.9 DP Model](image)

![Fig.10 Extended Thevenin Model](image)
The 1RC model describes the charge transfer characteristics of the electrolyte, solid electrolyte interface and electrodes. Diffusion process which takes place in the low frequency area is represented by the 2RC model. Diffusion as well as charge transfer characteristics are considered in the 3RC model. Three RC model is accurate compared to other two models.

![Fig.10.](image)

Table 3 shows the different equivalent circuit models and their characteristic equations.

<table>
<thead>
<tr>
<th>S.No</th>
<th>Equivalent Circuit Models</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Rint Model</td>
<td>$V_t = V_{oc} - I_b R_0$</td>
</tr>
<tr>
<td>2</td>
<td>Thevenin Model</td>
<td>$\frac{dV_t}{dt} = \left( \frac{I_b}{C_1} \right) - \left( \frac{V_1}{R_1 C_1} \right)$ $V_t = V_{oc} - I_b R_0 - V_1 - V_{bc}$</td>
</tr>
<tr>
<td>3</td>
<td>PNGV Model</td>
<td>$\frac{dV_t}{dt} = \left( \frac{I_b}{C_1} \right) - \left( \frac{V_1}{R_1 C_1} \right)$ $V_t = V_{oc} - I_b R_0 - V_1 - V_{bc}$</td>
</tr>
<tr>
<td>4</td>
<td>DP Model</td>
<td>$\frac{dV_{ep}}{dt} = -\left( \frac{V_{ep}}{R_{ep} C_{ep}} \right) + \left( \frac{I_b}{C_{ep}} \right)$ $\frac{dV_{cp}}{dt} = -\left( \frac{V_{cp}}{R_{cp} C_{cp}} \right) + \left( \frac{I_b}{C_{cp}} \right)$</td>
</tr>
<tr>
<td>5</td>
<td>Extended Thevenin Model</td>
<td>$\frac{dV_t}{dt} = -\left( \frac{V_1}{R_1 C_1} \right) + \left( \frac{I_b}{C_1} \right)$ $\frac{dV_n}{dt} = -\left( \frac{V_n}{R_n C_n} \right) + \left( \frac{I_b}{C_n} \right)$ $V_t = V_{oc} - V_1 - V_2 - \ldots - V_n - I_b R_0$</td>
</tr>
</tbody>
</table>

The 1RC model describes the charge transfer characteristics of the electrolyte, solid electrolyte interface and electrodes. Diffusion process which takes place in the low frequency area is represented by the 2RC model. Diffusion as well as charge transfer characteristics are considered in the 3RC model. Three RC model is accurate compared to other two models. Fig.10. shows the extended Thevenin model for n number of parallel RC pairs. Table 3 shows the different equivalent circuit models and their characteristic equations.

### 4.2.5 Comprehensive Model (Aging Model)

The Comprehensive model [29] is also called as “run time” based model. The battery self-discharge and capacity fade is considered in this model. The circuit consists of two parts. First part captures the battery degradation over cycling and calendar aging and the second part simulates the battery dynamic behavior. The capacity and run time of the battery is
modeled as a controlled current source and the voltage controlled source represents the OCV predicted from the SoC. In the second comprehensive model [30] a resistance with a capacity fade is added to find out the aging and remaining useful life of the battery.

![Comprehensive-Model 1](image1)

**Fig.11. Comprehensive-Model 1**

![Comprehensive-Model 2](image2)

**Fig.12. Comprehensive-Model 2**

<table>
<thead>
<tr>
<th>Model</th>
<th>Polarization Characteristics</th>
<th>Self-discharge</th>
<th>Capacity-fade</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rint</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Thevenin</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>PNGV</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>DP</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Extended Thevenin</td>
<td>✓</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Comprehensive-1</td>
<td>✓</td>
<td>✓</td>
<td>X</td>
</tr>
<tr>
<td>Comprehensive-2</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
</tbody>
</table>
Polarization characteristics are included in all the battery models. Comprehensive model 2 efficiently covers all the dynamic characteristics of a battery throughout its entire life. Table 3 explains about the different equivalent circuit models and their key influence factor.

In this paper [31], more than ten battery models including the mathematical and Electrical circuit model with multiple RC pairs are compared based on the modeling accuracy. It highlights that 1RC ECM is found to be the best applicable battery model for Li-NMC battery and 1RC model with one state hysteresis is the appropriate model for the LiFePO₄ battery.

The battery output error is reduced in the 2RC model compared to the 1RC model under steady state as well as dynamic discharge state, but not giving significant improvement. Therefore, 1RC model is the preferred model for portable consumer electronics. However, for precise applications such as electric vehicles and aerospace, the 2RC model could be the ideal choice [32]. For sensitive medical diagnostics more RC networks are added to predict the battery behavior exactly.

4.3 Electrochemical model

Electrochemical models also called as white box models or physical models, are used to acquire the transient behavior of the cells to achieve high accuracies and to describe complex electrochemical process happening inside the cell. Detailed key features of the battery chemical process are useful for battery designers but, it’s difficult to use this model for practical applications. Electrochemical models are based on the following laws

- Ohm’s law; it takes care of the potential distribution in the positive and negative electrode.
- Fick’s law, it includes the lithium ion material balancing in an active particle.
- Butler–Volmer equation, explains about the flux which exists at the boundary between the electrolyte and electrodes called as pore-wall flux.
- Faraday’s law which relates the pore wall flux with the deviation of the current flow in the electrolyte.

\[
\varphi_{i=n}(t) = \frac{i(t)}{f_{sn}} , \quad \varphi_{i=p}(t) = -\frac{i(t)}{f_{sp}}
\] (12)

The above equation is used to find out the pore wall flux where, \( i = n \) describes the negative electrodes and \( i = p \) describes the positive electrode. No flux in the middle portion of the particle, e.g. flux is zero in the separator.

Electrochemical models are classified as the Single Particle Model (SPM), Pseudo-2D model [33], the First principle model and the Quasi three...
dimensional full order physical models. The pseudo-2D model is based on [34-36] porous electrode theory. One of the important aspects of pseudo-2D model is that it analyses the battery mechanism. It considers the electrode as a multi particle, but SPM considers it as a single particle. The SPM and P2D models are very popular compared to other models [37-43]. Fig.13. shows P2D schematic model with the anode, cathode and separator.

![Fig.13 P2D schematic model with the anode, cathode and separator [44]](image.png)

P2D model includes solid phase diffusion, electrolyte and Butler-Volmer kinetics. The main drawback of this model is that, it consumes more time for simulation process as it contains lot of non-linear differential equations. So computationally this model is not an efficient model for large battery packs. It is not suitable for BMS applications. To overcome the drawbacks of this model, researchers prefer the SPM which is represented in Fig.14.

From the lithium ion concentration profile the SPM model can calculate the voltage drop in the electrolyte to increase the accuracy and calculates the battery SoC with minimum calculation error [46-48]. SPM accounts for solid, electrolyte concentration and thermal constraints. It considers different particle chemical reaction which is happening inside the positive and negative electrode as a single spherical particle. It explains the movement of the lithium ions inside a solid particle in the easiest way while comparing with the P2D model. Though the model is simplified, the estimation process is still time consuming and estimation accuracy is not up to the mark under varying working scenarios.
The first principle model is used to simulate the capacity fade of the battery under the constant current constant voltage (CC-CV) charging. The quasi three dimensional full order physical models represent the various chemical, physical and electrochemical processes happening inside the cell during the rest period and operating conditions.

### 4.4 Reduced Order Model

Simplified reduced order model [49] is a derivative of electrochemical model by considering with additional assumptions. An average battery model is made by ignoring the concentration distribution and diffusion inside the electrode material considered. It is suitable for control system based applications [50]. By assuming electrolyte material concentration as a constant, the model can be simplified but due to assumption there is a loss of information compared to the complete physical model. Nevertheless, it is the most preferred model for voltage estimation and SoC measurement.

### 5 Data-Driven Models

The most critical part of electric vehicle BMS is an accurate measurement of the battery SoC. Especially batteries like Li-ion overcharge and over discharge will reduce the battery lifespan and induce safety issues; sometimes it may harm the battery permanently. Thus, a data driven model is used for improving the accuracy of the SoC estimation. Compare to other types of battery chemistry the Li-ion battery is a highly complicated electrochemical structure, its performance vary with battery aging. It is a challenging task to find out the exact battery SoC using classical battery models.
Data-driven models are also called as black box models. Data-driven methods consider the battery current, voltage, temperature and SoC to develop a controller and based on that it estimates the system behavior which does not require a precise system model. This control approach can provide great benefit in the below scenarios [51]:

- The mathematical model of the system is not known
- The uncertainties happening in the system is high;
- The control system which cannot be modeled by using empirical set of equations
- The system which is not suitable for design and analysis

The fuzzy controller [52, 53], the support vector machine [54] and the neural network [55, 56] algorithms are used by the black box model. Statistical data is very useful for practical system modeling. Reference [57] uses the neural logic to build the battery model estimator to calculate SoC, which considers temperature, current and SoC as input and output is the battery voltage. Modeling accuracy is very high and can solve non-linear equations efficiently.

![Data-driven model](image)

**Fig.15** Data-driven model [6]

The data driven model can be combined with the model based method to achieve a superior data model. The model real time behavior will enhance
the controller performance. The data-driven model in Fig. 15 shows the relationship between the input and the output voltage.

6 Comparison of the Battery Modeling Methods

Based on the discussion in the previous sections, each method has its own advantages and the performance of the modeling methods are mainly based on the environmental condition, operating temperature, battery ageing and different SoC operating ranges. The accuracy of the same battery model under various SoC range is analyzed in [58] and the result shows that the battery models are sensitive for the above operating parameters especially in the electric vehicle application the pack contains large number of series and parallel connected cells and this in turn spreads the difference across an individual cell [59]. The battery stack level current and voltage is used to measure the SoC of the battery [60] but it cannot ensure in terms of the safety perspective. Alternate techniques for pack level SoC measurement is calculating the cell level SoC first then calculating the pack level SoC. It gives better accuracy but complexity is more and not applicable Electric vehicle BMS. Comparisons of modeling methods are presented in Table 4.

<table>
<thead>
<tr>
<th>Battery Models</th>
<th>Mathematical Model</th>
<th>ECM</th>
<th>Physical Model</th>
<th>Reduced order Model</th>
<th>Data-driven Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accuracy</td>
<td>Low accuracy</td>
<td>Medium Accuracy</td>
<td>Very High Accuracy</td>
<td>High Accuracy</td>
<td>High Accuracy</td>
</tr>
<tr>
<td>Voltage measurement</td>
<td>Limited capability in the terminal voltage estimation</td>
<td>Parameter estimation is complex for voltage measurement</td>
<td>Very complex and time consuming</td>
<td>Easy to do voltage measurement</td>
<td>Tedious data collection process</td>
</tr>
<tr>
<td>Physical interpretability</td>
<td>Low</td>
<td>Limited</td>
<td>High</td>
<td>Medium</td>
<td>Medium</td>
</tr>
<tr>
<td>Time</td>
<td>Simple and low time consuming</td>
<td>Simple and Easily understood so medium time consuming</td>
<td>Time consuming due to accurate voltage calculation</td>
<td>Average time consumption</td>
<td>Less time consuming as prior battery knowledge is not required</td>
</tr>
<tr>
<td>Computational Complexity</td>
<td>Low</td>
<td>Medium to low</td>
<td>High</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Configuration Effort</td>
<td>Low</td>
<td>Medium</td>
<td>High</td>
<td>Medium</td>
<td>High</td>
</tr>
<tr>
<td>Application</td>
<td>All energy storage system</td>
<td>Real-time monitoring and BMS</td>
<td>Battery system design stage &amp; diagnosis</td>
<td>SoC estimation, Control application</td>
<td>Electric vehicle, Hybrid electric vehicle</td>
</tr>
</tbody>
</table>
Electrochemical model is the base model for the entire battery model. By simplifying the electrochemical model the empirical model is obtained. Chemical process happening inside the battery is replaced by means of circuit component in the equivalent circuit. Data-driven model expresses the electrochemical characteristics by high accuracy data analysis.

The model should be as simple as possible for real time applications. For on line estimation the equivalent circuit model is more reliable and for high precision SoC measurement artificial neural network and adaptive filter based models are the perfect one. An electrochemical model explains the charge transfer between the two electrodes and reveals the electrochemical phenomenon, but it is not fit for online estimations due to high complexity.

SoC accuracy is based on how accurate the model is and if the accuracy is high then the model complexity is also high. So always there is a tradeoff between model accuracy and simplicity as shown in the table 5. Performance accuracy is improved by considering the following

- Battery system variables are modeled as a function of battery current, temperature and SoC.
- OCV and hysteresis are modeled as a function of temperature and SOC.
- RC network are modeled at different state of charge and temperatures
- Aging effects are included in the model

**Table 5 Battery models**

<table>
<thead>
<tr>
<th>Models</th>
<th>Merits</th>
<th>Demerits</th>
<th>Papers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mathematical Model</td>
<td>Simple and less time consumption</td>
<td>Low accuracy</td>
<td>[4,13-17, 26, 61]</td>
</tr>
<tr>
<td>Equivalent circuit model</td>
<td>Instinctive to be implemented and simple</td>
<td>Medium accuracy</td>
<td>[18-32, 62-65]</td>
</tr>
<tr>
<td>Electrochemical model</td>
<td>Very high accuracy</td>
<td>Complex and time consuming</td>
<td>[33-48, 66 ]</td>
</tr>
<tr>
<td>Reduced order model</td>
<td>Less computational cost</td>
<td>Not an accurate model because of assumptions</td>
<td>[49,50, 67]</td>
</tr>
<tr>
<td>Data driven model</td>
<td>Less time consumption and high accuracy</td>
<td>High complexity</td>
<td>[51-57, 68-78]</td>
</tr>
</tbody>
</table>
7 Battery Testing

7.1 Constant – Current Charge or Discharge Test

A simple battery test is done on a cell or a battery which is a constant-current charge/discharge test, where all cells are charged and discharged to and from 0% and 100% SoC at a constant current of 0.7A. Then the OCV ($V_{OC}$) of the battery is obtained. 18650 Li-ion cells are used for the test. From this test, it is possible to measure the simple model parameters like OCV and internal resistance of the battery which is represented in Fig.16 and Fig.17.

![Fig.16 SoC Vs OCV](image1)

![Fig.17 SoC Vs R0](image2)
7.2 EIS Test

EIS test is a non-invasive, high efficient technique to analyze the battery behavior and to find the battery parameters. The impedance studies are used to analyze the system variables with respect to current, SoC and operating temperature. Based on this, the State of health (SoH) and aging factor of the battery can be obtained at various working scenarios [79-84].

The EIS test applies a small sinusoidal signal to measure the system current, voltage for the given input amplitude and phase by finding out the impedance of the system while repeating for the range of frequencies which is continued until the cell is empty.

\[ \Delta V = V_{amp} \sin(2\pi f t) \quad (13) \]
\[ \Delta I = i_{amp} \sin(2\pi f t - \theta) \quad (14) \]
\[ Z = \frac{\Delta V}{\Delta I} (e^{i\theta}) \quad (15) \]

From the EIS measurement the impedance variation is compared with the reference cell to untested new cell impedance. The measurement is done at ambient temperature or calendar cycling temperature for all SoC or selected SoC range. EIS test was performed mostly under potentiostatic mode and conducted in a periodic manner with a periodicity of 30 minutes interval to ensure the cell reaches SoC level for each repetition of the test.

EIS test is conducted for 18650, 2200mAh, 4.2 V Li-ion cell by applying 3mV sinusoidal voltage under potentiostatic mode at 20ºC for the frequency range 1mHz to 100kHz. From the EIS data, the Nyquist plots are drawn for different SoC ranges.

Nyquist Plot (R, C and L behavior)

Fig.18 100% SoC

Fig.19 90% SoC
Electric Vehicle Battery Modelling Methods Based on State of Charge—Review

Fig. 20 80% SoC

Fig. 21 70% SoC

Fig. 22 60% SoC
Fig. 23 50% SoC

Fig. 24 40% SoC

Fig. 25 30% SoC
Fig. 18 to Fig. 28 shows the Nyquist plot of 100% to 0% SoC curves. The Nyquist plots show the resistive, inductive and capacitive behaviors of the battery cell considered at different SoC for the analysis. It shows the real part of the impedance (resistance on the X-Axis) and the imaginary part of the impedance (capacitance on the Y-Axis) at different SoC. The negative value in the impedance curve indicates the battery inductance.
Nyquist Plot (R and C behavior)

Fig. 29 100% SoC

Fig. 30 90% SoC

Fig. 31 80% SoC
Electric Vehicle Battery Modelling Methods Based on State of Charge – Review

**Fig. 32** 70% SoC

**Fig. 33** 60% SoC

**Fig. 34** 50% SoC
Fig. 35 40% SoC

Fig. 36 30% SoC

Fig. 37 20% SoC
The Nyquist plots shown in the Fig.29 to Fig.39 consider only the resistance and capacitance features of the battery at different SoC. The inductive part is not considered as it has negligible effect on the battery modeling.

The semi circles in the plot illustrate the behavior of RC model rather typical anode-cathode representation, as the cathode and anode impedance are not differentiated in the commercially available Li-Ion cells. The L represents the cable inductance; $R_0$ explains the internal resistance of the battery, $R_1$ and $R_2$ describe charge transfer resistance which occurs in both the electrodes, $C_1$ represents the capacitance of the electrode which is modeled through constant phase changing element, $Z_w$ describes the Warberg impedance which is related to the diffusion process [85] is represented in Fig.40. Using Nyquist plot the equivalent circuit parameters at different SoC and temperature can be measured by using the curve fitting algorithm.

The impedance variations are observed from 0% to 100% SoC as shown in the Nyquist plots (figures 18-39). So the impedance of the battery cell
varies based on the SoC. EIS is an accurate analytical technique for measuring critical battery parameters [57], including: SoC, SoH, Battery Ageing, temperature and internal faults.

8 Conclusion

Battery modeling is one of the fundamental processes to obtain accurate battery state analysis. The battery SoC can be influenced by various internal and external factors, and the battery SoC estimation techniques vary based on the application (Energy Storage System, EV and Hybrid EV). The modeling methods discussed in this paper is efficient and reliable for an application under certain operating conditions. Hence, the selection of the right model is based on the type of application and the designer choice and this paper helps in selection of a better model for a particular scenario. The parameters for the selected battery modeling methods can be obtained from constant discharge current tests, EIS test as discussed in section 7. This paper also presents the state of art techniques in battery modeling and testing methods available. The Li-ion battery ECM feasibility is considered in the analysis, model parameters are successfully derived from the EIS test.

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References


[38] H. Fang et al , “Adaptive estimation of state of charge for lithium-ion batteries”, American Control Conference (ACC), 2013.


Biographies

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